Abstract

We study the problem of using (partial) constituency parse trees as syntactic guidance for controlled text generation. Existing approaches to this problem use recurrent structures, which not only suffer from the long-term dependency problem but also falls short in modeling the tree structure of the syntactic guidance. We propose to leverage the parallelism of Transformer to better incorporate parse trees. Our method first expands a partial template constituency parse tree to a full-fledged parse tree tailored for the input source text, and then uses the expanded tree to guide text generation. The effectiveness of our model in this process hinges upon two new attention mechanisms: 1) a path attention mechanism that forces one node to attend to only other nodes located in its path in the syntax tree to better incorporate syntax guidance; 2) a multi-encoder attention mechanism that allows the decoder to dynamically attend to information from multiple encoders. Our experiments in the controlled paraphrasing task show that our method outperforms SOTA models both semantically and syntactically, improving the best baseline’s BLEU score from 11.83 to 26.27.

1 Introduction

Generating text that conforms to syntactic or semantic constraints benefits many NLP applications. To name a few, when paired data are limited, Yang et al. (2019) build templates from large-scale unpaired data to aid the training of the dialog generation model; Niu et al. (2017) and Liu et al. (2019) apply style constraints to adjust the formality or rhetoric of the utterances; Iyyer et al. (2018) and Li et al. (2019a) augment dataset using controlled generation to improve the model performance.

We study the problem of syntactically controlled text generation, which aims to generate target text with pre-defined syntactic guidance. Most recent studies on this topic (Chen et al., 2019a; Bao et al., 2019) use sentences as exemplars to specify syntactic guidance. However, the guidance specified by a sentence can be vague, because its syntactic and semantic factors are tangled. Different from them, we use constituency parse trees as explicit syntactic constraints. As providing full-fledged parse trees of the target text is impractical, we require only a template parse tree that sketches a few top levels of a full tree (§ 2). Figure 1 shows our pipeline.

Iyyer et al. (2018) adopt the same setting as ours. Their proposed SCPN model uses two LSTM (Hochreiter and Schmidhuber, 1997) encoders to respectively encode source text and parse tree, and connects them to one decoder with additional attention (Bahdanau et al., 2014) and pointer (See et al., 2017) structures. Nonetheless, recurrent encoders not only suffer from information loss by compressing a whole sequence into one vector but also are incapable of properly modeling the tree structure of constituency parse as well. Consequently, their network tends to “translate” the parse tree, instead of learning the real syntactic structures from it.

We propose a Transformer-based syntax-guided text generation method, named GuiG. It first expands a template constituency parse tree to a full-
fledged parse tree tailored for the input source text, and then uses the full tree to guide text generation. To capture the tree structure of the syntax, we apply a path attention mechanism (§ 3.2) to our text generation model. It forces one node to attend to only other nodes located in its path (i.e., its ancestors and descendants) instead of all the nodes in the tree. Such a mechanism limits the information flow among the nodes in the constituency tree that do not have the direct ancestor-descendant relationship, forcing the parent nodes to carry more information than their children. In cooperation with path attention, we linearize the constituency trees to a more compact node-level format (§ 3.1). Moreover, to address the challenge of properly integrating the semantic and syntactic information, we design a multi-encoder attention mechanism (§ 3.1). It enables the Transformer decoder to accept outputs from multiple encoders simultaneously.

We evaluated our model on the controlled paraphrasing task. The experiment results show that GuiG outperforms the state-of-the-art SCPN method by 6.7% in syntactic quality and 122.1% in semantic quality. Human evaluations prove our method generates semantically and syntactically superior sentences, with 1.13 semantic and 0.62 syntactic score improvements. Further, we find that the multi-encoder attention mechanism enhances the Transformer’s ability to deal with multiple inputs, and the path attention mechanism significantly contributes to the model’s semantic performance (§ 4).

Our contributions include: 1) a multi-encoder attention mechanism that allows a Transformer decoder to attend to multiple encoders; 2) a path attention mechanism designed to better incorporate tree-structured syntax guidance with a special tree linearization format; and 3) a syntax-guided text generation method GuiG that achieves new state-of-the-art semantic and syntactic performance.

2 Problem Setup

Syntax-guided text generation aims to generate target text $s_{tgt}$ from 1) a source sentence $s_{src}$ and 2) a syntax template $x_{tmpl}$, such that the generated sentence utilizes the semantics of $s_{src}$ and is syntactically aligned with $x_{tmpl}$.

