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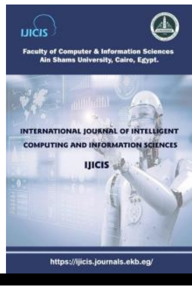

AN ANALYTICAL BASED MODEL FOR REMARKING ONLINE CONVERSATIONS

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Abstract: *The massive amount of social media data is considered as an effective resource to extract valuable knowledge. Nowadays, the social media analytical became an advanced informatics tool for collecting, monitoring, and analyzing data. So, it supports the business needs for improving the product/service in order to increase their profit. This paper proposes an analytical model for estimating the customer's perception based on the online conversation analysis. In addition, it investigates the impact of brand community features on the customer's perception. Based on that, the online conversation is automatically remarked by the conversation polarity as well as the impact of brand community. The findings emphasized that the brand community features have an impact on the customer's perception in percentage up to 45.6%. Thus, the remarks provide a significant feedback that forces the business for making decision and enhancing capabilities.*

Keywords: *social media analytical, Conversation Polarity, automatic remark*

1. Introduction

Recently, social media became the common way people interact and search for information through online digital platforms. The social media is the different online tools that facilitate the interaction between users by providing the opportunities of information sharing [9, 17]. Currently, it is considered as an effective resource to extract valuable knowledge for enhancing business intelligence [1, 16]. Thus, the business organizations concern with social media for gaining benefits from its massive amount of data. They actually need the customers' feedbacks for improving their marketing capabilities and making decision.

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In order to that, the customer's blogs, comments, tweets, and other feedbacks have to be analyzed. So, there is a need to automate the analysis process through using different analytical techniques.

Many researches emphasized that analyzing the social media can improve the decision making five times faster than the past [1, 9, 5]. Thus, the social media analytical concept became a growing trend. The social media analytical is "the common advanced informatics tools and analytics techniques to collect, monitor, and analyze social media data" [1]. It concentrates on analyzing the social media data based on Natural Language Processing (NLP) techniques as well as detecting influence of events on customer behavior [11, 12]. This provides an effective feedback about the customer's mood, the reasons of mood change, and predicting the customer's reaction as early as possible.

Nowadays, many Natural Language Processing (NLP) researches direct their efforts toward sentiment analysis for extracting meaningful knowledge from the writer's statements [7, 10, 14]. Sentiment analysis is an effective tool for studying the writer's opinions, feelings, and emotions expressed through different social media channels [4, 5]. Most sentiment analysis approaches focus on investigating the polarity of writer's statements at the documents, sentence, and aspect level. Moreover, the sentiment analysis process classifies the writer's opinion into subjective and objective polarity. The subjective sentiment represents the positive or negative writer's emotions toward the product/service. On the other side, the objective sentiment focuses on unbiased opinion.

Many researches exploited sentiment analysis for estimating the customer's opinion, and others for predicting the customer's behavior. Despite that, the studying of interactive sentiment analysis still represents a challenge [10, 12]. This due to the changes in customer's mood during the online conversation, which of course may be attributed to various causes.

This paper proposes an analytical model for detecting the customer's emotions through analyzing the interactive online conversation. It aims to apply the sentiment analysis and feature analysis techniques for estimating the whole conversation polarity. Based on that, the online conversation is automatically remarked by the conversation polarity and the impact of features on the customer's mood. This considers as supportive feedback that force the business organization to evaluate its performance. This paper is arranged as follows: section 2 shows the related work, section 3 shows the proposed model, section 4 is the experimental study and results, and section 5 is the conclusion and future work.

2. Related Work

Hutto, C., et al (2014) investigated the customer support data for a large Swedish Telecommunication corporation with the purpose of determining the sentiment of customers' emails [2]. VADER, sentiment analysis framework was used for labeling the individual emails, where the email is labeled by sentiment score. Moreover, the framework investigated the possibility of automatically classifying email content polarity (i.e. negative or positive sentiment) with the aim to enable customer support to see customer sentiment without reading through the complete email threads. Furthermore, they predicted the sentiment of future email responses. The findings show VADER would provide a better customer experience, and it outperforms individual human raters (F1 Classification Accuracy 0.96 and 0.84, respectively). The framework lacked of estimating the customer service impact, which might affect the customer mood.

