

Explaining and Generalizing Back-Translation through Wake-Sleep

Ryan Cotterell

Department of Computer Science
Johns Hopkins University
ryan.cotterell@jhu.edu

Julia Kreutzer

Department of Computational Linguistics
Heidelberg University
kreutzer@cl.uni-heidelberg.de

Abstract

Back-translation has become a commonly employed heuristic for semi-supervised neural machine translation. The technique is both straightforward to apply and has led to state-of-the-art results. In this work, we offer a principled interpretation of back-translation as approximate inference in a generative model of bitext and show how the standard implementation of back-translation corresponds to a single iteration of the wake-sleep algorithm in our proposed model. Moreover, this interpretation suggests a natural iterative generalization, which we demonstrate leads to further improvement of up to 1.6 BLEU.

1 Introduction

Recurrent neural networks have asserted hegemony in machine translation research. Whereas phrase-based machine translation systems consisted of a hodgepodge of individual components, expertly crocheted together to produce a final translation, neural machine translation (NMT) is a fully end-to-end system that treats learning a translator as parameter estimation in a single discriminative probability model. To train an NMT model in a semi-supervised fashion, an interesting heuristic has emerged—back-translation, a simple technique that hallucinates additional bitext from monolingual data. In this work, we interpret and generalize back-translation using techniques from generative modeling and variational inference.

In broad strokes, back-translation works as follows. The NMT practitioner trains *two* systems: a forward translation system that translates from the source to the target language and a second, backwards translation system that translates from the target back into the source language. The backwards translation system is then used to translate additional monolingual text into the source language, hallucinating, as it were, more bitext.

Then, the additional data is used to estimate a higher-quality forward translation model. Back-translation has recently risen to fame in the context of NMT (Senrich et al., 2016a) and has helped these systems achieve state-of-the-art results; the method’s provenance, however, is older: Bertoldi and Federico (2009) and Li et al. (2011) both applied back-translation to non-neural MT.

Our contribution is a novel interpretation and straight-forward extension of back-translation that rest on the construction of a fully generative model of bitext. Working within this model, we cast back-translation as a variational approximation, where the backwards translator is an inference network that approximates a posterior of a latent variable—the unobserved source sentence. Specifically, we show that back-translation is a *single iteration* of the wake-sleep variational scheme (Hinton et al., 1995); this interpretation suggests a simple extension to the model, where we iteratively re-estimate both the forward and backward translator in a fashion similar to expectation maximization. We experiment on two language pairs (English↔German and English↔Latvian) on two domains (WMT news translation and TED talks) and find that our extension brings consistent gain over vanilla back-translation, up to 1.6 BLEU.

We may summarize our paper concisely with the following koan: If back-translation is the answer, what was the question?

2 A Generative Model of Bitext

We construct a generative latent-variable model for the production of bitext with the goal of showing that back-translation corresponds to a form variational inference in the model. First, however, we establish the requisite notation. Let Σ_x and Σ_y be finite alphabets (of words) for the source

and target languages, respectively. Both are augmented with a distinguished end-of-sentence symbol EOS . Let $\mathbf{x} \in \Sigma_x^*$ and $\mathbf{y} \in \Sigma_y^*$ be strings, each of which ends with EOS . Formally, then, a monotext \mathcal{M} is a collection of sentences $\{\mathbf{y}^{(i)}\}_{i=1}^N$ and a bitext is a collection of *aligned pairs* of sentences $\mathcal{B} = \{\langle \mathbf{x}^{(i)}, \mathbf{y}^{(i)} \rangle\}_{i=1}^N$, where each $\mathbf{y}^{(i)}$, a sentence in the target language, is a translation of $\mathbf{x}^{(i)}$, a sentence in the source language.

We define then our generative model of bitext as

$$p(\mathcal{B}) = \prod_{\langle \mathbf{y}, \mathbf{x} \rangle \in \mathcal{B}} p(\mathbf{y}, \mathbf{x}) = \prod_{\langle \mathbf{y}, \mathbf{x} \rangle \in \mathcal{B}} p_{\theta}(\mathbf{y} | \mathbf{x}) p(\mathbf{x}) \quad (1)$$

The distribution may be viewed as a directed graphical model (a Bayesian network). We will term the model $p_{\theta}(\mathbf{y} | \mathbf{x})$ the **translation model** and $p(\mathbf{x})$ the **language model**. In general, both $p_{\theta}(\mathbf{y} | \mathbf{x})$ and $p(\mathbf{x})$ will be richly parameterized, such as by a recurrent neural network—see §5. As our end task is machine translation, the distribution $p_{\theta}(\mathbf{y} | \mathbf{x})$ is the final product—we will discard $p(\mathbf{x})$.

