A new method for evaluating tour online review based on grey 2-tuple linguistic

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Abstract

Purpose – Tour social network data that are heterogeneous contain not only the quantitative structured evaluation data, but also the qualitative non-structured data. This is a big data scenario. How to evaluate tour online review and then recommend to potential tourists quickly and accurately are important parts of social responsibility of tour companies. The purpose of this paper is to propose a new method for evaluating tour online review based on grey 2-tuple linguistic.

Design/methodology/approach – The phenomenon of “poor information” exists in some big data scenario. According to social responsibility, grey 2-tuple linguistic evaluation model for tour online review is proposed.

Findings – Tour social networks contain data that are valuable to each individual on tourism industry’s value chain. Grey 2-tuple linguistic evaluation model can be used for evaluating tour online reviews. This is a systems thinking method that takes social responsibility into account.

Research limitations/implications – Due to the complex links among reviewers in social network, network mining approaches and models are expected to be added to this research in the near future.

Practical implications – Grey 2-tuple linguistic evaluation method can contribute to the future research on evaluating a variety of tour social network comment data in the real world.

Originality/value – A new evaluation method for making evaluation and recommendations based on tour social network comment information is proposed.

Keywords Social network, Corporate social responsibility, 2-tuple linguistic, Grey systems, Tour online review evaluation

Paper type Research paper

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1. Introduction

With the popularity of online word-of-mouth activity, an increasing number of businesses have started to offer online word-of-mouth services. Amazon.com is well-known for its extensive customer review systems. Major television networks such as ABC, CBS, and NBC sponsor Usenet newsgroups to elicit viewers to talk about their programs and shows. Similarly, almost every studio and film distributor has utilized the Web as a critical marketing venue by creating web sites and discussion forums for their movies. Tourism is one of many industries that has benefited enormously from the thousands of hundreds of online reviews generated by users on the internet every minute. Lots of tour web sites now provide customers not only tour information about spots, nearby hotels and restaurants but allow tourists to comment for the tour service they experienced. Since the quality and utility of the tour service can only be determined by consumption, for tourists who plan to purchase tour service, they must rely on previous experiences from other tourists. It is argued that these reviews sometimes show more trustworthy than traditional sources in the printed press (Jiang and Benbasat, 2004; Senecal and Nantel, 2004). Online reviews exert even more influence in the case of products which are not one of the tangible nature such as tour service (Wolfinbarger and Gilly, 2001).

Business and organizations’ relationship to the society and environment in which they operate is a critical factor in their ability to continue to operate effectively. ISO 26000 provides guidance on how businesses and organizations can operate in a socially responsible way. Definition of social responsibility in accordance with ISO 26000 is responsibility of an organization for the impact of its decisions and activities on society and the environment, through transparent and ethical behavior that:

- contributes to sustainable development, including health and the welfare of society;
- takes into account the expectations of stakeholders;
- is in compliance with applicable law and consistent with international norms of behavior; and
- is integrated throughout the organization and practiced in its relationships (ISO 26000, 2010).

Jeong et al. (2013) investigated how marketers could maximize favorable consumer responses to brand pages on social network sites (SNSs) through the strategic use of corporate social responsibility (CSR). Sparks et al. (2013) tested experimentally how source, content style, and peripheral credibility cues in online postings influence four consumer beliefs, and how those in turn influence attitudes and purchase intentions for an eco-resort. Organizations around the world, and their stakeholders, are becoming increasingly aware of the need for and benefits of socially responsible behavior. CSR has become a strategic choice of enterprise’s sustainable development (Zhou and Zhang, 2007). In summary, CSR has been emphasized a lot around the world. It is time for Chinese enterprises to promote social responsibility in order for the sustainable development, especially in the rapidly growing field of tourism e-commerce.

