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Abstract

Product text snippets should highlight the product features that are appealing to customers. Nevertheless, the features in current product snippets mainly are often decided based on the understanding of vendors or advertisers, and may fail to contain the features appealing to customers. This paper investigates how product text snippets generation can benefit from online customer reviews. In doing so, an automated method is designed, in which features and the opinions are extracted from online reviews, and are further used for product text snippet generation. To verify the effectiveness of the proposed method, we conduct two experiments and the results show that the extracted features and the snippet are effective in inviting potential customers, compared with the baseline ones. Experimental results demonstrate that 1) the extracted features are more appealing to customers; and 2) the snippets generated based on the extracted features are more likely to be clicked.

Keywords: Product text snippet, Online reviews, Feature extraction, Experiment.

1 INTRODUCTION

Snippet, initially created as a short text under each piece of search result to give users a sneak preview of the webpage content, is of potential value in keyword advertising and product promotion in e-Commerce platforms. A product text snippet can be a short text alongside a search result or a product's title bar. The short text, sometimes fragmented, reflects important features of a product and then allows customers to learn about a product quickly without visiting the webpage. Moreover, it is appealing and more popular for mobile devices (e.g. tablets, smartphones), due to the limited screen.

This paper focuses on the content of snippets, as relevant content can increase customers' propensity to purchase due to its informational value (Goh et al. 2013; Jiang et al. 2009b).). As is designed to get customers' attention, a product snippet needs to highlight the features that customers think are most relevant and appealing, otherwise such a product will have no chance of even being considered for purchase (Shocker et al. 1991). In other words, a snippet containing features appealing to customers will have a better performance (e.g. invite more potential customers and call-to-actions). However, the features in a snippet are often decided based on the understanding of vendors or advertisers, and may fail to contain the features appealing to customers. Take two snippets of a Galanz microwave oven for example. One describes the oven as "Top-end U8 engine", and the other "Smart menu, Child lock". The two snippets follow different line of knowledge. The former introduces the high tech in a vendor's tone, while the latter discusses the product as customers do. According to consumer research (Escalas 2007; Dellarocas et al. 2007), customers are increasingly relying on consumers' opinion except professional-generated content in searching for information about products to make purchasing decisions (Bettman1973; Zhu and Zhang 2010). Thus, it is meaningful to provide snippets with information from the perspective of customers, i.e., what customers think and talk about a product.

A traditional way to know about customers' opinions is to do market survey or consult experts, which is costly and not timely enough. Recently, abundant and ever-growing user-generated content (UGC) become available in the form of online reviews, and offer a better glimpse into customers' preferences. Online reviews provide a number of product features that customers comment on, which often highlight the specific features they value the most (Dhar and Ghose 2009).The reviews are not only first-hand and up-to-date, but, more importantly, voluminous and comprehensive as they are from plenty of customers with various viewpoints (i.e., collective intelligence). Therefore, online reviews enable us to extract the valuable and appealing product features.

A first question we need to answer is whether the features extracted from online reviews are more appealing to customers. If so, how to generate text snippets based on online customer reviews? Will such a snippet outperform the traditional ones without considering information from UGC? To answer the questions, an automated method is designed to extract features from online reviews, since it is hard for human to get the features and the opinions at a glance. In the first experiment, the results show that the extracted features are effective in appealing to customers. Then a snippet can be generated as composition of extracted features and opinions. The a second experiment shows that a snippet generated in this way wins the potential click compared to the ones which could be commonly observed on search engines' sponsored links, typically reflecting advertisers/vendors' knowledge.

The remainder of the paper is organized as follows. Section 2 discusses the related streams of research. Section 3 proposes the research model and hypothesis, and section 4 introduces the proposed method and experiment design. The results are discussed in section 5, as well as the managerial implications. Finally, the paper is concluded in section 6.

