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Guo Qipeng, Qiu Xipeng, Xue XiangYang and Zhang Zheng

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Syntax-Guided Text Generation via Graph Neural Network

Qipeng GUO[1], Xipeng QIU[1*], Xiangyang XUE[1] & Zheng ZHANG[2]

[1]*School of Computer Science and the Shanghai Key Laboratory of Intelligent Information Processing, Fudan University, Shanghai 200433, China;*
[2]*NYU Shanghai and AWS Shanghai AI Lab, Shanghai 200335, China*

Abstract Text generation is a fundamental and important task in natural language processing. Most of the existing models generate text in a sequential manner and have difficulty modeling complex dependency structures. In this paper, we treat the text generation task as a graph generation problem exploiting both syntactic and word-ordering relationships. Leveraging the framework of the graph neural network, we propose the word graph model. During the process, the model builds a sentence incrementally and maintains syntactic integrity via a syntax-driven, top-down, breadth-first generation process. Experimental results on both synthetic and real text generation tasks show the efficacy of our approach.

Keywords Text Generation, Deep Learning, Graph Neural Network, Dependency Parsing

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1 Introduction

Generating coherent text sequences is crucial to a wide range of important natural language processing applications, such as language modeling [21], machine translation [2], and dialogue generation [20]. Some of the most popular text generation approaches train an autoregressive recurrent neural network (RNN) to maximize the conditional probabilities of next tokens based on the ground-truth histories, which are sequential in nature. Despite these encouraging results, the generated sentences are often unsatisfactory [6, 18, 25].

RNN experiences difficulties in remembering and distinguishing rich and often long dependencies embedded in a flattened sequence. This is true even for advanced variants such as LSTM and GRU [7, 14]. For this reason, the generated texts often lack consistency in long-term semantics and are not coherent syntactically.

The structural dependence relations among words in a sentence are not only sequential but also syntactical and hierarchical. Figure 1 groups word dependence relations into two sets: The first is the *sequential dependence* `seq-dep` relationship that governs word order in a sentence; The second is the *syntactical dependence* `syn-dep` relationship, which implies that, for each word in a sentence, there exists another word to govern it. Such a relationship is produced by word-based grammar; therefore, sequential models typically explore only the first relationship.

Taking both types of relationships into account, a sentence can be formulated as a directed cyclic graph (DCG), in which nodes are the words and edges are the unions of the two relationships. Evidently, text generation can be formulated as a graph generation problem; however, this perspective raises two

* Corresponding author (email: xpqiu@fudan.edu.cn)

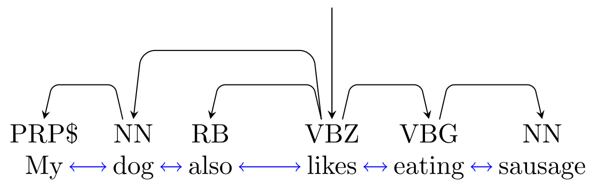


Figure 1 Word graph of a sentence. In this paper, we consider both syntactical (black arrows) and sequential (blue arrows) dependencies in the text generation process. As a result, the sentence is modeled as a graph instead of a sequence or a tree.

challenges: 1) inference modeling over the graph and 2) making generation process respect the graph topology.

We address the first challenge by borrowing the idea from recent studies on graph-structured neural networks [3, 11, 13, 15] and propose the *word graph* model. In this framework, word representations are propagated along the edges throughout the graph. As messages are aggregated, nodes obtain updated representations, and such propagation-and-aggregation rounds can be performed whenever the graph topology is modified during the generation process.

We deal with the second challenge by constructing the word graph incrementally along the dependency edges in a straightforward top-down breadth-first fashion. Since a dependency tree is inherently hierarchical, this method leads to partial sentences that are semantically meaningful, and internally emulates a curriculum learning [5] process.

The contributions of this paper are briefly summarized as follows.

- We regard text generation as a graph generation problem. This new perspective alleviates the long distance dependency problem that plagued the sequential models.
- We adopt the message-passing neural network framework, propose the word graph model, and learn the representation of a complex graph produced by a sentence. The proposed algorithm has a time complexity of $O(n^2)$.
- The top-down breadth-first generation order is an importance-first strategy that generates words carrying more information. An additional advantage is that the intermediate generated result is a simplified but still relatively fluent sentence.
- Our preliminary results on two generation tasks demonstrate the promise of this approach.

