Neural Machine Translation with Pivot Languages

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Abstract

Neural machine translation systems typically rely on the size of parallel corpora. Nevertheless, high-quality parallel corpora are scarce resources for specific language pairs and domains. For a source-to-target language pair with a small parallel corpus, we introduce the pivot language to “bridge” source language and target language under the existence of large source-to-pivot and pivot-to-target parallel corpora. We propose three kinds of connection terms to jointly train source-to-pivot and pivot-to-target translation models in order to enhance the interaction between two sets of model parameters. Experiments on German-French and Spanish-French translation tasks with English as the pivot language show that our joint training approach improves the translation quality significantly than independent training on source-to-pivot, pivot-to-target and source-to-target directions.

1 Introduction

End-to-end neural machine translation (NMT) has shown competitive results in recent years [Kalchbrenner and Blunsom, 2013; Sutskever et al., 2014; Bahdanau et al., 2015]. A number of techniques inspired by conventional statistical machine translation [Koehn et al., 2003] have been applied into NMT, such as attention mechanism improvement through prior knowledge incorporation [Luong et al., 2015a; Cheng et al., 2016a; Cohn et al., 2016; Tu et al., 2016], optimization with evaluation metric [Ranzato et al., 2016; Shen et al., 2016] and data augmentation with monolingual corpora [Gulcehre et al., 2015; Sennrich et al., 2016a; Cheng et al., 2016b; Zhang and Zong, 2016].

Compared with conventional statistical machine translation [Koehn et al., 2003], competitive translation quality has been obtained on high-resource language pairs such as English-French and German-English [Luong et al., 2015b; Jean et al., 2015]. However, as Zoph et al. [2016] indicate, the NMT system shows poorer performance than a standard tree-to-string statistical machine translation system for low-resource language pairs because neural network is a data-driven approach. In statistical machine translation, to overcome the bottleneck of the size of parallel corpora, many approaches have been investigated to introduce a pivot language to connect source and target languages with no or only a small parallel corpus [De Gispert and Marino, 2006; Cohn and Lapata, 2007; Utiyama and Isahara, 2007; Wu and Wang, 2007; Bertoldi et al., 2008; Zahabi et al., 2013; El Kholy et al., 2013].
One of the most representative approaches is to construct a source-to-target phrase table through merging source-to-pivot and pivot-to-target phrase tables.

However, exploiting pivot languages in NMT is non-trivial. Because NMT directly maximizes the probability of target sentences given source sentences without modeling latent structures. It is not applicable to induce phrase table like statistical machine translation. Firat et al. [2016] propose a multi-way, multilingual NMT model that enables zero-resource machine translation. The multi-way, multilingual NMT model is able to translate one of \( N \) languages to one of \( M \) languages where attention mechanisms are shared between different source-to-target NMT models. They propose multi-source translation strategy that combines source-language and pivot-language sentences. They also use a source-to-target parallel corpus to directly fine tune a model for source-to-target language pair from the multi-way, multilingual model.

In this paper, we propose joint training for NMT to “bridge” the source-to-target translation model with source-to-pivot and pivot-to-target translation models. The key idea aims at making the translation path from source language to target language with pivot-language translations as intermediate translations more accurate. We propose three kinds of connection terms that are incorporated to connect these two directional models. The first and second connection terms impose a constraint that word embeddings of the pivot language in source-to-pivot translation models and pivot-to-target translation models are projected onto the same space. In the third novel connection term, we use a small source-to-target parallel corpus to guide the translation path with pivot-language translations as intermediate translations.

Experiments on German-French and Spanish-French translation tasks with English as the pivot language show that our proposed approach achieves significant improvements not only on source-to-target direction but also on the source-to-pivot and pivot-to-target directions.

2 Background

Given a parallel sentence pair, source-language sentence \( x = x_1, ..., x_n \) and target-language sentence \( y = y_1, ..., y_m \), neural machine translation model [Kalchbrenner and Blunsom, 2013; Sutskever et al., 2014; Bahdanau et al., 2015] is a holistic neural network based on encoder-decoder that directly maximizes the conditional probability \( p(y|x) \).

