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The Application and Comparison of Web Services for Sentiment Analysis in Tourism

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Abstract—**The popularity of social computing and sentiment analysis has attracted an increasing attention of tourism industry and academia. The sentiment analysis of residents' and tourists' plays an important role to the development of tourism. It aims to identify and analyze opinions and emotions contained in reviews which are expressed by residents or tourists. Although it's a challenging task, many companies and research institutes are developing web services to provide public-access and cost-effective solutions to the problem. However, to the best of our knowledge, there are very few studies to apply and compare these web services in tourism. Therefore, in this work we make an initial attempt to explore a set of three web services and compare their sentiment analysis capabilities using the well-known TripAdvisor data collection. Experiment results lead to some interesting conclusions.**

Keywords-web services; sentiment analysis; tourism

I. INTRODUCTION

The sentiment analysis of residents' and tourists' plays an important role to the development of tourism. It aims to identify and analyze opinions and emotions contained in the reviews which were expressed by residents or tourists. With the popularity of social media and social computing, sentiment analysis has attracted more and more attention of tourism industry and academia.

It is well-known that opinions of other people are very important information for most of us in the decision-making process. Long before the wide spread of the Word Wide Web, Pang and Lee [6] have argued that many people tend to ask friends to recommend an automobile or give reasons for their vote in the election. The fast-growth of social media and mass volume of sentimental reviews online have made the automatic sentiment analysis a critical task to modern business and society. Sentiment analysis tries to identify the sentiment contained in texts and aims to classify these texts into different categories, including positive, negative and some others.

The application of sentiment analysis in tourism can make great contribution to tourism. For tourists, before their departures, they can obtain others' opinions about the scenic spots, the hotels and the restaurants from travel blogs, analyze sentiments of these blogs, and make decisions to choose hotels to live in or restaurants for dinners. For hoteliers and managers, they can make continuous improvements according to tourists' reviews so that they can attract more customers.

Sentiment analysis is also a very popular research topic in other domains. Many studies conducted experiments on sentiment analysis with the dataset of online movie reviews [3, 11, 32, 33]. Some researchers identified the important aspects of products by performing sentiment analysis for online consumer reviews [5, 20]. Local governments could also benefit from the sentiment analysis for the mass' attitudes toward policies and news using data collected from social media [25, 26, 34, 35].

Technically speaking, sentiment analysis is a quite challenging task, which encompasses many procedures: text pre-processing, feature extraction, text expression and classification. Despite the complexity and difficulty of this problem, many companies and research institutes are developing new tools and web services which can deal with several of the issues aforementioned. These web services are easy to use and users never need to be skillful at the techniques of sentiment analysis. Hence it's very convenient for researchers to carry on research on sentiment analysis.

However, there are very few studies discuss the application and comparison of these web services especially in the context of tourism applications. Considering the importance of sentiment analysis in tourism and the rise of web services for sentiment analysis, this paper aims to explore and compare three well-known web services focused on sentiment analysis and assess their functionalities by an experiment using the data which are collected from TripAdvisor.

The remainder of the paper is structured as follows: Section II reviews the related literature, Section III describes the relevant web services for sentiment analysis in tourism, Section IV presents the experiment and discusses the results, and finally Section V concludes the paper with implications and future research.

II. LITERATURE REVIEW

A. *Definitions of Sentiment Analysis*

Sentiment analysis tries to identify and analyze opinion and emotions [7]. There are two kinds of sentiment classification forms include binary sentiment classification and multi-class sentiment classification [10]. Given a document D, from the former angle, it will be classified in two categories: positive and negative; and it can be divided into more than two categories, such as positive, neutral and negative, from the latter perspective. In order to measure the strength of each sentiment, it uses a value in the range [-1, 1] to denote the sentiment value, where -1 indicates the maximum negative degree and 1 the maximum positive degree. According to Feldman [31], there are five main problems for sentiment analysis:

- Document-level sentiment analysis;
- Sentence-level sentiment analysis;
- Aspect-based sentiment analysis;
- Comparative sentiment analysis;
- Sentiment lexicon acquisition.

The document-level sentiment analysis is the typical form of sentiment analysis. It means a document contains an opinion on one main entity expressed by the author(s) of the document. In sentence-level sentiment analysis, we analyze the document via analyzing each sentence. Sometimes, people think an entity has many aspects and they have a different view for each aspect, then aspect-based sentiment analysis can be used. When viewers don't provide a direct opinion, we must try to extract the preferred entity from the sentences contains comparative opinions which is the meaning of comparative sentiment analysis. Sentiment lexicon is the most important resource when refers to sentiment analysis algorithms. There are three main approaches to acquire the sentiment lexicon: manual approaches in which people code the lexicon by hand; dictionary-based approach and corpus-based approach.

