CROSS-LINGUAL WORD SENSE DISAMBIGUATION FOR LOW-RESOURCE HYBRID MACHINE TRANSLATION

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For my mother, Lenoir, who challenges me to be as great as she thinks I am.

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Alexander James Rudnick

CROSS-LINGUAL WORD SENSE DISAMBIGUATION FOR LOW-RESOURCE HYBRID MACHINE TRANSLATION

This thesis argues that cross-lingual word sense disambiguation (CL-WSD) can be used to improve lexical selection for machine translation when translating from a resource-rich language into an under-resourced one, especially when relatively little bitext is available. In CL-WSD, we perform word sense disambiguation, considering the senses of a word to be its possible translations into some target language, rather than using a sense inventory developed manually by lexicographers.

Using explicitly trained classifiers that make use of source-language context and of resources for the source language can help machine translation systems make better decisions when selecting target-language words. This is especially the case when the alternative is hand-written lexical selection rules developed by researchers with linguistic knowledge of the source and target languages, but also true when lexical selection would be performed by a statistical machine translation system, when there is a relatively small amount of available target-language text for training language models.

In this work, I present the Chipa system for CL-WSD and apply it to the task of translating from Spanish to Guarani and Quechua, two indigenous languages of South America. I demonstrate several extensions to the basic Chipa system, including techniques that allow us to benefit from the wealth of available unannotated Spanish text and existing text analysis tools for Spanish, as well as approaches for learning from bitext resources that pair Spanish with languages unrelated to our intended target languages. Finally, I provide proof-of-concept integrations of Chipa with existing machine translation systems, of two completely different architectures.

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CHAPTER 1
OVERVIEW

A thing with just one meaning has scarcely any meaning at all.

– Marvin Minsky, *Society of Mind* [2]

In this dissertation, I investigate techniques for lexical selection in machine translation, with the goal of supporting language pairs for which there is little training data available for the target language. I propose that cross-lingual word sense disambiguation (CL-WSD) is a feasible and practical means for lexical selection in this setting. I demonstrate this with translation experiments covering several language pairs, focusing on translating from Spanish to Guarani (a co-official language of Paraguay) and Spanish to Quechua (broadly spoken around the Andes mountain range), and including some experiments involving English.

I describe new CL-WSD approaches, including the use of unsupervised clustering on source-language text and multilingual corpora for the source language as a source of classification features. I also evaluate their effectiveness in practice. All of these techniques have been implemented in a new CL-WSD software system called Chipa[1]. We also integrate Chipa into two machine translation systems of different architectures to show its practical applicability.

The research presented here is motivated in large part to allow primarily rule-based machine translation (RBMT) systems to make use of any available bitext training data, so that they can improve their translations without their human authors having to write new rules. Despite the enormous success of statistical machine translation (SMT) approaches over the past twenty years, they typically require large bitext corpora to be useful. RBMT

[1]Chipa the software is named for chipa the snack food, popular in many parts of South America. It is a cheesy bread made from cassava flour, often served in a bagel-like shape in Paraguay. Also *chipa* means 'rivet, bolt, screw' in Quechua; something for holding things together. The software is available at `http://github.com/alexrudnick/chipa` under the GPL.

approaches remain attractive for many language pairs due to a simple dearth of training data, and there is an active RBMT community working on developing machine translation systems for the world's under-resourced and under-represented languages.

My hope for this work is that it will provide techniques and tools useful for anyone working on machine translation into these languages, whatever the architecture of their MT software, allowing them to make use of bitext as it becomes available for their language pair. This combination of strategies is what is meant by "hybrid" in this work. We would like to combine existing RBMT systems with statistical methods where possible, neither throwing away the efforts and insights of linguists, nor ignoring the benefits of machine learning and corpus-based approaches.

1.1 WSD in Machine Translation

To appreciate the word-sense disambiguation problem embedded in machine translation, consider for a moment the different senses of "have" in English. In *have a sandwich*, *have a bath*[2], *have an argument*, and even *have a good argument*, the meaning of the verb "to have" is quite different. It would be surprising for our target language, especially if it is not closely related, to use a single light verb in all of these distinct contexts. Even in a language as closely related as Spanish, we see these English expressions rendered with some different verbs: *tomar un bocadillo* ('have a sandwich') but *tener un argumento* ('have an argument'), for example. By cross-lingual word sense disambiguation (CL-WSD), I mean exactly this problem: we consider *tomar* and *tener* to be two different senses of *have* – there are certainly more, for a verb like *have* – and the CL-WSD software must label each source-language word with its correct translation.

Another concrete example, due to Annette Rios [3], surfaces when translating from Spanish to Quechua. Here we see different lexicalization patterns in Spanish and Quechua for transitive motion verbs. The Spanish lemmas contain information about the path of the

[2]Compare with "take a bath", which has an additional metaphorical interpretation meaning "serious financial loss"

movement, e.g. *traer* - 'bring (here)' vs. *llevar* - 'take (there)'. Quechua roots, on the other hand, use a suffix (*-mu*) to express direction, but instead lexicalize information about the manner of movement and the object that is being moved. Some of these verbs are as follows:

general motion verbs:

- *pusa-(mu-)*: 'take/bring a person'
- *apa-(mu-)-*: 'take/bring an animal or an inanimate object'

motion verbs with manner:

- *marq'a-(mu-)*: 'take/bring something in one's arms'
- *q'ipi-(mu-)*: 'take/bring something on one's back or in a bundle'
- *millqa-(mu-)*: 'take/bring something in one's skirts'
- *hapt'a-(mu-)*: 'take/bring something in one's fists'
- *lluk'i-(mu-)*: 'take/bring something below their arms'
- *rikra-(mu-)*: 'take/bring something on one's shoulders'
- *rampa-(mu-)*: 'take/bring a person holding their hand'

The correct translation of Spanish *traer* or *llevar* into Quechua thus depends on the object being moved, and more descriptive translations can be chosen, given context clues. Furthermore, different languages simply make different distinctions about the world. The Spanish *hermano* 'brother', *hijo* 'son' and *hija* 'daughter' all translate to different Quechua terms based on the person with respect to whom we are describing the referent; a daughter relative to her father is *ususi*, but when described relative to her mother, *warmi wawa* [4].

Chipa, then, must somehow make these distinctions automatically if it is to help translation systems generate valid Quechua. It is possible to do this with hand-crafted lexical selection rules, or by treating this as a machine learning problem and basing lexical selections on the available data, or by some combination of the two.

Lexical ambiguity presents a daunting challenge for rule-based machine translation systems. Several translations of a given word may all be syntactically valid in context. Even when choosing among near-synonyms, we would like to respect the selectional preferences of the target language so as to produce natural-sounding output text.

Writing lexical selection rules by hand, while possible in principle and an approach taken by many MT system implementors, is tedious and error-prone. Bilingual informants, if available, may not be able to enumerate the contexts in which they would choose one alternative over another, and there will be many thousands of words that might need to be translated in any given source language. Thus we would like to learn from corpora when possible.

Given a sufficient bitext corpus, we can discover the different possible translations for each source-language word, and by applying supervised learning, we can learn how to discriminate between them.

We do not have very large sentence-aligned bitext corpora for most language pairs. Conveniently, however, we can get started by using the Bible as training data; it contains many commonly used words and contains enough text for us to meaningfully train our systems. [3] In the future, we would like to see larger bitext corpora constructed for under-resourced language pairs by their respective communities. Our research group has been working on this problem in parallel, though that is not the focus of this dissertation.

The major contributions of this work will be new approaches for CL-WSD, demonstrations that they can be used in practice for translating from higher-resourced languages into lower-resourced ones, and demonstrations that they can be integrated into practical machine translation systems, thus improving word choice. Additionally, on a practical level we will develop a suite of reusable open-source software, including the CL-WSD engine and demo MT systems of different architectures for for Spanish-Guarani and Spanish-Quechua.

All of the software used in this dissertation has been developed in public reposito-

[3]The Bible has been translated into a substantial fraction of the world's languages and contains more than thirty thousand verses (roughly, sentences) in a variety of text genres. For an overview of using the Bible for multilingual NLP applications, please see Resnik et al. [5] and Mayer and Cysouw [6].

ries, and is freely available online at `http://github.com/hltdi` and `http://github.com/alexrudnick`.

1.2 Thesis Statement

Cross-lingual word sense disambiguation is a feasible and practical means for lexical selection in a hybrid machine translation system for a language pair with relatively modest resources.

1.3 Questions to Address

1. Can we use monolingual resources from the source language to improve accuracy on the cross-lingual word sense disambiguation task?
2. Can we use multilingual resources, such as bitext corpora pairing the source language with languages other than the current target language?
3. Which kinds of machine translation systems can benefit from CL-WSD?

1.4 Dissertation Structure

In the following chapters, I will discuss the relevant background information and investigate these questions, as follows.

- Chapter 2 gives some background on word sense disambiguation, its history, and its applications in machine translation, as well as on Spanish and Guarani, the languages of Paraguay, and some of the social context for this translation pair.
- Chapter 3 reviews some recent work on CL-WSD and its applications.
- Chapter 4 presents the data sets used in this work, and our evaluation metrics for this project.

- Chapter 5 discusses the basic architecture of the Chipa system and its performance on the previously presented evaluation metrics.
- Chapter 6 explores some approaches for learning from the available resources for Spanish to give us better representations for translating out of it.
- Chapter 7 expands our approaches to include the multilingual resources for Spanish, integrating CL-WSD classifiers for languages other than Guarani and Quechua.
- Chapter 8 presents practical applications of Chipa; here we will see how to integrate CL-WSD software into different running machine translation systems.
- Finally, in Chapter 9, we will conclude and describe possible work for the future.

1.5 Previously Published Work

This dissertation draws heavily from several previously published papers, in which my coauthors and I explore early versions of some of the ideas and techniques described here. They are as follows:

- Rudnick 2011, "Towards Cross-Language Word Sense Disambiguation for Quechua" [7], in which I explored a simple CL-WSD system for Quechua adjectives.
- Rudnick, Liu and Gasser 2013, "HLTDI: CL-WSD Using Markov Random Fields for SemEval-2013 Task 10" [8], a SemEval submission in which we explored the use of multilingual evidence for CL-WSD.
- Rudnick and Gasser 2013, "Lexical Selection for Hybrid MT with Sequence Labeling" [9], in which we explored using Maximum-Entropy Markov Models (MEMMS) for CL-WSD for Spanish-Guarani.

- Rudnick, Rios and Gasser 2014, "Enhancing a Rule-Based MT System with Cross-Lingual WSD" [3], in which we integrated Chipa into an RBMT system for Spanish-Quechua and explored monolingual clustering to learn from Spanish data.
- Rudnick, Skidmore, Samaniego and Gasser 2014, "Guampa: a Toolkit for Collaborative Translation" [10], which describes our system for building larger corpora through enlisting the Guarani-language activist community to help. Guampa, or at least the idea of engaging the language-activist and language-learning communities, figures largely into the future of this work, rather than having been helpful for data gathering as of yet.

CHAPTER 2
BACKGROUND

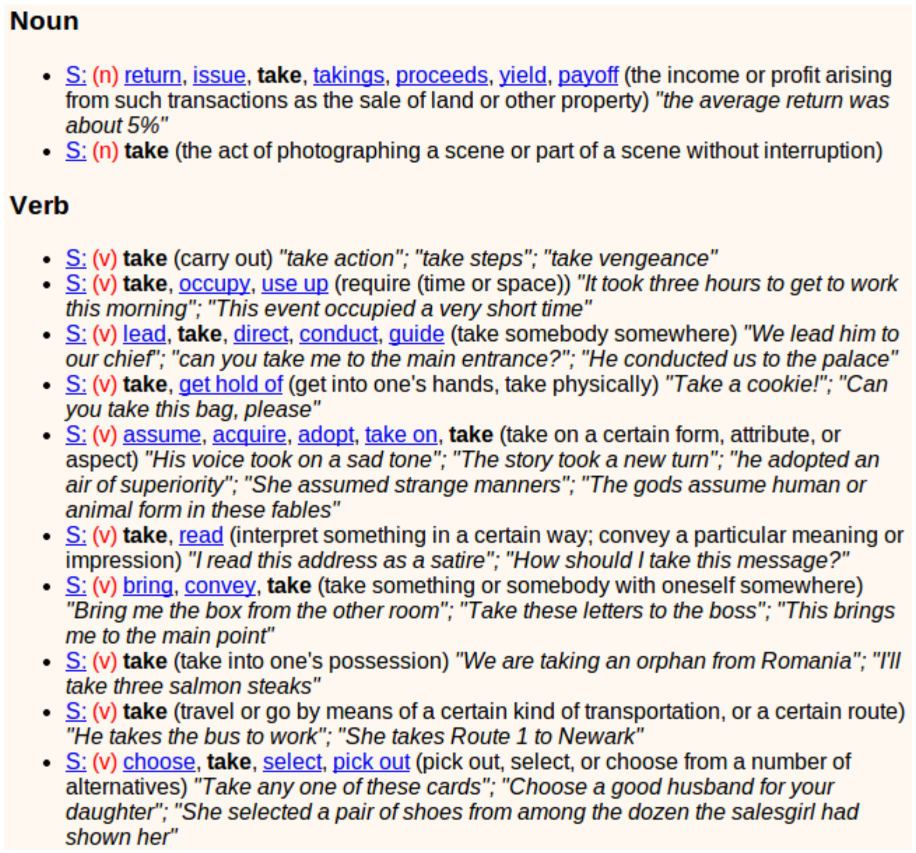
In this chapter, I will discuss some of the relevant background, including a short overview of word-sense disambiguation broadly, its history with respect to machine translation, and how the cross-lingual framing of WSD addresses some of the difficulties in successfully applying WSD techniques to MT. I also give a short description of the languages we would like to support with this work, Guarani and Quechua.

2.1 Word-Sense Disambiguation

Word types often – perhaps always – have many possible meanings. Given a string of characters or an utterance, the reader or listener must do some computational work to interpret the received message, and this may fail. In the simplest case, one could be faced with a homophone or homograph and need to distinguish between different lexemes that could be intended. There could be technical or jargon senses that conflict with colloquial uses of a word; consider the many different meanings of “kernel”, “type” and “kind” in computer science and mathematics. In the most difficult case, the usages can be hyperbolic, metaphorical, sarcastic, or oblique references. Understanding these usages will require understanding the broader discourse context and the goals of the speaker. Discourse modeling is outside the scope of this work, but in practice, for machine translation, we will need to get some sense of the particular meaning of polysemous words in context.

What we mean by word sense disambiguation is just this: when faced with a token in a piece of text, we want to be able to decide which *word sense* from a *sense inventory* is the intended meaning. The sense inventory might come from a pre-set ontology built by lexicographers, such as a dictionary or a wordnet[1], or it might have been discovered in some

[1]Such as WordNet®, the original wordnet for English [11]


Noun

- S: (n) return, issue, **take**, takings, proceeds, yield, payoff (the income or profit arising from such transactions as the sale of land or other property) *"the average return was about 5%"*
- S: (n) **take** (the act of photographing a scene or part of a scene without interruption)

Verb

- S: (v) **take** (carry out) *"take action"; "take steps"; "take vengeance"*
- S: (v) **take**, occupy, use up (require (time or space)) *"It took three hours to get to work this morning"; "This event occupied a very short time"*
- S: (v) lead, **take**, direct, conduct, guide (take somebody somewhere) *"We lead him to our chief"; "can you take me to the main entrance?"; "He conducted us to the palace"*
- S: (v) **take**, get hold of (get into one's hands, take physically) *"Take a cookie!"; "Can you take this bag, please"*
- S: (v) assume, acquire, adopt, take on, **take** (take on a certain form, attribute, or aspect) *"His voice took on a sad tone"; "The story took a new turn"; "he adopted an air of superiority"; "She assumed strange manners"; "The gods assume human or animal form in these fables"*
- S: (v) **take**, read (interpret something in a certain way; convey a particular meaning or impression) *"I read this address as a satire"; "How should I take this message?"*
- S: (v) bring, convey, **take** (take something or somebody with oneself somewhere) *"Bring me the box from the other room"; "Take these letters to the boss"; "This brings me to the main point"*
- S: (v) **take** (take into one's possession) *"We are taking an orphan from Romania"; "I'll take three salmon steaks"*
- S: (v) **take** (travel or go by means of a certain kind of transportation, or a certain route) *"He takes the bus to work"; "She takes Route 1 to Newark"*
- S: (v) choose, **take**, select, pick out (pick out, select, or choose from a number of alternatives) *"Take any one of these cards"; "Choose a good husband for your daughter"; "She selected a pair of shoes from among the dozen the salesgirl had shown her"*

Figure 2.1: Some of the WordNet 3.1 senses for "take": there are two noun senses and 42 distinct verb senses, though we only show the first ten. In WordNet and similar projects, word senses are called *synsets*, as there will be a set of synonyms that share the sense.

automatic way. Word-sense disambiguation tasks have historically been divided into two varieties, where *lexical sample* tasks require labeling occurrences of some small number of words types, and *all-words* tasks, in which every word in the input text must be labeled[12]. In NLP applications that must handle arbitrary text, this distinction breaks down somewhat, as the application will encounter previously unseen words for which there are no known senses in the ontology.

When making use of WSD for some other purpose – say in information retrieval, information extraction, or machine translation – choosing an appropriate sense inventory can be a difficult design task, as applications may require different granularities, while different lexicographers will have made their own editorial decisions about what constitutes a distinct sense of a word.

Treating WSD as a supervised learning problem requires labeled training data, which for this task means text where each token has been annotated with its appropriate sense identifier. Such corpora must be created manually specifically for this purpose, and this kind of annotation is very labor-intensive, especially when annotating data for an all-words WSD task, as the annotators must consider the many possible senses for each word, and new words will occur during the course of annotation.

Sense-annotated corpora have been created for supervised WSD for both the lexical sample and all-words settings, but they are only available for a few languages, due to the time and effort required to prepare them. Some famous sense-annotated corpora include the "hard/line/serve" corpus, originally prepared by Leacock et al. [13, 14], which marks occurrences of the adjective "hard", noun "line" and verb "serve" with their respective senses from WordNet.[2] These feature roughly four thousand annotated instances of each word. Larger lexical sample data sets [3] were prepared for the first three Senseval events [15, 16, 17] each of which featured thousands of instances of 35 to 73 different word types. For Senseval-2 and Senseval-3, verbs were labeled with senses from the WordSmyth online dictionary-thesaurus[4] rather than their senses from WordNet, as the WordNet sense distinctions for English verbs are very fine-grained, resulting in a very difficult task in the first Senseval. Larger corpora annotating word senses for many but not all content words include the sense-annotated portion of the American National Corpus [18], which provides a thousand annotated usages of a hundred individual word types, each checked by several annotators, with inter-annotator agreement data provided.

There have also been all-words annotated corpora, such as SemCor (described by Miller et al. [19] and developed by Landes et al. [20]), a large subset of the Brown Corpus with all content words manually annotated with their WordNet senses. "SemCor" is now often used as a generalized term for corpora tagged with senses from a wordnet; there are such corpora

[2]Available at `http://www.d.umn.edu/~tpederse/data.html`

[3]Archived at the same URL

[4]`http://www.wordsmyth.net/`

of varying sizes available for many different languages [5].

In order to ameliorate this WSD data acquisition bottleneck and allow WSD research to move forward in the absence of annotated training data, researchers have also created corpora with artificially-ambiguous “pseudo-words”, in which two distinct word types are merged into a synthetic new word, but the original word that was used is noted; for example, all occurrences of ‘shoe’ and “book” could be replaced with a synthetic token “bookshoe”. The original uses are then considered two senses of the new pseudo-word, and researchers can check whether their WSD algorithms can recover the original token.

Supervised learning approaches are by no means the only strand of research in WSD; there are also unsupervised word-sense induction approaches that try to discover senses automatically from corpora, knowledge-based algorithms that make use of hand-crafted resources such as dictionaries and wordnets to label tokens – such as, classically, the Lesk Algorithm [21], and more recently, graph-based algorithms that make use of the structure of very large knowledge bases, such as Babelfy [22] – and a host of others. For a broad overview of the different approaches to word senses, their disambiguation, and the history of the related techniques, please see Agirre et al.’s book on the topic [12].

It has long been held that word sense disambiguation is a central problem in NLP applications, including machine translation. Even in popular culture, the dangers of misunderstanding and thus mistranslating individual words is well-understood; many have heard the (apparently apocryphal [23]) story about an early MT system faced with the Biblical saying “the spirit is willing but the flesh is weak” in Russian and producing (variations on the story abound) “the vodka is good but the meat is rotten”. Warren Weaver described, in his prescient 1949 memorandum [24], both an essentially modern conception of WSD and why a translation system would need it.

As early as 1960, Yehoshua Bar-Hillel wrote that general-purpose machine translation

[5]For a list of such corpora, see `http://globalwordnet.org/wordnet-annotated-corpora/`. The English-language SemCor has been maintained and updated by Rada Mihalcea and is available at `http://web.eecs.umich.edu/~mihalcea/downloads.html`

("fully automatic high-quality translation", as it was called at the time) was impossible due to the insurmountable task of writing WSD routines for all source-language words. [25]

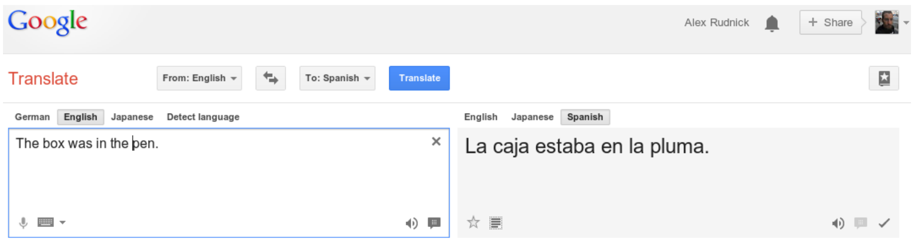
> During the past year I have repeatedly tried to point out the illusory character of the FAHQT ideal even in respect to the mechanical determination of the syntactical structure of a given source-language sentence... Here I shall show that there exist extremely simple sentences in English – and the same holds, I am sure, for any other natural language – which within certain linguistic contexts, would be uniquely (up to plain synonymy) and unambiguously translated into any other language by anyone with a sufficient knowledge of the two languages involved, though I know of no program that would enable a machine to come up with this unique rendering unless by a completely arbitrary and *ad hoc* procedure whose futility would show itself in the next example.
>
> A sentence of this kind is the following: *The box was in the pen.*

To produce a correct rendering of this sentence in Spanish, for example, the translation system must decide between translating "pen" as *corral* (an enclosure, like for an animal) or as *pluma* (the instrument for writing).

As of this writing, for this particular example, Google Translate picks the correct rendering, although in September 2013, it chose the less-sensible "in the writing implement" translation for Bar-Hillel's example sentence (see Figure 2.2).

One wonders how this could have come about – we would hope that the n-gram language model for Spanish would prefer sentences about things in enclosures to things in writing implements. But the word *en* can be a translation of either the English "in" or "on", and *pluma* can also mean "feather", so *en la pluma* will be attested in a large corpus of Spanish; we could easily imagine a sentence containing "on the feather". This situation is fairly complex.

In a translation task, even if we are able to assign a particular sense to a given word, we must still map these senses to translations in the target language, and there is no guarantee



The box was in the pen.

La caja estaba en la pluma.

Figure 2.2: Google Translate, September 17, 2013; interestingly, adding or removing the final period in the English sentence caused a switch between the "pluma" and "corral" renderings.

that senses identified by source-language lexicographers will map neatly to distinctions made by the target language.

2.2 Cross-Lingual Word Sense Disambiguation

This problem that Bar-Hillel identified as difficult, the one that arises in the apocryphal "spirit is willing" story, is a particular variant of word sense disambiguation that we here call *cross-lingual WSD* (CL-WSD). In a CL-WSD task, we want to label words or phrases in the input text with their contextually-appropriate translations in some target language. In this case the sense inventory for each word is defined as its possible translations. Typically, the possible translations are discovered automatically from a word-aligned bitext corpus, although a dictionary or other bilingual lexicon may also be used as source of possible translations.

This setting for WSD has an immediate application in machine translation, and in this case, it also neatly addresses the problem of choosing an appropriate sense inventory, which has historically been a difficult problem for the practical application of WSD systems [12]. The sense distinctions that the system should learn are exactly those that are lexicalized in the target language. CL-WSD also sidesteps the "knowledge acquisition bottleneck" hampering other work in WSD [26]. While supervised CL-WSD methods typically require bitext for training, this is more readily available than the sense-annotated text that would otherwise be required; Gale et al. suggested the use of sentence-aligned bitexts for WSD research as early as 1992 [27].

WSD applied directly to machine translation has a long history; practical work in integrating WSD with statistical machine translation particularly dates back to early SMT work at IBM [28]. Despite all of the ambiguities in translation, most statistical MT systems do not use an explicit WSD module [12, Chapter 3]; the language model and phrase tables of these systems mitigate lexical ambiguities by encouraging words used collocationally to appear together in the output. Entire phrases[6] such as verbs with their common objects may be learned and stored in the phrase table, and the language model will encourage common collocations as well. CL-WSD techniques have been successfully used to improve SMT, especially when it is applied not just to individual tokens but to phrases present in the phrase table, as in the work of Carpuat and Wu [29]; there have also been discriminative classifiers used to aid in selecting phrase table entries, as in the work of Žabokrtský et al. [30], which is a similar intuition, even if not described by the authors in terms of word-sense disambiguation.

This cross-lingual variant of WSD has received enough attention to warrant shared tasks at recent SemEval workshops: SemEval 2010 Task 3 [31] and SemEval 2013 Task 10 [32] were both classical cross-lingual lexical sample tasks. A similar task was also run in 2014 [33], although this task provides a target-language context rather than a source-language one, more closely representing the problem faced by an agent trying to help a second-language learner compose a sentence in their L2 than that faced by a machine translation system. Some approaches to the first two tasks, along with a number of other projects, are described in Chapter 3.

In general, there is a many-to-many relationship across language boundaries between words and their possible translations. This happens for a number of reasons: figurative or metaphorical uses may not translate directly, obligatory information in one language may be left unspecified in another, or the criteria for selecting a word may simply differ. To give some familiar examples, a "leg" of a trip in English is typically translated as *étape* in

[6]Not necessarily "phrases" in a syntactic sense, but subsequences of sentences

French, which is unrelated to limbs used for walking (see Figure 2.3 for a fuller view of the situation's complexity); translating "brother" to Japanese requires specifying whether the brother is older (*ani*) or younger (*otōto*); a soap bubble or a ceramic plate can be destroyed with the same word in Chinese, whereas English speakers distinguish between the verbs "pop" and "break" [34].

To take a look at some apparently easier examples, let us also consider the following usages of *letter*, from the test set of a recent SemEval shared task [32], and how to translate them into Spanish.

(1) But a quick look at today's *letters* to the editor in the Times suggest that here at least is one department of the paper that could use a little more fact-checking.

(2) All over the ice were little Cohens, little Levys, their names sewed in block *letters* on the backs of their jerseys.

We would want (1) to be translated with the word *carta*, and (2) to be translated with *letra* or something similar. Google Translate (as of this writing) handles both of these sentences well, rendering the first with "cartas" and the second with an even better choice, translating the phrase "block letters" as *mayúsculas*. However longer-distance relationships, search errors, or simple statistical accidents can still cause strange translations in practice.

2.3 Hybrid MT

Recently there has been renewed interest in machine translation systems that take into account syntactic structure, linguistic knowledge, and semantic representations, perhaps due to a perception that statistical approaches relying on flatter phrase-based representations and hierarchical representations not based on linguistic intuitions are reaching a performance plateau.

The boundaries between rule-based and statistical MT systems are becoming increasingly blurred, and hybrid systems are being developed in both directions, with RBMT systems

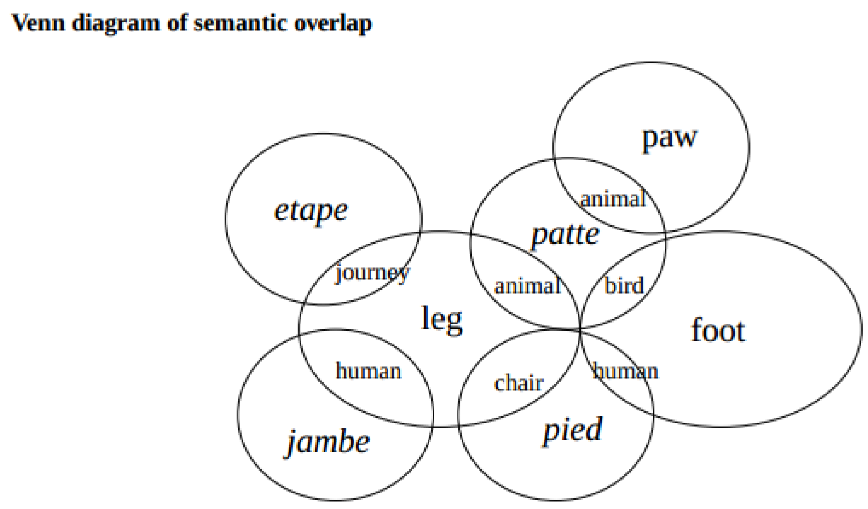


Figure 2.3: Overlap of words related to "leg"; relationships between English and French words. Figure 21.2 from [35]; example originally from [36, Chapter 6].

incorporating components based on machine learning, as well as SMT systems making use of linguistic knowledge for morphology and syntax. Rule-based components are especially applicable in cases where the language pair involves predictable reordering through syntactic divergences (as in the work of Collins et al. [37]) and in cases where one or both sides of the translation pair exhibits rich morphology; morphological analysis and generation software generally consists of hand-written rules in the form of finite-state transducers.

Additionally, for most of the world's language pairs, there is simply no large bitext corpus available, so training a purely statistical machine translation system is infeasible.[7] As such, RBMT approaches are still relevant for many language pairs, and there is a vibrant research community focused on building linguistically-informed primarily rule-based machine translation systems.

We would like for RBMT or hybrid systems, once developed, to be able to make use of any bitext resources that are available, or that become available later. Like SMT systems, they should be able to produce better translations as larger corpora are developed, without

[7]Techniques for learning from comparable corpora, such as translation spotting, are under development, and there has been some work on building sufficiently large bitext corpora through crowdsourcing, but these approaches have not yet reached wide adoption.

additional code changes: giving RBMT systems the ability to learn from available bitext resources is the main engineering goal for the Chipa software.

2.4 Paraguay and the Guarani Language

Guarani is an indigenous language spoken in Paraguay and the surrounding region. It is the historical native language of the indigenous Guarani people. The word for the Guarani language in Guarani is *avañe'ẽ* ("people's language", where *ñe'e* means "language").