The encoder reads the source sentence and encodes it into a sequence of hidden states \( h = h_1, ..., h_n \) using a bidirectional recurrent neural network (RNN).

The decoder, also based on recurrent neural network, optimizes the conditional probability:

\[
p(y_t|y_{<t}, x; \theta) \propto \exp\{g(y_{t-1}, s_t, c_t; \theta)\}
\]

where \( s_t \) is a hidden state of the decoder and the context vector \( c_t \) is introduced to capture the relevant part of the source-language sentence. The context vector \( c_t \) is weighted sum of all source annotations in \( h \).

\[
c_t = \sum_{i=1}^{n} \alpha_{ti} h_i
\]

where the weight \( \alpha_{ti} \) for each annotation \( h_i \) measures the contribution from the source word \( x_i \).

Given a parallel corpus \( D = \{ (x^{(n)}, y^{(n)}) \}^{N}_{n=1} \), the model is trained to maximize the probability of each target sentence given its corresponding source sentence with respect to model parameters \( \theta \):

\[
\theta^* = \arg\max_{\theta} \sum_{n=1}^{N} \log p(y^{(n)}|x^{(n)}; \theta)
\]
Building a machine translation system is in desperate need of amounts of parallel corpora, especially for the neural machine translation system. The unavailability of high-quality parallel corpora for specific language pairs and domains hinders the development of machine translation. Therefore, if there is only a small parallel corpus or even no parallel corpus for a language pair \((S, T)\), how can we build a fine machine translation system?

Fortunately, there usually exist a large number of parallel corpora between \(S\) or \(T\) and \(P\) despite no direct parallel corpora between \(S\) and \(T\). \(P\) can serve as the pivot language to “bridge” the translation between \(S\) and \(T\).

In statical machine translation, the triangulation approach [Wu and Wang, 2007; Cohn and Lapata, 2007] is one of the most representative approaches. Given a source-to-pivot phrase table \(M_{sp}\) and a pivot-to-target phrase table \(M_{pt}\), the source-to-target phrase table \(M_{st}\) is obtained by merging \(M_{sp}\) and \(M_{pt}\):

\[
M_{st} = M_{sp} \odot M_{pt}
\]

where \(\odot\) is merging operation, such as multiplication of translation probability of source-to-pivot and pivot-to-target phrases with identical pivot-language phrases.

The constructed source-to-target phrase table \(M_{st}\) facilitates building a source-to-target statistical machine translation system. However, free of latent structures such as phrase table, the NMT model directly maximizes the conditional probability \(p(y|x)\) as Eq. (3) indicates. Therefore, it is non-trivial to utilize pivot languages in NMT.

3 Joint Training for NMT with Pivot Languages

Formally, given two parallel corpora, source-to-pivot parallel corpus \(D_{sp} = \{(s^{(n)}, p^{(n)})\}_{n=1}^{N_{sp}}\) and pivot-to-target corpus \(D_{pt} = \{(p^{(n)}, t^{(n)})\}_{n=1}^{N_{pt}}\), let \(P(p|s; \theta_{sp})\) and \(P(t|p; \theta_{pt})\) be source-to-pivot and pivot-to-target NMT models respectively. As shown in Figure 1 we advocate a pivot translation strategy that the target-language sentence is generated for a source-language sentence after it is first translated to the pivot-language sentences. Our key idea is to jointly train two translation models \(P(p|s; \theta_{sp})\) and \(P(t|p; \theta_{pt})\) that conduces to establishing the
Our training objective contains three parts: source-to-pivot likelihood, pivot-to-target likelihood, and connection term. The hyperparameter $\lambda$ is used to balance the importance between likelihood and the connection term. The connection term involves two sets of parameters, $\theta_{sp}$ and $\theta_{pt}$, respectively for the source-to-pivot and pivot-to-target translation models. We leverage the connection term to allow two independently trained parameters from two different translation models to interact mutually. It is feasible that connection term can be replaced by any function with the parameters of these two directional NMT models included.

