Examining the Role of Semantic Similarity in Online Restaurant Review Evaluations

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Abstract

Both language and image are critical for the grasp of information embedded in online reviews. While a large quantity of research has focused on the role of textual features and visual features separately, the specific role of similarity between textual and visual information in online review evaluations (e.g., review usefulness and review enjoyment) remains unaddressed. Thus, drawing on dual coding theory, this study attempts to investigate the impacts of textual and visual features on review evaluations by employing the Latent Dirichlet Allocation (LDA) topic modeling and Google Vision API's web detection techniques in the context of online restaurant review (ORR). Moreover, the moderating role of semantic similarity is examined in the relationships between textual/visual features and ORR evaluations. It is believed that this study could provide implications on information comprehension, draw consumer interest, and provide suggestions for restaurant managers to tune levels of review evaluation in a proper manner.

Keywords

Online restaurant review, review evaluation, image mining, text mining, semantic similarity, dual coding theory

Introduction

As both language and image are important aspects for us to understand the information (Li et al., 2019), they are also critical for the grasp of information embedded in online reviews. While a large quantity of research has focused on the role of textual features of online reviews (e.g., Korfiatis et al., 2012; Liu and Park, 2015), some studies have examined the role of visual features, and others have further delved into the examination of roles of both features with the aid of image mining techniques (e.g., Kusumasondjaja and Tjiptono, 2019). However, the specific role of similarity between textual and visual information in online review evaluations (e.g., review usefulness and review enjoyment) remains unaddressed.

The importance of examining the similarity lies in the practical reality that when online review users browse a particular one among hundreds of thousands of reviews, they may tend to scan the review first and then begin reading it if they find both textual and visual information interesting and consistent with each other. This pattern of information processing indicates the importance of similarity between textual and visual features. What is new about this study is that, based on dual coding theory, we employ the Latent Dirichlet Allocation (LDA) topic modeling and Google Vision API's web detection techniques to measure textual and visual features and investigate their impact on online restaurant review (ORR) evaluations. Moreover, we calculate the score of semantic similarity between textual and visual information for each review and examine its moderating role in the relationships between textual/visual features and ORR evaluations. Semantic similarity scores are used to dig into the level of textual-visual matching, which is expected to outperform the lexical matching method in terms of performance (Mihalcea et al., 2006). We believe that this study could provide significant implications on information comprehension in the context of ORR, draw consumer interest, and provide suggestions for restaurant managers interested in tuning levels of review evaluation in a proper manner.

Literature Review and Theoretical Development

Dual Coding Theory and Textual and Visual Features in ORRs

Dual coding theory states that human memory is encoded and stored in two distinct yet interconnected code systems: verbal (textual content) and nonverbal (imagery/visual content) systems (Paivio, 1990). Therefore, the impacts of verbal and nonverbal cues as well as their interaction effect on human information processing (in the context of ORR evaluation) should be investigated from a comprehensive point of view. However, they have been separately examined or simply examined parallelly in ORR settings, which leads to the need for investigating their interaction effect on review evaluations.

In an ORR environment, textual features of online reviews play the fundamental role in helping users gather related information about restaurant experiences (Jeong and Jang, 2011). We thus hypothesize:

H1a~b: Textual description elaborateness is positively associated with review usefulness/enjoyment.

H2a~b: Textual narrative readability is positively associated with review usefulness/enjoyment.

As for visual features in an ORR setting, it is believed that they are as persuasive as textual features. For instance, Kusumasondjaja and Tjiptono (2019) found that the visual complexity of food advertising on Instagram brings more favorable responses of consumers. Visual stimuli such as images include various elements. Among them, images with more variations in pixel values are believed to be more complex than those with less brightness and fewer colors, thus attracting more attention (Machado et al., 2015). We believe that this rationale can be applied to the number of images (Cheng and Hu, 2015) and the level of semantic information complexity as well. Thus, we hypothesize:

H3a~b: Visual numerical complexity is positively associated with review usefulness/enjoyment.

H4a~b: Visual feature complexity is positively associated with review usefulness/enjoyment.

H5a~b: Visual semantic complexity is positively associated with review usefulness/enjoyment.

