End-to-End Neural Sentence Ordering Using Pointer Network

Jingjing Gong*, Xinchi Chen*, Xipeng Qiu, Xuanjing Huang

Shanghai Key Laboratory of Intelligent Information Processing, Fudan University
School of Computer Science, Fudan University
825 Zhangheng Road, Shanghai, China
{jjgong15, xinchichen13, xpqiu, xjhuang}@fudan.edu.cn

Abstract

Sentence ordering is one of important tasks in NLP. Previous works mainly focused on improving its performance by using pair-wise strategy. However, it is nontrivial for pair-wise models to incorporate the contextual sentence information. In addition, error propagation could be introduced by using the pipeline strategy in pair-wise models. In this paper, we propose an end-to-end neural approach to address the sentence ordering problem, which uses the pointer network (Ptr-Net) to alleviate the error propagation problem and utilize the whole contextual information. Experimental results show the effectiveness of the proposed model. Source code1 and dataset2 of this paper are available.

1 Introduction

Recently, sentence ordering task attracts more focus in NLP community (Chen et al., 2016; Agrawal et al., 2016; Li and Jurafsky, 2016) as its importance on many succeed applications such as multi-document summarization, etc.

The goal of sentence ordering is to arrange a set of sentences into a coherent text in a clear and consistent manner (Grosz et al., 1995; Van Berkum et al., 1999; Barzilay and Lapata, 2008).

Most of previous researches of sentence ordering are pair-wise models. Chen et al. (2016) and Agrawal et al. (2016) proposed pair-wise models followed by a beam search decoder to seek the ground truth sentence order. Li and Jurafsky (2016) additionally employed the graph based method (Lapata, 2003) to rank sentences. However, their methods could be easily affected by the performance of independent sentence pairs without their contextual sentences.

In this paper, we propose an end-to-end neural sentence ordering approach based on the pointer network (Ptr-Net) (Vinyals et al., 2015). Pointer network can deal with some combinatorial optimization problems with attention mechanism, such as sorting the elements of a given set. Our proposed model can take a set of random sorted sentences as input, and generate an ordered sequences. With pointer network, our proposed model could utilize the whole contextual information to specify the sort order. In addition, we further evaluate the robustness of our model by adding unrelated noisy sentence to the sentence set, which is nontrivial for pair-wise models. Experimental results on two datasets show that proposed model achieves the state-of-the-art performance even it only works with the greedy decoding.

The contributions of this paper can be summarized as follows:

1. Instead of pair-wise sentence ordering, we propose an end-to-end neural approach to generate the order of sentences, which could exploit the contextual information and alleviate the error propagation problem.
2. We perform extensive empirical experiments and achieve the state-of-the-art performance even it only works with the greedy decoding.
3. We design a new and harder experiment to eval-
2. Pointer Network for Neural Sentence Ordering

2.1 Task Description

Sentence ordering task aims to rank a set of sentences in a clear and consistent manner. Specifically, given \( n \) sentences \( s = s_1, s_2, \ldots, s_n \), the aim is to find the gold order \( o^* \) for these sentences:

\[
\text{s}_{o_1^*} \succ \text{s}_{o_2^*} \succ \cdots \succ \text{s}_{o_n^*} ,
\]

which has the maximal probability of given sentences \( P(o^*|s) \):

\[
P(o^*|s) > P(o|s), \forall o \in \Psi,
\]

where \( o \) indicates any order of these sentences and \( \Psi \) indicates the set of all possible orders.

2.2 Model Architecture

Previous works mainly focused on pair-wise models (Chen et al., 2016; Agrawal et al., 2016; Li and Jurafsky, 2016), which lack contextual information and introduce error propagation for the pipeline strategy. Instead of decomposing the score to independent pairs, in this paper, we propose an end-to-end neural approach based on pointer network (Ptr-Net) to score the entire sequence of sentences.

