Minimum Risk Training for Neural Machine Translation

Shiqi Shen[†], Yong Cheng[#], Zhongjun He⁺, Wei He⁺, Hua Wu⁺, Maosong Sun[†], Yang Liu^{†*}

†State Key Laboratory of Intelligent Technology and Systems
Tsinghua National Laboratory for Information Science and Technology
Department of Computer Science and Technology, Tsinghua University, Beijing, China
#Institute for Interdisciplinary Information Sciences, Tsinghua University, Beijing, China
+Baidu Inc., Beijing, China

Abstract

We propose minimum risk training for end-to-end neural machine translation. Unlike conventional maximum likelihood estimation, minimum risk training is capable of optimizing model parameters directly with respect to evaluation metrics. Experiments on Chinese-English and English-French translation show that our approach achieves significant improvements over maximum likelihood estimation on a state-of-the-art neural machine translation system.

1 Introduction

Recently, end-to-end neural machine translation (NMT) [Kalchbrenner and Blunsom, 2013; Sutskever et al., 2014; Bahdanau et al., 2015] has attracted increasing attention from the community. Providing a new paradigm for machine translation, NMT aims at training a single, large neural network that directly transforms a source-language sentence to a target-language sentence without explicitly modeling latent structures (e.g., word alignment, phrase segmentation, phrase reordering, and SCFG derivation) present in conventional statistical machine translation (SMT) [Brown et al., 1993; Koehn et al., 2003; Chiang, 2005].

Current NMT models build on the encoder-decoder framework [Cho et al., 2014; Sutskever et al., 2014], with an encoder to read and encode a source language sentence into a vector and a decoder to generate a target-language sentence from the vector. While early efforts encode the input into a fixed-length vector, Bahdanau et al. [2015] introduce the mechanism of attention to dynamically generate a context vector for a target word being generated.

Although NMT models have achieved results on par with or better than conventional SMT, they still suffer a major drawback: the models are optimized

^{*}Yang Liu is the corresponding author: liuyang2011@tsinghua.edu.cn.

to maximize the likelihood of training data instead of evaluation metrics that actually quantify translation quality. Ranzato et al. [2015] indicate two drawbacks of maximum likelihood estimation (MLE) for neural machine translation: (1) the models are only exposed to the training data distribution instead of model predictions and (2) the loss function is defined at the word level instead of sentence level.

In this work, we introduce minimum risk training (MRT) for neural machine translation. The new training objective is to minimize the expected loss on the training data. One advantage of MRT is that it allows for arbitrary loss functions, which are not necessarily differentiable. In addition, our approach does not assume the specific architectures of NMT and can be applied to any end-to-end NMT systems. While MRT has been widely used in conventional SMT [Och, 2003; Smith and Eisner, 2006; He and Deng, 2012] and deep learning based MT [Gao et al., 2014], to the best of our knowledge, this work is the first effort to introduce MRT into end-to-end neural machine translation. Experiments on Chinese-English and English-French show that MRT leads to significant improvements over MLE on a state-of-the-art NMT system [Bahdanau et al., 2015].

2 Background

Given a source-language sentence $\mathbf{x} = \mathbf{x}_1, \dots, \mathbf{x}_m, \dots, \mathbf{x}_M$ and a target-language sentence $\mathbf{y} = \mathbf{y}_1, \dots, \mathbf{y}_n, \dots, \mathbf{y}_N$, end-to-end neural MT directly models the translation probability:

$$P(\mathbf{y}|\mathbf{x};\boldsymbol{\theta}) = \prod_{n=1}^{N} P(\mathbf{y}_n|\mathbf{x}, \mathbf{y}_{< n}; \boldsymbol{\theta})$$
 (1)

where θ is a set of model parameters and $\mathbf{y}_{< n} = \mathbf{y}_1, \dots, \mathbf{y}_{n-1}$.

Predicting the n-th target word can be done by using a recurrent neural network:

$$P(\mathbf{y}_n|\mathbf{x},\mathbf{y}_{\leq n};\boldsymbol{\theta}) \propto \exp\left\{q(\mathbf{y}_{n-1},\mathbf{z}_n,\mathbf{c}_n,\boldsymbol{\theta})\right\}$$
 (2)

where \mathbf{z}_n is the *n*-th hidden state on the target side, \mathbf{c}_n is the context for generating the *n*-th target word, and q is a non-linear function. Current NMT approaches differ in calculating \mathbf{z}_n and \mathbf{c}_n and defining q. Please refer to [Sutskever et al., 2014; Bahdanau et al., 2015] for more details.