For the sentences, we tokenize them into subword units using byte pair encoding (BPE) (Sennrich et al., 2016). This prevailing encoding method not only solves the out-of-vocabulary (OOV) issue but also has the ability to model the character of word roots and affixes. Formally, the tokenized text sequence is represented by $s = (s^{(1)}, s^{(2)}, \ldots, s^{(M)})$ with $s^{(i)} \in C$, where $C$ is the set of all sub-word units and $M$ is the sequence length. Moreover, we assume the constituency parse tree of the source sentence $s_{src}$ is also available, denoted as the source parse $x_{src}$.

The syntax template $x_{tmpl}$ is a partial constituency parse tree that provides high-level syntax sketches. We use the top-$\ell$ ($\ell = 3$ in this work) levels of target parse $x_{tgt}$, which is the full-fledged constituency tree of $s_{tgt}$. $x_{tmpl}$ can be also frequent templates mined from any text corpora.

3 Methodology

Our method GuiG contains two models (Figure 1)—a syntax expander (§ 3.1) that expands the template parse, and a text generator (§ 3.2) that leverages the expanded parse to control text generation.

3.1 Syntax Expansion

The goal of our syntax expander is to construct a valid full-fledged target parse tree $\hat{x}_{tgt}$ from the template parse $x_{tmpl}$. To adapt $x_{tgt}$ to the source text $s_{src}$, we use the source parse $x_{src}$ of $s_{src}$ to guide the syntax expansion process.

**Parse Tree Linearization** We use a pair of node and level sequences to represent the constituency parse tree. A constituency parse tree $x$ is thus linearized to a node-level format sequence $x = (x^{(1)}, x^{(2)}, \ldots, x^{(N)})$ where $N$ is the number of nodes in the parse tree $x$. For each $x^{(i)} = \{p^{(i)}, l^{(i)}\}$, $p^{(i)}$ is the parse node and $l^{(i)}$ is its level. For example, the parse of the sentence “I ate an apple” is represented by the node sequence “S NP PRP VP VBD NP DT NN” and the level sequence “1 2 3 2 3 3 4 4”. Comparing with the existing bracketed format, which linearizes the above sentence to “(S (NP (PRP)) (VP (VBD) (NP (DT) (NN)) ) )”, our node-level representation reduces the parse sequence length to $1/3$. This more compact representation decreases the time consumption for both syntax encoding and prediction, thus facilitating the syntax expansion and text generation steps.

At the embedding layer, the parse node tokens and level tokens are embedded respectively and then added together to produce the syntax embedding at position $i$:

$$\text{Emb}(x^{(i)}) = \text{Emb}(p^{(i)}) + \text{Emb}(l^{(i)}).$$
Multi-Encoder Attention  Figure 2 illustrates the syntax expansion model in GuiG. As shown, the model has two Transformer encoders: a source encoder that encodes $x_{src}$, and a template encoder that encodes $x_{tmpl}$. Intuitively, $x_{tmpl}$ regulates $\hat{x}_{tgt}$’s high-level syntactic structure, while the expander fills the details according to $x_{src}$.

How to integrate the information from multiple encoders is critical. Wang et al. (2019b) chooses to use a linear layer to combine the encoder outputs and feed the result into the decoder. The input sequences in their work share the same length, and the tokens at the same position are corresponding to each other, e.g., one input sequence is the sentence and another is its part of speech (POS) tagging. Our inputs, however, have various lengths, making the simple integration with linear layer infeasible.

Inspired by the multi-head attention mechanism (Vaswani et al., 2017), we propose a multi-encoder attention mechanism, which extends the concept of multi-head attention by attaching different attention heads to different Transformer encoders (Figure 2). Suppose we have two Transformer encoders with encoding output $H_1 \in \mathbb{R}^{m_1 \times d_m}$ and $H_2 \in \mathbb{R}^{m_2 \times d_m}$, and the decoder’s former layer output $O \in \mathbb{R}^{m_O \times d_m}$ where $m_1, m_2$ and $m_O$ are sequence lengths, the multi-encoder attention is calculated as follows:

$$C = \text{Concat}(A_1^{(1)}, \ldots, A_1^{(h_1)}, A_2^{(1)}, \ldots, A_2^{(h_2)}),$$

$$A_j^{(i)} = \text{Attn}(O \cdot W_{Q,j}^{(i)}, H_i \cdot W_{K,j}^{(i)}, H_i \cdot W_{V,j}^{(i)}),$$

where $W_{Q,j}^{(i)}, W_{K,j}^{(i)} \in \mathbb{R}^{d_m \times d_k}$, $W_{V,j}^{(i)} \in \mathbb{R}^{d_m \times d_v}$, $d_m$, $d_k$ and $d_v$ are the vector dimensions; $h_1$ and $h_2$ are the number of decoder heads attached to different encoders. $A_j^{(i)} \in \mathbb{R}^{m_O \times d_e}$ is the result of the $j$th attention head connected to encoder $i$, calculated in the same way as Vaswani et al. (2017):

$$\text{Attn}(Q, K, V) = \text{Softmax}\left(\frac{Q \cdot K^T}{\sqrt{d_k}}\right) \cdot V.$$