The model architecture is shown in Figure 1. Specifically, the probability of a specific order \( o \) of given sentences \( P(o|s) \) could be formalized as:

\[
P(o|s) = \prod_{i=1}^{n} P(o_i|o_{i-1}, \ldots, o_1, s) . \tag{3}
\]

The probability \( P(o_i|o_{i-1}, \ldots, o_1, s) \) is calculated by Ptr-Net:

\[
P(o_i|o_{i-1}, \ldots, o_1, s) = \text{softmax}(u^j)_{o_i} \tag{4}
\]

\[
u_j = v^T \tanh(W^T \begin{bmatrix} e_j \\ d_i \end{bmatrix}), j = (1, \ldots, n) \tag{5}
\]

where \( e_j, d_i \in \mathbb{R}^h \) are outputs of encoder and decoder of Ptr-Net respectively. \( v \in \mathbb{R}^h \) and \( W \in \mathbb{R}^{(2h) \times h} \) are trainable parameters.

**Encoder** The encoding representation of Ptr-Net could be formalized as:

\[
e_j = \text{LSTM}(\text{Enc}(s_{o_j}), e_{j-1}), j = (1, \ldots, n) . \tag{6}
\]

where \( \text{Enc}(s_{o_j}) \) indicates the encoding of sentence \( s_{o_j} \). The sentence encoding function \( \text{Enc}() \) and function LSTM() will be further interpreted in Section 2.3.

Notably, the initial state of encoder is \( e_0 = 0 \).

**Decoder** Similarly, the decoding representation of Ptr-Net is formalized as:

\[
d_i = \text{LSTM}(\text{Enc}(s_{o_i}), d_{i-1}), i = (1, \ldots, n) . \tag{7}
\]

Notably, the initial state of decoder is \( d_0 = e_n \).

2.3 Sentence Encoding

Since Ptr-Net receives fixed length vectors as inputs, we need firstly encode sentences with variational length. Inspired by Chen et al. (2016), we tried three types of encoders: continues bag of words (CBoW), convolutional neural networks (CNNs) and long short-term (LSTM) neural networks.

2.3.1 Continues Bag of Words

Continues bag of words (CBoW) model (Mikolov et al., 2013) simply averages the embeddings of words of a sentence. Formally, given the embeddings of \( n_w \) words of a sentence \( s \), \( w_1, \ldots, w_{n_w} \), the sentence embedding \( \text{Enc}(s) \) is:

\[
\text{Enc}(s) = \frac{1}{n_w} \sum_{k=1}^{n_w} w_k , \tag{8}
\]
where $\text{Enc}(s), w_k \in \mathbb{R}^{d_e}$. $d_e$ is a hyper-parameter, indicating word embedding size.

### 2.3.2 Convolutional Neural Networks

Convolutional neural networks (CNNs) (Simard et al., 2003) are biologically-inspired variants of multiple layer perceptions (MLPs). Formally, sentence $s$ with $n_w$ words could be encoded as:

$$
\text{cov}_k = \phi(W^T_{\text{cov}}(\oplus_{u=0}^{l-1} w_{k+u}) + b_{\text{cov}}),
$$

$$
\text{Enc}(s) = \max_k \text{cov}_k,
$$

where $W_{\text{cov}} \in \mathbb{R}^{(d \times l_f) \times d_f}$ and $b_{\text{cov}} \in \mathbb{R}^{d_f}$ are trainable parameters, and $\phi(\cdot)$ is tanh function. Here, $k = 1, \ldots, n_w - l_f + 1$, and $l_f$ and $d_f$ are hyper-parameters indicating the filter length and number of feature maps respectively. Notably, max operation in Eq (10) is a element-wise operation.

### 2.3.3 Long Short-term Neural Networks

Long short-term (LSTM) neural networks (Hochreiter and Schmidhuber, 1997) are advanced recurrent neural networks (RNNs), which alleviate the problems of gradient vanishment and explosion. Formally, LSTM has memory cells $c \in \mathbb{R}^{d_c}$ controlled by three kinds of gates: input gate $i \in \mathbb{R}^{d_r}$, forget gate $f \in \mathbb{R}^{d_r}$ and output gate $o \in \mathbb{R}^{d_r}$:

