

# Experiments on Language Normalization for Spanish to English Machine Translation

**Paula Estrella**

University of Geneva - ISSCO  
40, Bvd du Pont-D'Arve  
CH-1211 Geneve 4, Switzerland  
Paula.Estrella@issco.unige.ch

**Pablo Ariel Duboue**

IBM T.J. Watson Research Center  
19 Skyline Drive,  
Hawthorne NY 10532, USA  
duboue@us.ibm.com

## Abstract

We describe a trained system we have built, using freely available statistical packages and present experiments specifically designed to improve the performance of the system in the Spanish into English task. We performed both qualitative and quantitative evaluations that show better perceived translation quality as well as better BLEU and NIST scores.

**Keywords:** Natural Language Processing, Statistical Machine Translation, Language Normalization, Stemming.

## 1 Introduction

Human beings naturally communicate and interact with each other. This need has always been achieved in different ways according to the available resources. Today, resources are almost limited and that need became a fundamental requisite in some aspects of daily life. For example, thanks to the Internet, it is common to find the information we need but written in a language we do not understand. The language barrier is still a problem nowadays,

We are interested in the problem of translating Spanish into English. In this article we describe a trained system we have built, using freely available statistical packages and present experiments specifically designed to improve the performance

of these systems in the Spanish→English task. The statistical packages we have used include the GIZA++ [16] package, the CMU-Cambridge Statistical Language Modeling Toolkit [5] and the ISI decoder [10, 9].

We improved the results by conflating the translation table generated by GIZA++ with a stemming algorithm adapted for Spanish. Afterwards, we normalize the training corpus according to the new translation table and re-train the system with this new corpus.

Our experiments show better translation quality as well as better scores when evaluating with automatic methods. Using the BLEU [17] evaluation metric (explained in Sec. 4.1) we obtained 0.2401 when translating without the improvement and 0.2523 for the system trained with a

normalized corpus. The NIST [6] metric (explained in Sec. 4.2) scored 5.1873 for the system without the improvement and 5.4067 for the improved system. We also performed a qualitative evaluation with human judges which preferred our system better or comparable to the existing system more than 72% of the time.

In Sec. 1.1, we briefly explain differences between Spanish and English and how they affect a translation system. We also mention related work on Spanish morphology and stemming. In Sec. 2, we expose the basics of Statistical Machine Translation and we relate it to the tools used in this work. Sec. 3 contains the details of our proposed technique and Sec. 4 explains our experiments measuring the impact of our proposed modification. In Sec. 5, we conclude by explaining the advantages and drawbacks of our technique and proposing further work.

## 1.1 The Problem

We work in Spanish to English translation for a number of reasons. First, this research has taken place in a Spanish speaking country, and therefore it poses regional impact. And second, Spanish is the third most spoken language in the world and has a level of similarity to English close enough to be appealing for Statistical Machine Translation (SMT).

The Spanish language is very rich and has a complex grammar. It has a number of articles (demonstrative, determinative, etc.) which, together with nouns and adjectives, suffer modifications depending on gender (female and male) and number (singular or plural). Conjugations in Spanish are more difficult than in English: three kinds of conjugations are distinguished, depending on the ending of the infinite verb (*-ar*, *-er*, *-ir*), there are eight verb times and six modes. Verbs also suffer modifications such as person and number, among others. Finally, as with any language, it has a large number of exceptions.

These situations are illustrated in the following examples:

*Example: Article, verb and noun agreement*

Singular: *La cocina es pequeña.*  
The kitchen is small.  
Plural: *Las cocinas son pequeñas.*  
The kitchens are small.

*Example: Pronoun, verb agreement*

Singular: *Ella comió una manzana.*  
She ate an apple.  
Plural: *Ellas comían una manzana.*  
They ate an apple.

These morphological changes make it harder to obtain an accurate translation, because the system should have plenty of evidence in the form of Spanish words (e.g., conjugations of the same verb) that translate into the same English word.

Instead of giving the machine translation system a huge amount of training data to solve this problem, we can improve the statistical evidence by means of normalizing the lexical differences between the two languages. Smarter algorithms has been shown to outperform large quantities of training material [13].

As shown in the previous examples, most of the changes in word morphology occur in the form of suffixes, so the stem of a word remains unchanged in most cases (with the exception of irregular verbs whose stem may also suffer changes). Therefore, our approach to neutralize these changes is to use a stemmer for the Spanish language and map groups of words with the same stem into one token.

