Query-Variant Advertisement Text Generation with Association Knowledge

Siyu Duan  
Research Center for Digital Humanities  
& Department of Information Management,  
Peking University  
Beijing, China  
duansiyu@pku.edu.cn

Wei Li  
School of Information Science,  
Beijing Language and Culture University  
Beijing, China  
lweitj47@pku.edu.cn

Jing Cai  
Yancheng He  
Platform and Content Group,  
Tencent  
Shenzhen, Guangzhou, China  
{samscai,collinhe}@tencent.com

Yunfang Wu  
Xu Sun  
MOE Key Lab of Computational Linguistics,  
School of EECS,  
Peking University  
Beijing, China  
{wuuf,xusun}@pku.edu.cn

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1 INTRODUCTION

The revenue of many Internet companies relies on advertising. In a typical online web search advertising system, each time a user inputs a search query in natural language words, the advertising system would respond with a list of advertisements of different items. However, one item involves different aspects. One predefined general purposed advertisement text can not address the focus of diverse personalized queries. The advertising system can provide advertisement texts that are closer to user needs considering the search queries, the ads will be more attractive to the users.

An example of query variant advertisement text is given in Figure 1. In this example, query 1 and query 2 pay attention to the camera and CPU performance separately, which are different selling points for the same item. The general purposed advertisement text fails to address these personalized needs for the two queries, while the ideal query-variant advertisement texts would emphasize the diverse needs that users are interested in. Although being a favourable feature for the advertising system, the manual creation of all the advertisement texts targeting different queries with different needs for massive items is too expensive.

In this paper, we propose the query-variant advertisement text generation task, which aims to automatically generate different advertisement texts considering the needs of various queries. This task serves the query-variant search ad system. An illustration of query-variant search ad system is shown in Figure 2. Although query-variant advertisement text generation is a very practicable
Figure 1: An example of the proposed query-variant advertisement text generation task. User Queries are natural language words given by users with various needs. Item Keywords are provided by ad sponsors, contains the core information of an item that usually reflects general needs.

Figure 2: The process of search ad system. “K” is item keywords, “Q” is user query. Query-variant search ad system would respond the user query with more focused ad text for each item, which arouses a demand for the proposed query-variant ad text generation.

Figure 3: Association and Activation. The red circle “L” represents the low-frequency words encountered, and the blue circles “H” represents the high-frequency words that the model dealt with in the training. The orange circles represent the associated words, which expands the receptive field of the model. The orange circles with “A” represent the shared words that are activated when being associated by our model. These associated words allow the modeling ability to transfer from familiar high-frequency words to unfamiliar low-frequency words.

When encountering the low-frequency word “Blackberry”, the ability to deal with the high-frequency word “Apple” can be transferred to “Blackberry” through “cellphone”.

To test the effectiveness of our method, we collect over 2,140,000 queries with the retrieved advertisement texts. We also build an association knowledge word graph based on 17,000,000 advertisement texts. Extensive experiments and human evaluations show that our model outperforms all the baselines, including the retrieved general purpose human written advertisement text.

Our contributions are summarized as follows:

- We apply query-variant advertisement text generation task to search advertisement scenario. This task aims to generate different advertisement texts that satisfy the needs for various queries.
- We propose a query-variant advertisement text generation model with a novel association method to transfer the modeling ability from familiar high-frequency words to unfamiliar low-frequency words, so as to better deal with the diverse and low-frequency personalized needs.
- We conduct extensive experiments and analyses. Both automatic and human evaluation results show that our model can generate attractive advertisement texts for various queries.

2 TASK AND DATA

In this section, we introduce our proposed task and the collection of experimental data.

2.1 Task

Before introducing our task formulation, we first describe the definitions of some phrases in this paper.

**Query and Item Keywords**: Queries are the natural language search content of users in the website. Item keywords are isolated words containing the core information of the item provided by advertisement sponsors.
Table 1: Statistics of the dataset. q/k indicates the number of user queries and item keywords.

| Data     | Train (q / k) | Dev (q / k) | Test (q / k) | Max Len | Vocab | AKWG-node | AKWG-edge |
|----------|---------------|-------------|--------------|---------|-------|-----------|-----------|
| Number   | 2,126,938     | 4,516 / 1,458 | 4,174 / 1,321 | 20      | 50,000 | 49,460    | 869,371   |

General and Personalized Needs: In online search advertising, for multiple user queries matching the same item, we treat the overlap words of different queries as general needs and the others as personalized needs. General needs are often included in item keywords, while personalized needs are distributed in different search queries.

