Inference of Phrase-Based Translation Models via Minimum Description Length

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Abstract
We present an unsupervised inference procedure for phrase-based translation models based on the minimum description length principle. In comparison to current inference techniques that rely on long pipelines of training heuristics, this procedure represents a theoretically well-founded approach to directly infer phrase lexicons. Empirical results show that the proposed inference procedure has the potential to overcome many of the problems inherent to the current inference approaches for phrase-based models.

1 Introduction
Since their introduction at the beginning of the twenty-first century, phrase-based (PB) translation models (Koehn et al., 2003) have become the state-of-the-art for statistical machine translation (SMT). PB models provide a big leap in translation quality with respect to the previous word-based translation models (Brown et al., 1990; Vogel et al., 1996). However, despite their empirical success, inference procedures for PB models rely on a long pipeline of heuristics (Och and Ney, 2003) and mismatched learning models, such as the long outperformed word-based models. Latter stages of the pipeline cannot recover mistakes or omissions made in earlier stages which forces the individual stages to massively overgenerate hypotheses. This manifests as a huge redundancy in the inferred phrase lexicons, which in turn largely penalizes the efficiency of PB systems at run-time. The fact that PB models usually cannot generate the sentence pairs in which they have been trained in, or that it is even possible to improve the performance of a PB system by discarding most of the learned phrases are clear indicators of these deficiencies (Sanchis-Trilles et al., 2011).

We introduce an unsupervised procedure to infer PB models based on the minimum description length (MDL) principle (Solomonoff, 1964; Rissanen, 1978). MDL, formally described in Section 2, is a general inference procedure that “learns” by “finding data regularities”. MDL takes its name from the fact that regularities allow to compress the data, i.e. to describe it using fewer symbols than those required to describe the data literally. As such, MDL embodies a form of Occam’s Razor in which the best model for a given data is the one that provides a better trade-off between goodness-of-fit on the data and “complexity” or “richness” of the model.

MDL has been previously used to infer monolingual grammars (Grünwald, 1996) and inversion transduction grammars (Saers et al., 2013). Here, we adapt the basic principles described in the latter article to the inference of PB models. The MDL inference procedure, described in Section 3, learns PB models by iteratively generalizing an initial model that perfectly overfits training data. An MDL objective is used to guide this process. MDL inference has the following desirable properties:

• Training and testing are optimized upon the same model; a basic principle of machine learning largely ignored in PB models.
• It provides a joint estimation of the structure (set of bilingual phrases) and the parameters (phrase probabilities) of PB models.
• It automatically protects against overfitting by implementing a trade-off between the expressiveness of the model and training data fitting.

The empirical evaluation described in Section 4 focuses on understanding the behavior of MDL-based PB models and their specific traits. That is, in contrast to a typical PB system building paper, we are not exclusively focused on a short term boost in translation quality. Instead, we aim at studying the adequacy and future potential of MDL as inference procedure for PB models.
2 The MDL Principle

Given a set of data \( D \), the MDL principle aims at obtaining the simplest possible model \( \Phi \) that describes \( D \) as well as possible (Solomonoff, 1964; Rissanen, 1978). Central to MDL is the one-to-one correspondence between description length functions and probability distributions that follows from the Kraft-McMillan inequality (McMillan, 1956). For any probability distribution \( \Pr(\cdot) \), it is possible to construct a coding scheme such that the length (in bits) of the encoded data is minimum and equal to \(- \log_2(\Pr(D))\). In other words, searching for a minimum description length reduces to searching for a good probability distribution, and vice versa. Taking these considerations into account, MDL inference is formalized as:

\[
\hat{\Phi} = \arg\min_{\Phi} \text{DL}(\Phi, D) \\
= \arg\min_{\Phi} \text{DL}(\Phi) + \text{DL}(D | \Phi)
\]

where \( \text{DL}(\Phi) \) denotes the description length of the model, and \( \text{DL}(D | \Phi) \) denotes the description length of the data given the model. A complete introductory tutorial of the MDL principle and methods can be found in (Grünewald, 2004).

3 MDL Phrase-Based Models

3.1 Description Length Functions

We start by defining how to compute \( \text{DL}(\Phi) \) and \( \text{DL}(D | \Phi) \) for any PB model and data set.

