Perceptible Sentiment Analysis of Students' WhatsApp Group Chats in Valence, Arousal, and Dominance Space

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Abstract

Sentiment analysis is a vastly established domain for social media monitoring, feedback insights, and commercial or political campaigns, as it allows us to gain an overview of the wider public opinion on certain topics. Nowadays, different social media platforms play a crucial role in web-based sentiment analysis and emotion detection from distinct perspectives. Likewise, WhatsApp is probably the most popular messaging app, allowing users to send messages, images, audio, or videos. However, it is still highly under-explored for any type of linguistic synthesis and analysis. Like many other groups of people, students use WhatsApp for various purposes, even more since the last two years of the pandemic phase. For instance, class communication, study group communication, etc. In this paper, we present a novel approach to analyze the sentiments and emotions of students in valence, arousal, and dominance space by classifying the messages from their WhatsApp group chat. The emotional dimensions of Valence, Arousal and Dominance (VAD) can derive a person's interest (attraction), level of activation, and perceived level of control for a particular situation from textual communication. We propose a vanilla SVM model fused with a language classifier to calculate each message's sentiment ratings. Finally, using the SVM classifier we classify the sentiment ratings concerning the degree of the VAD scale. The data were analyzed using a qualitative content analysis method. The results of the study in the form of cumulative sentiment scale and sentiment clustering in VAD space reveal that the students' WhatsApp groups were mostly used for sharing information, exchanging ideas, and discussing issues, with mostly neutral to positive sentiment viewpoints for the provided topics of discussions.

1. Introduction

Sentiment Analysis and Emotion Detection have been the subject of research attention for a decade now [1–5]. The majority of these works and overall sentiment classification have also experimented with the opinions of other social media users who use similar platforms. On large tweet corpora, the three fundamental perspectives of sentiment analysis: document level [6], sentence level [7], and aspect level sentiment analysis [8], have been applied in a variety of ways. These works go into great detail to explain whether a whole opinion document is positive or negative [9]. The level of analysis that is closely related to subjectivity classification is brought out even more by this filtration process [10]. Additionally, entity-level or aspect-based sentiment analysis concentrates solely on the opinion itself. It is based on the idea that an opinion is made up of a target and a sentiment—whether positive or negative. An opinion that does not specify its target is useless [11]. A structured summary of opinions about entities and their aspects can be produced based on this level of analysis. This transforms unstructured text into structured data that can be used for any kind of qualitative and quantitative analysis. These days, billions of people use social media for expressing their views and emotions toward others on different issues. This paper presents an approach to analyze the sentiment of students regarding their daily college life, day-to-day classes, and career opportunities from their social discussion. To make the model more efficient, we need lots of data, so our primary focus is to collect data from largescale data producers like WhatsApp, owned by Facebook. WhatsApp claims that nearly 55 billion messages are sent each day. The average user spends 195 minutes per week on WhatsApp and is a member of plenty of groups. So, we created a WhatsApp group of some post-graduate students where they can share their thoughts. Finally, we successfully exported the chat data from the group to build the dataset. This exported chat has been pre-processed for better computation all the messages are separated and sentiment analysis is applied to each of them. Sentiment analysis is a method or subprocess of natural language processing and data mining that is used for the identification of a user's opinion or emotion. Also, this concept works on the core principles of machine learning where a data set (corpus in terms of NLP) is used to train and process that data and a model is generated and used for evaluation of the emotion of text chat. We use the NLTK-based model to compute the sentiment ratings of the messages and for further classification, we used a machine learning classifier to classify the messages based on their Valence, Arousal, and Dominant scores. Finally, the result of our research shows that users consider the emotional expression of all kinds of sentiments as valid on social media.

1.1. Motivation & Objectives

In this decade the upcoming technologies are mainly dependent on data. This data can only be obtained if there is some research applied in the context of the requirements of the tool. Since a lot of machine learning enthusiasts develop models which help solve multiple problems the requirements of appropriate data are very large scale this project aims to provide a better understanding of various types of chats. This analysis proves to be better input to machine learning models which essentially explore the chat data. These models require proper learning instances which provide better accuracy for these models. Our project ensures to provide an in-depth exploratory data analysis on various types of WhatsApp chats. The remaining part of this paper is structured as follows. Section 2 describes some state-of-the-artwork related to our proposed approach. Section 3 presents the detail of our proposed methodology. The collection and pre-processing of data are presented in section 4. In section 5 we present the sentiment analysis on the pre-processed dataset. Section 6 presents the classifier deployment for the classification of the sentiment ratings in VAD dimensions. The conclusion and our future work are presented in section 7.

2. Related Works

Sentiment analysis is a process of computationally analyzing and identifying opinions and feelings from a piece of text. The sentiment analysis can be implemented for different purposes– Aspect-based, Document-level, and Sentence-level sentiment analysis. The Aspect-based sentiment analysis is a text analysis technique that categorizes data by aspect and identifies the sentiment attributed to each one [12]. The Document-level [13] sentiment analysis module analyzes a whole document containing a chunk of text to determine the sentiment of the text e.g., positive, negative, or neutral. Sentence-level sentiment analysis [14] is one of the main directions in the sentiment analysis area. Numerous research works on this domain concentrated on recognizing the polarity of a sentence (e.g., positive, neutral, negative), according to semantic information learned from the textual content of sentences.

