Research on improving the government service quality by public comments monitoring: take suburb park an example

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***Abstract*—Public service is a very important component in the life of citizens. Under the trend of the Internet economy, the use of online commentary data to assist the public service sector in improving public service satisfaction is an action of implementing service-oriented government. This paper takes the suburb park in Shanghai as an example and conducts research on online review through fine-grained sentiment analysis. Through the techniques of machine learning and natural language processing and drawing portraits of public satisfaction in suburb parks by Python, the visualization results can provide decision-making basis for public service. Finally, based on two of the suburb parks, the regression result on the features and the scores from the actual reviewers shows significant correlations.**

Keywords—Government Service, Opinion Mining, Fine-grained Sentiment Analysis, Machine Learning, LDA, suburb park

I. INTRODUCTION

Public services are the services provided by the government to meet the needs of citizens in living and enjoying. Under the vigorous advocacy for the construction of service-oriented government, government departments are paying more and more attention to the management and construction of public services. At present, government departments still have some problems in the field of public services. The main problem is that the response efficiency is not high [1]. The reasons for such problems are not only the growing demand of citizens, but also the fact that the quality of decision-making caused by the shortage of human resources in government departments [2].

As a vigorously promoted project for the government of Shanghai, the purposes of constructing suburb parks are not only to construct ecological environment and integrate humanistic resources with natural resources, but also to construct as a part of the citizens' leisurely entertainment. Therefore, as part of the construction of public services, the effects and problems during the construction and development of suburb parks in Shanghai have been highly concerned by government departments.

In public service management, the measurement of service quality and public satisfaction is popular in empirical research [3]. For the study of service quality, the SERVQUAL model [5] under the PZB model [4] has been used to measure service quality through the gap between expectation and perception. Based on this, Ye [6] established a service quality evaluation model for the express delivery industry through the method of dimensionality reduction with the aid of AHP. In the aspect of public satisfaction research, team in Guangzhou University [7] used commentary data from “Dianping” and “Koubei” and questionnaires to explore the factors affecting public satisfaction in six aspects including the park’s scenery and facilities. Lan [8] and Zeng [9], based on the data from questionnaire, adopted the method of fuzzy comprehensive evaluation to explore the factors affecting public satisfaction.

The assessment of service quality and public satisfaction is one of the most important issue during the construction of public services in suburb parks. Based on the discussion of the above, this paper will start from the following aspects. The second section is the introduction of the research technology and framework. The third section introduces the process of data source and model construction. The fourth section discusses the effect of the actual application of the model. The fifth part is the summary.

II. FRAMEWORK AND METHODOLOGY

A. Sentiment analysis

The research on the quality of service issues, on the one hand, needs to determine the dimensions involved in public services. On the other hand, data on public satisfaction is also needed.

In recent years, the development of social platforms such as Weibo, WeChat and other O2O community platforms like Ctrip and “Dianping” generated a large amount of online review data, which is an important supplement for government obtaining citizen opinions. So far, many research scholars at home and abroad have confirmed that the text of online reviews has a good ability to express quality problems in the service industry [10]. Bogicevic [11] based on the review data of the airport website, analyzed the problems of airport services, and also used visualization tools to demonstrate these issues. Li [12] used the LDA topic model to mine topics that tourists concern about and calculate the sentiment score of these topics, based on the online review data from “Ctrip”, “Dianping” and “Mafengwo”.

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In addition, there are many domestic and foreign scholars who have done a lot of research on the fine-grained sentiment analysis in the service industry. Wang [13] and Meng [14] studied the relationship between product sales and fine-grained sentiment. Kapukaranov [15] studied the relationship between Bulgarian film reviews and ratings based on fine-grained sentiment. Technically, Chen [16] and Priyanka [17] used deep learning techniques and natural language processing techniques, to extract and analyze fine-grained sentiments, respectively. Research of Hu [18], Cruz [19] and Moghaddam [20] are based on sentiment dictionary, extracting and scoring sentiment words.

In this paper, we will analyze the government services in the suburb parks, based on its' online reviews from "Weibo", "Dianping" and "Ctrip". With the help of fine-grained sentiment analysis technology, we analysis the inference factor of the quality of public service and public satisfaction in suburb parks. The fine-grained sentiment analysis is divided into three steps. The first step is to segment the review data and prepare fine-grained feature dictionary by means of extraction, dimension reduction, and screening. The second step is to mark the feature dimension of every review with the help of fine-grained feature dictionary. The third step is to perform emotional calculations on the review data. The obtained labeled feature and sentiment scores of suburb parks' service satisfaction can be used to analyze the problems of public services in different dimensions and the influencing factors.

