Unsupervised training of maximum-entropy models for lexical selection in rule-based machine translation

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Abstract
This article presents a method of training maximum-entropy models to perform lexical selection in a rule-based machine translation system. The training method described is unsupervised; that is, it does not require any annotated corpus. The method uses source-language monolingual corpora, the machine translation (MT) system in which the models are integrated, and a statistical target-language model. Using the MT system, the sentences in the source-language corpus are translated in all possible ways according to the different translation equivalents in the bilingual dictionary of the system. These translations are then scored on the target-language model and the scores are normalised to provide fractional counts for training source-language maximum-entropy lexical-selection models. We show that these models can perform equally well, or better, than using the target-language model directly for lexical selection, at a substantially reduced computational cost.

1 Introduction
Corpus-based machine translation (MT) has been the primary research direction in the field of MT in recent years. However, rule-based MT (RBMT) systems are still being developed, and there are many successful commercial and non-commercial systems. One reason for the continued development of RBMT systems is that in order to be successful, corpus-based MT requires parallel corpora in the order of tens of millions of words. Although for some language pairs these exist, they only exist for a fraction of the world’s languages.

An RBMT system typically consists of an analysis component,1 a transfer component and a generation component. As part of the transfer component it is necessary to make choices regarding words in the source language (SL) which may have more than one translation in the target language (TL). Lexical selection is the task of choosing, for a given SL word, the most adequate translation in the TL among a known set of alternatives. The task is related to the task of word-sense disambiguation (Ide and Véronis, 1998). However, it is different to word-sense disambiguation in that lexical selection is a bilingual problem, not a monolingual problem: its aim is to find the most adequate translation, not the most adequate sense. Thus, it is not necessary to choose among a series of fine-grained senses if all these senses result in the same final translation; however, it may sometimes be necessary to choose a different translation for the same sense, for example in a collocation.

1.1 Prior work
Dagan and Itai (1994) used the term word sense disambiguation to refer to what is actually lexical selection in MT; they used a parser to identify syntactic relations such as subject–object or subject–verb. After generating all the possible translations for a given input sentence using an ambiguous bilingual dictionary, they extract the syntactic tuples from the TL and count the frequency in a previously-trained TL model of tuples. They use maximum-likelihood estimation to calculate the probability that a given

1Such as a morphological or syntactic analyser.
TL tuple is the translation of a given SL tuple, with an automatically determined confidence threshold. Later, Berger et al. (1996) illustrated the use of maximum-entropy classifiers on the specific problem of lexical selection in IBM-style word-based statistical MT. Other authors (Melero et al., 2007) have used TL models to rank the translations resulting from all possible combinations of lexical selections. Nowadays, in state-of-the-art phrase-based statistical MT (Koehn, 2010), lexical selection is taken care of by a combination of the translation model and the language model. The translation model provides probabilities of translation between words or word sequences (often referred to as phrases) in the source and target language. The TL model provides probabilities of word sequences in the TL. Mareček et al. (2010) trained a maximum-entropy lexical selector for their dependency-grammar-based transfer system TectoMT using a bilingual corpus. More recently, Tyers et al. (2012) presented a method of lexical selection for RBMT based on rules which select or remove translations in fixed-length contexts, along with a training method for learning the rules from a word-aligned parallel corpus.2

2 Method

Lexical selection in this paper considers for each word a simple SL context made up of neighbouring lemma+part-of-speech combinations. Contexts considered include up to two words to the left and up to two words to the right of the word to be translated.

