Detecting Telecom Customers loyalty using Sentiment Analysis and Natural Language Understanding

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Abstract-- Loss of customers has affected all the local telecom companies in Egypt. Most times, it is because of the client's misunderstanding and then fail to contain and keep him. In this trial, Natural Language Understanding and Sentiment Analysis were combined with machine learning algorithms in the process of understanding customer’s feel. A lot of customers in our local telecom companies always leave and change between companies because of various reasons. If we determine expected leaving rate, we can try to keep them by any way. For that, we introduce this work that can analyze customer’s text and understand his/her emotions and sentiment to can understand his/her feelings then give best services to him. Using sentiment in conversation greatly affects the user and his relationship to the system. But not only, our study revolves five main emotions are helping us to make deep understanding of customer and help more to give appropriate solutions; various kinds need various solutions. A combination among three stages of machine learning, Natural Language Understanding API and feedback system is created to achieve the needed task. Combining among three stages using the obtained results achieve higher accuracy than using the traditional detection techniques. The proposed solution achieved high accuracy about the customer loyalty detecting. It is planned to use various Machine learning techniques instead of using sentiment analysis alone to make use of the higher performance in the detecting process.

Keywords: Natural Language Understanding – Sentiment Analysis – Telecom Companies – Customer Service – Customer Feelings – Positive Customers – Negative Customers – Loyalty – Departure – Solutions.

I. INTRODUCTION

In the last years. We noticed that many new telecom companies are starting to provide services, and competition is more difficult for other companies. Sometimes companies are surprised that the percentage of service users have moved to a competitor for some reasons. So, companies are trying to reduce it by improving their services. Yet there are people who leave and companies are unable to do more. We have noticed through some corporate pages via social networking sites that a customer does not leave before complaining about a specific service over and over again. The staff only respond and try to provide help without the person's knowledge or prior information. So, through our provider we can help companies to know who is complaining and who is expected to leave. In more accurately, knowing the proportion of people at risk of leaving. If the situation reached the risk ratio, the company must do something. From conversations with a customer several times and by evaluating sentiment and some emotions we detect how customer feels about services and the probability of leaving the system. We determine if the conversation is negative, positive or neutral. We will observe the user several times and save his feeling every time on a form of a pointer; at known point we will expect that customer will leave the service when the indicator is at 0.7 for example after several negative talks. If a surprising number of customers feel negative, it is annoying and must be addressed before it is too late to try to acquire and contain their feelings. In the end, the proportion of those who feel the most negative is identified. The ratio suggests to us the proportion of the risk and when the solution should be. Determine these customers helps us to provide personal solutions especially to people who are in a difficult situation. It is important if we want to improve the customer service, make the company work easier and keep customers and don't lose them for any reason. Over the past 10 years, there were some partially successful trials for raising the treatment effect to be 70%. Companies used social media by creating a hashtag and prompting followers to put their answers to some question [4] [7]. They can quickly get a large number of answers about a question while simultaneously engaging their customers. Additionally, consumers share their opinions about services and products in public and with their social circles. Doing the automatic detecting of sentiment with our algorithms is expected to increase the efficiency to be higher than 90%. First, we will use natural language understanding API that calculate customer sentiment and some emotions. Second, we make a peak point. If the user reaches it, it is mean that he will leave the service.

Our main contributions:

We study the effects of customer sentiment and use it to determine if the user has positive or negative emotions about the service.

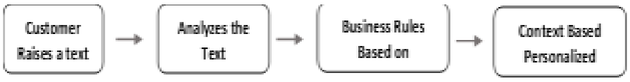
People are divided into five categories that are used to identify the negative ratio further and also help the company to provide necessary solutions.

We introduce a novel Chabot system that not only give response to users, but also detecting customer feel through backend system and save the feeling.

We use English, standard and slang Arabic languages to communicate with all user's cultures.

Natural Language Processing and Sentiment Analysis are the branches of science interested in automating logical decision making, and detecting and recognizing objects in a conversation. Sentiment Analysis is one of the speeches analyzes that analyzes emotional states in general [14] [23]. Where it analyzes a particular text and then find out whether the writer is feeling positive, negative or neutral [20]. Of course, it helps brand companies to know the feelings of customers and then planning for the future. Emotional analysis helps to better understand your customers and then prioritize assistance and follow-up. This helps to enhance the reputation of the brand. We want to know the general feeling of the customer whether negative or positive so we have used the sentiment analysis tool. but not only, we use some major customer emotions too, to give us more understand to customer emotions.

