Determination of Telecom Customers satisfaction from their Personality Traits using Natural-language understanding and SVM

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Abstract--Many studies have shown that many Telecom Companies have affected by customers dissatisfaction during solving problems by agents. Agents reply only without knowing what the affect of their replies is and how much this reply help customers. In this trial, we measure customer's satisfaction after conversation and use the result to know if customers get help or not. If the result is satisfaction, this is good. But if the result is dissatisfaction, agent should do another way of helping. This paper covers the affect of combination among three stages of the machine learning techniques, personality psychology and feedback system to measure satisfaction with high accuracy. Based on understanding the emotions behind customer's replies on conversation with expert chatbot, customer's satisfaction or dissatisfaction have been appeared clearly. All used techniques can achieve satisfaction measuring with accuracy of 93% with appropriate length of conversations and 88% at conversation with short length.

Keywords: Satisfied Customer, Dissatisfied Customer, Personality Traits, Natural Language Understanding, Tokenization, Customer Support, Telecom Companies, Customer understanding, Text analyzer, Service Quality, Chatbot.

I. INTRODUCTION

AI and text analysis are the branches of science interested in automating personality recognition and emotion detection from a text. Customer satisfaction affects each customer loyalty [1]. Nearly 42% of customers prefer customer support chatting, it is one of the main causes for interesting of customer satisfaction and keeps your brand and services ahead of the competitors.

Marketing is one of the main departments in any telecom company, it helps spread services around the world to reach the target people. The major functions of marketing are buying, selling, financing, transport, warehousing, risk bearing, etc. In each function there are different processes to achieve a specific goal. Only 45% of companies have an established marketing department or have someone who works as head of marketing [2].

According to (Deborah O. Aka; Oladele J. Kehinde; Olaleke O. Ogunnaike) [3] managers can plan their marketing strategies as they identified the significant variables which influence customer satisfaction. Their study suggests that the trust, commitment, communication, and service quality are major components of relationship between marketing and customer satisfaction.

It is important to know the customer satisfaction to make sure that the client got what he wants. This will help to improve the conversation with Chatbot if it automatic support, or agent trainee how to communicate if it manual support conversation. This can help companies to increase the customer loyalty so maybe they're doing some marketing about the company's services between them without making any significant effort for the good quality of the service provided.

For making this work done well, we would need to collect separate data to build a new dataset of conversation between customer and the customer support from different resources mentioned in dataset section.

The proposed engine is built with machine learning algorithms which are used for learning process of the text. It is developed by combining these three factors: (1) prediction, (2), learning, and (3) feedback process.

We seek to Run the algorithms on the collecting data and get a high accuracy. This paper presents the results of running the algorithms over the local environment using conversation between customers and customers support agent or Chabot. It shows the effectiveness of these algorithms and how learning curve increases with time. The curve starts with 86% accuracy till it reaches 90% at end of conversation and may reach to 96% with increasing in data stored by time.

Paper starts with previous related work, then the material and methods section presenting the experiment setup and used resources, then we show how the learning samples are collected to detect emotions from text and measure satisfaction with help of machine learning algorithms. After that, we show the statistical analysis of the results and discusses it showing the effect of the used algorithm. The final section contains the conclusion and recommended future work that will be added to increase the importance of our work.

RELATED WORK

There are many trials in this field to study customer's behaviors. For example, trying to examine the relationship between the personality of the agents and the customer perception on the service quality [4]. Another tried analyze which agents' traits influence on the customers satisfaction [5].

The previous works did not stop at finding just a simple relationship between personality Characteristics and customer satisfaction from the services providing, but they had reached to how to predict the customers behaviors to the services that are provided to him or when an agent communicate with him by any way. There are various works that studied customer's behaviors. For example, **Sulaimon Olanrewaju ADEBIYI, Hammed Ademilekan SHITTA** and **Olanrewaju Paul OLONADE** used the multiple regression analysis that were conducted to determine the explanatory and predictive strengths the customer preference and satisfaction on GSM mobile phone network services. The results were enhanced a little, but not enough to increase the performance [6]. Using SVM with a RBF kernel by Stefan Meinzer, Ulf Jensen, Alexander Thamm, Joachim Hornegger, Björn M. Eskofier gave a best classification rates with 88.8% [7]. The unique technique (textual, emotional and personality features) created by Jonathan Herzig.