As each matrix $A_j^{(i)}$ has the same dimension, the multi-encoder attention can easily integrate encoder outputs with different sequence lengths through concatenation. At last, a linear layer is used to fuse the information:

$$\text{Attention}_{\text{MultiEnc}} = C \cdot W_O,$$

with projection matrix $W_O \in \mathbb{R}^{(h_1+h_2)d_e \times d_m}$. In this way, multiple Transformer encoders can be attended by a Transformer decoder, even if their encoded sequences have different lengths.

Training  The last decoder block is followed by two classification modules to make two predictions at step $i - 1$: the parse node $p_{tgt}^{(i)}$ and the level token $l_{tgt}^{(i)}$. Given their probabilities $p_{tgt}^{(i)}$, $l_{tgt}^{(i)}$ and the one-hot encoded ground truth $y_p^{(i)}$, $y_l^{(i)}$, the step loss is the weighted sum of two L2L losses:

$$\text{loss}_{\text{syn}}^{(i-1)} = -\alpha \langle \log p_{tgt}^{(i)}; y_p^{(i)} \rangle - \beta \langle \log l_{tgt}^{(i)}; y_l^{(i)} \rangle,$$

where $\langle \cdot, \cdot \rangle$ is the inner product; $\alpha$ and $\beta$ are loss weights, which are both set to 0.5 in our work. The training objective is minimizing the sequence loss, i.e. the sum of all step losses.
3.2 Guided Text Generation

The goal of the text generator is to generate the target text $s_{tgt}$, which is syntactically aligned with the syntactic guidance $\hat{x}_{tgt}$ and meanwhile utilizes the semantics of the source text $s_{src}$. Similar to the syntax expander, we also use two Transformer encoders—a syntax encoder and a text encoder—to encode syntax sequence and text sequence separately and a Transformer decoder with the multi-encoder attention mechanism for the generation (see Figure 3). However, as the syntax and text representations belong to different spaces, the situation becomes tricky: when the provided syntactic structure is specific, chances are particular words are mapped onto the leaf nodes, resulting in a model overfitted to the surface names of syntactic tokens.

**Path Attention** To address the above issue, we propose a path attention strategy that forces the network to focus more on general syntactic guidance in higher-level part of the constituency tree. A path is a route in a tree from the root node to a leaf node (see Figure 3). Say $O \in \mathbb{R}^{m_O \times d_m}$ is the former layer’s output, with $m_O$ as the sequence length and $d_m$ as the model dimension. First, it is duplicated by $n_p$ times ($n_p$ is the total number of paths), forming a set $\{O^{(1)}, \ldots, O^{(n_p)}\}$ in which each element corresponds to a path. A mask is applied to each element to mask out (set to $-\infty$) those nodes not in the path. Then, each masked element $O_M^{(i)}, i \in [1, n_p]$ is separately fed into the same self-attention network:

$$C_i = \text{Concat}(A_i^{(1)}, \ldots, A_i^{(h)}) \cdot W_O,$$

$$A_i^{(j)} = \text{Attn}(O^{(j)} \cdot W_Q^{(j)}, O^{(j)} \cdot W_K^{(j)}, O^{(j)} \cdot W_V^{(j)}),$$

where $W^{(s)}_s$ are learnable weights; $h$ is the number of attention heads and $j \in [1, h]$. At last, the results are averaged to form the path attention output:

$$\text{Attention}_{\text{path}} = \frac{1}{n_p} \sum_{i=1}^{n_p} C_i.$$

Intuitively, the self-attention mechanism updates each token embedding with a weighted sum of all embeddings in the sequence. With path attention, however, one node can only exchange information with other nodes that share the same path. To acquire information from a node outside its path, one must turn to their common ancestor, who is able to get the desired information from former path attention layers, forcing the ancestors (higher-level guidance) to be more heavily attended to than the descendants. The path attention is executed twice in each block so that the information carried by each node flows around the entire sequence.

The reason we do not include the path attention strategy in the syntax expander is that the input and output of that model are both linearized parse trees. Using path attention in the encoder would create a mismatch between the encoding and decoding process that harms model performance.