The valuable information offered by tourists’ online reviews cannot only help tour web sites better understand the complaints from tourists but also influences potential tourists in their purchase decision making. However, it seems not easy to extract valuable information from the huge amounts of unstructured, subjective and fuzzy tour online reviews.
Online reviews are different from classic survey data and data gathered from questionnaires or interviews. These reviews are written entirely based on the willingness of tourists, from their angle of interests, in their language and without any prescribed questions to guide them. Furthermore, online tour service reviews often vary greatly particularly in terms of how tourists’ opinions are being expressed. Researches on analyzing online reviews started from 2003 and among them, which achieves remarkable success is opinion mining such as product feature identification and sentiment classification (Ding and Liu, 2007; Hu and Liu, 2004). But to offer customers clear and easy-understanding summary of online reviews, mining can be daunting and time-consuming.

Actually, much of the tour web sites allow tourists to give reviews as well as ratings for the tour services they just experienced. The ratings can be very satisfied, satisfied, so-so, bad and very bad or other adjectives that can express tourists’ sentiment level. By giving each level a numerical value as 5, 4, 3, 2, 1 and then calculating the average of all ratings, tour web sites can present potential customers a perfect degree of satisfaction for all their tour services even though their negative reviews seems quite a lot. Is the degree of satisfaction issued by tour web sites persuasive in the process of customers’ decision making? The answer seems to be NO since over 90 per cent of the interviewees we investigated said they usually ignore the statistical data such as degree of satisfaction or popularity issued by tour web sites based on the fact that average value and marketers often deceive people. Whether the average of all ratings can represent the degree of satisfaction is suspicious because ratings without reviews or with detailed reviews are sure to have different helpfulness on decision makings. For example, some reviews may contain few words but are centered on the user preferences with respect to several crucial tour services’ features (for example, hotel, journey and tour guides), while others are lengthy with only a few sentences containing opinions on tour service. Thus, the issue of helpfulness becomes more apparent for online reviews since its helpfulness can be influenced by several factors (Pavlou and Dimoka, 2006). An empirical study on influence factors of online reviews’ helpfulness in e-commerce shows that the factors can be review source, reviews’ expertise or even writing style (Liao et al., 2013). Another effect to consider is that reviews by individual consumers often express a personal view of their experience with the product, and this may differ from the expectations of the interested buyers (Korfiatis et al., 2012).

Can we find a method to get a more credible degree of tourists’ satisfaction from such a large number of online reviews in a way that both tourists and tour corporates consider useful to their target? How do tour corporates increase the number of tourists’ favorable reviews from a strategic perspective? Given previous limitations and challenges, this paper processes tourists’ online reviews considering both ratings and reviews and present a more persuasive degree of satisfaction which can serve as filters of tour services. The rest of the paper is organized as follows. The next section provides the relevant literature review. We then describe grey 2-tuple linguistic model in Section 3. Section 4 is the experiment and the paper ends with a discussion and conclusion. And in Section 5, conclusion and future research work are given.

2. Related works
2.1 Online reviews mining
Classification aims to automatically mine customers’ different attitudes towards products and features of online reviews. Lots of efforts have been devoted to improve the
effectiveness and accuracy of classification methods for online reviews. An algorithm based on extension of network words and feature selection is proposed to acquire the tendency of online movie comments. Garbage comments are eliminated using relevancy measurement. Features are selected for classification based on frequency of words and information gain (Zhang et al., 2011). An online reviews sentiment analysis model based on rough sets is presented to extract the complicated features for online reviews (Wang and Jiang, 2012). Yang, etc. propose a new method of sentiment classification named shortest covering path-X (SCP-X) for online comment based on the random network theory (Yang et al., 2010). Standard machine learning techniques naive Bayes and SVM are incorporated into the domain of online Cantonese-written restaurant reviews to automatically classify user reviews as positive or negative (Zhang et al., 2011). All of these contributions investigate ways to classify a review as positive, negative, or neutral at different levels or from particular perspectives, namely, the word level, the sentence level, the document level and the feature level.