2 Proposed Method

Our approach to sentence generation creates a *word graph*. In this section, we first explain the concepts and definitions of constructing such a graph and then describe the text generation process.

2.1 Word Graph

Given a text sequence $w_{1:L}$ and its dependency tree T, its word graph is defined as $G = (V, E)$, where $V = \{w_1, w_2, \cdots, w_L\}$ is the set of words and E describes the relations between the words. For each word w_i, there is an embedding x_i. In addition to encoding the usual semantic representation, $\mathbf{x}_i$ may contain other useful linguistic features such as its word form, part-of-speech tag, and others.

There are two types of edges: the ones of the first type run along the sequence itself capturing the word order (blue arrows in Figure 1) and ones of the second type signify hierarchical dependencies E_{seq} (black arrows in Figure 1). The subset of the former-type edges E_{seq} is reminiscent of an n-gram relationship in sequence learning and can be used to recover the sentence; although one direction suffices, in this work we maintain both directions.

The latter-type edges capture the syntactic structure of a sentence and play a key role in the graph generation process, as we will describe shortly.

For any word pair (w_i, w_j) in $w_{1:L}$, we denote its edge by the following:

$$e_{w_iw_j} = \begin{cases} 1 \textbf{ if } & j-i=1 \\ 2 \textbf{ if } & i-j=1 \\ 3 \textbf{ if } & T(i,j)=1 \\ 0 & \textbf{otherwise} \end{cases} \tag{1}$$

where $T(w_i, w_j) = 1$ denotes that the word w_i governs word w_j in the dependency tree T. $e_{w_iw_j} = 0$ means that no edge exists between w_i and w_j. A question arises when a neighboring edge is *also* a dependency edge; rather than dedicating a new edge type, we simply use both edge representations.

2.2 Message-Passing Neural Network

The message passing neural network (MPNN) [11] is a type of graph neural network. It is defined through a message-passing interface, and it has message as well as vertex update functions. The whole MPNN process comprises iterative message passing and vertex updating.

$$\mathbf{m}_u^{t+1} = \sum_{v \in N(u)} M_t(\mathbf{h}_u^t, \mathbf{h}_v^t, \mathbf{e}_{uv}), \tag{2}$$

$$\mathbf{h}_u^{t+1} = U_t(\mathbf{h}_u^t, \mathbf{m}_u^{t+1}), \tag{3}$$

where $\mathbf{h}$ is the state of the vertex, $\mathbf{e}$ is the edge, $N(u)$ represents the neighbors of the node u, M_t is the message function at step t, and U_t is the vertex update function at step t. Since the MPNN is a very general framework, we can use it to describe the min-sum or max-product belief propagation method with specific message and vertex update functions. However, the MPNN often works in a more "dirty" scenario where the goal of the MPNN is not only inference a given graph but also the estimation of the graph. For example, we omay know the connectivity of the nodes but lack the details; therefore, it would need to be learned from the data. In addition, training a text generation model from scratch is a problem involving both estimation and inference, and we want the model can estimate the parameter of a graph from the data and inference it to sentences in an end-to-end framework.

2.3 Word Graph Encoding via Message Passing

A word graph is represented by the message passing framework, similar to the existing graph convolutional network [15]. Each node $v \in V$ is represented by a state vector $\mathbf{h}_v \in \mathbb{R}^d$, initialized with $\mathbf{x}_v$, and is updated by aggregating information from its neighbours. To do that, for each edge we compute a message:

$$\mathbf{m}_{u \to v} = f_e(\mathbf{h}_u, \mathbf{x}_u; \theta^{(\mathbf{e}_{uv})}), \quad \forall (u,v) \in E \tag{4}$$

where $f_{\mathbf{e}_{uv}}(\cdot)$ is a fully-connected neural network. In our implementation, the parameters are shared between all edges of the same type. Note that, in propagating a message to other nodes, the word feature $\mathbf{x}_u$ is always inserted to reinforce coherence.