High-Frequency and Low-Frequency Words: We calculated the average Document Frequency and vocabulary size of general needs words and personalized needs words in the test set with multiple queries. The average Document Frequency of general needs words is 1.88 times that of personalized needs words, while the vocabulary size of personalized needs words is 1.52 times that of general needs words. It reveals that general needs words are high-frequency and centralized words, while personalized needs words are low-frequency and diverse words. Concretely, in the example shown in Figure 1, "phone, new, sale" rank at 44, 149, 761 respectively out of 50,000 words, while "camera, CPU" rank at 2070, 4921 respectively. The general needs (phone, new, sale) appear much more often than the personalized needs (camera, CPU).

Task Formulation:
Given the user query qi, the item keywords ki and the original advertisement text ti of the item. The objective of the task is to generate advertisement texts ai that are coherent to the item information while being closer to the focus of the given user queries (query-variant ads).

2.2 Data Collection
We collect the data from the search advertising system of the Tencent QQ Browser. Some statistics of the dataset are given in Table 1.

Query-Ad Pair Data
We use the query-ad pairs that are retrieved by online search advertising. Each pair of data consists of three parts: query qi from the user, human written advertisement text ti retrieved by the system and keywords ki of this item. The keywords are provided by the advertisement sponsors. The maximum length of the advertisement text is limited to 20 words. The number of item keywords and the length of user query in each case are limited to 10 words. This length constraint setting balances the coverage of data (95%) and calculation consumption. Furthermore, to ensure that the item keywords can reflect core item information, we set the number of the item keywords to be at least 3. There are 2.14 million different advertisement texts in our data, of which 2.12 million are used as the training set. For the test set and the validation set, the advertisement text that matches at least 2 queries in the system are selected from 10,000 advertisement texts. The test set is built in this way to evaluate the ability to satisfy the needs of different user queries.

Association Knowledge Data
We propose to construct the association knowledge word graph based on the co-occurrence information between words in the original advertisement text. The co-occurrence word graph extracted from the advertising text corpus with the same distribution brings the historical co-occurrence information of words in advertising text. We collect 17 million advertisement texts to build an Association Knowledge Word Graph (AKWG). Formally, we use point-wise mutual information (PMI) to calculate the correlation between words. In the AKWG (N, E), the nodes N are the words, and an edge e(i, j) ∈ E is built between wi and wj when the PMI(wi, wj) reaches a threshold ξ. In our construction setting, edges with PMI scores bigger than 8 are built in the AKWG, and the maximum number of neighbors for a word is limited to 20. Edge weight is normalized by dividing PMI by 8.

3 APPROACH
In this section, we formally introduce our proposed query-variant advertisement text generation method. Our model mainly consists of two modules, the Association module and the Generation module. A sketch of our model is given in Figure 4.
Figure 5: A sketch of association process. Blue circles are item keywords, red circles are query words, orange circles are the associated words retrieved by the Association Module from the AKWG.

The association module is designed to expand the receptive field of the model based on external knowledge, which can help improve the ability of the model in dealing with diverse personalized needs.

The generation module is designed to generate advertisement text based on the original input and the associated knowledge retrieved by the association module.

For each item, the forward process is as follows:

1. **Sub-graph Construction**: We first construct the sub-graph of input words $\mathcal{A}$ based on the item keywords $k$ and user queries $q$, which are connected by referring to the AKWG.

2. **Knowledge Association**: We associate external knowledge to $\mathcal{A}$ by referring to AKWG with the association module and obtain the extended sub-graph $\mathcal{A}'$. This step follows a coarse-to-fine paradigm by considering both statistical and semantic information.

3. **Ads Generation**: Finally, we generate the advertisement text based on the extended sub-graph $\mathcal{A}'$.

### 3.1 Sub-graph Construction

User queries are natural language text with many expressions, while item keywords are discrete words. To combine the two types of input, we choose to construct user query and discrete keywords into a sub-graph through the graph structure in AKWG, which provides historical information reflecting the co-occurrence between words in user query and item keywords.

Assume the bag-of-words containing item keywords $k$ and words in the user query $q$ as $\alpha$, we use the edges in AKWG($\mathcal{N}, \mathcal{E}$) to link the original input words. Formally, if $w_i \in \alpha, w_j \in \alpha$ and $e(i, j) \in \mathcal{E}$, we build an edge between $w_i$ and $w_j$ in the sub-graph $\mathcal{A}$.

