Stage-wise Fine-tuning for Graph-to-Text Generation

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Abstract

Graph-to-text generation has benefited from pre-trained language models (PLMs) in achieving better performance than structured graph encoders. However, they fail to fully utilize the structure information of the input graph. In this paper, we aim to further improve the performance of the pre-trained language model by proposing a structured graph-to-text model with a two-step fine-tuning mechanism which first fine-tunes the model on Wikipedia before adapting to the graph-to-text generation. In addition to using the traditional token and position embeddings to encode the knowledge graph (KG), we propose a novel tree-level embedding method to capture the interdependency structures of the input graph. This new approach has significantly improved the performance of all text generation metrics for the English WebNLG 2017 dataset.

1 Introduction

In the graph-to-text generation task (Gardent et al., 2017), the model takes in a complex KG (an example is in Figure 1) and generates a corresponding faithful natural language description (Table 1). Previous efforts for this task can be mainly divided into two categories: sequence-to-sequence models that directly solve the generation task with LSTMs (Gardent et al., 2017) or Transformer (Castro Ferreira et al., 2019); and graph-to-text models (Trisedya et al., 2018; Marcheggiani and Perez-Beltrachini, 2018) which use a graph encoder to capture the structure of the KGs. Recently, Transformer-based PLMs such as GPT-2 (Radford et al., 2019), BART (Lewis et al., 2020), and T5 (Raffel et al., 2020) have achieved state-of-the-art results on WebNLG dataset due to factual knowledge acquired in the pre-training phase (Harkous et al., 2020; Ribeiro et al., 2020b; Kale, 2020; Chen et al., 2020a).

Despite such improvement, PLMs fine-tuned only on the clean (or labeled) data might be more prone to hallucinate factual knowledge (e.g., “Visvesvaraya Technological University” in Table 1). Inspired by the success of domain-adaptive pre-training (Gururangan et al., 2020), we propose a novel two-step fine-tuning mechanism graph-to-text generation task. Unlike (Ribeiro et al., 2020b; Herzig et al., 2020; Chen et al., 2020a) which directly fine-tune the PLMs on the training set, we first fine-tune our model over noisy RDF graphs and related article pairs crawled from Wikipedia before final fine-tuning on the clean/labeled training set. The additional fine-tuning step benefits our model by leveraging triples not included in the training set and reducing the chances that the model fabricates facts based on the language model.

Meanwhile, the PLMs might also fail to cover all relations in the KG by creating incorrect or missing facts. For example, in Table 1, although the T5-large with Wikipedia fine-tuning successfully removes the unwanted contents, it still ignores the “sports Governing Body” relation and incorrectly...
The state of Karnataka is located southwest of Mumbai. The Institute offers tennis which is governed by the All India Council for Technical Education which was granted the Technical Campus status by the International Tennis Federation. Karnataka was given the ‘Technical Campus’ status by the All India Council for Technical Education which is located in Mumbai. The Institute offers tennis which is governed by the Visvesvaraya Technological University and offers the sport of tennis [International Tennis Federation] and has Telangana to its northeast and the Arabian Sea to its west. It was given the Technical Campus status by the All India Council for Technical Education which is located in the state of Karnataka. It is governed by the All India Council for Technical Education which is located in Mumbai. The Institute is affiliated with the Visvesvaraya Technological University and offers the sport of tennis [International Tennis Federation].