Some researches focus on evaluating the helpfulness of online reviews because reviews are closer to consensus that can be considered more helpful by potential consumers and companies than those exhibiting extremes of opinion (Jiang et al., 2010). From product designers’ perspective, Liu’s research focuses on how to automatically evaluate the helpfulness of an online review from a designer’s viewpoint entirely based on the review content itself since most of the existing methods which only rely on the review voting ratios given by customers to measure helpfulness may mislead designers in identifying those truly valuable and insightful opinions (Liu et al., 2013). From the perspective of online reviews’ text content, and using China’s large B2C e-commerce sites data, Yan investigates the impact of review’s content on its helpfulness. The finding is that review’s depth, objectivity, description richness of consistency and product characteristic have positive effect on the helpfulness of the review, but description richness of oneself experience and feelings have negative effect on the helpfulness of the review (Yan et al., 2012). Korfiatis et al. (2012) explores the interplay between online review helpfulness, rating score and the qualitative characteristics of the review text as measured by readability tests. They found that review readability had a greater effect on the helpfulness ratio of a review than its length.

Online reviews mining methods can effectively classify the text of written reviews or evaluate the helpfulness of reviews from customers. But it is unable to combine customers’ reviews and ratings and offer customers a direct, easy-understanding result which is definitely the customers need.

### 2.2 2-tuple linguistic model

In the real world there are many situations in which problems must deal with vague and imprecise information that usually involves uncertainty in their definition frameworks. In this case, 2-tuple linguistic method is widely used due to its easiness to implement and interpret, and can avoid the loss and distortion of information. So far, it has produced lots of successful results in different fields, especially in decision models (Mi et al., 2007). Herrera and Martinez (2001) proposed another method to solve the group decision-making problem with multi-granularity linguistic information. They constructed linguistic hierarchy term sets and generalized transformation functions to unify the multi-granularity linguistic information into the linguistic 2-tuples. Zhang and Guo (2011) proposed a method based on the 2-tuple linguistic model to deal with the
multiple attributes group decision-making problems. This method aggregates single users’ decision information to get group’s decision information and obtain the best compromise solution by maximizing group utility for the majority and minimizing individual regret for the opponent. Merigó and Gil-Lafuente (2013) presented an induced 2-tuple linguistic generalized ordered weighted averaging operator and applied it into a multi-person linguistic decision-making problem concerning product management. This new aggregation operator extends previous approaches by using generalized means, order-inducing variables in the reordering of the arguments and linguistic information represented with the 2-tuple linguistic approach.

Tourists are often allowed to give ratings for several attributes of a tour service such as hotel, restaurant or tour guide. In this paper, 2-tuple linguistic model will be applied to aggregate all the information of a tour service.

2.3 Corporate social responsibility
In 1924, Professor Oliver Sheldon proposed CSR in The Philosophy of Management. The term “CSR” became popular in the 1960s. And since then, concern about social responsibility of organization is increasing. Now, ISO 26000 is the recognized international standard for social responsibility. In October 2011, the European Commission (2011) put forward a new definition of CSR as “the responsibility of enterprises for their impacts on society”. ISO 26000 has mentioned seven principles for social responsibility: accountability, transparency, ethical behavior, respect for stakeholder interests, respect for the rule of law, respect for international norms of behavior, respect for human rights; and seven core subjects of social responsibility: organizational governance, human rights, labor practices, the environment, fair operating practices, consumer issues, community involvement and development.

In recent years, the significance of CSR for tourism has further increased (Lee et al., 2008). CSR as an approach to tourism governance and management is nevertheless growing as several policy prescriptions and corporate vision statements reveal (Coles et al., 2013). Rodriguez and Cruz (2007) show the evidence that higher levels of social and environmental responsibility in hotel firms improves their profit levels. Similarly, Nicolau (2008) argues that socially oriented activities carried out by tourism firms bring about benefits for society both directly (inherent to the purpose of such activities) and indirectly (via commercial performance). What is more, social reputation from CSR is a long-term project which is revealed in long-run shareholder value.

From a profit-seeking firm’s perspective, implications and benefits of investments in socially responsible activities are important matters to be considered, in particular, in the form of financial performance. This is because if the CSR investment does not enhance a firm’s bottom line, such investment may not be considered sustainable in a long run. Inoue and Lee (2011) find that CSR is proposed to have positive financial effects.

