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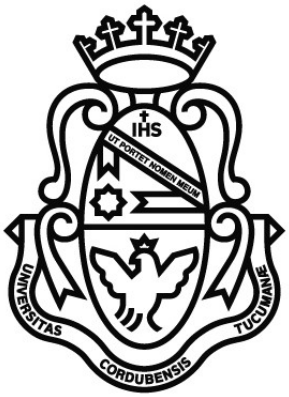


Doctoral Thesis

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# A Study on Semi-Supervised Methods for Spanish Verb Sense Disambiguation

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"*The aim of a PhD's to ensure that no one, including your advisor, understands what you're doing after the first couple of years.*"

China Miéville

"*There is no knowledge that is not power.*"

Ralph Waldo Emerson

# Abstract

This thesis explores the use of *semi-supervised learning techniques for Spanish verb sense disambiguation*. The objective is to study how can information from unlabeled sources help a classifier trained from a small labeled resource.

Word sense disambiguation is a crucial task for many applications, like machine translation or information extraction. However, it is still an open problem, specially verb sense disambiguation, due to the inherent complexity of verb senses. This, plus the fact that Spanish is a language with less resources than English, makes Spanish verb sense disambiguation an interesting area of study to contribute.

First I explore of purely supervised models to obtain a thorough understanding of how they work and what are their weaknesses. I find that the main shortcomings of the supervised approach are lack of coverage and tendency to overfit, as I explain in the corresponding chapter. I try to overcome these problems with different semi-supervised techniques.

I continue this work by exploring the use of *word embeddings* as unsupervised representations within supervised classifiers. This approach is known as *disjoint semi-supervised learning*: an unsupervised technique is used prior to a supervised one to aid the latter. Word embeddings certainly help to overcome lack of coverage and tendency to overfit, but at the expense of losing some performance in other aspects, like accuracy or F1-score.

I continue with the exploration self-learning, a *joint semi-supervised learning* algorithm that uses a supervised classifier, trained on an initial labeled dataset, to select instances from a pool of unlabeled data. Using some measure of certainty, it annotates those unlabeled examples for which the algorithm has the highest confidence and uses them to expand the labeled data to re-train the supervised classifier. I found that self-learning suffers strongly from unbalanced datasets. It amplifies the bias toward the most frequent class, so the expected increase in coverage by adding new examples to training is shaded because decision boundaries between classes are blurred.

Complementary to self-learning, I explore *active learning*. This approach uses a supervised model to select instances taken from a pool of unlabeled data, based on the impact these will have in the model, and gives them to a human expert to annotate. I show that information obtained via active learning, although little in comparison, can outperform the self-learning approach.

Finally, I explore *ladder networks*, a neural network which minimizes a combined cost function. This cost function is a sum of a supervised cost function and an unsupervised cost function, which helps to regularize the final model, and thus overcomes the tendency to overfit of supervised models. Also, the method's performance is shown

to be comparable or better to the rest of methods presented on this thesis, making the ladder network an interesting candidate for semi-supervised learning.

Español

Esta tesis explora el uso de *técnicas semi-supervisadas para la desambiguación de sentidos verbales del español*. El objetivo es estudiar cómo la información obtenida de distintas fuentes no anotadas puede ayudar a un clasificador entrenado desde un recurso anotado pequeño.

La desambiguación de sentidos de palabras es una tarea crucial para muchas aplicaciones, como la traducción automática o la extracción de información. Sin embargo, todavía es un problema abierto, especialmente la desambiguación de sentidos verbales, debido a la complejidad inherente de los sentidos verbales. Esto, sumado al hecho de que el español es un lenguaje con menos recursos disponibles que el inglés, hace de la desambiguación de sentidos verbales del español un área de estudio interesante sobre la cuál contribuir.

En primer lugar, exploro modelos puramente supervisado para obtener un entendimiento profundo de cómo es que funcionan y cuáles son sus debilidades. Encuentro que los principales problemas de los métodos supervisados son la falta de cobertura y la tendencia al sobreajuste. Intento resolver estos problemas con diferentes técnicas semi-supervisadas.

Continúo este trabajo explorando el uso de *vectores densos de palabras* como una representación no supervisada dentro de los clasificadores. Este enfoque es conocido como *aprendizaje semi-supervisado disjunto*: una técnica no supervisada se usa previamente a una técnica supervisada para ayudar a esta última. Los vectores densos de palabras ciertamente ayudan a superar la falta de cobertura y la tendencia al sobreajuste, pero lo hacen a expensas de perder cierto rendimiento en otros aspectos, como la exactitud o la métrica F1.

Sigo con la exploración del auto-aprendizaje, un algoritmo de *aprendizaje semi-supervisado conjunto* que utiliza un clasificador supervisado, entrenado en un conjunto de datos inicial, para seleccionar instancias de un conjunto de datos no anotados. Usando alguna medida de certeza, anota dichos ejemplos no anotados para los cuáles el algoritmo tiene la confianza más alta y los utiliza para expandir los datos anotados y re-entrenar el clasificador supervisado. Encuentro que el auto-aprendizaje sufre mucho los conjuntos de datos no balanceados. Amplifica el sesgo hacia la clase más frecuente, por lo que el aumento esperado en la cobertura (obtenido de nuevos ejemplos agregados al conjunto de datos de entrenamiento) es oscurecido porque las fronteras de decisión entre clases son borrosas.

Complementariamente al auto-aprendizaje, exploro el *aprendizaje activo*. Este enfoque utiliza un modelo supervisado para seleccionar instancias tomadas de un conjunto de datos no anotados, basado en el impacto que dichas instancias tendrán sobre el modelo, y se las brina a un experto humano para anotar. Muestro que la información obtenida mediante aprendizaje activo, aunque poca en comparación,

puede superar el enfoque del auto-aprendizaje.

Finalmente, exploro las *redes neuronales en escalera*, una variante de redes neuronales que minimiza una función de coste combinada. Esta función de coste es una suma de una función de costo supervisada y una función de costo no supervisada, lo que ayuda a regularizar el modelo final, y por lo tanto salva la tendencia al sobreajuste de modelos supervisados. Además, el desempeño de este método es comparable o mejor al resto de los métodos presentados en esta tesis, haciendo de las redes en escalera un candidato muy interesante a la hora de hacer aprendizaje automático semi-supervisado.

Classification (ACM CCS 2012)

- **Computing methodologies∼Semi-supervised learning settings**
- **Computing methodologies∼Natural language processing**
- Computing methodologies∼Artificial intelligence

Keywords

**English:** Artificial intelligence – Natural language processing – Word sense disambiguation – Spanish verb sense disambiguation – Machine learning – Semi-supervised learning – Deep learning.

**Spanish:** Inteligencia artificial – Procesamiento de lenguaje natural – Desambiguación de sentidos – Desambiguación de verbos del español – Aprendizaje automático – Aprendizaje semisupervisado – Aprendizaje profundo.

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Dedicado a toda mi familia (la tradicional, la fraternal y la académica)... Gracias por todo...

# Part I

# Preliminaries

# Chapter 1

# Introduction

## 1.1 Overview

This thesis explores the use of semi-supervised learning techniques for Spanish verb sense disambiguation. The objective is to study how adding information from unlabeled sources, which are larger, can help a classifier learned from a labeled but small resource, as is the disambiguated corpus for Spanish verbs SenSem [Alonso et al., 2007].

*Supervised machine learning* is the task that infers a function that maps unlabeled data to a label. This function is inferred from labeled data, which have been manually associated to a label. This is also known as modeling of the data. This function can be used then to find new mappings given unseen examples. However, supervised learning models are limited by the amount of labeled data available. The more labeled data a model has, the better the performance of the model. Right now *deep learning* requires large amounts of data in order to generate good models. As data labeling is a task requiring human labor, having large enough datasets is generally expensive. This is also dependent on the task. Some tasks are relatively easy for any person to label (e.g. see if a picture has a cat in it). For other tasks, labeled data is more difficult to obtain, as it requires that the human annotators are domain experts (e.g. a lawyer, a physician, a linguist, etc.).

*Unsupervised machine learning* is the task that tries to find patterns or hidden structures in unlabeled data. Because the data are unlabeled, these patterns cannot be evaluated based on accuracy. Unsupervised machine learning is more centered in the exploration of the data rather than finding a function useful for a particular prediction task, like supervised learning. The advantage of unsupervised learning is the vast amount of data available. As the data is not annotated, it makes it cheap to gather datasets.

*Semi-supervised learning* is an approach in between. A semi-supervised algorithm makes use of both labeled and unlabeled data in order to better infer a function for a specific task (whether it is supervised or not). In this case, given enough data, a good semi-supervised learning technique can improve on the purely supervised or unsupervised algorithm it is using. In particular, it has the advantage of having a way to evaluate it in means of accuracy or other metrics, but also has the advantage

of being able to expand its models based on the cheap available unlabeled datasets. The objective of this thesis is to explore different semi-supervised models in order to improve on a supervised task which has the properties stated above: lack of large labeled datasets, but availability of large unlabeled datasets.

*Natural language processing* helps humans interact with machines using the human language, instead of a formal language. The main challenge of the area is the ambiguity of human language. But this is not the only problem. Human language, as many other social phenomena, has a Zipfian distribution [Zipf, 1949], which is an exponential distribution. This law states that given a corpus of natural language utterances, the frequency of any word is inversely proportional to its rank in the frequency table. Thus, the most frequent word will occur approximately twice as often as the second most frequent word, three times as often as the third most frequent word, etc. In the case of classification tasks of natural language processing, the classes are unbalanced following Zipf's law, thus very few classes occur very often, and the rest of them have few to no occurrences in the labeled dataset. As with everything, the availability of good models for natural language tasks depends on the data available for that task. In particular, different languages have different amount of data, thus making it possible to obtain better or worse models. E.g, English is language with very good models because of the amount of resources; other languages are harder to work with because there are less available resources.

*Word sense disambiguation* is an intermediate task of natural language processing which, as it names indicates, given a word and its context tries to discriminate the meaning of that word among an inventory of pre-determined senses. E.g. the noun "granada" can be a fruit or a weapon depending on the context it is used in. A subtask of word sense disambiguation is *verb sense disambiguation*, which is crucial for a deep language processing tasks, especially those that could benefit from information about relations between participants provided by the verb, like machine translation, question answering or information extraction. E.g., in machine translation, sense disambiguation is needed to determine the correct translation of a word, and also the transformations needed in the syntactical structure of the sentence. Examples 1.1 and 1.2 shows how the different senses can change the translation of the same word.

**Example 1.1.**

- Juan **hizo** una torta de chocolate.
- *Juan* **made** *a chocolate cake.*

**Example 1.2.**

- Juan **hizo** la tarea por la tarde.
- *Juan* **did** *the homework in the afternoon.*

Another example, for question answering over linked data verb sense disambiguation is needed to determine the sense of a verb and the logical relations between the

participants to access the adequate nodes and edges in an ontology. Examples 1.3 and 1.4 show how the same verb has different connotations and thus establish different relationships between the participants it connects.

**Example 1.3.**

- El investigador no pudo **acceder** a la información reservada.

**Example 1.4.**

- Pedro **accedió** a escribir una nota de descargo.

Finally, an information extraction task like relation extraction where verb sense disambiguation is needed to disambiguate those relationships, generally represented as verbs in a unstructured text.

However, verb sense disambiguation is a highly difficult task, that achieves even lower precision rates than word sense disambiguation for other morphosyntactic categories (nouns, adjectives). This is arguably due to the inherent complexity of verb senses and the fact that their meaning is more pervasive than that of nouns, thus making it more difficult to discretize [Chen and Palmer, 2009]. Find below a detailed example of verb sense ambiguity for the lemma *h*ablar, with five senses in the SenSem lexicon. This can be seen in example 1.5.

**Example 1.5.**

- (...) una joven realizadora irlandesa que (...) **habla** castellano con acento malagueño ya que de pequeña vivió tres años en Estepona.

**Example 1.6.**

- El presidente del Gobierno (...) **hablará** con las principales autoridades de ambos estados sobre las perspectivas de la Unión Europea (...).

In Example 1.5 *hablar* is a state with the meaning of "being able to speak a language", while in example 1.6 it is a process with the meaning "talk". The subcategorization frames of each sense are also very different: for the first, we have two themes, while the second has the typical communication frame, with an Agent-Origin, a Theme and a Goal-Receiver.

## 1.2 Contributions and outline of this thesis

Word sense disambiguation is still an open problem in the area of natural language processing. Many different techniques and algorithms have been researched to attack this problem. Methods range from the use of lanaguage resources and knowledge databases, dictionary-based, rule-based, supervised machine learning and even purely

unsupervised techniques that seek to infer senses by word clustering. There are even hybrid methods which are a combination of these. Supervised machine learning techniques are based on corpora of disamgibuated words. Given this one can train a classifier to recognize senses in unseen examples.

Most of the work for Spanish word sense disambiguation is not specifically for verbs. Much of the work is using knowledge bases [Agirre et al., 2014, Agirre and Soroa, 2009]. There is some work using supervised learning techniques or unsupervised learning techniques [Mihalcea et al., 2004]. But at the time of writing this thesis, the work done specifically for Spanish verb sense disambiguation using the semi-supervised techniques explored in this work is non-existent to my knowledge. Moreover, the work in this thesis is using a resource that, save for the publications that derived in this thesis, has not been explored. I use as my basic resource the corpus of disambiguated verbs SenSem [Alonso et al., 2007].

This resource, although valuable as it was annotated by domain experts, is very small an has a limited amount of examples. But there is a large amount of unlabeled corpora available on the internet for Spanish (e.g. the SBWCE corpus [Cardellino, 2016]). This gives me the opportunity to study semi-supervised techniques applied to a problem that could really benefit from it, rather than a generic problem based on a toy dataset with properties that real world data might lack. Likewise, by studying the impact of semi-supervised machine learning techniques for Spanish verb sense disambiguation rather than for English verb sense disambiguation, I contribute to the improvement of NLP for a language whose resources are less developed. The main contribution of this thesis can be summarized in the study of how different semi-supervised systems overcome the problems of Spanish verb sense disambiguation.

The two following chapters introduce the fundamental concepts and related work of this thesis. Chapters 2 and 3 present a background review of the two main ares of this thesis: *machine learning* and *natural language processing*. Specifically Chapter 2 introduces the relevant concepts for the work in next chapters, and presents a brief description and analysis of previous work for the semi-supervised learning techniques studied in this thesis. Chapter 3 is a background chapter on natural language processing and word sense disambiguation. It introduces the fundamental concepts of the area and does a review of the previous work on supervised and semi-supervised learning techniques applied specifically to the areas of natural language processing and verb sense disambiguation. The five core chapters of this thesis explore different hypotheses for Spanish verb sense disambiguation and experiment and analyze results to test those proposed hypotheses. The final chapter recapitulates on the findings and lessons learned of this thesis and describes lines for future work.

**Summary of Chapter 4: Supervised Learning** This chapter explores supervised machine learning techniques for verb sense disambiguation. The main objective is to establish a baseline. The chapter explores verb sense disambiguation both for Spanish and English. The latter is needed as a comparison ground to ensure that

there is no language related bias. The chapter explores different classification algorithms and representations given by *hand-crafted features* to discard techniques that underperform. I also present a deep discussion about the insight provided by metrics and their biases. This is needed for a thorough understanding of models and their weaknesses to properly direct further developments. Finally, the chapter states the main shortcomings of the supervised approach: lack of coverage and tendency to overfit. I try to overcome these problems with the different semi-supervised techniques explored in the thesis.

**Summary of Chapter 5: Word Embeddings** This chapter explores the use of *word embeddings* as unsupervised representations within supervised classifiers. This approach is known as *disjoint semi-supervised learning*: an unsupervised technique is used prior to a supervised one to aid the latter. The chapter explores how the domain of the word embeddings affects the performance of the supervised classifiers, and how word embeddings help to overcome lack of coverage and tendency to overfit, even if at the expense of losing some performance in other aspects, like accuracy or F1.

**Summary of Chapter 6: Self-Learning** This chapter explores the self-learning algorithm, a well established method and one of the earliest semi-supervised algorithms in existence. Self-learning is a *wrapper algorithm*. The algorithm uses a supervised classifier, trained on an initial labeled dataset, to select instances from a pool of unlabeled data. Using some measure of certainty, it annotates those instances for which the algorithm has the highest confidence and uses them to expand the labeled data to re-train the supervised classifier. Experiments in this chapter focus primarily on increasing the amount of labeled data available to train a classifier. The final objective is to have a supervised model with a larger coverage by integrating part of the unlabeled data into the training process, assigning them a label automatically. Self-learning is the first of the *joint semi-supervised learning* techniques explored in the thesis. In this type of algorithms the labeled and unlabeled data are used together in the process of learning. I found that self-learning suffers strongly from unbalanced datasets. It amplifies the bias toward the most frequent class, so the expected increase in coverage by adding new examples to training is shaded because decision boundaries between classes are blurred.

**Summary of Chapter 7: Active Learning** This chapter explores active learning as a semi-supervised approach. Active learning is based on the same idea of self-learning. It is a wrapper algorithm that uses a supervised model to select instances taken from a pool of unlabeled data. However, instead of annotating the instances automatically, like self-learning, it uses an *intelligent approach* to select data and gives it to a human expert to annotate. The data is selected based on the impact it will have in the model to correctly annotate it (e.g. by giving more information to the model). As manual annotation is expensive, the idea is to reduce the resources spent

on annotation to a bare minimum. The chapter experiments show that information obtained via active learning, although little in comparison, can outperform the self-learning approach, which is generally biased by the nature of language and Zipf's law.

**Summary Chapter 8: Ladder Networks** Finally, this chapter explores *ladder networks*. This is a novel approach in the field of semi-supervised learning, which presents a neural network architecture based on the idea of simultaneously training the weights of the network by minimizing a combined cost function. This cost function is a sum of a supervised cost function and an unsupervised cost function. The network consists on two paths: an encoding path optimizing the supervised cost function and a decoder path which reconstructs the encoding input layer by layer. The idea is that the information gathered by the unsupervised path will help the supervised approach to better generalize, thus overcoming the tendency to overfit of supervised models. Also, the method's performance is shown to be comparable or better to the rest of methods presented on this thesis, making the ladder network an interesting candidate for semi-supervised learning.

# Chapter 2

# Machine Learning Background

The core of this thesis' work relies on two main areas: **machine learning** and **natural language processing**. More specifically, this thesis follows the application of semi-supervised learning techniques, a subarea of machine learning, for **Spanish verb sense disambiguation**, a subarea of natural language processing. This chapter reviews *machine learning*, specifically semi-supervised learning. The chapter starts with a set of basic definitions. It continues by revising the two wrapper algorithms: self-learning and active learning. And finishes with a brief introduction to the ladder network algorithm.

## 2.1 Fundamental concepts

Tom Mitchell [Mitchell, 1997] defines **machine learning** as "the field of artificial intelligence concerned with the question of how to construct systems that automatically improve based on experience". The experience, in this case, is acquired through the analysis of data with the final objective to generate a model that works on specific tasks. Examples of these tasks can be systems for anomaly detection, like fraudulent credit card transactions; recommender systems for movies, music, books, etc.; or computer vision.

Machine learning is divided in three main areas: *supervised learning*, *unsupervised learning*, and *reinforcement learning*. As this work is mostly based on supervised learning techniques with aid of unsupervised learning ones, I will go ahead and describe them.

**Supervised learning** has the objective to build a predictive model from labeled data. **Labeled data** consists in a set of *annotated examples*, where each is a pair of input data, generally a vector; and output data which, depending on the task, can be a real number, for regression, or a categorical value, for classification. E.g. spam filtering where an email is either classified as spam or not. In more formal terms, a supervised learning algorithm is a mapping from input $\mathbf{x}$ to output $\mathbf{y}$ with target $t$, trained from a set of $N$ pairs: $\{(\mathbf{x}(n), t(n)) | 1 \leq n \leq N\}$.

**Unsupervised learning** has the objective to describe or discover a hidden structure from unlabeled data. **Unlabeled data** consists in a set of *unannotated examples*: data without any information about belonging to some class or having an associated

value. E.g. clustering of news articles. In more formal terms, an unsupervised learning algorithm is the inference of a function that describes some pattern or structure from a set of unlabeled data points: $\{\mathbf{x}(m)|1 \leq m \leq M\}$.

There is a set of techniques which are in-between supervised and unsupervised machine learning: **semi-supervised machine learning**. These are the techniques I mostly explore in this thesis. Zhu and Goldberg [Zhu and Goldberg, 2009] describe it as "the task consisting in using both annotated and unannotated examples in order to better learn an otherwise supervised or unsupervised task". For the objective of this thesis, I will refer to semi-supervised techniques which explore the use of unlabeled data in aiding a supervised model. In more formal terms, given a supervised model from a training set of pairs $\{\mathbf{x}(n), t(n)|1 \leq n \leq N\}$. Semi-supervised learning, in the scope of this thesis, studies how auxiliary unlabeled data $\{\mathbf{x}(n)|N+1 \leq n \leq M\}$ can help in training the supervised model. It is often the case that labeled data is little whereas unlabeled data is plentiful, that is $N \ll M$. The idea is that unlabeled data can help expanding the supervised model as it has more information than a labeled dataset regarding the instances (since it has more). That underlying information helps expand the information present in the model. The information can be synthesized as new features for a class, latent variables coming from the representations, stronger associations between features and classes, etc.

In this work I explore two types of semi-supervised learning: *disjoint semi-supervised learning* and *joint semi-supervised learning*. In **disjoint semi-supervised learning** the supervised and unsupervised steps are trained separately, and then the information from one is fed into the other to improve it [Weston et al., 2008]. E.g the use of *word embeddings* trained on an unlabeled corpus for a supervised task. In contrast **joint learning** both supervised and unsupervised data affect the model training procedure simultaneously. There can be another subdivision in joint learning methods. Joint learning based on *wrapper* algorithms starts from a supervised classifier trained on labeled data, and uses the information of that model to expand it with feedback from unlabeled data (e.g. an *active learning* approach which makes an "intelligent" selection of candidates gathered from an unsupervised corpus to manually annotate and subsequently use to feed a supervised model). Other joint learning algorithms use both the labeled and unlabeled datasets in the training procedure of the algorithm ( e.g. *ladder networks* learn by the minimization of a joint objective function, composed by a supervised and an unsupervised target).

A categorization that can be done also in semi-supervised methods, but more generally in supervised methods as well is: *shallow learning* and *deep learning*. **Shallow learning** can be described as a process that tries to learn by approximation. It is rather a memorization rather than an understanding of underlying concepts or structures of the data. **Deep learning** is a machine learning approach whose objective is to allow computers to learn from experience and understand the world in terms of a hierarchy of concepts, with each concept defined in terms of its relation to simple concepts. By gathering knowledge from experience, this approach avoids the need for

human operators to formally specify all of the knowledge that the computer needs. The hierarchy of concepts allows the computer to learn complicated concepts by building them out of simpler ones [Goodfellow et al., 2016]. The most basic deep learning model is a **multilayer perceptron**, a feed-forward artificial neural network model, which maps a set of input values to a set of output values.

## 2.2 Relevant work

### 2.2.1 Disjoint Semi-supervised Learning

**Disjoint semi-supervised learning** was defined by Weston et al. [Weston et al., 2008], as the use of word embeddings to aid deep learning tasks in natural language processing. The concept can be understood as the use of a resource or an auxiliary task that is obtained from unlabeled data (e.g. word embeddings) and how it aids on a supervised task trained on labeled data that is disjoint the unlabeled data of the auxiliary task. As it was defined, there are no other uses of the term but inside the area of natural language processing. Thus, I will discuss it further on Chapter 3.

### 2.2.2 Self-learning

**Self-learning** (also known as *self-training*, *self-teaching*, or *bootstrapping*) is a commonly used technique for semi-supervised learning. It is probably the earliest idea about using unlabeled data in classification [Chapelle et al., 2010]. This is a *wrapper* algorithm that repeatedly uses a supervised learning method. The initial classifier is first trained with a seed labeled dataset (generally small) and then is used to classify data from an unlabeled pool of data. Generally the data points on which the classifier is more confident about alongside their predicted labels are added to the training set. The classifier is re-trained and the procedure repeated. Note that the classifier uses its own predictions to teach itself [Zhu, 2005], thus in this scheme is possible for the classification mistake to reinforce itself. There are different methods to try and control this phenomenon. Scudder [Scudder, 1965] presents an untaught adaptive pattern-recognition machine made from a simple taught pattern-recognition machine for detecting an unknown, fixed, randomly occurring pattern (derived using a Bayes' approach) and its probability of error is analyzed by using its own output instead of a teacher. In machine vision, Rosenberg et al. [Rosenberg et al., 2005] apply self-training to object detection systems from images, and show the semi-supervised technique compares favorably with a state-of-the-art detector. Culp and Michailidis [Culp and Michailidis, 2008] offer an iterative self-learning algorithm that extends a learner from a supervised setting to a semi-supervised one. They analyze the convergence properties of the algorithm, as self-learning is a hard algorithm to analyze in general.

### 2.2.3 Active learning

**Active learning** is another example of a joint learning task. It is also a wrapper algorithm which trains from an initial seed labeled dataset, but uses another approach to incorporate instances from the unlabeled dataset. The key hypothesis is that if the learning algorithm is allowed to choose the data from which it learns it will perform better with less training [Settles, 2009]. The algorithm inspects a set of unlabeled examples, and ranks them by how much they could improve the algorithm's performance if they were labeled. Then, a human annotator (called *oracle* or *domain expert*) labels the highest ranking examples, which are then added to the set of training examples from which the algorithm infers its classification model, and the loop begins again. In some active learning approaches, the oracle may annotate features describing instances, and not (only) instances themselves. This latter approach provides even faster learning in some cases [Druck et al., 2009].

Different strategies have been applied to determine the most useful instances to be annotated by the oracle, including expected model change, expected error reduction or density-weighted methods [Settles, 2009]. The most intuitive and popular strategy is **uncertainty sampling** [Lewis and Catlett, 1994], which chooses those instances or features where the algorithm is most uncertain, from a large set of automatically labeled data. As *self-training*, this is also a wrapper method, being the supervised algorithm to do the classification step chosen openly. This strategy has been successfully applied to Information Extraction tasks [Culotta and McCallum, 2005, Settles and Craven, 2008]. Uncertainty can be calculated by different methods depending on the learning algorithm. Specially popular are methods exploiting the margins of Support Vector Machines (SVM), as in [Tong and Koller, 2002]. The simplest methods exploit directly the certainty that the classifier provides for each instance that is classified automatically.

### 2.2.4 Ladder Networks

The **ladder network** is the last semi-supervised learning technique I will revise in this work. It is also a joint learning technique. But unlike self-learning or active learning, it is not a wrapper algorithm, but rather an special architecture for an artificial neural network. The semi-supervised approach studied by the ladder network is recent, being introduced in the work of Rasmus et al. [Rasmus et al., 2015a]. I will further discuss this work and the details of the ladder network algorithm in Chapter 8, since the explanation of it is core of this thesis's work. The work of Rasmus extends the original work by Valpola [Valpola, 2014] which introduces the concept of ladder networks for unsupervised learning. The work of Rasmus that I study in this thesis uses the basis of another work by Rasmus et al. [Rasmus et al., 2015b] which adds lateral connections to denoising autoencoders to help supervised learning (e.g. classification) with an unsupervised learning auxiliary task (e.g. reconstruction of input). The combination of works derived in the design of a ladder network as a semi-supervised algorithm.

# Chapter 3

# Natural Language Processing Background

Besides machine learning, the other main area of study in this thesis is **natural language processing**. In particular, I focus on a subarea of natural language processing: **word sense disambiguation**, with special attention on **Spanish verb sense disambiguation**. This chapter reviews *natural language processing* and *word sense disambiguation* (with particular interest on *Spanish verb sense disambiguation*). More specifically, it explores some of the relevant work on natural language processing and word sense disambiguation using the semi-supervised learning techniques described in the previous chapter. The chapter first describes the fundamental concepts of the area of natural language processing and word sense disambiguation. Then it explains the details of word embeddings and their applications on natural language processing. Finally it continues with the revision of self-learning and active learning algorithms in the area of natural language processing. There is no previous work for ladder networks specifically for natural language processing tasks as the technique is very recent, thus I will not discuss it in here.

## 3.1 Fundamental concepts

**Natural language processing** is the field of artificial intelligence that works on the human-machine interaction via natural languages (i.e. those spoken by humankind, e.g. English, Spanish, Chinese). In this area, machine learning has been increasingly gaining popularity since the "statistical revolution" to deal with tasks which used to be done with more ad hoc methods (e.g. based on complex sets of hand-written rules) [Johnson, 2009]. This kind of machine learning applied to natural language processing is also known as *statistical natural language processing*.

**Word sense disambiguation**, as its name implies, tries to automatically disambiguate words. Ide and Véronis [Ide and Véronis, 1998] established that this task has been a core objective since the conception of natural language processing as an artificial intelligence task. Word sense disambiguation has been categorized as an *intermediate task* by Wilks and Stevenson [Wilks and Stevenson, 1996], i.e. it is not an end task in itself, but rather a necessary step to accomplish in order to proceed with

most natural language processing tasks. It is essential for language understanding applications (e.g. man-machine communication); and helpful (and sometimes required) for applications that do not aim for language understanding (e.g. machine translation, information retrieval, information extraction, etc.).

This work focuses primarily in a sub task of word sense disambiguation, **verb sense disambiguation**. Particularly, this work focuses on the application of verb sense disambiguation in Spanish. Both word and verb sense disambiguation can be seen as supervised machine learning problems. Different approaches have been studied in these areas.

## 3.2 Relevant work

### 3.2.1 Supervised learning for word sense disambiguation

For word sense disambiguation the reference work at the time of writing this thesis is *It Makes Sense* [Zhong and Ng, 2010]. It is a system for English all-words word sense disambiguation. The system can be tweaked to the need of the user but is originally packed with a linear support vector machine classifier with multiple knowledge-based features.

McCarthy and Carroll [McCarthy and Carroll, 2003] worked on disambiguation of nouns, verbs and adjectives using selectional preferences acquired from automatically preprocessed and parsed text. The selectional preferences are acquired for grammatical relations (subject, direct objects, and adjective-noun) involving nouns and grammatically related adjectives or verbs. They use WordNet synsets to define the sense inventory. Their method exploits hyponym links given for nouns (e.g. *cheese* is an hyponym of *food*), troponym links for verbs (e.g., *limp* is a troponym of *walk*), and the "similar-to" relationship given for adjectives (e.g., one sense of *cheap* is similar to *flimsy*). From the paper, it is not clear whether selectional preferences impact positively in verb sense disambiguation.

Ye and Baldwin [Ye and Baldwin, 2006], use Selectional Preferences extracted with a Semantic Role Labeler for verb sense disambiguation. Their verb sense disambiguation framework is based upon three components: extraction of disambiguating features, selection of the best disambiguating features with respect to previously unseen data and the tuning of the machine learner's parameters. For their study they use a Maximum Entropy algorithm [Berger et al., 1996]. The verb sense disambiguation features they used include selectional preferences and syntactic features, e.g, bag of words, bag of PoS tags, bag of chunks; parsed tree based features using different levels of the tree as source of information; and non-parse trees based syntactic features, e.g., voice of the verb, quotatives, etc. They show improved performance of their system when selectional preferences are taken into account.

Another work on English verb sense disambiguation is the one by Chen and Palmer [Chen and Palmer, 2009], presenting a high-performance broad-coverage supervised word sense disambiguation system for English verbs that uses linguistically motivated

features and a smoothed maximum entropy machine learning model. Kawahara and Palmer [Kawahara and Palmer, 2014] presented a supervised method for verb sense disambiguation based on VerbNet. Contrary to the most common verb sense disambiguation methods, which create a classifier for each verb that reaches a frequency threshold, they created a single classifier to be applied to rare or unseen verbs in a new text. Their classifier also exploits generalized semantic features of a verb and its modifiers in order to better deal with rare or unseen verbs.

The work by Sudarikov et al. [Sudarikov et al., 2016] shows a direct application of verb sense disambiguation on another field of study. They present experimentation in machine translation using verb sense disambiguation information. They evaluate several options to use verb senses in the source language as an additional factor for the Moses statistical machine translation system. Their results show a statistically significant translation quality improvement.

Many of the features that are used for English verb sense disambiguation are not available for Spanish verb sense disambiguation because the preprocessing tools and annotated corpora are less developed.

In the SemEval 2007 task for multilevel semantic annotation of Catalan and Spanish [Màrquez et al., 2007b], Màrquez et al. [Màrquez et al., 2007a] primarily focused on Noun Sense Disambiguation. They used a three way approach: if the word has more than a threshold number of occurrences, it is classified with a SVM classifier; if the word has less occurrences than the threshold it is assigned the most frequent sense (MFS) in the training corpus; if the word is not presented in the training corpus then it is assigned the MFS in WordNet. The SVM classifier features were a bag of words, n-grams of part-of-speech tags and lemmas, and syntactic label and syntactic function of the constituent that has the target noun as head.

Anther work in WSD with applications in Spanish is the work of Montoyo et al. [Montoyo et al., 2011] where the task of WSD consists in assigning the correct sense to words using an electronic dictionary as the source of word definitions. They present a knowledge-based method and a corpus-based method. In the knowledge-based method the underlying hypothesis is that the higher the similarity between two words, the larger the amount of information shared by two of their concepts. The corpus-based method is based on conditional maximum-entropy models, it was implemented using a supervised learning method that consists of building word-sense classifiers using a semantically annotated corpus. Among the features for the classifier they used word forms, words in a window, part-of-speech tags and grammatical dependencies.

Is noticeable that the features for Spanish word sense disambiguation are more shallow than the features available for English word sense disambiguation. In this thesis we will explore more combinations of features aimed specifically to Spanish verb sense disambiguation.

### 3.2.2 Word embeddings

**Word embeddings** are distributed, continuous representations of words, in the form of dense vectors or real numbers. The concept behind this method is the mathematical embedding from a high-dimension sparse vector with one dimension per word (also known as *one-hot encoding*) to a continuous vector space with much lower dimension. There are different methods to obtain word embeddings, but all of them have the objective to generate word representations from an unlabeled corpus.

The use of word embeddings for supervised natural language processing tasks is an example of a disjoint learning task, and due to the nature of this work, one of my main areas of study. The idea behind word embeddings representations is to find a compact vectorial representation. Ideally, in this representation, each dimension captures underlying, latent properties of the word (syntactic or semantic). In this way, the embedding is superior to a representation of the words that stays at a shallow level, capturing word co-occurrences only.

Collobert and Weston [Collobert and Weston, 2008] designed a convolutional neural network architecture for multitask learning that, based on a language model, provides many different language processing predictions for a given sentence: part-of-speech tags, chunks, named entity tags, semantic roles, semantically similar words, and the likelihood that a sentence makes sense (both syntactically and semantically). Each task is trained using labeled corpora except for the language model which is obtained in a completely unsupervised manner. This language model is embedded in a more dense, continuous space, which improves the representation of words for all subsequent tasks. With this approach, known as end-to-end, they reach state-of-the-art performance on every task.

Turian et al. [Turian et al., 2010] do a general introduction to some of the most common unsupervised word representations: distributional representations (e.g. latent semantic analysis), cluster based representations (e.g. Brown clusters) and distributed representations (e.g. word embeddings). They present word embeddings as generally being derived from *neural language models*, which is a language model based on neural networks, exploiting the ability to learn distributed representations to reduce the impact of the curse of dimensionality [Bengio, 2008]. The problem with these models, historically, was slow training with scaling based on the vocabulary for the computation of each model [Bengio et al., 2003]. This has been subsequently tackled and the linear dependency on vocabulary size has been reduced [Morin and Bengio, 2005, Collobert and Weston, 2008, Mnih and Hinton, 2009]. In their work they improve the accuracy of different existing natural language processing systems by using unsupervised word representations as extra features. They evaluate three different unsupervised word representations: Brown clusters [Brown et al., 1992], Collobert and Weston [Weston et al., 2008] embedding, and HLBL embeddings of words [Mnih and Hinton, 2009]; and evaluate them on named entity recognition and chunking. Using these representations they effectively show improvement of performance in nearly state-of-the-art baselines.

#### 3.2.2.1 Word2Vec

The work by Mikolov et al. [Mikolov et al., 2013a] presented two architectures to compute continuous vector representations of words from very large datasets: the *continuous skip-gram model* and *continuous bag-of-words model*.

These models use an architecture for learning distributed representations of words that tries to minimize computational complexity. They explore other methods to create a language model using neural networks like the work of Bengio [Bengio et al., 2003], and they conclude that in such models most of the complexity is caused by the non-linear hidden layer in the model. Thus they go on to explore simpler models that might not be able to represent the data as precisely as neural networks, but can possibly be trained on much more data efficiently.

The continuous bag-of-words model (CBOW) consists of a neural network with a linear hidden layer where all the input words are projected into the same position and their vector is average. The idea is to represent the probability of a word occurring given a context of words as an input.

The continuous skip-gram model is similar to the CBOW model, but instead of predicting the current word based on the context, it tries to maximize prediction of a word based on another word in the same context. More precisely, they use each current word as an input to a log-linear classifier with continuous projection layer, and predict words within a certain range before and after the current word. They found that increasing the range improves quality of the resulting word vectors, but it also increases the computational complexity. Since more distant words are usually less related to the current word than those close to it, they give less weight to distant words by sampling less from those words in their training examples.

In summary, both models are based on a neural network with a linear hidden layer which given certain words (an average of the context in case of CBOW and a single word in the case of skip-gram) predicts words that are near in the text. The network is then trained on a large corpus and the projections are the word embeddings that the Word2Vec model produces.

#### 3.2.2.2 The skip-gram model with negative sampling

The skip-gram model is the architecture I worked with in this thesis. It is able to learn high-quality distributed vector representations that capture a latent syntactic and semantic word relationships. As I said before, it is a neural network whose training objective is to find word representations that are useful for predicting the surrounding words in a sentence or a document. More formally, given a sequence of training words $w_1, w_2, w_3, \ldots, w_T$, the objective of the Skip-gram model is to maximize the average log probability

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c, j\neq 0}\log p(w_{t+j}|w_t)$$

where $c$ is the training size context. In the basic skip-gram formulation the value of $p(w_{t+j}|w_t)$ is defined as a softmax function:

$$p(w_O|w_I) = \frac{e^{{v'_{w_O}}^\top v_{w_I}}}{\sum_{w=1}^{W} e^{{v'_w}^\top v_{w_I}}}$$

where $v_w$ and $v'_w$ are the vector projections (of "input" and "output" respectively) of $w$, and $W$ is the number of words in the vocabulary. This representation scales with the size of the vocabulary which can be in the millions or billions.

In another work of Mikolov et al. [Mikolov et al., 2013b], they present extensions to the original skip-gram model architecture which improve both the quality of the vectors and the training speed. First, they obtain significant speedup of the process by sub-sampling of the frequent words. This also helps by learning more regular word representations. However, the real added value of this paper is the presentation of the negative sampling model. To do that, they explore the Noise Contrastive Estimation (NCE) technique [Gutmann and Hyvärinen, 2012]. While NCE can be shown to approximately maximize the log probability of the softmax, the Skipgram model is only concerned with learning high-quality vector representations, so they are free to simplify NCE as long as the vector representations retain their quality. They define Negative sampling (NEG) by the objective:

$$\log \sigma({v'_{w_O}}^\top v_{w_I}) + \sum_{i=1}^{k} \mathbb{E}_{w_i \sim P_n(w)} \Big[ \log \sigma(-{v'_{w_i}}^\top v_{w_I}) \Big]$$

which is used to replace every $\log p(w_O|w_I)$ term in the objective of the Skip-gram model. In this case the $P_n(w)$ is a noise distribution from which the algorithm draws random examples of words not likely to happen in the context of the word they are trying to model. The distribution is an hyperparameter of the model. In the original paper, it is modeled after a unigram distribution.

#### 3.2.2.3 Word embeddings for word sense disambiguation

The work by Taghipour and Ng [Taghipour and Ng, 2015] investigates two ways of incorporating word embeddings in a word sense disambiguation setting and evaluates on some SensEval/SemEval lexical sample and all-words tasks and also a domain-specific lexical sample task. Results show that such representations consistently improve the accuracy of the selected supervised word sense disambiguation system.

Rothe and Schütze [Rothe and Schütze, 2015] presented a system to learn joint embeddings for synsets and lexemes. The synset/lexeme embeddings live in the same vector space as the word embeddings for words that are not in WordNet and thus have no synsets associated. The system achieves state-of-the-art performance on word similarity and word sense disambiguation tasks.

A very complete work on word embeddings as features for word sense disambiguation is the evaluation study by Iacobacci et al. [Iacobacci et al., 2016]. They propose

different methods through which word embeddings can be leveraged in a state-of-the-art supervised WSD system architecture, and perform analysis of how different parameters affect performance. They show how a word sense disambiguation system that makes use of word embeddings alone, if designed properly, can provide significant performance improvement over a state-of-the-art word sense disambiguation system that incorporates several standard word sense disambiguation features. They explore different dispositions of the embeddings to represent the sentences, like concatenation, average and weighted sums based on distance. They also compare different methods to obtain word embeddings.

For Spanish word sense disambiguation, at the time of writing this thesis, the only work I could find was my own (on which this thesis extends) in Cardellino and Alonso [Cardellino and Alonso i Alemany, 2017].

On a related area, the work by Gella et al. [Gella et al., 2016] explores a different kind of embeddings to aid on verb sense disambiguation. They introduce a novel task defined as *visual sense disambiguation*: given an image and a verb, assign the correct verb of the sense, i.e., the one that describes the action depicted in the image. The area is multimodal learning, this is an area that combines different areas of machine learning in a task that comprises them, in this case natural language processingwith machine vision. The work by Gella et al. introduces an extension on multimodal datasets to add sense labels. They propose an unsupervised algorithm which performs visual sense disambiguation using textual, visual, or multimodal embeddings.

### 3.2.3 Self-learning

Self-learning has been used in many natural language processing tasks. For example, Riloff et al. [Riloff et al., 2003] use self-learning to identify subjective nouns. Maeireizo et al. [Maeireizo et al., 2004] classify dialogues as "emotional" or "non-emotional" with a procedure involving two classifiers. Weld et al. [Weld et al., 2009] present the use of a self-learning algorithm as a case study of open information extraction. They use the algorithm in Wikipedia and show how the process of their algorithm uses a bootstrapping method to enable information extraction from a wider set of general web pages.

In the area of word sense disambiguation, the landmark work on self-learning is the 1995 Yarowsky publication [Yarowsky, 1995]. In his work, Yarowsky builds a disambiguation model based on the words co-occurring with manually labeled examples. Then, this model is applied to unlabeled examples. Examples that can be assigned a sense by the model are then incorporated as training examples, and a new model is trained. This process is iteratively applied until a termination condition is reached, namely, no new examples can be assigned a sense or the reliability of the evidence found by the model is too low. After each iteration, the resulting model has arguably larger coverage than previous versions. Therefore, this method is useful to build a real-life tool out of a limited number of examples.

Mihalcea [Mihalcea, 2004] investigates the application of co-training and selftraining to word sense disambiguation. In particular she investigates on hyperparameter selection with various degrees of error reduction. In her work she selects the top candidates returned by the supervised algorithm to add to the training examples (instead of using some threshold and add everything over that as I do in my work). She finally presents a method that combines co-training with majority voting to smooth the bootstrapping learning curves and improve the average performance.

In a related area, Yuan et al. [Yuan et al., 2016] explore a *label propagation classifier* for semi-supervised word sense disambiguationwith neural models. They study word sense disambiguationwith a recurrent long-short term memory network. They look to better capture the sequential and syntactic patterns of the text. The semi-supervised task is an extra they have to alleviate the lack of training data in word sense disambiguation. They demonstrate state-of-the-art results, especially on verbs for English. The label propagation classifier expands the labels of the unsupervised data based on the similarity the unlabeled data has to some of its labeled neighbors. A very similar approach is to use a self-learning algorithm as a wrapper for a nearest neighbors algorithm.

### 3.2.4 Active learning

Active learning techniques are not as widely used in natural language processing as one would expect from the good acceptance of machine learning techniques in general, and the need to develop labeled data. Besides the technical difficulty that many active learning systems pose, and the risk that an active learning method performs worse than passive learning, there is also the problem of class imbalance to be taken into account, frequent in natural language processing.

Class imbalance is one of the hardest problems in active learning, and one where uncertainty sampling may very probably perform worse than random sampling. Many approaches have been proposed to deal with the class imbalance problem within active learning [Tomanek and Hahn, 2009, Bloodgood and Vijay-Shanker, 2009, Zhu and Hovy, 2007, Ertekin et al., 2007, He and Carbonell, 2007], but no definitive solution has been found for the problem.

In the line of semi-supervised techniques for word sense disambiguation, active learning has been applied successfully to verb sense disambiguation in Dligach and Palmer [Dligach and Palmer, 2011], where they explore the benefits of using an unsupervised language model to select seed examples as a starting corpus for an iterative active learning approach. It involves training a language model on a corpus of unlabeled candidate examples and selecting the examples with low language model probability. This smart starting point seems to provide a better performance for verb senses, where there is a skewed distribution of classes, because it is able to select representative examples of minority classes. On my line of work I explored the use of active learning along self-learning for tasks of Spanish verb sense disambiguation in Cardellino et al. [Cardellino et al., 2015].

