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Research-in-Progress

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Abstract

The fast growing cross-border e-commerce makes it imperative for online merchants to deeply understand the cross-national differences in consumers' preferences and online shopping behaviors. Using a data-driven topic model, this study plans to investigate the semantic differences in online product reviews posted by consumers from China and the United Sates. The preliminary results from a pilot study of online reviews of books show that Chinese reviewers focus more on a product's concrete attributes while American reviewers prefer to express their general evaluations of the product.

Keywords: online reviews, cross-national differences, text mining, topic model, Latent Dirichlet Allocation (LDA)

Introduction

With the global penetration of electronic commerce, many companies are expanding their market reach by selling products to online shoppers all around the world. Most large-scale e-commerce platforms, such as Amazon, eBay, and Alibaba, have built websites or mobile apps of local languages for consumers in different countries or regions. Nevertheless, one major challenge in international marketing is that consumers from different countries, usually with their distinct national cultures, vary significantly in terms of their product preferences and shopping habits. Therefore, it is imperative for both online retailers and brand owners to become fully aware of the psychological and behavioral characteristics of consumers in every major market so as to optimize the product design and local services accordingly.

Nowadays, online reviews (also known as electronic word-of-mouth, eWOM) are being widely used by consumers for product information and decision making (Duan et al. 2008; Liu 2006). Meanwhile, the rich contents in online reviews are used as an effective data source for online merchants to get first-hand feedback about product performance and gain insights into consumers' preferences (Hong et al. 2017). Thus, online reviews have a huge potential in helping international e-commerce merchants build a deep understanding of the cross-national differences of their customers.

Nevertheless, most studies of online reviews have only targeted consumers in one particular country, mainly due to the challenges of collecting and analyzing reviews written in different languages. Only a limited number of papers have explored the cross-national consumer behavioral differences by means of online reviews. However, they only examined cross-national differences in terms of basic review features, such as rating (Fang et al. 2013), volume (Keh et al. 2015), and review length (Fong et al. 2008).

Although these studies have revealed some interesting findings, they have only taken advantage of the quantitative data of online reviews, which can merely reflect consumers' general product evaluations. In contrast, the rich contents in the review texts, which usually consist of the reviewers' comprehensive evaluations of multiple product attributes, specific reasons why they like or dislike a product, and detailed descriptions of their shopping experiences, have been largely ignored.

In this study, we plan to fill this gap and investigate the cross-national differences in online reviews by analyzing the semantic meanings in the review texts. Specifically, we choose to use the topic modeling to explore the differences on the topics commented by reviewers from China and the United Sates on the same products. In so doing, we aim to identify the product attributes that are mostly concerned by consumers in each country as well as the cross-national differences in terms of product preferences.

The rest of the paper is organized as follows. Section 2 first reviews online review studies that take a cross-cultural perspective, followed by a summarization of research works that apply various textual analysis tools in the context of online reviews. Section 3 describes the research method and a dataset for a pilot study. Section 4 reports some preliminary results and analyses of the pilot study.

Literature Review

Cross-Cultural Comparisons of Online Reviews

As an instance of significant cultural identities, online user-generated contents posted by people from different cultures have been investigated a long time ago. For example, Fong et al. (2008)examine the postings on discussion boards and describe the content differences between participants from China (an example of collectivist culture) and those from the United States (individualist culture). A few recent studies investigate the cultural differences in online reviews as well as their impacts on consumers' purchase decisions. It is revealed that online reviews in China are significantly shorter but more positive than American online reviews (Fang et al. 2013). Furthermore, researchers find that the average rating and the volume of online reviews have a stronger impact on consumers' perceived risk and purchase intention in Eastern culture than in Western culture (Keh et al. 2015). The positive effect of review rating on market share is stronger in a culture of high uncertainty avoidance than one of low uncertainty avoidance (Tang 2017).

Some recent studies apply text mining technologies in cross-cultural comparisons. For example, Chinese reviewers show more inconsistencies between the numerical rating and the sentiments expressed in the review texts than American reviewers (Zhang et al. 2016). Consumers from collectivist cultures express fewer emotions in their review texts than consumers from individualist cultures (Hong et al. 2016). However, most of these works have only studied the superficial characteristics of the review texts without paying much attention to the underlying meaning of the textual contents.

