Towards Reinforcement Learning for Pivot-based Neural Machine Translation
with Non-autoregressive Transformer

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Abstract

Pivot-based neural machine translation (NMT) is commonly used in low-resource setups, especially for translation between non-English language pairs. It benefits from using high-resource source→pivot and pivot→target language pairs and an individual system is trained for both sub-tasks. However, these models have no connection during training, and the source→pivot model is not optimized to produce the best translation for the source→target task. In this work, we propose to train a pivot-based NMT system with the reinforcement learning (RL) approach, which has been investigated for various text generation tasks, including machine translation (MT). We utilize a non-autoregressive transformer and present an end-to-end pivot-based integrated model, enabling training on source→target data.

1. Introduction

Machine translation (MT) research is heavily focused on the investigation of language pairs that include English either as a source or as a target language. Besides linguistic implications, translation between non-English language pairs frequently suffers from scarce direct parallel training data.

Pivot-based MT (Woszczyna et al., 1993; Utiyama & Isahara, 2007) mitigates the problem of data scarcity by translating via a pivot language (usually English), i.e., along the language pairs source→pivot and pivot→target (piv→trg). The pivot language is chosen in such a way that the src→piv and piv→trg models can be trained with more data than the direct source→target (src→trg) model. Pivot-based models require a sequential, two-step decoding, meaning that an explicit intermediate pivot representation is obtained from the src→piv model and then used as an input to the piv→trg model. Note that the src→piv model is optimized to produce the best possible src→piv translation, not to generate a hypothesis which maximizes the performance of the full src→trg model. Furthermore the pivot-based approach does not use the direct src→trg training data, meaning that the system is not adapted to the desired task.

Cascading of the src→piv and piv→trg models at training time is problematic since the gradient cannot be propagated through the argmax operation that generates the pivot hypothesis. Moreover, training two cascaded Transformer (Vaswani et al., 2017) models on src→trg data is complicated by the fact that the decoder of the src→piv model (Decoder s2p) requires the explicit pivot sequences as an input. Since src-piv-trg three-way data is rare in practice this requires e.g. a search over the src→piv model at each training step, which is computationally prohibitive.

In our work, we propose to (i) replace the autoregressive (AR) decoder of the src→piv system with a non-autoregressive (NA) Transformer decoder (Gu et al., 2018) and (ii) apply a reinforcement learning (RL) approach to train the src→piv model with direct feedback from the piv→trg system on the src→trg training data. Although there is a performance gap between NA and AR approaches (Gu et al., 2018; Ghazvininejad et al., 2019), the NA approach can generate a pivot hypothesis parallelizable without a computationally costly search procedure. The NA approach allows us to generate pivot hypotheses on-the-fly at training time. To the best of our knowledge, we are the first ones who applied the RL approach for training pivot-based NMT jointly.

2. Related Work

RL applications for neural machine translation (NMT) recently gathered interest in the research community (Choshen et al., 2020; Wu et al., 2018; Shen et al., 2016). In these cases RL is used to directly optimize a metric such as BLEU (Papineni et al., 2002) or TER (Snover et al., 2006) on sentence-level in contrast to conventional maximum like-
lihood training. Policy optimization methods such as REINFORCE (Williams, 1992) were successfully applied to various sequence generation tasks, including MT (Ranzato et al., 2016).

Previous works on pivot-based MT have already studied the possibility to jointly train the src→piv and piv→trg models (Cheng et al., 2017) or to transfer knowledge and parameters (Kim et al., 2019). Since translation between non-English languages in practice entails a problem of data scarcity, various methods have been proposed to leverage different data types. One of the most popular approaches is the use of multilingual machine translation (Zhang et al., 2020; Aharoni et al., 2019; Johnson et al., 2017) that is to transfer knowledge from one or more high-resource language pairs to the desired low-resource task. Another popular technique considers monolingual target-side data (Senrich et al., 2016a; Edunov et al., 2018) to generate synthetic end-to-end data. However, since this work focuses on the application of the RL, we do not aim for comprehensive comparisons with multilingual NMT systems and various data augmentation strategies. We refer to (Kim et al., 2019) for in-depth comparison studies.