*Example: Word stemming*

Consider the following words:

*acordada*  
*acordado*  
*acordadas*  
*acordados*

These words have a common stem that is *acord-*, so the system has to learn that they map into the word *agreed*, thus the four cases are reduced to one.

But not every word with the same stem should belong to one group (because we could lose important evidence for the learner).

*Example: Stemming drawback*

The following words have the same stem (*accept-*):

*aceptó*  
*aceptablemente*  
*aceptable*  
*aceptamos*  
*aceptando*

Suppose we group them together and the system learns these words translate into *acceptable*. Then, we might translate a verb (e.g., *aceptamos*, English *accept*) into an adjective (*aceptable*, English *acceptable*), thus losing accuracy.

The above examples show that stemming helps neutralizing differences among languages but it has the drawback of being too restrictive to our purpose.

## 1.2 Related Work

An overview of the importance of morphology in MT is given in [11] along with the related problems introduced by morphology; it also explains different techniques used in MT and compares some techniques used to solve these problems. Although Hui [11] exposes why stemming should work in SMT, he does not show empirical evidence or experiments that support his theory.

Spanish morphology is analysed and explained in Tzoukermann and Liberman [20], while presenting a system that generates and analyses inflectional and morphological forms with simple data structures, such as automata. We surveyed a range of recent publications (e.g. [2, 3]) and found that they work with the implicit assumption that large number of sentence pairs will make up for lack of stemming (a belief supported by IR experiments).

There are rather few works including stemming in SMT; stemming is widely used in Information Retrieval (IR). Fuller and Zobel [7] compare several stemming algorithms applied to IR and experiments show that the Porter Stemmer is very accurate for finding possible confluences of a word.

## 2 Statistical Machine Translation

The statistical tool we use is GIZA++<sup>1</sup> [1], that employs the noisy channel model. In noisy chan-

nel parlance, our source language is English and the target language is Spanish. This may seem a little confusing but in the noisy channel model we try to find out what was sent through the channel in order to understand what we received (in this case we want to find the sentence that produced a given translation). We can think of Statistical Machine Translation (SMT) in terms of programs that take as input sentence pairs  $(s, e)$  and outputs the conditional probability  $P(e|s)$ , interpreting it as “*e is the best translation for s*”; it thus looks for the English sentence  $e$  that maximizes  $P(e|s)$ , often written as

$$\underset{e}{\operatorname{argmax}} P(e|s) \tag{1}$$

The probabilities are obtained with the Bayes’ rule:

$$P(e|s) = \frac{P(e)P(s|e)}{P(s)} \tag{2}$$

A program that assigns a probability  $P(l)$  to each sentence  $l$  in a given language, is called a *language model*.<sup>2</sup> In our case,  $P(e)$  is the source language model,  $P(s)$  is the target language model and  $P(s|e)$  is the translation model.  $P(s)$  does not depend on  $e$ , so the problem is reduced to find the  $e$  that maximizes  $P(e)P(e|s)$ .

The source language model is the basic probability assigned to a sentence and is computed using the text corpus we input to the system.

*Example: Language model generation*

For the input corpus:

1. The film was boring but the actors were fantastic.
2. I like mexican food.
3. It all started about 300 years ago.
4. I like mexican food.

the first and third sentences have  $P(e) = 1/4$ , sentences 2 and 4 have  $P(e) = 1/2$  and any other sentence has  $P(e) = 0$ .

As shown in the previous Example, sentences never seen in the corpus will get zero probability even if they were correct. To overcome this problem the sentences are split into shorter strings

<sup>1</sup>Available at <http://www.isi.edu/~och/GIZA++.html>.

<sup>2</sup> $P(l)$  is the basic probability that the event  $l$  occurs.

called  $n$ -grams, that is, a  $n$  words string. Now, consider a sentence  $e$  composed by  $j$  words (i.e.,  $e = e_1 \dots e_j$ ); the probability can be computed:

$$P(e_1 \dots e_j) = P(e_1) * P(e_2|e_1) * \dots * P(e_j|e_1 \dots e_{j-1}) \quad (3)$$

The right side of the equation is the conditional  $n$ -gram probability and is called a parameter automatically estimated by Brown et al. [4]. In the case that any  $P$  is zero (because the corpus has not shown exactly that sequence of words), *smoothing* is done. Smoothing tries to find out whether or not subsequences are likely; by doing this, smaller  $n$ -grams are computed and a non-zero factor is added, so that no string will have zero probability.

