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# A Hybrid Model for Human Behavior Recognition Using Emotions, Sentiments, and Mood Features

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## Abstract

While social networking is a powerful communication tool, the obscured behavior of individuals on social networks remains a significant problem for users. Currently, research work is being focused on formulating mechanisms to determine the obscured behavior of users for secure and trustworthy social media. The proposed model employs mathematical formulation and multinomial classification of mood and emotions to analyze the conduct of an individual, thus enabling social trust on social media. First, natural language processing techniques are applied to predict the emotions, moods, and sentiments of an individual from the text, and then a mathematical model is applied to gather a comprehensive picture of one's behavior using calculations at numerous instants. Finally, a subsequent trust state log is built in terms of positive and negative states which show the devotion in behavior in terms of mood, sentiments, and more significantly emotions. The efficiency of the proposed work has been demonstrated using simulation-based and real-world datasets along with individual behavior graphs for various conversations.

**Keywords:** Social Networks, Social Trust, Positive and Negative state log, Mathematical framework, Hybrid tactic, Multinomial classification, Human behavior, Natural Language Processing

## 1. Introduction

A precise definition of Human behavior is "Human behavior is a dynamic interplay of three constituents in scientific research: attitudes, cognition, and emotions", which shows human actions and feelings play a great role in developing behavior and a cultural or environmental element causes the situation of some specific behavior. Understanding human behavior could help predict an individual's positivity or negativity. To estimate behavior mathematically, it is required to convert behavior-building elements such as mood, feelings, and emotions into numeric form. For this purpose, words can be categorized first as positive, negative, or neutral, and then a polarity score can be used to calculate human behavior. Social network users participate in various conversations daily. These conversations can play an important role in improving or deteriorating the mental health of individuals [1]. Therefore, it is necessary to understand the components of human behavior to extract patterns from their daily activities or actions [2]. Every human being has certain feelings, moods, sentiments, and emotions, and all these components play a vital role in building human behavior.

Despite recent advances in predicting human behaviors based on textual information, there is a dearth of major advances in data analytics systems for identifying, determining interrelationships, and forecasting human cognitive, emotional, and social behaviors [3].

In the quest for human behavior prediction on social networks (SN) which is constantly evolving, building trust has proven to be a challenging issue [4]. Social trust is not only an individual property but also a property of society [5], and it represents expectations of strangers' general cooperation and effectiveness while networking. The hidden behavior of SN users poses a challenge in maintaining social trust. The proposed research findings prove that "words" can be used to predict and analyze the polarity of human thoughts if certain patterns in textual data of a conversation could be computationally identified. In the presented work, the conduct or behavior of an individual on social networks is computed and a mechanism to maintain social trust in social networks is devised.

### 1.1 Factors that Influence the behaviour

In this section, factors that can significantly influence a person's behavior are discussed. A thorough understanding of such factors can enable behavior prediction of an active user with tag words typed by him/her on a social network such as Twitter or Facebook etc. Attitude is closely related to behavior as it can be defined as the tendency of perception to give a positive or negative response. A connection between behavior and attitude can be understood by "privacy paradox", a term used to explain people who often assert that they care about privacy on online systems, but their actions do not reflect their concerns [6]. A thorough study of various theories about the attitude-behavior relationships led Ajzan et al. to conclude that the aforementioned relationship might show inconsistent results with varying situations, [7]. It has been observed that individuals often hide their actual personalities to portray the best possible behavior on social networks. While physical environments have several constraints, virtual environments are prone to various communal threats such as irrational behavior, sudden changes in behavior, etc. Thus, unethical behavior on social networks cannot be explained accurately.

Intention is another factor that can be represented as the cognitive state of doing some action. However, the translation of intention into action has been an active area of research for the past few years. Behavioral intentions are self-instructions to perform specific actions to achieve desired outcomes [8]. People frequently share their intentions on social media, such as "I might go to the party at 6 PM," "I'm going abroad tomorrow," and so on, but these intentions do not provide a clear picture of the individual's thought polarity. Though intention is an important factor in understanding the current state of a person, it cannot help to estimate the action that can be performed by the subject. On social networks, conversation or communication is mainly performed via writing words, sentences, or symbols representing emotions. For certain systems, sentiment analysis might be insufficient and hence require emotion detection, which precisely determines an individual's mental state [9].

A human sentiment is a thought, perspective, proposition, or attitude about some state of affairs or precisely about a situation [10]. Popular techniques, including word embedding, can play a vital role in extracting information from sentiments hidden in some text [11]. Another important factor is mood, which is the state of a person and is less intensive as compared to feelings, emotions, and sentiments. Mood is an integrated and widespread affective reaction that is believed to influence cognition and behavior [12]. Adopting the concept of reinforcement learning, mood can be taken as an advantage of some action [13]. Mood and emotions are correlative, and if mood is correctly found, then, by applying intelligent techniques, emotions can also be detected with high precision [14].

### 1.2 NLP Techniques for Behaviour Analysis

Analyzing people's emotions through their writings is an emerging trend in NLP research [15]. Text-based data has now become a significant source of information regarding the relationships, links, and behaviors of individuals and groups. There are various methods to extract meanings from the text such as Neural Networks to find political partiality [16]. NLP techniques use numbers associated with words, and the statistical analysis of text then helps to predict patterns based on past behavior.