3. Methods
3.1 Grey 2-tuple linguistic evaluation model
Now more and more tourism corporates use internet, social network. Tourism social network data contain not only the quantitative structured evaluation data, but also the qualitative and non-structured data. How to evaluate tourism online review and then recommend to potential tourists quickly and accurately are important parts of social
responsibility of tourism enterprises. This is a hot and important issue should be solved. Grey 2-tuple linguistic evaluation model was first proposed by Mi Chuanmin in 2007 (Mi et al., 2007). It is one method that can evaluate system including grey information and 2-tuple linguistic information.

We set five ranks (VH (very high), H (high), M (middle), L (low) and VL (very low)) for each tour indicator (accommodation, traffic, tour guides, journey and reserving process). Value for each rank from VH to VL is 5-1. Let $S = \{VL, L, M, VH\}$. $a$ is the point difference between rating and its closest rank in set $S$. For example, $a = 0.5$ when ratings given by tourist is 4.5 and its closest rank in set $S$ is $H$ or VH.

In grey theory, the term of greyness means the varying degrees of uncertainty for information and value of greyness ranges from 0 to 1 (Liu et al., 2009). In this paper, we use greyness to express the credibility of ratings given by tourists based on their reviews’ content. Apparently, larger the greyness is, smaller the credibility is (Mi et al., 2013). By combining greyness and 2-tuple linguistic model, we get $((s_i, \alpha), v_i)$, where $v_i$ is the greyness of $(s_i, \alpha_i)$. There are five intervals of greyness which are $[0,0.2)$, $[0.2,0.4)$, $[0.4,0.6)$, $[0.6,0.8)$, $[0.8,1]$. $[0,0.2)$ means the information offered by online review is very lacking or the content of the review is empty.

If $((4,0.3),0.2)$ is a value in grey 2-tuple linguistic format, it means one tourist’s rating for tour service is 4.3 and information offered by his/her review is quite credible and helpful for other potential tourists.

### 3.2 Grey 2-tuple linguistic operations

**Operation 1.** Assume $s_i \in S$ and $i$ is the $i$th online review, $\beta_i \in [0, g]$ where $g$ is the maximum value for indicators, $v_i \in [0,1]$, then relation $(\beta_i, v_i)$ between $\beta_i$ and $v_i$ can be get by equation (1) while $\beta_i$ is the result of $S_i$ through aggregation operation:

\[
\Delta[0, g] \rightarrow [-0.5, 0.5], \quad v_i \rightarrow v_i \\
\Delta(\beta_i, v_i) = ((s_i, \alpha), v_i) \\
\begin{cases} 
    s_i = \text{round}(\beta_i) \\
    \alpha_i = \beta_i - i, \quad \alpha_i \in [-0.5, 0.5) \\
    v_i = v_i
\end{cases}
\] (1)

**Operation 2.** Assume that $((s_i, \alpha), v_i)$ is a value in grey 2-tuple linguistic format, there exists inverse function $\Delta^{-1}$ which can transform $((s_i, \alpha), v_i)$ to $(\beta_i, v_i)$, $\beta_i \in [0, g]$:

\[
\Delta^{-1} : S \times [-0.5, 0.5] \rightarrow [0, g], \quad v_i \rightarrow v_i \\
\Delta^{-1} : ((s_i, \alpha), v_i) = (i + \alpha, v_i) = (\beta_i, v_i)
\] (2)

**Operation 3.** Assume that $X = \{(r_1, \alpha_1), (r_2, \alpha_2), (r_3, \alpha_3), \ldots, (r_n, \alpha_n), (r_n, \alpha_n)\}$ is a set of grey 2-tuple linguistic values and $W = \{w_1, w_2, \ldots, w_n\}$ is the corresponding weight of each value in $X$, then $R$ is the weighted average of $X$: 

\[
R = \frac{\sum_{i=1}^{n} w_i \times v_i}{\sum_{i=1}^{n} w_i}
\]
\[ R[(r_1, \alpha_1), (r_2, \alpha_2), \ldots, (r_n, \alpha_n)] = \Delta \left[ \frac{\sum_{k=1}^{n} \Delta^{-1}(r_k, \alpha_k) v_k w_k}{\sum_{k=1}^{n} w_k} \right] \]

\[ = \Delta \left[ \frac{\sum_{k=1}^{n} \Delta^{-1} \beta_k w_k}{\sum_{k=1}^{n} w_k} \right] \cdot \frac{\sum_{k=1}^{n} \Delta^{-1} v_k w_k}{\sum_{k=1}^{n} w_k} \]  

