Scenario-based Multi-product Advertising Copywriting Generation for E-Commerce

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Abstract

In this paper, we proposed an automatic Scenario-based Multi-product Advertising Copywriting Generation system (SMPACG) for E-Commerce, which has been deployed on a leading Chinese e-commerce platform. The proposed SMPACG consists of two main components: 1) an automatic multi-product combination selection module, which itself is consisted of a topic prediction model, a pattern and attribute-based selection model and an arbitrator model; and 2) an automatic multi-product advertising copywriting generation module, which combines our proposed domain-specific pretrained language model and knowledge-based data enhancement model. The SMPACG is the first system that realizes automatic scenario-based multi-product advertising contents generation, which achieves significant improvements over other state-of-the-art methods. The SMPACG has been not only developed for directly serving for our e-commerce recommendation system, but also used as a real-time writing assistant tool for merchants.

1 Introduction

The Internet and mobile Internet develop rapidly over the last decade, online/mobile shopping has become a mainstay way for many people around the world. Advertising copywriting plays a significant role in e-commerce recommendation platforms, especially for these e-commerce technology giants like Taobao.COM, JD.COM, etc. In these e-commerce platforms, well-written advertising copywriting can be beneficial for attracting customers and further increasing sales. However, producing advertisements by human copywriters face a few of severe limitations: 1) the efficiency of human copywriters is not able to match the growth rate of products; 2) manpower cost becomes huge when number of products exponentially increases; 3) special training is required for different scenarios. Due to these reasons, automatic advertising copywriting generation has become an important and essential task in e-commerce.

Recent years there has seen a surge of interests in automatic advertising copywriting generation (Zhang et al., 2019; Chen et al., 2019; Zhang et al., 2021b; Guo et al., 2021), which however, most of them focus on single product description generation. Single product advertising copywriting typically focuses on only describing the characteristics of the product itself in order to help customers to better understand the product and facilitate potential sales. Single product advertising is the main sales mode in most of e-commerce platforms nowadays. However, as the shopping needs and habits of customers become more diverse, displaying and selling multiple products as a combination has become a trending feature. In the multi-product mode, customers avoid troubles in finding essential related products. More importantly, e-commerce platforms gain significant more sales by encouraging customers to view and buy more related products.
There are few existing research works in the multi-product advertising copywriting generation. A recent work on multi-product advertising generation (Chan et al., 2020) aimed to help customers make better selection among multiple products with similar characteristics, which however still generated one copywriting for one product and then simply assemble them together. In contrast, our proposed SMPACG is fundamentally different from theirs. Our scenario-based multi-product advertising copywriting is developed to find highly related products (rather than similar products) under the certain scenario, and generates only one copywriting for multi-product to encourage customers to buy products within the combinations all together. As shown in Figure 1, we encourage customers to buy the smartphone and earphones (or sofa and coffee table) together by highlighting how these two products work well together and why the customer should buy them together in our advertising copywriting.

To this end, the scenario-based multi-product combination advertising requires two essential parts: 1) an automatic product combination selection module, 2) an automatic multi-product advertising copywriting generation module. Product combination selection by human labors suffers similar issues as producing advertisements by human copywriters, and thus an automatic product combination selection algorithm is indispensable. In contrast with the automatic copywriting generation system (Zhang et al., 2021b) in earlier work, which serves for the E-commerce platforms and applies on single product only, in our scenario, the generated descriptions need to be able to describe not only the information of each single product in the combination, but also the overall feature of the combination under the certain scenario. In addition, unlike the single product copywriting generation, multi-product copywriting generation requires an additional product combination selection module to select highly related yet not similar products.

To overcome these challenges, we propose our automatic Scenario-based Multi-Product Advertising Copywriting Generation (SMPACG) system for e-commerce. The SMPACG is the first system that realizes automatic scenario-based multi-product advertising contents generation, which achieves significant improvements over other state-of-the-art methods. The SMPACG has been not only developed for directly serving for our e-commerce recommendation system, but also used as a real-time writing assistant tool for merchants.