We will propose three kinds of connection terms in the following sections which benefit to connect the source-to-pivot and pivot-to-target NMT models.

### 3.1 Hard Sharing of Word Embeddings

The first kind of connection term which we introduce here is to share parameters between the source-to-pivot and pivot-to-target NMT models. As the target side of source-to-pivot translation model and the source side of pivot-to-target translation model are from the same language, we conjecture that parameter sharing between the word embeddings of two translation models makes the parameters connection tight. This possibly results in closer distance in parameter space.

The vocabulary of the target side of the source-to-pivot model is denoted as $\mathcal{V}_1$, and the vocabulary of the source side of the pivot-to-target model is denoted as $\mathcal{V}_2$. A simple method to share word embeddings is to force them to be completely equal for each word $w \in \mathcal{V}_1 \cap \mathcal{V}_2$:

$$\mathcal{R}(\theta_{sp}, \theta_{pt}) = \prod_{w \in \mathcal{V}_1 \cap \mathcal{V}_2} \delta(\theta_{w, sp}, \theta_{w, pt})$$

where $\theta_{w, sp}$ and $\theta_{w, pt}$ are the embedding of word $w$ in the set of parameters $\theta_{sp}$ and the set of parameters $\theta_{pt}$, respectively.

### 3.2 Soft Sharing of Word Embeddings

In order to improve the flexibility and robustness, instead of hard sharing, we use soft sharing to penalize the distance between embeddings in each set of model parameters for every word $w \in \mathcal{V}_1 \cap \mathcal{V}_2$:

$$\mathcal{R}(\theta_{sp}, \theta_{pt}) = -\sum_{w \in \mathcal{V}_1 \cap \mathcal{V}_2} \| \theta_{w, sp} - \theta_{w, pt} \|_2$$
We expect the distance between two sets of word embeddings is as close as possible in Euclidean distance. The closeness of word embeddings brings the closeness for other parameters.

3.3 Likelihood with Source-to-target Parallel Corpora

In general, small corpora (Bridging Corpora) are ubiquitous for many language pairs and domains. Given a test source-language sentence, it will be translated to the target-language sentence in the end via the pivot-language translations. The supply for parallel sentence pairs between source language and target language is capable of reinforcing this translation path. Inspired by the autoencoder proposed by Cheng et al. [2016b] that exploits monolingual corpora in NMT, we propose an approach which treats the pivot-language sentences as latent variables. Given a source-to-target parallel corpus \( D_{st} = \{(s^{(n)}, t^{(n)})\}_{n=1}^{N_{st}} \), our training objective is as follows:

\[
    R(\theta_{sp}, \theta_{pt}) = \sum_{n=1}^{N_{st}} P(t^{(n)} | s^{(n)}; \theta_{sp}, \theta_{pt}) = \sum_{n=1}^{N_{st}} \sum_{p} P(t^{(n)}, p | s^{(n)}; \theta_{sp}, \theta_{pt}) = \sum_{n=1}^{N_{st}} \sum_{p} P(p | s^{(n)}; \theta_{ps}) P(t^{(n)} | p; \theta_{pt})
\]

where \( p \) is a latent pivot-language sentence. The intuition of Eq. (8) is to maximize the translation probability of target-language sentences given source-language sentences via the pivot-language candidate translations. The source-to-pivot translation model first transforms the source-language sentences into latent pivot-language sentences, from which the pivot-to-target translation model aims to construct the target-language sentences. This training criterion conforms to the pivot translation strategy adopted by the test procedure. We refer to this approach as LIKENESS.

