CUSTOM: Aspect-Oriented Product Summarization for E-Commerce

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Abstract. Product summarization aims to automatically generate product descriptions, which is of great commercial potential. Considering the customer preferences on different product aspects, it would benefit from generating aspect-oriented customized summaries. However, conventional systems typically focus on providing general product summaries, which may miss the opportunity to match products with customer interests. To address the problem, we propose CUSTOM, aspect-oriented product summarization for e-commerce, which generates diverse and controllable summaries towards different product aspects. To support the study of CUSTOM and further this line of research, we construct two Chinese datasets, i.e., SMARTPHONE and COMPUTER, including 76,279 / 49,280 short summaries for 12,118 / 11,497 real-world commercial products, respectively. Furthermore, we introduce EXT, an extraction-enhanced generation framework for CUSTOM, where two famous sequence-to-sequence models are implemented in this paper. We conduct extensive experiments on the two proposed datasets for CUSTOM and show results of two famous baseline models and EXT, which indicates that EXT can generate diverse, high-quality, and consistent summaries.

1 Introduction

Product summarization aims to automatically generate product descriptions for e-commerce. It is of great commercial potential to write customer-interested product summaries. In recent years, a variety of researches focus on product summarization and have proposed practical approaches [11, 13, 21, 23]. These models take product information as input and output a general summary describing a product. However, the general summaries usually face two problems: (1) they are singular and lack diversity, which may miss the opportunity to match products with customer interests; (2) it is not able to control the models to describe what aspects of the products in the general summaries, which hurts for personalized recommendations. Considering that different customers have preferences on different aspects of products on e-commerce platforms, e.g., the customers may care more about the “APPEARANCE” than the “PERFORMANCE” aspect of a smartphone, so generating aspect-oriented customized summaries will be beneficial to personalized recommendations.

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https://github.com/JD-AI-Research-NLP/CUSTOM
Motivated by the above issues and observation, in this paper, we propose CUSTOM, aspect-oriented product summarization for e-commerce, which can provide diverse and controllable summaries towards different product aspects. In detail, given a product with substantial product information and a set of corresponding aspects for this category, e.g., smartphone and computer, the task of CUSTOM is to generate a set of summaries, each of which only describes a specified aspect of the product. Figure 1 shows an example of a smartphone where the product information includes a product title and substantial product details in a natural language recognized from abundant product images. Different colors in the product information represent different aspects of the product. When a certain aspect, i.e., CAMERA, APPEARANCE, or PERFORMANCE, is specified, the corresponding aspect-oriented summary is generated based on the product information. For example, the “green” summary describes the appearance of the smartphone. To the best of our knowledge, our task is related to the conditional generation [2,6,10,16]. Specifically, KOBE [2] is the most similar task to CUSTOM. KOBE focuses on writing expansion from short input, i.e., product title, where the generated text is likely to disrespect the truth of products, while CUSTOM concentrates on generating summary from long input, i.e., substantial product information, where the generated summary is consistent with the truth of products.

To support the study of CUSTOM and further this line of research, we construct two Chinese datasets, i.e., SMARTPHONE and COMPUTER, including 76,279 / 49,280 short summaries for 12,118 / 11,497 real-world commercial products, respectively. Furthermore, inspired by the content selection methods proposed in [3,7,9,24], we introduce EXT, an extraction-enhanced generation framework for CUSTOM, which equips the model with the ability to select aspect-related sentences from product information to enhance the correlation between the generated summary and the aspect. We conduct extensive experiments on the two proposed datasets and show results of Pointer-Generator, UniLM, and EXT, which indicate that EXT can generate more diverse, high-quality, and consistent summaries. Our contributions are as follows:

- We propose CUSTOM, aspect-oriented product summarization for e-commerce, to generate diverse and controllable summaries towards different product aspects.
- We construct two real-world Chinese commercial datasets, i.e., SMARTPHONE and COMPUTER, to support the study of CUSTOM and further this line of research.
- We introduce EXT, an extraction-enhanced generation framework. Experiment results on SMARTPHONE and COMPUTER show the effectiveness of the EXT.

