Pruned Graph Neural Network for Short Story Ordering

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Abstract

Text coherence is a fundamental problem in natural language generation and understanding. Organizing sentences into an order that maximizes coherence is known as sentence ordering. This paper is proposing a new approach based on the graph neural network approach to encode a set of sentences and learn orderings of short stories. We propose a new method for constructing sentence-entity graphs of short stories to create the edges between sentences and reduce noise in our graph by replacing the pronouns with their referring entities. We improve the sentence ordering by introducing an aggregation method based on majority voting of state-of-the-art methods and our proposed one. Our approach employs a BERT-based model to learn semantic representations of the sentences. The results demonstrate that the proposed method significantly outperforms existing baselines on a corpus of short stories with a new state-of-the-art performance in terms of Perfect Match Ratio (PMR) and Kendall’s Tau ($\tau$) metrics. More precisely, our method increases PMR and $\tau$ criteria by more than 5% and 4.3%, respectively. These outcomes highlight the benefit of forming the edges between sentences based on their cosine similarity. We also observe that replacing pronouns with their referring entities effectively encodes sentences in sentence-entity graphs.

1 Introduction

Text coherence is a fundamental problem in natural language generation and understanding. A coherent text adheres to a logical order of events which facilitates better understanding. One of the subtasks in coherence modeling, called sentence ordering, refers to organizing shuffled sentences into an order that maximizes coherence (Barzilay and Lapata, 2008). Several downstream applications benefit from this task to assemble sound and easy-to-understand texts, such as extraction-based multi-document summarization (Barzilay and Elsadad, 2002; Galanis et al., 2012; Nallapati et al., 2017; Logeswaran et al., 2018), natural language generation (Reiter and Dale, 1997), retrieval-based question answering (Liu et al., 2018; Yu et al., 2018), concept-to-text generation (Konstas and Lapata, 2012), storytelling (Fan et al., 2019; Hu et al., 2020; Zhu et al., 2020), opinion generation (Yanase et al., 2015), conversational analysis (Zeng et al., 2018), image captioning (Anderson et al., 2018), recipe generation (Chandu et al., 2019), and discourse coherence (Elsner et al., 2007; Barzilay and Lapata, 2008; Guinaudeau and Strube, 2013).

In early studies, researchers modeled sentence structure using hand-crafted linguistic features (Lapata, 2003; Barzilay and Lee, 2004; Elsner et al., 2007; Barzilay and Lapata, 2008), nonetheless, these features are domain-specific. Therefore recent studies employed deep learning techniques to solve sentence ordering tasks (Golestani et al., 2021; Logeswaran et al., 2018; Gong et al., 2016; Li and Jurafsky, 2017; Chen et al., 2016).

(Cui et al., 2018) used graph neural networks, called ATTOderNet, to accomplish this task. They used a self-attention mechanism combined with LSTMs to encode input sentences. Their method could get a reliable representation of the set of sentences regardless of their input order. In this representation, an ordered sequence is generated using a pointer network. Since ATTOderNet is based on fully connected graph representations, it causes to build an association among some irrelevant sentences, which introduces massive noise into the network. Furthermore, since a self-attention mechanism only uses the information at the sentence level, other potentially helpful information such as entity information is missed.

To overcome these drawbacks, Yin et al. (2019) developed the Sentence-Entity Graph (SE-Graph), which adds entities to the graph. While in the ATTOderNet, every node is a sentence representation, SE-Graph consists of two types of nodes: sen-
sentence and entity\(^1\). Moreover, the edges come in two forms called SS and SE:

- **SS**: this edge is between sentence nodes that share a common entity,
- **SE**: this edge connects a sentence and an entity within the sentence labeled with the entity’s role.

However, the introduced methods perform poorly for short story reordering tasks. The SE-graph solution seems effective for long texts but not for short stories. In this paper, we suggest modifications to the introduced graph methods to improve the performance for short story reordering tasks. Some issues arise in short stories: First, entities are often not repeated in multiple sentences in a short story or text; instead, pronouns refer to an entity. To address this problem, we improve the semantic graph by replacing the pronouns with their corresponding entities. Another issue is a high correlation between the sentences in a short story along with a high commonality of entities across sentences, which leads us to end up with a complete graph in most cases. Our solution is moving towards a Pruned Graph (PG).

As with the ATTOrderNet and SE-Graph networks, the PG architecture consists of three components: 1. Sentence encoder based on SBERT-WK model (Wang and Kuo, 2020), 2. Graph-based neural story encoder, and 3. Pointer network based decoder.

With PG, the network nodes and SE edges are created based on SE-Graph, in a way that the first and third components are the same. However, in the story encoding phase, after generating the nodes and SE edges based on SE-Graph method, the pruning phase is started on SS edges. This pruning process is defined as follow: each sentence edged out its neighbors with the first and second most cosine similarities (Rahutomo et al., 2012). This method alleviates some problems of the previous two methods in the case of organizing short story sentences. It is noteworthy that pronouns are replaced with entities during pre-processing.