Given a set of training examples $D = \{\langle \mathbf{x}^{(s)}, \mathbf{y}^{(s)} \rangle\}_{s=1}^{S}$, the standard training objective is to maximize the log likelihood of the training data:

$$\hat{\boldsymbol{\theta}}_{\text{MLE}} = \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \left\{ \mathcal{L}(\boldsymbol{\theta}) \right\}$$
 (3)

$$= \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \left\{ \log \prod_{s=1}^{S} P(\mathbf{y}^{(s)} | \mathbf{x}^{(s)}; \boldsymbol{\theta}) \right\}$$
(4)

$$= \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \left\{ \sum_{s=1}^{S} \sum_{n=1}^{N^{(s)}} \log P(\mathbf{y}_{n}^{(s)} | \mathbf{x}^{(s)}, \mathbf{y}_{< n}^{(s)}; \boldsymbol{\theta}) \right\}$$
 (5)

The partial derivative with respect to a model parameter θ_i is calculated as

$$\frac{\partial \mathcal{L}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}_i} = \sum_{s=1}^{S} \sum_{n=1}^{N^{(s)}} \frac{\partial P(\mathbf{y}_n | \mathbf{x}^{(s)}, \mathbf{y}_{< n}; \boldsymbol{\theta}) / \partial \boldsymbol{\theta}_i}{P(\mathbf{y}_n | \mathbf{x}^{(s)}, \mathbf{y}_{< n}; \boldsymbol{\theta})}$$
(6)

Ranzato et al. [2015] argue that MLE for neural machine translation suffers from two drawbacks. First, while the models are trained only on the training data distribution, they are used to generate target words based on previous model predictions at test time. This is referred to as exposure bias [Ranzato et al., 2015]. Second, MLE usually uses the cross-entropy loss to maximize the probability of the next correct word, which might hardly correlate well with evaluation metrics such as BLEU [Papineni et al., 2002].

As a result, it is important to introduce new training algorithms for end-toend neural machine translation that optimize model parameters directly with respect to evaluation metrics.

3 Minimum Risk Training for Neural Machine Translation

Minimum risk training (MRT), which aims to minimize the expected loss on the training data, has been widely used in conventional statistical machine translation [Och, 2003; Smith and Eisner, 2006; He and Deng, 2012] and deep learning based MT [Gao *et al.*, 2014]. In this work, we introduce MRT into end-to-end neural machine translation. The training objective is given by

$$\hat{\boldsymbol{\theta}}_{\mathrm{MRT}} = \underset{\boldsymbol{\theta}}{\mathrm{argmin}} \left\{ \mathcal{J}(\boldsymbol{\theta}) \right\} \tag{7}$$

$$= \underset{\boldsymbol{\theta}}{\operatorname{argmin}} \left\{ \sum_{s=1}^{S} \sum_{\mathbf{y} \in \mathcal{Y}(\mathbf{x}^{(s)})} P(\mathbf{y}|\mathbf{x}^{(s)}; \boldsymbol{\theta}) \Delta(\mathbf{y}, \mathbf{y}^{(s)}) \right\}$$
(8)

$$= \underset{\boldsymbol{\theta}}{\operatorname{argmin}} \left\{ \sum_{s=1}^{S} \mathbb{E}_{\mathbf{y}|\mathbf{x}^{(s)};\boldsymbol{\theta}} \left[\Delta(\mathbf{y}, \mathbf{y}^{(s)}) \right] \right\}$$
(9)

where $\Delta(\mathbf{y}, \mathbf{y}^{(s)})$ is a loss function that measures the discrepancy between a predicted translation \mathbf{y} and the training example $\mathbf{y}^{(s)}$ and the expected loss $\mathbb{E}_{\mathbf{y}|\mathbf{x}^{(s)};\boldsymbol{\theta}}[\Delta(\mathbf{y}, \mathbf{y}^{(s)})]$ is referred to as risk.