2 Related Work

Natural language generation focuses on constructing computer systems that can generate understandable texts in human languages from some underlying textual or non-linguistic representation of information (Reiter and Dale, 2000). In recent years, NLG techniques have been developing rapidly and applied to a wide range of applications such as abstract text summarization (Rush et al., 2015; Banko et al., 2000; Knight and Marcu, 2000), dialogue generation (Tao et al., 2018; Zhang et al., 2020), machine translation (Bahdanau et al., 2016) and creative generation (Yao et al., 2019; Li et al., 2018).

At early stage of text generation research, since data and computational resources are limited, mod-
els relied heavily on feature engineering (Lafferty et al., 2001; Och et al., 2004). As the technology of deep learning develops, features are learned automatically and defined implicitly during model training. The natural language generation problem has been framed as a sequence-to-sequence task and various studies have been proposed to enhance the model architecture, such as convolutional neural networks (CNN) (Gehring et al., 2017), recurrent neural networks (RNN) (Sutskever et al., 2014), graph neural networks (GNN) (Xu et al., 2018; Li et al., 2020), and Transformer-based architectures (Bahdanau et al., 2016; Vaswani et al., 2017).

Text generation techniques have been widely used for automatic product description generation tasks. Early work focuses on applying template-based generation methods (Wang et al., 2017), while the template coverage and diversity are limited. Zhang et al. (2019) proposed a pointer-based generation model with a dual encoder to generate product description. Chen et al. (2019) proposed an external knowledge based transformer-based generation model, which utilized relevant information from customer reviews extracted by an adaptive posterior distillation module. Zhang et al. (2021b) presented the proposed automatic product copywriting generation system for single-product, which has been employed for the leading e-commerce platform. Guo et al. (2021) developed and deployed the intelligent online selling point extraction system to serve the recommendation system on the leading Chinese e-commerce platform. Chan et al. (2020) designed SMGNet to generate the advertising post for multi-product scenarios which consists of similar products for ease of choice for customers.

3 Approach

In this section, as shown in Figure 2, we first illustrate the overall architecture of the SMPACG system. Our system consists of an automatic multi-product advertising copywriting generation module that itself also serves as a real-time writing assistant tool for merchants, the automatic multi-product combination selection module and combination figure generation tool for directly serving for our e-commerce recommendation system, including various applications such as the searching channel and the “WoZhe” platform (mainly for home appliance). We will discuss SMPACG system in details in the following sections.

3.1 Data Collection

We built a real-world dataset from our in-house platform which includes three parts: 1) product combination data, 2) product combination advertising copywriting data, and 3) product information data. The product combinations and corresponding advertising copywriting are selected and written by professional copywriters with good knowledge of marketing. Within each product combination, highly related products under the certain scenario are selected, and the corresponding advertising copywriting includes both advertising content and title. For product data, we collect multiple types of data from our in-house database, including product titles, attributes and product detail images.

3.2 Automatic Product Combination Selection Module

3.2.1 Topic Channel Generation

We build a system to cluster our products into different topic channels based on their characteristics. The details of this topic channel system are not included in this work, it is still under development and will be discussed in more details in our further work. The first version of this system is adopted in our work to further build our automatic product combination selection algorithm.

3.2.2 Pattern and Attribute-based Automatic Selection

Given that we have products already labeled to certain topics, the simple approach is to randomly select products within the topics to build the combination. We use this approach as our baseline. Random selected combinations within the same topic may suffer some issues, for instance, products with same functions are selected as combination, or products with no obvious relationship are selected. In order to overcome these obstacles, we propose the pattern and attribute-based automatic selection algorithm. We extract attribute patterns from our product combination dataset, and map these patterns to each of our topic channels, which has been employed for the leading e-commerce platform. Guo et al. (2021) developed and deployed the intelligent online selling point extraction system to serve the recommendation system on the leading Chinese e-commerce platform. Chan et al. (2020) designed SMGNet to generate the advertising post for multi-product scenarios which consists of similar products for ease of choice for customers.
3.2.3 Arbitrator

Once we obtain the generated combinations, we need an arbitrator for further evaluation and selection of our selected combinations. We train two BERT-based classifiers (Devlin et al., 2019) as our arbitrators, the difference between these two arbitrators come from selection of negative samples. Both arbitrators are used for evaluation of our product combination selection algorithms, and the strict one acts as the filter for generating final results.

