GGP: A Graph-based Grouping Planner for Explicit Control of Long Text Generation

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ABSTRACT

Existing data-driven methods can well handle short text generation. However, when applied to the long-text generation scenarios such as story generation or advertising text generation in the commercial scenario, these methods may generate illogical and uncontrollable texts. To address these aforementioned issues, we propose a graph-based grouping planner (GGP) following the idea of first-plan-then-generate. Specifically, given a collection of key phrases, GGP firstly encodes these phrases into an instance-level sequential representation and a corpus-level graph-based representation separately. With these two synergic representations, we then regroup these phrases into a fine-grained plan, based on which we generate the final long text. We conduct our experiments on three long text generation datasets and the experimental results reveal that GGP significantly outperforms baselines, which proves that GGP can control the long text generation by knowing how to say and in what order.

CCS CONCEPTS

• Computing methodologies → Natural language generation.

KEYWORDS

planning based data-to-text, graph neural networks, copy mechanism, long text generation

1 INTRODUCTION

In recent years, live streaming is becoming an increasingly popular trend of sales in E-commerce. In live streaming, an anchor will attractively introduce the listed product items, and offer certain discounts or coupons, to facilitate user interaction and volume of transactions. However, script creation of product introduction is very time-consuming and requires professional sales experience. To alleviate this problem, we launched AliMe Avatar, an AI-powered Vtuber for automatically product broadcasting in the live-streaming sales scenario. Figure 1 reveals how our virtual avatar broadcasts products with scripts created by our proposed planning-based methods. In AliMe Avatar, the process of script creation is abstracted into a first-plan-then-generate data-to-text task. The task of data-to-text generation is to generate a natural language description for given structured data [3]. Data-to-text methods have a wide range of applications in domains like automatic generation of weather forecasting, game report and production description. Table 1 shows an example where the input data is a collection of key phrases, and the output texts are corresponding natural language descriptions generated from intermediate plans.

Recently several published articles are inspired by the first-plan-then-generate pipeline [7, 10] which includes content planning, sentence planning and surface realization. Moryossef et al. [11] proposed a planning-based method to split the generation process into a symbolic text-planning stage followed by a neural generation stage. The text planner determines the information structure and expresses it unambiguously as a sequence of ordered trees from...
which can represent the content of the key phrase. Instead of the conventional straightforward \( \text{first-plan-then-generate} \) approach, we adopt a graph-based grouping approach: (1) Encoding key phrases from the input into a combination of sequential representations and graph-based representations; (2) A plan \( p = \{c_1, \ldots, c_i; \ldots, c_l\} \) is generated by picking and regrouping key phrases from \( x \) instead of reordering these phrases only. For each \( c_{ij} \), it means the key phrase is chosen as the \( j \)th element of the \( i \)th group.

### 2.1 Model Overview

Given a collection of key phrases \( x = \{p_1, p_2, \ldots, p_n\} \), \( p_i \) represents a possible key phrase which consists of several tokens, in other words, \( p_i = \{w^i_1, \ldots, w^i_k\} \). Our goal is to generate a context which can represent the content of the key phrase. Instead of the conventional straightforward \textit{first-plan-then-generate} approach, we adopt a graph-based grouping approach: (1) Encoding key phrases from the input into a combination of sequential representations and graph-based representations; (2) A plan \( p = \{c_1, \ldots, c_i; \ldots, c_l\} \) is generated by picking and regrouping key phrases from \( x \) instead of reordering these phrases only. For each \( c_{ij} \), it means the key phrase is chosen as the \( j \)th element of the \( i \)th group.

### 2.2 Hierarchical Sequential Encoding

Given \( n \) key phrases, a hierarchical transformer-based encoder [16] is used to encode key phrases into a sequence of vector representations, and then these vectors are encoded again with another transformer to learn inter-relation among these key phrases. \( w^i \) means the raw input tokens of each key phrase \( p^i \). \( c^i \) is the final key phrase representation after being encoded with the hierarchical sequential encoder.

\[
p^i = \text{Encoder}([w^i_1; w^i_n])
\]

\[
c^i = \text{Encoder}([p^i_1; p^i_n])
\]