**Training** The guided generator is trained by minimizing the NLL loss between the probability $\hat{y}_s^{(i)}$ and the one-hot encoded ground truth word $y_s^{(i)}$:

$$\text{loss}_{\text{txt}} = -\sum_{i=1}^{M} \langle \log \hat{y}_s^{(i)}, y_s^{(i)} \rangle,$$

where $M$ is the sequence length. During inference, the syntax guidance of the text generator can be either the full-fledged target parse tree $\hat{x}_{tgt}$ or the output of the syntax expander $\hat{x}_{tgt}$. 

---

1 We substitute self-attention layers in the syntax encoder with our path attention layers.
Table 1: Text generation results with the ground truth target parse $x_{tgt}$ as syntactic guidance. “TG” represents the text generator. “Transformer” is introduced in § 4.1. “w/o syn” is a Transformer without syntactic constraint whereas “w/o txt” has no source text input. “w/o PA” is the GuiG.TG without path attention strategy applied to the syntax encoder. The arrows show the direction where better performance is.

| Model     | BLEU ↑ | ROUGE-1 ↑ | ROUGE-2 ↑ | ROUGE-L ↑ | METEOR ↑ | TED-f ↓ | TED-8 ↓ |
|-----------|--------|-----------|-----------|-----------|----------|---------|---------|
| VGV A/E   | 13.6   | 44.7      | 21.0      | 48.3      | 24.8     | 6.7     | -       |
| SCPN      | 23.23  | 53.21     | 31.05     | 57.22     | 51.91    | 6.55    | 6.21    |
| Transformer | 46.00  | 73.32     | 54.45     | 75.47     | 73.50    | 6.33    | 5.95    |
| w/o syn   | 15.96  | 50.11     | 23.83     | 49.68     | 46.84    | 11.88   | 11.44   |
| w/o txt   | 13.41  | 39.74     | 20.62     | 44.72     | 37.40    | 6.35    | 5.89    |
| w/o PA    | 38.91  | 68.01     | 47.78     | 70.67     | 67.26    | 6.36    | 5.88    |
| GuiG.TG   | 48.03  | 74.53     | 56.05     | 76.65     | 75.02    | 6.23    | 5.89    |

4 Experiments

4.1 Setup

Task and Data Preparation We evaluate GuiG on the paraphrase generation task. Following Iyyer et al. (2018), we first evaluate the guided text generator’s ability to follow the syntactic guidance by predicting paraphrases with the source text $s_{src}$ and the target parse $x_{tgt}$. Then, we assess the performance of our syntax expander by predicting text using the constituency tree $x_{tgt}$ expanded from the template parse $x_{tmpl}$.

Our dataset is a subset of ParaNMT-50M (Wieting and Gimpel, 2018) provided by Chen et al. (2019a). In our work, the number of total text subword tokens is 16,000. The constituency parsing tool is provided by AllenNLP (Gardner et al., 2018). The sentences whose parse trees contain infrequent tokens are excluded, and all trees are truncated to 8-level for simplicity, leaving 74 parse nodes and 12 level tokens in total. The dataset is standardized by removing all paraphrase pairs whose text or syntax sequences are longer than 50 or with non-ASCII characters. After the pre-processing, 447,536 paraphrase pairs remain in the dataset, in which 90% are randomly selected for training and the rest for validation. Independent from them, 500 and 800 high-quality paraphrase pairs manually annotated by Chen et al. (2019a) are used for model development and evaluation. The training details of GuiG are described in the Appendix.

Baselines We include three baselines:

- SCPN (Iyyer et al., 2018) is based on LSTM, attention and copy mechanism (See et al., 2017). It is trained and evaluated on the same dataset as ours, except that their parse tree is linearized to the bracketed format. The network hyper-parameters are set to default.
- VGV A/E (Chen et al., 2019a) uses reference sentences as the syntactic constraint instead of constituency trees.
- A standard Transformer (Vaswani et al., 2017) for syntax-guided text generation. We concatenate the input syntax guidance with the source text and feed the connected sequence into the model to generate target text.

In addition to the above baselines, we also include ablations of our model to study the effectiveness of different components in GuiG.

4.2 Quantitative Evaluation

To evaluate the performance of different methods, we use three metrics for semantic congruity and one for syntactic similarity. The semantic metrics are: 1) BLEU (Papineni et al., 2002); 2) ROUGE (Lin, 2004), including ROUGE-1, ROUGE-2, ROUGE-L; and 3) METEOR (Banerjee and Lavie, 2005). To assess syntactic alignment, we calculate the tree edit distance (TED) between the generated and target sentences’ constituency parse trees. It measures the number of insertion, rotation and removal operations needed for changing one tree to another.