In the year 2015, some researchers [15] found that the Document-level sentiment analysis can be improved by using Rhetorical Structure Theory which describes the structure of a document in terms of text spans that form discourse units and the relations between them. From this research, it is evident that reweighting the discourse units based on their position in a dependency representation can improve lexical-based sentiment analysis. Finally, they proposed a recurrent neural network over their evaluated data to further improvements in sentiment classification [16]. A document can comprise multilingual text phrases also; especially if it is an interpretation document or language rendering. A research work

demonstrates the machine translation of multilingual sentence-level sentiment analysis. In their experiment, they evaluated the sentiment prediction accuracy of 21 English sentiment-level methods on different datasets in 9 different languages. As the result, they found that SO-CAL, Union, and Vader methods have performed well on different datasets based on Macro-F1 score and Coverage [17]. Since the linguistics analysis contains layers of parse trees for tokenization and lemmatization, hence the deep analytical expressions of linguistics heavily rely on statistical models.

A group of researchers developed a three-stage statistical hybrid model to detect explicit and implicit polarity shifts from the reviews. After the elimination of the identified polarity shifts using the antonym reversion method, the piece of text is divided into four subsets as polarity-unshifted text, eliminated negations, explicit contrasts, and sentiment inconsistency. Finally, they trained different base classifiers on these textual subsets and computed a weighted ensemble as the final layer of the sentiment classifier to decrease the polarity shifts [18]. Polarity shifts in reviews are a common thing; however, most online reviews are free from meticulous linguistic synthesis; however, aspects are the primary things that have the most significant influence on any feedback or review. A recent research work presents an aspect-based sentiment analysis of different product reviews. After the pre-processing of data using part-of-speech (POS) tagging the researchers used Chi-Square probability distribution to extract highly relevant words from each opinion. At last, they used the Naïve Bayes classifier for sentiment classification of the polarity ratings and as the result, their model achieved 78.21% of the highest F1-score [19].

In 2016, some researchers proposed a group discussion model to analyze the sentiment of the messages from the group discussion. They also determined what has been decided and how the discussion is going on in an organized and fair way [20]. Another research work concludes that the clustered model can improve sentiment classification performance on two large collections of opinionated reviews. The researchers identified latent user groups by imposing a Dirichlet Process before the individual models [21]. In 2018, some researchers proposed an algorithm to find the person who is deviating from their normal behavior using unsupervised learning (clustering) and further classifying them into predefined categories. They used Latent Dirichlet Allocation (LDA) for extracting the relevant tweets from their dataset. The proposed approach helps to detect the drastic negative change in behavior so that a preventive measures can be taken to avoid any mishap [22]. A research work describes a novel approach for analyzing sentiment and emotions of the students in an online classroom so that the instructor can gauge their efficiency and can target interventions at both the population and individual levels. They presented two approaches for assessing the sentiment of a large population of learners. The first approach helps to analyze a large body of learner-generated posts and determining the overall sentiment. The second approach is used to analyze individual learners to target specific interventions to maximize their success [23].

In sentiment analysis, data visualization is an important part that helps us to understand the nature of the data through several visual representations. Another research work demonstrates 132 different data visualization techniques on sentiment-rated data using a fine-grained categorization comprising 7 groups with 35 categories respectively [24]. The NLP-based approach for detecting the fake message circulated on WhatsApp was proposed by some researchers. Initially, they identified the most common features of these fake messages and then they trained the Random Forest classifier on the fake message dataset. After completion of training, they used the trained classifier to classify the collected WhatsApp messages from the dataset and the model achieved 65% classification accuracy on the validation data [25]. A group of researchers proposed a methodology for analyzing textual information from WhatsApp groups and identified the presence of misinformation in the contents of these messages using a dataset of priorly checked misinformation from six Brazilian fact-checking sites. From the Bag-of-Words model, they represented TF-IDF vectorial representation of the textual data to compute the textual similarity using the cosine similarity. By using LDA topic modeling they identified textual messages with misinformation that is more concentrated on fewer topics, related to presidential candidates and government projects [26].

In the year 2019, a similar research work presents the application of a technique that tries to determine the semantic content of a text on a higher level of abstraction, namely sentiment analysis. From the representation of the linear fit model, they found human and algorithm evaluation has the best correlation for sentiment, while acceptance and annoyance they are negatively correlated. In their research work, it is evident that the accuracy of the algorithm compared to human judgment for both overall sentiment (65.92%) and the emotion with the highest k-value, optimism (54.8%) [27]. A few researchers proposed a model-agnostic and task-agnostic testing methodology named CheckList that tests individual capabilities of the model using three different test types. Checklist applies the behavioral testing principle of “decoupling testing from implementation” by treating the model as a black box, which allows for comparison of different models trained on different data, or third-party models where access to training data or model structure is not granted [28]. In the year 2021, a neural group-wise sentiment analysis model with data sparsity awareness is proposed. The user-centered document representations are generated by incorporating a group-based user encoder. Furthermore, a multi-task learning framework is employed to jointly model users’ rating biases and their degree of rating consistency. The initial task of the framework is vanilla population-level sentiment analysis and the other is Groupwise sentiment analysis [29].

In traditional media different form of text is available from which microblogging texts are short, noisy, and embedded with social relations. Zhang et al. proposed a novel sociological approach (SANT) to handle networked texts in microblogging [30]. They extracted sentiment relations between tweets based on social theories, and model the relations using the Laplacian graph, which is employed as a regularization to a sparse formulation to facilitate sentiment classification and effectively handle noisy

Twitter data. They developed an optimization algorithm for SANT to achieve consistent performance for different sizes of training data, a useful feature for sentiment classification. This approach is valid for most the social media blogs, posts, and texts, since the nature of such texts on social networks is often unstructured and none to semi-automated. Semi-automated sentiment analysis was developed based on the online social network using the probability model. In 2018, a group of authors proposed a model that reads sample text messages in a train set and builds a sentiment lexicon that contains the list of words that appeared in the text messages and the probability that a text message is a positive opinion if it includes those words [31]. Then, it computes the positivity score of text messages in a test set using the list of words in a message and sentiment lexicon. Each message is categorized as either positive or negative, depending on the threshold value calculated using a train set.