NLP-based techniques such as term frequency, inverse document frequency (TF-IDF), part of speech tagging (POS), etc., and prediction using machine learning provide better results for large datasets. Naive Bayes has been applied in the proposed work which is a classification approach that uses Bayes' theorem to calculate the likelihood of a given feature vector being linked with a label. Logistic regression is a linear classification approach that learns the likelihood of a sample belonging to a specific class. Logistic regression seeks the optimal decision boundary that optimally divides the classes. The logistical function, also known as the sigmoid function, is used to construct the logistic model, in which values range from negative infinity to positive infinity and the output is between 0 and 1. Both approaches are used classification and prediction of some classes. Furthermore, for the proposed work both approaches are used to extract or predict the emotions, moods, and sentiments from the test data.

The ongoing research is directed at uncovering the hidden semantics to predict intent. The objective of sentiment analysis is to classify the text's polarity like conflict, neutral, positive, and negative [17]. Therefore, human behavior can be modeled using a mathematical formulation that depends upon the polarity of an individual's feelings, emotions, and mood. Hence, if NLP is combined with mathematical models, then behavior recognition with a certain accuracy can be obtained.

### 1.3 Contribution of the proposed research

The presented research work contributes a novel hybrid model to detect human behavior and employs a mathematical model combined with natural language processing. The previous research studies [2]; [18]; [19] provided either theoretical backgrounds or learning methods to describe human behavior. Furthermore, [9] presents a statistical approach for the classification of text that is categorized as human behavior such as news articles or product data. Furthermore, Our proposed model takes emotions, moods, and sentiments as features and estimates behavior using mathematical formulation. The study findings show that human behavior can be modeled as a function of the mood, sentiments, and feelings of individuals, along with the environment and special events. Emotions' classification and predation provide the polarity of emotions and feelings. This research aims to go a step ahead and find the state of polarity in the behavior of an individual using the proposed mathematical model. In the presented work, textual data has proven to be a good tool to reveal divergence of thought and can be used to enable trust levels on social networks.

The paper has been organized as follows. Section 2 describes some techniques used to assess human behavior, especially for textual data. Section 3 explains the proposed model, while Section 4 provides both simulation-based and real-data-based results. Section 5 describes the conclusion and future work.

## 2. Literature Review

Spoken words are a great source to evaluate the emotions or moods of some individuals and the mapping of moods or emotions can give certain outcomes like frustration, happiness, etc [20]. For a linguistics-based automated system, words play an important role as they not only exhibit the continuity of actions but also reveal different aspects of human behavior. The language (combination of words) is shown to be used for evil purposes, such as wars, by humans [21]. The significance of words becomes the backbone for such problems as emotion detection, personality classification, mood-based sentiment analysis, and behavior prediction by analyzing the hidden meaning of words. Twitter, for example, is a well-known social network where millions of users share or express their feelings by leaving comments, and by analyzing those comments, personality can be judged or intentions can be predicted. Putting feelings into words, or "affect labeling", can attenuate our emotional experiences [22].

Applying behavioral theories as features in combination with machine learning yields the best results [23]. For the last decade, people have been communicating via social networks, and, therefore, online communication has become a great avenue of research [19]. Emotions significantly influence action, learning, and perception, but their role remains debated [20] . The authors in [14] describe that if a classical algorithm such as a neural network classifier is combined with an evolutionary algorithm like a genetic algorithm (GA), then it can produce better results. [24] gave a demonstration of a conceptual model that would detect risk by taking the user's observable actions into account. It was claimed by [25] . that various human behaviors can be predicted accurately by employing dynamic models [25]. If the communication is virtual or on social networks, especially textual conversation, then it becomes more difficult to identify the malicious activities. By predicting the future activities of an individual, it is possible to mitigate the risk of fraud and stop an individual from attempting dangerous actions like suicide. Therefore, a time-based evaluation is required.

The question of how to accurately predict human behavior has yet to be answered [18]. There are various intelligent systems based on machine learning developed to provide services to the community [26]. However, designing human-centered intelligent systems aims to develop human interaction-based systems with secure communication [18]. With the increased use of social networks, acquainting oneself with new people has become difficult, as in various reported cases, a factor of fraud or unexpected behavior has been observed. Such disorders in the behavior of an individual or group on social networks can be substantially examined through human behavior prediction [3].

Authors in [2] have proposed a probabilistic model to explore the specialty of each persona extracted from the texts and groupings and further investigate personae based on the specialties. In psychology, personality refers to consistencies in a person's behavior across various situations and, over time, how a person generally tends to respond. The diversity of human behavior depends upon various factors like culture, mood, surroundings, etc., which also makes it difficult to construct a concrete model to predict human behavior accurately [18]. Reinforcement learning formalism can be used for better results [20]. Emotions are a crucial aspect of human life, often characterized as complex patterns of reactions. These are the ways through which individuals cope with significant situations and can be communicated in various ways [27]. A summarised view of the adopted techniques is given in Table 1.