Textual Analysis of Online Reviews

Early studies of online reviews choose to concentrate on the quantitative elements of a review, such as volume, valence, variance, which are relatively easy to capture and empirically analyzed. Some studies attempt to further reveal the rich content in the review texts by exploring some structured features of the text, such as part-of-speech, readability, and subjectivity, and investigating their impacts on various perceptions of review readers (Ghose et al. 2011; Singh et al. 2017; Willemsen et al. 2011). Nevertheless, very few semantic characteristics of online reviews are examined in these studies, mostly due to the unstructured nature of the review texts.

With the development of text mining technologies, a variety of sophisticated textual analysis software tools make it much easier to convert unstructured texts into structured measurements. Researchers begin to use textual analysis tools such as SenticNet and Linguistic Inquiry and Word Count (LIWC) to extract various concepts and their corresponding sentiments from review texts and examine whether perceived review helpfulness may be influenced by the number of concepts, the concept density, and the sentiment intensity embedded in the texts (Qazi et al. 2016; Yin et al. 2014; Zhang et al. 2018).

A few more recent studies dig further into the semantic meanings of review texts by using a statistic method known as topic modeling. Topic model is a type of statistical model for discovering the abstract "topics" that occur in a collection of documents, which is mainly used for discovery of hidden semantic structures in a text body. Among various topic models, the Latent Dirichlet Allocation (LDA) model developed by Blei et al. (2003) is the most popular one. Using topic modeling, researchers manage to identify the topics that consumers are concerned about and use these topics to predict product sales and review helpfulness. For example, Archak et al. (2011) summarize the frequently discussed topics in product reviews of digital cameras and camcorders and examine the influence of different pairs of evaluation phrase and product features on product sales. The results show that positive evaluations on image quality have a positive effect on product sales. Lash et al. (2016) apply different topics about movie plots to predict a movie's return on investment (ROI) and identify a few topics that have negative coefficients in the prediction model. Ngo-Ye et al. (2014) suggest that adding textual information of reviews in the model can better predict review helpfulness.

A Pilot Study

For a pilot study, we used a small-scale dataset of online reviews for books. We selected the book industry as the context of this pilot study for several reasons. First, book is a typical experienced product that people are likely to write relatively long reviews with rich contents, which allows us to explore the cross-national differences through the review texts. Second, books are usually published in different languages and sold in multiple countries simultaneously, which fits the scenario of this research very well. Third, quite a few previous research works have used books as the focal product when examining the textual contents of online reviews (Lin et al. 2013; Tanawongsuwan 2015). In the future, we plan to expand the dataset to other product categories so as to examine the generalizability of our findings or investigate the potential moderating role of product type.

Data Sources and Sample Selection

We first identified the top 100 best-selling books under the category of "Business & Money" on Amazon China's website (Amazon.cn). Among them, 45 books are also sold on Amazon US website (Amazon.com)[1]. To make sure that all selected books have accumulated a minimal number of reviews, we removed three books that have less than fifty reviews in either country. We then retrieved all reviews of the remained 42 books from both Amazon.cn and Amazon.com, which produces a dataset of 23,649 reviews in Chinese and 26,621 reviews in English.

Data Pre-Processing

To process multilingual sources of reviews in a consistent manner, we followed the method introduced by Wan (2008) and translated the reviews written in Chinese into English by using Google Translate. We then employed the modules of the Natural Language Toolkit in the Python programming environment to pre-process all reviews, including tokenizing the word text, replacing stop-words, and tagging part-of-speech. Only the nouns, verbs, adjectives, and adverbs were kept to ensure that there are only meaningful words in each word sequence. We also converted the remained words into word stems so that different forms of a single word can be properly identified and analyzed.

Previous studies have found that when the texts are short, it is difficult for the topic model to distinguish ambiguous words due to the limited contexts (Yang et al. 2017). Therefore, we dropped reviews that have less than six words in their word sequences so that the topics can be more

[1] In fact, all these 45 books are originally written in English and translated into Chinese afterwards.

accurately identified by the LDA model. The final dataset for the LDA model contains 37,647 reviews, 15,318 from China and 22,329 from the U.S.