Analyzing text data from Twitter for meaningful insight has been a prime focus of research attraction since the early last decade. In 2016, a few researchers found that using Bidirectional LSTM with two-dimensional max-pooling improves text classification [32]. They introduced two combinational models one is BLSTM-2D Pooling and the other is BLSTM-2DCNN, which can be seen as an extension of BLSTM-2D Pooling. They achieved 52.6% of the highest accuracy with 2D filter size (5,5) and 2D max-pooling size (5,5). Following a similar research context, Wang et al. (2019) demonstrated a system for a possible combined approach between Social Network Analysis and Sentiment Analysis, which can operate on Twitter data [33]. They collected three types of data and used a classifier based on the Multinomial Naive Bayes algorithm to identify the tweets from different sentiment classes. They experimented with their approach on a couple of Twitter channels like the SamSmith channel during the Grammy Awards in 2015, and the #Ukraine channel during the crisis of 2014. They also mentioned a methodology and some guidelines for the automatic classification of Twitter content.

Social networks are not only about text data. Every form of media, such as video and audio on diverse topics and contents arcontented on all the popular social media. Videos, in fact, play a significant role in influencing or shifting people's opinions. Research work from 2014 describes the use of a multimodal feature learning approach, using neural network models such as Skip-gram and Denoising Autoencoders, to address sentiment analysis of micro-blogging content like tweets, that is composed of a short text and, possibly, an image [34]. The authors developed a semi-supervised model CBOW-LR for learning concurrent vector representation. By using a sentiment polarity classifier, the model achieved better accuracy over CBOW representation on the same quantity of tweets. For learning text and image representation another unified model (CBOW-DA-LR) works in an unsupervised and semi-supervised manner, and obtained a higher classification accuracy compared to SentiBank, a state-of-the-art approach on a publicly available Twitter dataset. Some researchers describe the Message-level and Topic-based sentiment analysis using a deep LSTM architecture [35]. It has been established that the LSTM networks are associated with two types of attention techniques, on top of word embeddings which have been pre-trained on a big collection of Twitter messages. For such corpus, Long Short-Term Memory (LSTM) networks are augmented with two different types of attention mechanisms. Additionally, the authors present a text processing tool for social network messages that performs segmentation, tokenization, word normalization, and spelling correction. For classification, their model is said to have performed exceptionally well, whereas, in the qualification tasks, they performed inconsistently.

3. Methodology

In the initial phase of our overall implementation, we mainly focus on the data collection part. We consider WhatsApp messenger as it is one of the most popular messaging platforms. We create a WhatsApp group of university students where they can share their thoughts regarding their career opportunities, daily classes, and many more. Finally, we export the group chat in textual format for pre-processing phase. Data pre-processing helps to remove noisy data which may consist of grammatical errors, misspelled words, extra white spaces, numbers, URLs, etc. After cleaning the dataset, we visualize some most important features of the dataset. We identified the active timing of the users, user activity in the group, most popular words used by the users of the group as the main features of the dataset. In the next phase, we introduce a Support Vector Machine associated with the TextBlob classifier to analyze the sentiment of the text from the dataset. Then we extracted the negative sentiment expansion concerning each participating person and plotted the negative to positive sentiment range mapping for each person in the group. Next, we extracted the popular unigrams to find the most popular used words in the group chat followed by Part-of-Speech tagging. Later we compared our extracted gram with several gold-standard lexicons to ensure the quality of our collection data. Finally, we use an SVM classifier to classify the sentiment-rated data concerning the degree of Valence, Arousal, and Dominance and plot the ratings in a 3D plane for visualization. In Fig. 1 we present the proposed methodology for the workflow.

4. Data Preparation

In the last few years, research on social media platforms in the form of data science and sentiment analysis has seen a major leap. The most popular platform regarding these experiments is Twitter, due to its public API tweet streaming access to the researchers (only 1%-2% of the total number of tweets), and the sheer volume of Twitter data. Other open community sites like Reddit, GitHub, and Pinterest are also popular in this particular domain of work. However, for our approach, we took the initiative to begin with WhatsApp texts. It is widely known that WhatsApp chats are end-to-end encrypted and they cannot be manipulated or tailored from any outside source. Only a member of a group can export a chat in text or other common textual formats to use it for any type of analytics. Hence the probability of intrusion or altering the users' opinions is prohibited. Moreover, in WhatsApp, whenever a group is created with several persons, that particular group is centrally focused on a mutually common topic of conversation. It can be an academic-related group created by the students, an office colleagues' group, a group about science and technology enthusiasts, and so on. But the common factor among all of these groups and further are:

- ,Unlike Facebook, no person from outside can come to know about that group, look for its members and try to join it.

- Also, a person only can join a WhatsApp group by an invitation sent to him by any of the admins or members of that group. However, only admins can add a member to a group.

These features make a WhatsApp group more secure, robust, and highly compact towards a particular topic or multi-topic of conversations. One downfall can be the size of the data volume of these chats; as WhatsApp groups are closed-proximity conversations with a number of people, though the chats are clean and topic-relevant, also, lack in volume.

For our approach, we created a group with 20 undergraduate (UG) students, focusing primarily on whether they are facing any obstructions or problems in their respective academic careers. Here the first author was a student representative, admin, and a mediator as well in the group, while the second author, being also a faculty member, was not part of the group, for the obvious reason of keeping the students' views, opinions, and sentiments biasness free and censorship-free. The chat was initiated from 5 p.m. onwards on 25th August 2022, and gradually the number of messages increased until it was midnight.

A proportional view from the conversations:

Student-1

I think introducing ML in under-graduation will give us an advantage over the other courses..

Student-2

That's ok. But how can you ignore the core Computer Science subjects?