Finally, we present a method based on majority voting to combine our proposed graph network-based method with the state-of-art methods to benefit from each. Contributions of this study are as follows:

1. Proposing a new method based on graph networks to order sentences of a short stories corpus by:
   
   (a) suggesting a new method for creating the edges between sentences,

   (b) creating a better sentence-entity graph for short stories by replacing pronouns in sentences with entities,

   (c) Moreover, taking advantage of BERT-based sentence encoder.

2. Using majority voting to combine sentence ordering methods.

2 Related Work

2.1 Sentence Ordering

In early studies on sentence ordering, the structure of the document is modeled using hand-crafted linguistic features (Lapata, 2003; Barzilay and Lee, 2004; Elsner et al., 2007; Barzilay and Lapata, 2008). Lapata (2003) encoded sentences as vectors of linguistic features and used data to train a probabilistic transition model. Barzilay and Lee (2004) developed the content model in which topics in a specific domain are represented as states in an HMM. Some other like Barzilay and Lapata (2008) utilize the entity-based approach, which captures local coherence by modeling patterns of entity distributions. Other approaches used a combination of the entity grid and the content model Elsner et al. (2007) or employed syntactic features (Louis and Nenkova, 2012) in order to improve the model.

However, linguistic features are incredibly domain-specific, so applying these methods across different domains can decrease the performance. To overcome this limitation, recent works have used deep learning-based approaches. Li and Hovy (2014) proposes a neural model of distribution of sentence representations based on recurrent neural networks. In (Li and Jurafsky, 2017), graph-based neural models are used to generate a domain-independent neural model. Agrawal et al. (2016) introduced a method that involves combining two points elicited from the unary and pairwise model of sentences. Chen et al. (2016) used an LSTM encoder and beam search to construct a pairwise model. Based on a pointer network that provides advantages in capturing global coherence, Gong et al. (2016) developed an end-to-end approach that predicts order of sentences. In another work, by applying an encoder-decoder architecture based

\(^1\)the entity should be common to at least two sentences
In (Pour et al., 2020), we presented a method that does not require any training corpus due to not having a training phase. We also developed a framework based on a sentence-level language model to solve the sentence ordering problem in (Golestani et al., 2021). Moreover, in several other studies, including (Cui et al., 2018) and (Yin et al., 2019), graph neural networks are used to accomplish this task, as explained in the following.

2.2 Graph Neural Networks in NLP

Graph neural networks (GNN) have shown to be effective in NLP applications, including syntactic dependency trees (Marcheggiani and Titov, 2017), neural machine translation (Beck et al., 2018), knowledge graphs (Wang et al., 2018), semantic graphs (Song et al., 2018), sequence-to-graph learning (Johnson, 2017), graph-to-sequence learning (Beck et al., 2018), sentence ordering (Yin et al., 2019), and multi-document summarization (Christensen et al., 2013; Yasunaga et al., 2017).

In particular, text classification is a common application of GNNs in natural language processing. A GNN infers document labels based on the relationships among documents or words (Hamilton et al., 2017). Christensen et al. (2013) used a GNN in multi-document summarization. They create multi-document graphs which determine pairwise ordering constraints of sentences based on the discourse relationship between them. Kipf and Welling (2017) proposed Graph Convolutional Networks (GCN), which is used in Yasunaga et al. (2017) to generate sentence relation graphs. The final sentence embeddings indicate the graph representation and are utilized as inputs to achieve satisfactory results on multi-document summarization.

Another method is presented in Marcheggiani and Titov (2017) where a syntactic GCN is developed with a CNN/RNN as sentence encoder. The GCN indicates syntactic relations between words in a sentence. In a more recent work, Yin et al. (2019) proposed a graph-based neural network for sentence ordering, in which paragraphs are modeled as graphs where sentences and entities are the nodes. The method showed improvement in evaluation metrics for sentence ordering task. In this work, we explore the use of GRN for NLP tasks, especially to perform sentence-ordering on a corpus of short stories.

3 Baselines

This section introduces ATTOrderNet (Cui et al., 2018) and SE-Graph (Yin et al., 2019), which achieve state-of-the-art performances and serve as baseline for our work.

3.1 ATTOrderNet

ATTOrderNet introduced in (Cui et al., 2018) is a model using graph neural networks for sentence ordering. The model includes three components as follows: a sentence encoder based on Bi-LSTM, a paragraph encoder based on self-attention, and a pointer network-based decoder. In the sentence encoder, sentences are translated into distributional representations with a word embedding matrix. Then a sentence-level representation using the Bi-LSTM is learned. An average pooling layer follows multiple self-attention layers in the paragraph encoder. The paragraph encoder computes the attention scores for all pairs of sentences at different positions in the paragraph. Therefore, each sentence node is connected to all others where the encoder exploits latent dependency relations among sentences independent of their input order.