3.4 Training

The partial derivative of \( J(\theta_{sp}, \theta_{pt}) \) with respect to the parameters \( \theta_{sp} \) of the source-to-pivot model can be calculated as:

\[
    \frac{\partial J(\theta_{sp}, \theta_{pt})}{\partial \theta_{sp}} = \sum_{n=1}^{N_{st}} \frac{\partial \log P(p^{(n)} | s^{(n)}; \theta_{sp})}{\partial \theta_{sp}} + \lambda \frac{R(\theta_{sp}, \theta_{pt})}{\theta_{sp}}
\]

The partial derivative with respect to the parameters \( \theta_{pt} \) is similar to Eq. (9).

For hard and soft sharing of word embeddings, the gradients of the connection term \( R(\theta_{sp}, \theta_{pt}) \) with respect to the parameters are easy to calculate.

However, in the third connection term, if we continue to expand the last term of Eq. (9) a challenge emerges:

\[
    \frac{\sum_{p \in P(s)} P(p | s; \theta_{sp}) P(t | p; \theta_{pt}) \frac{\partial \log P(p | s; \theta_{sp})}{\partial \theta_{sp}}}{\sum_{p \in P(s)} P(p | s; \theta_{sp}) P(t | p; \theta_{pt})}
\]
Due to the exponential search space for the pivot-language translations, it is intractable to enumerate all of pivot-language candidate translations \( p \in \mathcal{P}(s) \) in Eq. (10).

The subset approximation is commonly used as an alternative resolution. We use a subset \( \tilde{\mathcal{P}}(s) \subset \mathcal{P}(s) \) to approximate the full space. We try two methods to generate \( \tilde{\mathcal{P}}(s) \), sampling \( k \) translations from the full space and generating top-\( k \) list of candidate translations. We observe that generating top-\( k \) list performs better. In experiments, we find that \( k = 10 \) is an advisable choice considering the efficiency and translation quality.

Now we have three parallel corpora, source-to-pivot parallel corpus \( D_{sp} \), pivot-to-target parallel corpus \( D_{pt} \), and source-to-target parallel corpus \( D_{st} \) (available in LIKELIHOOD). We still use mini-batch stochastic gradient descent algorithm to update the parameters. However, in each iteration, we randomly pick three mini-batches of parallel sentence pairs from source-to-pivot, pivot-to-target and source-to-target parallel corpora (source-to-target parallel corpus is available in LIKELIHOOD). In LIKELIHOOD, we need to decode the source-language sentences of source-to-target mini-batch to get top-\( k \) pivot-language translations. The gradients for these batches are respectively calculated and then collected for updating parameters.

The decision rules for the source-to-pivot and pivot-to-target NMT models are given by

\[
\begin{align*}
\theta_{sp}^* &= \arg\max \left\{ \sum_{n=1}^{N_{sp}} \log P(p^{(n)}|s^{(n)}; \theta_{sp}) + \lambda \mathcal{R}(\theta_{sp}, \theta_{pt}) \right\} \\
\theta_{pt}^* &= \arg\max \left\{ \sum_{n=1}^{N_{pt}} \log P(t^{(n)}|p^{(n)}; \theta_{pt}) + \lambda \mathcal{R}(\theta_{sp}, \theta_{pt}) \right\}
\end{align*}
\]

(11)

4 Experiments

4.1 Setup

We evaluated our approach on the Spanish-French (ES-FR) and German-French (DE-FR) language pairs with English as the pivot language and French as the target language.

For each language pair, we remove the empty lines and retain sentence pairs with no more than 50 words. To avoid the tri-lingual corpora constituted by the source-to-pivot and pivot-to-target corpora, we split the overlapping part of pivot-language sentences of source-to-pivot and pivot-to-target corpora into two equal parts and merge them separately with the non-overlapping parts for each language pair.