The state vector $\mathbf{h}_v$ is then updated in multiple rounds of message propagation. In each round, v aggregates all the incoming messages from its neighbors $N(v) \equiv \{u : (u,v) \in E\}$:

$$\mathbf{h}_v = f_h\left(\sum_{u \in N(v)} \mathbf{m}_{u \to v}, \mathbf{h}_v; \theta^h\right), \quad \forall v \in V \tag{5}$$

where $f_h(\cdot)$ can be a fully-connected or recurrent neural network.

2.4 Word Graph Generation

Our algorithm incrementally inserts words (nodes) into an initially empty graph until completion, at which point all words are inserted and all edges are formed. This is achieved through a sequence of actions where each action generates a new word, modifies the graph topology, and updates its representation.

An identical word graph can be built with different traversal orders. We choose the most stable one by following the dependency edges E_{dep} in top-down and breadth-first order. We also impose a left-to-right order to generating the children. This procedure ensures a deterministic order when adding edges in the E_{dep} set. A partially completed sentence finds its sequential order by following an in-order walk of the tree, forming a dynamic E_{seq} set that precisely corresponds to those in the target graph at completion. This process is illustrated in Table 1.

Each step of the text generation process involves three actions: generating a new node, sampling its word, updating the graph. The process is described in Algorithm 1.

Generating a new node Assuming the node u is the current operating node, the first action determines whether to generate its child node according to its representation $\mathbf{h}_u$:

$$p(a|u,G) = \textbf{softmax}(f_a(\mathbf{h}_u)), \tag{6}$$

where $a \in \{LC, RC, STOP\}$ is the action. $LC, RC, STOP$ denote the actions of adding a child on the left, on the right, or not adding a child node for the current node, respectively. The choice between left and right is dependent on the relative position of the child to the operating node in the sentence. As mentioned earlier, an in-order walk recovers the order and the dynamic edges E_{seq}. Some of these edges may need to be broken as the graph grows.

Sampling a word Once a node v is generated, we set its initial representation vector $\mathbf{h}_v = 0$ since its word has not been generated yet. Then we update its representation via message passing, calculate the probability of the word choice, and sample an initial candidate w_v:

$$p(w|\mathbf{h}_v) = \text{softmax}(W\mathbf{h}_v + \mathbf{b}), \qquad w_v \sim p(w|\mathbf{h}_v) \tag{7}$$

Graph update After word the w_v is sampled, we re-initialize the representation $\mathbf{h}_v = \mathbf{x}_v$ and start updating the rest of the graph. Starting from v, this is done via message passing in a broadcast manner using Eq(4, 5) until all nodes are reached.

Final sentence generation After the words are added, we perform one more round of message passing and pick words with argmax of word choice probability at each node.

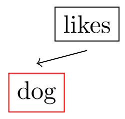
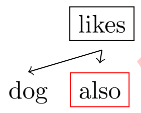
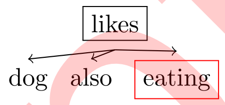
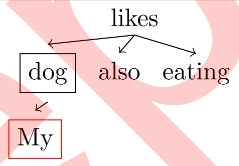
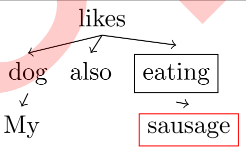
3 Training

The process of graph generation involves three kinds of predictions: action and word per step, and all words at the final step. As such, our loss function is divided into three components (Eq 8)

$$\mathcal{L} = \sum_{t=1}^{T} \mathcal{L}^a(\mathbf{a}_t, \hat{\mathbf{a}}_t) + \sum_{t=1}^{T} \mathbf{I}(\mathbf{a}_t \neq STOP)\mathcal{L}^w(\mathbf{w}_t, \hat{\mathbf{w}}_t) + \sum_{u \in V} \mathcal{L}^{tree}(\mathbf{w}_u, \hat{\mathbf{w}}_u), \tag{8}$$

where the indicator function $\mathbf{I}(x) = 1$ if x is true and zero otherwise; $\mathcal{L}^a(\mathbf{a}_t, \hat{\mathbf{a}}_t)$ and $\mathcal{L}^w(\mathbf{w}_t, \hat{\mathbf{w}}_t)$ are the losses per step, $\mathcal{L}^{tree}$ is the loss at the final round. $\mathbf{a}_t$ and $\mathbf{w}_t$ are the gold action and ground-truth words, respectively. All of the aforementioned loss functions are cross-entropy losses; In principle, each node receives two teaching signals: one when it is created and the other in the final round.

