TopNet: Learning from Neural Topic Model to Generate Long Stories

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ABSTRACT
Long story generation (LSG) is one of the coveted goals in natural language processing. Different from most text generation tasks, LSG requires to output a long story of rich content based on a much shorter text input, and often suffers from information sparsity. In this paper, we propose TopNet to alleviate this problem, by leveraging the recent advances in neural topic modeling to obtain high-quality skeleton words to complement the short input. In particular, instead of directly generating a story, we first learn to map the short text input to a low-dimensional topic distribution (which is pre-assigned by a topic model). Based on this latent topic distribution, we can use the reconstruction decoder of the topic model to sample a sequence of inter-related words as a skeleton for the story. Experiments on two benchmark datasets show that our proposed framework is highly effective in skeleton word selection and significantly outperforms the state-of-the-art models in both automatic evaluation and human evaluation.

CCS CONCEPTS
- Theory of computation → Machine learning theory; - Computing methodologies → Machine learning algorithms; Discourse, dialogue and pragmatics.

KEYWORDS
Long Story Generation, Story Telling, Topic Model, Natural Language Processing, Deep Learning

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1 INTRODUCTION
Long story generation (LSG) is one of the desired goals for artificial intelligence systems and has many real-world applications such as automatic news generation, tutoring systems, etc. Given a short text description or even a single word, the task of LSG is to teach the machine to generate a long narrative story (Table 1). The recent introduction of high capacity language models (e.g., GPT-2) [39] have shown their ability to generate stylistically coherent text but also suffer from uncontrollability in topics and content, which makes them have very few opportunities in industrial or commercial usage.

Most state-of-the-art works [11, 50, 51] tackle the challenges of LSG with a hierarchical structure, which first generates several skeleton keywords indicating the topic of the story, and then generates the story based on this skeleton. However, almost all of them generate the keywords by a supervised sequence-to-sequence model, which relies heavily on the maximum likelihood estimation objective and often leads to problems: sequences are dull, generic and repetitive [28, 42]. Moreover, at the training stage, the labeled keywords are often created by word-frequency based methods or initialized by other sentence compression datasets, and suffer from lack of diversity and bias from different domains.

Probabilistic topic modeling, which infers latent topics from documents is one of the greatest dimension reduction technologies. Given a corpus, the topic model assigns a topic distribution vector to each document and also builds a decoder that can reconstruct words in the document from the vector. This topic distribution contains the major information and latent features of the long document but is in the form of a low-dimensional vector, thus is an ideal distillation of the document and has been widely applied to various tasks such as text analysis and information retrieval [4, 19, 44].
Short Description: sunflower seeds

Story: Misty took a bag of sunflower seeds downstairs without asking. This made her father irritated, but he allowed her to do this. Then, she began spilling sunflower seeds. She spilled sunflower seeds even after her father said to be careful. Now, sunflower seeds are banned from the entire house.

Table 1: An example from the ROCStories dataset.

Recently, neural topic models have attracted much attention [13, 23, 32]. They typically approximate the posterior of a variational distribution with an inference model parameterized by a neural network, permitting unbiased and low-variance estimates of the gradients, and can provide a robust, scalable and theoretically sound foundation for long text modeling.

Inspired by the recent success of neural topic models, we focus on exploring whether they can further help provide knowledge for long story generation. Intuitively, the topic distribution assigned for each document by the topic model is a low-dimensional vector, which is easy for the given short description to map to; with the reconstruction decoder, it is also informative enough to generate diverse and inter-related topic words. Moreover, since the topic models are unsupervised learning methods, there is no need to annotate labels and they can be applied to large-scale datasets.

Given the above discussion, we propose TopNet, a long story generation framework that leverages the neural variational inference [23] as in a topic model to tackle the information sparsity challenge in LSG (i.e., lack of information in the short input). Our key ideas lie in two folds: (1) Given a short text input, predict the low-dimensional topic distribution of the to-be-generated story, rather than directly generate a word sequence. More specifically, we first compress each story in the training set into a topic distribution, which is easy for the given short description to map to; with the reconstruction decoder, it is also informative enough to generate diverse and inter-related topic words. Moreover, since the topic models are unsupervised learning methods, there is no need to annotate labels and they can be applied to large-scale datasets.