As shown in Table I, these three language pairs are from Europarl corpus. For Spanish-English, the training corpus contains 850K sentence pairs with 23.23M Spanish words and 21.44M English words. The German-English corpus consists of 840K sentence pairs with 20.88M German words and 21.91M English words. They share the same English-French corpus which has 900K sentence pairs with 22.56M English words and 25.00M French words. The sentences from these corpora are tokenized by the tokenize.perl script. The development and test datasets are from shared task 2006. The evaluation metric is case-insensitive BLEU [Papineni et al., 2002] as calculated by the multi-bleu.perl script.
Table 1: Characteristics of Spanish-English, German-English and English-French datasets on the Europarl corpus and WMT corpus.

| Language Pair         | Source | Target |
|-----------------------|--------|--------|
| ES-EN (Europarl)      | 850K   | 22.32M | 21.44M |
|                       | 118.81K| 78.37K |
| DE-EN (Europarl)      | 840K   | 20.88M | 21.91M |
|                       | 242.87K| 80.44K |
| EN-FR (Europarl)      | 900K   | 22.56M | 25.00M |
|                       | 80.08K | 98.50K |
| ES-EN (WMT)           | 6.78M  | 183.01M| 166.28M|
|                       | 0.98M  | 0.91M  |
| EN-FR (WMT)           | 9.29M  | 227.06M| 258.95M|
|                       | 0.23M  | 1.19M  |

Table 2: Comparison on Spanish-French and German-French translation tasks from Europarl corpus. English is treated as the pivot language. We propose three kinds of connection terms that jointly train source-to-pivot and pivot-to-target translation models. The comparison of translation quality for source-to-pivot, pivot-to-target and source-to-target directions are shown. Source-to-target translation results are obtained by translating pivot language sentences. The BLEU scores are case-insensitive. "*": significantly better than independent training ($p < 0.05$); "**": significantly better than independent training ($p < 0.01$). We use the statistical significance test with paired bootstrap resampling [Koehn, 2004].

Table 3 shows the Spanish-English and English-French corpora from WMT which include Common Crawl, News Commentary, Europarl v7 and UN. The number of sentence pairs is much larger than corpora in Europarl corpus. The Spanish-English corpus consists of 6.78M sentence pairs with 183.01M Spanish words and 166.28M English words. 9.29M sentence pairs with 227.06M English words and 258.95M French words compose English-French corpus. All the sentences are tokenized by the tokenize.perl script. The newstest2011 and new-
Table 3: Results on Spanish-French translation task from WMT corpus. English is treated as the pivot language. “***”: significantly better than independent training ($p < 0.01$).

| Training | Spanish-French (WMT) |
|----------|----------------------|
|          | es→en | en→fr | es→fr |
| INDEP.   |        |       |       |
| Dev.     | 27.62  | 27.90 | 19.55 |
| Test     | 29.03  | 25.82 | 19.81 |
| LIKELIHOOD |        |       |       |
| Dev.     | 28.82**| 28.52**| 21.45**|
| Test     | 30.43**| 26.36**| 21.78**|

Table 4: Translation performance on Bridging Corpora

| Corpus                  | source-target | source-pivot-target |
|-------------------------|---------------|---------------------|
| es → fr (Europarl)      | 26.37         | 29.79               |
| de → fr (Europarl)      | 14.02         | 23.70               |
| es → fr (WMT)           | 11.75         | 19.81               |

Table 5: Effect of the data size of source-to-target parallel corpora (Bridge Corpora) used in LIKELIHOOD.

| # Sent. | es→en | en→fr | es→fr |
|---------|-------|-------|-------|
| 0K      | 31.53 | 30.46 | 29.52 |
| 1K      | 32.64 | 30.29 | 30.23 |
| 10K     | 32.92 | 30.93 | 31.51 |
| 50K     | 33.29 | 31.57 | 32.40 |
| 100K    | 33.35 | 31.63 | 32.45 |

stest2012 serve as development and test set. We use case-sensitive BLEU to evaluate the translation results.

RNNsearch [Bahdanau et al., 2015] is used as our attention-based neural machine translation system. For the Europarl corpus in Table 1, we set the vocabulary size of all the languages to 30K which covers over 99% of the text for English, Spanish and French and over 97% of German text. We follow Jean et al. [2015] to address rare words. For Spanish-English and English-French corpora from the WMT corpus, due to large vocabulary size, we adopt byte pair encoding [Sennrich et al., 2016b] to split rare words into sub-words. The size of sub-words is set to 43K, 33K, 43K respectively for Spanish, English and French. They can cover 100% of the text.