2 LITERATURE REVIEW

2.1 Online Customer Reviews

The online customer reviews on e-Commerce websites offer companies a better glimpse into customers and are playing a considerable role in the marketing communication (Albuquerque et al. 2012; Forman et al. 2008). Compared to PGC, customers increasingly rely on user-generated content (Escalas2007; Dellarocas et al. 2007). A wide body of studies has reported that the sentiment or valence of online reviews has a significant impact on sales**.** For example, Chevalier and Mayzlin (2006) find that online consumer ratings significantly influence sales in book market. Zhang and Dellarocas (2006) obtain similar results in the movie industry. Music blog buzz has been shown to impact music listening and sales (Dewan and Ramprasad 2009; Dhar and Chang 2009).

On the other hand, as online reviews proliferate, many efforts have been conducted to develop new methods to provide a review summary or a compact set of reviews that satisfies customers' need and relieves information overload (Hu and Liu 2004; Chen and Karger 2006; Xu et al, 2011; Tsaparas et al. 2011; Zhang et al. 2012). In doing so, product features as well as the opinions on them are extracted from the reviews, then statistical results typically in form of percentage are presented, or a compact summarized set of reviews are selected. Another category of methods is to rank reviews with certain criteria, such as freshness or helpfulness (Mamoulis et al. 2007; Ghose and P. G. 2007; Dai and Davison, 2011; Mudambi and Schuff 2010; Pan and Zhang 2011). However, existing studies have largely been limited in organizing reviews themselves without using reviews to enhance snippets.

2.2 Online Advertising

Online advertising is gaining acceptance and market share due to its better targeting nature. According to IAB Report, online advertising revenues totaled $20.1 billion for the first six months of 2013 [PWC 2013]. In marketing research, relevance, the degree to which the ad content is relevant to the webpage and customer's intent/goal (Tam and Ho 2006), has been adopted as a key measure. Tam and Ho (2006) suggested that content relevance enhances customers' cognitive performance and help websites gain competitive advantages. Jiang et al. (2009a; 2009b) showed that content relevance also has a positive effect on customers' flow experience, i.e., the customer is completely absorbed in their online shopping activities. Broder et al. (2008) showed a distinction between placing ads related to query and placing unrelated ads: users may find the former beneficial as an additional web navigation facility while the latter are likely to annoy the searchers and disturb their experience. Bertrand et al. (2010) also found that ad content significantly affects demand through a direct email field experiment.

Therefore, it is a crucial task to find out the related content (features) for advertising. As search engine advertising is a successful business model in online advertising based on keyword targeting technology, a number of methods have so far focused on suggesting, with good precision and recall, a group of terms that are highly relevant yet non-obvious to the given input (Abhishek and Hosanagar 2007; Thomaidou and Vazirgiannis 2011; Chen et al. 2008). The current technologies use query log and advertiser log, or are based on proximity searches, and meta-tag crawlers (Chen et al. 2008).

Product snippets, which allow users to preview of a product, can be regarded as a type of advertising and significantly help in promotion, especially on mobile platforms due to the compact screen. Existing studies mostly focus on efficient methods of generating snippets for searching results (Turpin et al. 2007). Thomaidou et al. (2011, 2013) proposed to generate promotional text snippets based on relevant n-grams from landing page, but they did not explore the potential of online customer reviews yet. To the best of our knowledge, there is no such a study or application that introduces the features extracted from online customer reviews into product text snippet generation.

3 RESEARCH MODEL AND HYPOTHESES

The research model is as shown in Figure 1. To be concrete, for a given product, the corresponding online reviews are collected and processed, and the most valuable features as well as opinions are extracted and recommended as fragments of a snippet. Then a snippet is generated accordingly. More technical details will be discussed in the following section.

Figure 1. Research Model

For the proposed model, we have two questions about its effectiveness. Are the features extracted from online reviews (namely, extracted features) more appealing to customers? Do customers tend to click the snippets composed of the extracted features? Existing consumer research indicates consumers increasingly rely on online reviews, often highlighting the specific features they value the most. Thus, the extracted features are expected to be more useful and attract customers, compared to the features provided by advertisers/vendors. As search engine ads are among the most popular and successful ads in use, we use the features in search engine ads texts as the baseline (namely, baseline features), since the search engine ads snippets are composed directly by advertisers, mostly reflecting vendors' attentions and understandings on products.