LDA Model

The LDA model was used to extract common topics from the reviews in the final dataset. Proposed by Blei et al. (2003), the LDA algorithm has been widely applied in textual mining studies (Guo et al. 2017; Tirunillai et al. 2014). The LDA model assumes the existence of a fixed number of latent topics that appear across multiple reviews. Each review is characterized by its own mixture of topics, and each topic is characterized by a discrete probability distribution over words. That is, the probability that a specific word is present in a review depends on the presence of a latent topic. Each topic is defined by a unique probability vector of potential word use. Words with high probability are used to characterize the latent topics.

Specifically, we assumed that there are K meaningful topics in the reviews. Each review d is a distribution over the topics with its own set of probabilities θ_d, where the k^{th} element of θ_d, θ_{dk}, is the probability of topic k in review d. Each topic k is associated with its own set of word probabilities ϕ_k, where the j^{th} element of ϕ_k, ϕ_{kj}, is the probability of word w_j under topic k. The topic probabilitie θ_d are assumed to come from a homogeneous Dirichlet distribution with hyperparameter α, and the word probabilities θ_d are assumed to come from a homogeneous Dirichlet distribution with hyperparameter β.

We ran the GibbsLDA++ to extract topics. Both α and β were set to default values (α = 50/K, β = 0.1). The Gibbs sampling with 1000 iterations was used to estimate the statistical parameters in the LDA. The number of topics is set to 20 because the topics are best clustered and the words of each topic are the easiest to summarize under this circumstance.

Results of Preliminary Analysis

LDA Model Results

Table 1 lists the 20 topics extracted from the reviews. As shown in the table, twelve topics are related to the contents of specific books, four topics talking about reviewers' general evaluations of a book (namely positive/negative evaluation, recommendation, reading experience), and the remaining four about certain concrete attributes of a book (namely writing style, format, appearance and delivery, printing and translation).

Table 1. Topics Extracted from All Reviews

Topics	**Example Words with the Highest Probabilities**	**Average Probability**	
		China	**U.S.**
General Evaluation Topics			
Positive Evaluation	book, read, lot, really, great, want, inspire, love, finish, definite	0.05113	0.0513
Negative Evaluation	not, say, know, get, thing, people, make, something, really, go	0.04653	0.05326
Recommendation	book, read, recommend, understand, easy, anyone, well, interest, highly, insight	0.04964	0.05214
Reading Experience	get, go, year, work, start, never, got, want, day	0.04736	0.05177
Concrete Attribute Topics			
Writing Style	book, author, point, interest, idea, many, little, seem, write, reader	0.04838	0.05131
Format	book, page, chapter, first, review, much, edit, star, actual, text	0.04935	0.04998
Appearance and Delivery	good, book, look, also, buy, quality, bought, amazon, bad, excellent	0.06398	0.04312
Printing and Translation	content, good, feel, see, look, translate, version, paper, buy, worth	0.07067	0.03936
Book-Specific Topics			
Time Management	time, manage, work, need, make, thing, effect, import, use, plan	0.05060	0.04810

Success	great, company, busy, good, success, concept, Collins, right, level, research	0.04493	0.05392
Habit	habit, change, power, life, story, new, help, live, interest, form	0.04528	0.05189
Transaction	book, trade, principle, year, read, story, basic, man, technic, wisdom	0.04808	0.05013
Globalization	world, new, Friedman, global, future, technology, American, country, china, job	0.04665	0.04909
Data	use, data, big, example, author, inform, case, provide, theory, many	0.05010	0.04820
Ways of Thinking	think, way, learn, differ, idea, people, person, book, see, open	0.04958	0.04990
Negotiation	book, life, help, use, busy, get, learn, practice, negotiate, person	0.04840	0.05085
National Economy	economy, value, Smith, product, hand, wealth, individual, capital, free, nation	0.04769	0.04791
Rational Decision	make, decision, experiment, human, think, system, behavior, people, Kahneman, mind	0.04646	0.05274
Finance	money, rich, finance, dad, poor, Kiyosaki, invest, work, make, people	0.04724	0.05652
Stock	market, invest, stock, investor, price, buy, posit, value, sell, product	0.04796	0.04853

Results on Cross-National Differences

Figure 1 shows the cross-national difference in the probability distribution of each topic.