Table 1. Inspiration from the existing work

| Research paper | Features | ML Techniques | ML +NLP | Psychological Theories |
|---|---|---|---|---|
| [11] | Words | - | | - |
| [12] | Mood (lexions) | - | * | - |
| [13] | Mood (lexions) | - | - | * |
| [14] | Emotions & mood (theoritical concept) | * | - | * |
| [18] | Behaviour (theoritical concept) | * | - | * |
| [9] | Behaviour (Text data) | - | * | - |
| [16] | Classification of Text | - | * | - |
| [20] | Emotions (lexicons) | - | * | * |
| [27] | Emotions (lexicons) | - | * | - |

## 3. Proposed Model to Detect Human Behaviour

### 3.1 Logical description of the proposed model

The proposed model performs a temporal evaluation of texts. Since an initiated conversation is often continued for various time intervals, the proposed model predicts the polarity of sentiment, mood, and emotions for each comment written by some user during time intervals to the conversation. Then, the polarities are summed using mathematical formulations at different compute and evaluate the behavior of each user or ID participating in the conversation. Figure 1 depicts the described model of behavior recognition and evaluation.

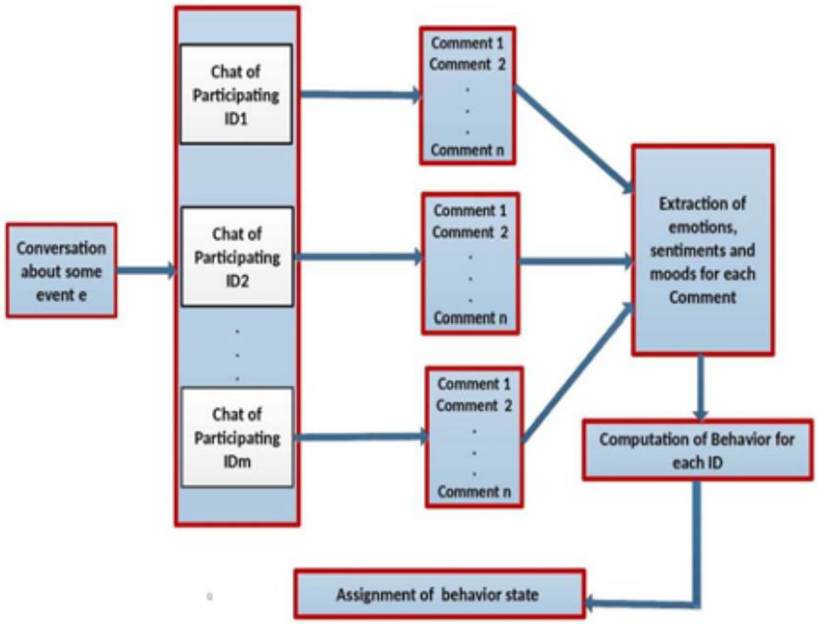


Figure 1. Proposed Model

The theoretical model of the proposed research is inspired by Ajzen [7] , which emphasizes that attitude is directly proportional to behavior. In the presented study, while emotions and sentiments of words have been directly calculated, mood has been derived from emotions. A person can have positive or negative sentiments due to his or her perspective of belief [16] . For instance, if someone says, "I don't like this movie because the director of the movie is kind of a flop director," or, "the person is very nice, as I know his family is reputed to be," etc., then it is obvious that negative, neutral or positive sentiments are all influenced by some percentage of belief.

Along with sentiments, emotions E too play an important role in carrying out some intentions or intending to do some actions. "*The paper was very difficult* (belief) *and the result is very scary* (negative sentiments), *but I scored 80% marks* (emotions: happiness, because of the high score). "*Intuitively, I was expecting that in a few days everything would be going very well*". The above-mentioned example shows a positive action that could be taken by the subject. Emotion lexicons creating a positive sense would make the mood positive, such as "*happiness on success*," while those that may have a negative sense can negatively impact the mood, such as "*gloomy moon*." Since the polarity of each emotion has been considered, it is easier to define the mood in a two-dimensional bi-polar space and cluster all those words as positive, negative, mixed, or moderate.

Russell [28] discusses direct circular scaling for words showing emotions shown in Figure 2.

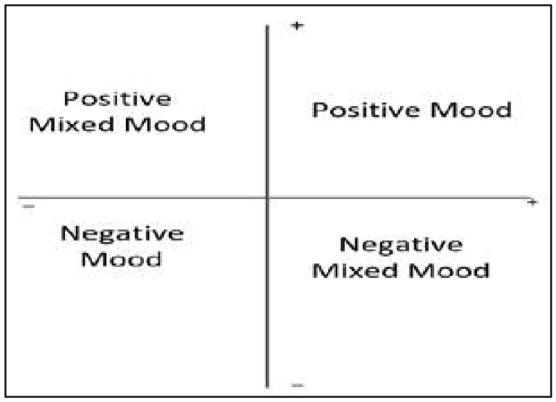


Figure 2. Circular scaling for mood

Few definitions have been furnished below to elaborate the proposed model and to device a mathematical equation for human behavior calculation.

*Definition:* A conversation is a text-based social engagement regarding a certain topic.
*Definition:* A human activity is an action at a particular time instant that can be performed by some individual or can cause another event to happen.
*Definition:* An event is something that will be under discussion at some instant of time
*Definition:* A situation in a social interaction is a proposal or opinion upon which a response is expected.
*Definition:* An environmental factor is a feeling that can cause a person to think positively or negatively.