Guarani is unique among indigenous American languages in that a substantial number of non-indigenous people speak it. The majority of Paraguayans are conversant in Guarani, although they are likely to be bilingual with Spanish. In practice, many Paraguayans use a combination of Guarani and Spanish called *Jopará*, which is the Guarani word for "mixture".

Paraguay is officially a bilingual, pluricultural country, as described by its famous *Ley de Lenguas* [8] ("Law of Languages"). However, the Guarani language is at a significant social and economic disadvantage and is typically not used in formal situations, as Spanish is considered more prestigious. There are, however, an engaged activist community, many Guarani-language educators, and a government agency devoted specifically to policy regarding language. The Guarani language figures significantly into a sense of Paraguayan national identity and history.

Guarani has a rich, polysynthetic, agglutinative morphology, in which roots can derive into different parts of speech, and often several roots can combine into a single word. Guarani morphology can mark tense, aspect (even on nouns), number, negation, and other features. However, unlike Spanish, it has no grammatical gender. Guarani's rich morphology can make many NLP tasks, including ones seemingly as simple as spell-checking, rather challenging.

We are in contact with a number of collaborators in Paraguay, including language activists and educators from the *Ateneo de la Lengua y Cultura Guaraní* [9] and the *Fundación Yvy*

[8] http://www.cultura.gov.py/lang/es-es/2011/05/ley-de-lenguas-n%C2%BA-4251/
[9] http://www.ateneoguarani.edu.py/

Marãe'ỹ [10], both of which are schools that offer training for Guarani-language translators. We have also been discussing plans with several local software developers, including members of the local One Laptop Per Child organization and the Secretariat of Language Policies. Our crowdsourcing and collaborative translation system [10] is currently under development with feedback from professors from the *Ateneo* and policymakers at the Secretariat.

2.4.1 Online Language Tools for Guarani

There are currently very few online language tools for Guarani; one of the largest available ones are iGuarani [11], a searchable online dictionary and gisting translation system developed by Paraguayan programmer Diego Alejandro Gavilán.

There is also a small searchable online dictionary developed by Wolf Lustig [12], which has versions in Spanish, German, and English. He has graciously made this dictionary available for our use; this could provide a fine starting point for a lexicon for Spanish-Guarani translation systems.

The Guarani activist and education community has a presence on the Web, although a startlingly large fraction of this presence is a single author, David Galeano Olivera, the president of the *Ateneo*. He has collected a number of resources, written in Spanish and Guarani, about the Guarani language and the culture surrounding it. [13]

2.5 Quechua

Quechua is a group of closely related indigenous American languages spoken in South America, particularly around the Andes mountain range. There are many dialects of Quechua spoken throughout the region, which have varying degrees of mutual intelligibility.

For the experiments in this work, we focus on the Cuzco dialect, spoken in and around the Peruvian city of Cuzco. This choice is primarily for compatibility with the SQUOIA machine

[10]`http://yvymaraey.org/`
[11]`http://iguarani.com/`
[12]`http://www.uni-mainz.de/cgi-bin/guarani2/dictionary.pl`
[13]`http://cafehistoria.ning.com/profiles/blogs/la-lengua-guarani-o-avanee-en`

translation system, which can translate from Spanish into this dialect. Cuzco Quechua has about 1.5 million speakers and some useful freely available language resources, including a small treebank [38], bilingual dictionaries (such as one published by the Quechua language academy [4]), and morphological analysis and generation software.

Quechuan languages also feature rich morphology. Particularly unfamiliar to speakers of European languages may be evidentiality; Quechua words (of various parts of speech, not only verbs [39]) can carry information about how a speaker came to know the information contained in a sentence: whether it was directly observed, personally inferred or doubtful, or whether it is hearsay. The Chipa software does not directly try to predict evidential markers, but a machine translation system targeting Quechua will have to contend with this feature of the language.

CHAPTER 3
RELATED WORK

In this chapter, I will review some of the recent related work, including techniques for CL-WSD considered as a task on its own, the application of classifiers to lexical selection in various machine translation architectures, techniques used in recent runnings of the SemEval task on CL-WSD, and some relevant approaches for word-sense disambiguation more broadly. The Chipa software and the work described in the rest of the dissertation draws heavily from ideas described here; how particular ideas have been influential will be highlighted as we get to them.

3.1 CL-WSD *in vitro*

Some of the related work on CL-WSD has studied the CL-WSD task in isolation, without being embedded into a machine translation system or other NLP application, such as cross-language information retrieval (CLIR).[1] It is sensible to explore CL-WSD on its own for several reasons. Firstly, even if our motivation for developing CL-WSD is to improve machine translation output, from an engineering perspective, we still want to get a sense of how well the individual components of our pipeline are functioning. Furthermore, if the MT pipeline is relying on a CL-WSD system to help it with lexical selection, one expects that improved disambiguation accuracy will result in better translations overall – though of course in complex software, unexpected interactions may occur.

[1] CL-WSD has broader applications aside from its clear use in lexical selection for MT. When retrieving documents in some target language based on a source-language query, we might want to first disambiguate the user's query with respect to target-language terms.

3.1.1 Multilingual Evidence for CL-WSD

One of the most interesting CL-WSD systems of recent years, which inspired our use of multilingual evidence in Chipa, is ParaSense [26], developed by Els Lefever and colleagues.

ParaSense uses memory-based learning to predict target-language translations of individual source-language words in a lexical sample task. It starts with features that one would expect for a text classification problem: the surface forms, POS tags, and lemmas for the focus word and the tokens in a small window around it, as well as some syntactic information from a chunk parser. But ParaSense also includes bag-of-words features for translations of the input sentence into languages *other* than the target language. ParaSense handles translation from English into French, Spanish, Italian, Dutch and German, so for example when translating from English to French, it includes bag-of-words features extracted from the translations of the English sentence into Spanish, Italian, Dutch and German (but not French).

Given corpora that are parallel over many languages, such as Europarl, this is straightforward at training time. However, at testing time it is faced with a novel sentence for which it has no translation. Here ParaSense requires a complete MT system for each of the four other languages: it generates a translation into the other four languages. When ParaSense was being developed, it simply called out to the Google Translate API (which is, as of this writing, no longer available gratis) to generate the bag-of-words features required for test sentences. This seems unwieldy and arguably detrimental to reproducible research: it benefits from whatever techniques Google Translate uses for word choice, which are not necessarily discussed with the public, and will change without warning over time.

Critiques aside, ParaSense posted excellent results. When applied to the SemEval 2010 CL-WSD task test data (described in [31]), it outperformed all of the systems submitted for that task for nearly all of the target languages, being outperformed, by a small margin, for one system when targeting Spanish [26]. A later version, described in Lefever's dissertation, outperformed all of the SemEval systems.

In our earlier work, we prototyped a system that addresses some of the issues with ParaSense [8]; these ideas are developed further in Chapter 7. Chipa requires neither a locally running MT system nor access to an online translation API for its feature extraction, but still learns from several mutually parallel bitexts that share a source language.

3.2 WSD with Sequence Models

To my knowledge, there has not been work that explicitly frames all-words CL-WSD as a sequence labeling problem, other than our earlier application of MEMMs to Spanish-Guarani [9]. However, machine translation systems, and especially statistical machine translation systems, address this problem implicitly – jointly along with other problems – when they use language models to encourage coherent word choices in the generated text. The decomposition of SMT systems into a translation model and a language model allows LMs to be trained on very large target-language corpora. In contrast, in our earlier work on CL-WSD with sequence models, we only trained on sentence-aligned bitext.

There have, however, been some uses of sequence models for monolingual WSD; in this setting, systems can find an assignment disambiguating the entire input jointly. Molina et al. [40] have described the use of hidden Markov models for WSD, situating all-words WSD as a tagging problem. They also used this approach in a Senseval entry [41] in the English all-words task at Senseval-3, where it posted results towards the middle of the pack.

Ciaramita and Altun [42] frame both coarse-grained WSD and information extraction as a tagging problem, using a discriminative variation of HMMs trained with perceptrons [43] to map nouns and verbs in the input text onto one of 41 “supersenses”, a small ontology developed by Ciaramita and Johnson.

While it is not explicitly about sequence models, there is a related research program underway in the world of graph-based algorithms for knowledge-based word-sense disambiguation, exemplified by the work of Moro et al. [44]; they perform word-sense disambiguation and entity linking jointly, searching for a globally coherent solution to both problems.

3.3 Lexical Selection in RBMT

A purely rule-based approach to lexical selection – a more declarative version of the special-cased disambiguation procedures that Bar-Hillel imagined as futile – has been tried in many cases, with variants in both direct and interlingual RBMT systems. In one recent example, Bick presented a Danish-English RBMT system with purely rule-based lexical selection [45]. The Dan2eng system includes roughly $17,000$ individual Constraint Grammar rules for lexical selection alone, over 70% of all of the rules written. Development took over two years, and Bick suggests that statistical models (including target-language LMs) might be used in the future to avoid having to cover all the idiosyncrasies of lexical transfer. A similar approach, though not with the same enormous number of lexical selection rules, was taken by Brandt et al. [46], with their Apertium-based Icelandic-English MT system.

Francis Tyers, in his dissertation work [47], develops a practical approach for improving lexical selection for the Apertium RBMT system when parallel corpora are available. As he describes in [48], his software learns finite-state transducers for lexical selection from parallel corpora. His dissertation expands on this, additionally learning, via maximum entropy, weights with which different rules can be applied in different contexts. He also describes experiments in which linguists wrote lexical selection rules with the framework. Having human linguists write rules in this formalism can improve MT output to an extent, but seems tedious, as it took a full day's work for a linguist to write 156 rules, and this only covered lexical selection for 3% of the thousand-sentence test corpus.

In this formalism, translations are selected via rules that can reference the lexical items and parts of speech surrounding the focus word; when a rule fires, it selects a translation. These rules are stored in an XML encoding, so that they can be examined, modified, or written from scratch by human linguists, but are then compiled to compact finite-state transducers for speedy application.

Tyers' system is intended to be both very fast, for use in practical translation systems, and to produce easily human-interpretable lexical selection rules, for modification by linguists. It is currently in use for some language pairs in the Apertium project.

3.4 CL-WSD for Statistical Machine Translation

While the idea has, for the most part, fallen by the wayside in recent years,[2] some of the earliest work on statistical machine translation at IBM included an explicit WSD module [28]. Brown et al. considered the senses of a word to be its possible translations, explicitly distancing their work from other WSD efforts that focused on dictionary senses. The WSD module described in the 1991 paper used binary classifiers similar to decision stumps. Each focus word was allocated a single classifier, which could check a single feature, e.g., the identity of the nearest noun to the right of the focus word. These simple classifiers would then bias the decoder to choose a translation from one of two classes of target-language translations, which often significantly reduced the decoder's uncertainty. The inclusion of WSD improved the translation output markedly; the authors deemed 45 of the output sentences "acceptable" with WSD enabled, over only 37 without it. Later versions of IBM's CANDIDE system included a more sophisticated disambiguation system: contextually-tuned translation models based on maximum entropy modeling for the most common words in the source language [50].

The idea of training classifiers on source-language context to help lexical selection is an attractive one, and has resurfaced several times in the SMT literature. However, by the early-to-mid 2000s, phrase-based SMT techniques [51], which translate short coherent chunks of text rather than individual words and thus often get correct word choice "for free", seemed to make WSD modules unnecessary. Work by Cabezas and Resnik [52] and early attempts by Carpuat and Wu [53] cast doubt as to whether phrase-based SMT systems, or even word-based SMT systems trained on large data sets, could benefit from WSD; Cabezas and

[2]There are a number of papers on the topic, but for the past decade or so, the "standard" model of phrase-based SMT has not included WSD as a component. There are a just three paragraphs on the topic in Koehn's book on SMT [49, §5.3.6], and the major open-source SMT systems have not enabled WSD modules by default.

Resnik, though expressing enthusiasm for future developments, did not manage to improve translation performance with WSD, and initially (in 2005) Carpuat and Wu argued that SMT could be considered a generalization of word-sense disambiguation. Vickrey et al. [54] noted that lexical selection to translate phrases as units would be important for applications in MT, though they did not implement it in their work on the topic.

Not long thereafter, Carpuat and Wu showed how to use classifiers to improve modern phrase-based SMT systems with a series of papers on the topic [29, 55, 56, 57]. In this work, they show that in order for phrase-based SMT systems to benefit from classifiers for lexical selection, the system should do *phrase*-sense disambiguation, rather than word sense. This is to say, the classifiers should be used to select the translations of source-language phrases from the corresponding target-language phrases, better matching the model used by the rest of the pipeline. Here Carpuat and Wu use an ensemble of classifiers, including naïve Bayes, a maximum entropy model, an Adaboost classifier, and a nearest-neighbor model in which feature vectors have been projected into a new space with a kernel and PCA has been performed to reduce dimensionality. They used features based on local word context, some syntactic features, and the position of the focus phrase in the sentence. Their classifiers interact with the decoder by modifying the phrase table just before decoding, adding features usable by the decoder's log-linear model. This approach outperformed the earlier attempts in which individual words had been labeled either with senses from some sense inventory or with target-language translations; they posted significant improvements for Chinese-English SMT on a variety of test sets and metrics.

There have been a number of related efforts in the SMT world recently. Gimpel and Smith [58] build phrase table entries in which the probabilities of target-language phrases are conditioned not only on the source-language phrase, but also on features extracted from the broader source-language context; their approach is "omnivorous" in that it can include any number of features based on source-language analysis. They tune feature weights directly with MERT (Minimum Error Rate Training [59], a widely used optimization technique from the SMT literature) to produce a linear model for the contextual probability of the target-language phrase. Features used here include the n-grams in the surrounding context, the parts of speech of the focus word and the surrounding context, a number of syntactic features based on a parse of the input, and the focus phrase's approximate position in the sentence.

Mauser et al. [60] present a similar approach, although in their work they model translations of individual words independently, rather than using phrases from the phrase table, and their classifiers consider input sentences as sets of words. They argue that phrase-based SMT models are already good at predicting sequences, and many of the signals that might trigger a different word choice, especially in their source language, Chinese, can be placed freely in the input text. They also include a probability model similar to IBM Model 1 [61], but conditioned on two source-language words rather than one. Like IBM Model 1, this model is trained with Expectation-Maximization.

Žabokrtský et al. [30] use discriminative MaxEnt models to adapt the "forward" translation model probabilities in an SMT system based on dependency grammars. While it has much the same effect, this work does not describe itself in terms of word sense disambiguation.

Recently, Tamchyna et al. – a team that notably includes Marine Carpuat – have integrated CL-WSD software into the popular open source Moses SMT system [62]. This approach does not use one classifier per source phrase, as had been done in Carpuat's earlier work, but one enormous classifier for all known source words, trained with the Vowpal Wabbit (VW) machine learning toolkit. This approach allows generalizations to be learned across different source-language phrases, which might be otherwise lost. The software is designed for speed and is significantly faster than earlier architectures, they report.

3.5 WSD for lower-resourced languages

Scaling WSD techniques to new languages is a particularly thorny issue; the resource acquisition bottleneck presents a problem even for English. The problem is alleviated somewhat when we are interested in supervised CL-WSD, with its reliance on bitext rather than sense-annotated corpora.

There has been some work on using WSD techniques for translation into lower-resourced languages. Špela et al. [63] discuss applying WSD to machine translation for the English-Slovene language pair, using a graph-based WSD system and the linked Slovene wordnet to disambiguate English words to aid in Slovene lexical selection.

Dinu and Kübler [64] presented work on monolingual WSD for Romanian. They use memory-based learning for classification, with a small number of contextual features. With all of its features included, the system substantially outperformed the "most frequent sense" baseline, but adding a feature selection step caused a significant further improvement.

In other work on lower-resourced languages, Sarrafzdadeh et al. develop a version of the Extended Lesk algorithm for Farsi [65], Lesk algorithms (due to early work by Michael Lesk [21]) being a knowledge-based approach to WSD that relies on dictionaries, counting the occurrences of words that occur in a particular sense's dictionary definition; there have been many variations on this theme.

One point that should be made about this dissertation is that it is ultimately not about word-sense disambiguation for an under-resourced language. Here we are focusing on WSD for Spanish, for which we have very large data sets and a number of good NLP tools. While our sense inventory happens to be extracted from bitext corpora where the other languages involved are under-resourced, the decisions to be made are about the meanings of Spanish words.

3.6 CL-WSD at Senseval and SemEval

There have been many related Senseval and SemEval shared tasks, covering different variations on cross-lingual WSD.

Senseval-2 featured a Japanese Translation Task [66], in which Japanese words were to be labeled with their most appropriate English translations from the provided translation memory (TM); the task thus combined aspects of word sense disambiguation and example-based machine translation.

At Senseval-3, there was an English-Hindi translation task [67], in which participants were to label a lexical sample of English words with their Hindi translations. Here the gold standard translations were created collaboratively online, using the Open Mind Word Expert software developed by Chklovski and Mihalcea, but the set of possible translations were extracted from a bilingual dictionary. There were two subtasks provided; in the more general subtask, systems were provided with unannotated text in English. For the "translation-and-sense" subtask, the provided text was previously-used Senseval-2 data, already annotated with its WordNet senses. These annotations provided a significant boost to classification accuracy for the participating systems.

In SemEval 2007, there were two related tasks covering translation between English and Chinese. Task 5 [68] was a lexical sample task in which Chinese texts were manually annotated with English translations from a predefined dictionary, and participants had to predict these labels. Task 11 [69], in contrast, had its training and test data gathered from automatically word-aligned parallel corpora, and the direction of translation was from English to Chinese.

In the 2010 and 2013 SemEval CL-WSD tasks [31, 32], both organized by Lefever and Hoste, participants were asked to translate twenty different polysemous English nouns into five different European languages (Dutch, French, German, Italian and Spanish), given their containing source-language sentence as context. There were no explicit bilingual dictionaries provided as sense inventories; the possible target-language labels were those found in Europarl [70] through automatic word alignment, though they were lemmatized by hand. The test set was manually annotated with the appropriate (lemmatized) translations from the sense inventory for each of the five target languages.

Most recently, for SemEval 2014, there was a variant on the CL-WSD task: the Writing Assistant task [33]. In this setting, rather than complete source-language sentences, short source-language text segments were included in nearly complete target-language sentences, representing the task faced by an agent assisting a writer trying to compose sentences in a second language but facing gaps in their vocabulary.

3.7 Translation into Morphologically Rich Languages

Both Guarani and Quechua feature rich morphology, which means that the space of possible output tokens in these languages is quite large. In order to build a complete MT system targeting these languages, one needs a means to predict the appropriate morphological features and synthesize correctly inflected words, either starting from lemmas and modeling the inflection process, or simply by concatenating pieces of words during decoding. This problem is large, difficult, and related to the problem of CL-WSD, but we consider it out of scope in this work. For completeness, here we will quickly mention some of the work on morphological prediction and generation for statistical and hybrid MT systems.

Koehn and Hoang describe *factored* phrase-based SMT models for predicting target-language morphology [71]. In this kind of approach, instead of having one translation model containing surface forms, there can be several different translation models. As a basic strategy, they suggest having separate models for the translation of lemmas and another for translating parts-of-speech and morphological features. This approach allows the MT system to learn more generalized models, both for the translation of lemmas and for mapping the morphological features of the source language to the target. Yeniterzi and Oflazer [72] describe an application of this model for SMT on English-Turkish. They situate their work in terms of the earlier strategy of considering Turkish inflectional and derivational morphemes as "words" to be handled by the SMT system as normal and then recombined in a post-processing step, which would sometimes fail when the morphemes were not generated in the correct order. Contrastingly, their factored model produces Turkish lemmas, then finds the relevant inflectional features based on English syntax.

Toutanova et al. describe another technique for generating rich morphology in SMT [73].

In their model, they consider inflection prediction separately from the task of producing the target-language text. One version of their system produces fully-inflected text, which may be changed by their inflection-prediction system; the other produces uninflected target-language text, relying on the morphology prediction. In either case, the morphology of all of the target-language lemmas is predicted with a Maximum Entropy Markov Model (MEMM), a discriminative sequence prediction model that can take into account both any features extracted from the analysis of the source sentence and its own previous morphology predictions. They apply this model to both English-Russian and English-Arabic translation, posting improvements for both phrase-based and tree-based SMT.

Chahuneau et al. have recently presented yet another method for SMT into morphologically rich languages [74]. Here they also use discriminative models to predict target-language inflections based on the available source-language annotations, but instead of inflecting the text after the decoder has been run, their system generates new phrase-table entries with the appropriate inflections included, just before the decoder executes, allowing the decoder to optimize for many concerns jointly, informed by the language model. Their software is described in more detail in Schlinger et al. [75], and has had an open-source release.

CHAPTER 4
DATA SETS, TASKS AND EVALUATION

In this chapter, I describe the tasks and data sets that we will investigate for the rest of the dissertation, so that we can measure performance in selecting translations for our source-language lexical items. In order to evaluate our CL-WSD approaches and their effects on translation quality, we will need to have a basis for comparison between our proposed techniques and sensible baselines, including results reported by other researchers. Here we cover some *in vivo* and *in vitro* approaches for evaluating CL-WSD systems, then we characterize the corpus that we have available for the language pairs of interest.

As discussed in Section 2.1, for many years word sense disambiguation systems have been evaluated *in vitro* and in a monolingual setting. The test sets for such WSD evaluations include sentences hand-annotated with a word senses from a particular sense inventory, such as, typically, the WordNet senses. These monolingual WSD evaluations often include both coarse-grained and fine-grained distinctions and allow for several possible correct answers; some word senses identified by lexicographers are more closely related than others. While the senses in a sense inventory will contain many useful and interesting distinctions, they do not necessarily make the distinctions most appropriate for a given task, which will vary by application. As such, accuracy improvements on these tasks do not necessarily lead to performance gains for an NLP system making use of word-sense disambiguations [76].

This style of evaluation relies on a fairly scarce resource: sentences hand-annotated with a particular sense inventory. In the CL-WSD setting, where we consider target-language lexical items to be the salient senses of source-language words, we could also ask annotators to hand-label each word of our test sentences with their translations. For many language pairs, however, this annotation task has nearly been performed by translators: the available bitext allows us to find the translations of source words within the corresponding target-language sentence.

4.1 Measuring CL-WSD Classification Accuracy

One straightforward *in vitro* approach for evaluating a CL-WSD system is to measure classification accuracy over pre-labeled data. Here by classification accuracy, we mean measuring how often the system is able to correctly choose an appropriate translation for the focus word in a given context. Strictly speaking, for this application, we do not have pre-labeled data: our bitext does not come with sub-sentential alignments. But automatic word alignments provide a good approximation, as long as our sentence alignments (or verse alignments, for Bible text) are accurate. For the purposes of this work, we will assume that the automatic word-level alignments are correct, putting in our best effort at preprocessing the available text so that the aligner can produce useful output. This allows us to infer the labels for source tokens – their translations into the target language – with high confidence.

Using our automatically-aligned bitext as labeled data allows us to closely mirror the lexical selection task faced by an MT system while translating running text. We can train classifiers for many different word types, but we will generally not have training examples available for all words in the input at test time. This is a problem faced by data-driven NLP systems broadly.

For comparison with other work, in Section 5.2 we run our systems on the SemEval CL-WSD shared task test sets, which are publicly available. Our larger task here is framed in the same way as the CL-WSD shared tasks from 2010 and 2013, so measuring performance on these test sets allows a straightforward comparison between the variations explored in this work and several other CL-WSD systems from recent years. These test sets are limited in scope, however, and will only demonstrate Chipa's performance for translating individual English nouns. These comparisons are interesting in part because they show the strength of the "most frequent sense" baseline – simply returning the most common translation in the training data for a given focus word. Many of the posted results in the 2010 and 2013

SemEval competitions did not pass this bar; due to Zipfian distributions of words, the most common lexical items in the target language are quite common. In that section we can see how Chipa is situated among other recent CL-WSD systems on a that particular task, translating English nouns, but this cannot be the whole of our evaluation for Chipa; our more general goal for Chipa is to support MT from Spanish into lower-resourced languages.

4.2 Measuring MT Improvements

We will additionally want to conduct *in vivo* evaluations of our CL-WSD techniques as applied to running MT systems. Here we can use standard approaches for evaluating MT, such as BLEU and METEOR scores, or simply show that where word choices differ with the application of CL-WSD, the changes are for the most part improvements. For these experiments, we sample sentences from the available bitext – particularly sentences that contain polysemous words for which we can train classifiers – and run the MT systems both with and without the CL-WSD software enabled.

We want to make the argument that improved classification accuracy on CL-WSD tasks leads to improved translation results. But in general, the addition of CL-WSD has not been an overwhelming success in statistical machine translation, especially when we have large corpora available for language modeling [29]. It seems intuitive that a classifier producing correct word choices would lead an MT system to produce better results. But we do not have a system that always indicates correct word choices, nor are we likely to have one in the near future. And it is an empirical question, whether the suggestions made by the CL-WSD system, imperfect as they are sure to be, will improve translation results. We could imagine gains failing to materialize, for example, if the CL-WSD system's correct choices are mostly those that the MT system would have made on its own, say with the guidance of a language model and phrase-table probabilities. We could imagine its incorrect choices being misleading to the point of doing harm to our translation quality, or even correct CL-WSD choices causing other cascading errors, perhaps by surprising the language model.

These experiments are described in more detail in Chapter 8, where I also discuss how to integrate Chipa into the different machine translation packages.

4.3 Data Sets and Preprocessing

The largest corpus that we have available for all of our source and target languages is the Bible. There are translations available for many different languages, and while these were not always produced by native speakers, the translators are often driven by missionary zeal to produce high-quality translations [5], so we can be reasonably confident of the (linguistic) accuracy of our text.

In this work, we focus on one Bible translation per language. For Spanish, we use the Reina-Valera translation (1995 edition), which I was able to scrape from a Bible study website. Our Guarani translation, *Ñandejara Ñe'e* (1997 edition) was scraped from the same site. Our Quechua version (the 2004 translation published by the Peruvian Bible Society) was provided by Chris Loza and Rada Mihalcea; the preparation of the Quechua corpus is described in Loza's masters thesis [77]. For English, we use the public domain World English Bible translation. While there are a large number of translations available online, different "Bible societies" often own the associated copyrights and thus redistribution of the complete texts is often restricted [6].

4.3.1 Source-side annotations

In order to gracefully include a variety of features and build on any available analysis tools for the source language, Chipa's input format and feature functions allow for arbitrary annotations on source-language tokens.

Chipa's input file format describes one token per line, with fields split by tabs. The first field of a line is a token's lemma, and the second field is its surface form. Following this are an arbitrary number of annotations for that token, which may encode information such as part-of-speech, dependency relations, or similar. Any arbitrary features that we think

```
the The pos=DET
quick quick pos=ADJ
brown brown pos=ADJ
fox fox pos=NOUN
jump jumped pos=VERB
over over POS=ADP
the the POS=DET
lazy lazy POS=ADJ
sleep sleeping POS=VERB
dog dog POS=NOUN
. . POS=.
```

Figure 4.1: Example annotated sentence.

could be helpful can be added here; these annotations will typically be derived from external NLP tools such as taggers or parsers, or come from unsupervised methods; exploring these possibilities is the focus of Chapter 6. Sentence boundaries are indicated by blank lines. An annotated sentence with one annotation per token might look like Figure 4.1, for example.

The Chipa software has been developed with a number of tools that consume and produce this format, typically taking in sentences annotated in this way, calling another NLP tool to generate more annotations, and then adding the new annotations to those already present. The experiments in this chapter only use one of these tools, `freeling_to_annotated.py`, which produces Chipa's input format given output from Freeling[78], a suite of text analysis tools that supports a variety of European languages, notably Spanish. In the following chapters, we will make use of these tools and the extra information they make available to our classifiers; in Chapter 6 we add annotations learnable with monolingual resources, and in Chapter 7 we describe tools and annotations that require parallel data.

4.3.2 Preprocessing

There is a nontrivial amount of preprocessing required in order to get our Bible text into a format suitable for our tools. This is largely due to the varying markup formats used by different translation publishers. For each of the available translations, we need to understand its formatting enough to know which text comes from which book, chapter, and verse number.

This triple uniquely identifies a unit of text, and verse numbers are nearly standardized across translations. There are a few exceptions, however: translations produced by different religious traditions may include different books. Most notably, Catholic editions have a superset of the books found in modern Protestant editions, and include slightly different chapters. Additionally, in some translations, such as our Guarani edition, a few verses have been combined into a single segment for a more natural translation.

In any case, if a particular book/chapter/verse is present in two Bibles, then the two verses are very likely translations of one another. Once we find all of the matching verses, we can build a bitext corpus suitable for use in our pipeline. In all four of our translations, we find all 66 books of the Protestant Bible. Furthermore, we find matches for nearly all of the verses across all of the language pairs considered. For English/Spanish and Spanish/Quechua, the intersection of book/chapter/verse tuples across Bibles contains over 99% of the verses in any given Bible. For the Guarani translation, however, we are only able to match 95.2% of the verses. The Guarani text contains fewer verses, $29,867$ versus the $31,104$ in Spanish, showing that the translators were more willing here to combine verses and that the translations may be more interpretive. To filter out matched text where different amounts of material have been combined into the same verse number, we additionally use a sentence-alignment tool; see Section 4.3.4 for details.

Our English translation is distributed in a format called USFM (Unified Standard Format Markers), which is a markup language developed by a working group of Bible translators and used widely by the Bible-related software community; see Figure 4.2 for some sample input text in this format. [1] While there are a number of tools that consume USFM, I did not find one that handles our particular use case of stripping metadata and simply mapping from verses to flat text, so I wrote a short script, `parse_usfm.py`, to parse USFM and produce

[1]See `http://paratext.org/about/usfm` for more about USFM. USFM is widely deployed; the website from which we scraped the Spanish and Guarani corpora appears to render its HTML from a USFM source. There is an entire community of Bible software developers, and it has a wing that advocates Open Source software and translations unencumbered by copyright. One could delve arbitrarily deeply into the history of religious-text translators and their relationships with technology and copyright, but one has an NLP dissertation to write.

text in an easily-alignable format.

Our Spanish and Guarani corpora are extracted from HTML pages scraped from an online Bible study website. In practice, the scraping was done by predicting the URLs for each chapter of each book and requesting those URLs programmatically. We then extract the text from the saved HTML pages with a Python script and the BeautifulSoup library for HTML parsing. [2] As a side note, since websites change over time and we downloaded the Guarani translation at an earlier date (from a mobile version of the site that is no longer available), the HTML takes a significantly different structure in the Spanish and Guarani editions, so they require different versions of the script for preprocessing; see Figures 4.4 and 4.5 respectively for representative Spanish and Guarani input.