Student-3 (Replying to Student-2)

Yeah right! They are like the building blocks for us

Student-1

I'm not ignoring them, but AI-ML-NLP really is the skill to master nowadays.

Mediator

Okay guys, I don't think there is any point of argument over here. In my opinion every bit of skill and knowledge is important to learn.

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On the other hand, obviously the students could not participate in the conversations during a large amount of daytime, as they are involved in classes at university and several other activities.

We represent the timeframe of the message exchanges on hourly basis in Fig. 2.

Based on the data collection process, we plotted another graph in Fig. 2, which depicts the activity of the group members within the group. Each person is labeled here with a different color scale for recognizability. Obviously, as the admin and moderator, one of the researchers (from us) created the group and initiated the conversation, also, elaborated to the students about what is the focus and objective of the group. Hence his number of messages sent and participation in the chats is much higher than that of the others. We represent this graph in Fig. 3 below:

5. Approach For Sentiment Rating

We used an NLTK-based SVM model associated with the TextBlob classifier for our sentiment rating against each user's chats (messages). We chose the rule-based SVM as it is capable of operating in the n dimensions hyperplane to create separable margins to label negative and positive data for each person. For fragmenting each message is separated into single words, and the descriptive function of SVM is given in Eq. 1 as below:

$$[M \approx w(X\ )] = zx\phi\,(X) + c\,(1)$$

Where the feature vector is represented by X. In our experiment, the most number of messages from any user within the closed group can be considered as the feature, because the more a person is willingly participating in the conversation, the more he or she wants to express themselves, which is a key point to achieve the sentiments. z suggests the vector of different weights, which is the frequency of a word that occurred. And non-linear mapping function is given by φ and c is the bias vector. Both z and c learn from the training data set automatically. We used the gold standard datasets such as the training data, and we fit our exported chat from the WhatsApp group as the testing set for our model. We have applied the linear kernel for sentiment classification. That is why it maintains the wide gap between the two classes. As compared to a Naïve Bayesian classifier, SVM produces higher precision and recall. We present the person-to-sentiment rating generated from our sentiment generator model in Table 1 below:

Table 1
Negative and positive ratings against each user with their IDs along with absolute prediction.

ID of Students	Negative Rating	Positive Rating	Absolute Prediction
ID-01	Negative: -3.499480881230387	Positive : 6.2804482836569338	Overall Evaluation: Positive
ID-02	Negative : 0.3010299956639812	Positive : 0.3010299956639812	Overall Evaluation: Neutral
ID-03	Negative : -7.299991758124754	Positive : 4.393760150911112	Overall Evaluation: Negative
ID-04	Negative : 0.3010299956639812	Positive : 0.3010299956639812	Overall Evaluation: Neutral
ID-05	Negative : -3.499480881230387	Positive : 1.2804482836569338	Overall Evaluation: Negative
ID-06	Negative : -5.139794083330566	Positive : 8.630004772075992	Overall Evaluation: Positive
ID-07	Negative : -3.3233896221747057	Positive : 6.648425068951528	Overall Evaluation: Positive
ID-08	Negative : -7.643150688908429	Positive : 3.610821455703652	Overall Evaluation: Negative
ID-09	Negative : -7.11619607680684	Positive : 4.15702373549396	Overall Evaluation: Positive
ID-10	Negative : -5.05176529507063	Positive : 6.01360164306416	Overall Evaluation: Positive
ID of Students	**Negative Rating**	**Positive Rating**	**Absolute Prediction** O
ID-11	Negative : -3.0223596265107244	Positive : 5.1713038142318655	Overall Evaluation: Positive
ID-12	Negative : -2.774453195557886	Positive : 5.321050298592194	Overall Evaluation: Positive
ID-13	Negative : -4.194891183991096	Positive : 7.47369680531234	Overall Evaluation: Positive
ID-14	Negative : -5.715830082576637	Positive : 2.1203993908708	Overall Evaluation: Negative
ID-15	Negative : -5.67165463989372	Positive : 6.612041148893134	Overall Evaluation: Negative
ID-16	Negative : -1.26751798218954	Positive : 3.913674212556305	Overall Evaluation: Positive

ID of Students	Negative Rating	Positive Rating	Absolute Prediction
ID-17	Negative : -6.890099640662104	Positive : 2.120815790630644	Overall Evaluation: Negative

For the above-generated sentiment rating table, we have basically used 3 labels with range of -10, 0 and 10. Here the – 10 represents negative range, 10 represents positive range and 0 as the pivotal point or the neutral centre point for capturing the neutral opinionated messages. We label the negative sentiments as N_s and positive sentiments as P_s, where:

$$\sum_{s=0ton-1} N \approx N_s = N_{s0} + N_{s1} + N_{s2} + \ldots \cdots + N_{s17}$$

2

and,

$$\sum_{s=0ton-1} P \approx P_s = P_{s0} + P_{s1} + P_{s2} + \ldots \cdots + P_{s17}$$

3

Here, *s* is the sentiment labeling for each corresponding person.

Both the opinions from the negative and positive range can head towards 0, even if they do not converge, the closeness of any negative or positive opinion with the central neutral point can help us to determine how these opinions are leaning towards the neutral opinion. Not only that, since a message can both have negative and positive flavors within it, hence our model generated two labels for each person, as we used a model for non-separable patterns. Furthermore, these bi-ratings are helping us to mathematically understand how much the person is depending towards negative sentiment or positive sentiment to express his or her opinion about a particular academic topic. At next, depending upon the sentiment which is scoring a higher rating within the range of -10 or 10, the absolute predictions are made against each person on which class exactly their sentiments belong to. These class ratings are given to an SVM classifier to classify the ratings for fitting them in the valence, arousal and dominance space.