3. Pivot-based NMT

Given the two independently trained sequence-to-sequence models namely src→piv ($p_{2p}$) and piv→trg ($p_{2t}$), the goal of pivot-based NMT is to find the target hypothesis $e^t_1$ given the source sentence $f^I_1$ which requires the intermediate pivot representation $z^K_1$. Conventional pivot-based NMT does not involve training on the src→trg data, and the models are connected in search via so-called two-step decoding:

$$
\hat{z}^K_1 = \text{argmax}_{K, z^K_1} \prod_{k=1}^{K} p_{2p}(z_k|z^{k-1}_1, f^I_1) \quad (1)
$$

$$
e^{t}_1 = \text{argmax}_{I, e^t_1} \prod_{i=1}^{f} p_{2t}(e_i|e^{i-1}_1, \hat{z}^K_1). \quad (2)
$$

Although it is possible to decode multiple pivot hypotheses on the first step and apply re-ranking to obtain final target hypothesis (Och et al., 1999; Cheng et al., 2017), usually only one pivot hypothesis is used as an input to the piv→trg model.

4. RL for Pivot-based NMT

Starting with the setup described in Section 3, we aim to perform training on the src→trg data to optimize the performance of the cascaded model. However, in practice, src→trg corpora do not provide a pivot reference which is needed to calculate the Decoder$_{trg}$ as shown in Figure 1a. In such cases, synthetic pivot data can be obtained ‘offline’ via (back-)translation (Sennrich et al., 2016a), or ‘online’ by performing a search for every update step of the training process. For an offline generation, the pivot reference does not change, even if the parameters of the src→piv model are updated and online updates are computationally too expensive. We replace the autoregressive decoder with a non-autoregressive one as shown in Figure 1b which generates pivot hypothesis in parallel without the need for a search. That allows to speed up the sampling from the src→piv model, as described in Appendix C. Specifically, we rely on the Conditional Masked Language Model (CMLM) (Ghazvininejad et al., 2019) as non-autoregressive model. Similar to (Devlin et al., 2019), during training CMLM tries to predict the probabilities of masked tokens $Y_{\text{mask}}$ which depend on the source sequence and observed tokens $Y_{\text{obs}}$ of the target sequence $Y$ where $Y_{\text{obs}} = Y \setminus Y_{\text{mask}}$. The number of masked tokens is randomly chosen between one and sequence length. During decoding CMLM allows to perform multiple decoder iterations, which leads to the performance improvements (Ghazvininejad et al., 2019). Since the CMLM model have seen fully-masked sequences during training, it allows us to use the sequence of unknown symbols as an input to the Decoder$_{trg}$ and naturally solve the problem of missing pivot references in src→trg data.

In pivot-based MT neither the src→piv nor the piv→trg model are optimized for the intended task. In this work we focus on improving the src→piv model which is optimized for src→trg performance on an extrinsic metric (typically BLEU). Instead we propose to use reinforcement learning to train the src→piv model to produce pivot hypotheses that the piv→trg can translate well. For each training pair $(f^I_1, e^{t}_1)$ we aim to maximize the expected reward:

$$
\mathcal{J}(\theta) = \mathbb{E}_{p_{2p}(z^K_1, f^I_1)}[R(p_{2t}(\bullet|z^K_1), e^{t}_1)] \quad (3)
$$

where $R(p_{2t}(\bullet|z^K_1), e^{t}_1)$ denotes a reward function, which is based on the distribution of the piv→trg model $p_{2t}$ for the suggested pivot sample $z^K_1$.