2 Methodology

2.1 CUSTOM: Aspect-Oriented Product Summarization for E-Commerce

In this section, we formulate the CUSTOM task as follows. With respect to Figure 1, the input of the model includes product information $S$ and an aspect category $a$, where $S=\{s_i\}_{i=1}^{N}$ is a series of sentences by concatenating the title and product details, $N$ represents the maximum number of sentences. The output is a short summary $y$ that only describes the specified aspect $a$ of the product.
Fig. 1. An example of CUSTOM: aspect-oriented product summarization for e-commerce.

### 2.2 SMARTPHONE and COMPUTER

To support the study of CUSTOM and further this line of research, we construct two Chinese datasets, i.e., SMARTPHONE and COMPUTER, including 76,279 / 49,280 short summaries for 12,118 / 11,497 real-world commercial products, respectively. We split the two datasets into training, development, and test for experiments. The number of instances and products of train, development, and test sets are shown in Table 1. As described in Section 2.1, each dataset is consist of a set of ⟨product information, aspect, aspect summary⟩ tuples. In the SMARTPHONE training set, the average number of different aspect summaries for each product is about 6.3, while it is 1.8 and 2.1 in development and test sets respectively. The reason is that we keep the pair of ⟨product information, aspect⟩ unique in the development and test sets in order to ensure that an input ⟨product information, aspect⟩ pair corresponds to an unique output summary. The same is true for COMPUTER dataset. For SMARTPHONE dataset, there are five kinds of aspects, i.e., APPEARANCE, BATTERY, CAMERA, PERFORMANCE, and FEATURE. For
COMPUTER dataset, there are three kinds of aspects, i.e., FEATURE, PERFORMANCE, APPEARANCE. Figure 2 shows the aspect distributions on training, development, and test set for SMARTPHONE and COMPUTER.

Table 1. Statistics of SMARTPHONE and COMPUTER. #sum: the number of aspect summaries. #prod: the number of products.

| Category  | Overall | Train | Dev | Test |
|-----------|---------|-------|-----|------|
|           | #sum    | #prod | #sum | #prod | #sum | #prod |
| SMARTPHONE| 76,279  | 12,118| 73,640| 10,738| 1,639 | 896 |
| COMPUTER  | 49,280  | 11,497| 47,284| 10,268| 996  | 615 |

The datasets are collected from a Chinese e-commerce platform and we have summaries written by professional writers that describe multiple aspects of the product. Since there are no ⟨product information, aspect, aspect summary⟩ tuples, we use a heuristic method to construct the datasets. First, we split the origin summary by periods, and only keep fragments with character lengths between 15 and 55. The shorter fragments may contain insufficient information while the longer fragments could contain more than one aspect description. We then use BERT [4] to obtain continuous vectors of each fragment and used them as input to the K-Means [17] clustering algorithm. The resulting clusters represent the description set of different aspects of the product, that is, the aspect summary set. The cluster label of each instance is the aspect category. We experiment with different numbers of clusters, and manually select 100 from each clustering result for evaluation, and select the result with the highest degree of separation of the clustering results as the final number of clusters. We have also tried some methods to automatically detect clustering results, such as the silhouette coefficient, but the results are not ideal. Finally, we find that the best number of clusters is 5 and 3 for the SMARTPHONE and COMPUTER, respectively.
2.3 EXT: Extraction-Enhanced Generation Framework

We introduce EXT, an extraction-enhanced generation framework for CUSTOM. As shown in Figure 3, the framework consists of two parts: extractor and generator.

The extractor is responsible for scoring each sentence in the product information and outputs the sentence-level attention:

\[ \beta_i = \text{Ext}(s_i, a) \]  

(1)

where \( s_i \) is the \( i \)th sentence and \( a \) is the input aspect category, the greater the \( \beta_i \), the more relevant this sentence is to the current aspect, and vice versa. The binary cross-entropy loss function is used to train the extractor:

\[ L_{\text{ext}} = -\frac{1}{N} \sum_{i=1}^{N} (g_i \log \beta_i + (1 - g_i) \log (1 - \beta_i)) \]  

(2)

where \( g_i \) is the aspect label for the \( i \)th sentence. \( g_i = 1 \) means that the description of the current sentence is consistent with the current aspect. We use a heuristic rule to obtain the aspect labels. Specifically, we calculate the overlap rate \( r = \frac{\text{#overlap_length}}{\text{#sentence_length}} \) between each sentence in the product information and the aspect summary, where \#overlap_length is calculated by longest common subsequence (LCS) [8]. The aspect label is 1 if the overlap rate is above a certain threshold, which is 0.35 in our setting.