Our Quechua translation came in an easily parseable format, with individual verses already identified by Loza and Mihalcea; for this corpus, relatively little preprocessing was necessary since lines begin with the book, chapter, and verse already labeled. See Figure 4.3 for a sample of the input format. It is conceivable that there are inconsistencies introduced by the text-extraction processes for these different data sources, but for the most part the scripts seem reliable, since they result in approximately the same number of verses and tokens for our different languages, and the great majority of the sentences are alignable (see subsequent discussion on bitext alignment). Additionally, hand inspection of the text for the languages that I can personally read (English and Spanish) show that the text contains fairly close translations, and loan words and similar named entities appear in the Quechua and Guarani texts.

Each of the different formatting schemes uses its own encoding to identify the different books of the Bible, so when producing output for alignment, we must map to a standard encoding. For example, our Quechua edition marks the book of Lamentations with the numerical code 31 (it is the thirty-first book in modern Catholic editions), but in the USFM markup for the English translation, we find a header with the string "Lamentations". For

[2]`http://www.crummy.com/software/BeautifulSoup/`

```
\id LAM 25-LAM-web.sfm World English Bible (WEB)
\ide UTF-8
\h Lamentations
\toc1 The Lamentations of Jeremiah
\toc2 Lamentations
\toc3 Lam
\mt2 The
\mt Lamentations
\mt2 of Jeremiah
\c 1
\p
\v 1 How the city sits solitary,
\q2 that was full of people!
\q She has become as a widow,
\q2 who was great among the nations!
\q She who was a princess among the provinces
\q2 has become a slave!
\b
\q
\v 2 She weeps bitterly in the night.
\q2 Her tears are on her cheeks.
\q Among all her lovers
\q2 she has no one to comfort her.
\q All her friends have dealt treacherously with her.
\q2 They have become her enemies.
```

Figure 4.2: The first two verses of the Book of Lamentations (World English Bible translation) in USFM format.

```
[999,31,1,1] ¡Ay, imaraqmi Jerusalenqa sapan kapushan, haqay hina
  askha runakunayoq llaqta! ¡Ay, imaraqmi viuda warmi hina kapushan,
  lliw suyukunaq uman kashaqqa! Mit'anipina llank'apushan, lliw
  llaqtakunaq ñust'an kashaqqa.
[999,31,1,2] Tutan-tutanmi unuy-parata waqayku- shan, uyapas
  p'aspay-p'aspallaña. Llapan munaqninkunamanta manan hukllapas kanchu
  sonqochay- kuqnin. Llapan reqsinakuq-masinkunapas manan rikuqpas
  tukupunkuchu, llapallanmi awqanman tukupunku.
```

Figure 4.3: The first two verses of the Book of Lamentations in Quechua, from the 2004 Peruvian Bible Society translation. Whitespace changes added here for readability.

```
<div id="reader" class="content text_ltr">
  <a name="1"></a>
  <a href="/bible/more/Lam.1.1"
     style="color:black;text-decoration:none">
    <h2>El profeta </h2>
    <span class="verse" id="Lam_1_1">
    <strong class="verseno">1</strong>
    &nbsp;¡Pobrecita de ti, Jerusalén! <br />
    Antes eras la más famosa <br />
    de todas las ciudades. <br />
    ¡Antes estabas llena de gente, <br />
    pero te has quedado muy sola, <br />
    te has quedado viuda!  <br />
    ¡Fuiste la reina de las naciones, <br />
    pero hoy eres esclava de ellas! <br /> <p> </p></span>
  </a>
  <a name="2"></a>
  <a href="/bible/more/Lam.1.2"
     style="color:black;text-decoration:none">
    <span class="verse" id="Lam_1_2">
  <strong class="verseno">2</strong>
    &nbsp;Olvidada y bañada en lágrimas <br />
    pasas todas las noches. <br />
    Muchos decían que te amaban, <br />
    pero hoy nadie te consuela. <br />
    Los que se decían tus amigos <br />
    hoy son tus enemigos. <br />
    <p> </p></span>            </a>
```

Figure 4.4: The first two verses of the Book of Lamentations, *Traducción en Lenguaje Actual* (TLA) version, in HTML as scraped from the web. Whitespace changes added here for readability.

```
<div class="ltr" data-abbreviation="gdc" data-reference="lam.1.gdc"
     data-usfm="LAM.1" id="version_primary">
    <div class="version vid66 iso6393nhd" data-vid="66"
         data-iso6393="nhd">
        <div class="book bkLAM">
            <div class="chapter ch1" data-usfm="LAM.1">
                <div class="label">1</div>
                <div class="s">
                    <span class="heading">Ñembyasy Jerusalén oñehundi
                    haguére</span>
                </div>
                <div class="q1">
                    <span class="content" />
                    <span class="verse v1" data-usfm="LAM.1.1">
                        <span class="label">1</span>
                        <span class="content">Ajépa ha'eño
                        ajejuhu</span>
                    </span>
                </div>
                <div class="q1">
                    <span class="verse v1" data-usfm="LAM.1.1">
                        <span class="content">upe táva
                        guasuete,</span>
                    </span>
                </div>
    ...
```

Figure 4.5: The beginning of the Book of Lamentations in Guarani, *Ñandejara Ñe'e* version, in HTML as scraped from the web. Whitespace changes added here for readability. Note the metadata included here, suggesting that the HTML is generated programmatically from an underlying USFM document.

our Spanish and Quechua editions from the web, we find the code “LAM” in the markup. In any case, we map each of these identifiers to a single code “Lam”, so that we can match books, chapters and verses across translations.

4.3.3 Lemmatization

For each of our languages, whether on the source or target side, in addition to lowercasing and verse-alignment, we extract the lemmas (the citation forms, normalized with respect to inflection) from each surface word. Especially when working with smaller data sets and morphologically rich languages, this is an important step, since it provides a small amount of abstraction over the surface forms. Working primarily with lemmas rather than surface-form words allows us to group, for example, the plural form of a word with its singular. Dedicated morphological analysis software provides the necessary knowledge for mapping from the (potentially complex or irregular) inflected forms to their associated lemmas.

For English and Spanish, we use the FreeLing suite of NLP tools [78] to extract lemmas. FreeLing provides a variety of analyses, including tokenization, sentence splitting, multi-word expression and named entity detection, part-of-speech tagging and parsing. We start out using just a few of these tools – initially only tokenization and lemmatization. We discuss making use of more of them in Chapter 6, leveraging the quality NLP tools that we have for our resource-rich source languages. While it is a more pressing problem in more morphologically rich languages, there are examples of morphological ambiguity in English and Spanish. A familiar example from Spanish is that *ir* 'to go' and *ser* 'to be' sharing their preterite-tense forms. However, the FreeLing analysis tools can typically resolve these ambiguities for us[3], and in this work we assume that the Freeling output is correct, or at least correct enough to be useful for our purposes. In effect, we here assume that this kind of ambiguity – ambiguities about the appropriate lemma for a given token – are satisfactorily

[3]FreeLing performs morphological analysis jointly with part-of-speech tagging. Concretely, the token *fue* is given the tag `VSIS3S0` if it is deemed to be an inflection of *ser*, and the tag `VMIS3S0` for an inflection of *ir*. Here the ‘S’ stands for “semiauxiliary”. See `http://nlp.lsi.upc.edu/freeling/doc/tagsets/tagset-es.html` (page in Spanish) for more on the tagset used by FreeLing for Spanish.

resolved before the CL-WSD system itself comes into play.

The use of FreeLing for English is a noted improvement over initial experiments, which used NLTK's WordNet lemmatizer and default part-of-speech tagger [79]; these tools do not, as distributed, support Spanish. The WordNet lemmatizer has a fairly small vocabulary, did not provide a good strategy for dealing with unknown words, and could only address nouns, verbs, and adjectives. There are a very large number of named entities in the source text, most of which are not present in WordNet. It cannot, by itself, help us know that "Zebulonites" is the plural of "Zebulonite". 37% of the tokens in our English translation of the Bible are not present in WordNet; and many of these tokens are function words and named entities. In any case, these words can often carry inflection.

For Guarani and Quechua, we use Michael Gasser's ParaMorfo and AntiMorfo analyzers.[4] Guarani text is analyzed with ParaMorfo 1.1, and Quechua with AntiMorfo 1.2. These packages are based on software originally developed for Ethiopian Semitic languages [80], and use cascades of finite-state transducers (FSTs), which is a common approach in morphological analysis [81]. ParaMorfo and AntiMorfo use weighted FSTs to handle long-distance dependencies between morphemes, but rather than having weights correspond to probabilities to be combined with multiplication, the FSTs are weighted with feature structures that are combined via unification. This approach was originally introduced by Amtrup [82]. In an FST weighted with feature structures, the result of a successful traversal is the unification of the feature structure "weights" on the traversed arcs, as well as an output string. All possible paths through the FST are searched, though many of these paths will not lead to accepting states, or will fail due to unification conflicts. Because a feature structure is accumulated during the process of transduction, each traversal through the transducer retains a memory of where it has been, permitting the incorporation of long-distance constraints such as those relating the negative prefix and suffix of Guarani verbs.

Here the result of morphological analysis of a word is a root and a feature structure

[4]Prof. Gasser's morphology software for Guarani, Quechua, Spanish, and other languages is available at `http://homes.sice.indiana.edu/gasser/plogs.html`

- Quechua: *Llapan munaqninkunamanta manan hukllapas kanchu sonqochay- kuqnin.* is analyzed by AntiMorfo as `llapan munaqninkunamanta ma/mana huk/huklla ka/kanchu sonqochay - kuqnin`. *manan* here could be an inflection of *ma* 'certainly' or *mana* 'no, none'. Similarly with *huk* 'one, another one' / *huklla* 'only, lonesome, single' and *ka* 'yours' / *kanchu* (a kind of bird).
- Guarani: *Upe che ro'o ha upe che pire ombyaipa, umi che kãngue omopẽmba.* is analyzed by ParaMorfo as `upe che so'o ha upe che pire ombyaipa , umi che kã mopẽ/pẽ .` . Here *omopẽmba* is ambiguous, and could be an inflection of *mopẽ* 'to break (something)' or *pẽ* 'to break (oneself)'.

Figure 4.6: Examples of morphological ambiguity in Quechua and Guarani, having been run through AntiMorfo and ParaMorfo. The Quechua text is the first sentence of Lamentations 1:2; the Guarani is Lamentations 3:4.

representing the grammatical features of the word. For the basic version of Chipa, we are only concerned with the lemmatized forms of the words in our corpora, so we ignore the grammatical features for now. In cases of morphological ambiguity, which is to say cases where a surface form could be an inflection of multiple distinct lemmas, we maintain this ambiguity rather than trying to disambiguate from context. The different possible lemmas are separated by a slash; there are examples of this in Figure 4.6. ParaMorfo and AntiMorfo, for many cases, treat verbs with derivational affixes as lemmas in their own right; here for simplicity we include both versions of the lemma[5].

4.3.4 Alignment

As a precaution against verses that are not close translations, or perhaps have combined several parts of the text together into one verse on only one side, we run the cdec [83] filtering tool (`filter-length.pl`) with its default settings, which checks for unusual length disparities in the bitext. This ends up removing roughly 7% of the verses[6], but manual inspection shows that those verses removed are in general very loose translations, or that

[5]For example, in Guarani, *ahechauka* 'I show (cause to see)' contains the causative suffix *-uka*. In this case we treat both *hechauka* 'show' and *hecha* 'see' as lemmas (Gasser 2016, personal communication).

[6]Specifically, length filtering removes 7.12% of the verse pairs for Spanish-English and thus English-Spanish, 6.69% for Spanish-Guarani, and 6.72% for Spanish-Quechua.

additional material is present on one side.

Having tokenized, lowercased, verse-aligned and lemmatized, our corpora, we are ready to extract word-level alignments. For this we use the `fast_align` tool from cdec [83], with its default settings[7] and the lemmatized text as input. `fast_align` runs several iterations of Dyer et. al's alignment algorithm, which is a variant of IBM Models 1 and 2, and was shown to provide both relatively fast training times and good results for downstream MT systems [84]. It improves on Model 1 by encouraging diagonal alignments, rather than Model 1's simplistic view that any token in the source might just as well be aligned to any token in the target, and on Model 2 in having fewer parameters to fit. In any case, it is the default aligner for use with cdec. `fast_align` produces the single most likely one-to-many word alignment for each verse, such that each source language token is linked with zero or more target-language tokens in the corresponding verse. For a visualization of `fast_align`'s output, see Figure 4.7.

4.3.5 A deeper dive: producing Spanish-Guarani bitext

To get a concrete idea about the process of producing our bitext and our annotated source corpus, we will now step through the bitext production process for our Spanish-Guarani language pair. For the precise process, please see the source code [8].

We consider the "raw materials" for this process to be the scraped Spanish and Guarani bibles; see Figures 4.4 and 4.5 for examples. In order to replicate this work, or to extend it to more languages, one will have to acquire bitext covering one's preferred language. There are translations in many different languages available on various Bible websites, however.

The result of the scraping process is a directory full of HTML files, the raw HTML that was served by the Bible websites. For the sites that we scraped, each chapter is served as an individual HTML file. From these HTML files, we must extract the flat text of all of the available Bible verses. We do this with the `get_verses.py`, a tool that uses BeautifulSoup

[7]With the command given at `http://www.cdec-decoder.org/guide/fast_align.html`
[8]`https://github.com/alexrudnick/terere/tree/master/bibletools`

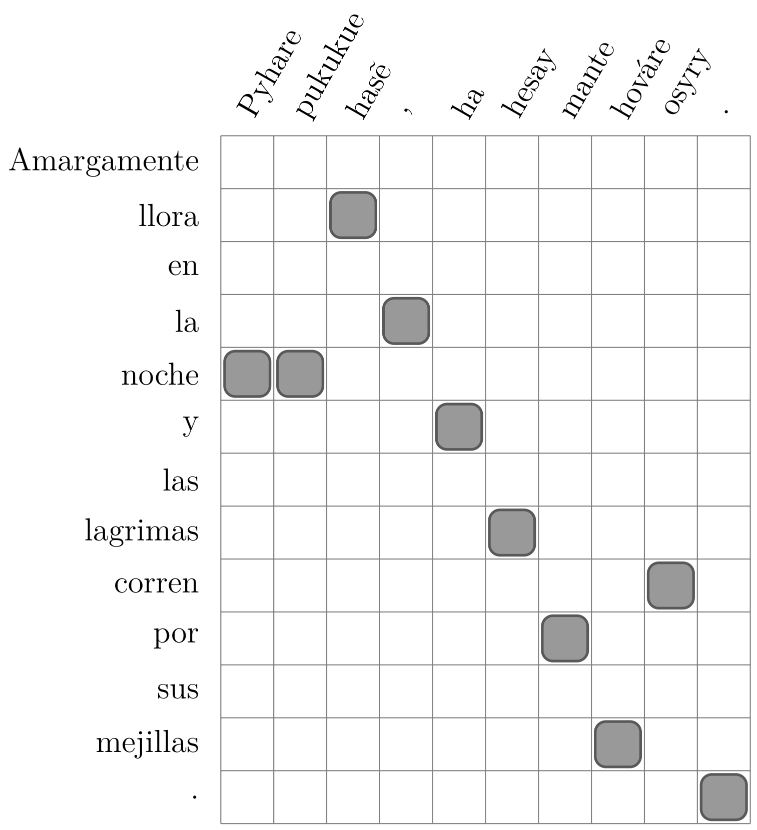


Figure 4.7: A sample word alignment. The beginning of Lamentations 1:2, mapping from Spanish to Guarani. Alignment produced with `fast_align`.

(3) He put the wood in order, and cut the bull in pieces, and laid it on the wood. He said, “Fill four jars with water, and pour it on the burnt offering, and on the wood.”

(4) Preparó la leña, cortó el buey en pedazos, lo puso sobre la leña,

Figure 4.8: Segments filtered due to length disparity. Our English and Spanish versions of 1 Kings 18:33.

to parse the input HTML and navigate its structure, extracting the verse identifiers and verse text as it goes. We call the output of `get_verses.py` a “Bible file”; it consists of tab-separated values, one per line, in which (book, chapter, verse) tuples are paired with the text of those verses.

We then call the `print_bitext.py` on pairs of Bible files. This script finds matching verses (book, chapter, verse tuples) and produces bitext files in the format expected by the cdec alignment tools, which is simply source-language segments and target-language segments, separated by `|||`. The output of `print_bitext.py` is called `bible.es-gn.unfiltered`, which contains some non-parallel ”sentences” and is untokenized. Individual sentences have not been preprocessed at all.

We then run a script from cdec, `filter-length.pl`, which filters out segments where either side is too long, or where there is a large disparity in length between source and target text, which indicates input segments that are not close translations. After this filtering step, we have selected the bitext from which we will train Chipa. See Sentences 3 and 4 for an example of a pair of segments that is filtered by this step. This is 1 Kings 18:33, and the beginnings of these segments clearly have the same meaning; for the Spanish translation, though, the material in the second sentence of the English text has simply been moved into the subsequent verse (1 Kings 18:34) for whatever reason.

Given the sentence-aligned bitext corpus, which contains only the subset of the source and target Bibles that we were able to verse-align (roughly, “sentence align”, in more common MT terms, though a verse need not be a single sentence), we now want to preprocess the source text to produce the annotated version used for training. We call cdec's `cut-corpus.pl` to select just the source side of the bitext, in this case the Spanish. Then we call Freeling to do basic analysis on the input Spanish text: it provides tokenizing (for example, splitting out punctuation adjacent to words), lemmatizing and tagging [9]. Then we run a Python script, `freeling_to_annotated.py`, to convert the FreeLing output format into Chipa's source-language input format.

Now on the target language side, we do something analogous, although less analysis of the target text is required, and Freeling does not support our target languages. We again use `cut-corpus.pl` to select just the target side, in this case the Guarani, and cdec's `tokenize-anything.sh` and `lowercase.pl` to tokenize and lowercase the Guarani text. Then we run Chipa's lemmatizer script over the Guarani text. It calls the ParaMorfo morphological analyzer on the Guarani tokens, producing Guarani lemmas. In cases of morphological ambiguity, we produce tokens that maintain that ambiguity, simply joining the possible lemmas with a slash. Once lemmatization is complete, we have produced the target-language lemmatized text.

Then we join together each line of the source-language lemmatized text with its corresponding target-language lemmatized text, using cdec's `paste-files.pl` script. The output of this is the sentence-aligned, tokenized, lowercased, lemmatized bitext corpus, which is ready for word alignment. To generate the word alignments, we call cdec's `fast_align` tool.

After all of this preprocessing and alignment, we have produced three files of interest to Chipa: first, we have the lemmatized bitext corpus. Second, we have the one-to-many word alignments between the two sides of the bitext. These two files taken together constitute the ground truth for the Chipa system – the source lemmas, and the subsequences of the target text that are considered to be their translations. Note that these alignments could be NULL – a source word could correspond with an empty subsequence of target-language tokens. At test time, we will want to predict those translations, whatever they happen to be.

[9]See the checked-in Freeling configuration file for the exact settings used: `https://github.com/alexrudnick/terere/blob/master/bibletools/freeling-config/es.cfg`

The third file contains the annotated version of the source text, which includes all of the information of the source side of the preprocessed bitext, in addition to the original surface forms and the annotations extracted from FreeLing analysis. Further annotations can be added by other tools; in general, annotated source-language corpora could contain whatever kinds of signals we might like to add to aid classifiers in predicting translations. In Chapter 6, for example, we discuss features learnable with monolingual resources such as part of speech tags, Brown clusters, and embeddings learned with neural networks. In Chapter 7, we discuss features that require parallel corpora, such as CL-WSD predictions into languages other than the current target language. But in all of these cases, the additional features are passed to the classifiers via this corpus-annotation approach.

4.4 Exploring the Bitext

Even using only the Bible as bitext, we find a substantial number of training examples for many of the most common word types, which, due to the Zipfian distribution of word types in most texts, constitute a significant fraction of the tokens exhibited. The most common lemmas and surface forms found in the source text are shown in Figures 4.9 and 4.10, but here we see that the most common few dozen types cover the majority of the text, though they are likely, as we will discuss later, to exhibit substantial ambiguity.

Once we skip past stop words, we also see that some of the most common word types in the text are proper names (place names, personal names, names referring to God) or exhibit very few translations in the target language, but for the most part we see, through the aligned bitext, that the most common words are polysemous. To take a few salient examples from the Spanish-English aligned text, the verb *hacer* can translate in a number of different ways: 'do', 'make', 'cause'; for *decir*, we must choose between 'say', 'tell' or 'speak'; *mujer* can mean either 'wife' or 'woman'; and *reina* can translate to 'reign' or 'queen'.

In the English-Spanish direction, we see that the 'be' can be translated as either *ser* or

lemma type	count	percentage of corpus	cumulative percentage
el	66151	9.91	9.91
de	45671	6.84	16.75
y	30370	4.55	21.30
a	23684	3.55	24.85
que	18992	2.84	27.69
en	14309	2.14	29.83
su	11861	1.78	31.61
ser	11856	1.78	33.39
haber	9205	1.38	34.76
no	7624	1.14	35.91
se	6942	1.04	36.95
decir	6565	0.98	37.93
todo	6415	0.96	38.89
por	6360	0.95	39.84
jehová	6204	0.93	40.77
lo	6181	0.93	41.70
uno	5822	0.87	42.57
con	5549	0.83	43.40
para	5544	0.83	44.23
hijo	5344	0.80	45.03
tu	4862	0.73	45.76
él	4424	0.66	46.42
hacer	4372	0.65	47.08
mi	4116	0.62	47.70
este	4052	0.61	48.30
estar	3993	0.60	48.90
le	3874	0.58	49.48
dios	3730	0.56	50.04
como	3257	0.49	50.53
porque	3088	0.46	50.99
pero	2965	0.44	51.43
tierra	2841	0.43	51.86
yo	2779	0.42	52.28
rey	2714	0.41	52.68
sobre	2584	0.39	53.07
ellos	2450	0.37	53.44
hombre	2417	0.36	53.80
me	2381	0.36	54.15
te	2363	0.35	54.51
dar	2301	0.34	54.85
tener	2289	0.34	55.20
israel	2193	0.33	55.52
día	2101	0.31	55.84
entonces	2019	0.30	56.14
casa	2010	0.30	56.44
cuando	1961	0.29	56.74
pues	1940	0.29	57.03
pueblo	1924	0.29	57.32
ni	1807	0.27	57.59
si	1685	0.25	57.84

Figure 4.9: Word ranks versus fraction of Spanish Bible tokens covered, for lemmas.

estar[10]. The English verb 'have' can be translated as *haber* (an auxiliary verb in Spanish, very much like the 'have' in "I have often thought..."), or as *tener* ('to have (something)'). Notably 'shall' is typically translated as NULL, since Spanish can form a future tense with a verb conjugation rather than an auxiliary verb. In the English text, when we see 'woman', this is usually translated as *mujer*, although *esposo* (in the text, surely *esposa* – morphological analysis normalizes to masculine gender) is also seen.

There are analogous lexical ambiguities when translating from Spanish to Guarani and Quechua. For example, the Spanish *pueblo* 'town' or 'people' can translate into Quechua

[10]This distinction is often somewhat vexing to second-language learners of Spanish; both verbs roughly correspond with 'to be' in English, but *ser* is generally for more permanent states of being, rather than the more fleeting *estar*. The particularities are fairly idiomatic.

surface word type	count	percentage of corpus	cumulative percentage
de	45671	6.84	6.84
y	29944	4.49	11.33
el	27483	4.12	15.44
a	23684	3.55	18.99
que	18992	2.84	21.83
la	18021	2.70	24.53
los	16236	2.43	26.97
en	14309	2.14	29.11
no	7624	1.14	30.25
su	7115	1.07	31.32
se	6942	1.04	32.36
por	6360	0.95	33.31
jehová	6204	0.93	34.24
con	5549	0.83	35.07
para	5544	0.83	35.90
las	5523	0.83	36.73
lo	5132	0.77	37.50
sus	4748	0.71	38.21
dios	3489	0.52	38.73
él	3401	0.51	39.24
tu	3373	0.51	39.74
como	3257	0.49	40.23
es	3235	0.48	40.72
mi	3103	0.46	41.18
porque	3088	0.46	41.64
un	3041	0.46	42.10
pero	2965	0.44	42.54
yo	2779	0.42	42.96
tierra	2744	0.41	43.37
hijos	2665	0.40	43.77
sobre	2585	0.39	44.16
le	2570	0.38	44.54
dijo	2471	0.37	44.91
rey	2397	0.36	45.27
me	2381	0.36	45.63
te	2363	0.35	45.98
ellos	2205	0.33	46.31
israel	2193	0.33	46.64
hijo	2190	0.33	46.97
todos	2166	0.32	47.29
todo	2157	0.32	47.62
ha	2141	0.32	47.94
entonces	2019	0.30	48.24
cuando	1961	0.29	48.53
pues	1940	0.29	48.82
casa	1836	0.28	49.10
ni	1807	0.27	49.37
una	1805	0.27	49.64
pueblo	1691	0.25	49.89
si	1685	0.25	50.15

Figure 4.10: Word ranks versus fraction of Spanish Bible tokens covered, for (case-insensitive) surface forms.

as *llaqta* 'town/city', or *runa* 'person'. For translating from Spanish to Guarani, we see the verb *volver* 'turn/return/repeat' translated as *jey* 'again', but also as *jere* 'turn'.

Figures 4.11 and 4.12 give the most common lemmas, after stopword removal, used in our corpus for the four languages, along with their counts. In Figure 4.13, we see common lemmas from Spanish along with their most likely translations into English, Guarani and Quechua (as extracted from the bitext). For the purposes of this work, we will consider words to be in-vocabulary for disambiguation if they appear at least fifty times in the training corpus; we also do not include punctuation marks and stopwords (as defined by the default NLTK stopword lists for English and Spanish) other than common verbs.

As an approximation of the difficulty of the classification task we face when addressing these ambiguities, we can take a look at the entropy of the possible translations for various source word types. One bit of entropy corresponds to a choice between two a priori equally likely options. For example, if a given source word can be translated in four different ways, and they are all equiprobable, this will be two bits of entropy. Of course in practice, some translations will be much more common than others.

Some concrete examples of Spanish-language words with their entropy scores from the source text are presented in Figure 4.14; a few words, such as *dios* and *pueblo*, seem straightforward to translate into English. Here we have less than 1 bit of uncertainty about the translation a priori. But verbs often used in idiomatic expressions like *hacer* and *poner* introduce much more uncertainty. Some of these numbers are higher than they would be without the morphological analysis process normalizing gender; here both *hijo* 'son' and *hija* 'daughter' have been normalized to the masculine form. Lemmatization here does introduce some apparent ambiguity, but it pools the evidence from the various surface forms into the training data for a single classifier for that lemma, allowing us to take into account similarities between the usage of, for example, *hijo*, *hija*, *hijos* and *hijas*. But a classifier with access to the surface form will have an easier job than the entropy value suggests.