### 2.3 Graph Encoding

To learn the graph-based representation, we first build a probability transition graph obtained from the statistics of the entire corpus, in which each node represents a key phrase. Then for each sample, we can build a subgraph according to the given key phrases. The nodes in this subgraph are encoded with a graph neural network. In our setting, we choose Graph Attention Networks (GAT) [17] instead of Graph Convolutional Networks (GCN) [6] as GAT performs slightly better in our experiments than GCN does. Let \( M_g \) be the relation matrix of the current data input.

\[
c^g = \text{GAT}([M_g; c^g])
\]

### 2.4 Grouping Copynet

The graph-based representation may not preserve the original sequential information. In this way, we combine two representations...
from the graph encoder and the sequential encoder together. Specifically, given the graph-based representation $c^g_t$ and the sequential representation $c^s_t$, we merge these two vectors into one vector $m_t$ with MLPs:

$$m_t = \text{MLP}(c^g_t; c^s_t)$$  \hspace{1cm} (4)

Suppose there are $n$ key phrases in the key phrase list, a transformer-based decoder [16] with a copy mechanism is used to pick key phrases from the input, and the generated plan is a sequence of groups. The white node in Figure 2 represents the group boundary, and each group represents the plan of each sentence. For every decoding step, the decoder is required to discriminate whether it should be separated as a group boundary or pick a key phrase from the input collections.

$$z_t = \text{Decoder}(z_{t-1}; y_{t-1}; m_{1:n})$$ \hspace{1cm} (5)

Finally, the loss function is calculated as cross entropy for each decoding step.

3 EXPERIMENTS

3.1 Dataset

- **Advertising Text Generation (ATG)** [15]: we used the same dataset from Shao et al. [15], which consists of 119K pairs of Chinese advertising text.
- **Now You’re Cooking (Cooking)** [5]: we used the same dataset and pre-processing process from Kiddon et al. [5]. In the training set, the average recipe length is 102 tokens, and the vocabulary size of recipe text is 14,103.
- **Tao Describe (TaoDesc)** [2]: TaoDesc dataset is from Chen et al. [2]. This dataset contains 2.1M pairs of product descriptions created by shop owners. We extract key phrases from these descriptions with our sequence labeling model. The format of this dataset is the same as the format of the ATG dataset.

3.2 Baselines

We compared our model with four strong baselines, including a pre-trained language model baseline, BART [8], and three planning-based baselines, PHVM, Step-By-Step and DualEnc.

- **BART** [8]: a pre-trained autoencoder whose input is a collection of key phrases or the generated plan, and output is the generated text in our settings.
- **PHVM** [15]: this model achieves state-of-the-art results on ATG. In our experiments, we use the exact implementation in Shao et al. [15] as a strong baseline on ATG.
- **Random Planner (RP)**: it chooses the key phrases from the phrase list randomly as a plan.
- **Step-By-Step (SBS)** [11]: this method captures the division of facts into sentences and the ordering of the sentences. Again we use the exact implementation in Moryossef et al. [11] on our datasets.
- **DualEnc (DE)** [18]: this is a dual encoding model that can not only incorporate the graph structure but also can cater to the linear structure of the output text to extract plans. Our implementation is according to Zhao et al. [18] on our datasets.

3.3 Automatic Evaluation Metrics

We adopted the following automatic metrics to evaluate the quality of generated outputs: (1) **BLEU-4** [12]. (2) **PLAN BLEU-4 (PB-4)** [12]: this metric is exactly BLEU-4, but hypotheses and references are generated plans and golden plans individually. (3) **PLAN ROUGE-L (PR-L)** [9]: the same as PLAN BLEU-4, but the metric is ROUGE-L instead of BLEU-4. PLAN BLEU-4 and PLAN ROUGE-L measure the quality of generated plans while BLEU-4 focuses on measuring the generated text.

3.4 Experimental Results

Table 2 reveals our experimental results. Our model outperforms the baselines in terms of BLEU-4, PLAN BLEU-4 and PLAN ROUGE-L on three datasets, which indicates that our proposed method can better make the plan according to the given key phrase list without missing important input items in a long text. The most competitive
Table 2: Generation results on three test datasets evaluated by BLEU-4, PLAN BLEU-4 and PLAN ROUGE-L. We compare our methods with BART, PHVM, Step-By-Step, and DualEnc as our baselines. Our methods outperform all baselines on all metrics.