(3)

**Operation 4.** Assume \((\beta, v_i) = ((s_i, \alpha_i), v_i)\) and \(\bar{R} = [\beta_i(1 - v_i), \beta_i(1 + v_i)]\). Let \(f_i(x) = ax_i^2 + bx_i + c\) and the quadratic function satisfies the following equations:

\[ \int_{\beta_i(1-v_i)}^{\beta_i(1+v_i)} (ax_i^2 + bx_i + c)dx = 1 \]  

(4)

\[ f_{\text{max}} = f(\beta_i) \]  

(5)

\[ f(\beta_i(1 - v_i)) = 0 \]  

(6)

**Operation 5.** Let \(v_i^j\) is the greyness of the \(j\)th indicator based on the \(i\)th online review and \(\bar{v}_i\) is the average greyness of the review. And \(n\) is the total number of indicators:

\[ \bar{v}_i = \frac{1}{n} \sum_{j=1}^{n} v_i^j \]  

(7)

**Operation 6.** Let \(\beta_i^j\) is a 2-tuple linguistic value of the \(j\)th indicator based on the \(i\)th online review and \(\bar{\beta}_i\) is the average of the \(i\)th online review. And \(n\) is the total number of indicators:

\[ \bar{\beta}_i = \frac{1}{n} \sum_{j=1}^{n} \beta_i^j \]  

(8)

**Operation 7.** Assume the total number of online reviews is \(m\), \(\bar{v}_i\) is the greyness of the \(i\)th review, then \(\omega_i\) means the contribution of the \(i\)th review to the final grey 2-tuple linguistic value of the whole online reviews for the related tour service:

\[ \omega_i = \frac{1/\bar{v}_i}{\sum_{i=1}^{m} (1/\bar{v}_i)} \]  

(9)

### 3.3 Steps of grey 2-tuple linguistic tour online review

Based on proposed grey 2-tuple linguistic evaluation model above, the steps of tour online review are as follows:

- **Step 1.** Get greyness of each tour online review by experts’ evaluation.
- **Step 2.** Convert the given linguistic evaluation information by experts into the integrated form of grey information and 2-tuple linguistic.
- **Step 3.** Calculate of expert’s evaluation vector. By applying operations 5 and 6 defined in Section 3.2, get the aggregation of grey 2-tuple linguistic value for all the online reviews.
4. Experiments

4.1 Data source

Due to no benchmark data available, we developed a web crawler to randomly download 300 pieces of reviews containing both the positive and the negative from a Chinese well-known tour web site (www.Tuniu.com). The site allows tourists to input text feedback and a five-point satisfaction rating with five being most satisfied for accommodation, traffic, tour guides, journey and reserving process as shown in Figure 1 (a screenshot of online reviews of Tuniu). Ratings are in the rectangle and only the last review has text feedback (some comments on tour guides). Clearly, both potential tourists and tour corporates benefit most from the last review even though all the three tourists’ ratings for each indicator are five (very satisfied).

One reason for selecting Chinese web site online reviews is that there is not much research for process Chinese online reviews. Chinese language is quite different from those languages such as English. Context is more necessary for understanding Chinese. Another reason is that Tuniu web site is one of the most popular tour web sites in China. Data in Tuniu is representative and can reflect tourists’ opinion in some way.

4.2 Acquisition of grey 2-tuple linguistic value

To get the greyness for each tour online review, three experts were invited to evaluate the greyness for all the reviews. Table I shows a record for one review.

For this online review, its greyness for accommodation is \( \frac{0.2 + 0.1 + 0.2}{3} = 0.17 \) and the same method applies to the rest of indicators. Table II shows the grey 2-tuple...
linguistic value for 30 online reviews (considering the length of the article, we did not show all 300 online reviews data).