From the sentiment ratings of each person, we plotted a graph in Fig. 4 to measure the sentiment peaks with respect to time. The graph is as following:

Also, as the negativity can have a greater impact on further VAD values, we tried to plot each person negative sentiment range with respect to sequential users (along with their ID tags) participating in the group conversation. We represent the polar scatter chart in Fig. 5 as following:

6. Deploying Svm Classifier

Support Vector Machine or SVM is a supervised machine learning algorithm which can be used for both classification or regression challenges. Classification is predicting a label or group and Regression is predicting a continuous value. For our approach, we obviously took the approach for the classification problem solving using the SVM. SVM performs classification by finding the hyper-plane that differentiate the classes we plotted in n-dimensional space. SVM draws that hyperplane by transforming our data with the help of mathematical functions popularly also known as the Kernels.

There can be multiple numbers of SVM kernels to choose from. Tuning the kernel is equally important for the best classification and fitting of data. We have used the Sigmoid function as the kernel of our classifier model. The main reason why we used the sigmoid function is that it is a differentiable function with a fixed range. That means, we can find the slope of the sigmoid curve at any two points, be it a negative one or a positive one. While being neutral about any certain given topic usually does not exhibit any natural or unnatural behavioral conditions, hence we have ignored the neutrally opinionated messages for these classifications. That being said, it will obviously help to classify two distinct labels of class data (here negative and positive) with a steep learning curve. Therefore, it is especially used for models where we have to predict the probability as an output, especially which is nonlinear in nature. Combinations of this function are also nonlinear, which helped us to develop our SVM classifier based on this kernel function to work properly in a hyperplane region.

Also, the sigmoid function tends to bring the activations to either side of the curve (above x = 2 and below x = -2 for example), making clear distinctions on predictions for both the + ve and -ve ranges of positive and negative sentiments.

We depict the model kernel function (or activation function) used in our classifier below:

Now, for the traditional rule based SVM classifier model, for achieving the optimal hyperplane for non-linearly separable patterns, the margin level of separation between the negative and positive classes can be labelled as considerable allowance if a data point consisting the negative and positive sentiment from Eq. (2) and Eq. (3) breaches the following condition:

$$\sum_{s=0ton-1} N_s \sum_{s=0ton-1} P_s = \frac{(\omega^T + b)}{NP} \geq +1$$

4

Where ω is the adjustable weight vector, and T is the index of weight, b is the bias.

Here, hypothetically two cases can arise.

- Either N_s P_s are naturally separable but on the same side of the marginal space. In that scenario, they also belong into the non-hyperplane category.
- Or, N_s P_s are non-naturally separable and falls on both sides of the marginal surface. This is a classic non-linearly separable hyperplane problem, which is the working forte of an SVM classifier. We are

separable patterns.

For formally treating these non-separable sentiment ratings (patterns) on a common plane, for classifying the point locations from their regions, we derive the following equation further from Eq. (4):

$$\sum_{s=0ton-1} N_s \sum_{s=0ton-1} P_s = \left(\omega^T + b\right) \geq 1 - \in_{N,P}$$

5

Where $\in$ is the variable for common point mapping of both negative and positive ratings, hence $\in_{N,P}$.

For $0 < \in_{N,P} \leq 1$, the data point is existing inside the separable region, and for $\in_{N,P} > 1$, existing inside the non-separable hyperplane.

5.1. Deploying the SVM Classifier

The measuring of VAD rating is primarily associated with the SVM classifier model for better understandability of the labelled classes and thereafter accurate mapping of each of the 3 coordinates into a common 3-dimensional hyperplane. The sentiment rated scores for each person's ID is fed to the classifier model for per person valence, arousal calculation and determining the dominance from these already derived two factors. The range of the persons' individual VAD score is computed by taking both of their negative and positive ratings, which depict their mindset while taking painnto a conversation. For each case, our Valence and Arousal may have an inversely proportional value, because often stating something most negative or something actually positive from our comfort zones (valence) does not activate the stimulus, hence the state (arousal) remains fairly low in these cases. To calculate the VA factor, we derived our formula from SentiStrength [36] [37], which is a state-of-the art strength tool to measure the negativity or positivity in the valence and arousal region. The average VA values calculated are W_{avg}, which is the mid-point and the maximum and minimum values are W_{max} and W_{min} respectively, where either of the peak valence or arousal values cannot come down below the mid-point, also the surface values of valence and arousals can reach beyond the average mid-point.

More formally, our equation is as follows:

- For both negative and positive:

$$\text{Valence (V) and Arousal (A)} \approx \left[\begin{array}{l} W_{max} \geq W_{avg}, \text{ if } (W_{max} > W_{min}) \\ W_{max} \geq W_{avg} \geq W_{min} \text{ if } (W_{avg} > W_{min}) \\ Win < W_{avg} \text{ if } (W_{max} > W_{min}) \end{array}\right] \qquad (5)$$

Where W is score of valence and arousal respectively.

Following up these equations, we determined the valence and arousal scores as a percentage (out of 100%) for each participating person in the group conversation. As we already mentioned hypothetically, we practically also observed wherever the valence scores are high, the corresponding arousal scores are low for the same person, and vice versa.

Next, we further calculated the dominance as the median between the VA factors in the same common plane. While the average sums up all the numbers and divides them by the numbers in the set, the median is the middle point of a number set, in which half the numbers are above the median and half are below. For our dominance score calculation, we chose to determine it as the median because, this particular dominance center point generated from the median series for each person can help to establish a threshold value, and the valence or arousals breaching that margin can be labeled as the abrupt showcase of sentiment. Formally, our dominance deterministic equation holds as:

For an odd number of values (here participants):

Dominance Median (D_M) = $b\left\{\frac{(n+1)}{2}\right\}^{th}$ (6)

Where '*n*' is the number of participants in the conversation, '*b*' is the central tendency coefficient and '*th*' signifies the *(n)the* number. Following this equation, we plotted the scatter graph in Fig. 7.