He, W., et al (2015) proposed a framework for social media competitive intelligence to enhance the business value [1]. It used the data mining techniques for analyzing the social media data -at-rest as well as data-in motion. It categorized the customer's statements polarity into five categories; respectively very negative, negative, neutral, positive, and very positive. Further, it focused on studying the impact of the features which reflect the brand image. The practical experiments evaluated the most significant impact for estimating the customer's perception, and constructed comparison between competitors. This in order to support them by feedback that may drive to enhance their capabilities. This framework concerned with analyzing social media data regardless the interaction between customer and business company. Moreover, it ignored investigating many features that reflect the customer's bad mood.

Ibrahim, N.F., et al (2017) proposed approach for investigating the impact of retailers' engaged (online brand community) on users' perceptions of brand image [3]. They statistically measured polarity of customer's opinion towards different products, then they patterned the customer engagement for five popular online retail brands (Amazon UK, Tesco, Argos, John Lewis and Asda). Moreover, they examined the different factors that may affect customer engagements like tweet length, attitude, number of replies, media types. Their experiments show the retailer's attitude, tweet length and media types of tweets have a significant impact on customer sentiment. These factors lead to emotional transition of tweets during conversation time, and change the polarity. The findings show that there was 4.8% decrease of negative sentiments and 0.3% increase of positive sentiments for customers' tweets and retweets between the beginning and the final stage of conversations in amazon UK. The future work may enhance this approach by studying additional features.

S. Sirsat, et al (2019), proposed a model for estimating the success of product to process and analyze Twitter data [6]. They exploited many analysis techniques such Natural Language Processing (NLP), Machine Learning (ML), and Naïve Bayes Classification. Further, the users' comments are analyzed based on sentiment, and classified into three categories; positive, negative and neutral. The sentiment classification is performed by classifying Twitter data into three levels; document level, sentence level, and aspect level. The experimental study estimated the success of the product through the length of tweets, the length versus number of likes and retweets, and the whole sentiment response. It lacked of estimating the interactive conversation, where it focused on analysis tweets one by one.

3. Online Conversation Remark Model (OCAM)

Social media became one of the effective tools for deducing the user opinion toward a product, service, events, and etc. Based on that, the sentiment analysis provides valuable view that help the service/product provider in making discussion and improve their capabilities [6, 15]. Despite that, many previous studies focused on analyzing customer's tweet, the interactive conversation analysis still represents as challenge [3]. The customer's attitude in the interactive conversation is changeable from one tweet to another, where the customer's first tweet may carry negative feeling and the last carries positive. This needs more analysis to estimate the customer's perception and the factors that affects his opinion during conversation. In order to achieve that, this paper proposes Online Conversation Remark Model (OCAM) that aims to estimate the customer's perception through analyzing the interactive online conversation.

It concerns with supporting the service provider by yielding an immediate feedback after each mid and long online conversation between the customer and service provider. This feedback is formed as remark which answering two questions; "what's the customer perception about product/service?", and "Is the service provider has hand on the customer's attitude?". For answering the first, the sentiment analysis is applied for estimating the conversation polarity which represent the customer's perception. On the other side, the brand community features have to be analyzed for answering the second question.