### 3.2 Association Module

The Association Module is designed to expand the receptive field of the model based on external knowledge, which can help improve the ability of the model in dealing with diverse personalized needs. It can retrieve the relevant external knowledge and combine it into the input words. The input words can be linked and expanded according to the graph structure in the AKWG. When the model encounters diverse and low-frequency input words, the associated words shared with some high-frequency words could be activated. The activated associated words can be regarded as a bridge to help the model transfer its ability in dealing with familiar high-frequency words to unfamiliar low-frequency words. In this way, the ability of the model to deal with low-frequency words can benefit from it. Furthermore, only applying statistical information would bring too much noise. Therefore, we propose to take advantage of the local semantic information within each case to select appropriate associated words.

To expand the receptive field and select the expanded information, we design two steps in the association module, extension and denoising. An illustration is shown in Figure 5.

**Association: Extension**

We take the one-hop neighboring nodes of the input words $(k, q)$ in AKWG as the candidate nodes to be added to the sub-graph $\mathcal{A}$. The edges in AKWG reflect the historical co-occurrence relation between words, which can help the model make reasonable associations. These candidate words that frequently co-occur with the keywords in the advertisement text data have similar semantic information with original input words, which allows the candidate words to be relevant. The candidate nodes introduced here can be noisy and needed to be filtered before being added to the graph.

**Association: Denoising**

In sub-graph extension, we roughly select candidate neighboring nodes by retrieving all the one-hop neighboring nodes of the input words in AKWG. This rough selection procedure only makes use of the historical co-occurrence information and does not consider the semantic connection of different input words in each case, which means these candidate additional words can be noisy. Therefore, to combine the semantic information in each case, we propose a reinforcement learning (RL) based method to score (select) the suitable candidates based on the semantic information and the graph structure within the sub-graph $\mathcal{A}$ of input words.

We propose to use a **graph encoder** and a **score predictor** to score the candidates. The graph encoder is designed for encoding the sub-graph $\mathcal{A}$ into dense vectors, which contains the semantic information and structure information of the nodes. The score predictor is to predict the probability of the candidate nodes from AKWG to be extended into the sub-graph $\mathcal{A}$ based on the graph representation learned by the graph encoder and the AKWG edges.

**Graph Encoder**: We propose a Gated Graph convolutional neural networks (GatedGCN) with gated attentive pooling as the graph encoder, which is calculated as follows:

\[
\tilde{H}^l = GCN(H^{l-1}, \text{adj}) \quad (1)
\]

\[
H^l = LSTM(\tilde{H}^l, H^{l-1}) \quad (2)
\]

\[
\tilde{g}^l = \text{AttnPooling}(H^l) \quad (3)
\]

\[
g^l = LSTM(g^{l-1}, \tilde{g}^l) \quad (4)
\]

where $H^l$ is the hidden states of the $l$-th layer in the graph, $\text{adj}$ is the normalized adjacency matrix following the setting of GCN [14], $g$ is the global representation of the graph learned with attentive pooling in [18]. Attentive pooling allows the model to get a graph representation with calculated importance weights.

This encoder applies GCN to aggregate the neighboring information and uses the gate mechanism in LSTM [11] to decide which part of the aggregated information should be transmitted into the next layer in the update of both node and global representation. GCN can combine semantic information and topological structure information to encode features. The gate mechanism of LSTM can select out important information between the two layers of GCN.
Score Predictor: After we get the global graph representations, we score the candidates with the score predictor:

$$score = w([g^I; c_t])$$  \hspace{1cm} (5)$$

where $g^I$ is the global representation of the last layer, $c_t$ is the embedding of the candidate word $w_c$, $[,]$ means concatenation, and $w \in \mathbb{R}^K$ is a learnable parameter matrix. The candidates with top $\phi$ scores are added to the original sub-graph $A$, which form the new sub-graph $A'$.

3.3 Generation Module

After association, the original input words and the associated words are connected through the graph structure. We treat the original input words and the associated words as a kind of heterogeneous graph to make use of the associated words without damaging the original input information. The generation module is designed to generate advertisement text based on the extended sub-graph $A'$ obtained in the association. This module is developed based on Transformer [27]. Although Transformer has proved to be successful in modeling linear structure data, it is not suitable for the graph structure information in $A'$.