Having an input set of sentences, the decoder aims to predict a coherent order, identical to the original order. In this method, LSTM-based pointer networks are used to predict the correct sentence ordering from the final paragraph representation. Based on the sequence-to-sequence model, the pointer network-based decoders predict the correct sentence sequence (Sutskever et al., 2014). Specifically, input tokens are encoded using the pointer network as summary vectors\(^2\), and the next token vector is decoded repeatedly. Finally, the output token sequence is derived from the output token vector.

3.2 SE-Graph

SE-Graph, similarly to ATTOrderNet, consists of three components: 1. a sentence encoder based on Bi-LSTM, 2. a paragraph encoder, 3. a pointer network based decoder. Nevertheless, the difference between SE-Graph and ATTOrderNet is only in the encoder paragraph component, described in the following. In contrast to the fully connected

\(^2\)The paragraph vector is nonetheless influenced by the permutations of input sentences.
graph representations explored by ATTOderNet, Yin et al. (2019) represented input paragraphs as sentence-entity graphs. The SE-Graph includes two types of nodes: sentence and entity. The entity should be common to at least two sentences to be considered as a node of the graph. There are also two types of edges: SS edges that connect sentence nodes with at least a common entity, and SE edges that link a sentence with an entity within that and with a label of the entity’s role. SE edges are labeled based on the syntactic role of the entity in the sentence, such as a subject, an object, or other. When an entity appears multiple times in a sentence with different roles, the role that has the highest rank is considered. The highest rank of roles is the subject role; after that are the object roles. SE-Graph framework utilizes a GRN-based paragraph encoder that integrates the paragraph-level state along with the sentence-level state.

4 Methodology

In this section, first, the problem is formulated, second the dataset is introduced and explains why this dataset is suitable for the sentence ordering task. Then two methodologies are proposed. The first proposed method, called Pruned Graph, is based on graph networks, and the second is based on the majority voting to combine the outputs of three different models.

4.1 Problem Formulation

Consider $S(O)$ is a set of $n$ unordered sentences taken from a coherent text:

$$O = s_1, s_2, \ldots, s_n,$$

$$s(o_1) > s(o_2) > \cdots > s(o_n)$$  \hspace{1cm} (1)

The goal of sentence ordering is to find a permutation of sentences of $O$ like $S(o')$.

$$s(o'_1) > s(o'_2) > \cdots > s(o'_n)$$  \hspace{1cm} (2)

that corresponds to the gold data arrangement. In other words, sentence ordering aims to restore the original orders:

$$s(o^*_1) > s(o^*_2) > \cdots > s(o^*_n)$$  \hspace{1cm} (3)

Where $S(o^*)$ represents the original or gold order. As a result a correct output leads to $S(o') = S(o^*)$. Based on the above definition and notions we propose our sentence ordering method.

4.2 Dataset

In this paper, we used a corpus of short stories, called ROCStories (Mostafazadeh et al., 2016). It contains 98,162 commonsense stories, each with exactly five sentences and an average word count of 50. Mostafazadeh et al. (2017) created ROCStories corpus for a shared task called LSDSem, in which models are supposed to predict the correct ending to short stories. 3,742 of the stories have two options for the final sentence. It is worth noting that humans generated all of the stories and options.

We can learn sequences of daily events from this dataset because it contains some essential characteristics: The stories are rich with causal and temporal relations among events, which makes this dataset a highly useful resource for learning narrative structure across a wide range of events. The dataset consists of a comprehensive collection of daily and non-fictional short stories useful for modeling the coherence of a text (Mostafazadeh et al., 2016).

Due to these features, ROCStories can be used to learn sequences of sentences. Thus, the corpus is useful for organizing sentences in a text.

4.3 Pruned Graph Sentence Ordering (PG)

We propose a neural network based on the pruned graph for arranging the sentences of short stories, a modified version of the ATTOderNet (Cui et al., 2018) and Sentence-Entity Graph (Yin et al., 2019). The PG method consists of three components: sentence encoder, story encoder, and decoder. In order to be a fair comparison, we used the same decoder as ATTOderNet and SE-Graph. Due to space limitations, here we explain our sentence encoder and our story encoder. The Sentence encoder uses BERT encoding to encode sentences, while Story encoder uses a graph neural network for encoding stories.

4.3.1 Sentence Encoder: SBERT-WK

We use fine-tuned pre-trained SBERT-WK model to encode sentences. BERT contains several layers, each of which captures a different linguistic characteristic. SBERT-WK found better sentence representations by fusing information from different layers, Wang and Kuo (2020). The system geometrically analyzes space using a deep contextual model that is trained on both word-level and sentence-level, without further training. For each word in a sentence, it determines a unified word representation then computes the final sentence
embedding vector based on the weighted average based on the word importance of the word representations. Even with a small embedding size of 768, SBERT-WK outperforms other methods by a significant margin on textual similarity tasks (Wang and Kuo, 2020).

