Graph-based Multi-hop Reasoning for Long Text Generation

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Abstract
Long text generation is an important but challenging task. The main problem lies in learning sentence-level semantic dependencies which traditional generative models often suffer from. To address this problem, we propose a Multi-hop Reasoning Generation (MRG) approach that incorporates multi-hop reasoning over a knowledge graph to learn semantic dependencies among sentences. MRG consists of two parts, a graph-based multi-hop reasoning module and a path-aware sentence realization module. The reasoning module is responsible for searching skeleton paths from a knowledge graph to imitate the imagination process in the human writing for semantic transfer. Based on the inferred paths, the sentence realization module then generates a complete sentence. Unlike previous black-box models, MRG explicitly infers the skeleton path, which provides explanatory views to understand how the proposed model works. We conduct experiments on three representative tasks, including story generation, review generation, and product description generation. Automatic and manual evaluation show that our proposed method can generate more informative and coherent long text than strong baselines, such as pre-trained models (e.g. GPT-2) and knowledge-enhanced models.

Introduction
Long text generation is an important task and is applicable in a number of fields. It requires a model to generate a coherent and informative long text sequence which consists of several sentences based on free-format source text, such as a table, a topic sentence, or even some keywords (Barzilay and Lapata 2005, McIntyre and Lapata 2009, Feng et al. 2018). Recently, these techniques have been applied to many real-world tasks, like automatic story generation (McIntyre and Lapata 2009), review generation (Zang and Wan 2017) as well as product description generation (Chen et al. 2019).

Long text generation is more challenging than single sentence generation (Langkilde 2000) in that it requires a model to learn the sentence-level semantic dependencies. Compared with word-level semantic dependencies in a single sentence, sentence-level semantic dependencies are a kind of long-distance dependency that are harder to learn. Current end-to-end generative models (Sutskever, Vinyals, and Le 2014, Vaswani et al. 2017) often adopt an attention mechanism to model the context dependencies, which fuses all word information together to generate the next word in a weighting way. Despite promising results in single sentence generation, these models suffer from complicated and sparse dependencies in long text generation with much longer contexts. Such dependencies make models hard to learn sufficient knowledge to infer semantic transfer among sentences. Thus, these models tend to generate repetitive and boring sentences like a context-free language model, as shown in Figure 1. In comparison, human can write diverse texts with coherent semantic transfer among sentences with their imagination. Imagination is said to be a part of literacy process and it highly contributes to writing (Colella 2007).

Motivated by human writing, we propose to endow text generation models with the imaginative power. To achieve this goal, we present a novel two-stage approach that imitates the semantic transfer in human writing. In the first stage, a graph-based reasoning module is responsible for inferring paths to select skeleton concepts based on the topic sentence and previously generated sentences via multi-hop reasoning on a knowledge graph. In the second stage, the path-aware sentence realization module approximates the semantic transfer in human writing. For illustration, we highlight several skeleton words important for sentence-level semantic dependencies. In contrast, the machine-generated text is boring and repetitive.

Figure 1: The comparison between stories generated by a human and a widely-used generative model Transformer. As shown in the example, human can create diverse and coherent sentences with their imagination. For illustration, we highlight several skeleton words important for sentence-level semantic dependencies. In contrast, the machine-generated text is boring and repetitive.
Overview

The architecture illustration of the proposed MRG model is shown in Figure 2. At each sentence-level generation, the reasoning module first infers skeleton paths from a knowledge graph to imitate the imagination in the human writing for coherent sentence-level semantic transfer. Specifically, the inferred paths start from the concepts in the input sentences for initialization. The reasoning module iteratively adds new nodes into the inferred paths. At each reasoning step, the module first finds all neighbor nodes of current inferred paths as candidate nodes and predicts their labels. We define three kinds of labels, including target concept (ending of the inferred path), intermediate concept (middle node in the inferred path), and other concept (node not in the inferred path). For intermediate concepts, the module adds them into the inferred path and keeps the reasoning process. For target concepts, the module adds them to the inferred path and stops the reasoning process. For other concepts, the module just stops the reasoning process. We treat the inferred skeleton paths as pivots connecting semantics among sentences. Then, the realization module takes the inferred paths as inputs and decodes a complete sentence.

