Meet Changes with Constancy: Learning Invariance in Multi-Source Translation

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Abstract

Multi-source neural machine translation aims to translate from parallel sources of information (e.g. languages, images, etc.) to a single target language, which has shown better performance than most one-to-one systems. Despite the remarkable success of existing models, they usually neglect the fact that multiple source inputs may have inconsistencies. Such differences might bring noise to the task and limit the performance of existing multi-source NMT approaches due to their indiscriminate usage of input sources for target word predictions. In this paper, we attempt to leverage the potential complementary information among distinct sources and alleviate the occasional conflicts of them. To accomplish that, we propose a source invariance network to learn the invariant information of parallel sources. Such network can be easily integrated with multi-encoder based multi-source NMT methods (e.g. multi-encoder RNN and transformer) to enhance the translation results. Extensive experiments on two multi-source translation tasks demonstrate that the proposed approach not only achieves clear gains in translation quality but also captures implicit invariance between different sources.

1 Introduction

Neural machine translation (NMT) systems in general translate one source language to a target language. Various one-to-one attentional encoder-decoder architectures (Bahdanau et al., 2014; Luong et al., 2015b; Vaswani et al., 2017) were designed to learn word and structure mappings including formations, grammatical correspondences between source and target languages.

Recently, multi-source NMT (Zoph and Knight, 2016), which simultaneously takes multiple different languages (Dabre et al., 2017; Libovický et al., 2018; Currey and Heafield, 2018) as input when translating to another one, is emerging. Its intuitive idea is ambiguity between one source language and the target language could be reduced by another source language via the “triangulation” proposed by (Kay, 2000). For example, it is hard to tell who was with a telescope by the ambiguous English sentence in Figure 1 (a). But it could be more easily to be translated to Spanish if provided with the corresponding Chinese phrase “我通过望远镜”, which corresponds to “I see through a telescope” in English. Besides, the complementary source could be extended to non-language input such as images, also known as multi-modal NMT (Libovický and Helcl, 2017; Elliott et al., 2017). It takes an image with description in source languages, that is then translated into a target language. The images are expected to provide additional signals for better translations, which abides by similar assumptions in multi-source NMT with different languages. A specific instance is illustrated in Figure 1 (b). In this paper, we consider general multi-source NMT which contains more than one source as input. Our proposed model could be naturally adapted to these two specific sub-tasks, namely multi-lingual translation and multi-modal translation. For simplicity and convenience to describe, we use multi-source NMT to denote both tasks.

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The existing approaches for multi-source NMT mainly adopt multi-encoder-single-decoder as a paradigm, where multiple encoders extract features of different sources, and the single decoder jointly use the learnt sources’ representations to predict the target words. They have already shown better performance than most one-to-one systems (Zoph and Knight, 2016; Junczys-Dowmunt and Grundkiewicz, 2018). Despite the remarkable success of existing methods, they usually neglect the fact that parallel corpus in multiple sources may have inconsistencies, which might derive noise to confuse the decoding process and cause unsatisfactory translation results. Take multi-lingual translation as an example, two inconsistent cases are exhibited in Figure 2. The target English sentence “this is a big dog” only requires simple sequential translation process from Chinese but necessary inversions from Spanish. However, this kind of pattern is not always true and an opposite case is shown in Figure 2 (b). The analogous cases also could happen in multi-modal NMT since images might contain noisy information brought by image background, rotation and scaling, etc. Even with attention mechanisms, we find the conflicts may limit the performance of existing approaches due to their indiscriminate usage of input sources. We will verify our findings in the experiment section (refer to Section 6.2).

In this paper, we attempt to take advantage of the potential complementary information among multiple sources and alleviate the serendipitous conflicts of them. We accomplish it by proposing a component named Source Invariance Network (SIN) for multi-encoder based multi-source NMT approaches. SIN separates the invariant information of parallel input sources from their individual representations. The learnt invariant representations could be utilized into decoding processing to enhance the translation quality. SIN is easily integrated with popular multi-encoder based multi-source NMT frameworks such as RNN-based and transformer-based approaches. Experiments on both multi-lingual and multi-modal translation tasks demonstrate the effectiveness of SIN. Our contributions can be summarized as follows,

• To the best of our knowledge, we are the first considering the problem of learning invariance of multi-source translation to address the occasional conflicts among different parallel input sources.