$$
\begin{bmatrix}
i_t \\
o_t \\
f_t \\
c_t \\
h_t
\end{bmatrix} =
\begin{bmatrix}
\sigma \\
\sigma \\
\sigma \\
\phi
\end{bmatrix}
\begin{bmatrix}
W_g^T & w_t & h_{t-1} & b_g
\end{bmatrix},
$$

$$
c_t = c_{t-1} \odot f_t + c_t \odot i_t,
$$

$$
h_t = o_t \odot \phi(c_t),
$$

where $W_g \in \mathbb{R}^{(d+d_r) \times 4d_r}$ and $b_g \in \mathbb{R}^{4d_r}$ are trainable parameters. $d_r$ is a hyper-parameter indicating the cell unit size as well as gate unit size. $\sigma(\cdot)$ is sigmoid function and $\phi(\cdot)$ is tanh function. Here, $t = 1, \ldots, n_w$. Thus, we would represent sentence $s$ as:

$$
\text{Enc}(s) = h_{n_w}.
$$

### 2.4 Order Prediction

Given $P(o|s)$, the predicted order $\hat{o}$ is the one with highest probability:

$$
\hat{o} = \arg \max_o P(o|s).
$$

Since the decoding process, to find $\hat{o}$, is a NP hard problem. Instead, we use two strategies to decode a sub optimal result: greedy decoding and beam search decoding.

**Greedy Decoding** At decoding phase of Prt-Net, greedy strategy determines $\hat{o} = \hat{o}_1, \ldots, \hat{o}_n$ step by step as:

$$
\hat{o}_i = \arg \max_{o_i} P(o_i|\hat{o}_{i-1}, \ldots, \hat{o}_1, s).
$$

**Beam Search Decoding** Beam search strategy always keeps top $b$ terms as candidates each step. Formally, at step $t$, each candidate $\hat{o}_t^i = \hat{o}_1, \ldots, \hat{o}_t$ has a probability:

$$
P(\hat{o}_t^i|s) = \prod_{i=1}^{t} P(\hat{o}_i|\hat{o}_{i-1}, \ldots, \hat{o}_1, s),
$$

and $b$ candidates with higher probabilities will be kept at $t$ step in the beam.

### 3 Training

Assuming that we have $m$ training examples $(x_i, y_i)_{i=1}^m$, where $x_i$ indicates a sequence of sentences with a specific permutation of $y_i$, and $y_i$ is in gold order $o^*$. For obtaining more training data, we randomly generate new permutation for $x_i$ at each epoch. The goal is to minimize the loss function $J(\theta)$:

$$
J(\theta) = -\frac{1}{m} \sum_{i=1}^{m} \log P(y_i|x_i; \theta) + \frac{\lambda}{2} \|\theta\|^2_2,
$$

where $P(y_i|x_i; \theta) = P(o^*|s = x_i; \theta)$ and $\lambda$ is a hyper-parameter of regularization term. $\theta$ indicates all trainable parameters.

In addition, we use AdaGrad (Duchi et al., 2011) with shuffled mini-batch to train our model. We also use pre-trained embeddings (Turian et al., 2010) as initialization.

### 4 Experiments

#### 4.1 Datasets

To evaluate proposed model, we adopt two datasets: abstracts on arXiv (Chen et al., 2016) and SIND (Sequential Image Narrative Dataset) (Ferraro et al., 2016). Examples in SIND dataset all contain 5 sentences, and we only use captions in this paper. The details of two datasets are shown in Table [1].
Table 3: Performances of different models on test sets of datasets. Since there is no noisy sentence here, we constrain the number of output sentences as the same as input, and three scores of PM and LSR are the same in this table.

| Models                  | arXiv | SIND |
|-------------------------|-------|------|
|                         | PM    | LSR  | PMR |
| (Chen et al., 2016)     | 82.97 | -    | 33.43 |
| (Agrawal et al., 2016)  | -     | -    | -    |
| CBoW+Ptr-Net            | 81.93 | 78.47| 33.09 |
| CNN+Ptr-Net             | 85.00 | 81.49| 38.62 |
| LSTM+Ptr-Net            | 85.62 | 82.15| 40.00 |
| +beam search            |       |      |      |
| CBoW+Ptr-Net            | 82.10 | 78.69| 33.43 |
| CNN+Ptr-Net             | 85.26 | 81.85| 39.28 |
| LSTM+Ptr-Net            | 85.79 | 82.40| 40.44 |