The generator is basically a sequence-to-sequence structure with attention mechanism [1]. Inspired by the study [9], at each decoding step \( t \), we combine the sentence-level score \( \beta_i \) generated by the extractor and word-level attention \( \alpha^t_m \) at time step \( t \) as follows:

\[ \hat{\alpha}_m^t = \frac{\alpha^t_m \times \beta_{i(m)}}{\sum_m \alpha^t_m \times \beta_{i(m)}} \]  

(3)
where \( m \) is the word index. The updated word-level attention weight \( \hat{\alpha}_m^t \) is then used to compute context vector \( c_t \) as follows:

\[
c_t = \sum_{m=1}^{\|w\|} \hat{\alpha}_m^t o_m
\]

where \( o_m \) stands for the \( m^{th} \) word representation.

We reuse the aspect information and fuse it to the generator to calculate the final word distribution \( P(w) = \text{Gen}(y_{t-1}, c_t, a) \) at step \( t \). We train the generator with the average negative log-likelihood loss:

\[
L_{gen} = -\frac{1}{T} \sum_{t=1}^{T} \log P(y_t)
\]

where \( y_t \) is the ground-truth target word. The extractor and generator are trained end-to-end, the final loss is as below:

\[
L = L_{ext} + L_{gen}
\]

We apply this framework to two typical summarization models, one is an RNN-based end-to-end model called Pointer-Generator [20], and the other is a Transformer-based pretrained model called UniLM [5]. We noticed that UniLM, T5 [19], and BART [12] are all SOTAs of pretrained generative models. In this paper, we choose UniLM since it is representative and only UniLM has released the Chinese version pretrained parameters.

**EXT on Pointer-Generator** First, we concatenate each sentence in \( S \) with a period to form a sequence of words \( \{w_m\}_{m=1}^{\|w\|} \). Then each word \( w_m \) and the aspect category \( a \) are embedded to obtain continuous vector \( e_{w_m} \) and \( e_a \) respectively. The word embedding and aspect embedding are added by column to obtain the fused aspect-aware word embedding \( e_{f_m} \). The fused embedding is used as initial input for both extractor and generator.

For extractor, we use a hierarchical bidirectional GRU as in [18] to extract sentence representations \( \mathbf{H} \). Then we apply a matrix dot operation and uses the sigmoid function to predict the sentence-level attention \( \beta_i \):

\[
\beta_i = \text{Sigmoid}(e_a^T \mathbf{h}_i)
\]

where \( \mathbf{h}_i \) stands for \( i^{th} \) sentence vector.

The generator is basically the pointer-generator network and we combine the sentence-level attention and word-level attention as described in equation (3). Besides being used to compute context vector \( c_t \), the updated word attentions are also used as the new copy distribution. The aspect embedding is also added to the previous word embedding by column at each decoding step.
CUSTOM

EXT on UniLM We use the same fused embedding $e_{f_{m}}$ as input, except $e_{w_{m}}$ is the summation of 3 kinds of embeddings including word embedding, position embedding, and segment embedding. The input embeddings are encoded into contextual representations $O = [o_{1}, \ldots, o_{|w|}]$ using Transformer. Since the sentences are separated by periods, we simply take out the hidden vector of each period to represent the sentence representation $H$:

$$H = O[I_{1}, \ldots, I_{M}]$$ (8)

where $I_{i}$ denotes the index of period of sentence $s_{i}$. Then we apply a two-layer feedforward network to compute the sentence score:

$$\beta_{i} = \text{Sigmoid}(\text{FFN}(h_{i}))$$ (9)

The sentence scores are used to update word-level attention as in equation (3). The generator shares the parameters of the transformer encoder with the extractor. Finally, we apply the same fine-tuning method as in UniLM [5].