The graph structure of AKWG contains prior information of massive advertising text, which can help our text generation task. To make use of the graph structure that links the input words, we propose to add a GatedGCN layer used in the association module before the Transformer encoder. The decoder follows the same architecture of the original Transformer. To distinguish the role between the original input words and the associated knowledge words, we add type embedding $emb_t$ to the word embedding $emb_{w_t}$, $x = emb_{w_t} + emb_t$, which is similar to the positional encoding. In this way, the original input words and associated words can be seen as one kind of heterogeneous graph. The model can make use of the associated words without damaging the original input information.

3.4 Training and Inference

In the search advertisement system shown in figure 2, the ad of the same item can be recalled by multiple queries focusing on different aspects of the item. Item keywords usually indicate the general type of needs for the item, which is tightly coupled with the item. On the contrary, different user queries contain different personalized needs that are loosely coupled with the item. If simply treating both keywords and queries as the input, the model tends to treat the loosely coupled parts of queries as noise and ignore them. As a consequence, the model would ignore the personalized needs and fail to generate query-variant advertisement text.

Therefore, we use different input setting strategies in training and inference. An illustration is shown in Figure 6. In the training phase, we use item keywords as input and advertisement text as generation target. In the inference phase, words in the query are treated as discrete words like item keywords. Item keywords and query are both used as input to generate query-variant advertisement text. In this way, the model in the training phase will not be confused by the multiple loosely-coupled queries. It can learn the ability to generate general purpose advertisement text from tightly-coupled item keywords during training, and generate advertisement text for each query in the inference.

Training: We propose a three-stage training process that facilitates RL training with supervised training.

In the first stage, we omit the score predictor in the forward pass. The extended keywords are randomly selected from the candidates (words connected with $A$ in the AKWG). This first supervised training process gives the model the clue of the extended graph with new words from the AKWG, which can be used to roughly train the parameters (e.g. embeddings) of both the association module and the generation module. The generation module is trained for 15 epoch with cross-entropy weighted by the sentence length.

In the second stage, we use policy gradient [33] based RL to train the association module. This stage aims to train the module to select the associated words by referring to the supervised objective of the task. The reward is calculated by comparing the advertisement text generated by the model in the first stage with the original human-written one. Formally, the reward is calculated as follows:

$$Reward = 1 - \tanh\left(-\frac{1}{n} \sum_{j=1}^{n} t_j \log(p_j)\right)$$  \hspace{1cm} (6)$$

where $t$ is the gold label, $p$ is the prediction probability. For different inputs, the value of the sampling probability is affected by the total number of sampled words, thus affecting the RL loss. Therefore the probability for each sample is normalized by the total number of words. In this stage, the embedding of the generated model learned in the first stage is used as the embedding of the association module. Fine-tuning for reinforcement learning costs 5 epochs.

In the third stage, we also apply supervised training after the reinforcement learning process when the parameters of the association module are settled.

Inference: In inference, we treat the query as discrete words like keywords. These words, together with item keywords, are used as input during inference. We split the query of the natural sentence into a bag of words and removed the stop words, and merged with the item keywords. The sub-graph is constructed with the merged bag of words, which forms the basis of association and generation.

4 EXPERIMENT

In this section, we give the experiment results. Extensive analysis is conducted to demonstrate the effectiveness of our model.
Table 2: Automatic evaluation results. Original means the human written advertisement text retrieved by the advertising system. We show the change of Recall(q) and Recall(q+k) compared with the Original ads in parentheses. In Train and Test columns we show the input settings. k is Item Keywords, q is User Query. Our model beats all the baseline models in all the metrics except Dist-1. Although the diversity promoting model Transformer+itf gets a higher Dist-1 score, its Recall (q) is very low, which means the generated text is not targeted on the query.

| Model                  | BLEU  | Recall(k) | Recall(q) | Recall(q+k) | Dist-1 | Dist-2 | Train  | Test  |
|----------------------|-------|-----------|-----------|-------------|--------|--------|--------|-------|
| Original             | ——   | 95.45     | 65.54     | 74.51       | 9.28   | 21.73  | ——     | ——   |
| Pointer Network      | 21.58 | 84.43     | 75.91 (+10.37) | 77.70 (+3.19) | 11.11  | 36.65  | k      | k+q   |
| Transformer          | 23.65 | 90.77     | 88.06 (+22.52) | 87.66 (+13.15) | 13.07  | 38.85  | k      | k+q   |
| GPMM                 | 20.69 | 90.10     | 63.45 (-2.09) | 71.04 (-3.47) | 7.96   | 20.20  | k+q    | k+q   |
| ExpansionNet         | 21.40 | 89.68     | 66.26 (+0.72) | 71.87 (-2.64) | 8.88   | 25.80  | k+q    | k+q   |
| Transformer+itf      | 10.79 | 89.77     | 64.40 (-1.14) | 71.13 (-3.38) | 14.84  | 25.81  | k      | k     |
| Proposal             | 27.12 | 92.36     | 91.03 (+25.49) | 90.28 (+15.77) | 13.53  | 41.36  | k      | k+q   |