An opinion is a positive or negative sentiment and it can be defined as a 5-tuple (e_j, a_{jk}, so_{ijkl}, h_i, t_l) [39].

- e_j: a target entity;
- a_{jk}: the k-th aspect of the entity ej;
- h_i: the opinion holder;
- t_l the time when the opinion was expressed;
- so_{ijkl}: the sentiment value the for the opinion holder h_i expressed at time t_l for the aspect a_{jk} of the entity e_j.

B. Web Services

Web service technologies have been regarded as a public-access and cost-effective solution in deploying understandable applications used for business-to-business integration [4]. In paper [1], web services are defined as software applications identified by URIs, whose interfaces and bindings are capable of being defined, described, and discovered as XML artifacts.

Web services seem like black boxes for users and programmers. It is easy to use and users do not need to acquire the expertise to understand the background mechanism or the technical details regarding a complex problem.

C. Techniques of Sentiment Analysis

Yousef, Medhat and Mohamed [37] present a categorization of well-established sentiment analysis techniques depicted in Fig. 1. Two general categories are machine learning approaches and lexicon-based approaches.

- Machine Learning Approach

Machine learning approaches can be divided into two finer categories: supervised learning and unsupervised learning. The former is more popular in recent research. Many sentiment analysis researchers have widely studied the techniques of Support Vector Machine (SVM), Naive Bayes, Maximum Entropy [16, 24, 29], Neural Network, and Bayesian Network.

- Lexicon-based Approach

In [2], Hu and Liu present a lexicon-based method which refers to use opinion bearing words (or simply opinion words) to perform sentiment analysis. Such analysis relies on a sentiment lexicon. This category contains two major approaches: a dictionary-based approach and a corpus-based approach. In addition, the latter can be further categorized into two types of methods: Statistical-based methods and Semantic-based methods. In [8, 19], we can see detailed descriptions of these methods.

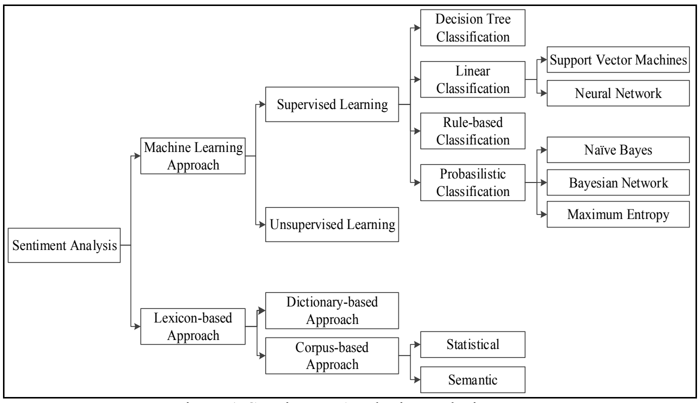

Figure1 Sentiment Analysis Techniques

D. Sentiment Analysis in Tourism

Sentiment is a synonym of attitude in tourism research. The attitudes of both tourists and residents play important roles in tourism development, since friendly interactions between visitors and residents create great impact on visitors' satisfaction [41]. Recent tourism literature has studied issues of place identity in understanding resident attitudes toward tourism [9, 27, 28, 36, 38]. These studies conclude that local people's sentiment is crucial to the sustainability of tourism development. Woo, Kim and Uysal [40], Vargas-Sánchez et al. [21], Nunkoo and Ramkissoon [22] describe different models of residents' attitude for tourism development. The sentiments of tourists are also important for the development of tourism.

The rapid growth in Internet applications in tourism has led to an enormous amount of personal online reviews for travel-related information on the Web. These reviews appear in different forms like twitter, blogs, Wiki or forum. More importantly, the information in these reviews is valuable to both travelers and practitioners for various understanding and planning processes. Many tourism researchers attempt to examine different aspects of online word-of-mouth [12]. Beverley, Sparks, and Browning explore the impact of online reviews on hotel booking intentions and perception of trust [18]. In [15], the researchers try to find the impact of e-word-of-mouth on the online popularity of restaurants. Tourists' online reviews also can guide people to choose travel agency and destination.

Since the application of sentiment analysis in tourism has become more and more popular. Most researchers study the sentiment classification in tourism with machine learning approaches. In [17], standard machine learning techniques naive Bayes and SVM are incorporated into the domain of online Cantonese-written restaurant reviews to automatically classify customers' reviews as positive or negative. In [14], Zheng and Ye conduct an exploring research on sentiment analysis to Chinese traveler reviews by SVM algorithm. Compared to study of machine learning approaches, in tourism, there are only a few papers study the lexicon-based approach. For example, Kang, Yoo and Han [23] propose a new seniti-lexicon for the sentiment analysis of restaurant reviews.