# Chapter 4

# Supervised Learning for Verb Sense Disambiguation

## 4.1 Overview

I will introduce in the present chapter the basis on which I will build the work of the thesis. In the following chapters I will incrementally construct over what is developed in this chapter. The results of this chapter will be used as a baseline to assess the impact of the additions worked on subsequent chapters.

Recapitulating on Chapter 1, Section 1.1, I state the problem at hand. I have available a labeled dataset of disambiguated verb senses which is small. Developing a manual annotated resource is expensive because the manual annotation is done by domain experts. Because of the nature of language the distribution of the classes (i.e. senses) in the dataset is Zipfian [Zipf, 1949]. Therefore I have a resource where the distribution of the annotations is highly biased toward a most frequent class. This resource poses two challenges: the number of annotated examples, and the distribution of the labels.

To obtain an algorithm for verb sense disambiguation the simplest approach is to train a supervised automatic classifier. However with a purely supervised approach and as consequence of the challenges stated above, I have to deal with two problems: overfitting of the data and bias of the algorithm to tag everything as the most frequent class. I will show these problems exist and discuss with the results and conclusions of this chapter what I can do to improve the learning process to overcome these problems.

To explore these challenges I formalize so with the following Hypothesis:

**Hypothesis I** *The size of the dataset affects the quality of the final model.*

In order to accept or reject such Hypothesis, I divide it in more specific ones:

**Subhypothesis 1.1** *With larger training sets, the performance improves.*

**Subhypothesis 1.2** *With larger datasets the classifier is less prone to overfitting.*

**Subhypothesis 1.3** *The number of classes affects the tendency to overfit.*

**Subhypothesis 1.4** *Linear models have less tendency to overfit than non-linear models.*

These hypotheses will be accepted or rejected using the following layout:

- Experiment 4.2 reports the performance of a model as the number of examples increases. The performance is measured by the macro and weighted average F1-score (Metric 1). Results shown in Section 4.4.3 serve to accept Hypothesis 1.1, that the performance improve with larger training sets.
- Experiment 4.3 reports the variance of different models trained over different subsets of the training data. This variance is measured by Metric 3 which reflects the tendency of a model to overfit, with aid of the learning curve. From this experiment and metric, using different visualizations according to the task, I show that the classifier is less prone to overfitting with larger datasets (Hypothesis 1.2, in Section 4.4.4), with less classes (Hypothesis 1.3, in Section 4.4.5). I also show that linear models have less tendency to overfit (Hypothesis 1.4, in Section 4.4.6).

In Section 4.2 I recapitulate on previous work done in supervised learning for word sense disambiguation both for English and Spanish, with a special focus on verb sense disambiguation and the problem of learning with very few examples and class imbalance.

In Section 4.3 I explain all relevant items concerning what is used to carry out the experimentation of this chapter. First, in Section 4.3.1 I introduce the resources I work with. The SenSem annotated corpus on which the rest of the Thesis's work is done and SemEval Corpus for the sake of comparison with the standard and to ensure that there is no language related bias. These resources are represented in this stage with what I name *hand-crafted features* taken from the resources themselves, this is what I present in Section 4.3.2. I also explore techniques to reduce the dimensionality of the representations and see how this is a necessary step to be able to train some classifiers. I introduce the classification algorithms used for the automatic word sense disambiguation task in Section 4.3.3. Section 4.3.4 lists the experiments done. And Section 4.3.5 lists the set of metrics I use to measure the experiments.

Section 4.4 reports the results of the experiments and analyses them in order to accept or reject the stated hypotheses of the chapter.

Finally Section 4.5 draws the conclusions of this chapter, recapitulating the Hypotheses and accepting or rejecting them according to the evidence gathered in the results. It states the shortcomings of the methods explores in this chapter and what I want to accomplish on the next and ends by listing the future work.

## 4.2 Relevant Work

I recall from Chapter 3, in Section 3.2.1, there is some work done for English verb sense disambiguation and some for Spanish word sense disambiguation, but not much

for Spanish verb sense disambiguation. To my knowledge the work done exclusively for Spanish verb sense disambiguation is almost non-existent. Moreover the features used in English verb sense disambiguation, like selectional preferences and abstract semantic features, are not available for Spanish.

In particular, to design the supervised machine learning system I took inspiration from the *It Make Sense* system [Zhong and Ng, 2010], and use a pipeline similar to theirs.

First, there was a preprocessing step of the labeled corpora where it was analyzed automatically. Then I use the available information to generate features to represent the instances to use as training data. Finally different supervised classifiers were tried in the experimentation phase.

To design the features I was based on the work already mentioned in Section 3.2.1. Specially from Ye and Baldwin [Ye and Baldwin, 2006], Màrquez et al. [Màrquez et al., 2007a], and Montoyo et al. [Montoyo et al., 2011].

## 4.3 Methodology

In this Section, I explain the general methods used to carry out the experiments of this chapter. Once again, for the scope of this thesis, the words *dataset* and *corpus* are interchangeable. On the other hand when I use the word **model** I mean the result of training a *classifier* with a specific *representation* for a specific *corpus*.

### 4.3.1 Resources

As the project focus mainly on verb sense disambiguation, there are two corpora I worked with: SenSem [Alonso et al., 2007] labeled corpus of Spanish verb senses and SemEval-2007 Task 17 [Pradhan et al., 2007] corpus for English.

The main focus is the work on SenSem as the areas of word sense disambiguation, in general, and verb sense disambiguation, in particular, for Spanish language can greatly benefit from the results I can find; specially since the basic resource exists but is small and in need of improvements. Plus, as this is the work from an Spanish born speaker, it surely is a research interest of me.

SemEval, being of English language, is mostly used as a comparison to the work for Spanish in this chapter, since the work in English in the area is more solid than that of Spanish.

#### 4.3.1.1 SenSem

SenSem [Alonso et al., 2007] is a manually annotated corpus for both Spanish and Catalan. It serves as main resource for the experiments in Spanish. It contains the 248 most common verbs of Spanish, annotated with senses defined in a provided lexicon, some of them with mappings to the Spanish Wordnet Ontology [Montraveta et al., 2008].

A version of the SenSem corpus has part-of-speech tags automatically annotated with Freeling [Padró and Stanilovsky, 2012]. However these tags are annotated on a word based level, thus there is a large proportion of them annotated with the wrong tag (e.g. verbs annotated as nouns). Furthermore, Spanish has some words that are multi-words (i.e. words formed of two ore more different terms) which tag is not the same than those of each of the words compounding the multi-word. E.g. "más_allá_de" is tagged as a multi-word with Part-of-Speech tag "SP", it is a preposition, however, the words "más" and "allá" are by themselves adverbs and only "de" is a preposition.

In order to gather information more useful for feature extraction, there was a two step preprocessing of the SenSem corpus. First, an automatic annotation using an statistical parser. In this step the SenSem's sentences, which are tokenized, are given to Freeling. Using the statistical dependency parser, the sentences are annotated with: lemma, part-of-speech tag, morphosyntactic information and dependency triples. Also, there is multi-word detection and named entity recognition (treated by Freeling as multi-words).

Nevertheless, the automatic annotation is not enough as errors come not only from Freeling but other problem SenSem has as well: sentences without a defined sense, sentences where the verb to disambiguate is not present and sentences truncated before finishing. For this reason, the second step of preprocessing was manual, where each of the automatically annotated sentences where the main lemma to disambiguate was lost (because of mistagging, not being correctly marked in the original resource, etc.), is found manually. Besides this, all cases that are erroneous in the original corpus (e.g. truncated sentences or sentences without a defined sense) were discarded.

After the text preprocessing, the SenSem corpus was split in train/test. For this all those senses with less than two occurrences in the corpus are filtered out and the remaining senses are split with stratified sampling using 80% for training and 20% for testing, where the train corpus has at least two occurrences of every sense and the test corpus has at least one occurrence of every sense. These splits also preserve the distribution of classes observed in the whole dataset. This implies that in each split you cannot find more examples of a class than you could find in a stratified sample of the dataset, that is, a sample that preserves the distribution of the whole dataset. However, this does not necessarily hold for minority classes, because at least one example must be found in each split, even if that implies over-representing the class.

The test corpus is always the same for every experiment in the thesis, and is held out from training to use for measuring the performance of the different algorithms studied in this thesis. I need two occurrences in the training corpus of each sense because in the future experiments (the ones comprising semi-supervised approach), a validation corpus is needed to aid the early stopping criterion of the algorithms and thus the same approach for splitting train and test corpus is used (in this case with at least one example per sense for each split).

Table 4.1 shows some of the statistics of the SenSem corpus after the preprocessing

of the text and removal of erroneous sentences. I want to focus specially on the average number of instances for the most frequent sense per lemma in comparison to the average number of instances for the second most frequent sense per lemma. Is clear to see the imbalance of the senses in the corpora as the most frequent class has more than 3 times more occurrences than the next.

| **Statistic** | **Value** |
|---|---|
| Total no. of instances (before filtering) | 23938 |
| Total no. of instances (after filtering) | 20138 |
| Total no. of lemmas (before filtering) | 248 |
| Total no. of lemmas (after filtering) | 208 |
| Total no. of senses (before filtering) | 772 |
| Total no. of senses (after filtering) | 732 |
| Average no. of senses per lemma | 3.52 |
| Average no. of instances per lemma | 96.82 |
| Average no. of instances per sense | 27.51 |
| Average no. of instances for the most frequent sense per lemma | 67.08 |
| Average no. of instances for the second most frequent sense per lemma | 19.67 |

Table 4.1: SenSem statistics

In summary, the original version of the SenSem was automatically parsed with Freeling to gather more data to use for the features construction, and then was manually revised in order to correct mistagging and discard incorrect sentences (e.g. truncated sentences). After this, it was split in train and test datasets.

#### 4.3.1.2 SemEval

To compare the results with a standard experimental setting, I replicate experiments using the SemEval-2007 Task-17 corpus [Pradhan et al., 2007]. The corpus has information of the senses of 100 different lemmas, 65 verbs and 35 nouns (unlike SenSem which only has information about verb senses). Since this work want to asses the results of Spanish verb sense disambiguation, it was decided to leave out the 35 nouns from the experimental settings of English and only work with the verbs.

Unlike SenSem, the SemEval corpus was already split in train and test corpora. There are senses that only occur once in the whole corpus, either in the train or in the test data. In order to not alter SemEval so is still useful for comparison, no filtering of the dataset was done. However, given the nature of the classifiers used here, those cases where the sense only exists in the test corpus will have no way of being predicted by the classifiers.

Other differences between SenSem and SemEval is the way the examples are presented. In SenSem each example represents only one sentence where a specific token is the one being disambiguated. SemEval on the other hand can be conformed by multiple sentences for one example, again specifying the token to be disambiguated. This sentences have no other information besides being already tokenized. ll To gather extra

information, the SemEval corpus was preprocessed using Stanford CoreNLP [Manning et al., 2014] tools. Similar to SenSem, the information gathered was: lemma, part-of-speech tag (with morphosyntactic information) and dependency triples. Also, there was named entity recognition and classification, but the tool (unlike Freeling) treat every word of a named entity as a unique value. Besides this, every example was trimmed so that only the sentence holding the target word was left.

As the SemEval corpus also deals with cases like American slang or some other informal uses of English part of the corpus needed to be manually revised in order to find the target token after preprocessing the sentences.

Table 4.2 shows some of the statistics of the SemEval corpus after the preprocessing of the text and removal of erroneous sentences. As you can see, the number of lemmas and instances is much less than SenSem, but the average instances per lemma and per sense duplicates the one of SenSem. Still, what happened to SenSem happens to SemEval regarding the most frequent sense in comparison to the second most frequent sense. Is clear to see the imbalance of the senses in the corpora as the most frequent class has more than 5 times more occurrences than the next. As I can see, the unbalance of the data is even worse than with SenSem.

| **Statistic** | **Value** |
|---|---|
| Total no. of instances (before filtering) | 11280 |
| Total no. of instances (after filtering) | 10167 |
| Total no. of lemmas (before filtering) | 65 |
| Total no. of lemmas (after filtering) | 51 |
| Total no. of senses (before filtering) | 230 |
| Total no. of senses (after filtering) | 194 |
| Average no. of senses per lemma | 3.80 |
| Average no. of instances per lemma | 199.35 |
| Average no. of instances per sense | 52.41 |
| Average no. of instances for the most frequent sense per lemma | 148.78 |
| Average no. of instances for the second most frequent sense per lemma | 28.75 |

TABLE 4.2: SemEval statistics

In summary, like SenSem, SemEval was automatically annotated using Stanford CoreNLP, and manually revised later in order to correct mistagging and other errors. Unlike SenSem, the corpus is already split in train and test subsets.

### 4.3.2 Features

In order to train a supervised classifier algorithm, I need to define some features to represent the instances of the dataset. Such instances, particularly for verb sense disambiguation, are defined by the word (specifically the verb) to be disambiguated in a sentence. With that word as focus the following features are used to represent the instance:

- The main word.

- The main word's lemma.
- The main word's part-of-speech tag: in the case of Spanish part-of-speech tags, only the abbreviated form is used (generally the 2 or 3 first letters).
- In case of Spanish, the morphosyntactic information of the main word is given separately from the part-of-speech tag.
- The bag-of-words of a symmetric 5-word window (i.e. 5 words before and 5 words after the main word): this feature represents the number of occurrences of each words surrounding the main word (without considering it) giving no importance to the position.
- The words, lemmas and part-of-speech tags of the surrounding words collocationally in a 5-word window.
- The bigram and trigram formed by the words before and after the main word.
- The dependency triples formed by the main word, the relation and the words dependent on the main word (inbound dependency triples). And the dependency triple formed by the main word, the relation and the word from which the main word depends or if it is the root word (outbound dependency triple).

**Example 4.1.** The feature extraction is exemplified with the following sentence extracted from the SenSem corpus. It shows all the features extracted from it.

**Sentence and verb to disambiguate**

"Una serie de controles para que las industrias y los bancos se **abran** a un control efectivo desde EE.UU.".

**Extracted features**

**Main word** abran

**Main word's lemma** abrir

**Main word's part-of-speech tag** VMS

**Main word's morphosyntactic info**

**Part of speech** Verb

**Type** Main

**Mood** Subjunctive

**Tense** Present

**Person** Third

**Number** Plural

**Bag-of-words in 5-word window** { a, bancos, control, desde, efectivo, industrias, los, se, un, y }

**Collocational words, lemmas and tags in a 5-word window**

**Main word position - 5** { industrias, industria, NC }

**Main word position - 4** { y, y, CC }

**Main word position - 3** { los, el, DA }

**Main word position - 2** { bancos, banco, NC }

**Main word position - 1** { se, se, P0 }

**Main word position + 1** { a, a, SP }

**Main word position + 2** { un, uno, DI }

**Main word position + 3** { control, control, NC }

**Main word position + 4** { efectivo, efectivo, AQ }

**Main word position + 5** { desde, desde, SP }

**Bigrams/Trigrams**

**Left bigram** { bancos, se }

**Left trigram** { los, bancos, se }

**Right bigram** { a, un }

**Right trigram** { a, un, control }

**Inbound dependency triples** { ( que - conj - target ) , ( industria - suj - target ), ( se - pass - target ), ( a - cc - target), ( desde - cc - target ) }

**Outbound dependency triple** { ( target - S - para ) }

#### 4.3.2.1 Feature selection

The representation obtained by the previously presented features is highly sparse, as many of the features will appear once or twice in the whole dataset. Moreover the amount of different possible combinations for it will end up with a large amount of features to represent each instance. This is something that, as I will explain later, not all the supervised classifier can handle.

Dimensionality reduction techniques improve data representations by reducing the number of variables under consideration. They represent an instance via the principal variables. In particular I use feature selection techniques in which the main variables are the ones to retain more information regarding the represented data.

Feature selection relies on some underlying assumption: the features used to represent the data have a lot of redundancy, as the creation is done *ad-hoc* and may not be perfect (e.g. unfamiliarity with the domain, impossibility to obtain more relevant features automatically, etc). Thus, there is a lot of noise as there are so many features to represent data and many of them may be caused by noise rather than actual useful information. This noise and redundancy of the features also affects the overfitting tendency of a model, and applying some selection can help reducing this as the representation became more general by taking out the noise and smoothing the representation.

For the experimentation I use *univariate feature selection* with the ANOVA F-value [Fisher, 1921] to pick the top 10 thousand most representative features. This technique works by selecting the best features based on univariate statistical tests. It can be seen as a preprocessing step to an estimator. The method estimates the degree of linear dependency between two random variables.

#### 4.3.2.2 Feature hashing (or hashing trick)

Feature selection, as a way to reduce dimensionality of the input vector of a classifier, attains some interesting properties as described before. Nevertheless, it adds to the computational cost of training a model. In order to filter the features one needs to explore the whole dataset and then select the features from there. Moreover, there is no guarantee that new examples to annotate will be represented by those selected features.

*Feature hashing* [Weinberger et al., 2009], also known as the hashing trick, is an efficient way of vectorizing features. Unlike feature selection, it is not based on the assumption that some features carry more information than others. It consists in applying a data structure specifically designed to optimize dimensionality assuming sparse representations. In this method, features are vectorized into an array of fixed length by applying a hash function to the features and using the value as an index of the array. The feature count is then stored in the corresponding position of the array.

I explore this technique as a way to represent data with a limited amount of memory without fixing the representation to only some selected features. This is useful in case of having examples on which the selected features using the previously shown method are not present.

### 4.3.3 Classifiers

Different classifiers are being tested on the following sections in order to find those which apply better to the problem. There are mainly two types of classifiers: linear and non-linear.

#### 4.3.3.1 Linear Classifiers

A linear classifier algorithm does the classification process by using a linear combination of the features. For binary classification problems it can be seen the operation as splitting a high-dimensional input space with an hyperplane: all the points on one side of the hyperplane are considered of one class and all the points in the other side are of the other class. These classifiers have the advantage of being easier and faster to train, while reaching accuracy levels comparable to those of non-linear classifiers.

**Multinomial Naive Bayes** Naive Bayes [Russell and Norvig, 2003] methods are a set of supervised learning algorithms based on applying Bayes' theorem with the "naive" assumption of independence between each pair of features. The multinomial

naive Bayes method, implements naive Bayes algorithm for multinomial distributed data.

**Logistic Regression Classifier** Logistic regression [Walker and Duncan, 1967], despite its name, is a linear model for classification rather than regression. Logistic regression is also known in the literature as logit regression, maximum-entropy classification (MaxEnt) or the log-linear classifier. In this model, the probabilities describing the possible outcomes of a single trial are modeled using a logistic function.

**Support Vector Machines (with Linear Kernel)** Support vector machines [Cortes and Vapnik, 1995] are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary classifier.

As in future chapters I will need a probabilistic classifier, since some of the semi-supervised algorithms I use are based on this, and also a neural network, as other semi-supervised algorithm are based on those; this classifier is used mostly as a comparison.

#### 4.3.3.2 Non-linear Classifiers

A non-linear classifier uses a more complex function in order to better approximate the problem. The features can be combined in non linear ways. Thus more complex patterns in the data can be found. Plus, some problems are strictly non-linearly separable. A common problem with this kind of classifiers is the tendency to overfit the data.

**Decision Tree Classifier** Decision trees [Quinlan, 1986] are a supervised learning method used for classification and regression. The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features.

**Multilayer Perceptron** A multilayer perceptron (MLP) [Rosenblatt, 1962] is a feed-forward artificial neural network model that maps sets of input data onto a set of appropriate outputs. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training the network. MLP is a modification of the standard linear perceptron and can distinguish data that are not linearly separable.

### 4.3.4 Experiments

Experiments, alongside metrics, are fundamental to test the hypotheses of this and each of the following chapters of the thesis. Experiments and metrics are very closely related as an experiment is only useful through a metric giving an insight on its performance.

Experiment 4.1 is a general experiment to apply using a train/test split architecture, that is already present in the resources. The idea of this schema is to compare the performance of different classifiers and representations for the whole dataset. This kind of experiment is needed as a baseline comparison for the possible models.

**Experiment 4.1.**

**4.1a** Train a model with the train subset of the corpus for each lemma of the corpus.

**4.1b** Classify the test corpus, of each lemma, with the trained model.

**4.1c** Compare the model's predicted results, of each lemma, with the gold standard results using some metric.

Experiment 4.2 is designed to check the performance of a model as the number of examples increases, assuming that a higher number of examples will improve the performance of the classifier. The idea is to divide the original corpus into smaller parts and train new models gradually adding new examples.

**Experiment 4.2.**

**4.2a** Select a number of *splits* for the corpus.

**4.2b** For each lemma, divide the corpus in the number of splits, ensuring there is one split with all the available labels and take that for the initial training.

**4.2c** Train a model.

**4.2d** Test the model using the test set and store the results.

**4.2e** Add the next split to the training data and retrain the model.

**4.2f** Finish the experiments when all the *splits* were used for train.

Finally, Experiment 4.3 is similar to Experiment 4.2 as it also tries to check the performance of a model by gradually adding new data. However, this experiment objective is to measure the variance of different models trained over different subsets of the training data to assess the impact of the amount of data on how the model overfits the data.

**Experiment 4.3.**

**4.3a** For each lemma, randomly split the whole corpus in a selected *number of splits*. The size of the splits should be uniform. Ensure there is one split with all the complete dataset's classes and take that for the initial iteration.

**4.3b** Take the initial dataset and split it in train and test.

**4.3c** Train a model with the training dataset obtained in the previous step and store the predictions over the train and test datasets obtained in the previous step.

**4.3d** Add the next *split* to the dataset and repeat from step 4.3b.

**4.3e** When all the *splits* are added proceed to repeat the whole algorithm $n$ times with a new set of random splits.

The idea behind repeating this algorithm $n$ times is to represent how training the same model over different datasets vary, and find an estimator of the model's tendency to overfit over those datasets.

### 4.3.5 Metrics

The experiments defined in the previous section require metrics in order to be evaluated. Metrics work alongside visualizations to show different views of a result. However, both these tools are subject to interpretability, as each metric and visualization highlights some aspects of the evaluation, whilst obscuring some other. I work with three kinds of metrics in this thesis: performance, significance and tendency to overfit. Each kind of metric shows a partial view of the results. It is difficult (if not impossible) to combine different metrics without losing the objective the specific metric has.

#### 4.3.5.1 Performance metrics

Performance metrics are the ones measuring how well an experiment does in respect to a test corpus, held out from the training corpus, that roughly represents, minor in scale, the same classes. These metrics are the ones used in Experiments 4.1 and 4.2, and compare one model with another model.

When dealing with tasks of automatic classification in NLP I need a metric to determine the performance of a classifier for all classes. In accuracy, a standard metric, the imbalance of a class can affect the final result. In precision and recall, also standard metrics, I need to check the value for each class, difficult when dealing with many classes. In particular, word sense disambiguation is a task dealing with a Zipfian [Zipf, 1949] distribution. This causes that a metric biased towards the most frequent class affects the perception of how well an algorithm is doing.

**Accuracy** Accuracy is defined as the proportion of correctly classified instances. This is an example of a biased metric, as with many instances belonging to one class, any classifier biased to the most frequent class (MFC) can have a good performance.

**Precision, recall and F1-score** The first two metrics generally go side by side as one of them is not enough to measure the performance by itself. Although originally defined for information retrieval [Rijsbergen, 1979], they have become standard in

many classification tasks. Particularly, these are the metrics used by SemEval competition to compare results. **Precision** is defined as the number of instances classified with certain class that are effectively instances of that class. **Recall** is defined as the number of instances of a class that were effectively classified with such class. These metrics have the advantage over accuracy of showing results for each sense, which can be a good indicator when dealing with a small amount of classes. However problems with many classes, like in verb sense disambiguation, need simpler values to measure the performance, thus making it easier to compare to an established baseline. The **F1-score**, a harmonic mean between precision and recall does solve the problem of having a single value, but still deals with having one value for every possible class.

**Precision, recall and f1-score averages** Averages deal with the problem of having precision and recall results for multiple classes compressed in one single class. There are different kind of averages:

**Macro [Manning et al., 2008]** average is defined as the unweighted mean of the metric's values for each class. With this average the least frequent classes are as important as the most frequent ones, nevertheless, it also means that extreme class imbalance will drastically impact the final results.

**Micro [Manning et al., 2008]** average is calculated by getting each true positive (tp), false positive (fp), true negative (tn) and false negative (fn) generally, instead of using a per-class basis. With that information the precision and recall is calculated. This means that those classes with more occurrences are more relevant as the tp/tn/fp/fn will belong mostly to the most frequent classes.

**Weighted** average is calculated on a per-class basis, but then each class metric is averaged weighted by the number of occurrences it has. Similar to what happens with micro average, classes with more occurrences have more relevance in the final results.

**Precision of the most frequent class (PMFC) and recall mean of least frequent classes (RMLFC)** These two metrics were explored as a possible addition to the metrics explained before. PMFC has the idea of revealing the tendency of a classifier to categorize all instances as being part of the MFC, the lower the value the more biased the classifier is. RMLFC is the macro average of the recall in the classes leaving out the most frequent, thus showing how good is the classifier to correctly classify the instances of the less frequent classes. Though some experiments were done following this metrics, there was not a real impact or visible difference to choose these metrics over the usual averages.

**Selected metrics** After a series of experiments it is concluded that none of these metrics can show the performance of the classifiers and biasing of them by itself, rather the combination of them show a better pattern.

**Metric 1.** The performance of an experiment is shown by the comparison of the following metrics:

**1a** Macro-averaged F1-score.

**1b** Weighted average F1-score.

As imbalanced classes is a challenge I have to deal with, it is important to show how this affects the overall performance of the models. Metric 1 is useful to see whether a model is having a large bias to the most frequent class.

#### 4.3.5.2 Significance metrics

The significance metrics are used to compare different models and check whether the difference in performance between them is statistically significant or not. These are useful to rule out two, or more, models which perform similarly and whose difference does not really improve the results but is merely a result of chance. They are used in Experiment 4.1.

**Cohen's kappa coefficient** The Cohen's kappa coefficient has been originally conceived as a metric to measure inter-annotator agreement in tasks of manual labeling. It can be used in some way as a performance metric comparing the test results of a model against the ground truth and thus normalizing the accuracy, adjusting the result for the expected agreement with the perfect classifier by chance [Cohn and Cohn, ]; however, I find it useful to apply it as a measure of how significantly different are the results of two classifiers. To check if the performance of the different classifier is statistically significant Metric 2 is used.

**Metric 2.**

**2a** Take a pair of classifiers, a dataset and a feature representation.

**2b** Train the model for each classifier.

**2c** Test the model on the test set for the trained classifier.

**2d** Use Cohen's kappa coefficient to analyze the annotators agreement for the pair of classifiers over the predicted results in the test corpus.

Other significance metrics like Fleiss's Kappa [Fleiss et al., 1971] and Krippendorff's alpha [Krippendorff, 1970] have also been used to asses significance and reproducibility but in this work we are restricted to Cohen's Kappa because it is a more standard metric.

#### 4.3.5.3 Learning curve and tendency to overfit

Another important measure in this work is the tendency of a model to overfit the training examples. This can be measured by analyzing the *error due to high variance*. Manning et al. [Manning et al., 2008] defines it as the variation of the prediction of learned classifiers: it measures how inconsistent the predictions are from one another, over different datasets, not whether they are accurate or not.

This metric is closely related to Experiment 4.3 because it needs it in order to see the variation of the model for different datasets. To calculate it I base the algorithm on the one of Experiment 4.3:

**Metric 3.** The learning curve is calculated with the following steps:

**3a** For each lemma, randomly split the whole corpus in a selected *number of splits*. The size of the splits should be uniform. Ensure there is one split with all the complete dataset's classes and take that for the initial iteration.

**3b** Take the initial dataset and split it in train and test.

**3c** Train a model with the training dataset obtained in the previous step and store the predictions over the train and test datasets obtained in the previous step.

**3d** Add the next *split* to the dataset and repeat from step 3b.

**3e** When all the *splits* are added proceed to repeat the whole algorithm $n$ times with a new set of random splits.

**3f** Calculate the mean and standard error of the mean of the misclassification error of both training and test sets predictions for each step of the algorithm.

The resulting curve shows the variance error of a model as the number of training examples increases. Models with higher variance are more prone to overfit the data.

## 4.4 Analysis of Results

The next section reports the results obtained through the different experiments. These results are outlined with the use of some visualization tools I chose in order to gain a better insight according to the metrics assigned to each experiment for each hypothesis. The final objective is to draw conclusions regarding the results and use them to accept or reject the hypotheses.

Although I looked and experimented with different visualization techniques and metrics, it is important to recall that each metric can obscure some results or favor others. I wanted to be as objective as possible and chose those metrics and visualizations to show the most possible information. But there is a trade-off between the amount of results I can show and the amount of information I can get from them before it starts being too difficult to handle.

In particular, for verb sense disambiguation as I trained one model per lemma, I had to select some visualizations, like box and whiskers plots, which are good to give a general idea of many different results (in this case, the results of each lemma) but obscure the more specific results.

### 4.4.1 Representation Selection

As explained in Section 4.3.2, the problem with using a representation with all the features is its sparsity and high dimensionality. This affects the performance of the multilayer perceptron classifier as the large number of combinations between the input layer and the hidden layer make it too big for the machine memory to handle at the time of writing this thesis. The multilayer perceptron classifier is needed as it is the base for the semi-supervised method discussed in Chapter 8. This is the reason to try some techniques to limit the number of features as explained before. A first approach was to use feature selection, however, this had a drawback as it takes time to train the algorithm to select the features based on some metric (e.g. variance or information gain). Thus, I also experimented with the *hashing trick* to see how this technique worked.

In order to rule out the reduction of dimensionality affects the final result I trained different models using the different approaches (reducing the dimensionality and not reducing it) and, using the F1-score macro and weighted average (Metric 1), I compared the results.

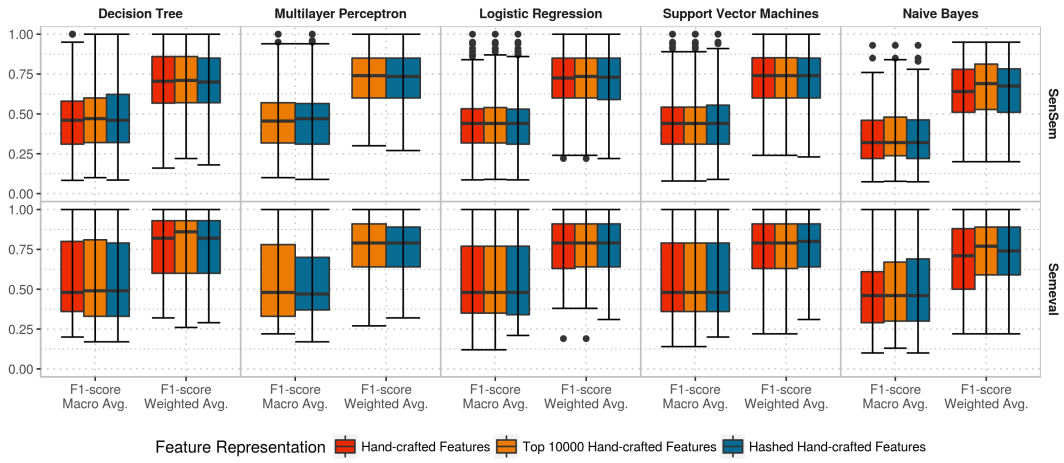


FIGURE 4.1: Comparison of feature representations for different classifiers using F1-score macro and weighted average

Figure 4.1 showcases the different results of the different models changing the features representation using a box and whiskers plot. The plot is structured in the following way:

- Each row shows the results for a corpus: SenSem and SemEval.

- Each column represents a classifier: decision tree, multilayer perceptron (with two hidden layers one of 250 neurons and the other with 100 neurons), naive Bayes, logistic regression, and support vector machines.
- Each group of box-plots in each plot represents a metric: F1-score macro average and F1-score weighted average.
- Each box-plot of different color inside a group is the type of representation: all the features, top 10 thousand features selected by the feature selection method, and hashed features.
- The box and whiskers plots represent the distribution of the values of the metrics through their quartiles. Each value is the performance for a lemma of the corpus. The black thick line in the middle of a box-plot represents the median and the whiskers at the end of each box-plot represents maximum and minimum value (except for eventual outliers represented by black dots outside the box-plot).

First thing to notice in the Figure is the absence of a representation box-plot in the column corresponding to the multilayer perceptron. This is because of what was said in the previous paragraph, about a multilayer perceptron being unable to handle all possible features.

From the graphic I can figure out that there is no distinctive difference from one representation to the other. In general terms the quartiles are similar, and the performance depends more on the classifier than the representation. It is true however that in many (if not all) cases there is a minimal improvement on the performance by using dimensionality reduction, probably because it makes the classifiers overfit less when the noise of rare features is removed. Although it is also true that the use of a feature selection technique has a little more performance (though still minimal) than the hashing trick, there was also a trade off because of the computational cost of doing feature selection for the classification task, which in future experiments using semi-supervised techniques would become a heavier problem as the number of new features grows at high pace.

For these reasons, *the rest of the experiments were carried out using the hashing trick representation* as it shows no great drop in performance over the test set and it is also the cheapest to work with in computational terms.

### 4.4.2 Classifier selection

In the following chapters I will focus on working with the multilayer perceptron classifiers. This, again, is to have a point of comparison particularly in Chapter 8 as Ladder Networks are based on a multilayer perceptron classifier. It is however important to compare the multilayer perceptron against other classification methods in order to rule out the possibility of it being a bad choice to work with from the start.

#### 4.4.2.1 Architecture selection

One of the main hyperparameters for a neural network is the architecture. In a multilayer perceptron this is the selection of the number of layers and size of each layer (i.e. number of neurons). As the amount of data is small, there is a high risk of the network memorizing the datasets. With enough neurons available, each instance can be mapped to a path in the network. Thus I cannot work with a very deep neural network without falling into this problem. That is why I only look up to three hidden layers.

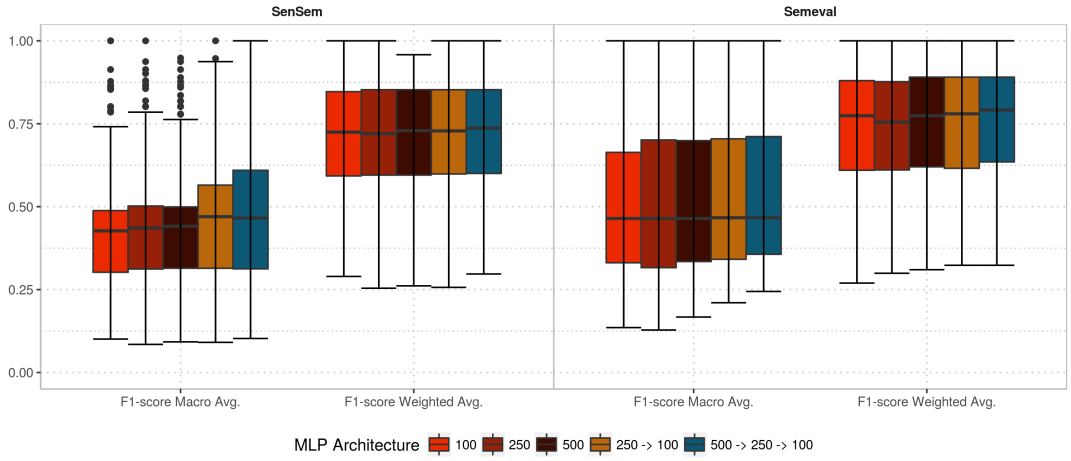


FIGURE 4.2: Comparison of multilayer perceptron architectures

Figure 4.2 compares different architectures for a multilayer perceptron using the hashing trick representations (as it was selected before). This is done only for the following architectures:

1. A hidden layer with 100 neurons.
2. A hidden layer with 250 neurons.
3. A hidden layer with 500 neurons.
4. Two hidden layers: the first with 250 neurons, and the second with 100 neurons.
5. Three hidden layers: the first with 500 neurons, the second with 250 neurons, and the third with 100 neurons.

The Figure has a similar structure to that of Figure 4.1 as it is also a box and whiskers plot to showcase the performance of each lemma:

- Each column represents the corpus: SenSem and SemEval.
- The group of box-plots represents the metric: F1-score macro average and F1-score weighted average.

- Each box-plot of different color represents an architecture of the network as described before.
- The box and whiskers plots represent the distribution of the performance for each lemma as described for Figure 4.1.

In this case I can see that the number of neurons does not affect the result but the number of layers does. The three layer architecture shows the best results avoiding a high tendency to overfit. There were some other experiments adding more layers but the improvement on the results was not much more than with a three layer architecture and, as the number of hyperparameters grow, the networks were more prone to overfit the data by memorizing it. Plus, the training time became considerably higher for deeper architectures.

#### 4.4.2.2 Comparison of classifiers

Figure 4.3 showcases the comparison of the classifiers described in Section 4.3.3, with an addition of a baseline classifier which assigns the most frequent sense to every instance.

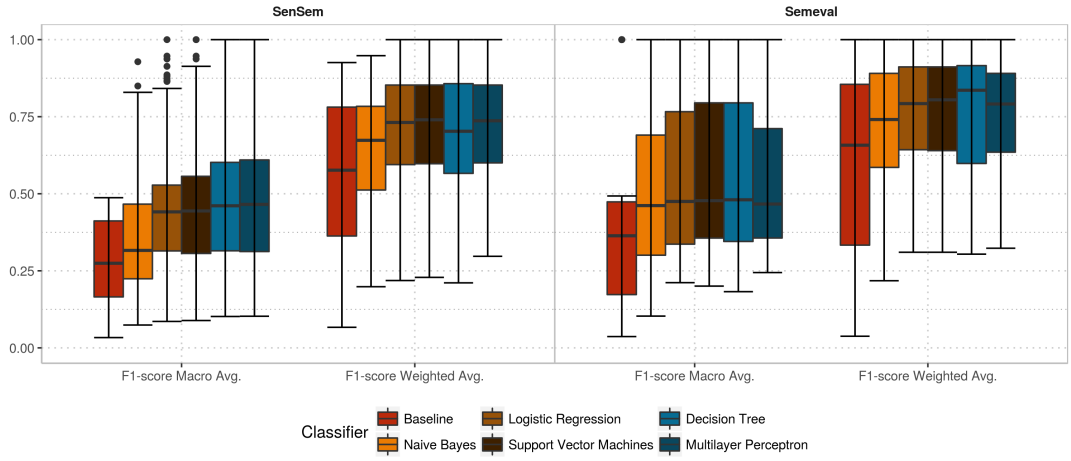


FIGURE 4.3: Comparison of classifiers

Since it was established that the supervised representation to use in the rest of the experiments of this thesis is using the hashing trick, the comparison here is only for such representation. The Figure also has a box and whiskers plot with a similar structure to that previously shown:

- Each column shows the results for a corpus: SenSem and SemEval.
- Each group of box-plots represents a metric: F1-score macro average and F1-score weighted average.
- Each box of different colors inside a group is the classifier: baseline, decision tree, multilayer perceptron, naive Bayes, logistic regression, and support vector machines.

- The box and whiskers plots follows what is described previously for Figure 4.1.

First thing to strike out from the plot is that all the classifiers outperform the baseline classifier described above. In particular, naive Bayes is the one to show the worst results among the other classifiers, very near to the performance of the baseline classifier, clearly biased by the most frequent sense. On the other hand, the decision tree classifier as well as the multilayer perceptron classifier (with the architecture defined in the previous section) show the best performances for SenSem corpus if we focus in minority classes. However, in a weighted average the decision tree has a worse performance than SVM, LR or MLP.

For SemEval there is less disparity between the performance of the classifiers (still being naive Bayes the one with worse performance, besides the baseline), with the median being similar for all of them, and being the decision tree the one having the best performance in a weighted average.

Seeing that decision trees and multilayer perceptrons are the ones with the best performances, there is a strong indication that the problem of verb sense disambiguation is non-linear.

#### 4.4.2.3 Significance

The previous results are good enough to assert that a multilayer perceptron is a good approach to model the problem of verb sense disambiguation. However, in order to see whether the difference in performance is significant or not, I should test it using Metric 2 and seeing the Cohen's kappa coefficient between the different classifiers.

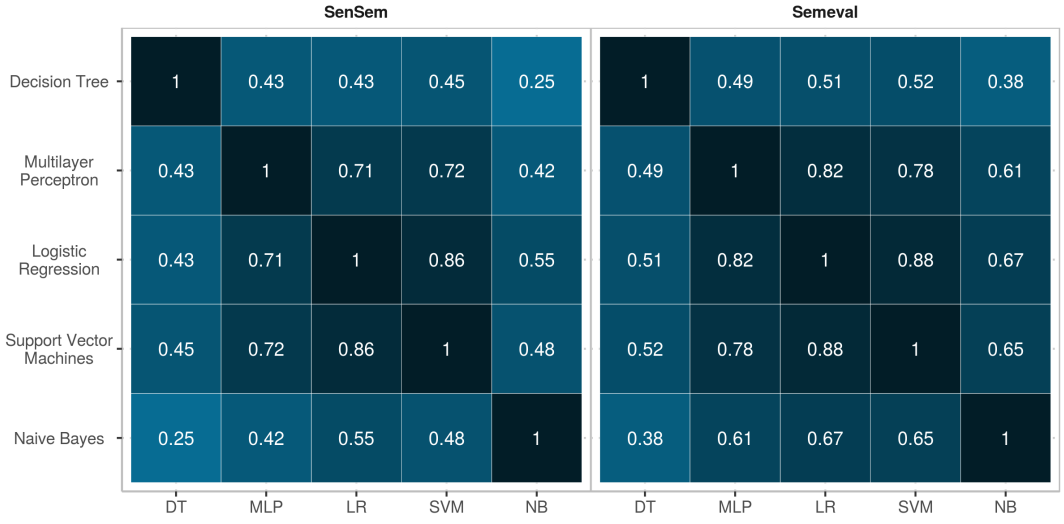


FIGURE 4.4: Cohen's kappa coefficient between classifiers

Figure 4.4 shows with a heatmap the mean of the Cohen's kappa coefficient between the classification results of each classifier per lemma over the test corpus. The higher the kappa, the more similar the classification, thus the less significant the difference between classifiers. The color of the heatmap defines the value for inter-classifier

kappa between the classifier of the row and the classifier of the column. The heatmap is symmetric.

The logistic regression and SVM classifiers are the ones having the most agreement, probably because they are both linear classifiers. Thus the difference in performance between them is not really significant. The multilayer perceptron is the most similar to these two. Decision trees and naive Bayes are the ones to show the less agreement compared to the other classifiers. Naive Bayes is likely to have a low agreement as it is one of the classifiers with worse performance. Although it is not trivial to set a threshold for which the kappa statistic is good to denote statistical significance, I can infer from this plot that decision tree learning is clearly having good performance with statistically significant difference with other classifiers that are also performing well, which makes it more interesting to continue exploring in future work.

### 4.4.3 Hypothesis 1.1

Once the base model to work with for the following experiments is selected, I can start testing the hypotheses set in Section 4.1.

I start by looking at the results to test Hypothesis 1.1. Recall the hypothesis states that larger training datasets help improving the performance. To check the validity of this I follow the steps of Experiment 4.2. I use the multilayer perceptron with three layers I selected in previous paragraphs.

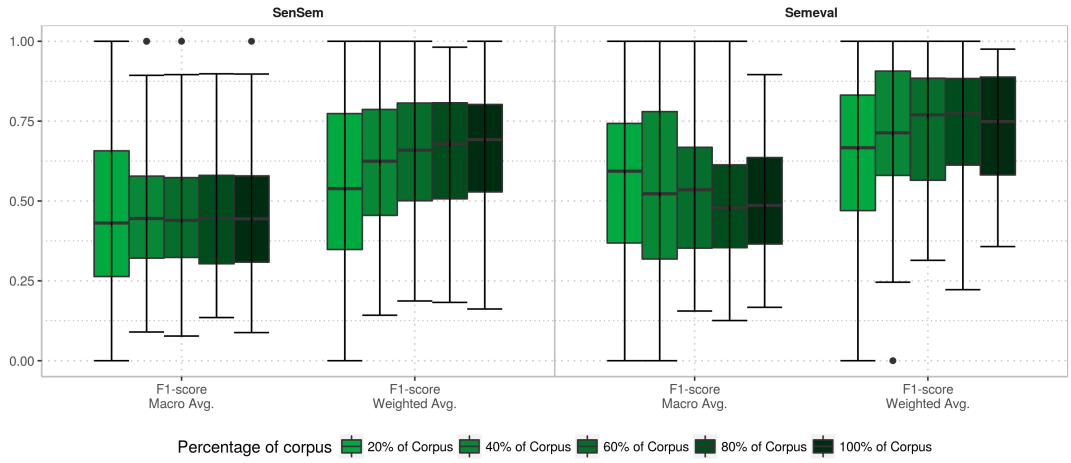


FIGURE 4.5: Performance per lemma on the test corpus for different sizes of training corpus

Figure 4.5 shows the performance on the test corpus for different sizes of the training corpus (as a percentage of the full training corpus). The figure shows a box and whiskers plot following a similar structure shown before:

- Each column shows the results for a corpus: SenSem and SemEval.
- Each group of box-plots shows the different metrics: F1-score macro and weighted average.

- Each box-plot of a different shade of color shows the performance for different sizes of the training set (as percentage of the total training data).
- Each box and whiskers plot follows what is described previously for Figure 4.1.