By introducing the pattern and attribute-based automatic selection algorithm and the arbitrator, our automatic product combination selection module gain the ability of automatically generation of combinations with highly related products. As shown in Figure 3, after obtaining the combination, combination figure generation tool is applied for producing a combination figure. The combination selection module and figure generation tool serve as a significant part of our SMPACG system.

3.3 The DSPLM Model

3.3.1 Prefix Language Model

The prefix LM (Dong et al., 2019) is a left-to-right Language Model that decodes b on condition of a prefixed sequence a, which is encoded by the same model parameters with a bi-directional mask. As shown in Figure 4, the input tokens can attend to each other bidirectionally, while the output tokens can only attend to tokens on the left. To realize this, a corrupted text reconstruction objective is usually applied over input tokens, and an auto regressive language modeling objective is applied over output tokens, which encourages the prefix LM to better learn representations of the input.

The flexible model structure of prefix LM makes it a good choice for our application, where the power of language is utilized to realize our special training goals. Language can specify different parts of inputs and outputs as a sequence of symbols in a flexible way. Multiple kinds of information are embedded into the inputs represented by languages with specific tricks in building up the dataset, and the language model will learn the tasks implicitly. In this way, one model with the same structure can be reused for different tasks by only changing the input data which contains information of inputs, outputs and tasks all together.

3.3.2 Backbone Network

We utilize a 12-layer Transformer as our backbone network, the input vectors are encoded to contextual representations through the Transformer blocks. Each layer of Transformer block contains multiple self-attention heads, which takes the output vectors of the previous layer as inputs.

In our model, different mask matrices are fed into the model depending on the inputs. These mask matrices help control what context a token can attend to when calculating its contextual representation. As shown in Figure 4, within the input segment, the mask matrix is bidirectional, where the token can attend to both information before and behind. While for the output segment, the mask matrix is diagonal, where the current token can only attend to the tokens before.

3.3.3 Domain-Specific Pretraining for Prefix LM

Due to the limitation of training data, our model sometimes suffer the issues of generating descriptions with bad fluency or inaccurate information. In this case, our model never see any similar of
related information before, which makes it hard for the model to generate accurate descriptions. Thus, we introduce pretraining into our prefix LM to solve the problem. Usually, when talking about pretraining, we focus on those open-domain models obtained with large amounts of data and compute resources. But this kind of pretraining models consume large training efforts, and are not applicable for serving online in production. As shown in recent work (Zhang et al., 2021a), domain-specific pre-training is a good idea to solve the problem, where we can also get benefits from pre-training with small amounts of data and small models. In this paper, we propose the DSPLM (Domain-Specific Pretrained prefix Language Model). We collect domain specific data from our in-house dataset, parts of our single product descriptions are utilized here. Although the task of single-product and multi-product copywriting are different, they are within the same domain: e-commerce copywriting. The domain-specific pretraining helps the model learn the e-commerce copywriting styles and obtain knowledge of a large range of products.

3.4 Knowledge-based data enhancement

At early stage of experiments, we observe that although the machine evaluation metrics are improved significantly by introducing new model architectures, human evaluation scores are low. The reason is that the earlier collected copywritings written by human experts suffer several issues. Through human screening, we classify the data issues to three main categories: 1) containing forbidden patterns, 2) limit coverage of product information, 3) too simple. To overcome these issues, we introduce our knowledge-based data enhancement model to ensure the quality of training data. Our data enhancement model consists of the following components: 1) Avoided pattern filtering and cleaning: filtering or altering copywritings with certain patterns. 2) Product word based checking model: ensuring the advertising copywriting cover information of all products in the combination. 3) Creative information checking model: avoiding the advertising copywriting from simply listing all products.