Table 1 An illustration of our graph generation. “Graph” and “Sequence” illustrate the generated word graph and its flatten word sequence. The node in the black box is the current operating node, and the node in the red box is the newly generated node. “Action” can be “LC” or “RC” for generating a left or right child of the operating node, respectively, and “root” or “STOP” is for starting or terminating the process.

			Action		
Step	Flatten sequence	Graph	Node	Word	Surrounding
1	likes		root	likes	-
2	dog likes		LC	dog	likes
3	dog also likes		LC	also	likes, dog
4	dog also likes eating		RC	eating	likes
5	My dog also likes eating		LC	My	dog
6	My dog also likes eating sausage		RC	sausage	eating

Maximum likelihood training is known to suffer from the exposure bias problem; therefore, we adopt schedule sampling [4] to bridge the gap between training (gold input) and inference (predicted input at test time). Specifically, when computing a message using (Eq 4), the input $\mathbf{x}_u$ picks the ground-truth with probability ϵ or the model prediction otherwise.

Note that the top-down breadth-first generation order implicitly generates a simple sentence first and then makes it progressively more complex. In other words, the process implicitly embeds a sort of curriculum learning [5], and we observe that the model is easier to train than general graphs.

4 Experiments

To evaluate the effectiveness of our approach, we conducted two experiments on unconditional text generation tasks: one on a synthetic dataset and another on real-world texts. We compared the proposed method against similarly configured sequential generators based on the recurrent neural network: vanilla LSTM, SeqGAN, and LeakGAN [12,27]. SeqGAN and LeakGAN sidestep exposure bias by adopting an adversarial training paradigm, and LeakGAN optimizes further for long sequences. However, our results show that the GAN approach suffers from mode collapsing.

Implementation: All models had a hidden size of 32 and an embedding size of 128. We used the Adam optimizer with an initial learning rate of 0.01 and annealed it gradually after a few epochs until it reached $1e-5$; scheduled sampling probability was annealed from 1.0 (fully ground-truth) to 0.5 (half-half).

Algorithm 1 Graph-Based Text Generation

```
 1: initialize operating queue: $Q \leftarrow \emptyset$
 2: $Q$.append($root$)                                  // use special parameters for root
 3: while $Q$ is not empty do
 4:   $u \leftarrow Q.pop()$                             // pop the node from the queue
 5:   for i=1 to MAX_CHILDREN do
 6:     sampling an action $a_i \sim p(a|u, G)$          // Eq( 6)
 7:     if $a_i$ = stop then break                       // stop the generation of operating node
 8:     $v \leftarrow$ empty node                        // if not break, there is a new node
 9:     if $a_i$ = LC then $u$.left_children.append($v$)   // left child
10:     if $a_i$ = RC then $u$.right_children.append($v$)  // right child
11:     modify the *seq-dep* edges related to $v$
12:     $MP : N(v) \rightarrow v$                        // update the new node $v$; Eq( 4, 5)
13:     sampling a word $w_v \sim p(w|\mathbf{h}_v)$     // Eq( 7)
14:     $MP : v \rightarrow N(v) \rightarrow ... \rightarrow G$   // global update from $v$; Eq( 4, 5)
15:     $Q$.append($v$)
16:   end for
17: end while
18: for $v \in V$ do                                     // final round, re-sample words for the entire sentence
19:   $MP : N(v) \rightarrow v$                          // collect messages from its neighbors
20:   pick the word with highest probability $w_v = \mathrm{argmax}_w\, p(w|\mathbf{h}_v)$
21: end for
```

4.1 Synthetic Tree Generation

Since it is difficult to measure the quality of a generated text with syntactic structure, we first conducted a simulated experiment with synthetic data. Following the idea in SeqGAN and LeakGAN, we chose a randomly initialized LSTM as our oracle. Instead of generating a sequence, we modified the oracle LSTM to output a linearized tree. To this end, we maintained several counters to determine the legal actions at each step. The possible actions included an opening and a closing bracket in addition to predicting (artificial) words and tags. The generation process had to obey some basic rules, such as tags and words should appear in pairs and all the brackets should be closed at the end. We added a constant negative bias to the unnormalized output of illegal actions to force the model to choose the legal ones. This mechanism affected both the generation and evaluation processes. As a result, the illegal action received a fixed penalty in the evaluation. We made sure that a depth-first walk of a tree is converted appropriately. We chose the vocabulary size for artificial tags and words to be 50 and 5k, respectively. The oracle allowed us to fabricate an arbitrary training set and evaluate the likelihood of generated sentences. This task required the model to capture both sequential dependencies (tag and word pair, patterns in oracle LSTM) as well as syntactic dependencies (matched brackets, these could be long dependencies).