The first thing to note from this figure is how, increasing the number of examples does not necessarily improve the performance of the classifier. This is due to the fact that in the process to progressively enlarge the corpus examples are added aiming to have each class represented. When the corpus is very small, minority classes are comparatively well represented. But as the number of examples increases, the imbalance between classes also increases. This results in no performance gain (SenSem) or even degradation of the performance (SemEval)for minority classes, as can be well seen in the macro average metric. The weighted average improves with the number of examples in the case of SenSem, which is a very small corpus, but not so much in the case of SemEval, which is much bigger. Thus increasing the number of examples seems good to improve a small corpus but not necessarily a bigger corpus. The main reason for this seems to be the problem of class imbalance, that becomes more and more acute as the number of examples increases.

This however is difficult to see clearly, as the box-plots are useful for giving a general idea of the performance for many different models, but they obscure the particular performance of a specific model. As I have one model per lemma, I would need to examine more closely 200 hundred different models to see how it is working for each lemma, something outside the scope of this thesis.

There is a clear pattern nevertheless in how a model improves performance with more training data, specially in cases of models with extremely low performance: there are models that initially have an F1-score of 0 for the models trained with the less data, something that does not happen with more added data.

### 4.4.4 Hypothesis 1.2

To check Hypothesis 1.2 I recall that I would do so with aid of Experiment 4.3. The hypothesis states that the size of the dataset not only affects the performance (measured by Metric 1), but also the tendency to overfit (measured by Metric 3) of a model.

Figure 4.6 shows the learning curve for different sizes of the training data. The structure of the learning curve plot is as follows:

- The plot is divided in two columns, each represents a corpus: SenSem and SemEval.
- The x-coordinate shows the size of the training data, as a percentage of the total training data available, starting from 20% of the corpus (the corpus was split in 5 parts according to Experiment 4.3).
- The y-coordinate shows the misclassification error of a model.

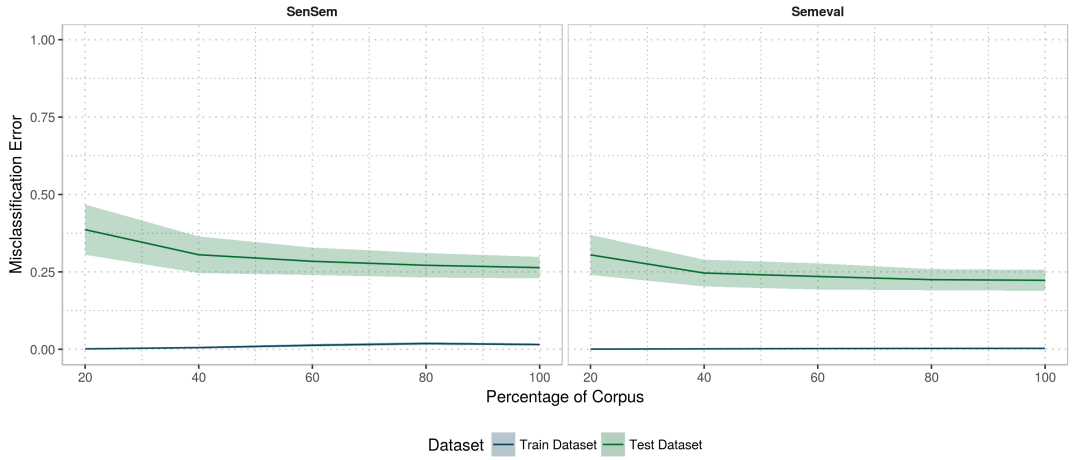


FIGURE 4.6: Learning curve for different sizes of training corpus

- There are two colors representing the datasets: train and test.
- The solid darker lines represent the mean of misclassification error trough the different splits of the datasets over all the models.
- The shadowed area, which have a lighter color, represent the standard error of the mean of the misclassification error.

Recall Experiment 4.3 first split the corpora in uniform size parts and gradually added those new parts to the training and evaluation of the model. It trained a model on a portion and evaluated it on the other, held-out, portion and recorded the results. It repeated the algorithm a number of times over different ways of splitting the data to see how the same model behaves on different datasets. Figure 4.6 shows the mean and standard error of the mean over the misclassification error each model has in the training and test datasets.

The test data is having a visible variance of the misclassification error, seen in the wide shadowed area, while the training data is having almost no misclassification error, as the shadowed area is indistinguishable of the line representing the mean of the misclassification error.

In the plot there are two indicators of an error due to variance:

- A wider shadowed area: means that the misclassification error of different models has a high variance, thus making the models more inconsistent over different datasets.
- A higher mean of the misclassification error of the test set in comparison to the mean training set error, means the model is overfitting to the training data.

As I clearly see in Figure 4.6, this variance is smaller the more training data I have. This is a strong indication of Hypothesis 1.2 being true, as there is less overfitting in the different models the more data is used for training.

### 4.4.5 Hypothesis 1.3

To check Hypothesis 1.3 I would do so with aid of Experiment 4.3. I recall the Hypothesis stated that the number of classes affects the tendency to overfit (as measured by Metric 3). To show this I plot the training curve measuring the mean of lemmas having different number of total labels.

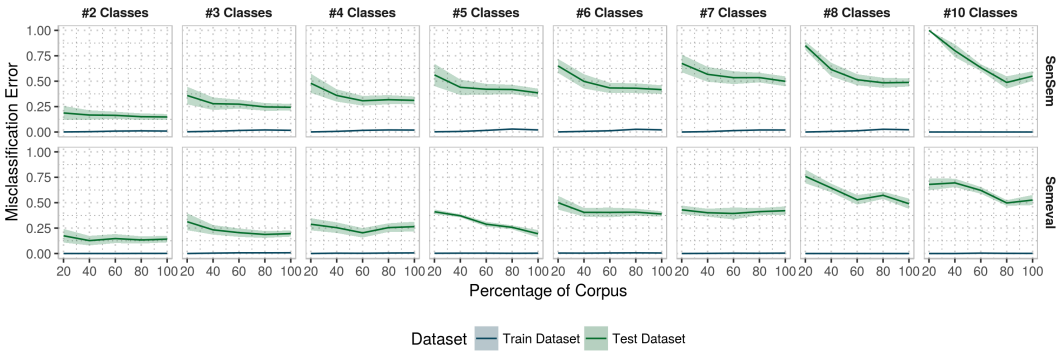


FIGURE 4.7: Learning curve for different number of classes

Figure 4.7 shows the learning curve for different number of classes. The structure of the plot is similar to Figure 4.6 with some minor changes to showcase what the Hypothesis states:

- The plot is divided in two rows, each represents a corpus: SenSem and SemEval.
- The columns of the plots represent the number of classes of the models: 2, 3, 4, 5, 6, 7, 8, and 10 classes.
- The x-coordinate is the size of the training data as explained in Section 4.4.4.
- The y-coordinate shows the misclassification error.
- The colors, lines and shadowed area represent the same thing described in Section 4.4.4.

The models are one for each lemma, thus Figure 4.7 shows in each column the mean of all the models having that number of classes (senses). The pattern of the Figure is clear, as the mean of the error due to variance is larger the more classes the model has. The error due to high variance is higher in the models with more classes as a result of the distribution of the classes, which is Zipfian. As the tendency to classify all the data as part of the most frequent class when there is not enough data of the other classes, the misclassification error of the test data is higher than the training error. These results give evidences to not reject Hypothesis 1.3.

### 4.4.6 Hypothesis 1.4

To check Hypothesis 1.4 I use Experiment 4.3. This Hypothesis states that linear models have less tendency to overfit that non-linear models. This Hypothesis is looking to check whether the non-linearity of a model affects its tendency to overfit the data.

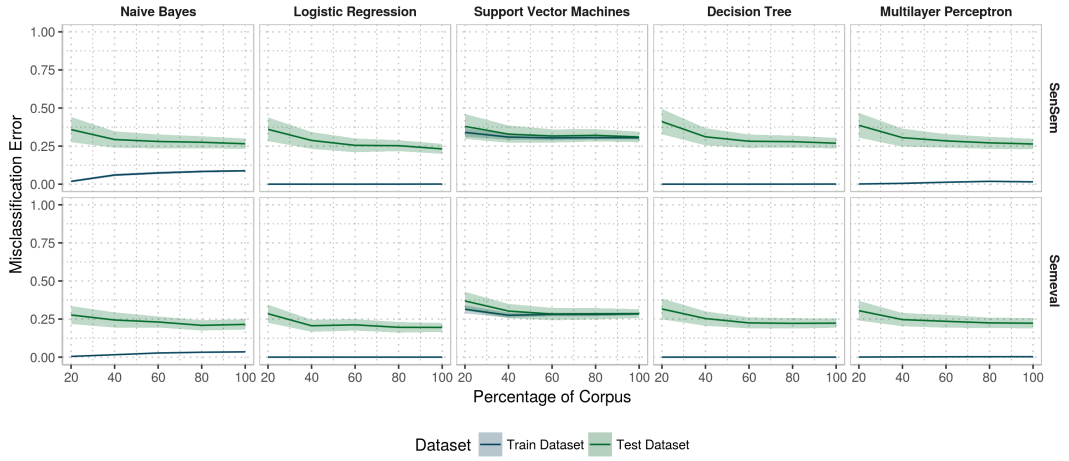


FIGURE 4.8: Learning curve for different sizes of training corpus per classifier

Figure 4.8 showcases the learning curve for different kind of classifiers (the ones presented in Section 4.3.3). The Figure uses a similar structure to that of Figure 4.7, but changes what the columns represent:

- The rows of the plot represent the different corpora: SenSem and SemEval.
- The columns of the plot represent the different classifiers: Naive Bayes, Logistic Regression, Support Vector Machines, Decision Tree and Multilayer Perceptron. Note that the linear classifiers are the first three ones from the left and the non-linear classifier are the last two from the left.
- The x-coordinate represents the size of the training data as a percentage of the total training data.
- The colors, lines and shadowed area represent the same thing described in Section 4.4.4.

The first thing that highlight in the plot are the results for Naive Bayes and Support Vector Machines. In both cases, the training error is not so close to 0 as it is for the other classifiers.

In Naive Bayes, the error of the training data increases with the number of training instances. Remember in Section 4.4.2.2, I saw Naive Bayes was the classifier with the lowest performance and I figure out this was a result of it being biases towards the most frequent class. Figure 4.8 gives even more evidence to support that claim. Naive Bayes then shows less difference between the training error and the test error as it sacrifices the performance of the model for more generality of it.

Support Vector Machines shows a wider shadowed area of the training dataset misclassification error, which means a higher variance of the performance in the training data. SVM with a linear kernel separates the data with an hyperplane of maximum

margins, just as naive Bayes, it sacrifices good performance of the training data for a better performance over the general data.

The other three methods show very similar results, with decision trees being slightly higher than the rest and logistic regression being slightly lower. However, from the visual results I see the significance of this difference in performance is not significant.

The results shown are supportive of Hypothesis 1.4, as the linear classifiers show less tendency to overfit, although is at expense of a higher error due to bias.

## 4.5 Conclusions

This chapter introduces the problem of verb sense disambiguation using purely supervised methods. The hypothesis I want to test is that the size of the training set affects the performance of a model. This initial hypothesis was divided into more specific subhypotheses, which the experimentation and analysis of results tried to accept or reject.

I designed some experiments to see if there was a significant difference between different models. A first step was to rule out that techniques to reduce dimensionality of the representations affected the performance of the models. This was shown true with the results in Section 4.4.1.

For the neural network classifier, I needed to set the architecture of the network. The results reported that an architecture with more layers improved the performance of the model. This was not the case for the number of neurons per layer. Section 4.4.2.1 shows these results.

Finally, I compared the performance of the neural network classifier with the other classifiers defined in Section 4.3.3. Section 4.4.2.2 shows the neural network had one of the best performances for the SenSem corpus. Nevertheless, the Kappa coefficient did not report significance in this improvement over the other classifiers. In any case the objective was to check whether the neural network was outperformed by other classifiers, which was not the case. The neural network, as I will show, is the classifier that I finally chose because its performance was not worse than the others and it is comparable to the classifiers explored in future chapters.

The experiments done to accept or reject Hypothesis 1.1 that larger training dataset improve on the performance are observable in Section 4.4.3. The reported results give strong indications about the validity of the Hypothesis, since there is a visible improvement in the overall results as the number of training examples increases, thus the Hypothesis cannot be rejected.

Hypothesis 1.2 cannot be rejected since results of Section 4.4.4 give a strong evidence to support it. Indeed, the tendency to overfit and the error due to variance decrease the more training data the model has.

In the same way Hypothesis 1.3 cannot be rejected because of the evidence in results of Section 4.4.5. The number of classes (senses) affects the overfitting of the model. The more classes, the more difficult for the model not to overfit.

Finally, experiments to test Hypothesis 1.4, which expects linear models to have less tendency to overfit than non-linear models, do not yield conclusive results, although in a shallow observation the results can be interpreted in favor of not rejecting the Hypothesis. Two of the linear classifiers have the training error closer to the validation error. The methods sacrifice accuracy in their training data in order to improve the generalization. The problem however is that the test set misclassification error does not look significantly better than for the other classifiers.

The objective for this chapter was to lay the foundations on which the following chapters will compare and try to overcome its shortcomings. In particular, the purely supervised models present challenges in two main aspects: the tendency to overfit when training a model with a small dataset and the coverage that these models may have over new unseen examples. The semi-supervised approaches I will explore in the following chapters try to resolve these challenges from different angles.

One of the latent causes to overfit in purely supervised models is given by the very nature of such models. They generate a representation of the training examples based on features obtained from the same annotated data the classifiers is attempting to represent. The way I aim to attack this flaw is by using features which generalize better, not tied to a particular labeled dataset but obtained from a more general language sample. This is explored in Chapter 5. Smoother representations of the labeled data are used by unsupervised methods with word embeddings.

Another of the latent problems in purely supervised models occur in the coverage of such models. This is difficult to measure and quantify, since to do so a much larger number of annotated examples are needed.

The coverage problem can only be measured through the silence metric. Silence captures those examples that belong to one of the data classes, but are not available in the annotated corpus, thus models cannot learn from these data. The annotated data can only consider a limited universe of features, leaving out other characteristics of the labels that may improve the model on new candidates to classify.

Other semi-supervised methods, studied in more detail in later chapters, study ways to overcome this shortcoming of purely supervised approaches, for example, by annotating new data (automatically or manually) contributing to supervised models to have more latent information so as to improve the performance over new data.

# Part II

# Disjoint Semi-Supervised Methods

# Chapter 5

# Word Embeddings

## 5.1 Overview

In this chapter I explore the use of unsupervised word embeddings to aid the task of Spanish verb sense disambiguation. The work on English verb sense disambiguation done in Chapter 4 served as a comparison point to the work done for Spanish, however to simplify the study of semi-supervised techniques I am from now focusing on Spanish only.

The previous chapter showed us two of the main problems with the purely supervised approaches with small labeled data: overfit of the data and little coverage. The model learns to adapt to the available features, and although it manages to do so well, it generalizes poorly, thus ends up overfitting. The coverage of the data, on the other hand, depends on the amount of labeled data available, which was established to be small.

The previous chapter also showed that the size of the training dataset affects the final performance of a model. Based on these results it is possible to argue that the reason behind this phenomenon is that the more data there is, the more features can be included in the model. Thus, new examples have better representation because those features which represent them are more probably included in the training dataset already.

To tackle this coverage problem, I want to expand the labeled data with new data from unlabeled sources while keeping the effort of human annotation to a minimum. However, in order to do so, I first need to find a way for the available data to decrease the tendency to overfit, as I need a model to generalize well to new examples so these add to the coverage of the model. I will explore the impact of adding more examples with low annotation cost in the following chapter. In this chapter I will focus on reducing the tendency to overfit of classic supervised approaches.

Hand-crafted features pose a problem for generalization because they are are literally taken from the labeled dataset, and thus do not play well with domain change. This is important because the labeled data is contained in one particular domain, the journalistic domain, because it is taken from a newspaper. However, the model should adapt to other domains as well.

Finally, there are two other latent problems of the hand-crafted features representations described in the previous Chapter, which add to the complexity of any problem one would like to represent: high dimensionality and sparseness of the representations. The dimensionality, as we saw in Section 4.3.2 can be managed through some dimensionality reduction technique (i.e. the *hashing trick*). Nonetheless, the sparseness is still a problem, as most of the designed features occur on a single instance basis, thus the representation vectors have little information. This high dimensionality and sparseness of the data adds to the computational cost of solving the problem with classifiers.

To deal with these problems of sparse representations, I apply unsupervised word representation methods, namely Word2Vec [Mikolov et al., 2013a]. These techniques have recently gained attention in the natural language processing community, specially with the resurgence of neural networks and deep learning. These are called word embeddings and represent words with fewer dimensions and dense vectors.

This chapter takes the domain and experiments from the previous chapter, i.e. verb sense disambiguation for Spanish, and develops on new experiments upon this basis, with the addition of word embeddings as features for the models.

This chapter will test the following hypothesis:

**Hypothesis II** *Unsupervised representations improve upon supervised models by avoiding the overfitting caused by the features taken from the same dataset where the model is trained.*

I will do this by proving the following subhypotheses:

**Subhypothesis 2.1** *The performance of an unsupervised representation depends on the domain of the unlabeled dataset where they are trained.*

**Subhypothesis 2.2** *Using word embeddings produces less overfitting over supervised models than hand-crafted features.*

These hypotheses will be tested using the following layout:

- Experiment 5.1 reports the performance of different representations, which can be supervised or unsupervised. The performance is measured by the macro and weighted average F1-score (Metric 1). Results shown in Section 5.4.1 serve to accept Hypothesis 1.1, that the domain where word embeddings are obtained affects the final performance of the model.

- Experiment 5.2 reports the variance of different models trained over different subsets of the training data. This variance is measured by Metric 3 which reflects the tendency of a model to overfit, with aid of the learning curve. From this experiment and metric, using different visualizations according to the task, I show that the classifier is less prone to overfitting using word embeddings instead of hand-crafted features as stated by Hypothesis 2.2.

In Section 5.2 I recapitulate on previous work on unsupervised representations and word embeddings. The special focus is on the algorithm of word2vec. I also point out the work done in word sense disambiguation done using word embeddings.

In Section 5.3 I explain all relevant items concerning what is used to carry out the experimentation of this chapter. First, in Section 5.3.1 I introduce the resources I work with. A quick recap of the SenSem corpus is done, followed by the unlabeled corpora used to train the word embeddings: SBWCE, journalistic corpora, and regulations corpora. In Section 5.3.2 I describe the two types of features used for experimentation: supervised features from the previous chapter and word embeddings trained from the unlabeled corpora. Section 5.3.4 lists the experiments. Section 5.3.5 lists the set of metrics I use to measure the experiments.

Section 5.4 reports the results of the experiments and analyzes them in order to accept or reject the stated hypotheses of the chapter.

Finally Section 5.5 draws the conclusions of this chapter, recapitulating the Hypotheses and the implications of accepting or rejecting them according to the evidence gathered in the results. It states the shortcomings of the methods explored in this chapter and what I want to accomplish on the next. It ends by outlining future work.

## 5.2 Relevant work

The method I explored the most for this chapter is the one proposed by Mikolov et al. [Mikolov et al., 2013b]: the skip-gram model with negative sampling. It consists of a language model which maximizes the probability of a pair of words (i.e. a skip-gram) co-occurring in some natural language text, while minimizing the probability of a pair of random words co-occurring. For more detail on this process please refer to Chapter 3, Section 3.2.2.

There are however other approximations to unsupervised word representations, which are very well explored on the work by Turian et al. [Turian et al., 2010]. In this work, the authors improve the accuracy of different existing natural language processing systems by using unsupervised word representations as features.

On word sense disambiguation systems, as explained in Chapter 3, Section 3.2.2, Taghipour and Ng [Taghipour and Ng, 2015] show the use of word embeddings consistently improve the accuracy of the SemEval lexical sample and all-words tasks and also in a domain-specific lexical sample task. Rothe and Schütze [Rothe and Schütze, 2015] presented a system to learn embeddings for synsets/lexemes. Finally, there is a good work on word embeddings as features for word sense disambiguation by Iacobacci et al. [Iacobacci et al., 2016].

For Spanish word sense disambiguation, to my knowledge, there is little to none work done. I was only able to find my own on which this thesis expands upon [Cardellino and Alonso i Alemany, 2017].

## 5.3 Methodology

This chapter explores how word embeddings aid a supervised learning classifier (e.g. multilayer perceptron) by replacing supervised hand-crafted features. From this Chapter onwards, there is an important remark: the phrases *word embeddings* and *word vectors* can be used interchangeably.

### 5.3.1 Resources

There are two kinds of resources needed for the experimentation done in this chapter: the labeled corpora to train the supervised classifier, and the unlabeled corpora to train the unsupervised representations (word embeddings).

In contrast to the previous Chapter, the experimentation is done only on the Spanish data, as this is my main concern of study and the previous chapter provided enough information from the English dataset to assert the validity of the supervised models.

#### 5.3.1.1 SenSem

SenSem serves as the main resource to train the verb sense disambiguation model as the labeled data. It is described in detail in Section 4.3.1.1. Please refer the Section for more information.

#### 5.3.1.2 SBWCE

The main resource from where the word embeddings used in the experiments of this Chapter come from is the *Spanish Billion Words Corpus and Embeddings* [Cardellino, 2016] (SBWCE), which is a compilation of more than 1.4 billion raw words of the Spanish language, taken from different sources available on Internet, most of them coming from corpora used for statistical machine translation tasks, as well as corpora from the Wikimedia foundation, which makes it a general domain corpus.

The corpus has over 45 million sentences with more than 3 million unique tokens. Is also preprocessed to remove all the punctuation symbols and replace all the digits with the tag "DIGITO".

#### 5.3.1.3 Journalistic Corpus

SenSem provides an annotated corpus based on two newspapers from the region of Catalunya in Spain: "El Periódico" and "La Vanguardia". This make the resource heavily based on senses which have more to do with the journalistic domain. Thus, to check on Hypothesis 2.1 we needed to train some unsupervised representations from a journalistic domain corpus.

I extracted the documents coming from journalistic sources available on the SBWCE and other newspapers available online. In comparison to the SBWCE corpus, the corpus we could gather for this task was much smaller, having nearly 71 million

words available, which became 70 million after filtering out all those words with less than 3 occurrences. There was a final list of approximately 240 thousand unique words to generate the word embeddings which dimension was 50.

#### 5.3.1.4 Regulations Corpus

Finally, to test Hypothesis 2.2 I also need a specific domain corpus, but one that is not from the same domain the SenSem is based upon. Originally I intended to use a corpus based on free software documentation, as the technical aspect of such corpora would be a good contrast to that of a journalistic domain corpora. However, the available corpus I could find online was too small to generate good word embeddings representations.

Besides journalistic domain texts, the other domain available with enough information available was a regulations corpora, based on corpora such as the European Parliament, the United Nations, etc. where the text is more formal as it deals with laws, normatives, etc.

The amount of data available is approximately the same available in the Journalistic Corpus, with 72 million tokens, but a vocabulary of 100 thousand unique words and embeddings of dimension 50.

### 5.3.2 Features

#### 5.3.2.1 Supervised

For the purely supervised experiments, the data is represented using all the features described in Section 4.3.2 and the *hashing trick* presented in Section 4.3.2.2.

#### 5.3.2.2 Word embeddings

For the word embeddings representations I used Word2Vec algorithm [Mikolov et al., 2013a] to train the word embeddings from the unlabeled corpora. The first set of word embeddings, for the general domain experiments, are the pre-trained available on the SBWCE.

The word embeddings pre-trained from this resource were created using Word2Vec's *skip-gram* model and the gensim library [Řehůřek and Sojka, 2010]. It filters out words with less than 5 occurrences leaving out roughly 1 million unique words. The final word vectors dimension is 300.

The general idea of using pre-trained embeddings is the availability of them. In general terms, embeddings trained on a big amount of data perform relatively well for general tasks, however, we wanted to see the impact of training embeddings specifically for the data available and what effect does this have on the results.

The word embeddings are straightforward to use. The idea is to represent each instance (i.e. the sentence with the verb to disambiguate) as a concatenation of word vectors. I use the token of the verb to disambiguate as the central vector in the concatenation, and choose a symmetric window of 5 tokens at each side of the central

word making the final vector a concatenation of 11 words. In this way, the final representation not only captures the semantic of the words through the embeddings but also through the relative position of each word with respect to the verb embedding.

If the token is not available in the word embeddings model we try the token with all lowercase characters and capitalized (first character uppercase and the rest lowercase). If neither version of the token is available we use a vector of zeros of the same dimension that the word embeddings.

For the case when the central word is near to the beginning or end of the sentence, we pad the amount of words left to complete the whole vector with zeros. E.g., the verb is located as the third word from the beginning of the sentence, then to complete the right window we use the word vectors for the first and second token of the sentence and pad with three zero valued vectors before the vectors of two tokens.

Following this adjustment, the input vector when using the SBWCE corpus are of dimension 3300 and the vectors for the journalistic domain are of dimension 550.

### 5.3.3 Classifiers

In the previous Chapter I explored different types of classifiers. The conclusion was there was no significant difference between any of the classifiers. Thus, for comparison reasons, I select the multilayer perceptron classifier with three layers of size 500, 250, and 100. In this chapter, the experiments will be only done with that classifier. The configuration is the same as for supervised learning experiments, with the difference being in the features to use.

### 5.3.4 Experiments

The experiments in this chapter follow the structure given in Section 4.3.4. However, in this chapter we do not explore all possible combinations but we focus on the ones that proved more interesting in Section 4.3.4: the corpus is always the SenSem corpus and the classifier is the multilayer perceptron.

Experiment 5.1 compares supervised and unsupervised representations. Within unsupervised representations, I compare different word embeddings. This experiment is the base to test Hypothesis 2.1 that evaluates the performance difference of the same classifier trained using embeddings obtained from different domains. It follows the structure of Experiment 4.1.

**Experiment 5.1.**

**5.1a** Train a model with the train subset of the corpus for each lemma of the corpus.

**5.1b** Classify the test corpus, for each lemma, with the trained model.

**5.1c** Compare the model's predicted results, for each lemma, with the true results using some metric.

Experiment 5.2 follows the structure of Experiment 4.3, it measures the variance of different models trained over different subsets of the training data. Results are used to measure the tendency of a model to overfit. This is needed to test Hypothesis 2.2. The structure of this experiment is as follows:

**Experiment 5.2.**

**5.2a** For each lemma, randomly split the whole corpus in a selected *number of splits*. The size of the splits should be uniform. Ensure there is one split with all the complete dataset's classes and take that for the initial iteration.

**5.2b** Take the initial dataset and split it in train and test.

**5.2c** Train a model with the training dataset obtained in the previous step and store the predictions over the train and test datasets obtained in the previous step.

**5.2d** Add the next *split* to the dataset and repeat from step 5.2b.

**5.2e** When all the *splits* are added proceed to repeat the whole algorithm $n$ times with a new set of random splits.

### 5.3.5 Metrics

The metrics in this chapter are the ones used in the previous chapter for measuring performance and tendency to overfit.

Section 4.3.5.1 defines Metric 1, that is the macro and weighted average of the F1-score. This metric is useful to deal with the problem of assessing performance when classes are unbalanced. The metric highlights whether the model is performing well not only on the most frequent class but also in the less frequent classes.

Section 4.3.5.3 defines Metric 3. It is useful to measure the tendency of a model to overfit as the size of the dataset increases. It does so by measuring the error due to variance of a model trained on one training set, over all the other available training sets.

## 5.4 Analysis of Results

The next section reports the results obtained through the experiments presented above. As in Section 4.4, I want to recall the figures shown here through the metrics and visualization tools are views of the results. Any view can show something at expenses of obscuring something else.

In particular, box and whiskers plots show the behaviour of all the models (one per lemma) as a whole, obscuring what is happening with the particular case of each lemma. To do that I would need a more detailed analysis, which is outside the scope of this thesis.

### 5.4.1 Hypothesis 2.1

The first results to analyze are the ones to test Hypothesis 2.1, which states that the performance of an unsupervised representation depends on the domain. I want to see if a more specific domain affects the final results. To do so I follow the steps of Experiment 5.1, where I distinguish word embedding representations based on domain. I general domain embeddings from SBWCE, specific in-domain embeddings, shared with the domain of the supervised corpus, using the journalistic domain embeddings, and specific out-of-domain embeddings, not shared with the domain of the supervised corpus, using the regulations word embeddings. Using each of the word embeddings representations I train a multilayer perceptron classifier to see the performance of the selected representation.

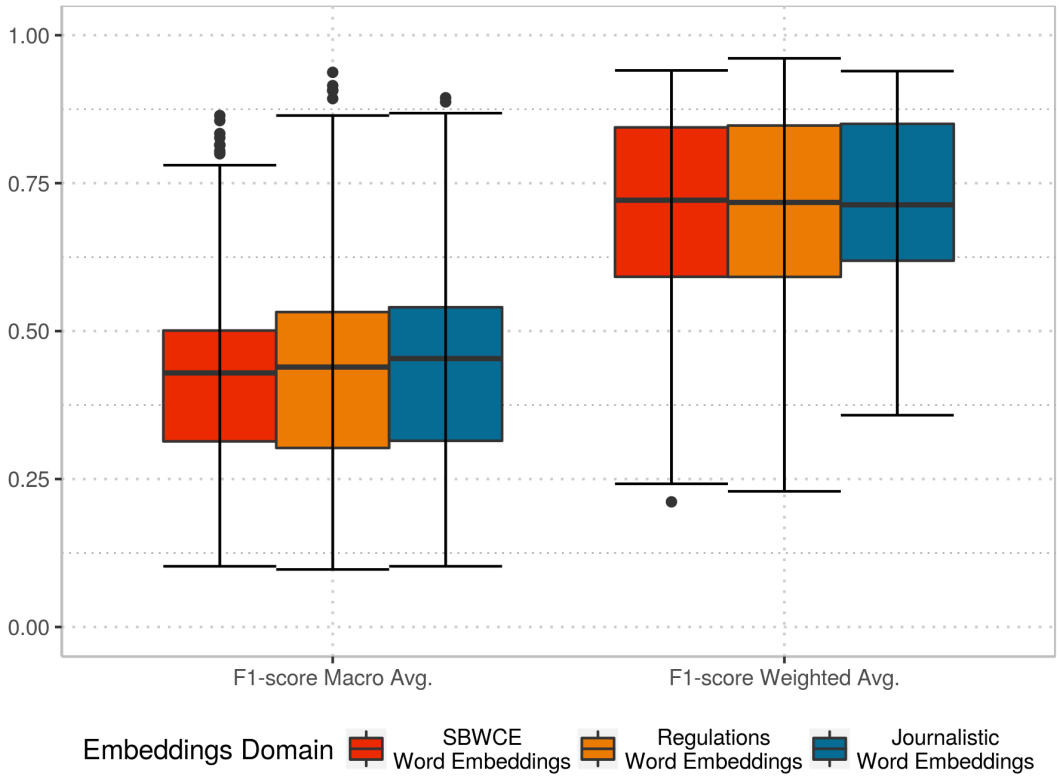


FIGURE 5.1: Performance per lemma on the test corpus for general, specific in-domain, and specific out-of-domain embeddings.

Figure 5.1 reports the performance results on the test corpus for each lemma using these three different domains to train the word embeddings. The plot is a box and whiskers plot structured in the following way:

- Each group of box-plots shows the different metrics: F1-score macro and weighted average.
- Each box-plot of a different color shows the performance for different training domains of word embeddings: general domain (SBWCE), specific domain outside the task (Regulations), and specific domain of the task (Journalistic).

- The box and whiskers plots represent the distribution of the values of the metrics through their quartiles. Each value is the performance for a lemma of the corpus. The black thick line in the middle of a box-plot represents the median and the whiskers at the end of each box-plot represents maximum and minimum value (except for eventual outliers represented by black dots outside the box-plot).

From the figure, it is noticeable the increase in performance of the median of the experiments with journalistic, in-domain word embeddings with the F1-score macro average. Besides the better median, the maximum values are also higher for in-domain embeddings than for general domain embeddings. In the case of the F1-score weighted average there is less error for in-domain embeddings than for general or out-of-domain embeddings, and the difference for the median in favor of the general corpus is marginal. Recall that the macro average is good to measure the performance for the minority classes. Since it is clearly better for the journalistic in-domain word embeddings, it shows that in-domain specific word embeddings model less frequent senses better.

On the other hand it is not clear if the regulations out-of-domain embeddings affect performance negatively or positively. They show better performance in some of the better models and worse in some of the worse models, as is reflected in a wider spread of the whiskers. Thus, I find a clear sign that I need a close look to each model and see in particular which are the lemmas that are doing better and which are the ones doing worse. In particular, I need to look into the outliers. The plot shows that there are 4 (or maybe 5) lemmas which have better performance with out-of-domain embeddings than with in-domain embeddings. In any case the journalistic word embeddings are still better in the general terms for both metrics, because they reduce error.

The reasons behind this results can be many. As a first explanation, the regulation corpus may not be as dissimilar to the journalistic domain as I would have expected a priori. A better corpus to test this hypothesis might be one based in documentation which can be very technical. However, the available corpus to train such an embedding, at this stage, was not big enough. A line of future work is to obtain more documentation via web scrapping and train an embedding from that.

Another possible explanation, which requires the analysis from the point of view of a linguist expert, is that there are some lemmas (and thus some models) which show better performance in the particular domain of regulations and thus this is reflected in the results. This better performance may be due to a higher frequency in the regulations corpus of words that are relevant to distinguish senses for that lemma. This line of work will be pursued in future research.

Finally, the SBWCE has some noise due to the size of the corpus, another line of future work can be in that area, with embeddings trained from a cleaner version of the SBWCE.

From these results I have strong evidence to accept the Hypothesis statement, as the domain from where the word embeddings are trained effectively affects the final performance of a model.

### 5.4.2 Performance comparison of supervised and semi-supervised representations

Hypothesis 2.2 states that using word embeddings produces less tendency to overfit over supervised models. Next section reports the results regarding that hypothesis in order to accept it or reject it. However, so far I have only compared the results of different word embeddings for the models.

In this Section, before showing the results of the experiments for Hypothesis 2.2, I want to show how these new models perform in comparison to the models selected in Chapter 4. Recall the final model I want to compare is the multilayer perceptron classifier with three layers.

Again I follow the steps of Experiment 5.1 that trains a model with the whole dataset and evaluates such model in a test dataset. For these results the chosen representations are the hashed hand-crafted features for the supervised approach and the specific (journalistic) domain word embeddings for the unsupervised approach.

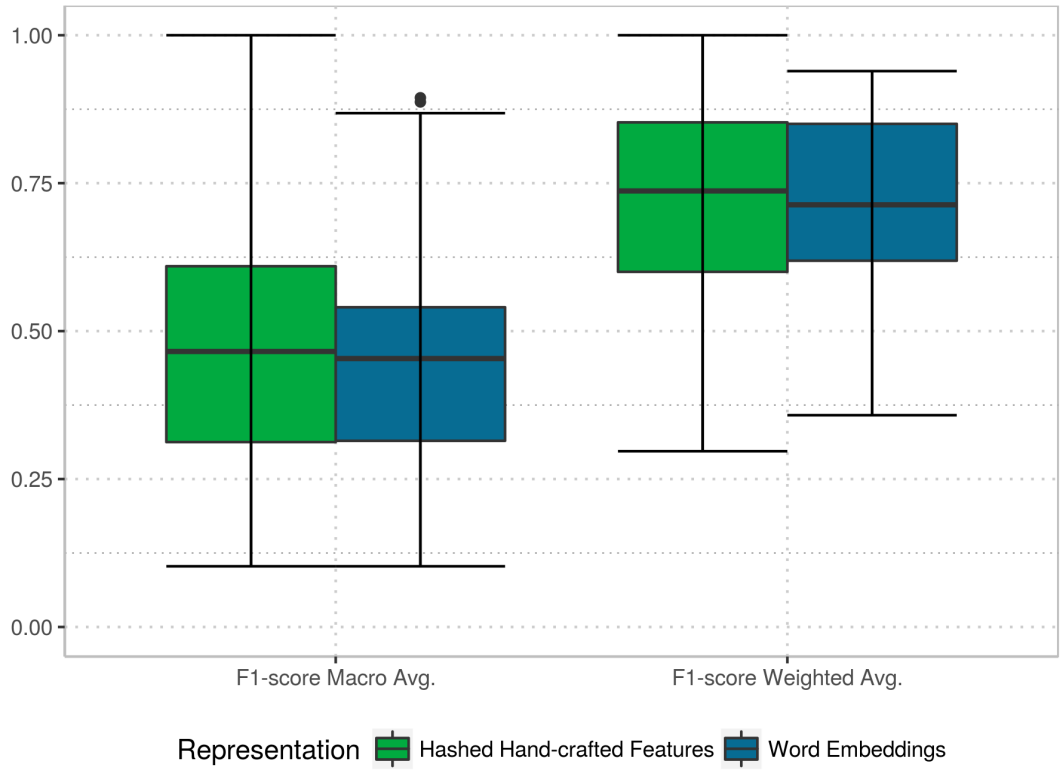


FIGURE 5.2: Performance per lemma on the test corpus for hashed hand-crafted features and word embeddings of specific domain

Figure 5.2 reports the results of Experiment 5.1 and testing it in the held out test dataset. As in previous Figures, it uses a box and whiskers plot to display the distribution of the results for each model:

- Each group of box-plots shows the different metrics: F1-score macro and weighted average.

- Each box-plot of a different color shows the performance for different representations. For the supervised representation I use the hand-crafted hashed features. For the unsupervised representations I use a specific domain of the task (Journalistic).
- The box and whiskers plots represent the distribution of the values of the metrics through their quartiles. The same as explained for Figure 5.2.

In Figure 5.2 it can be seen a clear advantage of hashed hand-crafted features over word embeddings. F1-score macro average performs specially better, indicating that those senses with low occurrence count are better represented.

Word embeddings serve as a way of smoothing features by reducing the dimensionality to a lower, more general representation. Besides, the representation from which the embeddings are obtained takes into account less features than hand-crafted features. Indeed, hand-crafted features encode syntactic and PoS information, while to obtain word embeddings only word co-occurrences are used.

Taking this into account, it can be interpreted that hand-crafted features represent the domain better than the semi-supervised model. This may be due to the fact that the features are taken from the supervised data itself, unlike the journalistic word embeddings, which are taken from a corpus that shares domain with the supervised data. Supervised features have a better performance because they can fit more closely to the data, and that is the reason why supervised features are less able to generalize a model, specially a domain driven model, into data from more general domain. In the next section I will explore the tendency of these models to overfit or generalize.

The adequacy of these two kinds of models to adapt to an out-of-domain corpus will be displayed in the following Chapter. There we will see that word embeddings are able to perform well on a self-learning approach on a big corpus. In contrast, hand-crafted features fail to generalize and their performance quickly degrades across iterations.

### 5.4.3 Hypothesis 2.2

The results of the previous section showed that supervised features perform better than unsupervised features for the verb sense disambiguation task. The results of the experiments for Hypothesis 2.2 give a hint on what is happening underneath these results.

These results are taken from Experiment 5.2, and report the learning curve of a model as the number of examples increases. It shows the mean and error due to variance of both the training and test sets on each iteration. The comparison is done using a supervised representation via hashed hand-crafted features and an unsupervised representation via word embeddings, in this case the specific domain word embeddings.

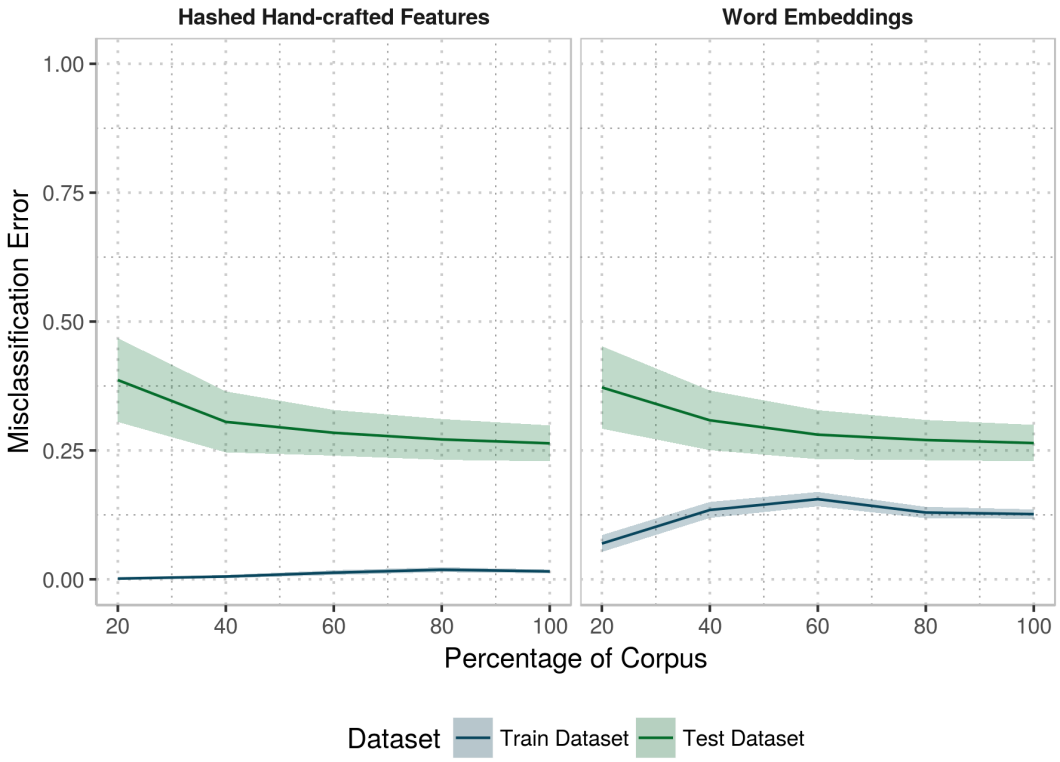


FIGURE 5.3: Learning curve for different sizes of training corpus for supervised and unsupervised representations

Figure 5.3 shows the learning curve for different sizes of the training data over two different representations for the input features: supervised hand-crafted features and unsupervised word embeddings. The structure of the learning curve plot is as follows:

- The plot is divided in two columns, each represents an input to the model: supervised hand-crafted features and unsupervised word embeddings of the specific domain (journalistic).
- The x-coordinate shows the size of the training data, as a percentage of the total training data available, starting from 20% of the corpus (the corpus was split in 5 parts according to Experiment 5.2).
- The y-coordinate shows the misclassification error of a model.
- There are two colors representing the datasets: train and test.
- The solid darker lines represent the mean of misclassification error trough the different splits of the datasets over all the models.
- The shadowed area, which has a lighter color, represent the standard error of the mean of the misclassification error.

It is possible to see in the Figure the difference between representations when the tendency to overfit is measured. Word embeddings show less difference between the

training data and the test data regarding misclassification. This could also be seen in Section 4.4.6, where SVM and Naive Bayes showed less tendency to overfit the model.

In this case the classifier is a non linear classifier with a strong tendency to overfit, and the word embeddings are helping it to not overfit as much as the supervised representation does. Still, it is important to note that the misclassification error in test data is still roughly the same for one representation or the other, thus the model is not sacrificing training performance in order to gain test performance. What the model is actually sacrificing is anecdotal, non-generalizing information. These results support evidence to accept Hypothesis 2.2.

It is important to recall that the models are small and neural networks models work better the more information they have. In order to gather more information, more examples are needed. However, manual annotation of examples is expensive and beyond my possibilities. Thus I pursue increasing the number of examples available to the model via incorporating examples from unsupervised corpora. And to do so we need models which generalize better to out-of-domain corpora, as is the case of models with word embeddings.

## 5.5 Conclusions

This chapter introduced a disjoint semi-supervised technique for Spanish verb sense disambiguation. From the challenges stated in Chapter 4 I wanted to overcome the shortcoming of having a model with a high tendency to overfit the data. I stated a main hypothesis I want to test, which is that unsupervised representations help improve upon purely supervised models by reducing the tendency to overfit given by features taken from the same data where the model is trained. The reason to state this hypothesis is that unsupervised representations give a smoothed version as input to a classifier and thus this helps the classifier in having a more generalized version of the data it is learning from. I subdivided the hypothesis in smaller, more focused subhypotheses.

Hypothesis 2.1 states that the performance of an unsupervised representation, in this case a word embedding, depends on the domain from where the unlabeled data to train the embeddings is taken. The results to accept this hypothesis are in Section 5.4.1. It was shown that a more specific domain gives better results for the same task. Still some of the results regarding the use of a domain outside the domain of the supervised need a more thorough analysis left for future work.

Before analyzing the results of the experiments to test Hypothesis 2.2 I needed a comparison between supervised and unsupervised representations. This is reported in Section 5.4.2. In this experiment I train two different models using the neural network classifier with three layers described in Section 5.3.3, and changing the input representation for the classifier. From this comparison, hand-crafted features show better performance than the unsupervised features. However the reason behind this is that hand-crafted features obtain a more fitted representation of the supervised

dataset as the features come directly from there. The results of the experiments to test Hypothesis 2.2 show that hand-crafted features are strongly dependent on the dataset, and that the resulting representation is highly fitted to the training examples.