4.3.2 Story Encoder

To use graph neural networks for encoding stories, input stories should be represented as graphs. We propose a pruned graph (PG) representation instead of SE-Graph (Yin et al., 2019) for encoding short stories. Nodes in PG are composed of sentences and entities. We replace pronouns with the entities they refer to since entities are not often repeated from one sentence to another during a short story3, we will go into more detail in the experiments. We consider all nouns of an input story as entities at first. After that, we eliminate entities that do not occur more than once in the story.

We can formalize our undirected pruned graphs as $G = (V_s, V_e, E)$, where $V_s$ indicates the sentence-level nodes, $V_e$ denotes the entity-level nodes, and $E$ represents edges. Edges in PG graphs are divided into two types: SS and SE. The SS type links two sentences in a story that have the highest or second-highest value of cosine similarity with each other; and the SE type links a sentence with an entity within that with a label of the entity’s role. Equation 4 shows the formula for calculating the cosine similarity, where $CosSim$ is cosine similarity and $Emb_{s_i}$ represents vector of sentence $i$.

\[
CosSim(Emb_{s_i}, Emb_{s_j}) = \frac{Emb_{s_i} \ast Emb_{s_j}}{|Emb_{s_i}| \times |Emb_{s_j}|}
\]  

SE edges are labeled according to the syntactic role of the entity in the sentence, such as a subject, an object, or other. The role that has the highest rank in an instance of an entity appearing multiple times is considered. The ranking is as follows: subject role, object roles, and other. The use of referring entities rather than pronouns is crucial.

Thus, sentence nodes are linked to both sentence and entity nodes, whereas an entity node is not connected to any other entity nodes. For graph encoding, we use GRN (Zhang et al., 2018), which has been found effective for various kinds of graph encoding tasks. GRN used in our PG is the same as GRN in (Yin et al., 2019), so we do not explain it.

4.4 Majority Voting

We combine the output of three methods to achieve better results in majority voting. Since the stories in Rocstories all have five sentences, there are 20 possible pair sentence orderings as follow:

1. $s_1s_2$ or 2. $s_2s_1$, 3. $s_1s_4$ or 4. $s_3s_1$, 5. $s_1s_4$ or 6. $s_4s_1$, 7. $s_1s_5$ or 8. $s_5s_1$, 9. $s_2s_3$ or 10. $s_3s_2$, 11. $s_2s_4$ or 12. $s_4s_2$, 13. $s_2s_5$ or 14. $s_5s_2$, 15. $s_3s_4$ or 16. $s_4s_3$, 17. $s_3s_5$ or 18. $s_5s_3$, 19. $s_4s_5$ or 20. $s_5s_4$

Each suggested order for a story includes 10 of the above pair orderings, either of the two pair orderings that have an “or” between them. Through majority voting4, we can combine the outputs of three separate methods to generate a final order.

According to the number of occurrences in each of the three output arrangements, we assign scores to each of the 20 possible pairings. As a result, each of these possible pairings is scored between 0 and 3. 0 indicates that this pairing does not appear in any of the three methods’ outputs, while 3 indicates that it appears in all of them. In the end, all pairs with a greater score of 1 occur in the final orderings3. Indeed, these are ten pairs5, and with the chosen pairs, the sentences of the story are arranged uniquely.

In the following subsection, we are proving that majority voting is a valid way to combine the outputs generated from three different methods for arranging sentences. By using contradiction, we demonstrate the validity of the majority voting method for combining three distinct methods of sentence ordering to arrange two sentences.

Assuming the majority voting of three methods fails to create an unique order, then two orders are possible, $s_1s_2$ and $s_2s_1$. In the first case, $s_1$ appears before $s_2$ in two or more outputs of the methods, and in the second case, $s_2$ appears before $s_1$ in two or more outputs. Due to the three methods, this assumption causes a contradiction. To

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3we use the Stanford’s tool (Lee et al., 2011)
4For example, either $s_1s_2$ or $s_2s_1$ occurs, and without a doubt, the co-occurrence of these is a vast and impossible contradiction.
5Suppose the outputs of the three methods for arranging $sentence_1 (s_1)$ and $sentence_2 (s_2)$ are: Method 1: $s_1s_2$, Method 2: $s_1s_2$, and Method 3: $s_2s_1$. Therefore, the order $s_1s_2$ gets two points and the order $s_2s_1$ gets one, so $s_1s_2$ applies to the final output.
6either of the two pair orderings that have an “or” between them.
ordering more than two sentences, it can be proved by induction.

5 Experiment

5.1 Evaluation Metrics

We use two standard metrics to evaluate the proposed model outputs that are commonly used in previous work: Kendall’s tau and perfect match ratio, as described below.

- **Kendall’s Tau ($\tau$)**

  Kendall’s Tau (Lapata, 2006) measures the quality of the output’s ordering, computed as follows:

  $$\tau = 1 - \frac{2 \times \text{# of Inversions}}{N \times (N - 1)/2} \quad (5)$$

  Where $N$ represents the sequence length (i.e. the number of sentences of a story, which is always equal to 5 for ROCStories), and the inversions return the number of exchanges of the predicted order with the gold order for reconstructing the correct order. $\tau$ is always between -1 and 1, where the upper bound indicates that the predicted order is exactly the same as the gold order. This metric correlates reliably with human judgments, according to Lapata (2006).