From the graph, we can observe that the dominance is acting as a threshold rift between valence and arousal. It is the margin between the other two parameters to predict the normal and abnormal spikes of comfort and stimulus of any person while participating in a conversation on a given topic. The spikes that are exceeding the marginal dominance threshold, can thus be stated as the abrupt peaks of valence and arousal. From this graph, we also plotted a 3D coordinate cluster within the VAD region. We represent it in Fig. 8 as follows:

Where the Valence, Arousal, and Dominance represent the '*x*', '*y*', and '*z*' coordinates respectively. Here each dot is representing their respective coordinate's scores, and as we can visualize naturally, there is a threshold margin within the range of 65 to 70. That is the region of center dominance, which is precisely 66.1883835. That is where the threshold margin is established, and very few numbers of other scores have breached that. The scores which have breached this margin of center dominance point, be it negative or positive, can be stated as a hyper condition of mind, which is not a natural expression of sentiment. Even if a few of these sentiments are positive, the abrupt spikes in their ratings from Fig. 7 can help us to understand that these positive sentiments can very well be 'fake positives', as the persons conveying them are going above the central dominance margin, i.e., their perception of the situation that they can control.

7. Conclusion

This paper contributes a novel representation of the sentiment analysis technique based on data collected from Students' WhatsApp groups. Different extracted features have been presented through several visualizations. To calculate the sentiment ratings, we used a reliable machine learning model i.e., the Support Vector Machine associated with the TextBlob classifier, and the SVM classifier is used to classify the sentiment-rated data into 3D VAD space to understand the proper distribution of the data. For future work, we will try to apply the transformer-based or hybrid approach to achieve better prediction accuracy on categorical data.

References

1. Pak, A., & Paroubek, P. (2010, May). Twitter as a corpus for sentiment analysis and opinion mining. In LREc (Vol. 10, No. 2010, pp. 1320-1326).
2. Pandarachalil, R., Sendhilkumar, S., & Mahalakshmi, G. S. (2015). Twitter sentiment analysis for large-scale data: an unsupervised approach. Cognitive computation, 7(2), 254-262.
3. Das, S., & Kolya, A. K. (2017, November). Sense GST: Text mining & sentiment analysis of GST tweets by Naive Bayes algorithm. In 2017 third international conference on research in computational intelligence and communication networks (ICRCICN) (pp. 239-244). IEEE.
4. Das, S., Das, D., & Kolya, A. K. (2020). Sentiment classification with GST tweet data on LSTM based on polarity-popularity model. Sadhana, 45(1).
5. Turney, P. (2002, July). Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews. In Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics (pp. 417-424).
6. Canales, L., & Martínez-Barco, P. (2014, October). Emotion detection from text: A survey. In Proceedings of the workshop on natural language processing in the 5th information systems research working days (JISIC) (pp. 37-43).
7. Wiebe, J., Bruce, R., & O'Hara, T. P. (1999, June). Development and use of a gold-standard data set for subjectivity classifications. In Proceedings of the 37th annual meeting of the Association for Computational Linguistics (pp. 246-253).
8. Hu, M., & Liu, B. (2004, August). Mining and summarizing customer reviews. In Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 168-177).
9. Liu, B. (2012). Sentiment analysis and opinion mining. Synthesis lectures on human language technologies, 5(1), 1-167.
10. Montoyo, A., MartíNez-Barco, P., & Balahur, A. (2012). Subjectivity and sentiment analysis: An overview of the current state of the area and envisaged developments. Decision Support Systems, 53(4), 675-679.
11. Jiang, L., Yu, M., Zhou, M., Liu, X., & Zhao, T. (2011, June). Target-dependent twitter sentiment classification. In Proceedings of the 49th annual meeting of the association for computational linguistics: human language technologies (pp. 151-160).

12. Chatterji, S., Varshney, N., & Rahul, R. K. (2017). AspectFrameNet: a frameNet extension for analysis of sentiments around product aspects. The Journal of Supercomputing, 73(3), 961-972.
13. Behdenna, S., Barigou, F., & Belalem, G. (2018). Document level sentiment analysis: a survey. EAI Endorsed Transactions on Context-aware Systems and Applications, 4(13), e2-e2.
14. Araújo, M., Pereira, A., & Benevenuto, F. (2020). A comparative study of machine translation for multilingual sentence-level sentiment analysis. Information Sciences, 512, 1078-1102.
15. Bhatia, P., Ji, Y., & Eisenstein, J. (2015, September). Better Document-level Sentiment Analysis from RST Discourse Parsing. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing (pp. 2212-2218).
16. Araujo, M., Reis, J., Pereira, A., & Benevenuto, F. (2016, April). An evaluation of machine translation for multilingual sentence-level sentiment analysis. In Proceedings of the 31st Annual ACM Symposium on Applied Computing (pp. 1140-1145).
17. Xia, R., Xu, F., Yu, J., Qi, Y., & Cambria, E. (2016). Polarity shift detection, elimination and ensemble: A three-stage model for document-level sentiment analysis. Information Processing & Management, 52(1), 36-45.
18. Mubarok, M. S., Adiwijaya, & Aldhi, M. D. (2017, August). Aspect-based sentiment analysis to review products using Naïve Bayes. In AIP Conference Proceedings (Vol. 1867, No. 1, p. 020060). AIP Publishing LLC.
19. Ma, B., Yuan, H., & Wu, Y. (2017). Exploring performance of clustering methods on document sentiment analysis. Journal of Information Science, 43(1), 54-74.
20. Morente-Molinera, J.A., Kou, G., Peng, Y., Torres-Albero, C. and Herrera-Viedma, E., 2018. Analysing discussions in social networks using group decision making methods and sentiment analysis. *Information Sciences*, *447*, pp.157-168.
21. Gong, L., Haines, B. and Wang, H., 2017, April. Clustered model adaption for personalized sentiment analysis. In *Proceedings of the 26th International Conference on World Wide Web* (pp. 937-946).
22. Jindal, S. and Sharma, K., 2018. Intend to analyze Social Media feeds to detect behavioral trends of individuals to proactively act against Social Threats. *Procedia computer science*, *132*, pp.218-225.
23. Schubert, M., Durruty, D. and Joyner, D.A., 2018. Measuring learner tone and sentiment at scale via text analysis of forum posts. In *Proceedings of the 8th Edition of the International Workshop on Personalization Approaches in Learning Environments (PALE). London, United Kingdom*.
24. Kucher, K., Paradis, C. and Kerren, A., 2018, February. The state of the art in sentiment visualization. In *Computer Graphics Forum* (Vol. 37, No. 1, pp. 71-96).
25. Nath, G. and Adhi, G., 2019. An Attempt to Detect Fake Messages Circulated on WhatsApp. In *Proceedings of 7th International Conference of Business Analytics and Intelligence*.
26. Resende, G., Melo, P., CS Reis, J., Vasconcelos, M., Almeida, J.M. and Benevenuto, F., 2019, June. Analyzing textual (mis) information shared in WhatsApp groups. In *Proceedings of the 10th ACM Conference on Web Science* (pp. 225-234).

