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Dynamic Content based Behavior Analysis Model for Users on Social Media

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Abstract: Social media is now widely used for uploading photos and sharing one's thoughts by posting them as status. This context collected from users is better than the conventional ones which requires tedious user involvement to study their behavioral characteristics. These posts made by individuals in their profile directly or indirectly reflects the interests, opinions and thoughts over a particular topic or an incident. By analyzing those posts, the correlation between the contents of the post and behavior characteristics can be understood. However it is difficult to find the individual's characteristics accurately since the posts have to be monitored over a certain period of time and all the posts within the period of time has to be analyzed together. The presented approach investigates the datasets containing the user posts over a period of time and predict the user's behavioral characteristics. We also define and classify a number of characteristics based on the posts made by an individual. The results obtained after the analysis reveal the behavioral characteristics of the user which can be used for service provision to a specific type of crowd.
Keywords: User, Posts, Behaviour, Characteristics, Analysis

I. INTRODUCTION

Data mining, also called knowledge discovery in database, in computer science, the process of discovering interesting and useful patterns and relationship in large volumes of data. Data mining is the practice of automatically searching large stores of data to discover patterns and trends that go beyond simple analysis. There are many types of data mining typically divided by the kind of information. Big data is data sets that are so voluminous and complex that traditional data processing application software are inadequate to deal with them. Big data challenges include capturing data, data storage, data analysis, search, sharing, transfer, visualization, query, updating, information and data source.

II. OBJECTIVE

To analyze the behavior of a user in social media with the help of the dataset containing the tweets posted by the user in the user's twitter account.

III. LITERATURE SURVEY

In the paper , "Design of A Universal User Model for Dynamic Crowd Preference Sensing and Decision-Making Behaviour Analysis."[1].It is based on the exploration of dynamic crowd preference and decision-making behavior analysis based on users' previous behavior/behaviors through the external factors. The INPUT is obtained from the IDS and the EDS and collectively stored in the Big Data Pool .In the Knowledge Discovery Engine, pre-processing is done to remove noise and ensure quality of data. The data is then analyzed on sentiment, emotion, behavior and preference. This approach using the Apriori and Association rule mining algorithm results in extremely slow candidate generation. The candidate generation could also generate duplicates depending on the implementation and also the counting method also makes the algorithm a lot heavier and resulting in huge memory consumption. In our paper, we suggest two algorithms namely content based filtering and collaborative filtering, which can overcome the above problem.

In the paper, "A Dataset for Psychological Human Needs Detection From Social Networks."[5], a theoretical based multi-layer framework for a psychological needs analysis that is guided by research in the field of motivational psychology is proposed. The framework's layers are constructed to identify the psychological needs, measure their satisfaction level, and assess the individual's surrounding environment in different aspects of life. A psychological needs corpus: a collection of Twitter posts annotated based on three universal needs proposed by the self-determination theory framework is created and Several techniques were employed to encourage high-quality annotations. A Descriptive statistics of the annotated corpus is provided. This corpus can be used in the development of automatic detection systems and predication models to detect individual needs and measure their satisfaction. It can also be used to better interpret and understand the individual's surrounding social contexts.

In the paper , "Influence analysis of emotional behaviors and user relationships based on Twitter data."[9] the influence of emotional behaviors to user relationships based on Twitter data using two dictionaries of emotional words is analyzed and Emotion scores are calculated via keyword matching. Moreover, three experiments with different settings: calculate the average emotion score of a user with random sampling, calculate the average emotion score using all emotional tweets, and calculate the average emotion score using emotional tweets, excluding users of few emotional tweets is designed. The influence of emotional behaviors is evaluated and the result shows that a positive user is more active than a negative user in constructing user relationships in a specific condition. In our paper, this methodology of calculating the scores for the content is incorporated.