In this section, we train a neural variational inference framework [23, 32, 33] on the stories from the dataset with the goal of obtaining their latent topic distributions and a well-trained reconstruction decoder. In the next section, we will learn a map between the input text and the latent topic distribution and utilize the reconstruction decoder to sample informative keywords from the predicted topic distribution as a skeleton for long story generation.

2.1 Parameterizing Topic Distributions

Let \( X \in \mathbb{Z}_D^D \) denote the bag-of-words representation of a story, with \( \mathbb{Z}_D \) denoting nonnegative integers. \( D \) is the vocabulary size, and each element of \( X \) reflects the frequency of the corresponding word in the story. Following [32], we use a Gaussian random vector through a softmax function as the prior to parameterize the multinomial topic distribution. The generative process is:

\[
\begin{align*}
t & \sim \mathcal{N}(\mu_0, \sigma_0^2), \quad \theta = g(t) \\
z_n & \sim \text{Multi}(\theta), \quad w_n \sim \text{Multi}(\beta_{z_n})
\end{align*}
\]

where \( \mathcal{N}(\mu_0, \sigma_0^2) \) is an isotropic Gaussian distribution, with mean \( \mu_0 \) and variance \( \sigma_0^2 \) in each dimension; \( \theta \in \mathbb{R}^K \) is the topic distribution of the story where \( K \) is the number of topics; \( z_n \) is the topic assignment for the observed word \( w_n \); \( g(t) = \text{softmax}(W_g t + b_g) \), where \( W_g \) and \( b_g \) are trainable parameters; \( \beta_{z_n} \in \mathbb{R}^D \) represents the word distribution given topic assignment \( z_n \).

2.2 Neural Variational Inference

The neural variational inference is a simple instance of unsupervised learning where a continuous hidden variable \( \theta \), which generates all the words in a document independently, is introduced to represent its semantic content. Inspired by [32], we calculate the word distribution over topics by:

\[
\beta_k = \text{softmax}(U_k^T)
\]

where \( U \in \mathbb{R}^{K \times H} \) is the trainable topic vectors, and \( V \in \mathbb{R}^{D \times H} \) is the word vectors. Therefore, \( \beta \in \mathbb{R}^{K \times D} \) is the topic-to-word probability distribution matrix, which can be regarded as a decoder. The marginal likelihood for story \( X \) is:

\[
\begin{align*}
\rho(X|\mu_0, \sigma_0, \beta) \\
= \int_{\theta} p(\theta|\mu_0, \sigma_0^2) \prod_n \sum_{z_n} p(w_n|\beta_{z_n}) p(z_n|\theta) d\theta
\end{align*}
\]

To parameterize the latent variable \( \theta \), we construct a neural variational inference \( q(\theta|X, \theta(X), \sigma(X)) \) to approximate the posterior \( p(\theta|X) \), where \( \mu(X) \) and \( \sigma(X) \) are functions of \( X \) that are implemented as multi-layer perceptrons (MLP). We optimize the
Neural Topic Model

\[ \mathcal{L} = \mathbb{E}_{q(\theta|X)} \left[ \sum_{n=1}^{N} \log \sum_{z_n} \left( p(w_n|\beta_{z_n}) p(z_n|\theta) \right) \right] \]

\[ - D_{KL}[q(\theta|X)||p(\theta|\mu_0, \sigma^2_0)] \]

where \( q(\theta|X) = q(\theta|\mu(X), \sigma(X)) \). In practice, we re-parameterize \( \theta = \mu(X) + \epsilon \cdot \sigma(X) \) with the sample \( \epsilon \in \mathcal{N}(0, 1) \) to reduce the variance in stochastic estimation [23]. Since \( p(\theta|\mu_0, \sigma^2_0) \) is conditioned on a standard Gaussian prior, the KL term in Equation 4 can be easily integrated as a Gaussian KL-divergence. Given a sampled \( \theta \), the topic \( z_n \) can be integrated out as:

\[ p(w_n|\beta, \theta) = \sum_{z_n} p(w_n|\beta_{z_n}) p(z_n|\theta) = \beta^T \cdot \theta \]

Hence we obtain a \( K \)-dimensional topic distribution \( \theta \) for each story and a shared reconstruction decoder matrix \( \beta \) where each row corresponds to one topic.