3 Experiment

3.1 Comparison Methods

In this section, we note the baselines and our proposed methods. PGen w/o Aspect and UniLM w/o Aspect denotes the original Pointer-Generator Network and UniLM model without aspect information as input. PGen w/ Aspect and UniLM w/ Aspect means we fuse aspect information as describe in Section 2.3 but without incorporating EXT. EXT-PGen denotes our proposed PGen-based model. EXT-UniLM represents our proposed UniLM-based model.

3.2 Implementation Details

For PGNNet-based models, the model parameters remain the same as work [9]. For UniLM-based models, we use the base version and load the pre-trained parameters published in work[2] for initializing. The maximum numbers of the characters in the input and target are 400 and 70, respectively. During training, the mini-batch size is set to 20. We choose the model with the smallest perplexity on the development dataset for evaluation. During inference, the beam size is set to 5, and the maximum decoding length is set to 80 for all models.

3.3 Diversity Evaluation for CUSTOM

We argue that CUSTOM generates more diverse summaries than conventional product summarization. To evaluate diversity, we follow [14] to use Dist-2/3/4. Since different instances of the same product have the same product information, conventional models without aspect information as input (PGen/UniLM w/o Aspect) generate the same summaries for different aspects of the same product (Top-1). To improve the diversity of

https://github.com/YunwenTechnology/Unilm
the conventional models, we also report results of conventional models without aspect information (PGen/UniLM w/o Aspect) which keep the top $K$ candidates in the beam as outputs for evaluation (Top-$K$), where $K$ is the number of instances for the product in the test set. Experiment results are shown in Table 2. Our proposed CUSTOM achieves the highest performance on all diversity indicators on two datasets.

### Table 2. Diversity evaluation results. Dist-2: Distinct-2. Dist-3: Distinct-3. Dist-4: Distinct-4.

| Model                           | SMARTPHONE | COMPUTER |
|---------------------------------|------------|----------|
|                                 | Dist-2     | Dist-3   | Dist-4   | Dist-2     | Dist-3   | Dist-4   |
| PGen w/o Aspect (Top-1)         | 0.126      | 0.187    | 0.226    | 0.034      | 0.047    | 0.056    |
| PGen w/o Aspect (Top-K)         | 0.155      | 0.242    | 0.307    | 0.038      | 0.053    | 0.065    |
| PGen w/ Aspect                  | **0.199**  | **0.313**| **0.387**| **0.107**  | **0.160**| **0.196**|
| UniLM w/o Aspect (Top-Y)        | 0.140      | 0.216    | 0.268    | 0.077      | 0.107    | 0.126    |
| UniLM w/o Aspect (Top-K)        | **0.232**  | **0.372**| **0.462**| **0.140**  | **0.205**| **0.246**|

3.4 Quality Evaluation for EXT

Following the traditional text generation tasks, we calculate character-based Rouge-1, Rouge-2 and Rouge-L [15] F1 scores to evaluate the text quality. We use the same ROUGE-1.5.5 toolkit as in UniLM [5]. We evaluate Rouge scores for overall-level and the aspect-level at the same time. Experiment results are shown in Table 3 and Table 4. We can conclude that, compared with the original models, both the EXT-PGen and EXT-UniLM models can obtain better Rouge scores by incorporating with the EXT framework, which verifies that EXT can boost the quality of generated aspect summaries.