### 3.2 Mathematical description of proposed model

Consider a conversation $C_t$ initiated at any time instant $t$for a time interval $[0,\ T]$, $\forall t \epsilon R^{+}$as a series of $n$words $\sum W_i$ ,$\forall i \epsilon Z$ which could be defined as follows:

$$C_t = \sum_{i=1}^{n} W_i (1)$$

Further, these words can be categorized as useless words or Non-keywords ($NKW$) and keywords ($KW$). Hence Eq. (1) can be re-written as:

$$C_t = \sum_{i=1}^{n} W_i = \sum_{i=1}^{n} (NKW + KW)(2)$$

As discussed above that behavior is proportional to overall attitude [7] .A relationship among behavior traits such as mood$M$, emotions$E$, and sentiments $S$ for human behavior $B_{ID}$ of a user ID from a conversation $C_t$ ,has been described as follows:

$$B_{ID}(C_t) \propto (S + M + E)(3)$$

At any instant of time *t*, a user on social network may have certain sentiments with a percentage or probability of belief. The overall user sentiments in a conversation are represented as given below:

$$S = \sum_{j=1}^{n} s_j\, b_j (4)$$

Where $s_j$ denotes the sentiment and $b_j$ shows the belief at time index $j$ . Negative, neutral, or positive sentiments are all mostly influenced by some percentage of belief. The overall emotion *E of a user* along with the effects of cause on emotions is expressed as:

$$E = \sum_{j=1}^{n} e_j c_j \quad (5)$$

$e_j$ represents the emotion at any time index $j$ *and* $c_j$ is the causal effect on emotion $e_j$. Equation 6 represents the mood of a user at time index j of a conversation, including all mood variances *m* for environmental factors *v,* as follows:

$$M = \sum_{j=1}^{n} m_j\ v_j (6)$$

Finally, by integrating all of the elements, human behavior can be estimated as given in Equation 7:

$$B_{ID}(C_t) = \Psi(S + M + E)(7)$$

The constant $\Psi$ is termed as event intensity which plays an important role in changing the overall behavior of a user of social network and can be calculated as follows:

$$\Psi = \frac{E_n}{C_t} \times \frac{KW}{C_t}(8)$$

Here $E_n$ represents $n$ occurrences of an event $e_v$. An event $e_v$ can be repeated several times during a single conversation continued over several intervals of time as often observed on Facebook or other social networks, therefore

$$e_v = \begin{cases} 1 & if\, e_v \in TE \\ 0 & otherwise \end{cases} (9)$$

Here $TE$ represents a set of time-based events. It is a subset of keywords represented as follows:

$$TE \subseteq KW \text{ (set of keywords) } (10)$$

## 3.3 Implementation Steps

### 3.3.1 Simulation-based implementation

To perform the task random values were generated and calculations have been done for sentiments, moods, and emotions. Event intensity has also been calculated with the help of random values. Finally, behaviour patterns were generated for random IDs. The values for emotions, sentiments, and moods are calculated using equations 4, 5, and 6 for emotions, sentiments, and moods. Simulations with random numbers have demonstrated the importance of belief for sentiments, cause for emotion, and environmental factors for mood. All these values are generated following equation 11.

$$b_t, c_t, v_t \leq 1\ \forall t \in T\ (11)$$

### 3.3.2 Real data based simulations

The implementation of proposed human behavior detection model is carried out using the steps of data set preparation, classification of mood and sentiments and finally calculation of user/ID behavior.

*3.3.2.1 Data set preparation*

Two emotion datasets were used to evaluate the performance of the proposed behavior detection model. Between the two, dataset 1 is a simple dataset, and dataset 2 is a complex dataset that consists of unclear and short sentences. The purpose of using two different datasets is to evaluate the proposed model for all kinds of sentences that are frequently used in conversations. Necessary steps such as conversion of each sentence to small case, tokenization, removing punctuation, special character removal, and removal of web links have been carried out to prepare the dataset for the proposed model implementation. Both datasets were recompiled, adding the moods feature as described above in Figure 2 as well as Tables 2 and 3. All the calculations are based on the parameters mentioned below in Table 3.

Table 2. Mood categorization

| Class/ Category | Features based categorization | | |
|---|---|---|---|
| Mood | Good | Moderate | Bad |
| Emotions | Joy, Surprise, Exited | Neutral | Anger, disgust, sadness, fear |
| Sentiments | Positive | Neutral | Negative |

Table 3. Depiction of datasets

| Comments | Speaker | Emotion | Sentiment | Mood | Conversation |
|---|---|---|---|---|---|
| ive been taking or milligrams or times recommended amount and ive fallen asleep a lot faster but i also feel like so funny | ID6 | Surprise | Positive | G | 1 |
| i feel like i have to make the suffering i m seeing mean something | ID6 | Sadness | Negative | B | 1 |
| Really? | ID4 | Joy | Positive | G | 1 |

*3.3.2.2 Behavior Computation*

As aforementioned, the proposed model is a combined approach of both NLP and mathematical computation. The dataset contains about 9 conversations and more than 10000 sentences. The model has been trained for 70% data and the remaining 30% is used to test the system. For multinomial classification and prediction of emotions, moods, and sentiments, the logistic regression (LR) model and the Naive Bayes (NB) approach are used, while mathematical equations are used to compute behavior. The frequency count technique (TFIDF) is employed to find events and event intensity, while keyword finding has also been carried out by using the same**.** An event's intensity (Psi) is calculated by using equations 1, 2, and 8. The calculated value is then used to compute behavior as described in equation 7 for all IDs engaged in conversations on social networks.