Graph-based Multi-hop Reasoning

The graph-based multi-hop reasoning module is responsible for learning the semantic dependencies among sentences via conceptual paths. This module explores on the knowledge graph to find a path that can connect concepts in the context with concepts in its subsequent sentence through intermediate concepts. Specifically, for a concept $v_1$ in a source sentence and $v_2$ in its subsequent sentence, their connected path is essential to semantic transfer. MRG performs reasoning on a knowledge graph, which starts at the concepts in the source sentence and ends at the target concepts. The inferred concept chains form multiple conceptual paths. In the implementation, the reasoning module performs sequence labeling for nodes in a knowledge graph conditional on source input. Concretely, at the 1st hop, the input for the module is a sequence of the
source context and their concepts on the graph \( T^{(1)} = \{x_1, \ldots, x_n, [SEP], v_1^{(1)}, \ldots, v_n^{(1)}\} \). The reasoning module learns to predict their labels of the concepts. When reaching an intermediate concept, MRG moves to the next hop and collects its neighbors. The reasoning of neighbors continues and the module repeats the learning of sequence labeling until it meets concepts other than intermediate ones or the module reaches the max number of hop. In the inference stage, the reasoning module infers multiple paths and finds out possible target concepts and intermediate concepts. We adopt the powerful pretrained model BERT (Devlin et al. 2019) as the backbone. Below we provide more details of the module.

**BERT-based Labeller** The module is a sequence labeling model with BERT as the encoder. The goal of BERT encoder is to provide a representation for conditional sequence labeling. At the \( k \)-hop reasoning step, it takes \( T^{(k)} = \{x_1, \ldots, x_n, [SEP], v_1^{(k)}, \ldots, v_n^{(k)}\} \) as the input, where \( l \) is the number of neighbors of the previous intermediate nodes, and generates hidden representations:

\[
h^{(i)} = BERT(T^{(i)}),
\]

where \( h^{(i)} \) is a vector sequence. Each vector is the representation of the word at the corresponding position. For simplicity, we omit the details of BERT, and refer the readers to the original work (Devlin et al. 2019).

On top of the BERT encoder, we add a classifier layer for labeling based on Multi-Layer Perceptron (MLP). The input of the classifier is the representation in the last layer of the BERT encoder \( h^{(i)} \). The following computation demonstrates how to predict the label \( l_r \) at position \( r \):

\[
p(l_r|h^{(i*)}) = \text{softmax}(W_e h^{(i*)} + b_e),
\]

where \( W_e \) and \( b_e \) are the weight matrix and bias term. We mask the losses of context words when doing sequence labeling.

**Path-aware Sentence Realization**

The path-aware sentence realization module aims at generating a sentence that approximates the target based on the inferred paths. We adopt the architecture of Transformer (Vaswani et al. 2017) for sentence realization. In the following, we illustrate the details of data preparation and module architecture.

**Data Preparation** As shown in Figure 2, we extract the inferred paths from the knowledge graph \( G \) to build a subgraph \( G^\prime = \{x_{i_1}, y_{i_2}, \ldots, x_{i_n}, [SEP], v_1^{(k)}, \ldots, v_m^{(k)}\} \) for sentence realization. Specifically, for each concept \( \hat{n}_1 \) in inferred target concepts set \( \hat{n} \), without changing the topology of the nodes that directly connect to \( \hat{n}_1 \) on \( G \), we also connect the intermediate nodes in the reasoning path which can point to \( \hat{n}_1 \) with \( \hat{n}_1 \). In this sub-graph all the intermediate concepts directly connect with its corresponding target concepts.

**Transformer** It builds upon on a encoder-decoder framework. For each node in target node set \( \hat{n} \) of the input graph \( G_{x,y<1} \), we concatenate its directly linked nodes as its features. Then we use the sum of target node embedding and its feature node embeddings as node representation. The node representation of \( \hat{n} \) is denoted as \( \hat{e} \). On the transformer encoder, we find modeling the order of paths is more complicated but cannot improve the final results, so we remove the positional encoding to eliminate the effects of reasoning order. The Transformer encoder (TrmEnc) encodes \( \hat{e} \) to a list of representations \( \hat{h} \):

\[
\hat{h} = TrmEnc(\hat{e}).
\]

At the \( i - th \) decoding time step, the Transformer decoder (TrmDec) generates a probability distribution for word prediction by attending to both \( \hat{h} \) and previous decoder outputs:

\[
p(y_{i,t}|y_{<i}, \hat{h}) = TrmDec(y_{<i}, t, \hat{h}).
\]

Both the encoder and decoder consist of multiple layers, each with a multi-head self-attention sub-layer and a point-wise feed-forward neural network (FFN) sub-layer, and each of the layers of the decoder has an additional encoder-decoder attention sub-layer.