| Category   | Output                                                                 |
|------------|--------------------------------------------------------------------------|
| Reference  | The Acharya Institute of Technology in Karnataka state was given Technical Campus status by All India Council for Technical Education in Mumbai. The school offers tennis which is governed by the International Tennis Federation. Karnataka has the "Aranmula" and "Arabian Sea". The Institute was given the Technical Campus status by the All India Council for Technical Education which is located in the state of Karnataka. It was given the Technical Campus status by the All India Council for Technical Education which was granted the Technical Campus status by the International Tennis Federation. Karnataka has the \[International Tennis Federation\]                        |
| T5-large   | T5-large                                                               |
| + Wiki     | The Acharya Institute of Technology in Karnataka state was given Technical Campus status by All India Council for Technical Education in Mumbai. The school offers tennis which is governed by the International Tennis Federation. Karnataka has the "Aranmula" and "Arabian Sea". The Institute was given the Technical Campus status by the All India Council for Technical Education which is located in the state of Karnataka. It was given the Technical Campus status by the All India Council for Technical Education which was granted the Technical Campus status by the International Tennis Federation. Karnataka has the \[International Tennis Federation\]                        |
| + Position | The Acharya Institute of Technology in Karnataka state was given Technical Campus status by All India Council for Technical Education in Mumbai. The school offers tennis which is governed by the International Tennis Federation. Karnataka has the "Aranmula" and "Arabian Sea". The Institute was given the Technical Campus status by the All India Council for Technical Education which is located in the state of Karnataka. It was given the Technical Campus status by the All India Council for Technical Education which was granted the Technical Campus status by the International Tennis Federation. Karnataka has the \[International Tennis Federation\]                        |
| T5-large   | The Acharya Institute of Technology in Karnataka state was given Technical Campus status by All India Council for Technical Education in Mumbai. The school offers tennis which is governed by the International Tennis Federation. Karnataka has the "Aranmula" and "Arabian Sea". The Institute was given the Technical Campus status by the All India Council for Technical Education which is located in the state of Karnataka. It was given the Technical Campus status by the All India Council for Technical Education which was granted the Technical Campus status by the International Tennis Federation. Karnataka has the \[International Tennis Federation\]                        |
| + Wiki     | The Acharya Institute of Technology in Karnataka state was given Technical Campus status by All India Council for Technical Education in Mumbai. The school offers tennis which is governed by the International Tennis Federation. Karnataka has the "Aranmula" and "Arabian Sea". The Institute was given the Technical Campus status by the All India Council for Technical Education which is located in the state of Karnataka. It was given the Technical Campus status by the All India Council for Technical Education which was granted the Technical Campus status by the International Tennis Federation. Karnataka has the \[International Tennis Federation\]                        |
| + Position | The Acharya Institute of Technology in Karnataka state was given Technical Campus status by All India Council for Technical Education in Mumbai. The school offers tennis which is governed by the International Tennis Federation. Karnataka has the "Aranmula" and "Arabian Sea". The Institute was given the Technical Campus status by the All India Council for Technical Education which is located in the state of Karnataka. It was given the Technical Campus status by the All India Council for Technical Education which was granted the Technical Campus status by the International Tennis Federation. Karnataka has the \[International Tennis Federation\]                        |

Table 1: Human and System Generated Description in Figure 1. We use the color box to frame each entity out with the same color as the corresponding entity in Figure 1. We highlight fabricated facts, missed relations, and incorrect relations with different color.

links the university to both “Telangana” and “Arabian Sea”. To better capture the structure and interdependence of facts in the KG, instead of using a complex graph encoder, we leverage the power of Transformer-based PLMs with additional positional embeddings which have been proved effective in various generation tasks (Herzig et al., 2020; Chen et al., 2020a,b). Here, we extend the embedding layer of Transformer-based PLMs with two additional triple role and tree-level embeddings to capture graph structure.

We explore the proposed stage-wise fine-tuning and structure-preserving embedding strategies for graph-to-text generation task on WebNLG corpus (Gardent et al., 2017). Our experimental results clearly demonstrate the benefit of each strategy in achieving the state-of-the-art performance on most commonly reported automatic evaluation metrics.

2 Method

Given an RDF graph with multiple relations $G = \{(s_1, r_1, o_1), (s_2, r_2, o_2), \ldots, (s_n, r_n, o_n)\}$, our goal is to generate a text faithfully describing the input graph. We represent each relation with a triple $(s_i, r_i, o_i) \in G$ for $i \in \{1, \ldots, n\}$, where $s_i$, $r_i$, and $o_i$ are natural language phrases that represent the subject, type, and object of the relation, respectively. We augment our model with additional position embeddings to capture the structure of the KG. To feed the input for the large-scale Transformer-based PLM, we flatten the graph as a concatenation of linearized triple sequences:

$|S s_1|P r_1|O o_1| \ldots |S s_n|P r_n|O o_n$

following Ribeiro et al. (2020b), where $|S, |P, |O$ are special tokens prepended to indicate whether the phrases in the relations are subjects, relations, or objects, respectively. Instead of directly fine-tuning the PLM on the WebNLG dataset, we first fine-tune our model on a noisy, but larger corpus crawled from Wikipedia, then we fine-tune the model on the training set.

Positional embeddings Since the input of the WebNLG task is a small KG which describes properties of entities, we introduce additional positional
embeddings to enhance the flattened input of pre-trained Transformer-based sequence-to-sequence models such as BART and TaPas (Herzig et al., 2020). We extend the input layer with two position-aware embeddings in addition to the original position embeddings as shown in the Figure 2:

- Position ID, which is the same as the original position ID used in BART, is the index of the token in the flattened sequence $|S \ s_1 \ |P \ r_1 \ |O \ o_1 \ ... \ |S \ s_n \ |P \ r_n \ |O \ o_n$.