However, to the best of our knowledge, there are very few studies to explore and compare web services for sentiment analysis in tourism. So the aim of this paper is to study three web services to conduct sentiment analysis in tourism area and compare their sentiment analysis capabilities by an experiment with a benchmark dataset.

III. WEB SERVICES

In this section, we will introduce three web services which incorporate functionalities related to sentiment analysis. Apart from the three web services, there are also some other ones, such as Lymbix, Musicmetric and Opendover. Since the following three tools are very popular and easy to use, we decide to focus on them as an exploratory study and more web services will be considered in our future work.

A. AlchemyAPI

AlchemyAPI can help a computer understand human language and vision via an easy-to-use SaaS API. It offers 12 API functions as part of its text analysis service, each of which uses sophisticated natural language processing techniques to analyze text content and generate high-level semantic information. These functions are consist of entity extraction, sentiment analysis, keyword extraction, concept tagging, relation extraction, taxonomy classification, author extraction, language detection, text extraction, microformats parsing, feed detection, linked data support.

From the sentiment analysis point of view, AlchemyAPI is capable of computing document-level sentiment, sentiment for a user-specified target, entity-level sentiment, quotation-level sentiment, directional-sentiment and keyword-level sentiment. These multiple modes of sentiment analysis provide for a variety of use cases ranging from social media monitoring to trend analysis. AlchemyAPI's sentiment analysis algorithm looks for words that carry a positive, negative or neutral connotation then figures out which person, place or thing they are referring to. It gives every sentiment a polarity with the range in [-1, 1] .It also understands negations (i.e. "this car is good" vs. "this car is not good") and modifiers (i.e. "this car is good" vs. "this car is really good"). The sentiment analysis API works on both long and short documents, including news articles, blog posts, product reviews, comments and Tweets.

B. Semantria

Semantria is a multilingual sentiment engine which can handle several languages such as English, French, German, Spanish, or Chinese. It applies text and sentiment analysis to tweets, Facebook posts, surveys, reviews or enterprise content. It supports the following functions: entity extraction, categorization, sentiment analysis, multilingual processing, clustering and visualization.

When it comes to sentiment analysis, it can be carried out at different levels, including paragraph, sentence, entity and document level. Texts can be split up into three categories: positive, negative and neutral. In order to measure the intensity of each sentiment, it also gives every sentiment a polarity range from -1 to 1 which is similar to AlchemyAPI. It is worth mentioning the polarity can only calculated on document level.

C. Text2Data

The team of Text2Data is a London based start-up offering Text Analysis SaaS services. They aim to deliver affordable, quality text analysis services to help the companies to understand their customers better. They provide the following text analytics services: Sentiment analysis; Text summarization; Document classification; Entity extraction; Themes discovery; Keyword analysis; Citation detection and Slang detection.

Text2Data's real-time Sentiment Analysis API enables users to analyze texts based on content through a scalable and RESTful API service. It combines for sentiment analysis techniques including keyword spotting, lexical affinity, statistical methods and concept-level to determine document sentiment, depending on many factors such as: document type (Twitter content, Amazon comment, email content etc.), its length and lexical coherence. As a result, the texts will be split up into three categories: positive, negative and neutral along with values scoring sentiment strength in the range [-1, 1].

IV. EXPERIMENT

A. Data Collection

Web services for sentiment analysis can perform several tasks, in this study we focus on their capabilities on sentiment classification. Considering the maximum amount of reviews that can be handled within these three web services and the objectives of the experiment, we choose hotel reviews gathered from TripAdvisor as our benchmark data collection. TripAdvisor is the world's largest travel site and it's also the world's largest travel review site. Its global monthly visits at almost 35 million and it has 10 million register members and 25 million reviews. At present, it has become a large online database. The dataset [42] we attained from the website http://www.arguana.com contains 2100 texts. It consist of 300 texts (60 for each sentiment score between 1(worst) and 5 (best)) of seven of the 15 most-represented locations in the original dataset which was gathered from TripAdvisor and also can be downloaded from the aforementioned website. Every sentence in each document has been classified as three categories: positive, negative and facts relied on *Amazon Mechanical Turk. Based on that and considering the length of documents can be handled by all the three tools, we clear away some too short ones and split up these left texts into three categories: positive category which contains 1002 texts, negative category including 989 texts and neutral category with 67 texts included.*

B. Evaluation Measures

According to recent studies [13, 30], we select the accuracy, recall and precision as the evaluation criteria to assess the performance of each web service.

The *accuracy* can be defined as the following equation:

$$accuracy = \frac{accurate\_reviews}{total\_reviews}, \quad (1)$$

where *total_reviews* is the number of all reviews which are used in the experiment and *accurate_reviews* represents the number of the reviews including positive reviews, negative reviews and neutral reviews which can be classified correctly.