**Pseudo Parallel Data Construction** Owing to the lack of human-annotated training corpus, we adopt a self-supervised approach to construct pseudo parallel data to train our two modules. Given a long text, we first cut the long text into the form of sentence pairs, of each pair consist of two consecutive sentences. For each sentence pair, we search the concepts that exist in the knowledge graph. If a concept \( v_1 \) in the former sentence can reach a concept \( v_2 \) in the latter sentence via \( k + 1 \) hops, the path with \( k + 1 \) nodes are labeled. To be specific, \( v_1 \) is labeled as target concepts, \( v_1 \) and \( k \) intermediate nodes are labeled as intermediate concepts. We set a constraint for the max number of hops and neighbors of a concept to avoid over-exploration. Then, we collect pairs with at least one labeled path to form a dataset for sequence labeling. Besides, we collect the pairs of paths with its subsequent sentence to form a dataset for sentence realization.

**Self-constructed Graph for MRG**

Although there are several widely-used artificial knowledge graphs, such as ConceptNet (Liu and Singh 2004). However, for some specific fields, we still lack in an artificial knowledge graph. To make MRG applicable in such scenarios, we propose to build a graph based on the training data. Inspired by Yao, Mao, and Luo (2019); Liu et al. (2020), we build a graph via PMI (Point-wise Mutual Information) (Morris, Schwartz, and Escudier 1993), a popular measure for word associations. The behind motivation is that words in the same text are more likely semantically connected, so we can connect those words with edges to build a graph called as Self-constructed Graph. Specifically, we compute the PMI between any two words in the training vocabulary except for stop words with:

\[
PMI(w_i; w_j) = \log \frac{p(w_i, w_j)}{p(w_i) p(w_j)}
\]
where \( p(w_i, w_j) \) refers to the probability of the two words \( w_i \) and \( w_j \) in the same text. \( p(w_i) \) and \( p(w_j) \) are the probabilities of words in the entire training data. For each words, we connect those words with top-\( k \) PMI values.

Experiments

Dataset

Here we describe the used datasets and Table 1 demonstrates the detailed statistics.

Story Generation This dataset comes from a visual storytelling dataset [Huang et al. 2016] which consists of pairs of an image sequence and a human-written story. Following Xu et al. [2018], we only use the text data for our experiments. For each story, we extract the first topic sentence as the source input and the rest of the story as the target.

Review Generation This dataset is provided by Yelp Challenge [1]. Similarly, for each review, the first sentence is the source input and the rest is the target.

Description Generation This dataset is crawled from Taobao [2], a Chinese e-commerce platform. It consists of pairs of product titles and the corresponding product descriptions, which are composed by professional content producers on the website. We discarded pairs with a description less than 20 tokens or longer than 150 tokens to remove noisy samples. We will release this dataset if this paper is published.

Baselines

We compare our models with the following widely-used text generation approaches.

- Seq2Seq [Sutskever, Vinyals, and Le 2014] with attention mechanism [Bahdanau, Cho, and Bengio 2015] is a widely-used model for text generation.
- Transformer [Vaswani et al. 2017] is the state-of-the-art architecture for a series of tasks of nature language generation.
- Skeleton2Seq [Xu et al. 2018] is a two-stage generative method, which first generates a skeleton and then expands it to a complete sentence. This method also uses the sentence-level recurrent generation framework.
- Plan&Write [Yao et al. 2019] is a two-stage generative method, which first generates a sequence of keywords as a storyline and then expands it to a complete story.
- GPT-2 [Radford et al. 2019] is a large Transformer-based language model with 12 layers and 110M parameters, which has reached state-of-the-art performances on many language generation tasks. We fine-tune GPT-2 on training data for better performance, and name the model GPT-2-FT.
- GPT-2-KE [Guan et al. 2020] is a knowledge-enhanced pre-training model, which incorporates commonsense knowledge into GPT-2 and adopts a multi-task learning method during fine-turning to improve coherence.