Let the probability of a word \( t \) being the translation of a word \( s \) in a SL context \( c \) be \( p_s(t|c) \). In principle, this value could be estimated directly from the available corpora for every combination of \( (s, t, c) \). This would however present two questions: (1) how should the relevant contexts be chosen? and (2) what should be done when \( (s, t, c) \) is not found in the corpus? A maximum-entropy model answers both of these questions. It allows the contexts that we consider to be linguistically interesting to be defined \textit{a priori} and then integrate these seamlessly into a probabilistic model (Manning and Schütze, 1999). In answer to the second question, a maximum-entropy model maximises the entropy subject to the expected counts of the designed features with those found in the training data. That is, if there is no information in the training data, then it assumes that all outcomes—that is, all possible translations—are equally likely. As previously mentioned, the principle of maximum entropy has been applied to the problem of lexical selection before; in particular, Berger et al. (1996) cast the problem of lexical selection in statistical MT as a classification problem. They learn a separate maximum-entropy classifier for each SL word form, using SL context to distinguish between possible translations. These classifiers are then incorporated into the translation model of their word-based statistical MT system. In their approach, a classifier consists of a set of binary feature functions and corresponding weights for each feature. In both Berger et al. (1996) and our method, features are defined in the form \( h_k^t(s, c) \), where \( t \) is a translation, and \( c \) is a SL context. One difference is that Berger et al. (1996) take \( s, t \) and \( c \) to be based on word forms, whereas in our method they are based on lemma forms. An example would be the following feature where the Spanish word \( \text{pez} \) (‘fish’ as a living animal) is seen as the translation of \( \text{arrain handi} \) (‘big fish’) and would therefore be defined as:

\[
h^\text{arrain handi}_{+}^\text{+}(t, c) = \begin{cases} 
1 & \text{if } t = \text{pez} \\
0 & \text{and } \text{handi follows arrain} \\
 & \text{otherwise}
\end{cases}
\] (1)

This feature considers a context of zero words to the left of the problem word and one word (+ \text{handi}) to the right of it.

As a result of training, each of the \( n_F \) features \( h_k^t(s, c) \) in the classifier is assigned a weight \( \lambda_k^s \). Combining these weights of active features as in equation (2) yields the probability of a translation \( t \) for word \( s \) in context \( c \).

\[
p_s(t|c) = \frac{1}{Z^s(c)} \exp \sum_{k=1}^{n_F} \lambda_k^s h_k^t(s, c) \] (2)

In this equation, \( Z^s(c) \) is a normalising constant. Thus, the most probable translation \( t^* \) can be found using

\[
t^* = \arg \max_{t \in T_s(s)} p_s(t|c) = \arg \max_{t \in T_s(s)} \sum_{k=1}^{n_F} \lambda_k^s h_k^t(s, c), \] (3)

2We follow the notation of Berger et al. (1996)
\[ S \rightarrow \text{pre-lexsel} \rightarrow (\{ g_i \}_{i=1}^{\left| G \right|}, S) \rightarrow \text{lexsel} \rightarrow (g^*, S) \rightarrow \text{post-lexsel} \rightarrow \tau(g^*, S) \]

\[ \forall (s, t, c) \text{ found in } g_i, \text{ that is, when in } g_i \text{ the translation for } s \text{ in context } c \text{ is } t. \text{ That is, if event } (s, t, c) \text{ had been seen a fractional number } p(g_i|S) \text{ of times. We prune } (s, t, c) \text{ occurring less than a certain number of times in the corpus, using a development corpus to guide pruning (see section 4).} \]

\[ \text{The method used here for lexical selection is analogous to the method used by Sánchez-Martínez et al. (2008) to train a hidden-Markov-model-based part-of-speech tagger in a RBMT system.} \]

\section{Experimental setting}

This section describes the training and evaluation settings used in the remainder of this paper. The primary motivation behind the evaluation is that it should be automatic, meaningful, and be performed over a test set which is large enough to be representative. It should evaluate both performance on the specific subtask of lexical selection, and on the whole translation task. Evaluating lexical-selection performance is an intrinsic module-based evaluation. It measures how well the lexical selection module disambiguates the lexical-transfer output as compared to a gold-standard corpus. The lexical transfer output is the result of looking up the translations of the SL lexical forms — lemmas and tags — in the bilingual dictionary.

The whole translation task evaluation is an extrinsic evaluation, which tests how the system improves as regards final translation quality in a real system.

The lexical-selection module should be as language-independent as possible. To that end, the language pairs tested show a wide variety of linguistic phenomena. It is also important that the methodology be as applicable to lesser-resourced and marginalised languages as to major languages.

This section begins with a short description of the Apertura platform (Forcada et al., 2011). This is followed by an overview of each of the language pairs chosen for the evaluation. The corpora to be used for training and evaluation will subsequently be described, along with the method used for annotating them. This is followed by a description of the performance measures to be used in the evaluation, and the reference results using these metrics for
each of the language pairs.