Let \( \Pr_{\Phi}(D) \) be the probability of data set \( D \) according to PB model \( \Phi \). We follow the Kraft-McMillan inequality and define the description length of the data given the model as \( \text{DL}(D | \Phi) = - \log_2(\Pr_{\Phi}(D)) \), which is the lower bound for the description length of the data.

Regarding the description length of the PB model, \( \text{DL}(\Phi) \), we compute it by serializing \( \Phi \) into a sequence of symbols and then computing the length of the optimal encoding of such sequence. To do that, we need one symbol for each word in the source and target languages, another symbol to separate the source and target sides in a phrase pair, and one additional symbol to distinguish between the different pairs in the phrase lexicon. For example, the following toy PB model:

\[
\text{La casa azul}||\text{The blue house} \\
\text{Esta casa azul}||\text{This blue house} \\
\text{Esta casa verde}||\text{This green house}
\]

It can be segmented to obtain a new PB model:

\[
\text{La}||\text{The} \| \text{casa azul}||\text{blue house} \\
\text{Esta}||\text{This} \| \text{casa verde}||\text{green house}
\]

which is able to generate one new sentence pair (\( \text{La casa verde} \rightarrow \text{The green house} \)) and has a shorter description length (19 symbols) in comparison to the original model (23 symbols). We only consider segmentations that bisect the source and target phrases. More sophisticated segmentation approaches are beyond the scope of this article.

Algorithm 1 describes the proposed PB inference by iterative generalization. First, we collect the potential segmentations of the current PB
Algorithm 1: Iterative inference procedure.

| input  | Φ (initial PB model) |
| output | ˆΦ (generalized PB model) |
| auxiliary | collect(Φ) (Returns the set of possible segmentations of model Φ) |
|          | ΔDL(s, Φ) (Returns variation in DL when segmenting Φ according to s) |
|          | sort(S) (Sorts segmentation set S by variation in DL) |
|          | commit(S, Φ) (Apply segmentations in S to Φ, returns variation in DL) |

1 begin
2 repeat
3 S ← collect(Φ);
4 candidates ← [];
5 for s ∈ S do
6 Δ′ ← ΔDL(s, Φ);
7 if Δ′ ≤ 0 then
8 candidates.append({Δ′, s});
9 sort(candidates);
10 Δ ← commit(candidates, Φ);
11 until Δ > 0;
12 return Φ;
end

The length difference between the phrase lexicons (DL(Φ′) − DL(Φ)) is trivial. We merely have to compute the difference between the lengths of the phrase pairs added and removed. The difference for the data is given by \( -\log_2 \frac{P_{\Phi}(D)}{P_{\Phi}(D)} \), where \( P_{\Phi}(D) \) and \( P_{\Phi}(D) \) are the probability of D according to \( \Phi' \) and \( \Phi \) respectively. These

\[
\Delta DL(s, \Phi) = DL(\Phi') - DL(\Phi) + DL(D | \Phi') - DL(D | \Phi) \tag{3}
\]

probabilities can be computed by translating the training data. However, this is a very expensive process that we cannot afford to perform for each candidate segmentation. Instead, we estimate the description length of the data in closed form based on the probabilities of the phrase pairs involved. The probability of a phrase pair \( \{f, e\} \) is computed as the number of occurrences of the pair divided by the number of occurrences of the source (or target) phrase. We thus estimate the probabilities in the segmented model \( \Phi' \) by counting the occurrences of the replaced phrase pairs as occurrences of the segmented pairs. Let \( \{f_0, e_0\} \) be the phrase pair we are splitting into \( \{f_1, e_1\} \) and \( \{f_2, e_2\} \). The direct phrase probabilities in \( \Phi' \) will be identical to those in \( \Phi \) except that:

\[
P_{\Phi'}(e_0 | f_0) = 0
\]

\[
P_{\Phi'}(e_1 | f_1) = \frac{N_{\Phi}(\{f_1, e_1\}) + N_{\Phi}(\{f_0, e_0\})}{N_{\Phi}(f_1) + N_{\Phi}(f_0, e_0)}
\]