As the probability distribution on book-specific topics are heavily affected by the fact that consumers in these countries may have significantly different opinions on the contents of a particular book, in the following analysis we only focused on the general evaluation and concrete attribute topics.

As shown in Figure 1, Chinese reviewers tend to give more positive than negative comments. They are also very interested in commenting the printing and appearance of a book, followed by the comments on appearance and delivery. By contrast, American reviewers are more likely to express negative evaluations and focus more on a book’s writing style and format in terms of concrete attribute topics.

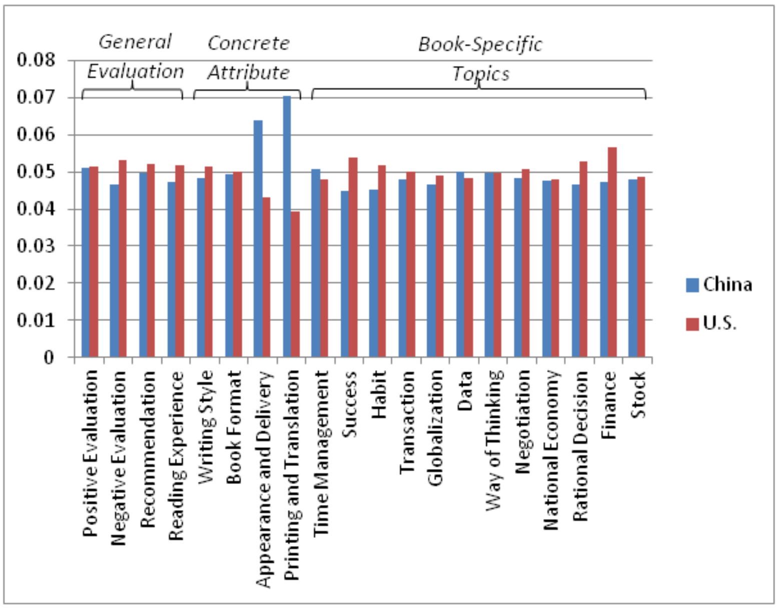

Figure 1. Average probability on each topic

A quick examination also reveals some interesting cross-national differences in a few topics. The most noticeable discrepancies are in the topics of “Printing and Translation” and “Appearance and Delivery”. Chinese reviewers talk significantly more on these two topics than their American counterparts. Instead, American reviewers are more willing to share their general evaluations of a book, especially the negative feelings toward a book.

To have a more rigorous examination on these differences, we conducted some follow-up analyses so as to control the effects of text length, review rating, posting date, book format, and book title. We regressed review's source country on distribution probability on each topic (excluding the book-specific ones). The variables used in the model are listed in Table 2.

Table 2. Variable Definitions

Variables	Explanation
$\boldsymbol{P^c}$	The distribution probability on the c^{th} topic of the review，$Topic_c \in Common\ Attributes$
$\boldsymbol{Country}$	The source country of the review：0 = China; 1 = The United States
$\boldsymbol{Textseg\_length}$	The length of the final word sequence of the review.
$\boldsymbol{Score}$	The rating of the review.
$\boldsymbol{Day\_to\_current}$	Days between the writing date of the reviews and the data collecting date.
$\boldsymbol{Book\_dummy_b}$	A series of dummy variables which represent specific books. b is the ordinal of a specific book.
$\boldsymbol{Format\_dummy_f}$	A series of dummy variables which represent the format of the book discussed in the review. f is the ordinal of a specific format. $f = 1$, Unknown Format; $f = 2$, Paperback; $f = 3$, Audio Format; $f = 4$, Hardcover; $f = 5$, Loose Leaf; $f = 6$, Kindle Edition; $f = 7$, Others.