3.1 Apertium

Apertium is a free/open-source RBMT platform, it comprises an engine, a toolbox and data to build RBMT systems. Translation is implemented as a pipeline consisting of the following modules: morphological analysis, morphological disambiguation, lexical transfer, lexical selection, structural transfer and morphological generation.

3.2 Language pairs

Evaluation will be performed using four Apertium (Forcada et al., 2011) language pairs. These pairs have been selected as they include languages with different morphological complexity, and different amounts of resources available — although for all pairs there is a parallel corpus available for evaluation (see Section 3.3).

Breton–French (Tyers, 2010): Bilingual dictionaries were not built with polysemy in mind from the outset, but some entries were added later to start work on lexical selection.

Macedonian–English: The Macedonian–English pair in Apertium was created specifically for the purposes of running lexical-selection experiments. The lexical resources for the pair were tuned to the SETimes parallel corpus (Tyers and Alperen, 2010). The most probable entry from automatic word alignment of this corpus using GIZA++ (Och and Ney, 2003) was checked to ensure that it was an adequate translation, and if so marked as the default. As a result of attempting to include all possible translations, the average number of translations per word is much higher than in other pairs.

Basque–Spanish (Ginesti-Rosell et al., 2009): alternative translations were included in the bilingual dictionary. English–Spanish: The English–Spanish pair was developed from a combination of the English–Catalan and Spanish–Catalan pairs, and contains a number of entries in the bilingual dictionary with more than one translation.

3.3 Performance measures

This section describes the measures that will be used to evaluate the performance of the lexical selection method proposed here: a (intrinsic) lexical selection performance measure and an (extrinsic) machine translation performance measure.

3.3.1 Lexical-selection performance

This is an intrinsic module-based evaluation of the performance of the lexical-selection module. It measures how well the lexical-selection module disambiguates the output of the lexical-transfer module as compared to a gold-standard corpus. For this task, we define a metric, the lexical-selection error rate (LER), that focuses on the problem of lexical selection by restricting the evaluation to this feature; other features of the MT system, such as the transfer rules and morphological generation, are not taken into account.

The lexical-selection error rate is the fraction of times the given system chooses a translation for a word which is not the one found in an annotated reference. The process uses a SL sentence, $S = (s_1, s_2, \ldots, s_{|S|})$ and three functions. The first function, $T_s(s_i)$, returns all possible translations of $s_i$ according to the bilingual dictionary. The second function, $T_t(s_i)$, returns the translations of $s_i$ selected by the lexical-selection module: $T_t(s_i) \subseteq T_s(s_i)$; and usually $|T_t(s_i)| = 1$. If the lexical-selection module returns more than one translation, the first translation is selected. The function $T_r(s_i)$ returns the set of reference translations which are acceptable for $s_i$ in sentence $S$.

For a single sentence, we define the lexical selection error rate (LER) of that sentence as

$$LER = \frac{\sum_{i=1}^{|S|} \text{amb}(s_i) \text{diff}(T_r(s_i), T_t(s_i))}{\sum_{i=1}^{|S|} \text{amb}(s_i)}, \quad (5)$$

where

$$\text{amb}(s_i) = \begin{cases} 1 & \text{if } |T_s(s_i)| > 1 \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

Revision 41375: https://svn.code.sf.net/p/apertium/svn/trunk/apertium-br-fr

Revision 41476: https://svn.code.sf.net/p/apertium/svn/trunk/apertium-mk-en

Revision 44846: https://svn.code.sf.net/p/apertium/svn/trunk/apertium-eu-es
In practice this does not happen as each ambiguous word has
would test how much the system improves as re-
tions. The BLEU metric is included only as it is
tions may not lead to successful translations
the bilingual dictionaries of the RBMT system in
module will depend greatly on (a) the coverage of
This is not ideal for evaluating the task of a
between the set of reference translations $T_r(s_i)$
states that there is a difference if the intersection
recognition process, and was not possible. A description of how the
The table in Figure 2 gives an overview of the
inputs. In the description it is assumed that the refer-
hand annotation is a time-consuming process,
and the function
\[
\text{diff}(T_r(s_i), T_l(s_i)) = \begin{cases} 
1 & \text{if } T_r(s_i) \cap T_l(s_i) = \emptyset \\
0 & \text{otherwise} 
\end{cases}
\]
states that there is a difference if the intersection
set of translations from the lexical selection
the set will be a singleton, as when
and the first one of not.$^{12}$

The table in Figure 2 gives an overview of the
inputs. In the description it is assumed that the refer-
ence translation has been annotated by hand. How-
ner, hand annotation is a time-consuming process,
was not possible. A description of how the
reference was built is given in Section 3.4.