Fig. 1. Shows A simple chronology of how sentiment analysis works in contact center includes of following steps.



Communication through social communication is critical to communicating with customers in recent years. The Pew Research Center says 74% of adults use social networking sites on the Internet. However, a new study by social bakers shows that most companies do not meet customer service expectations via social media. To engage customers in the individual contacts they are looking for, we have introduced this paper, which is based primarily on the Chabot, on which this work depends. Companies should be proactive in monitoring social communication and immediate response. Good companies are trying to understand their customers, but ideal companies try to understand their customers' feelings. They care about customer needs by identifying their feelings about their products and meeting growing customer expectations. A new study by LogMeIn and Ovum revealed that 76% of the surveyed clients left work with a brand after the experiment failed to meet their expectations. Through our indicator to follow the client's situation, we can remember that it has reached a dangerous stage and must be contained in any way. For example - one of your customers receives a frequent service problem and wants to help. Now, imagine if your customer support system has an advance background that this customer is not satisfied with your services so you should treat him carefully, it is possible to skip the chat and connect it to an agent looking at his problem. This will certainly help in calming customers who are getting worse in the first place. When your agents know how your customers feel before entering into a conversation, they can intelligently analyze their next moves and deliver customized experiences to customers. When customers are treated in a sympathetic way, you are sure to earn their loyalty. When agents have such tools, it is easy for them to understand where they lack leadership of sympathetic customer service. Therefore, the emotion analysis gives them the peak of the real-time intrusion into the client's mood to prepare for participation in advance.

RELATED WORK

The commercial companies analyzed the emotions in the traditional way of voting, which is to put some questions on a service or a specific product and then look at the answers of customers where you get a large number of answers and get the result [7] [9]. But there are many reasons why surveys are less ideal: (1) Fixed: Questions in the survey cannot be changed to complete. This makes the surveys inflexible and limits the speed of asking new questions to investigate the recent results of customer satisfaction. (2) Not popular: 72% of consumers said the studies interfere with their experiences on the website. (3) Limited: More than half of customers will spend more than three minutes filling out a customer satisfaction questionnaire. This limits the range of knowledge that you can get each time. These flaws ensure that any company that relies entirely on surveys to measure customer satisfaction is likely to end up with an inaccurate impression, which could lead to a bad decision. In addition, consumers share their views on services and products in public places and with their social circles. [Marcelo

Drudi Mirand and Renato José Sassi] [10] used the proposal as a tool to help assess customer satisfaction at the Brazilian Job Search Company through the use of emotion analysis. They analyzed an online job search company database containing customer feedback collected from the service cancellation form. This database, among other parameters, has a certain degree by the client and comment on services. They categorized the sentiments expressed in the user's comments with the help of a written program in Python, and then calculated the relationship between the confidence score and the result identified by the clients. Also, [Shaha Al-Otaibi, Allulo Alnassar, Asma Alshahrani] [21] used Twitter data to get statistics from public opinion hidden in the data. The support vector machine algorithm is used to classify the feeling of tweets if positive or negative, and unigram is applied as a method of extraction feature. Experiments were conducted using a large set of training data set and the algorithm achieved high accuracy about 87%. Both results were improved slightly, but not enough to increase performance. The use of SVM by [Shaha Al -taayby] has given a strong boost to the emotion process by adding up to 87% accuracy, but not so efficiently because it takes too long to identify only 30% of the sample collected.

All of the above with [IBM API] experience are catalysts for the methodology used in this paper. What has been done here is an innovative three-phase technique that has benefited from the previous three trials, by taking the accuracy of [SVM] and improving the algorithm to be faster by adding a pre-learning step. The newly created phase is post-recognition processing using the closest machine learning technique. The uniqueness comes from combining recognition, learning and feedback processes together. We will use another work but we will use standard English and Arabic and colloquial language through Chabot not in social media, and we will use automated learning algorithms to improve accuracy to 90% or more.