The values in this table are calculated with the familiar formula for entropy; the entropy

rank	word type	count
1	be	23549
2	1	9445
3	have	9439
4	say	6281
5	yahweh	5721
6	shall	4382
7	come	3652
8	god	3641
9	man	3629
10	go	3221
11	son	3149
12	do	2814
13	king	2735
14	make	2367
15	israel	2269
16	day	2221
17	people	2061
18	one	2041
19	give	2031
20	house	2013
21	child	1927
22	take	1870
23	hand	1801
24	land	1770
25	father	1708
26	may	1688
27	bring	1489
28	also	1472
29	thing	1400
30	let	1383
31	many	1362
32	know	1362
33	speak	1334
34	us	1318
35	behold	1305
36	city	1243
37	therefore	1215
38	word	1193
39	even	1149
40	like	1108
41	hear	1097
42	servant	1085
43	name	1063
44	see	1056
45	away	1004
46	place	1003
47	david	979
48	great	947
49	among	940
50	lord	936

rank	word type	count
1	ser	11399
2	haber	8848
3	decir	6442
4	jehová	5961
5	hijo	4626
6	hacer	4228
7	estar	3862
8	dios	3590
9	tierra	2666
10	rey	2567
11	hombre	2310
12	dar	2247
13	tener	2207
14	israel	2074
15	día	2019
16	entonces	1984
17	casa	1928
18	pues	1885
19	pueblo	1835
20	si	1669
21	vosotros	1632
22	ver	1602
23	así	1568
24	venir	1539
25	mano	1463
26	padre	1421
27	poner	1414
28	ir	1302
29	delante	1264
30	señor	1200
31	ciudad	1184
32	aquel	1171
33	palabra	1075
34	oír	1059
35	tomar	1046
36	hablar	990
37	cosa	983
38	poder	968
39	hermano	962
40	responder	920
41	salir	920
42	mujer	920
43	david	915
44	saber	898
45	siervo	862
46	volver	860
47	lugar	847
48	sacerdote	822
49	sino	821
50	nombre	816

Figure 4.11: Some of the most common (lemmatized, non-stopword) word types in our English and Spanish Bibles

of the set of possible translations (of a given source-language term) X is the sum, over all individual translations x, of the negative log-probability of that translation, weighted by its probability.

$$H(X) = -\sum_x p(x) \log_2 p(x)$$

Using larger bitexts, once they become available, will allow us to construct training and test sets for a broader vocabulary, and with better statistical support for the words already present. However even when working with the Bible, we have at least fifty uses of over a thousand different lemmas, for English and Spanish, and roughly a thousand lemmas when

rank	word type	count
1	ha	32007
2	che	11649
3	upe	10300
4	kuéra	9751
5	ha'e	8394
6	nde	8202
7	'e	8005
8	mba'e	7940
9	umi	7750
10	pe	6345
11	pende	6224
12	tupã	5941
13	haguã	5607
14	vaekue	5071
15	katu	4746
16	'e/ha'e	4636
17	ñandejára	4617
18	⟨japo	4606
19	opa/pa	4321
20	guasu	4218
21	ramo	4043
22	peteĩ	3483
23	yvy	2978
24	iko/ko	2950
25	ñe'ẽ	2938
26	ra'y	2724
27	ĩ	2706
28	rehe	2690
29	⟨hetã	2636
30	vai	2606
31	ára	2606
32	me'ẽ	2532
33	avei	2360
34	⟨hecha	2328
35	niko	2299
36	kuaa	2215
37	rupi	2182
38	⟨hague	2170
39	ru	2105
40	hína	2080
41	po/porã	2049
42	ndive	1948
43	gua	1927
44	hikuái	1903
45	ore	1896
46	mburuvicha	1765
47	ko	1735
48	israel	1725
49	ñande	1704
50	ju	1659

rank	word type	count
1	ni	13535
2	ma/mana	9630
3	chay	9307
4	runa	8534
5	señor	6694
6	hina	5950
7	ka	5028
8	pay	5012
9	paykuna	3613
10	hina/hinan	3430
11	ka/kay	3150
12	diospa	2950
13	qan	2930
14	ruwa	2795
15	chaymi	2783
16	llaqta	2775
17	suyu	2686
18	karqan	2415
19	ichaqa	2286
20	wasi	2250
21	churi	2232
22	qankuna	1991
23	huk	1925
24	israel	1914
25	ima	1901
26	diosqa	1872
27	p'unchay	1866
28	diosmi	1851
29	ama	1827
30	ri	1759
31	tukuy	1667
32	chayqa	1572
33	llaq/llaqta	1516
34	ka/kasha	1498
35	pacha	1491
36	kanqa	1466
37	ma	1464
38	chunka	1447
39	allin	1370
40	llapan	1302
41	muna	1299
42	llapa	1286
43	yupay/yupaycha	1282
44	warmi	1246
45	ayllu	1229
46	dios	1180
47	ri/riku	1156
48	kamachi	1151
49	rey	1149
50	hallp'a	1086

Figure 4.12: Some of the most common lemmatized word types in our Guarani (left) and Quechua (right) Bibles. Preprocessing does not force morphological disambiguation; if the morphological analyzer cannot choose a lemma, we separate possible lemmas with a slash.

es	translations (en)	translations (gn)	translations (qu)
ser	be, will be, it be, shall be	hína, niko, mba'e, 'e/ha'e	ka, kanqa, karqan, chayqa
haber	have, there, be, there be	vaekue, ⟨hague, ⟨ha'e, mba'e	ka, ma/mana, qan, chay
decir	say, tell, speak, say to	'e, 'e ha'e, ha'e, 'e/ha'e	ni, chaymi, hina/hinan, tapu
dios	god, lord, yahweh, toward god	tupã, tupã nguéra, jára, ñandejára	diospa, diosqa, dios, diosmi
estar	be, stand, now, behold	ĩi, ime, iko/ko, hína	ka/kasha, kasha, ka, kaq
hacer	do, make, cause, he	⟨japo, mba'e, ⟨hembiapo, japouka	ruwa, ruwa/ruwana, ruwa/ruwaq, ruwa/ruway
tierra	land, earth, ground, country	yvy, ⟨hetã, ko yvy, yvy ári	suyu, hallp'a, ka/kay pacha, ka/kay
pueblo	people, among, nation, multitude	⟨hetã, ⟨hetã gua, opavave, israelgua	llaqta, runa, llaq/llaqta, israel runa
pues	for, therefore, so, then	upe, niko, aipórõ, pende	chay, chaymi, chay hinaqa, chayrayku
si	if, if you, but if, whether	ramo, rire, ime, pende	chayqa, ma/mana, chaypas, qankuna
así	so, thus, this, therefore	upe, péicha, kóicha, che	chay, ahi/ahina, chay hina, apu
padre	father, parent, his father	ru, ru ypy, ru kuéra ypy, ypy	tayta, ñawpa tayta, yaya, tayta/tay-tay
señor	lord, master, sir, ruler	ñandejára, jára, karai, che jára	señor, apu, señorpa, wiraqocháy
poner	put, set, lay, make	moĩi/ĩi, moĩi, moĩi/ñemoĩi/ĩi, upéi	chura, hina, churayku, chu/chura
mujer	woman, wife, a wife, a woman	kuña, ⟨hembireko, menda, kuñakarai	warmi, war, warmi/warmiy, qhari
volver	return, turn, again, back	jey, jeýta, ju jey, jere	kutipu, wakmanta, kuti/kutimu, kuti
poder	can, power, able, could	katu, pu'aka, ndaikatu, mbarete	ti, ati/atiy, ma/mana, atiyniyoq
ir	go, come, will, let	ha, sĩie, ha ha, haguã	ri, ripu, ri/rina, ri/risa
salir	go out, come out, out, go	sĩie, upe, ju, ha	ri, lloqsispa, puriri, hina/hinan
judá	judah, jew, belongs, of judah	judá, judagua, judápe, judá ñe-moña/ñemoñare	judá, judá suyu, judapi, judá ayllu
mismo	same, himself, own, myself	voi, avei, upe, vaerã	kikin, kaq, chay, hina/hinalla
llevar	bring, carry, take, bear	raha, ⟨hupi, guerahauka, hikuái	apa, pusa, apa/apamu, apari/apariku
cielo	heaven, sky, out, cloud	yvága, ára, tupã, yvága pe/pegua	hana/hanaq pacha, pacha, hana/hanaq, hana/hanaq pa
ojo	eye, sight, in, his eye	⟨hesa, ⟨hecha, ma'ĩie, che	ñawi, qhawari, ri/riku, ruwa
llegar	come, have come, reach, when	guahẽ, NULL, ke, guahẽ hikuái, ja/m-boja/ñemboja	chaya, chaya/chayamu, hamu, ri
entrar	enter into, come, come into, go	ke, guahẽ, ndoike, moinge	hayku, hayku/haykuna, ri, hay
llamar	call, name, summon	⟨héra, ⟨henói, ⟨henoika/henoika, ⟨henói/nói	waq/waqya, sutiyoq, waqya, suti/su-ticha
subir	go up, come up, up, ascend	jupi, ha, sĩie, ju	wicha, ri, hina/hinan, wichari
obra	work, do, deed, doing	⟨hembiapo, ⟨japo, mba'e, mba'e ⟨japo	ruwa, llank'a, ruwa/ruwana, ruwa/ruway
hijo	son, child, daughter, the son	ra'y, ñemoña/ñemoñare, kuéra, ra'y kuéra	churi, wawa, ususi, karqan
dejar	leave, let, forsake, allow	⟨heja, poi, ja, jei	kachari, ma/mana, wikch'u, ama

Figure 4.13: Selected common Spanish word types with their most likely translations. These were picked for interesting polysemy from the 100 most common word types.

es	entropy (en)	entropy (gn)	entropy (qu)
ser	2.11	3.79	3.29
haber	2.89	3.69	2.75
decir	1.74	2.19	1.81
dios	0.50	1.67	3.90
estar	2.02	3.14	2.69
hacer	3.93	2.57	2.66
tierra	1.93	2.89	3.51
pueblo	0.54	3.31	3.09
pues	3.28	3.74	2.97
si	2.82	3.17	2.97
así	2.94	3.12	3.55
padre	0.64	1.64	2.74
señor	1.70	3.20	3.60
poner	4.07	2.91	2.79
mujer	2.09	2.30	1.88
volver	3.86	3.53	3.57
poder	3.22	3.04	3.30
ir	2.61	2.91	2.87
salir	3.13	2.43	4.05
judá	0.29	2.12	2.77
mismo	3.36	2.98	2.77
llevar	3.46	1.75	2.72
cielo	1.49	2.27	2.12
ojo	1.81	2.51	2.67
llegar	3.04	2.72	3.32
entrar	3.54	2.06	2.56
llamar	1.82	2.56	3.32
subir	2.64	3.50	3.20
obra	2.02	3.25	3.25
hijo	1.72	2.66	2.63
dejar	3.53	2.49	2.77

Figure 4.14: Common Spanish word (lemma) types and the uncertainty (entropy in bits), faced by a CL-WSD classifier choosing among translations for this word.

translating Spanish into Guarani and Quechua.

In the next chapter, we will cover the archictecture of the Chipa system and evaluate its baseline version on the tasks and data sets described here.

CHAPTER 5
THE BASELINE CHIPA SYSTEM

Here we describe the baseline version of the Chipa software and evaluate its performance on the tasks described in the previous chapter. At its core, the Chipa software takes in a word-aligned bitext corpus, with annotations for the source tokens. It then trains CL-WSD classifiers for source-language word types on demand.

By default, the software holds all of the available bitext in memory, or optionally on disk, when training from larger corpora. On request, it constructs a training set for learning to disambiguate a particular lemma by retrieving all sentences that contain the lemma, finding the instances of that lemma and its aligned translations, and extracting features (see Figure 5.1) from the source sentence's surface text and annotations. If a source-language lemma has been seen aligned to only one target-language type, then this is simply noted, and if the lemma is not present in the training data, then it is marked as out-of-vocabulary. This situation will not arise in our *in vitro* evaluation, but during *in vivo* machine translation, OOV words will occur in practice. In either of these cases, we do not train a classifier for that lemma, since there is no ambiguity present in our examples and the Chipa software cannot provide any useful guidance to its caller. A machine translation system may, for example, refuse to translate sentences with OOV words, or more likely, will simply assume the identity translation, effectively passing them through untranslated.

Since source-language tokens may be NULL-aligned (i.e., not all words in the source text will have corresponding words in the target text), both in the training data and in translations, Chipa provides the option to request classifiers that consider NULL as a valid label for classification, or not, as appropriate for the translation application. For example, function words found in one language may not need to have a surface representation in the

name	description
`bagofwords`	a feature counting each lemma in the source sentence
`bagofsurface`	like `bagofwords`, but with surface forms
`window`	a binary feature for each of the lemmas in the immediately surrounding three-word context window
`surfacewindow`	like `window`, but with surface forms

Figure 5.1: Features for the baseline Chipa system

target text[1]. We here report classification accuracies for both settings.

Memory permitting, Chipa classifiers are kept cached for later usage. Chipa can also be run as a server, providing an interface whereby client programs can request CL-WSD decisions over remote procedure calls (RPC).

Chipa's classifiers are trained with the scikit-learn machine learning toolkit [85] for Python and its associated NLTK interface, though in earlier versions, we used the megam package [86], also through NLTK. By default, we use Logistic Regression classifiers (also known as Maximum Entropy), with the default scikit-learn settings. Maximum entropy classifiers are well-suited to this sort of classification task, as they are robust to adding large numbers of features, even highly-correlated ones [87]. Here we have exactly this situation, large numbers of sparse features, where some of them are likely to be highly correlated, since our features contain several representations of the tokens from the input sentence – their surface forms and their lemmatized forms, and the presence of a word in the window surrounding the focus word guarantees its presence in the bag of words representing the entire sentence. This is fairly typical of text classification problems.

Because we have a large number of features but a relatively small number of samples per classifier, the literature would encourage us to train with L1 regularization rather than L2 [88], but we found that the results are consistently slightly better when using L2. We could also search for an optimal regularization hyperparameter – the number that controls the tradeoff between simple solutions and ones that closely fit the input, perhaps at the risk

[1]As one concrete example, the Spanish "personal *a*" typically gets no translation in any of the other languages addressed in this work. Spanish syntax requires *a* before the object of a verb, but only when that object is a human being or (controversially) a beloved animal.

of overfitting. We did try a few different values for the regularization parameter, but found that the results were not dramatically different; furthermore, we do not want to overfit our corpus by tuning parameters too much after running tests. Here we will keep the default regularization setting of $C = 1.0$.

We have also tried a variety of classification algorithms; scikit-learn makes experimentation with different classifiers and parameter settings straightforward. In particular, we tried random forests and linear support vector machines, as well as the familiar "most frequent sense" baseline. For the baseline feature set, for the most part we see the the best performance from the logistic regression classifiers with L2 normalization, although the differences are not large; the other classification algorithms that we tried in these experiments did nearly as well.

5.1 Classification Results for the Baseline System

In Figures 5.2, 5.3, 5.4, and 5.5, we see the results for the baseline Chipa system running with a a variety of common classification algorithms, chosen for familiarity and availability within our machine learning toolkit, on different language pairs. Here we report classification accuracy as a percentage – there is only one reference translation given, and the classifier only gets credit for predicting it correctly, independent of any other classification tasks. We performed ten-fold cross-validation, using all of the available training data for each of the lemmas in a given language pair's bitext that appear at least fifty times.

As mentioned previously, there are two settings for this task; in the "regular" setting, we consider "null" to be a valid translation, i.e., the classifier must consider the possibility that the focus word is not explicitly represented in the target-language sentence. In the "nonnull" setting, we only consider the instances where there is an alignment from the focus word to at least one token in the target sentence. For most of the language pairs, we see that our results in the "nonnull" setting are higher, which is not surprising, since there are fewer options to pick from. In Spanish-Quechua (Figure 5.3), however, we see that the scores are lower in the

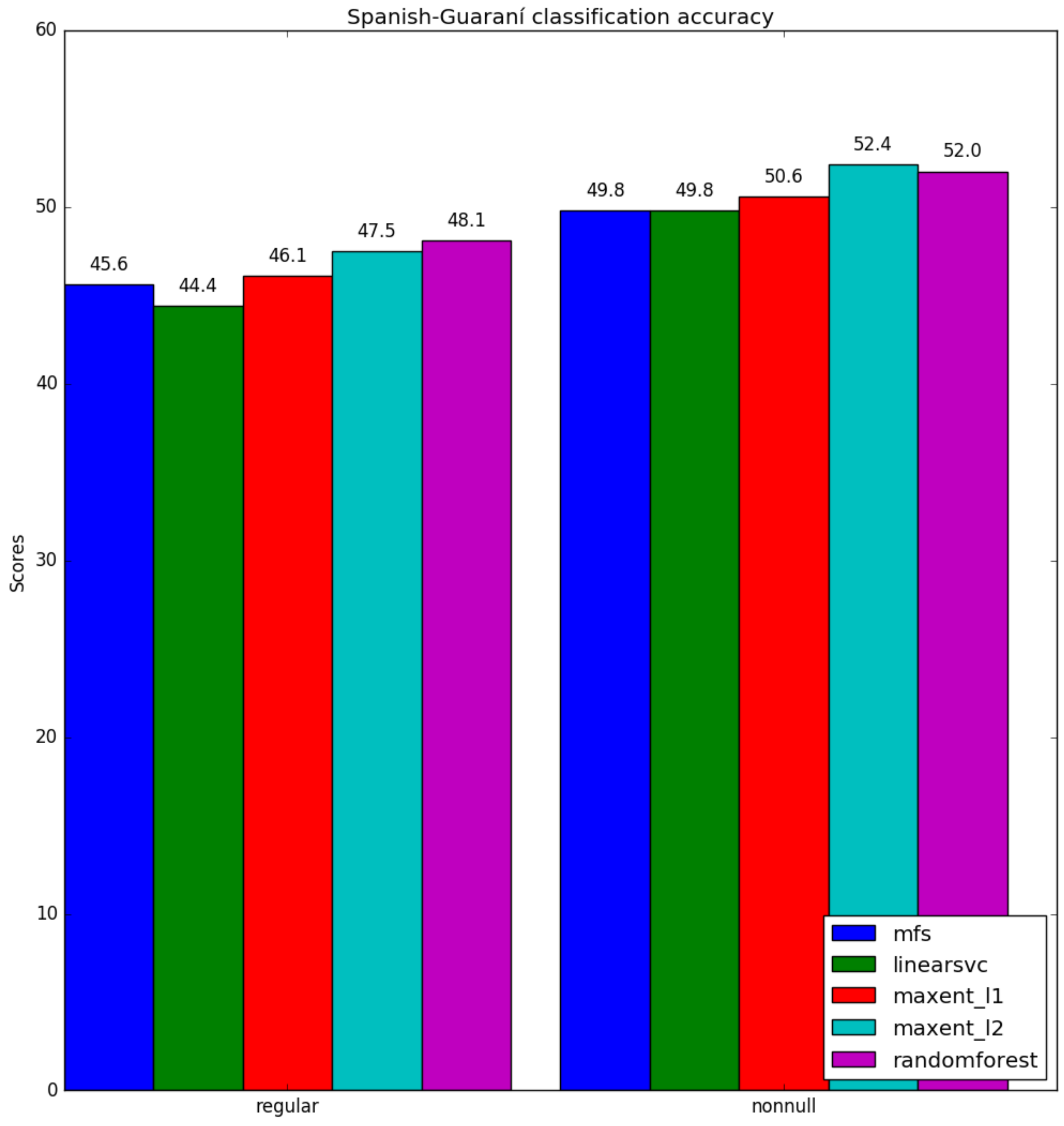


Figure 5.2: Baseline Chipa scores for Spanish-Guarani, by classifier.

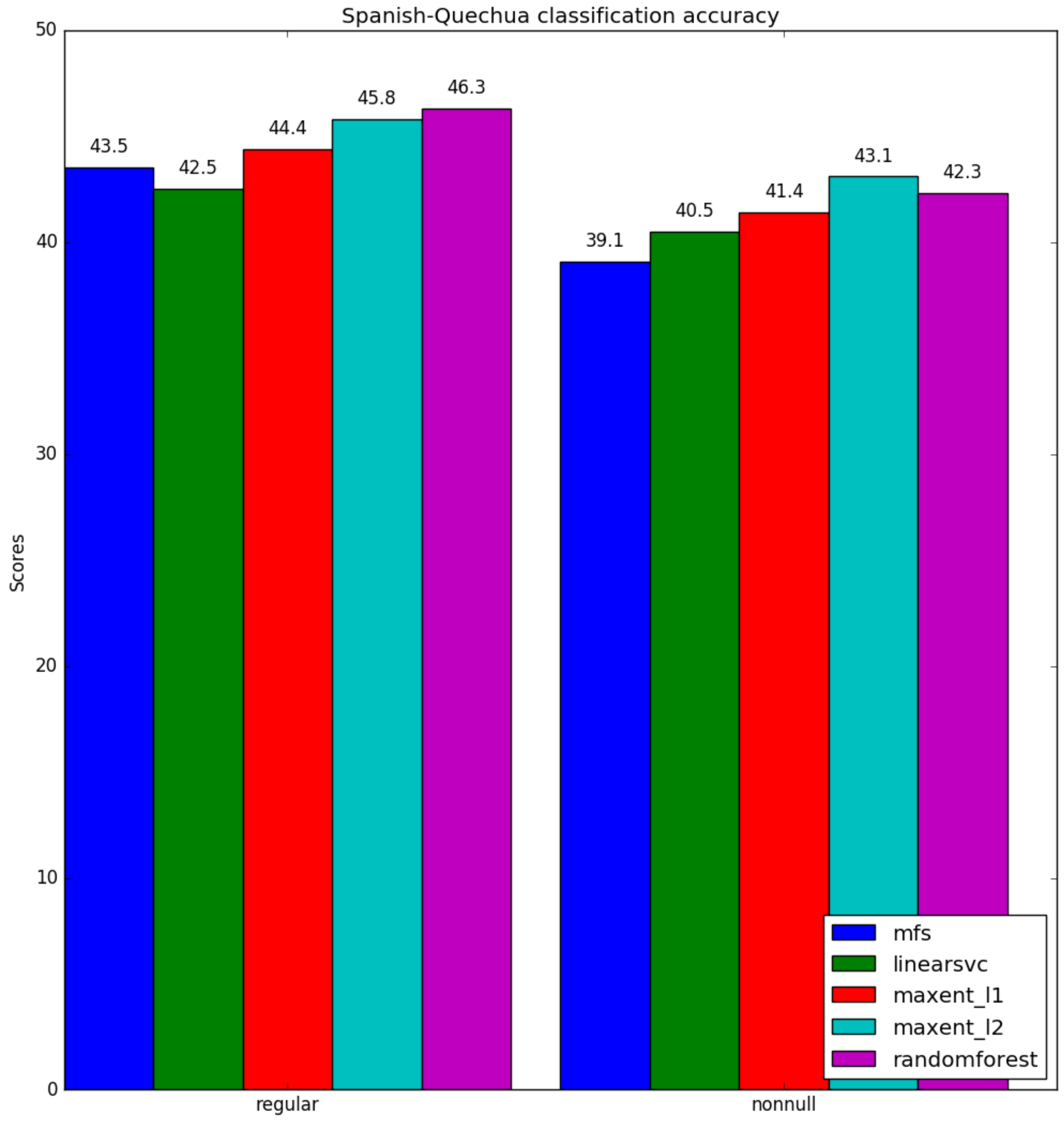


Figure 5.3: Baseline Chipa scores for Spanish-Quechua, by classifier.

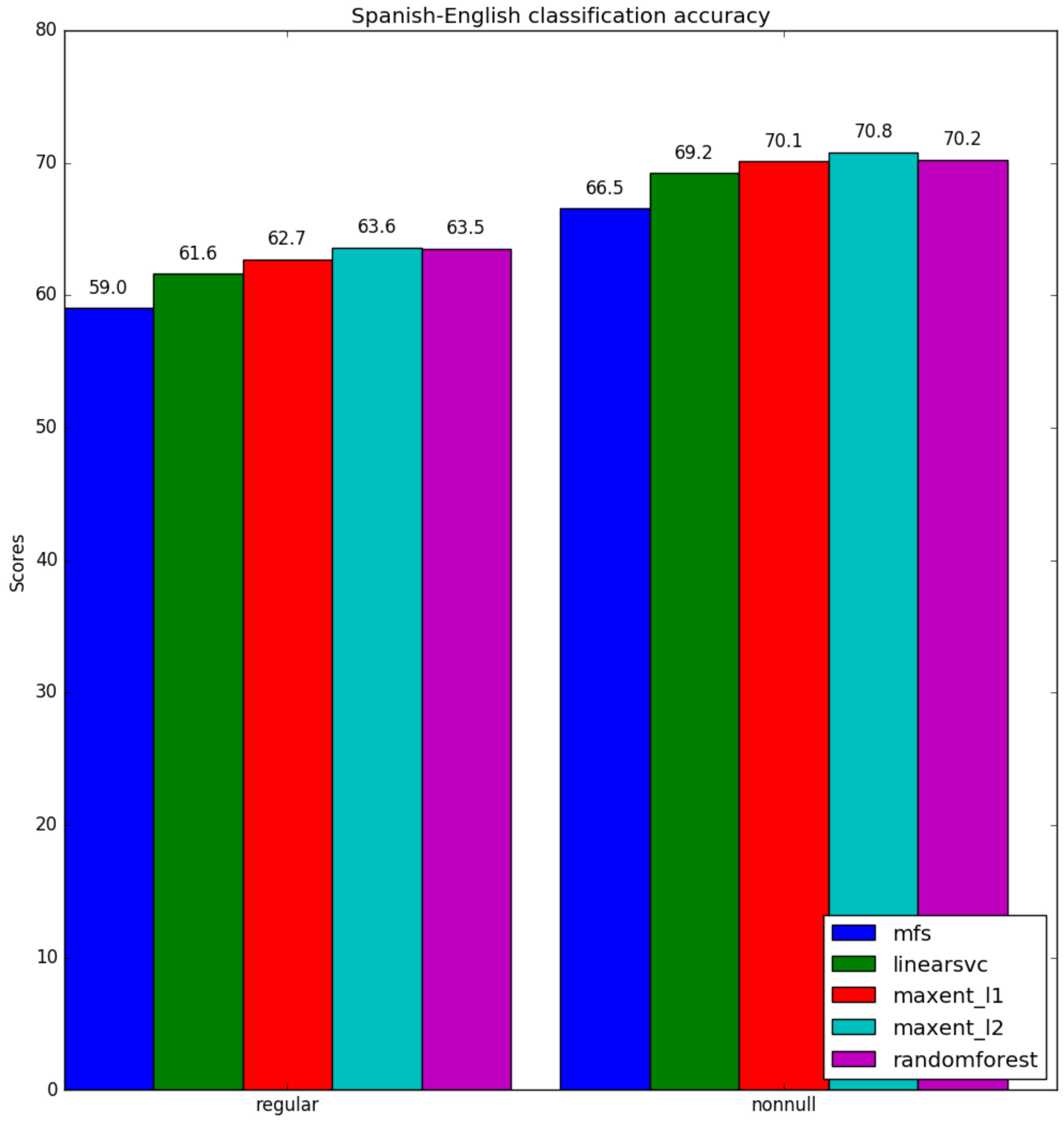


Figure 5.4: Baseline Chipa scores for Spanish-English, by classifier.

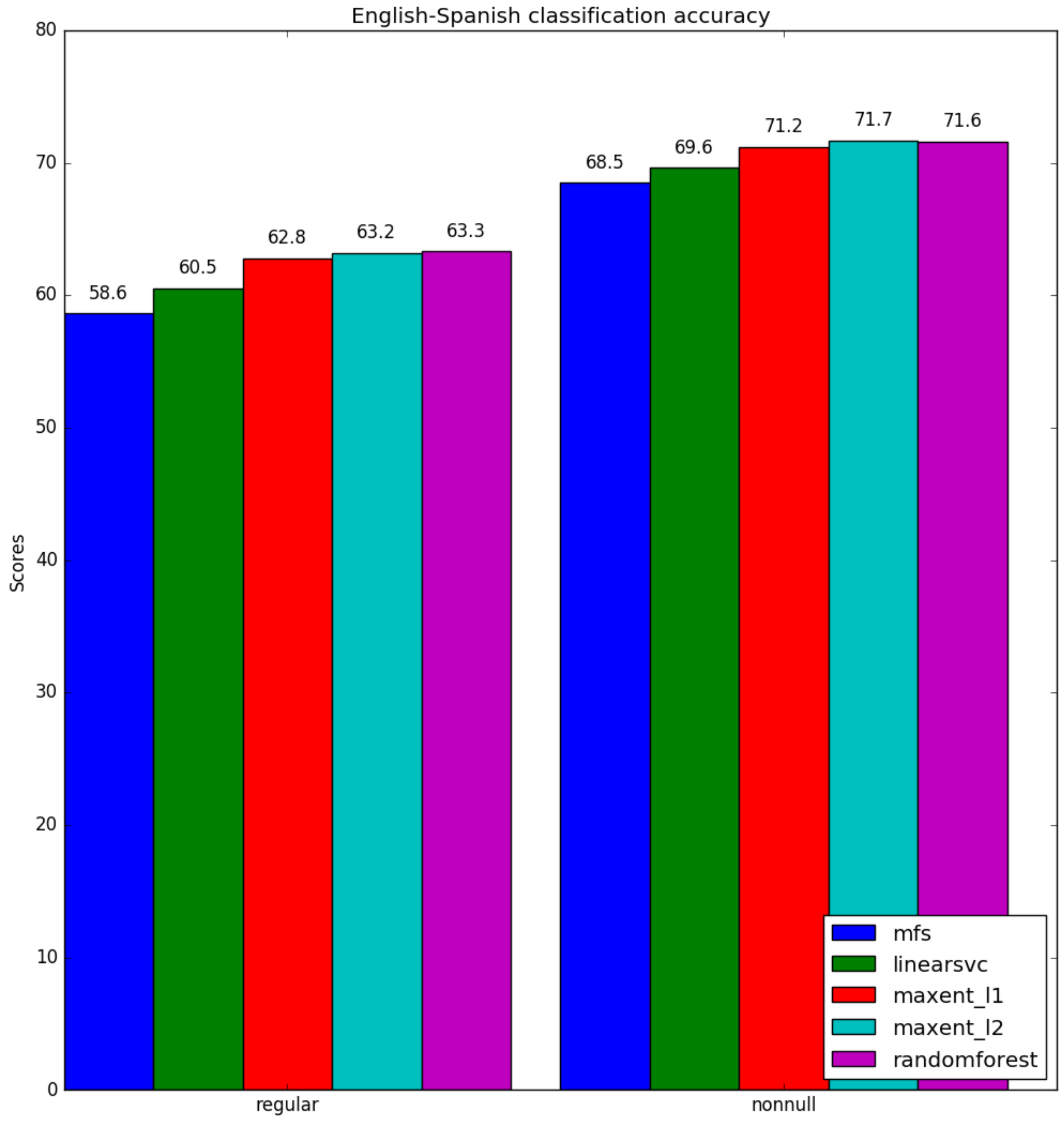


Figure 5.5: Baseline Chipa scores for English-Spanish, by classifier.

"nonnull" setting. This seems to be due to the Spanish and Quechua texts not being close translations of one another – it is fairly likely that words in the Spanish text are simply not present in the Quechua text, so when this possibility is eliminated, the classifier must make a more difficult choice from among the remaining options.

In nearly all of the settings for this task, the use of a classifier outperformed the most-frequent sense baseline. We see a little variety in the top results, for the four different language pairs and both task settings, but the most successful classifiers here seem to be the maximum entropy classifier with L2 regularization and random forests. The other classifiers post slightly worse performance, but nearly always beat the MFS baseline.

So far, with commonly-used classifiers trained on commonly-used features, we achieve a substantial boost on our ability to translate common polysemous words from Spanish into two under-resourced languages, as well as between English and Spanish, over a simple baseline. In subsequent chapters, we will see how to build on this simple approach, largely through making additional features available to the learning algorithms.

5.2 For Comparison: the Baseline Chipa System On the SemEval 2010 and 2013 Shared Tasks

In order to situate this baseline Chipa system among other recent approaches to CL-WSD, we ran Chipa on the SemEval CL-WSD test sets from 2010 and 2013, for English-Spanish. In the full 2010 and 2013 tasks, systems were also asked to translate into four other European languages: German, Dutch, French and Italian. Here for simplicity, we focus on English-Spanish, since Chipa's preprocessing pipeline already handles these languages, and the results across language pairs were not drastically different in the original shared tasks. In this task, we are presented with sentences in English, with a particular focus word marked, and the goal is to select the lemma of a contextually appropriate translation for that word[31, 32]. The task here guarantees that the appropriate translations are only those present in the Europarl bitext, and several possible gold-standard translations are provided by human annotators.

We made no particular additional effort to tune Chipa for these tasks – it was run here with the same settings used for the Spanish-Guarani and Spanish-Quechua CL-WSD tasks, although the Chipa codebase is descended from a system originally built for the 2013 task [8].

The training data for this task is considerably larger than the Bible text used for the main CL-WSD task described in this work; Europarl bitext corpora contain nearly 2 million parallel sentences. We applied the preprocessing steps described in Section 4.3 to the Europarl bitext, with the simplification that the individual sentences need not be extracted from the various distribution formats used for Bibles. Here we use only a very small modification to the Chipa system in order to address the larger training data size; rather than holding the entire corpus in memory, the corpus is kept on disk and scanned for sentences that contain the current focus word before we need to train the CL-WSD classifier for a given lemma.

There were two settings for the evaluation, *best* and *oof*. In either case, systems may present multiple possible answers for a given translation, although in the *best* setting, the first answer is given more weight in the evaluation, and the scoring encourages only returning the top answer. In the *oof* setting, systems are asked to return the top-five most likely translations. In both settings, the answers are compared against translations provided by several human annotators for each test sentence, who provided a number of possible target-language translations in lemmatized form. More points are given for matching the more popular translations given by the annotators. For a complete explanation of the evaluation and its scoring, please see the shared task descriptions.