Supervised Machine Translation. Most machine translation models are estimated in the fully supervised setting: one directly estimates the distribution $p_{\theta}(\mathbf{y} | \mathbf{x})$ through maximum likelihood estimation, i.e., maximizing $\log p(\mathcal{B}) = \sum_{\langle \mathbf{x}, \mathbf{y} \rangle} \log p_{\theta}(\mathbf{y} | \mathbf{x})$. As $p_{\theta}(\mathbf{y} | \mathbf{x})$ is often a continuous function of its parameters θ , gradient-based methods are typically employed.

Semi-Supervised Generalization. Lamentably, bitext in the wild is a relatively rare find, but monolingual text abounds. A natural question is, then, how can we exploit this monolingual text in the estimation of machine translation systems? Generative modeling provides the answer—we may optimize the marginal likelihood, where we marginalize out the translation of the unannotated source sentence; formally, this yields the following:

$$\prod_{\mathbf{y} \in \mathcal{M}} p(\mathbf{y}) = \prod_{\mathbf{y} \in \mathcal{M}} \sum_{\mathbf{x} \in \Sigma_x^*} p_{\theta}(\mathbf{y} | \mathbf{x}) p(\mathbf{x}) \quad (2)$$

Unfortunately, there are an infinite number of summands, which makes eq. (2) intractable to compute. Thus, we rely on an approximate strategy, one iteration of which will be shown to be equivalent to the back-translation technique.

Algorithm 1 Wake-sleep for Semi-Supervised Neural Machine Translation

Input: initial forward & backward NMT parameters θ, ϕ ; monotext \mathcal{M} ; language model $p(\cdot)$

Output: final model parameters θ, ϕ

```

1: for  $i = 1$  to  $I$  do
2:    $\mathcal{B}_{back} \leftarrow \emptyset$ 
3:   for  $\mathbf{y} \in \mathcal{M}$  do
4:      $\tilde{\mathbf{x}} \sim q_{\phi}(\cdot | \mathbf{y})$ 
5:      $\mathcal{B}_{back} \leftarrow \mathcal{B}_{back} \cup \{\langle \mathbf{y}, \tilde{\mathbf{x}} \rangle\}$ 
6:   estimate  $\theta$  by maximizing  $\log p_{\theta}$  of  $\mathcal{B} \cup \mathcal{B}_{back}$ 
7:    $\mathcal{B}_{dreamt} \leftarrow \emptyset$ 
8:   for  $\tilde{\mathbf{x}} \sim p(\cdot)$  do
9:      $\tilde{\mathbf{y}} \sim p_{\theta}(\cdot | \tilde{\mathbf{x}})$ 
10:     $\mathcal{B}_{dreamt} \leftarrow \mathcal{B}_{dreamt} \cup \{\langle \tilde{\mathbf{y}}, \tilde{\mathbf{x}} \rangle\}$ 
11:   estimate  $\phi$  by maximizing  $\log q_{\phi}$  of  $\mathcal{B} \cup \mathcal{B}_{dreamt}$ 

```

3 Variational Back-Translation

Semi-supervised learning in the model requires efficient marginal inference. To cope, we derive an approximation scheme, based on the wake-sleep algorithm. Wake-sleep, originally presented in the context of the Helmholtz machine (Dayan et al., 1995), is an iterative procedure that, prima facie, resembles the expectation maximization (EM) algorithm of Dempster et al. (1977). Much like EM, wake-sleep has two steps that are to be alternated: (i) the sleep phase and (ii) the wake phase.

