Boosting Neural Machine Translation with Dependency-Scaled Self-Attention Network

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Abstract. Neural machine translation model assumes that syntax knowledge can be learned from the bilingual corpus via attention network automatically. However, the attention network trained in weak supervision actually cannot capture the deep structure of the sentence. Naturally, we expect to introduce external syntax knowledge to guide the learning of attention network. Thus, we propose a novel, parameter-free, dependency-scaled self-attention network, which integrates explicit syntactic dependencies into attention network to dispel the dispersion of attention distribution. Finally, two knowledge sparse techniques are proposed to prevent the model from overfitting noisy syntactic dependencies. Experiments and extensive analyses on the IWSLT14 German-to-English and WMT16 German-to-English translation tasks validate the effectiveness of our approach.\textsuperscript{1}

Keywords: Neural machine translation · Syntax knowledge · Transformer · Self-attention network

1 Introduction

Neural machine translation (NMT) \cite{6, 30} assumed that the model could automatically learn syntax knowledge from the bilingual corpora through the attention network \cite{1, 12}. However, Li et al. \cite{11} found that NMT model failed to capture this internal deep structure of sentence. Yang et al. \cite{27} then revealed that this limitation mainly arose from the attention network was solely controlled by two training parameter matrices without any external parsing when modeling the correspondences of element:

\[ QK^T = (HW_Q)(HW_K)^T = H(W_QW_K^T)H^T, \]

\textsuperscript{1} Our code and experimental results will be published after accepted.
which indicated that the attention network was trained in a weakly supervised manner. For example, as shown in Fig. 1(a), the conventional attention network learns the correspondence between "experiments" and "simple" without considering the syntactic dependency. Naturally, we expect to exploit syntactic dependency to guide the training of attention network for the better translation in Fig. 1(b).

Recent studies have substantiated that syntax knowledge are promised to refine the translation of NMT models [4, 8, 20]. However, these syntax-aware methods mostly focused on RNN-based models and scarcely attended to Transformer [24]. For instance, Wu et al. [26] adopted three RNN encoders and two RNN decoders to leverage the source-side and target-side dependency tree to improve NMT. Zhang et al. [31] integrated source-side syntax implicitly to NMT by concatenating the intermediate representations of an independent dependency parsing model to word embeddings. Currey and Heafield [7] proposed two data augmentation methods using source-side constituency parsing as source input and target input to enhance NMT. No matter how considerable the gains achieved by these methods, the additional modules and representations render the model heavy and slow, and they do not modify the core component of Transformer, the self-attention network (SAN).

In response, we propose a novel, parameter-free, dependency-scaled self-attention network (Deps-SAN). Specifically, we first compute the dependency distance sequence of all words based on the dependency tree, then construct a dependency-scaled matrix through the Gaussian distribution. The dependency-scaled matrix is equivalent to the quantification of the syntactic dependence among words, which can supply explicit syntactic constraints for SAN to dispel the dispersion of attention distribution. Finally, two knowledge sparse techniques are proposed, including random sampling sparse (RS-Sparse) and k-value window sparse (Wink-Sparse), to prevent Deps-SAN from overfitting noisy syntactic dependencies. Experiments and extensive analyses over the IWSLT14 German-
to-English and WMT16 German-to-English translation tasks demonstrate the significance of our approach.

2 Approach

Before elaborating the Deps-SAN, we first introduce the dependency distance applied to measure the dependency correspondences:

**Dependency distance** In line with previous work [5, 17, 18, 25], the dependency tree is extracted from the sentence by an external syntax parser, which is employed to derive the word-level dependency distance. The dependency distance is defined as the length of path traversed from a word to another word on the tree, and the distance between two connected words is assigned as 1. For example, as shown in Fig. 2(a), the dependency distance of “experiments” itself is 0, the dependency distance of “simple” and “The” is 1, and the dependency distance of “are” and “very” is 2. Consequently, the attention network can discriminatively focus on words that are more correlated with its dependence when encoding ”experiment”.

