International Journal of Business and Administrative Studies
volume 5 issue 1 pp. 01-08 doi: https://dx.doi.org/10.20469/ijbas.5.10001-1

Predicting User Motivation Towards Retention of e-Services: An NLP-based Approach

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Abstract: In this modern era, the dynamic business world has led to the emergence of 'market orientation', and social CRM (Diffley, McCole, & Carvajal-Trujillo, 2018; Kohli & Jaworski, 1990; Narver & Slater, 1990). The benefits of e-Services are often not fully utilized because of users' unwillingness to use it (Devaraj & Kohli, 2003; Venkatesh & Davis, 2000). Hence, understanding the user's motivation in an e-service through Twitter data can help companies better retain users. Though people adopt services quickly, they tend to discontinue the service after limited use. Productivity benefits and maximum Customer Lifetime Value (CLV) are typically obtained in the continued use phase (Kim & Malhotra, 2005; Venkatesh, Morris, Davis, & Davis, 2003). With the emergence of social media, extracting and processing information (Crooks, Croitoru, Stefanidis, & Radzikowski, 2013; Kosala & Blockeel, 2000; Russell, 2011; Sakaki, Okazaki, & Matsuo, 2010), can help in understanding the motivation of users (DeVaro, Kim, Wagman, & Wolff, 2018) towards using an eService. This has motivated us to analyze Twitter data to understand customer motivation levels in eService retention. In this study, 1000 tweets were downloaded from ten different e-Service providers based on the company's official Twitter handle and analyzed. The results show that using Naïve Bayes on function and content words help in predicting retention intention. Predicting the IS continuance intention of users through tweets analysis can help companies perform better sentiment analysis and provide customized benefits to users. This study can help organizations influence less motivated customers to retain their services through proper marketing strategies.

Keywords: *E-service, motivation, Natural Language Processing (NLP), naive bayes, retention intention*

Received: 4 December 2018; ***Accepted:*** 8 January 2019; ***Published:*** 19 February 2019

INTRODUCTION

E-services are interactive software-based information systems that are accessed over the Internet and act as means of driving new revenue streams and creating efficiencies (Featherman & Pavlou, 2003; Van Riel, Liljander, & Jurriens, 2001). Prior research shows that benefits of IT investments are often not fully utilized because of users' unwillingness to use them (Devaraj & Kohli, 2003; Venkatesh & Davis, 2000). Often users form initial positive judgments about a service, but these judgments may change over time, which may even result in service discontinuance (Venkatesh & Goyal, 2010). Motivation to continue using an e-service plays a major role. But, motivation which is the psychological factor that drives user action, has long been the object of scientic inquiry (Carver & Scheier, 2001; Festinger, 1957; Fishbein & Ajzen, 1974; Hull, 1932; Ilias, Razak, & Rahman, 2015; Lewin, 2013; Miller, Galanter, & Pribram, 1960; Mischel, Shoda, & Rodriguez, 1989; Shah & Kruglanski, 2000; Touré-Tillery & Fishbach, 2014; Zeigarnik, 1927). Since motivation is a psychological construct, measuring motivation is difficult. However, previous researchers measured motivation in terms of observable cognitive (e.g., recall, perception), affective (e.g., subjective experience), behavioral

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(e.g., performance), and physiological (e.g., brain activation) responses and self-reports (Ayuningrat, Noermijati, & Hadiwidjojo, 2016; Touré-Tillery & Fishbach, 2014). Furthermore, there are different aspects of motivation, namely, outcome-focused motivation and process-focused motivation. In this study, we have used the observable cognitive behaviour and the outcome-focused dimension of motivation to understand the retention intention of users.

In case of microblogs sites like Twitter, messages can be annotated with hashtags. Even though hashtags are reliable indicators of the emotion being expressed by the tweets, (e.g., happy, joy, sad), people often do not use hashtags. We have utilized hashtags (happy, greatful, etc to fall under motivated category, and sad, angry, etc. to fall under the not-motivated category) for our dataset. We have used supervised learning, through Naive Bayes classifier, by using a class of features for differentiating the tweet (motivated and not-motivated). The results show that the tweets can be classified successfully to differentiate between motivated customers from non-motivated ones. This study can help organizations to influence the less motivated customers to retain their services through proper marketing strategies.