To obtain a language model we use the Carnegie Mellon Statistical Language Modeling Toolkit<sup>3</sup> [5]. Starting from a monolingual corpus, it generates a file containing the corresponding language model.

When a word  $s$  produces a word  $e$ , they are said to be aligned; sometimes a word produces zero or more words, the number of English words produced by a Spanish word is called the Spanish word *fertility*. Word alignments are likely to have nearby positions in the source and target sentences (for example, words at the beginning align to words at the beginning, and so on), however some words may appear far from the word that produced it. That is, for instance, the case of adjectives and nouns: in Spanish adjectives are usually preceded by nouns but in English their order is inverted. This effect is called *distortion*.

The estimation of the translation model is done using different algorithms or models (IBM-1 to IBM-5) [4]. These models differ, for example, in the way they treat alignments: Model 1 assigns equal probabilities to all possible alignments, that means a Spanish word can produce an English word at any position. Model 2 is modified to let the order of both the Spanish and English word affect the probability  $P(s|e)$ ; here two words are connected depending on the position they have and the length of the sentences they belong to. In Model 3 words only connect to at most another word and this connection has the same constraints as in Model 2. Model 4 improves the distortion probabilities, thus allowing better Subject-Verb

relations. Model 5 is a refinement of Model 4, being this model the most efficient, in the sense that it does not lose probability on strings that are of no interest; in contrast Models 3 and 4 are not efficient.

GIZA++ is based on GIZA[1], the SMT toolkit developed during the summer workshop in 1999 at Johns-Hopkins University. GIZA++ extends the GIZA toolkit by implementing IBM Models 4-5 and improving some features like smoothing for fertility, among others. Och [15, 14] describes and compare the alignment models implemented in GIZA++.

The main tables GIZA++ generates are:

**Translation:** contains the distribution for  $P(s|e)$ .

**Fertility:** contains a list of numbers per source token, indicating the probability of having fertility zero, one, etc. up to the maximum defined in the program.

**Alignment:** contains the probability of moving a source word to given position; it also has the length of the source and target sentences.

**Distortion:** contains the distortion probabilities for each token.

**P0:** the probability of not inserting NULL tokens.

So far we have presented, a minimal overview of the process of obtaining the probabilities  $P(e|s)$  from a set of sentence pairs  $(e, s)$ ; this process is called *training*. The final stage to determine the translation of a string, is the search of the sentence that maximizes Equation 1, called *decoding*. There are many implementations of decoding algorithms but some of these tools are not freely available, as is the case of the original decoder implemented by IBM. We decided to use the ISI ReWrite Decoder<sup>4</sup> [10] not only because of its availability, but also because it can be run as server making the decoding process lighter.

### 3 Our Technique

In addition to an aligned bi-lingual corpus, we need a vo-ca-bu-la-ry file to per-

<sup>3</sup>Available at <http://mi.eng.cam.ac.uk/~prc14/toolkit.html>.

<sup>4</sup>Available at <http://www.isi.edu/licensed-sw/rewrite-decoder/>.

form the training. GIZA++ requires a vocabulary file with the following format:

Unique Id String No. occurrences

Example: Vocabulary file sample

Unique Id	String	No. occurrences
597	primero	248
598	propio	248
599	estructurales	248

The translation table generated by GIZA++ has the following format:

$$s\_id \quad t\_id \quad P(t\_id|s\_id)$$

where *s\_id* is the unique id assigned to source words, *t\_id* is the unique id of the target word and *P* is the probability of translating *s\_id* as *t\_id*. These ids correspond to the vocabulary file used to train the model.

Example: Translation table sample

s_id	t_id	P
1284 (amplia)	1166 (broad)	0.1677
4759 (ampliada)	4859 (enlarged)	0.3619
9349 (amplitud)	3556 (breadth)	0.4988
2758 (anciana)	17047 (senior)	0.0355

This table do not store the strings learned but a unique identifier; the words in parenthesis are extracted from the vocabulary file.

The first step we propose (Step 1), is to use a stemmer over the translation table. The candidate algorithm is an adaptation for Spanish of the Porter stemmer<sup>5</sup> [19]. One stem produces a family of words that may include different grammatical entities. If we map a whole family into the same token, we might lose important evidence. Therefore, we decided to cluster family words during the stemming process (proposed as Step 2).