### 3.3.2 Machine translation performance

This is an extrinsic evaluation, which ideally
would test how much the system improves as reg-
grades an approximate measurement of final trans-
quality in a real system. For this task, we
use the widely-used BLEU metric (Papineni et al.,
2002). This is not ideal for evaluating the task of a
lexical selection module as the performance of the
module will depend greatly on (a) the coverage of
the bilingual dictionaries of the RBMT system in
question, and (b) the number of reference trans-
lations. It is also worth noting that successful lexical
selections may not lead to successful translations
due to inadequate transfer of morphological fea-
tures. The BLEU metric is included only as it is
commonly used to evaluate MT systems.

| $S$ | $el$ | estiu | ser | un | estació | llarg |
|-----|------|-------|-----|----|---------|------|
| $T_r(s_i)$ | {the} | {summer} | {be} | {a} | {station, season} | {long, lengthy} |
| $T_l(s_i)$ | {the} | {summer} | {be} | {a} | {season} | {long} |

\[ \text{amb}(s_i) = 0 \quad 0 \quad 0 \quad 0 \quad 1 \quad 1 \]

\[ \text{diff}(T_r(s_i), T_l(s_i)) = 0 \quad 0 \quad 0 \quad 0 \quad 1 \quad 0 \]

### 3.3.3 Confidence intervals

Confidence intervals for both metrics will be cal-
culated through bootstrap resampling (Efron and Tibshirani, 1994) as described by Koehn (2004). In all cases, bootstrap resampling will be carried out for 1,000 iterations. Where the $p = 0.05$ confidence intervals overlap, we will also perform paired bootstrap resampling (Koehn, 2004).

### 3.4 Corpora

For creating the test corpora, providing a SL corpus
for training, and a TL corpus for scoring, we used
four parallel corpora:

- **Ofis ar Brezhoneg** ($\text{OAB}$): This parallel cor-
  pus of Breton and French has been col-
  lected specifically for lexical-selection experi-
  ments from translations produced by Ofis ar
  Brezhoneg ‘The Office of the Breton language’.
  The corpus has recently been made available
  online through OPUS.$^{13}$

- **South-East European Times** ($\text{SETimes}$): Described by
  Koehn (2005), this corpus is a multilingual corpus of the Balkan
  languages (and English) in the news domain.
  The Macedonian and English part will be used.

- **Open Data Euskadi** ($\text{OpenData}$): This is a
  Basque–Spanish parallel corpus made from
  the translation memories of the Herri Ardu-
  ralitzaren Euskal Erakundeak ‘Basque Insti-
  tute of Public Administration’.$^{14}$

- **European Parliament Proceedings** ($\text{EuroParl}$): Described by
  Koehn (2005), this is a multilingual corpus of the European
  Union official languages. We are using the
  English–Spanish data from version 7.$^{15}$

$^{12}$In practice this does not happen as each ambiguous word has a
default translation.

$^{13}$http://opus.lingfil.uu.se

$^{14}$http://tinyurl.com/eu-es-tm

$^{15}$http://www.statmt.org/europarl/
There are a number of approaches to creating evaluation corpora for lexical selection in the literature. Vickrey et al. (2005) use a parallel corpus to make annotated test and training sets for experiments in lexical selection applied to a simplified translation problem in statistical MT. They use word alignments from GIZA++ (Och and Ney, 2003) to annotate SL words with their translations from the reference translation in the parallel corpus. One disadvantage of this method is that only one translation is annotated per SL word, meaning that accuracies may be lower because of missing translations — this happens when the system chooses a translation which is adequate, but is not found in the reference translation. A second disadvantage is that the word alignments may not be 100% reliable, which decreases the accuracy of the annotated corpus. An alternative method is described by Zinovjeva (2000), who manually tags ambiguous words in English sentences with their translation in Swedish.

Ideally we would have had a hand-annotated evaluation corpus, as described by Zinovjeva (2000), but as this did not exist, we decided to automatically annotate a test set using a process similar to that described by Vickrey et al. (2005).