This paper is divided into various sections. Section 2 following this discusses the extant literature. Section 3 contains the methodology followed. Section 4 discusses the findings of this study followed by the conclusion, implications, limitations and references.

LITERATURE REVIEW

Since motivation is a psychological aspect, understanding the type of motivation one is trying to analyze plays an important role (Touré-Tillery & Fishbach, 2014; Yaemjamuang, 2017). As explained in previous literature studies, motivation is broadly classified into two broad dimensions: outcome-focused motivation and the process-focused motivation. The outcome-focused motivation is defined as the will to achieve a goal (Brehm & Self, 1989; Locke & Latham, 1990; Pandla, 2016; Powers & Powers, 1973), while, the process-focused motivation is defined as the will to work on the elements that help in attaining the goal. Furthermore, process-related elements may be classified into means-focused motivation (Higgins, Freitas, Spiegel, & Molden, 2003; Mohamad Yusof, Munap, Mohd Badrillah, Ab Hamid, & Md Khir, 2017; Touré-Tillery & Fishbach, 2012) and intrinsic-focused motivation (Deci & Ryan, 1985; Fishbach & Choi, 2012; Sansone & Harackiewicz, 1996; Shah & Kruglanski, 2000). Touré-Tillery and Fishbach (2014) has shown that motivation can be measured in various ways. The cognitive measures of motivation can be measured by the different goal activation and goal oriented constructs, the evaluation, devaluation and perception, experience, and perceptual biases. The behavioural measures of motivation can be measured by speed, performance, and choice.

A variety of work has been going on retention of e-Services. Naidoo and Leonard (2007) in a quantitative based study on financial healthcare tried to establish the relationship of perceived usefulness, service quality and loyalty on retention of eServices. They found that perceived usefulness has the highest impact followed by service quality. Another recent survey based study by Belanche, Casaló, Flavián, and Schepers (2014) on public eServices found that trust positively influences eService continuance decisions. A recent work by Ray and Bala (2019) has tried to find out how a Natural Language (NLP) based technique can be combined with Structural Equation Modeling (SEM) for better analysis of social media data in context of eHealth services. There are several studies on retention of eServices in different contexts like, automated CRM systems (Ilieva & Gashurova, 2015; Thanasripanitchai, 2017), SNS switching intention (Yao, Phang, & Ling, 2015), mobile applications (Salo & Makkonen, 2018), etc. Also researchers have studies motivation in eServices retention in various contexts like ICT-based healthcare (Papanastasiou, Drigas, Skianis, Lytras, & Papanastasiou, 2018), continued social media use (Hu, Kettinger, & Poston, 2015), etc. However, there are limited studies using NLP to understand the consumer motivation in retention of eServices. Hence, through this study we try to bridge the gap of using NLP in finding out motivation of consumers in eServices continuance.

Though Twitter data has been used in various contexts, like, sentiment analysis, to the best of our knowledge we have not found articles where twitter data has been used for understanding the user motivation towards eService retention. Agrifoglio, Black, Metallo, and Ferrara (2012) had worked on building an integrated research model to explore the motives of users that lead them to continued Twitter usage. Yoon and Rolland (2015) had also used social network data to understand users continuance use in social network services. In line with these researches, we have made an attempt to understand the user motivation in retention of eServices.

RESEARCH METHOD

In this study, 1000 tweets were downloaded from ten different e-Service providers using relevant keywords and hashtags of the companys official twitter handle. Supervised learning was applied to extract the relevant features from the data set in order to identify the motivation behind using an e-Service and predict the retention intention based on the motivational levels. Re-tweets were removed in the cleaning phase. In the cleaned data set, tweets were manually labeled based on author understanding as motivated or not-motivated. The data set was split into two sets randomly in a ratio of 3:1 for training and testing the model (Schurer & Muskal, 2013). A k-fold cross validation was performed on the training data set. The k-fold validation helps in generalizing the results and in addressing the class imbalance problem (Yao et al., 2015). In this research, K value was taken as 10 (Pennacchiotti & Popescu, 2011). Various features extracted from the tweets were then tested for accuracy and F-measure. The feature extraction process mentioned by S. Mukherjee and Bala (2017) has been utilized for predicting the user behaviour in tweets. Feature extraction, useful in reducing the number of resources for describing a dataset (Guyon & Elisseeff, 2003) has been used. The features defined by S. Mukherjee and Bala (2017) used in our study are content words, function words, parts of speech tags, parts of speech n-grams and a combination of the above four in various ways. The content words convey specific meanings (Winkler, 2012), while, the function words express the grammatical relationships with other words specifying the attitude or mood (Klammer & Volpe, 2000). The parts of speech tags is the marking up of a word in a text with reference to a corpus (Church, 1989), and the parts-of-speech n-grams where prediction is done on the basis of a single preceding item (bigram), two preceding items (trigram) or more items (Koppel, Argamon, & Shimoni, 2002). The other combinations of content words, function words and parts of speech are also used (S. Mukherjee & Bala, 2017).