#### 3.3.3 Setting the states of individuals

If an individual remains positive throughout a conversation, he or she will be in a Positive (*P)* state whereas if any individual shows a negative attitude then he or she will be in a Negative (*N)* state. Figure 3 depicts state transition at some time instant $t_j \in T$. If this state diagram is recorded for a series of events, it could produce a chain of positive and negative behavior which will be helpful to predict the individual's future intensions.

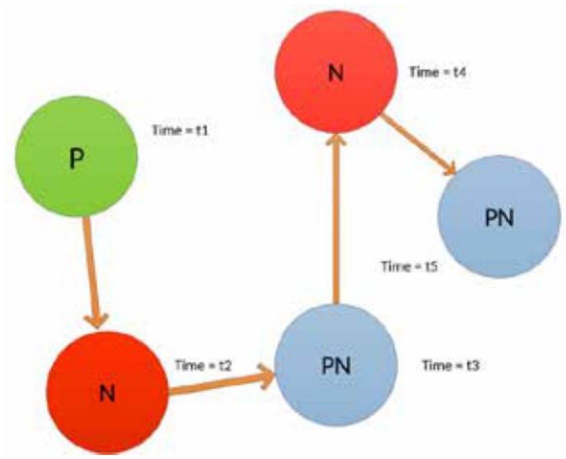


Figure 3. State assignment to IDs

## 4. Results

### 4.1 Simulation-based results

For the evaluation of the presented technique on a simulation, random numbers are generated to obtain 100 observations. In Table 4, all the data that is required to estimate sentiments, emotions, and moods has been mentioned. Belief $b_t$, environment factor $v_t$, cause $c_t$, mood $m_t$, emotion $e_t$, and sentiments $s_t$ are used to calculate overall Sentiments (S), Moods (M), and Emotions(E).

Table 4. Random values for calculation of behavior state of a sample ID for conversation $C_i$

| Time interval | $b_t$ | $c_t$ | $v_t$ | $s_t$ | $m_t$ | $e_t$ | $S=s_t*b_t$ | $M=m_t*v_t$ | $E=e_t*c_t$ |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.105 | 0.448 | 0.203 | 0.105 | 0.23 | 0.286 | 0.011 | 0.128 | 0.047 |
| 2 | 0.924 | 0.192 | 0.916 | 1.029 | 0.203 | -0.838 | 0.951 | -0.161 | 0.186 |
| 3 | 0.976 | 0.653 | 0.789 | 0.053 | -0.586 | -0.838 | 0.052 | -0.547 | -0.462 |
| 4 | 0.624 | 0.992 | 0.788 | 0.0913 | 0.202 | 0.39 | 0.057 | 0.387 | 0.159 |
| 5 | 0.86 | 0.523 | 0.607 | 0.0913 | 0.809 | 0.663 | 0.079 | 0.347 | 0.491 |
| 6 | 0.907 | 0.713 | 0.738 | 0.653 | 0.809 | -0.09 | 0.592 | -0.064 | 0.597 |
| 7 | 0.726 | 0.825 | 0.226 | 0.453 | 0.98 | -0.09 | 0.329 | -0.074 | 0.221 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 8 | 0.569 | 0.788 | 0.194 | 0.92 | 0.615 | 1.153 | 0.523 | 0.909 | 0.119 |
| 9 | 0.842 | 0.864 | 0.887 | 0.786 | 0.615 | 2.057 | 0.662 | 1.777 | 0.546 |
| 10 | 0.702 | 0.851 | 0.259 | -0.89 | 0.874 | -3.599 | -0.625 | -3.063 | 0.226 |

Random data was generated for total words, keywords, and the total count of event words (Table 5), to simulate text-based data for event intensity calculation. Equations 5, 6, and 7 are used to calculate values for S, E, and M, respectively, and then B is estimated by using equation 8. The aforesaid calculation will demonstrate the complete scenario of the system.

Table 5. Behavior state calculation from textual data for ID ,'0'

| **Conversation** | **ID** | **Tot_Words** | **Key_Words** | **Event_Count** | **Psi($\Psi$)** | **Beh_State** |
|---|---|---|---|---|---|---|
| 1 | 0 | 870 | 653 | 27 | 0.023 | Positive |
| 2 | 0 | 1554 | 1166 | 31 | .015 | Negative |
| 3 | 0 | 928 | 696 | 23 | 0.019 | Negative |
| 4 | 0 | 193 | 145 | 27 | 0.105 | Positive |
| 5 | 0 | 1421 | 1066 | 25 | 0.013 | Negative |
| 6 | 0 | 1533 | 1150 | 32 | 0.016 | Positive |
| 7 | 0 | 570 | 428 | 30 | 0.040 | Negative |
| 8 | 0 | 326 | 245 | 26 | 0.060 | Positive |
| 9 | 0 | 1338 | 1004 | 33 | 0.019 | Positive |
| 10 | 0 | 1892 | 1419 | 34 | 0.013 | Negative |

To show the graphical results, values for 30 observations have been generated, and for each conversation, a behavior state of each of the 4 IDs has been computed that can show the behavior pattern of that ID. Figure 4 (from A to D) shows the graphical representation of the behavioral states of different users who participated in conversations. The values of emotions, moods, and sentiments along with event intensity($\Psi$) are used to calculate behavior state for each conversation. The value of behavior can be either positive or negative which describes the user's behavior for each conversation as the sum of all values. Conversations are represented on the X-axis, while an estimated user's conduct, such as ID1, is represented on the Y-axis. Results show that ID1 usually exhibit the moderate behavior whereas ID2 shows the negative behavior. While ID3 shows great change for some interval of time which is natural, ID4 remains positive in almost all conversations.

