SENTIMENT ANALYSIS OF PEER TO PEER ACCOMMODATION APPS ON GOOGLE PLAY

(COUCHSURFING- AIRBNB-HOMEAWAY)

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Abstract:

Due to the explosive growth of social media which has enabled customers to write reviews about experiences and express opinions about services and products, to understand the attitude implied in their reviews, the study of sentiment analysis has attracted attention in different fields. Peer-to-peer (P2P) accommodation as a new model of business, has increasingly being used by tourists. Based on this reason, different types of p2p are entering to the accommodation market. The present paper is an attempt to documenting, assessing and visualising the emotions and attitudes of Couchsurfing, AIRBNB and Homeaway users on Google play. Overall sentiment toward these apps is pretty good. Interestingly, the main keywords about all of them are partially same (great-easy use- good). The Comparison analysis of three Apps based on seven dimensions: design- user experience (UX), bugs, performance, privacy, satisfied users, complexity and customer support, indicates better situation for Airbnb.

Keywords: Sentiment Analysis, Peer To Peer Accommodation, Apps, Google Play, Couchsurfing, AIRBNB, Homeaway

1. Introduction

By introducing Web 2.0 the obstacle to public engagement were decreased. Offering motivations for creating and sharing of information and contents (Hopkins, Hare, Donaghey, & Abbott, 2014:3), facilitating information sharing, user-centered, collaboration and interaction (Power & Phillips-Wren, 2011) shaped new culture known as "participatory culture" (Jenkins & Deuze, 2008: 7). Participating in and exchanging opinions through social media has made a huge volume of information available. The phenomenon of online reviews of products and services is similar to traditional "word-of-mouth" (WOM). The spread of WOM through the Internet and Web 2.0 is currently known as "electronic Word of Mouth" (eWOM) (Mellinas, Martínez María-Dolores, & Bernal García, 2015). A review is basically a form of user-generated content (Jiawei Chen, Hongyan Liu, & Jun He, 2015). Generally, it is an evaluation of customer toward a service, product (Selvam & Jananee M., 2016), company, destination, hotel, app. accordingly it can provide much valuable information. Based this, online reviews have been accepted as an important source of information (Liang, 2016), even more credible and more trustworthy than traditional advertising. "Today's, consumers are no longer limited to the traditional one-way seller-to-buyer communications" (Zhang, Wu, & Mattila, 2016). Actually, people have moved from only being receiver of information and advertisement to more active roles. Some new terms such as "prosumers" (Han, Song, & Han, 2013: 159) or even "prodsumer" (Koçak, 2011:18) reflect this change. As consumers become both producer and consumer this is called prosumer (Han, Song, & Han, 2013b).

Due to increasing the power of consumer and potential of EWOM to significantly influence a company's reputation and other consumers' decision (Rose & Blodgett, 2016), online review has attracted the attention of both academics and practitioners (Tripathy, Agrawal, & Rath, 2016). In addition to web 2.0, smart phones and mobile apps, are others influential and effective factors (Wang, Lai, & Chang, 2016).

"According to the last report of International Telecommunications Unit (ITU, 2015) there were more than 7.000 million users in the world with a mobile line by end 2015 (Briz-Ponce, Pereira, Carvalho, Juanes-Méndez, & García-Peñalvo, 2016:1). By growing use of smartphones, mobile applications (Apps) have emerged a new business (Chang, Chou, Yeh, & Tseng, 2016). With the fast growth in smart phones, apps markets and the big success of the mobile application (app) sales, the competition is increasing between apps (Ning-Yao Pai; Yung-Ming Li, 2014). Accordingly, satisfying existing users and try to attract new user is vital for its developers. "Since the revenue and profit of a mobile app is often proportional to the size of its user base" (Vu, Nguyen, Pham, & Nguyen, 2015:749).

The sharing economy based apps are new players in the apps markets. They help individual to become businessman. Exactly, by help of these apps individuals do not act as consumers; only, but also by actively participate in different social media act as contributors or producers of information, service and product (Aaron Alan & Jacobs Henderson, 2013). For instance, "peer to peer accommodation" (Zhexembayeva, 2014: 54). It is fueling by startups such as Couchsurfing, Airbnb, Homeaway, Uber, Mealsharing and BlaBlaCar. This new model of business provides opportunities to individuals to share their entire home or spare rooms with others(Koch & Lockwood, 2016). It "has the potential of becoming a mainstream phenomenon in travel" (Pizam, 2014:118), and bring phenomenal changes to tourism. According to World Travel Market (WTM) London (2014), alternative accommodation and peer-to-peer sharing will continue to dominate the global travel trend in 2015. Accordingly, the number of newcomers to this market and the competition between apps is increasing.