4.1 Setting
The embedding size is 128. The hidden size is 256. For a fair comparison, the generation module of our model is obtained by replacing the first layer in the Transformer encoder with the mentioned GatedGCN, which has parameters of the same scale as Transformer. Both the GatedGCN and the Transformer encoder have two layers, while the decoder has three layers. We use Adam optimizer [13] to train the model. Considering the memory consumption and model performance, we set the value of $\phi$ to 10 in our experiment.

4.2 Baseline
In this work, we compare our model with five strong baselines in addition to the original human-written one. The numbers of parameters are all of the comparable scales to our model.

General End-to-End Baselines:
To compare the modeling capabilities of the proposed models, we introduced two end-to-end text generation models with different architectures.

- **Pointer network** [26]: A Seq2Seq model with copy mechanism. The attention mechanism is used to calculate the additional probability of the input words to be combined with the original output probability. This baseline is applied because the advertisement text usually shares many words in the item keywords and user query.
- **Transformer** [27]: Powerful text generation model. Our generation module is a graph suitable improvement over it.

Personalized Text Generation Baselines:
The task proposed in this paper is close to the personalized text generation task that uses search queries as personalized information, so we introduce two personalized text generation baselines.

- **GPMM** (Generative Profile Memory Network) [36]: A Seq2Seq based method aiming at personalized text generation. We adapt the model to our task by treating each word of user query as individual memory representations in the memory network.
- **ExpansionNet** [23]: Another Seq2Seq based method aiming at personalized text generation, which calculates two attention scores between decoder hidden state and the word embedding in the user query.

Diversity Promoting Baseline:
The proposed task hopes to obtain diversified texts corresponding to different search queries, so we add a pure diversity promoting baseline.

- **Transformer + itf** [22]: A diversity-promoting method that weights the loss function by inverse token frequency. The network is the same as Transformer.

The Seq2Seq models in GPMM, ExpansionNet and Pointer Network are all LSTM-based [11] Seq2Seq model with attention mechanism [20]. Both encoder and decoder have three layers.

4.3 Automatic Evaluation

**Metrics:**
we choose three widely applied automatic metrics to evaluate the quality of the generated text regarding the expression ability, query coverage, and diversity.

- **BLEU** [24]: BLEU is calculated between the original human-written advertisement text and the one generated under the same input setting during training. This metric is to measure the expression ability of the model from item keywords to advertisement text. If the model can fit general-purpose advertisement text well when using keywords as input, then when the query is added as input, the model can also generate smooth advertisement text corresponding to specific query.

  - **Recall**: Recall(k), Recall(q), Recall(q+k) calculate the recall between the generated advertisement text and item keywords (k), user query (q), the union of item keywords and user query (q+k) respectively in inference. We also present the recall improvement over the original advertisement text in parentheses to measure the ability to absorb the query information. We calculate the recall by averaging over the results of different queries of the item, which reflects the ability to generate query-variant advertisement texts when facing different queries for the same item.

  - **Dist-1, Dist-2** [15]: These two metrics count the number of distinct unigrams and bigrams divided by the total number of unigrams and bigrams in the generated text. These two metrics reflect informativeness and diversity.