Text Generation with Target Parse When the full constituency trees of target sentences $x_{tgt}$ are given as syntactic guidance, Table 1 shows that our generator has better semantic and syntactic performance than SCPN and VGV A/E by doubling their BLEU scores as well as presenting a smaller TED. Comparing our generator with the standard Transformer, we find that encoding different information separately is a better way than mixing them together in the same encoder.

*BLEU & METEOR: https://www.nltk.org/; ROUGE: https://github.com/Diego999/py-rouge; https://github.com/JoaoFelipe/apted
Table 2: Synthetic evaluation of the syntax expansion and text generation models. SE and TG are syntax expansion and text generation models respectively. “w/o tmpl” uses only source parse to predict target parse. xtmpl indicates that the template parses are directly fed into the text generation model without expansion. “w/ PA” is our syntax expander with path attention applied to its source syntax encoder.

| SE   | TG       | BLEU ↑ | ROUGE-1 ↑ | ROUGE-2 ↑ | ROUGE-L ↑ | METEOR ↑ | N-TED-f ↓ |
|------|----------|--------|-----------|-----------|-----------|----------|-----------|
| SCPN | SCPN     | 11.83  | 41.83     | 20.36     | 45.63     | 38.59    | 0.5074    |
| SCPN | GuiG.TG  | 19.52  | 55.14     | 31.11     | 57.89     | 51.69    | 0.5125    |
| w/ PA| GuiG.TG  | 19.47  | 53.06     | 29.39     | 55.87     | 50.81    | 0.4946    |
| w/o tmpl| GuiG.TG| 13.29  | 45.56     | 18.62     | 45.38     | 42.48    | 0.6843    |
| xtmpl| GuiG.TG  | 20.22  | 56.00     | 32.73     | 58.57     | 50.63    | 0.6227    |
| GuiG.SE| GuiG.TG | 26.27  | 61.10     | 37.13     | 63.04     | 59.88    | 0.4732    |

The table also shows that both source text and syntactic guidance are indispensable. Paraphrasing with only source text gives fair semantics, but completely fails to control the syntactic structure; whereas text generated without source text, as one may predict, has fair syntactic structure but poor semantics. The last two rows indicate that path attention significantly contributes to the semantic expression without losing the syntactic integrity. The results support our claim that it encourages the model to attend to higher-level guidance and learn the real syntactic structure instead of a parse-to-word mapping.

Text Generation with Expanded Parse  Table 2 and Figure 4 present the performance of text generators when their syntax guidance comes from SCPN’s syntax expansion model. With the same expanded parse, our text generator again demonstrates better semantic results and similar syntactic results. This proves our text generator’s superiority is independent of the source of syntactic guidance.

Syntax Expansion  Since our ultimate goal is to generate text, we indirectly evaluate the syntax expander through the assessment of the text generated under the guidance of the expanded parse xtgt. To make it fair, here we uniformly use our text generator to generate sentences with xtgt expanded from different syntax expanders. Also, the maximum syntax sequence length of SCPN is set to 150 as their linearization method takes 3 times the length as ours. In addition, TED unfairly favors shorter generated sentences. Therefore we report its normalized version—N-TED, i.e., TED divided by the number of nodes in a tree, when the expanded syntax sequences are of different lengths. Specifically, we report N-TED-ℓ and “N-TED-f” to give a full description of how the consistency trees of generated sentences aligned to the target syntax at different levels. ℓ indicates how many levels of parse trees are kept when we compare the syntax of the generated and target sentences, and “f” (full) means the parse trees are intact.

Table 2 mainly presents the semantic results whereas Figure 4 illustrates the detailed syntactic performance. Comparing our syntax expander to SCPN’s, one can see that our model is more capable of predicting reasonable syntactic structures, with which the text generator can generate sentences more semantically analogous to the targets. Although Figure 4a implies that SCPN’s syntax expansion model produces better syntactic results, it is because our syntax expander predicts larger parse trees. When the trees are larger, the text generator is prone to output longer sentences, biasing the evaluation against our model. Removing the interference of length, our syntax expander gives better scores when the trimmed syntax trees are deeper than 4 levels, as shown in Figure 4b. Benefited from the copy mechanism, SCPN is more...
We perform a crowdsourced evaluation of the semantic and syntactic similarities between the generated and target sentences from 1 to 5, the higher the better.