• We devise the source invariance network to automatically separate the invariant information of parallel input sources and leverage such component to enhance two prevail multi-encoder based multi-source NMT frameworks.

• We verify the performance of our model on both multi-lingual and multi-modal NMT tasks. Extensive experimental results show that our SIN can provide large-margin improvements on both tasks and the invariant information between different sources are encouragingly learnt by our model.

2 Related work

Multi-lingual Machine Translation Multilingual machine translation addresses the machine translation between multiple source and target languages, which contains one-to-many (one-source-to-many-target), many-to-many, many-to-one approaches. (Dong et al., 2015) combines a single encoder with multiple attentional decoders for one-to-many translation, based on which (Wang et al., 2018) have proposed three strategies to improve the performance. (Luong et al., 2015a) combined multiple encoders and decoders, one encoder for each source language and one decoder for each target language respectively, for many-to-many translation. Based on that, (Firat et al., 2016) devised a sharing attention mechanism while (Lu et al., 2018) incorporated an explicit neural interlingua into such multilingual encoder-decoder.
Afterwards, (Ha et al., 2016) and (Johnson et al., 2017) proposed one universal encoder and decoder to take place of multiple encoders and decoders. (Blackwood et al., 2018) devised a task-specific attention mechanism to improve the translation quality. In addition, (Sen et al., 2019) considered unsupervised multilingual NMT by utilizing a shared encoder and some language-specific decoders. As regard to many-to-one translation, RNN-based (Zoph and Knight, 2016) and Transformer-based multi-source translation (Junczys-Dowmunt and Grundkiewicz, 2018) are two multi-encoder methods.

Multi-modal Machine Translation Multi-modal have been extensively studied due to multi-modal MT shared tasks (Specia et al., 2016; Elliott et al., 2017; Barrault et al., 2018). Prior to the shared tasks, (Hitschler et al., 2016) proposed a phrase-based statistical MT model (PBSMT) to generate translation candidates and re-rank them with image features. Afterwards, RNN-based architectures have been adopted in multi-modal machine translation (Elliott et al., 2015). Based on such framework, (Libovický and Helcl, 2017) devised attention mechanism to improve the translation while (Caglayan et al., 2016) leveraged spatial visual features to a separate visual attention mechanism. Apart from that, (Calixto et al., 2019) incorporated image features through latent variables. (Libovický et al., 2018) adopted multi-source Transformer with different input combination strategies.

To the best of our knowledge, previous methods did not consider the conflicts among various input sources. We are the first to consider this problem in multi-source translation and learn the invariance to improve the translation quality.

3 Background

In this section, we introduce two general multi-encoder based multi-source NMT frameworks, namely RNN-based and Transformer-based approaches. They basically have the same architecture with multiple encoders and a single decoder corresponding to different sources and one target, respectively.

3.1 RNN-based Multi-source NMT

In RNN-based multi-source NMT, various inputs are firstly encoded by individual encoders. Then, in the decoding process, e.g. at step $t$, context vectors $c_1^t, c_2^t, \ldots, c_N^t$ corresponding to $N$ different encoders are all combined with the decoder hidden state $h_t$ to obtain a new state $\tilde{h}_t$, which is further utilized for the word prediction. For example, (Zoph and Knight, 2016) simply concatenate the context vectors with decoder hidden state as,

$$\tilde{h}_t = \tanh(W_c[h_t, c_1^t, \ldots, c_N^t]) .$$

where $W_c \in \mathbb{R}^{d \times (N+1)d}$, $h_t, c_1^t, \ldots, c_N^t \in \mathbb{R}^d$ and $d$ represents the dimension of hidden states.

