Towards Efficient Large-Scale Feature-Rich Statistical Machine Translation

Vladimir Eidelman\textsuperscript{1}, Ke Wu\textsuperscript{1}, Ferhan Ture\textsuperscript{1}, Philip Resnik\textsuperscript{2}, Jimmy Lin\textsuperscript{3}

\textsuperscript{1} Dept. of Computer Science \hspace{1cm} \textsuperscript{2} Dept. of Linguistics \hspace{1cm} \textsuperscript{3} The iSchool

Institute for Advanced Computer Studies
University of Maryland
{vlad, wuke, fture, resnik, jimmylin}@umiacs.umd.edu

Abstract

We present the system we developed to provide efficient large-scale feature-rich discriminative training for machine translation. We describe how we integrate with MapReduce using Hadoop streaming to allow arbitrarily scaling the tuning set and utilizing a sparse feature set. We report our findings on German-English and Russian-English translation, and discuss benefits, as well as obstacles, to tuning on larger development sets drawn from the parallel training data.

1 Introduction

The adoption of discriminative learning methods for SMT that scale easily to handle sparse and lexicalized features has been increasing in the last several years (Chiang, 2012; Hopkins and May, 2011). However, relatively few systems take full advantage of the opportunity. With some exceptions (Simianer et al., 2012), most still rely on tuning a handful of common dense features, along with at most a few thousand others, on a relatively small development set (Cherry and Foster, 2012; Chiang et al., 2009). While more features tuned on more data usually results in better performance for other NLP tasks, this has not necessarily been the case for SMT.

Thus, our main focus in this paper is to improve understanding into the effective use of sparse features, and understand the benefits and shortcomings of large-scale discriminative training. To this end, we conducted experiments for the shared translation task of the 2013 Workshop on Statistical Machine Translation for the German-English and Russian-English language pairs.

2 Baseline system

We use a hierarchical phrase-based decoder implemented in the open source translation system cdec\textsuperscript{1} (Dyer et al., 2010). For tuning, we use Mr. MIRA\textsuperscript{2} (Eidelman et al., 2013), an open source decoder agnostic implementation of online large-margin learning in Hadoop MapReduce. Mr. MIRA separates learning from the decoder, allowing the flexibility to specify the desired inference procedure through a simple text communication protocol. The decoder receives input sentences and weight updates from the learner, while the learner receives $k$-best output with feature vectors from the decoder.

Hadoop MapReduce (Dean and Ghemawat, 2004) is a popular distributed processing framework that has gained widespread adoption, with the advantage of providing scalable parallelization in a manageable framework, taking care of data distribution, synchronization, fault tolerance, as well as other features. Thus, while we could otherwise achieve the same level of parallelization, it would be in a more ad-hoc manner.

The advantage of online methods lies in their ability to deal with large training sets and high-dimensional input representations while remaining simple and offering fast convergence. With Hadoop streaming, our system can take advantage of commodity clusters to handle parallel large-scale training while also being capable of running on a single machine or PBS-managed batch cluster.

System design To efficiently encode the information that the learner and decoder require (source sentence, reference translation, grammar rules) in a manner amenable to MapReduce, i.e. avoiding dependencies on “side data” and large transfers across the network, we append the reference and

\textsuperscript{1}http://cdec-decoder.org
\textsuperscript{2}https://github.com/kho/mr-mira
per-sentence grammar to each input source sentence. Although this file's size is substantial, it is not a problem since after the initial transfer, it resides on Hadoop distributed file system, and MapReduce optimizes for data locality when scheduling mappers.

A single iteration of training is performed as a Hadoop streaming job. Each begins with a map phase, with every parallel mapper loading the same initial weights and decoding and updating parameters on a shard of the data. This is followed by a reduce phase, with a single reducer collecting final weights from all mappers and computing a weighted average to distribute as initial weights for the next iteration.

**Parameter Settings** We tune our system toward approximate sentence-level BLEU (Papineni et al., 2002), and the decoder is configured to use cube pruning (Huang and Chiang, 2007) with a limit of 200 candidates at each node. For optimization, we use a learning rate of $\eta=0.01$, regularization strength of $C=0.01$, and a 500-best list for hope and fear selection (Chiang, 2012) with a single passive-aggressive update for each sentence (Eidelman, 2012).