Section 5.4.3 shows the results of Experiment 5.2, which measures the tendency to overfit of a classifier. The experiment is done to test Hypothesis 2.2, which states that unsupervised representations (e.g. word embeddings) produce less overfitting over the supervised models than supervised representations (e.g. hand-crafted features). The experiment compared hashed hand-crafted features and specific domain word embeddings. As the hypothesis states, the model trained with word embeddings showed a closer learning curve between training and test data. This gives enough evidence to support the acceptance of Hypothesis 2.2.

Unsupervised feature representations, particularly those trained from the same domain as the supervised dataset, show promising results. However, the performance is still under what I can achieve using purely supervised representations. And although there can be many reasons to explain this result, according to what I see, most likely it has to do with the (over)fitting of the supervised features to the supervised data, in contrast to the more smooth representation of word embeddings.

Recall from the previous Chapter I found two main challenges. The first challenge was that models trained with little data tend to overfit. Using non-linear classifiers such as neural networks could have a great impact in minimizing the error and even maximizing the performance of the test data. But the cost is the generalization of such models. Unsupervised features help in that respect by giving a smoother representation helping the neural network to avoid the tendency to overfit.

The other challenge was the coverage of the model. Coverage can be understood as the ability to predict over unseen examples that belong to one of the target classes and the model should be able to label. These examples could eventually be incorporated to the training corpus and thus add information to the model. But since they are not annotated, the model does not have such information yet. Given our limitations to annotate examples manually, new examples are gathered from unlabeled data and classified with the model. If the model is only driven by the information it already has (i.e. the features extracted from the supervised data), then is difficult to add the information from unseen data and expand the coverage. Word embeddings hold information about the supervised data, used for the model to classify it, and about unsupervised data not present in the model yet. Thus, this information helps a model trained from unsupervised features generalize better and be able to gather information from new examples expanding its coverage.

Following these reasons, word embeddings seem specially adequate to apply an approach to obtain new examples from previously unseen corpus.

In the next chapter I will focus on a first approach to a semi-supervised method which adds data from unlabeled sources and use that to expand the model. Such method is self-learning, a basic approach to semi-supervised learning.

Future work of this chapter includes using other unsupervised representations, like the ones listed by Turian et al. [Turian et al., 2010]: Collobert and Weston [Collobert and Weston, 2008] and Brown clusters [Brown et al., 1992]. Another line of work would be doing a more thorough error analysis on the the different word embeddings domain, seeing if a better preprocessing of the data can provide better results.

# Part III

# Joint Semi-Supervised Methods

# Chapter 6

# Self-Learning

## 6.1 Overview

With a task like Spanish verb sense disambiguation, where the annotated data is small, a purely supervised approach has to overcome two challenges: the model overfits the data, and the model's coverage is small. These were the findings of Chapter 4. Chapter 5 explored a semi-supervised approach by providing word embeddings as input to a supervised classifier.

The results of the previous chapter gave evidence in favor of Hypothesis . Recall the hypothesis states that word embeddings had less tendency to overfit than supervised features. The results served to accept this hypothesis. However, this improvement in overfitting came with a decrease in performance: supervised features adapted better to the problem, word embeddings performed worse. Still the results of word embeddings were promising, because having less overfitting implies a better performance in general domain corpora.

The other challenge for this task was coverage. Coverage can be thought of as the unseen examples, part of a class, that the model can reach (i.e. classify to the correct class). Examples not in training could add information to the model that is not integrated in the model yet. One way to add such information is by adding previously unseen examples to the model. Word embeddings help in this direction, not by adding new examples to the model, but by adding information from unlabeled data. With this additional information, the model is able to cover a wider range of examples.

To increment the model coverage with new examples I explore *self-learning*. This is a semi-supervised technique that expands labeled data by using the certainty of the model over unlabeled data. It adds new examples automatically, using a supervised model to label unlabeled examples. This is a *joint semi-supervised learning* algorithm. This means that labeled and unlabeled data are used jointly in the process of learning. In contrast, the approach with word embeddings is *disjoint* because embeddings are obtained independently from the model for verb sense disambiguation.

The self-learning algorithm works basically as follows. A supervised algorithm is trained on a seed labeled dataset. Then the obtained model is used to classify unlabeled examples obtained from a big unlabeled corpus. The certainty of the algorithm

in classification is used to add automatically labeled examples to the labeled dataset. The algorithm uses this bigger dataset (coming from both supervised and unsupervised data) to train a new model. This process is iterated until a stopping criterion is met.

In general terms, self-learning is a simple algorithm that applies a *bootstrap technique* to improve on a supervised model that improves with unlabeled data. The objective of exploring this technique relies on incrementing the model coverage as I said before. The underlying assumption is that the new examples will help the model integrate the information that is latent on those examples.

However there is a challenge I need to face when coming to train a model using a self-learning approach. This challenge resides in the imbalance of the classes in the corpus. If the initial model is biased to classify the instances as part of the most common class, this error will be dragged by the self-learning model and will automatically annotate new examples as the most frequent class just because the original model does so.

Moreover, in this particular case there is another problem, and that is the specific domain of the corpus on which the initial model is trained. Recall that SenSem, the resource I am basing the experiments on, comes from a specific domain: journalistic. Having a biased domain also affects which classes appear the most. Thus some classes are the most common in a general domain but this is not the case for the specific domain as the next examples illustrates:

**Example 6.1.** The verb "llegar" has 8 different senses in SenSem. Of them, one is "to reach certain height or point". This sense is not the most common one available in the SenSem corpus as it has a few labeled examples in the corpus. However in a more broad domain it can be used with a higher prevalence than in this domain.

These are the reasons behind studying different techniques in the previous chapters to avoid overfitting and bias to the most frequent class in the supervised algorithm. This is important for the self-learning algorithm to avoid diverging to the most frequent class too quickly and thus not adding enough useful, diverse information to the model.

This chapter will test the following hypothesis:

**Hypothesis III** *The target classes of a model trained on labeled data can be better represented by integrating more examples, even if they are automatically labeled (and thus contain error and bias). Increasing the number of examples to train a model helps to avoid overfitting of the model and improves coverage.*

In order to accept or reject such Hypothesis, I divide it in more specific ones.

First I make two hypotheses about the general goodness of this approach to improve upon a mostly supervised approach:

**Subhypothesis 3.1** *The performance of the model over the held-out test data improves after the self-learning algorithm adds new automatically annotated examples.*

**Subhypothesis 3.2** *The model obtained in each iteration shows an increase in the average certainty to predict the class of unseen examples.*

Concerning overfitting, I make the following hypothesis:

**Subhypothesis 3.3** *Increasing the number of examples helps reducing overfitting.*

Concerning coverage, I make the following hypothesis:

**Subhypothesis 3.4** *The self-learning algorithm increases the number of features associated to the model, which is an indicator of an increment in the coverage of the model.*

Given the initial bias in the distribution of classes and the bias of the self-learning algorithm to amplify this initial bias and overpopulate a majority class, the following hypotheses are expected to be rejected:

**Subhypothesis 3.5** *Self-learning helps improving the performance of the model on each of the classes uniformly.*

**Subhypothesis 3.6** *The representativity of each class in the dataset is kept through all iterations of the algorithm.*

**Subhypothesis 3.7** *The coverage of the features is uniformly distributed across classes.*

These hypotheses will be accepted or rejected using the following layout:

- Experiment 6.1 reports the performance of a model before and after running the self-learning algorithm. The performance is measured by the macro and weighted average F1-score (Metric 1). Results shown in Section 6.4.1 serve to test and mildly reject Hypothesis 3.1, that the performance over a model on held-out test data improves after the self-learning iterations.

- Experiment 6.2 shows the certainty the model over predicted classes for each iteration of the algorithm. The average of this value is what I need to test Hypothesis 3.2 which states that the model has an increase in the average certainty along self-learning iterations (Metric 5). The results of this experimentation are shown on Section 6.4.2 and show that certainty is not increased, thus this Hypothesis is rejected.

- Experiment 6.3 assesses overfitting by measuring the error due to variance of a model trained on one dataset over other datasets. To measure this I use the learning curve (Metric 3) I already explained in previous chapters. The results of the experiments shown in Section 6.4.3 serve to mildly reject Hypothesis 3.3 which states that adding new examples to the dataset helps to decrease the model tendency to overfit.

- Experiment 6.4 records the number of features a model has. This number of features is measured by raw count. Results shown in Section 6.4.4 serve to accept Hypothesis 3.4 that the self-learning algorithm increases the number of features associated to the model.

- Experiment 6.1 also serves as the base to test Hypothesis 3.5, that the self-learning algorithm improves the performance of each class uniformly. To test this hypothesis I look at the results from a different perspective. Section 6.4.5 discusses the results regarding this hypothesis. This time however I do not use the average of F1-score (Metric 1), but rather the F1-score of each class before and after the self-learning iteration. Results show that, as expected, the hypothesis is rejected.

- Experiment 6.5 records the distribution of the classes in the training dataset for each of the iterations in the self-learning algorithm. This distribution is measured by the proportional count of such classes. The results of this experiment measured with the metric are displayed in Section 6.4.6 and serve to reject Hypothesis 3.6 of the classes being uniformly distributed across self-learning iterations.

- Experiment 6.4 is also used, measured differently this time, to test Hypothesis 3.7. The experiment collects the number of times a feature and a class co-occur in the training dataset. These results are measured by two different metrics. First the raw count of features per class. On the other hand I also look into the association each class has to each feature. To do this I use the pointwise mutual information defined in Metric 4. The results that serve to reject the Hypothesis are shown on Section 6.4.7.

In Section 6.2 I revise some previous work done in self-learning in general and also specifically applied to verb sense disambiguation. Also I mention some other semi-supervised methods based on bootstrap techniques.

In Section 6.3 I go through the relevant items that concern to the experimentation done in the chapter. Section 6.3.1 reintroduces the resources I work with in the experimentation. Most of them were already introduced and I only do a quick summary with references to the section where the resource is better explained. Next in Section 6.3.2 I explain the features and representations I work with in this chapter, and particularly give some hints on how to deal with the add of new examples by the model and how this affects the representation by adding new features as well. Section 6.3.4 explains the fine detail of the self-learning algorithm, including certainty threshold and stopping criterion the algorithm uses. Finally Sections 6.3.5 and 6.3.6, as in previous chapters, lists the experiments and metrics I use to measure the results respectively.

Section 6.4 reports the results of the experiments and analyzes them in order to accept or reject the stated hypotheses of the chapter.

Finally Section 6.5 draws the conclusions of this chapter, recapitulating the Hypotheses and the implications of accepting or rejecting them according to the evidence gathered in the results. It states the shortcomings of the methods explored in this chapter and what I want to accomplish on the next. It ends by outlining future work.

## 6.2 Relevant Work

As explained in Section 2.2.2, of Chapter 2, self-learning is one of the first approaches in using a semi-supervised learning technique with quite some time in the literature [Scudder, 1965]. The idea has been applied in many natural language tasks besides word sense disambiguation: subjectiveness in nouns [Riloff et al., 2003], dialogue classification [Maeireizo et al., 2004].

For self-learning applied to word sense disambiguation, the work of Yarowsky [Yarowsky, 1995] to build a disambiguation model based on the words co-occurring with manually labeled examples is fundamental in the area. The exploration done in this chapter takes most of its ideas from this work. Another work is the one by Mihalcea [Mihalcea, 2004], on which she explores the different settings of hyperparameters one can have in the algorithm to improve the performance of the supervised task.

## 6.3 Methodology

This chapter explores the self-learning algorithm to expand a supervised model with unlabeled data annotated automatically based on certainty. The self-learning algorithm is a *wrapper*. This means the self-learning algorithm does not classify data by itself. It does it by wrapping a supervised classifier. Then it uses the information the supervised classifier gets from the data to augment the model.

Recall that independent classifiers are learnt for each lemma. I describe the methodology in general terms, but I still run one self-learning algorithm model per each lemma. It is important to keep in mind that evaluation metrics may obscure differences in performance across lemmas.

### 6.3.1 Resources

Self-learning requires two main resources: a labeled and an unlabeled dataset. The labeled dataset is the seed of the initial model. From this data the algorithm bootstraps the iterations. The unlabeled dataset is the source of new examples to annotate automatically. The experimentation for this chapter is done only on the Spanish corpora.

Initially I wanted to do a general analysis of the results of verb sense disambiguation for all the available lemmas. However, while working on the analysis, giving a much closer look to the data, it was concluded the best method was to take some token lemmas and analyze them with a much closer look to see how the algorithm works on each of those cases. Besides this, the other reason to do so was to have

some point of comparison when doing active learning in the following chapter as the availability to manually labeled data was limited.

As token lemmas, I selected a communication verb, originally "hablar" was intended, but there were annotated examples of only one sense, thus "explicar" was chosen instead. I also selected "pensar", another verb of the communication class, to observe similarities and differences. Two verbs of movement were next: "acceder" and "llegar". Finally two transitive verbs were selected: "buscar" and "facilitar".

#### 6.3.1.1 SenSem

The SenSem corpus is used as the annotated seed on which the self-learning algorithm starts. For more information on this resource please refer to Section 4.3.1.1.

The main problem with using SenSem as it is in self-learning is how it is affected by the algorithm's tendency to diverge to the most frequent class. As I will show in the results further in this chapter, this is a big problem regarding self-learning. A first approach I had to follow in order to deal with this problem was oversampling.

I randomly oversampled the examples of the less frequent classes in order for the initial (seed) dataset had an equivalent number of examples for each class. This did not completely fixed the algorithm's tendency to classify everything as part of the most frequent class, but it did help in smoothing this. If I used in the experiments the original dataset without oversampling then the algorithm's drifting was much more quicker. This oversampling had no impact on the performance of the supervised algorithm (i.e. the classifier trained only on labeled data) over the test corpus, but did help in the case of the self-learning iterations to delay the drifting to the most frequent class.

#### 6.3.1.2 SBWCE

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The unlabeled data source of new instances for the algorithm is the SBWCE. This resource was already described in Chapter 5, Section 5.3.1.2.

Due to time and resources constrains I was not able to use the full resource. The algorithm takes and classifies the unlabeled data to select the instances. Then with the full SBWCE dataset each iteration would take a large amount of time to complete. The solution was to randomly sample a fixed number of unlabeled sentences for each lemma. For each lemma I chose 1000 unlabeled sentences and used them as unlabeled data for self-learning.

Once the sentences were selected the corpus is preprocessed to add PoS and dependency annotations. The preprocessing step is done with Freeling. The key idea is to have in the unlabeled dataset the same type of information as the supervised dataset, as described in 4.3.1.1. This information is used to build the hand-crafted features.

### 6.3.2 Features

The previous chapter showed that word embeddings are promising but supervised features still have the best performance. I decided to keep both kinds of features and compare how each performs on jointly semi-supervised learning tasks. Parameters for both kinds of representations are the ones with the best performance in previous chapters.

#### 6.3.2.1 Hand-crafted features

For hand-crafted features I use the features described in Chapter 4, Section 4.3.2.

Recall the whole set of hand-crafted features for the supervised data was already large even though the labeled dataset was small. When this is done for unlabeled datasets the amount of features are most likely too big to fit in memory.

Moreover, the original supervised model of the self-learning algorithm is trained only on the supervised data. Then it only has the features the supervised corpus has. These features are not likely to be the only ones available in the unlabeled dataset.

As most of the classifiers take a fixed size input, having new features from unlabeled data gives two options: ignore the features or generate a representation with the features of the whole dataset (i.e. labeled and unlabeled).

Feature hashing, described in detail in Section 4.3.2.2, gives a very efficient solution to this problem. It was developed with online learning in consideration where the labeled data is ongoing.

#### 6.3.2.2 Word embeddings

In Chapter 5 I conclude from the experimentation that the domain of the word embeddings affected the performance of the model. For these experiments I selected the word embeddings that showed the best results in the previous chapter. This are the ones obtained from the journalistic corpus described in Section 5.3.1. The embeddings were trained using word2vec and the instances are constructed by concatenation of the embeddings, the process is described in Section 5.3.2.2.

### 6.3.3 Classifiers

In the next Section I describe the details of the self-learning algorithm. However recall this is a wrapper method. Then I still need a supervised classifier to use as parameter of the self-learning model. The classifier is an hyperparameter of the self-learning algorithm.

Based on the results of Chapter 4 I selected the multilayer perceptron with three layers of size 500, 250 and 100. For the chapter all the experiments have this classifier fixed.

### 6.3.4 Self-learning algorithm

As I explained before, the self-learning algorithm is a wrapper algorithm over a classifier. The algorithm takes the following initial parameters:

- A labeled training dataset to train the initial supervised model.
- A labeled test dataset to report the model performance before and after finishing all the iterations of the self-learning algorithm.
- A labeled validation dataset to keep track of the self-learning algorithm automatically added instances and avoid divergence of the original model.
- An unlabeled dataset to get the new data to annotate automatically.
- A probabilistic classification algorithm, to use in the process of automatic annotation.
- A tolerance error for the stopping criterion.

The labeled test dataset is the same one used in the experiments of previous chapters. The validation dataset is taken from the training dataset following the same structure as described in Section 4.3.1.1. The SenSem corpus was split with 80% for training and 20% for test, but keeping at least one instance for each class (sense) in test dataset and two instances in the training dataset. The validation dataset was taken from the training dataset by splitting it again into 80%-20%. This split was also ensuring there was at least one example for training and one example for validation for each class in the dataset.

As with the training/test splits, the training/validation splits also preserve the distribution of classes observed in the whole dataset. This implies that in each split you cannot find more examples of a class than you could find in a stratified sample of the dataset, that is, a sample that preserves the distribution of the whole dataset. However, this does not necessarily hold for minority classes, because at least one example must be found in each split, even if that implies over-representing the class.

The algorithm starts by training an initial model from the labeled training data. From that model I get the initial performance of the classifier over the test and the misclassification error of the validation data. The former are used to compare the model before and after the self-learning iterations. The latter is used as a stopping criterion for the algorithm.

The self-learning algorithm consists of a loop which uses the trained model to gather new data from the unlabeled dataset. In the first iteration the model is the initial one trained with the labeled training data.

On each iteration of the loop the model classifies the whole unlabeled dataset. From this classification, the algorithm selects the instances to automatically annotate. These instances are selected based on the certainty (probability) the classifier has that the instances are part of the class they were classified.

The certainty of the model over the instances needs to be over a threshold to be annotated automatically. This threshold is another hyperparameter of the self-learning algorithm. How I select this threshold is further explained in the next section.

With the instances and its corresponding labels (given by the classifier), plus the labeled data collected so far (consisting of the original training dataset and the new data added after each iteration) the algorithm trains a new model. The model is tested on the validation dataset to get the misclassification error. The error can not be larger than the lowest validation error so far plus the error's tolerance hyperparameter, otherwise the algorithm stops and the final model is the last model obtained so far. In case the error is lower than the tolerance, the model is updated for the next iteration. The selected instances are added as part of the new training set for the next iteration and removed from the unlabeled dataset.

The algorithm continues the loop until the stopping criterion is met or there's no more data to add. This may happen in two occasions: all the unlabeled data is already part of the model or the classifier does not have enough certainty over any of the possible instance to add them to the new model. Once the algorithm's loop finishes for any reason the last model is used to measure the performance over the test dataset.

The algorithm has two important parameters: the certainty threshold to add new examples, and the error tolerance to stop the algorithm before all data is consumed. There are many ways to set those. In the next two sections I will further explain my decisions over these two parameters.

#### 6.3.4.1 Certainty threshold

In each iteration of the algorithm after training a new model (i.e. using the initial training data plus the instances added from previous iterations) the model is used to gather new training examples from the unlabeled dataset pool. The classifier is probabilistic, thus it naturally has a certainty over the data it classifies. This certainty is the probability given to an instance by the classifier to belong to a certain class. The certainty threshold is the minimum probability the classifier needs over an instance for the self-learning algorithm to integrate it as a new training example: any example on which the classifier has a certainty larger than the threshold are annotated automatically and added to train a new model.

On initial experiments the threshold was fixed at the beginning of the algorithm. The same initial value was used for all the iterations. This value was the same for all the lemmas. Recall that I have one classifier per lemma to disambiguate. In this case, I run one set of the algorithm's iterations per lemma as explained before. Having a fixed threshold for the different lemmas may not be adequate, as each lemma has its own properties which make it different from the rest.

Looking for a more adequate solution, the first thing to explore is to define an initial threshold for the first iteration and adapt it after each step until a good value

is found. However, there are two problems with this approach: how to set the initial threshold value and how to define a "good value" automatically.

Another option is discussed by Mihalcea [Mihalcea, 2004]. She presents a self-training algorithm which selects the top N instances according to the certainty of the classifier on them and integrates them as new training examples. Nevertheless, the only way to choose that number N for this case is empirically. Thus, we still suffer the same problem as with the threshold, the way to estimate the parameter.

One way or another, I have the same challenge: not being able to define with enough confidence which values to set for the hyperparameters. Plus, there are no rules of thumb to do so either. Thus I decided to go with a threshold of certainty so the algorithm is not limited to add only a fixed number of elements. Using a threshold, the self-learning algorithm can add all the elements with high certainty.

To avoid selecting the threshold manually, I decided for the threshold to be 100% of certainty in each iteration. If there are no instances at this level of certainty the threshold is lowered by an alpha hyperparameter, in this case 5%. With the new threshold the algorithm looks for instances. The threshold is lowered until at least one instance above the threshold is found or the selection of instances becomes random. Random selection is identified whenever the certainty threshold is equal to the random chance of selecting a class in the algorithm (i.e. if the dataset has 2 classes, the threshold is near to 50%, if the dataset has 3 classes, the threshold is near to 33%, etc.). When this is the case the algorithm stops and does not select any instances. In the implementation, I restrict this stopping criterion further by stopping a 10% before the figure for random selection for each lemma.

A more adequate stopping criterion would use the distribution of classes actually observed in the data instead of a uniform distribution. Further work will explore this variation of the algorithm.

#### 6.3.4.2 Stopping criterion from validation dataset

Once the instances were selected by the classifier (assuming a selection was made and the algorithm did not stop because it did not add any examples), their impact in the model is evaluated. This is the purpose of the validation dataset. The algorithm trains a new model with the instances and the data accumulated so far, that is, the original supervised data and the automatically annotated instances added in previous iterations. With the model obtained the algorithm gets the misclassification error from evaluation the model on the validation dataset. The error is compared to the minimum misclassification error obtained so far plus a tolerance. Similarly to the classification threshold, the error tolerance begins in zero and is incremented gradually up to a maximum misclassification error that is 10% less than random chance.

The reason to use a validation dataset for the stopping criterion is avoiding to overfit the model to the test dataset. The parameters and hyperparameters of the model are adapted this way to the validation dataset. This is also known as tuning

of the model. Afterwards, when the model is evaluated on the test corpus, results are actually representative.

An alternative approach to this would be *k-fold cross-validation* over the training dataset in each iteration (i.e. the training set with both the labeled data and the automatically annotated data). Then, the mean misclassification error could be used as a stopping criterion. However, the tendency of the algorithm to include more examples of the most frequent class undermines the adequacy of this approach. Indeed, the misclassification error may get lower and lower simply because I am evaluating it in a dataset that has grown unbalanced. Then, when the classifier predicts new instances as belonging to the most frequent class, there is a higher probability that they are correctly classified. In contrast, evaluating in a held out test dataset preserves the original distribution of classes.

### 6.3.5 Experiments

Recall all the experiments use an oversampled version of the initial labeled dataset in order to avoid for the dataset to drift to the most frequent class immediately.

Experiment 6.1 reports the performance of the model over the test dataset before and after the self-learning iterations. First the experiment reports the performance of the model trained only with supervised data. Afterwards it reports the performance of the model trained with the original supervised data plus the automatically annotated data added by the self-learning algorithm. Recall all the experiments are done in a per lemma basis.

**Experiment 6.1.**

**6.1a** Train a model with the supervised training dataset.

**6.1b** Evaluate the model over the test dataset.

**6.1c** Run the self-learning algorithm until it stops.

**6.1d** Evaluate the model obtained with the self-learning algorithm over the test dataset.

Experiment 6.2 keeps track of the average certainty for each iteration of the self-learning algorithm. The experiment records the certainty the algorithm has over the classification of the instances.

**Experiment 6.2.**

**6.2a** Start with the self-learning iterations.

**6.2b** Run the model obtained up to this point into the whole unlabeled dataset (part of the self-learning algorithm).

**6.2c** Before selecting the instances record the predicted classes for each instance and the probability (certainty) they have for the model.

**6.2d** Continue with the self-learning algorithm.

Experiment 6.3 is done to evaluate the *error due to variance* of the model trained by the self-learning algorithm. The objective of this experiment is to measure the tendency to overfit of a model as the number of examples increases with the self-learning algorithm. It is based on the experiments of previous chapters which report the overfitting as well. It changes however in one fundamental aspect. The previous chapter had to work with a limited size corpus and showed the learning curve of the experiment by splitting the dataset. In this case the dataset adds new examples by the design of the self-learning algorithm. Thus, I measure how these new examples affect the learning curve. Remember this is done on a per lemma basis. The structure of the experiment is as follows:

**Experiment 6.3.**

**6.3a** Take only a portion of the whole unsupervised dataset to use as instances.

**6.3b** Shuffle both training and validation datasets and split them randomly with stratified sampling.

**6.3c** Start the self-learning algorithm.

**6.3d** In each step, train the classifier with the training data obtained before starting the training algorithm plus the automatically annotated instances.

**6.3e** Record the predictions over training and validation data.

**6.3f** Repeat the whole procedure $n$ times with a different portion of the unsupervised dataset.

The repetition of the procedure $n$ times emulates what in the previous chapters was done using the random splitting of the supervised dataset. Changing the unsupervised dataset and reshuffling and splitting training and validation datasets evaluates the classifier on new sets of data and shows how much it varies over different datasets. This is used to generate an estimator of the model's tendency to overfit.

Experiment 6.4 reports the features associated to the model. The experiment records the features for each instance of each class. This displays the number of features the whole model is covering as well as the number of features for each class.

**Experiment 6.4.**

**6.4a** Record the number of times a tuple $(class, feature)$ occurs for each class and each feature of the supervised training dataset.

**6.4b** Run an iteration of the self-learning algorithm.

**6.4c** Record the number of times a tuple $(class, feature)$ occurs for each class and each features of the training dataset comprised of the supervised data and the automatically annotated instances.

**6.4d** Repeat the previous step for each iteration of the algorithm.

Experiment 6.5 records the distribution of the classes through an execution of the self-learning algorithm. The experiment records the number of instances belonging to a class in each step of the algorithm. This figure is the sum of the original supervised data plus the automatically annotated data.

**Experiment 6.5.**

**6.5a** Record the number of times each class occurs in the supervised training dataset.

**6.5b** Run an iteration of the self-learning algorithm.

**6.5c** Record the number of times each class occurs in the new training dataset comprised of the supervised data and the automatically annotated instances.

**6.5d** Repeat the previous step for each iteration of the algorithm.

### 6.3.6 Metrics

The metrics seen in previous chapters are used in this chapter as well. Recall I have defined so far two main metrics to report different results. Metric 1 (defined in Section 4.3.5.1) is the macro and weighted average of the F1-score. This metric is useful to deal with the problem of assessing performance when classes are unbalanced.

The error due to variance is measured by Metric 3 (defined in Section 4.3.5.3). The objective of this metric is to measure how much a model overfits the data as the size of the dataset increases.

The pointwise mutual information (PMI) is a statistical measure of association between events. It is defined as:

$$\text{pmi}(x;y) = \log \frac{p(x,y)}{p(x)p(y)}$$

**Metric 4.** The PMI between features and classes is evaluated through iterations using the following steps for each iteration of the algorithm:

**4a** Calculate PMI for each tuple of $(class, feature)$

**4b** Each feature is associated to the class with greater PMI.

**4c** Calculate the mean and standard error of the mean of all the PMIs for all the features associated to one class, per each class.

**4d** The PMI data for that iteration is stored and the process is repeated in the next iteration.

To obtain the average certainty of the classifier over the data I use the following metric:

**Metric 5.** For each iteration of the algorithm calculate:

**5a** Obtain the certainty of the model over the unannotated examples to predict.

**5b** Store the mean and standard error of the mean for the certainty of all examples in that iteration.

**5c** Continue with the next iteration.

## 6.4 Analysis of results

This section reports the results obtained through the experiments described above. This chapter has a bigger number of results and graphics than any of the others. This is as a consequence of having the biggest number of hypothesis in all the chapters. This means the results shown in the figures made it quite heavy to follow. The visualization and metrics show only some part of all these results, those that I considered more relevant. However this can lead to having some results obscured. I will do my best to make it clear when some result is being obscured.

### 6.4.1 Hypothesis 3.1

I explore the results to test Hypothesis 3.1, which states that the performance of a model over a held-out test dataset improves with the self-learning algorithm.

Recall there were only two moments when the model is evaluated over the test data: the initial and the final iteration. The initial iteration is evaluated before starting the self-learning algorithm iterations, when the model is trained only on supervised data. The final iteration is evaluated after the self-learning algorithm stops. This time the model is the last one obtained by the self-learning algorithm, trained both with manually supervised and automatically annotated data. The idea is to assess the impact of the newly added data in the model, as evaluated on the held-out original test dataset.

Figure 6.1 reports the performance results on the test corpus before and after self-learning for each of the token lemmas I presented in Section 6.3.1. The plot is a bar plot structured in the following way:

- Each row shows the results for a token lemma: “acceder”, “buscar”, “explicar”, “facilitar”, “llegar”, and “pensar”.
- Each column stands for a feature representation: hand-crafted hashed features and journalistic word vectors.
- Each group of bars in each plot represents a metric: F1-score macro average and F1-score weighted average.
- Each bar plot in a different color inside a group represents the evaluation moment: initial iteration and final iteration.

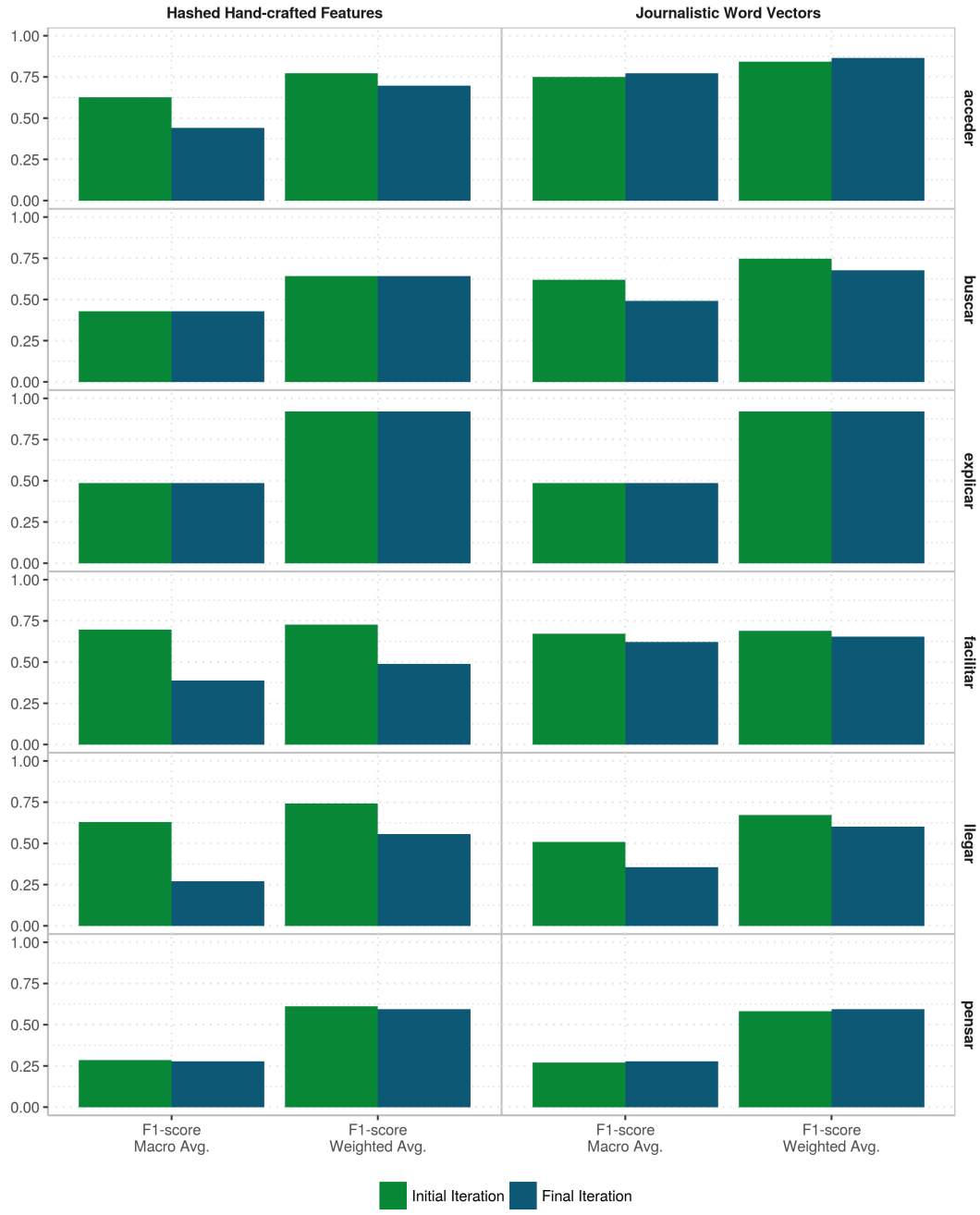


FIGURE 6.1: Comparison of macro and weighted averaged F1-score before and after the self-learning algorithm's iterations

- The bar plot represents the value of the metric.

As explained in Section 4.3.5.1, the weighted average is useful to show the performance of the algorithm given the class distribution (i.e. most frequent classes are more important in the final result). On the other hand, the macro average is useful to see the performance in less frequent classes. Then the spread between the macro and weighted average shows how biased is the algorithm to the most frequent class.

Note that, as described in the previous chapter, word embeddings have worse average performance than hand-crafted features. However, in two of the token verbs

shown here, word embeddings perform better than hand-crafted features, in one of the verbs they perform at the same level and in three cases they perform slightly worse. Actually, even if the average was different, the median was very similar for word embeddings and hand-crafted features, so we can still consider that these token verbs are representative of the population.

The figure shows that, except for two lemmas, hand-crafted features lose performance after the self-learning algorithm ends. In none of the lemmas the algorithm improves the performance over the original model without the new data. For word embeddings the case is a little different, as in half of the lemmas it does not lose performance, and it even improves in two of them.

Comparing the loss in performance for the two different representations, the drop is stronger for hand-crafted features, specially in the macro average. From this results I can hypothesize that for hand-crafted features the self-learning algorithm is more prone to add instances of the most frequent class. This impacts in the performance of less frequent classes and is the reason why the macro average drop in performance is much larger.

This drop in the performance measured by the macro average for word vectors is not as pronounced as for hand-crafted features. Moreover, the general drop in performance, in the cases when it happens, is not as big as for hand-crafted features even if the latter have better performance for the initial iteration (e.g. “facilitar”, “llegar”).

It can be concluded that, in general terms, word vectors work better than hand-crafted features in this setting. This gives a strong indication of the bias of the domain in the task. Hand-crafted features may have better performance in the task with the original supervised dataset but they do not generalize well to a bigger domain. In this case word embeddings provide a better representation because, as we saw on the previous chapter, recalling Hypothesis 2.2, word embeddings have less tendency to overfit a model. This is crucial in a setting like self-learning where new examples are annotated automatically. In this setting, a better representation makes the model adapt better to new data. I.e, hand-crafted features are overfitting the model to the initial labeled dataset and that overfitting is being transferred to the self-learning algorithm decisions regarding instances to annotate automatically, producing a drift with a bias to the majority class. Therefore, I can conclude that word vectors yield a better generalization of the data for unseen examples.

The results do not show enough evidence to accept Hypothesis 3.1. In particular, hand-crafted features show evidence to reject the Hypothesis as the general performance degrades after the self-learning algorithm runs. Nevertheless, when word embeddings are integrated in the setting, results are stronger to accept the Hypothesis, even if not conclusive.

### 6.4.2 Hypothesis 3.2

The present section discusses the results I found regarding Hypothesis 3.2. The Hypothesis stated that the model trained after each self-learning iteration, thus adding new data from unlabeled sources, increased the average certainty to predict the class of new unseen examples. Behind this hypothesis there is the assumption that the model, by adding new unlabeled examples, can represent new examples better.

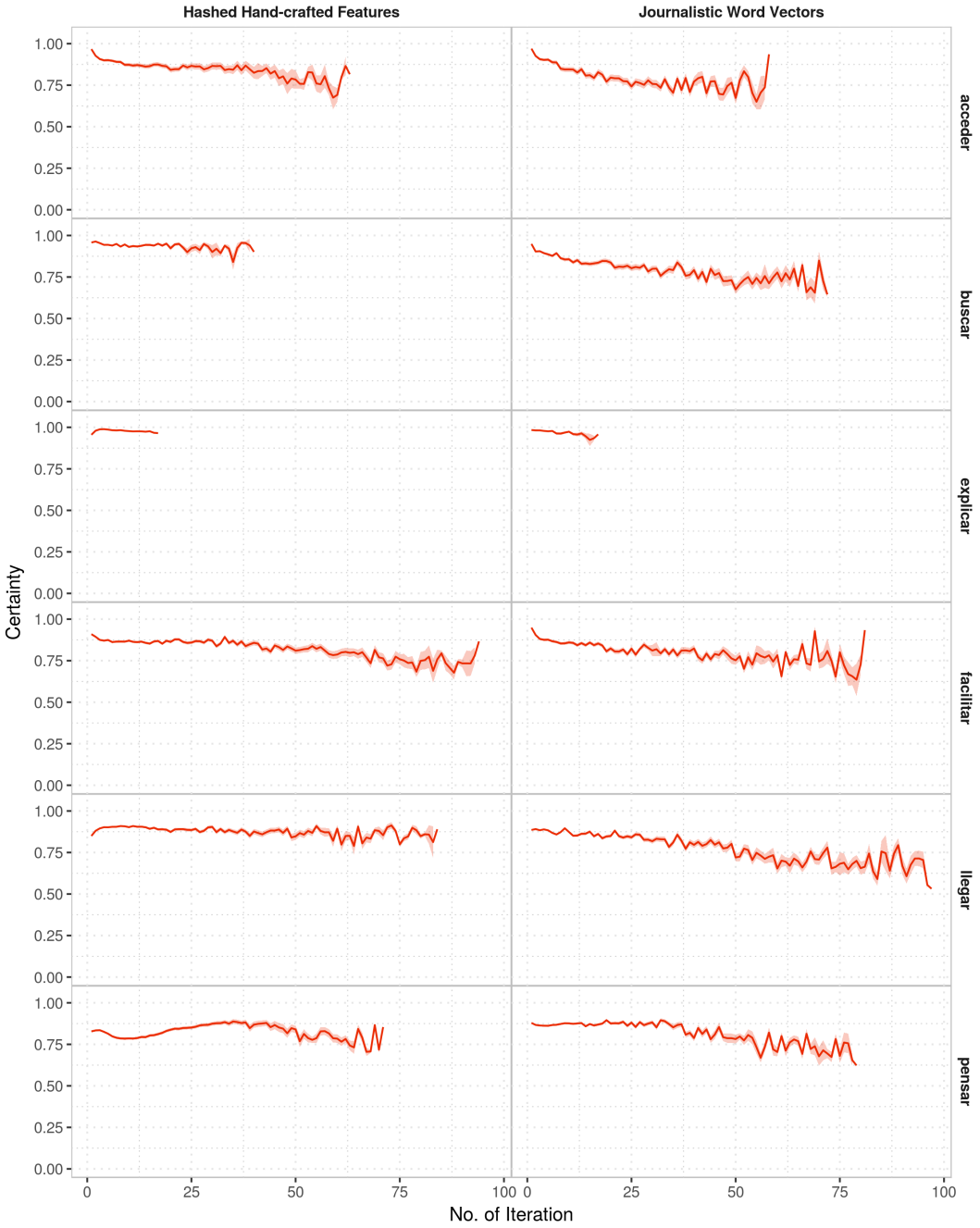


FIGURE 6.2: Average certainty to predict new classes for each self-learning iteration

Figure 6.2 shows the average certainty of the model on new examples throughout the self-learning iterations. The data is obtained running Experiment 6.2, which

records the predicted classes' certainty of the model for all the new examples from the pool of unlabeled data. The metric to measure this is an unweighted average described in Metric 5. The figure shows a line plot with the following structure:

- Each row shows the results for a token lemma: "acceder", "buscar", "explicar", "facilitar", "llegar", and "pensar".
- Each column stands for a feature representation: hand-crafted hashed features and journalistic word vectors.
- The x-coordinate axis represents the iteration number in the self-learning algorithm.
- The y-coordinate axis represents the raw count of features.
- The solid darker line represents the mean of certainty the mode has over the unlabeled data it is predicting.
- The shadowed area, which has a lighter color, represents the standard error of the mean of the certainty.

The plots I show are quite complex to follow and reason about. What is most noticeable is that the certainty of the algorithm over the unseen examples is less uniform as more iterations are added. In contrast to what I originally assumed in Hypothesis 3.2, the algorithm shows a lower certainty over new examples.

It is noticeable that hand-crafted features start with a certainty that is more uniform through the initial iterations. Nonetheless as iterations go further, certainty becomes more and more variable. Meanwhile, word vectors always show a variable certainty over unseen examples. How certainty evolves through the iterations in the self-learning algorithm gives us the idea that the model is not converging, at least not in terms measured by certainty.

It is clear that the new examples add more uncertainty to the model, something that becomes worse by adding more examples. Since the algorithm is drifting to classify examples into the most frequent class, one would expect that the certainty for the majority class is increased. However, what actually happens is that the majority class accumulates many different examples. Most of these examples are poorly characterized by the model, because most of their features are unknown to the model. Thus, the classifier does not have a big certainty over the majority class. Instead, it seems that many instances are classified in that class only because the model does not have enough information to classify them in any class, and it simply chooses the most probable one. In sum, integrating more examples does not seem to increase the certainty because they are not integrated in a smart manner, but relying only on the probability of the majority class. Then, no new examples are added to minority classes (and their certainty does not increase), and examples added to the majority class only contribute to disperse the certainty.

### 6.4.3 Hypothesis 3.3

Hypothesis 3.3 is based on what I discussed in previous chapters regarding the tendency of a model to overfit the training data. It states that adding new unseen examples automatically through the self-learning algorithm helps reducing the overfit of the model.

The Hypothesis is tested with the results reported by Experiment 6.3. The experiment is similar to what I did in the previous chapter to see the evolution of the *error due to variance* using the learning curve of the model. The main difference lies in that in previous chapters I needed to split the labeled dataset in order to simulate adding new examples to a model. Thus, in previous chapters, new added examples were actually labeled examples I left outside in the beginning.

Self-learning gives me the possibility to explore how real unseen examples affect the tendency to overfit of a model measured by the learning curve defined as Metric 3 in Chapter 4.

There are however two possible views of the learning curve in this case. The first approach is by plotting the curve in function of the iterations of the algorithm. The second approach is to plot the curve in function of the number of examples used for training.

The first approach is more focused on how the self-learning algorithm works rather on how the model evolves. In each iteration the number of examples added can be high or low. As I did not limit the number of new examples to add, there is no certain way of telling how many the algorithm is adding for each iteration. What the results show in this case is rather how the added examples affect the model in that iteration. The second approach is more analogous to what is shown in previous chapters, as the plot is done based on the number of examples of the training dataset rather than the iteration they were added.

Both views are useful on their own ways, nevertheless for comparison with the previous methods I opted for analyzing the second approach as it is closer to what I already discussed for supervised and word embeddings approaches before.

Figure 6.3 shows the learning curve plot as a function of the number of examples of the training dataset. The structure of the learning curve plot is as follows:

- Each row shows the results for a token lemma: “acceder”, “buscar”, “explicar”, “facilitar”, “llegar”, and “pensar”.
- Each column stands for a feature representation: hand-crafted hashed features and journalistic word vectors.
- The x-coordinate axis represents the number of examples in the self-learning algorithm.
- There are two colors representing the datasets: train and validation (in this case is the validation set).