The results presented in Table 3 are largely parallel to the objective metrics (§ 4.2). Compared with SCPN, our text generator generates more semantically reasonable text with the syntactic guidance comes from either the target parse \(x_{tgt}\) (1st and 2nd rows) or the parse \(x_{tgt}\) expanded from template \(x_{tmpl}\) by SCPN (3rd and 4th rows). The 4th and 5th rows in the table prove that our syntax expander also contributes to the performance improvement.

Table 3: Human evaluation scores. \(x_{tgt}\) is the case where we use target parses \(x_{tgt}\) as generator’s syntactic guidance without expansion model. \(x_{tmpl}\) is the case where the generator takes the expanded parse.

### 4.3 Human Evaluation

We perform a crowdsourced evaluation of the semantics and syntax of the generated sentences. 200 examples are randomly selected. Each of them is evaluated by three workers in the way of scoring the semantic and syntactic similarities between the generated and target sentences from 1 to 5, the higher the better.

The results presented in Table 3 are largely parallel to the objective metrics (§ 4.2). Compared with SCPN, our text generator generates more semantically reasonable text with the syntactic guidance comes from either the target parse \(x_{tgt}\) (1st and 2nd rows) or the parse \(x_{tgt}\) expanded from template \(x_{tmpl}\) by SCPN (3rd and 4th rows). The 4th and 5th rows in the table prove that our syntax expander also contributes to the performance improvement.

Analyzing the sentences that get low (\(\leq 2\)) semantic or syntactic average scores, we find our text generator sometimes suffers from several defects: 1) the generated sentence is semantically opposite to the target, especially when the source text has multi-negation; 2) one word gets repeated for several times; and 3) incomprehensible words.

Table 4: Examples generated with expanded parse \(x_{tgt}\). are given due to the usage of BPE. These issues are universal in all text generation models and deserve further investigation. However, these situations are rare, and our method generates fluent and well-structured sentences most of the time.

### 4.4 Qualitative Analysis

#### Text Generation with Expanded Parse

Table 4 shows a few examples generated under the guidance of expanded parses. It can be observed that most of the time the semantic meanings of source sentences are well-preserved while the syntactic structures are successfully transferred. However, in some cases, the predicted text fails to entirely follow the references’ syntactic structures due to the imperfection of the syntax expansion model. In the second example, the syntactic distinction of the source and reference sentences lies in micro rather than macro scale. Consequently, the predicted parse copies heavily from the source parse, making the generated sentence more similar to the source text instead of the target. Nonetheless, compared with SCPN, our model is more capable of using appropriate expression and suffers less from the repeated words issue, leading to more comprehensible and better-structured sentences.

#### Text Generation with Common Templates

We take a step further and demonstrate our model’s ability to generate sentences from the templates that appear most frequently in the dataset. Table 5 shows that the sentences generated with the same template parses have similar high-level structures.
Moreover, the semantic analogy between the source and generated sentences proves our method’s ability to successfully keep the semantics during the syntax transfer process.

5 Related Works

Constrained text generation has attracted much attention in recent years. Categorized by the object to be controlled, there are two tracks of works: one seeks to manipulate the semantic attributes (Hu et al., 2017; Li et al., 2018b,a; Yin et al., 2019; Wang et al., 2019a). For example, Hu et al. (2017) generate text with specified sentiments, whereas Li et al. (2018b) and Wang et al. (2019a) try to transfer the sentiments or styles of the source sentences. The other track, to which our research belongs, focuses on making generated text follow a particular style or structure (Niu et al., 2017; Ficler and Goldberg, 2017; Fu et al., 2018; Liu et al., 2018; Iyyer et al., 2018; Chen et al., 2019a; Li et al., 2019b; Balasubramanian et al., 2020). For instance, Niu et al. (2017) constrain the output styles in neural machine translation task and Liu et al. (2018) impose length limitation to the summarization.

Based on the constraint source, syntactically controlled text generation models can be further divided into three groups. The first group (Chen et al., 2019b; Bao et al., 2019; Balasubramanian et al., 2020) takes sentences as syntactic exemplars. They attempt to disentangle the semantic and syntactic representations into different VAE (Kingma and Welling, 2014) latent spaces during training, and then use the exemplar to assign a prior distribution to the syntactic latent space at the inference stage. The second group (Iyyer et al., 2018; Zhang et al., 2019) directly employs the constituency tree as an auxiliary input, controlling the syntax of generated text with the structure specified by it. Instead of importing externally, the third group (Wiseman et al., 2018; Akoury et al., 2019; Casas et al., 2020) learns the syntax guidance from the training data and apply it in the generation phrase in return.