3 TOPNET FRAMEWORK

To generate a long story, one crucial challenge we have to attack is the lack of information on the input side (e.g., the length is much shorter than the target side). With little input information, the neural model degenerates to language model [8, 11, 21, 39] that generates a story without taking the input into consideration. Such degeneration harms the fidelity of the generated story as it improves the story diversity. Intuitively, the above neural topic model captures what humans tend to write in a low-dimensional topic distribution, based on which, as well as the \( \beta \) matrix, we can map a new input text to a topic vector and then decode it to a word distribution to sample skeleton words for story generation.

3.1 Topic Generator

Given the short input text \( s = \{s_1, s_2, \ldots, s_m\} \) where \( m \) is the number of the words, we use pre-trained word embeddings GloVe [38] to transform the words into vectors \( \{\text{Emb}(s_1), \text{Emb}(s_2), \ldots, \text{Emb}(s_m)\} \). We use the average of these vectors, \( \text{Emb}_{\text{mean}}(s) \), to represent the input text and approximate its topic distribution via:

\[ \hat{\theta} = G(s) \]

\[ = \text{softmax}(W_1 \cdot \text{ReLU}(W_2 \cdot \text{Emb}_{\text{mean}}(s))) \]

where \( W_1, W_2 \) are trainable parameters. For training, we use the short description text \( s \) from the training set and the mean of their topic distributions \( \hat{\theta} = \mu(X) \) computed by the topic model in Section 2.2 to train the Topic Generator \( G \), and we adopt the cross-entropy loss as our objective function. Note that given the low dimensionality of \( \hat{\theta} \) and the short input text, it is more practical to predict its topic distribution than, e.g., directly predict the word distribution of the to-be-generated story, as the latter is over the entire vocabulary. Moreover, the Gaussian prior of the variational distribution can also improve the robustness of the topic approximation.

3.2 Auto-regressive Word Sampler

Since \( \beta \) is a shared topic-to-word matrix for all the stories, it stores the knowledge about the common constituents for various types of topics. We compute the word distribution \( p \) for a to-be-generated story by decoding its estimated topic distribution \( \hat{\theta} \):

\[ p = \text{softmax}(\beta^T \cdot \hat{\theta}) \]

To complement the short text input for long story generation, we aim to select skeleton words that can follow the content of the short text as well as interrelate with each other. Hence, instead of independently sampling a number of words from \( p \), we pre-train a forward language model on the collection of stories in the dataset as an auto-regressive Word Sampler. Specifically, we use 3 layers of
bi-directional Gated Recurrent Unit (GRU) [7] to form the language model and the top layer of the GRU output is used to predict the next token with a softmax function. We adopt the same vocabulary of the neural topic model in this language model and take out all the stop words in the stories. This means our language model does not focus on syntactic structure, but aims to capture the intrinsic semantic coherence of a story.

When sampling, we use the short description \( s \) as the initial input. Formally, the language model computes the probability of a sampled word sequence by modeling the conditional probability:

\[
p(s_1, s_2, ..., s_m, c_1, c_2, ..., c_N) = \prod_{i=1}^{N} p(c_i | s_1, s_2, ..., s_m, c_1, c_2, ..., c_{i-1})
\]

where \( s_m \) is the m-th word in the original short text input, \( c_i \) is the sampled complementary word and \( N \) is a fixed number. We confine the language model to select words that are ranked in the top \( N' \) \( (N < N') \) of \( p \), by which we aim to obtain the skeleton words \( \{c_1, c_2, ..., c_N\} \) that have a strong topical connection with the given short description and are also interrelated with each other so as to form a coherent story.