The stemming algorithm has three main procedures to remove suffixes:

**Delete attached pronoun:** pronouns can be removed when attached to verbs because they are implicitly mentioned. Some pronouns are *me*, *te*, *se*, *le*, *la*.

**Delete standard suffix:** there are many suffixes that identify different grammatical entities. For example, *mente* stands, in most cases, for adverbs and *logía* for nouns. In this step we decided to form three categories: nouns (*logía*, *logías*, *encia*, *encias*), adverbs (*mente*, *amente*) and other suffixes.

**Verb suffix removal:** because of the complexity of verbs conjugation in Spanish there are many suffixes that can be removed; we distinguish three categories depending on the suffix: past (for example *aba*, *ía*, *ido*), continuous (*iendo*, *ando*) and other verbs (examples are *iera*, *iese*, *ar*, *er*, *ir*).

After that, we have a normalizer specific to a corpus and a translation model. The normalization table should have the following format:

acortar	TOKEN11
acorten	TOKEN11
acortándolo	TOKEN12
acortada	TOKEN13
acortado	TOKEN13
acertadamente	TOKEN15
acertar	TOKEN16
acertemos	TOKEN17
acertada	TOKEN17

Finally, the source language corpus should be normalized according to the results previously obtained (we propose this as Step 3); these steps must preserve corpus alignment in order to retrain GIZA++ with the new corpus.

The process described in this Section makes Spanish a little more like English, by means of treating many words as English does. Another reason to expect it to work, is that we are reducing the number of parameters, a situation similar to having less noise in our channel.

Figure 1 shows an example normalized sentence (the original sentence was “*creo que precisamente suecia , un ejemplo de transparencia en el marco de su actual presidencia , sería la llamada para dar aquí un paso hacia delante ; debe quedar claro que este debate es muy importante para el ciudadano europeo*”). The words between curly brackets are replaced by the same token during the normalization process.

<sup>5</sup>Available at <http://www.tartarus.org/~martin/PorterStemmer/>.

## 4 Experiments

We performed experiments to find out whether the proposed technique improves translation or not. The system was trained twice: the first time with the original bilingual corpus and the second time, the Spanish part was normalized according to the previous Section. These two systems translated 120 test sentences and we evaluated the output with BLEU and NIST methods.

We used a subset of the Europarl corpus as training set consisting of 64,281 sentences. Europarl is a multilingual corpus containing the Proceedings of the European Parliament in the 11 official languages. Koehn built Europarl as described in [12] and it has been used afterwards in numerous works. For the evaluation process we selected 104 sentences from a test set built by Koehn (not contained in the training set).

We applied the improvement as follows:

**Align a parallel corpus:** The data from Europarl was aligned at the sentence level using *align* [8], a program for aligning sentences at the paragraph and sentence level. *Align* is based on the fact that parallel translations of text do not differ much in length.

**Normalize the corpus:** the stemming algorithm was implemented maintaining the modifications detailed in Sec. 3. We trained GIZA++ to obtain the translation table corresponding to the aligned corpus. After that, we applied the normalization algorithm to the table. To prepare the corpus to re-train we used a script that replaces words (from the translation table) with the corresponding tokens; the corpus structure remains unaltered.

**Build a translation model:** as explained in Sec. 2, a translation model is generated by training GIZA++ with the new corpus (i.e. re-train GIZA++).

**Build a language model:** we used the tables generated in the previous step to build a language model using CMU-Cambridge toolkit.

**Translate test sentences:** in order to translate text, the test corpus must be consistent with the data used to train the system.

Therefore, we first normalized the test set and then used the ISI ReWrite decoder.

### 4.1 BLEU metric

Evaluating a MT system is very important to measure the impact of the system and also to find out whether the ideas involved are effective or not. There are many ways to achieve evaluations but it is preferably to have human judges evaluate the translations. Unfortunately, this is a time consuming task and the work done is not reusable. Papineni [17] propose a method (*Bilingual Evaluation Understudy*) to automatically evaluate translations, making this process quicker and with no human labor costs.

BLEU is based on *Word Error Rate* (WER) metric used in speech recognition but appropriately modified to deal with multiple references. BLEU uses WER to measure *closeness* to human translations and human references as ideal translations. The main idea behind BLEU is to assign higher scores to translations more likely to the human translations (scores range from 0 to 1); this algorithm uses a weighted average of  $n$ -grams matches against the given references (the more  $n$ -gram match the reference, the higher the score would be) and it penalises translations whose lengths differ significantly from the references given.