Textual-Visual Matching and Semantic Similarity

Textual-visual matching is referred to as the measurement of the similarity between texts and images (Li et al., 2019). It has been proven by Edell and Staelin (1983) that disparities between textual and visual information negatively impact cognition and attitude towards brand and advertisement. Therefore, we believe that these results can be extrapolated to the context of ORRs as they share the goal of attracting consumers. Thus, we hypothesize:

H6a~g: Semantic similarity between textual and visual information is positively associated with the impacts of textual/visual features on review usefulness/enjoyment.

Data and Empirical Model

Data and Variables

The unit of analysis of the study is a single online review from restaurants on Yelp.com. Our data will be calculated from all the ORRs of the year of 2019 on Yelp.com, especially focusing on restaurants in New York City of the United States. The variables in an ORR posted on Yelp.com, including five independent (two for textual features, three for visual features), one moderating (semantic similarity), two dependent (review usefulness and review enjoyment), and six control variables are illustrated in Figure 1. In addition, the operational definitions and measurements of the variables are shown in Table 1.

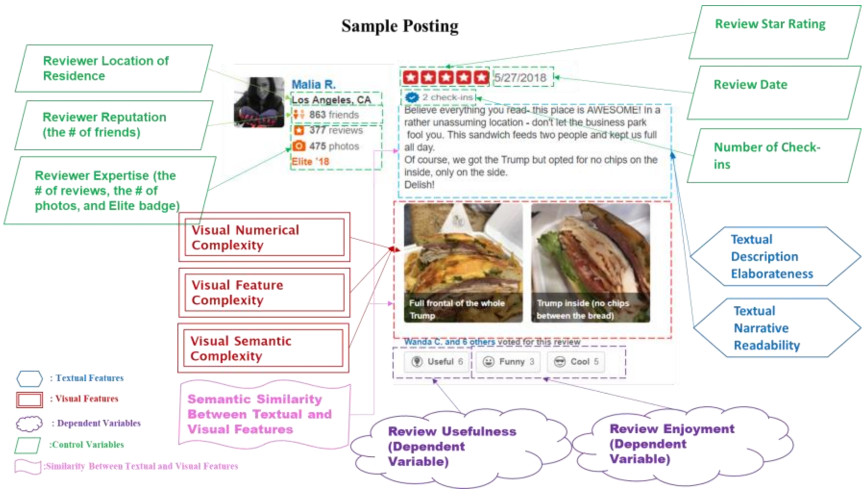

Figure 1. The Illustration of Variables in an ORR

Category	Variable	Operational Definition	Measurement	Reference
Textual Features	Textual Description Elaborateness	The extent of how many details are provided in the text corpus	The number of total words in each review	Racherla and Friske (2012)
	Textual Narrative Readability	The extent of how much a review is understood by readers	The Flesch readability score calculated in each review	Korfiatis et al. (2012)
Visual Features	Visual Numeral Complexity	The extent to how many images is included in a review	The total number of images in each review	Cheng and Hu (2015)
	Visual Feature Complexity	The degree of how many variations in pixel values (e.g., brightness and colors) are embedded in review image(s) in a review	$\frac{\sum image\ compressed\ file\ size(s)}{Total\ number\ of\ images}$	Machado et al. (2015)
	Visual Semantic Complexity	The degree of how complicated the semantic content of image(s) in a review is	The average number of Google Vision API predicted image labels	Takanob et al. (2018)
Moderating Variable	Semantic Similarity	The extent of how consistent and similar the textual and visual contents are to each other	Semantic similarity score between Google Vision API predicted image labels and topic words extracted from the review texts using LDA topic modeling	Mihalcea et al. (2006)
Dependent Variables	Review Usefulness	The degree of how beneficial a review is perceived to be	The number of total useful votes in a review	Ghose and Ipeirotis (2011)
	Review Enjoyment	The degree of how enjoyable a review is perceived to be	The summated number of total funny and cool votes in each review	Liu and Park (2015)
Control Variables	Reviewer Reputation	The extent of how much a reviewer has been socially identified and validated on Yelp.com	The number of friends a reviewer has	Racherla and Friske (2012)
	Reviewer Expertise	The extent of competence and knowledge that a reviewer holds regarding restaurants	The total number of reviews, photos, and Elite badge a reviewer has	Racherla and Friske (2012)
	Reviewer Location of Residence	The extent of how close a reviewer lives to the city where the restaurant is located	0: local 1: non-local	Liu and Park (2015)
	Review Star	The degree to which a review is	The star rating (1-5) given	Mudambi and