### 3.3 Story Generation

To generate content-rich and coherent stories, we adopt the Transformer [45] model which is known as good at drawing long dependencies and one of the state-of-the-art architectures for text generation. Transformer is a sequence transduction model based entirely on attention, replacing the recurrent layers most commonly used in encoder-decoder architectures with multi-headed self-attention. We concatenate the given short text description \( \{s_1, s_2, ..., s_m\} \) with the skeleton \( \{c_1, c_2, ..., c_N\} \) as the input of the model, and the output is the story text. Note that our framework is not limited to the Transformer and other more advanced generative models can apply as well.

### 4 EXPERIMENTS

#### 4.1 Datasets

We apply our approach to two long story generation tasks, which differ in terms of the input text length and are representatives of two realistic application scenarios, and conduct comprehensive analyses to show its effectiveness.

1. **Title-to-article**: Given a title that usually consists of less than three words, the task aims to create a narrative article about it. In this task, we use ROCStories\(^1\) [35], which is a popularly used dataset whose input text is a short title and target is a five-sentence article, which captures a rich set of causal and temporal commonsense relations between daily events, making it a good resource for evaluating story generation models [37, 51].

2. **Summary Expansion**: This task can be thought of the reverse of the text summarization task, and aims to expand the summary text by adding more details. We evaluate our model on CNN/DailyMail\(^2\) [17] dataset, which is widely studied for text summarization tasks [36, 41]; in this paper we use it to evaluate models for expanding a short summary to a long story. Table 2 shows the statistics of the datasets.

#### 4.2 Implementation Details

##### 4.2.1 Neural Topic Model

We train our neural topic model on the stories in a given dataset. The stories are preprocessed by stemming, filtering stopwords, and we choose the top 5000 most frequent words to compose vocabulary. We use gL0ve.840B.300d [38] as the word vectors (Eq. 2). For the inference network \( q(\theta | X) \), we use an MLP with 2 layers and 500-dimension rectifier linear units. The dropout of 0.8 is applied to the output of the MLP before parameterizing the diagonal Gaussian distribution. The model is trained by Adam [22] and tuned by hold-out validation perplexity. We follow [35] to alternately optimize the generative model and the inference network by fixing the parameters of one while updating the parameters of the other.

##### 4.2.2 TopNet Framework

For the TopNet Generator, we set the dimension of the weight matrix as 512. We optimize the model by Adamax [22] with a learning rate as 0.002. Our batch size is set as 128, and the dropout rate as 0.2. For the language model sampler, the dimension of the GRU is set as 512 and the model is trained with Adadelta [52] with a learning rate of 0.001. The batch size is set as 20 and the dropout rate as 0.15. For the title-to-article task, we set the number of topics \( K \) as 50, the \( N \) and \( N' \) in Section 3.2 as 10 and 100 respectively and train the Transformer for 220k steps. For the summary expansion task, since its target length is relatively longer as shown in Table 2, we set the number of topics \( K \) as 80, the \( N \) and \( N' \) in Section 3.2 as 60 and 200 respectively and train the Transformer for 340k steps. For the Transformer model, we set hyperparameters the same as [45], and use the base model in its official implementation\(^3\) for this work.

#### 4.3 Baselines

To demonstrate the effectiveness of our model, we choose several representative and state-of-the-art models from the current open-source works:

- **Inc-Seq2seq** [2] denotes the incremental sentence-to-sentence generation baseline, which is built upon the Long-Short Time Memory Network (LSTM) [6] along with attention mechanism.

- **Skeleton Model** [50] is also LSTM-based model, and trains its skeleton extraction module on other sentence compression datasets [12].

- **Fusion Model** [11] uses the human-annotated skeletons for training and adopts the gated self-attention along with Convolutional Sequence-to-Sequence Model [14] to learn the long-range context.