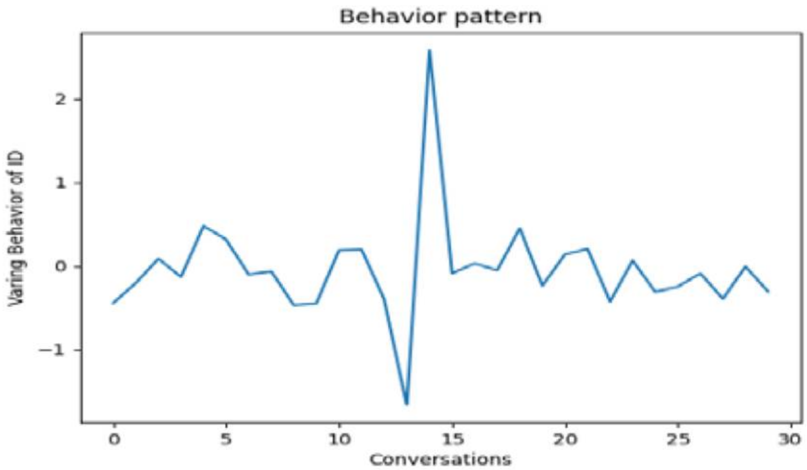


Figure 4(A). Behavoiur pattern of $ID_1$

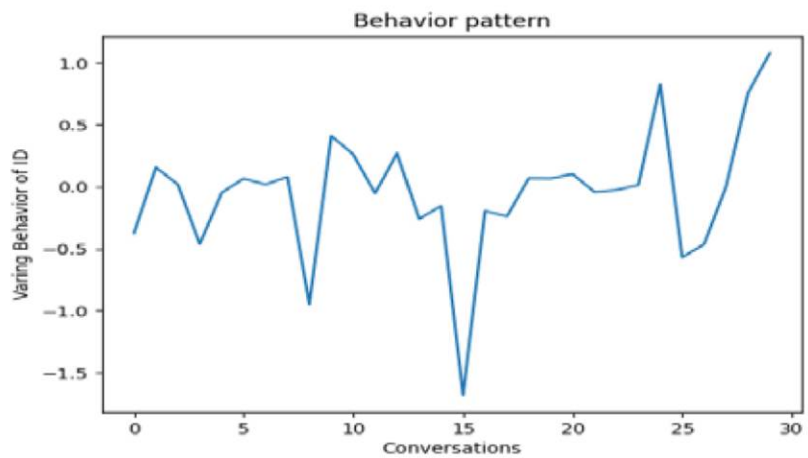


Figure 4(B). Behavoiur pattern of $ID_2$

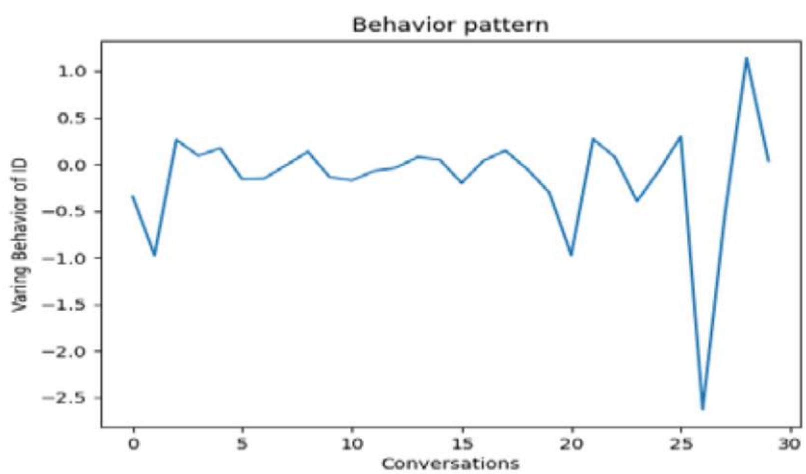


Figure 4(C). Behavoiur pattern of $ID_3$

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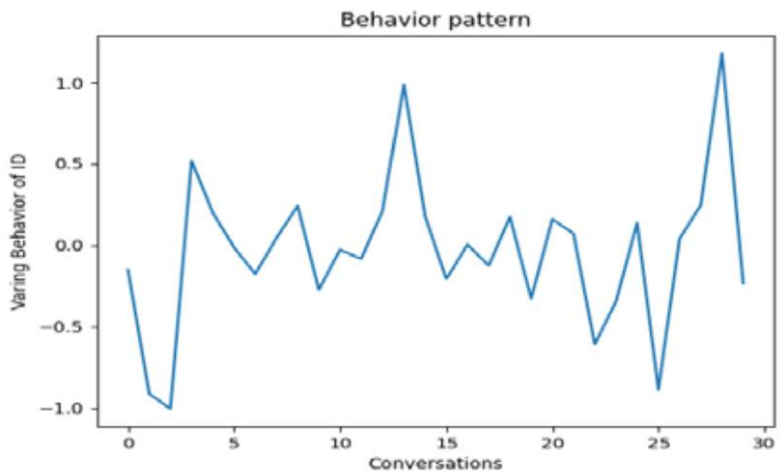