The scores for the baseline Chipa system, as well as for other systems entered in the 2010 and 2013 competitions, are reported in Figures 5.6 and 5.7. In the 2010 competition, none of the posted systems were able to beat the simple most-frequent-sense baseline for the out-of-five setting, but Chipa surpasses it handily. Chipa also does better than all but one of the posted systems in the one-best setting. On the 2013 test set, Chipa also did fairly well, scoring better than several of the posted systems in the one-best setting, and

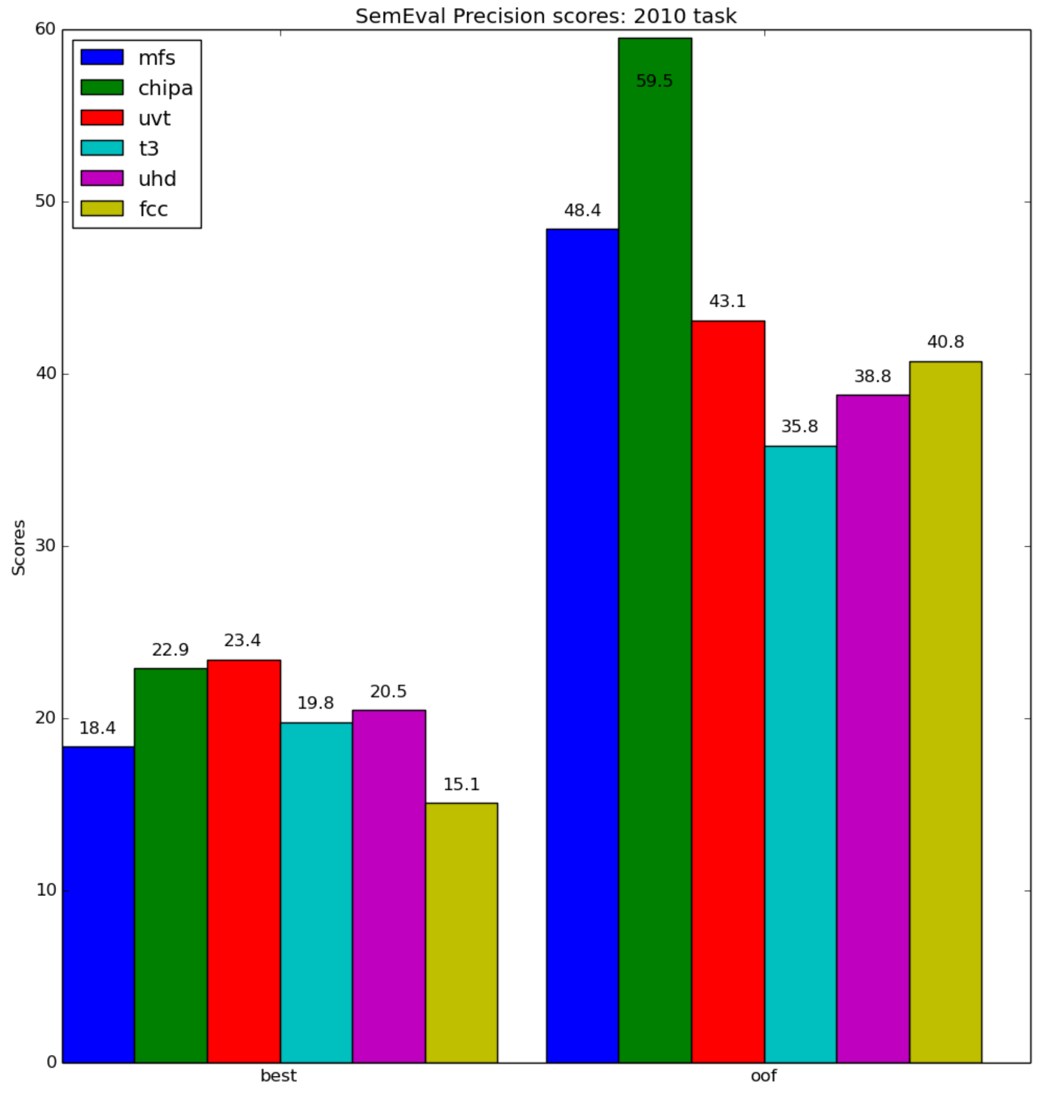


Figure 5.6: Scores on the SemEval 2010 test set, including results posted in the shared task and the baseline Chipa system running on the same test set.

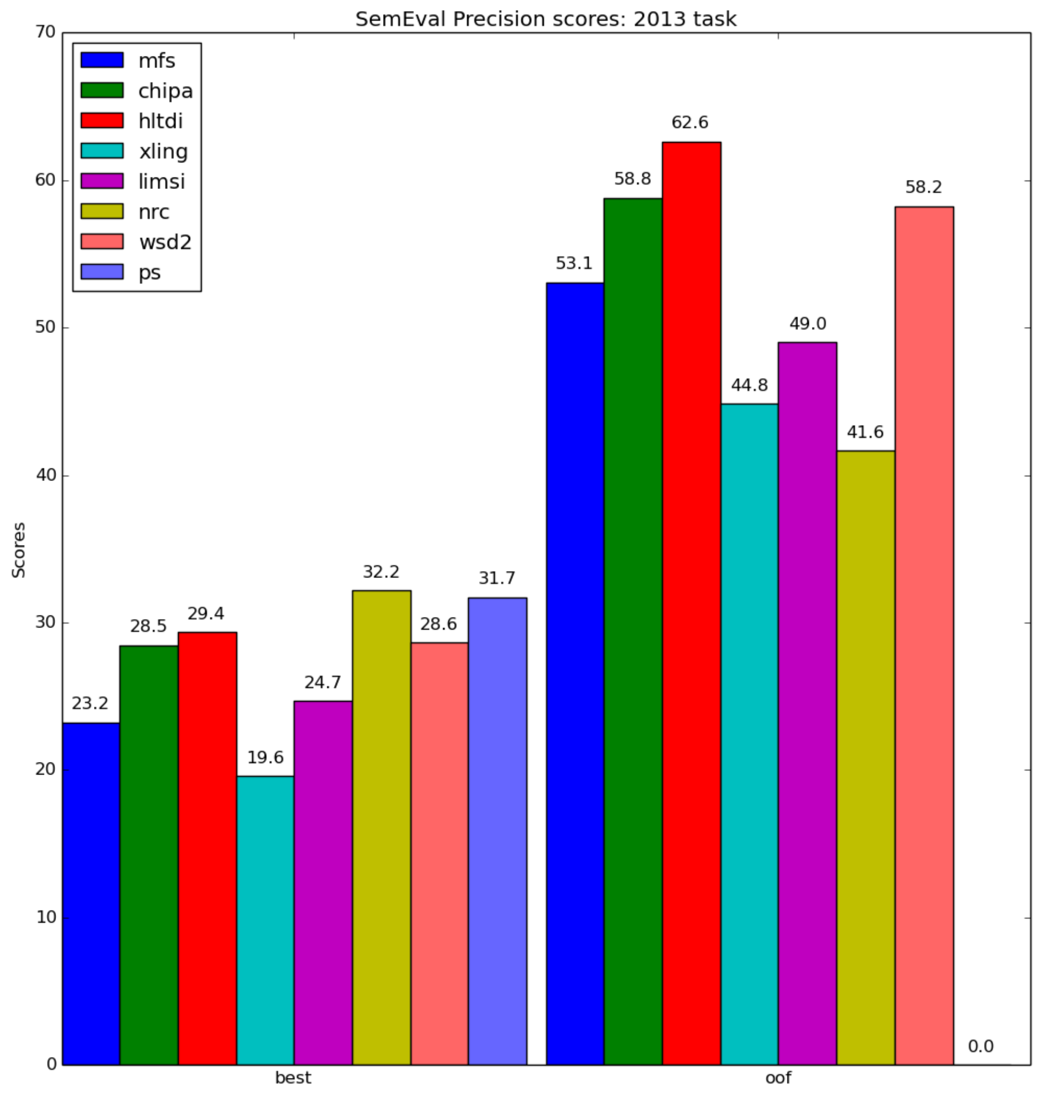


Figure 5.7: Scores on the SemEval 2013 test set, including results posted in the shared task and the baseline Chipa system running on the same test set. When one team presented multiple results, here we take the best result from that team.

all but one of the posted systems in the best-of-five. It should be noted that in the 2013 competitions, one of the posted systems showing higher scores than the Chipa baseline was "HLTDI", developed by myself and Can Liu[8], which made use of early versions of some of the techniques described in subsequent chapters.

But we see here that this straightforward approach, using a maximum entropy classifier with features extracted from the words and lemmas surrounding the focus word, works quite well compared with the other systems in the shared task, and so I claim that this system is a sensible baseline on top of which we can build more advanced approaches.

CHAPTER 6
LEARNING FROM MONOLINGUAL DATA

While in this work our target languages are under-resourced, we have many resources available for the source languages. We would like to use these to make better sense of the input text, giving our classifiers clearer signals and better representations for lexical selection in the target language. The approaches considered in this chapter make additional features or different representations available to the CL-WSD classifiers based on knowledge of the source language, either gleaned through unsupervised methods or baked into extant tools. Since we have relatively little bitext available for Spanish-Guarani and Spanish-Quechua, we will need to lean more on our Spanish resources, software and data, in order to make better sense of the input text.

Perhaps most saliently for Spanish, we have abundant monolingual text available, which suggests that we could use unsupervised methods to discover regularities in the language, yielding better features for our classifiers. This approach has been broadly successful in the literature [89, 90], and here we adapt some of the methods explored in previous work on text classification to our task.

Concretely, in this chapter we explore labels learned from existing NLP tools such as off-the-shelf taggers and parsers for Spanish, Brown clustering [91], and a few related approaches to neural embeddings. There are of course other related methods that one could investigate, especially making use of the broader literature on distributional semantics, but we consider them to be outside the scope of this work. First we will describe the methods used in some detail, and then towards the end of the chapter, in Sections 6.5 and 6.6 respectively, we describe experiments and present experimental results.

6.1 Monolingual features from existing NLP tools

There are a large number off-the-shelf NLP tools available for Spanish. Here we will look into part of speech taggers and syntactic parsers specifically. Tagging can help us capture abstractions over particular word types, and provides some disambiguation on its own. For example, in Spanish, *poder* can be the infinitive verb "to be able", or it can be a noun, meaning "power, ability". And if these different meanings are surfaced as different words in the target language (as they are in English), then simply having an accurate POS tag makes the CL-WSD task much easier. More generally, perhaps a noun in the window surrounding a focus word could be indicative of a particular meaning.

Similarly, syntactic structure may also provide useful features. Verbs especially may have drastically different translations in the target language based on their objects. There are many familiar examples of this phenomenon, especially among the "light verbs" and "phrasal verbs" with noncompositional meanings in English and Spanish.

In the Chipa software, we can make use of arbitrary annotations for the input text (see Section 4.3.1), so adding more features based on analysis by external tools is straightforward.

As a first step, we synthesize features based on the part-of-speech tags of the tokens surrounding the focus word, and using a syntactic parser, the heads and children of the current focus word. In principle, we could use other annotations, such as sense annotations from a monolingual WSD system, given a good one. This idea is akin to one that we will explore in Chapter 7, in which we use Chipa itself (trained for other language pairs, and with larger data sets) to provide annotations, effectively using some other target language as a sense inventory for WSD.

For POS tagging, we run the open source FreeLing text analysis suite [78] on input sentences. FreeLing can perform a number of analyses for Spanish, including POS tagging, dependency parsing, lemmatization, and named entity recognition, of which the latter two are part of the standard preprocessing done for all experiments in this work. When all the text for an experiment is known beforehand, as in the experiments reported in this chapter, we can run FreeLing during the data annotation step (see Section 4.3) and simply record FreeLing's output as text annotations. When running on novel test sentences, as in server mode, we must run it on those sentences just before inference time.

Similarly, for syntactic features, we use MaltParser[92] [1] to get dependency parses of the input sentence. This is also performed as a corpus annotation, making the syntactic relationships for each token available during feature extraction. The parser here depends on the POS tags produced by FreeLing. Conveniently, FreeLing and the espmalt parser model assume the same tag set, but as with any pipeline of NLP systems, using the inferred output from the tagger as input to the parser carries the risk that errors at early stages in the pipeline could propagate and cause problems at the later stages of processing. Here we note this concern but move on; it is a very general problem, and solutions to it are an open area of research. The parser also depends on the coarse-grained "universal" POS tags [94], which we map from the IULA tagset to universal coarse tags during corpus annotation.

Operationally, before training our CL-WSD system, we parse all of the training data with the "espmalt" model, using the tags inferred by FreeLing during preprocessing, and store all of MaltParser's dependency parses on disk. Then with a corpus annotation script, we walk those dependency graphs to find each token's immediate syntactic head (or the root of the sentence) and every token's immediate syntactic children, if any. All of these dependency heads and children are annotated in the training data, to be made available during feature extraction. Then at feature extraction time, chipa turns these stored annotations into sparse binary features. The list of all syntactic features made available to the classifier is given in Figure 6.1.

To give a concrete example, consider the dependency graph for an English sentence in Figure 6.2, and the scenario in which we want to classify the main verb of the sentence,

[1] Available at `http://maltparser.org/` ; in this work we use version 1.9.0 of the parser, and the "espmalt" pretrained model, which is available at `http://www.iula.upf.edu/recurs01_mpars_uk.htm`, and was trained on the IULA Treebank[93], by researchers from the IULA group at Universitat Pompeu Fabra.

name	description
`postag`	part-of-speech tag for the focus token
`postag_left`	POS tag for the token to the left of focus token
`postag_right`	*ibid.*, for the right
`head_lemma`	lemma of the focus word's syntactic head, or ROOT if it has no head).
`head_surface`	*ibid.*, but for the syntactic head's surface form.
`child_lemma`	lemma of the syntactic child or children of the focus word. Feature appears multiple times for multiple children.
`child_surface`	*ibid.*, but for the children's surface forms.

Figure 6.1: Additional syntactic features

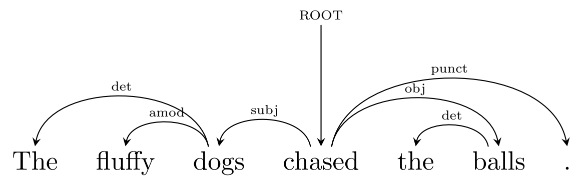


Figure 6.2: An example dependency graph for an English sentence.

"chased". The syntactic features that we would extract for this situation would be as follows: `postag(VERB)`, `postag_left(NOUN)`, `postag_right(DET)` (assuming that the English sentence has been labeled with Universal POS tags), `head_lemma(ROOT)`, `head_surface(ROOT)` (since the main verb is attached to the ROOT node of the dependency tree), `child_lemma(dog)`, `child_lemma(ball)` (the lemmas of the subject and object of the verb), and finally `child_surface(dogs)`, and `child_surface(balls)` (the surface forms of the subject and object of the verb).

6.2 Brown Clustering

The Brown clustering algorithm[91], also known as IBM clustering, as it was developed by the Candide group at IBM, finds a hierarchical clustering for all the word types in a corpus, such that words that are clustered nearby have similar usage patterns, and thus presumably similar meanings. The tree of clusters is binary-branching, so the identity of a cluster is simply its path from the root of the tree, and clusters that are close in the tree have similar usage patterns. The desired number of "leaf" clusters must be set ahead of time as a tunable

$$P(\boldsymbol{w}; C) = \prod_{w_i} p(w_i | C(w_i)) p(C(w_i) | C(w_{i-1})) \tag{6.1}$$

Figure 6.3: The Brown clustering expression for the probability of a corpus with a specific clustering C. It is the product, for each token, of the probability of that token given its cluster, and the probability of that current cluster given the previous cluster. This is analogous to the "emission" and "transition" probabilities used in an HMM-based tagger.

parameter.

Each of the word types present in the input corpus is allocated to one of the leaf clusters, such that the assignment attempts to maximize the probability of the input corpus. These clusters were originally intended for use in class-based language modeling, and as such the scoring function is the mutual information between subsequent tokens. Concretely, the optimization process is searching for a clustering C that maximizes the probability of the corpus $\boldsymbol{w}$, according to the formula in Figure 6.3; intuitively, word types that occur in similar bigrams should be in similar clusters.

Finding an optimal assignment of all word types in the corpus into these hierarchical clusters is an intractable problem, but several greedy approaches that find local optima have been explored in the literature. Notably, in addition to Liang's approach, Franz Och's `mkcls` package (familiar to Moses users, and described in [95]) optimizes the same function when assigning words to classes. In any case, with the available software running on modern hardware, we can find a clustering for the corpora used in this work in a fairly short time, on the order of hours.

Here our immediate use for these clusters is to create more features for our classifiers, interpreting the clusters into which a word type falls as a tag for instances of that type. These annotations give a more abstract, less sparse representation than surface forms or lemmas, hopefully providing useful semantic and syntactic generalizations. We may also preprocess the input to the clustering algorithm beforehand, as long as we can reproduce the preprocessing for unseen input text at query time.

In applying Brown clusters to this task, we would like to answer several questions.

- Can learning Brown clusters from monolingual source text improve our performance on this CL-WSD task?
- Does more source-language text help us learn more helpful Brown clusters, with respect to the CL-WSD task? Can a large enough monolingual corpus help us overcome domain mismatches?
- What kinds of preprocessing should we do on the source text? Particularly, should Spanish source text be lemmatized?

6.2.1 Clustering in practice

In this work we use Percy Liang's implementation [2] of Brown clustering [96]. We ran this tool on two different monolingual corpora, the Spanish section of the Europarl corpus [70] (2 million sentences) and a dump of Spanish-language Wikipedia (20 million sentences). In all cases, we set the number of leaf clusters to 1000, which is the default for the package. When working with Spanish, considering its relative morphological richness, we may consider lemmatizing our input text before clustering. This decision will be more significant than it would be for English, given the inflections present in Spanish, especially verb conjugations and adjective-noun agreement. We might expect that Brown clustering on surface forms would help us find abstractions over syntax, and that lemmatization will turn it towards more semantic abstractions. This is an empirical question, and we briefly look into it here, first by qualitatively examining the clusters that we learned, but later extrinsically evaluating the clusters to see how they affect the CL-WSD task.

Figures 6.4, 6.5, 6.6 and 6.7 show some hand-selected illustrative examples of clusters that we found in our monolingual Spanish corpora, Europarl and Wikipedia, in both surface-form and lemmatized versions. Examining the output of the clustering algorithm, we see some intuitively satisfying results; there are clusters corresponding to the names of many countries, nouns referring to people by profession, and some semantically similar verbs. The

[2] Available at `https://github.com/percyliang/brown-cluster`

category	top twenty word types by frequency
countries	Irlanda Francia Alemania Grecia Italia España Portugal Rumanía Polonia Suecia Bulgaria Austria Palestina Corea Finlandia Hungría Bélgica Bosnia Dinamarca Eslovaquia
more countries	Turquía Rusia China Israel Ucrania Croacia Serbia Georgia Europol Cuba Marruecos Canadá Albania Brasil Moldova Libia Siria Suiza Sudáfrica Eslovenia
continuation verbs	sigue siguen siga seguirá seguimos continúa sigan continúe seguirán seguiremos continúan continuará sigo sigamos continúen acabará continuarán continuaremos continuamos seguiré
proposition verbs	propone establece prevé aprobó presentó mantiene garantice adopte tome adoptó decidió mantenga presentará establezca realiza proponen realice propuso adopta reconozca
past participles	recibido tomado escuchado apoyado mantenido perdido seguido debatido cumplido formulado encontrado leído defendido examinado ofrecido discutido superado reunido acogido consultado
feminine nouns	formación educación tecnología infraestructura publicidad enseñanza ocupación religión vivienda ética propaganda banda fusión huelga creatividad medicina manipulación tribuna cualificación comida

Figure 6.4: Selected clusters found in the surface version of Spanish Europarl

words listed in these figures are the top twenty terms from that cluster, by frequency in the corpus. Note that the names given for the clusters were also chosen by hand, rather than through some automatic process. It is reassuring that the clustering process, over all of these corpora, is finding some interpretable generalizations in the text.

Comparing the lemmatized versus the surface-form versions of the clustering, we note that, as expected, the clusters capture more syntactic regularities when given the inflected forms. Consider, for example the cluster containing *infraestructura* in Figure 6.5, as compared to its cluster in Figure 6.4. In the lemmatized version, we see that *infraestructura* falls into a cluster primarily composed of words pertaining to transportation-related concepts, such as *vehículo* 'vehicle', *billete* 'ticket' and *avión* 'airplane'. In the Wikipedia lemma clusters, shown in Figure 6.7, we see some satisfying semantic clusters as well, such as adjectives

cluster description	top twenty word types by frequency
countries	francia irlanda alemania grecia italia españa rumanía portugal polonia bulgaria suecia austria finlandia hungría bélgica japón gran_bretaña dinamarca eslovaquia luxemburgo
political entities	comisión comisión_europea estados_miembros gobierno_de_el_reino_unido presidente_putin gobierno_de_los_estados_unidos pelota presidencia_de_la_ue presidente_lukashenko gobierno_de_israel presidente_klaus presidente_musharraf república_de_croacia comisión_de_la_ue comité_de_expertos presidente_milosevic gobierno_de_sudán gobierno_de_zimbabue secretaría_general gobierno_de_irlanda
mostly abstract nouns	riesgo gravedad lujo alivio molestia desperdicio riego horno superposición desprestigio variabilidad presupuesto_general deshumanización adquirente cabildero desposeimiento streamlining vigía política_estructural_de_la_ue acuerdo_kedo
infrastructure	infraestructura vehículo equipo buque instalación barco avión motor planta ruta coche cabeza mina tren fusión billete fábrica camión arte pasaporte
common verbs	pagar perseguir regir practicar percibir soportar gobernar sustentar recaudar abonar respirar profesar tragar devengar lucir pagar+le abanderar tributar glorificar sobresalir

Figure 6.5: Selected clusters found in the lemmatized version of Spanish Europarl

describing political positions, verbs about making choices, and a cluster of locations, mostly cities.

Contrastingly, on the surface-form side, the cluster that contains *infraestructura* does not immediately reveal the same conceptual similarity: we see *formación* 'education (formal)' *creatividad* 'creativity', and *comida* 'food' in the same cluster. While a few of the words have similar meanings, the clustering seems to have found that these words cluster together as singular feminine nouns, which is more of a syntactic commonality than a semantic one. This is not to say that the surface-form clusters do not exhibit semantic relatedness; in the "profession nouns" cluster in Figure 6.6, we see nouns that refer to people's professions,

category	top twenty word types by frequency
surnames	León Castro Mendoza Franco Herrera Colón Guerrero Rivera Miranda Silva Guzmán Medina Belgrano Molina Lara Guadalupe Juárez Hidalgo Trujillo Cáceres
women's names	Isabel Ana Rosa Teresa Juana Catalina Cristina Margarita Anna Mercedes Elena Laura Luisa Clara Sofía Marta Lucía Julia Gloria Alicia
conjugations of *haber*	había habría haya hubiera habiendo he hubiese hemos has habiéndose habíamos hubiere habia hayamos habéis habiéndolo habiéndole hubiéramos habremos hubieras
organization name parts	Internacional Municipal Cultural Regional Oficial Histórico Metropolitana Universitario Naval Industrial Universitaria Especial Musical Público Nobel Metropolitano Juvenil Comercial Penal Rural
profession nouns	actor escritor compositor poeta productor médico pintor arquitecto músico abogado guitarrista historiador ingeniero sacerdote escultor empresario bajista guionista filósofo investigador
cardinal directions	sur norte oeste noroeste noreste sureste suroeste sudeste oriente sudoeste nordeste poniente voivodato NE centro-sur SW centro-norte centro-oeste sur-oeste nororiente

Figure 6.6: Selected clusters found in the surface version of Spanish Wikipedia

although it should also be noted that these are all singular masculine nouns. Also in the Wikipedia surface clusters, we see a cluster containing almost entirely words referring to cardinal directions[3].

So a qualitative look at the clusters found in these corpora shows some promising regularities found in the text. As expected, when we cluster on the surface forms, we find both syntactic and semantic similarities, but using the lemmatized forms seems to push the clusters towards conceptual similarity. It is still an empirical question which of these approaches will help more for our CL-WSD task, so we will run experiments using each one.

[3]With the inclusion of *voivodato* (English: 'voivodeship' or Polish 'województwo') which, I have just learned from Wikipedia, is an administrative region in eastern Europe, similar to a historical duchy or modern province.

category	top twenty word types by frequency
Spanish places	castilla aragón granada toledo mendoza janeiro zamora mallorca tenerife guadalupe ávila extremadura trujillo segovia cáceres baviera gimnasia soria catalunya maga-llanes
locations	londres sudamérica oxford boston columbia cambridge indiano harvard houston baltimore dallar berlin berkeley leipzig stanford cleveland stuttgart sydney melbourne princeton
common noun locations	bosque lago puente jardín hotel coro pozo molino faro espejo almacén pantano muelle casino balneario arrecife circo balcón rancho mosaico
parts of things	elemento aspecto pieza instrumento factor componente rasgo ingrediente parámetro cualidad atributo trazo isó-topo acepción ítem alelo pasatiempo renglón morfismo intrumentos
choice verbs	elegir seleccionar escoger nominar reelegir redesignar ungir sindicar preseleccionar cooptar procesionada re-electo re-elegido eligido reimplementar renominar elegio recomisionar estandardizar indiscutidamente
political adjectives	socialista republicano liberal comunista revolucionario conservador radical nacionalista demócrata anar-quista unitario progresista independentista bolchevique fascista marxista patriótico libertario socialdemócrata monárquico
empires	romano colonial bizantino otomano inca visigodo mon-gol cartaginés mexica austrohúngaro galáctico motors carolingio hitita incaico almohade virreinal isabelino omeya lusitano

Figure 6.7: Selected clusters found in the lemmatized version of Spanish Wikipedia

6.2.2 Classification features based on Brown clusters

Given a clustering learned from a large monolingual corpus, we must still decide how to extract classification features from those clusters. If we know, for example, that the token to the left of the focus word is in cluster "010111111100", what information do we provide to the classifier? We could interpret this cluster atomically, as a tag for that token, and create sparse features for an input sentence based on the clusters present in it, perhaps focusing on the window surrounding the focus word. However, following the work of Turian *et al.* [89],

name	description
`brown_bag`	Bag of all Brown clusters for the entire sentence
`brown_window`	All Brown clusters for the three-token window around the focus word

Figure 6.8: Features extracted from Brown clusters. These came in surface-form and lemma variants, and were trained on both the Europarl for Spanish, and our Wikipedia dump. Additionally, we add variants for the 4, 6, and 10-bit prefixes of the clusters.

we also take the prefixes of each cluster's bit strings at 4, 6, and 10 bits, taking advantage of the hierarchical structure in the clusters, and used these separate sparse features.

As a concrete example using the lemmatized Wikipedia clusters, if we find that the lemma *rioplatense* is in a three-token window around the current focus word, and that this lemma is in cluster "111110111111111110", then we extract the following features, setting each of them to 1.

- `brown_window_wikipedia_lemma(111110111111111110)`
- `brown_window_wikipedia_lemma_4(1111)`
- `brown_window_wikipedia_lemma_6(111110)`
- `brown_window_wikipedia_lemma_10(1111101111)`

We additionally extract analogous features for all tokens in the sentence; these would be called `brown_bag_wikipedia_lemma`, `brown_bag_wikipedia_4`, and so on. If we are using clusters based on the surface forms, these simply do not have `lemma` in their name, and features based on Europarl, are marked with `europarl` rather than `wikipedia`.

In cases of unknown words, where we do not have a cluster assignment for a word in the input text, we simply do not extract cluster features for that word. This will happen in practice, even for a fairly large monolingual corpus, but may be especially common in this setting due to domain mismatches. Many biblical names, for example, are not present in Europarl.

6.3 Neural Word Embeddings

Another rich source of features that has proved useful for many text classification problems in recent years is neural word embeddings, perhaps most famously developed in the work of Mikolov et al. [97] and their associated open source implementation of the technique, word2vec[4]. In this work we investigate the use of "word2vec"-style word embeddings, as well as the related technique, "doc2vec" or "paragraph vectors" [98, 99]. These techniques let our classifiers operate on lower-dimensional dense vectors (of a few hundred dimensions, typically), as opposed to the high-dimensional sparse vectors typically used in earlier NLP literature[5].

There is a rich literature on continuous representations for words; the idea has a long lineage in NLP, and we could try any number of dimensionality reduction or distributional semantics approaches here. However, recent empirical work by Baroni et al [90] (summed up by the title of the paper, "Don't Count, Predict!") has shown that representations built during discriminative learning tasks are typically more effective for text classification problems similar to ours.

Unlike Brown Clustering, which infers hierarchical clusters for each word type, but like other embedding techniques, word2vec learns multidimensional representations for word types, turning the very sparse "one hot" representation in which words with similar uses or meanings do not have any obvious similarity into a much denser continuous space, wherein words with related meanings are placed nearby. These "embeddings", or placements of word types in a continuous space, are learned latently during some other classification task, and are performed by the early layers of a neural network.

The word2vec model in particular has two variations, useful in different contexts. One, called Continuous Bag-of-Words (CBOW) learns a classifier that can predict individual words

[4]Available at `https://code.google.com/archive/p/word2vec/`

[5] What we might consider to be "symbolic" binary features used in machine learning systems for NLP in recent decades – such as "the word 'dog' appears in the sentence" – are effectively equivalent to these very sparse "one hot" representations of words, in which, for a vocabulary of size $|V|$, words are represented by a length-V vector in which all but one of the elements are 0.

based on their context, while the "skip-grams" variant does the reverse and learns to predict context words based on an individual focus word. The received wisdom[6] is that CBOW is more appropriate when training on smaller data sets, but this is an empirical question, so here we run experiments with both variants.

In either case, running a word2vec training process results in a static mapping from word types to their embeddings in a vector space of a given size, typically a few hundred dimensions. These embeddings have been shown to be helpful as features in a number of different NLP tasks [90], allowing us to learn richer representations of word types from plentiful unannotated monolingual text. This effectively turns what was a purely supervised task, requiring labeled training data, into a semi-supervised task, in which the representation-learning phase can be carried out on unlabeled data by synthesizing a supervised learning task that can be performed with simple monolingual text as its training data.

We trained a variety of word2vec embeddings for our text classification tasks, again training on the Spanish-language section of the Europarl corpus (roughly 57 million words or 2 million sentences) and a dump of Spanish Wikipedia (449 million words, 20 million sentences). We learned embeddings using both CBOW and skip-gram approaches, in 50, 100, 200, and 400 dimensions. We also used the associated `word2phrase` tool, distributed with the public `word2vec` implementation, which finds collocations in the input text and treats them as individual tokens. The same collocations must be identified in the input text for their embeddings to be used. At lookup time, we keep a list of all the multiword expressions present in the dictionary of embeddings, sorted from longest to shortest, first considering number of tokens, then breaking ties by considering number of characters, and greedily replace any of these multiword expressions (starting with the longest) found in the input text with the token representing that MWE.