Table 1: Dataset statistics. “Avg. #w” and “Avg. #s” are the average amounts of word and sentence per text, respectively. “Train”, “Dev”, and “Test” are the sizes of the training set, development set, and test set.

| Dataset       | Avg. #w | Avg. #s | Train | Dev | Test |
|---------------|---------|---------|-------|-----|------|
| Story         | 44.8    | 4.1     | 40K   | 5K  | 5K   |
| Description   | 55.1    | 2.9     | 342K  | 5K  | 5K   |
| Review        | 64.8    | 4.8     | 1,086K| 5K  | 5K   |

Table 2: Knowledge graph statistics. “Story-S”, “Review-S” and “Description-S” are the self-constructed graphs for story, review and description generation datasets, respectively. “# Nodes” and “# Triples” are the total number of nodes and triples.

| Knowledge Graph | # Nodes | # Triples | Language |
|-----------------|---------|-----------|----------|
| Story-S         | 16,000  | 318,823   | English  |
| Review-S        | 16,000  | 320,000   | English  |
| Description-S   | 16,000  | 320,000   | Chinese  |
| ConceptNet      | 21,471  | 149,809   | English  |

Implementation Details

Based on our preliminary experiments, the size of vocabulary is limited to 16,000. For each concept we explore up to 20 neighbors in the knowledge graph without going through loops. \( k \) in Self-constructed graph is set to 20. We set the maximum reasoning number to 3. Both the modules are optimized with the Adam optimizer [Kingma and Ba 2015]. We fine-tune the BERT-based labeller with the learning rate of 2e-5 and the batch size of 64 for 3 epochs. We implement the sentence realization module with a two-layer encoder and a two-layer decoder. We train this module with the learning rate of 0.001 and the batch size of 64 for 50 epochs. We set the size of hidden dimension and embedding dimension to 128. The number of heads in multi-head attention is 8. The dropout rate is tuned in range of \{0.1, 0.2, 0.3\}. We adopt greedy sampling for all the models during decoding. We also use the same hyper-parameters and settings for Seq2Seq and Transformer. For GPT2-FT, we use the hyper-parameters provided by Huggingface [Wolf et al. 2019]. For other baselines, we use the released code and adopt the default settings for implementation.

Our method has two variants, MRG-S and MRG-C, which refer to MRG that performs reasoning on Self-constructed Graph and ConceptNet (Liu and Singh 2004) respectively. The statistics of the knowledge graphs are shown in Table 2.

Evaluation Metrics

In this paper, we evaluate the quality of the generated texts by automatic and human evaluation. For automatic evaluation, because of the lack of reliable evaluation metrics in terms of coherence, we only evaluate the diversity and novelty of the generated texts and similarity between the generated texts with human texts. For human evaluation, we evaluate their coherence, informativeness and fluency.

1https://www.yelp.com/dataset/challenge
2www.taobao.com
Table 3: Results of automatic evaluation. We evaluate the diversity and novelty using Dist-n and n-Jaccard respectively. Higher Dist-n represents higher diversity, and lower n-Jaccard represents higher novelty. Token denotes the amount of generated words. Dist-n denotes the number of distinct n-grams in the generated text. Uni-J, Bi-J and Tri-J represent the Jaccard similarity scores based on unigram, bigram and trigram.

**Automatic evaluation** Long text generation expects the generated texts to be diversified and novel. **Diversity** is measured by the number of distinct n-grams in the generated texts. **Novelty** is measured by Jaccard similarity coefficient (Niwattanakul et al. 2013) between the generated texts and the training data. Specifically, for each generated sentence, we compute its similarity with every sentence in the training data and select the highest one as the score. The average of the similarity scores is the overall novelty score. **BLEU** (Papineni et al. 2002) is a widely used metric for text generation, which calculates the n-gram overlap between generated texts and references. However, BLEU is inappropriate for open-ended generation task (Fan, Lewis, and Dauphin 2018) in that there are multiple plausible texts for the same input, while only one is given as gold text. Here, we provide BLEU-4 scores for reference.

**Human evaluation** For each baseline, three annotators with linguistic background are required to score 100 samples randomly chosen from the test set. Each sample consists of a source sentence and two generated texts from our approach and a baseline. Annotators have no idea which system texts come from. They are asked to decide which output is better in terms of the following three aspects: **Fluency** measures whether the output is fluent, **Coherence** evaluates whether the output is semantically coherent, including topic sentence with generated sentences and generated sentences inside. **Informativeness** measures whether the output is diverse. The winner gets 2 points and loser gets 0 points. If two outputs are equally good or equally bad, they both get 1 point. We report the average score as the final result.