Figure 4(D). Behavoiur pattern of $ID_4$

### 4.2 Real data based results

A total of 70% of the datasets were used for training, with the remaining 30% for testing the system. Results were evaluated for nine conversations among 100 IDs who participated in opinion sharing at different intervals of time. The proposed approach has been tested on two different datasets, one of which consists of simple sentences and the other of which is a complex dataset generated from speech (Table 6).

Table 6. Parameter of the datasets

| **Dataset1 ( Simple dataset)** | | | | | **Dataset2 ( Complex dataset)** | | | | |
|---|---|---|---|---|---|---|---|---|---|
| No of Conversations | (Min-Max) no of comments per conversation | | (Min-Max). no of intervals per conversation | | No of conversations | (Min-Max) no of comments per conversation | | Min-Max). no of intervals per conversation | |
| 9 | 289 | 1609 | 23 | 25 | 9 | 1473 | 11481 | 18 | 23 |

#### 4.2.1 Classification-based emotion, mood, and sentiment prediction

The employed technique is temporal information extraction, in which each word representing mood, sentiments, or emotions is assigned a weight. For each conversation, the features, including emotions, sentiments, and moods, are predicted for certain IDs using multinomial Naïve Bayes and logistic regression approaches for both datasets (Table 7 and Table 8). Experiments show that for simple or well-defined sentences, prediction accuracy is high, while for sentences with mixed emotions or very short sentences, prediction accuracy is low.  However, prediction accuracy should be good because our model uses data from the prediction module to calculate behaviour.

Table 7. Comparison of classification techniques of emotions, moods, and sentiments for Dataset1

| Emotions | Naive Bayes Approach | | | Logistic Regression Approach | | |
|---|---|---|---|---|---|---|
| | Precision | Recall | F1 score | Precision | Recall | F1 score |
| Anger | 0.95 | 0.09 | 0.17 | 0.83 | 0.72 | 0.77 |
| Fear | 0.94 | 0.06 | 0.12 | 0.84 | 0.62 | 0.71 |
| Joy | 0.57 | 0.98 | 0.72 | 0.88 | 0.75 | 0.81 |
| Love | 1.00 | 0.01 | 0.01 | 0.54 | 0.83 | 0.65 |
| Sadness | 0.64 | 0.88 | 0.74 | 0.78 | 0.88 | 0.83 |
| Surprise | 0.00 | 0.00 | 0.00 | 0.56 | 0.78 | 0.65 |
| **Mood** | | | | | | |
| Good | 0.87 | 0.98 | 0.92 | 0.88 | 0.88 | 0.88 |
| Bad | 0.97 | 0.82 | 0.89 | 0.86 | 0.86 | 0.86 |
| **Sentiment** | | | | | | |
| Pos | 0.87 | 0.98 | 0.92 | 0.88 | 0.88 | 0.88 |
| Neg | 0.97 | 0.82 | 0.89 | 0.86 | 0.86 | 0.86 |

Table 8. Comparison of classification techniques of emotions, moods and sentiments for Dataset 2

| Emotions | Naive Bayes Approach | | | Logistic Regression Approach | | |
|---|---|---|---|---|---|---|
| | Precision | Recall | F1 score | Precision | Recall | F1 score |
| Anger | 0.06 | 0.00 | 0.00 | 0.19 | 0.26 | 0.22 |
| Fear | 0.00 | 0.00 | 0.00 | 0.02 | 0.01 | 0.01 |
| Joy | 0.32 | 0.06 | 0.10 | 0.31 | 0.18 | 0.23 |
| Sadness | 0.00 | 0.00 | 0.00 | 0.09 | 0.05 | 0.07 |
| Surprise | 0.34 | 0.05 | 0.08 | 0.24 | 0.17 | 0.20 |
| Disgust | 0.00 | 0.00 | 0.00 | 0.03 | 0.02 | 0.02 |
| **Mood** | | | | | | |
| Good | 0.40 | 0.59 | 0.47 | 0.41 | 0.49 | 0.45 |
| Bad | 0.37 | 0.18 | 0.24 | 0.36 | 0.45 | 0.40 |
| **Sentiment** | | | | | | |
| Pos | 0.39 | 0.11 | 0.17 | 0.39 | 0.20 | 0.26 |
| Neg | 0.39 | 0.71 | 0.51 | 0.41 | 0.52 | 0.46 |

#### 4.2.2 Behaviour recognition applying proposed mathematical model

The conversation is considered as a series of comments. Therefore, $m$, $s$, and $e$ are predicted for each comment, while event $e_v$and event intensity $\Psi$are calculated using the entire conversation.Finally, the result is obtained by putting all values in equation 5. For real datasets belief, cause and enviroment factor has been cosidered between 0 and 1. A tag or label has been assigned to participating IDs to maintain social trust on social networks (Table 9).