Analyzing of app reviews can help developers. They are often contain complaints or suggestions which can help developer to improve user experience and satisfaction. However, the volume of reviews makes their analyzing more difficult (Vu, Pham, Nguyen, & Nguyen, 2015) and time consuming. To address this problem, it seems that "sentiment analysis" (W. Wang, Wang, & Song, 2016: 1) can be useful. So, the present paper is an attempt to documenting, assessing and visualizing the emotions and attitudes of Couchsurfing, AIRBNB and Homeaway users on google play. In addition, based on 6 dimensions: design- user experience (UX), bugs, performance, security, satisfied users and customer support, their situation in each factor will be identified.

Sentiment Analysis

Sentiment Analysis (SA) or opinion mining aims to extract subjective information (Ma, Yuan, & Wu, 2015) . Generally, it is a trying to extract and categorizing opinions, attitudes, emotions of users as positive, negative or neutral (Fernández-Gavilanes, et all 2016). From the sentiment viewpoint, textual information can be divided into two types, namely, facts and opinions (Schouten & Frasincar, 2016).

Generally Textual information can be classified as factual (objective) or opinion (subjective). Objective statements expressing facts about nature of a product, while subjective statements represent judgments, perceptions, perspectives or opinions (Singh, Paul, & Kumar, 2014& Khan, Baharudin, Khan, & Ullah, 2014). From the technical view, "Bag of Words (BOW) (Tripathy et al., 2016) and "Feature-Based Sentiment (FBS)"(Zhai, Xu, Li, & Jia, 2009). In the Bag of Words, a review is analyzed based on how many times a word appears. Based on the total score, text will be classified as positive or negative. One of the main disadvantages of this method is focusing only on statistics of words and ignoring the relations (Daniilidis, Maragos, & Paragios, 2010). In trying to solve it, feature based sentiment (FBS) has emerged. Generally, involves three steps: "first, identify the attributes (features, that is, nouns and compound nouns) customers commented on. Second, identify the sentiment words (i.e. good and bad), and third, map sentiment words to the attributes to which they refer (Hao et al., 2013:274).

2. Methodology:

The main aim of opinion mining or sentiment analysis (SA) is categorizing text as positive, negative or neutral (Fernández, et.all. 2016). In the recent years particularly due to the remarkable growth web 2.0, (SA) has received increasing attention (Ceron, Curini, & Iacus, 2016). "Sentiment analysis is an interdisciplinary field that crosses natural language processing, artificial intelligence, and text mining" (Karamibekr & Ghorbani, 2013). In generally, it can be said that it is a subfield of text mining; because the most of the opinions are in the text.

The samples of this study include the top three peer to peer accommodation apps. For studying of our samples (Airbnb, Couchsurfing, Homeaway), APPBOT has been selected as the main tools for extraction and analysis of reviews. It is a monitor tool and able to analyses app reviews from iTunes, Google Play, Windows and Amazon, globally (appbot, 2016). It can automatically collect, cluster categorizes, and summarises off emotions, feelings, and the attitude. For doing this research we used the trial version (free for 14 days) of APPBOT.

Firstly, in the manage apps menu, our three apps added. By using of keywords algorithm in APPBOT, namely: last 365 days, all languages and all stars, pre-analysis settings were done and analysis started at 24.05.2016. After extracting reviews, based on the aims of this research- opinions classification - feature based opinion mining - comparative analysis were extracted.

3. Samples

The research samples include top three peer to peer accommodation (P2P) apps, namely: Couchsurfing, Airbnb and Homeaway.

Couchsurfing founded in 2004. It is an online social networking to facilitate the free exchange of accommodation among travelers. In this sense, Couchsurfing is based on a "moral economy" (Germann Molz, 2013:211). it's user from December 14, 2014, has been risen from 9 million members in more than 120,000 cities(Luo & Zhang, 2016) to 10 million people in more than 200,000 cities worldwide(Couchsurfing, 2015). This 4.1 Stars app on google play had been downloaded over 1 million times by Jun 2016(Googleplay, 2016b).

Another important p2p accommodation is AIRBNB. that "with over 1.5 million listings- homes, apartments, guest rooms, even houseboats and tree houses - in more than 34,000 cities in over 190 countries"(Somerville, 2015) is going to become bigger than Marriott and Hilton (Morrow, 2015). Airbnb had served 9 million guests since its founding in August 2008. Until Jun 2016, users had installed this 4.3 stars app for more than 10 million times (Googleplay, 2016a).