**Experiment Results**
Table 3 presents automatic evaluation results. As expected, MRG outperforms baselines by a large margin in terms of diversity and novelty. For instance, MRG-C achieves 22.6% relative improvements in terms of Dist-3 over the best baseline in story generation and review generation, respectively, with a small sacrifice in BLEU score. It demonstrates that with the help of conceptual skeleton paths, MRG can generate more diversified and novel text than baselines while maintaining good readability.

Table 4: Results of human evaluation. Flu., Infor., and Coher. denote fluency, informativeness and coherence respectively. $G$ is the geometric mean of the three metrics. **"*"** means $p < 0.01$ and **"**" means $p < 0.05$ in t-test. For each metric, the averaged Cohen’s coefficient is in range of 0.3 to 0.6, which ensures inter-annotator agreements.
Figure 3: Ablation studies of MRG-C on story generation. Diversity is measured by Dist-3, novelty is measured by Tri-Jaccard. Informativeness, fluency and coherence is measured by human evaluation on 100 randomly sampled pairs. Y-axis shows the percentage of the performance change compared with MRG-C.

Ablation Study

Here we conduct ablation studies to verify the effectiveness of two modules. Figure 3 demonstrates the results.

Multi-hop Reasoning Ablation  Specifically, in reasoning stage we replace the multi-hop reasoning module with a random reasoning module which randomly labels 1/3 concepts as target concepts, 1/3 as intermediate concepts. As we can see from Figure 3 the coherence and informativeness declines significantly when the reasoning module is removed. This illustrates that the multi-hop reasoning module is crucial to generating coherent text. The multi-hop reasoning module infers skeleton paths which bridge the preceding sentence with the following ones, and random reasoning cannot model such semantic dependencies.

Path-aware Sentence Realization Ablation  Specifically, we only use the target concepts to generate the subsequent sentence without using the conceptual path information. As shown in Figure 3 when the inferred paths are replaced with the target concepts, all five indicates drop, indicating that the intermediate path information are essential for improving the quality of generated text. The inferred conceptual skeleton paths provide plenty of information which is crucial to informative and coherent text generation.

Figure 4: An example of the inferred paths on the self-constructed graph. Blue words denote intermediate concepts. Orange words denotes target concepts. Green words denote other concepts.

Case Study

Table 5 presents several examples generated by different systems. The baselines tend to generate low-quality texts in story generation. For example, texts generated by Seq2Seq and Transformer are very generic and suffer from bad inter-sentence coherence and repetition issues. Because they do not explicit model semantic dependencies among sentences. For GPT-2-FT, much of the content except for the first sentence is unrelated to the input. Besides, it suffer from repetition issues (e.g. went to beach for a day of fun). Neither Skeleton2Seq nor GPT-2-KE can express information about keyword “dance” in the topic sentence. Although Plan&Write can embody content about both keywords “wedding” and “dance”, its output is relatively incoherent and less informative. In comparison, our methods can generate more diversified and coherent sentences with a multi-hop reasoning module to introduce external knowledge into sentence-level dependencies modeling. For a better demonstration, Figure 4 presents the reasoning path, which provides an explanatory way to help understand how MRG works. As to product description, it can also be found that MRG reaches a better result than Seq2Seq and Transformer. Specifically, it has stronger ability in generating longer texts with abundant information. The case shows that MRG is able to provide a detailed description of the features.

Related Work

Multi-hop Reasoning. Multi-hop reasoning has been drawing attention in the fields of natural language processing and machine learning. The most representative tasks are Meta QA (Zhang et al. 2018) and PathQuestion (Zhou, Huang, and Zhu 2018) in open-domain question answering over knowledge bases and Hotpot QA (Yang et al. 2018) in reading comprehension. Recently, researchers have conducted a series of methods for multi-hop reasoning on graphs and obtained significant performance gains (Zhou, Huang, and Zhu 2018; Qiu et al. 2019; Jiang and Bansal 2019; Tu et al. 2019; Ding et al. 2019). Those methods formulate multi-hop reasoning as a sequential decision problem and solve it using GNNs (Kipf and Welling 2017; Velickovic et al. 2018) or Memory Networks (Sukhbaatar et al. 2015; Kumar et al. 2016). In this work, we propose to perform sequential decision on a knowledge graph with a powerful pre-trained model BERT. In addition, our work can be seen as the first step to study how multi-hop reasoning can help long text generation.
Input 2: there was an Indian dance wedding today.

