PORTAGE: with Smoothed Phrase Tables
and Segment Choice Models

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Abstract

Improvements to Portage and its participation in the shared task of NAACL 2006 Workshop on Statistical Machine Translation are described. Promising ideas in phrase table smoothing and global distortion using feature-rich models are discussed as well as numerous improvements in the software base.

1 Introduction

The statistical machine translation system Portage is participating in the NAACL 2006 Workshop on Statistical Machine Translation. This is a good opportunity to do benchmarking against a publicly available data set and explore the benefits of a number of recently added features.

Section 2 describes the changes that have been made to Portage in the past year that affect the participation in the 2006 shared task. Section 3 outlines the methods employed for this task and extensions of it. In Section 4 the results are summarized in tabular form. Following these, there is a conclusions section that highlights what can be gleaned of value from these results.

2 Portage

Because this is the second participation of Portage in such a shared task, a description of the base system can be found elsewhere (Sadat et al, 2005). Briefly, Portage is a research vehicle and development prototype system exploiting the state-of-the-art in statistical machine translation (SMT). It uses a custom built decoder followed by a rescoring module that adjusts weights based on a number of features defined on the source sentence. We will devote space to discussing changes made since the 2005 shared task.

2.1 Phrase-Table Smoothing

Phrase-based SMT relies on conditional distributions $p(s|t)$ and $p(t|s)$ that are derived from the joint frequencies $c(s, t)$ of source/target phrase pairs observed in an aligned parallel corpus. Traditionally, relative-frequency estimation is used to derive conditional distributions, i.e. $p(s|t) = c(s, t) / \sum_s c(s, t)$.

However, relative-frequency estimation has the well-known problem of favouring rare events. For instance, any phrase pair whose constituents occur only once in the corpus will be assigned a probability of 1, almost certainly higher than the probabilities of pairs for which much more evidence exists. During translation, rare pairs can directly compete with overlapping frequent pairs, so overestimating their probabilities can significantly degrade performance.

To address this problem, we implemented two simple smoothing strategies. The first is based on the Good-Turing technique as described in (Church and Gale, 1991). This replaces each observed joint frequency $c$ with $c_g = (c + 1) n_{c+1} / n_c$, where $n_c$ is the number of distinct pairs with frequency $c$ (smoothed for large $c$). It also assigns a total count mass of $n_1$ to unseen pairs, which we distributed in proportion to the frequency of each conditioning
phrase. The resulting estimates are:

\[ p_g(s|t) = \frac{c_g(s, t)}{\sum_s c_g(s, t) + p(t)n_1}, \]

where \( p(t) = c(t)/\sum_c c(t). \) The estimates for \( p_g(t|s) \) are analogous.

The second strategy is Kneser-Ney smoothing (Kneser and Ney, 1995), using the interpolated variant described in (Chen and Goodman, 1998):\(^1\)

\[ p_k(s|t) = \frac{c(s, t) - D + D n_{1+}(s, t) p_k(s)}{\sum_s c(s, t)} \]

where \( D = n_1/(n_1 + 2n_2), n_{1+}(s, t) \) is the number of distinct phrases \( s \) with which \( t \) co-occurs, and \( p_k(s) = n_{1+}(s, *)/\sum_s n_{1+}(s, *) \), with \( n_{1+}(s, *) \) analogous to \( n_{1+}(s, t) \).

Our approach to phrase-table smoothing contrasts to previous work (Zens and Ney, 2004) in which smoothed phrase probabilities are constructed from word-pair probabilities and combined in a log-linear model with an unsmoothed phrase-table. We believe the two approaches are complementary, so a combination of both would be worth exploring in future work.

### 2.2 Feature-Rich DT-based distortion

In a recent paper (Kuhn et al, 2006), we presented a new class of probabilistic ”Segment Choice Models” (SCMs) for distortion in phrase-based systems. In some situations, SCMs will assign a better distortion score to a drastic reordering of the source sentence than to no reordering; in this, SCMs differ from the conventional penalty-based distortion, which always favours less rather than more distortion.

We developed a particular kind of SCM based on decision trees (DTs) containing both questions of a positional type (e.g., questions about the distance of a given phrase from the beginning of the source sentence or from the previously translated phrase) and word-based questions (e.g., questions about the presence or absence of given words in a specified phrase).

The DTs are grown on a corpus consisting of segment-aligned bilingual sentence pairs. This

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\(^1\)As for Good-Turing smoothing, this formula applies only to pairs \( s, t \) for which \( c(s, t) > 0 \), since these are the only ones considered by the decoder.
were the results of the third and fourth exercises where rescoring had been applied.

3.2 Open Resource Exercise

Our goal in this exercise was to conduct a comparative study using additional training data for the French-English shared task. Results of WPT 2005 showed an improvement of at least 0.3 BLEU point when exploiting different resources for the French-English pair of languages. In addition to the training resources used in WPT 2005 for the French-English task, i.e. Europarl and Hansard, we used a bilingual dictionary, *Le Grand Dictionnaire Terminologique* (GDT)\(^2\) to train translation models and the English side of the UN parallel corpus (LDC2004E13) to train an English language model. Integrating terminological lexicons into a statistical machine translation engine is not a straightforward operation, since we cannot expect them to come with attached probabilities. The approach we took consists on viewing all translation candidates of each source term or phrase as equiprobable (Sadat et al, 2006).