3.1 Overview

Before discussing the algorithmic details, we give the intuition behind the connection we draw. Wake-sleep will iterate between learning a better forward-translator $p_{\theta}(\mathbf{y} | \mathbf{x})$ and a better back-translator $q_{\phi}(\mathbf{x} | \mathbf{y})$. Typically in back-translation, however, the back-translator is trained and then additional bitext is hallucinated *once* in order to train a better forward-translator $p_{\theta}(\mathbf{y} | \mathbf{x})$. However, under the view that $q_{\phi}(\mathbf{x} | \mathbf{y})$ should be an approximation to the posterior $p(\mathbf{x} | \mathbf{y})$ in the joint model eq. (1), the wake-sleep algorithm suggests an iterative procedure that gradually refines q_{ϕ} , taking information from p into account. Thus, under wake-sleep, we constantly retrain the forward-translator $p_{\theta}(\mathbf{y} | \mathbf{x})$ using the updated back-translator and vice versa.

3.2 The Sleep Phase

Had we access to the true posterior of our joint model $p(\mathbf{x} | \mathbf{y})$, we could apply EM in a straightforward manner, as one does in models that admit tractable computation of the quantity, e.g., the hidden Markov model (Rabiner, 1989). However, in general we will choose a rich neural parameterization that will prohibit its direct computation; thus, we seek a distribution $q_\phi(\mathbf{x} | \mathbf{y})$ that well-approximates $p(\mathbf{x} | \mathbf{y})$. What is $q_\phi(\mathbf{x} | \mathbf{y})$? In the machine learning literature, this distribution is termed an **inference network**—a parameterized distribution that approximate the posterior over \mathbf{x} for *any* observed sentence \mathbf{y} . Inference networks have been applied to a wide variety of problems, e.g., topic modeling (Miao et al., 2016) and inflection generation (Zhou and Neubig, 2017).¹

A common principled manner to approximate a probability distribution is to minimize the Kullback-Leibler (KL) divergence. The sleep step dictates that we choose q_ϕ so as to minimize the quantity

$$\sum_{\mathbf{y} \in \mathcal{M}} D_{KL}(p(\cdot | \mathbf{y}) || q_\phi(\cdot | \mathbf{y})) \quad (3)$$

These inclusive KL divergences are still intractable—we would have to normalize the distribution $p_\theta(\mathbf{x} | \mathbf{y})$, which is hard since it involves a sum over $\Sigma_{\mathbf{x}}^*$. By design, however, our model $p(\mathbf{y}, \mathbf{x})$ is a directed generative model so we can efficiently generate samples through forward sampling; first, we sample a sentence $\tilde{\mathbf{x}}^{(i)} \sim p(\cdot)$ and then we sample its translation $\tilde{\mathbf{y}}^{(i)} \sim p_\theta(\cdot | \tilde{\mathbf{x}}^{(i)})$. We term the new bitext of M samples the “dreamt” bitext $\mathcal{B}_{dreamt} = \{(\tilde{\mathbf{y}}^{(i)}, \tilde{\mathbf{x}}^{(i)})\}_{i=1}^M$. Using these samples from the joint $p(\mathbf{y}, \mathbf{x})$, we may approximate the true posterior $p(\mathbf{y} | \mathbf{x})$ by maximizing the following Monte Carlo approximation to eq. (3): $\sum_{(\tilde{\mathbf{y}}, \tilde{\mathbf{x}}) \in \mathcal{B}_{dreamt}} \log q_\phi(\tilde{\mathbf{x}} | \tilde{\mathbf{y}})$. To find good parameters ϕ , we will optimize the log-likelihood of $\mathcal{B} \cup \mathcal{B}_{dreamt}$ through a gradient-based method, such as backpropagation (Rumelhart et al., 1986).

3.3 The Wake Phase

Equipped with our approximate posterior $q_\phi(\mathbf{x} | \mathbf{y})$, the wake phase proceeds as follows. For every observed sentence $\mathbf{y} \in \mathcal{M}$, we sample a back-translation $\tilde{\mathbf{x}} \sim q_\phi(\cdot | \mathbf{y})$, creating a bitextual

¹While both of these approaches employ inference networks to reconstruct the latent variables, neither makes use of the wake-sleep procedure.