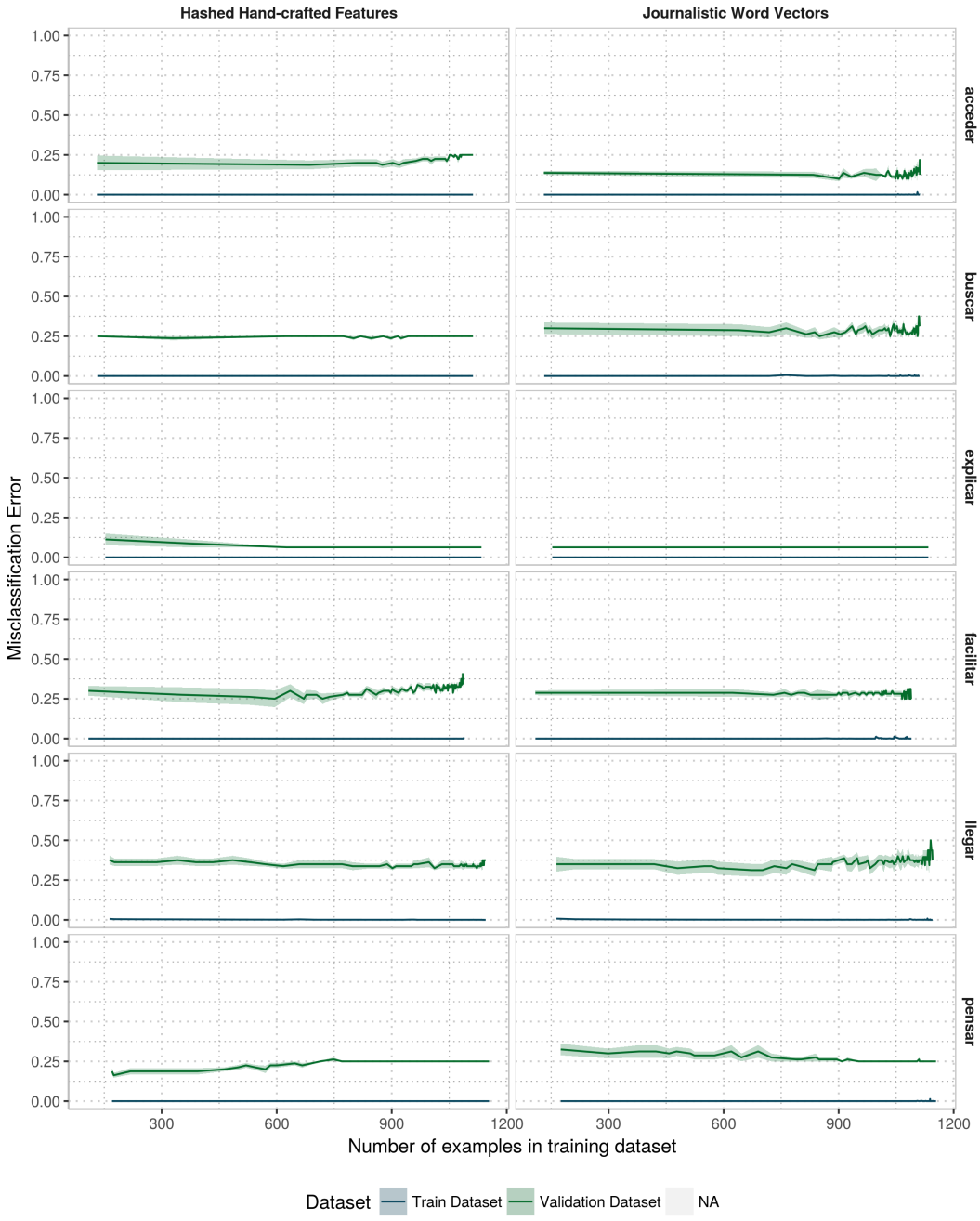


FIGURE 6.3: Learning curve as a function of the number of examples added by the self-learning algorithm

- The solid darker lines represent the mean of misclassification error trough the different iterations of the datasets over all the models.
- The shadowed area, which have a lighter color, represent the standard error of the mean of the misclassification error.

Recall I am limiting my unlabeled pool of data to 1000 unannotated examples and that is why none of the plots go beyond 1150 examples total (that is the original supervised dataset plus the automatically annotated examples).

A first look into the graphics shows that the misclassification error drops a little after the first set of automatically annotated examples is added. This is more or less uniform for all the lemmas for the first increments. If I take into consideration that these examples are added in the first iterations, it is interesting to see that the first iterations are the ones adding up to improve the generalization of the model. This happens regardless of the representation used.

It is also interesting to see that in general terms the shadowed area, which is the standard error of the mean for the misclassification error, becomes narrower the more examples are added. This means the model has less variance over the validation dataset. This is an indication of the model reducing the error due to variance, which is one of our indicators of reduced overfitting.

Besides that, it is striking how the error in the validation dataset starts to become highly irregular for every new example added. This happens in most of the cases for the examples added in later iterations. This can be due to the fact that in the final iterations of the algorithm, the tolerated error level in the validation dataset is bigger. Indeed, the tolerated error in the validation dataset is slowly increased by the method as iterations go, and until it reaches the stopping threshold. This is specially relevant for the case of word embeddings. It may require a further analysis left for future work for now.

This tendency could be further explore and systematized to the point that it can be used as a stopping criterion for the algorithm. Indeed, the difference in validation and training error over the iterations could be a good stopping criterion.

### 6.4.4 Hypothesis 3.4

Hypothesis 3.4 is based on what I talked about previously regarding model coverage. To measure the coverage I do so by counting the features the model recognizes. For hand-crafted features this means all the features obtained from the training data (which includes words, tokens, part-of-speech, etc. as explained in Section 4.3.2). For the case of word embeddings, the features are the words surrounding the verb to disambiguate and the position relative to that verb. There is more than one way to measure the coverage of a model by its features. Hypothesis 3.4 is interested in showing that the model increases it is number of features by adding new examples so I get the raw count of the total number of features the model has in the training dataset over the self-learning iterations.

Figure 6.4 reports the features' growth of the model across the self-learning iterations. That is the total number of unique features up to that iteration obtained both from the original supervised dataset and the automatically annotated data. The figure shows a line plot with the following structure:

- Each row shows the results for a token lemma: “acceder”, “buscar”, “explicar”, “facilitar”, “llegar”, and “pensar”.

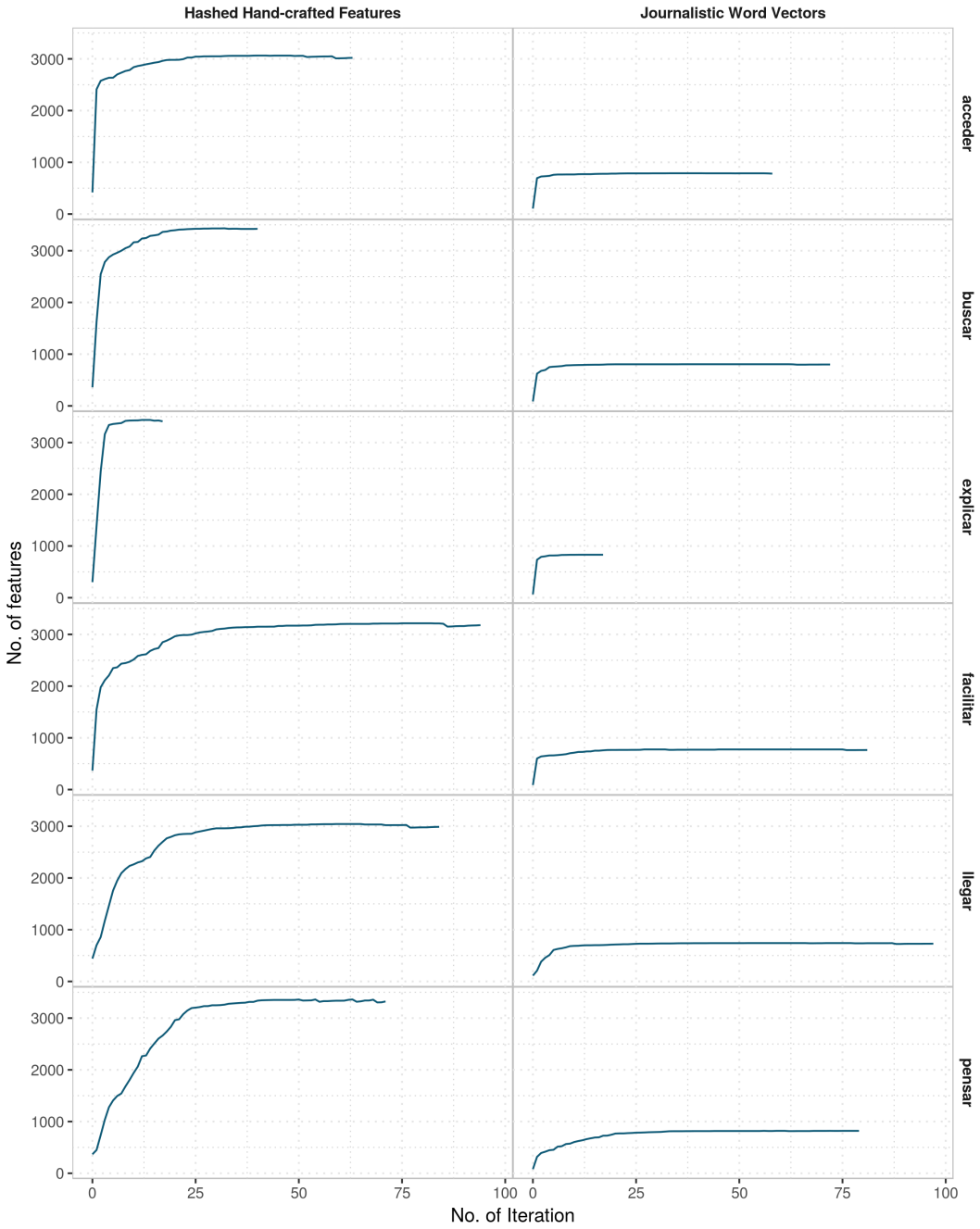


FIGURE 6.4: Features' growth in the model across self-learning iterations

- Each column stands for a feature representation: hand-crafted hashed features and journalistic word vectors.
- The x-coordinate axis represents the iteration number in the self-learning algorithm.
- The y-coordinate axis represents the raw count of unique features.

From the figure it is visually striking that most of the new features are acquired in the first iterations of the self-learning algorithm. After that the number of features

stales. This is an indication of the algorithm adding lot of examples in the first iterations while almost none in the following ones.

It is interesting to note the difference between hand-crafted features and word vectors. It is natural because of what I explained previously regarding what is that I am considering as features for each type of representation. The pool of features for the word embeddings model is much smaller than for hand-crafted features. Regardless of the scale, there is a shared pattern for both representations regarding the way the features in the models grow.

These results show that the model effectively increases the features associated to it, which is stated by Hypothesis 3.4. The hypothesis is accepted in that way. However, this is not necessarily an increase in the coverage of the model as I will show in further sections.

### 6.4.5 Hypothesis 3.5

In this section I discuss the results regarding Hypothesis 3.5. This hypothesis together with the following two in this chapter are expected to be false (in contrast to the previous ones). Hypothesis 3.5 states that self-learning helps improving the performance of the model on each class uniformly.

To test this hypothesis I work on the results of Experiment 6.1 again. Remember that in that experiment the idea is to evaluate the model over the held-out test dataset before and after running the self-learning iterations. However, this time, instead of reporting the averages defined in Metric 1, I show the F1-score for the most frequent, second most frequent and, in some cases, third most frequent class of the lemma. I do this because these are the classes of the token lemmas that were not filtered out in the preprocessing of the corpus. From the 6 token lemmas, 4 of them have only two senses with instances in the labeled dataset ("acceder", "buscar", "explicar", and "facilitar"), and only 2 of them have 3 senses with instances in the dataset ("llegar" and "pensar").

Figure 6.5 reports the performance results on the test corpus for supervised (i.e. before the self-learning iteration starts) and self-learning algorithms for each class (i.e. sense) of each of the token lemmas I presented in Section 6.3.1. The plot is a bar plot structured in the following way:

- Each row shows the results for a token lemma: "acceder", "buscar", "explicar", "facilitar", "llegar", and "pensar".
- Each column stands for a feature representation: hand-crafted hashed features and journalistic word vectors.
- Each group of bars in each plot represents the class (i.e. sense) for that lemma. These are ordered according to number of occurrences of the class in the dataset.

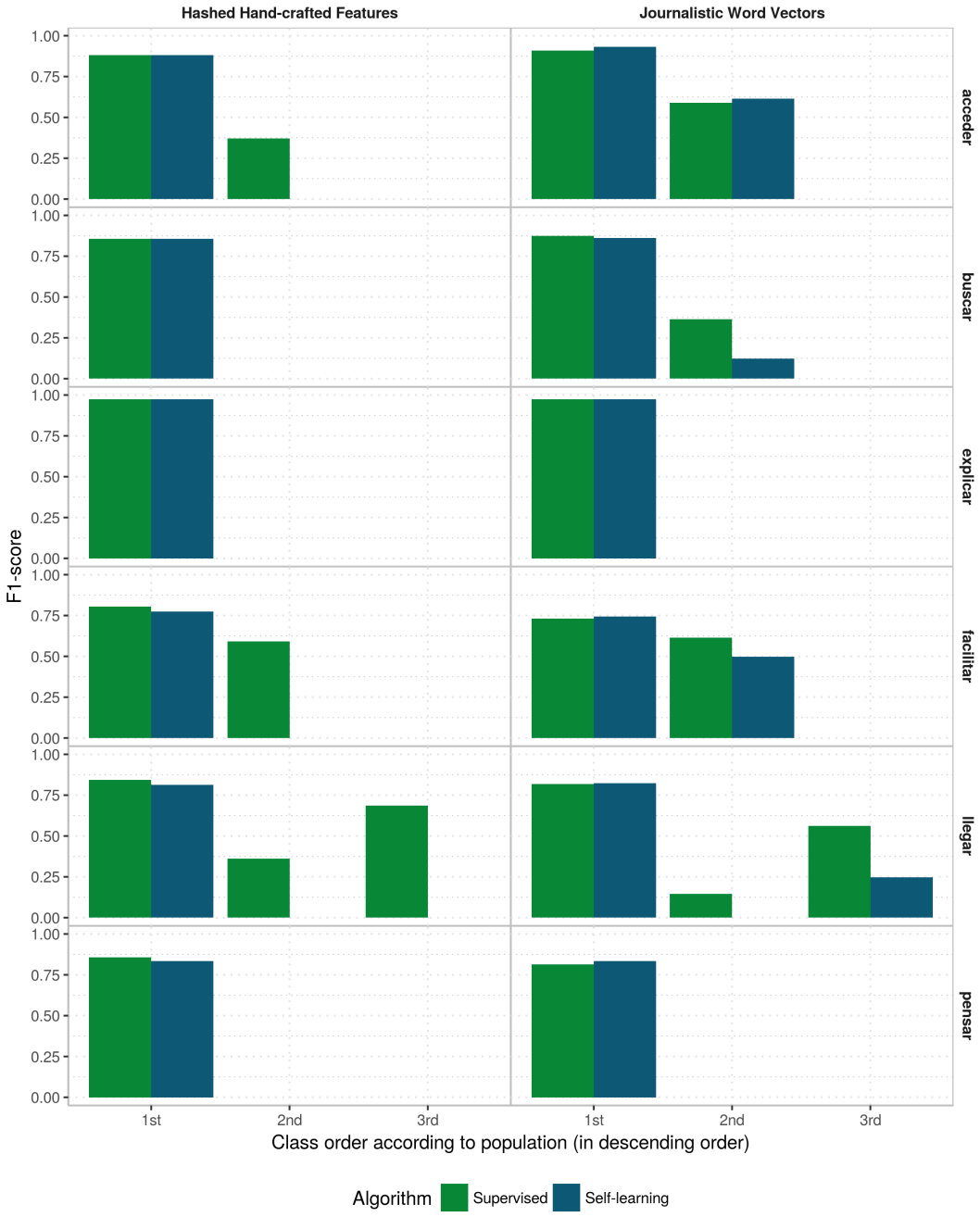


FIGURE 6.5: Comparison of F1-score for each class before and after the self-learning algorithm's iterations for the token lemmas

- Each bar plot in a different color inside a group represents the algorithm: supervised (i.e. evaluation moment of the initial iteration), self-learning (i.e. evaluation moment of the final iteration after self-learning finishes).
- The height of the bar represents the value of the F1-score per each class.

Recall again that only the last two rows of the graphics have lemmas with 3 senses (i.e. "llegar" and "pensar"). The first four lemmas can at most show results for two senses.

From the figure it is clear that the self-learning algorithm is affecting negatively the performance of all the classes that are not the most frequent class. The only lemma in which there is a slight improvement in performance for a class that is not the most frequent one is the lemma "acceder" and only does so with the word embeddings representation.

This plot gives more information based on each class rather than obscuring everything into an averaged metric. From it I can see that even though word embeddings may have less performance in classes other than the most frequent, the self-learning algorithm does not affect it as much as it does for hand-crafted features. With hand-crafted features the F1-score directly drops to zero for all classes other than the most frequent one. This is clearly a sign of divergence to the most frequent class when new examples are added by the self-learning algorithm.

The results are clear in this case and it is safe to reject Hypothesis 3.5 as I originally thought.

### 6.4.6 Hypothesis 3.6

The next Hypothesis to test is 3.6. This is an extension of the explanation for the previous hypothesis as it states that the representativity of each class in the dataset is maintained through all the iterations of the self-learning algorithm. By representativity I mean the number of classes as a proportion of the whole training dataset. This Hypothesis is expected to be false and is a result of the self-learning algorithm tendency to classify every new instance as the most frequent class.

Experiment 6.5 is used in this section to report the results of the self-learning algorithm with respect to the representativity of each class through iterations. The experiment records the distribution of the classes in the training dataset in each iteration. The metric to measure this is the proportional count of occurrences each class, with respect to the whole data available

To visualize these results I focus on two aspects I find relevant when considering the hypothesis. First is the proportional count of number of instances per class along the iterations of the algorithm. Second I want to show how many examples of each class are added in each of the iterations of the algorithm as a proportion of all the examples added in that iteration.

#### 6.4.6.1 Classes' population distribution across iterations

Figure 6.6 showcases the distribution of the population of the classes across the self-learning iterations of the algorithm. Each class's population is represented as the proportion of the total number of examples in the training dataset for that iteration. The plot is a stacked area plot that follows this structure:

- Each row shows the results for a token lemma: "acceder", "buscar", "explicar", "facilitar", "llegar", and "pensar".

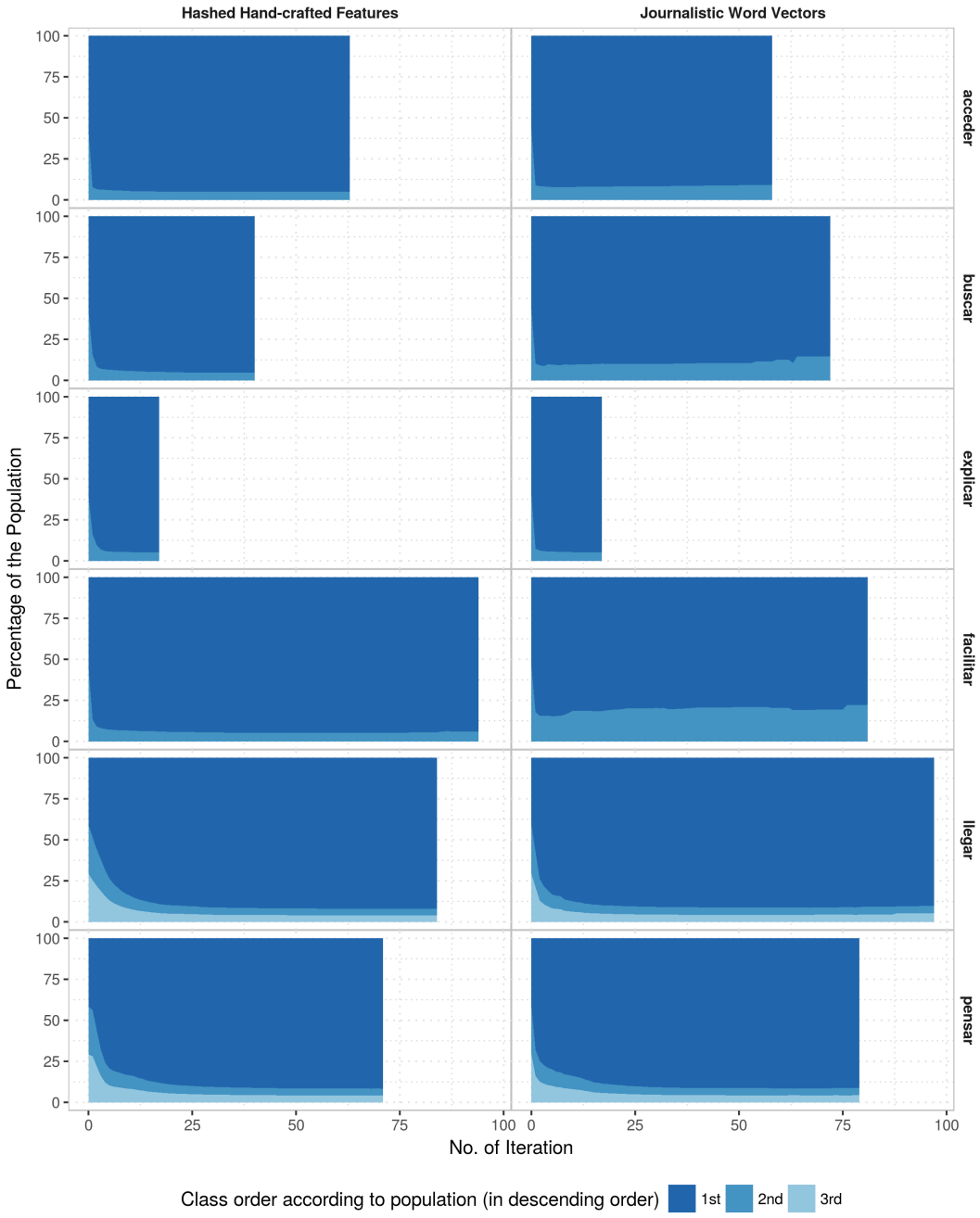


FIGURE 6.6: Distribution of the classes' population across self-learning algorithm's iteration as a proportion of the whole training dataset

- Each column stands for a feature representation: hand-crafted hashed features and journalistic word vectors.
- The x-coordinate represents the iteration in the self-learning algorithm.
- The y-coordinate represents the percentage of population.
- Each area of a different color represents the proportion of examples for each of the classes in the dataset. The classes again are ordered according to number of

examples in the original supervised dataset.

Figure 6.6 shows the clear predominance of the most frequent class in the self-learning algorithm. For some lemmas the progress is a little less steep, for others the algorithm starts to classify most instances into the most frequent class from the beginning.

Recall that the number of classes is very unbalanced in the original manually annotated corpus. To make this less of a problem, the corpus I have been using in all these experiments has minority classes oversampled so that the number of examples per class is more uniformly distributed. Even so, the models still diverge quickly to the majority class.

From this figure I have evidence to reject the hypothesis regarding the classes' distribution being uniform across the self learning iterations. This figure gives me insight on that. However, to see more clearly what happens with the classes on a per iteration basis the following visualization provides a better view of the data.

#### 6.4.6.2 Population added per sense per iteration

Figure 6.7 shows the proportion of examples added per class on each iteration. It is a stacked bar plot where each bar represents the total examples added in the iteration, and each color in the bar represents the proportion of classes automatically annotated as such. The structure of the plot is the following:

- Each row shows the results for a token lemma: "acceder", "buscar", "explicar", "facilitar", "llegar", and "pensar".
- Each column stands for a feature representation: hand-crafted hashed features and journalistic word vectors.
- The x-coordinate represents the iteration in the self-learning algorithm.
- The y-coordinate represents the percentage of examples automatically annotated and added to the model.
- Each bar plot represents the distribution of the examples added in the iteration. Each color of the stacked bar represents the class into which the examples were annotated.

This figure gives a better insight of what is happening on each iteration of the algorithm and helps explain the distribution shown on Figure 6.6, as it shows the proportion of classes added in each iteration of each class.

I am able to see that the model trained with hand-crafted features practically does not label the unlabeled data as something that is not the most frequent class. This adds up to what is shown in previous paragraphs regarding hand-crafted features having problems generalizing well to other domains.


FIGURE 6.7: Population added per sense on each iteration of self-learning as a proportional count of all the examples added in that iteration

The representation with word embeddings on the other hand is also affected, as I saw in the previous figure, with the model diverging to the most frequent class. However, there is a clear tendency for the model to also annotate classes other than the most frequent one in the examples. And as I discussed in Section 6.4.1 the results of the self-learning algorithm using word embeddings were quite superior to the ones obtained for hand-crafted features. This means the word embeddings have a good impact on a self-learning model as they help the classifier generalize better thus being

able to add new examples, even from different domains, to the model.

From this and the previous analysis I can conclude Hypothesis 3.6 is false. Clearly it does not happen that the self-learning model is adding new data uniformly distributed across classes. Nevertheless word embeddings do help the model to add relevant data and not labeling everything as part of the most frequent class. This is an interesting line of future work as a deeper analysis, perhaps with manual evaluation, to see how well word embeddings are helping to classify examples as part of the less frequent classes.

### 6.4.7 Hypothesis 3.7

The last hypothesis I wanted to reject in this chapter is Hypothesis 3.7. The hypothesis states that the coverage given by the features is uniform across classes. Recall that I showed in Section 6.4.4 that the number of features grew across iterations of the self-learning algorithm, this was stated by Hypothesis 3.4. The previous section showed that the number of classes is not maintained uniformly across the self-learning iterations, thus it is natural to think this will happen with features as well. However, the results I will show in this part are useful to throw some more light on the results of the previous sections.

To test this hypothesis I want to measure two things: the raw count of the features for each of the classes, and how strongly a feature is associated to a class based on the pointwise mutual information it has with that class. These results are obtained from Experiment 6.4 which reports the number of times a feature occurs with a class in the training dataset for each iteration of the self-learning algorithm. To reduce the noise in the data I filtered out all the pairs of $(features, classes)$ that co-occur less than 2 times.

#### 6.4.7.1 Features raw count

The first view of the data I want to show is what comes to measure the results of Experiment 6.4 using the raw count. This shows the number of unique features occurring with each class in each iteration of the self-learning algorithm. In this view of the results, features can be present in two classes at the same time, if they occurred more than twice with that class, regardless of how strongly associated they are with the class.

Figure 6.8 displays the results of counting the different features occurring with each of the classes in the datasets. That is the total number of unique features up to that iteration obtained both from the original supervised dataset and the automatically annotated data. The figure shows a line plot with the following structure:

- Each row shows the results for a token lemma: “acceder”, “buscar”, “explicar”, “facilitar”, “llegar”, and “pensar”.
- Each column stands for a feature representation: hand-crafted hashed features and journalistic word vectors.

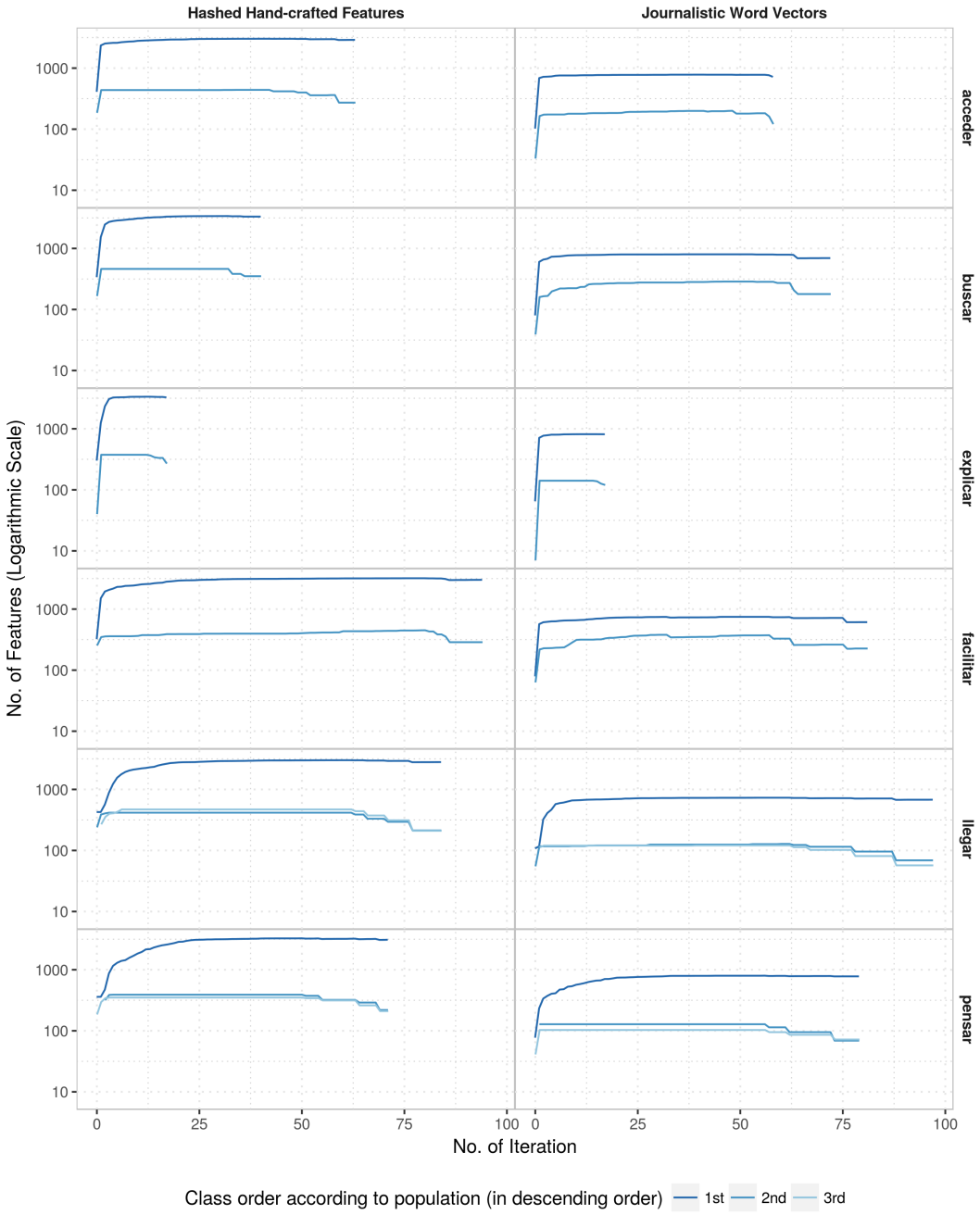


FIGURE 6.8: Features growth per class across self-learning iterations (in logarithmic scale)

- The x-coordinate axis represents the iteration number in the self-learning algorithm.
- The y-coordinate axis represents the raw count of unique features in a logarithmic scale. The scale selected is logarithm because, in comparison, the number of features of the most frequent class is an order of magnitude larger than those of the less frequent classes, and any variation (i.e. adding more features) of the less frequent classes is lost when compared to the most frequent class if I use a linear scale.

- Each line represents the number of features and the different colors represents the class that features belong to.

The figure shows that there is always a class for which the number of features increases much more quickly and in a higher number than the others. This is a consequence of the model diverging to the most frequent class. Most of the new features also come from the first iterations of the algorithm and in the following ones there are practically no more new features added. This is particularly noticeable for the less frequent classes. As a consequence of this, after some initial few iterations the algorithm diverges and all new instances are directly added to the most frequent class. Thus in the last iterations of the algorithm there are not new features for the less frequent classes.

Once again the difference between hand-crafted features and word embeddings resides in the pool of features. As I explained previously, the pool of features that comprise the word embeddings model is much smaller than for hand-crafted features. Nevertheless it is interesting that in some of the lemmas the features grow for each class in the latter iterations for word embeddings, while it does not for hand-crafted features. This comes from what I saw in the previous Section regarding word embeddings helping the model generalize better and annotate new classes besides the most frequent one.

There is an effective increase in the coverage, as many features are added to the model. However these features belong mostly to a single class, the majority class. In the following section I will show that this increase in the number of features does not directly imply an improvement of the model.

#### 6.4.7.2 Features PMI

The second view of the data I want to show is based in the results of the experiment measuring the correlatedness between features and classes. This is given by the pointwise mutual information (PMI) between the features and the associated classes given by Metric 4.

Figure 6.9 displays the mean and standard error of the mean of the pointwise mutual information between features and classes across the self-learning iterations. Thus it is higher when the features associated to a class are associated more strongly to the class. Recall that the metric associates each feature to the class it has a higher PMI with. The figure shows a line plot with the following structure:

- Each row shows the results for a token lemma: “acceder”, “buscar”, “explicar”, “facilitar”, “llegar”, and “pensar”.
- Each column stands for a feature representation: hand-crafted hashed features and journalistic word vectors.
- The x-coordinate axis represents the iteration number in the self-learning algorithm.

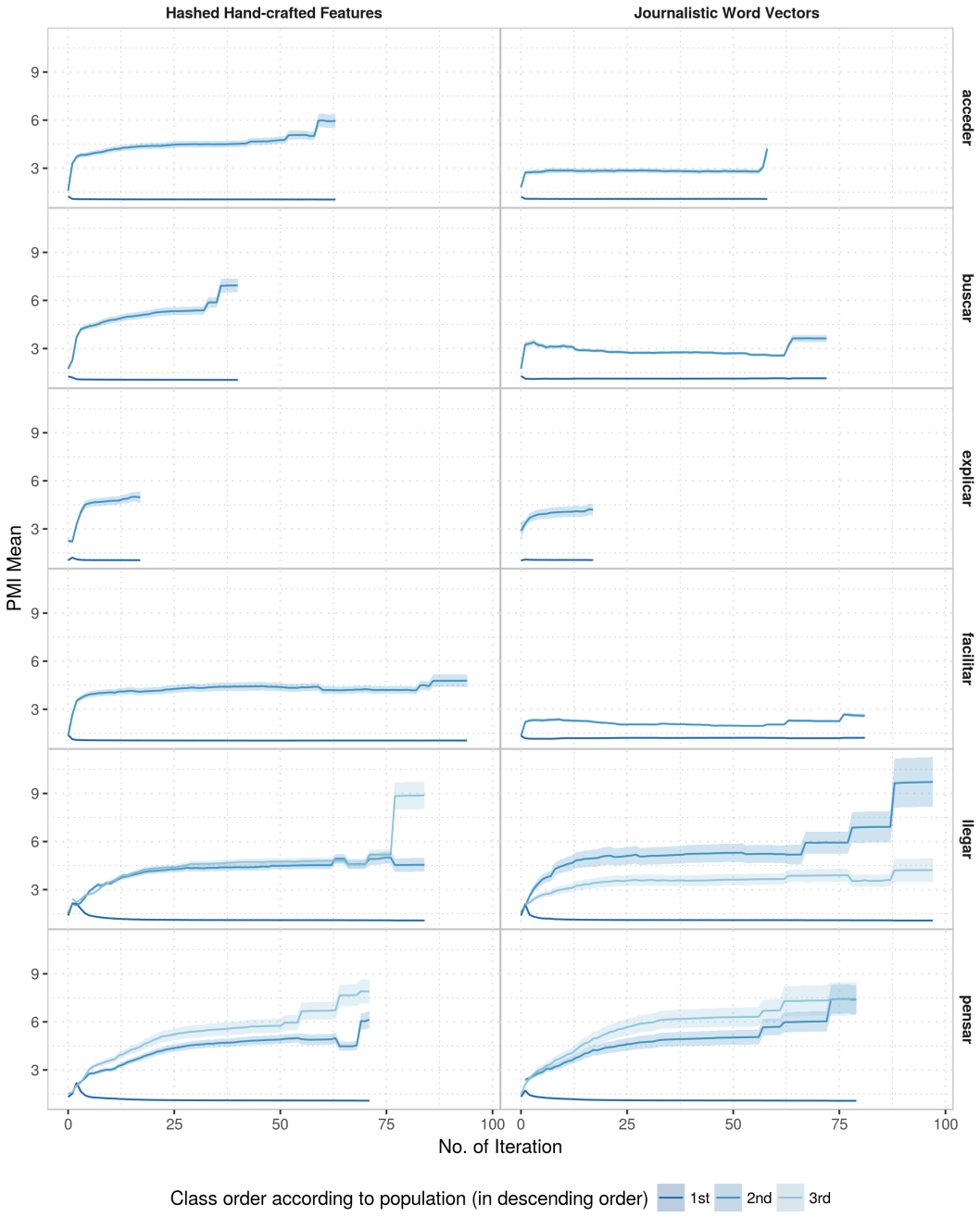


FIGURE 6.9: Features pointwise mutual information with each of the classes across self-learning iterations

- The y-coordinate axis represents the raw count of unique features in a logarithmic scale.
- Each color represents a class.
- The line of darker color in the middle represents the mean of the PMI for the class and the shadowed area represents the standard error of the mean for that PMI.

Different from the previous figure, now the classes with a smaller number of features are the ones having the larger values in the plot. It seems that in classes with a smaller number of features, these are associated more strongly to the class. In contrast, in classes with a bigger number of features, these are associated more weakly. It seems that the most frequent class is working as a "catch all" for new examples, mostly those without features strongly associated to any other class, and because of the algorithm's tendency to annotate examples to it. Then, the features in these new examples are associated to that class. However, these features are not strongly related to that class, because they belong to examples that have been classified into the class by weak reasons, like the probability of the class or the lack of characterizing features. This makes these features not a good parameter to help discriminate this class. On the other hand the features for the less frequent classes become much more discriminative of such classes because new examples are only classified into those classes when there is strong evidence that they belong to the class, that is, when evidence is stronger than the default to classify them into the majority class.

Even if it looks like the classifier's coverage is increasing, because of the number of features doing so, from this data there is a clear indication that it is not like that because the new features belong mostly to the most frequent class and do no contribute to increase the certainty of the model, which is reflected on a low mean of the PMI with the most frequent class.

On the other hand, those features that are associated to the less frequent classes do so with a strong association to the point that as the self-learning iterations add new examples the features become more discriminative of this less frequent classes. However, the number of these features does not increase as much, as was shown in the previous section.

### 6.4.8 Summary

The results of the evolution of certainty and tendency to overfit in the model give the impression that hand-crafted features have less variance than word embeddings. However, a more detailed analysis shows that even though the variability is less in hand-crafted features, the reason behind this is that it only adds new examples of a particular class, the most frequent one. This is not the case for word embeddings.

Word embeddings show more variability in the tendency to overfit and the mean of the certainty as it is effectively adding new examples annotated into classes that are not only the most frequent one. Moreover, Figure 6.7 shows there are some instances where only elements of the less frequent classes are added.

## 6.5 Conclusions

In this chapter I have presented an approximation to self-learning to overcome the problems of overfitting and coverage presented in the previous chapters. My initial

hypothesis was that the overfit is caused by the low number of examples and that increasing such number helps reducing it.

I saw that adding new examples effectively helps reducing the overfit in the initial iterations. However, self-learning is biased to the most frequent class. This makes the model add many examples to that class, ignoring the less frequent classes. This is particularly noticeable for hand-crafted features.

To draw this conclusion I defined some subhypotheses in the beginning of the chapter. The experiments done to test these hypotheses gave me the possibility to draw the following conclusions.

Hypothesis 3.1 that the performance of the model over a held-out test dataset improves after the self-learning algorithm was shown false for the case of hand-crafted features but I could not obtain conclusive results to reject it with respect to word embeddings. In the latter case the results depended on the lemma, as for some the performance decreased but for others it increases or remains the same. An important results I could gather from this is that hand-crafted features had a steeper drop in performance than word embeddings, a sign that the representation fits the labeled dataset well but fails to generalize.

Hypothesis 3.2, which stated that the model's average certainty on unseen examples in each iteration is increased, is rejected in light of the obtained results. This is because there is a clear tendency of the certainty of the mean that the algorithm has over unseen data to decrease across iterations.

Hypothesis 3.3, which states that overfitting is reduced across self-learning iterations, is mildly rejected. The fact is that the number of examples effectively reduced overfitting in the first iterations of the algorithm. However, as I do not use this as a stopping criterion in the algorithm, when it starts to diverge to the most frequent class, the tendency to overfit increases.

Hypothesis 3.4 stated that the coverage of the model increases as a result of increasing the number of features associated to this model. The number of features associated to the model indeed increases as the results did show. These results are enough to accept the stated hypothesis. However, as I saw in the results associated to Hypothesis 3.7, which conclusions are in the next paragraphs, these results are not enough to show that there is an indication of the model effectively increasing coverage as a result of increasing the number of examples.

The previous hypotheses were formulated with the idea to accept them. This was not exactly the case. However, the other three hypotheses in this chapter were formulated with the idea they would be rejected.

Hypothesis 3.5 states that the performance of the self-learning algorithm over all the classes is improved. The hypothesis is rejected because only the performance of the most frequent class increases through iterations of the self-learning algorithm, while the rest of the classes show a degraded performance.

Hypothesis 3.6 states that the representativity of each class in the dataset is kept through all the iterations of the algorithm. The hypothesis is also rejected. The results

show that new examples added to the model belong mostly to the most frequent class and the distribution of the classes is highly biased across the iterations. In particular, hand-crafted features have the worst performance in this as the model only adds examples of the most frequent class. Word embeddings have better performance as the algorithm adds examples of the less frequent classes as well. This last has relation to what happens in the results of the previous hypothesis where there are some cases where the less frequent classes' performance does not drop to zero as in hand-crafted features.

Hypothesis 3.7 states that the coverage of the features is uniformly distributed across the classes. The results obtained serve to prove the hypothesis false. This hypothesis is related to Hypothesis 3.4 which states that the number of features associated to the model increases after the self-learning iterations, which is true, but not in the way the model needs in order to effectively increment the coverage. This is because the certainty of the model does not increase with the number of features. In a detailed analysis it is seen that most of the features are weakly associated to the classes (in particular to the most frequent class). So, their contribution to the model is small. Thus a bigger number of features does not imply a better model, not even better coverage, because they are not discriminative enough. A possible cause of this is that, when the model starts to overfit, the most frequent class begins to coopt elements that are not part of the class. This makes the model drift and starts to have less certainty over new examples.

As I saw in the results of this chapter, the biggest problem for self-learning is the tendency to diverge and add everything to the most frequent class. A way of attacking this problem is using techniques which help stop that bias. There are different ways to do so. One is by re-sampling the data. I only explored random oversampling of the less frequent classes, which did not prove useful. Other re-sampling methods include the random sub-sampling of the most frequent class or a mix of both.

In the next chapter I will explore a technique based on human annotation which selects examples based on high uncertainty and give that to a domain expert in order to correctly annotate them. The idea is that this examples will help the model better define the decision boundaries over the most frequent class, which is something the self-learning algorithm is not doing well.

Future work of this chapter includes the change of the stopping criterion for something to stop once the model becomes to overfit again (the spread between training error and validation error grows). Another line of future work is a more general analysis of all the lemmas, and some more specific analysis on some more lemmas beside the selected tokens.

I also have to do more thorough analysis of the certainty the model has over new examples (i.e. previously unseen) and why it becomes so irregular as the algorithm's iterations go further.

Finally, as word embeddings proved to have interesting results and, unlike hand-crafted features, they did not drift so quickly or so firmly to the most frequent class,

it would be interesting to do some manual evaluation and error analysis to see what is happening under the hood.

# Chapter 7

# Active Learning

## 7.1 Overview

In Chapter 4 I concluded that the number of examples has a direct impact in the performance of a supervised verb sense disambiguation algorithm. I also explained that small supervised corpora have a direct impact in both the coverage and the tendency to overfit of a supervised model. To attack the latter I saw in Chapter 5 that the use of word embeddings, although decreasing performance in the test portion of the supervised corpus, did help in the tendency to overfit of a model. In the self-learning approach, word embeddings show an interesting performance as well: even if coarse accuracy figures are more or less comparable for hand-crafted features and for word embeddings, the latter have better recall in minority classes and incorporate more informative features.

In Chapter 6 I explored self-learning as a joint semi-supervised method. The original idea of using this method was to overcome the problem regarding the model's coverage by adding new data, that is automatically annotated, to the training set. The chapter also gave me more insight of the benefits of using word embeddings as a representation when faced with a task where the domain changes. However, there is a challenge in the method of self-learning: the tendency of the method to add only examples of the most frequent class.

This chapter introduces another semi-supervised joint learning framework: *active learning*. Like self-learning, active learning consists in expanding the training examples with new data provided by an unannotated corpus. Also, as a wrapper method, it does so by training a model from labeled data and improving that model with new labeled data obtained from the unlabeled corpus.

The difference between self-learning and active learning lies in how the last method labels the unlabeled data. This is not done automatically, but by the means of an oracle, i.e. an annotator who has high certainty over the data it is labeling (generally speaking, this is done by a human annotator, more specifically a domain expert).

But this is not the only difference, since the way unlabeled instances are selected for annotation also differs from the method used by self-learning. While self-learning relies on the certainty the algorithm has over the data to safely assume the given label is right, active learning seeks for data which, once labeled, will yield the biggest

improvement on the model. This data is near the decision boundaries of the model and is generally more difficult to tell it apart from data with other labels.

One of the most popular techniques to select data that will improve the model is *uncertainty sampling*. I briefly introduced it in Chapter 2. In this technique the underlying hypothesis is that those instances on which the classifier has the least confidence are the ones closest to the decision boundary and thus the ones to make the most difference after being labeled.

In our setting, those instances which have the most impact on a model are typically the ones that are underrepresented in the labeled dataset. And this is precisely where active learning overcomes one of the problems of self-learning: the bias to the most frequent class. As self-learning is a model based on certainty, this implies that it will add mostly instances of the most frequent class (typically the one the model has better certainty about, even if only by probability). Active learning, on the other hand, helps the model spot useful instances of those underrepresented classes in the labeled dataset and provides the means to add them for a broader coverage.

Moreover, active learning not only adds examples of the pre-existing classes of the model but of new classes as well. Remember in previous chapters I explained that some classes of the SenSem corpus were filtered out because they did not had enough occurrences in the supervised dataset. Besides those cases there are also senses in the SenSem lexicon that did not have any examples in the annotated corpus. As the labeled corpus is domain specific, this results in the corpus not having examples of some of the possible senses. However, when applying active learning over an unlabeled corpus of a general domain, examples of these senses pop up in the flow of the algorithm. This is a common phenomenon as the certainty the model has over those examples it never saw before will be low, thus it will be picked up by the uncertainty sampling technique. There are even senses that are directly not taken into account by the resource, but these are left out as it is outside the scope of this thesis because it requires the extension of the SenSem lexicon.