Sentiment Dataset

Perhaps the greatest benefit of Sentiment is to give the general feelings of the customer and the way he sees the company. IS it positive, negative or neutral? This feeling gives us an initial rate of negative feel. It helps us to know the general feeling of the full text of the customer and understand his tendencies for the company's services. For example, if the text gives a negative result. This result is sufficient to understand the customer's position. System is provided to have a prior background to the previous feelings of the customer so it can be considered and skip some stages to acquire the customer even if a small percentage. This is one of the main reasons for its use here and it is the most widely used in the main work, which is related to the expected leaving. there is a detailed explanation in methodology and results sections. Table I shows the sentiment results of some texts for some people. Depending on the degree of words in the text, the results are. Where the results vary from 0 micro to 1 bone value with negative or positive.

TABLE I. SHOWS SOME SENTIMENT VALUES OF SAMPLE CONVERSATIONS.

Conversation	Value
Hello, I'm having a problem with your service. nothing is working. The service here is very bad. I am really very upset. I was expecting better than that.	-0.84

what's going on, please. The service here is very bad. I am really very upset. I was expecting better than that. I need some help; my service has been disabled since yesterday.	-0.72
Hi, Thanks for your service all the time. You are one of the best companies that provide fast and useful services. You have to continue that way.	0.90
The service here is good sometimes, and sometimes are bad. Why not keep up the good work. Some had leaved your service for this reason.	0.10
I'm fed up with complaining from the service again and again and I do not get help. I will leave this service. Good-bye.	-0.54
I have been suffering from this problem for a long time and cannot find a solution. I wait. Wow! It’s working. I really enjoyed the service. thank you. I hope to improve some services and offer some offers soon.	0.30

Emotions Used

We have also used some of the emotions that help in this work. Not only for knowing the feeling, this may be done by sentiment only, but also to help provide appropriate solutions. we have done several studies to determine which emotions are used before to understand the customer feeling. We found several emotions used and selected from several other usable emotions. After a long search, we have been chosen some motions and they are Joy, Anger, Disgust, Sadness, Fear.

It is widely expected that the customer will come to speak only to make a complaint of service. So, it will start with a negative status. Given that, negative emotions are more than positive and this is normal. These emotions are described in detail in table II.

TABLE II. SHOWS USED EMOTIONS WITH DEF.

Emotion	Def
Joy	Joy is a feeling of great happiness. Salter shouted with joy. ...tears of joy. Synonyms: delight, pleasure, triumph, satisfaction More Synonyms of joy. A joy is something or someone that makes you feel happy or gives you great pleasure.
Anger	Anger is the strong emotion that you feel when you think that someone has behaved in an unfair, cruel, or unacceptable way. He cried with anger and frustration.
Disgust	a strong feeling of dislike for something that has a very unpleasant appearance, taste, smell, etc.: annoyance and anger that you feel toward something because it is not good, fair, appropriate, etc.
Sadness	Sadness is an emotional pain associated with, or characterized by, feelings of disadvantage, loss, despair, grief, helplessness, disappointment and sorrow. An individual experiencing sadness may become quiet or lethargic, and withdraw themselves from others.

Fear	an unpleasant often strong emotion caused by anticipation or awareness of danger. (1): an instance of this emotion. (2): a state marked by this emotion.

EMOTIONS DATASET

After the conversation ends with the customer. We collect all the text of the customer, then we analyze it through IBM API. We have done some tests of some of the texts for customers through the pages of telecom companies through the Facebook. The following table illustrates the IBM API's emotions Dataset. Each emotion has a different value than the other. Through these emotions we calculate the specific feeling and be closer to the customer. If we want to dig deeper, we must look for the feelings that brought the customer to the negative, so we used the five emotions mentioned earlier. Table III shows the five emotions results of some texts for some people. Depending on the degree of words in the text, the results are. Where the results vary from 0 micro to 1 bone value.

TABLE III. SHOWS SOME EMOTION VALUES OF SAMPLE CONVERSATIONS.

conversation	Joy	Anger	Disgust	Sadness	Fear
Hello, I'm having a problem with your service. nothing is working. The service here is very bad. I am really very upset. I was expecting better than that.	0.01	0.30	0.05	0.77	0.15
what's going on, please. The service here is very bad. I am really very upset. I was expecting better than that. I need some help; my service has been disabled since yesterday.	0.01	0.32	0.07	0.73	0.14
Hi, Thanks for your service all the time. You are one of the best companies that provide fast and useful services. You have to continue that way.	0.82	0.04	0.01	0.02	0.00
The service here is good sometimes, and sometimes are bad. Why not keep up the good work. Some had leaved your service for this reason.	0.20	0.20	0.05	0.66	0.04
I'm fed up with complaining from the service again and again and I do not get help. I will leave this service. Good-bye.	0.07	0.36	0.20	0.57	0.01
I have been suffering from this problem for a long time and cannot find a solution. I wait. Wow! It's working. I really enjoyed the service. thank you. I hope to improve some services and offer some offers soon.	0.62	0.03	0.01	0.62	0.04