- **Perfect Match Ratio (PMR)**

  According to this ratio, each story is considered as a single unit, and a ratio of the number of correct orders is calculated. Therefore no penalties are given for incorrect permutations (Gong et al., 2016). PMR is formulated mathematically as follows:

  $$PMR = 1/N \sum_{i=1}^{N} o_i' = o_i^* \quad (6)$$

  where $o_i'$ represents the output order and $o_i^*$ indicates the gold order. $N$ specifies the sequence length. Since the length of all the stories of ROCStories is equal to 5, $N$ in this study is always equal to 5. PMR values range from 0 to 1, with a higher value indicating better performance.

5.2 Contrast Models

We compare our PG to the state of the arts, namely the following: 1. LSTM + PtrNet (Gong et al., 2016), 2. LSTM + Set2Seq (Logeswaran et al., 2018), 3. ATTOrderNet (Cui et al., 2018), 4. SE-Graph (Yin et al., 2019), 5. HAN (Wang and Wan, 2019), 6. SLM (Golestani et al., 2021), 7. Rank-TxNet ListMLE (Kumar et al., 2020), 8. Enhancing PtrNet + Pairwise (Yin et al., 2020), 9. B-TSort (Prabhumoye et al., 2020). We teach LSTM + PtrNet, ATTOrderNet, SE-Graph, and B-TSort on the ROCStories. The following is a brief description of the mentioned methods, but We refer to Section 3 to explain ATTOrderNet and SE-Graph.

Gong et al. (2016) proposes LSTM + PtrNet as a method for ordering sentences. In this end-to-end method, pointer networks sort encrypted sentences after decoding them by LSTM. Logeswaran et al. (2018) recommended LSTM + Set2Seq. Their method encodes sentences, learns context representation by LSTM and attention mechanisms, and utilizes a pointer network-based decoder to predict sentences’ order. A transformer followed by an LSTM was added to the sentence encoder in (Wang and Wan, 2019) to capture word clues and dependencies between sentences; and so on, HAN is developed.

In (Golestani et al., 2021), we developed the Sentence-level Language Model (SLM) for Sentence Ordering, consisting of a Sentence Encoder, a Story Encoder, and a Sentence Organizer. The sentence encoder encodes sentences into a vector using a fine-tuned pre-trained BERT. Hence, the embedding pays more attention to the sentence’s crucial parts. Afterward, the story encoder uses a decoder-encoder architecture to learn the sentence-level language model. The learned vector from the hidden state is decoded, and this decoded vector is utilized to indicate the following sentence’s candidate. Finally, the sentence organizer uses the cosine similarity as the scoring function in order to sort the sentences.

An attention-based ranking framework is presented in (Kumar et al., 2020) to address the task. The model uses a bidirectional sentence encoder and a self-attention-based transformer network to encode paragraphs. In (Yin et al., 2020), an enhancing pointer network based on two pairwise ordering prediction modules, The FUTURE and HISTORY module, is employed to decode paragraphs. Based on the candidate sentence, the FU-
TURE module predicts the relative positions of other unordered sentences. Although, the HISTORY module determines the coherency between the candidate and previously ordered sentences. And lastly, Prabhumoye et al. (2020) designed B-TSort, a pairwise ordering method, which is the current state-of-the-art method for sentence ordering. This method benefits from BERT and graph-based networks. Based on the relative pairwise ordering, graphs are constructed. Finally, the global order is derived by a topological sort algorithm on the graph.

5.3 Setting

For a fair comparison, we follow Yin et al. (2019)’s settings. Nevertheless, we use SBERT-WK’s 768-dimension vectors for sentence embedding. Furthermore, the state sizes for sentence nodes are set to 768 in the GRN; The Batch size is 32. In preprocessing, we use Stanford’s tool (Lee et al., 2011) to replace pronouns with the referring entities.

5.4 Results

In this paper, we propose a new method based on graph networks for sentences ordering short stories called Pruned Graph (PG). In order to achieve this, we propose a new method for creating edges between sentences (by calculating the cosine similarity between sentences), and we create a better sentence-entity graph for short stories by replacing pronouns with the relevant entities. Besides, to make a better comparison, we also teach the following cases:

1. All nodes in the graph are of the sentence type, and the graph is fully connected. In other words, we train ATTOrderNet on ROC-Stories7.

2. The nodes include sentence and entity nodes, and each sentence’s node has the edge over all other sentences’ nodes (semi fully connected SE-Graph8).

3. The network comprises sentence and entity nodes, and every two sentences with at least one entity in common are connected (SE-Graph9).

4. Replacing pronouns with the relevant entities in SE-Graph (SE-Graph + Co-referencing).

5. Similar to PG, but each sentence is connected to a sentence with the highest cosine similarity (semi $PG_1$).

6. Similar to PG; however, each sentence is connected to three other sentences based on their cosine similarity (semi $PG_3$).