The third sample of our study is Homeaway. Founded in 2005, HomeAway with "Over 1 million properties in 190 countries" (HomeAway, 2016) is "the world biggest online vocation rental platform" (Lin, Wei, & Zhu, 2015). Until Jun 2016, this 4.3 stars had been downloaded over 1 million times. (Googleplay, 2016c).

Figure ١: Airbnb, Couchsurfing and Homeaway on Google play

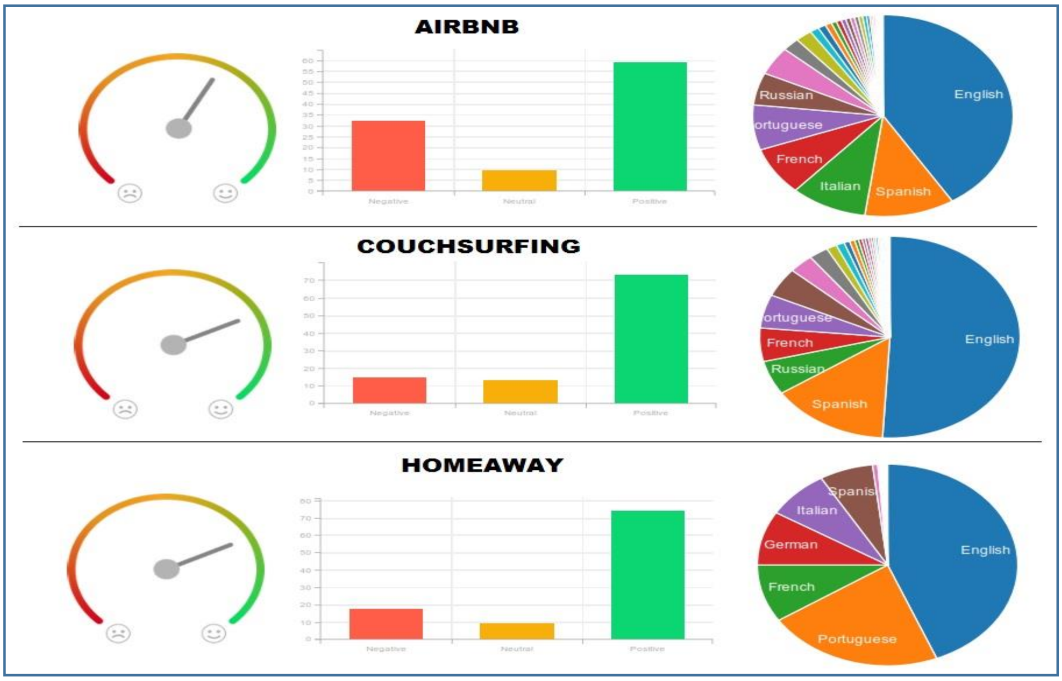
4. Analysis and findings

4.1. Sentiments

As mentioned, SA is categorizing text as positive, negative or neutral. In a general view, more or less all three apps have a pretty good situation. The most of the users are having a positive experience. The main difference is related to the negative sentiment of Airbnb. However reminding the user numbers of three apps can be helpful. In comparison to other two apps with one million, Airbnb has been downloaded for more than 10 million. In addition, the overall sentiment is based on 8,610 reviews of Airbnb, 2,671 of Couchsurfing, and 2861 of Homeaway. According to the results of sentiment analysis the ranking of apps can be like follow:

1. Couchsurfing with 12.5 negative 11.5 neutral and 76.1 positive
2. Homeaway with 17.3 negative, 9.2 neutral and 73.5 positive.
3. Airbnb with 33.1 negative 9.4 neutral and 57.5positive.