Our regression model is:

$$P^c = \beta_1{}^c Country + \beta_2{}^c Textseg\_length + \beta_3{}^c Score + \beta_4{}^c Day\_to\_current + \gamma_b{}^c Book\_dummy_b + \delta_f{}^c Format\_dummy_f + \varepsilon^c \tag{1}$$

By examining the value of $\beta_1{}^c$, we can check the difference on topic c between the reviews from China and the U.S.

The results of all regression models are shown in Table 3.

Table 3. Aggregate Results of the Regression Models

Variables	*General Evaluation Topics*				*Concrete Attribute Topics*			
	Positive Evaluation	Negative Evaluation	Recommendation	Reading Experience	Writing Style	Book Format	Appearance and Delivery	Printing and Translation
Country	0.00367***	0.00563***	0.00569***	0.00451***	0.00282***	0.00287***	-0.0153***	-0.0268***
	(0.000249)	(0.000274)	(0.000259)	(0.000276)	(0.000257)	(0.000271)	(0.000318)	(0.000303)
Text_seg_length	-9.95e-05***	1.94e-05***	-0.000100***	8.10e-06***	-3.31e-05***	-3.08e-05***	-8.81e-05***	-6.99e-05***
	(1.64e-06)	(1.81e-06)	(1.71e-06)	(1.82e-06)	(1.70e-06)	(1.79e-06)	(2.10e-06)	(2.00e-06)
Score	0.00175***	-0.00395***	0.00268***	-0.000116	-0.00233***	-0.00398***	-0.000366***	-0.00293***
	(8.69e-05)	(9.57e-05)	(9.06e-05)	(9.63e-05)	(8.99e-05)	(9.45e-05)	(0.000111)	(0.000106)
Day_to_current	-7.99e-07***	8.17e-07***	-3.53e-07***	7.69e-08	6.02e-07***	-5.37e-07***	-1.10e-06***	-9.68e-07***
	(9.00e-08)	(9.91e-08)	(9.38e-08)	(9.98e-08)	(9.31e-08)	(9.79e-08)	(1.15e-07)	(1.10e-07)
Book_dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Format_dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.0435***	0.0606***	0.0239***	0.0576***	0.0520***	0.0714***	0.0768***	0.112***
	(0.00400)	(0.00440)	(0.00417)	(0.00443)	(0.00414)	(0.00435)	(0.00513)	(0.00487)
Observations	37,647	37,647	37,647	37,647	37,647	37,647	37,647	37,647
R-squared	0.130	0.118	0.146	0.048	0.044	0.074	0.221	0.364

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The results show that, for general evaluation topics, American reviewers score significantly higher on all four topics than Chinese reviewers. This pattern might be explained by collectivism vs. individualism difference between the Eastern and Western cultures (Hofstede 1983; Schwartz 2006). Consumers in the Western culture tend to attach more importance to self-expression (Schwartz 2006). As a result, they are more open to express their attitudes and opinions in public occasions (Kim et al. 2007) through which they can show their personal values and self-identity (Herek 1986). By contrast, consumers in the Eastern culture, such as the Chinese, are more reluctant to commit themselves to an opinion (Young 1994). Research has found that Chinese prefer to indirectly show their attitude and are socialized not to openly express their love and disgust (Hsu 1971).

Meanwhile, the cross-national differences in concrete attribute topics are more varied. American consumers focus more on writing styles and book formats while Chinese consumers are more inclined to talk about a book's peripheral attributes, such as appearance, delivery, printing, and translation. These differences might be attributed to some characteristics of the book industry and people's online shopping habits in China. Firstly, some Chinese consumers are used to posting reviews right after they receive the product[2] . However, as most book buyers cannot finish reading a book in such a short period, they would only comment on peripheral attributes of a book, such as packaging, printing quality, or delivery. Secondly, most books sold in China are paperbacks, the prices of which are significantly lower than their U.S. versions. Therefore, it is possible that Chinese consumers have a higher chance of having problems with a book's printing, binding, or packaging. Lastly, as all books in our dataset are originally written in English and translated into Chinese, it is understandable that only the Chinese reviewers talk about the translation issue.

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[2] On some online shopping websites, reviewers can only receive a reward from the website for writing a review if they post the review within a month of their order.

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