3.2 Transformer-based Multi-source NMT

Another essential multi-encoder based multi-source NMT framework (Junczys-Dowmunt and Grundkiewicz, 2018) is built upon Transformer (Vaswani et al., 2017). Compared with RNN-based methods, the major distinction of transformer-based multi-source NMT is that there are multiple encoder-decoder attentions, which are connected in series as shown in Figure 4. Each attention layer conducts multi-head attention by considering the output of the previous attention layer as the “Query” while taking in the output from the corresponding encoder as “Key” and “Value”, respectively.

4 The Proposed Model

In this section, we detail our Source Invariance Network (SIN). Our SIN is inspired by Domain Separation Networks (DSN) (Bousmalis et al., 2016), which is used for learning domain-shared representations in transfer learning field. While in this paper, SIN attempts to learn the invariance among different inputs in multi-source translation tasks and alleviate the occasional conflicts of inputs.

In this section, we first detail the architecture of our SIN, then illustrate how to integrate it with RNN-based and Transformer-based multi-source NMT frameworks. Furthermore, we raise a discussion on how SIN can strengthen the performance on multi-encoder based frameworks.
4.1 Source Invariance Network

The architecture of the proposed SIN is shown in Figure 3, in which \( h^1 \) and \( h^2 \) denote the corresponding source representations of two different encoders, respectively. To be noticed, the source representation can be generated either from text or images.

For a specific description, we denote \( E_s(h, \theta_s) \) as the invariant encoder in Figure 3, which is a function parameterized by \( \theta_s \). The invariant encoder maps \( h^1 \) and \( h^2 \) to \( h^1_s \) and \( h^2_s \) representing the invariant representations, respectively. Analogously, the private encoder is denoted by \( E_p^i(h, \theta_p^i) \) \((i = 1, 2)\) which maps the \( i \)-th source representation \( h^i \) to a new private representation \( h^i_p \). Both \( E_s(h, \theta_s) \) and \( E_p^i(h, \theta_p^i) \) can be any neural networks and we adopt fully-connected networks in our experiment. Recall that \( h^1_s \) and \( h^2_s \) represent invariant representations, we encourage SIN to narrow down the disparity between \( h^1_s \) and \( h^2_s \) by introducing similarity loss (denoted as \( L_{sim} \)). In more detail, we adopt maximum mean discrepancy (MMD), a non-parametric estimate criterion (Gretton et al., 2012) which is defined in terms of particular function spaces, to measure the correlations among different source representations,

\[
L_{sim} = \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \frac{k(h^1_{si}; h^1_{sj})}{n_1^2} + \sum_{i=1}^{n_2} \sum_{j=1}^{n_2} \frac{k(h^2_{si}; h^2_{sj})}{n_2^2} - 2 \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \frac{k(h^1_{si}; h^2_{sj})}{n_1 n_2},
\]

where the characteristic kernel \( k(z_1, z_2) = e^{-||z_1 - z_2||^2/b} \) is the Gaussian kernel function with bandwidth parameter \( b \) of vector \( z \), and \( n_1 = n_2 \) representing the number of parallel sources. Note that it can also be applied in the case of more than two sources by computing pairwise MMD. Furthermore, recall that \( h^1_s \) and \( h^2_s \) represent invariant and private representation split from source representation \( h^1 \), we encourage SIN to learn orthogonality between the invariant and private representation of each input. So we adopt the difference loss following (Bousmalis et al., 2016),

\[
L_{dif} = \sum_{i=1}^{N} \left\| H^T_s H^i_p \right\|_F^2
\]

where \( N \) represents the number of input sources, \( \left\| . \right\|_F^2 \) is the squared Frobenius norm. \( H^i_s \) and \( H^i_p \) are matrices whose rows are invariant and variant representations, individually.
4.2 Combine with RNN and Transformer

Our proposed SIN can be easily combined with multi-encoder based multi-source methods. In the paper, we leverage SIN to two representative frameworks, i.e., RNN and Transformer, and then derive two models SIN-RNN and SIN-Transformer, respectively. The key issue of combination is how to generate source representations from RNN and Transformer encoders and connect them with SIN. Considering the particularity between RNN-based and Transformer-based multi-source NMT, SIN-RNN adopts the last hidden states from RNN-based encoders, while SIN-Transformer (shown in Figure 4) takes the average of encoder outputs as source representations corresponding to different encoders. After that, source representations are fed to SIN as described in Section 4.1.