The annotation process proceeds as follows: First we word-align the corpus to extract a set of word alignments, which are correspondences between words in sentences in the source side of the parallel corpus and those in the target side. Any aligner may be used, but in this paper we use GIZA++ (Och and Ney, 2003).16 We then use these alignments along with the bilingual dictionary of the MT system in question to extract only those sentences where: (a) there is at least one ambiguous word; (b) that ambiguous word is aligned to a single word in the TL; and (c) the word it is aligned to in the TL is found in the bilingual dictionary of the MT system. Sentences where there are no ambiguous words (approximately 90%, see Table 1) are discarded. The source side of the extracted sentence is then passed through the lexical transfer module, which returns all the possible translations, and for each ambiguous word, the translation is selected which is found aligned in the reference.

After this process, we selected 1,000 sentence pairs at random for testing (test), 1,000 for development (dev)17 and left the remainder for training.

### Table 2: Statistics about the test corpora

| Pair | SL   | TL   | Amb. | % amb. |
|------|------|------|------|--------|
| br-fr| 13,854 | 13,878 | 1,163 | 8.39   |
| mk-en| 13,441 | 14,228 | 3,872 | 28.80  |
| eu-es| 7,967  | 11,476 | 1,360 | 17.07  |
| en-es| 19,882 | 20,944 | 1,469 | 7.38   |

Table 2: Statistics about the test corpora. The columns SL and TL give the number of tokens in the source and target languages respectively. The columns amb. words and % ambig give the number of word with more than one translation and the percentage of SL words which have more than one translation respectively.

### 3.5 Reference systems

We compare our method to the following reference (or baseline) systems:

- **Linguist-chosen defaults.** A bilingual dictionary in an Apertium language pair contains correspondences between lexical forms. The dictionaries allow many lexical forms to translate to one lexical form. But a single lexical form may not have more than one translation without further processing. If there are many possible translations of a lexical form, then one must be marked as the default translation.

- **Oracle.** The results for the oracle system are those achieved by passing the automatically annotated reference translation through the rest of the modules of the MT system. This is included to show the upper bound for the performance of the lexical-selection module.

- **Target language model (TLM).** One method of lexical selection is to use the existing MT system to generate all the possible translations for an input sentence, and then score these translations on-line on a model of the TL. The highest scoring sentence is then output. This is the method used by Melero et al. (2007).

### 4 Results

As we are working with binary features, we use the implementation of generalised iterative scaling

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16The exact configuration of GIZA++ used is equivalent to running the MOSES toolkit (Koehn et al., 2007) in default configuration up to step three of training.

17The development corpus was used for checking the value for frequency pruning of features.
Table 1: Statistics about the source corpora. The column no. amb gives the number of unique tokens with more than one possible translation. The column av. amb gives the average number of translations per ambiguous word. This is calculated by looking up each word in the corpus in the bilingual dictionary of the MT system and dividing the total number of translation by the number of words. Both av. amb and no. amb are calculated over the whole corpus.

| Pair   | Lines  | Extract. | train | dev | test | No. amb | Av. amb |
|--------|--------|----------|-------|-----|------|--------|---------|
| br-fr  | 57,305 | 4,668    | 2,668 | 1,000 | 1,000 | 603    | 3.06    |
| mk-en  | 190,493| 19,747   | 17,747| 1,000 | 1,000 | 13,134 | 3.06    |
| eu-es  | 765,115| 87,907   | 85,907| 1,000 | 1,000 | 1,806  | 3.11    |
| en-es  | 1,467,708| 312,162 | 310,162| 1,000 | 1,000 | 2,082  | 2.28    |

Table 3: Features in each rule set and pruning frequency.

| Pair   | Pruned | # features |
|--------|--------|------------|
| br-fr  | < 5    | 5,277      |
| mk-en  | < 7    | 205,494    |
| eu-es  | < 7    | 196,024    |
| en-es  | < 7    | 195,605    |

Evaluation results are presented in table 4, which compares the results of the new approach with respect to the default behaviour (the linguist-chosen defaults), with respect to the oracle (which represents the upper bound to performance), and with respect to the results obtained by using the TL model online, for each of the language pairs in Apertium with respect to our two evaluation metrics. Note that the high error rate for the Breton–French pair may be as a result of having the linguistic defaults tuned to a different domain than that of the corpus.