**Result:**
In Table 2 we show the automatic evaluation results of our model compared with the baselines and the original advertisement text.
Table 3: Human evaluation results. “win” indicates the ratio of the generated advertisement text that our proposed model is better than the counter model. “win-lose” means our proposal is better than the other one. The Pearson’s r for each metric is shown in the header within the braces.

| Versus                  | Attractiveness (p=0.44) | Informativeness (p=0.46) | Fluency (p=0.22) |
|------------------------|-------------------------|--------------------------|------------------|
|                        | win     | lose | tie | win     | lose | tie | win     | lose | tie |
| Proposal-Original      | 57.27   | 8.47 | 34.27 | 60.53   | 21.73 | 17.73 | 25.40   | 19.53 | 55.07 |
| Proposal-Transformer   | 38.00   | 14.87 | 47.13 | 48.07   | 22.33 | 29.60 | 21.67   | 10.93 | 67.40 |
| Proposal-NoQuery       | 58.67   | 4.13 | 37.20 | 69.07   | 9.07  | 21.87 | 21.73   | 18.93 | 59.33 |

We can observe that the Recall(q) of the original advertisement text is significantly lower than Recall(k), showing that the original coverage of query words is not satisfactory, which means that the general purposed advertisement text can not meet the diverse personalized needs of different queries focusing on different aspects of the item. This phenomenon testifies the necessity of our proposed task, which aims to generate query-variant advertisement text.

From the results, we can also see that traditional personalized text generation baseline methods (GPMM, ExpansionNet) do not perform well. Due to the loose-coupling problem of item-queries that one item can be matched with different queries, the model tends to treat the queries as noise and ignore them in the training, which makes the model unable to generate various advertisement texts corresponding to different queries in the inference. As a result, these common methods that model query information in the training phase are not suitable for search advertisement text generation task. It also proves that our different input setting strategies in the training and inference phase are necessary.

Note that although the pure diversity promotion method (Transformer + itf) gets a higher ratio in Dist-1, the Recall(q) is too low to be applicable, which means the generated text ignores the query. This indicates that general-purpose diversity promotion method is not suitable for the proposed task where the generated advertisement texts should answer the needs of different user queries.

Compared with the Transformer and the Pointer Network that take the same input setting in training and inference with our model, our model achieves much better results for all metrics. This is because that the associated external knowledge not only brings more fruitful information but also enhances the ability of the model to deal with words with different exposure frequency, so that the model can better fit the inputs in the training phase, and achieve better generalization effects after adding query in the inference phase. The proposed model gains the highest Recall(q) improvement among different user queries, which means that our proposed method can be adapted to variant user queries and generate query-variant advertisement texts.

4.4 Human Evaluation

Evaluation Data:
In the human evaluation, we focus on the cases where the default retrieved advertisement text does not meet the needs of the queries. If more than 50% of the characters in the query without stop words do not appear in the advertisement text, we assume that there exists a major divergence between the query and the retrieved advertisement text, which are chosen as the candidates for human evaluation. After sensitive data violating privacy issues is automatically filtered out, we randomly sample 500 cases as human evaluation data and invite 3 human annotators to do the evaluation. Evaluators are employees hired by IT companies to review various online text, which means they have expertise in reviewing advertisement text.

Evaluation Guideline:
In human evaluation, the user query and two advertisement texts options are provided to the evaluators. The evaluators are asked to choose the better one out of the two optional advertisement texts in terms of three aspects:

- Attractiveness is a comprehensive and the most important indicator, representing which advertisement text the users prefer given the query.
- Informativeness represents which advertisement text provides more useful information regarding the user query.
- Fluency represents the language smoothness of the advertisement text.

User Query 1:
胃不消化能吃什么蔬菜
What vegetables can I eat if my stomach does not digest
User Query 2:
脾胃亏虚不消化
Indigestion due to deficiency of spleen and stomach
Item Keywords:
eat, not, digest

Original Ad Text written by human:
吃什么不好食物告诉你一个简单解决消化不好的方法
What food is not good to eat. Tell you a simple way to solve poor digestion.

Auto-Generated Ad Text without Query:
消化不好吃什么食物告诉你一个简单解决消化不好的方法
What to eat when indigestion. Tell you a simple way to solve indigestion.

Auto-Generated Ad Text with Query1:
胃不消化吃什么蔬菜食物好看看大家如何养胃
What vegetables are good to eat when the stomach is not digesting? See how others care for the stomach.

Auto-Generated Ad Text with Query2:
不消化吃什么食物好看看大家如何养胃
What kind of food is good for not digesting, professional interpretation and suggestions for spleen and stomach deficiency.