The partial derivative with respect to a model parameter θ_i is calculated as

$$\frac{\partial \mathcal{J}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}_{i}} = \sum_{s=1}^{S} \mathbb{E}_{\mathbf{y}|\mathbf{x}^{(s)};\boldsymbol{\theta}} \left[\Delta(\mathbf{y}, \mathbf{y}^{(s)}) \sum_{n=1}^{N^{(s)}} \frac{\partial P(\mathbf{y}_{n}|\mathbf{x}^{(s)}, \mathbf{y}_{< n}; \boldsymbol{\theta}) / \partial \boldsymbol{\theta}_{i}}{P(\mathbf{y}_{n}|\mathbf{x}^{(s)}, \mathbf{y}_{< n}; \boldsymbol{\theta})} \right]$$
(10)

Unfortunately, the expectations in Eq.(10) are usually intractable to calculate due to the exponential search space as well as the non-decomposability of the loss function.

To alleviate this problem, we propose to only use a subset of the search space and introduce a new training objective:

$$\tilde{\mathcal{J}}(\boldsymbol{\theta}) = \sum_{s=1}^{S} \sum_{\mathbf{y} \in \mathcal{S}(\mathbf{x}^{(s)})} \frac{P(\mathbf{y}|\mathbf{x}^{(s)};\boldsymbol{\theta})^{\alpha}}{\sum_{\mathbf{y}' \in \mathcal{S}(\mathbf{x}^{(s)})} P(\mathbf{y}'|\mathbf{x}^{(s)};\boldsymbol{\theta})^{\alpha}} \Delta(\mathbf{y},\mathbf{y}^{(s)})$$
(11)

$$= \sum_{s=1}^{S} \sum_{\mathbf{y} \in S(\mathbf{x}^{(s)})} Q(\mathbf{y}|\mathbf{x}^{(s)}; \boldsymbol{\theta}, \alpha) \Delta(\mathbf{y}, \mathbf{y}^{(s)})$$
(12)

$$= \sum_{s=1}^{S} \mathbb{E}_{\mathbf{y}|\mathbf{x}^{(s)};\boldsymbol{\theta},\alpha} \left[\Delta(\mathbf{y}, \mathbf{y}^{(s)}) \right]$$
 (13)

where $S(\mathbf{x}^{(s)}) \subset \mathcal{Y}(\mathbf{x}^{(s)})$ is a subset of the full search space, $Q(\mathbf{y}|\mathbf{x}^{(s)};\boldsymbol{\theta},\alpha)$ is a distribution defined on the subspace $S(\mathbf{x}^{(s)})$, and α is a hyper-parameter that controls the sharpness of the Q distribution [Och, 2003].

Intuitively, while MLE aims to maximize the likelihood of training data, our training objective is to discriminate between candidates in the sampled subspace $\mathcal{S}(\mathbf{x}^{(s)})$. In practice, we find that this approximation works well (see Section 4).

Therefore, the partial derivative with respect to a model parameter θ_i of $\tilde{J}(\theta)$ is given by

$$\frac{\partial \tilde{J}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}_{i}} = \alpha \sum_{s=1}^{S} \mathbb{E}_{\mathbf{y}|\mathbf{x}^{(s)};\boldsymbol{\theta},\alpha} \left[\Delta(\mathbf{y}, \mathbf{y}^{(s)}) \times \left(\sum_{n=1}^{N} \frac{\partial P(\mathbf{y}_{n}|\mathbf{x}^{(s)}, \mathbf{y}_{< n}; \boldsymbol{\theta}) / \partial \boldsymbol{\theta}_{i}}{P(\mathbf{y}_{n}|\mathbf{x}^{(s)}, \mathbf{y}_{< n}; \boldsymbol{\theta})} - \mathbb{E}_{\mathbf{y}'|\mathbf{x}^{(s)};\boldsymbol{\theta},\alpha} \left[\sum_{n=1}^{N} \frac{\partial P(\mathbf{y}'_{n}|\mathbf{x}^{(s)}, \mathbf{y}'_{< n}; \boldsymbol{\theta}) / \partial \boldsymbol{\theta}_{i}}{P(\mathbf{y}'_{n}|\mathbf{x}^{(s)}, \mathbf{y}'_{< n}; \boldsymbol{\theta})} \right] \right) \right] (14)$$

4 Experiments

4.1 Setup

We evaluated our approach on two translation tasks: Chinese-English and English-French. The evaluation metric is BLEU [Papineni *et al.*, 2002] as calculated by the multi-bleu.perl script.