III. Construction and Evaluation of Models

A. Pre-process of the text data

The structure of online review data is quite different from other textural data. The existence of a lot of emotions in online reviews, the misuse of punctuation and the irregularity of the grammar will lead to difficulties in the following work. In addition, the length of the review data varies, with the shortest being only 11 characters and the long being more than 2,000 characters.

In many times, online reviews often cover descriptions in multiple dimensions. So, it is unreasonable to use a one comment as a unit to evaluate a dimension of service satisfaction. Therefore, we first need to preprocess the data.

1) Sentence division

First of all, in order to make all the content of the reviews being simple, with the features described by the service satisfaction being as accurate as possible, we divided the comments by punctuation. For example, comment like " The food is delicious, but the transportation is not convenient" has two features described, but totally negative sentiment tendency expressed. Through the division by punctuation, we may have two pieces of comments matched with the original one. Considering the difference of the punctuation habit of the online reviews and the official sentences. We divide the sentences by 7 kinds of punctuation. Thus, every original review may matched with several pieces of comments, but has single sentiment feature.

2) Duplicate comments

Then, in order to avoid misunderstandings when identifying the content of the reviews by machine, special symbols and emoji expressions in online reviews need to be removed. Secondly, in order to emphasize their own feelings, someone will repeatedly upload same or highly similar comments. In the face of this situation, we can use Jarcard similarity (equation (1)) to judge and filter it [22]. When the repetition rate exceeds 80%, the machine will take them as the same comment.

$$J(A,B) = \frac{A \cap B}{A \cup B} \tag{1}$$

3) Similar content

Finally, there may be situations that the text content of the online commentary being simple, but the expression being very long. For example, in the phrase "very good very good", the word "very good" is repeated twice, but only one meaning has expressed, which may exaggerate the expression and miscalculate the sentiment score. So, we use an indicator called content-similarity [22] (equation (2)) to help filter reviews with high content repetition rate.

$$contentSimilarity = 1 - \frac{size\ of\ Set}{size\ of\ List} \tag{2}$$

B. Prepare fine-grained feature dictionary

In order to measure the service satisfaction of suburb parks in different dimensions, we firstly need to define the dimensions of service satisfaction. The LDA topic model is used here to extract the topic of public concern for the suburb park service [12]. Based on this, we filter several nouns extracted in each topic. With the help of the synonym [31], the noun words related to each topic are filtered. The words, called fine-grained feature dictionary, are evaluation variables of the public service satisfaction for each specific feature. In order to determine the number of features, we use coherence as a criterion. The lowest point in Fig.1 means that when the number of features is 5, LDA model can explain the result better.

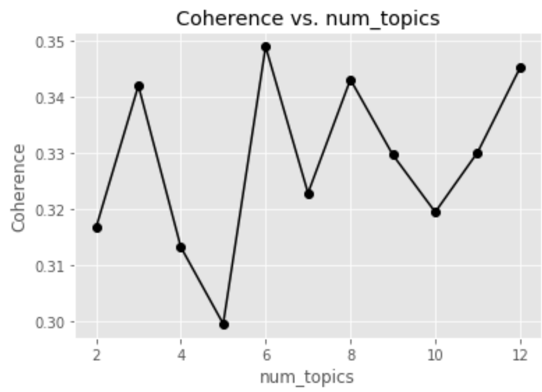

Fig. 1. Coherence of LDA model under diffierent number of topics

C. Sentiment analysis

As the basis of sentiment analysis, the construction of sentiment dictionary is related to the accuracy of the sentiment analysis results. The construction of sentiment dictionaries started earlier [23-25] abroad than that of Chinese sentiment dictionaries. HowNet, one of the most famous sentiment dictionaries emotional dictionary, is developed by Dong [26]. In addition, scholars have established sentiment dictionary for various fields. Tsinghua University's has established sentiment dictionary for tourist industry [27] and Shanghai Jiaotong University has established sentiment dictionary for automobile industry [28].