The above trials Predict Customer Satisfaction at the end of Customer Support Conversations. Using Affective Features are the triggers for the methodology that are used in this paper. What has been done here is considered an innovative usage of personality traits and co-operate with emotions that are extracted from understanding customer's replies, learning and feedback processes. In this paper, we try to measure satisfaction from customer support conversation using SVM machine learning technique on dataset combining the traits and emotions extracted from customer's conversation.

II. MATERIALS AND METHODS

To create the experiment in this paper, personality detection [IBM Personality insights], text Emotions and SVM algorithm were studied. Also, python was practiced and studied. These assumptions were set in order to start the experiment:

The emotion's features tell us whether the customer satisfied about the reply in chat or not. It shows the mode of the customer if he angry, joy, Sad, disgusted or afraid from his conversation

The personality insights influence on his emotion. For example, if someone like helping others, this means that his angry that is detected from his text should decrease

Our approaches based on personality characteristics that are predicted from customer's replies and Natural Language Understanding (NLU) that understand what customer emotions in his replies. For Natural Language Understanding (NLU) method, there are more than one resources to use and finally we decided to use **[**IBM Natural Language Understanding API] for this job. For the other method (Personality characteristics), the only clear and Believable one is **[**IBM Watson Personality insights API].

Natural Language Understanding approach is used for understanding customer emotions if he talks normal, negative or positive and understanding the current mood for him. Measure client feelings during the conversation with agent help to measure his satisfaction.

Personality Models: Personality Insights service provided by IBM infers personality characteristics from textual information based on an open-vocabulary approach. It is one of the most studied of the personality models that were developed by psychologists. It is the most widely used personality model to describe how a person generally engages with the world. Based on three primary models:

Big Five personality characteristics [8] describing how a person engages with the world. The model includes five primary dimensions: Agreeableness, is a person's tendency to be compassionate and cooperative toward others. Conscientiousness, is a person's tendency to act in an organized or thoughtful way. Extraversion, is a person's tendency to seek stimulation in the company of others. Emotional range, is the extent to which a person's emotions are sensitive to the person's environment. Finally Openness, is the extent to which a person is open to experiencing different activities.

Needs: describe which aspects of a product are likely to resonate with a person

Values: describe motivating factors that influence a person's decision making.

In this work we will use only the Big Five personality characters that detected from customer replies.

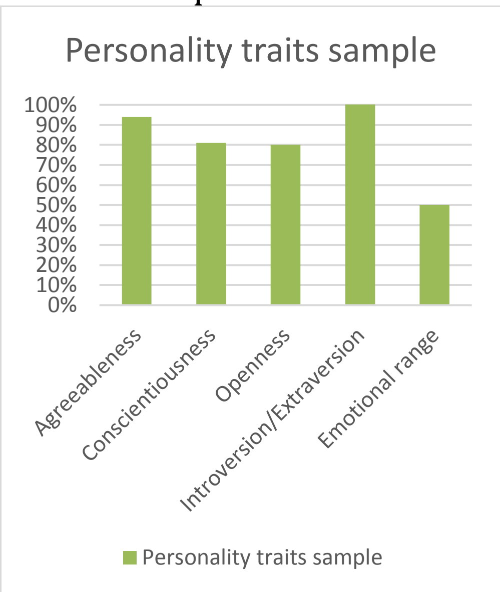

Figure 1. Showing sample of personality traits.

Experiment design

Using SVM Algorithm as a post processer of Satisfaction measure is what is designed here. Experiments were executed on conversation between customers and customer support agent. This experiment executed along the conversation.

Figure 2 shows experiment processes. First, divide the conversation to five parts to detect the customer emotions in different stages along the conversation. Second, tokenization for each part in two phases; tokenization sentences and tokenization words, to split each word alone. Third, remove the whole stop words and spaces that aren't necessary and may be affect efficiency then apply the **TF-IDF** algorithm to remove the normal and repeating word that would have had no effect in customer's emotion. Fourth, words in each part extract the emotion's features using [**IBM Natural Language Understanding**] then calculate the percentage for each emotion (negative, normal, positive) by apply the following equation.