We measure the quality of generated texts using the negative log-likelihood (NLL) of the oracle generator. As shown by the synthetic task results in Table 2, our approach beats the two sequential models with adversarial training (SeqGAN and LeakGAN [1)]) and achieves a performance close to that of the oracle. Since our process models syntactic structure explicitly, it rarely generates ill-formed samples, whereas the sequential models often do. To eliminate the influence of the explicit syntactic structure in the evaluation process, we also report an additional score NLL(-) that does not count the symbols "(" and ")". And our model still beats the others under this measurement. In addition, varying sentence length shows that the proposed model is the most robust. Table 3 gives a comparison of the models from the point of view of a case study. Overall, the results demonstrate that the word graph model can generate well-formed sentences with hierarchical syntactic structure.

1) We use their open-source code for both the synthetic tree and real text generation.

Table 2 Results on synthetic datasets. "Len" indicates the number of nodes in the tree; the number after the slash is the length of brackets sequence. "NLL" and "NLL(-)" represent Negative Log-Likelihood, and the latter didn't count brackets in "(" and ")". "Fail" denotes the percentage of ill-formed generated samples, which have unmatched brackets or do not satisfy the "tag word" pattern. † indicates that the performance falls after a few iterations during the training and in such a case, we perform an early-stop.

Model	Len	NLL	NLL(-)	Fail (%)	Len	NLL	NLL(-)	Fail (%)	Len	NLL	NLL(-)	Fail (%)
Oracle	5/20	3.27	6.21	–	10/40	3.32	6.21	–	15/60	3.34	6.21	–
LSTM	5/20	4.04	6.47	41.7	10/40	4.10	6.49	49.5	15/60	4.14	6.54	72.4
SeqGAN	5/20	4.40†	6.60	59.4	10/40	4.52†	6.64	74.4	15/60	4.67†	6.75	79.7
LeakGAN	5/20	4.81†	6.66	53.0	10/40	4.97†	6.63	62.1	15/60	5.10†	6.74	78.9
Ours	5/20	**3.34**	6.23	0.7	10/40	**3.37**	6.23	0.6	15/60	**3.39**	6.23	0.8

Table 3 Samples generated on the synthetic task of different models. We use symbols "T" and "W" to represent an arbitrary tag and word, respectively. Symbols that are underlined indicate mistakes. Our model succeeds in preserving structure integrity most of the time.

Model	Sample
Oracle	`(TW(TW(TW(TW)(TW)(TW))(TW(TW(TW)(TW)))))`
LSTM	`(TW(TW(TW))(TW)(TW(TW))(TW))(TW(TW)(TW(T`
SeqGAN	`(TW(TW))(TW)(TW(TW))(TW(TW(TW)(TW(TW(TW)`
LeakGAN	`(TW)(TW(TW(TW(TW(TW(TW(TW))(TW))(TW)(TW)`
Ours	`(TW(TW)(TW)(TW(TW(TW(TW)))(TW)(TW(TW)))`

4.2 Real Text Generation

Results on the synthetic data highlight the need for dealing with structure explicitly. Now, we showcase the advantages of our model in generating real-world texts. We performed unconditional text generation, as was done in many previous generation studies [10,12,27].

We used a large IMDB text corpus [8] to train our model. This dataset is a collection of 350K movie reviews and contains various kinds of compound sentences. We selected sentences with a length between 17 and 25 words, set the threshold for high-frequency words at 180, and only selected the sentences with words above that threshold. Finally, we randomly chose 80,000 sentences for training and 3,000 for testing, with the vocabulary size of 4979 and the average sentence length of 19.6 words. We used the Stanford Parser[2)] to obtain the dependency tree as the ground-truth labels to train our model. This was done by first obtaining a constituency tree and then converting it into a dependency tree. We used such a strongly restricted dataset to stabilize the training process of GAN methods. The MLE (maximum likelihood estimation) method was used to train the LSTM and our model.