IV. EXISTING SYSTEM

The input is obtained from the IDS and the EDS and collectively stored in the Big Data Pool, from which the behavior analysis is done using the Apriori and Association rule mining algorithm. The dataset used here in existing system is Airbnb by considering factors such as nationality, gender and age as internal factors and social media, device and time as external factors. These two factors reflect the preference of the crowd and its behavior. This paper targets on two main things such as crowd preference and decision making behavior.

V. PROPOSED SYSTEM

In the proposed system, we have implemented two effective algorithms namely, Content-based filtering and Collaborative filtering. We use the dataset from twitter. This paper targets the behavior analysis of the users based on the tweets in their Twitter profile .We ultimately aim to produce a graphical representation (charts, graphs, histograms etc.) to show how much the person is inclined towards each characteristics. So, the characteristics we wish to analyze are Emotional Quotient, Scientific Curiosity, Aggressive Nature and Social Awareness. We initially perform the pre-processing followed by the behavior analysis of the user.

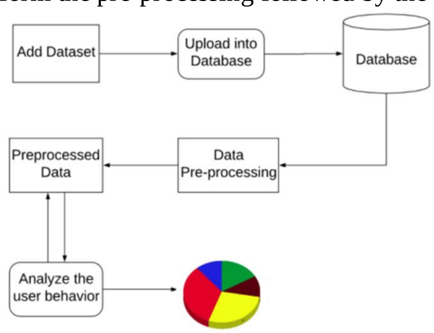

Fig. 1 Architecture of the Proposed System

A. *Content-based Filtering*

Content-based filtering, also referred to as cognitive filtering, recommends items based on a comparison between the content of the items and a user profile. The content of each item is represented as a set of descriptors or terms, typically the words that occur in a document. The user profile is represented with the same terms and built up by analyzing the content of items which have been seen by the user. In our paper , we use content based algorithm to compare the data with the words pertaining to certain traits and calculate the level of behavior traits present in the user.

B. *Collaborative Filtering*

Collaborative filtering also referred to as social filtering, filters information by using the recommendations of other people. It is based on the idea that people who agreed in their evaluation of certain items in the past are likely to agree again in the future. In our paper , collaborative filtering algorithm is used for identifying certain traits which can be identified only through a collaborative method of combining the user's posts and analyzing them.

C. *Pre-Processing*

In this step, the stop words as removed from the user data by comparing each word with the words in the stop words library. After stop words removal, stemming process i.e. Converting each word to it root or stem form is done.

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D. Behavior Analysis

We use the two algorithms, content based filtering and collaborative filtering to analyze the behavioral characteristic of the user.