Table 1: Details of datasets. N indicates the number of texts. $S_{avg}$ is the average sentence number per text. $W_{avg}$ is the average word count per text.

| Attributes | arXiv | SIND |
|------------|-------|------|
|            | Train | Dev  | Test |
| Train      | 884,912| 110,614| 110,615|
| Dev        | 110,614| 110,615| 110,615|
| Test       | 40,155 | 4,990 | 5,055 |

Table 2: Hyper-parameter configurations.

4.2 Hyper-parameters

Table 2 gives the details of hyper-parameter configurations. The CNN sentence encoder uses three different filter lengths as Kim et al. (2015).

4.3 Metrics

To evaluate our model, we use three different metrics: (1) Pairwise metrics; (2) Longest sequence ratio; (3) Perfect match ratio.

**Pairwise Metrics** Pairwise metrics (PM) is the fraction of pairs of sentences whose predicted relative order is the same as the ground truth order (higher is better). Formally, pairwise metrics can be denoted as three scores: precision $P$, recall $R$ and $F$-value.

$$P = \frac{1}{m} \sum_{i=1}^{m} \frac{|S(\hat{o}_i) \cap S(o^*_i)|}{|S(\hat{o}_i)|},$$

$$R = \frac{1}{m} \sum_{i=1}^{m} \frac{|S(\hat{o}_i) \cap S(o^*_i)|}{|S(o^*_i)|},$$

$$F = \frac{2 \cdot P \cdot R}{P + R},$$

where function $S(\cdot)$ denotes the set of all skip bi-gram sentence pairs of a text, and function $|\cdot|$ indicates the size of set.

Concretely, we take $\{\hat{o} = (2, 3, 1, 4), o^* = (1, 3, 4)\}$ as an example, where 2nd sentence is a noisy term. The pairwise scores of this example are: $P = 1/6$, $R = 1/3$, $F = 2/9$.

**Longest Sequence Ratio** Longest sequence ratio (LSR) calculates the ratio of longest correct sub-sequence (consecutiveness is not necessary, and higher is better). Formally, LSR can be denoted as three scores: precision $P$, recall $R$ and $F$-value.

$$P = \frac{1}{m} \sum_{i=1}^{m} \frac{|L(\hat{o}_i, o^*_i)|}{|\hat{o}_i|},$$

Table 2: Hyper-parameter configurations.
Table 4: Performances of different models on test sets of datasets.

| Models         | arXiv | SIND |
|----------------|-------|------|
|                | Head  | Tail | Head  | Tail |
| (Chen et al., 2016) | 84.85 | 62.37 | -     | -    |
| CBoW+Ptr-Net   | 85.18 | 59.93 | 69.89 | 45.67 |
| CNN+Ptr-Net    | 89.59 | 64.48 | 72.54 | 48.80 |
| LSTM+Ptr-Net   | 90.77 | 65.80 | 75.24 | 52.62 |
| +beam search   | CBoW+Ptr-Net | 84.70 | 60.54 | 72.61 | 51.23 |
|                | CNN+Ptr-Net | 89.43 | 65.36 | 73.53 | 53.26 |
|                | LSTM+Ptr-Net | 90.47 | 66.49 | 74.66 | 53.30 |

Moreover, we investigate the performance of our model when sentence number varies. As Chen et al. (2016) did not evaluate their results on LSR metrics, we only compare with them on PM and PMR. As shown in Figure 2, our model with CNN and LSTM sentence encoders outperforms the work of (Chen et al., 2016). Although the accuracy of our model drops as the number of sentences increases, we could find that our model performs better on text with more sentences compared to pair-wise model.

Since first and last sentences are more special, we also evaluate the accuracy of finding the first and last sentences. As shown in Table 4 we also achieve significant boost compared to work of (Chen et al., 2016). As we can see, by using beam search, our model obtains higher accuracy on finding last sentence whereas performance of seeking first sentence drops. However, the performance in total is boosted by using beam search according to the results shown in Table 3, which implies that beam search strategy concentrates more on the entire text.