[6]According to the TensorFlow tutorial on word2vec, available at `https://www.tensorflow.org/tutorials/word2vec`

6.3.1 From word embeddings to classification features

We should note that, like Brown clusters, the embeddings learned for a word type are fixed for that word type, and do not reflect the context of a particular token, so a focus word's embedding vector will not provide useful classification features on its own. This leaves us with the problem of how to make use of the word vectors in a given sentence. Concretely, we must decide how to combine several word vectors together, and which word vectors in a sentence to choose for combination. A typical approach is to take element-wise sums or averages over the embedding vectors for the tokens in a context [100, Chapter 8].

There are a variety of approaches we could take, even within summing and averaging. We could sum (element-wise) all of the word vectors for all the tokens in the entire sentence. We could only consider the words in a narrow window around the focus word. Or we could perform a weighted sum, in which words nearer to the focus word are given more weight, but these weights drop off according to some function, scaling with the distance from the focus word. We might expect the tokens closest to the current focus word to be most important for building a representation of the meaning of that word – which would lead us to expect the best results from summing uniformly over the context window, or a weighted sum with gradually dropping weights – or perhaps we might expect that we want to represent the meaning of the entire sentence, and so could sum over all the tokens. How well any of these approaches work in practice is an empirical question, so we run experiments using each of these these different approaches, resulting in three different feature sets.

In the first feature set, called "window", we present the classifier with the element-wise sum of the vectors for the focus word (or the token containing the focus word, if it is inside a multi-word expression) and the three tokens on either side. The resulting vector thus has the same dimensionality as the word embeddings that we learned. Secondly, in the "fullsent" feature set, we perform an unweighted element-wise sum of the word embeddings for the entire input sentence. Finally, in the "pyramid" feature set, we sum the embeddings for each token in a broad window around the focus word, but before summing, scale each embeddings by $max(0, 1.0 - (0.1 * d))$, where d is the distance between that token and the focus word.

For all of the variations considered here, whether we are using skipgrams or CBOW, for whichever dimensionality we choose, and for any of the methods of combining the vectors, when using these word embeddings without other resources, we end up representing a CL-WSD problem as a dense vector of the same dimensionality as the current set of word embeddings; these dense vectors can be passed along to any machine learning algorithm that we care to use.

6.4 Neural Document Embeddings

Rather than coming up with representations for individual words and then combining them to get a representation of a sentence or a local context, we might want a technique that directly finds representations of sequences of text. One such technique, called "paragraph vectors" or "doc2vec", does just this. doc2vec was developed by some of the same researchers that produced word2vec, and it can build representations for arbitrary sequences of text, rather than individual word types [98, 99]. This approach takes unlabeled text and learns representations for word types jointly with representations for each *document*. Here a "document" is an arbitrary sequence of tokens, perhaps a single sentence, or perhaps much longer, depending on the intended application.

Similar to word2vec, here doc2vec uses a neural network with a single hidden layer to predict words in the current context. Here however, the hidden layer contains not only an embedding trained for word types, but also an embedding for the current document. Training proceeds by loading the current representation for the current word and the current document, attempting to predict some other word in the context (analogous to training for word2vec), and then updating both of these representations based on the gradients between the desired output and the actual output.

Also similar to word2vec, there are two variants of the approach that can be used for training. One variant of doc2vec, the "Distributed Memory Model of Paragraph Vectors", uses a paragraph embedding combined with word embeddings for several words in the current context to predict a single individual word. The other variant, the “Distributed Bag of Words model of Paragraph Vectors”, simply uses the current paragraph vector to predict all of the words in the current context, which despite containing “bag of words” in its name, is more closely analogous to the skip-gram artitecture for word2vec [99], since the model is trained to predict the entire context based on a single embedding.

In either case, the resulting stored model consists of the embeddings for individual word types. The embeddings for any particular document in the training set are not stored, since that document is unlikely to appear again at inference time, but the embeddings for individual word types provide a useful generalization, since they constrain embeddings for new documents.

At inference time, doc2vec produces new vectors representing previously unseen documents based on these fixed word embedding vectors. In our work, as in many text classification tasks, documents will be input sentences, or perhaps sentence-length Bible verses, or smaller windows of text around a word-in-context. To produce a representation for a new document, the embeddings for word types are held constant and we run stochastic gradient descent optimization to infer an embedding for the current document, based on the fixed word embeddings, such that it helps predict words in the current context.

doc2vec thus provides a straightforward approach for learning to produce representations of new documents, based on an unlabeled training corpus. Here we use the implementation of doc2vec provided by the gensim package [7], with its default settings, which uses the “distributed memory” model [101].

In order to use doc2vec for our experiments, we train and save a doc2vec model on our 20 million sentences from Spanish-language Wikipedia. Then, during training data annotation for the CL-WSD model, we pass over our bitext corpus, take the source-language sentence from each training pair, and infer a new embedding for it based on that doc2vec model.

[7]Available at `https://radimrehurek.com/gensim/`

These sentence-level embeddings are stored as a token annotation on the first token of each sentence, so they can be made available during feature extraction. We can also show the gensim software a small context window around the focus word, rather than the entire sentence to generate a more focused representation.

In either case, the result is a dense vector of the specified dimensionality, again typically a few hundred, which we can pass to whichever machine learning algorithm we like, as we did previously with the vectors based on word2vec.

6.5 Experiments

Here we repeat the experiments from Chapter 5 for Spanish-Guarani and Spanish-Quechua, using the features extracted from syntactic tools, Brown clusters, and the various kinds of neural embeddings presented in this chapter. These experiments were carried out with the top classification algorithms that we used in Chapter 5, focusing on maximum entropy (using both L1 and L2 regularization) and random forests. While most of the experiments here are a combination of the baseline features with the features introduced in this chapter, we also used the neural embeddings features on their own, as a replacement for the baseline features. While there are many possible combinations of the features, we did not run experiments for all (exponentially many) possibilities exhaustively.

Specifically, we experimented with the following feature sets, based on the techniques described in this chapter, for both Spanish-Guarani and Spanish-Quechua.

- POS tag features, with baseline features
- POS tag and dependency parse features, with baseline features
- Brown cluster features, with baseline features, in combinations of ...
  - trained on Europarl or Wikipedia
  - based on lemmas or surface forms

  - context-window only, or including both context-window and all clusters for the sentence as a bag.

- word2vec embeddings on their own, in combinations of …
  - trained on Europarl and Wikipedia
  - skipgrams and CBOW
  - using multi-word expression embeddings or not
  - dimensions: 50, 100, 200, 400
  - combination strategies: full sentence, context window, and “pyramid” (summing embeddings with a weight that decreases with distance from the focus word)

- doc2vec embeddings on their own, trained on Wikipedia…
  - embeddings for a full sentence or embeddings for a context window

- Combination of promising features: baseline features, with syntactic features and Brown clusters (context window, surface form, Wikipedia).

- Combination of promising features: “pyramid” word2vec embeddings, with syntactic features and Brown clusters (also context window, surface form, Wikipedia).

In the next section, we present and discuss the results from these experiments.

6.6 Experimental Results

This section contains many tables of numbers; in general, for each set of experimental results presented, the top result for each setting is presented in *italics*, and the top result for a setting presented in the whole chapter is presented in **bold**.

classifier	es-gn regular	es-gn non-null	es-qu regular	es-qu non-null
MFS	0.456	0.498	0.435	0.391
maxent l1				
baseline features	0.461	0.506	0.444	0.414
+pos tags features	0.464	0.510	0.449	0.420
+all syntactic features	0.465	0.511	0.450	0.422
maxent l2				
baseline features	0.475	0.524	0.458	0.431
+pos tags features	0.479	0.527	0.462	0.438
+all syntactic features	0.480	**0.530**	0.465	*0.441*
random forest				
baseline features	0.481	0.520	0.464	0.424
+pos tags features	0.485	0.523	0.467	0.430
+all syntactic features	*0.486*	0.527	*0.471*	0.434

Figure 6.9: Classification results for adding syntactic features to the default feature set, as compared with the MFS baseline.

6.6.1 Results: adding syntactic features

Taking a look at the scores from the features based on easily available Spanish-language taggers and parsers, which are presented in Figure 6.9, we see small but fairly consistent improvements over the baseline features as we add syntactic features. In all of our settings, we see a few tenths of a percentage point gain by adding the POS tag features, and then another small gain on top of that by adding syntactic dependency features.

These gains seem to be of roughly the same (small) magnitude; it is not obvious whether any of the classifiers are more able to make use of the additional features than others, but this is somewhat reassuring, and it looks like we are easily able to add some helpful features when we have syntactic analysis tools available for our source language.

6.6.2 Results: adding clustering features

We see the experimental results for adding our Brown Cluster features (explained in Figure 6.8) in Figure 6.10. In general, we do not see gains from adding all of the Brown Cluster features together; this typically seems to diminish performance by a few tenths of a percent-

features	es-gn regular	es-gn non-null	es-qu regular	es-qu non-null
MFS	0.456	0.498	0.435	0.391
maxent l1				
baseline features	0.461	0.506	0.444	0.414
+Europarl clusters, surface	0.446	0.491	0.429	0.399
+Europarl clusters, lemmatized	0.448	0.492	0.432	0.401
+Wikipedia clusters, surface	0.446	0.490	0.428	0.399
+Wikipedia clusters, lemmatized	0.448	0.490	0.429	0.401
+Europarl, surface, window	0.460	0.505	0.444	0.415
+Europarl, lemmas, window	0.460	0.506	0.444	0.415
+Wikipedia, surface, window	0.460	0.506	0.445	0.416
+Wikipedia, lemmas, window	0.460	0.506	0.443	0.415
maxent l2				
baseline features	0.475	0.524	0.458	0.431
+Europarl clusters, surface	0.462	0.512	0.445	0.420
+Europarl clusters, lemmatized	0.462	0.512	0.445	0.419
+Wikipedia clusters, surface	0.461	0.512	0.445	0.420
+Wikipedia clusters, lemmatized	0.463	0.512	0.445	0.419
+Europarl, surface, window	0.476	*0.525*	0.458	0.435
+Europarl, lemmas, window	0.475	*0.525*	0.459	0.435
+Wikipedia, surface, window	0.475	*0.525*	0.460	*0.436*
+Wikipedia, lemmas, window	0.475	0.524	0.459	0.434
random forest				
baseline features	0.481	0.520	0.464	0.424
+Europarl clusters, surface	0.476	0.519	0.461	0.423
+Europarl clusters, lemmatized	0.476	0.518	0.459	0.420
+Wikipedia clusters, surface	0.477	0.518	0.460	0.423
+Wikipedia clusters, lemmatized	0.478	0.517	0.459	0.418
+Europarl, surface, window	0.483	0.524	0.466	0.430
+Europarl, lemmas, window	0.483	0.524	0.466	0.428
+Wikipedia, surface, window	*0.484*	0.524	*0.468*	0.430
+Wikipedia, lemmas, window	0.483	0.524	0.466	0.427

Figure 6.10: Classification results for adding Brown cluster features to the default feature set.

age point, in many cases making the performance as a whole dip below the MFS baseline. While they are intended to be helpful abstractions, we may be adding too many irrelevant features, perhaps overwhelming the useful signals present in the baseline feature set. There does not seem to be a consistent or significant change due to using the lemmatized or surface forms.

However, we get substantially better results when we limit the Brown cluster features to a narrow context words of three words on either side of the focus word; this seems to lead to roughly the same results as the baseline features, for the maximum entropy classifiers. But for the random forest classifiers, we see consistent gains of three to six tenths of a percentage point. So for random forest classifiers, it seems worthwhile to add these window-based Brown cluster features. Within the “window only” variants of the Brown cluster features, the scores are fairly similar, but by a small margin we see the strongest results coming from using the clusters trained on the surface form of our Spanish Wikipedia.

Neither of these corpora, Europarl or the Spanish Wikipedia, are similar in genre to the Bible verses in our test set, but we can get a small benefit from adding the Brown cluster features here. The substantially larger size of the Wikipedia corpus does not seem to confer clusters that are much more helpful; if there had been a large performance gap between using the Wikipedia and Europarl clusters, we could have run additional experiments with clusters trained on a 2-million sentence sample of Wikipedia to determine whether it was the additional size or the genre of the text that had improved performance.

6.6.3 Results: combining sparse features

We present the experimental results for combinations of all of the sparse features presented in this chapter in Figure 6.11. Here in general we see some good gains over the baseline features, from a few tenths of a percentage point to just over a full percentage point; we see that as before, the maximum entropy classifiers do not seem to benefit from the addition of Brown cluster features, but they do benefit from the syntactic features. The random

classifier	es-gn regular	es-gn non-null	es-qu regular	es-qu non-null
MFS	0.456	0.498	0.435	0.391
maxent l1				
baseline features	0.461	0.506	0.444	0.414
+syntactic features, maxent l1	0.465	0.511	0.450	0.422
combined sparse features	0.464	0.510	0.448	0.422
maxent l2				
baseline features	0.475	0.524	0.458	0.431
+syntactic features, maxent l2	0.480	**0.530**	0.465	0.441
combined sparse features	0.479	**0.530**	0.465	**0.443**
random forest				
baseline features	0.481	0.520	0.464	0.424
+syntactic features	0.486	0.527	0.471	0.434
combined sparse features	**0.488**	0.528	**0.472**	0.437

Figure 6.11: Results for baseline features with the sparse features introduced in this chapter: features from a POS tagger, a dependency parser, and Brown clustering.

forest classifiers benefit from both additional kinds of features; our best performance with the sparse feature sets is with random forests given these combined features, and this is consistent for both language pairs, and in the regular and non-null settings.

6.6.4 Results: word2vec embeddings alone

Taking a look at Figures 6.12 and 6.13, we see the results for the experiments for using only word2vec embeddings for our features. There were many variations, but we see a few general trends. We performed experiments for 50, 100, 200, and 400 dimensions, but the dimensionality of the vectors did not seem to change the results more than a few tenths of a percentage point. Here we report the results for 200 dimensions to save space and for easier comparison; in general the results for 200 dimensions were on the slightly more favorable side of representative. Also, because there were so many variations to try, some of the less promising combinations were cut. Specifically, almost all of the experiments with the CBOW embeddings, the “fullsent” combination approach, and random forest classifiers gave results

classifier	es-gn regular	es-gn non-null	es-qu regular	es-qu non-null
MFS	0.456	0.498	0.435	0.391
maxent l1				
baseline features	0.461	0.506	0.444	0.414
fullsent, europarl	0.421	0.465	0.406	0.369
fullsent, europarl, mwes	0.421	0.465	-	-
fullsent, wikipedia	0.428	0.468	0.408	0.374
fullsent, wikipedia, mwes	0.428	0.469	-	-
pyramid, europarl	0.463	0.507	0.448	0.418
pyramid, europarl, mwes	0.462	0.505	0.447	0.418
pyramid, wikipedia	*0.469*	*0.512*	*0.453*	*0.424*
pyramid, wikipedia, mwes	*0.469*	*0.512*	0.452	0.423
window, europarl	0.462	0.506	0.447	0.417
window, europarl, mwes	0.460	0.504	0.447	0.416
window, wikipedia	0.468	0.511	0.451	0.423
window, wikipedia, mwes	0.467	0.511	0.450	0.422
maxent l2				
baseline features	0.475	0.524	0.458	0.431
fullsent, europarl	0.421	0.469	0.406	0.375
fullsent, europarl, mwes	0.421	0.469	-	-
fullsent, wikipedia	0.427	0.472	0.408	0.379
fullsent, wikipedia, mwes	0.427	0.472	-	-
pyramid, europarl	0.459	0.505	0.443	0.417
pyramid, europarl, mwes	0.457	0.504	0.443	0.418
pyramid, wikipedia	0.465	*0.512*	0.449	*0.424*
pyramid, wikipedia, mwes	0.464	0.511	0.449	0.423
window, europarl	0.455	0.501	0.440	0.414
window, europarl, mwes	0.453	0.500	0.439	0.413
window, wikipedia	0.461	0.507	0.445	0.420
window, wikipedia, mwes	0.461	0.506	0.445	0.420
random forest				
baseline features	0.481	0.520	0.464	0.424
fullsent, europarl	0.432	0.474	-	-
fullsent, europarl, mwes	0.431	0.474	-	-
fullsent, wikipedia	0.432	0.477	-	-
fullsent, wikipedia, mwes	0.433	0.476	-	-
window, europarl	0.447	0.491	-	-
window, europarl, mwes	0.448	0.489	-	-
window, wikipedia	0.453	0.494	-	-
window, wikipedia, mwes	0.451	0.493	-	-

Figure 6.12: Results for classification using only word2vec skipgram embeddings to create features. For space, here we only show results for 200-dimensional embeddings.

classifier	es-gn regular	es-gn non-null	es-qu regular	es-qu non-null
MFS	0.456	0.498	0.435	0.391
maxent l1				
baseline features	0.461	0.506	0.444	0.414
fullsent, europarl	0.389	0.433	-	-
fullsent, europarl, mwes	0.388	0.434	-	-
fullsent, wikipedia	0.391	0.433	-	-
fullsent, wikipedia, mwes	0.391	0.433	-	-
pyramid, europarl	-	-	*0.401*	0.374
pyramid, wikipedia	-	-	0.401	0.375
window, europarl	0.414	0.455	0.396	0.367
window, europarl, mwes	0.411	0.454	-	-
window, wikipedia	0.414	0.456	0.395	0.368
maxent l2				
baseline features	0.475	0.524	0.458	0.431
fullsent, europarl	0.392	0.442	-	-
fullsent, europarl, mwes	0.392	0.441	-	-
fullsent, wikipedia	0.394	0.440	-	-
fullsent, wikipedia, mwes	0.394	0.441	-	-
pyramid, europarl	-	-	0.398	0.375
pyramid, wikipedia	-	-	0.398	*0.377*
window, europarl	0.403	0.448	0.386	0.363
window, europarl, mwes	0.402	0.447	-	-
window, wikipedia	0.408	0.451	0.389	0.366
window, wikipedia, mwes	0.406	0.451	-	-
random forest				
baseline features	0.481	0.520	0.464	0.424
fullsent, europarl	0.432	0.472	-	-
fullsent, europarl, mwes	0.431	0.474	-	-
fullsent, wikipedia	0.434	0.478	-	-
fullsent, wikipedia, mwes	0.434	0.478	-	-
window, europarl	0.449	0.492	-	-
window, europarl, mwes	0.448	0.489	-	-
window, wikipedia	*0.452*	*0.494*	-	-
window, wikipedia, mwes	0.451	*0.494*	-	-

Figure 6.13: Results for classification using only word2vec CBOW embeddings to create features. For space, here we only show results for 200-dimensional embeddings.

lower than the MFS baseline, so not all combinations were carried out.

However, if we focus on Figure 6.12, we can see some fairly promising results. We note that for the maxent classifiers, we can often surpass the MFS baseline by using the word2vec embedding features alone, and for some settings, even surpass the baseline features. Particularly, we note that using the "window" and "pyramid" results, we can do fairly well – the "fullsent" approach does not seem to help here – and that for the L1-norm maxent classifier, we can outperform the baseline features with word2vec features alone.

Interestingly, despite its strong performance on the sparse feature sets, the random forest classifier does not do as well with the dense vectors; it does not outperform the MFS baseline. In general, the L1-norm maxent classifier seems to do best with these feature sets, and the embeddings trained on the larger (and more general-domain) Wikipedia corpus seem to be most effective; using the multi-word expression embeddings seems to have little to no effect. The "pyramid" combination scheme generally comes out on top. So this is encouraging, for features for maxent classifiers.

6.6.5 Results: doc2vec embeddings alone

Taking a look at the results for using doc2vec embeddings on their own, presented in Figure 6.14, we see a few general trends. As with the word2vec feature sets, the random forests did not outperform the MFS baseline when given a dense vector as input. Also as we saw with the word2vec features, trying to build a representation of the entire sentence was not as effective as building a vector to represent just the tokens around the focus word. The full-sentence representations were more effective than the corresponding full-sentence vector sums from word2vec, however – in a few instances they outperform the MFS baseline.

However, when we restrict the doc2vec optimizer to looking at a narrow context window around the focus word, we outperformed the MFS baseline on all of the test sets, for maxent classifiers. For some, but not all, of the L1-norm maxent cases, the doc2vec features surpass the baseline features by a slim margin. There may be a way to make doc2vec embeddings,

classifier	es-gn regular	es-gn non-null	es-qu regular	es-qu non-null
MFS	0.456	0.498	0.435	0.391
maxent l1				
baseline features	0.461	0.506	0.444	0.414
fullsent	0.462	0.496	0.441	0.391
window	0.463	0.502	0.445	0.395
maxent l2				
baseline features	0.475	0.524	0.458	0.431
fullsent	0.462	0.497	0.442	0.390
window	*0.467*	*0.506*	*0.449*	*0.402*
random forest				
baseline features	0.481	0.520	0.464	0.424
fullsent	0.420	0.497	0.404	0.390
window	0.421	0.461	0.405	0.352

Figure 6.14: Top results for classification using only doc2vec embeddings to create features. For comparison, also included are the MFS baseline and the top results from the previous chapter.

or some other kind of document-level embedding features, work well for this setting, but further exploration is outside the scope of this work.

6.6.6 Results: combining neural embeddings with sparse features

In Figure 6.15, we present the experimental results for combining the most successful word2vec embeddings with the most promising additional sparse features described in this chapter. In these experiments, we started with the 200-dimensional Wikipedia embeddings, combined them in the "pyramid" style, and also made the Brown cluster and syntactic features available to the classifiers to see if these would improve performance.

And in general, we see that the addition of these features does make an improvement over using the word2vec features by themselves. In fact, for all of the classifiers, and each of the test sets, we see an improvement over the word2vec features; this only results in consistent improvements over the baseline features for the L1-norm maximum entropy classifer, however. But it is the best results presented thus far for that classifier, and the most effective feature set that we have tried, using neural embeddings.

classifier	es-gn regular	es-gn non-null	es-qu regular	es-qu non-null
MFS	0.456	0.498	0.435	0.391
maxent l1				
baseline features	0.461	0.506	0.444	0.414
word2vec alone	0.469	0.512	0.453	0.424
+sparse features	*0.472*	0.519	*0.458*	0.436
maxent l2				
baseline features	0.475	0.524	0.458	0.431
word2vec alone	0.465	0.512	0.449	0.424
+sparse features	*0.472*	*0.522*	*0.458*	*0.438*
random forest				
baseline features	0.481	0.520	0.464	0.424
word2vec alone	0.452	0.493	0.438	0.394
+sparse features	0.461	0.504	0.449	0.410

Figure 6.15: Results for combining word2vec embeddings (Wikipedia skipgrams, 200 dimensions, "pyramid" strategy) with syntactic features and Brown clusters. For comparison, also included are the MFS baseline, word2vec results without additional features.

6.7 Discussion

In this chapter, we have shown a number of different approaches for making use of the available resources for our source language in the CL-WSD task, including three different ways of learning from unannotated source-language text – clustering and two kinds of neural embeddings – and making use of existing source-language syntactic analysis tools.

Using each of these different tools, we were able to overcome the relatively strong most-frequent sense baseline, and with many of the different feature sets, we were able to show small but consistent gains over the baseline feature set described in the previous chapter. Overall, the best results posted for Spanish-Guarani were with the combined sparse features; the random forest classifier had the strongest results for the "regular" setting, and the maximum entropy classifier with L2 regularization came out ahead for the non-null setting (this result was tied with the one for using the syntactic features with maximum entropy, L2 regularization). For Spanish-Quechua, the top results were similarly posted with the combined sparse features, with random forests coming out ahead for the "regular" setting and maximum entropy, L2, posting the best results for “non-null”.

All of the approaches explored in this chapter make more abstract representations of the source text available to our classifiers, whether these representations were learned from the available text, or encapsulate some kind of syntactic knowledge about the language.

We found, in general, that adding features that represent the text closely surrounding the focus word was more effective than attempting to represent the entire source-language sentence at once; we observed this effect for Brown cluster features, and for features built from both word and document embeddings. Additionally, we found that we could not only add some of these features to our baseline sparse feature set, but also that our new sparse features could be added to dense feature vectors based on word2vec embeddings, resulting in gains over using the neural embeddings by themselves.

In general, our random forest classifiers seem to benefit more from adding many sparse features, like the ones we extracted from Brown clusters, than the maxent classifiers do. However, the random forest classifiers do not perform as well when given dense vectors, like those produced by word2vec and doc2vec. Contrastingly, the maximum entropy classifiers have better performance in this setting.

In the next chapter, we will make use of another one of our available resources for a resource-rich language like Spanish: bitext with other language pairs.

CHAPTER 7
LEARNING FROM MULTILINGUAL DATA

As discussed in previous chapters, while our target languages are under-resourced, we have many resources available for our source languages. Concretely for Spanish, in addition to the abundant monolingual text and off-the-shelf NLP tools discussed in Chapter 6, we have a significant amount of bitext, pairing Spanish with languages other than our under-resourced target languages. We would like to be able to learn from these available bitext corpora when translating from Spanish to Guarani and Quechua, and ideally when translating from resource-rich source languages into under-resourced target languages in general.

Each bitext corpus may contain useful examples of a given source language word, and senses of that word may be lexicalized in distinct ways in different target languages, giving us clues about the meaning of each token in its context. Selecting a contextually correct translation for source-language words is evidence that we have understood the meaning of those words, at least implicitly, in as far as sense distinctions are surfaced in the target language. So we would like to be able to learn relationships between the senses of a given source word as they are represented in different target languages. Two target languages may happen to surface similar sense distinctions, perhaps due to being related languages, or perhaps because a word sense ambiguity is unusual in the source language, or simply by coincidence. Additionally, a combination of translations into several languages may provide evidence for a certain lexical choice in the target language of interest.

In this chapter, we present strategies for learning from the available bitext corpora that do not include our under-resourced target languages, to help us make better CL-WSD decisions when translating into them. To establish consistent terminology, we will call these *supplemental* bitext corpora. Primarily we discuss a "classifier stacking" approach, in which we train "supplemental" CL-WSD classifiers translating from Spanish to other European languages, based on our supplemental corpora, and use their outputs to provide more features for the Spanish to Quechua and Spanish to Guarani classifiers.

As a concrete example of how we can use classifier stacking, say we are trying to translate a Spanish sentence to English and we would like to make a lexical selection for the word *estación*, which can translate to English as either "station" (like a train station) or "season".

(5) Mi *estación* favorita es la primavera.

If we had a Spanish to French CL-WSD system, and this system returned *saison* (rather than *gare*, the French word for a train station) for this instance of *estación*, we would expect that this would be a useful signal for our Spanish to English classifier, helping it pick the "season" sense.

The approaches in this chapter are particularly informed by the work of Els Lefever *et. al* (see especially [26]), in which entire source sentences are machine-translated into several different target languages just before feature extraction, and these translated sentences are used to produce features for CL-WSD classifiers. One drawback of this technique is that it could be considered unwieldy from a software engineering perspective; it requires multiple complete MT systems to perform CL-WSD, when we want to use CL-WSD as a subcomponent of a machine translation system in the first place.

In earlier work, considering the work of Lefever *et. al*, we developed prototype CL-WSD systems that made use of multilingual evidence [8] and produced some of the top results in a SemEval shared task on CL-WSD [32]. We found here that our systems that used multilingual evidence had better performance than the one that used only monolingual features. Our top results in every language came from either classifier stacking or a classifier based on Markov networks, an approach which we will discuss briefly in Section 7.2. This suggests that it is possible to use evidence in several parallel corpora for CL-WSD without translating input sentences into many target languages.

For the rest of the chapter, we will describe some of the supplemental bitext corpora that we can use for CL-WSD from Spanish, the Markov network approach described in our SemEval entry, and the classifier stacking approach. Then we present experiments and experimental results using classifier stacking for Spanish-Guarani and Spanish-Quechua CL-WSD tasks.

7.1 Supplemental multilingual corpora

Following our earlier work and that of Lefever *et. al*, we limit the scope of our supplemental corpora to adding five additional languages; there is an enormous combinatorial space for running experiments with different subsets of the available bitexts in different languages; in the interest of not only constraining the search space, but also not fishing for impressive-seeming results when we only have a small amount of bitext for the language pairs directly addressed in this work, we will only make use of Spanish to Dutch, English, French, German, and Italian. Note that these are all resource-rich European languages, not related to our indigenous American target languages. So if we can learn from bitext pairing Spanish with these languages, it suggests that our approaches can be applied to a broad range of target languages. Experimenting with more language pairs, or different language pairs, may be effective or appropriate in other settings, but here we consider it outside the scope of the current effort.

7.1.1 Europarl

There are several freely available bitext resources for many European languages, especially the official languages of the European Union. Through the Europarl corpus [70], for example, we have bitext corpora in which Spanish is paired with English, German, French, and 17 other European languages. This corpus is derived from the human-translated proceedings of European Parliament, and so its subject matter pertains to parliamentary procedure and modern-day European policy issues; while it provides a substantial sample of bitext, it does not at first glance seem particularly similar to our Bible bitext for Spanish-Guarani and Spanish-Quechua. We will investigate the differences in text domain further in Section 7.4,

Language pair	number of sentence pairs
Spanish-Dutch	$1,801,844$
Spanish-English	$1,816,554$
Spanish-French	$1,834,957$
Spanish-German	$1,747,525$
Spanish-Italian	$1,740,939$

Figure 7.1: Classifier features based on classifier stacking, used in the experiments in this chapter.

but whether this text is helpful for our task in practice is an empirical question.

Using the automatic tools distributed with the corpus[1], we produced sentence-aligned and tokenized bitext, ending up with roughly 1.8 million sentence pairs per language pair, though this number varies somewhat; see Figure 7.1 for specific bitext corpora sizes. We then preprocess the extracted bitext with the same steps used on our Bible text, as described in Section 4.3. Where possible, we lemmatize the target-language text with FreeLing. However, as of this writing FreeLing does not support Dutch, so for Dutch, we use the Frog text analysis tool[2] [102] for lemmatization. With the exception of the different lemmatizer for Dutch, the preprocessing steps are the same as those described in the previous chapters, resulting in automatically aligned Spanish-Dutch, Spanish-English, Spanish-French, Spanish-German, and Spanish-Italian bitext corpora for our experiments.

7.1.2 Bible translations

For the additional European languages, Bible translations were made available as part of a project by Christodouloupoulos *et al.*[103][3]. It is fortunate that these translations are freely available online; as discussed previously in Section 4.3, not all languages have publicly redistributable full-text Bibles available. As an additional convenience, the Bible translations provided by Christodouloupoulos *et al.* come in a standardized XML-based format[4],

[1]Available online at `http://statmt.org/europarl/`

[2]Frog was developed by groups at Tilburg University and the University of Antwerp. It is available at `http://languagemachines.github.io/frog/`

[3]Their provided Bible text is available online at `https://github.com/christos-c/bible-corpus`

[4]Appropriately called the Corpus Encoding Standard, described at `https://www.cs.vassar.edu/CES/`

making extraction of the text and reuse of the text with our tooling straightforward. Preparation and preprocessing for the supplemental Bible corpora proceeds as before, similarly to the preparation done for our Europarl supplemental bitext and the Spanish-Guarani and Spanish-Quechua Bibles bitext.