**Baseline Features** We used a set of 16 standard baseline features: rule translation relative frequency $P(e|f)$, lexical translation probabilities $P_{lex}(\pi|\overline{f})$ and $P_{lex}(\overline{f}|\pi)$, target n-gram language model $P(\overline{e})$, penalties for source and target words, passing an untranslated source word to the target side, singleton rule and source side, as well as counts for arity-0.1, or 2 SCFG rules, the total number of rules used, and the number of times the glue rule is used.

**3 Evaluation**

This section describes the experiments we conducted in moving towards a better understanding of the benefits and challenges posed by large-scale high-dimensional discriminative tuning.

**3.1 Sparse Features**

The ability to incorporate sparse features is the primary reason for the recent move away from Minimum Error Rate Training (Och, 2003), as well as for performing large-scale discriminative training. We include the following sparse Boolean feature templates in our system in addition to the aforementioned baseline features: rule identity (for every unique rule in the grammar), rule shape (mapping rules to sequences of terminals and nonterminals), target bigrams, lexical insertions and deletions (for the top 150 unaligned words from the training data), context-dependent word pairs (for the top 300 word pairs in the training data), and structural distortion (Chiang et al., 2008).
Table 1: Corpus statistics in tokens for German.

| Set      | # features | Tune | Test | Test2 |
|----------|------------|------|------|-------|
| de       | 16         | 22.38| 22.69| 60.61 |
| +sparse  | 108k       | 23.86| 23.01| 59.89 |
| ru       | 16         | 30.18| 29.89| 49.05 |
| +sparse  | 77k        | 32.40| 30.81| 48.40 |

Table 3: Results with the addition of sparse features for German and Russian.

All of these features are generated from the translation rules on the fly, and thus do not have to be stored as part of the grammar. To allow for memory efficiency while scaling the training data, we hash all the lexical features from their string representation into a 64-bit integer.

Altogether, these templates result in millions of potential features, thus how to select appropriate features, and how to properly learn their weights can have a large impact on the potential benefit.

3.2 Adaptive Learning Rate

The passive-aggressive update used in MIRA has a single learning rate $\eta$ for all features, which along with $\alpha$ limits the amount each feature weight can change at each update. However, since the typical dense features (e.g., language model) are observed far more frequently than sparse features (e.g., rule identity), it has been shown to be advantageous to use an adaptive per-feature learning rate that allows larger steps for features that do not have much support (Green et al., 2013; Duchi et al., 2011). Essentially, instead of having a single parameter $\eta$,

\[
\alpha \leftarrow \min \left( C, \frac{\text{cost}(y') - w^T (f(y^+) - f(y'))}{\|f(y^+) - f(y')\|^2} \right)
\]

\[
w \leftarrow w + \alpha \eta (f(y^+) - f(y'))
\]

we instead have a vector $\Sigma$ with one entry for each feature weight:

\[
\Sigma^{-1} \leftarrow \Sigma^{-1} + \lambda \text{diag} \left( ww^T \right)
\]

\[
w \leftarrow w + \alpha \Sigma^{1/2} (f(y^+) - f(y'))
\]

Figure 1 shows learning curves for sparse models with a single learning rate, and adaptive learning with $\lambda=0.01$ and $\lambda=0.1$, with associated results on Test in Table 4. As can be seen, using a single $\eta$ produces almost no gain on Dev. However, while both settings using an adaptive rate fare better, the proper setting of $\lambda$ is important. With $\lambda=0.01$ we observe 0.5 BLEU gain over $\lambda=0.1$ in tuning, which translates to a small gain on Test. Henceforth, we use an adaptive learning rate with $\lambda=0.01$ for all experiments.

Table 3 presents baseline results for both languages. With the addition of sparse features, tuning scores increase by 1.5 BLEU for German, leading to a 0.3 BLEU increase on Test, and 2.2 BLEU for Russian, with 1 BLEU increase on Test. The majority of active features for both languages are rule id (74%), followed by target bigrams (14%) and context-dependent word pairs (11%).