According to the experimental results above, we could find that Ptr-Net with LSTM sentence encoder almost outperforms the one with CBoW or CNN sentence encoder. Thus, we mainly focus on evaluating our model with LSTM sentence encoder in the rest of this paper.

4.5 Visualization

To further understand how our model works, we do some visualizations of Ptr-Net with CNN and LSTM sentence encoders. As shown in Table 5 the left side (first three columns) blue terms are input sentences. They are firstly encoded by sentence encoder (CNN or LSTM sentence encoder), then sent to the decoder of Ptr-Net. The right side (last column) red term is the first sentence that our model predicts. After that, this red item is encoded and sent to Prt-Net decoder to generate the 2nd sentence. This visualization shows how important each word is in generating the 2nd sentence. The more important the words are, the darker the color is. As we can see, by using CNN sentence encoder, the model focuses more on individual words, like “first”, “second”, which give strong signal for ordering. Contrastly, the model with LSTM sentence encoder trends to find a specific pattern (or compositional features). In this case, the model emphasizes the pattern “Our X
question regarding”, where X could be ordinal numbers like first and second here. However, both of them have some signals like words “indices”, “algorithm”, which might be disturbances and hard to interpret.

There still a question remains. How could we determine the importance of each word (the color)? Inspired by the back-propagation strategy (Erhan et al., 2009; Simonyan et al., 2013; Li et al., 2015; Chen et al., 2016), which measures how much each input unit contributes to the final decision, we can approximate the importance of words by their first derivatives. Formally, we aim to rank $n$ sentences in gold order $s_1, \ldots, s_n$. Assuming the predicted order would be $\hat{o}$ and we are predicting the $i$-th sentence $s_{\hat{o}_i}$, the importance of each word $w_{j,k}$ ($k$-th word in $j$-th sentence $s_{\hat{o}_j}$) is:

$$A(w_{j,k}^i) = \left| \frac{\partial P(\hat{o}_i|\hat{o}_{i-1}, \ldots, \hat{o}_1, s)}{\partial w_{j,k}^i} \right|,$$ (26)

where $w_{j,k}$ is word embedding of word $w_{j,k}^i$. Function $|\cdot|$ is the second order normalization operation. $P(\hat{o}_i|\hat{o}_{i-1}, \ldots, \hat{o}_1, s)$ is detailed in Eq. 5. For CBoW sentence encoder, the gradients of words in a sentence are the same for the simple average operation. Thus, we only visualize Ptr-Net with CNN and LSTM sentence encoders.

4.6 Noisy Sentences

Interestingly, we find our model could deal with the case well when additional noisy sentence exists. To evaluate the performance of our model on noisy sentences, we compare three different strategies in adding noises: (1) 0 noisy sentence (0 noise); (2) 1 noisy sentence (1 noise); (3) 1 noisy sentence with 50% probability (0/1 noise). All noisy sentences come from own datasets. Since all texts in SIND dataset contain 5 sentences, it is easy for model to tell if there is noisy sentence. Thus, we only evaluate our model on arXiv dataset as shown in Table 6.

As mentioned above, we only use the model with LSTM sentence encoder to evaluate the ability of our model on disambiguating noisy sentences, since it always performs better than the one with CBoW or CNN sentence encoder.

Although 0 noise version seems the same as the case in Table 3, they are actually different with each other. In this section, 0 noise version do not constrain the length of predicted sequence to be the same with input. In addition, the $P, R, F$ values of
Our second question regarding the function which computes minimal indices is whether one can compute a short list of candidate indices which includes a minimal index for a given program. We give some negative results and leave the possibility of positive results as open questions.