H1: The extracted features are more appealing to customers than the baseline features.

In marketing research, content relevance analysis has been adopted as an effective strategy for promotion. Online ads with relevant content enhances the possibility to capture more attention from customers (Tam and Ho 2006; Jiang et al. 2009b). So a product snippet containing extracted features, which are indeed and directly relevant to the product from customers' perspective, is expected to have a better performance (e.g. more clicks), compared to those baseline ones.

H2: The snippet with the extracted features is more likely to be clicked than that with the baseline features.

4 RESEARCH METHOD

4.1 Framework

Figure 2 shows the proposed method framework. For a specific product, corresponding review texts are crawled and stored in a collection. The texts are analyzed using natural language processing tools, including parsing and tagging. Further, nouns are extracted as candidate features, for each of which, the most adjacent adjective, if any, is extracted as corresponding opinion. Next, the top features that appear most, together with the mostly used opinion, could be integrated to compose a recommended snippet for the product. Note that only the features which customers express positive opinions on will be recommended for text snippet generation, due to their “call-to-action” value in promotion.

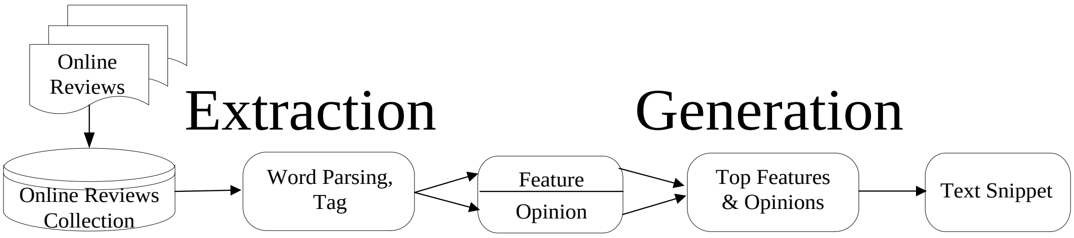

Figure 2.Research framework

Take the product “Joyoung Soymilk Maker” as an example. Based on the hundreds of reviews crawled, 72 nouns were extracted and the top 5 are: *taste*, *noise*, *appearance*, *price*, and *operability*, which are the features customers are most interested in. We can see that besides the common features like *price*, special features of the product like *noise*, *appearance*, *operability* and *taste* also included. The corresponding opinions towards these features are: *good*, *low*, *beautiful*, *reasonable* and *easy*. So a recommended snippet for this product could be “*good taste, low noise, beautiful appearance, reasonable price, easy operability*”. Nevertheless, typical features included in the snippets on search engine ads on the same product are usually “*discount*”, “*coupon*”, “*authentic*”, “*steel*”, etc., while “*low noise*” and “*easy operability*”, though quite important to customers, are not considered.

4.2 Data Preparation and Processing

In order to verify the effectiveness of the proposed method, real data experiments are conducted based on the customer reviews across various categories. To ensure the representativeness of the experiments, the product category on Jing Dong (www.jd.com), which is one of the biggest online shopping platforms in China, is chosen as the product list. Finally, 30 products are listed in Table 1.

1	Haier refrigerator	11	Bear coffee machine	21	L’Oreal shampoo
2	Siemens washing machine	12	ROCHE blood glucose meter	22	L’Oreal hair conditioner
3	Joyoung soybean milk machine	13	Thinkpad laptop	23	Pampers diaper
4	Panasonic shaver	14	HP All-in-one PC	24	Veet hair remover
5	EPSON Photocopying machine	15	Panasonic hairdryer	25	Septwolves Men’s Tshirt
6	Clarks Men’s casual shoes	16	Philips digi photo frame	26	Breo massager
7	Canon digital video camera	17	PENTAX digital camera	27	Samsung mobile
8	Intel CPU	18	GREE air-conditioner	28	Swatch watch
9	SONY flat screen TV	19	Midea induction cooker	29	INTEX air bed
10	FOTILE cooker hood	20	OLAY foaming cleanser	30	Philips home theatre