Regarding what is stated in the previous paragraph there is a remark to do about self-learning. Recall that the last chapter showed that with the self-learning model the certainty over new examples decreased in each iteration. Thus it is possible that the self-learning algorithm was marking those examples the model had less certainty about as part of the most frequent class. However these examples were not even part of the initial labeled dataset as the classes of those examples are not present.

This chapter will test the following hypothesis:

**Hypothesis IV** *Active learning improves the performance of a supervised model by reducing the bias of the initial dataset that is correlated to overfitting of the supervised model.*

In order to accept or reject such hypothesis, I divide it in more specific ones:

**Subhypothesis 4.1** *The representativity of the population for each class in the dataset is maintained through all the iterations of the algorithm.*

**Subhypothesis 4.2** *The active learning algorithm increases the number of features associated to the model more quickly than self-learning, which is an indicator of a quicker increment in the coverage of the model.*

These hypotheses will be tested using the following layout:

- Experiment 7.2 records the number of occurrences per each class in the training dataset on every iteration of the active learning algorithm. The population of the classes is measured by the proportional count with respect to the whole training dataset. The results of this experiment, shown in Section 7.4.2, serve to accept Hypothesis 4.1 which states that the population of all the classes is maintained along the algorithm's iterations.

- Experiment 7.3 records the number of times a feature and a class occur together in an instance of the training dataset. I measure these results using two different metrics. First, in comparison to the results gathered from Experiment 6.4 (which records the same data but for the self-learning algorithm), I use the normalized count of features by number of examples per iteration (Metric 6). It is necessary to normalize because the number of examples added in each active learning is much smaller than in self-learning, thus normalization is necessary for a meaningful comparison. On the other hand I analyze the PMI along the iterations for the classes and the features associated to it (Metric 4). The results are shown on Section 7.4.3 and serve to accept Hypothesis 4.2 which states that the active learning algorithm improves the model's coverage quicker than self-learning.

In Section 7.2 I revise some previous work in active learning in general and also specifically applied to verb sense disambiguation.

In Section 7.3 I go through the relevant items that concern the experimentation in the chapter. Most of the methodology is very similar to that in previous chapters, I mostly provide pointers to the sections where this methodology is first described. In particular Section 7.3.4 explains the fine detail of the active learning algorithm, e.g. the stopping criterion the algorithm uses, how the instances to annotate are selected and how the annotation is carried out, as well as some of the difficulties of the annotation.

Section 7.4 reports the results of the experiments and analyzes them in order to accept the stated hypotheses of the chapter.

Finally Section 7.5 draws the conclusions of this chapter, recapitulating the Hypotheses and the implications of accepting or rejecting them according to the evidence gathered in the results. It states the shortcomings of the methods explored in this chapter and what I want to accomplish on the next. It ends by outlining future work.

## 7.2 Relevant work

Active learning is a task for semi-supervised learning, based on the key idea that if the learning algorithm is allowed to choose the data from which it learns it will perform better with less training. A very complete survey in the area is the one done by Settles [Settles, 2009]. It covers all the main topics in the area of active learning.

A particularly important subject in active learning is the strategy to select the instances to present to the oracle. Different strategies have been studied, being *uncertainty sampling* the most intuitive and popular one [Lewis and Catlett, 1994] and the one used in this chapter. For other strategies refer to Section 2.2.3 of Chapter 2.

One of the main problems in applying active learning to natural language processing tasks is class imbalance, something common in the are. In this cases, uncertainty sampling not always proves being the best way to select data given some difficulties it arises as I will explain in Section 7.3.4.3. There are some approaches to deal with it, but nothing definitive.

In particular, Dligach and Palmer [Dligach and Palmer, 2011] applied active learning to verb sense disambiguation. They explored the benefits of using an unsupervised language model to select seed examples as a starting corpus for an iterative active learning approach.

## 7.3 Methodology

This chapter explores the use of active learning with a human annotator to expand a model trained with labeled data. Like the self-learning algorithm in the previous chapter, active learning is also a *wrapper*. The algorithm uses a supervised classifier to select instances from the unlabeled data and gives it to a human to verify it.

The objective of this chapter is to show the tendencies I have found using active learning. I do not present an exhaustive analysis of active learning, as it requires annotating resources using human experts which I are outside the possibilities of research of this thesis. The idea is to analyze preliminary results which can help as an initial start for future work using more resources.

### 7.3.1 Resources

In this chapter I keep using the datasets I have been working on so far: the SenSem corpus as labeled corpus and SBWCE as the unlabeled.

Analyzing active learning was the main reason to reduce the analysis to some of the lemmas in the lexicon. The selected lemmas on which I make my analysis are: “explicar”, “pensar”, ““acceder””, “llegar”, “buscar” and “facilitar”. A detailed explanation of this is done in Section 6.3.1, please refer to it for more information.

The SenSem corpus is used as the annotated seed on which the active learning algorithm starts. For a detailed description of the resource please refer to Section 4.3.1.1.

The unlabeled data source for new instances to give to the human expert to manually annotate is taken from the SBWCE corpus. Please refer to Section 5.3.1.2 for more details on the corpus. The corpus is the one pre-processed with Freeling obtained by the methodology described in Section 6.3.1.2. Please refer to that section for more details on how this is done.

### 7.3.2 Features

The features used in this part are the same ones used in the previous chapters. Both hand-crafted features using the hashing trick and word embeddings follow what has been discussed in all the previous chapters.

For more information on the detail of what are the hand-crafted features used in this chapter please refer to Section 4.3.2. For detailed information on how to deal with the expansion of features given by the new examples added to the model please refer to Section 6.3.2.1.

The word embeddings are the ones trained from the journalistic corpus described in detail in Section 5.3.1.3. The method for combining them into an instance is the concatenation of word vectors described in Section 5.3.2.2.

### 7.3.3 Classifiers

As in self-learning, active learning is a wrapper method that is built around a supervised classifier. The selected classifier is the same as in the previous chapters. I use a multilayer perceptron with three layers of size 500, 250 and 100 each.

### 7.3.4 Active learning algorithm

The active learning algorithm follows the same structure as the self-learning algorithm described in Section 6.3.4, taking as input almost the same initial parameters:

- A labeled training dataset to train the initial supervised model.
- A labeled test dataset to report the model performance before and after finishing all the iterations of the self-learning algorithm.
- An unlabeled dataset to get the new data to annotate automatically.
- A probabilistic classification algorithm, to use in the process of automatic annotation.
- A maximum number of elements to annotate each iteration.
- A tolerance error for the stopping criterion.

The fundamental differences in this case reside in the following items: (i) how the model selects instances to label from the unlabeled dataset, (ii) how those instances are annotated, (iii) how the model decides whether new instances are to be included in the training corpus, (iv) how the algorithm finishes.

#### 7.3.4.1 Instance selection and annotation

In each iteration of the algorithm, once the classifier is trained with the examples gathered so far (both part of the initial seed dataset or from the oracle's annotations) the algorithm applies the classifier to the whole pool of unannotated data. From the automatic annotation of that pool of unlabeled examples, the algorithm takes the ones the classifier is less certain about and presents them to the oracle for manual annotation. This is called *uncertainty sampling*, i.e. selecting those instances for which the certainty of the classifier is low. It is assumed that those instances are near the decision boundaries of the model. The intuition behind using this method instead of randomly giving the oracle examples to annotate is that these examples will have the largest impact on the final model, that is, the model will improve its accuracy the most. This is because the classifier gains confidence on those classes and instances it has less information about in the seed labeled corpus. This is a way to optimize learning with a given amount of training data, by improving the quality (not the quantity) of the training examples.

Unlike self-learning, which selects all the instances over a threshold, in active learning there is a maximum number of possible instances. It is given as an initial parameter of the algorithm. This number is selected empirically and should be large enough to make a difference in the new model but not too big to have the oracle devoting too much time annotating, since active learning gives an intelligent way to minimize the annotation effort. After some experimentation, the number of 10 examples per iteration was selected as the base for the experiments in this chapter.

The oracle annotates the examples selected by the active learning algorithm, which are then added to the model. There is however a problem, as I explained before: the initial annotated corpus may not have a correct label for some examples because it was not considered originally when designing the lexicon. In those cases, to reduce the number of possibilities to consider and as it is outside the scope of this thesis to extend the resource, I decided to ignore examples belonging to an sense not present in SenSem.

#### 7.3.4.2 Validation of the model and early stopping

Once the instances are annotated by the oracle, the next step is, like in self-learning, to add them as new training examples. However, the algorithm first checks the impact of adding these new examples to the model, by assessing the performance of the model with the bigger training corpus.

For self-learning, this was done using a validation dataset extracted from the original dataset. I originally thought about using cross validation over the training dataset in self-learning, but finally I abandoned the idea. The tendency of the self-learning algorithm to add everything as part of the most frequent class may have introduced bias in that method of validation.

For active learning however this is not a problem. As the annotation is not left to the classifier but to a human, the tendency to annotate everything as the most frequent class does not prevail as much. I decided then to use cross-validation over the training examples and see the mean of the misclassification error obtained from it as the metric to validate the impact of the new training examples in the model.

The main reason to use cross validation over the training dataset and not a validation dataset like in self-learning is because unlike in self-learning, this algorithm may add examples of classes not seen by the model so far. Remember some senses were filtered out from the SenSem corpus because they did not have enough available instances. Moreover, some of the senses in the lexicon do not have any examples at all. Well, these senses occur in a larger corpus like SBWCE, and as the classifier will not have enough information initially over those senses, it is likely that examples of those are chosen to give to the oracle using the uncertainty sampling technique.

As new examples of unseen classes may be added to the training data this might result on the validation corpus not reflecting the model's real performance. The reason behind this is that the validation corpus does not have any information regarding the new unseen classes the model is adding.

Once the algorithm calculates the misclassification error from the cross-validation over the training dataset it applies the same principle the self-learning algorithm did, it compares it to the minimum error obtained so far and gives a tolerance of maximum 10% less than random chance. If the error in the new model is larger than that, the algorithm discards the model and returns the last model obtained so far. As it requires human annotation, the algorithm also provides the option for the human to stop iterations whenever he wants.

#### 7.3.4.3 Difficulties in the annotation

There were two major difficulties when dealing with the annotation of the examples selected by the algorithm based on high uncertainty: ambiguity and coverage of the classes available in the resource.

Since the inventory of senses is human given, it is arbitrary, shaped by the humans creating the resource and the final objective such resource has. This means that depending on these variables, the inventory of senses may be coarse or fine-grained. This of course affects the possibilities to annotate, as a more coarse inventory may fall in the problem of having senses that are suitable for more than one sense. As the algorithm selected those instances that are near decision boundaries, a common problem is giving the oracle examples that are ambiguous even for the oracle to discern.

Besides the problem of having senses with blurry decision boundaries, which overlap with each other, the other problem the resource may have is lack of coverage. Thus there are some examples that are not suitable for any of the senses given in the resource. This is particularly common since an important part of the SBWCE corpus consists on books written in old Spanish (i.e. the ones compiled in the Wikisource

initiative). Thus there are some senses which fell into disuse and were not considered in the construction of the resource.

### 7.3.5 Experiments

There are three major experiments I did in this chapter: one to compare the performance of the active learning algorithm with the self-learning algorithm, and two others to test the hypotheses.

First, Experiment 7.1 is very similar to Experiment 6.1 in Chapter 6. The experiment is not aimed at testing any of the hypotheses of this chapter but rather as a comparison with the previous chapter. It basically tests the active learning algorithm and how it affects the performance of the supervised classifier over the held-out test data.

**Experiment 7.1.**

**7.1a** Train a model with the supervised training dataset.

**7.1b** Evaluate the model over the test dataset.

**7.1c** Run the active algorithm until it stops.

**7.1d** Evaluate the model obtained with the active algorithm over the test dataset.

Experiment 7.2 is the first experiment to test a hypothesis in this chapter. The experiment is to evaluate the representativity of the population for each class across the active learning iterations. It is done to test Hypothesis 4.1, which states that this representativity is maintained through all the iterations of the algorithm. This experiment is based on Experiment 6.5 in the previous chapter.

**Experiment 7.2.**

**7.2a** Record the number of times each class occurs in the supervised training dataset.

**7.2b** Run an iteration of the active learning algorithm.

**7.2c** Record the number of times each class occurs in the new training dataset comprised of the supervised data and the new annotated examples.

**7.2d** Repeat the previous step for each iteration of the algorithm.

Finally, to test Hypothesis 4.2 regarding the number and association of features to classes, there is Experiment 7.3, which is based on Experiment 6.4 in the previous chapter. The experiment records the number of times each tuple of classes and features appear in the dataset.

**Experiment 7.3.**

**7.3a** Record the number of times a tuple $(class, feature)$ occurs for each class and each feature of the supervised training dataset.

**7.3b** Run an iteration of the active learning algorithm.

**7.3c** Record the number of times a tuple $(class, feature)$ occurs for each class and each features of the training dataset comprised of the supervised data and the automatically annotated instances.

**7.3d** Repeat the previous step for each iteration of the algorithm.

### 7.3.6 Metrics

To report the results of Experiment 7.1 I use the F1-score for each class in the test dataset of the token lemmas, for each of the three algorithms: supervised, self-learning and active learning.

For Hypothesis 4.2, which compares the features association that comes from the active learning iterations, I mainly focus on two metrics. One is Metric 4, which calculates the PMI between features and classes and associates each feature to the class it has a higher PMI with. The other is Metric 6 which is the normalized count of features by examples:

**Metric 6.**

**6a** Count the total number of features in an iteration of a joint learning algorithm.

**6b** Divide it by the total number of examples added in that same iteration.

## 7.4 Analysis of results

This section reports the results obtained by the experiment described before, with the mentioned metrics. There is an important remark to do on these results. This is an exploratory and preliminary work. Active learning, as it requires resources of annotation from a domain expert, is very costly. For this thesis, the amount of effort that could be devoted to annotation was very limited, so active learning is presented here as a proof of concept, showing tendencies instead of clearly defined results. Results however are interesting to show and analyze. Once again, the visualization and metrics used here can obscure some aspects of the results in favor or others. I will try to give the most impartial analysis over this data.

### 7.4.1 Performance comparison for self-learning and active learning

Before delving into the analysis of the hypotheses of this chapter, I want to do a quick review on how the two different algorithms seen so far (self-learning and active learning) compare in terms of performance against the supervised algorithm. This is done to establish some common ground for all the joint learning algorithms.

These results are gathered from Experiment 7.1, which measures the performance of the model by using F1-score per class, showing the performance for the most frequent, second most frequent and third most frequent class of the lemma. I do this because these are the classes of the token lemmas that were not filtered out in the preprocessing of the corpus. From the 6 token lemmas, 4 of them have only two senses with instances in the labeled dataset ("acceder", "buscar", "explicar", and "facilitar"), and only 2 of them have 3 senses with instances in the dataset ("llegar" and "pensar").

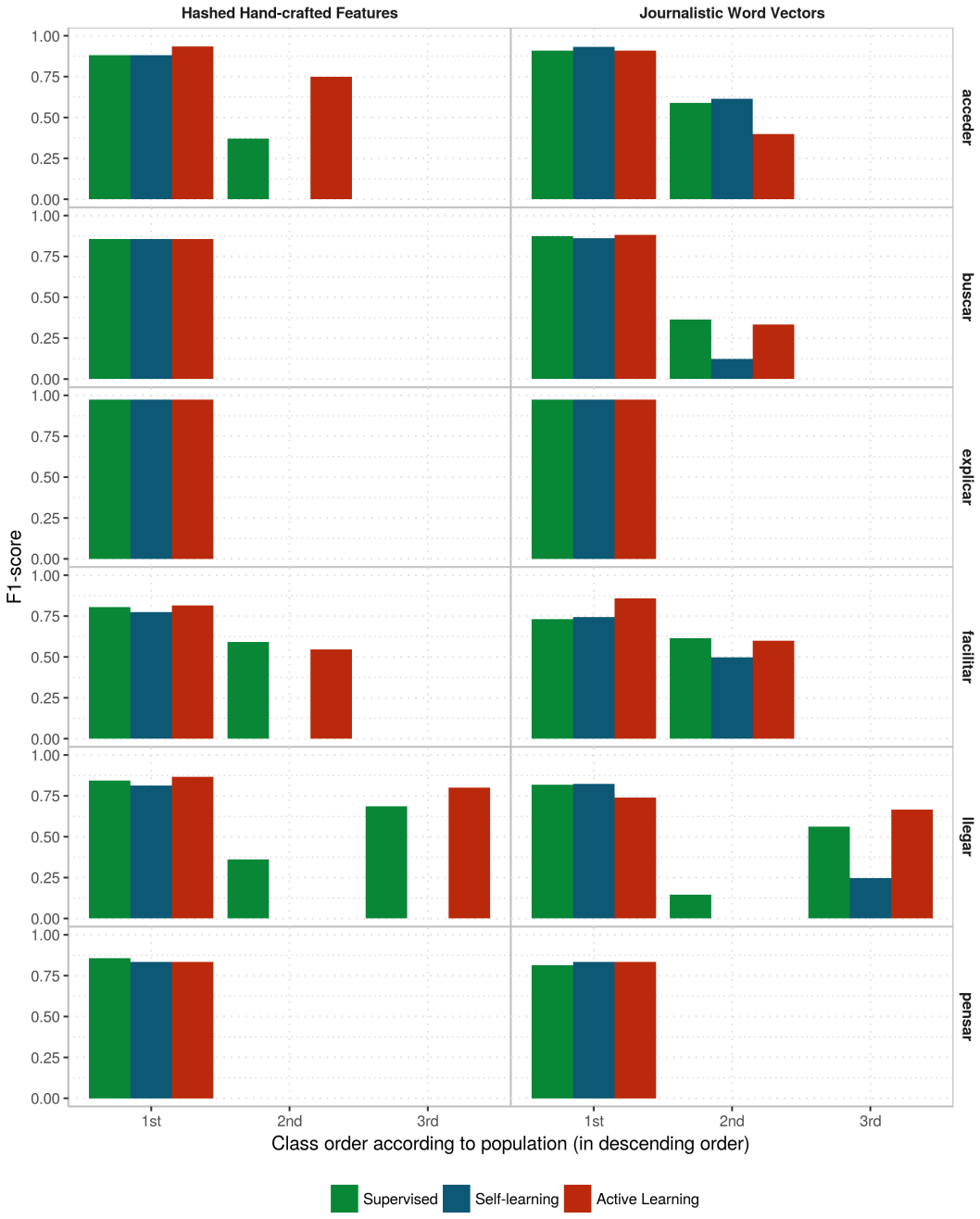


FIGURE 7.1: Comparison of macro and weighted average F1-score for supervised, self-learning and active learning

Figure 7.1 shows the F1-score macro and weighted average for supervised, self-learning and active learning over the test dataset. In this case, "supervised" is the evaluation of the model in the initial iteration of any of the joint learning algorithms (as it is the same for both, i.e. only using the manually labeled data). The self-learning/active learning bars represent the performance of the model over the held-out test dataset after finishing the iterations of the corresponding algorithm. The structure of the graphic is as follows:

- Each row shows the results for a token lemma: "acceder", "buscar", "explicar", "facilitar", "llegar", and "pensar".
- Each column stands for a feature representation: hand-crafted hashed features and journalistic word vectors.
- Each group of bars in each plot represents the class (i.e. sense) for that lemma. These are ordered according to number of occurrences of the class in the dataset.
- Each bar plot in a different color inside a group represents the algorithm: supervised (i.e. evaluation moment of the initial iteration), self-learning (i.e. evaluation moment of the final iteration after self-learning finishes), and active learning (i.e. evaluation moment of the final iteration after active learning finishes).
- The height of the bar represents the value of the F1-score per each class.

Recall again that only the last two rows of the graphic represent lemmas with 3 senses (i.e. "llegar" and "pensar"). The first four lemmas can at most show results for two senses.

In general, active learning performs better than self-learning and even better than supervised in some cases for both the most frequent class and the less frequent classes. It might be that active learning performed better than supervised learning simply because the amount of annotated examples increases. However, the amount of annotated examples also increases for self-learning, but it does not impact in the performance. This is a clear sign that the selection of examples to give to the oracle to annotate is in the right track, because it does have a visible impact in the performance of the resulting model, beyond the mere increment in the number of annotated examples.

Once again, like in the previous chapter, word embeddings still show better overall performance than hand-crafted features: minority senses are better represented, without an important loss of performance in majority senses. In combination with active learning, word embeddings become particularly useful, as they properly characterize minority senses.

Now that I have a base comparison of the two algorithms I have strong evidence that active learning is better for the performance of the model. To check why this is the case I will look further into the hypotheses.

### 7.4.2 Hypothesis 4.1

This section tests Hypothesis 4.1. The hypothesis states that the representativity of each class's population in the training dataset is maintained through all the algorithm iterations. Recall that for the self-learning algorithm I found evidence to accept Hypothesis 3.6, which states the opposite of Hypothesis 4.1.

More precisely, I established that the fact that self-learning was not representing all classes properly was the cause for the self-learning degrading the performance of the less frequent classes, as stated in Hypothesis 3.5 in the previous chapter. As I saw in the previous section, this is not the case for active learning, since it does improve on the performance of classes other than the most frequent one.

I show the results for Hypothesis 4.1 to assess whether the reason behind the improvement in performance is effectively a better representation of the minority classes with the active learning algorithm.

To test the hypothesis I measure the results obtained after doing Experiment 7.2 which records the number of instances each of the classes has in the training dataset after each active learning iteration.

Once again, as in the previous chapter, to visualize these results I use two techniques to show what, for me, is relevant on the checking of the Hypothesis: the proportional count of the number of instances per class along the iterations, and the proportional number of instances added for each class per iteration. These two results will allow to accept Hypothesis 4.1.

#### 7.4.2.1 Classes' population distribution across iterations

Figure 7.2 shows the distribution of the population of the classes across the active learning iterations. Each class's population is represented as the proportion of the total number of examples in the training dataset for that iteration. The plot is a stacked area plot that follows this structure:

- Each row shows the results for a token lemma: "acceder", "buscar", "explicar", "facilitar", "llegar", and "pensar".
- Each column stands for a feature representation: hand-crafted hashed features and journalistic word vectors.
- The x-coordinate represents the iteration in the self-learning algorithm.
- The y-coordinate represents the percentage of population.
- Each area of a different color represents the proportion of examples for each of the classes in the dataset. The classes again are ordered according to number of examples in the original supervised dataset.

The first thing to notice from the figure, specially compared to the similar figure of the previous chapter, is the number of iterations. While for self-learning iterations

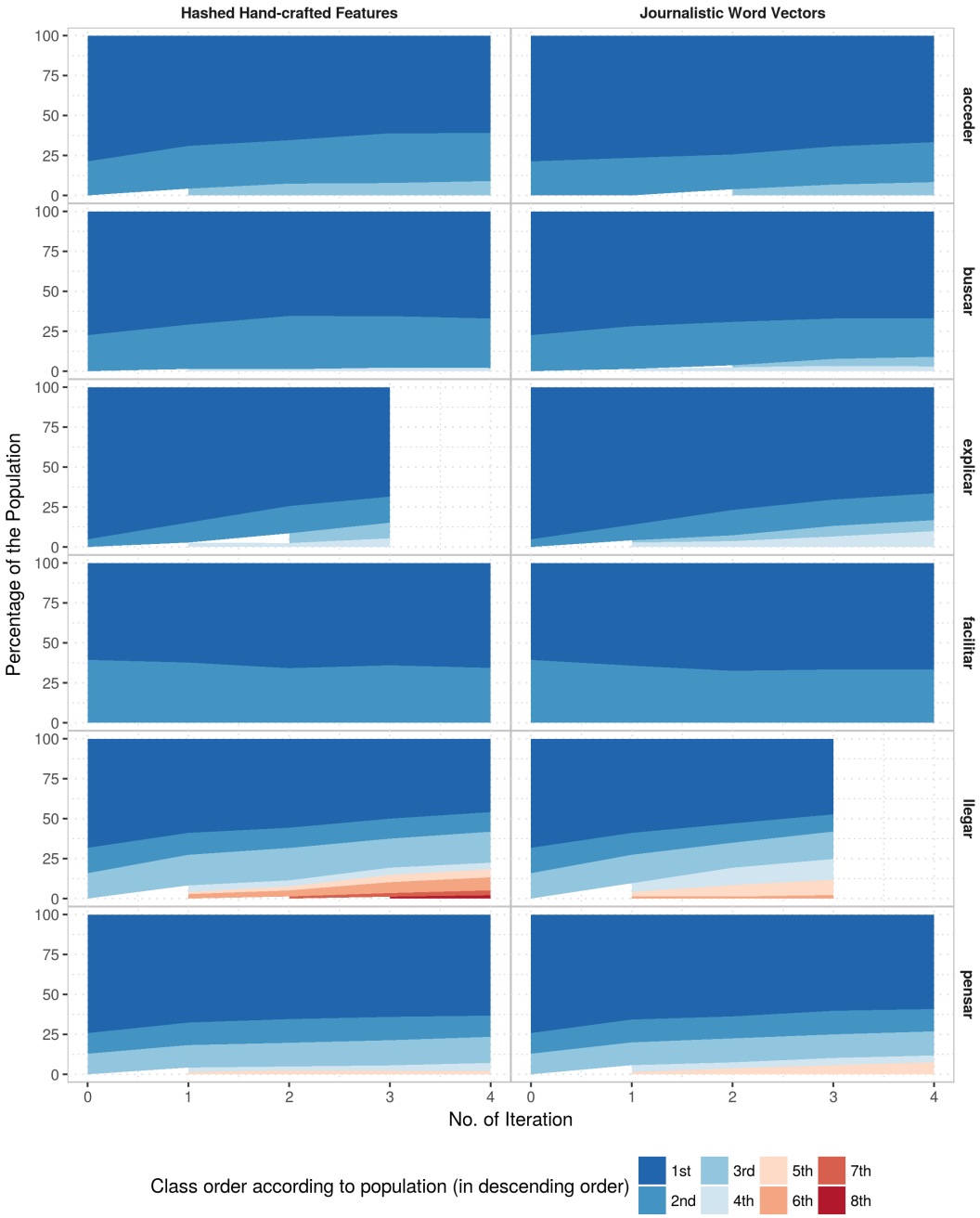


FIGURE 7.2: Distribution of the classes' population across active learning algorithm's iteration as a proportion of the whole training dataset

could go up to 100, for active learning I only did the annotations for 4 iterations total (plus the initial iteration, which is represented in the number 0). This is why I say that the work done for active learning is mostly exploratory.

Note that there are two cases where the iterations are less: "explicar" (for the hand-crafted features representation) and "llegar" (for the word embeddings representation). In this cases the iteration finished before because the stopping criterion of the validation error was met.

The second noticeable thing in the figure is the increase in the number of classes that occur as the iterations advance. This is a result of what I explained before: the algorithm selects those instances on which it does not have enough information, which are generally those that are not part of the original supervised corpus. This is a marked difference with self-learning: in active learning the less frequent classes also grow in number of examples through the iterations, not only the most frequent one.

#### 7.4.2.2 Population added per sense per iteration

Figure 7.3 shows the proportion of examples added per class on each iteration. It is a stacked bar plot where each bar represents the total examples added in the iteration split by the proportion of classes automatically annotated as such. The structure of the plot is the following:

- Each row shows the results for a token lemma: "acceder", "buscar", "explicar", "facilitar", "llegar", and "pensar".
- Each column stands for a feature representation: hand-crafted hashed features and journalistic word vectors.
- The x-coordinate represents the iteration in the self-learning algorithm.
- The y-coordinate represents the percentage of examples automatically annotated and added to the model.
- Each bar plot represents the distribution of the examples added in the iteration. Each color of the stacked bar represents the class which the examples were annotated.

In the figure there is a better view of what is happening along each iteration. In general, the less frequent classes add more examples than the most frequent class through iterations. This is a consequence of using uncertainty sampling, which selects those classes near the decision border of the classifier.

In general, word embeddings are more uniform when adding examples of many different classes. The consequence of this, I can hypothesize, is that for hand-crafted features, and as a consequence of the low generalization they have, the classifier is more certain about the most frequent class and thus when applying the uncertainty sampling technique it choses mostly examples of the less frequent classes. Word embeddings, on the other hand, have better generalization from the start, thus when sampling elements with uncertainty it can have low certainty also for some of the examples of the most frequent class.

In any case, from these results I have enough evidence to support Hypothesis 4.1 which states that the distribution of the different classes through the active learning algorithm iterations is maintained.

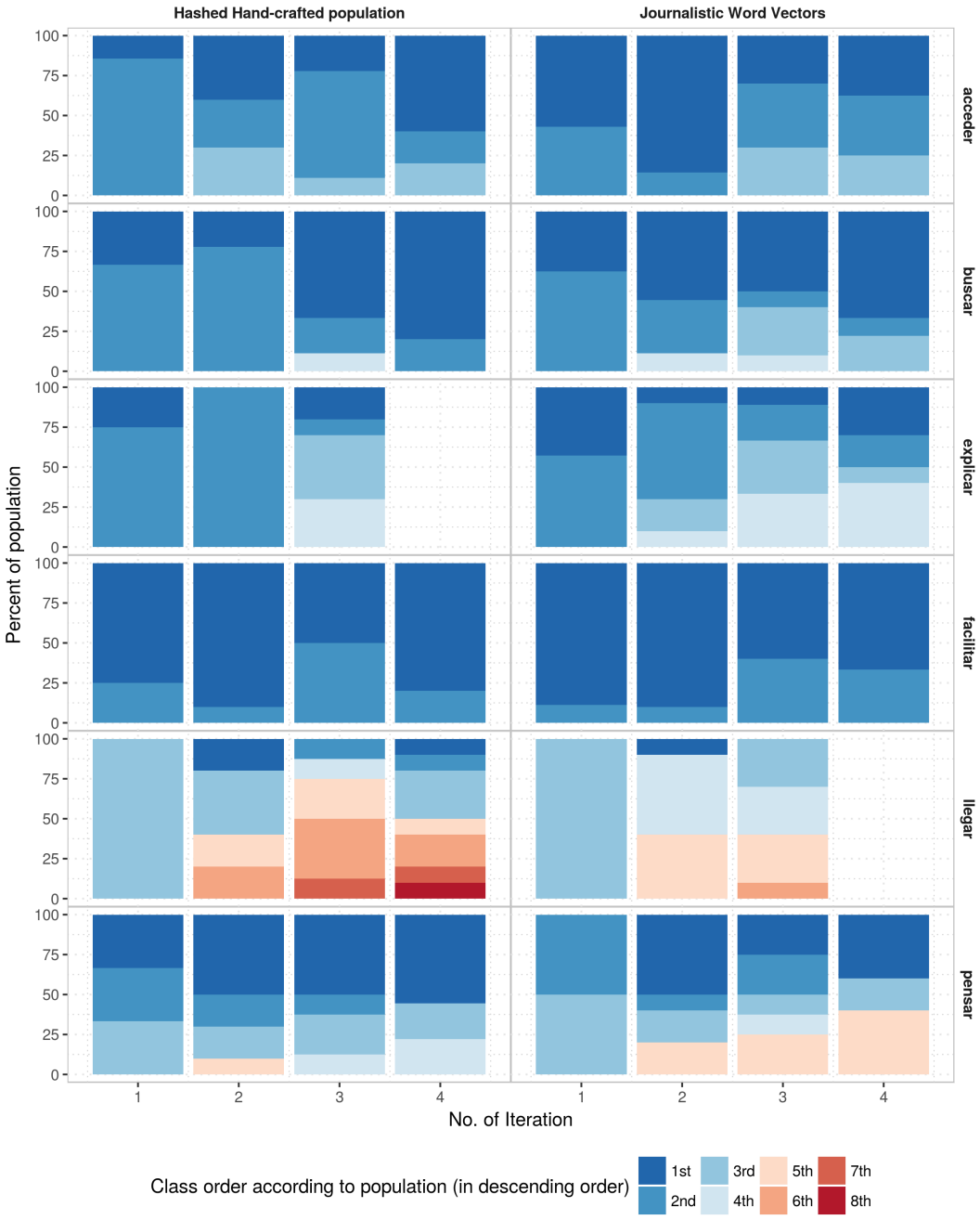


FIGURE 7.3: Population added per sense on each iteration of active learning as a proportional count of all the examples added in that iteration

### 7.4.3 Hypothesis 4.2

I follow up with the test of Hypothesis 4.2. Recall that the hypothesis states the active learning algorithm adds more information with the examples it adds to the model in comparison to self-learning. This is a consequence of the examples added being of classes the model has already less information about due to the uncertainty sampling technique.

To test the Hypothesis I measure the results of Experiment 7.3, which records the

number of times a feature appears with a class. However, what I am mostly interested about in this occasion is the total number of features added per iteration of both self-learning and active learning algorithms. These results are measured by Metric 6 which is the normalized count of features added in an iteration by the examples added in the same iteration. The reason to use this measure instead of the raw count is because it is clear that the number of features for self-learning will be higher than for active learning since the number of examples that self-learning annotates in each iteration is of a magnitude greater than active learning. However, what the Hypothesis states, and what I am interested about, is whether these fewer examples of the active learning algorithm actually add more information than the self-learning algorithm.

Figure 7.4 shows the amount of features added in each iteration of both self-learning and active learning normalized by the amount of examples added. The structure of the graphic is as follows:

- Each row shows the results for a token lemma: "acceder", "buscar", "explicar", "facilitar", "llegar", and "pensar".
- Each column stands for a feature representation: hand-crafted hashed features and journalistic word vectors.
- The x-coordinate axis represents the iteration number in the self-learning algorithm.
- The y-coordinate axis represents the normalized count of unique features by the number of examples added.
- Each line represents the number of features and the different colors represents the algorithm: self-learning and active learning.

The tendency shown in Figure 7.4 is clear enough. Active learning is adding more information to the model by adding more features per examples in comparison to self-learning. This is clearly a consequence of active learning adding examples of less frequent classes in contrast to self-learning as I showed in the previous Hypothesis's results. Moreover, active learning is adding examples of classes that are non-existent for self-learning since the classes are not part of the initial seed model.

For active learning, the most frequent class, which contains most of the features in the initial model, is not the only one to grow in each iteration (in fact, sometimes it is the one with the lowest number of examples added in an iteration). Thus that class is not overtaking all the features added per iteration. Then, when instances of classes with less occurrences are added the data enriches more the model initial model. This can also be seen by inspecting the PMI of the features and the classes, as in the next section.

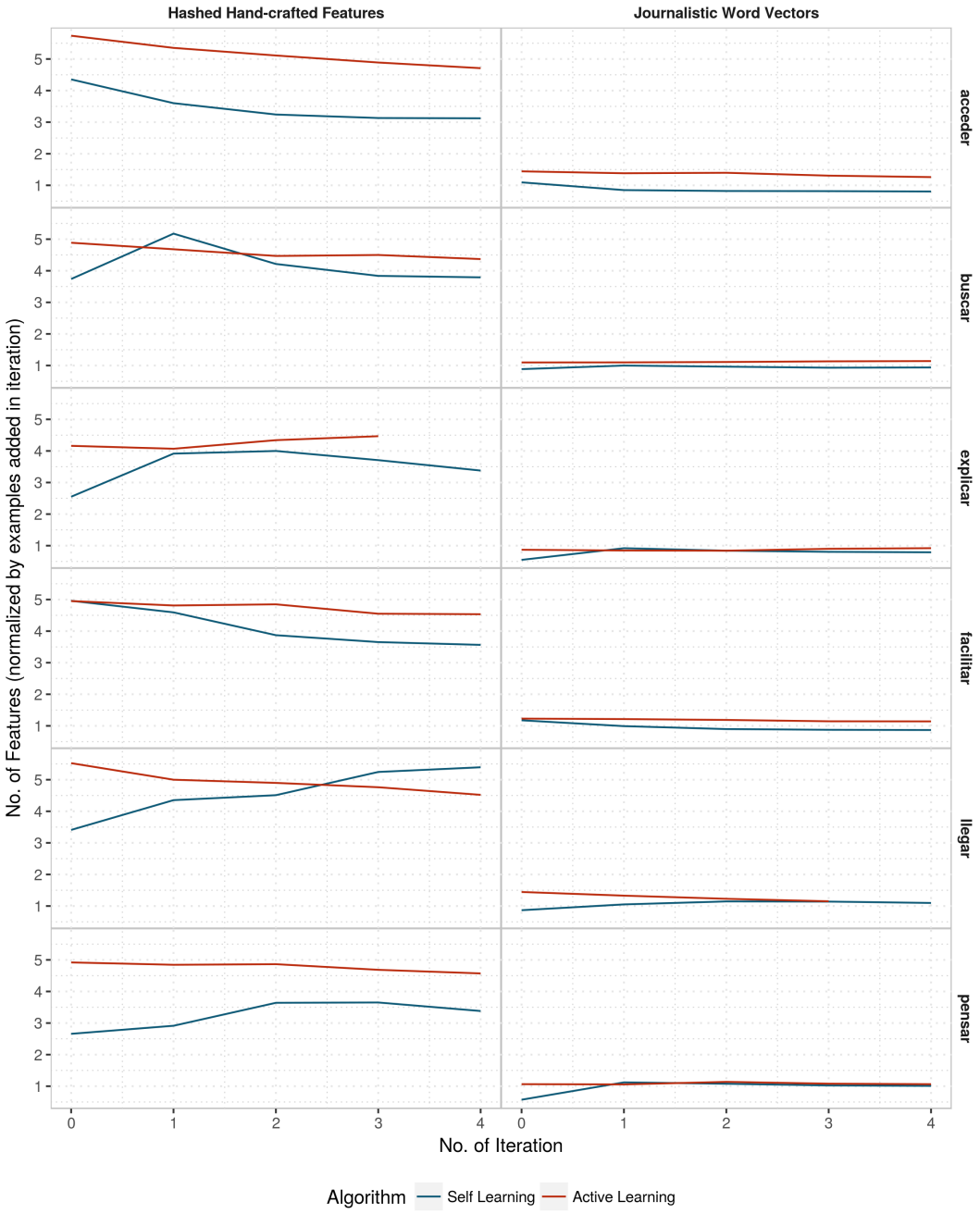


FIGURE 7.4: Number of features added in each iteration of both self-learning and active learning. The features are normalized by the number of examples added in the iteration

#### 7.4.3.1 Features PMI

There is another view for the results of Experiment 7.3, that is the one measured by the PMI defined in Metric 5, which associates the features to the classes with a higher PMI and then gets the mean PMI per class. In this section I show the results as measured by that metric and draw conclusions regarding the Hypothesis.

Figure 7.5 displays the mean and standard error of the mean of the pointwise mutual information between features and classes across the active learning iterations.

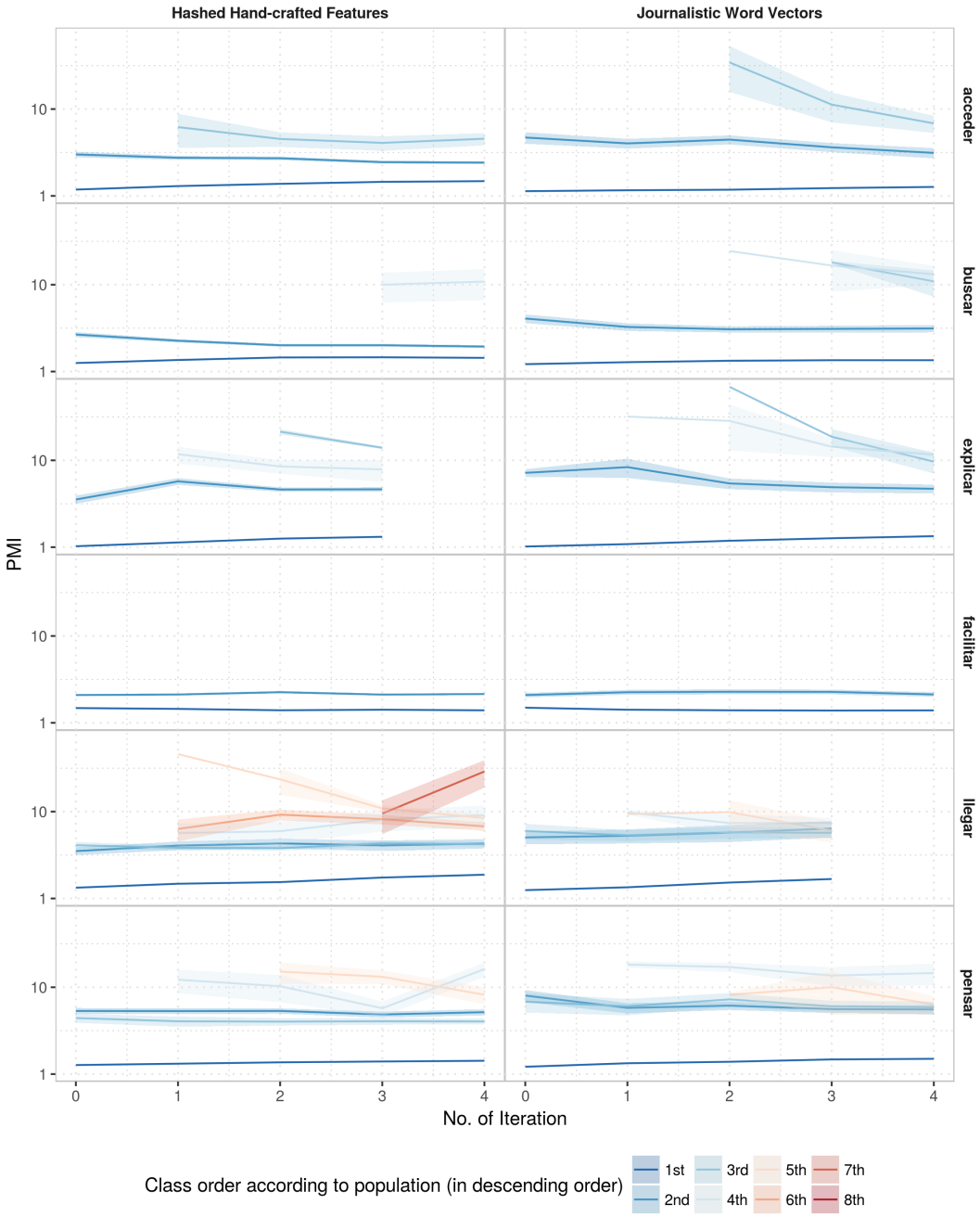


FIGURE 7.5: Features pointwise mutual information with each of the classes across active learning iterations

Recall that the metric associates features to the class it has a larger PMI with. The figure shows a line plot with the following structure:

- Each row shows the results for a token lemma: "acceder", "buscar", "explicar", "facilitar", "llegar", and "pensar".
- Each column stands for a feature representation: hand-crafted hashed features and journalistic word vectors.

- The x-coordinate axis represents the iteration number in the self-learning algorithm.
- The y-coordinate axis represents the raw count of unique features in a logarithmic scale.
- Each color represents a class.
- The line of darker color in the middle represents the mean of the PMI for the class and the shadowed area represents the standard error of the mean for that PMI.

The figure shows that the mean of the PMI of the most frequent class with respect to the features it is associated to is still the lowest one in comparison to the rest of the classes. This is analogous to what happened in self-learning and I already showed in Section 6.4.7.2.

However, in contrast to what happened in self-learning, the PMI is not decreasing in particular for the most frequent class or for those classes which are consolidated in the model. It decreases for those new classes added through the iterations which have few examples. This however may be a direct consequence of Metric 5 inadequately modeling classes with few examples. In any case, the examples of classes unknown to the seed supervised model have little information to start with, specially in the first iterations after they first occur. In some cases, where there is no shadowed area is because the examples added for such class are less than 3 total, thus it does not have any variance.

The fact that the PMI of the consolidated classes (those appearing in the original supervised dataset) does not decrease contrasts with what I showed for self-learning. Since active learning does not drift to add only examples of the most frequent class, then we have that the class does not drag noise by adding features that are not necessarily from the class. That is, whichever information is present in the class is maintained as the number of examples increases.

I can conclude that the way new examples are incorporated to the model is radically different for each algorithm. Self-learning adds as examples of the most frequent class those instances weakly defined for the mere weight that class has in the model decisions. This weakly defined instances blur the decision boundaries the model has over that class. In contrast, the strategy based on uncertainty sampling is oriented precisely to increase the definition of the decision boundary.

From the results seen in this Section it is safe to assume Hypothesis 4.2 has enough evidence to be accepted.

## 7.5 Conclusions

The experiments I did in this chapter had very little data because of the extra cost of annotating examples, necessary for active learning. I decided to go further with this

option instead of doing some sort of simulation based on the already annotated examples since the labeled dataset was so small that selecting examples in that universe invalidates one of the assumptions of active learning, which is obtaining the examples from the universe which will maximize the learning in the model. This is because the number of possible examples using a simulation like that does not cover enough of the universe of possible examples.

First of all, active learning shows better general performance than self-learning, by showing better results in the held-out test corpus. This is not only for the most frequent class but for some of the less frequent classes as well. This better performance can be explained by the results obtained to accept both hypotheses of the chapter.