Our first question regarding the set of minimal indices is whether there exists an algorithm which can correctly label 1 out of k indices as either minimal or non minimal.

| Encoding | Decoding |
|---------|----------|
| **CNN sentence encoder** | | |
| 2 | 3 | 1 | 1 |
| **Our second question** | We give some negative results and leave the possibility of positive results as open questions | **Our first question regarding the set of minimal indices is whether there exists an algorithm which can correctly label 1 out of k indices as either minimal or non minimal** | **Our first question regarding the set of minimal indices is whether there exists an algorithm which can correctly label 1 out of k indices as either minimal or non minimal** |
| **Our first question regarding the set of minimal indices is whether there exists an algorithm which can correctly label 1 out of k indices as either minimal or non minimal** | **Our second question** regarding the function which computes minimal indices is whether one can compute a short list of candidate indices which includes a minimal index for a given program | **Our first question regarding the set of minimal indices is whether there exists an algorithm which can correctly label 1 out of k indices as either minimal or non minimal** | **Our first question regarding the set of minimal indices is whether there exists an algorithm which can correctly label 1 out of k indices as either minimal or non minimal** |
| **Encoding** | **Decoding** |
| **LSTM sentence encoder** | | |
| 2 | 3 | 1 | 1 |
| **Our second question** regarding the function which computes minimal indices is whether one can compute a short list of candidate indices which includes a minimal index for a given program | We give some negative results and leave the possibility of positive results as open questions | **Our first question regarding the set of minimal indices is whether there exists an algorithm which can correctly label 1 out of k indices as either minimal or non minimal** | **Our first question regarding the set of minimal indices is whether there exists an algorithm which can correctly label 1 out of k indices as either minimal or non minimal** |
| **Our first question regarding the set of minimal indices is whether there exists an algorithm which can correctly label 1 out of k indices as either minimal or non minimal** | **Our second question** regarding the function which computes minimal indices is whether one can compute a short list of candidate indices which includes a minimal index for a given program | **Our first question regarding the set of minimal indices is whether there exists an algorithm which can correctly label 1 out of k indices as either minimal or non minimal** | **Our first question regarding the set of minimal indices is whether there exists an algorithm which can correctly label 1 out of k indices as either minimal or non minimal** |

Table 5: Case Study. Color indicates importance of words in order prediction. The more important the words are, the darker the color is. In this case, models with CNN and LSTM sentence encoders all make correct predictions.

PM and LSR of 0 noise and 1 noise version are not the same actually, and very little difference exists (4 numbers after decimal point). It is because that our model is very good at eliminating the noise terms on 0 noise and 1 noise cases.

As we can see, our model performs best on 0 noise case, which implies that it is easier than 1 noise and 0/1 noise cases for our model. However, it is hard to say which one is more difficult among 1 noise and 0/1 noise cases, as the performance on different metrics are not consistent.

Similarly, the performance of our model is boosted by using beam search instead of greedy decoding.

### 4.7 Potential Oracle

In this section, we evaluate the potential of our model by figuring out what we find in the beam. With beam search strategy, we additionally obtain candidates in beam where the ground truth might appear.

According to the further analysis of candidates in beam, we find our model could hit ground truth with a very high probability. As show in Figure 3, our model could obtain 69.03% in PMR with beam size of 8 on test set of arXiv dataset without noisy sentences, and performance is further boosted with the larger beam size (82.78% in PMR with beam size of 64 on test set of arXiv dataset without noisy sentences). Notably, the performance boosts faster when beam size is smaller, which shows our model could rank ground truth in a top position in beam (the ground truth has higher score). Additionally, according to the results in Figure 3, we could tell that 0/1 noise case is a more difficult task for our model as the performance are worse than the 1 noise case. Notably, the results of potential oracle under PM and LSR metrics shown in Figure 3 are using F-value. When determining the best case in beam, we take the one with the highest F-value of PM or LSR metrics for each specific case.