![Diagram](image)

**Fig. 2.** (a) Derivation pipeline of dependency-scaled matrix and (b) architecture of Deps-SAN.
2.1 Deps-SAN

Fig. 2(a) and 2(b) give the derivation pipeline of dependency-scaled matrix and the architecture of Deps-SAN, respectively. Given the input sentence $x$ with length $S$, we traverse each word according to the original order, and compute the dependency distance between the current word and other words (including itself) based on the parsed dependency tree $T$. Then, we combine all dependency distance sequences $d_i$ and derive a dependency-scaled matrix $D^s \in \mathbb{R}^{S \times S}$ by the Gaussian distribution. Each row of the matrix denotes the closeness of syntactic dependence of each word to other words.

Transformer [24], as the NMT baseline model in this paper, abandons the recurrence and convolutions, and solely relies on SANs to achieve remarkable progress. Here, for the Deps-SAN, the dependency-scaled matrix $D^s$ and the word embedding vector $E_x$ are both fed as the input of the H attention heads. Following Vaswani et al. [24], we compute three vectors (query, key and value) for the input sentence, and pack them into three matrices $Q^h, K^h, V^h \in \mathbb{R}^{S \times d_k}$, where $d_k = d_{model}/H$:

$$\{Q^h, K^h, V^h\} = \{QW^Q_h, KW^K_h, VW^V_h\}. \quad (2)$$

In particular, the initial query, key and value are learned from the word embedding vector through position encoding [9]. Next, we compute the dot product between each query and all keys, and divide by $\sqrt{d_k}$ to obtain the alignment score $S^h$, which indicates how much attention should be placed on other words when annotating current word. Then, we impose explicit constrains on the alignment score by point-wise weighting the dependency-scaled matrix $D^s$, and force the model to focus on the syntactic dependencies among words.

$$S^h = \frac{Q^h K^h^T}{\sqrt{d_k}} \quad (3)$$

$$\bar{S}^h = S^h \odot D^s, \quad (4)$$

where $\bar{S}^h$ is the $i$-th row of $\bar{S}^h \in \mathbb{R}^{S \times S}$, which represents the refined alignment score based on the dependency distance of the $i$-th word $x_i$. In detail, we quantify the dependency closeness used for weighting alignment scores as the probability density value of a Gaussian distribution with the variance $\sigma^2$. Here, $GaussDist(d_{ij})$ is the $(i, j)^{th}$ entry of the dependency-scaled matrix, and $d_{ij}$ is the dependency distance of the word pair $x_i$ and $x_j$:

$$D^s = GaussDist(d_{ij}) = \frac{1}{\sqrt{2\pi\sigma^2}}exp\left(-\frac{(d_{ij})^2}{2\sigma^2}\right), (i, j) = 1, ..., S \quad (5)$$

$$Z^h = softmax(\bar{S}^h)V^h \quad (6)$$

$$O^h = Concat(Z^1, ..., Z^H)W^O. \quad (7)$$

Finally, the attention weights normalized by the softmax function are multiplied by the value vector to obtain the output representation of the $h^{th}$ attention
head. The output representations of all attention heads are concatenated together, followed by a linear projection layer to generate a context vector. In summary, when encoding sentences, the proposed Deps-SAN guide the model to attend on each word in varying scales according to the dependence closeness with the encoded word.

2.2 Knowledge Sparse

Since the bilingual corpus lacks syntactic parsing, we are obliged to extract it from an external syntax parser. However, transition-based parser have high accuracy on shorter dependency relations but accuracy declines significantly as the distance between the head and dependent increases [13]. To alleviate it, we propose two knowledge sparse techniques as shown in Fig. 3:

![Fig. 3. Illustration of two knowledge sparse techniques. Left figure denotes the RS-Sparse, and right figure denotes the Wink-Sparse.](image)

**RS-Sparse** Refer to the dropout [23], partial syntactic information is diluted to prevent the model from overfitting noisy dependencies during training. In practice, we randomly set each elements of $D^s$ to $k$ with probability $q$.