7. Pruned Graph with a Bi-LSTM based sentence encoder10 ($PG'$).

Note that in the above methods, where the graph also contains the nodes of the entity, there is an edge between a sentence and an entity within it11. Table 1 reports the results of Pruned Graph (PG) and the above seven methods.

To get the training, validation, and testing datasets, we randomly split ROCStories into 8:1:1. Therefore, the training set includes 78,529 stories, the validation set contains 9,816 stories, and the testing set consists of 9,817 stories.

As shown in table 1, our PG beats all seven other methods. The results show that all three of our innovations to the graph-based method have improved the performance. Based on our analysis, the SBERT-WK sentence encoder is more beneficial than the Bi-LSTM. Our experiences also find that using referring entities instead of pronouns is helpful to create a more effective sentence-entity graph. Additionally, it indicates connecting each sentence to two others using cosine similarity is efficient to encode a story.

Table 2 reports the results of the proposed method of this paper in comparison with competitors. When compared with ATTOrderNet, PG improved the Tau by over 8.5% as well as PMR by 13.5%. Furthermore, the Tau is increased by 10.8% and the PMR by more than 16.8% compared to SE-Graph. PG outperforms the state-of-the-art on ROCStories with a more than 1.8% increase in pmr and a more than 3.9% improvement in $\tau$.

Finally, we merged the outputs of the three methods using the majority voting method, including Enhancing PtrNet, B-TSort, and Our Pruned Graph. Table 3 shows the results of the combination, which improves the PMR and $\tau$ criteria by more than 5% and 4.3% on ROCStories, respectively.

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7(Cui et al., 2018) did not train ATTOrderNet on the ROC-Stories dataset.

8Entity nodes are not connected to all nodes.

9We train SE-Graph on ROCStories since (Yin et al., 2019) did not.

10To demonstrate the advantages of the PG’s BERT-based sentence encoder, this component is considered exactly like the sentence encoder of SE-Graph and ATTOrderNet.

11Entity nodes can only have a link to sentence nodes.
| Method               | $\tau$  | PMR   |
|---------------------|---------|-------|
| ATTOrderNet         | 0.7364  | 0.4030|
| Fully connected SE-Graph | 0.7300  | 0.3927|
| SE-Graph            | 0.7133  | 0.3687|
| SE-Graph + Co-ref   | 0.7301  | 0.3981|
| PG+ 1 SS            | 0.7534  | 0.4349|
| PG + 3 SS           | 0.7379  | 0.4100|
| PG + Bi-LSTM-based sentence encoder | 0.7852  | 0.4769|
| Pruned Graph        | 0.8220  | 0.5373|

Table 1: Reporting the results of the proposed network called Pruned Graph in comparison with the seven methods mentioned above

| Model               | $\tau$  | PMR   |
|---------------------|---------|-------|
| LSTM+PtrNet         | 0.7230  | 0.3647|
| LSTM+Set2Seq        | 0.7112  | 0.3581|
| ATTOrderNet         | 0.7364  | 0.4030|
| SE-Graph            | 0.7133  | 0.3687|
| HAN                 | 0.7322  | 0.3962|
| SLM                 | 0.7547  | 0.4064|
| RankTxNet ListMLE   | 0.7602  | 0.3602|
| Enhancing PtrNet + Pairwise | 0.7681  | 0.4600|
| B-TSort             | 0.8039  | 0.4980|
| Our Pruned Graph    | 0.8220  | 0.5373|

Table 2: Results of our PG compared to baselines and competitors

### 6 conclusion

This paper introduced a graph-based neural framework to solve the sentence ordering task. This framework takes a set of randomly ordered sentences and outputs a coherent order of the sentences. The results demonstrate that SBERT-WK is a reliable model to encode sentences. Our analysis examined how the method is affected by using a Bi-LSTM model in the sentence encoder component. In addition, we found that replacing pronouns with their referring entities supplies a more informative sentence-entity graph to encode a story. The experimental results indicate that our proposed graph-based neural model significantly outperforms on ROCStories dataset. Furthermore, we recommend a method for combining different methods of sentence ordering based on majority voting that achieves state-of-the-art performance in PMR and $\tau$ scores. In future, we plan to apply the trained model on sentence ordering task to tackle other tasks including text generation, dialogue generation, text completion, retrieval-based QA, and extractive text summarization.

### References

Harsh Agrawal, Arjun Chandrasekaran, Dhruv Batra, Devi Parikh, and Mohit Bansal. 2016. Sort story: Sorting jumbled images and captions into stories. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 925–931, Austin, Texas. Association for Computational Linguistics.

Peter Anderson, Xiaodong He, Chris Buehler, Damien Teney, Mark Johnson, Stephen Gould, and Lei Zhang. 2018. Bottom-up and top-down attention for image captioning and visual question answering. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 6077–6086.

Regina Barzilay and Noemie Elhadad. 2002. Inferring strategies for sentence ordering in multidocument news summarization. Journal of Artificial Intelligence Research, 17:35–55.