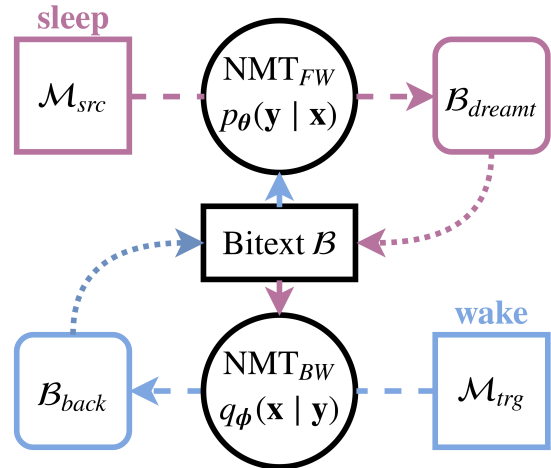


Figure 1: Diagram for semi-supervised back-translation with NMT_{FW} translating $src \rightarrow trg$, NMT_{BW} translating $trg \rightarrow src$, two monotexts \mathcal{M}_{src} , \mathcal{M}_{trg} and a bitext \mathcal{B} . Solid arrows indicate training, dashed translation and dotted a union.

extension $\mathcal{B}_{back} = \{\mathbf{y}, \tilde{\mathbf{x}}\}_{\mathbf{y} \in \mathcal{M}}$ of the monotext \mathcal{M} . Now, we may train full joint model $p(\mathbf{y}, \mathbf{x})$ using both the original bitext and the sampled bitext, i.e., we train on $\mathcal{B} \cup \mathcal{B}_{back}$, in the fully supervised setting. More concretely, in the wake phase we train the model parameters θ with backpropagation. Both steps are alternated, as in EM, until convergence. The pseudocode for the full procedure is given in Alg. 1. The procedure also resembles variational EM (Beal et al., 2003). The difference is that wake step minimizes an inclusive KL, rather than the exclusive one found in variational EM.

Implicitly Defining the Language Model. We are uninterested in the language model $p(\mathbf{x})$ —we only require it in order to generate samples for the sleep phase. Thus, rather than taking the time to estimate a language model $p(\mathbf{x})$ and to sample from it, which would almost certainly be of lower quality than additional monolingual text, we simply randomly sample existing sentences from a large monolingual corpus in the source language. Note that this corresponds to defining $p(\mathbf{x})$ to be a categorical distribution over entire sentences attested in the monotext considered.

3.4 Interpretations and Insight

Interpretation as Back-translation. One iteration ($I = 1$) of the algorithm described in Alg. 1:

we first train a back-translator and then annotate monolingual data to improve p_θ . Note that the dream phase is irrelevant here. One difference that is worth noting is that in Alg. 1, additional forms are *sampled*, whereas many attempt a one-best decode to get back-translations. We may simply view the (approximation) maximization as a Viterbi approximation to the expectation, as justified by Neal and Hinton (1998). The back-translation algorithm of Sennrich et al. (2016b) is best termed one iteration of Viterbi wake-sleep, illustrated in Fig. 1.

Interpretation as an Autoencoder. As Kingma and Welling (2013) saw, we can alternatively view the relation between the original model p_θ and the inference network q_ϕ as an autoencoder. Specifically, we may think this procedure as optimizing the autoencoding objective: $\sum_{\mathbf{x} \in \Sigma_x^*} p_\theta(\mathbf{y} | \mathbf{x}) q_\phi(\mathbf{x} | \mathbf{y})$, where we have temporarily neglected the prior $p(\mathbf{x})$. Indeed, this is an interesting autoencoder as our latent variable is structured, Σ_x^* , rather than \mathbb{R}^n , as in Kingma and Welling (2013). Such structure suggests a relation to the conditional random field autoencoder of Ammar et al. (2014).

4 Related Work

Back-translation as a technique for semi-supervised machine translations dates to the phrase-based era; see Bertoldi and Federico (2009). Interestingly, many techniques explored in the context of phrase-based translation have yet to be neuralization—consider (Li et al., 2011), who offered a minimum risk back-translation strategy.

The contemporary use of back-translation in state-of-the-art (e.g. Hassan et al. (2018)) and unsupervised neural machine translation (Artetxe et al., 2018) dates back to large empirical gains found by Sennrich et al. (2016a) in the context of neural MT and automatic post-editing (Junczys-Dowmunt and Grundkiewicz, 2016). Our work is distinguished from these previous papers in that we are interested in a principled interpretation of back-translation as a strategy, independent of the particular parameterization in place; our analysis will hold parameterization of a probabilistic MT model, e.g., Liang et al. (2006) and Blunsom and Osborne (2008). Moreover, our analysis suggests an iterative extension that we will show leads to better empirical performance in §5.