**Wink-Sparse** Similarly, as a fixed variant, we explicitly concentrate on position whose dependency distance is within $k$ and sparse out others.

In general, both knowledge sparse aim to confront noisy dependencies by preserving partial syntactic information of words instead of discarding them, which may encounter severe information loss.

3 Experiment

3.1 Datasets

We evaluated the proposed approach on IWSLT14 German-to-English (DE-EN), WMT14 German-to-English translation tasks. For the low-resource DE-EN translation task, the training set contained 160K sentence pairs. Following the instructions (Cettolo. et al. [3]), we randomly sampled 5% of the training data for validation and combined multiple test sets IWSLT14.TED.{dev2010,

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2 https://wit3.fbk.eu/archive/2014-01/texts/de/en/de-en.tgz
dev2012, tst2010, tst1011, tst2012} for testing. For large-scale DE-EN translation task, the training set consisted of 4.5M sentence pairs. We selected the newstest2015, newstest2016 as validation sets and test sets respectively. We remained the word form rather than sub-word unit [21] for better dependency parsing.

3.2 Baseline Systems

We trained a Transformer model as a robust baseline, and reproduced the following SAN variant models for comparison:

- **PASCAL**: The parent-scaled SAN proposed by Bugliarello et al. [2] enable the model to focus on the dependency parent of each token when encoding sentence, appending with a regularization technique parent ignoring to avert over-fitting noisy dependencies;
- **Localness**: The localness-aware SAN proposed by Yang et al. [29] casts localness modeling as a learnable Gaussian bias to incorporate into SAN, which three alternatives of fixed, layer-specific and query-specific localness are proposed according to the local region to be paid attention;
- **Context**: The context-aware SAN proposed by Yang et al. [28] aimed to leverage the internal states as context vectors to improve the SAN, which is divided into Global, Deep and Deep-Global according to the diversity of embedded internal state and contextualization.
- **RPE**: Shaw et al. [22] extended the SAN by efficiently considering the representation of the relative positions (i.e. linear distance) between sequence elements representation of words;

3.3 Experiment Setting

We extracted the dependency parsing results from Stanford parser [14]. The source and target vocabularies size were both limited to both 60K. All sentences were limited within 80 words and without aggressive hyphen splitting. Case-sensitive 4-gram BLEU [16] was used as the evaluation metric and paired bootstrap sampling [10] was applied for statistical significance test. We trained 80K and 200K steps on the low-resource dataset and large-scale dataset respectively to guarantee that the model had reached convergence. The hyperparameters $k$ and $q$ for knowledge sparse were assigned to 6 and 0.1 respectively, which were enough to dilute the noisy dependencies of the sentence. We employed beam search with a beam size of 5 and length penalty $\alpha = 0.6$ for inference. Other configurations kept the same as Vaswani et al [24]. All NMT models were trained on a NVIDIA TITAN RTX using Fairseq toolkit [15].
Table 1. Translation results of different NMT systems on IWSLT14 DE-EN and WMT16 DE-EN tasks. ‡/† indicated that the significance of our models were significantly better than that of the Transformer (p < 0.01/0.05). “#Speed” and “#Param” denoted the training speed (seconds/each 100 batches) and the size of model parameters, respectively. We highlighted the best results in bold for both tasks.