EFFECT OF EMOTIONS

Some may ask why you don't use sentiment only without using emotions? It's like the scales of things, but we want to be deeper in understanding the customer. Sentiment may help to know who has negative feelings but we want to determine what these feelings and then find the best solution to treat them. So, we use emotions as well. In short, we use sentiment as a general feeling for the customer, whether negative or positive, and then we use this to know the proportion of the feeling of public customers, which we say the proportion expected to leave. To provide solutions to this, we cannot give a radical solution without being closer to the feelings of the customer. So, we derive the emotions that caused this negative emotion. And then we work to treat them. Definitely a collective solution is the first option and this depends on the sentiment result. But this solution may not work with some people, so you must also provide special solutions. Of course, we will not give the same solution to the same people, for example who has a high rate of anger much different from who has a large proportion of fear. Solutions should therefore be different if they are presented in particular. Add emotions with a sentiment make accuracy increase by nearly 90%. Of course, there is a relationship between sentiment and emotions. If the sentiment has a positive value, the joy emotion is expected to be the most valuable, and if it has a negative value, the other emotions will be the most valuable. By doing this, we can make sure the customer's situation is different. We assume that (sentiment value = S_i) and values at the emotions are (joy value = J_i), (anger value = A_i), (disgust value = D_i), (sadness value = 〖SD〗_i) and (fear value = F_i). We want to evaluate sentiment from emotions (FR(i)).

FR(i) = (J_i - 0) + (0 - A_i) + (0 - D_i) + (0 - 〖SD〗_i) + (0 - F_i) + & (1)

& is an extra value is placed to make equation is balanced, since the negative emotions are more than positive emotions. We assume that the value = 1

By experimenting with the first and last conversation:

In First conversation, sentiment S_i= -0.84

FR(i) = (0.01 - 0) + (0 - 0.30) + (0 - 0.05) + (0 - 0.77) + (0 - 0.15) +1 = -0.26 negative

In Last conversation, sentiment S_i= 0.30

FR(i) = (0.62 - 0) + (0 - 0.03) + (0 - 0.01) + (0 - 0.62) + (0 - 0.04) +1 = 0.3 positive

Fig. 2. SHOWS RELATIONSHIP BETWEEN SENTIMENT AND EMOTIONS.

II. Data collection for testing

We collect our data from Facebook, which is now the largest platform for customer service through Social Media. We have focused on the telecom companies and the official pages that are related to them. We then follow processes to restore conversations between agents and users then follow publication's comments were written by the users and agent. We downloaded all publications and conversations using Facebook for developer's API from January 2017 to January 2018. The API return if this publication is replying to another or separate publication. And we continue to do that until we reach the maximum publication. We retrieve conversations between the agent and client in chronological order, then filter the conversations and then delete which it does not meet the criteria and then clean the conversations by deleting the @ mentions, the # hashtags, the URL addresses, and the numbers. At the end we have only user request 〖(U〗_r) and agent reply 〖(A〗_r).

Also, we use data dictionary that convert from slang to standard Arabic. We use social media text to collect data from public publications and comments in telecom companies or profiles. The data set used in this search contains 5000 frequently used words. Training dataset contains accuracy with 80%, and we work to increase it to 90% or more.

III. Materials and Methods

Now we have emotions and sentiment, we started to test System that understands these emotions. As we said earlier, IBM Watson can calculate those things by API was introduced. But, we did not take this without research, we did several tests, about 500 tests, and 100 persons. We put the customer's request in API and then ask real persons, what can this text contain of emotions? and then compare the results. We obtained a percentage of efficiency by the ratio of 96%. Where API had the same expectations as real people. So, we started to use it as a helper or benchmark to our work.