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

Regina Barzilay and Lillian Lee. 2004. Catching the drift: Probabilistic content models, with applications to generation and summarization. In Proceedings of the Human Language Technology Conference of the North American Chapter of the Association for Computational Linguistics: HLT-NAACL 2004, pages 113–120.

Daniel Beck, Gholamreza Haffari, and Trevor Cohn. 2018. Graph-to-sequence learning using gated graph neural networks. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 273–283, Melbourne, Australia. Association for Computational Linguistics.

Khyathi Chandu, Eric Nyberg, and Alan W Black. 2019. Storyboarding of recipes: grounded contextual generation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 6040–6046.
Xinchi Chen, Xipeng Qiu, and Xuanjing Huang. 2016. Neural sentence ordering. *arXiv preprint arXiv:1607.06952*.

Janara Christensen, Mausam, Stephen Soderland, and Oren Etzioni. 2013. Towards coherent multi-document summarization. In *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1163–1173, Atlanta, Georgia. Association for Computational Linguistics.

Baiyun Cui, Yingming Li, Ming Chen, and Zhongfei Zhang. 2018. Deep attentive sentence ordering network. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 4340–4349.

Micha Elsner, Joseph Austerweil, and Eugene Charniak. 2007. A unified local and global model for discourse coherence. In *Human Language Technologies 2007: The Conference of the North American Chapter of the Association for Computational Linguistics: Proceedings of the Main Conference*, pages 436–443.

Angela Fan, Mike Lewis, and Yann Dauphin. 2019. Strategies for structuring story generation. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 2650–2660, Florence, Italy. Association for Computational Linguistics.

Dimitrios Galanis, Gerasimos Lampouras, and Ion Androutsopoulos. 2012. Extractive multi-document summarization with integer linear programming and support vector regression. In *Proceedings of COLING 2012*, pages 911–926.

Melika Golestani, Seyedeh Zahra Razavi, Zeinab Borhanifar, Farnaz Tahmasebian, and Hesham Faili. 2021. Using bert encoding and sentence-level language model for sentence ordering. In *Text, Speech, and Dialogue*, pages 318–330, Cham. Springer International Publishing.

Jingjing Gong, Xinchi Chen, Xipeng Qiu, and Xuanjing Huang. 2016. End-to-end neural sentence ordering using pointer network. *arXiv preprint arXiv:1611.04953*.

Camille Guinaudeau and Michael Strube. 2013. Graph-based local coherence modeling. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 93–103.

William L. Hamilton, Rex Ying, and Jure Leskovec. 2017. Inductive representation learning on large graphs. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, NIPS’17, page 1025–1035, Red Hook, NY, USA. Curran Associates Inc.

Junjie Hu, Yu Cheng, Zhe Gan, Jingjing Liu, Jianfeng Gao, and Graham Neubig. 2020. What makes a good story? designing composite rewards for visual storytelling. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 7969–7976.

D. Johnson. 2017. Learning graphical state transitions. In *ICLR*.

Thomas N Kipf and Max Welling. 2017. Semi-supervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907*.

Ioannis Konstas and Mirella Lapata. 2012. Concept-to-text generation via discriminative reranking. In *Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 369–378.

Pawan Kumar, Dhanajit Brahma, Harish Karnick, and Piyush Rai. 2020. Deep attentive ranking networks for learning to order sentences. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 8115–8122.

Mirella Lapata. 2003. Probabilistic text structuring: Experiments with sentence ordering. In *Proceedings of the 41st Annual Meeting of the Association for Computational Linguistics*, pages 545–552.

Mirella Lapata. 2006. Automatic evaluation of information ordering: Kendall’s tau. *Computational Linguistics*, 32(4):471–484.

Heeyoung Lee, Yves Peirsman, Angel Chang, Nathanael Chambers, Mihai Surdeanu, and Dan Jurafsky. 2011. Stanford’s multi-pass sieve coreference resolution system at the conll-2011 shared task. In *Proceedings of the 15th conference on computational natural language learning: Shared task*, pages 28–34. Association for Computational Linguistics.

Jiwei Li and Eduard Hovy. 2014. A model of coherence based on distributed sentence representation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 2039–2048.

Jiwei Li and Dan Jurafsky. 2017. Neural net models of open-domain discourse coherence. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 198–209, Copenhagen, Denmark. Association for Computational Linguistics.

Xiaodong Liu, Yelong Shen, Kevin Duh, and Jianfeng Gao. 2018. Stochastic answer networks for machine reading comprehension. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1694–1704, Melbourne, Australia. Association for Computational Linguistics.
Lajanugen Logeswaran, Honglak Lee, and Dragomir Radev. 2018. Sentence ordering and coherence modeling using recurrent neural networks. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 32.

Annie Louis and Ani Nenkova. 2012. A coherence model based on syntactic patterns. In *Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning*, pages 1157–1168.

Diego Marcheggiani and Ivan Titov. 2017. Encoding sentences with graph convolutional networks for semantic role labeling. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 1506–1515, Copenhagen, Denmark. Association for Computational Linguistics.