| Systems                                    | IWSLT14 DE-EN | WMT16 DE-EN |
|--------------------------------------------|---------------|-------------|
|                                           | BLEU  #Speed  #Param  BLEU  #Param |
| **Existing NMT systems**                   |               |             |
| Transformer                                | 29.88 23s     | 74.85M      | 27.48 105.57M |
| +PASCAL                                    | 29.75 23s     | 74.85M      | 27.55 105.57M |
| +PASCAL+parent ignoring                    | 29.70 24s     | 74.85M      | 27.53 105.57M |
| +Fixed Localness                           | 28.72 24s     | 74.87M      | 27.21 105.59M |
| +Layer-Spec. Localness                     | 29.89 25s     | 74.88M      | 27.23 105.60M |
| +Query-Spec. Localness                     | 29.63 25s     | 74.87M      | 27.46 105.59M |
| +Global Context                            | 29.92 26s     | 74.90M      | 27.45 105.62M |
| +Deep Context                              | 30.03 26s     | 74.98M      | 27.63 105.70M |
| +Deep-Global Context                       | 30.07 26s     | 75.03M      | 27.55 105.75M |
| +RPE                                       | 30.34 25s     | 74.88M      | 27.71 105.60M |
| **Our NMT systems**                        |               |             |
| +Deps-SAN                                  | **30.44‡** 29s | 74.85M      | **27.94‡** 105.57M |
| +Deps-SAN+RS-Sparse                        | 29.76 29s     | 74.85M      | 27.63 105.57M |
| +Deps-SAN+Wink-Sparse                      | 29.69 29s     | 74.85M      | 27.53 105.57M |

3.4 Main Results

The translation results of all NMT systems on the IWSLT14 DE-EN, WMT16 DE-EN translation tasks were shown in Table 1. Obviously, our models achieved the best performance on both translation tasks, and accomplished considerable gains compared with other models. Besides, all localness-aware SANs were generally inferior to their adjacent context-aware SANs, which owing to the context vector directly enhanced the sentence semantics compared with implicit localization. Moreover, PASCAL did not derive practical improvement from focusing on the dependency parent of the word. This probably was related to the word closest to each word was not its dependency parent but its multiple dependency children. Finally, injecting relative position representation into self-attention simply and effectively improved the translation performance.

Avoiding overfitting noisy dependencies Both +parent ignoring and our knowledge sparse techniques brought no improvement over both translation tasks. We speculated that the accuracy of dependency parsing of two bilingual datasets were precise enough so that was unnecessary to denoise the noises. In the future, we anticipated exploring the effect of sparse knowledge in datasets with coarse syntactic parsing.

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3 https://github.com/pytorch/fairseq/blob/master/examples/translation/prepare-iwslt14.sh
4 https://github.com/moses-smt/mosesdecoder/blob/master/scripts/analysis/bootstrap-hypothesis-difference-significance.pl
Table 2. Validation and test BLEU score for ablation experiments on the IWSLT14 DE-EN translation task. (a) Different combination of Deps-SAN layers, (b) Grid search of Gaussian variance.

(a) Different combination of Deps-SAN layers

| Layer | Valid | Test | $\Delta v$ | $\Delta t$ |
|-------|-------|------|-----------|-----------|
| 1-3   | 31.42 | 30.44| -         | -         |
| 1-1   | 30.71 | 29.83| -0.63     | -         |
| 1-2   | 30.82 | 30.06| -0.64     | -0.44     |
| 1-4   | 30.82 | 29.89| -0.64     | -0.58     |
| 4-6   | 30.41 | 29.46| -0.66     | -0.55     |
| 1-6   | 29.20 | 28.79| -2.42     | -1.65     |

(b) Grid search of Gaussian variance

| Variance | Valid | Test | $\Delta v$ | $\Delta t$ |
|----------|-------|------|-----------|-----------|
| 1        | 31.42 | 30.44| -         | -         |
| 2        | 30.77 | 29.84| -0.66     | -0.6     |
| 4        | 30.64 | 29.82| -0.70     | -0.68     |
| 8        | 30.60 | 30.03| -0.82     | -0.41     |
| 16       | 30.86 | 30.08| -0.56     | -0.36     |
| 32       | 30.46 | 29.64| -0.96     | -0.8      |

4 Analysis

4.1 Ablation Studies

In this section, we conducted ablation experiments over the IWSLT14 DE-EN translation task to evaluate the impact of different components of our approach. First, we investigated the effect of replacing any combination of the encoder layer with the Deps-SAN layer. Then, we considered to find the best variance value of Gaussian distribution via a grid search. To eliminate the interference of control variables, we only implemented all ablation experiments on the encoder-side SAN.