7.2 CL-WSD with Markov Networks

In our SemEval entry [8], we investigated a CL-WSD approach based on Markov networks (also known as "Markov Random Fields"), building a network of interacting variables (see Figure 7.2) to solve CL-WSD classification problems for the five target languages of the SemEval 2013 task [32]. In this task, we were given English source sentences with an annotated focus word (from a given set of possible focus words types), and asked to make correct lexical selections for translating into Dutch, French, German, Italian and Spanish. The ground truth for the task was determined by human annotators familiar with those languages.

Here the nodes in our Markov network represent random variables that take on values corresponding to the possible translations for each of the five target languages. The probability distributions over these translations are produced by language-specific maximum entropy classifiers, effectively applying the baseline Chipa system on the given input sentence.

The edges in the graph correspond to pairwise potentials that are derived from the joint probabilities of target language labels co-occurring in the available bitext for the two target languages along that edge of the graph. This approach thus requires a bitext corpus for each pair of languages in the set of languages involved; for the SemEval task, we worked with a subset of the Europarl corpus, provided by the task organizers, in which every sentence was provided for all six languages.

We frame the task of finding the optimal translations into five languages jointly as a MAP inference problem, wherein we try to maximize the joint probability of all five variables, given the single source language sentence. We perform inference with loopy belief propagation [104], which is an approximate but tractable inference algorithm that, while

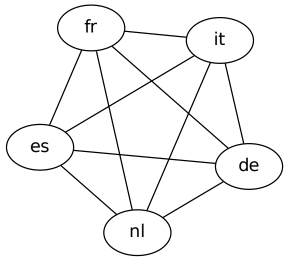


Figure 7.2: The network structure used in the MRF system for SemEval: a complete graph with five nodes, in which each node represents the random variable for the translation into a target language.

giving no guarantees, often produces good solutions in practice. We used the formulation for pairwise Markov networks that passes messages directly between the nodes rather than first constructing a "cluster graph", which is described in [105, §11.3.5.1] of Koller and Friedman's book on graphical models. This Markov network approach has the theoretically satisfying property that it takes seriously the uncertainty present in the predictions of each of the component classifiers and solves the entire problem jointly.

Intuitively, at each time step loopy belief propagation passes messages around the graph that inform each neighbor about the estimate, from the perspective of the sender and what it has heard from its other neighbors, of the minimum penalty that would be incurred if the recipient node were to take a given label. As a concrete example, when the *nl* node sends a message to the *fr* node at time step 10, this message is a table mapping from all possible French translations of the current target word to their associated penalty values. The message depends on three things: the probability distribution from a monolingual classifier just for Dutch, joint probabilities estimated from our Dutch-French bitext, and the messages from the *es*, *it* and *de* nodes from time step 9.

While we were able to achieve fairly good results with these MRF-based classifiers on the Semeval CL-WSD task, our strategy for setting the weights in the Markov network requires, for each edge in the graph, a parallel corpus for the corresponding language pair. The bitext

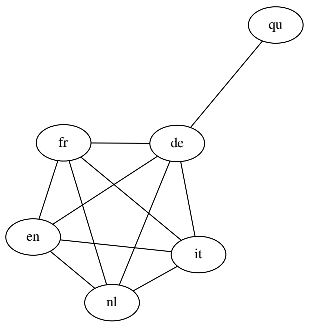


Figure 7.3: Hypothetical network structure – not fully connected – that could be used for a Markov network translating from Spanish to all of the six languages shown, if we had a bitext corpus for Spanish and every other language, for also for German-Quechua.

for each language pair need not be mutually parallel among all of the languages present; each edge in the graph may correspond to an unrelated bitext corpus. Also, in principle the graph need not be fully connected, as it was for our SemEval entry; see Figure 7.3 for a hypothetical graph structure that could be used with the right bitext corpora available. But this approach does require bitext between the source language and all other languages involved, as well as our target language of interest and at least one of the other language, so that our choices for that other language can inform our choices for the target language of interest.

Considering the limited bitext resources available, this approach is less easily applicable for the under-resourced target language use case; concretely, we do not have Europarl corpora available for Quechua and Guarani. In the classifier stacking approach, it is clear how we can include information from many heterogeneous sources. The Markov network approach may be useful for future CL-WSD systems in other settings, but for now we will not make further use of it for translating into under-resourced languages, since we do not have many parallel corpora available for Guarani or Quechua.

7.3 Classifier stacking

The simpler approach that we use in practice in this work is a form of classifier stacking. In order to predict the translation of a word into our intended target language, we use features based on our predictions for translations of tokens in the current sentence into *other* available target languages. For example, in our SemEval prototype systems, in order to translate an English word into Spanish, we predict that word's translations into French, Italian, Dutch and German, and then encode those predicted translations as features for our English to Spanish classifier.

This approach only requires that the classifiers used for generating new features make *some* prediction based on the input text. These classifiers need not be trained from the same source text, or depend on the same features, or even necessarily produce words as output. Similar to our use of syntactic NLP tools in the previous chapter, we could use any annotation on the text for extracting features, if we expect it will provide a meaningful clue about the meaning of the input. For example, we could use this technique with a monolingual WSD system that output word sense annotations and extract features from these sense labels. However, in this work, our classifiers output predicted translations for source-language tokens into other languages, having been trained on supplemental corpora. We can use as features not only the predicted translation for the current token, but also predicted translations for any tokens in the input sentence.

See Figure 7.4 for an overview of the features made available to classifiers based on these supplemental classifiers in our stacking experiments.

7.3.1 Annotating the bitext with stacking predictions

Here we train the baseline Chipa system with the default feature set described in Chapter 5, separately on Europarl bitext and verse-aligned Bible translations, for the same five European target languages. For all of the stacking classifiers mapping from Spanish to another

name	description
`stacking_en`	Predicted translation of the current token into English, if one was available. Feature is not present if no prediction was made for this token.
`stacking_de`, `stacking_fr`, `stacking_it`, `stacking_nl`	as before, but with a prediction into the corresponding language.
`stacking_window`	The predictions for any tokens in the surrounding context window, into any of the available languages for this run.

Figure 7.4: Classifier features based on classifier stacking, used in the experiments in this chapter.

European language, we trained a random forest classifier on the "nonnull" setting. So as a result, we came up with ten different sets of stacking classifiers, the first five of which were trained with Europarl data, and the latter five with Bible data.

We then annotate our bitext for Spanish-Guarani and Spanish-Quechua, finding each instance of the in-vocabulary focus words for that language pair (see Section 4.4) and classifying that instance with each of the trained CL-WSD classifiers. The prediction for each instance, for each classifier, is recorded as an annotation on that token (see Section 4.3.1), for use in later feature extraction. If no prediction was made for a given token, either because a word is not in our list of focus words for the given language pair, or because there were too few instances of that word in the supplemental bitext, then no annotation is recorded.

7.4 Considering domain mismatches

We might be concerned about the domain mismatch between our larger supplemental bitexts, from the Europarl corpus, and the Bible text that we are using for Spanish-Guarani and Spanish-Quechua. The subjects discussed in European Parliament may not match that of our Spanish-Guarani and Spanish-Quechua Bible corpora; we could imagine an unfortunate scenario in which common word types used in the different corpora simply do not have large overlaps. This issue is especially relevant for the techniques described in this chapter; if we do not have any examples of a given word type in our supplemental bitext, then we cannot train supplemental classifiers to help us with our main classification task.

Comparing our bitext corpora, we find that, indeed, many of the word types used in our Spanish Bible translation either never appear, or only appear very rarely in the Europarl text. However, while there are many word types that are commonly used in the Bible text that never appear in our Europarl corpus, these make up a small fraction of the tokens of the Bible text overall, and thus a small number of the CL-WSD problem instances in our experiments.

Here we focus on word types that appear at least fifty times in the Bible bitext and are thus included in our set of CL-WSD classification instances, per the standard established in Chapter 4. Comparing, for example, our Spanish-German Europarl text with our Spanish-Guarani Bible corpus, 24% of the focus word types for which we want to build classifiers appear fewer than fifty times in the Europarl corpus. 13% appear fewer than ten times, and 6% of the word types never appear at all.

Out of the word types that appear in our Bible bitext but never in the Europarl bitext, the majority are either names for people (*e.g.*, *Zacarías*, *Nabucodonosor*, *Balaam*) or Biblical locations (*Galilea*, *Galaad*). Other common themes are colocations referring to God (these are joined into a single token during preprocessing; *e.g.*, *Cristo_Jesús*, *Señor_Jesucristo* and *Dios_de_Israel.* We also see concepts that are simply not often discussed in European Parliament, such as *fornicación* ('fornication'), *ungir* ('to anoint'), *heredad* ('inheritance'), and *querubín* ('cherub')[5].

However, turning our focus to tokens, rather than word types, our annotation process based on the Europarl bitext is able to come up with some prediction for about 96.4% of the Spanish-Guarani CL-WSD problems, so the absence of these particular word types, should not, on its own, prevent the Europarl corpus from providing useful signal for the

[5]Those familiar with the English word "cherub" and its Hebrew-style plural "cherubim" might expect that the Spanish *querubín* would be plural. However, this word refers to a singular angel, and the plural of *querubín* is *querubines*.

great majority of our CL-WSD problems. We are left with the empirical matter of whether training classifiers on a larger out-of-domain supplemental corpus will be more helpful for our task than a small in-domain supplemental corpus.

7.5 Experiments

The experiments in this chapter are analogous to the ones in previous chapters, with the addition of features based on classifier stacking. We ran the same machine learning algorithms on the same training and test sentences as in previous chapters, for both Spanish-Guarani and Spanish-Quechua.

For all tasks in this section, we trained classifiers with the baseline features described in Chapter 5, as well as the new features introduced in this chapter; these are presented in Figure 7.4. We also trained classifiers with the addition of the syntactic features described in Chapter 6. Classifier stacking experiments were done with both "English only" variants, in which the only additional features added were based on the Spanish-English classifier, and the "five languages" variant, where we added features based on the predictions for Spanish to Dutch, English, French German and Italian. The predictions provided were based on classifiers trained on Europarl, on the Bible, and then both classifiers together; this last approach added two distinct sets of stacking features to the classifiers. In addition to simply including the predictions for the current focus word as features, we also include features based on predictions that we were able to make for any tokens in a context window three tokens on either side of the current focus word.

7.6 Experimental Results

This section contains several tables of numbers; as before, for each set of experimental results presented, the top result for each setting is presented in *italics*, and the top result for a setting presented in the whole chapter, or a result tied for the top result, is presented in **bold**.

7.6.1 Results: classifier stacking with Europarl

In Figure 7.5, we present results for the experiments with stacking using the Europarl bitext. We see a performance improvement here for the L2-norm maximum entropy and random forest classifiers; for both language pairs and both settings, we see an improvement of two to four tenths of a percentage point when using all five Europarl languages, and a smaller benefit from using Spanish-English only.

7.6.2 Results: classifier stacking with Bibles

In Figure 7.6, we see our results for the experiments with stacking using Bibles as bitext. In general, we see some of the most significant improvements in this work in these experiments. The addition of features based on the classifiers trained on European-language Bibles provided a performance boost comparable with (and largely greater than) that of using syntactic analysis features. In general, we gain a few tenths of a percentage point by simply adding the English-language Bible features, and then a few more tenths of a percent by adding stacking predictions for the other four languages. In all of these cases, the inclusion of syntactic features along with the stacking features seems to additionally help.

7.6.3 Results: classifier stacking with both Europarl and Bibles

Finally, in Figure 7.7, we show the results for experiments where we used stacking features from both Bibles and the Europarl corpus. The results in general were quite similar those we saw with using Bible stacking features alone; the inclusion of the features from classifiers trained on Europarl did not provide additional benefit for our task, over using the features from the supplemental Bible bitexts.

classifier	es-gn regular	es-gn non-null	es-qu regular	es-qu non-null
MFS	0.456	0.498	0.435	0.391
maxent l1				
baseline features	0.461	0.506	0.444	0.414
+all syntactic features	0.465	0.511	0.450	0.422
europarl stacking, en only	0.461	0.506	0.444	0.414
europarl stacking, en only +syntactic	0.465	0.511	0.450	0.422
europarl stacking, 5 languages	0.460	0.505	0.444	0.414
europarl stacking, 5 languages +syntactic	0.464	0.510	0.449	0.422
maxent l2				
baseline features	0.475	0.524	0.458	0.431
+all syntactic features	0.480	0.530	0.465	0.441
europarl stacking, en only	0.476	0.525	0.458	0.433
europarl stacking, en only +syntactic	0.481	0.530	0.466	0.442
europarl stacking, 5 languages	0.477	0.526	0.461	0.435
europarl stacking, 5 languages +syntactic	0.482	*0.531*	0.467	*0.444*
random forest				
baseline features	0.481	0.520	0.464	0.424
+all syntactic features	0.486	0.527	0.471	0.434
europarl stacking, en only	0.482	0.522	0.464	0.425
europarl stacking, en only +syntactic	0.486	0.527	0.472	0.436
europarl stacking, 5 languages	0.483	0.523	0.466	0.428
europarl stacking, 5 languages +syntactic	*0.487*	0.527	*0.473*	0.438

Figure 7.5: Results for stacking with Europarl.

classifier	es-gn regular	es-gn non-null	es-qu regular	es-qu non-null
MFS	0.456	0.498	0.435	0.391
maxent l1				
baseline features	0.461	0.506	0.444	0.414
+all syntactic features	0.465	0.511	0.450	0.422
bible stacking, en only	0.463	0.508	0.446	0.416
bible stacking, en only +syntactic	0.466	0.513	0.451	0.425
bible stacking, 5 languages	0.466	0.512	0.449	0.419
bible stacking, 5 languages +syntactic	0.469	0.516	0.453	0.427
maxent l2				
baseline features	0.475	0.524	0.458	0.431
+all syntactic features	0.480	0.530	0.465	0.441
bible stacking, en only	0.478	0.527	0.461	0.435
bible stacking, en only +syntactic	0.482	0.532	0.467	0.444
bible stacking, 5 languages	0.484	0.533	0.468	0.443
bible stacking, 5 languages +syntactic	0.487	**0.538**	0.472	**0.450**
random forest				
baseline features	0.481	0.520	0.464	0.424
+all syntactic features	0.486	0.527	0.471	0.434
bible stacking, en only	0.484	0.525	0.466	0.428
bible stacking, en only +syntactic	0.488	0.529	0.473	0.439
bible stacking, 5 languages	0.488	0.530	0.470	0.434
bible stacking, 5 languages +syntactic	**0.492**	0.533	**0.476**	0.441

Figure 7.6: Results for stacking with Bibles.

classifier	es-gn regular	es-gn non-null	es-qu regular	es-qu non-null
MFS	0.456	0.498	0.435	0.391
maxent l1				
baseline features	0.461	0.506	0.444	0.414
+all syntactic features	0.465	0.511	0.450	0.422
both stacking, 5 languages	0.465	0.511	0.448	0.419
both stacking, 5 languages +syntactic	0.468	0.516	0.452	0.426
maxent l2				
baseline features	0.475	0.524	0.458	0.431
+all syntactic features	0.480	0.530	0.465	0.441
both stacking, 5 languages	0.484	0.533	0.469	0.444
both stacking, 5 languages +syntactic	0.487	**0.538**	0.473	**0.450**
random forest				
baseline features	0.481	0.520	0.464	0.424
+all syntactic features	0.486	0.527	0.471	0.434
both stacking, 5 languages	0.489	0.530	0.471	0.434
both stacking, 5 languages +syntactic	**0.492**	0.533	*0.475*	0.443

Figure 7.7: Results for stacking with Bibles.

7.7 Discussion

In this chapter we have described a straightforward approach for making use of supplemental bitext corpora that pair our resource-rich source language with languages other than our under-resourced target languages, adding annotations to our bitext corpus based on the predictions of CL-WSD classifiers trained on these supplemental bitext corpora.

We see a small but consistent performance gains from this approach when we train on corpora of a different domain (the Europarl corpora), and a larger gain when we train on corpora that match the domain of our bitext for the under-resourced languages (our multilingual Bibles). The gain from using the supplemental corpora with a close domain match was roughly as large as that from adding syntactic annotations, described in the previous chapter. Happily, we find that multilingual evidence and syntactic annotations can be used together effectively; we can train the highest-performing CL-WSD classifiers in this work so far by adding both sets of features.

In the next chapter, we will switch our focus to practical applications of CL-WSD and the Chipa software, showing how it can be integrated into a sampling of MT systems of different architectures, improving MT performance in practice.

CHAPTER 8
INTEGRATION INTO MACHINE TRANSLATION SYSTEMS

In this chapter, we demonstrate how our CL-WSD techniques can be integrated into running machine translation systems, with the goal of improving lexical selection in practice, while minimizing code changes to the MT software. We translate from Spanish to Guarani with Moses[106], an off-the-shelf phrase-based statistical MT system, and from Spanish to Quechua with SQUOIA[107], a primarily rule-based MT system developed by Rios *et al.* at the University of Zürich. These two integrations are meant to be simple proofs of concept, rather than an attempt to define a best practice, but they demonstrate at least conceptually how CL-WSD can be used with these kinds of translation systems. Afterwards, we look at evaluating Chipa's effect on MT output in both of these use cases.

A common thread in the MT settings addressed in this work is that there is a relatively small amount of text available for training a target-side language model, so we should not rely on the LM on its own for making contextually appropriate word choices. This problem is especially significant for RBMT systems without weights built into their lexicons; many translation options will be licensed for a given input word, and selecting the most appropriate choice among them can be difficult. In SQUOIA, for example, there are some rules for lexical selection, but they were written by hand and only cover a small subset of the system's lexicon, in a limited number of contexts.

The difficulty of resolving these ambiguities is mitigated for statistical machine translation systems for language pairs with substantial bitext corpora and target-language monolingual corpora, as large n-gram language models and phrase tables containing common multi-word expressions can encourage coherent word choices. However, for most language pairs in the world, these resources are not readily available. As a result, many research groups, especially those with backgrounds in Linguistics, have sought to build MT systems based around rule-based approaches for under-resourced language pairs.

Given such a rule-based system, in cases where some training data is available, we can investigate combining machine learning and rule-based approaches, resulting in hybrid MT systems that can benefit from the small, but potentially growing resources for the relevant language pair. These could include bitext corpora for the language pair, or with techniques like the ones described in Chapters 6 and 7, monolingual resources such as source-language corpora and NLP tools, or even bitext corpora pairing the source language with other target languages. So adding trained CL-WSD classifiers to existing lexical selection rules can allow these hybrid MT systems to make use of regularities that may not be obvious to human rule-writers, providing lexical selection guidance for word types with sufficient coverage in the training corpus.

With these additional classifiers, a primarily RBMT system can take advantage of statistical evidence without significantly changing its design, and gradually improve its word choices as additional bitext or other resources become available. WSD techniques can also be applied to statistical machine translation, as has been shown by, for example, Carpuat *et al.* [29] and Tamchyna *et al.* [62]. In this chapter we demonstrate specifically how to add the Chipa CL-WSD system to Moses, for a language pair with an under-resourced target language.

Among other pieces of software related to this work, especially the corpus preparation scripts, the code to integrate Chipa into these machine translation systems is bundled in a package called Tereré [1].

8.1 Integrating Chipa into Phrase-Based Statistical Machine Translation

Moses[2] is a mature, well-maintained and popular statistical machine translation package, in broad use for both research and practical purposes. Like many SMT systems, Moses

[1]Available at `http://github.com/alexrudnick/terere` ; Tereré is a cold variety of yerba mate brewed with ice water; it is a specifically Paraguayan specialty.

[2]Available at `http://statmt.org/moses/`

combines signals from different subcomponents when searching through the space of possible translations for an input sentence. It does this using a log-linear model, in which each component scores a candidate translation, and then the scores from the different components are combined in a weighted sum. Some typical components are the probabilities learned for a given phrase during phrase extraction (without regard to context) in both translation directions, scores from the target-language language model, distortion models that reflect estimated differences in word order between source and target languages, and a handful of other features[3].

Conveniently for our work here, Moses includes an interface for adding new feature functions[4] to be combined in the log-linear model, so we can add new information to help guide the decoding process.

Scores in this framework are expected to represent log probabilities, meaning that, concretely, they are real numbers less than 0, as the logarithm of a number between 0 and 1 will be negative. The decoder's beam search procedure then attempts to maximize the total score for a translation, which means finding a translation with a score as high as possible, *i.e.*, maximally close to 0.

During the search through the space of possible translations, Moses proposes candidate translations for each source word to the Chipa feature function, and this function returns a score based on how likely the translation seems to the CL-WSD system, considering the source-language sentence context. This score is returned to Moses, which combines all of the available features in a log-linear combination.

The weights for all of the features provided to the system (translation probabilities, LM scores, CL-WSD scores, and perhaps others) are typically tuned on a development set with Minimum Error-Rate Training, or "MERT" [59]; thus, if CL-WSD scores turn out to be useful for achieving high BLEU scores on the development set sentences, Chipa's feature

[3]For an overview of techniques commonly used in phrase-based statistical MT, please see Koehn's book on the subject [49].

[4]See `http://www.statmt.org/moses/?n=Moses.FeatureFunctions` for documentation.

function will be assigned more weight. If not, its advice will carry less weight than that of more informative feature functions.

8.1.1 Interfacing between Moses and Chipa

The Moses decoder is written in C++, and the typical approach for adding new feature functions is to write new C++ classes following the feature function interface. All of the feature function classes are linked in with the decoder binary, and Moses users can configure their SMT systems to use specific feature functions with a configuration file that references these classes. However, the Chipa software is built in Python, so for simplicity of implementation and to avoid having to add too many dependencies to Moses, we implemented a protocol for communication between the Moses C++ code and the Chipa server, based on Unix pipes[5]; see Figure 8.1 for a visual aid. Named Unix pipes, or FIFOs, allow the creation of a special kind of filesystem object whereby messages can be passed between processes in the same computer. Here Moses requests an evaluation for a certain translation of a source-language phrase given the source-language sentence as context, and Chipa returns a score based on how likely it considers that phrase, represented as a log probability.

Moses also allows for phrase tables to contain arbitrary annotations in their entries, and one might ask whether it would be possible to avoid the trouble of implementing a new feature function in C++, when we could simply add features to a translation of a phrase, in the phrase table on disk. However, this misses the point of using our CL-WSD classifiers – we want to know about which translation is most appropriate for a given source-language phrase, *in this context.* We could imagine running our classifiers as a preprocessing step, and simply producing a phrase table specific to each individual sentence that we want to translate, but there could be multiple instances of a source phrase in a single input sentence. So here we run our classifiers during decoding, using the current source sentence as context.

So concretely, during the search for a translation for an input sentence, the decoder

[5]In earlier work with SQUOIA [3], we had communicated between Chipa and a machine translation system with XML-RPC [6], but for simplicity of implementation, here we built a new text-based protocol.

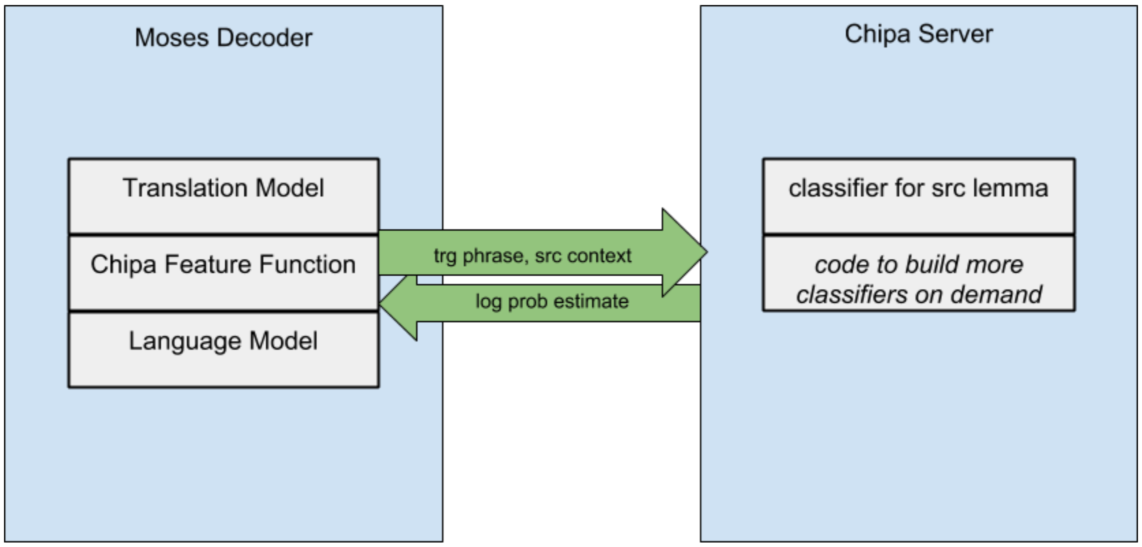


Figure 8.1: Schematic diagram showing the relationship between the Moses decoder process, running the custom-made Chipa feature function, which communicates with the Chipa server process. The Chipa server returns probability estimates for proposed target-language phrases based on the given source-sentence context, when available.

requests a score for each candidate phrase used to translate a source-language phrase. The new Moses feature function then makes a call (over the FIFO communication channel) to the Chipa server, which takes a string of tokenized surface-form Spanish as its input. The Chipa server runs our standard text preprocessing pipeline for Spanish on demand, and then trains a CL-WSD classifier for the lemma of the current focus token, unless a classifier has already been trained for that lemma, in which case it is retrieved from memory. It then extracts features and uses the CL-WSD classifier to estimate a probability distribution over the possible translations for that focus word, given the current context. The Chipa server passes back the log probability for the proposed translation for the current focus word.

For performance reasons, trained CL-WSD classifiers are kept in cache, as are the probability distributions for the translations of a given token in context. For focus words for which we have no CL-WSD classifiers (*i.e.*, they are not sufficiently supported in the training data, or are considered stop words), the server returns a constant (log 0.5), and to avoid causing search errors, probabilities are clipped to be in the range $[0.01, 0.99]$. Also, it should be noted that Moses internally stores phrases using XML escaping, rather than the Unicode strings,

Guarani-language corpus	size
Guarani side of Bible bitext	27, 627 verses
All articles from gn.wikipedia.org	33, 894 sentences

Figure 8.2: Sizes of Guarani-language corpora for training the language model.

so the Chipa server must unescape these strings before working with them, and then pass escaped strings back to Moses.

8.1.2 Moses SMT for Spanish-Guarani

We built a simple phrase-based SMT system with Moses and used the feature function API mentioned previously to have Chipa score candidate translations. Our bitext, as with the CL-WSD classifiers, was our Spanish-Guarani Bible corpus; specifically, we used the surface forms for Spanish, but lemmas for the output Guarani. We sampled our development and test sets from this bitext, taking 100 pairs of Bible verses for tuning, and 100 for testing. For simplicity, we added a constraint to the Moses phrase-extraction system[7] so that the source side of all phrases must be at most one token long, to match the alignments used in the previous chapters. Otherwise, we used the default settings for training a phrase-based SMT system with Moses.

As is common practice with SMT systems, we trained our target-language model with KenLM[108], based on both the target side of the bitext corpus, together with some monolingual Guarani data, the text of the Guarani-language Wikipedia[8]. All input text for the language model was preprocessed in the same way as our bitext, as described in Section 4.3, and the language models were trained over lemmas, matching the target side of the bitext. We tuned the decoder's feature function weights with MERT, using the standard Moses tuning scripts, over the sampled development set.

Experimental results for this MT system are discussed in Section 8.3.

[7]Changes were made in `phrase-extract/extract-main.cpp`, for those familiar with the Moses codebase

[8]Available at `https://gn.wikipedia.org/` . Dumps of Wikimedia projects are available, in general, at `https://dumps.wikimedia.org/backup-index.html`

8.2 Integrating Chipa into Rule-Based Machine Translation

8.2.1 The SQUOIA RBMT system

SQUOIA[9] is a hybrid but primarily rule-based MT system, developed to translate Spanish to Quechua[10].

SQUOIA was developed by a team at the University of Zurich. For the most part, it is a classical rule-based system, although the team has added machine learning techniques to a few subcomponents, such as predicting verb morphology for cases when its rules cannot reliably disambiguate [109]. It does not, by default, use machine learning for lexical selection as such, although it does include a language model to help select among the translations licensed by its transfer rules. Also its initial input analysis stages call open-source NLP tools based on learned models. SQUOIA uses FreeLing [78] for morphological analysis and named-entity recognition, Wapiti [110] for tagging, and DeSr [111] for parsing.

SQUOIA's architecture is based on the Matxin system[112], which was originally intended for translating from Spanish to Basque. It consists of a pipeline of smaller steps, each of which passes along a tree describing the current input text and transformations that have been applied to it, in XML form. As the steps progress, the input Spanish is analyzed and gradually transformed into Quechua output. Many modules focus on very particular aspects of the representation, leaving most of their input unchanged; for example, one phase performs coreference resolution, and another phase uses rules to try to decide whether an instance of the Spanish preposition *de* should be translated into Quechua as indicating the ablative case (direction of motion), or the genitive case (possession). Please see Figure 8.3 for an overview of the most important steps in the SQUOIA pipeline.

In order to integrate Chipa CL-WSD into SQUOIA, we added an additional intermediate

[9]Code available at `https://github.com/a-rios/squoia` ; the project is more broadly described at `https://www.cl.uzh.ch/en/research/machine-translation/hybridmt.html`

[10]Particularly the Cuzco dialect of Quechua, which is spoken around the Peruvian city of Cuzco. There are many varieties of Quechua, as noted in Section 2.5, spoken across the Andes mountain range. SQUOIA also supports translating Spanish to German.

step to the pipeline, occurring just after rule-based lexical disambiguation. This new module reads the XML representation output by the previous step, extracts the original Spanish input text from the intermediate representation, and finds lexical-selection ambiguities that we can attempt to resolve with Chipa. These ambiguities are found where there are nodes in the tree with several possible Quechua lemmas that could be chosen as a translation. It then calls the Chipa CL-WSD classifiers to get an estimated probability distribution over possible translations for that input focus word, in its particular context.