27. Provoost, S., Ruwaard, J., van Breda, W., Riper, H. and Bosse, T., 2019. Validating automated sentiment analysis of online cognitive behavioral therapy patient texts: an exploratory study. *Frontiers in psychology*, *10*, p.1065.
28. Ribeiro, M.T., Wu, T., Guestrin, C. and Singh, S., 2020. Beyond accuracy: Behavioral testing of NLP models with CheckList. *arXiv preprint arXiv:2005.04118*.
29. Zhou, D., Zhang, M., Zhang, L. and He, Y., 2021, May. A Neural Group-wise Sentiment Analysis Model with Data Sparsity Awareness. In *Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 35, No. 16, pp. 14594-14601).
30. Hu, X., Tang, L., Tang, J., & Liu, H. (2013, February). Exploiting social relations for sentiment analysis in microblogging. In Proceedings of the sixth ACM international conference on Web search and data mining (pp. 537-546).
31. Dey, A., Jenamani, M., & Thakkar, J. J. (2018). Senti-N-Gram: An n-gram lexicon for sentiment analysis. Expert Systems with Applications, 103, 92-105.
32. Zhou, P., Qi, Z., Zheng, S., Xu, J., Bao, H., & Xu, B. (2016, December). Text Classification Improved by Integrating Bidirectional LSTM with Two-dimensional Max Pooling. In Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers (pp. 3485-3495).
33. Wang, L., Niu, J., & Yu, S. (2019). SentiDiff: combining textual information and sentiment diffusion patterns for Twitter sentiment analysis. IEEE Transactions on Knowledge and Data Engineering, 32(10), 2026-2039.
34. He, X., Gao, J., & Deng, L. (2014, May). Deep learning for natural language processing and related applications (Tutorial at ICASSP). In IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP).
35. Dabiri, S., & Heaslip, K. (2019). Developing a Twitter-based traffic event detection model using deep learning architectures. Expert systems with applications, 118, 425-439.
36. Thelwall, M., Buckley, K., Paltoglou, G., Cai, D. and Kappas, A., 2010. Sentiment strength detection in short informal text. *Journal of the American society for information science and technology*, *61*(12), pp.2544-2558.
37. Thelwall, M., Buckley, K., Paltoglou, G., Skowron, M., Garcia, D., Gobron, S., Ahn, J., Kappas, A., Küster, D. and Holyst, J.A., 2013, March. Damping sentiment analysis in online communication: discussions, monologs and dialogs. In *International conference on intelligent text processing and computational linguistics* (pp. 1-12). Springer, Berlin, Heidelberg.