Experimental results lead me to accept Hypothesis 4.1. The model for active learning maintains the representativity in the data through the algorithm, unlike what happened with self-learning, where the new examples were added as part of the most frequent class. In particular, the less frequent classes are the ones to benefit the most with this model as a consequence of the nature of the uncertainty sampling technique itself, which selects for annotation the instances the model has less information about.

Hypothesis 4.2 can also be accepted according to experimental results. The tendency shows that active learning adds in each iteration more information than self-learning, taking into account the number of examples it adds in each iteration. Indeed, the model adds more information by adding more new features per example, which also happen to be more informative of the classes, specially the less frequent ones (this is what is shown when PMI is graphically displayed). This way there are clearer boundaries for the less frequent classes and, reciprocally, in the most frequent class as well. In contrast, I had found that self-learning associates new features mostly to the most frequent class and thus weakening the decision boundaries the model had over it.

Again this are only preliminary results and the conclusions I could draw from them are only tentative. To do a more thorough study I should annotate more data with the aid of a domain expert and see how these results are expanded with more iterations. A possible hypothesis to develop in this sense is that eventually the less frequent classes will find an upper bound for the model to have enough certainty over each of the less frequent classes. In that moment, the algorithm will start to converge and will select instances from the unlabeled pool of almost all classes uniformly.

In any case the main conclusion from this chapter is that active learning is an interesting source to extend the coverage of a model. It does not suffer from the fundamental problem of self-learning, namely the drift to the most frequent class. This is a direct consequence of the way the instances to annotate are selected by the algorithm. Indeed, this selection of instances plus the added value of a domain expert doing the annotation instead of the algorithm itself based on certainty, results in a more robust model with more information on classes it originally had little to no information about.

However, there are still challenges left. First, the annotation process is costly. In

comparison to self-learning, which does the annotation automatically, active learning requires a human doing manual labor. Although the algorithm tries to select those instances having the highest impact in the model, the manual labor is still expensive. Moreover, the annotation is not easy, as I explained in Section 7.3.4.3, because the resource is not perfect as it is arbitrary in some aspects like the granularity of the senses or what senses are considered.

In the next chapter of this thesis I will explore yet another joint learning technique. In that case the algorithm is not a wrapper over some supervised classifier which adds unannotated data to the model. The algorithm named *ladder networks* is an algorithm that minimizes two different objectives, one for the supervised data and another for the unsupervised data. The algorithm does the whole process automatically, in contrast to active learning, but as it does not add the noise of examples as labeled dataset it does not drift to the most frequent class as self-learning does.

The future work of this chapter will focus on doing more thorough experimentations, using more annotation resources. In particular I want to focus on two main aspects: how much does the number of annotations per iteration affects the final outcome, and how much annotation is needed to be done in order to have better representation for each class. More future work is checking on other techniques for selecting the examples of active learning. In particular, a comparison between selecting the instances with less certainty and selecting random instances.

I also did some preliminary work on combining both active learning with self-learning to attack the problem of the most frequent class drifting by constantly adding examples manually via uncertainty sampling and an oracle. However this work was not further explored in this thesis and is left out as future work as well.

# Chapter 8

# Ladder Networks

## 8.1 Overview

In this thesis so far I have been working in different techniques to help expand a purely supervised model for Spanish verb sense disambiguation. The last two chapters presented two approaches for *joint semi-supervised learning*, where the labeled and unlabeled data (annotated either automatically or manually) are used together as part of the training data for a supervised classifier (e.g. a neural network). In this chapter I will cover the last semi-supervised technique I studied in this thesis.

**Ladder network** is a deep learning model which uses a neural network architecture to learn both from supervised and unsupervised data presented by Rasmus et al. [Rasmus et al., 2015a]. The technique is another example of a semi-supervised joint learning task. In contrast to self-learning and active learning, which are wrapper algorithms that use a supervised classifier under the hood to expand the data from an unlabeled source, ladder networks combine both datasets in a common *objective function* that minimizes using back-propagation and gradient descent. In the original work, the model was tested in a machine vision task, but the architecture was general enough to be able to apply it in the area of Spanish verb sense disambiguation.

The key concept behind the construction of a ladder network is to take a feed-forward neural network (e.g a multilayer perceptron) and treat it as the encoder part of an autoencoder. Then add a decoder part and use a reconstruction error calculated layer by layer. The labeled data is used to minimize the error given by the encoder and a labeled cost function (e.g. cross-entropy). The unlabeled data traverse the whole autoencoder and the reconstruction error is minimized. The ladder network cost function is a sum of both labeled and unlabeled cost functions.

*Stacked autoencoders* [Vincent et al., 2010] were a key idea to help the training of deep neural networks. Using them for *unsupervised pre-training* (also known as *fine tuning*), helped deep neural network architectures converge faster to a solution and avoid the problem of *vanishing gradient* [Bengio et al., 1994]. Ladder networks draw inspiration from that idea, but instead of doing the fine tuning of the layers in the network in a previous step like in unsupervised pre-training, they fine tune during the training of the network by adding the value of the unsupervised cost function (of the autoencoder) to the cost function of the feed-forward neural network.

This scheme contrasts the one of the wrapper algorithms which uses the purely labeled cost function of the wrapped classifier. For wrapper algorithms the unlabeled data adds information by converting an unlabeled instance into a labeled one. The new information in a ladder network, which comes from the unlabeled data, is added to the model in a different way. In each epoch the training algorithm fits the parameters of the network using the whole labeled dataset (randomly shuffled) but only a portion of the unlabeled dataset. The unlabeled data adds an extra cost to the train of the networks that avoids it to overfit the labeled dataset. In the same way, that information helps the network find a better encoded representation of the unlabeled data that is useful for the task the ladder network is trying to learn.

I want to assess this particular neural network architecture in the task of Spanish verb sense disambiguation and see how it affects the final performance. The idea is to tackle the problem of self-learning and its deviation to the most frequent class. To do that, ladder networks will not start by a supervised model and then add unlabeled data to it, but rather learn from both the labeled an unlabeled data in parallel. On the other hand, as the method does not require human intervention, it overcomes the annotation cost of active learning.

This chapter works on testing the following hypothesis:

**Hypothesis V** *Ladder networs obtain a better model of the data.*

I expect that the cause for a better model is the integration of unsupervised data to choose the model that is consistent with the labeled data and at the same time most adequate to explain the distribution of unlabeled data.

This can be worked through the following subhypotheses:

**Subhypothesis 5.1** *The ladder network model improves over the purely supervised and other semi-supervised methods on a held-out test corpus.*

**Subhypothesis 5.2** *On new annotated examples with this classifier, the representativity of the classes is maintained.*

**Subhypothesis 5.3** *Overfitting of the labeled corpus is avoided by the use of unlabeled data to minimize an unsupervised cost function.*

- Experiment 8.1 reports the performance of the ladder network model over the held-out test set. The performance is measured by the F1-score per class. Results shown in Section 8.4.1 serve to accept Hypothesis 5.1, that the performance over a model on held-out test data for the ladder network improves over the previous methods.

- Experiment 8.2 shows the distribution of the classes that the model has by automatically annotating instance drawn from an unlabeled corpus. This are measured by the proportional count of the classes. The results shown in Section 8.4.2 serve to partially accept Hypothesis 5.2 as it is valid for word embeddings but not for hand-crafted features.

- Experiment 8.3 seed the tendency overfitting by measuring the error due to variance of a model trained on one dataset over other datasets. To measure this I use the learning curve (Metric 3) I already explained in previous chapters. It is important to note that, this time the learning curve is not measured using the information given by labeled data, but it is measured based on the information that unlabeled data give to the model. The results of the experiments shown in Section 8.4.3 serve to accept Hypothesis 5.3 which states that the use of unlabeled data to minimize an unsupervised cost function help to decrease the model tendency to overfit.

In Section 8.2 I introduce a brief summary of the ladder network model, citing the original work and the works from where the authors draw inspiration to come with this novel approach.

In Section 8.3 I go through the relevant items that concern the experimentation in the chapter. Most of the methodology is very similar to that in previous chapters, I mostly provide pointers to the sections where this methodology is first described. Section 8.3.3 is the most important part, where I go through the fine-grained details concerning the model, including the architecture of the ladder network, the training of the algorithm and the definition of the cost functions and auxiliary functions.

Section 8.4 reports the results of the experiments and analyzes them in order to accept the stated hypotheses of the chapter.

Finally Section 8.5 draws the conclusions of this chapter, recapitulating the Hypotheses and the implications of accepting or rejecting them according to the evidence gathered in the results. It ends by outlining future work.

## 8.2 Relevant work

The idea of using unsupervised learning to help training a neural network was proposed by Suddarth and Kergosien [Suddarth and Kergosien, 1990]. Most of the methods that use an auxiliary task to help the supervised learning are only applied at pre-training, followed by normal supervised learning [Hinton and Salakhutdinov, 2006]. In contrast, with ladder networks [Rasmus et al., 2015a] representations are learnt jointly. Unsupervised learning is implemented through an auxiliary task, for example, reconstructing the input. In learning, the hidden representations among supervised and unsupervised tasks are shared, and thus the network generalizes better. I provide details of the method in what follows.

The Ladder network method presented by Rasmus et al. follows the work by Valpola [Valpola, 2014], who proposed a Ladder network where the auxiliary task is to denoise representations at every level of the model. The model structure is an autoencoder with skip connections from the encoder to decoder and the learning task is similar to that in denoising autoencoders but applied to every layer, not just the inputs. The skip connections relieve the pressure to represent details in the higher layers of the model because, through the skip connections, the decoder can recover any

details discarded by the encoder. Originally, the ladder networks were only applied to unsupervised learning [Valpola, 2014, Rasmus et al., 2014] but then they were combined with supervised learning.

The key aspects of ladder networks, as described in [Rasmus et al., 2015a], are the following:

**Compatibility with supervised methods** The unsupervised part complements what is found by supervised learning, adding information while maintaining compatibility with the purely supervised model. Furthermore, it can be added to existing feed-forward neural networks, for example multilayer perceptrons or convolutional neural networks.

**Scalability resulting from local learning** In addition to a supervised learning target on the top layer, the model has local unsupervised learning targets on every layer, making it suitable for very deep neural networks.

**Computational efficiency** The encoder part of the model corresponds to normal supervised learning. Adding a decoder, as proposed in the paper, approximately triples the computation during training but not necessarily the training time since the same result can be achieved faster through better utilization of the available information. Overall, computation per update scales similarly to whichever supervised learning approach is used, with a small multiplicative factor.

The steps involved in implementing the Ladder network are typically as follows: (i) take a feed-forward model which serves for supervised learning as the encoder; (ii) add a decoder which can invert the mappings on each layer of the encoder and supports unsupervised learning; and (iii) train the whole Ladder network by minimizing the sum of all the cost function terms.

## 8.3 Methodology

This chapter explores the use of ladder networks for Spanish verb sense disambiguation. The model learns by minimizing a cost function composed of a supervised and an unsupervised objectives. As it is defined in the original publication, ladder networks do not add or treat unlabeled data as labeled (unlike self-learning and active learning). The best comparison possible with the other methods is done in the held-out test set. However, to have some more reference points I did some changes over the original scheme in order to make it more comparable to the self-learning approach.

Once again, the results I show in this chapter try to be as objective as possible, but there is only a number of possible evaluation metrics and visualization tools I can use, and some of them may obscure other results.

### 8.3.1 Resources

As with self-learning, there are two main resources required for ladder networks: a labeled and an unlabeled dataset. I will keep using the same datasets I have used through all the thesis: SenSem as supervised data, and SBWCE as unsupervised data.

Please refer to Section 4.3.1.1 to see the details of the SenSem corpus and how it was split intro training/test datasets following a stratified split application, but retaining at least one example of each class per split. Like what was done in Chapter 6, in the experiments of this chapter the SenSem dataset was randomly oversampled in the less frequent classes to have a more uniform distribution of all the classes of the supervised dataset.

The unlabeled instances are taken from the SBWCE dataset that was described in Section 5.3.1.2 and processed as described in Section 6.3.1.2. Please refer to those sections for more information regarding this dataset.

### 8.3.2 Features

The features used in this part are the same ones used in the previous chapters. Both hand-crafted features using the hashing trick and word embeddings follow what has been discussed in all the previous chapters.

For more information on the detail of what are the hand-crafted features used in this chapter please refer to Section 4.3.2. For detailed information on how to deal with the expansion of features given by the new examples added to the model please refer to Section 6.3.2.1.

The word embeddings are the ones trained from the journalistic corpus described in detail in Section 5.3.1.3. The method for combining them into an instance is the concatenation of word vectors described in Section 5.3.2.2.

### 8.3.3 Ladder network model

In this section I will explain in more detail the Ladder network model. This is but a brief introduction following the work presented by Rasmus et al. [Rasmus et al., 2015a]. I recommend the reader to refer to their work which presents a more detailed version of what I describe here.

#### 8.3.3.1 Architecture

The architecture of a ladder network is based on an autoencoder whose encoding part also works as a supervised classifier and whose decoder part works as an unsupervised learner by reconstructing the input. The structure of a ladder network typically follows these steps:

1. Set an encoder which works as a supervised classifier using a feed-forward model. The network has two encoder paths –clean and corrupted. The only difference

is that the corrupted encoder adds Gaussian noise at all layers. Adding noise serves to avoid overfitting of the resulting model.

2. Set a decoder which works as an unsupervised learner by inverting the mappings on each layer of the encoder. The decoder uses a denoising function to reconstruct the activations of each layer given the corrupted version. The target at each layer is the clean version of the activation and the difference between the reconstruction and the clean version serves as the denoising cost of that layer.

3. The supervised cost, that is, the error between the predicted label and the ground truth label, is calculated from the output of the corrupted encoder and the target label. On the other hand, the unsupervised cost is the sum of the denoising cost of all layers scaled by a hyperparameter that denotes the importance of each layer. For example, the first layers are more important than the last to reconstruct the input. The final cost is the sum of the supervised and the unsupervised cost.

The whole network is trained in a fully-labeled or semi-supervised setting using standard optimization techniques (such as stochastic gradient descent) to minimize these costs. Keep in mind the ladder network can work even without auxiliary unlabeled data, but the original motivation was to make it possible to take well-performing feed-forward classifiers and augment them with an auxiliary decoder.

Figure 8.1 shows the structure of a ladder network. The corrupted path (left in the Figure) adds Gaussian noise $\mathcal{N}(0, \sigma^2)$ to each layer of the encoder. Every layer contributes to the cost function, a term $C^{(l)} = ||\mathbf{z}^{(l)} - \hat{\mathbf{z}}^{(l)}||^2$ which trains the layers above (both encoder and decoder) to learn the denoising function $\hat{\mathbf{z}}^{(l)} = g^{(l)}(\tilde{\mathbf{z}}^{(l)}, \hat{\mathbf{z}}^{(\mathbf{l+1})})$ which maps the corrupted $\tilde{\mathbf{z}}^{(l)}$ onto the denoised estimate $\hat{\mathbf{z}}^{(l)}$. As the estimate $\hat{\mathbf{z}}^{(l)}$ incorporates all prior knowledge about $\mathbf{z}$, the same cost function term also trains the encoder layers below to find cleaner features which better match the prior expectation.

Since the cost function needs both the clean $\mathbf{z}^{(l)}$ and corrupted $\tilde{\mathbf{z}}^{(l)}$, during training the encoder is run twice: a clean pass for $\mathbf{z}^{(l)}$ and a corrupted pass for $\tilde{\mathbf{z}}^{(l)}$.

In denoising autoencoders [Vincent et al., 2010], an autoencoder is trained to reconstruct the original observation $\mathbf{x}$ from a corrupted version $\tilde{\mathbf{x}}$. Learning is based simply on minimizing the norm of the difference of the original $\mathbf{x}$ and its reconstruction $\hat{\mathbf{x}}$ from the corrupted $\tilde{\mathbf{x}}$; that is the cost is $||\hat{\mathbf{x}} - \mathbf{x}||^2$. The main difference is that in ladder networks the cost of reconstruction is calculated layer by layer adding the denoising functions $\hat{\mathbf{z}} = g(\mathbf{z})$.

One way to picture the Ladder network is to consider it as a collection of nested denoising autoencoders which share parts of the denoising machinery with each other via the cost function $C_d$. If this function were not used, from the viewpoint of the autoencoder on layer $l$, the representations on the higher layers would be opaque, treated as hidden neurons. In other words, there would be no particular reason why intermediate representation $\hat{\mathbf{z}}^{(l+i)}$ as produced by the decoder should resemble the corresponding representations $\mathbf{z}^{(l+i)}$ as produced by the encoder. It is only the cost

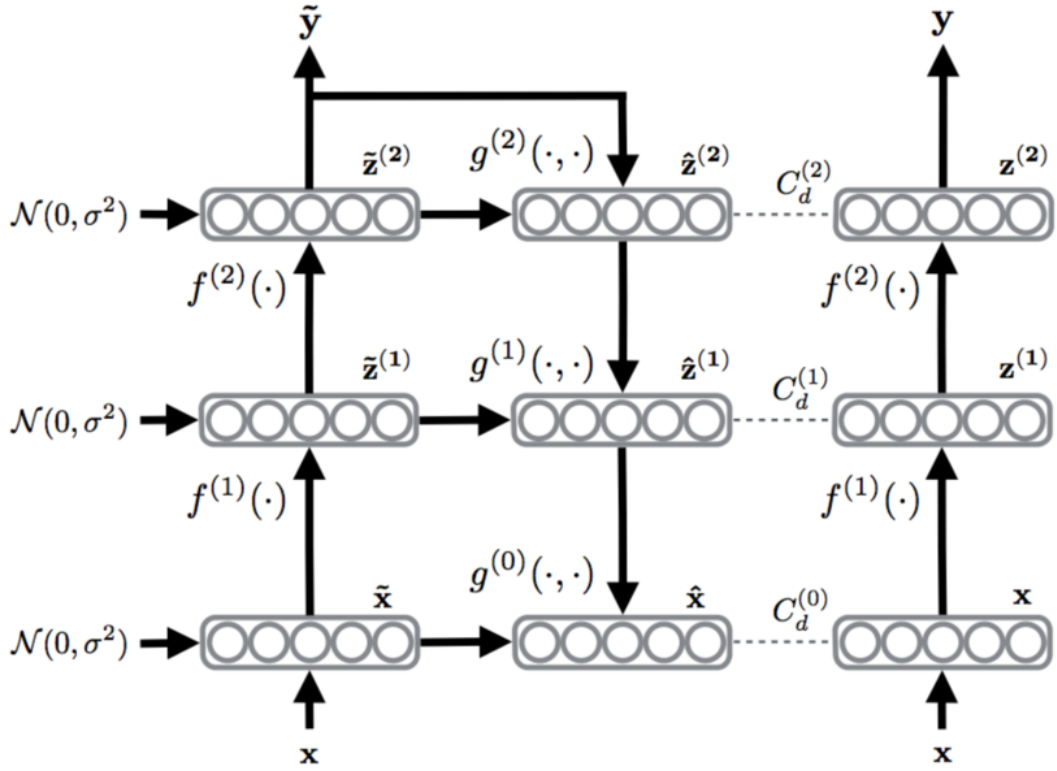


FIGURE 8.1: A conceptual illustration of a ladder network with two hidden layers ($L = 2$). The feed-forward path ($\mathbf{x} \rightarrow \mathbf{z}^{(1)} \rightarrow \mathbf{z}^{(2)} \rightarrow \mathbf{y}$) shares the mappings $f^{(l)}$ with the corrupted feed-forward path, or encoder ($\mathbf{x} \rightarrow \tilde{\mathbf{z}}^{(1)} \rightarrow \tilde{\mathbf{z}}^{(2)} \rightarrow \tilde{\mathbf{y}}$). The decoder ($\hat{\mathbf{z}}^{(2)} \rightarrow \hat{\mathbf{z}}^{(1)} \rightarrow \hat{\mathbf{x}}$) consists of the denoising functions $g^{(l)}$ and has cost functions $C_d^{(l)}$ on each layer aimed to minimize the difference between $\hat{\mathbf{z}}^{(l)}$ and $\mathbf{z}^{(l)}$. The output $\tilde{\mathbf{y}}$ of the encoder can also be trained to match available labels $t(n)$. Original figure found in the work of Rasmus et al. [Rasmus et al., 2015a].

function $C_d^{(l+i)}$ that ties these together and forces the inference to proceed in reverse order in the decoder. This sharing helps a deep denoising autoencoder to learn the denoising process as it splits the task into meaningful sub-tasks of denoising intermediate representations.

Batch normalization [Ioffe and Szegedy, 2015] is applied to each preactivation including the topmost layer to improve convergence (due to reduced covariate shift) and to prevent the denoising cost from encouraging the trivial solution (encoder outputs constant values as these are the easiest to denoise). Direct connection between a layer and its decoded reconstruction are used. The network is called a Ladder network because the resulting encoder/decoder architecture resembles a ladder because the cost function between mirroring layers could be seen as the strings in ladder steps.

#### 8.3.3.2 Training of the network

Algorithm 1 lists the feed-forward pass of the full Ladder network given one training instance (labeled or unlabeled). The results of the algorithm are the prediction

**Algorithm 1** Calculation of the output and cost function of the Ladder Network. Taken from Rasmus et al. [Rasmus et al., 2015a]

**Require:** $\mathbf{x}(n)$
  # Corrupted encoder and training output
  $\tilde{\mathbf{h}}^{(0)} \leftarrow \tilde{\mathbf{z}}^{(0)} \leftarrow \mathbf{x}(n) + \texttt{noise}$
  **for** $l = 1$ **to** $L$ **do**
    $\tilde{\mathbf{z}}^{(l)}_{\text{pre}} \leftarrow \mathbf{W}^{(l)}\tilde{\mathbf{h}}^{(l-1)}$
    $\tilde{\boldsymbol{\mu}}^{(l)} \leftarrow \texttt{batchmean}(\tilde{\mathbf{z}}^{(l)}_{\text{pre}})$
    $\tilde{\boldsymbol{\sigma}}^{(l)} \leftarrow \texttt{batchstd}(\tilde{\mathbf{z}}^{(l)}_{\text{pre}})$
    $\tilde{\mathbf{z}}^{(l)} \leftarrow \texttt{batchnorm}(\tilde{\mathbf{z}}^{(l)}_{\text{pre}}, \tilde{\boldsymbol{\mu}}^{(l)}, \tilde{\boldsymbol{\sigma}}^{(l)}) + \texttt{noise}$
    $\tilde{\mathbf{h}}^{(l)} \leftarrow \texttt{activation}(\boldsymbol{\gamma}^{(l)} \odot (\tilde{\mathbf{z}}^{(l)} + \boldsymbol{\beta}^{(l)}))$
  **end for**
  $P(\tilde{\mathbf{y}}|\mathbf{x}) \leftarrow \tilde{\mathbf{h}}^{(L)}$
  # Clean encoder
  $\mathbf{h}^{(0)} \leftarrow \mathbf{z}^{(0)} \leftarrow \mathbf{x}(n)$
  **for** $l = 1$ **to** $L$ **do**
    $\mathbf{z}^{(l)}_{\text{pre}} \leftarrow \mathbf{W}^{(l)}\mathbf{h}^{(l-1)}$
    $\boldsymbol{\mu}^{(l)} \leftarrow \texttt{batchmean}(\mathbf{z}^{(l)}_{\text{pre}})$
    $\boldsymbol{\sigma}^{(l)} \leftarrow \texttt{batchstd}(\mathbf{z}^{(l)}_{\text{pre}})$
    $\mathbf{z}^{(l)} \leftarrow \texttt{batchnorm}(\mathbf{z}^{(l)}_{\text{pre}}, \boldsymbol{\mu}^{(l)}, \boldsymbol{\sigma}^{(l)})$
    $\mathbf{h}^{(l)} \leftarrow \texttt{activation}(\boldsymbol{\gamma}^{(l)} \odot (\mathbf{z}^{(l)} + \boldsymbol{\beta}^{(l)}))$
  **end for**
  # Prediction output
  $P(\mathbf{y}|\mathbf{x}) \leftarrow \mathbf{h}^{(L)}$
  # Decoder and denoising
  **for** $l = L$ **to** $0$ **do**
    **if** $l = L$ **then**
      $\mathbf{u}^{(L)}_{\text{pre}} \leftarrow \tilde{\mathbf{h}}^{(L)}$
    **else**
      $\mathbf{u}^{(l)}_{\text{pre}} \leftarrow \mathbf{V}^{(l+1)}\hat{\mathbf{z}}^{(l+1)}$
    **end if**
    $\boldsymbol{\mu}^{(l)} \leftarrow \texttt{batchmean}(\mathbf{u}^{(l)}_{\text{pre}})$
    $\boldsymbol{\sigma}^{(l)} \leftarrow \texttt{batchstd}(\mathbf{u}^{(l)}_{\text{pre}})$
    $\mathbf{u}^{(l)} \leftarrow \texttt{batchnorm}(\mathbf{u}^{(l)}_{\text{pre}}, \boldsymbol{\mu}^{(l)}, \boldsymbol{\sigma}^{(l)})$
    $\forall i : \hat{z}^{(l)}_i \leftarrow g(\tilde{z}^{(l)}_i, u^{(l)}_i)$
    $\forall i : \hat{z}^{(l)}_{i,\text{BN}} \leftarrow \frac{\hat{z}^{(l)}_i - \mu^{(l)}_i}{\sigma^{(l)}_i}$
  **end for**
  # Cost function $C$ for training
  $C \leftarrow 0$
  **if** t(n) **then**
    # NLL cost for labeled data
    $C \leftarrow -\log P(\tilde{\mathbf{y}} = t(n)|\mathbf{x}(n))$
  **end if**
  $C \leftarrow C + \sum_{l=0}^{L} \lambda_l \left|\left|\mathbf{z}^{(l)} - \hat{\mathbf{z}}^{(l)}_{\text{BN}}\right|\right|^2$

results $\mathbf{y}$ of the network as well as the cost function $C$. As it can be seen from the figure, the algorithm goes through the two paths of the encoder –clean and corrupted– as well as the decoder path. As seen in Algorithm 1 the cost function results from the sum of the supervised cost given by the negative log-likelihood (if applicable, i.e. the instance has a label), and the unsupervised cost of reconstruction layer by layer.

Algorithm 1, however, shows how the cost function is obtained for only one instance. For a batch of instances, the supervised cost function is the average negative log probability of the noisy output $\tilde{\mathbf{y}}$ matching the target $t(n)$ given the inputs $\mathbf{x}(n)$

$$C_c = -\frac{1}{N}\sum_{n=1}^{N} \log P(\tilde{\mathbf{y}} = t(n)|\mathbf{x}(n)).$$

The unsupervised denoising cost function, which is calculated layer by layer, for more than one instance is

$$C_d = \sum_{l=0}^{L} \lambda_l C_d^{(l)} = \sum_{l=0}^{L} \frac{\lambda_l}{N m_l} \sum_{n=1}^{N} \left|\left|\mathbf{z}^{(l)}(n) - \hat{\mathbf{z}}^{(l)}_{\text{BN}}(n)\right|\right|^2,$$

where $m_l$ is the layer size, $N$ is the number of training instances, and the hyperparameter $\lambda_l$ is a layerwise multiplier determining the importance of the denoising cost. Finally, the cost function is obtained as the sum of the supervised and unsupervised cost functions $C = C_c + C_d$.

Both in the encoders –clean or corrupted– and the decoder, each layer uses batch normalization, as explained before, to improve convergence and prevent the denoising cost from encouraging the trivial solution. The clean path differs from the corrupted path in that the latter adds gaussian noise before activation. Also, the corrupted output is used for training but the clean output is used for prediction.

The function $g$ is the *combinator function* such that $\mathbf{z}^{(l)} = g(\tilde{\mathbf{z}}^{(l)}, \hat{\mathbf{z}}^{(l+1)})$ which can approximate the optimal denoising function for the family of observed distributions. The function $g$ is therefore expected to form a reconstruction $\hat{\mathbf{z}}^{(l)}$ that resembles the clean $\mathbf{z}^{(l)}$ given the corrupted $\tilde{\mathbf{z}}^{(l)}$ and the higher-level reconstruction $\hat{\mathbf{z}}^{(l+1)}$.

The work by Rasmus et al. [Rasmus et al., 2015a] presents the instatiation of $g$ that I used in the implementation for the experiments of this chapter. However, there can be other versions of the combinator function. Pezeshki et al. [Pezeshki et al., 2015] presented another version of the combinator function which, they claim, outperforms the original. Further experimentation with other combination functions, or even the design of a combinator function for the task of Spanish verb sense disambiguation in particular, is left for future work. The combinator function used for this experiments, defined by Rasmus et al. [Rasmus et al., 2015a], is the following:

$$\hat{z}_i^{(l)} = g_i(\tilde{z}_i^{(l)}, u_i^{(l)}) = \left(\tilde{z}_i^{(l)} - \phi_i(u_i^{(l)})\right) \psi_i(u_i^{(l)}) + \phi_i(u_i^{(l)}),$$

Where the functions $\phi_i(u_i^{(l)})$ and $\psi_i(u_i^{(l)})$ are modeled as expressive nonlinearities:

$$\begin{aligned}
\phi_i(u_i^{(l)}) &= a_{1,i}^{(l)} \sigma(a_{2,i}^{(l)} u_i^{(l)} + a_{3,i}^{(l)}) + a_{4,i}^{(l)} u_i^{(l)} + a_{5,i}^{(l)} \\
\psi_i(u_i^{(l)}) &= a_{6,i}^{(l)} \sigma(a_{7,i}^{(l)} u_i^{(l)} + a_{8,i}^{(l)}) + a_{9,i}^{(l)} u_i^{(l)} + a_{10,i}^{(l)},
\end{aligned}$$

where $\sigma$ is the *sigmoid function*.

The model has the following trainable parameters, which can be trained simply by using the back-propagation algorithm to optimize the cost function $C$:

**$\mathbf{W}^{(l)}$, $\mathbf{V}^{(l)}$** The weight matrices of the encoder and decoder respectively for each layer $l$ of the network. Note that $\mathbf{V}^{(l)}$ has the same dimension as the transpose of $\mathbf{W}^{(l)}$.

**$\boldsymbol{\gamma}^{(l)}$, $\boldsymbol{\beta}^{(l)}$** The bias and scaling parameters respectively for each layer $l$ of the network.

**$a_{1,i}^{(l)}, \ldots, a_{10,i}^{(l)}$** The parameters of the functions $\phi_i(u_i^{(l)})$ and $\psi_i(u_i^{(l)})$, proposed by the authors.

The cost function $C$ is minimized using stochastic gradient descent. On each iteration (also called epoch), the algorithm takes a batch of elements of the same

size both from the labeled and the unlabeled dataset. It uses those elements to do a forward propagation. This goes on batch by batch until all the instances in one of the two datasets, either the labeled or unlabeled dataset, have been used for training. Normally, the labeled dataset is smaller than the unlabeled dataset, so it usually happens that the labeled dataset is consumed much sooner than the unlabeled dataset. Then, the dataset that has been completely used for training (usually the supervised dataset) is shuffled and the algorithm starts over to take batches from that dataset as if it were new. The dataset that has not been fully used up keeps being consumed in the same way. Using the original implementation of the algorithm, the size of the batch was equal to the size of the labeled dataset. This means that on each iteration the ladder network minimized the cost function over the whole labeled data (with a random order) and a chunk of the unlabeled dataset (which is larger).

#### 8.3.3.3 Hyperparameters

The ladder network algorithm has an important number of hyperparameters to tune and experiment with. Some of these hyperparameters are given by the neural network (e.g. the number and size of the layers), others are given by the ladder network model (e.g. the scaling factor for noise) and others are given by the training procedure (e.g. the stopping criterion). As the number of experiment grows exponentially the more hyperparameters I tune, I decided to keep it as simple as possible to avoid losing focus of the experimentation of the chapter.

First of all is the structure of the network. To keep a comparison point with the experiments of previous chapters, the encoder has three hidden layers ($L = 3$) with 500, 250 and 100 neurons each. As such, the decoder, which is symmetric to the encoder, has three layers with 100, 250 and 500 neurons each.

The hyperparameters defined by the ladder network algorithm are the scaling factor for noise in the corrupted encoder, and the layer-wise factor that denotes the imporance of each denoising cost (i.e. $\lambda_l$). To avoid an exponential growth in the number of experiments I decided to use the hyperparameters described in the experiments in the work by Rasmus et al. The scaling factor for noise was 0.3 and the importance of the denoising cost layers was set to $\lambda^{(0)} = 1000$, $\lambda^{(1)} = 10$, and $\lambda^{(l \geq 2)} = 0.01$.

#### 8.3.3.4 Stopping criterion

Ladder networks, unlike the wrapper algorithms I discussed before, do not start from a supervised algorithm that was previously trained on the supervised data. Instead it learns by minimizing the objective function with both supervised and unsupervised data from scratch. Thus, the way to stop the algorithm is precisely by looking for convergence or by establishing a maximum number of iterations.

I added another stopping criterion to avoid the ladder networks algorithm to overfit the supervised dataset. Section 6.3.4 explains that for self-learning 20% of the training data is reserved for validation, ensuring that each class is represented at least by one

example in both corpora. I use this same technique to select a validation dataset from the training data. The validation dataset serves to check at every iteration that the algorithm is not reducing the cost error at the expense of generalization.

The stopping criterion then became one of three:

1. The algorithm reached the maximum number of given iterations.
2. The error in the cost function converges: the error of a new iteration is larger than or equal to the error of the previous iteration plus some error tolerance $\epsilon$.
3. The validation dataset error is larger than or equal to the previous validation error registered by the algorithm plus some error tolerance $\eta$.

A set of experiments was done to verify which values of $\eta$ and $\epsilon$ improve the convergence of the model without losing too much information. However, in the experiments, the value that really made a difference was the number of iterations as I will discuss further in the chapter.

### 8.3.4 Experiments

The experiments presented in this section help in the acceptance or rejection of the presented hypotheses in the beginning of this chapter.

First, Hypothesis 5.1 calls for an experiment to compare between ladder networks and the algorithms seen so far: supervised, self-learning and active learning. Experiment 8.1 tests the ladder network model on the held-out test set and uses that to compare it to the previous algorithms.

**Experiment 8.1.**

**8.1a** Train the model with ladder networks until a stopping criterion is met.

**8.1b** Evaluate the model on the held-out test dataset.

Experiment 8.2 reports the distribution of classes taking into account both the labeled data and some automatically annotated data taken from an unlabeled pool of examples different from the one given to the ladder network to minimize the unsupervised cost function.

**Experiment 8.2.**

1. Run the ladder network algorithm over the labeled dataset $L_1$ and the unlabeled dataset $U_1$.
2. In each iteration use the model obtained so far to predict the labels of a pool of unlabeled data $U_2$, different from the data in unlabeled dataset $U_1$.
3. From that pool annotate those with a predicted class which the model has a certainty over a threshold. This threshold is calculated following the steps described on Section 6.3.4: it starts at 100% and it is slowly lowered until it has at most a certainty that is 10% more than the random chance.

4. Take those automatically annotated instances off the unlabeled pool. If there is no instance on which the model has the required certainty, do not annotate any instance.

5. Record the distribution of the classes of both the labeled dataset and the automatically labeled instances obtained so far.

Experiment 8.3 measures the tendency to overfit of the ladder network classifier. It does so by monitoring both the training dataset and the validation dataset. This is very similar to what self-learning does. However, in this case the number of examples in the model is not augmented since the model itself does not add unannotated examples. However, recall that each training iteration takes the whole supervised dataset and only a portion of the unsupervised dataset. Thus on each iteration the algorithm adds more information from the unsupervised data by aiming to minimize the unsupervised part of the cost function of the algorithm. This is until the algorithm has covered all the unlabeled instances. After that, the algorithm does not add new data to the model, but carries on successive iterations aimed to fit better the available data. Nevertheless, to compare with the previous algorithms, for this experiment the algorithm stops after it traverses the whole unlabeled dataset once.

**Experiment 8.3.**

**8.3a** Take only a portion of the whole unsupervised dataset to use as unsupervised data for the algorithm.

**8.3b** Shuffle both training and validation datasets and split them randomly with stratified sampling.

**8.3c** Start the ladder networks algorithm.

**8.3d** In each step, run an iteration of training and record the predictions over training and validation data.

**8.3e** Stop the algorithm once the whole unlabeled dataset is traversed once.

**8.3f** Repeat the whole procedure $n$ times with a different portion of the unsupervised dataset, until the whole unsupervised dataset is traversed.

### 8.3.5 Metrics

The results of Experiment 8.1 are reported with the F1-score for each class in the test dataset of the token lemmas. This is done for each of the four algorithms seen so far: supervised, self-learning, active learning and ladder networks.

The results of Experiment 8.2 report the proportional count of elements of each class as done for the experiments in previous chapters of this thesis.

Finally, for Experiment 8.3 I use the error due to variance defined by Metric 3 to report the results of the experiment. This measures the model tendency to overfit as new unlabeled data is added to the model.

## 8.4 Analysis of results

This section reports the results obtained by the experiments and measures by the metrics I explained previously.

In a first set of experiments, I run the algorithm for a total of 100 iterations. However, the algorithm did not stop because it converged, but rather because of reaching the maximum number of iterations. Nevertheless, by the 100th iteration the improvement on the error was low enough to consider the algorithm had converged.

Nevertheless, as I will show next, once I visualized the results regarding the distribution of classes (Experiment 8.2), I found that when the algorithm was about 25 iterations the distribution of the classes began to drift to the most frequent one (regardless of the lemma). Thus I decided to run the same experiments with 25 iterations only and see what the results were.

Of course these results are just a view of the data available that I will try to interpret as objectively as possible. However, there might be some results that are obscured by the chosen visualizations.

### 8.4.1 Hypothesis 5.1

Hypothesis 5.1 states that the ladder network model improves over the purely supervised and other semi-supervised methods on a held-out test corpus. To test this Hypothesis I measure the results of Experiment 8.1 which asseses the impact of using a ladder network model in the task of Spanish verb sense disambiguation. These results are compared with the performance results of the previous algorithms in the test corpus. The metric to report the results is the F1-score per class. As I explained before, I will show the results training the ladder network with 100 iterations and also with 25 iterations.

As this is only done in the held-out test dataset, the performance showed in this Section is done for the most frequent, second most frequent and, if it applies, third most frequent class of the lemma. Recall that only two of the six lemmas had three classes in the held-out test dataset: “llegar” and “pensar”. The other four lemmas had only two classes in the dataset.

Figure 8.2 shows the F1-score macro and weighted average for supervised, self-learning, active learning, and ladder networks (using 100 iterations) over the test dataset. In this case, “supervised” is the evaluation of the model in the initial iteration of any of the wrapper algorithms (as it is the same for both, i.e. only using the manually labeled data). The self-learning/active learning/ladder networks bars represent the performance of the model over the held-out test dataset after finishing the iterations of the corresponding algorithm. The structure of the graphic is as follows:

- Each row shows the results for a token lemma: “acceder”, “buscar”, “explicar”, “facilitar”, “llegar”, and “pensar”.

- Each column stands for a feature representation: hand-crafted hashed features and journalistic word vectors.
- Each group of bars in each plot represents the class (i.e. sense) for that lemma. These are ordered according to number of occurrences of the class in the dataset.
- Each bar plot in a different color inside a group represents the algorithm: supervised (i.e. evaluation moment of the initial iteration for a wrapper algorithm, in

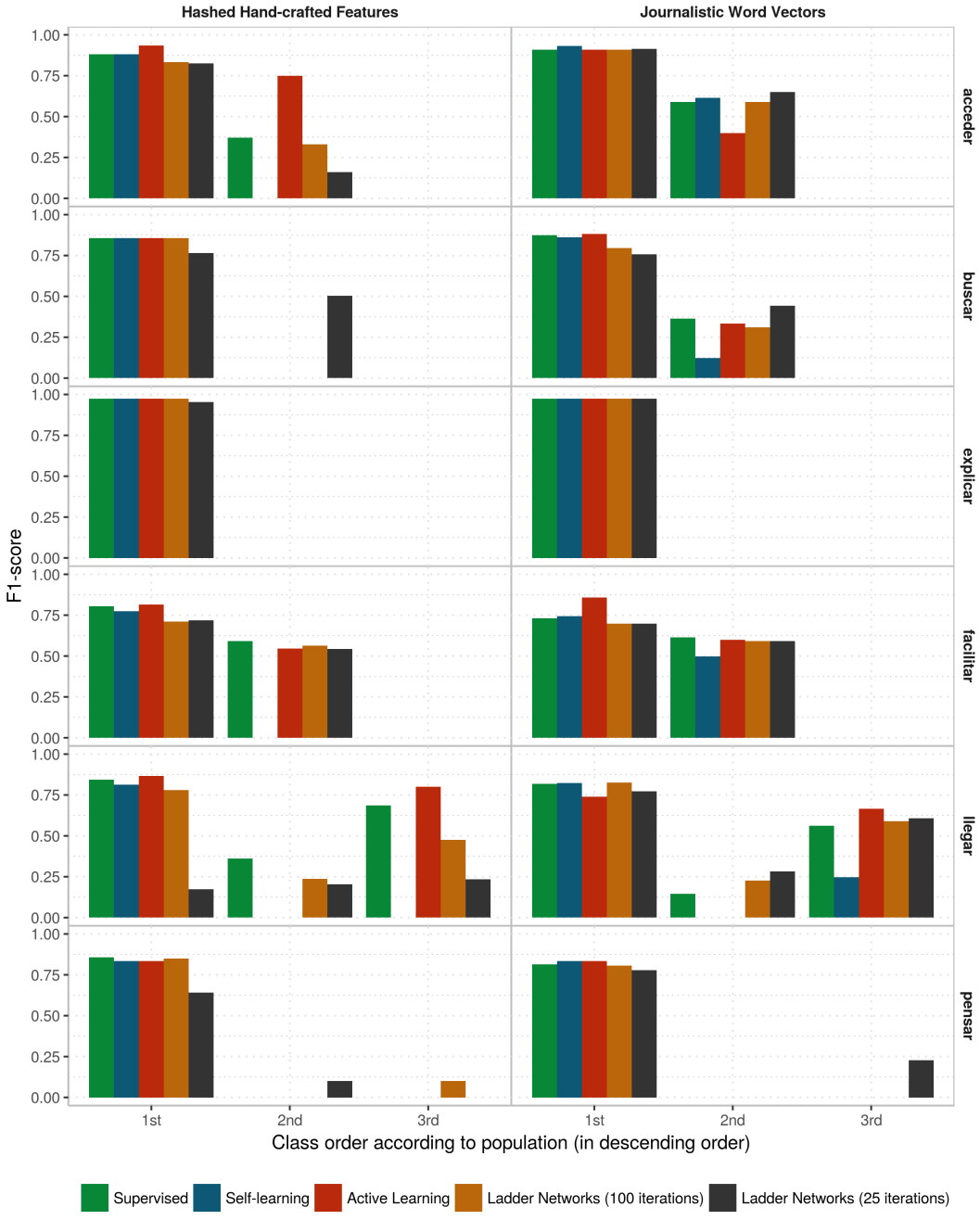


FIGURE 8.2: Comparison of macro and weighted average F1-score for supervised, self-learning, active learning, and ladder networks (using 100 iterations first and using 25 iterations secondly)

this case self-learning), self-learning (i.e. evaluation moment of the final iteration after self-learning finishes), active learning (i.e. evaluation moment of the final iteration after active learning finishes), and two versions of ladder networks (i.e. distinguishing different moments when the ladder networks algorithm stops, in this case after reaching 100 or 25 iterations).

- The height of the bar represents the value of the F1-score per each class.

Once again, recall that only the last two rows of the graphic represent the lemmas with 3 senses (i.e. "llegar" and "pensar"). The first four lemmas can at most show results for two senses.

Note that ladder networks (in either case) performs equally or even better than active learning in most of the senses. Remember that so far active learning have shown the best results as it can be appreciatted in the Figure.

Moreover, there are a couple of cases where the ladder network (with 100 or 25 iterations) performs better than supervised learning on a class that supervised learning does not recognize at all (e.g. the third most frequent class of the lemma "pensar"). Of course this might happen by random chance, but it is still something to consider as ladder networks, unlike active learning, is completely automatic (i.e. there is no human involvement). Moreover it happens differently for ladder networks using 100 iterations and using 25 iterations.

Clearly, ladder networks is also a better alternative (or at least has better performance) than self-learning. And it also has better performance using word embeddings than using hand-crafted features, as we have seen along this thesis.

Notice also that in general (specially for word embeddings) stopping ladder networks at 25 iterations has better performance than going the full 100 iterations. As I will show further, around 25 iterations begins the drift to the most frequent class which is a good indication that this is why ladder networks with only 25 iterations performs better than with 100 iterations. Notice specially that ladder networks with 25 iterations tend to perform worse than ladder networks with 100 iterations for the case of the most frequent class. This is yet more evidence that stopping the algorithm when it begins to drift to the most frequent class is a good solution to the problem of having worse performance for less frequent classes.

In summary, ladder networks present some impressive results, specially in comparison to active learning and taking into account that it is a purely automatic method. It has much better results also than self-learning and it seems that more insightful diagnostics over the iterations of the algorithm can help balance the performance for the classifier on classes besides the most frequent one.