For each such node with such multiple translation possibilities, we look at each of the translations under consideration by SQUOIA, and if any of them was the top classification output from the Chipa classifiers, we constrain SQUOIA to take that choice by removing the other available options. We could imagine other strategies for turning the output of the Chipa classifiers into constraints on lexical selection here, such as removing lexical choices that the classifier considers improbable, or enforcing that the MT system pick the available choice with the highest score from the classifier, even if the one-best output from the classifier was not under consideration. We did not experiment with other approaches here, only the strategy in which, if the one-best output is an available choice, we take it.

A wrinkle to consider is that since Chipa classifiers for Spanish-Quechua use one-to-many alignments, the classifier output can contain short Quechua phrases. Furthermore, the classifiers are trained on the output of the AntiMorfo morphological analyzer for Quechua (see Section 4.3.3 for details), so morphological ambiguities can make their way into the Chipa output; this is represented by two or more lemmas adjoined with a slash. This happens, for example, when multiple lemmas can plausibly inflect to the same surface form. However, the SQUOIA bilingual lexicon contains specific lemmas; it means to pick a particular one, for a specific meaning. In order to overcome both of these ontological mismatches, we consider a candidate lemma to be a match if it is found anywhere in the Chipa output.

If there are no such overlapping translations, or if no Chipa classifier was available for that word, we make no changes to the input tree, and allow SQUOIA to proceed as normal.

- Tokenization, morphological analysis, tagging, parsing.
- Disambiguating Spanish verbs with rules that match on contextual clues (low recall; the rules are manually crafted by linguists)
- Disambiguating Spanish verbs with an SVM classifier.
- Lexical lookup and transfer: insert all possible translations for every input token from the bilingual dictionary.
- Rule-based disambiguation, attempting to eliminate possible lexical-selection ambiguities and morphological choices. (similarly low coverage; it is not feasible for linguists to write rules for all possible contexts for every word type in the lexicon)
- *DISAMBIGUATION WITH CHIPA INSERTED HERE*
- Syntactic transfer, building more Quechua-like syntactic structures (rule-based).
- Reordering based on new syntactic trees (rule-based).
- Use KenLM language models trained over Quechua words and morphemes to choose most likely alternatives remaining.
- Morphological generation: produce Quechua surface forms with a finite state transducer, output n-best list.

Figure 8.3: An overview of the steps in the SQUOIA MT system; there are a few more, handling specific circumstances and parts of speech.

Notably, since Chipa and SQUOIA do not share the same lexicon and bitext alignments may be noisy, translations observed in the bitext may be unknown to the SQUOIA system, and lexical entries in the SQUOIA dictionary may not be attested in the training data.

Having made any possible updates to the representation of our input sentences, we serialize the current state to XML again, to pass the choices along to subsequent steps, which complete the process of turning the input into Quechua output.

8.3 Translation Evaluation for Spanish-Guarani

In order to evaluate our phrase-based statistical machine translation system, with the included CL-WSD classifiers, we sampled a test set from our bilingual Bible corpus, which,

setting	BLEU
Moses with Chipa enabled	16.24
Same system, with Chipa disabled	10.01

Figure 8.4: BLEU scores on our Spanish-Guarani test set. Note that this is translating to *lemmatized* Guarani, rather than having to predict fully-inflected forms.

like the development set, consists of 100 Bible verses. Verses are roughly sentence length, and many in the corpus are complete sentences, but it is also common for verses to be part of a longer sentence, or even to contain several sentences. For phrase-based SMT, this does not require any particular changes to the system; the decoder simply tries to produce a sequence of tokens and has no explicit concept of syntax. We tuned our Moses system on the development set with Chipa enabled, and then for comparison, to see if the system was getting useful information from CL-WSD, disabled the CL-WSD feature function.

For our experimental results here, we report BLEU scores for our lemmatized Guarani output, compared with the lemmatized target side of the test set. See Figure 8.4 for a table of the BLEU scores. Here we see that the system learned to rely on the output of Chipa for useful guidance; when running with the same MERT-tuned weights, but the CL-WSD classifiers disabled, we get a BLEU score drop of roughly six points. The presence or absence of guidance from Chipa changes our translation output significantly here – we produce different output in 97 of the 100 test verses, across these two settings. For comparison, we additionally tried tuning the same Moses system with the Chipa feature function disabled, but found that the variance among BLEU scores for runs of this experiment was quite high[11], so comparison with our results for the tuned system with Chipa enabled do not seem particularly illuminating.

[11]This is due to the MERT search procedure starting at different, randomly-chosen points in the space of weight assignments; the phenomenon is sometimes called "MERT noise" informally.

8.4 Translation Evaluation for Spanish-Quechua

In order to evaluate the effect of Chipa on lexical selection in a live translation task, we used SQUOIA to translate a hundred verses sampled from our Spanish-Quechua Bible bitext, both in its default settings, and with the addition of Chipa. The addition of SQUOIA resulted in lexical selection changes for the SQUOIA output for 41 of the 100 verses translated; there were 15 more changes only in order or punctuation (for a total of 56 sentences that differed in some way), but the majority were local differences in word choice.

The BLEU scores for SQUOIA output on this test set were quite low (lower than one BLEU point), and were not improved by adding Chipa's CL-WSD. But this is a rather more difficult task than our Spanish-Guarani setting, since we are attempting to generate fully-inflected Quechua surface forms, rather than selecting appropriate lemmas, and BLEU scoring requires us to match n-grams exactly, which is made less likely by the rich morphology, including evidential markers, of Quechua. Additionally, as Rios notes [107, §5.9], translations into Quechua tend to be fairly free, rather than close analogues of the source Spanish.

In any case, for evaluation, here we show examples of word choices that were changed with the addition of Chipa CL-WSD, and, armed with our Spanish-Quechua dictionary[4], determine whether they are more or less appropriate than the choices that the SQUOIA system would have made on its own[12]. For some examples chosen from the sampled test set, see Figure 8.6. Counts of how many changes were judged by a non-expert reader to be improvements, neutral or unclear, or worse than the output without Chipa, are presented in Figure 8.5.

One pattern that we find among the changed output is that Chipa tends to encourage SQUOIA to choose *churi* (a son, when discussed with regard to his father) rather than the more generic *wawa*, which can refer to any child; for most of the test sentences where we saw this change happen, it seemed like an appropriate choice. For example, in Sentence 6,

[12]Specifically, in this case, by "we", we mean the author, a native English speaker who can read and speak Spanish but not Quechua.

Total verses with lexical changes	41 (out of 100)
Number of changes judged to be improvements	12
Number of changes judged to be neutral or unclear	22
Number of changes judged to be worse	7

Figure 8.5: Evaluation by hand (by a non-Quechua-speaking author using a dictionary) of the changes to the Spanish-Quechua MT output with SQUOIA.

we are referring to a son of a particular man, so this seems like a good choice.

We see when translating Sentence 7 from Spanish to Quechua, without Chipa, SQUOIA translates *llamando* ('calling') to *sutikuspa*, where *suti* is the sense of "llamar" that refers to naming. However, with Chipa, SQUOIA picks *waqyaspa*, where *waqyay* is the communicative sense, rather than the naming sense.

Many changes caused by Chipa seem to be different choices among near synonyms. For example, in Sentence 8, without Chipa, we translate *ardiente* as *k'anaq*, which seems to be a good translation, meaning "glowing, ardently burning". With Chipa, it becomes *'yawraq'* 'burning, glowing'. And one difference revealed an ambiguity in Spanish that is clearly distinguished in Quechua: in Sentence 9, without Chipa, we translate *labios* 'lips' as an inflection of *wirp'a*, which apparently only refers to the lower lip; with Chipa, we choose an inflection of *sirphi*, which seems to refer to only the upper lip [13].

We note in Sentence 10 a serious word-sense issue that Chipa did not manage to fix; in both cases, SQUOIA failed to interpret *llama* as 'flame'[14]; this seems to be a cascading error from part-of-speech tagging, as SQUOIA's bundled tagger marked it as a verb. In any case, without Chipa, we choose an inflection of *waqya*, which is the 'call out' sense of *llamar*, and with Chipa, we choose an inflection of *suti*, the 'naming' sense. Neither of these are correct.

[13]Also, more modern English translations seem to choose something like "innermost being" rather than referring to one's innards, but the King James Version uses the term "reins", which apparently historically referred to the kidneys.

[14]The Spanish token *llama* can be an inflection of the verb *llamar* 'to call', or as a noun, 'flame', or of course it can refer to llama the animal, which is a loan word from Quechua.

(6) Jehová dijo a Moisés: – Toma a Josué hijo de Nun, hombre en el cual hay espíritu, y pon tu mano sobre él. *"Jehovah said to Moses: - Take Joshua son of Nun, man in whom there is spirit, and put your hand on him.", Numbers 27:18*

(7) Pilato se sorprendió de que ya hubiera muerto, y llamando al centurión, le preguntó si ya estaba muerto. *"Pilate was surprised to hear that he had already died, and calling the centurion, asked him if he was already dead.", Mark 15:44*

(8) Y cualquiera que no se postre y adore, inmediatamente será echado dentro de un horno de fuego ardiente. *"And whoever does not fall down and worship will immediately be thrown into a blazing furnace.", Daniel 3:6*

(9) Y mis entrañas también se alegrarán cuando tus labios hablen con rectitud. *"And my innermost being will also rejoice when your lips speak with rectitude.", Proverbs 23:16*

(10) Por tanto, como la lengua del fuego consume el rastrojo y la llama devora la paja, así será su raíz como podredumbre y su flor se desvanecerá como polvo, porque desecharon la ley de Jehová de los ejércitos y abominaron la palabra del Santo de Israel. *"Therefore, as a tongue of fire consumes straw and dry grass shrivels in the flame, so their roots will decay and their blossoms will blow away like dust; for they have rejected the instruction of the Lord of Hosts and despised the word of the Holy One of Israel.", Isaiah 5:24*

Figure 8.6: Selected Spanish passages for which adding Chipa generated different Quechua translations.

8.5 Discussion

In this chapter we have demonstrated approaches for integrating our CL-WSD classifiers into two different MT systems of completely different styles and architectures. First, we added Chipa to Moses, a phrase-based statistical MT system, by adding an additional feature function to the decoder's log-linear model. Secondly, we integrated Chipa into SQUOIA, a primarily rule-based hybrid MT system developed by computational linguists for an under-resourced language pair. This second integration acts by making concrete lexical selection choices in cases where the rule-based lexical selection routines have not made a firm decision, but we have an available CL-WSD classifier.

Both of these integrations provide a proof-of-concept for how to integrate our CL-WSD approaches into running MT systems, without changing the overall architecture of these systems, and with very modest changes to their code. These integrations allow the MT systems more ways to benefit from our available bilingual and monolingual resources, and can result in better lexical selection, or at least provide a means to adapt an existing system to a different domain.

In the final chapter, we will summarize the contributions of this work overall and discuss some possible future directions.

CHAPTER 9
SUMMARY AND OUTLOOK

In this work, I have developed approaches for cross-lingual word sense disambiguation in the setting where we are translating from a resource-rich language into an under-resourced one, and implemented these approaches in running software. I have shown how cross-lingual word sense disambiguation can be applied to lexical selection in hybrid machine translation for language pairs with relatively modest resources, particularly when translating from Spanish to two different indigenous languages of South America, Guarani and Quechua.

In the initial three chapters, we describe CL-WSD and situate it among efforts to integrate word-sense disambiguation over the history of work on machine translation. In Chapter 1, we explain how word-sense disambiguation is relevant to translation and lay out the structure of the rest of the work.

In Chapter 2, we provide a broad overview of the field of word-sense disambiguation, considering some framings for WSD that have been applied in the past, and the difficulties that these framings cause when our goal is to support MT, or to process arbitrary running text more generally. We explain how the CL-WSD framing overcomes two major difficulties in applying WSD to machine translation in practice. Firstly, CL-WSD provides a concrete sense inventory for lexical items in the source language, since we consider the senses of a word to be its possible translations, and secondly, it provides a source of labeled training data in the form of any available bitext, thus allowing us to apply supervised machine learning techniques. Also in this chapter, we briefly describe Guarani and Quechua, two of the largest indigenous languages in the Americas, and explain some motivations for building hybrid rule-based and statistical MT systems to support them: for most of the world's language pairs, there are no large bitext corpora available, so using rule-based components may provide a useful starting point for NLP systems, especially where there are well-known linguistic regularities, such as morphology and syntax.

Chapter 3 covers some of the relevant related work, including some of the work most similar to ours. Especially notable are the ParaSense work by Els Lefever [26], which pioneered the use of multilingual corpora to support CL-WSD, and the development of learned lexical selection models for Apertium, a mostly rule-based MT system, by Francis Tyers [47].

Having described relevant context and background information, in Chapter 4, we describe the evaluation settings for our CL-WSD systems, as well as the available data sets for our language pairs, and describe in detail the preprocessing steps that allow us to take sentence- or verse-aligned bitext and produce training data suitable for training our classifiers. For our *in vitro* evaluation setting, we can report classifier accuracy, or report benchmarks based on shared tasks like the 2010 and 2013 SemEval CL-WSD tasks. For *in vivo* evaluation, we want to look at the downstream task, and see how the addition of our CL-WSD approaches contributes to machine translation quality, either through automatic metrics like BLEU, or by examining MT output by hand.

We described, in Chapter 5, an initial version of the Chipa software based on common text classification features – the tokens of the input text, their lemmas, and then also the token and lemmas in a small context window around the focus word – and showed how it outperforms the relatively strong most-frequent sense baseline. We compared a few different machine learning algorithms on this task, and found that we got the best results with either random forests or logistic regression classifiers, with L2 regularization, and this held consistently, across language pairs. We also compared Chipa to other systems presented at recent SemEval events for CL-WSD on the task of translating from English to other European languages, using considerably more training data. By applying Chipa to both of these tasks, we showed that this initial approach is a fairly strong starting point, comparable with CL-WSD systems developed by other research groups, and that it can be used in multiple settings fairly successfully.

In Chapter 6, we extended our initial approach with strategies that make use of the available resources for Spanish, including NLP tools for analyzing Spanish text and unsupervised learning techniques that allow us to learn representations for our classifiers from the wealth of available unannotated Spanish text. We showed how to extract features based on syntactic analyses of the input text, done with a POS tagger and a dependency parser, and how adding these features provided modest, but very consistent, accuracy improvements. We also showed some gains, especially when using random forest classifiers, by adding features based on Brown clusters trained on larger samples of monolingual Spanish text. The best results in the chapter came from adding these syntactic and Brown clustering features to the baseline sparse feature set.

We also showed that we could use dense vector representations, built with word2vec and doc2vec trained on available monolingual Spanish text, with moderate success. However, these did not outperform the baseline sparse features for our task, at least not with the data sets and machine learning techniques used in this work; particularly, our random forest classifiers saw accuracy drops when using these features. We learned that when using these dense representations, it is better to focus on the text immediately surrounding the focus word, either by limiting the context window or by giving more weight to words close to the focus word. Trying to build a doc2vec representation of the entire input text, or summing the word embeddings uniformly across the text was less effective. Also, we found that it was possible to combine the dense representations based on word embedding vectors with the sparse features from syntactic analysis and Brown clustering, and that this gave us performance boosts over using the dense features alone.

In Chapter 7, we showed how to use Chipa for classifier stacking, which allows us to learn from bitext corpora that pair our source language with languages other than our intended target language; this technique is broadly applicable when we want to translate out of a language with many available bitext resources, and could also be applied when we have a good monolingual WSD system available. Here we trained CL-WSD classifiers on both Bible translations, which are available for many languages and directly match the domain of our

Spanish-Guarani and Spanish-Quechua corpora, and also Europarl bitext corpora, which are much larger, at roughly 1.8 million sentence pairs. We showed that we are able to get some gains by adding features based on the output of the Europarl-trained CL-WSD classifiers, but larger gains when adding the output of the in-domain classifiers. Furthermore, the gains are larger when adding classifier output for five different language pairs, rather than relying on just Spanish-English CL-WSD, and these classifier stacking features work alongside the syntactic features discussed in Chapter 6; our best results came from using them in tandem.

Finally, in Chapter 8, we demonstrated prototypes for integrating our CL-WSD classifiers into existing machine translation systems of two completely different architectures, requiring only small changes to existing code. We presented a phrase-based SMT system for Spanish-Guarani[1] that uses Chipa classifiers in a feature function that guides its decoding process. For Spanish-Quechua, we augmented a primarily rule-based hybrid machine translation system, using our classifiers to supplement the existing hand-written lexical selection rules. This first integration shows how CL-WSD techniques can reasonably be applied to phrase-based SMT even in relatively low-data scenarios[2], when translating between two unrelated languages, and the second is a proof-of-concept for how to add a CL-WSD into an existing rule-based MT system, allowing it to learn from any available bitext, with increasing benefits as more bitext is collected in the future

One interesting difficulty that came up, and is particularly relevant for MT systems that deal with morphologically rich languages, is the potential for mismatches between the different inventories of lemmas known to the interacting NLP systems; this is to say, the recommendations made by the CL-WSD system must be, for the most part, lexical selections that the MT system can make. Thankfully, for the most part the Chipa CL-WSD system and SQUOIA have a large overlap in their inventories of Quechua citation forms, but this need not be the case, and some care must be taken. For our integration of Chipa into the Spanish-Guarani phrase-based SMT system, this difficulty was largely avoided, because

[1]Ignoring, for the moment, the admittedly substantial problem of morphological generation.
[2]There is prior work on using CL-WSD for SMT; see Section 3.4.

the lexical entries were all based on the output of the same morphological analyzers. In both cases, we showed some modest improvements to MT output on a small test set, using automatic metrics for Spanish-Guarani and manual evaluation for Spanish-Quechua.

9.1 Applying techniques like this to neural machine translation

During the course of this work, the field of machine translation has undergone a dramatic shift, in which statistical MT research, and in many cases, practice[113], has moved from phrase-based and tree-based SMT systems to models based on recurrent neural networks.

It may not be immediately useful to add explicit CL-WSD classifiers to a neural MT architecture, although this is an empirical question. In a sense, though, we can say that NMT systems are already performing CL-WSD; they have a vector representation of the whole input sentence available while making output decisions, tuned specifically for the translation task. This vector representation is similar to the doc2vec representations discussed in Chapter 6, but uses deeper, and recurrent, networks. The sentence-encoding process in neural machine translation thus automates much of the feature engineering work that would go into building a CL-WSD system.

However, many of the difficulties addressed in this work still apply in the neural machine translation setting. We still must come up with good ways to leverage the available corpora and tools for resource-rich source languages, when we have little available bitext. Can source-language taggers and parsers be integrated with NMT? Will this help when translating into under-resourced languages? How can other existing NLP tools be applied, such as monolingual WSD?

In our CL-WSD setting, we did not find immediate benefits when using neural embeddings based on comparatively large source-language corpora. How can monolingual source-language resources be used for NMT, when only very small bitext corpora are available? There has been some recent work, including by Johnson *et al.* [114], on training multilingual neural machine translation systems that learn to share representations among different translation tasks; these systems can even perform "zero shot" translation, in which a single network trained to translate from, *e.g.*, Portuguese to English and English to Spanish can also translate reasonably well from Portuguese to Spanish. Additionally, there has been work, such as that of Artetxe *et al.* [115] and Lample *et al.* [116], that creatively uses back-translation and adversarial networks to make up for the lack of bitext for some language pairs, but to my knowledge this has not yet been practically applied to translating into under-resourced languages. Broadly, there do not yet seem to be widely-accepted approaches for leveraging existing resources to improve neural translation into under-resourced languages, but neural machine translation is still in its early stages and the field is developing rapidly.

Hopefully we will see effective strategies for making use of what we do have for building NMT systems targeting under-represented and under-resourced languages in the near future.

9.2 Building resources for Guarani and other under-represented languages

While we have explored techniques in this work that allow us to lean somewhat on the resources available for resource-rich source languages, a clear way to improve translation for currently under-resourced languages is to make them less under-resourced. Languages like Guarani and Quechua have a number of speakers comparable with that of some relatively resource-rich European languages, as well as their own engaged activist communities. Ethnologue, for example, reports[3] that there are about six million Guarani speakers in the world, which is more than the number of Danish or Norwegian speakers. To support these languages and better serve these communities, we can as technologists find better ways to work with the speakers of these languages.

While this work has focused on languages spoken in South America, there are under-represented languages around the world with millions or possibly many millions of speakers, but relatively little text on the web thus far, and no easily available MT or other NLP

[3]`https://www.ethnologue.com/language/grn`

tools. Many languages in India and Southeast Asia are quite large by number of speakers, but nonetheless dramatically under-resourced. However, Internet usage is spreading quickly throughout the world, and the speakers of these languages are coming online; we are presented with great opportunities to build great linguistic resources and NLP tools for these languages.

There have already been fairly successful campaigns by technologists to work with speakers of these languages on resource-gathering projects for them. For example, in 2016, Mozilla Paraguay managed to localize the Firefox web browser for Guarani, with the help of Guarani-speaking volunteers, a local university, and Guarani-language activists[4]. Localizing an application as complex as a web browser is an enormous task, requiring the translation of thousands of sentence-length messages, along with the in-browser documentation. Also notably, this task requires choosing appropriate Guarani-language terms for technical concepts.

As a success story directly pertinent to machine translation, in 2013, Google ran a crowdsourcing campaign in New Zealand that managed to collect enough training data to build a phrase-based SMT system for the Māori language[5]; since then, Google Translate has operated a crowdsourcing platform called Google Translate Community[6], on which volunteers can rate and submit translations, including for some languages that are not currently supported by the main Google Translate product. For languages that are already supported by Google Translate, the submissions and ratings are used to improve MT output.

Our research group has started some efforts along these lines, but a more sustained effort will be needed to provide benefits for language communities in practice. We (the author, working together with Alberto Samaniego and Taylor Skidmore, directed by Michael Gasser) prototyped two websites for collecting Guarani and Spanish-Guarani language resources, but these have not been used beyond the prototype stage. The first website is called

[4]See a description of the process, and the launch announcement, at `http://mozillanativo.org/2016/lanzamiento-oficial-de-firefox-en-guarani.html` (in Spanish). Firefox in Guarani can be downloaded at `https://www.mozilla.org/gn/firefox/`

[5]Post on the Google New Zealand blog: `https://newzealand.googleblog.com/2013/12/kua-puta-google-whakamaori-ki-te-reo.html`

[6]https://translate.google.com/community

"Tahekami", which means *let's search together* in Guarani. Tahekami[7] is a repository of Guarani and bilingual documents that allows full-text search and browsing documents by tag. Our initial version of the site contained a collection of masters theses from the *Ateneo de Lengua y Cultura Guaraní*. We developed a second website, called "Guampa" [8], which is a bilingual wiki, designed to be used by Guarani speakers and learners to collaboratively translate documents from Spanish to Guarani or vice-versa. We presented an initial version of this software at LREC 2014[10]. This site is meant to serve at least three purposes: helping Guarani-language learners practice and get feedback on their translations, creating more Guarani-language documents for the web (we started initially with translating Spanish Wikipedia), and building bitext corpora for training MT systems.

Michael Gasser is currently, as of 2018, developing successors to these websites, in the form of *mitmita* and *mainumby*, online computer-aided translation systems for Amharic and Guarani respectively[9]. The goal of these tools is to help users translate documents by providing both searches over translation memories and automatic suggestions from an integrated machine translation system.

In any case, while there remains much work to be done — both technical and social — for supporting the under-represented languages of the world, it is outside the scope of this dissertation, and will be addressed in the future, hopefully in part by the author.

[7]Prototype code at `http://github.com/hltdi/gn-documents`

[8]A "guampa", in Paraguay, is the cup from which one drinks yerba mate or tereré. The term "guampa" is also local to Paraguay; in other parts of South America, the container itself is called a "mate". The Guampa software is available at `https://github.com/hltdi/guampa`

[9]Code for these sites is being developed at `https://github.com/hltdi/mitmita` and `https://github.com/hltdi/mainumby`

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- **Georgia Institute of Technology**, College of Computing, 2001–2007
  - M.S. Computer Science, May 2007.
  - B.A. Computer Science (with high honors), May 2005.

Employment history

- **Google**
  - *Software Engineer*, Google Translate team, Mountain View, California. September 2014–present.
  - *Software Engineering Intern*, Google Translate team, Mountain View, California. Summer 2012.
  - *Software Engineering Intern*, Google Translate team, Mountain View, California. Summer 2011.

- *Software Engineering Intern*, Google Research, New York City. Summer 2010.
- *Software Engineer*, Google Web Toolkit team, Atlanta, Georgia. August 2007–July 2009.

Publications, tech reports, and workshop presentations

- Clayton A. Davis, Giovanni Luca Ciampaglia, Luca Maria Aiello, Keychul Chung, Michael D. Conover, Emilio Ferrara, Alessandro Flammini, Geoffrey C. Fox, Xiaoming Gao, Bruno Gonçalves, Przemyslaw A. Grabowicz, Kibeom Hong, Pik-Mai Hui, Scott McCaulay, Karissa McKelvey, Mark R. Meiss, Snehal Patil, Chathuri Peli Kankanamalage, Valentin Pentchev, Judy Qiu, Jacob Ratkiewicz, **Alex Rudnick**, Benjamin Serrette, Prashant Shiralkar, Onur Varol, Lilian Weng, Tak-Lon Wu, Andrew J. Younge, Filippo Menczer.
  OSoMe: the IUNI observatory on social media. In *PeerJ Computer Science*, October 2016.
- Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V. Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, Jeff Klingner, Apurva Shah, Melvin Johnson, Xiaobing Liu, Łukasz Kaiser, Stephan Gouws, Yoshikiyo Kato, Taku Kudo, Hideto Kazawa, Keith Stevens, George Kurian, Nishant Patil, Wei Wang, Cliff Young, Jason Smith, Jason Riesa, **Alex Rudnick**, Oriol Vinyals, Greg Corrado, Macduff Hughes, Jeffrey Dean.
  Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation. Google tech report released on arXiv, September 2016.
- **Alex Rudnick**, Levi King, Can Liu, Markus Dickinson and Sandra Kübler
  IUCL: Combining Information Sources for SemEval Task 5. Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014).
- **Alex Rudnick**, Taylor Skidmore, Alberto Samaniego and Michael Gasser.

Guampa: a Toolkit for Collaborative Translation. Ninth International Conference on Language Resources and Evaluation (LREC 2014).

- **Alex Rudnick**, Annette Rios and Michael Gasser. Enhancing a Rule-Based MT System with Cross-Lingual WSD. The 9th International Workshop of the Special Interest Group on Speech and Language Technology for Minority Languages (SaLTMiL 2014).
- **Alex Rudnick** and Michael Gasser. Lexical Selection for Hybrid MT with Sequence Labeling. Second Workshop on Hybrid Approaches to Translation (HyTra 2013).
- **Alex Rudnick**, Can Liu and Michael Gasser. HLTDI: CL-WSD Using Markov Random Fields for SemEval-2013 Task 10. Proceedings of the 7th International Workshop on Semantic Evaluation (SemEval 2013).
- Pavel Golik, Boulos Harb, Ananya Misra, Michael Riley, **Alex Rudnick** and Eugene Weinstein. Mobile Music Modeling, Analysis and Recognition. International Conference on Acoustics, Speech, and Signal Processing (ICASSP) 2012.
- Karissa McKelvey, **Alex Rudnick**, Michael Conover and Filippo Menczer. Visualizations of Communication on Social Media: Making Big Data Accessible. Computer Supported Cooperative Work 2012 - Collective Intelligence as Community Discourse and Action.
- **Alex Rudnick**. Towards Cross-Language Word Sense Disambiguation for Quechua. RANLP 2011 Student Research Workshop.
- **Alex Rudnick**. A resource-light approach to learning verb valencies. Machine Translation and Morphologically-rich Languages 2011.
- James Clawson, Kent Lyons, **Alex Rudnick**, Robert A. Iannucci Jr. and Thad Starner. Automatic whiteout++: correcting mini-QWERTY typing errors using keypress timing. In CHI'08: Proceeding of the twenty-sixth annual SIGCHI conference on Human factors in computing systems, pages 573-582.
- James Clawson, **Alex Rudnick**, Kent Lyons and Thad Starner. Automatic Whiteout:

Discovery and Correction of Typographical Errors in Mobile Text Input. In MobileHCI'07: Proceedings of the 9th conference on Human-computer interaction with mobile devices and services.

Teaching

- **Course Instructor**
  - CSCI B490: Natural Language Processing, Indiana University. Fall 2012. Taught a special topics course on Natural Language Processing for about thirty undergraduates at Indiana University. Covered basic ideas from linguistics and machine learning, sequence models and tagging, context-free grammars and parsing. Gave overviews of speech recognition and machine translation.
- **Teaching Assistant**
  - Google Tech Exchange: Machine Learning. Fall 2018. Helped run a machine learning class for students from Historically Black Colleges and Universities (HBCUs) and Hispanic-Serving Institutions at Google.
  - CSCI B553: Probabilistic Graphical Models, Indiana University. Fall 2013. David Crandall's class on probabilistic graphical models, covering Bayes Networks, Markov Networks, exact and approximate inference on them, and some applications from computer vision and NLP.
  - CSCI B651: Natural Language Processing, Indiana University. Fall 2010. Michael Gasser's introductory NLP course; wrote some new homework assignments, introduced the ideas behind automatic speech recognition and grammar extraction.
  - C211: Introduction to Computer Science, Indiana University. Fall 2009, Spring 2010, Spring 2011. Helped run Indiana's introductory CS class in Scheme. Wrote class-infrastructure software, including a web application to assign lab partners and a system to manage student programming contests.

    - CS2130: Languages and Translation, Georgia Institute of Technology. Spring 2003, Fall 2003, Spring 2004. Georgia Tech's course covering C programming and basic ideas behind compilers. Wrote new assignments and automatic grading programs. Taught weekly recitations and review sessions.

- **Other Teaching**

    - Recurse Center, Hacker in Residence. December 2013. Met with Recurse Center students, had discussions and pair programming sessions on their projects, and gave talks and workshops about NLP.

    - Institute for Computing Education, Georgia Institute of Technology. Summers 2005, 2006, 2007. Helped teach a Media Computation summer camp for high school and middle school students, as well as high school computer science teachers. Taught media concepts and basic programming with Python, Alice, and Scratch.

Service and Open Source contributions

- Conference and workshop reviewer for: LREC 2018, COLING 2016, LREC 2014, SemEval 2013, ACL 2012, CICLing 2011, COLING 2010, CIKM 2009.
- Project member and committer for NLTK, the Natural Language Toolkit for Python.
- Contributor to CLDR, the Unicode Common Locale Data Repository.

Other activities

- Distance running (12 marathons so far), juggling, recreational cycling. Playing the drums.
- Competed (with Martin Robinson) as *Team "They Are On A Team"* in the ICFP Programming Contest, 2014.

- Competed (with Lindsey Kuper) as *Team K&R* in the ICFP Programming Contest, 2016, 2011, 2009, 2008.