- **Static Planning** [51] uses word-frequency methods to train a skeleton extraction model and generates each sentence using each word of the skeleton.

#### 4.4 Topic Models

Table 3 presents the comparison of LDA and the neural topic model. As we can see, the neural topic model (NTM) performs much better than the traditional LDA on both datasets. The improvement over LDA indicates that the neural topic model can keep the information more accurately after compressing the original document, thus

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\(^1\)https://bitbucket.org/VioletPeng/language-model/src/master/Datasets/

\(^2\)https://cs.nyu.edu/~kcho/DMQA/

\(^3\)https://github.com/tensorflow/models/tree/master/official/transformer
We also follow [27] to calculate words (randomly select words from the vocabulary as the skeleton).

### Table 3: Perplexity of different topic models. "NTM" denotes neural topic model.

| Topic Model | ROCStories | CNN/DM |
|-------------|------------|--------|
| LDA         | 617.13     | 1325.1 |
| NTM         | 344.54     | 952.93 |

Table 2: Statistics of the ROCStories and CNN/DailyMail datasets.

| Dataset      | Training Set | Validation Set | Testing Set | Source Length | Target Length |
|--------------|--------------|----------------|-------------|---------------|---------------|
| ROCStories   | 78529        | 9816           | 9816        | 2.2           | 52.0          |
| CNN/DailyMail| 287113       | 13368          | 11490       | 66.1          | 778.3         |

For human evaluation in Table 5, we randomly sample 120 titles from the dataset to mix them up with the original title. For each skeleton and the 5 titles, 5 people are asked to select the most relevant title according to the skeleton, and they obtain the highest averaged accuracy under TopNet’s skeletons, which shows that our skeleton words are topical, meaningful, and loyal to the input text.

### 4.5 Title-to-article Task

In this task, we conduct experiments on the ROCStories dataset. For evaluation, we follow [51] to use inter-story and intra-story repetition scores, which denote the repetition rate of trigrams between stories at sentence level and the average trigrams repetition of sentences comparing with former sentences in a story respectively. We also follow [27] to calculate Dist-2, which is the proportion of unique bigrams over the total number of bigrams in the generated stories, and [53] to use the Ent-4 metric, which reflects how evenly distributed the 4-grams are over all generated stories. Since the input titles are usually less than three words, there can be various kinds of output that are all relevant so the evaluation metrics such as ROUGE [29] for generating a particular piece of text are not suitable for this task.

Results: As shown in Table 4, our TopNet outperforms all the baseline models and achieves the state-of-the-art results, and the skeleton words generated by our method are more diverse than all other hierarchical models. In the bottom part, we conduct an ablation study: We replace the neural topic model with LDA [4], and the performance is better than the Transformer’s but still has a gap with the results of our TopNet. We conjecture that this is because the predicted top N words for many stories are overlapped as we observe high-frequency words tend to be selected as the skeleton under the LDA model, while the neural inference network is more capable of learning complicated non-linear distributions.

For human evaluation in Table 5, we randomly sample 120 titles along with the generated stories and consider 4 aspects: Coherence (whether the story as a whole is coherent in meaning and theme), Meaningfulness (whether the story conveys some certain messages), Fidelity (the relevance between the generated story and the title), Richness (the amount of information in the story). We compare our TopNet with the Fusion Model [11], Transformer with random words (randomly select words from the vocabulary as the skeleton), and Transformer with top N words (directly select the top N words from the probability p (Eq. 7) instead of using our Word Sampler). For each sample, 5 people are asked to decide which of the two stories are better in the above aspects, and we show the average scores across the five annotators on all samples. As we can see, similar to the previous quantitative results, our TopNet almost outperforms their counterpart baselines in all evaluation aspects, thus demonstrating the effectiveness of the proposed framework.

In Figure 2, we show the correlation between the generated skeleton words and their short input text. We randomly pick up 100 <title, generated skeleton> pairs and for each pair, we randomly sample 4 other titles from the dataset to mix them up with the original title. For each skeleton and the 5 titles, 5 people are asked to select the most relevant title according to the skeleton, and they obtain the highest averaged accuracy under TopNet’s skeletons, which shows that our skeleton words are topical, meaningful, and loyal to the input text.