By applying operations 5 and 6 defined in Section 3.2 to the data in Table II, we get the aggregation of grey 2-tuple linguistic value for 30 online reviews in Table III.

By applying operations 2, 3 and 7 for the whole 300 pieces of online reviews, we get the final grey 2-tuple linguistic value $X = (4.378, 0.553)$ for the related tour service. This value means the weighted average ratings of tourists for one tour service is 4.378 but this number is worth doubting because its uncertainty is 0.553.

### 4.3 Sorting of grey 2-tuple linguistic tourism online review values

If there are more than one grey 2-tuple linguistic value, for example, $(4.5, 0.6)$ and $(4.3, 0.2)$, which is better? Though $4.5 > 4.3$, uncertainty for 4.5 is greater than 4.3. This paper proposes a method for sorting the grey 2-tuple linguistic values.

Supposing there are three tour services and we need to sort them by their grey 2-tuple linguistic value. First, we need to get a quadratic function for No. 1 service by applying operation 4. Then, to compare No. 2 service and No. 3 service, integral must be done by using their grey 2-tuple linguistic values $R = [\beta_i(1 - v_i), \beta_i(1 + v_i)]$.

<table>
<thead>
<tr>
<th>Online review</th>
<th>Accommodation</th>
<th>Traffic</th>
<th>Tour guide</th>
<th>Journey</th>
<th>Reserve</th>
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</thead>
<tbody>
<tr>
<td>C1</td>
<td>(5, 0.4)</td>
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<td>(5, 0.8)</td>
<td>(3, 0.3)</td>
<td>(5, 0.8)</td>
</tr>
<tr>
<td>C28</td>
<td>(5, 0.1)</td>
<td>(5, 0.8)</td>
<td>(5, 0.8)</td>
<td>(3, 0.3)</td>
<td>(5, 0.8)</td>
</tr>
<tr>
<td>C29</td>
<td>(5, 0.2)</td>
<td>(5, 0.8)</td>
<td>(5, 0.8)</td>
<td>(5, 0.8)</td>
<td>(5, 0.8)</td>
</tr>
<tr>
<td>C30</td>
<td>(5, 0.2)</td>
<td>(5, 0.8)</td>
<td>(5, 0.8)</td>
<td>(5, 0.8)</td>
<td>(5, 0.8)</td>
</tr>
</tbody>
</table>

Table II. Grey 2-tuple linguistic value for 30 online reviews
refer to operation 4 and the established quadratic function of No. 1 service. Finally, three quadratic functions are established and we get a matrix like the below:

\[
P = \begin{bmatrix}
  - & p_{12} & \cdots & p_{1m} \\
p_{21} & - & \cdots & p_{2m} \\
  \vdots & \vdots & \ddots & \vdots \\
p_{m1} & p_{m2} & \cdots & -
\end{bmatrix}
\]

where \( p_{ij} \) means the possibility that service\( _i \) is better than service\( _j \). According to the members whose value is greater than 0.5 in the above matrix, we can get the order of the tour services.

5. Conclusion and future studies
For many people, shopping is a social experience. When shopping online, people tend to seek the suggestions and help of similar people, and close friends (Li et al., 2013).
Recently, e-commerce tour companies examine how to leverage social network to improve customers’ purchase decision making. One of core subjects in ISO 26000 is to offer factual and unbiased information to consumers. It is important to evaluate online reviews in tour social network. The contribution of this paper is that we established grey 2-tuple linguistic model to combine online reviews with ratings. This new method can offer potential tourists and tour corporates a more credible result. Compared to the average of ratings, final result got by grey 2-tuple linguistic model is more credible and worth considering when making decisions. Compared to online reviews mining, it is easier to operate and understand.

There are some directions for future studies. First, in this paper, greyness for each online review is given by experts. How to calculate greyness automatically by computer instead of manually by experts should remain a concern. Second, due to the complex links among reviewers in social network, network mining approaches and models are expected to be added to this research in the near future. Finally, the method for sorting grey 2-tuple linguistic value can be further studied.

References


Further reading

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