Figure 7: Concrete example of advertisement text generation. Blue words represent general needs information, which is usually included in the item keywords that match the item. Red words represent diverse personalized needs contained in different user queries.
Table 4: Ablation study on the effect of association module and graph structure in generation module. -Association means that the association module is removed. -Graph Structure means to replace GatedGCN in the generation module with normal Transformer encode layer.

| Model            | BLEU | Recall(k) | Recall(q) | Recall(q+k)   | Dist-1 | Dist-2 |
|------------------|------|-----------|-----------|---------------|--------|--------|
| Proposal         | 27.12| 92.36     | 91.03 (+25.49) | 90.28 (+15.77) | 13.53  | 41.36  |
| -Association     | 23.91| 89.39     | 86.54 (+21.00) | 86.16 (+11.65) | 13.18  | 39.05  |
| -Graph Structure | 25.77| 91.89     | 90.05 (+24.51) | 89.97 (+15.16) | 13.39  | 40.66  |

Table 5: Effect of different retrieving methods. “Random” means randomly selecting $\phi$ neighbors from AKWG. “PMI” means selecting neighbors with top-$\phi$ PMI scores. “no-filter” means selecting all the neighbors in AKWG. “Proposal” means selecting with our proposed association module.

| Model       | BLEU | Recall(k) | Recall(q) | Recall(q+k)   | Dist-1 | Dist-2 |
|-------------|------|-----------|-----------|---------------|--------|--------|
| random      | 24.52| 91.60     | 89.52 (+23.98) | 89.09 (+14.58) | 13.48  | 41.13  |
| pmi         | 24.77| 91.65     | 89.66 (+24.12) | 89.14 (+14.63) | 13.39  | 40.46  |
| no-filter   | 25.20| 90.63     | 88.41 (+22.87) | 87.82 (+13.31) | 13.14  | 39.19  |
| Proposal    | 27.12| 92.36     | 91.03 (+25.49) | 90.28 (+15.77) | 13.53  | 41.36  |

If the two advertisements are equally good (bad), they are given a tie. In the final statistical results, if win > lose, it means that our proposed model beats the baseline.

**Result:**
In Table 3 we show the human evaluation results. We compare our model with three baselines, namely, the original human written advertisement text, Transformer and NoQuery. NoQuery means the result is generated by the proposed model without query during inference, which means that the query information is totally ignored. Results show that our proposed model beats all the baselines, especially in attractiveness and informativeness. The results on attractiveness and informativeness show good correlation among different evaluators, while rather low correlation on fluency. This is expected because the concept of being fluent is hard to define, especially in the advertisement text area.

We provide concrete advertisement text generation cases in Figure 7. The advertisement generated by our method takes into account both general needs contained in item keywords and query preference, which is not available in general-purpose human written advertisement and advertisement generated without query.

**4.5 Ablation Study**

**Effect of Association and Graph:**
Table 4 shows the ablation study results on association and graph structure. The removal of associative thinking (-Association) causes the decrease of the BLEU score and the Recall (q+k) by 3.21 and 4.12. We think this is because the ability of the model to deal with different types of words is benefited from the association module. This allows the model to achieve better fitting results in training. In the inference phase, the model can better absorb the query information, which makes the model less likely to generate irrelevant advertisement text.

As for the graph structure in the generation module, after replacing the GatedGCN with the normal Transformer encode layer(-Graph Structure) in the generation module, the BLEU score drop by 1.35. This shows that the graph structure with prior information can help to organize discrete input information into a fluent natural language sentence.

**Effect of Different Retrieval Methods:**
In Table 5 we show the results of different retrieving methods. Among all the retrieving methods, our proposed method achieves the best on all the metrics. Although the “no-filter” method adds all the one-hop neighbors on AKWG to the input, its performance on all metrics is still weaker than our proposed model. We think that this is because there is too much noise brought by adding all the neighbors in AKWG to the input sub-graph. This testifies that the denoising procedure of the association module is necessary.

“PMI” signifies the correlation of the candidate knowledge and gains higher recall improvement (+14.63) than “random” and “no-filter”. However, the PMI score only concerns the global historical co-occurrence knowledge, while our method not only makes use of the PMI score via the edge weight in the GCN component in the association module but also considers the semantic information of the keywords encoded in the graph representations. This design helps our method achieve the best BLEU score (27.12) and the highest recall improvement (+15.77) among all the retrieval methods.

**Effect of RL:**
In Figure 8 we show the performance trend during the RL training stages (dictated in section 3.4). From the figure, we can see that all three stages are necessary to train the model. In the reinforcement learning stage, the improvement proves that the association module can denoise the associated candidate words after reinforcement learning and obtain association words that dynamically consider the semantic information in the sub-graph of a specific case. With the help of the two supervised stages, RL training can indeed improve the performance of the model.