\[
P_{\Phi'}(e_2 | f_2) = \frac{N_{\Phi}(\{f_2, e_2\}) + N_{\Phi}(\{f_0, e_0\})}{N_{\Phi}(f_2) + N_{\Phi}(f_0, e_0)}
\]

where \( N_{\Phi}(\cdot) \) are counts in \( \Phi \). Inverse probabilities are computed accordingly. Finally, we compute the variation in data description length using:

\[
\frac{Pr_{\Phi'}(D)}{Pr_{\Phi}(D)} \approx \frac{P_{\Phi'}(e_1 | f_1) \cdot P_{\Phi'}(e_2 | f_2)}{P_{\Phi}(e_0 | f_0)} \cdot \frac{P_{\Phi'}(f_1 | e_1) \cdot P_{\Phi'}(f_2 | e_2)}{P_{\Phi}(f_0 | e_0)} \tag{4}
\]

Table 1: Main figures of the experimental corpora. M and k stand for millions and thousands of elements respectively. Perplexity was calculated using 5-gram language models.
Table 2: Size (number of phrase pairs) of the MDL-based PB models, and quality of the generated translations. We compare against a state-of-the-art PB inference pipeline (SotA).

|               | EuTransI | News Commentary |
|---------------|----------|-----------------|
|               | BLEU [%] | Size (tune/test) |
| SotA          | 91.6 / 90.9 | 39.1k 31.4 / 30.7 |
| MDL           | 88.7 / 88.0 | 2.7k 24.8 / 24.6 |

For a segmentation set, we first estimate the new model $\Phi'$ to reflect all the applied segmentations, and then sum the differences in description length.

4 Empirical Results

We evaluated the proposed inference procedure on the EuTransI (Amengual et al., 2000) and the News Commentary (Callison-Burch et al., 2007) corpora. Table 1 shows their main figures.

We inferred PB models (set of phrase pairs and their corresponding probabilities) with the training partitions as described in Section 3.2. Then, we included these MDL-based PB models in a conventional log-linear model optimized with the tuning partitions (Och, 2003). Finally, we generated translations for the test partitions using a conventional PB decoder (Koehn et al., 2007).

Table 2 shows size (number of phrase pairs) of the inferred MDL-based PB models, and BLEU score (Papineni et al., 2002) of their translations of the tune and test partitions. As a comparison, we display results for a state-of-the-art (SotA) PB system (Koehn et al., 2007). These results show that MDL inference obtained much more concise models (less than one tenth the number of phrases) than the standard inference pipeline. Additionally, the translations of the simple EuTransI corpus were of a similar quality as the ones obtained by the SotA system. In contrast, the quality of the translations for News Commentary was significantly lower.

To better understand these results, Figure 1 displays the histogram of phrase lengths (number of source words plus target words) of the SotA model and the MDL-based model for the News Commentaries corpus. We first observed that the length of the phrase pairs followed a completely different distribution depending on the inference procedure. Most of the phrase pairs of the MDL-based model translated one source word by one target word with an exponential decay in frequency for longer phrase pairs; a typical distribution of events in natural language (Zipf, 1935). Longer phrase pairs, about 45% of the total, contain sequences of words that only appear once in the corpus, and thus, they cannot be segmented in any way that leads to a reduction in description length. Although formally correct, long phrase pairs generalize poorly which explains the comparatively poor performance of MDL inference for the News Commentaries corpus. This problem was largely attenuated for EuTransI due to its simplicity.

5 Conclusions and Future Developments

We have described a simple, unsupervised inference procedure for PB models that learns phrase lexicons by iteratively splitting existing phrases into smaller phrase pairs using a theoretically well-founded minimum description length objective. Empirical results have shown that the inferred PB models, far from the artificial redundancy of the conventional PB inference pipeline, are very parsimonious and provide competitive translations for simple translation tasks.

The proposed methodology provides a solid foundation from where to develop new PB inference approaches that overcome the problems inherent to the long pipeline of heuristics that nowadays constitute the state-of-the-art. Future developments in this direction will include:

- A more sophisticated segmentation procedure that allow to divide the phrases into more than two segments.
- A hybrid approach where the long phrase pairs remaining after the MDL inference are further segmented, e.g., according to a word lexicon.
- The inclusion of lexical models in the definition of the PB model.
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