Even if ladder networks are not the best solution for all the cases, it is clear that being a semi-supervised method that is completely automatic, it improves on what other methods can achieve. E.g. the model has more information, and thus more coverage, than a purely supervised method, and it also avoids the use of an oracle for the annotation procedure. From these results I accept Hypothesis 5.1 that ladder

networks improves over the purely supervised or other semi-supervised methods. It can be argued that, even if the raw performance of the purely supervised approach and the active learning approach is comparable to that of ladder networks, the latter are less expensive than active learning and in general do a better job of maintaining good performance in all classes.

### 8.4.2 Hypothesis 5.2

Hypothesis 5.2 was planned to compare how ladder networks work when facing a similar task to that of the wrapper algorithms I explored in the previous chapters. The hypothesis states that the representativity of the classes if using the model to classify some unsupervised data will be maintained through the iterations. In particular, it was in the visualization of this experiment's results that I found that around iteration number 25 there was a drifting of the algorithm to the most frequent class. In this section there are two plots of the same results, varying only in the number of iterations the ladder network algorithm is given to finish.

Like for self-learning and active learning in the previous chapter, to analyze these results I use two forms of visualization: one explores the distribution of the classes along the iterations of the algorithm and the other explores the proportional count of each class added on each iteration of the algorithm.

#### 8.4.2.1 Classes' population distribution across iterations

Figure 8.3 shows the distribution of the population of the classes across ladder network iterations (with a maximum of 100 iterations) of the algorithm. Each class's population is represented as the proportion of the total number of examples in the training dataset for that iteration. The plot is a stacked area plot that follows this structure:

- Each row shows the results for a token lemma: "acceder", "buscar", "explicar", "facilitar", "llegar", and "pensar".
- Each column stands for a feature representation: hand-crafted hashed features and journalistic word vectors.
- The x-coordinate represents the iteration in the self-learning algorithm.
- The y-coordinate represents the percentage of population.
- Each area of a different color represents the proportion of examples for each of the classes in the dataset. The classes again are ordered according to number of examples in the original supervised dataset.

As I already explained in previous sections of this chapter, it is around the iterations number 25 (although not in all cases, in some cases is much earlier and in some is later) that the distribution of the classes from the labeled and automatic annotated

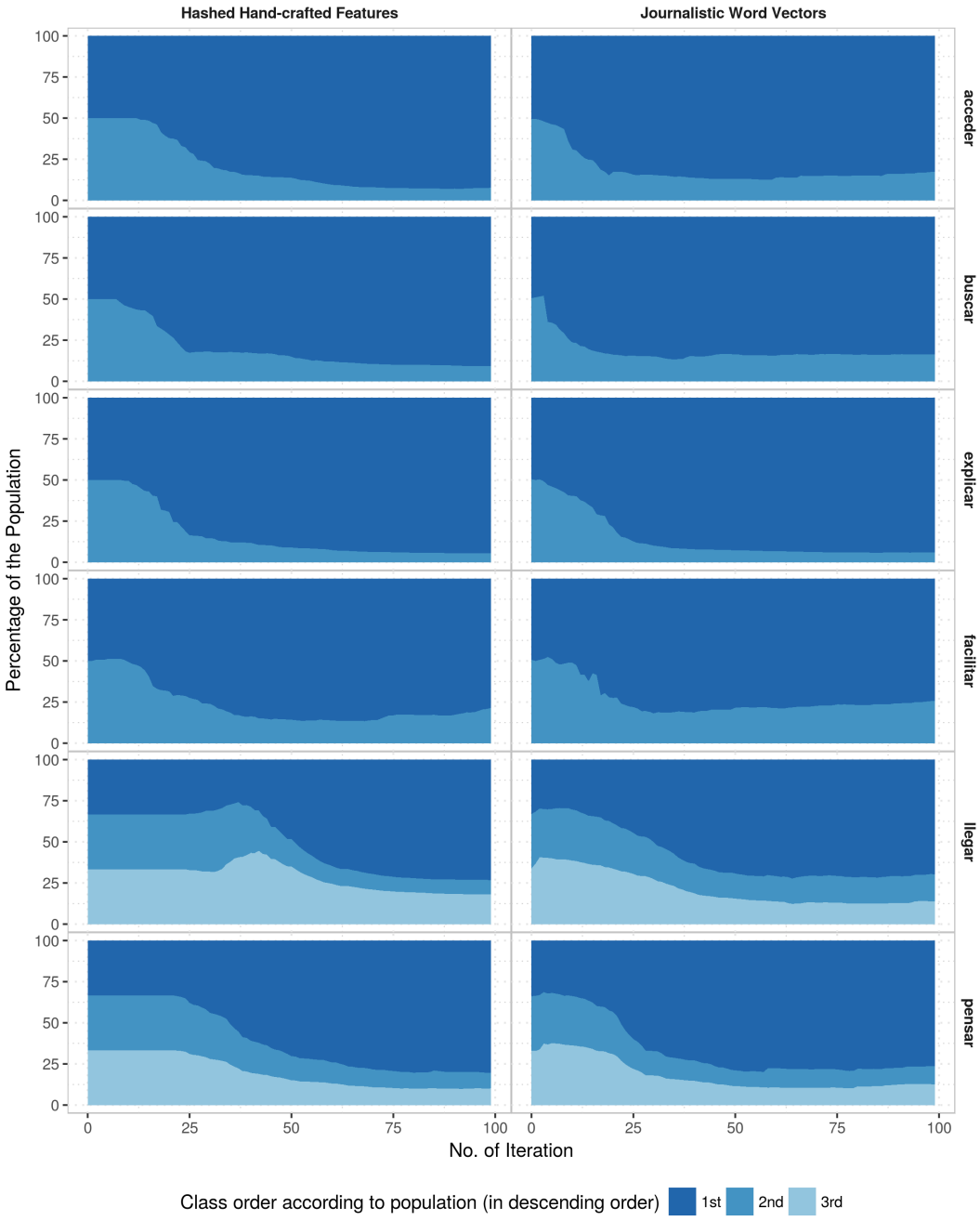


FIGURE 8.3: Distribution of the classes' population across ladder networks algorithm's iterations (with a maximum of 100 iterations) as a proportion of the whole training dataset

classes of the unlabeled corpus used for the task (as described in Experiment 8.3) begin to drift to the most frequent class. Once again, the prevalence of the most frequent class is more acute for hand-crafted features than for journalistic word embeddings.

If I decide to stop the algorithm by the iteration number 25, the distribution of classes looks like the one in Figure 8.4. The figure has the exact same structure as the previous figure with the only difference being in the maximum number of training iterations of the ladder network model.

In this case however, the drift of the model to automatically annotate everything as the most frequent class is not so strong as in the previous figure. The algorithm stops before that happens (although there are exceptions, after all, like all, each lemma has its own set of properties the algorithm needs to adapt to).

In any case, the drifting of the ladder network model to the most frequent class is not as strong as in self-learning, where it is practically immediate, right after the first iteration. This can well be a consequence of the ladder network learning the model

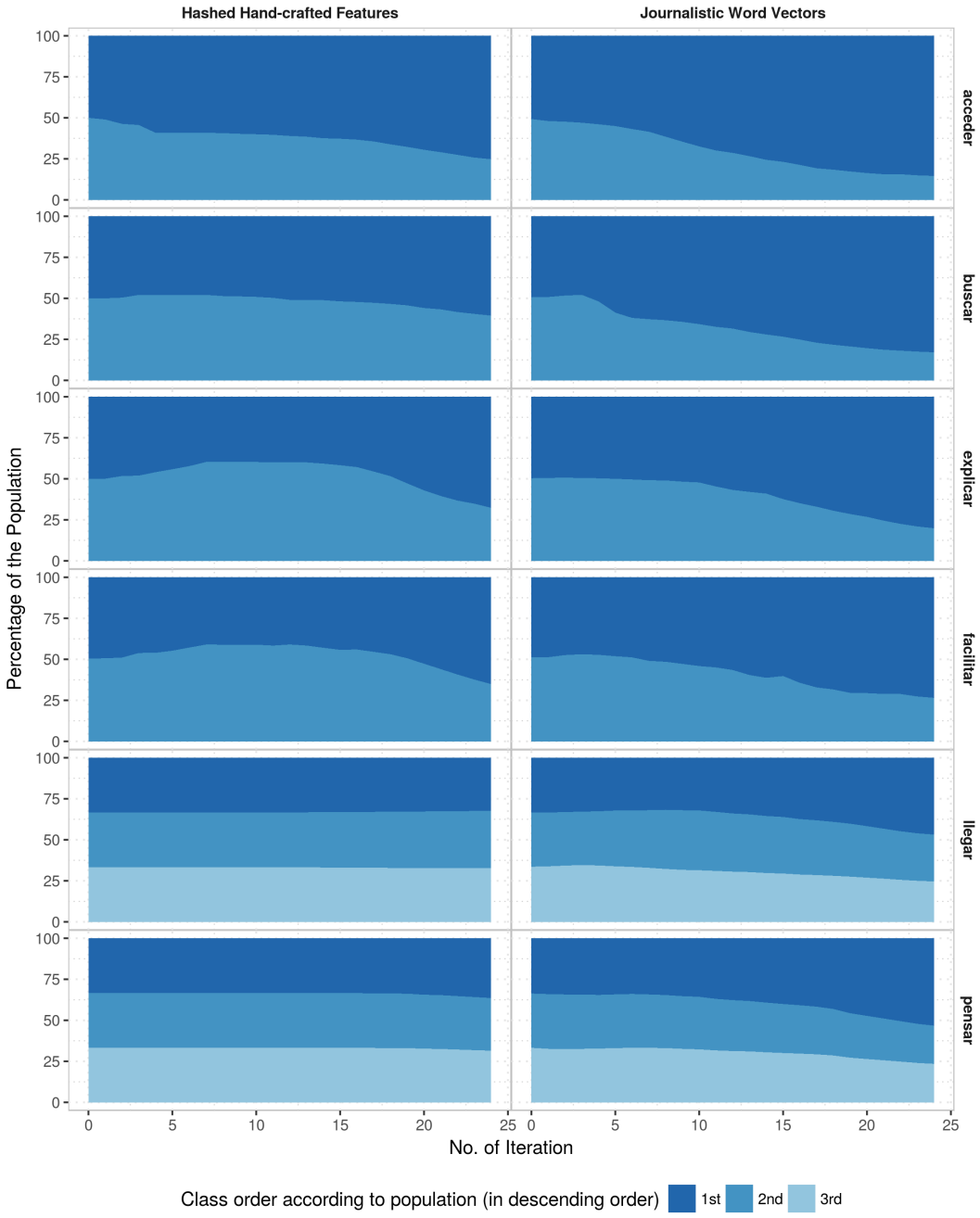


FIGURE 8.4: Distribution of the classes' population across ladder networks algorithm's iterations (with a maximum of 25 iterations) as a proportion of the whole training dataset

through the iterations as it slowly gains confidence of the decision boundaries. Unlike in self learning, the use of unlabeled data in this case serves to delay and avoid the drift to the most frequent class.

Eventually, with more iterations, the most frequent class starts gaining more and more probability, which is expected as the data has a Zipfian distribution. However, the fact that the results on the test dataset are better than those for self-learning seems to indicate that the ladder network is actually classifying the examples of the most frequent class correctly (better precision), unlike self-learning, which might well classify them as majority class just because it cannot tell them apart from any other class.

#### 8.4.2.2 Population added per sense per iteration

Figure 8.5 shows the proportion of examples added per class on each iteration. It is a stacked bar plot where each bar represents the total examples added in the iteration split by the proportion of classes automatically annotated as such. The structure of the plot is the following:

- Each row shows the results for a token lemma: “acceder”, “buscar”, “explicar”, “facilitar”, “llegar”, and “pensar”.
- Each column stands for a feature representation: hand-crafted hashed features and journalistic word vectors.
- The x-coordinate represents the iteration in the self-learning algorithm.
- The y-coordinate represents the percentage of examples automatically annotated for each sense.
- Each bar plot represents the distribution of the examples annotated in the iteration. Each color of the stacked bar represents the class with which the examples were annotated.

Similarly, Figure 8.6 shows the same information but this time for the ladder network algorithm stopping at 25 iterations.

The first thing to note from these Figures is that, in this case, unlike in the same figures of previous chapters, there are missing bars in some cases. This is because, unlike self-learning, for the ladder network algorithm it is not mandatory to annotate examples from the unlabeled dataset. Thus, in the first iterations, where the algorithm generally does not annotate anything, it is because the model is not certain enough about the annotated instances.

This is a consequence of the model not only learning from the labeled corpus, but from the unlabeled corpus as well. The model has less certainty as the unlabeled data, which is added in batches, adds information that avoids the model to converge, but also to overfit the supervised dataset.

There are some lemmas on which the model has better certainty than others. In particular the lemma "llegar", for the hand-crafted features representation, is the one on which the model takes the most to begin adding examples. This means that the model cannot handle the information from the lemma given by the unsupervised data in the first iterations and thus takes more time to adjust the parameters to that lemma. A quick look to Figure 8.2 shows that it is precisely for "llegar" that, at 25 iterations, the ladder network algorithm shows the worst performance. Also, a quick

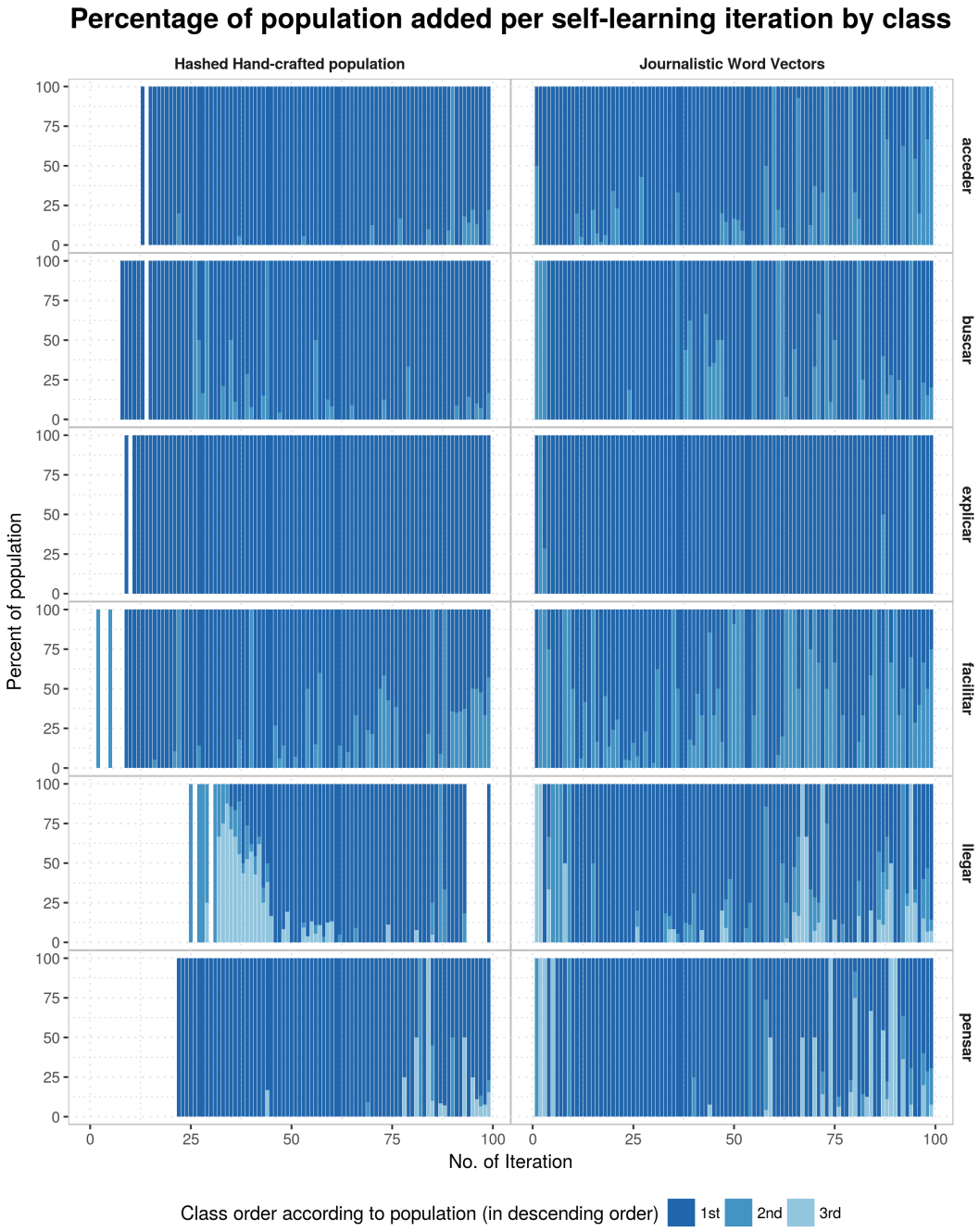


FIGURE 8.5: Population added per sense on each iteration of ladder network (with a maximum of 100 iterations) as a proportional count of all the examples added in that iteration

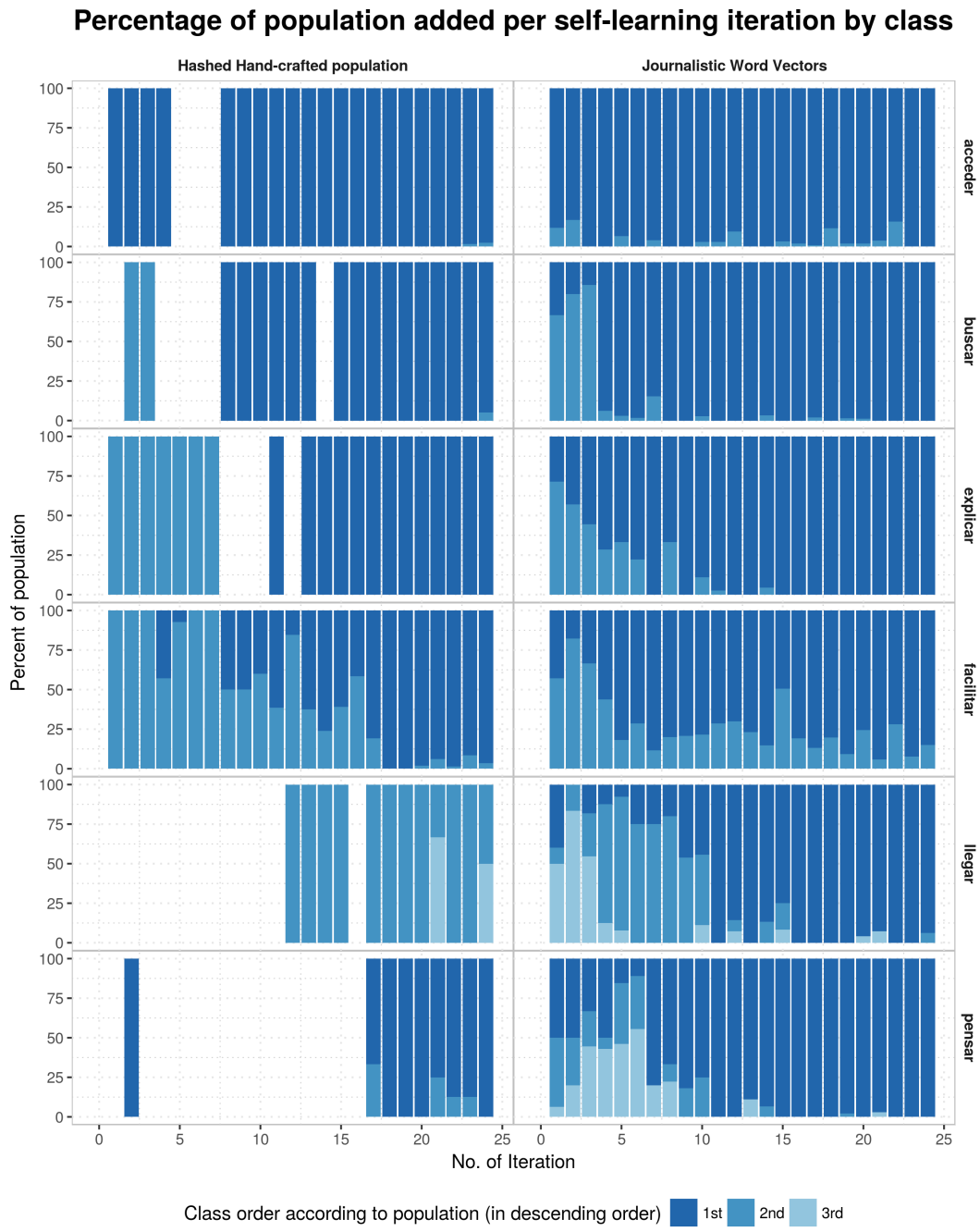


FIGURE 8.6: Population added per sense on each iteration of ladder network (with a maximum of 25 iterations) as a proportional count of all the examples added in that iteration

look to Figure 7.2 in the previous chapter shows that "llegar" has the highest number different senses occurring in the unlabeled dataset. Moreover, it was the example I used when I introduced self-learning in Chapter 6 to exemplify a lemma that has one sense as most frequent in the SenSem corpus but it is not precisely the same one as in a general corpus (thus, it is domain biased). Remember that unlabeled instances are taken from a general domain corpus.

The lemma "llegar" is a particular case, and we see that the use of hand-crafted

features undermines the performance of the model over a lemma that is so domain biased. However, it is important to note that this is not the case for all the lemmas or even that the same happens with a less domain dependant representation, as is the one provided by word embeddings.

Following the figures, both for 100 and for 25 iterations, it is clear that in most of the cases the most frequent class starts to dominate the automatically annotated examples. It is also important to notice how this is more clear for hand-crafted features. Thus, the idea of stopping the iterations once the ladder networks begins to drift is not so unjustified after all, specially seeing the results given in the previous section. It is however important to notice something: in the first couple of iterations there are more instances of the less frequent classes, something that gradually turns over. However, it is more notorious on the hand-crafted features that the distribution is all or nothing, since the bars start being of one color and then suddenly turn into the other color. This does not happen for word embeddings. In that case the representativity of each of the classes is more uniform and more similar to the original distribution of the classes (that is, the most frequent class is still the most frequent, but is not the only one). Given what I have discussed over this thesis work, it is safe to assume this is a direct consequence of the word embeddings being able to provide a better generalization to a model.

From the results shown in this and the previous section, there is enough evidence to accept Hypothesis 5.2 for word embeddings. However, there is not enough evidence to accept it for hand-crafted features.

### 8.4.3 Hypothesis 5.3

The final hypothesis of the chapter explores how the unlabeled data helps the ladder network model reduce the tendency to overfit. Hypothesis 5.3 states that the overfit of the ladder network model over the labeled data is prevented by the use of unlabeled data to calculate the global cost function, which is composed of the labeled and unlabeled cost functions.

It is important to notice that the experiments and results shown in this section capture the spirit of experiments on previous chapters which also explore how adding data to a model impacts on the tendency to overfit. However, what I could accomplish here does not directly compare to what I did for other algorithms, such as self-learning or even the supervised methods. This is because, unlike in those cases, the ladder networks algorithm integrates the information from the unlabeled dataset in a different way than the previous methods. In this case, the unsupervised information is integrated in the weights of the network.

Figure 8.7 shows the learning curve plot as a function of the number of examples of the training dataset. The structure of the learning curve plot is as follows:

- Each row shows the results for a token lemma: “acceder”, “buscar”, “explicar”, “facilitar”, “llegar”, and “pensar”.

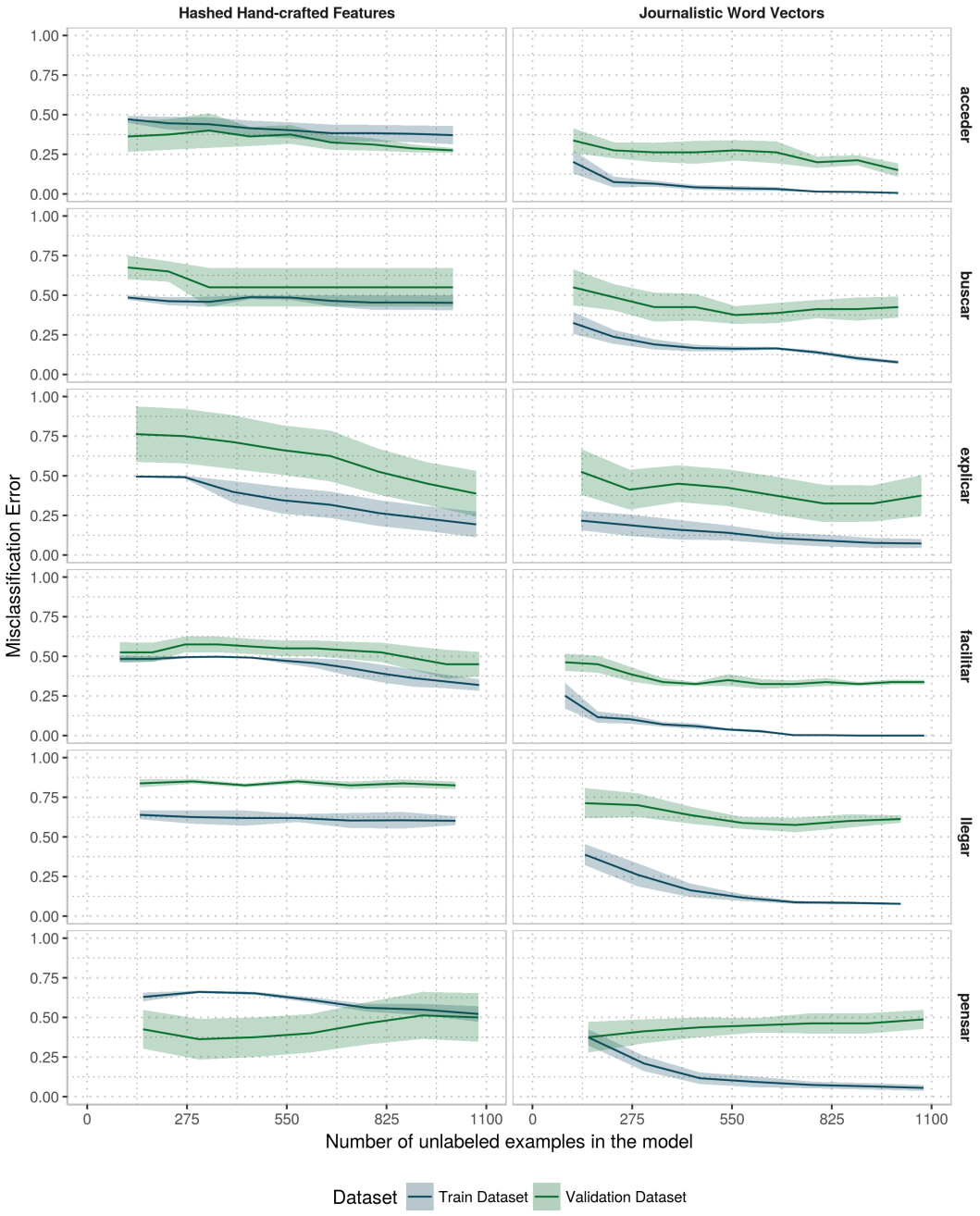


FIGURE 8.7: Learning curve as a function of the number of unlabeled examples added by the ladder network algorithm in each training iteration

- Each column stands for a feature representation: hand-crafted hashed features and journalistic word vectors.
- The x-coordinate axis represents the number of unlabeled examples added in each successive iteration by the ladder networks algorithm.
- The y-coordinate axis represents the misclassification error.

- There are two colors representing the datasets: training and validation (in this case, the validation set).
- The solid darker lines represent the mean of misclassification error through the different iterations of the datasets over all the models.
- The shadowed area, which has a lighter color, represents the standard error of the mean of the misclassification error.

Remember that in this case, the Experiment stops once all the unlabeled dataset is traversed once. As the batch size is equal to the number of labeled instances, which are around 100 instances per lemma and the maximum number of unlabeled data is 1000, then the algorithm stops near iteration number 10, because it already covers all the unlabeled data by that iteration.

The figure shows a very different picture of what similar plots for other approaches have shown so far. Unlike what happened for supervised or other semi-supervised methods, the misclassification error of the training dataset is not close to zero this time. In this case, the classification error drops slowly and in most of the cases it is accompanied by the validation error. There is however more error due to variance (represented by the wider shadowed area) of the validation dataset. However it seems to be slowly decreasing as more unlabeled examples are added to the model. Also, except perhaps for the last two lemmas, the validation error slowly converges to the training error as well.

Handcrafted features seem to have larger error due to variance than word embeddings. As seen through this thesis, this looks like a product of the difficulty of hand-crafted features being to generalize over their domain bias. Word embeddings, being smoother, model the data in a more generalized way.

It is important to notice that, no matter the representation, the error progression for most of the cases is quite uniform, that is, even if the training error is smaller than the validation error, the way both progress is similar. Moreover, as the ladder network model is adding unlabeled data to help the network generalize better, from these results it seems that in many cases it does so precisely by avoiding a huge drop in the error of the training data whilst having a larger error of the validation data. Once again, this is also dependant on the lemma, as each lemma has its own set of properties. These experiments were done on a limited unlabeled corpus due to time and resource constrains, a future line of work would be to explore the learning curve of the algorithm with a much larger number of unannotated examples.

The evidence shown by these results is enough to accept Hypothesis 5.3 that the use of unlabeled data prevents the model to overfit.

## 8.5 Conclusions

In this chapter I presented a joint semi-supervised method that, to my knowledge, had no previous applications in the area of word sense disambiguation: the ladder

network.

The experiments and results shown in this chapter have proven very interesting for its implications and its possibilities in the area of Spanish verb sense disambiguation, but also as a general semi-supervised method, applicable to many different areas.

The ladder network is a semi-supervised algorithm that uses a cost function which is a combination of the supervised cost function given by a feed-forward neural network (in this case a multilayer perceptron) and an unsupervised cost function that results in the layer by layer reconstruction of an autoencoder. The first is used to train on labeled data while the second is used to train on unlabeled data. The use of a cost functions that has an unsupervised part in the training of the classifier helps smoothing the fitting of the labeled data in the same network.

As a consequence, the ladder network improves on other methods by overcoming some of the shortcomings they had. By integrating an unlabeled dataset it has more coverage than a purely supervised method. It also has better performance than self-learning because it keeps under control the bias to the most frequent class. Finally, it is cheaper than active learning by avoiding the need for a human annotator to add new examples to the training dataset.

Hypothesis 5.1 states that the ladder network model improves over purely supervised methods and other semi-supervised methods. The hypothesis is accepted as shown by the results of Section 8.4.1. The experiments reported that the ladder network effectively reached the performance of other methods such as active learning or purely supervised, and in some cases it even outperformed them. What was most important from these results was to see how ladder networks could sacrifice some performance in the most frequent class to better represent the less frequent classes given the right conditions (i.e. stopping at 25 iterations). Moreover, ladder networks could perform better in senses that the supervised approach could not recognize at all in the test corpus. Even if the ladder network could not perform as well as active learning in some cases, it is still important to note that ladder networks do not rely on a human for the unsupervised part.

Hypothesis 5.2 was partially accepted. The hypothesis stated that if the model was used to automatically annotate instances from an unlabeled corpus, the representativity of the classes in those instances would be maintained. The results of Section 8.4.2 show how the distribution of the classes evolved across iterations. In these results, the number of iterations also had an important effect on the outcome, as I explained that when running the algorithm for 100 iterations it was around iteration number 25 that the model began to drift to the most frequent class. This is why I decided to truncate the models at 25 iterations and compare the results. These results showed that for hand-crafted features the Hypothesis could not be accepted as it was too extreme. In each iteration, the hand-crafted features model would mark all the unlabeled examples as being part of only one class, first the less frequent classes and eventually the most frequent one. However, the model based on word embeddings did show better results in line with what Hypothesis 5.2 stated. In the latter, the representativity of

the classes was more uniformly maintained through the iterations. A line of future work would be to use the difference between the original corpus's distribution and the distribution of the predicted batch as a stopping criterion, similar to the work by Zhao et al. [Zhao et al., 2017].

Hypothesis 5.3 stated that the use of unlabeled data helps the ladder network model reduce the tendency to overfit. I discussed the results of the experiments regarding this hypothesis in Section 8.4.3. In previous chapters I explored how the learning curve evolved by adding labeled data to the model. In this case however I decided to explore how adding unlabeled data to the model impacts on the tendency to overfit of the model. Even if it was not directly comparable to what I have seen in previous chapters, the basic idea of seeing the tendency to overfit is the same: how new information on the model affects the way it takes decisions. The results showed that the learning curve kept uniform while unlabeled data was added to the model. Both training error and validation error slowly dropped over time for most of the lemmas, and the error due to variance was reduced as well.

The results of this chapter show the potential ladder networks have as a semi-supervised approach, not only for Spanish verb sense disambiguation, but as a method in general. There is still work to be done regarding this method.

In future work, the first line would be to explore how the learning curve evolves when it is not limited to a limited number of unlabeled instances. The ideal approach would be to have an online learning [Bottou, 1998] method where new unsupervised data could be added indefinitely.

Another line of work would be to do a manual evaluation of the automatically annotated instances and compare that to what self-learning does. Finally, as this method is an algorithm on its own right, it could be used along some of the previous wrapper methods. It would be interesting then to see how a combination of the ladder network wrapped by active learning would evolve.

Regarding the customization of the ladder network algorithm, there is plenty future work to do: the exploration of different types of combination functions, the use of other types of neural networks such as recurrent or convolutional, and the design of a more end-to-end approach that holds the ladder network as its core.

# Part IV

# Conclusions

# Chapter 9

# Conclusions

## 9.1 Contributions

The experimentation of this thesis showed that the lack of data produces a tendency to overfit in purely supervised learning models, together with small coverage. To tackle these problems I explored different semi-supervised methods, each one with advantages and disadvantages on their own. The *ladder network* model was found the most promising one in terms of taking advantage of the unlabeled data to improve the performance of purely supervised models.

My proposed goal for this thesis was to study how different semi-supervised techniques could improve a task that would greatly benefit from them. Throughout the experiments and results of this work I researched on the properties, benefits, and shortcomings of different semi-supervised approaches on a particular task. To select the task I decided to explore a domain which would effectively find it useful the use of a semi-supervised technique. I did not want just to use some toy dataset on which the properties of semi-supervised learning would apply just because it was designed to have such results. What I was interested in was a task that had its own set of challenges, and in particular, a task that had already the ideal setting which would make semi-supervised learning an logical solution: the task should have a small amount of labeled data, good enough for a baseline solution, and large amount of unlabeled data.

Word sense disambiguation, as discussed in the introduction of this work, is a fundamental task in the field of natural language processing. It is what is known as an intermediate task, needed for more complex tasks such as machine translation or information extraction. In particular, the task of verb sense disambiguationis useful in relation extraction, as a verb is the lexical piece that establishes the relations betwen the participants in a sentence. My particular interest inside the area of verb sense disambiguationwas the area of Spanish verb sense disambiguation. In this area there has been only minimial previous work, as most of the work in disambiguation is for nouns. In particular, I was interested in the task of Spanish verb sense disambiguation because of the availability of the SenSem corpus, which is a manually disambiguated corpus for Spanish verbs. This resource gives a supervised baseline and the initial seed needed for semi-supervised methods. On the other hand, the resources available for unlabeled data are more than enough for the unsupervised part of the

semi-supervised tasks.

Chapter 4 starts by exploring the different supervised algorithms to bring their shortcomings into focus and plan how I could address them as challenges. The chapter does a research on different techniques using what I called *hand-crafted features*, i.e. features taken from the labeled corpus itself. First, the chapter's main focus was to set a common ground for the experimentation avoiding an exponential explosion of possible experiments and results that would have become impossible to analyze and draw conclusions from. This starting point was set to explore different ways of representing the data and to reduce the resources consumed by those representations using dimensionality reduction techniques. The chapter then explores also different classifiers, linear and non-linear, to rule out big differences before selecting one of them. Once the base structure of the experiments is set, the chapter explores how the number of labeled data in a model can impact on the final performance of the model. What the experimentation results show is that the main problem of the supervised approach is the lack of labeled data to train a good model that can generalize well. In particular, the model is trained over a labeled dataset of a specific domain, which makes the challenge of overfitting even worse. On the other hand, the model has little information: the coverage is greatly affected by the few available examples to train. Once the results of this chapter were clear, in successive chapters I explored the impact of different semi-supervised learning techniques on these two challenges: overfitting of the model in the training dataset, and coverage of the model by adding more information from new examples.

Chapter 5 introduced the use of *word embeddings* as an alternative representation of the instances used to train the classifier. This is known as *disjoint semi-supervised learning*, where an unsupervised task is performed previously (i.e. training word embeddings) and the result of this task is integrated into a supervised task (i.e. verb sense disambiguation). This chapter explored how the use of word embeddings impacts on a supervised classifier. In particular, the chapter experimented on different types of word embeddings trained with different domains. Those embeddings trained on the same domain as the labeled dataset (i.e. journalistic domain) improve the performance of the supervised classifier. However, the supervised classifier trained with word embeddings representations did not reach the performance levels of the model trained with hand-crafted features. Although this could be interpreted as a problem, successive chapters show the contrary. The purely supervised model obtained better performance figures than the model based on word embeddings because hand-crafted features were closer to the data, thus having a higher tendency to overfit. Other experiments in this chapter and the analysis of results showed that, in contrast, word embeddings are a good representation to reduce the model's tendency to overfit the training data. This is more strongly supported by evidence in Chapter 6, with experiments in a more general corpus.

Chapter 6 was the first to introduce a *joint learning* algorithm in which both the labeled and the unlabeled dataset contribute to the task of semi-supervised learning.

The chapter explores *self-learning*, a wrapper algorithm over a supervised classifier. In this scheme, the labeled dataset serves as an initial seed to train a base model for a classifier. This classifier is used to augment the information available in the model by automatically annotating new instances from an unlabeled dataset based on certainty and adding them as labeled instances to train a new model. This process is repeated iteratively to have more and more training examples taken from the unlabeled data. The experiments in this chapter explored how this new data affected the performance of the model. In particular, I wanted to see how the new data effectively increased the initial model with more information gathered from the new instances. This new information could help expanding the model's coverage. Adding new examples of a new dataset would also help the model prevent the tendency to overfit. However, what I found was that the expansion of the model's coverage was done at expense of the quality of the model. The self-learning algorithm had problems specially when dealing with a largely unbalanced dataset, that is, with a clearly majority class. This configuration is common in a task such as Spanish verb sense disambiguation, as well as for any natural language processingtask, because of the Zipfian distribution of natural language itself. Then, while more information seems to be added to the model, what is actually happening is that the model is drifting to classify new data almost exclusively as part of the most frequent class in the dataset. Then, the model did not actually expand its coverage, but it was just blurring the decision boundaries of the original supervised classifier. From this chapter however there was an important finding given by the general results and performance obtained with word embeddings. These last were proven to behave much better than hand-crafted features. They represented minority classes better, mitigating the drift to the majority class. As they are trained from a more general domain than hand-crafted features, they also dealt better with the change of domain given by the unlabeled instances the self-learning algorithm used to expand the supervised model.

Chapter 7 explored a second joint learning technique: *active learning*. Like self-learning, this is also al wrapper algorithm. It trains based on an initial seed and then adds examples from an unlabeled pool of available instances. These instances serve to augment the pool of labeled examples which are used to train a new model which is used again to fetch new data to add. The main difference between this algorithm and self-learning is the way the unlabeled dataset is annotated. In self-learning the annotation is automatic, and automatically annotated instances are included as training if the classifier has high confidence over the instance. In contrast, active learning uses a human (generally a domain expert) to annotate unlabeled examples selected in an "intelligent" way. This means instances should be those which, once annotated, have the largest impact on the new model, increasing its certainty or reducing error. The experimentation done for this chapter was merely exploratory, because the active learning approach is by itself an expensive method that requires manual annotation. However, results were promising enough to have some insights on how this method could help improve the task of Spanish verb sense disambiguation. The results of the

chapter were interesting because the model not only improved on the most frequent classes but also in the less frequent classes as well. Moreover, because of the algorithm's way to select instances for annotation, it did not suffer from the drifting to the most frequent class that self-learning showed. Indeed, active learning was shown to increase the model's information with less examples provided in comparison. But, as it requires a human annotator in order to work, active learning becomes an expensive approach for semi-supervised learning.

Finally, chapter 8 explored a fairly new semi-supervised learning technique: *the ladder network*. In this neural network, the architecture is designed to train the parameters by optimizing a cost function that is a combination of a supervised cost function and an unsupervised cost function. The neural network has an architecture that resembles that of an autoencoder, with an encoder and a decoder paths. The encoder path is given by a feed-forward neural network with an output layer that is trained by using a supervised cost function. The decoder path is used to reconstruct the training instances and thus helps smooth the neural network by avoiding overfitting to a small supervised dataset. In this model the unlabeled examples are not tagged and added to the model as in previous algorithms. Still, unlabeled instances still help to expand the coverage of the model as the information they provide is integrated to that of the labeled dataset. The experiments in this chapter explored the use of ladder networks as an alternative semi-supervised approach that overcomes the shortcoming of self-learning that adds new instances only as if they were part of the most frequent class. Also, the ladder network model overcomes the problem of active learning, that is, the cost of manual annotation. The results of the chapter were promising as the ladder network had good performance results, not only in the most frequent class but in all classes in general. Very often it surpassed the results obtained by a purely supervised approach or active learning. The use of unlabeled data to help training the model added more information which would help to expand the coverage of the model. Moreover, the model proved to be able to avoid overfitting as the unlabeled examples and the unsupervised cost function prevented the supervised part to overfit the labeled data. Ladder networks showed impressive results coming from a purely automatic process for semi-supervised learning and is a good candidate to keep exploring.

## 9.2 Future Work

The main obstacle through the experiments done in this thesis was the unbalanced dataset. The presence of a majority class which unbalanced the distribution of the classes is something common for a task in natural language processing. This unbalance had great impact in how the semi-supervised techniques could work their way in the task of Spanish verb sense disambiguation. As I saw in Chapter 6, the problem of unbalance, even if it was small at the beginning, can quickly grow and end up hitting on the algorithm's quality, making the final model useless. Unbalanced classes is a

problem on its own right, that I could not cover more thoroughly in this work. There are techniques, besides oversampling or undersampling, which help dealing with this kind of situations and that would require further exploration in future work. However, the best approach so far to deal with the problem of unbalance and bias to the most frequent class was given by active learning with uncertainty sampling, which by design would tend to add those instances the model had less information about, i.e. the less frequent classes.

The domain of the labeled corpus also had a great impact in the experiments and results I analyzed through this thesis. The labeled corpus was the base resource to work with in this thesis and as such the quality of the resource impacted directly on how good the models could be. It is important to note that as it was a heavily domain-based resource, it could also obscure some of the results, e.g. when it showed a better performance for the hand-crafted features than the word embeddings just because the latter generalized better. This put in consideration how I interpret the results: a model that shows a drop in performance in comparison to another model is not automatically a bad model. Sometimes there are other metrics and other views of the data that help identify what a model is leaving out in order to gain performance, for example, representativity of minority classes or better generalization to data from other domains. Also, the heavy influence on the domain showed the importance of having more heterogeneous data in order to seek a good model. Indeed, semi-supervised learning techniques, which acquired information from a corpus from a general domain, improved some aspects of the original model, which was too close to the labeled dataset.

The two main challenges tackled in this work were coverage, observed as the information actionable by the model, as well as tendency to overfit or generalize. These challenges were direct results of having a small amount of labeled data and such data being part of a very specific domain. Semi-supervised techniques were explored in order to overcome these two challenges. It is left for future work to carry out experiments that are more driven by the domain and see how the domain really affects the final results when exploring other domains. For example, it is interesting to explore how the use of unlabeled data from the same domain or a contrasting domain affects semi-supervised models.

With more resources available, some of the most important future work I have is the use of larger unlabeled corpora with different semi-supervised techniques. This ranges from training word embeddings with more corpora coming from different resources available online, to the use of more unlabeled training instances in the ladder network. For active learning, the manual annotation was done mostly by me with the help of my thesis supervisor, but it would benefit of a domain expert that could also work with more examples than the very little amount I could manage to annotate manually. Finally, I would like to do the analysis on more of the available lemmas, as due to time constraints I could only explore a small sample of all the available possibilities the area of Spanish verb sense disambiguation has to offer. With more

resources as well, I will also work on a more thorough error analysis of the experiments, specially those regarding overfitting and distribution of classes. I am most interested in seeing how semi-supervised models deal with the annotation of new examples by doing a manual evaluation on examples myself, specially for the cases of self-learning and ladder networks.

Finally, in a more technical approach, future work is left for exploring different combinations of the semi-supervised techniques such as the use of a combined algorithm between self-learning and active learning or moreover using a combination of one of the wrapper algorithms with the ladder network itself. In particular, the ladder network is a very promising approach that would require further exploration to tune its components. A line of future work would be to use the difference between the original corpus's distribution and the distribution of the predicted batch as a stopping criterion. Also, many of the hyperparameters can be modified trying to reach better performance of the algorithm in the task: from the denoising cost weights to the architecture of the encoder layer, also changing the combinator function given by the authors. Still, the most interesting line of work on ladder networks would be to check how they work by integrating a more complex neural network than just a plain multilayer perceptron. It would be interesting to see how a ladder network constructed over a convolutional neural network or a recurrent neural network can help the final performance of the models. In general terms, ladder networks, being the most novel approach studied in this thesis, gives ample room for improvement and exploration.

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