In our research, we have also used the classification based approach to compare the feeds coming or in from twitter for classification. In an English sentence the function words generally reveal the mood and attitude, while the content words typically carry semantic content (A. Mukherjee & Liu, 2010; S. Mukherjee & Bala, 2017; Rao, Yarowsky, Shreevats, & Gupta, 2010).

The conditional probability model, Naive Bayes states that when a problem instance for classification, represented by a vector $\mathrm{x} = (\mathrm{x}_1, \ldots, \mathrm{x}_\mathrm{n})$ having n features (independent variables) is given, the instance probabilities $\mathrm{p}(\mathrm{C}_\mathrm{k}|\mathrm{x}_1, \ldots, \mathrm{x}_\mathrm{n})$ is assigned for each of the k possible outcome classes C_k.

$$p(\text{Class}|\text{Tweet}) = \frac{\text{p(Class)p(Feature}_1\text{|Class)p(Feature}_2\text{|Class).....p(Feature}_\text{n}\text{)|Class)}}{\text{p(Tweet)}}$$

Where Class = $\{$authentic, not authentic$\}$ and we need to calculate the posterior probabilities P (Class = authentic|T) and P(Class = not authentic|T) (S. Mukherjee & Bala, 2017).

We tested the data using confusion matrix as shown in Table 1 to find the performance of the classification system through a several metrics, like, precision, recall, accuracy and F-measure. Accuracy in case of unbalanced classes, accuracy can gives incorrect results. Hence for better results in these situations, Precision and F-measure are used. F-measure is denoted by the below formula:

$$F- \text{ Measure } = \frac{2(\text{ Precision*Recall })}{\text{precision } + \text{ Recall}}$$

Table 1 *CONFUSION MATRIX FOR ANALYSIS*

		Predicted Class	
		Yes	No
Actual Class	Yes	True Positive (TP)	False Negative (FN)
	No	False Positive (FP)	True Negative (TN)

$$\text{Precision } = \text{TP}/(\text{TP}+\text{FP}),\ \text{Recall } = \text{TP}/(\text{TP}+\text{FN})$$
$$\text{Accuracy } = (\text{TP}+\text{TN})/(\text{TP}+\text{TN}+\text{FP}+\text{FN})$$

FINDINGS

For analysis, tweets made by customers about 10 Indian companies (Amazon, Flipkart, ShopClues, Snapdeal, BookMyShow, FoodPanda, Myntra, Nykaa, Yahoo, and MakeMyTrip) were considered. Data was downloaded from 2014-01-01 using the official twitter handle of the companies. During this period, we could retrieve 10000 tweets made in both Amazon and Flipkart, 379 tweets made in BookMyShow, 1700 tweets made in Food Panda, 1300 tweets made in MakeMyTrip, 2200 Tweets made in Myntra, 286 tweets made in Nykaa, 132 tweets made in ShopClues, 1388 Tweets made in SnapDeal and 377 Tweets made for Yatra. It is to be noted that these contained retweets as well. The retweets were removed to form the cleaned files.

From these, 1000 tweets were considered randomly. This data is randomly separated into training and test data set using a 3:1 ratio. So while a tweet like .Thank you for the prompt response, corrective action and great customer relationship shows a satisfied customer and motivation to pursue the services in future, tweets like. No acknowledgement on DM and no one has called as yet shows a dis-satisfied customer and he/she should not be motivated to use the services in future. Once the model is trained, the Naïve Bayes algorithm is tested on the test data set. The Table 2 below shows how the accuracy and precision varied with the increase of data.