### Table 3. Experiment results on SMARTPHONE. R-1: Rouge-1. R-2: Rouge-2. R-L: Rouge-L.

| Model                           | Overall | APPEARANCE | BATTERY | CAMERA | PERFORMANCE | FEATURE | R-1/R-2/R-L | R-1/R-2/R-L | R-1/R-2/R-L | R-1/R-2/R-L |
|---------------------------------|---------|------------|---------|--------|-------------|---------|-------------|-------------|-------------|-------------|
| PGen w/ Aspect                  | 36.3/20.4/33.4 | 37.0/20.3/33.8 | 37.7/23.0/35.9 | 39.7/25.0/37.2 | 40.7/26.9/38.3 | 28.5/13.3/25.6 |
| EXT-PGen                        | 37.4/21.1/34.3 | 38.7/20.9/34.8 | 39.2/22.4/35.8 | 40.1/23.0/37.4 | 42.4/25.4/39.1 | 29.3/14.5/26.9 |
| UniLM w/ Aspect (Top-Y)         | **38.8/22.7/35.5** | **41.6/24.3/38.1** | **38.9/22.5/35.5** | **43.0/27.3/39.5** | **28.7/14.7/26.3** |
| EXT-UniLM                       | 38.0/22.3/34.8 | 38.3/22.3/34.7 | 43.5/25.7/38.9 | 40.9/24.1/37.7 | 42.9/27.9/39.4 | **29.5/15.7/27.2** |

### Table 4. Experiment results on COMPUTER. R-1: Rouge-1. R-2: Rouge-2. R-L: Rouge-L.

| Model                           | Overall | FEATURE | PERFORMANCE | APPEARANCE | R-1/R-2/R-L | R-1/R-2/R-L | R-1/R-2/R-L | R-1/R-2/R-L |
|---------------------------------|---------|---------|-------------|------------|-------------|-------------|-------------|-------------|
| PGen w/ Aspect                  | 31.4/14.9/28.1 | 24.1/9.6/21.7 | 35.5/17.7/31.7 | 34.6/17.3/30.9 |
| EXT-PGen                        | 32.5/16.4/29.6 | 23.9/9.6/21.8 | 36.3/19.5/33.1 | 38.1/20.5/34.4 |
| UniLM w/ Aspect (Top-Y)         | **33.1/16.6/30.1** | **26.2/11.9/24.3** | **33.6/18.2/34.4** | **34.1/20.4/34.4** |
| EXT-UniLM                       | 33.9/17.7/31.0 | 26.8/12.6/25.0 | 36.1/19.2/32.6 | 39.8/22.3/36.4 |
3.5 Human Evaluation

We conduct a human evaluation study where three participants were asked to compare summaries generated by EXT-PGen and PGen in terms of summary quality and aspect-summary consistency. We randomly sample 100 instances for each participant from the test set for evaluation. Table 5 shows the human evaluation results, where Win means the summary generated by EXT-PGen is better than PGen w/ Aspect, Lose means the summary generated by EXT-PGen is worse than PGen w/ Aspect and Tie means the summaries generated by EXT-PGen and PGen w/ Aspect obtain similar scores. We can see that EXT-PGen surpasses the PGen w/ Aspect model at a large margin (over 10%) on both datasets.

3.6 Extractor Analysis

We randomly select one instance from the SMARTPHONE test set and plot heat maps of the extractor module. As shown in Figure 4 we find that the extractor module learned to capture sentences most relevant to the specified aspect from the product information.

(a) "CAMERA" aspect

Outdoor look more comfortable. Software algorithm upgrade to unlock faster, smarter. 639 AMOLED extreme full screen. Sony 48MP super wide-angle triple camera. Faster click response. Set 20 million panoramic selfies. 3D four-curved glass body. Front 20 million lift camera. The unlocking speed is one step faster, the seventh-generation screen fingerprint recognition technology. Press protection. The seventh-generation screen fingerprint unlock. Qualcomm Snapdragon 855 Plus processor. Powerful camera combination. The larger the memory of the same processor, the stronger the performance, 12GB large memory. Elevating front camera achieves the 919's full screen. Super night view. 4000mAh long battery life. Large memory. Fast charging in 30 minutes 58, no longer waiting.

(b) "APPEARANCE " aspect

Fig. 4. Heatmap of the Extractor
3.7 Case Study

We perform a case study on the SMARTPHONE dataset and compare the generation results of EXT-UniLM and UniLM on different aspects. Table 6 shows the comparison results. We can see that when incorporated with the EXT framework, the summary is more informative and descriptive. For example, when describing the APPEARANCE aspect of the first instance, the EXT-UniLM generates more details, including the screen size is 6.4 inches and the screen-to-body ratio is 90.77%. This shows that our EXT framework can select key information related to the current aspect from the input to improve the quality of the generated summaries.