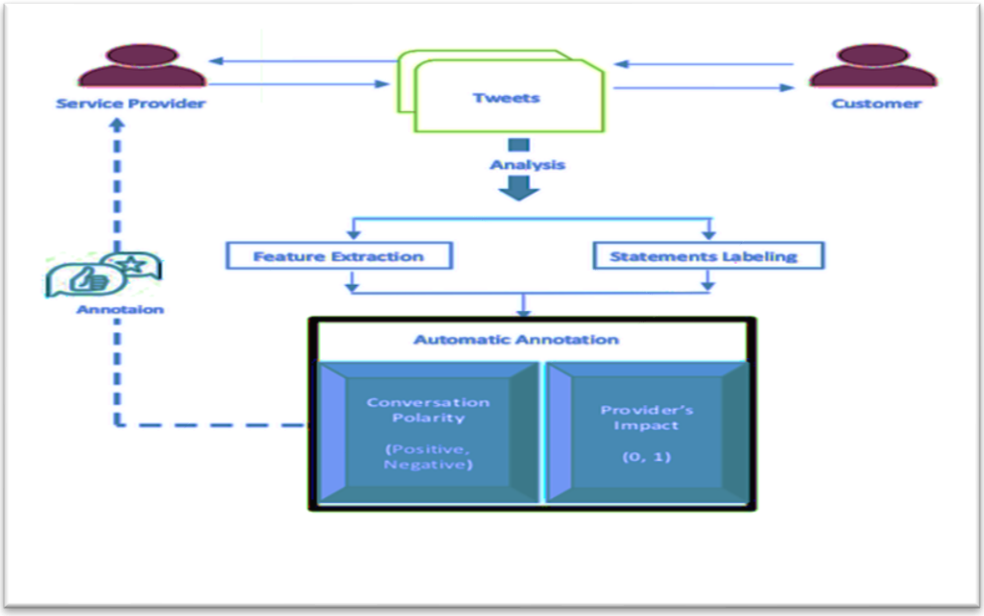

Figure 1: The Online Conversation Remark Model

As figure (1), the OCAM concentrates on the online conversation between the customer and service provider through the Twitter API. For each online conversation, each tweet will be analyzed and labeled by their sentiment. In addition, many features will be extracted, calculated, analyzed and associated with impact weight. Then, the automatic remark process labels the whole conversation by its polarity and investigate the impact of service provider attitude on the conversation direction polarity. By the end of that, the remark will be shared with the service provider to give him a timely feedback about the customer's perception and the provider attitude through conversation.

3.1.Online Conversation Preprocessing

One of the valuable and common service provider is AmazonHelp, which provides an online conversation with customer for answering their requests. The dataset is obtained by crawling from the AmazonHelp Twitter account. The data clean process is applied for removing the noise. Then, the preprocessing phase preparing the data for the analysis process.

As Twitter allows the user to express his/her opinion by writing only 280 characters per tweet, this may drive the customer to deliver his/her perception through consecutive tweets. The consecutive tweets represent a challenge which may hinder the sentiment analysis in the Online Statements Labeling (OSL) process. In such case, analyzing tweets one by one will be misleading. So, they have to be merged together to actually represent the customer's perception. For extracting the consecutive tweets from the dataset, they identified as the consequence tweets which the customer wrote without any replies from the service provider within a specific time window (for example 60 minutes).

3.2.Online Statements Labeling (OSL)

The customers' tweets carry their perception toward the product/service and reflect the brand image. Thus, the sentiment analysis is an important step for estimating the customer's emotion toward the service/product. The online statement Labeling (OSL) process aims to apply the sentiment analysis in the each customers' statement (tweet) during the mid/long online conversation.

OSL concerns with the statement sentiment with keeping the sentence's semantics. Thus, it concentrates on the sentence structure for investigating the polarity. This is through applying the Deep Machine Learning technique which has been performed using the Recursive Neural Network (RNN) model [8]. The RNN model eliminates the problems of losing sentence's meaning and semantics. In addition, it improves the sentence polarity classification accuracy up to 80.4%.

The OSL process applies the RRN model to each customer's tweets, and keep in consideration the merged tweets which prepared in the preprocessing (3.1). The merged tweets are considered as a special case that cannot be ignored, where it carries more clear emotions compared to the short tweets. This due to the number of words that reflect the meaning and feeling. Further, The OSL estimates the strength of polarity which categorizes into three terms 1, 0, and -1. Sequentially, the first term express the positive sentiment, the zero expresses the neutral sentiment which represents unbiased sentiment, and the last term expresses the negative sentiment.

3.3. Feature Extraction

The Twitter API provides main features that associated to each tweet, so these features are extracted and became part of the feature analysis (section 3.3). Each tweet associated with many features like; the date of creation, tweet's author, and time of reply, which will be analyzed. Basically, each online conversation has an original author who starts the chat (always the customer has the initial step), and the service providers answer his requests. The OCAM focuses on analyzing the communication factors, thus the author's tweets text will be extracted as well as the service provider's tweets.