In Table 6, we present a randomly selected title from ROCStories and the stories generated by humans (original story), Static Planning [51], and TopNet, and we also compare the skeletons generated by the latter two methods. It is obvious that our TopNet generates a more complicated and interesting story compared to the Static Planning and even the human-generated one. While the Static Planning produces redundant and repetitive content such as “She decided to go to the doctor”, our method generates a story that is much more informative and has more complex sentence structures. Since the number of the skeleton words in our TopNet is adjustable, we can produce more keywords than Static Planning, and thus provide more detailed information to support story generation. We also observe that some sampled words are not directly used in the generated story (e.g. lunch, happy), but in general the complementary words are interrelated and pertinent to the given title, which can be attributed to the latent feature extraction of the topic model.

### 4.6 Summary Expansion Task

We further apply our model to another task named summary expansion, which typically has a relatively longer input than the previous title-to-article task. In particular, we use the summaries in CNN/DailyMail dataset as the input to predict the corresponding...
Table 4: Quantitative evaluation on the ROCStories dataset shows that our model achieves the state-of-the-art performance. “Dist-2 (SW)” denotes the Dist-2 score for the generated skeleton words.

| Models           | Inter-S | Intra-S | Dist-2 | Ent-4 | Dist-2 (SW) |
|------------------|---------|---------|--------|-------|-------------|
| Inc-Seq2seq      | 0.95    | 0.16    | 0.074  | 7.929 | –           |
| Skeleton Model   | 0.89    | 0.09    | 0.082  | 8.573 | 0.285       |
| Static Planning  | 0.82    | 0.06    | 0.093  | 9.238 | 0.473       |
| Fusion Model     | 0.71    | 0.05    | 0.101  | 11.558| 0.604       |
| Transformer      | 0.88    | 0.09    | 0.091  | 8.623 | –           |
| TopNet (LDA)     | 0.69    | 0.05    | 0.124  | 11.593| 0.828       |
| TopNet           | 0.65    | 0.04    | 0.151  | 11.682| 0.856       |

Table 5: Human comparison with the state-of-the-art method and ablation study on the ROCStories dataset.

| Choice %  | TopNet vs. Fusion | TopNet vs. Random | TopNet vs. Top Words |
|-----------|-------------------|-------------------|----------------------|
| Coherence | 55.1              | 44.9              | 73.5                 | 26.5 | 56.4 | 45.6 |
| Meaningfulness | 54.6 | 45.4 | 64.1 | 35.9 | 55.2 | 44.8 |
| Fidelity  | 52.0              | 48.0              | 78.3                 | 21.7 | 47.5 | 52.5 |
| Richness  | 66.7              | 33.3              | 51.6                 | 48.4 | 66.1 | 33.9 |

Table 6: Examples of skeletons and stories generated by human, Static Planning, and TopNet on the ROCStories dataset.

| Title: Allergies |
|------------------|
| Human: Kia had a runny nose and headache for weeks. She finally went to her doctor. He told her she had allergies. He gave her an antihistamine to take. Soon Kia was feeling much better. |
| Static Planning: Anna had a bad cough. She went to the doctor. The doctor told Anna she had a fever. Anna was very sick. She decided to go to the doctor. |
| TopNet: Will had seasonal allergies. He sneezed and snuffled throughout the summer. He took allergy medication daily, which helped his symptoms. One morning he forgot to take a pill, and his allergies were terrible. Will made sure to take his pill with breakfast so he wouldn’t forget. |

Table 7 shows the performance of the models on the CNN/DailyMail dataset, and we can see that our TopNet achieves the best results over almost all the baselines, and our generated skeleton words also perform well in diversity comparing to other results (except random sampling). These results demonstrate that our TopNet is able to generate relevant, diverse yet fluent stories which further verifies the effectiveness of our approach. For GPT-2, we see that the results of diversity and fluency are much better than the other approaches since it is pre-trained on an extremely large corpus and the model itself is much more complex than the others. However, we observe the articles it generates are almost irrelevant to the original ones, and many of them even deviate from the topic of the summaries. This indicates that although the large-scale language models have impressive improvements under various metrics, it is still challenging to control their generated text content, which is to some extent improved by our TopNet according to the results under relevance. Such phenomenon also reflects that neural model is easy to ignore the model input when it contains little information for the model to take into consideration. With the informative supplement, our TopNet can theoretically remedy this problem.