For Chinese-English, the training data consists of 2.56M pairs of sentences with 67.5M Chinese words and 74.8M English words, respectively. We used the

NIST 2006 dataset as the validation set for optimizing hyper-parameters and model selection and the NIST 2002, 2003, 2004, 2005, and 2008 datasets as test sets. For English-French, to compare with the results reported by previous work on neural machine translation [Sutskever et al., 2014; Bahdanau et al., 2015], we used the same subset of the WMT 2014 training corpus that contains 12M sentence pairs with 348M French words and 304M English words. The concatenation of news-test 2012 and news-test 2013 serves as the validation set and news-test 2014 as the test set.

We compare our approach with two state-of-the-art SMT and NMT systems:

- 1. Moses [Koehn and Hoang, 2007]: a phrase-based SMT system;
- 2. Groundhog [Bahdanau et al., 2015]: an attention-based NMT system with maximum likelihood estimation.

Moses uses the parallel corpus to train the phrase-based translation model and the target part to train a 4-gram language model using the SRILM toolkit [Stolcke, 2002]. The log-linear model is trained using the minimum error rate training (MERT) algorithm [Och, 2003].

GROUNDHOG uses the parallel corpus to train the neural translation model on a cluster with 20 Telsa K40 GPUs. It takes the cluster about one hour to train 20,000 minibatchs, each of which contains 80 sentences.

Our system extends Groundhog by replacing maximum likelihood estimation with minimum risk training. We initialize our model with the RNNsearch50 model [Bahdanau et al., 2015]. We sample 100 candidate translations from the search space to build the Q distribution. As the samples might be identical, we remove duplicate candidates in the subspace. The gold-standard translation in the training data is included in the sampled space. We set the vocabulary size to 30K for each language. The training time for MRT is longer than MLE: 13,000 minibatchs can be processed in one hour on the same cluster. The beam size for decoding is 10. The hyper-parameter α is set to 0.005. The loss function is negative smoothed sentence-level BLEU.

4.2 Results on Chinese-English Translation

Table 1 shows BLEU scores on Chinese-English datasets. We find that introducing minimum risk training into neural MT leads to surprisingly substantial improvements over Moses and Groundhog with MLE as the training criterion (up to +7.74 and +6.86 BLEU points, respectively) across all test sets. All the improvements are statistically significant.

Table 2 shows some example translations. We find that Moses translates a Chinese string "yi wei fuze yu pingrang dangju da jiaodao de qian guowuyuan guanyuan" that requires long-distance reordering in a wrong way, which is a notorious challenge for statistical machine translation. In contrast, GROUNDHOGMLE seems to overcome this problem in this example thanks to the capability of gated RNNs to capture long-distance dependencies. However, as MLE uses

System	Training	MT06	MT02	MT03	MT04	MT05	MT08
Moses	MERT	32.74	32.49	32.40	33.38	30.20	25.28
GROUNDHOG	MLE	30.39	34.59	33.20	34.16	31.23	23.30
	MRT	36.71	39.58	40.06	40.75	37.94	28.67

Table 1: Case-insensitive BLEU scores on Chinese-English translation. Moses is a state-of-the-art phrase-based statistical machine translation system [Koehn and Hoang, 2007] that uses the minimum error rate training (MERT) algorithm for training the log-linear model. Groundhog is a state-of-the-art end-to-end neural machine translation system [Bahdanau et al., 2015] with maximum likelihood estimation (MLE) as the default training criterion. We find that introducing minimum risk training (MRT) into Groundhog leads to substantial improvements.

Source	meiguo daibiao tuan baokuo laizi shidanfu daxue de yi wei zhongguo zhuanjia , liang ming canyuan waijiao zhengce zhuli yiji yi wei fuze yu pingrang dangju da jiaodao de qian guowuyuan guanyuan .
Reference	the us delegation consists of a chinese expert from the stanford university, two senate for- eign affairs policy assistants and a former state department official who was in charge of dealing with pyongyang authority.
Moses	the united states to members of the delegation include representatives from the stanford university, a chinese expert, two assistant senate foreign policy and a responsible for dealing with pyongyang before the officials of the state council.
GROUNDHOG-MLE	the us delegation comprises a chinese expert from stanford university, a chinese foreign of- fice assistant policy assistant and a former offi- cial who is responsible for dealing with the py- ongyang authorities.
GROUNDHOG-MRT	the us delegation included a chinese expert from the stanford university, two senate foreign pol- icy assistants, and a former state department official who had dealings with the pyongyang au- thorities.