Regarding the forbidden patterns, we divide them to two groups: alterable and non-alterable. We filter out the data with non-alterable avoided patterns and modify those with alterable patterns to build new dataset.

We introduce the product word prediction model mentioned in Section 3.2.2 to our system for solving issues of limit coverage. The product word prediction model is a Bert-based model, with inputs of product title and other attributes, it can predict a group of matched product words with difference confidence scores. Utilizing these predicted product words, we build a rule-based algorithm to classify whether a advertising copywriting covers enough information of all products within the combination. Copywritings which don’t meet the criterion are filtered out from the dataset.

However, some copywritings cover information from all the products in the combinations by simply listing their titles or attributes, which we regard as too simple for using as an advertising copywriting. We build a rule-based creative information checking model to filter out these kinds of data. Our rule-base algorithm classify the advertising copywriting as too simple when no enough additional information beyond the product titles or attributes is provided in the copywriting.

4 Results

In this section, we first compare our approach with several baselines and then provide case studies.

4.1 Comparisons of Text Generation Models

We evaluate our proposed DSPLM discussed in Section 3.3.3 on our in-house multi-product advertising copywriting dataset. For comparison, we train a T5-base model on the same dataset as baseline, and a Prefix LM to demonstrate the effectiveness of our proposed model. The T5-base model is randomly initialized due to the lack of pretrained models in Chinese, while the Prefix LM is initialized with Chinese Bert (Turc et al., 2019). Table 1 shows evaluation metrics on these three different methods. The DSPLM exceeds performance of Prefix LM and the T5-base model. Our DSPLM and PLM have 12 layers of transformer blocks each, while the T5-base model consists of a 6-layer encoder and 6-layers decoder, the total number of parameters are the same for these three models. The results are generated with beam search algorithm with beam size of 3.

4.2 Effects of Knowledge-based Data Enhancement System

In section 3.4, we discussed the knowledge-based data enhancement system proposed to ensure data
Table 1: Comparison of metrics of different generation methods

| Model          | SacreBLUE | ROUGE-1 | ROUGE-2 | ROUGE-L | BLEU-1  | BLEU-4  | Meteor |
|----------------|-----------|---------|---------|---------|---------|---------|--------|
| T5-base        | 5.07      | 10.36   | 3.02    | 9.13    | 19.18   | 4.89    | 11.10  |
| Prefix LM      | 16.15     | 28.92   | 12.96   | 24.86   | 35.86   | 16.53   | 20.49  |
| DSPLM          | 16.97     | 29.36   | 13.76   | 25.24   | 37.23   | 17.34   | 21.47  |

Table 2: Comparison of accuracy of different combination selection algorithms

| Arbitrator | random | cid-based | pattern |
|------------|--------|-----------|---------|
| Strict     | 6.56   | 6.67      | 16.41   |
| Normal     | 5.09   | 10.29     | 20.16   |

4.3 Comparisons of automatic combination selection algorithms

For evaluation of the proposed pattern and attribute-based automatic selection algorithm discussed in Section 3.2.2, we compare results of our method with two baselines. The first baseline is random selection within the topic channel, and the second one “cid-based” is random selection within detailed category within the topic channel. Table 3 shows comparison of accuracy score of different combination selection algorithms, where the scores are predicted with the two arbitrators we discussed in Section 3.2.3. We can observe significant accuracy improvement of our proposed method compared with the other two baselines.

5 Conclusions and Future Work

In this paper, we discuss our proposed SMPACG system for e-commerce platform. The proposed system consists of an automatic product combination selection module and an automatic multi-product advertising copywriting generation module to generate combination with highly related products and corresponding advertising contents automatically. The SMPACG has been deployed for serving directly for our e-commerce recommendation system for customers as well as a real-time writing assistant tool for merchants. In future work, we will focus on enhancing the model performance by expanding to multi-modality scenarios.
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