We jointly train the model with a combination of the cross entropy loss (Eq. 5), similarity loss (Eq. 2) and difference loss (Eq. 3) as,

$$\mathcal{L} = \mathcal{J} + \alpha \mathcal{L}_{\text{sim}} + \beta \mathcal{L}_{\text{dif}}$$

$$\mathcal{J} = \frac{1}{|D|} \sum_{(S_1, S_2, T) \in S} - \log P(T|S_1, S_2)$$

where $\alpha$ and $\beta$ are user-specific constants, $D$ is the training set, $S_1, S_2$ denotes the sources and $T$ stands for correct translation.

4.3 Discussion

We emphasize that SIN can influence the performance of multi-encoder based multi-source NMT framework. Specifically, SIN tries to separate the invariant representation $h_s$ from private representation $h_p$ across all the encoders by minimizing the difference and similarity loss. Although SIN only acts on loss function directly, the parameters of all the encoders would be updated at the same time via back-propagation. The transformation of encoders would influence the word predictions via encoder-decoder pipeline either by attention mechanism (SIN-Transformer) or initializing decoder (SIN-RNN).
Table 1: The result between single-source NMT methods and multi-source methods.

| Languages | Method          | Test 2013 | Test 2014 |
|-----------|----------------|-----------|-----------|
|           | BLEU | METEOR | BLEU | METEOR |
| \(D_e\rightarrow Fr\) | 16.42 | 19.9 | 14.80 | 18.5 |
| \(E_n\rightarrow Fr\) | 27.23 | 26.2 | 25.18 | 25.0 |
| \{\(E_n, D_e\}\} \rightarrow Fr | **35.07** | **55.4** | **33.04** | **52.7** |
| \(D_e\rightarrow Fr\) | 23.84 | 23.9 | 21.30 | 22.3 |
| \(E_n\rightarrow Fr\) | 36.05 | 30.8 | 33.67 | 29.4 |
| \{\(E_n, D_e\}\} \rightarrow Fr | **39.82** | **57.8** | **36.88** | **55.7** |

5 Experimental Set-up

We conduct our experiments on two tasks: multi-lingual and multi-modal NMT. In this section, we describe the datasets, baselines, the evaluation protocol and implementation details.

5.1 Datasets

For multi-lingual translation task, we evaluate our proposed models on the standard benchmark IWSLT*. We collect translation pairs of three languages including German (De), French (Fr) and English (En) from IWSLT evaluation campaign 2016. In addition, we use TED-dev-2010 as the development set and TED-test-2013, TED-test-2014 as the test sets. Since IWSLT dataset is not a multi-parallel corpus that required by multi-source NMT, we remove the sentences whose corresponding sentences in English are not present in the corpus. Based on this, we obtain eligible trilingual sentence triples from each language, and result in 188K triples in the training set.

For multi-modal translation task, we evaluate our models in Multi30K dataset (Elliott et al., 2016). The dataset contains triplets of images, English captions and corresponding sentences in German, French and Czech (Cz). The training, validation and test set contain 29,000, 1,014 and 1,000 triplets, respectively.

In both tasks, all the sentences are firstly tokenized by Moses tokenizers†, and then segmented into subword units with Byte Pair Encoding (BPE) (Sennrich et al., 2016)‡. The score is computed on tokenized text after merging the BPE-based sub-word symbols. We use single reference in our evaluation and they are case sensitive.

5.2 Baselines and Evaluation Protocol

We compare our proposed SIN-RNN and SIN-Transformer with two corresponding baselines: RNN-based multi-source NMT (Zoph and Knight, 2016) (denoted as RNN in the following part), and Transformer-based multi-source NMT (Junczys-Dowmunt and Grundkiewicz, 2018) (denoted as Transformer in the following part). We measure translation quality using BLEU (Papineni et al., 2002)‡ and METEOR (Denkowski and Lavie, 2011)§. The score is computed on tokenized text after merging the BPE-based sub-word symbols. We use single reference in our evaluation and they are case sensitive.