Considering that the fully specified exemplar sentences are hard to be effectively retrieved (Goyal and Durrett, 2020), we follow Iyyer et al. (2018) and use constituency trees as the syntax guidance. We further take advantage of the parallel attribute of Transformer (Vaswani et al., 2017) to accommodate the tree structure in the encoding process. There are works (Eriguchi et al., 2016; Chen et al., 2017; Ding and Tao, 2019) that adapt the recurrent encoder to the trees, but the transition matrix that RNNs depend on is less effective than our attention mechanism, especially when the tree is large.

6 Conclusion

We have proposed a novel syntactically guided text generation method GuiG. 4 It expands the template constituency parse tree to a full-fledged tree, using it as the syntactic constraint to guide the text generation process. A syntax expander based on the multi-encoder Transformer is designed to predict a convincing target parse tailored for the source text, and a guided text generator powered by path attention strategy is introduced to generate text that has the semantics specified by the source text as well as complies with the syntactic guidance. Evaluated on the paraphrasing task, ablation studies justify the necessity of the components of our method, while quantitative and qualitative experiments demonstrate our method’s ability to generates more semantically reasonable and syntactically aligned sentences than SOTA baselines. We believe our method can play an important role in style transfer and text data augmentation applications.

4The code and data are available at https://github.com/Yinghao-Li/GuiGen.
References

Nader Akoury, Kalpesh Krishna, and Mohit Iyyer. 2019. Syntactically supervised transformers for faster neural machine translation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1269–1281, Florence, Italy. Association for Computational Linguistics.

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2014. Neural machine translation by jointly learning to align and translate. Cit arxiv:1409.0473 Comment: Accepted at ICLR 2015 as oral presentation.

Vikash Balasubramanian, Ivan Kobyzev, Hareesh Bahuleyan, Ilya Shapiro, and Olga Vechtomova. 2020. Polarized-vae: Proximity based disentangled representation learning for text generation.

Satanjeev Banerjee and Alon Lavie. 2005. METEOR: An automatic metric for MT evaluation with improved correlation with human judgments. In Proceedings of the ACL Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization, pages 65–72, Ann Arbor, Michigan. Association for Computational Linguistics.

Yu Bao, Hao Zhou, Shujian Huang, Lei Li, Lili Mou, Olga Vechtomova, Xin-yu Dai, and Jiajun Chen. 2019. Generating sentences from disentangled syntactic and semantic spaces. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 6008–6019, Florence, Italy. Association for Computational Linguistics.

Noe Casas, José A. R. Fonollosa, and Marta R. Costajussa. 2020. Syntax-driven iterative expansion language models for controllable text generation.

Hudong Chen, Shujian Huang, David Chiang, and Jiajun Chen. 2017. Improved neural machine translation with a syntax-aware encoder and decoder. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1936–1945, Vancouver, Canada. Association for Computational Linguistics.

Mingda Chen, Qingming Tang, Sam Wiseman, and Kevin Gimpel. 2019a. Controllable paraphrase generation with a syntactic exemplar. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 5972–5984, Florence, Italy. Association for Computational Linguistics.

Mingda Chen, Qingming Tang, Sam Wiseman, and Kevin Gimpel. 2019b. A multi-task approach for disentangling syntax and semantics in sentence representations. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 2453–2464, Minneapolis, Minnesota. Association for Computational Linguistics.

Liang Ding and Dacheng Tao. 2019. Recurrent graph syntax encoder for neural machine translation.

Akiko Eriguchi, Kazuma Hashimoto, and Yoshimasa Tsuruoka. 2016. Tree-to-sequence attentional neural machine translation. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 823–833, Berlin, Germany. Association for Computational Linguistics.

Jessica Ficler and Yoav Goldberg. 2017. Controlling linguistic style aspects in neural language generation. In Proceedings of the Workshop on Stylistic Variation, pages 94–104, Copenhagen, Denmark. Association for Computational Linguistics.

Zhenxin Fu, Xiaoye Tan, Nanyun Peng, Dongyan Zhao, and Rui Yan. 2018. Style transfer in text: Exploration and evaluation. In Thirty-Second AAAI Conference on Artificial Intelligence.

Matt Gardner, Joel Grus, Mark Neumann, Oyvind Tafjord, Pradeep Dasigi, Nelson F. Liu, Matthew Peters, Michael Schmitz, and Luke Zettlemoyer. 2018. AllenNLP: A deep semantic natural language processing platform. In Proceedings of Workshop for NLP Open Source Software (NLP-OSS), pages 1–6, Melbourne, Australia. Association for Computational Linguistics.