- Triple Role ID takes 3 values for a specific triple $(s_i, r_i, o_i)$: 1 for the subject $s_i$, 2 for the relation $r_i$, and 3 for the object $o_i$.

- Tree level ID calculates the distance (the number of relations) from the root which is the source vertex of the RDF graph.

### Two-step Fine-tuning

To get better domain adaptation ability (Gururangan et al., 2020; Herzig et al., 2020), following TaPas and Wikipedia Person and Animal Dataset (Wang et al., 2018), we perform intermediate pre-training by coupling noisy English Wikipedia data with Wikidata triples, both of which are crawled in March 2020. We select 15 related categories (Astronaut, University, Monument, Building, ComicsCharacter, Food, Airport, SportsTeam, WrittenWork, Athlete, Artist, City, MeanOfTransportation, CelestialBody, Politician) that appear in the WebNLG dataset (Gardent et al., 2017) and collect 542,192 data pairs. For each Wikipedia article, we query its corresponding Wikidata triples and remove sentences which contain no values in the Wikidata triples to form graph-text pairs. Unlike (Chen et al., 2020a) which focuses on individual entity-sentence pairs for distant supervision, our pre-training corpus, on the other hand, is designed to better adapt to translating deeper graph structure into text. We remove triples and description pairs that have already appeared in the WebNLG dataset. After intermediate pre-training on this noisy corpus, we continue with fine-tuning our model on the WebNLG dataset.

### 3 Experiments

#### 3.1 Dataset and Implementation details

| Model | BLEU(%) | METEOR(%) | TER(%) |
|-------|---------|-----------|--------|
|       | Seen    | Unseen    | All    | Seen | Unseen | All    | Seen | Unseen | All    |
| Without Gardent et al. (2017) | 54.52 33.27 | 45.13 0.41 | 0.33 0.40 | 0.55 0.47 |
| Pretrained Moryossef et al. (2019) | 53.30 34.41 | 47.24 0.44 | 0.34 0.47 | 0.56 0.51 |
| LM Zhao et al. (2020) | 52.86 37.85 | 45.89 0.42 | 0.41 0.33 | 0.53 0.42 |
| Without Nan et al. (2021) | 53.30 34.41 | 47.24 0.44 | 0.34 0.47 | 0.56 0.51 |
| Pretrained Kale (2020) | 64.42 38.23 | 52.78 0.45 | 0.37 0.41 | 0.53 0.42 |
| Our model T5-large + Wiki + Position | 66.07 53.87 | 60.56 0.46 | 0.42 0.32 | 0.41 0.36 |

Table 2: System Results on WebNLG Test Set Evaluated by BLEU, METEOR, and TER with Official Scripts

We use the original version of English WebNLG2017 (Gardent et al., 2017) dataset which contains 18,102/2,268/4,928 graph-description pairs for training, validation, and testing set respectively. For this task, we investigate a variety of the BART and T5 models with our novel tree-

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2For this baseline, we use the results reported from Zhao et al. (2020) who also use official evaluation scripts.

3For T5 models, we only keep the Triple Role and Tree-level embeddings.

https://github.com/KaijuML/parent
level embeddings. The statistics and more details of those models are listed in Appendix A.

| Model                  | P↑  | R↑   | F1↑  |
|------------------------|-----|------|------|
| Gardent et al. (2017)  | 88.35 | 90.22 | 89.23 |
| Moryossef et al. (2019)| 85.77 | 89.34 | 87.46 |
| Nair et al. (2021)     | 89.36 | 92.35 | 90.83 |
| Ribeiro et al. (2020b) | 89.36 | 91.96 | 90.59 |
| T5-large + Wiki + Position | 96.36 | 96.13 | 96.21 |

Table 4: System Results on WebNLG Test Set Evaluated by BERTScore precision, recall, F1 (%)

3.2 Results and Analysis

We use the standard NLG evaluation metrics to report results: BLEU (Papineni et al., 2002), METEOR (Lavie and Agarwal, 2007), and TER (Snover et al., 2006), as shown in Table 2. Because Castro Ferreira et al. (2020) has found that BERTScore (Zhang* et al., 2020) correlates with human evaluation ratings better, we use BERTscore to evaluate system results as shown in Table 4. When selecting the best models, we also evaluate each model with PARENT (Dhingra et al., 2019) metric which measures the overlap between predictions and both reference texts and graph contents. Dhingra et al. (2019) show PARENT metric has better human rating correlations. Table 3 shows the pre-trained models with 2-step fine-tuning and position embeddings achieve better results. We conduct paired t-test between our proposed model and all the other baselines on 10 randomly sampled subsets. The differences are statistically significant with $p \leq 0.008$ for all settings.