The online conversation direction could not be estimated only through the tweets sentiment analysis; particularly since it's surrounded by many features that may affect the customer's perception. Mainly, the brand community features have a great impact on the customer attitude negatively / positively. The brand community features include all feature that represents the service provider reaction toward the customer's tweets. So, some provider's tweets features are extracted from Twitter API and others could be calculated. With more detailed, the brand community features are as follow:

- **Provider's Tweets Polarity (PTP)**: the labels that attached to each tweet through applying sentiment analysis (section 3.2),

- **Provider Response (PR)**: the PR is the service provider response, it represents the time duration between the customer's request (CR) and the service provider reply (SPR). Equation 1 shows the PR by calculating the difference between the customer's tweet creation time and the service providers tweet time (the first service providers tweet after customer's tweet). This step is iterative, where the PR is calculated for each customer's tweet (i). Furthermore, the merged tweet is a special case that has to keep in consideration; in this case the CR is the time of creation for the first tweet in the merged list and (i) is the number of last tweet.

$$PR_i = SPR_{i+1} - CR_i \quad , \quad \text{where } i \text{ the tweet identifier} \qquad (1)$$

- **Provider Reply Length (PRL**): it shows the number of characters per tweet. It has been calculated by counting the number of characters for each service provider reply. The special case is the merged tweet, where the PRL represents the number of characters of all merged tweets.

The brand community features may affect the customer's perception, where the provider attitude may change the customer' mood negatively/positively. Always the customer starts the online conversation by complain which reflects his/her bad mood toward the product/ service. At that time the service provider role is getting him to calm down through a quick response, positive words, and etc. The brand community features reflects the service provider's attitude.

Actually, the brand community features have different impact weight which needs to be analyzed. For identifying the impact of each on the customer's perception many Machine Learning (ML) techniques were applied. Then, the brand features were classified and associated with weight for using them further in the automatic remark process.

3.4. Automatic Remark

The Automatic Remark process aims to remark e the whole online conversation between service provider and customer. It provides timely feedback by estimating the polarity of conversation direction by the end of the conversation. Moreover, the remark provides a feedback about the service provider's attitude during the conversation. This allows the service providers improve their capabilities and attitude to keep their customers and satisfy their needs.

The remark consists of two parts the conversation direction's polarity, and the service provider's attitude. The conversation direction's polarity is the sentiment analysis of whole the customer's tweet for evaluating the nature of conversation in term of positive, neutral, and negative. Furthermore, by analyzing the impact of each brand community features; it will be easy to determine is the service provider has hand in the customer's positive/negative attitude, which labeled by 0 and 1 respectively; has no hand, has a hand in customer's attitude.

3.4.1. Estimating the Conversation Direction Polarity

The customer's perception may be changed from one tweet; thus for estimating the conversation direction's polarity a stream of customer's tweets' polarity has to be analyzed. AS the tweet's polarity represented in term -1, 0, and 1 which sequentially are negative, neutral, and positive, the conversation direction's polarity is represented as the same. In order to estimate conversation direction's polarity, the customer's tweets polarity are summed up, as equation (2). The Polarity Score (PS) represents the conversation direction's polarity till the last customer tweet (n). PS calculation is an iterative process which summing up the customer's tweet's polarity form the first tweet to the last. The Tweet_J Polarity (TP_j) represents the polarity of the first customer's tweet TP_1, then the iteration is carried out till the TP_{n-1}. Further, the Tweet_{j+1} Polarity (TP_{j+1}) represents the polarity of the second customer's tweet, then the iteration is carried out till the TP_n .

$$PS_j = TP_{j+1} + TP_j \qquad (2)$$

Where $1 >= j < n$

By the end of that, the PS value has three verities; positive value, negative value, and zero. For the positive and negative values, it means the customer's attitude was not stable and the more value of both indicate how much the conversation positivity/negativity. On the other side, the zero value means the customer keeps his position till the end. Based on the PS value the conversation polarity is identified, where the positive and negative values will be labeled by 1 and -1 respectively. However, the zero value has to be manipulated to estimate the polarity; this by comparing the first and last tweet polarity; in case of equality consider one of them.