Moreover, to identify whether the high performance in potential oracle is cause by the short texts (arXiv dataset has lots of texts with a few sentences) or not, we also evaluate the performance on SIND dataset (whose texts all contain 5 sentences). As
Table 6: Performances of different configuration of noise on test sets of arXiv dataset using Prt-Net with LSTM sentence encoder.

| Noise Configuration | PM     | LSR     | PMR     |
|---------------------|--------|---------|---------|
|                     | P      | R       | F       | P      | R       | F       |
| 0 noise             | 85.62  | 85.62   | 85.62   | 82.15  | 82.15   | 82.15   |
| 1 noise             | 81.82  | 81.82   | 81.82   | 80.47  | 80.47   | 80.47   |
| 0/1 noise           | 83.05  | 83.40   | 83.22   | 81.27  | 81.46   | 81.36   |
| **+beam search**    | **85.79** | **85.79** | **85.79** | **82.40** | **82.40** | **82.40** |
| 0 noise             | 82.28  | 82.28   | 82.28   | 80.92  | 80.92   | 80.92   |
| 1 noise             | 83.44  | 84.04   | 83.74   | 81.68  | 81.98   | 81.83   |

Figure 3: Oracles on different noise configurations on test set of arXiv dataset using LSTM sentence encoder. Data are selected with the beam sizes of 1, 2, 4, 8, 16, 32, 64 respectively.

shown in Figure 4, the performance in PMR metrics on SIND dataset is very similar to that on arXiv dataset, and our model could obtain 94.01% in PMR with beam size of 64 on test set of SIND dataset without noisy sentences.

Thus, we believe that we could further boost our performance a lot if we design a model to rerank the candidates.

5 Related Work

Previous works on sentence ordering mainly focused on the external and downstream applications, such as multi-document summarization and discourse coherence (Van Dijk, 1985; Grosz et al., 1995; Van Berkum et al., 1999; Elsner et al., 2007; Barzilay and Lapata, 2008). Barzilay and Elhadad (2002) proposed two naive sentence ordering techniques, such as majority ordering and chronological ordering, in the context of multi-document summarization. Lapata (2003) proposed a probabilistic model that assumes the probability of any given sentence is determined by its adjacent sentence and learns constraints on sentence order from a corpus of domain specific texts. Okazaki et al. (2004) improved chronological ordering by resolving antecedent sentences of arranged sentences and combining topical segmentation. Bollegala et al. (2010) presented a bottom-up approach to arrange sentences extracted for multi-document summarization.

Recently, increasing number of researches studied sentence ordering using neural models (Agrawal et al., 2016; Li and Jurafsky, 2016; Chen et al., 2016). Chen et al. (2016) framed sentence ordering as an isolated task and firstly applied neural methods on sentence ordering. In addition, they designed an interesting task of ordering the coherent sentences from academic abstracts. Agrawal et al. (2016) focused on a very similar ordering task which ranks image-caption pairs, additionally considering the image information. Li and Jurafsky (2016) mainly applied neural models to judge if a given text is coherent.
Despite of their success, they are all pair-wise based models, lack of contextual information. Unlike these work, we propose an end-to-end neural model based on Ptr-Net to address sentence ordering problem. A few days ago, Logeswaran et al. (2016) proposed a similar model based on recurrent neural networks to address sentence ordering problem. However, their work did not consider neither the case that noisy sentences involve nor alternative sentence encoders exist.

6 Conclusions

Sentence ordering is an important factor in natural language generation and attracts increasing focus recently. Previous works are mainly based on pairwise learning framework, which do not take contextual information into consideration and always lead to error propagation for their pipeline learning strategy. In this paper, we propose an end-to-end neural model based on Ptr-Net to address sentence ordering problem. Experimental results show that our model achieves the state-of-the-art performance even using greedy decoding strategy.

In the future, we would like to further improve the performance by reranking the candidates derived by beam search.

References

[Agrawal et al.2016] Harsh Agrawal, Arjun Chandrasekaran, Dhruv Batra, Devi Parikh, and Mohit Bansal. 2016. Sort story: Sorting jumbled images and captions into stories. arXiv preprint arXiv:1606.07493.

[Barzilay and Elhadad2002] Regina Barzilay and Noemie Elhadad. 2002. Inferring strategies for sentence ordering in multidocument news summarization. Journal of Artificial Intelligence Research, pages 35–55.

[Barzilay and Lapata2008] Regina Barzilay and Mirella Lapata. 2008. Modeling local coherence: An entity-based approach. Computational Linguistics, 34(1):1–34.