We consider two different types of reward. First, to use the negative cross-entropy (Neg. CE) as the target reference, interpreted as a one-hot distribution, and the distribution of the piv→trg model $p_{2t}$:

$$
- \sum_{i=1}^{f} \log(p_{2t}(e_i|e^{i-1}_1, z^K_1)). \quad (4)
$$

Second, we perform a search over the possible target hypotheses and utilize a sentence-level metric to compare the result $e_{p_{2p}}(z^K_1)$ against the reference $e^{t}_1$:

$$
\text{SCORE}(e_{p_{2p}}(z^K_1), e^{t}_1) \quad (5)
$$

where \text{SCORE} can be any sentence-level metric. Although in MT the common evaluation metric is corpus-level BLEU (Papineni et al., 2002), in this work we consider sentence-level BLEU and sentence-level chrF (Popović,
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Figure 1. Autoregressive (AR) and non-autoregressive transformer (NAT) architectures for pivot-based translation

Algorithm 1: Pivot-based NMT with RL training

5. Experiments

5.1. Data

We validate the approach described in Section 4 on two translation datasets, which do not contain English as a source or target language: French→German (Fr→De) with 2.3M sentences and German→Czech (De→Cs) with 230K sentences of direct data from the WMT 2019 translation task. We apply a byte-pair encoding (BPE) (Sennrich et al., 2016b) model with 32000 merge operations for each dataset. Detailed data description and preprocessing steps can be found in Appendix A.

5.2. Model Training

We use the fairseq framework for all our experiments and compare the results to three different baselines:

- **direct baseline**: a ‘base’ Transformer (Vaswani et al., 2017) trained only on the on direct src→trg data
- **pivot baseline**: Cascading a ps2p and pp2t are ‘base’ Transformer model, each trained on src→piv and piv→trg data respectively.
- **NAT pivot baseline**: ps2p is a CMLM model (non-autoregressive) trained on the src→piv data and pp2t is a Transformer model (autoregressive) trained on piv→trg data. Both models are individually trained and are only cascaded in src→trg decoding.

For all models based on the CMLM we set the effective batch size to be 65K tokens. The learning rate varies between $10^{-6}$ and $10^{-5}$. We utilize the Adam optimizer (Kingma & Ba, 2015) with $\beta = \{(0.9, 0.98)\}$. Dropout is set to 0.1 for both language pairs. To perform the validation steps with the CMLM, we apply five decoding iterations for the CMLM decoder. If sentence-level BLEU scores are needed we use the SacreBLEU (Post, 2018) library.

5.3. Results

We report the results for three different kinds of rewards (Neg. CE, BLEU and chrF) in Table 1 and compare them against the baselines. We scale Neg. CE by the sentence length and additionally reduce it by factor 10 to avoid large
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| Method     | RL reward | French→German BLEU[^{\%}] | German→Czech BLEU[^{\%}] |
|------------|-----------|----------------------------|---------------------------|
|            |           | dev | test | dev | test | dev | test |
| AR         | direct baseline | -   | 20.0| 20.4| 13.5| 14.0|
|            | pivot baseline  | -   | 19.5| 20.7| 18.8| 18.1|
| NAT        | pivot baseline  | -   | 17.1| 18.1| 17.3| 16.6|
|            | +RL Neg. CE | BLEU | 18.7| 19.7| 18.2| 17.5|
|            |            | chrF | 19.0| 19.9| 18.3| 17.6|
|            |            |      | 18.6| 19.7| 18.1| 17.3|

Table 1. Results on the pivot-based NMT with different RL rewards. All pivot/cascaded models are pre-trained on the respective data. We use newstest\{2011,2012\} as dev and test respectively.

loss numbers. BLEU and chrF are calculated using SacreBLEU and remain unchanged during training. We report case-sensitive BLEU scores, ranging from 0 to 100 while chrF ranges from 0 to 1. Our RL approach consistently outperforms the non-autoregressive pivot baseline by up to 1.6% BLEU on Fr→De and 0.9% BLEU on De→Cs. However, it is still under the performance of the autoregressive pivot baseline for both languages.

In reported experiments, we do not rely on Knowledge Distillation (KD) (Kim & Rush, 2016), even though it is typically used for training NA models. The detailed discussion on KD is presented in Appendix B

Directly optimizing the BLEU score yields the best performance among all reinforcement learning setups by a small margin and overall the performance of all rewards gives comparable results.