Three kinds of connection terms that we propose are referred to as HARD, SOFT and LIKELIHOOD in order. When LIKELIHOOD is applied, we pick out 100K source-to-target parallel sentence pairs which do not overlap with training corpora.

In SOFT, the hyper-parameter $\lambda$ for the connection term is set to 1.0. In LIKELIHOOD, we set the sample size $k$ to 10, the hyper-parameter $\lambda$ to 1.0 and the threshold of gradient clipping to 0.1. The parameters for the source-to-pivot and pivot-to-target translation models in LIKELIHOOD are initialized by pre-trained model parameters.

4.2 Results on the Europarl Corpus

Table 2 shows the comparison results between our approaches and independent training on the Europarl Corpus. For source-to-target translation task, we present source-to-pivot, pivot-to-target and source-to-target translation results compared with independent training. In Spanish-to-French translation task, SOFT achieves significant im-
Table 6: Examples and corresponding sentence BLEU scores of pivot-language and target-language translations using the pivot translation strategy. We observe that our approaches generate better translations for both pivot-language and target-language sentences. We italicize correct translation segments which are no short than 2-grams.

| GroundTruth | source | uno no debe empezar a dudar en público del valor, tampoco del valor inmediato en el aspecto material, de esta ampliación. |
|-------------|--------|----------------------------------------------------------------------------------------------------------------|
| pivot       | it makes little sense to start to doubt in public the value, including the direct value at a material level, of this enlargement. |
| target      | il ne faut pas commencer à douter en public de la valeur, ni de la valeur immédiate, de la portée matérielle de cet élargissement. |
| INDEP.      | pivot | one should not begin to doubt in terms of the value of courage, or of the immediate effect on material, of enlargement. [BLEU: 13.33] |
|             | target | il ne faudrait pas se tromper en termes de valeur de courage ou d’effet immédiat sur le matériel, de cet élargissement. [BLEU: 8.69] |
| HARD        | pivot | one must not start to doubt in the public, not the immediate value in the material, of this enlargement. [BLEU: 19.02] |
|             | target | il ne faut pas que l’on commence à douter, ni au public, ni à la valeur immédiate, à l’élargissement. [BLEU: 25.36] |
| SOFT        | pivot | one cannot start thinking of the value of the value, and the immediate courage, of this enlargement. [BLEU: 21.57] |
|             | target | on ne peut pas commencer à penser à la valeur de la valeur, au courage immédiat, de cet élargissement. [BLEU: 26.60] |
| LIKELIHOOD  | pivot | one must not start to question the value of the value, either of the immediate value in the material aspect, of this enlargement. [BLEU: 24.60] |
|             | target | il ne faut pas commencer à remettre en question la valeur de la valeur, ni de la valeur immédiate de l’aspect matériel, de cet élargissement. [BLEU: 56.40] |

provements in Spanish-to-French and Spanish-to-English directions although HARD still performs comparably with independent training. In German-to-French translation task, SOFT and HARD also achieve comparable performances with independent training.

In contrast, we find that LIKELIHOOD dramatically improves translation performance on both Spanish-to-French and German-to-French corpora (up to +2.80 BLEU scores in Spanish-to-French and up to 2.23 BLEU scores in German-to-French). The significant improvements for source-to-pivot and pivot-to-target directions are also observed. This suggests that introducing source-to-target parallel corpus to maximize $P(t|s; \theta_{sp}, \theta_{pt})$ with $p$ as latent variables makes the source-to-pivot and pivot-to-target translation models improved collaboratively.

Table 6 shows pivot-language and target-language translation examples of independent training and our three approaches. Apparently, our approaches improve translation quality of both pivot-language sentences and target-language sentences.