After completing the conversation, we take the text written by the customer from chat and send it to our system to calculate the sentiment and the five emotions. Each customer has a unique identifier in our large Database, which contains a graph that measures the ratio of sentiment either negative or positive, and there is another graph showing the ratio of each emotion of the five emotions. We use the sentiment as an indicator that rises negatively and falls in favor. When this indicator reaches a specific point, this customer will be placed in another Database was is called the people who expected to leave. By doing this, you can find out how many people are at risk of leaving the service, and their percentage rate for all customers. If this percentage reaches a certain number, for example, 5%, this is dangerous and requires a radical solution. It is natural that the company does not attempt to reach this number and makes permanent solutions with small percentages. In short, through the system presented, and by the general sentiment, we can determine the number of people who expected to leave and their proportion and who, and then provide solutions either individually or collectively. Each person also has a value for each of the five emotions. From here we can also find the most used emotion among customers. This helps when providing solutions. You must take into consideration the customer's feeling so that the solution is appropriate for them. For example, if disgust is the most valuable, it means that customers do not like some of the services provided, they must be found and improved. If fear is the most valuable, it means that customers have the impression of fear of services, must provide a solution that makes them feel safe with the service. Or if sadness is the most valuable it means that the customers have been disappointed with the service, must provide a solution that brings them confidence back to service. So, we had to study some emotions to help us provide the right solutions. Through our Database, it is possible to calculate the percentage of who feel negative and are expected to leave. We can also calculate the percentage of who are afraid, who are angry, or who are frustrated for example. These ratios will give a clear perception of the problem and statistics will help the company avoid customer sudden loss by providing urgent solutions. Percentage of expected to leave (〖EXP〗 _leave) = neg / All.

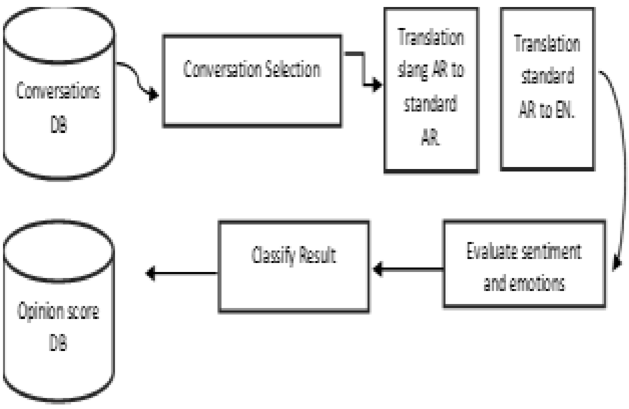
$$(2) CUS_{neg} = \sum_{neg=0.7}^{1} CUS_n \qquad : n = number\ of\ user$$

$$(3)\ CUS_{all} = \sum_{1}^{n} CUS_n \qquad : n = number\ of\ user$$

$$(4) \qquad EXP_{leave} = \frac{\sum_{neg=0.7}^{1} CUS_n}{\sum_{1}^{n} CUS_n}$$

We assume that number of customers in company (〖CUS〗 _all= 20 millions), and the number of exceeding the peak point of negative feeling (〖CUS〗 _neg= one million). Then 1000000/20000000 = 0.05 = 5%. This means that, out of every hundred people, five feel negative, and this is not desirable for large companies. By the same way, we can calculate the ratio of each emotion of the five emotions, especially the negative ones, they are four without joy.

Fig. 3. SHOWS CONVERSATION CLASSIFICATION PROCESS.



IV. EXPERIMENT

Figure 3 shows the process of classify user conversation. First, the conversation between the customer and the agent is saved within a Database. It contains conversation text, user ID, and conversation result. Of course, there will be many conversations, so that the conversations are not mixed up. Second, we take the conversation and send it to our system where emotions and sentiment are calculated. Then, we take the results of sentiment and insert them into the classification tool. If the result is negative value, it is placed in the negative database. And if the result is positive or neutral, it will be ignored. If the value of the customer's negative conversations reaches 0.7, the customer is placed in other database called the expected leaving customers. It contains the customer ID and its percentage of negativity. There is a permanent link between first and second databases to follow the ablution and rise in emotion. It is possible that one of negative customers will come out of the second database again if the ratio is less than 0.7. It should be noted that, it is very difficult to put the customer in the second database after the first conversation. According to our first work which talk about Chatbot, it helps to provide solutions to customers and Emotional responses depend on Tone Analysis to change their negative feelings. Already the results proved that. But, there are people who are angry, don’t calm down or calm down a little and keep the negative feelings or part of them. Finally, to create the experiment in this paper, classification algorithms were studied. Also, advanced python was practiced and studied.