Table 2 *PERFORMANCE MEASURES OF THE MODEL ACROSS DATASETS*

Number of Tweets	Accuracy	Precision	Recall	F-measure	Specificity
300	0.51	0.67	0.45	0.54	0.61
500	0.53	0.71	0.54	0.61	0.53
700	0.54	0.61	0.53	0.56	0.55
900	0.54	0.82	0.53	0.64	0.58
1000	0.56	0.74	0.57	0.64	0.54

The results show that the model can help in predicting motivation of particular user in retention intention. We see that the performance increases with the increasing number of tweets. Except the specificity and precision, we find that the measures accuracy, recall and f-measure increase with increase in the number of tweets. The accuracy measure shows that the model is correctly measuring what it actually should measure. Recall and precision values denoting the relevant instances also show good measures for this case. However, a slight drop in precision value after 900 tweets shows that the number of relevant cases among the retrieved values is decreasing. In this study we are more interested with the F-measure value since it captures both the precision and recall values. A good F-measure shows that the model is working fine. However, it is to be noted that the words used in developing the corpora for motivational words was based on internet sources, like, Trans4mind, YourTnago, Huffingtonpost, Quora, Collins Dictionary, Oxford Dictionary, Thesauraus, etc. The words can vary in meaning based on situation and context. We will be taking up the influence of situations on user motivation in future studies.

DISCUSSION

The main aim of this study was to capture the consumer perspectives from Twitter data and check whether the customer is motivated to continue using an eService or not. Only a few studies have been conducted which analyzes the motivation of consumers in eServices retention and there are hardly any studies utilizing NLP and Twitter data to understand the consumers viewpoint. To bridge this gap, through this study, utilizing 1000 Tweets from 10 main eService providers in India, we tried to find if the model developed to compare the tweets indicated a motivated customer from a non-motivated one, work properly or not. The results of this study show that the Naïve based classifier worked well with the dataset.

However, it needs to be noted that the testing was done with only a very small dataset and so when working with a larger dataset, it will be better to use fuzzy techniques rather than Naïve Bayes. The main motive behind this study was to demonstrate the process of using consumer feeds from social media platforms and way to utilize these feeds for market survey. But with the abundance of data getting generated every day from consumers, it is important for companies to understand what the customers want and take necessary steps to keep them motivated. The social media feeds provide a cheap and easy channel for marketers to capture consumer perspectives and to take necessary actions. While following consumer posts, when an organization can understand that the customer is facing, and feel that the customer is not motivated to continue using the product though the comments he/she posts, the organization can take steps to prevent a customer from leaving. These steps can include a better consumer service, providing perks and/or discounts, etc. However, whether the consumer will stay or leave, cant be predicted by this simple algorithm. For capturing that customer behaviour needs to be tracked over a period of time. This can be taken up in future studies.

CONCLUSION

Extracting meaning out of online texts to find the motivation of users in different situations is still limited in micro text. In detecting motivation of users towards use of eServices, companies can benefit by providing perks to the less motivated ones and strategizing ways to keep them motivated. However, with the increasing complexity in day to day communications, it becomes difficult to extract the meaning out of texts properly. Our results reveal that the motivation level can also be tracked by developing the corpora accordingly. Including features that are not so much dependent on the text as explained by S. Mukherjee and Bala (2017) leads to an increase in the motivation detection accuracy even in our case. With users more inclined to post opinions on social media, companies can leverage on the large amount of available data and take necessary actions.

THEORETICAL AND PRACTITIONER IMPLICATIONS

Predicting the IS continuance intention of users through tweets analysis can help companies perform better sentiment analysis and offer personalized benefits. This study can also help health-care organizations track people fighting depression through their dialog exchange over social media platforms. This study can help organizations find reasons behind employee attrition and the perks that can keep them motivated through conversation over social media. From the researchers angle, this study can be expanded to capture the influence of factors like demography, culture, politics, social network analysis, etc. on the motivation of individuals towards a particular thing.

LIMITATIONS

Though Twitter analytics can serve a good medium for analyzing users motivation towards retention, the behavioural intentions depends on a large number of factors like, societal influence, political situation, etc. Also the words can be used differently in different situations which changes the meanings conveyed, for example, in sarcastic comments. The other limitation is that we have just used Naïve Bayes Classifier for our study and the dataset for our study is also very small. In future, we can test the results with other classifiers and for a larger dataset. We also intend to find the effect of other variables like social network, demography, etc. on the motivation of individuals.

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