5.3 Implementation Details

We use two-layer bidirectional-LSTM as encoder and four-layer LSTM as decoder in our RNN models with hidden size of 512. The Transformer-based methods have 6 layers in both encoder and decoder, while 16 heads in multi-head attention. In loss function (Eq. 4), \(\alpha\) and \(\beta\) are set to 1.0 and 0.1 by grid search, individually. We adopt the optimizer Adam (Kingma and Ba, 2014) with \(\beta_1 = 0.9, \beta_2 = 0.98\) and a weight decay of \(\epsilon = 10^{-9}\). For the multi-lingual translation task, we set batch size to 64 and the learning rate to 0.001 for all the RNN-based methods, and set 2,048 tokens in each batch and the learning rating to 1.0 for all transformer-based ones. For the multi-modal translation task, we set batch size to 32 and the learning rate to 0.01 for all the RNN-based methods, and set batch size to 32 and the learning rating to 0.2 for transformer-based models following (Libovický et al., 2018). For image processing in multi-modal translation task, we adopt the last convolutional layer of ResNet network (He et al.,

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*https://wit3.fbk.eu/mt.php?release= 2016-01
†https://github.com/moses-smt/mosesdecoder/blob/master/scripts/tokenizer/tokenizer.perl
‡https://github.com/moses-smt/mosesdecoder/blob/master/scripts/generic/multi-bleu.perl
§https://github.com/jhclark/multieval
Table 2: The performances of four approaches, including two our proposed methods SIN-RNN, SIN-Transformer and two baseline methods RNN-based and Transformer-based multi-source NMT.

| Languages      | Method      | Test 2013 BLEU | Test 2013 METEOR | Test 2014 BLEU | Test 2014 METEOR |
|---------------|-------------|----------------|-----------------|----------------|-----------------|
| \{De, Fr\} → En | RNN         | 40.75          | 36.2            | 37.30          | 35.3            |
|               | SIN-RNN     | **42.19**      | **37.6**        | **37.90**      | **35.7**        |
|               | Transformer | 45.33          | 39.1            | 41.72          | 37.7            |
|               | SIN-Transformer | **45.90**  | **39.3**        | **41.94**      | **37.8**        |
| \{En, Fr\} → De | RNN         | 24.72          | 44.5            | 21.22          | 40.5            |
|               | SIN-RNN     | **26.30**      | **45.9**        | **22.65**      | **41.4**        |
|               | Transformer | 29.32          | 48.0            | 25.43          | 43.7            |
|               | SIN-Transformer | **29.78**  | **48.4**        | **25.65**      | **43.8**        |
| \{En, De\} → Fr | RNN         | 35.07          | 55.4            | 33.04          | 52.7            |
|               | SIN-RNN     | **36.93**      | **55.7**        | **34.27**      | **53.3**        |
|               | Transformer | 39.82          | 57.8            | 36.88          | 55.6            |
|               | SIN-Transformer | **39.85**  | **57.9**        | **37.40**      | **55.7**        |

Table 3: Quantitative results of the multi-modal translation experiments on the test-set-2016.

| Methods  | En → De | En → Fr | En → Cz |
|----------|---------|---------|---------|
|          | BLEU    | METEOR  | BLEU    | METEOR  | BLEU    | METEOR  |
| RNN      | 35.81   | 53.7    | 55.43   | 67.9    | 26.98   | 25.7    |
| SIN-RNN  | **36.7**| **54.5**| **59.75**| **68.3**| **27.86**| **26.1**|
| Transformer | 38.37   | 56.9    | 38.72   | 71.6    | 30.21   | 29.3    |
| SIN-Transformer | **39.01**| **57.4**| **59.75**| **72.3**| **30.31**| **29.4**|

In this section, we exhibit the overall performance among our methods and baselines in Sec 6.1, examine the conflicts caused by the inconsistency among different sources in Sec 6.2, and evaluate the effectiveness of learning invariance in Sec 6.3.