Table 8 presents an example of the generated skeleton and stories generated by human, GPT-2, and TopNet on the CNN/DailyMail dataset. As we can see, most of our generated skeleton words have strong correlation with the given summary, such as “power”, “energy”, “facility”, “collapse”, etc. These words together with the summary support a long and coherent story. However, there are some words like “lab”, “foot” that seem to be less relevant to the given summary, such as “energy”, “facility”, “collapse”, etc. These words together with the summary support a long and coherent story. However, there are some words like “lab”, “foot” that seem to be less relevant to the given summary, such as “energy”, “facility”, “collapse”, etc. These words together with the summary support a long and coherent story. Moreover, some words, such as “Beijing”, induces the model to generate the sentence “The plant is located in the nearby city of Beijing, about 240 kilometers (150 miles) north of tokyo”, but it doesn’t make sense because it is a wrong information.

As for the generated stories, both our method (TopNet) and GPT-2 have produced a long and interesting story. We notice that the story generated by GPT-2 is longer and has more complex choices of words, and the GPT-2 is very good at making up specific name entities such as address, date, name and organization. However, we observe that the story generated by GPT-2 has deviated from the given summary, let alone the original story in the CNN/DailyMail dataset.
dataset. It seems the GPT-2 is more skillful in continue writing, rather than expanding the given short text by adding details. We also find that the story generated by our TopNet has repetitive phrases such as “since the march 11 earthquake and tsunami”, indicating that the regular generators (e.g. Transformer) still have a lot of room for improvement on content selection, even if provided with sufficient knowledge at the input side.

5 RELATED WORK

5.1 Long Story Generation

Recently, deep learning models have been demonstrated effective for LSG [10, 15, 20, 24, 40, 43]. Most state-of-the-art methods [11, 50, 51] proposed to decompose the story generation procedures with a hierarchical generation strategy to first produce a skeleton and then generate a story based on the skeleton. However, these work either do not have skeletons informative enough to support a long story, or they require human annotators to label skeletons for training. Unlike previous work, we integrate the tricks of topic modeling into the story generation task through projecting an input text to its latent topic space and leveraging the reconstruction decoder of a neural topic model to obtain abundant inter-related skeleton words in an unsupervised fashion for story generation.

Large-scale language models (e.g., GPT-2) have also achieved impressive performance on long text generation [31, 39]. However, training such a language model can cost in excess of $10,000 and also requires a huge amount of external data [46], making it prohibitively expensive and time-consuming to perform a fully-fledged model exploration. Moreover, large-scale language models are usually uncontrollable because the local dependencies among the story itself are easier to model than the subtle dependencies between the input text and the story [11]. Different from tasks such as text abstract summarization [41] or Neural Machine Translation (NMT) [16], where the semantics of the target are fully specified by the source, the generation of stories from the model input is far more open-ended. How to tackle the degeneration problem of story generation model that the neural models ignore the input and focus purely on previously generated sequence, is crucial in the scenario of generating long story. In such situation, it is hard for GPT-2 to produce loyal stories. In this paper, we make full use of the given corpus by unsupervised learning while eliminating the need of large-scale external data or human interactions, and show that generating an informative skeleton for LSG is still important and challenging.