Finally, our work is related to the dual learning method of He et al. (2016) who, like us, suggested an iterative approach to back-translation. While spiritually related, the motivation for our respective algorithms are quite different; they motivate their procedure game-theoretically. Furthermore, translation models in both directions are updated with online reinforcement learning, after one batch of translations each.

5 Experiments

A core contribution of this paper is theoretical—we sought a principled interpretation back-translation, which is commonly seen as a heuristic. However, our analysis motivated an iterative extension to the algorithm. Naturally, we will want to show that extension leads to better results. Our experimental paradigm is, then, a controlled comparison between the original back-translation method and the wake-sleep extension. Note that our algorithm recovers the original back-translation method in the special case that we only run 1 iteration.

Data. We consider translations from English to German, English to Latvian and vice versa and use the news translation WMT 2017 and TED data from IWSLT 2014 for our experiments. Pre-processed WMT17 data was provided by the official shared task.² Pre-processed data splits for TED were the same as in (Bahdanau et al., 2017).³ Table 2 lists number of sentences for the data used in the experiments.

We investigate two scenarios: 1) standard back-translation with additional monolingual data from the same domain (WMT) and 2) back-translation for semi-supervised domain adaptation (TED). In both cases we start with standard supervised training on the WMT bitext. For WMT experiments, 500k sentences from monolingual news crawls provided in the shared task are randomly selected and used for back-translation iterations. For TED, each side of the training data (153k sentences) serves as monotext for semi-supervised domain adaptation via back-translation.

Machine Translation Model. We choose a classic recurrent encoder-decoder architecture with attention (Cho et al., 2014; Sutskever et al., 2014;

²<http://www.statmt.org/wmt17/translation-task.html>

³Obtained from <https://github.com/rizar/actor-critic-public/tree/master/exp/ted>.

	TED		WMT 2017			
	en-de	de-en	en-de	de-en	en-lv	lv-en
Iteration 0	24.38	27.29	20.73	25.41	11.41	12.53
Iteration 1	25.58 [*] †	29.80 [*] †	21.63 [*] †	26.63 [*] †	12.76 [*] †	12.42
Iteration 2	26.73 [*] †	30.02 [*] †	22.33[*]†	26.80[*]†	12.91[*]†	13.43 [*] †
Iteration 3	27.20[*]†	30.21[*]†	21.72 [*] †	26.26 [*] †	12.77 [*] †	13.53[*]†
Δ (best, Iteration 1)	+1.62	+0.41	+0.70	+0.17	+0.15	+1.10
Δ (best, Iteration 0)	+2.82	+2.92	+1.59	+1.39	+1.5	+1.0

Table 1: Results on the TED and WMT 2017 test data as reported by SACREBLEU (TED: BLEU+case.lc+numrefs.1+smooth.exp+tok.13a.version.1.2.3, WMT: BLEU+case.mixed+numrefs.1+smooth.exp+tok.13a.version.1.2.3). Iteration 0 is the MLE-trained model without back-translation, Iterations 1-3 describe the models resulting from subsequent iterations of Algorithm 1. Significant differences (at $p < 0.05$) to the respective previous iteration are marked with ‘*’, significant differences to Iter 0 with ‘†’.

Domain	Language(s)	Train	Dev	Test
WMT	de↔en	5.9M	2999	3004
WMT	lv↔en	4.5M	2003	2001
TED	de↔en	153k	6969	6750
WMT	de	500k	-	-
WMT	en	500k	-	-
WMT	lv	500k	-	-

Table 2: Number of sentences in mono- and bitexts used in the experiments. The WMT monotexts are selected randomly from the WMT news crawls.

Bahdanau et al., 2015). The NMT has a bidirectional encoder and a single-layer decoder with 1024 Gated Recurrent Unit (Cho et al., 2014) each, and subword embeddings of size 500 for a shared vocabulary of subwords obtained from 30k byte-pair merges (Sennrich et al., 2016c). Maximum input and output sequence length are set to 60. The model parameters are optimized with Adam ($\alpha = 10^{-4}$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-8}$) (Kingma and Ba, 2014) on mini-batches of size 60. To prevent the models from overfitting, dropout with probability 0.2 (Srivastava et al., 2014) and l2-regularization with weight 10^{-8} are applied during training. The gradient is clipped when its norm exceeds 1.0 (Pascanu et al., 2013). All models are trained on a maximum of 10 epochs on their respective training data.