Figure ٢: overall sentiment analysis



4.2. Keywords

In this part based on 8,610 reviews of Airbnb, 2,671 of Couchsurfing, and 2861 of Homeaway, Popular and critical Words are identified. The Critical are words that users have been written about the problem they have come across when using apps. The most common words are:

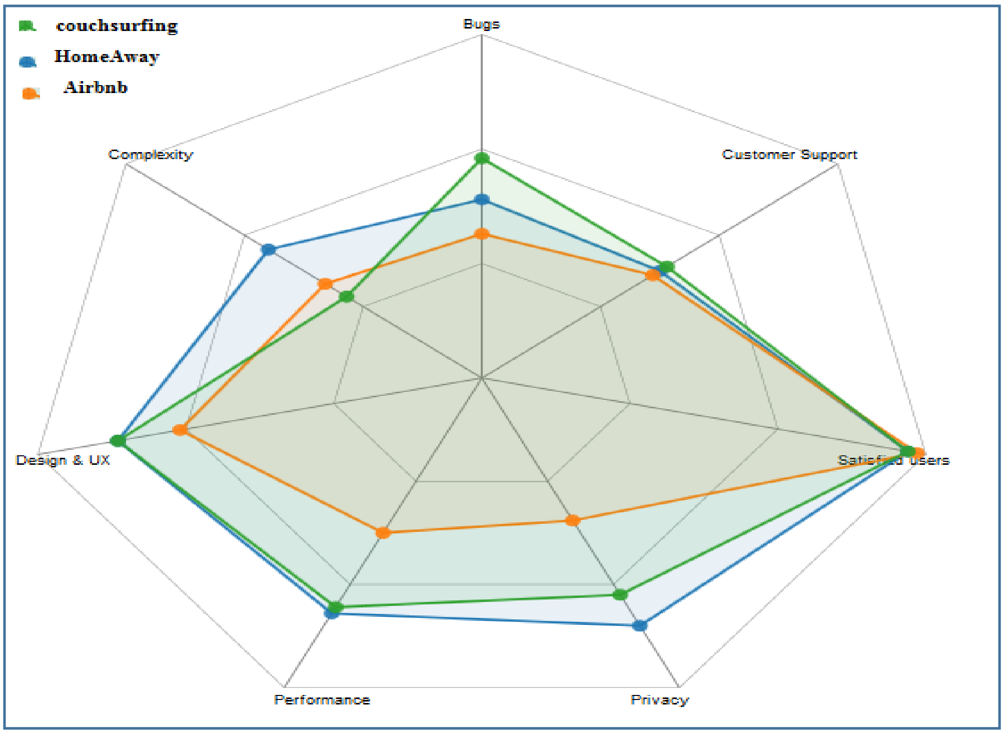
- Couchsurfing: great 331, good 328, useful 288 are the most popular and bug 35, error 17, cash 10 are the three critical words.
- Airbnb: useful 727, great 588, and good 396 are the most popular and error 210, bug 193, and crash 167 are the three critical words.
- Homeaway: useful 350, great 308, and easy use 257 are the most popular and error 10, bag 11, and crash 8 are the three critical words.

Accordingly, it can be said that more or less, they received same keywords. İn the filed of the Critical words, Homeaway has received the least negative words about its performance.

4.3. Compression

This section includes the results about, how apps are performing against multiple topics. Multiple topics are design- user experience (UX), bugs, performance, privacy, satisfied users, complexity and customer support. Comparing sentiments show the same results for factors such as satisfied users and customer support. It shows their success in the overall user satisfaction. (fig3). Interestingly, Airbnb in the four factors (performance, privacy, UX, and bugs) is closer to the centre. This means that in compression of Couchsurfing and Homeaway, Airbnb has received more negative sentiments in that factors. In addition, as figure 3 shows, in all factors (exception bugs) Homeaway is close to the outside which represents positive sentiment and its better performance in comparing with other apps.

Figure ۳: sentiment comparing[1]



Conclusion

By explosive growth of reviews, reading millions of reviews could be difficult, time consuming or even an unfeasible. It seems that sentiment analysis of reviews can be helpful tool for developers. In this paper we presented a useful tool (Appbot) for developers which uses sentiment analysis and text analysis for sentiment analysis of app reviews. However, due to the complexity of human language, sentiment analysis has its limitations. Machine learning is still at an early stage of development and teaching a machine to accurately analysis the humans' opinion is difficult. For example, a positive or negative sentiment word can have different meaning in different contexts. For instance, this app uses a lot of battery implies a negative opinion about the app. However, it can be considered as a positive, if extracted word is "use".

The findings of this study can being an evidence for support "the technology acceptance model (TAM)" (Davis, 1989:319). "The TAM shows that a user's attitude toward accepting a particular technology is determined by the individual's perceived usefulness (PU) and perceived ease of use (PEOU) of the technology" (Kim & Woo, 2016:267). It's same as our finding that the most of users have indicated usefulness and ease of use as a main reasons for accepting and using of peer to peer accommodation apps.

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۱ When comparing sentiment close to the center represents negative sentiment and towards the outside represents positive sentiment.

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