Deps-SAN Layer As shown in Table 2(a), the performance of replacing different encoder layers by the Deps-SAN layer went up with the increase of layers from bottom to top, until the 3rd-layer was replaced. Our model benefits more from replacing lower three layers than that of the higher three layers, which points to the identical conclusion as recent studies [19], i.e., different layers tend to capture different features. We further inferred that the lower layers of the SAN were inclined to focus on syntactic information among words, while the higher layers preferred to concentrated on the semantic information of sentence-level. Accordingly, we applied the Deps-SAN layer in the lower three layers to keep the performance maximally.

Gaussian Variance From Table 2(b), we found $\sigma = 1$ as the optimal Gaussian variance. The best results with a variance of 1 benefitted from strong supervision of syntactic dependencies by setting a minimum scale. The Gaussian distribution allowed the model to focus on the center of distribution and ensured the integrity of information simultaneously via the bell-shaped curve and non-zero properties.

4.2 Performance over Sentence Length

Following Bahdanau et al. [1], on the IWSLT14 DE-EN translation task, we divided all sentences of test set into 9 disjoint groups according to their lengths.
Fig. 4. Translation scores of different NMT models over different length sentences of the test set. These groups [0-10], [10-20], [20-30], [30-40], [40-50], [50-60], [60-70], [70-80] and [80-] contained 1657, 2637, 1381, 614, 252, 122, 43 and 27 sentence pairs respectively.

Fig. 4 presented the performance of all NMT systems over groups of different sentence lengths. We observed that the performance of the proposed method maintained superiority over different sentence lengths, which symbolized our method applied to both long and short sentence translation. This was attributable to our method that explicitly incorporated the syntactic dependencies to guide the SAN. Except for our model, the best performing model was RPE, which was consistent with the translation results in Table. 1.

4.3 Case Study

We listed the translation results of different NMT models for a test example sentence in Table. 3. For this interrogative sentence, the translation mistakes of other models were mainly divided into three categories: sentence pattern errors, misuse of prepositions, and under-translation, which correspond to the different annotations of red, blue, and underline in the table. Our model relied on explicit constraints of syntactic dependencies to capture the correct sentence pattern, and attained an accurate translation without any omissions, which substantiated the reliability of our approach once again.
Table 3. Translation examples of generated by different attentional models, mistakes are highlighted in red and some correct translation segments highlighted in blue.

| Source                        | Reference                                  |
|-------------------------------|--------------------------------------------|
| wie wäre es, länger bei guter gesundheit zu leben? | how about living longer with good health? |
| **Existing NMT systems**      |                                            |
| Transformer                   | what would it be like to live on good health longer? |
| +PASCAL                       | what would it be to live longer with good health? |
| +PASCAL+parent ignoring      | how about living in good health longer?     |
| +Fixed Localness              | what would it be like to live longer on good health? |
| +Layer-Spec. Localness        | what would it be like to live longer on good health? |
| +Query-Spec. Localness        | what would it be like to live longer on good health? |
| +Global Context               | how would it be to live longer with good health? |
| +Deep Context                 | how about living longer?                   |
| +Deep-Global Context          | how about living longer for good health?   |
| +RPE                          | what would it be like to live in good health longer? |
| **Our NMT systems**           |                                            |
| +Deps-SAN                     | how about living longer with good health?  |

5 Conclusion

This paper proposes a novel dependency-scaled self-attention network to integrate syntactic knowledge for dispelling the dispersion of attention distribution in Transformer. Two knowledge sparse techniques are used to avoid overfitting the external noisy dependencies. We also investigate the sensitivity of the proposed approach to hyperparameters and their performance over the translation of different sentence length and a test example sentence. Our experimental results and analyses show that compared with previous methods, the proposed approach can yield higher benefits.

Acknowledgment

This work was supported in part by the National Natural Science Foundation of China under Grants 62071131, 61771149 and 61772146. The authors would like to thank the anonymous reviewers for their valuable comments and suggestions.

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