| Dataset | Method     | BLEU-4 | PB-4 | PR-L  |
|---------|------------|--------|------|------|
| ATG     | PHVM       | 2.9    | 13.8 | 64.7 |
|         | BART       | 4.0    | 17.5 | 66.3 |
|         | RP + BART  | 2.6    | 5.9  | 52.8 |
|         | SBS + BART | 1.7    | 2.9  | 47.1 |
|         | DE + BART  | 2.7    | 9.4  | 58.5 |
|         | GGP + BART | 4.3    | 20.8 | 68.7 |
| Cooking | BART       | 7.3    | 17.7 | 73.1 |
|         | RP + BART  | 0.6    | 4.6  | 58.7 |
|         | SBS + BART | 0.5    | 4.4  | 45.1 |
|         | DE + BART  | 1.4    | 12.0 | 55.7 |
|         | GGP + BART | 7.5    | 19.5 | 74.1 |
| TaoDesc | BART       | 14.6   | 13.7 | 59.4 |
|         | RP + BART  | 13.0   | 5.6  | 51.8 |
|         | SBS + BART | 3.6    | 1.7  | 44.2 |
|         | DE + BART  | 13.2   | 12.9 | 59.5 |
|         | GGP + BART | 16.8   | 16.8 | 61.6 |

Table 3: Ablation study on the ATG dataset reveals that grouping copynet can impressively improve the performance of PLAN BLEU-4 and PLAN ROUGE-L, and GAT can further improve the performance of PLAN ROUGE-L.

| Method                  | BLEU-4 | PB-4 | PR-L  |
|-------------------------|--------|------|------|
| GGP + BART              | 4.3    | 20.8 | 68.7 |
| w/o graph networks      | 4.2    | 20.8 | 67.9 |
| w/o grouping copynet    | 4.0    | 16.7 | 64.8 |

baseline on ATG is PHVM, but BART performs a better result than PHVM. With GGP, it outperforms PHVM by 1.4% on BLEU-4, 7.0% on PLAN BLEU-4 and 4.0% on PLAN ROUGE-L, indicating the effectiveness of our planner. As for Now You’re Cooking and TaoDesc, DualEnc achieves state-of-the-art results on WebNLG [1]. However, it performs even worse than Random Planner on PLAN ROUGE-L on Now You’re Cooking and much worse than BART on all metrics as it only considers instance-level information of a sentence. However, our GGP considers constructing plans from the current instance and the corpus perspective. On Now You’re Cooking, our GGP outperforms DualEnc by 6.1% on BLEU-4, 7.5% on PLAN BLEU-4 and 18.4% on PLAN ROUGE-L. And on TaoDesc, our proposed GGP outperforms DualEnc by 3.6% on BLEU-4, 3.9% on PLAN BLEU-4 and 2.1% on PLAN ROUGE-L. In conclusion, GGP significantly outperforms baselines on PB-4 and PR-L on all of these three long text generation datasets, which proves that GGP can better control the long text generation process according to the given plan.

3.5 Ablation Study

To further investigate the effectiveness of graph networks and grouping copynet, we conduct ablation experiments on GGP. Table 3 reveals that graph networks can improve PLAN ROUGE-L by 0.8%. And with grouping copynet, PLAN BLEU-4 is improved by 4.1% while PLAN ROUGE-L is improved by 3.9%, and there is almost no effect on BLEU-4 which is exploited to measure generated texts. It can be analyzed from the results that grouping copynet can learn plans well from the whole corpus and graph information can slightly help improve the results. The reason is that copynet can directly extract phrases from source data which are also revealed in generated plans. However, the model is more flexible with the graph structure as we can use the knowledge graph or the graph extracted from other corpora in our future work.

3.6 Case Study

To observe how graph-based representations affect the planning process, we extract the graph attention from GAT and the corresponding generated plan which is exactly the same as the golden plan from the ATG dataset.

Figure 3: An example of graph attention and the corresponding generated plan which is exactly the same as the golden plan from the ATG dataset.

4 CONCLUSION AND FUTURE WORK

In this work, we present a graph-based grouping planner (GGP) for sentence planning and content planning together with graph-based information to explicitly control the process of long text generation. GGP combines the grouping copynet with graph neural networks to better capture the global information from the whole corpus and it can regroup plans from sentence-level to paragraph level. Experiments on three data-to-text corpora reveal that our model is more competitive to extract plans than state-of-the-art baselines. In the future, we will conduct more experiments on plan generation with the knowledge graph or graphs constructed from human live streaming corpus, and further apply it to our industrial scenarios.
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