3.4.2. Brand Community Analysis

The brand community features which represent the service provider attitude may interpret the positive/negative conversation direction. The service provider attitude may affect the customer's perception, thus the remark could not be valuable without adding feedback about the provider's attitude. Definitely, not all the brand features have the same impact in customer behavior based on the analysis in (3.3). The most important case we have concentrated are the subjective conversation polarity. This due to the instability of customer's attitude during the online conversation which certainly carry reasons behind that. In order to discover this reason the Brand Community Impact (BCI) has to be considered.

Based on the features analysis in (3.3), each feature identified by its impact weight as PTPW, PRW, and PRLW. As equation 3, the BCI is the average of the Brand Community Impact for each conversation, by summing each feature weight multiplied by the feature value per conversation (i) then divide all by the summation of features' weight. Based on the BCI the remark labeled by 0 or 1, where the conversation that has BCI more than 45% is labeled by 1 otherwise 0.

$$BCI_i = \frac{PTPW * PTP_i + PRW * PR_i + PRLW * PRL_i}{PTPW + PRW + PRLW} \quad (3)$$

Where i is the conversation number

4. Experiments

Two main experiments were performed, each with a different objective. The first experiment investigates the impact of brand community features on the customer's perception. This was applied by using different machine learning algorithms to test the performance of each algorithm. The second experiment is for remarking the online line communication by the polarity of communication direction and the impact of features if it exists.

4.1.Dataset

Amazon is one of the most popular service provider that provides online conversation to customers. This study focuses on Amazon Twitter account which known as AmazonHelp. The AmazonHelp allows customers to requests and it responsible to answer. Moreover, it concentrates on the English tweets. The online conversation period of time was one of the constraints, where only the mid and long conversations were gathered. The data were gathered for 3 months from February 2021 to April 2021, where the collected dataset consisted of 6500 online communication and within 70000 tweets. The dataset was filtered and manipulated to eliminate the noise, and mixed language tweets.

4.2. Identifying The Features Priorities

The first experiment performed different Machine Learning model for investigating the impact of brand community features on the customer's perception. Thus, it concerned with the subjective conversation polarity, where the customer's perception was hesitated. In order to apply ML models, Weka [18] was used, which is a powerful tool that provides a wide variety of machine learning algorithms for data mining tasks. The following are the classifiers used and their equivalents on Weka:

- Classical Classifiers: C4.5 Decision Trees: J48, IBK, Bayes NET, and Support Vector Machine (SVM).
- Ensemble Classifiers: Bagging, and RandomForest

The classical classifiers realized accuracy and f-measure up to 65%. Further, the Ensemble Classifiers especially Random Forest realized accuracy and f- measure up to 57%. Thus, they gave good indicator about the impact of whole brand community features in the customer's perception polarity.

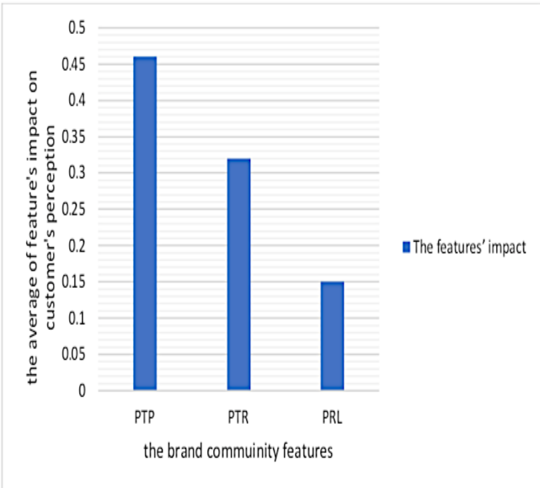

Figure 2: The impact of each brand community feature in customer's perception polarity

In order to measure the impact of each feature, the Correlation Attribute Evaluation algorithm (Ref) was applied. The Correlation Attribute Evaluation algorithm measures the correlation between each feature and the target class attribute (customer's polarity change). As shown in figure (2), the most effective feature was the provider's Tweets Polarity (PTP) with an average up to 45.6%. This proves the service provider's negative/positive replies affect the communication direction. Additionally, the impact of Provider's Response (PR) feature is up to 32.1%, which interpret the bad customer's mood in case of delay response. Moreover, the Provider Reply Length (PRL) has the lowest impact on the customer's perception within 15.3%. The PRL represents the length of the provider's reply, which may be categorized into three levels; short, mid, and long reply. Since the number of characters per tweet for short reply is up to 150 character, the mid reply is up to 280 character, and the long reply is more than 300 character. The data analysis emphasized that the short and long replies are indicators about the negative customer's polarity.