These assumptions were set in order to start the experiment:

1- Adding [IBM API] to the post processing stage will increase the accuracy of sentiment and emotions detection.

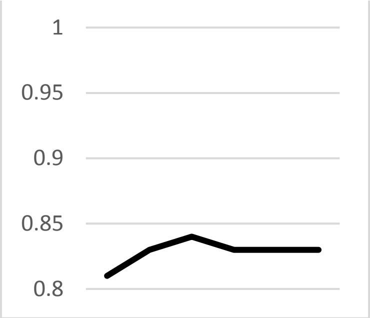
2- Adding some emotions with sentiment increase the accuracy more than sentiment only.

3- Combining [SVM] with [API] in the learning process will increase the efficiency of score classification.

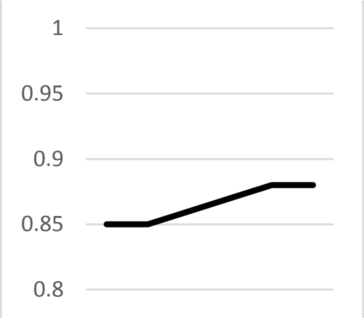
SVM is used here as a classification tool in two important cases. First case: outside the expecting leaving database. After calculating the result of sentiment by IBM API. If the result is negative, the customer is placed inside the negative database (initial neg DB). We had set a value for the classification which is 0.7 as we set it beforehand. The negative rating will be followed up by monitor the results each conversation’s time and add the new negative ratio if it exists to the old value. The new ratio is calculated by the following simple equation: (new neg value & old neg value)/2. If the new ratio of customer reaches to 0.7 or more, he or she is classified as expected to leave then placed in the expecting leaving database. If it is less than 0.7, that is fine. Second case: inside the expecting leaving database. It is used to classify the database as negative groups according to the higher value of the four negative emotions which are mentioned above and they are Anger, Disgust, Fear, Sadness. By this, the ratio of each feeling is defined. Then solutions are handled and presented according to each feeling, so that the solution is more specialized and influential.

To obtain the highest accuracy of the determination of the negative ratio and provide help to them, figure 4 shows the difference between the three main elements are used and how each affect the accuracy.

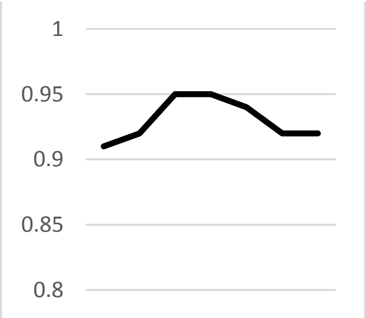
Fig. 4. SHOWS COMPARE BETWEEN TECHNIQUES ACCURACY.



a) only sentiment



b) sentiment & emotions



c) sentiment & emotions & SVM

From figure 4, we can see that when we used sentiment with five emotions and SVM classification, it gives us good accuracy more than only sentiment or sentiment and emotions. We thought that 92% of accuracy is good for this work with English and standard Arabic languages until now.

Experiments were executed in the local company of [telecom company] with [100] customers of different severity types. The system used in this process have different languages as we mention according to customer language. Tests ran all day for three days. There were 100 customers participating in this test, with each customer having a unique ID. [IBM API] is chosen to run first to calculate emotions, then in the [SVM] is executed to classify the result. Using the above execution order hasn't been tested before especially on the API Running. After the processing is done, the results are saved to one big database and media files with metadata are stored in the repository folder. Data is then analyzed using analysis technique and statistical diagrams are plotted using an incremental way showing different reports listed in the results section before and after conversation.

The following pseudocode explain the process that we want to do:

Initialize the peak value

Initialize total result

Initialize customer id

Initialize leaving DB

Add customer id

Input the result

Total result equal the average to new result plus old result

while peak value not equal total result

→ skip customer id

if peak value equal total result

→ save customer id into leaving DB

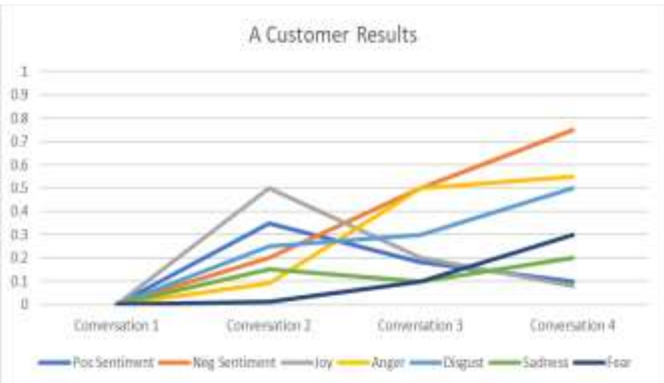
if num of customer id in leaving DB to num of all customers id equal 5%