3.3 Feature Selection

As the tuning set size increases, so do the number of active features. This may cause practical problems, such as reduced speed of computation and memory issues. Furthermore, while some

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Table 2: Corpus statistics in tokens for Russian.

| Set      | # features | Tune | Test | Test2 |
|----------|------------|------|------|-------|
| ru       | 46k        | 24.02| 24.01| 49.05 |
| +sparse  | 77k        | 32.40| 30.81| 48.40 |

In practice, this update is very similar to that of AROW (Crammer et al., 2009; Chiang, 2012).

4All sparse models are initialized with the same tuned baseline weights. Learning rates are local to each mapper.
Table 4: Results with different λ settings for using a per-feature learning rate with sparse features.

| λ     | Set       | # feat | Tune ↑BLEU | Test ↑BLEU | Test ↓TER |
|-------|-----------|--------|------------|------------|-----------|
| none  | all       | 510k   | 32.99      | 22.36      | 59.26     |
|       | top 200k  | 373k   | 34.26      | 28.84      | 49.29     |
| λ=0.01| all       | 200k   | 32.96      | 22.35      | 59.29     |
|       | top 200k  | 200k   | 34.45      | 28.98      | 49.30     |
| λ=0.1 | 62k       | 23.32  | 22.92      | 60.09      |

Table 5: Comparison of using all features versus top k selection.

| Set     | # feat | Tune ↑BLEU | Test ↑BLEU | Test ↓TER |
|---------|--------|------------|------------|-----------|
| all     | 510k   | 32.99      | 22.36      | 59.26     |
| top 200k| 373k   | 34.26      | 28.84      | 49.29     |
| all     | 200k   | 32.96      | 22.35      | 59.29     |
| top 200k| 200k   | 34.45      | 28.98      | 49.30     |

3.4 Large-Scale Training

In the previous section, we saw that learning sparse features on the small development set leads to substantial gains in performance. Next, we wanted to evaluate if we can obtain further gains by scaling the tuning data to learn parameters directly on a portion of the training bitext. Since the bitext is used to learn rules for translation, using the same parallel sentences for grammar extraction as well as for tuning feature weights can lead to severe overfitting (Flanigan et al., 2013). To avoid this issue, we used a jackknifing method to split the training data into \( n = 10 \) folds, and built a translation system on \( n - 1 \) folds, while sampling sentences from the News Commentary portion of the held-out fold to obtain tuning sets from 5,000 to 50,000 sentences for German, and 15,000 sentences for Russian.

Results for large-scale training for German are presented in Table 6. Although we cannot compare the tuning scores across different size sets, we can see that tuning scores for all sets improve substantially with sparse features. Unfortunately, with increasing tuning set size, we see very little improvement in Test BLEU and TER with either feature set. Similar findings for Russian are presented in Table 7. Introducing sparse features improves performance on each set, respectively, but Dev always performs better on Test.

While tuning on Dev data results in better BLEU on Test than when tuning on the larger sets, it is important to note that although we are able to tune more features on the larger bitext tuning sets, they are not composed of the same genre as the Tune and Test sets, resulting in a domain mismatch. This phenomenon is further evident in German when testing each model on Test2, which is selected from the bitext, and is thus closer matched to the larger tuning sets, but is separate from both the parallel data used to build the translation model and the tuning sets. Results on Test2 clearly show significant improvement using any of the larger tuning sets versus Dev for both the baseline and sparse features. The 50k sparse setting achieves almost 1 BLEU and 2 TER improvement, showing that there are significant differences between the Dev/Test sets and sets drawn from the bitext.