Table 6. Comparison of the generated aspect summaries of two models on SMARTPHONE dataset. Only English translation are shown in table due to space limitation.

| Product Information | Aspect      | UniLM                                                                 | EXT-UniLM                                                                 |
|---------------------|-------------|----------------------------------------------------------------------|---------------------------------------------------------------------------|
| OPPO Reno 10x zoom version Qualcomm Snapdragon 855 | PERFORMANCE | Equipped with Qualcomm Snapdragon 855 processor, the performance is strong and the operation is smooth and not stuck. | Equipped with Qualcomm Snapdragon 855 processor, it has strong performance, greatly improves the running speed, and brings a smoother gaming experience. |
| 48MP ultra-clear triple camera 6GB+256GB Extreme night black Full Netcom Full screen camera Smart game phone Smart protection The night scene is more pure Panoramic screen 48 million pixels Make beauty more natural | CAMERA | The rear 48 million ultra-clear three-shot, the picture is clearer. | The rear 48MP ultra-clear three-shot, supports 10x hybrid optical zoom, and the photos are clearer. |
| Honor 20 Youth Edition AMOLED screen fingerprint 4000mAh large battery 20W fast charge 48 million mobile phone 6GB+128GB blue water emerald full screen gestures The night is more moving Ultra-wide-angle photography has a wider field of view 209 slender design | APPEARANCE | Adopting a full-screen design to bring an immersive visual experience. | This phone uses a 6.4-inch panoramic screen design with a screen-to-body ratio of 90.77%, bringing you an immersive visual experience. |
| Battery | BATTERY | Built-in 4000mAh high-capacity battery, long-lasting battery life. | Built-in 4000mah high-capacity battery, support 20w fast charge, longer battery life. |
| Feature | FEATURE | Equipped with a full-scene acceleration engine, it brings a smooth experience without stuttering. | Equipped with a full-scene acceleration engine and multiple core optimizations, it brings a smooth experience without stuttering. |
| Appearance | APPEARANCE | With a 6.3-inch amoled pearl screen design, the screen display is clear and delicate. | With a 6.3-inch amoled pearl screen design, the screen display is clear and vivid, bringing you an immersive viewing experience. |

4 Related Work

4.1 Product Summarization

Xiao et al. [22] present two extractive summarization approaches using a bi-directional LSTM encoder-decoder network with attention mechanism to summarizing titles of e-commerce products. Khatri et al. [11] propose a novel Document-Context based Seq2Seq models for abstractive and extractive summarizations in e-commerce, which should be started with contextual information at the first time-step of the input to obtain better summaries. Shao et al. [21] propose a Planning-based Hierarchical Variational Model to generate long and diversified expressions. They decompose long text generation into dependent sentence generation sub-tasks and capture diversity with a global planning latent
variable and a sequence of local latent variables. Li et al. [13] propose an Aspect-aware Multimodal Summarizer to improve the importance, non-redundancy, and readability of the product summarization.

4.2 Conditional Text Generation

Hu et al. [10] propose a generative model which combines variational auto-encoders (VAEs) and attribute discriminators to produces sentences with desired attributes. Fan et al. [6] present a neural summarization model to enable users to control the shape of the final summary in order to better suit their needs, such as selecting desired length or style. They introduce special marker tokens when training and testing. Chen et al. [2] propose KOBE which is the most similar task to CUSTOM. KOBE focuses on writing expansion from short input where the generated text is likely to disrespect the truth of products, while CUSTOM concentrates on generating consistent summary from long input.

5 Conclusion

In this paper, we propose CUSTOM, aspect-oriented product summarization for e-commerce, to generate diverse and controllable summaries towards different product aspects. To support the study of CUSTOM and further this line of research, we construct two real-world Chinese commercial datasets, i.e., SMARTPHONE and COMPUTER. Furthermore, we introduce EXT, an extraction-enhanced generation framework for CUSTOM. Experiment results on SMARTPHONE and COMPUTER show the effectiveness of the proposed EXT.

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