The *recall* is used to compute the accuracy of only one kind (positive, negative and neutral) of the reviews. We take the positive reviews as an example:

$$positive\_recall = \frac{pos\_correct}{total\_pos}, \quad (2)$$

where *total_pos* is the number of total positive reviews in the test dataset and *pos_correct* is the portion of total positive reviews which are classified as positive ones in the experiment. The other kinds of reviews include negative kind and neutral kind can be computed as the same manner.

The *precision* is also used as a tool to calculate only one kind of the reviews (positive, negative or neutral) that has been correctly classified.

$$positive\_precision = \frac{pos\_correct}{pos\_correct + pos\_wrong} \quad (3)$$

where *pos_correct* is the amount of original positive reviews that are correctly labeled as positive and *pos_wrong* means the other kinds of reviews(negative and neutral) are be classified as positive reviews. Negative and neutral kind of reviews also can be computed in the same way.

C. Experiment Results

With the hotel review dataset, Table 1 shows the percentage of the correctly classified reviews in accordance with the evaluation measures mentioned in the last section.

From this table, we can see AlchemyAPI is the best tool to classify hotel reviews since its accuracy is 88.36%. Since most of the reviews are labeled as positive, the positive recall and precision are higher than the other categories. In general, AlchemyAPI presents a better behavior for both positive and negative texts with the positive recall equals 91.14% and negative recall equals 84.03%. It is very interesting that there is few texts in the kind of positive and neutral were be divided into the kind of negative. As a result, the precision of every web service are very high. However, all of them cannot work well when deal with neutral reviews. In our experiment, there are hardly any texts which were classified into neutral category with AlchemyAPI and Text2Data. What's more, the recall of semantria is also very low.

Besides, when we applied these web services in tourism practice, we find that although all of the three web services have high accuracies, there have several technical limitations when analyzing in practice.

Firstly, the length of documents that can be managed by the web services is limited especially for AlchemyAPI. It cannot work, if the length of the text is too short.

Secondly, the efficiency of Text2Data is low. It takes too long time for us to use Text2Data to do sentiment analysis for these texts when comparing with the other two web services.

TABLE 1 SUMMARY OF CLASSIFICATION RESULTS FOR HOTEL REVIEW DATASET

	Accuracy	**Positive_ Recall**	**Negative_ Recall**	**Neutral _ Recall**	**Positive_ Precision**	**Negative_ Precision**	**Neutral_ Precision**
AlchemyAPI	82.17%	96.70%	73.00%	-	75.34%	93.52%	-
Semantria	59.38%	82.23%	37.31%	43.28%	81.91%	96.09%	4.34%
Text2Data	73.10%	89.56%	64.07%	-	75.15%	74.74%	-

Notes: "-" represents the correct classfication is too limited to indicate.

Thirdly, all of the web services support limited languages, such as English and Germany.

Finally, the accuracy of neutral and negative reviews is worse than positive ones. From the results of our experiment, we infer that semantria tends to classify texts with unconspicuous negative sentiment as neutral category rather than negative category and all the web services try to classify texts with unconspicuous positive sentiment as positive category rather than neutral category. In other words, they prefer to show a better result for subjects which are reviewed.

V. CONCLUSIONS AND FUTURE RESEARCH

In this paper, we explore three web services with several functionalities related to sentiment analysis and compare their performance when they are used to classify texts in tourism. All of them are public to access and easy to use. In order to accomplish the aim of this paper, we collected hotel reviews from TripAdvisor as our benchmark collection for experiments. Drawing from the experiment results, we can conclude that all of the web services have high accuracies. Since most of the reviews are classified as positive ones, the accuracy for positive kind is higher than the other two kinds. Unfortunately, when dealing with reviews belonging to neutral category, all of the tools cannot work well.

There are several limitations of this study that deserve intensive future research. Firstly, in this paper, we present only three popular web services as our starting point. The number of web services is limited. Secondly, the type of data collections is limited. In the experiment, we use only one dataset belongs to the type of long texts written in English without considering other types include short texts and texts written in others languages, such as Chinese. Thirdly, when it comes to the evaluation metrics, we just consider three typical ones: accuracy, recall and precision. However, there are still many measures can be used to evaluate the result of this experiment. For example, the efficiency of each web service. Last but not the least, since the original data collection do not have a polarity score, we can't compare the intensity of classification for each web service. These limitations entail broad future research.

Notwithstanding these limitations, the study has important implications. This study provides an innovative aspect for researchers to study sentiment analysis. They can select the most appropriate tool based on the information offered by this paper and then make full use of it to classify texts for their research to simplify their work. What's more, when they want to present a new classification algorithm, they can compare the results with web services to verify the efficiency of the algorithm.

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