For Russian, we amplified the effects by selecting Test2 from the portion of the bitext that is separate from the tuning set, but is among the sentences used to create the translation model. The effects of overfitting are markedly more visible here, as there is almost a 7 BLEU difference between tuning on Dev and the 15k set with sparse features. Furthermore, it is interesting to note when looking at Dev that using sparse features has a significant negative impact, as the baseline tuned Dev performs worse than the baseline tuned Test.
Table 8: Results for German with 2 iterations of tuning on Dev after tuning on larger set.

| Tuning | Test |
|--------|------|
|        | ↑BLEU | ↓TER |
| 5k     | 22.81 | 59.90 |
| 10k    | 22.77 | 59.78 |
| 25k    | 22.88 | 59.77 |
| 50k    | 22.86 | 59.76 |

reasonably well, while the introduction of sparse features leads to overfitting the specificities of the Dev/Test genre, which are not present in the bitext.

We attempted two strategies to mitigate this problem: combining the Dev set with the larger bitext tuning set from the beginning, and tuning on a larger set to completion, and then running 2 additional iterations of tuning on the Dev set using the learned model. Results for tuning on Dev and a larger set together are presented in Table 7 for Russian and Table 6 for German. As can be seen, the resulting model improves somewhat on the other genre and strikes a middle ground, although it is worse on Test than Dev.

Table 8 presents results for tuning several additional iterations after learning a model on the larger sets. Although this leads to gains of around 0.5 BLEU on Test, none of the models outperform simply tuning on Dev. Thus, neither of these two strategies seem to help. In future work, we plan to forgo randomly sampling the tuning set from the bitext, and instead actively select the tuning set based on similarity to the test set.

4 Conclusion

We explored strategies for scaling learning for SMT to large tuning sets with sparse features. While incorporating an adaptive per-feature learning rate and feature selection, we were able to use Hadoop to efficiently take advantage of large amounts of data. Although discriminative training on larger sets still remains problematic, having the capability to do so remains highly desirable, and we plan to continue exploring methods by which to leverage the power of the bitext effectively.

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Table 6: German evaluation with large-scale tuning, showing numbers of mappers employed, number of active features for best model, and test scores on Test and bitext Test2 domains.

| Tuning   | # mappers | # features | Tune | Test   | Test2   |
|----------|------------|------------|------|--------|---------|
|          |            |            | ↑BLEU| ↓TER   | ↑BLEU   |
| Dev      | 120        | 16         | 22.38| 22.69  | 29.31   | 54.26   |
| 5k       | 120        | 16         | 32.60| 59.60  | 29.69   | 52.96   |
| 10k      | 120        | 16         | 33.16| 59.43  | 29.93   | 52.37   |
| Dev+10k  | 120        | 16         | 19.40| 59.37  | 30.17   | 52.45   |
| 25k      | 300        | 16         | 32.48| 59.54  | 30.03   | 51.71   |
| 50k      | 600        | 16         | 32.21| 59.39  | 29.94   | 52.55   |
| Dev      | 120        | 108k       | 23.86| 59.89  | 29.65   | 53.86   |
| 5k       | 120        | 159k       | 33.70| 59.26  | 30.53   | 51.84   |
| 10k      | 120        | 200k       | 34.00| 59.24  | 30.51   | 51.71   |
| Dev+10k  | 120        | 200k       | 19.62| 59.17  | 30.26   | 52.21   |
| 25k      | 300        | 200k       | 32.96| 59.29  | 30.39   | 52.14   |
| 50k      | 600        | 200k       | 32.86| 59.15  | 30.54   | 51.88   |

Table 7: Russian evaluation with large-scale tuning, showing numbers of mappers employed, number of active features for best model, and test scores on Test and bitext Test2 domains.

| Tuning   | # mappers | # features | Tune | Test   | Test2   |
|----------|------------|------------|------|--------|---------|
|          |            |            | ↑BLEU| ↓TER   | ↑BLEU   |
| Dev      | 120        | 16         | 30.18| 29.89  | 57.14   | 32.56   |
| 15k      | 200        | 16         | 34.65| 28.60  | 59.64   | 30.65   |
| Dev+15k  | 200        | 16         | 33.97| 28.88  | 58.24   | 31.81   |
| Dev      | 120        | 77k        | 32.40| 30.81  | 52.90   | 36.85   |
| 15k      | 200        | 200k       | 35.05| 28.34  | 59.81   | 30.59   |
| Dev+15k  | 200        | 200k       | 34.45| 28.98  | 57.61   | 32.71   |

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