Find (Yj) equal Summation of each emotion (Xj) in all five parts (n =5)

$$Yj = \sum_{i=1}^{n} Xj \qquad (1)$$

Find (**zj**) by normalize the value of each emotion summtion (Yj) from all five parts where
($h = 5$) using **sigmoid** function

$$\mathbf{zj} = \sum_{i=1}^{h} \mathbf{1/(1+exp(-Yj))} \qquad (2)$$

Use the sigmoid function again on personality traits.
Fifth, take the normalized value for each emotion summation with the personality insights (normalized value) that extracted from customer replies using [**IBM Personality insights**] to the **SVM** model to make satisfaction classification.

Algorithm for Satisfaction Model

Input: c =conversation replies

```
t ← divided(C)
for I = 0 to I < 5
  for I = 0 to I < length (ti)
    X ← tokenization (ti)
    Y ← stop words removal (X)
      for each word w in Y
        f ← calculate TF-IDF (w)
      end
  end
  e ← add emotion (f)
end
Q ← sigmoid (emotions (a))
P ← sigmoid (personality (c))
Run SVM model (P, Q)
S ← classification satisfaction
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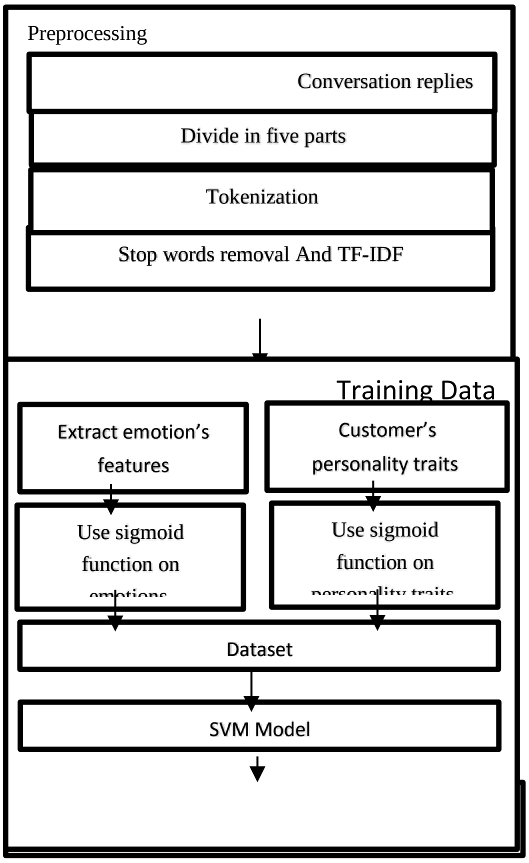


ID	Conversation	Joy	Anger	Disgust	sadness	Fear
1	Thanks for your help. This is what I want.	0.5	0.57	0.2	0.34	0.5
2	I can't understand you. I am very sad for not help me.	0.6	0.1	0.1	0.8	0.35
3	I am not sure that this help me. Thanks any way.	0.95	0.23	0.4	0.49	0.7
4	No body answer me This is not good I will leave your company.	0.51	0.1	0.1	0.8	0.76
5	This service is Good. Can you tell me more about it.	0.7	0.36	0.5	0.2	0.42

Figure 2. Showing Experiment processes to measur customer satisfaction.

The implemented parts are TF-IDF, tokenization and SVM algorithms to measure the satisfaction of the customer.

III. DATASET

The dataset in this research contains customers conversation replies as input for the algorithm showed in table 1. Training dataset contains 80% of conversation. Training conversation are at least 15 replay per customer. And each reply are also at least 10 words. The training data is collected from different sources; conversations from internet free search, rest of conversation were taken from the Volunteer with Older than 18 years old and social media pages.

ID	Conversation	Agreeableness	Conscientiousness	Openness	Introversion/Extraversion
1	Thanks for your help. This is what I want.	0.94	0.81	0.8	0.64
2	I can't understand you. I am very sad for not help me.	0.8	0.75	0.9	0.85
3	I am not sure that this help me. Thanks any way.	0.6	0.78	0.69	0.75
4	No body answer me This is not good I will leave your company.	0.7	0.8	0.5	0.62
5	This service is Good. Can you tell me more about it.	0.8	0.6	0.79	0.74

Table 1: Showing dataset of the sample conversation with meta-data.

Ensuring that Volunteers who's participating in this experiment have age more than 18 years old. The conversation with appropriate length is selected in training stage.
Personality insights used first to extract the personality traits for each client from their conversation replies. Second, extract the targeted emotions of the content using Natural Language Understanding (NLU).
Using the above execution order hasn't been tested before especially the relation between personality insights and Natural Language Understanding in conversation to measure satisfaction. After the processing is done, the model is ready to test to calculate the accuracy.