**5 RELATED WORK**

**Product Information Generation:** Product text information (e.g., advertisement, product description) is widely displayed in various...
Internet scenarios. Previous researchers have conducted many studies for different application scenarios. Wang et al. [29] propose a statistical framework that generates product descriptions from product attributes. [6, 32] generate personalized product descriptions on e-commerce platforms. Chan et al. [3] utilize the entity information for fidelity-oriented product descriptions. [12, 31] use user clicks feedback information to guide the generation of advertisement text. Wang et al. [30] apply a multi-task learning approach for improving product title compression with user search log data. [5] propose a new task, i.e., how to generate a multi-product advertisement post. The task we proposed is applied to search advertising, which is to generate advertisement text for a specific query. Our method is to generate query-variant ad text offline, which are then recalled online. The existing methods cannot completely solve the problems in our task scenarios.

**Personalized and Diverse Text Generation:** Many previous works have been proposed to use personalized information for text generation. [4, 17, 36] make use of speaker information and capture characteristics of speakers in neural conversation. Xing et al. [34] incorporate topic information into the Seq2Seq framework to generate informative and interesting responses for chatbots. Ni and McAuley [23] aim at generating personalized reviews by expanding short phrases with aspect-level information. These works provide good views of personalized generation. However, there is one big obstacle making their methods not suitable for our proposed task, that is, there is no strict coupled personalized query-advertisement pair in our task. In our experiment, we compared several personalized text generation methods and revealed their inapplicability to the proposed task.

There are also works focusing on generating general purposed diverse text. With the idea of reducing the frequency of high-frequency text and increasing the frequency of low-frequency text, various methods [16, 19, 22, 35] have been used to increase the diversity of text generation. Vijayakumar et al. [28] propose to diversify the outputs by optimizing diversity-augmented objective in beam search. Unlike the diversity-promoting works above, our proposed task aims to generate query-variant advertisement text that can diversify the advertisement text in the context of meeting the purpose of different query needs. Therefore, those methods that do not consider the queries are not applicable.

**External Knowledge:** External knowledge is an important information source for natural language understanding. Earlier attempts using the knowledge graph mainly focus on answering questions with a single clue retrieved from the knowledge graph [1, 2, 9, 10]. Although these works achieve big success, the applications are limited because of the idealized task setting. Other works propose to supplement the state-of-the-art model with external knowledge [7, 8, 25]. The knowledge usage in these works remains latent, and it is hard to tell the effect of the knowledge. Zhou et al. [37] use large-scale commonsense knowledge in conversation generation. Mihaylov and Frank [21] integrate external knowledge in a cloze-style setting for the reading comprehension task. These works try to reason over the graph, which is a good way to use external knowledge. However, there is no pre-defined knowledge in our task. Therefore, we propose to first construct an association knowledge word graph based on the co-occurrence information in the advertisement text.

### 6 ETHICAL ISSUES

**Industrial Application:** For the industrial application, the generated ad candidates will be further checked by human annotators before added to the online advertising system to prevent fake and misleading advertisement text from being shown to users. In the manual review phase, 85.80% of generated ads are accepted. This acceptance rate can meet the efficiency and accuracy requirements of industrial applications. In the industrial application, item keywords and possible queries are provided by the advertising sponsor, which means that our method will not use user information in the training and inference phase.

**Dataset Open-Sourced:** The data set contains search query content of website users and brand information of advertising sponsors. To protect the their privacy, the data set will be open-sourced after ID projection, which means that the mapping between word ID and word text will not be open-sourced. This approach allows peers to reproduce our automatic evaluation results and conduct computational experiments, but cannot get the original text information. Although this will affect the reproducibility of human evaluation, we believe that the protection of users and customers privacy is the highest priority.

### 7 CONCLUSION AND FUTURE WORK

In this paper, we propose the query-variant advertisement text generation task that aims to generate candidate advertisement texts for different search queries with various needs. An association method based on external knowledge is proposed to improve the ability to deal with diverse personalized needs of search queries. Both automatic and human evaluation results show that our model can generate attractive and query-variant advertisement text. Our work provides a new perspective on the industrial application and research of search advertisement text generation.

Pre-training is an important method of using historical text knowledge. In future work, we want to explore how to incorporate pre-training into existing methods. Furthermore, our data and experiments are conducted on the Chinese data set. Because the quality of the Chinese open lexicon is not ideal, the lexicon we currently use only includes AKWG constructed using historical advertising text. In the future, we will explore using lexicon from different information sources.