In total, the data used in this second part of our contribution to WMT 2006 is described as follows: (1) A set of 688,031 sentences in French and English extracted from the *Europarl parallel corpus* (2) A set of 6,056,014 sentences in French and English extracted from the *Hansard parallel corpus*, the official record of Canada’s parliamentary debates. (3) A set of 701,709 sentences in French and English extracted from the bilingual dictionary *GDT*. (4) Language models were trained on the French and English parts of the Europarl and Hansard. We used the provided Europarl corpus while omitting data from Q4/2000 (October-December), since it is reserved for development and test data. (5) An additional English language model was trained on 128 million words of the *UN Parallel corpus*.

For the supplied Europarl corpora, we relied on the existing segmentation and tokenization procedures. English preprocessing simply included lower-casing, separating punctuation from words and splitting off ‘s.

4 Results

The results are shown in Table 1. The numbers shown are BLEU scores. The MC rows correspond to the multi-corpora results described in the open resource exercise section above. All other rows are from the restricted resource exercise.

The devtest results are the scores computed before the shared-task submission and were used to drive the choice of direction of the research. The test results were computed after the shared-task submission and serve for validation of the conclusions.

We believe that our use of multiple training corpora as well as our re-tokenization for French and an enhanced language model resulted in our overall success in the English-French translation track. The results for the in-domain test data puts our group at the top of the ranking table drawn by the organizers (first on Adequacy and fluency and third on BLEU scores).

5 Conclusion

Benchmarking with same language model and parameters as WPT05 reproduces the results with a tiny improvement. The larger language model used in 2006 for English yields about half a BLEU. Good-Turing phrase table smoothing yields roughly half a BLEU point. Kneser-Ney phrase table smoothing yields between a third and half a BLEU point more than Good-Turing. Decision tree based distortion yields a small improvement for the devtest set when rescoring was not used but failed to show improvement on the test set.

In summary, the results from phrase-table smoothing are extremely encouraging. On the other hand, the feature-rich decision tree distortion modelling requires additional work before it provides a good pay-back. Fortunately we have some encouraging avenues under investigation. Clearly there is more work needed for both of these areas.

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\(^2\)http://www.granddictionnaire.com/
Table 1: Restricted and open resource results

|                   | fr → en | es → en | de → en | en → fr | en → es | en → de |
|-------------------|---------|---------|---------|---------|---------|---------|
| **devtest:** with rescoring |         |         |         |         |         |         |
| WPT05             | 29.32   | 29.08   | 23.21   |         |         |         |
| LM-2005           | 29.30   | 29.21   | 23.41   |         |         |         |
| LM-2006           | 29.88   | 29.54   | 23.94   | 30.43   | 28.81   | 17.33   |
| GT-PTS            | 30.35   | 29.84   | 24.60   | 30.89   | 29.54   | 17.62   |
| GT-PTS+DT-dist    | 30.09   | 29.44   | 24.62   | 31.06   | 29.46   | **17.84** |
| KN-PTS            | **30.55** | **30.12** | **24.66** | **31.28** | **29.90** | 17.78   |
| **MC WPT05**      | 29.63   |         |         |         |         |         |
| **MC**            | 30.09   |         |         |         |         |         |
| **MC+GT-PTS**     | **30.75** |         |         |         |         | **31.37** |

|                   |         |         |         |         |         |         |
| **devtest:** 1-best after decoding |         |         |         |         |         |         |
| LM-2006           | 28.59   | 28.45   | 22.22   | 29.22   | 28.30   | 16.94   |
| GT-PTS            | 29.23   | 28.91   | **23.67** | 30.07   | 28.86   | 17.32   |
| GT-PTS+DT-dist    | 29.48   | 29.07   | 23.50   | 30.22   | 29.46   | 17.42   |
| KN-PTS            | **29.77** | **29.76** | 23.27   | **30.73** | **29.62** | **17.78** |
| **MC WPT05**      | 28.71   |         |         |         |         |         |
| **MC**            | 29.63   |         |         |         |         |         |
| **MC+GT-PTS**     | **29.90** |         |         |         |         | **31.22** |

|                   |         |         |         |         |         |         |
| **test:** with rescoring |         |         |         |         |         |         |
| LM-2006           | 26.64   | 28.43   | 21.33   | 28.06   | 28.01   | 15.19   |
| GT-PTS            | 27.19   | 28.95   | 21.91   | 28.60   | 28.83   | 15.38   |
| GT-PTS+DT-dist    | 26.84   | 28.56   | 21.84   | 28.56   | 28.59   | 15.45   |
| KN-PTS            | **27.40** | **29.07** | **21.98** | **28.96** | **29.06** | **15.64** |
| **MC**            | 26.95   |         |         | 29.12   |         |         |
| **MC+GT-PTS**     | **27.10** |         |         |         |         | **29.46** |

|                   |         |         |         |         |         |         |
| **test:** 1-best after decoding |         |         |         |         |         |         |
| LM-2006           | 25.35   | 27.25   | 20.46   | 27.20   | 27.18   | 14.60   |
| GT-PTS            | 25.95   | 28.07   | 21.06   | 27.85   | 27.96   | 15.05   |
| GT-PTS+DT-dist    | 25.86   | 28.04   | 20.74   | 27.85   | 27.97   | 14.92   |
| KN-PTS            | **26.83** | **28.66** | **21.36** | **28.62** | **28.71** | **15.42** |
| **MC**            | 26.70   |         |         | 28.74   |         |         |
| **MC+GT-PTS**     | **26.81** |         |         |         |         | **29.03** |

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