Results with Wikipedia fine-tuning. The Wikipedia fine-tuning helps the model handle unseen relations such as “inOfficeWhileVicePresident”, and “activeYearsStartYear” by stating “His vice president is Atiku Abubakar” and “started playing in 1995” respectively. It also combines relations with the same type together with correct order, e.g., given two death places of a person, the model generates: “died in Sidcup, London” instead of generating two sentences or placing the city name ahead of the area name.

Results with positional embeddings. For the KG with multiple triples, additional positional embeddings help reduce the errors introduced by processes.

3.3 Remaining Challenges

However, pre-trained language models also generate some errors as shown in Table 5. Because the language model is heavily pre-trained, it is biased against the occurrence of patterns that would enable it to infer the right relation. For example, for the “activeYearsStartYear” relation, the model might confuse it with the birth year. For some relations that do not have a clear direction, the language model is not powerful enough to consider the deep connections between the subject and the object. For example, for the relation “doctoralStudent”, the model mistakenly describes a professor as a Ph.D. student. Similarly, the model treats an asteroid as a person because it has an epoch date. For KGs with multiple triples, the generator still has a chance to miss relations or mixes the subject and the object of different relations, especially for the unseen category. For instance, for a soccer player with multiple clubs, the system might confuse the subject of one club’s relation with another club.

4 Related Work

The WebNLG task is similar to Wikibio generation (Lebret et al., 2016; Wang et al., 2018), AMR-to-text generation (Song et al., 2018) and ROTOWIRE (Wiseman et al., 2017; Puduppully et al., 2019). Previous methods usually treat the graph-to-text generation as an end-to-end generation task. Those models (Trisedya et al., 2018; Gong et al., 2019; Shen et al., 2020) usually first linearize the knowledge graph and then use attention mechanism to generate the description sentences. While the linearization of input graph may sacrifice the inter-dependency inside input graph, some papers (Ribeiro et al., 2019, 2020a; Zhao et al., 2020)
Table 5: System Error Examples. We highlight fabricated facts, missed relations, incorrect relations, and ground truth relations with different color.

| Category | Output |
|----------|--------|
| T5-large | Andrew White (born in 2003) is a musician who is associated with the band Kaiser Chiefs and Marry Banilow. He is also associated with the label Polydor Records and is signed to B-Unique Records. S: Aleksandra Kovac P: activeYearsStartYear O: 1990 |
| T5-large | Walter Baade was born in the German Empire and graduated from the University of Gottingen. He was the doctoral student of Halton Arp and Allan Sandage and was the discoverer of 1036 Ganymed. S: Walter Baade P: doctoralStudent O: Halton Arp; S: Walter Baade P: doctoralStudent O: Allan Sandage; T5-large | +Wiki |
| T5-large | 11264 Claudiomaccone was born on the 26th of November, 2005. He has an orbital period of 1513.722 days, a periastris of 296521000.0 kilometres and an apoapsis of 475426000.0 kilometres. S: 11264 Claudiomaccone P: epoch O: 2005-11-26; S: Aleksandr Prudnikov P: club O: FC Amkar Perm |
| T5-large | The chairman of FC Spartak Moscow is Sergey Rodionov. Aleksandr Prudnikov plays for FC Spartak Moscow and manages FC Amkar Perm. [ S: FC Amkar Perm P: manager O: Gadzhi Gadzhiyev; S: Aleksandr Prudnikov P: club O: FC Amkar Perm ] |

5 Conclusions and Future Work

We propose a new two-step structured generation task for the graph-to-text generation task based on a two-step fine-tuning mechanism and novel tree-level position embeddings. In the future, we aim to address the remaining challenges and extend the framework for broader applications.