6.1 Quantitative Results

Firstly, we compare the multi-source NMT methods against the single-source ones as shown in Table 1. It reports that multi-source methods outperform single-source ones by a large margin, which indicates the effectiveness of information enhancements brought by parallel multi-source inputs. And we present the overall performance of our SIN-RNN and SIN-Transformer on multi-lingual and multi-modal translation tasks in this section. For both tasks, we compare our SIN-RNN, SIN-Transformer with RNN-based multi-source NMT (Zoph and Knight, 2016) and Transformer-based (Junczys-Dowmunt and Grundkiewicz, 2018), while reporting the BLEU, METEOR score.

In the multi-lingual translation task, the overall performance is reported in Table 2. From the table, we can observe that our methods outperform corresponding baselines on almost all the language pairs. In detail, SIN-RNN achieves up to 1.86 BLEU (1.4 METEOR) improvement over RNN-based multi-source NMT translating from \{En, De\} to Fr on TED-test-2013, while SIN-Transformer outperforms the Transformer baseline 0.57 BLEU from \{De, Fr\} to En.

In the multi-modal translation task, shown in Table 3, SIN-RNN gains a maximum improvement of 0.96 BLEU (0.8 METEOR) over RNN-based method from En to De while SIN-Transformer beats its corresponding baseline by 1.03 BLEU (0.7 METEOR) from En to Fr. In general, both SIN-RNN and SIN-Transformer enhance the translation quality on multi-lingual and multi-modal tasks by learning invariance among sources. It also shows positive influence of SIN on updating parameters of encoders.

Recall that multi-source NMT are always better than single-source NMT as shown in (Zoph and Knight, 2016; Junczys-Dowmunt and Grundkiewicz, 2018).
Figure 5: The attention mappings between the source sentences (shown in X-axis) and the prediction sentence (shown in Y-axis) of RNN baseline and SIN-RNN.

Figure 6: An example used in Case Study translating from German and French to English.

Figure 7: How to swap source representations of two encoders.

6.2 Case Study

Next, we conduct case studies to show our model can alleviate inconsistencies of sources and improve translation quality. We firstly select 200 sentences from the test sets of IWSLT where the inconsistency of grammar structures occurs as shown in Figure 6. Then we test the performance of trained RNN-based multi-source NMT and SIN-RNN in the same experimental settings on the selected sets. The former method achieves 35.19 while our SIN-RNN obtains 36.83 BLEU score, achieving 1.64 improvement.

Furthermore, we visualize the attention on the word mappings (via hard attention) of the selected sentences from which we randomly choose one example for demonstration (shown in Figure 5). The word alignment between the two source sentences and one target sentence of the picked example is illustrated in Figure 6. In this case, conflict occurs when reference both French and German to translate to English phrase “stands before us”. From Figure 5, we can see that both these two methods capture the main idea except that RNN-based multi-source NMT neglects the object “us”. Furthermore, RNN-based multi-source NMT mainly focuses on one source language at a time. We conjecture that it might be a reason why it drops some information when inconsistency between different sources exists. While our SIN-RNN can better take advantages of both source language for translation.

| Method       | 1-gram | 2-gram | 3-gram | 4-gram |
|--------------|--------|--------|--------|--------|
| Before Swap  | RNN baseline | 67.4   | 45.0   | 31.8   | 22.8   |
|              | SIN-RNN | 67.9   | 45.7   | 32.5   | 23.4   |
| After Swap   | RNN baseline | 47.1 (▽ = 20.3) | 1.6 (▽ = 43.4) | 0.8 (▽ = 31) | 0.0 (▽ = 22.8) |
|              | SIN-RNN | 65.8 (▽ = 2.1) | 30.2 (▽ = 15.5) | 17.8 (▽ = 14.7) | 11.0 (▽ = 12.4) |