Nasrin Mostafazadeh, Nathanael Chambers, Xiaodong He, Devi Parikh, Dhruv Batra, Lucy Vanderwende, Pushmeet Kohli, and James Allen. 2016. A corpus and cloze evaluation for deeper understanding of commonsense stories. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 839–849, San Diego, California. Association for Computational Linguistics.

Nasrin Mostafazadeh, Michael Roth, Annie Louis, Nathanael Chambers, and James Allen. 2017. LS-DSem 2017 shared task: The story cloze test. In *Proceedings of the 2nd Workshop on Linking Models of Lexical, Sentential and Discourse-level Semantics*, pages 46–51, Valencia, Spain. Association for Computational Linguistics.

Ramesh Nallapati, Feifei Zhai, and Bowen Zhou. 2017. Summarunner: A recurrent neural network based sequence model for extractive summarization of documents. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 31.

Melika Golestani Pour, Seyedeh Zahra Razavi, and He-shaam Faihli. 2020. A new sentence ordering method using bert pretrained model. In *2020 11th International Conference on Information and Knowledge Technology (IKT)*, pages 132–138. IEEE.

Shrimai Prabhumoye, Ruslan Salakhutdinov, and Alan W BlacK. 2020. Topological sort for sentence ordering. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 2783–2792, Online. Association for Computational Linguistics.

Faisal Rahutomo, Teruaki Kitsuka, and Masayoshi Artsugi. 2012. Semantic cosine similarity. In *The 7th International Student Conference on Advanced Science and Technology ICAST*, volume 4, page 1.

Ehud Reiter and Robert Dale. 1997. Building applied natural language generation systems. *Natural Language Engineering*, 3(1):57–87.

Linfeng Song, Yue Zhang, Zhiguo Wang, and Daniel Gildea. 2018. N-ary relation extraction using graph-state LSTM. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2226–2235, Brussels, Belgium. Association for Computational Linguistics.

Ilya Sutskever, Oriol Vinyals, and Quoc V. Le. 2014. Sequence to sequence learning with neural networks. In *Proceedings of the 27th International Conference on Neural Information Processing Systems - Volume 2*, NIPS’14, page 3104–3112, Cambridge, MA, USA. MIT Press.

Bin Wang and C-C Jay Kuo. 2020. Shert-wk: A sentence embedding method by dissecting bert-based word models. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 28:2146–2157.

Tianming Wang and Xiaojun Wan. 2019. Hierarchical attention networks for sentence ordering. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 7184–7191.

Zhichun Wang, Qingsong Lv, Xiaohan Lan, and Yu Zhang. 2018. Cross-lingual knowledge graph alignment via graph convolutional networks. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 349–357, Brussels, Belgium. Association for Computational Linguistics.

Toshihiko Yanase, Toshinori Miyoshi, Kohsuke Yanai, Misa Sato, Makoto Iwayama, Yoshiki Niwa, Paul Reisert, and Kentaro Inui. 2015. Learning sentence ordering for opinion generation of debate. In *Proceedings of the 2nd Workshop on Argumentation Mining*, pages 94–103.

Michihiro Yasunaga, Rui Zhang, Kshitij Meelu, Ayush Pareek, Krishnan Srinivasan, and Dragomir Radev. 2017. Graph-based neural multi-document summarization. In *Proceedings of the 21st Conference on Computational Natural Language Learning (CoNLL 2017)*, pages 452–462, Vancouver, Canada. Association for Computational Linguistics.

Yongjinyu Yin, Fandong Meng, Jingsong Su, Yubin Ge, Lingeng Song, Jie Zhou, and Jiebo Luo. 2020. Enhancing pointer network for sentence ordering with pairwise ordering predictions. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 9482–9489.

Yongjinyu Yin, Linfeng Song, Jingsong Su, Jiali Zeng, Chulun Zhou, and Jiebo Luo. 2019. Graph-based neural sentence ordering. In *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI-19*, pages 5387–5393. International Joint Conferences on Artificial Intelligence Organization.

Adams Wei Yu, David Dohan, Minh-Thang Luong, Rui Zhao, Kai Chen, Mohammad Norouzi, and Quoc V Le. 2018. Qanet: Combining local convolution
with global self-attention for reading comprehension. arXiv preprint arXiv:1804.09541.

Xingshan Zeng, Jing Li, Lu Wang, Nicholas Beauchamp, Sarah Shugars, and Kam-Fai Wong. 2018. Microblog conversation recommendation via joint modeling of topics and discourse. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 375–385.

Yue Zhang, Qi Liu, and Linfeng Song. 2018. Sentence-state LSTM for text representation. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 317–327, Melbourne, Australia. Association for Computational Linguistics.

Yutao Zhu, Ruihua Song, Zhicheng Dou, Jian-Yun Nie, and Jin Zhou. 2020. ScriptWriter: Narrative-guided script generation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 8647–8657, Online. Association for Computational Linguistics.