Table 1. 30 Products chosen for experiments

The corresponding ads snippets on Bing.com are selected as the baselines, since Bing.com is one of the widely used search engines and keyword advertising providers in China. Given a product keyword, the first appeared ad text was chosen. The online reviews were also crawled from Jing Dong, due to its richness in customer reviews. To ensure the quality, we filtered out the default reviews (e.g. “The customer has not reviewed yet.”), and the reviews with less than 5 words (e.g. “Good!”). The collected reviews were further pre-processed by ICTCLAS, a tool commonly used for Chinese lexical analyzing, into the parsed and tagged texts. Then a Java program is developed to extract nouns and the most adjacent adjective, as well as the negative (e.g., “not”) ahead of the adjective if any. For each product, all reviews (e.g., usually hundreds or more) were collected, and top 5 features were extracted for further comparison and snippet generation. In the same way, the ad text for each product crawled from Bing.com was also processed and a list of features and opinions was extracted accordingly.

For each product, a snippet is generated as a composition of the extracted feature-and-opinion pairs, sorted by frequency. Meanwhile, the ad text from Bing.com is adjusted in order to avoid the potential rhetoric effect. Concretely, the two texts are organized in plain words in the forms of subject-predicate, verb-object and modifier-core, to ensure to be close in the length, style, and the amount of phrases.

4.3 Experiment Design

The first experiment was to test the effectiveness of the extracted features (i.e. H1). For each of the 30 products, a list of 6 features was created by randomly mixing top three extracted features and first three baseline features. There could be some extracted features same as baseline ones, which are excluded from the list. Table 2 shows some of the products and their randomly mixed feature lists. A total of 20 students (10 males and 10 females) with online shopping experiences and knowledge were recruited as subjects. They were asked to vote 3 features they value most for each product.

P#	Randomly mixed features (partial products)
1	Noise, appearance, space, wind, electronic, voice
13	Quality, appearance, gift, smart, Thinkpad, speed
22	Smell, effect, hair, restore, smooth, salon
27	Screen, color, Samsung, speed, week, quarter
…	…

Table 2. The feature list examples

A second experiment is designed to test the effectiveness of the generated snippets (i.e. H2). For each product, the generated snippet and the revised ad text are shown in random order (Table 3). Another group of 20 subjects (10 males and 10 females) was recruited. Each subject was asked to vote a snippet that he or she prefers to click.

Product	**Snippet 1 text**	**Snippet 2 text**
Haier refrigerator	Low noise, air-cooling, power saving, …	quiet sound, pretty appearance, large space, …
Samsung mobile	Smart, prized event, sale, …	Large-screen, high speed, high resolution touch-screen, …
ThinkPad laptop	pretty appearance, high speed, good quality, …	Good-gift, 2nd generation smart, Intel, …
Pampers Diaper	Upgraded design, mom’s care, flagship, …	Water absorption, good quality, cheap, …
L’Oreal Hair condt	Fresh smell, soft, …	Restore, touch, …
…	…	…

Table 3. Products and snippets (partial)

5 RESULTS AND DISCUSSIONS

This section discusses the experiment results and the managerial implications. Table 4 shows how many extracted features (E) and baseline features (B) are voted, respectively. Since there are 60 (20 subjects * 3 vote) votes for each product, the group of features, either extracted or baseline, with more than 30 votes is regarded to outperform the other group.

P#	**E**	**B**	**P#**	**E**	**B**	**P#**	**E**	**B**	**P#**	**E**	**B**	**P#**	**E**	**B**	**P#**	**E**	**B**
1	29	**31**	6	**53**	7	11	**53**	7	16	**54**	6	21	**53**	7	26	**40**	20
2	**44**	16	7	**45**	15	12	**43**	17	17	**47**	13	22	**40**	20	27	**56**	4
3	**36**	24	8	**48**	12	13	**52**	8	18	30	30	23	**50**	10	28	**42**	18
4	**42**	18	9	**48**	12	14	**41**	19	19	**52**	8	24	**47**	13	29	**48**	12
5	**59**	1	10	**49**	11	15	**47**	13	20	**52**	8	25	29	**31**	30	**42**	18

Table 4. The number of voted features

According to the t-test, the extracted features averagely obtain 45.7 votes out of 60, and the votes on extracted features was significantly larger than 30 (p=0.01). The ANOVA test (Table 5) shows that there is significant difference between the two groups (p<0.01). That is, the extracted features perform better in appealing to customers, i.e. the proposed method is effective in extracting appealing features as expected.