| Seq2Seq: | the bride and groom were very happy to be married. the bride and groom danced the night away. |
| Transformer: | the bride and groom exchanged vows, the bride and groom were so happy to be married, the bride and groom were so happy to be married. |
| Skeleton2Seq: | the bride and groom are happy to be married. the bride and groom are happy to be married. the wedding party is very beautiful and happy, the little family pose for a photo. |
| Plan&Write: | the bride was happy to be married. the bride and groom took their first dance; then they took a picture together. they danced the night away. |
| GPT-2-FT: | the bride and groom were very happy, the family went to the beach for a day of fun. they had a great time. they had a great time swimming. they had a great time playing in the water. the family went to the beach for a day of fun...[repetition] |
| GPT-2-KE: | the bride and groom were very excited, the ceremony was held indoors. the bride and groom had a great time. the flower girl was so happy. |
| MRG: | the bride dances with her bridesmaids. the bride and groom wore matching glasses. the bride and groom share a romantic kiss. the bride and groom exchanging vows. the bride and groom walked down the aisle. |
| Ground Truth: | there was a lot of dancing. the bride and groom’s first dance. it was all smiles and laughter. the whole family was there! |

Table 5: Examples generated by the proposed approach and baselines. The top and bottom groups list the generated text on story generation and product description, respectively. The examples demonstrate that MRG can generate more coherent and informative text with less repetition in both tasks.

**Long Text Generation.** The most popular models for text generation are **Seq2Seq** (Sutskever, Vinyals, and Le 2014) with attention (Bahdanau, Cho, and Bengio 2015) and **Transformer** (Vaswani et al. 2017). However, these models have limited capacity in modeling complicated semantic dependencies among sentences (Wiseman, Shieber, and Rush 2017), often suffer from logic conflicts. There are two lines of work to tackle this challenge. The first line attempts to model long-term semantic dependencies among sentences by a huge-size model pre-trained on a large-scale dataset (Radford et al. 2019; Dong et al. 2019; Song et al. 2019; Guan et al. 2020). These methods can be categorized into implicit semantic dependencies modeling. Another line is to explicitly model semantic relationship by simplifying sentence structures, i.e., models first plan a skeleton and then expand this skeleton to a long text. Martin et al. (2018) extracted event sequences as skeletons. Xu et al. (2018) adopted a reinforcement learning method to extract sentence skeletons. Li et al. (2019) produced a syntactic sketch with additional part-of-speech tagging tasks. Yao et al. (2019) generated a sequence of keywords as planning conditioned upon the input. Shao et al. (2019) planed input items as a sequence of groups and then realized each sentence conditioned on the planned result and the previously generated context. Different from those models, our methods build sentence-level dependencies by inferred skeleton paths on a knowledge graph, which is more interpretative and can cover more knowledge important for semantic transfer.

**Knowledge-aware Text Graph** Recently, it has proven effective to integrate commonsense knowledge into text generation. Young et al. (2018) employed an additional knowledge encoder to improve dialogue system. Yang et al. (2019) proposed to exploit commonsense knowledge for topic-to-essay generation with a memory-augmented generator. Guan, Wang, and Huang (2019) adopted a multi-source attention mechanism to attend commonsense knowledge for story ending generation. Guan et al. (2020) incorporated commonsense knowledge into pre-trained models during fine-tuning phrases. Despite their success, those methods only attend triple-level knowledge and need the decoder to perform complicated commonsense reasoning to leverage multiple triples for reasonable text generation. In comparison, our approach adapts a separate reasoning module to integrate multiple triples into a chain-like conceptual skeleton paths. The decoder just needs to focus on generating a fluent sentence based on the inferred paths, which is more effective.

**Conclusions**

In this paper, we propose a novel multi-hop reasoning generation model to generate coherent and informative long text via modeling complicated semantic dependencies among sentences. We adopt a self-supervised way to construct the supervisory signals to train the new model. We evaluate our model on three representative long text generation tasks, and propose to build a Self-constructed graph to make the new model applicable on tasks without appropriate artificial knowledge graphs. Automatic and human evaluation show that the new model achieves substantial improvements over a series of state-of-the-art baselines, such as pre-trained models and knowledge-enhanced models, in terms of coherency, informativeness, and novelty. Furthermore, the inferred paths enhance the interpretability of text generation. In the future, we will elaborate the reasoning mechanism to support controllable text generation. Besides, we will make the two modules interact with and promote each other to avoid error propagation.
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