[Bollegala et al.2010] Danushka Bollegala, Naoaki Okazaki, and Mitsuru Ishizuka. 2010. A bottom-up approach to sentence ordering for multi-document summarization. Information processing & management, 46(1):89–109.

[Chen et al.2016] Xinchi Chen, Xipeng Qiu, and Xuanjing Huang. 2016. Neural sentence ordering. arXiv preprint arXiv:1607.06952.

[Duchi et al.2011] John Duchi, Elad Hazan, and Yoram Singer. 2011. Adaptive subgradient methods for online learning and stochastic optimization. The Journal of Machine Learning Research, 12:2121–2159.

[Elsner et al.2007] Micha Elsner, Joseph L Austerweil, and Eugene Charniak. 2007. A unified local and global model for discourse coherence. In HLT-NAACL, pages 436–443.

[Erhan et al.2009] Dumitru Erhan, Yoshua Bengio, Aaron Courville, and Pascal Vincent. 2009. Visualizing higher-layer features of a deep network. University of Montreal, 1341.

[Ferraro et al.2016] Francis Ferraro, Nasrin Mostafazadeh, Ishan Misra, Aishwarya Agrawal, Jacob Devlin, Ross Girshick, Xiaodong He, Pushmeet Kohli, Dhruv Batra, C Lawrence Zitnick, et al. 2016. Visual storytelling. arXiv preprint arXiv:1604.03968.

[Grosz et al.1995] Barbara J Grosz, Scott Weinstein, and Aravind K Joshi. 1995. Centering: A framework for modeling the local coherence of discourse. Computational linguistics, 21(2):203–225.

[Hochreiter and Schmidhuber1997] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural computation, 9(8):1735–1780.

[Kim et al.2015] Yoon Kim, Yacine Jernite, David Sonntag, and Alexander M Rush. 2015. Character-aware neural language models. arXiv preprint arXiv:1508.06615.

[Lapata2003] Mirella Lapata. 2003. Probabilistic text structuring: Experiments with sentence ordering. In Proceedings of the 41st Annual Meeting on Association for Computational Linguistics-Volume 1, pages 545–552.

[Li and Jurafsky2016] Jiwei Li and Dan Jurafsky. 2016. Neural net models for open-domain discourse coherence. arXiv preprint arXiv:1606.01545.

[Li et al.2015] Jiwei Li, Xinlei Chen, Eduard Hovy, and Dan Jurafsky. 2015. Visualizing and understanding neural models in nlp. arXiv preprint arXiv:1506.01666.

[Logeswaran et al.2016] Lajanugen Logeswaran, Honglak Lee, and Dragomir Radev. 2016. Sentence ordering using recurrent neural networks. arXiv preprint arXiv:1611.02654.

[Mikolov et al.2013] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781.

[Okazaki et al.2004] Naoaki Okazaki, Yutaka Matsuo, and Mitsuru Ishizuka. 2004. Improving chronological sentence ordering by precedence relation. In Proceedings of the 20th international conference on Computational Linguistics, page 750.
[Simard et al.2003] Patrice Y Simard, Dave Steinkraus, and John C Platt. 2003. Best practices for convolutional neural networks applied to visual document analysis. In null, page 958. IEEE.

[Simonyan et al.2013] Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. 2013. Deep inside convolutional networks: Visualising image classification models and saliency maps. arXiv preprint arXiv:1312.6034.

[Turian et al.2010] Joseph Turian, Lev Ratinov, and Yoshua Bengio. 2010. Word representations: a simple and general method for semi-supervised learning. In Proceedings of ACL.

[Van Berkum et al.1999] Jos JA Van Berkum, Peter Hagoort, and Colin Brown. 1999. Semantic integration in sentences and discourse: Evidence from the n400. Cognitive Neuroscience, Journal of, 11(6):657–671.

[Van Dijk1985] Teun A Van Dijk. 1985. Semantic discourse analysis. Handbook of discourse analysis, 2:103–136.

[Vinyals et al.2015] Oriol Vinyals, Meire Fortunato, and Navdeep Jaitly. 2015. Pointer networks. In Advances in Neural Information Processing Systems, pages 2692–2700.