IV. RESULTS AND DISCUSSION

After applying the algorithms to the conversations, there was 5% of conversations not be suitable to measure the satisfaction because when we divide the conversation in 5 parts. Each part give us what the customer mode in this moment .it was about 90% of the total customers who successfully measured their satisfaction. We change in the divided parts of the conversation and give us difference accuracy.
By changing the algorithm, we get a different accuracy. In this case, the accuracy was presented by SVM (linear) algorithm with an accuracy of 90% showed in figure 2.

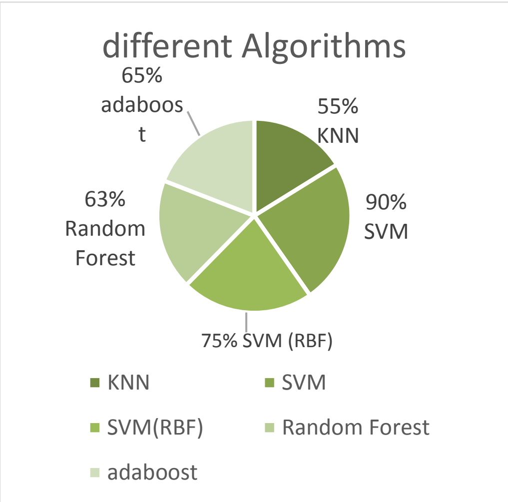
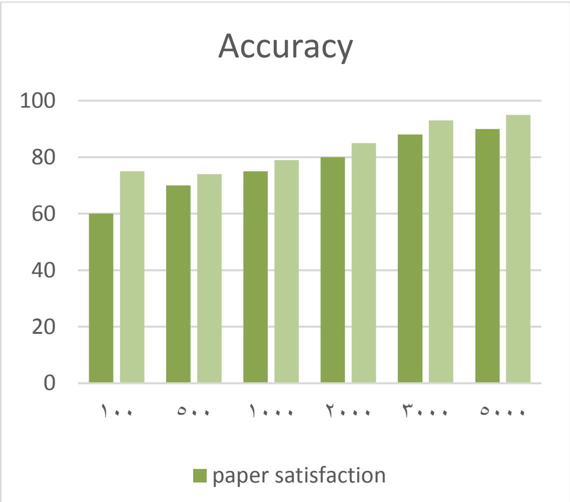


Figure 3. Showing results of different algorithm with their accuracy.
The presented work answers two questions. What affects customer satisfaction on the telecom company? How it will be combined to give us the right decision of customer satisfaction?
The satisfaction is measured because the relation between the personality traits of the customer and the emotions of his replies in conversation. The conversations should be with suitable length to be divided in different parts.

The results are near to what was expected when we change the conversations with short length with another have suitable length. The accuracy increased to 3% accuracy from expected accuracy.

BENCHMARKED

For prove this result, we tested the same conversation replies on tone analysis service provided by **IBM** that can give us a satisfaction tone of text. The following chart shows the different between accuracy using different conversations lengths in number of words.



V. CONCLUSION

This work provided an approach that can answer two important questions that help the Telecom services to increase the customer satisfaction and thus securing competitive leads; can satisfied customers be classified based on data which produced during a service visit? Can the satisfaction indicators be derived from service process data? In the presented.

The presented approach is intended to be implemented in business areas of the Telecom services. Therefore, the run time of the application is significant importance regarding to the practical use. In order to allow a short runtime, cross validation has not been performed for the evaluation of the classifiers so this would increase the runtime significantly with the available machine.

This paper reports on a first attempt to utilize affect features (Personality Traits and emotion) to improve the prediction of customer satisfaction in customer care scenario. We showed how to utilize these personality traits features to gain an improvement in the customer satisfaction prediction.

It is planned to use video during conversation to measure the customer satisfaction in another way with human expressions .it will give us another chance to increase the accuracy of our work.

Future work

There are suggested direction to continue this work in the future, first is to add the service prediction for any customers based on his personality traits and service features , this work will be implemented by using RNN.

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