Wake-Sleep. First, we train models for all directions with maximum likelihood estimation on the original WMT bitext. Then, each model translates the monolingual data to serve as back-translator

for the opposite direction. Pairing the “dreamt” sources with the original targets, the models are further trained on the new bitext (see Fig. 1). Early stopping points are determined on the development set for each iteration. For back-translation we use greedy decoding (Viterbi approximation, see §3.4), for testing beam search of width 10.

Results and Discussion. The results may be found in Tab. 1. The models are evaluated with respect to BLEU (Papineni et al., 2002) using the SACREBLEU tool (v.1.2.3) (Post, 2018) on detokenized (WMT: recased) system outputs.⁴ When comparing the results between iterations, we observe the largest relative improvements in iteration 1, the original back-translation, with the exception of lv-en, where it is in iteration 2. Our iterative extension further improves over these results in all experiments. The gains are highest in the TED domain, since the back-translations enable adaptation to the new domain. For WMT the gains are smaller (and come earlier) since the monotext, bitext and test data originate from the same (or at least similar) domain. Despite the wide range of absolute BLEU scores, WMT en-lv being the weakest, TED de-en being the strongest model, back-translation iterations can in all cases achieve an overall improvements over at least 1 BLEU using relatively small amounts of monotexts. Potentially larger gains could be achieved by leveraging more monolingual data, and by employing more sophisticated data selection strategies to filter out potential noise in the monotexts.

⁴<https://github.com/aws-labs/sockeye/tree/master/contrib/sacrebleu>

6 Conclusion

We have provided a principled interpretation and generalization of back-translation as variational inference in a generative model of bitext. Experimentally, we have shown that this leads to improvements of up to 1.6 BLEU over a back-translation baseline. We believe that a cleaner understanding of nature of back-translation will yield future innovations and extensions and hope our attempt is a step in that direction.