Based on the sentiment dictionary form HowNet and Tsinghua University mentioned above, we have integrated and adjusted it for suburb parks. We classify sentiment words into three categories (Fig.2). Except for positive words and negative words, degree words are divided into categories of "Inverse", "Insufficient", "Ish", "More", "Very" and "Most", with the initial weights assigned.

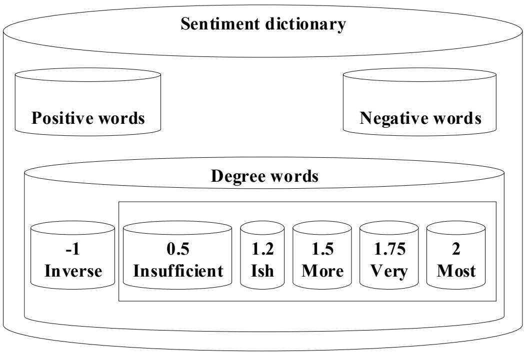

Fig. 2. Structure of sentiment dictionary

Based on the method mentioned by Ku [29] and Shi [30], combined with the design concept of segmenting sentence, we formulate such a rule in the algorithm, such as Equation (3). Firstly, we screen out valid comments based on fine-grained feature dictionaries. Then, we calculate the sentiment scores one by one. Later, based on the difference between the number of positive word P and negative word N, we multiply the difference and the degree score (D) to determine the sentiment score of this piece of comment. In the expression of calculating degree score (D), Σs_degree represents the sum of sentiment score of words in five other categories and the parameter "inverse" represents the number of inverse words.

$$sentiment\_score = (P - N) \times D$$
$$D = \frac{-1^{inverse} \times \sum s\_degree}{\#degree\_words} \quad (3)$$

IV. APPLICATION OF MODELS

A. *Portrait of public satisfaction in suburb parks*

In order to measure public satisfaction of the suburb parks, we used fine-grained sentiment analysis techniques to evaluate the public satisfaction of suburb parks from five different feature dimensions. First of all, according to the result of LDA topic model, we extract key nouns words in each topic and obtain a fine-grained feature dictionary table (Table. I) after cleaning and dimension reduction.

TABLE I. KEY NOUN WORDS FOR FIVE FEATURES

Feature (# of words)	Key noun words
Food (24)	canteen / food / restaurant / wine / local style cuisines …
Facility (59)	toilet / amusement park / boat / shop / roller coaster…
Consumption (24)	deposit / free ticket / fee / expense / rent…
Ecosystem (53)	Cherry blossom / rapeseed / peach blossom / sunflower / river...
Transportation (23)	Subway / bike / sharing bike/ bus / car…

Next, we need to mark features and calculate sentiment scores for all comments, which is shown in Fig.3. After dividing long comments in advance, features will be marked for every short comments by fine-grained feature dictionary, and the sentiment scores will be calculated after filtering valid comments with features. The distribution of marked comments' feature is shown in Fig.4.