Tanya Goyal and Greg Durrett. 2020. Neural syntactic preordering for controlled paraphrase generation.

Sepp Hochreiter and Jurgen Schmidhuber. 1997. Long short-term memory. Neural Comput., 9(8):1735–1780.

Zhitong Hu, Zichao Yang, Xiaodan Liang, Ruslan Salakhutdinov, and Eric P Xing. 2017. Toward controlled generation of text. In Proceedings of the 34th International Conference on Machine Learning-Volume 70, pages 1587–1596. JMLR. org.

Mohit Iyyer, John Wieting, Kevin Gimpel, and Luke Zettlemoyer. 2018. Adversarial example generation with syntactically controlled paraphrase networks. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1875–1885, New Orleans, Louisiana. Association for Computational Linguistics.

Diederik P. Kingma and Max Welling. 2014. Auto-encoding variational bayes. In 2nd International Conference on Learning Representations, ICLR 2014, Banff, AB, Canada, April 14-16, 2014, Conference Track Proceedings.

Chenliang Li, Weiran Xu, Si Li, and Sheng Gao. 2018a. Guiding generation for abstractive text summarization based on key information guide network. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies,
Zichao Li, Xin Jiang, Lifeng Shang, and Qun Liu. 2019b. Decomposable neural paraphrase generation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 3403–3414, Florence, Italy. Association for Computational Linguistics.

Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In Text Summarization Branches Out, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

Yizhu Liu, Zhiyi Luo, and Kenny Zhu. 2018. Controlling length in abstractive summarization using a convolutional neural network. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 4110–4119, Brussels, Belgium. Association for Computational Linguistics.

Zhiqiang Liu, Zuohui Fu, Jie Cao, Gerard de Melo, Yik-Cheung Tam, Cheng Niu, and Jie Zhou. 2019. Rhetorically controlled encoder-decoder for modern Chinese poetry generation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1992–2001, Florence, Italy. Association for Computational Linguistics.

Xing Niu, Marianna Martindale, and Marine Carpuat. 2017. A study of style in machine translation: Controlling the formality of machine translation output. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 2814–2819, Copenhagen, Denmark. Association for Computational Linguistics.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: A method for automatic evaluation of machine translation. In Proceedings of the 40th Annual Meeting on Association for Computational Linguistics, ACL ’02, pages 311–318, Stroudsburg, PA, USA. Association for Computational Linguistics.

Abigail See, Peter J. Liu, and Christopher D. Manning. 2017. Get to the point: Summarization with pointer-generator networks. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1073–1083, Vancouver, Canada. Association for Computational Linguistics.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Neural machine translation of rare words with subword units. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1715–1725, Berlin, Germany. Association for Computational Linguistics.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Advances in neural information processing systems, pages 5998–6008.

Ke Wang, Hang Hua, and Xiaojun Wan. 2019a. Controllable unsupervised text attribute transfer via editing entangled latent representation. In Advances in Neural Information Processing Systems, pages 11034–11044, Curran Associates, Inc.

Su Wang, Rahul Gupta, Nancy Chang, and Jason Baldridge. 2019b. A task in a suit and a tie: Paraphrase generation with semantic augmentation. Proceedings of the AAAI Conference on Artificial Intelligence, 33:7176–7183.

John Wieging and Kevin Gimpel. 2018. ParaNMT-50M: Pushing the limits of paraphrasic sentence embeddings with millions of machine translations. In Proceedings of the 36th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 451–462, Melbourne, Australia. Association for Computational Linguistics.

Sam Wiseman, Stuart Shieber, and Alexander Rush. 2018. Learning neural templates for text generation. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 3174–3187, Brussels, Belgium. Association for Computational Linguistics.

Ze Yang, Wei Wu, Jian Yang, Can Xu, and Zhoujun Li. 2019. Low-resource response generation with template prior. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 1886–1897, Hong Kong, China. Association for Computational Linguistics.

Di Yin, Shujian Huang, Xin-Yu Dai, and Jiajun Chen. 2019. Utilizing non-parallel text for style transfer by making partial comparisons. In Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, Volume 2 (Short Papers), pages 55–60, New Orleans, Louisiana. Association for Computational Linguistics.
Xinyuan Zhang, Yi Yang, Siyang Yuan, Dinghan Shen, and Lawrence Carin. 2019. Syntax-infused variational autoencoder for text generation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 2069–2078, Florence, Italy. Association for Computational Linguistics.