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A Hyperparameters and Statistics of the Model

| Origin  | + Position |
|---------|------------|
| BART-base | 139.42M | 139.43M |
| distil-BART-xsum | 305.51M | 305.53M |
| BART-large | 406.29M | 406.31M |
| T5-base | 222.88M | 222.90M |
| T5-large | 737.64M | 737.65M |

Table 6: # of Model Parameters

Our model is built based on the Huggingface framework (Wolf et al., 2020). Because the average lengths for source and target text in the training set are 31 and 22 words respectively, we set the maximum length for both source and target to 100 words. For T5 preprocessing, we prepend “translate RDF to English:” before the input. For BART-base, distil-BART-xsum, and T5-base, we use a batch size of 32 and train the model. We use a batch size of 16 for Bart-large, and 6 for T5-large. We use the Adam optimizer (Kingma and Ba, 2015) to optimize each model with learning rate of $3 \times 10^{-5}$ with $\epsilon = 1 \times 10^{-8}$ for a maximum of 10 epochs. We run each experiment on one Nvidia Tesla V100 GPU with 16G DRAM. We first fine-tuned the PLMs on crawled Wikipedia pairs for 3 epochs. The Wikipedia Fine-tuning stage takes about 24 hours for T5-large and 10 hours for the rest of models. The final WebNLG fine-tuning stage takes less than 1 hour for all the models. We chose our best model based on multi-BLEU score. For inference, we use beam search with beam size in the range \{3,5\}. Table 6 shows the number of the parameters for each pre-trained model.

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8https://github.com/huggingface/transformers
9https://gitlab.com/webnlg/webnlg-baseline/-/blob/master/multi-bleu.perl
9# of parameters are slightly different because we add special tokens to the vocabulary
### B Sample Generation Results

#### Table 7: Human and System Generated Description
We use the color box to frame each entity out with the same color as the corresponding entity. We highlight fabricate facts, [missed relations], and incorrect relations with different color.

| Category | Output |
|----------|--------|
| Input    | S | Aaron Turner | associatedBand/associatedMusicalArtist | Twilight (band) |
|          | S | Aaron Turner | associatedBand/associatedMusicalArtist | Lotus Eaters (band) |
|          | S | Aaron Turner | genre | Sludge metal |
|          | S | Aaron Turner | origin | Massachusetts |
|          | S | Aaron Turner | activeYearsStartYear | 1995 |
| Reference| Aaron Turner was born in Massachusetts and started performing in 1995. He formerly played with the band Twilight and is now in the Lotus Eaters. He is is closely associated with the Sludge metal genre. |
| T5-large| Aaron Turner, who is from Massachusetts, is a member of the Twilight band and the Lotus Eaters band. He is also associated with the Sludge metal genre and started playing in 1995. |
| T5-large + Wiki| Twilight and the band Lotus Eaters. His music style is Sludge metal. |
| T5-large + Position| Aaron Turner, who was born in Massachusetts, is associated with Twilight and Lotus Eaters. He is a member of Sludge metal band and has also been a musical artist. [1995] |
| T5-large + Wiki + Position| Aaron Turner was born in Massachusetts and started playing Sludge metal in 1995. He is also associated with Twilight and Lotus Eaters. |

#### Table 8: Human and System Generated Description
We use the color box to frame each entity out with the same color as the corresponding entity. We highlight fabricate facts, [missed relations], and incorrect relations with different color.

| Category | Output |
|----------|--------|
| Input    | S | American Civil War | commander | Jefferson Davis |
|          | S | Alfred Moore Scales | country | United States |
|          | S | United States | ethnicGroup | Native Americans in the United States |
|          | S | Alfred Moore Scales | battles | Siege of Petersburg |
| Reference| The American Civil War was fought in the Siege of Petersburg. Jefferson Davis was the commander of the war. Alfred Moore Scales was born in the United States where Native Americans are one of the ethnic groups. Jefferson Davis was the commander of the American Civil War. |
| T5-large | He fought in the Siege of Petersburg which was part of the American Civil War commanded by Jefferson Davis. |
| T5-large + Wiki| The American Civil War was fought in the Siege of Petersburg. Jefferson Davis was the commander of the war. Alfred Moore Scales was born in the United States where Native Americans are one of the ethnic groups. He fought in the American Civil War, which was led by Jefferson Davis. The Siege of Petersburg is part of the American Civil War. |
| T5-large + Position| Alfred Moore Scales was born in the United States where Native Americans are an ethnic group. He fought in the American Civil War, which was led by Jefferson Davis. The Siege of Petersburg is part of the American Civil War. |
| T5-large + Wiki + Position| Alfred Moore Scales is from the United States where Native Americans are one of the ethnic groups. He fought in the Siege of Petersburg which is part of the American Civil War. Jefferson Davis was the commander of the American Civil War. |
Table 9: Human and System Generated Description. We use the color box to frame each entity out with the same color as the corresponding entity. We highlight fabricate facts, [missed relations], and incorrect relations with different color.