Significant improvements with respect to the results obtained using the TL model online are apparent with the Breton–French — the pair with the least data— and the English–Spanish language pairs. In the remaining cases, the maximum-entropy method comes close to the TL model performance in terms of similar or better BLEU and LER scores, at a much smaller computational cost.

Improvements with respect to the TL model performance are likely due to the effective use that the maximum-entropy model makes of information about the relevant SL contexts and their translations, through the weighting of features representing those SL contexts across the whole corpus.

5 Conclusions

This paper has presented a method to perform lexical selection in RBMT, and one that can be trained in an unsupervised way, that is, without the need for an annotated corpus, (in this case a word-aligned bilingual corpus): one just needs a SL corpus, a statistical TL model, and the RBMT system itself. The input to the method is simply the part-of-speech tagged source text in which each word is annotated with all the translations provided by the bilingual dictionary in the system: this makes it applicable to almost any RBMT system. The system uses a maximum-entropy formalism for lexical selection, as Berger et al. (1996) and Mareček et al. (2010), but instead of counting actual lexical selection events in an annotated corpus, it counts fractional occurrences of these events as estimated by a TL model. The method is evaluated both intrinsically (just looking at the actual lexical selection events) and extrinsically (measuring the quality of MT). Results on four language pairs using the Apertium (Forcada et al., 2011) MT system show that the method obtains similar or better results than those expensively obtained by scoring an exponential number of lexical selections for each sentence using the TL model online.

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Improvements with respect to the TL model performance are likely due to the effective use that the maximum-entropy model makes of information about the relevant SL contexts and their translations, through the weighting of features representing those SL contexts across the whole corpus.

5 Conclusions

This paper has presented a method to perform lexical selection in RBMT, and one that can be trained in an unsupervised way, that is, without the need for an annotated corpus, (in this case a word-aligned bilingual corpus): one just needs a SL corpus, a statistical TL model, and the RBMT system itself. The input to the method is simply the part-of-speech tagged source text in which each word is annotated with all the translations provided by the bilingual dictionary in the system: this makes it applicable to almost any RBMT system. The system uses a maximum-entropy formalism for lexical selection, as Berger et al. (1996) and Mareček et al. (2010), but instead of counting actual lexical selection events in an annotated corpus, it counts fractional occurrences of these events as estimated by a TL model. The method is evaluated both intrinsically (just looking at the actual lexical selection events) and extrinsically (measuring the quality of MT). Results on four language pairs using the Apertium (Forcada et al., 2011) MT system show that the method obtains similar or better results than those expensively obtained by scoring an exponential number of lexical selections for each sentence using the TL model online.

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| Pair  | Metric | System |  |  |  |  |
|-------|--------|--------|-----------------|-----------------|---------|---------|
|       |        |        | *Ling*           | *TLM*            | *MaxEnt* | *Oracle* |
| br-fr | LER (%)| [54.8, 60.7] | [44.2, 50.5]    | [40.8, 46.9]    | [0.0, 0.0] |
|       | BLEU (%)| [14.5, 16.4] | [15.4, 17.3]     | [14.8, 16.6]     | [16.7, 18.6] |
| mk-en | LER (%)| [28.8, 32.6] | [26.8, 30.5]     | [25.2, 28.8]     | [0.0, 0.0] |
|       | BLEU (%)| [28.6, 31.0] | [30.7, 32.3]     | [29.1, 31.5]     | [30.9, 33.3] |
| eu-es | LER (%)| [43.6, 48.8] | [38.8, 44.2]     | [40.9, 46.2]     | [0.0, 0.0] |
|       | BLEU (%)| [10.1, 12.0] | [10.6, 12.6]     | [10.3, 12.2]     | [11.5, 13.5] |
| en-es | LER (%)| [20.5, 24.9] | [15.1, 18.9]     | [10.4, 13.8]     | [0.0, 0.0] |
|       | BLEU (%)| [21.5, 23.4] | [21.9, 23.8]     | [22.2, 24.1]     | [22.8, 24.7] |

Table 4: LER and BLEU scores with 95% confidence intervals for the reference systems on the test corpora. The max-ent system has been trained using fractional counts. The results in bold face show statistically significant improvements for the maximum-entropy model compared to the TL model according to pair-bootstrap resampling.

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