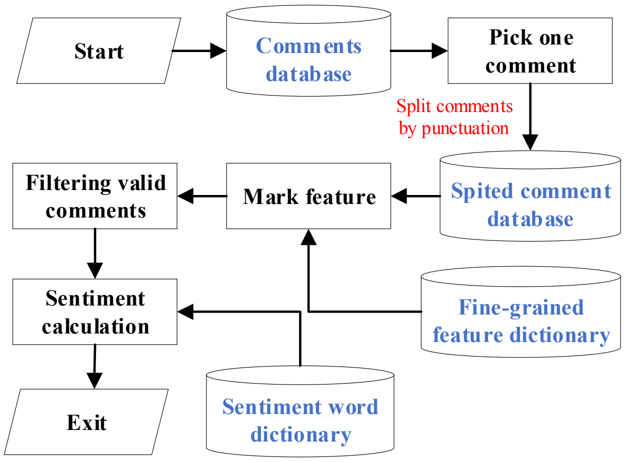

Fig. 3. Flow chart of feature marking and sentiment scoring

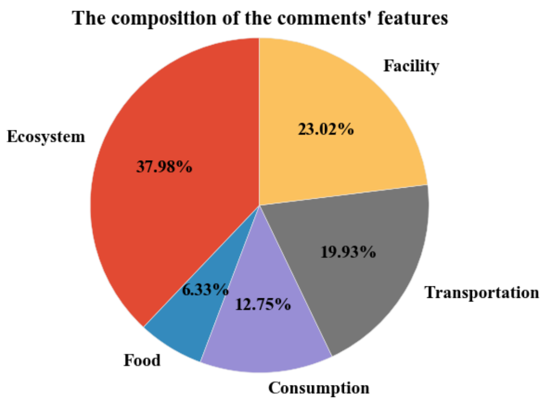

Fig. 4. Pie chart for composition of the comments' features

Then, taking Pujiang suburb park and Changxingdao suburb park as examples, we summarized sentiment scores for each feature in both parks. In order to display the portraits of public satisfaction of the suburb parks more intuitively, we map the summarized sentiment scores of each suburb park to the unified dimensions of the scope of zero to five, and then draw a radar map by Python's Matplotlib package. The result of the visualization is shown in Fig.5.

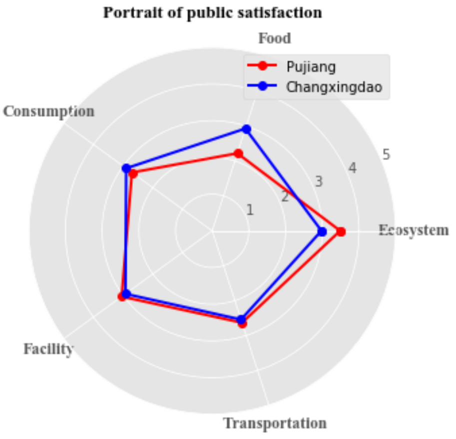

Fig. 5. Portrait of public satisfaction in Pujiang suburb park and Changxingdao suburb park

B. *Regression test for the five features*

Finally, taking the Pujiang suburb park and Changxingdao suburb park as examples, we conducted a regression test on the calculated sentiment score of five features and the actual scores marked by the reviewer. The results for Pujiang suburb park (Table II.) shows that there are positive correlations between the five features and the actual scores. Among them, the four of the features are significant under 1% significance level, and the variable "Transportation" is significant under 5% significance level. Similarly, we run the same regression test on Changxingdao suburb park, the result (Table III.) also shows that these five features are under 1% or 5% significance level. From the regression result, we find that people concern more about consumption in both suburb parks, which is closely related to the free opening policy of the suburb park in Shanghai.

TABLE II. REGRESSION RESULT OF PUJIANG SUBURB PARK

Coefficients [a]					
	Unstandardized Coefficients		*Standardized Coefficients*		
	B	*Std. Error*	*Beta*	*t*	*Sig.*
(Constant)	3.426	0.069		49.680	**0.000**
Ecosystem	0.125	0.024	0.152	5.176	**0.000**
Food	0.082	0.024	0.098	3.442	**0.001**
Consumption	0.150	0.045	0.079	3.365	**0.001**
Facility	0.052	0.017	0.077	3.089	**0.002**
Transportation	0.030	0.013	0.054	2.256	**0.024**

a. Dependent Variable: Score

TABLE III. REGRESSION RESULT OF CHANGXINGDAO SUBURB PARK

Coefficients [a]					
	Unstandardized Coefficients		*Standardized Coefficients*		
	B	*Std. Error*	*Beta*	*t*	*Sig.*
(Constant)	2.688	0.114		23.629	**0.000**
Ecosystem	0.173	0.055	0.176	3.146	**0.002**
Food	0.371	0.088	0.261	4.223	**0.000**
Consumption	0.255	0.085	0.162	3.002	**0.003**
Facility	0.237	0.069	0.222	3.435	**0.001**
Transportation	0.126	0.050	0.128	2.522	**0.012**

a. Dependent Variable: Score

V. CONSLUSION

This paper studies the public satisfaction of suburb parks through fine-grained sentiment analysis techniques. First, a fine-grained feature dictionary and a sentiment dictionary were established, and the sentiment scores of the reviews was obtained by extracting features and calculating sentiment scores after the sentences were divided first. Then, the sentiment scores are summarized and the public satisfaction portrait of public services in suburb parks is presented through radar maps. Finally, the regression test of the features and scores from online reviewers verified correlations.

The study of calculating fine-grained sentiment scores and the portrait of the public satisfactions can bring governmental personnel intuitive perception to the public service. And in response to the weak points in public services in suburb parks, active and effective measures can be taken in time to increase the quality of government service. Through the use of public comments, government can take more active and efficient actions to help citizens enjoy better government service.

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