	Rating	evaluated numerically by a reviewer	by a reviewer for each review	Schuff (2010)
	Review Date	The degree of the day elapsed from the day the review was published	The current date minus the date the review was published	Fang et al. (2016)
	Number of Check-ins	The degree of how often a reviewer has visited the restaurant that he/she reviews	The number of check-ins provided by a reviewer for each review	Banerjee et al. (2017)

Table 1. Operational Definitions and Measurements of Variables

LDA Topic Modeling and Semantic Similarity Scores

Topic modeling is an unsupervised machine learning method and it can be defined as the followings (see Equations (1) and (2)) (Fu et al., 2013):

$$p(\theta, \mathbf{z}|\mathbf{w}, \alpha, \beta) = \frac{p(\theta, \mathbf{z}, \mathbf{w}|\alpha, \beta)}{p(\mathbf{w}|\alpha, \beta)} \tag{1}$$

where

$$(\theta, \mathbf{z}|\mathbf{w}, \alpha, \beta) = p(\theta|\alpha) \prod_{i=1}^{N_d} p(z_i|\theta) p(w_i\, |z_i, \beta)$$ and

$$p(\mathbf{w}|\alpha, \beta) = \int p(\theta|\alpha)(\prod_{i=1}^{N_d} \sum_{z_i} p(z_i\,|\theta) p(w_i|z_i, \beta) d_\theta \tag{2}$$

Where α and β are two Dirichlet priors; θ indicates the document-topic distribution, Φ designates the topic-word distribution, and d means a given document. $p(w|\alpha, \beta)$ in Eq. (1) indicates the probability of the extracted word, and the probability implies the relative importance of every word in each topic.

Our measurement for semantic similarity comes down into three steps: in step 1, we will extract keywords from texts using LDA topic modeling; in step 2, we will use the international well-recognized image classification software, Google Vision API, to extract image labels; and in step 3, the semantic similarity scores will be calculated based on the textual keywords T_1 and image labels T_2 in the following function (see Equation (3)) (Mihalcea et al., 2006):

$$\mathrm{Sim}(T_1, T_2) = \frac{1}{2}\left(\frac{\sum_{w\epsilon\{T_1\}}(maxSim(w,T_2)*idf(w))}{\sum_{w\epsilon\{T_1\}} idf(w)} + \frac{\sum_{w\epsilon\{T_2\}}(maxSim(w,T_1)*idf(w))}{\sum_{w\epsilon\{T_2\}} idf(w)}\right) \tag{3}$$

Where *idf* indicates the inverse document frequency, $maxSim(w, T_2)$ designates the highest semantic similarity. The semantic similarity scores have a range from 0 to 1, where 0 indicates no semantic similarity in between the segments, while 1 implies identical segments.

Empirical Model

We will use a log-nonlinear model with fixed effects for the empirical analysis as below:

$Y_i = \alpha$ + *textual description elaborateness*$_i$ + *textual narrative readability*$_i$ + *visual numeral complexity*$_i$ + *visual feature complexity*$_i$ + *visual semantic complexity*$_i$ + *similarity*$_i$ + *similarity*$_i$**textual description elaborateness*$_i$ + *similarity*$_i$**textual narrative readability*$_i$ + *similarity*$_i$**visual numeral complexity*$_i$ + *similarity*$_i$**visual feature complexity*$_i$ + *similarity*$_i$**visual semantic complexity*$_i$ + Z_i + *restaurant*$_i$ + ε_i

Where Y_i is the logarithm of the dependent variables (i.e., review usefulness and review enjoyment), Z_i is a set of control variables, and ε_i is an idiosyncratic random error for a review *i*. In order to avoid the endogenous problems caused by the restaurant's own characteristics, such as restaurant decoration, cuisine, traffic, and location, which will affect visual features, we will add the restaurant fixed effect.

Expected Contributions

Theoretically, this paper builds one more layer on the literature on image mining, text mining, and topic modeling technologies. We further identify and examine the moderating role of semantic similarity between textual and visual information in increasing review evaluation in the context of ORRs. Practically, these findings will suggest a way to make a more useful ORR for general users and provide managerial implications for managers in the hospitality and tourism industry, especially those who work with ORRs.

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