5.2 Topic Models

Topic models have been studied for a variety of applications in document modeling and information retrieval. Beyond LDA [4] that consists of multiple layers of Bayesian networks, various extensions have been explored to discover topics [44], model temporal dependencies [3], among many others. Recently, neural topic models have gained much attention [13, 18, 25, 32, 33], which improved the performance of traditional methods. Different from prior approaches that sought closed-form derivations on the discrete text to train the topic model, Miao et al. [33] presented a generic variational inference framework for the intractable distributions over latent variables. Given the discrete text, they build an inference network in order to obtain the variational distribution. They further proposed to provide parameterisable distributions over topics [32], so that it will permit training with back-propagation in the framework of neural variational inference, which makes it easy to obtain powerful topic models. In this work, we also construct our topic model by a variational inference framework [32, 33], in which the latent topic vector is constrained by a prior distribution (e.g. Gaussian distribution) and is easier to be approximated from the input text.

5.3 Topic Learning in NLP

The idea of using learned topics to improve NLP tasks has been explored previously, including methods combining topic and neural language models [1, 9, 26, 34, 47], leveraging topic and word embeddings [30, 49], as well as topic-guided VAEs [48]. Wang et al. [47] presented a Topic Compositional Neural Language Model (TCNLM), which can not only maintain the overall topic representing the global information, but also learn the local semantic information of a document. In order to discriminate the ubiquitous homonymy and polysemy, Liu et al. [30] utilized the topic model to assign topic vector to each word embedding, and finally obtained the topical word embeddings. Xu et al. [49] proposed to conduct the joint training of the word embedding and topic model to obtain topic-aware word embedding. Wang et al. [48] extended the VAE through specifying the prior of Gaussian distribution parametrized by latent topic distribution. Unlike previous works that mainly focus

| Models                  | Relevance | Diversity | Fluency | Skeleton |
|-------------------------|-----------|-----------|---------|----------|
|                         | RG-1      | RG-L      | Dist-2  | Ent-4    | Perplexity | Dist-2  |
| Inc-Seq2seq             | 22.4      | 13.8      | 0.051   | 10.024   | 38.73      | –       |
| Fusion Model            | 28.3      | 20.5      | 0.076   | 13.021   | 36.12      | 0.179   |
| Transformer             | 25.1      | 16.9      | 0.060   | 11.565   | 38.15      | –       |
| Transformer + Random Words | 24.4  | 15.8      | 0.076   | 13.024   | 38.29      | 0.246   |
| Transformer + Top N Words | 27.9   | 19.4      | 0.070   | 12.754   | 36.38      | 0.127   |
| TopNet (LDA)            | 28.5      | 20.8      | 0.075   | 13.011   | 36.25      | 0.204   |
| TopNet                  | 29.3      | 21.6      | 0.078   | 13.033   | 35.73      | 0.219   |
| GPT-2                   | 11.2      | 8.3       | 0.121   | 14.380   | 30.25      | –       |
| GPT-2 + TopNet          | 12.8      | 9.6       | 0.114   | 14.133   | 30.21      | 0.219   |

Table 7: Quantitative evaluation on the CNN/DailyMail dataset, where the summary is the input and the article is the target. "GPT-2 + TopNet" means we use the GPT-2 as the story generation module of the TopNet.
Table 8: Examples of the generated skeleton and stories generated by human, GPT-2, and TopNet on the CNN/DailyMail dataset.

on modeling the latent topics, we propose to leverage the topic-to-word decoder of a topic model as well, which is knowledgeable and robust to help obtain skeleton words based on the approximated latent topics.

6 CONCLUSION

In this paper, we propose a novel framework TopNet, which leverages the document modeling of the neural topic model for long story generation. To tackle the information sparsity challenge, we learn to map the short input text to a low dimensional topic distribution and use the decoder of the topic model to transform it to the word distribution, based on which we finally develop a language model to sample skeleton words for story generation. The experimental results on different tasks show that our model significantly outperforms the state-of-the-art approaches and can produce interesting and coherent stories. We also demonstrate that our method has the potential to improve the large-scale language model by providing appropriate topic words. Future works include further research into controllable long sequence generation as well as exploring unsupervised or self-supervised learning in other NLP tasks.

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