Table 2: Example Chinese-English translations. "Source" is a romanized Chinese sentence, "Reference" is a gold-standard translation. "Moses", "Groundhog-MLE", and "Groundhog-MRT" are three MT systems.

System	Architecture	Training	Vocab	BLEU					
Existing end-to-end NMT systems									
Bahdanau et al. [2015]	single gated RNN with search		30K	28.45					
Jean $et \ al. \ [2015]$	single gated RNN with search		30K	29.97					
Luong <i>et al.</i> [2015]	single LSTM with 4 layers	MLE	40K	29.50					
Luong <i>et al.</i> [2015]	single LSTM with 6 layers		40K	30.40					
Sutskever et al. [2014]	single LSTM with 4 layers		80K	30.59					
Our end-to-end NMT systems									
this work	single gated RNN with search	MLE	30K	29.02					
UIUS WOIK	Single gated Itiviv with Search	MRT	30K	30.63					

Table 3: Comparison with previous work on English-French translation. The BLEU scores of this work are case-sensitive.

a loss function defined only at the word level, its translation lacks sentence-level consistency: "chinese" occurs twice while "two senate" is missing. By optimizing the model parameters directly with respect to sentence-level BLEU, GROUNDHOG-MRT seems to be able to generate translations more consistently at the sentence level.

4.3 Results on English-French Translation

Table 3 shows the results on English-French translation. We list existing end-to-end NMT systems that are comparable to our system. All these systems use the same subset of the WMT 2014 training corpus and adopt MLE as the training criterion. They differ in terms of network architecture and vocabulary size. Our Groundhog-MLE system achieves a BLEU score comparable to that of Bahdanau et al. [2015]. Groundhog-MRT achieves the highest BLEU score in this setting even with a smaller vocabulary size than Luong et al. [2015] and Sutskever et al. [2014]. Note that our approach does not assume specific architectures and can in principle be applied to any NMT systems.

5 Related Work

Our work originates from the minimum risk training algorithms in conventional statistical machine translation [Och, 2003; Smith and Eisner, 2006; He and Deng, 2012]. Och [2003] describes a smoothed error count to allow for calculating gradients, which directly inspires us to use a parameter α to adjust the smoothness of the objective function. Smith and Eisner [2006] introduce minimum risk annealing for training log-linear models that is capable of gradually annealing to focus on the 1-best hypothesis. He and Deng [2012] apply minimum risk training to learning phrase translation probabilities.

¹We have not adopted the recently introduced techniques such as ensemble of multiple model predictions [Sutskever et al., 2014], increasing vocabulary by importance sampling [Jean et al., 2015], and addressing the rare word problem [Luong et al., 2015] to further improve translation performance. We leave this for future work.

More recently, Gao et al. [2014] use MRT for learning continuous phrase representations for statistical machine translation. The difference is that they use MRT to optimize a sub-model of statistical machine translation while we are interested in directly optimizing end-to-end neural translation models.

The Mixed Incremental Cross-Entropy Reinforce (MIXER) algorithm [Ranzato et al., 2015] is in spirit most close to our work. Building on the REINFORCE algorithm proposed by Willams [1992], MIXER allows for incremental learning and the use of hybrid loss function that combines both REINFORCE and cross-entropy. The major difference is that Ranzato et al. [2015] leverage reinforcement learning while our work resorts to minimum risk training. Our experiments confirm their finding that taking evaluation metric into account when optimizing model parameters does help to improve sequence-level text generation.

6 Conclusion

In this paper, we have presented a framework for minimum risk training in end-to-end neural machine translation. Experiments show that minimum risk training leads to significant improvements over maximum likelihood estimation for neural machine translation, especially for distantly-related languages such as Chinese and English.

In the future, we plan to test our approach on more language pairs and more end-to-end neural MT systems. We believe that minimum risk training will also benefit end-to-end neural architectures for other NLP tasks.

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