5.4. Pivot BLEU vs. target BLEU

For analysis we construct a three-way test set from the data of the Tatoeba challenge (Tiedemann, 2020), that provides both a pivot and target references for each source sentence, obtaining 10K sentence triples for En→De→Fr, that are not seen in training.

On this test set we study the relationship between the pivot and target BLEU score. Given the AR pivot baseline and NAT pivot baseline, we perform two-pass decoding obtaining a pivot and a target hypothesis as well as a sentence-level BLEU score for each. Figure 2 shows that src→piv sentence-level BLEU score does not correlate well with the src→trg score. This indicates that simply improving src→piv translation quality in terms of BLEU will not necessarily result in the best src→trg performance. Instead, optimizing src→piv directly for the src→trg task may lead to the better model performance.

![Figure 2. Sentence-level BLEU score of the intermediate pivot hypothesis vs the sentence-level BLEU of the target hypothesis. Both hypotheses are obtained from the same two step decoding for a pivot Fr→En→De system.](image)

6. Conclusion

In this work, we propose a novel approach to pivot-based NMT. Applying reinforcement learning allows us to fine-tune a src→piv model and obtain better performance of the cascaded src→trg system. While this works in principle, our approach relies on a weaker, non-autoregressive src→piv system and performance degradation of the NAT model could not be overcome and thus the conventional autoregressive pivot baseline still dominates in translation performance. However, we believe that the proposed method can be used in the pivot-based NMT and other cascaded models, like speech translation, where the hard decisions are required. For future work, we suggest focusing on sampling and length modelling strategies for the non-autoregressive parts of the pipeline as well as investigating how autoregressives src→piv models can be incorporated into the reinforcement pipeline.
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A. Training Data

Training data for French→German includes Europarl corpus version 7 (Koehn, 2005), CommonCrawl corpus and the newstest2008-2010. The original German→Czech task was constrained to unsupervised translation, but we utilized the available parallel data to relax these constraints. The corpus consists of NewsCommentary version 14 (Tiedemann, 2012) and we extended it by including newssyscomb2009 and the concatenation of previous years test sets newstest2008-2010 from the news translation task. For both tasks we use newstest2011 as the development set and newstest2012 as the test sets. The data statistics, including pre-training data, are collected in Table 2.

![Table 2](https://www.aclweb.org/anthology/D18-1397)

| Method | BLEU [%] |
|--------|----------|
| NAT pivot baseline | 17.1 | 17.3 |
| + knowledge dist. | 18.4 | 18.0 |
| + RL | 19.0 | 18.3 |
| + knowledge dist. | 18.4 | 18.4 |

Table 3. Results of the knowledge distillation on pivot systems with non-autoregressive src→piv model. All results are reported on the development set.

B. Knowledge Distillation

Non-autoregressive translation models are often trained using knowledge distillation (KD) (Kim & Rush, 2016) to improve the model performance (Ghazvininejad et al., 2019; Zhou et al., 2020). To strengthen the src→piv CMLM we run an experiment in which we apply knowledge distillation in the training during the CMLM pre-training. Although knowledge distillation does improve the performance of the src→piv model, our experiments show that it does not lead to performance improvements on top of reinforcement learning in the end-to-end model. The resulting BLEU score with and without knowledge distillation are depicted in Table 3.

C. Autoregressive vs. Non-autoregressive Sampling

To obtain samples for gradient estimation, we apply multinomial sampling on top of the model distribution as discussed in Section 4. In non-autoregressive model, the length is predicted beforehand and each token of the sampled sequence can be obtained in parallel with one decoder pass. However, the sampling from the autoregressive model is not possible in parallel and has to be done left-to-right, which requires \( K_{max} \) passes of the decoder, where \( K_{max} \) is the maximum pivot sequence length. Thus, the training speed decreases significantly. To compare the sampling speed between non-autoregressive and autoregressive models, we measure the execution time for the sampling function using pytorch profiler. We do sampling on CMLM model and Transformer model using the validation set. On average, sampling with the non-autoregressive model takes 73.807 milliseconds while with the autoregressive model sampling takes 5.780 seconds, which makes non-autoregressive model more suitable in terms of training speed.