Table 9. Assigning social trust labels

| Data | No of IDs | Polarity | ID with social trust label |
|---|---|---|---|
| Dataset 1 | 36 | Negative | ID4, Most negative |
| | 46 | Positive | ID3, Most positive |
| | 18 | Neutral | Neutral |
| Dataset 2 | 58 | Negative | ID19,Most negative |
| | 33 | Positive | ID82, Most positive |
| | 9 | Neutral | Neutral |

The below-given graphs (Figure 5 and Figure 6) for both datasets show the most negative IDs, the most positive IDs, and those who remain neutral during all conversations. The results obtained from random observations show that an individual may have either positive or negative feelings or mixed feelings, which have been considered neutral and denoted by the PN state. A person turns positive after being neutral for a long time or would behave negatively under some discussion.

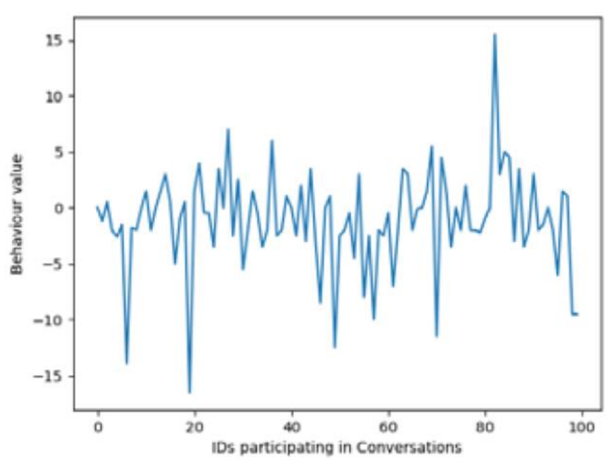


Figure 5. Behavior of each ID for Dataset 1

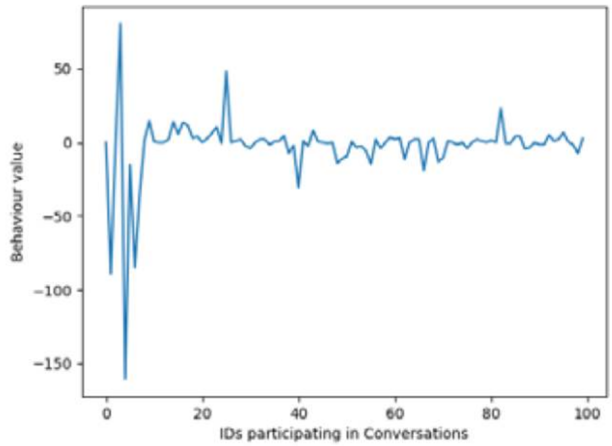


Figure 6. Behavior of each ID for Dataset 2

The following cases have been concluded after analyzing the obtained results:

Case 1: If a person stays in the P state, it indicates that the person is harmless.

Case 2: If a person stays in N state for various time-duration, he or she should be removed or warned, then removed.

Case 3: If a person changes states like P→P→N→P; it's normal for an individual to get emotional at the point under discussion.

When we created the Trust State log for real data it depicted that some IDs remain in a positive state or neutral state for instance ID3(dataset 1) while ID4(dataset 1) mostly uses bitter wordings so filter-out as a negative person or might harmful for others.

## 5. Conclusion

In the presented research work, an ensemble model has been proposed that detects human behavior using a mathematical model combined with natural language processing from textual data. The presented study shows that human behavior can be modeled as the function of mood, sentiments, and feelings of some individuals. Fennell et al., employed structured sum-of-squares decomposition (S3D) for the data such as stack exchange data, to identify the human behavior. S3D claims that it gives good performance for classification. If we compare S3D and proposed mathematical behavior model conceptually, it shows that NLP and mathematical formulation give a blend with vivid clarity for the structured sentences. Our model also requires less number of features. Simulation-based results show that the model is effectively performing the tasks where we used random numbers. For real datasets, it has been shown that runtime prediction of emotions and sentiments has been done with good accuracy for simple sentences. However, for complex and very short sentences, prediction accuracy was low. As stated in Section 3.3.1, belief, emotion's cause, and environmental elements are assumed to have constant values equal to 0.5, which is a limitation of the proposed work. Behavior state estimation can help us to predict the positivity or the negativity of some individuals that may ensure social trust on social networks. The proposed model evaluates and predicts the behavioral actions that can help achieve the following:

1. Textual data can be a good tool to reveal the hidden intentions, thoughts, sentiments, or emotions which can consequently help predict the forthcoming activities of individuals in term of positive or negative attitude. Any individual who remains in negative state, according to our model possesses negative nature and could be ignored.
2. A huge amount of data is available on social networks and, by applying machine learning techniques, hidden thoughts in terms of words might be discovered from texts.
3. Behavior at various times can assist in filtering out people with negative or positive intentions
4. Based on the mathematical modeling, a software system can give a suggestion to the individual about other user's trust level.
5. Behavior identification through technology can resolve the fear of scamming efficiently.

## 6. Future Work

In the future work, proposed technique will be applied to compute the behavior of social network users in the context of some specific events. Using evaluation of text in terms of mood, emotions, and sentiments, and machine learning; a categorization model for different actions with respect to some specific event will be designed.

**Conflicts of interest**

The authors declare that they have no conflicts of interest to report regarding the present study.

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