### 4.3 Results on the WMT Corpus

LIKELIHOOD obtains the best performance in our three proposed approaches according to experiments on the Europarl corpus. To further verify its practicability, Table 6 shows results on the WMT corpus which is a much larger corpus. We find that LIKELIHOOD still outperforms independent training significantly in Spanish-to-English, English-to-French and Spanish-to-French directions (up to +1.97 BLEU scores in Spanish-to-French).
4.4 Effect of Bridging Corpora

As Bridging Corpora are used in LIKELIHOOD for “bridging” the source-to-pivot and pivot-to-target translation models, why do we not directly build NMT systems with these corpora?

We train source-to-target models using Bridging Corpora and show translation results in Table 4. We observe that performance is much worse than that in Table 2 and Table 3 using the pivot translation strategy. It indicates that NMT yields poor performance on low-resource languages and the pivot translation strategy remedies the drawback to alleviate data scarcity effectively.

We also investigate the effect of the data size of Bridging Corpora on LIKELIHOOD. Table 5 shows that using a small parallel corpus (1K sentence pairs) has made a measurable improvement. When more than 50K sentence pairs are added, the improvement becomes modest. This finding suggests that a small corpus suffices to enable the LIKELIHOOD approach to reach the reasonable performance.

5 Related Work

Our work is inspired by two lines of research: (1) machine translation with pivot languages and (2) incorporating additional data resource for NMT.

5.1 Machine Translation with Pivot Languages

Machine translation suffers from the scarcity of parallel corpora. For low-resource language pairs, a pivot language is introduced to “bridge” source and target language in statistical machine translation [De Gispert and Marino, 2006; Cohn and Lapata, 2007; Utiyama and Isahara, 2007; Wu and Wang, 2007; Bertoldi et al., 2008; Zahabi et al., 2013; El Kholy et al., 2013]. One of the most representative approaches is triangulation approach that a source-to-target phrase table is generated by combining source-to-pivot and pivot-to-target phrase tables.

In NMT, Firat et al. [2016] propose a multi-way, multilingual NMT model that enables zero-resource machine translation. Zoph et al. [2016] adopt transfer learning to fine tune parameters of the low-resource language pairs using trained parameters on the high-resource language pairs. They are mainly committed to directly building a source-to-target NMT model. However, based on the pivot translation strategy, our approach aims to improve source-to-pivot and pivot-to-target NMT models which are in charge of the translation path. We use connection terms to “bridge” these two models and make them benefit each other.

5.2 Incorporating Additional Data Resource for NMT

Due to the limit in quantity, quality and coverage for parallel corpora, additional data resource has raised attention recently. Gulcehre et al. [2015] propose to incorporate target-side monolingual corpora as language model for NMT. Sennrich et al. [2016a] pair the target monolingual corpora with its corresponding translations then merge them with parallel corpora for retraining source-to-target model. Zhang and Zong [2016] propose two approaches to incorporate source-side monolingual corpora. One is to employ self-training algorithm to generate parallel corpora from monolingual corpora. The other adopts multi-task learning framework to enhance the encoder network of NMT. Cheng et al. [2016b] introduce an autoencoder framework to reconstruct monolingual sentences using source-to-target and target-to-source NMT models. The proposed model can exploit both source and target monolingual corpora. In contrast to Cheng et al. [2016b], the objective of our LIKELIHOOD approach is to maximize the probability of target-language sentences through pivot-language sentences given source-language sentences. We use a small source-to-target parallel corpus to jointly train source-to-pivot and pivot-to-target NMT models.
6 Conclusion

We have presented joint training for neural machine translation with pivot languages. The connection terms in our joint training objective make the source-to-pivot and pivot-to-target translation models interact better. Experiments on different language pairs confirm that our approach achieves significant improvements. It is appealing to combine source-language and pivot-language sentences for decoding target-language sentences [Firat et al., 2016] or train a multi-source model directly [Zoph and Knight, 2016]. We also plan to study better connection terms for our joint training.

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