This method correlates with human evaluations and is language-independent, which makes it reusable and accurate. Papineni et al. gives enough details of the method, so it can be easily implemented.

### 4.2 NIST metric

Based on BLEU, NIST designed its own evaluation method and implemented it as a freely available toolkit.<sup>6</sup> The major difference between NIST and BLEU is the formula used to compute the  $n$ -gram matches: BLEU uses a geometric average of  $n$ -gram counts and NIST uses an arithmetic average. This formula also modifies the brevity penalty to minimize the influence of small variations in lengths over the final score.

A comparison between NIST and BLEU scores [6], showed that NIST score improves significantly

<sup>6</sup>Available at <http://www.nist.gov/speech/tests/mt/mt2001/resource/>.

in score stability and reliability. It also showed that NIST score correlates better than BLEU for human judges.

### 4.3 Results

At this point, we had two translations of the same test corpus (one with normalized corpus (1) and the other without the normalization (2)). We evaluated these two translations using two references. Table 1 summarizes the overall scores and Table 2 shows  $n$ -gram precision.<sup>7</sup>

	System 1	System 2
BLEU	0.2812	0.2699
NIST	6.0452	5.9045

**Table 1. BLEU and NIST scores for translation 1 and 2.**

	1-gram	2-gram	3-gram
BLEU System 1	0.6558	0.2783	0.1420
BLEU System 2	0.6431	0.2663	0.1297
NIST System 1	5.1282	0.8116	0.0915
NIST System 2	5.0364	0.7717	0.0800

**Table 2.  $N$ -gram precision score.**

Koehn [18] states that the difference (in BLEU scores) between the two systems, should be at least 2 – 3% to rule out an improvement due to chance. Although this difference in our case, is about 1% there is an improvement in System 1; as shown by our qualitative evaluation.

We also made a qualitative evaluation of twenty sentences out of the fifty used for the quantitative evaluation; to avoid benefiting any of the MT systems, the sentences were randomly chosen. We count with three native speakers, who contributed to our work. The judges received the following instructions:

*You have here a Spanish sentence (E), a reference translation (M) and two automatically translated English sentences, that come (in random order) from our two systems (TA, TB). We ask you to choose which one is better or say if both are equally good.*

Table 3 shows the results obtained for System 1 and System 2. To summarize results we counted the votes each sentence received, assessing a better performance of the system to which we applied the normalization technique. The differences are significant according to a three-column  $\chi^2$ -square test. The human judges mentioned most of the times the differences were at the verb, with the wrong (baseline) translation having a completely outrageous verb form. We believe the reason behind this behavior of the baseline system lies in the fact that very few training cases are available for each inflected verb form, strongly misleading the statistical system into picking surrounding words as the real translation.

Sent. #	Sys. 1	Sys. 2	Both
1	3	0	0
2	0	2	1
3	2	0	1
4	2	0	1
5	0	2	1
6	1	1	1
7	0	1	2
8	3	0	0
9	0	3	0
10	1	1	1
11	2	0	1
12	1	0	2
13	2	1	0
14	0	2	1
15	0	2	1
16	2	0	1
17	3	0	0
18	3	0	0
19	2	0	1
20	2	0	1
Total	29	17	14

**Table 3. Qualitative evaluation results.**

## 5 Conclusion

This work focuses on the unresolved problem of obtaining automatic translations with human quality. We made a small scale experiment that turned out to work fine but has some drawbacks. First, the normalization we applied should be refined or combined with other techniques, because

<sup>7</sup>This is additional information about the scores obtained; they are not correlated with the scores in Table 3.

it still can lose evidence by mapping too many words into the same token. Second, we did not count with the necessary resources to try the technique with a larger corpus. Moreover, aside from its computational complexity, SMT also demands a large amount of human effort to try an idea or implement a system. Nevertheless we find it a very interesting area with plenty of work to do in MT.

## 5.1 Further Work

We propose the extension of this technique to other language pairs where the target is more complex than the source. To name a few examples: English→Chinese, Korean→English, and German→English. New language pairs can be a challenging task because of the differences, for example, among English and German; in our opinion German has a more more complex grammar than Spanish. The normalization technique should be improved to overcome the drawbacks explained in Sec. 5, it could be combined with other techniques or it could be implemented including some linguistic information (for example Part-of-Speech tagging).

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