E. Experimental Results

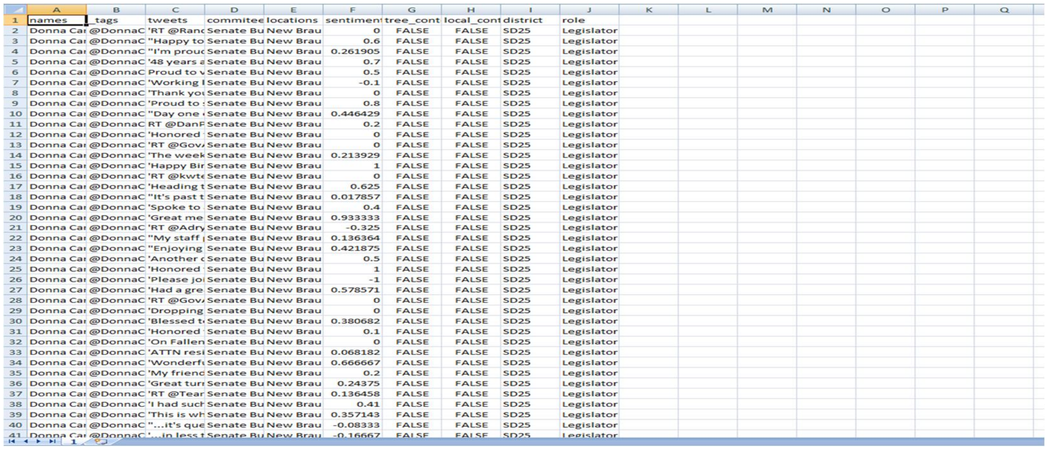

Fig. 2 Dataset containing the user's tweets

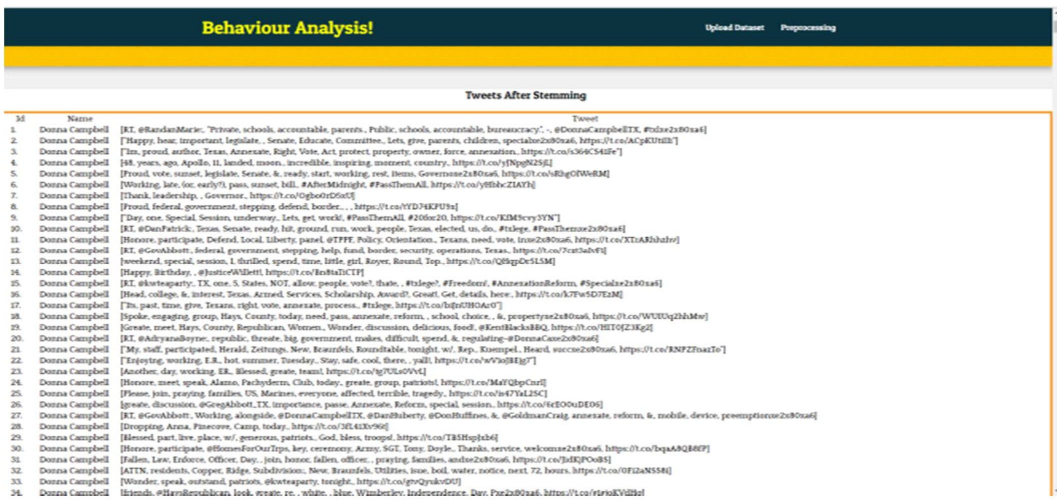

Fig. 3 User's tweets after the Stemming process is done

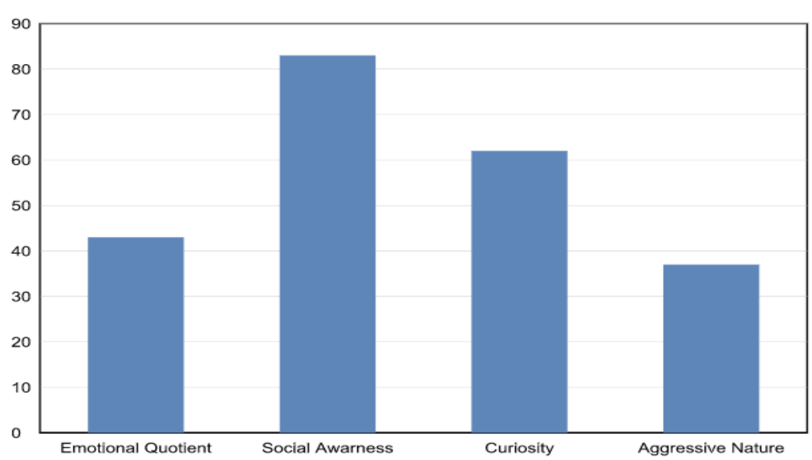

Fig. 4 Graphical representation of the user's behaviour

F. Admin

The admin logs into the admin homepage and the admin uploads the user data from twitter in the form of a dataset. Once the admin uploads the dataset, a message indicating the successful upload of the dataset is displayed.

G. Database

The user data containing the Username, Twitter ID, Tweets are stored in the database.

VI. CONCLUSION

In this paper, we have shown that the methodology used by us in analyzing the user's behavior through the user's tweets is quicker and more efficient than the existing system where the behavior analysis is done using the Apriori and Association rule mining algorithm. This can be extended to a higher level for a large number of users.

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