We set the iterations of the message passing procedure to 4. The weight of action loss was 5 to make the overall action loss (accumulated over all the steps of a sample) comparable to the overall word loss. Finally, the ratio of schedule sampling was increasing from 0.0 to 0.5 stepping by 0.05 per epoch.

We used the BLEU score [17] to measure the similarity degree between the generated texts and the test set texts. Specifically, we use the dataset-level BLEU, which means that the reference set is the whole test set for each generated sample. In addition, we add an informal measure of novelty by looking at the BLEU score and edit distance *against the training set*. There is a similar measurement proposed in [24]; they use the Jaccard Distance, which is weaker than BLEU, and the edit distance for measuring sentence similarity. Intuitively, "novelty" encourages the model to generate unseen samples and patterns and punishes repetition. However, "novelty" does not measure the rationality of the unseen patterns. In this case, a good model should have high "novelty" and "quality" simultaneously. They are different measures that serve the same purpose: a higher BLEU score or a lower edit distance indicate that the

2) https://nlp.stanford.edu/software/

Table 4 Results on the IMDB dataset. The top half gives the results of generation quality. The bottom half shows the novelty measure by comparing the BLEU score and edit-distance ("ED/LEN" means normalized over sentence length) of generated samples against the training set. ↑ means higher is better, and ↓ means lower is better. BLEU-N means the BLEU score average over $1 \sim N$ grams.

			LSTM	SeqGAN	LeakGAN	Ours
Test/Quality	↑	BLEU-2	0.652	0.683	0.809	**0.876**
	↑	BLEU-3	0.405	0.418	0.554	**0.643**
	↑	BLEU-4	0.304	0.315	0.358	**0.415**
	↑	BLEU-5	0.202	0.221	0.252	**0.286**
Train/Novelty	↓	BLEU-2	**0.915**	0.997	0.987	0.941
	↓	BLEU-3	**0.750**	0.990	0.949	0.827
	↓	BLEU-4	**0.545**	0.980	0.892	0.613
	↓	BLEU-5	0.387	0.971	0.840	**0.361**
	↑	Edit Dist	14.88	1.05	6.09	**18.40**
	↑	ED/LEN	**71.2%**	5.7%	27.4%	70.2%
Human Evaluation	↑		0.494	0.535	**0.644**	0.552

model is more likely just memorizing and copying text from the training set.

Results Since this is a pure generation task (i.e. there is no message to decode), the sentences are typically not meaningful. In general, our texts are more well-formed syntactically. On the other hand, while the texts produced by SeqGAN and LeakGAN appear to have high quality, usually they are just slight variations of those in the training set. See Table 5 for fully generated samples, and Table 6 for step-wise partial sentences produced by our model. More examples can be found in the Appendix.

The quantitative results are shown in Table 4, which indicates our approach outperforms all the other methods. When generating text, it manages to keep both the quality as well as novelty high due to a number of factors. Our model employs message passing along the dependency and word order edges, exploring structures much better than a vanilla LSTM generator. Mode collapsing is a known problem in models using adversarial training; however, our framework uses maximum likelihood and thus we reduce the problem of distribution drift with scheduled sampling.

We also provide a human evaluation (last row of Table 4). We sampled 50 unique sentences from different models and asked 20 people to score it; On average, each sentence was evaluted by 5 different people. The scores were between 0 and 1, where a higher score indicates the sentence is more realistic. LeakGAN received the highest score, likely because it was copying from the training set.

5 Discussion

5.1 Complexity

One drawback of adopting the message passing paradigm is the computational overhead. Since multiple passes are needed, the computation overhead is $O(N^2)$, N being the length of a sentence. When the outer loop inserts a new node, the inner loop processes the propagation. In addition, the trees within a mini-batch are usually unaligned in their structures, and thus we have to process one tree at a time and aggregate gradients over a mini-batch of trees before updating.