Table 4: Comparison results on swapping experiment. BLEU of 1-gram, 2-gram, 3-gram and 4-gram of RNN baseline and SIN-RNN are reported. ▽ represents the decrease of BLEU score after swapping.
| Source | Target | Source | Target | Source | Target | Source | Target |
|--------|--------|--------|--------|--------|--------|--------|--------|
| Fr     | En     | De     | Fr     | En     | De     | Fr     | En     |
| J’ai une photo ici lieu dans le Kentucky. | I’ve got a picture here. | Hier ist ein Bild eines Ortes in Kentucky. | I have a picture here. | La ferme est incroyable. | The farm is amazing. |

| Source | Target | Source | Target | Source | Target |
|--------|--------|--------|--------|--------|--------|
| Fr     | En     | De     | Fr     | En     | De     |
| So, what do we do? | And what do we do? | So, what do we do? | Merci | Thank you | Dankeschön |

6.3 Intrinsic Evaluation

Experiment results on two multi-source translation tasks demonstrate that our proposed methods can enhance the translation performance by learning the invariance. Next, we further investigate intrinsic evaluations, aimed to examine whether our methods can learn better invariance. Due to the space limitation, we only report the results of SIN-RNN and RNN-based multi-source NMT method in this part.

6.3.1 Quantitative Evaluation

Recall that our proposed SIN can learn invariance among multiple source inputs. Hence, source representation of each encoder might be replaceable by each other since they are hoped to contain the invariant information. Therefore, we conduct an experiment by swapping the source representations ($h_1$ and $h_2$) from two encoders as shown in Figure 7, to prove whether our methods can obtain better invariance among distinct sources. We begin with the TED-test-2014 composed of 1,305 trilingual translation pairs from \{Fr, De\} to En and prepare the pre-trained models of RNN-based multi-source NMT and SIN-RNN, both of which have been trained in the same settings. After generating source representations $h_1$ and $h_2$ in the encoding process, we swap $h_1$ and $h_2$ as shown in Figure 7 and apply them to predict target words based on the pre-trained models. Thus, two groups of predicted sentences of baseline and SIN-RNN are yielded by performing above process, and the results on BLEU score of 1-gram, 2-gram, 3-gram and 4-gram are reported in Table 4. We see that all the BLEU scores of RNN-based multi-source method are significantly decreased, especially on the 2-gram and 3-gram BLEU. While the performance of SIN-RNN slightly decreases and can even keep similar score on 1-gram matching. Furthermore, there is a clear gap between multi-encoder and our methods on the 2-gram, 3-gram, 4-gram BLEU scores. It indicates that our methods can match more words and longer phrases even after swapping source representations. These observations demonstrate that our method is able to incorporate the invariance cross sources.

6.3.2 A Closer Look

Next, we take a closer look at the results of the previous evaluation. We select four representative translation results (\{Fr, De\} → En) and report them in Figure 8. We can see that SIN-RNN generally performs better than RNN-based multi-source method. In case (a), RNN-based multi-source method just translates an irrelevant symbol rather than a meaningful sentence in English, while SIN-RNN captures the main idea of source sentences. For case (b), the target is a common interrogative sentence in English. But we can see that German has inconsistent word order with French and English, which might cause ambiguity when translating them to English. We observe that the baseline lost the basic grammar structures. We conjecture the reason is that RNN baseline can well learn mappings of words among different languages, but fails to deal with inconsistent grammatical structures. In contrast, our methods perform well on such inconsistency. While for some simple cases, e.g. case (c) and (d), both methods translate correctly even swapping the source representations. From above four cases, we find our methods can
obtain better invariance representations, which could be helpful for improving translation quality.

7 Conclusion

In this paper, we observed the drawbacks of multi-encoder based multi-source NMT on neglecting the potential inconsistency among sources. We thus proposed SIN to learn the invariance among multiple sources. With the equipped invariant encoder, the invariant features are explored by minimizing the maximum mean discrepancy between source representations. Meanwhile, the private encoder is devised to distill the corresponding particular features of different sources. SIN can be easily integrated with conventional multi-encoder based multi-source NMT frameworks. We conducted extensive experiments in two main multi-source tasks, and the results demonstrate the effectiveness of the proposed model.

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1132