4.3. Automatic Remark s Experiment

This experiment aims to associate the estimated communication polarity to the impact of brand community features. As explained in (3.4), the remark consists of two parts; one for representing the communication direction’s polarity which shows as negative, positive, and neutral. While the second part represents the impact of brand community on direction’s polarity if exist; this through calculating the BCI for each conversation. The impact will be represented in remark as 0, and 1; sequentially provider has no hand in the communication direction’s polarity, and the provider has influence in it. As shown in the above experiment, each feature has a different impact. So, the average of features’ impact was calculated per online conversation.

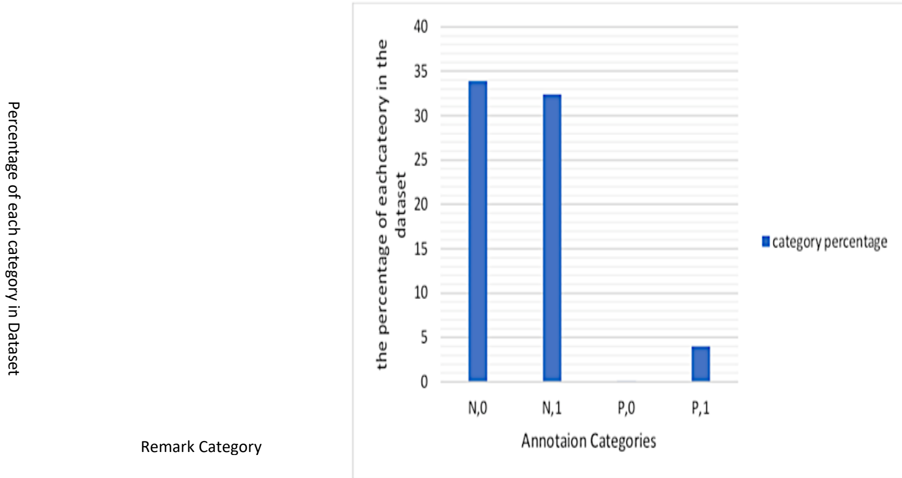

Figure 3: The remark categories’ percentage in dataset

As shown in figure 3, the remarks were categorized into four categories (N, 0), (N, 1), (P, 0), (P, 1). First, the (N, 0) remark is the negative conversation, but the service Provider had no hand in the customer’s negative mood. The experimental result shows 33.9% of conversations were remarked by (N, 0) remark ; this indicates the customer’s keep his/ her negative attitude but the service provider was aware that the negative customer attitude has to be handled smoothly. Second, the (N, 1) remark is the negative conversation, but the service provider had a real role in that. The experimental result shows 32.4% of negative conversation in overall dataset; where the provider’s attitude was bad. The third and fourth sequentially (P,0) and (P,1) remark s are the positive conversation that had the lowest provider’s impact percentage 0.01% and 4% respectively. In case of positive conversation, the provider’s attitude mostly good, and sometimes provider drives the conversation toward positivity.

5. Conclusion and Future Work

The social analytical became an essential requirement for improving the business plans and enhancing the service provider’s capabilities. It is considered as an efficient tool for investigating the customer’s perception toward product/service. Many factors surround the customer may drive him to has a bad image about product/service. Thus, this paper concerned with analyzing the customer’s perception and study some of the factors that has an impact on him. The result emphasized that the brand community factors have a real effect on the customer’s perception. In order to investigate more factors, the further studies will concentrate more about other features that surrounded the customer community. This will support the service provider and add a new level of knowledge, which actually may make their decision.

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