→ print "risk position"

V. RESULT

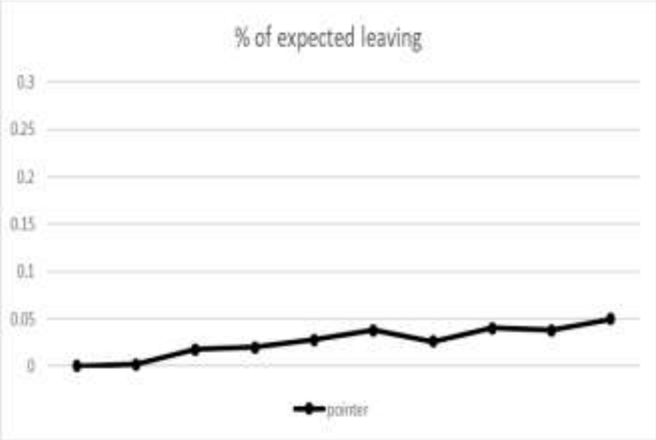
In this work, we offer our software based on customer care through social media. Through this work we seek to expect who will leave the service with negative emotions and when should provide solutions to reduce this feeling. We would like to get customer satisfaction and hold on the system. After conversation between user and system, the user text will be analyzed and the emotions will be detected. From the results obtained through our software and IBM API, conversations can be classified as negative, positive or neutral. In addition, there is a correlation between the results and the scores that are determined for the correct impression of service. The results were classified as in Table I and Table III. Of course, there is a great deal of positive talks but there are also a lot of negative emotions. The largest part is neutral talks. In figure 5, we can see customer sentiment and emotions values for one conversation. By these results for each conversation we can detect if the customer reaches the peak value or not.

Fig. 5. SHOWS A CUSTOMER CONVERSATION RESULT



Talking about figures 5, we can see customer conversations, it shows that this customer has a negative feeling of service. As we see his neg sentiment line Increasing constantly and reach the peak value. So, this customer will put in expected to leave DB. By applying the statistical models on the DB output data, and drawing the normalized curve, we get the percentage of who expect to leave.

Fig. 6. SHOWS PRECENTAGE OF WHO EXPECTED TO LEAVE.



From the previous figure 6, we note that the proportion of those who feel negative of service decreases and then increases. It is normal if it does not reach our specified value which is 0.05. If the ratio reaches 0.05, this is a serious matter and a quick solution must be presented. If it is more than that, it is a real disaster for the company. Large companies must continually monitor this indicator and provide ongoing solutions.

Finally, and by all previous steps, the system will detect if the customer has loyalty or he will leave the company.

VI. Conclusion

In this study, sentiment analysis was used to assess customer sentiment and emotions of customer in Telecommunications companies. We found the problem of finding tools to analyze feelings for word processing in Arabic. However, by providing a translation step in the process, as seen in Figure 3, we can circumvent this difficulty. This extra step consisted Translate conversations into English and then use available opinion analysis tools for English. It is necessary to follow up on the results index and follow it up to reach the critical situation. Using a machine learning algorithm in the preprocessing and post processing stages of sentiment analysis increases not only performance, but also accuracy. The accuracy level was increased to be above 92% after using [IBM API], [SVM] with the different stages of the recognition process. It is recommended to do researches with deep learning techniques and applying dynamic detection to the process. Search about NLP, linguistics analysis and sentiment analysis and machine algorithms are used. We should note that text may contain revile words, or user talk about what he doesn't really feels so we can't help him. Other words were easily recognized and with time, accuracy increases exponentially.

VII. FUTURE WORK

Now with new results, other researches can start from this point on to focus on the dynamic detection instead of using pattern matching techniques. There are two suggested directions to continue this work in the future, first, is to add the dynamic approach to the detection by testing either algorithms to do this task. Second, is to test the effect of using more accurate algorithm and switching it with a faster technique after passing a specific threshold. The next step to this work is adding a dynamic approach to help companies to introduce suitable solutions as soon as using a different API that can detect slang Arabic without converting.

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