References

- Waleed Ammar, Chris Dyer, and Noah A. Smith. 2014. Conditional random field autoencoders for unsupervised structured prediction. In *Advances in Neural Information Processing Systems*, pages 3311–3319.
- Mikel Artetxe, Gorka Labaka, Eneko Agirre, and Kyunghyun Cho. 2018. Unsupervised neural machine translation. In *International Conference on Learning Representations*, Vancouver, Canada.
- Dzmitry Bahdanau, Philemon Brakel, Kelvin Xu, Anirudh Goyal, Ryan Lowe, Joelle Pineau, Aaron Courville, and Yoshua Bengio. 2017. An actor-critic algorithm for sequence prediction. In *ICLR*.
- Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. *International Conference on Learning Representations*, abs/1409.0473.
- Matthew James Beal et al. 2003. *Variational Algorithms for Approximate Bayesian Inference*. University of London London.
- Nicola Bertoldi and Marcello Federico. 2009. Domain adaptation for statistical machine translation with monolingual resources. In *Proceedings of the Fourth Workshop on Statistical Machine Translation*, pages 182–189, Athens, Greece. Association for Computational Linguistics.
- Phil Blunsom and Miles Osborne. 2008. Probabilistic inference for machine translation. In *Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing*, pages 215–223, Honolulu, Hawaii. Association for Computational Linguistics.
- Kyunghyun Cho, Bart van Merriënboer, Dzmitry Bahdanau, and Yoshua Bengio. 2014. On the properties of neural machine translation: Encoder–decoder approaches. In *Proceedings of SSST-8, Eighth Workshop on Syntax, Semantics and Structure in Statistical Translation*, pages 103–111, Doha, Qatar. Association for Computational Linguistics.
- Peter Dayan, Geoffrey E. Hinton, Radford M. Neal, and Richard S. Zemel. 1995. The Helmholtz machine. *Neural Computation*, 7(5):889–904.
- A. P. Dempster, N. M. Laird, and D. B. Rubin. 1977. Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society. Series B (Methodological)*, 39(1):1–38.
- Hany Hassan, Anthony Aue, Chang Chen, Vishal Chowdhary, Jonathan Clark, Christian Federmann, Xuedong Huang, Marcin Junczys-Dowmunt, William Lewis, Mu Li, Shujie Liu, Tie-Yan Liu, Renqian Luo, Arul Menezes, Tao Qin, Frank Seide, Xu Tan, Fei Tian, Lijun Wu, Shuangzhi Wu, Yingce Xia, Dongdong Zhang, Zhirui Zhang, and Ming Zhou. 2018. Achieving human parity on automatic chinese to english news translation. *CoRR*, abs/1803.05567.
- Di He, Yingce Xia, Tao Qin, Liwei Wang, Nenghai Yu, Tieyan Liu, and Wei-Ying Ma. 2016. Dual learning for machine translation. In *Advances in Neural Information Processing Systems*, pages 820–828.
- Geoffrey E. Hinton, Peter Dayan, Brendan J. Frey, and Radford M. Neal. 1995. The wake-sleep algorithm for unsupervised neural networks. *Science*, 268(5214):1158–1161.
- Marcin Junczys-Dowmunt and Roman Grundkiewicz. 2016. Log-linear combinations of monolingual and bilingual neural machine translation models for automatic post-editing. In *Proceedings of the First Conference on Machine Translation*, pages 751–758, Berlin, Germany. Association for Computational Linguistics.
- Diederik Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *CoRR*, abs/1412.6980.
- Diederik P. Kingma and Max Welling. 2013. Auto-encoding variational Bayes. *arXiv preprint arXiv:1312.6114*.
- Zhifei Li, Ziyuan Wang, Jason Eisner, Sanjeev Khudanpur, and Brian Roark. 2011. Minimum imputed-risk: Unsupervised discriminative training for machine translation. In *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing*, pages 920–929, Edinburgh, Scotland, UK. Association for Computational Linguistics.
- Percy Liang, Alexandre Bouchard-Côté, Dan Klein, and Ben Taskar. 2006. An end-to-end discriminative approach to machine translation. In *Proceedings of the 21st International Conference on Computational Linguistics and 44th Annual Meeting of the Association for Computational Linguistics*, pages 761–768, Sydney, Australia. Association for Computational Linguistics.
- Yishu Miao, Lei Yu, and Phil Blunsom. 2016. Neural variational inference for text processing. In *International Conference on Machine Learning*, pages 1727–1736.

- R. M. Neal and G. E. Hinton. 1998. A new view of the EM algorithm that justifies incremental, sparse and other variants. In M. I. Jordan, editor, *Learning in Graphical Models*, pages 355–368. Kluwer Academic Publishers.
- Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics (ACL)*, Philadelphia, PA, USA.
- Razvan Pascanu, Tomas Mikolov, and Yoshua Bengio. 2013. On the difficulty of training recurrent neural networks. In *Proceedings of the 30th International Conference on Machine Learning (ICML)*, Atlanta, GA.
- Matt Post. 2018. A call for clarity in reporting bleu scores. *arXiv preprint arXiv:1804.08771*.
- Lawrence R. Rabiner. 1989. A tutorial on hidden Markov models and selected applications in speech recognition. *Proceedings of the IEEE*, 77(2):257–286.
- David E. Rumelhart, Geoffrey E. Hinton, and Ronald J. Williams. 1986. Learning internal representations by error propagation. Technical report, California Univ San Diego La Jolla Inst for Cognitive Science.
- Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016a. Edinburgh neural machine translation systems for WMT 16. In *Proceedings of the First Conference on Machine Translation*, pages 371–376, Berlin, Germany. Association for Computational Linguistics.
- Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016b. Improving neural machine translation models with monolingual data. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 86–96, Berlin, Germany. Association for Computational Linguistics.
- Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016c. Neural machine translation of rare words with subword units. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics*, Berlin, Germany.
- Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. 2014. Dropout: A simple way to prevent neural networks from overfitting. *Journal of Machine Learning Research*, 15:1929–1958.
- Ilya Sutskever, Oriol Vinyals, and Quoc V. Le. 2014. Sequence to sequence learning with neural networks. In *Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8–13 2014, Montreal, Quebec, Canada*, pages 3104–3112.
- Chunting Zhou and Graham Neubig. 2017. Multi-space variational encoder-decoders for semi-supervised labeled sequence transduction. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 310–320, Vancouver, Canada. Association for Computational Linguistics.