	SS	df	MS	F	P-value	F crit
Between groups	14789.4	1	14789.4	249.6029	1.12E-22	4.0069
Within groups	3436.6	58	59.2517			
Total	18226	59				

Table 5. ANOVA test on the votes for two groups

Table 6 shows how many votes on clicking each snippet composed by, i.e., either extracted features or baseline features, over total 20 experimental clicks for each product. According to the t-test, the average vote on snippets with extracted features is 11.4 and significantly higher than 10 (p = 0.05). The ANOVA test (Table 7) shows that there is significant difference between the two groups (p<0.05). That is, customers tend to click the snippets composed with extracted features than current snippets with baseline features, and the proposed method is effective in inviting potential customers.

P#	**E**	**B**	**P#**	**E**	**B**	**P#**	**E**	**B**	**P#**	**E**	**B**	**P#**	**E**	**B**	**P#**	**E**	**B**
1	9	**11**	6	9	**11**	11	**14**	6	16	**16**	4	21	**18**	2	26	**17**	3
2	**11**	9	7	**14**	6	12	3	**17**	17	**15**	5	22	**14**	6	27	**16**	4
3	**11**	9	8	10	10	13	7	**13**	18	**11**	9	23	9	**11**	28	5	**15**
4	**12**	8	9	**17**	3	14	**11**	9	19	10	10	24	8	**12**	29	**11**	9
5	9	**11**	10	10	10	15	**13**	7	20	**12**	8	25	2	**18**	30	**16**	4

Table 6. Selected snippets of products

	SS	df	MS	F	P-value	F crit
Between groups	106. 7	1	106.6667	6.6286	0.0126	4.0069
Within groups	933.3	58	16.0920			
Total	1040	59				

Table 7. ANOVA test on the numbers of clicks on snippets

Generally speaking, this study has two main findings. First, the features extracted from online reviews are what customers care about more and may enhance cognition towards the product, which suggests the snippet focuses on the extracted features to capture more attention from customers. Second, the snippet generated as is proposed performs better in terms of potential clicks. Hence, compared to the snippets provided by vendors now, the generated text snippets in this paper are effective in advertising and promotion. The findings also have implications for online advertising and promotion, beyond snippet. The online reviews provide a chance to detect customers' interest or goals, and suggest what messages the advertising should deliver in marketing and promotion. The analysis based on UGC in online product reviews, social networks, and blogs will be valuable to attract more potential customers and benefit vendors essentially. In order to explore the potential of online reviews, it is certainly preferable to develop automated methods to deal with the massive reviews.

6 CONCLUSION

Product text snippets should highlight key features that customers favor. This paper investigated how product text snippets generation can benefit from online customer reviews. A method was designed to extract features and the opinions from online customer reviews, and recommend feature-opinion pairs for text snippet generation. To verify the effectiveness of the method, we have conducted two experiments and the results show that the extracted features and the snippet generated based on the extracted features are effective in inviting potential customers, compared with the baseline ones.

This paper has its own limitations. First, we only compared the extracted features and generated snippets with those provided by Bing.com, which limits the scope of this study to some extent. Further studies are needed, e.g. comparing with other methods, testing on data from other sources, testing on specific categories, in order to examine the generalizability of our findings. Second, the subjects in the study are college students who are not sufficiently experienced in some household appliances, and an experiment needs to be conducted in the future where online shopping behaviors in the real e-commerce environment are tested. Besides, the proposed method needs to be further improved in terms of effectiveness.

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