We applied a number of optimizations. For example, we maintain a flag to avoid redundant updates when the representations of a node's neighbors have not changed. Since the graphs are often sparse, this optimization brings significant computational saving. we also tried stopping updates for nodes that are too far away or are leaves. Without these optimizations, training was almost 10 times slower than that

Table 5 Samples from different models, † demonstrates a direct copy from training set.

Method	Generated samples
LSTM	This is a heart but after the news reporter comes together of survival and lost and do you'd really simply work.
	But that and their is a great score just as a good start to entertain because it genuine.
	I think it would leave an impression which bad is the exact same formula pretty big .
SeqGAN	† This does not star Kurt Russell, but rather allows him what amounts to an extended cameo.
	This does good to make a movie and film relies a stupid sense of credibility for the genre or any movie not going to it.
	This also too hard at all, but is also a scene but I am not sure of anything, humor and I think you shouldn't go
LeakGAN	† This movie is very creepy and has some good gory scenes that would be rather disturbing .
	† The story itself we may have seen a dozen times before but it doesn't much matter .
	† This was a great family film and one of my new favorites from Disney and Pixar .
Ours	I guess I was some good elements for that attempt in the country movie .
	It 's a movie ends up in this franchise and say this is a fan of his girlfriend.
	The beauty of the film, in this movie, I was a good man and that I don't know.

for a similarly configured LSTM; however, with this optimization it is five times slower, which is still very significant. Making the training process more efficient is one of our future research directions.

6 Related Work

Although deep neural networks have made great progress in text generation, most of them employ sequential models performing auto-regression directly on the text sequence. For example, [23] linearizes parsing trees to bracket expression form and uses an attention-enhanced sequence-to-sequence model to parse a sentence. Although this method can generate a tree-structured text with slight modifications, the linearization process only exacerbates the long-standing challenge of dealing with long-distance dependencies in sequential models.

While structures for sentence representation have been explored in works such as Tree-LSTM [22], text generation models attempting to explicitly incorporate syntactic structures have started to appear only recently. In contrast, we adopt the MPNN framework and explicitly treat text generation as a graph generation problem. Some of the other related works are as follows:

[9] uses a transition-based method to generate phrase-structure trees. A parser works from the bottom-up, consuming the sentence while building the hierarchy. This mechanism can be converted to a generative model, by replacing the SHIFT operator with an action that generates a word. We observe two difficulties here. One is that the bottom-up parsing actions can have difficulties dealing with partially complete texts; Second, the depth-first nature ignores the opportunity to have global planning with future contexts.

[1] uses a doubly recurrent neural network model comprised of separate width and depth recurrences to generate tree structured sentence directly. Same as [23], they use an encoder-decoder framework to generate a tree structure from a given sentence.

Table 6 Step-by-step examples. word is the new word at a step and **final sentence** is the result of re-sampling at the final round. Note how re-sampling helps to correct mistakes (c.f. the correction of "liked" in the first example).

Step	Case 1	Case 2
1	get	is
2	I get	This is
3	I get racing	This is one
4	I get racing because	This is a one
5	I get racing because I	This is a good one
6	I get racing because I liked	This is a good one ,
7	I get racing because I liked .	This is a good one , and
8	I get the racing because I liked .	This is a good one , and excellent
9	I get the racing because I would liked .	This is a good one , and excellent .
10	**I get the racing because I would like .**	This is a good one , and excellent job .
11		This is a good one , and excellent job of .
12		This is a good one , and excellent job of NUM .
13		This is a good one , and excellent job of the NUM .
14		**This is a good film , and excellent job of the film .**

[28] also proposes a sequence-to-tree approach, which transforms trees into equivalent ternary trees, and then, uses a tree-structured search to generate the text in the form of dependency trees.

The graph neural network [19] and its more recent variant, the message passing neural network, have been applied to a variety of graph problems [3,11,13,15,16,26]. To the best of our knowledge, our method is the first to directly adopt MPNN for text generation.

7 Conclusion

Text generation has been considered as a sequential problem for a long time. The conventional approach is to decompose a sentence into a series of words via chain rule and generate the words in that order. This is an effective strategy, but it only covers a part of word relationships and ignores the structure of language. In this paper, we introduced a graph-based text generation approach that considers the syntactic dependency relationships between words. Experimental results on synthetic and real text generation tasks show that our approach outperforms the sequential methods.

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