Figures

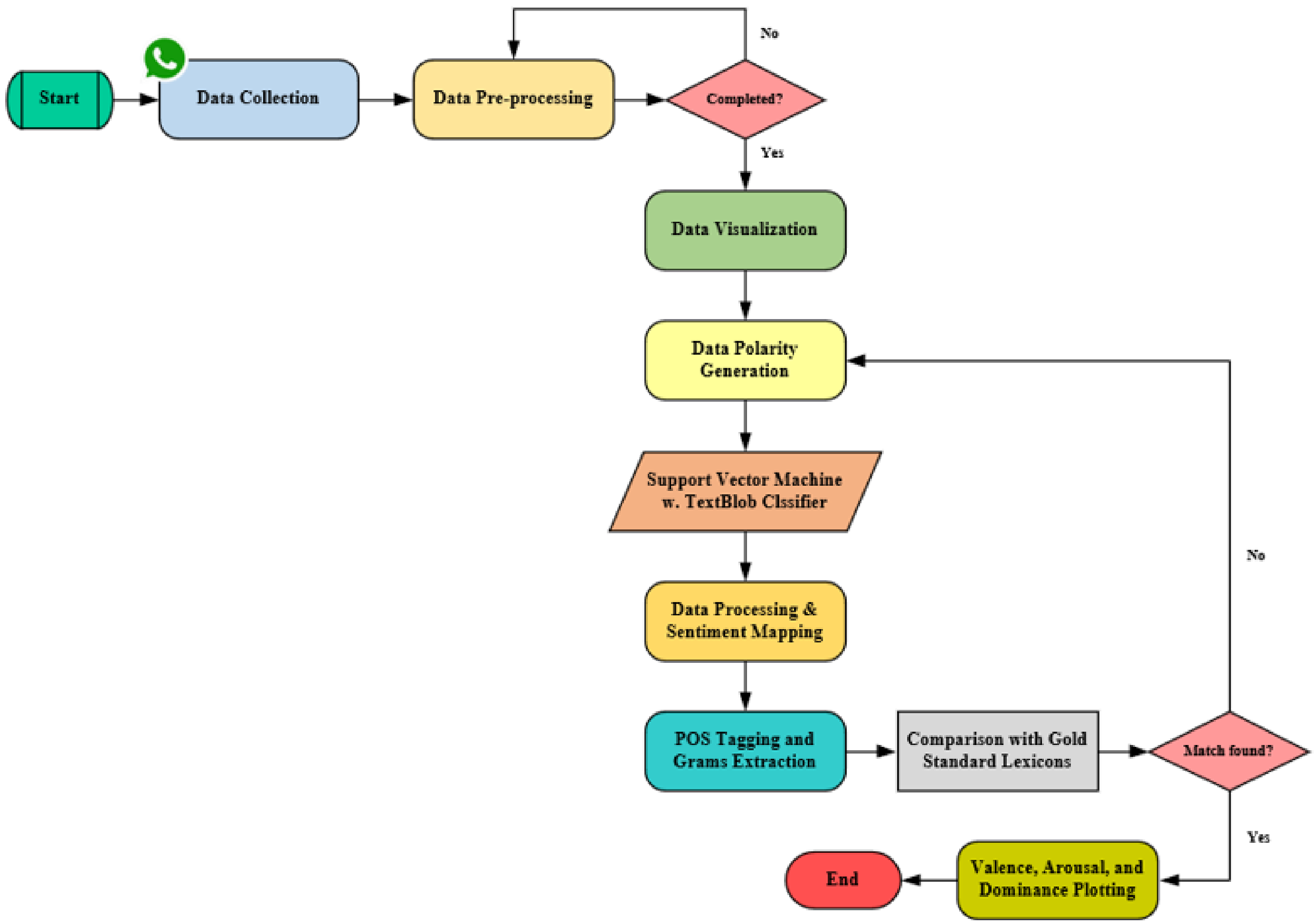


Figure 1

System architecture of the proposed methodology.

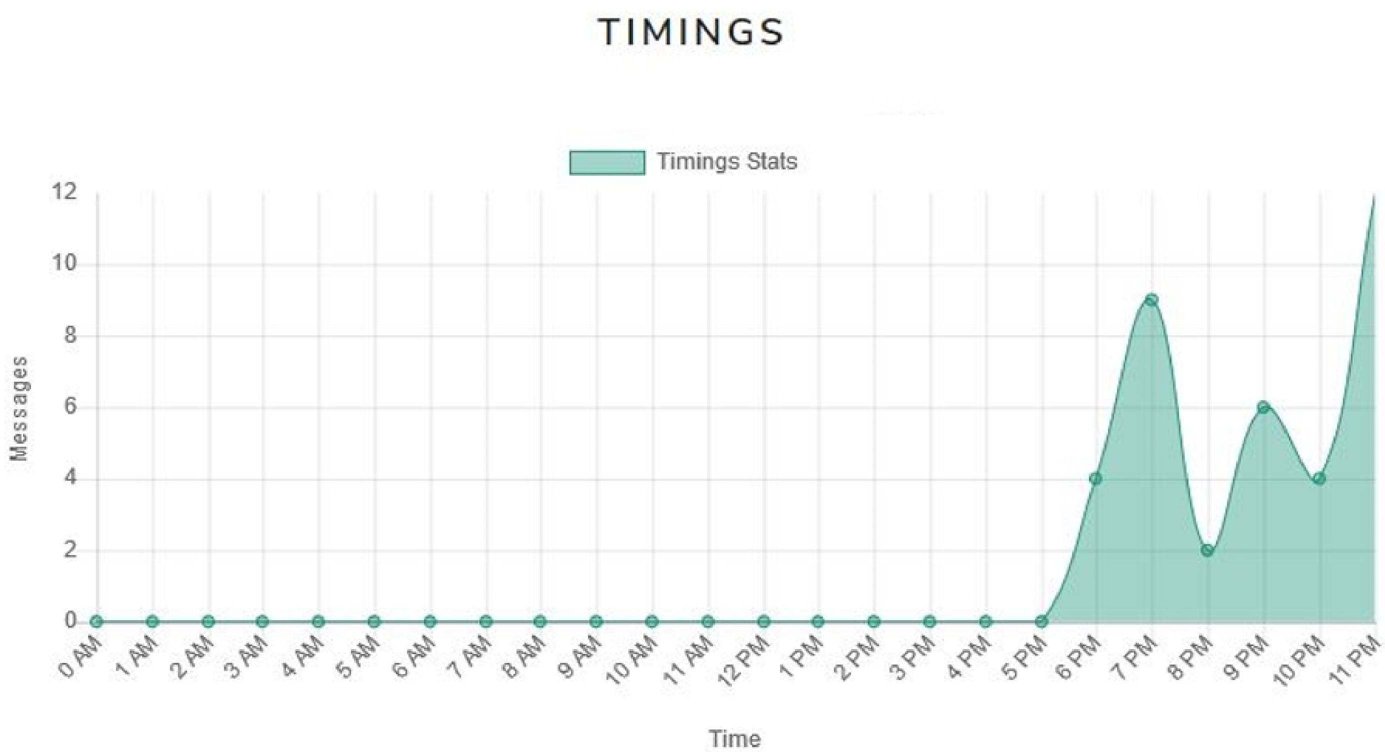


Figure 2

Message exchange rates on hourly basis.

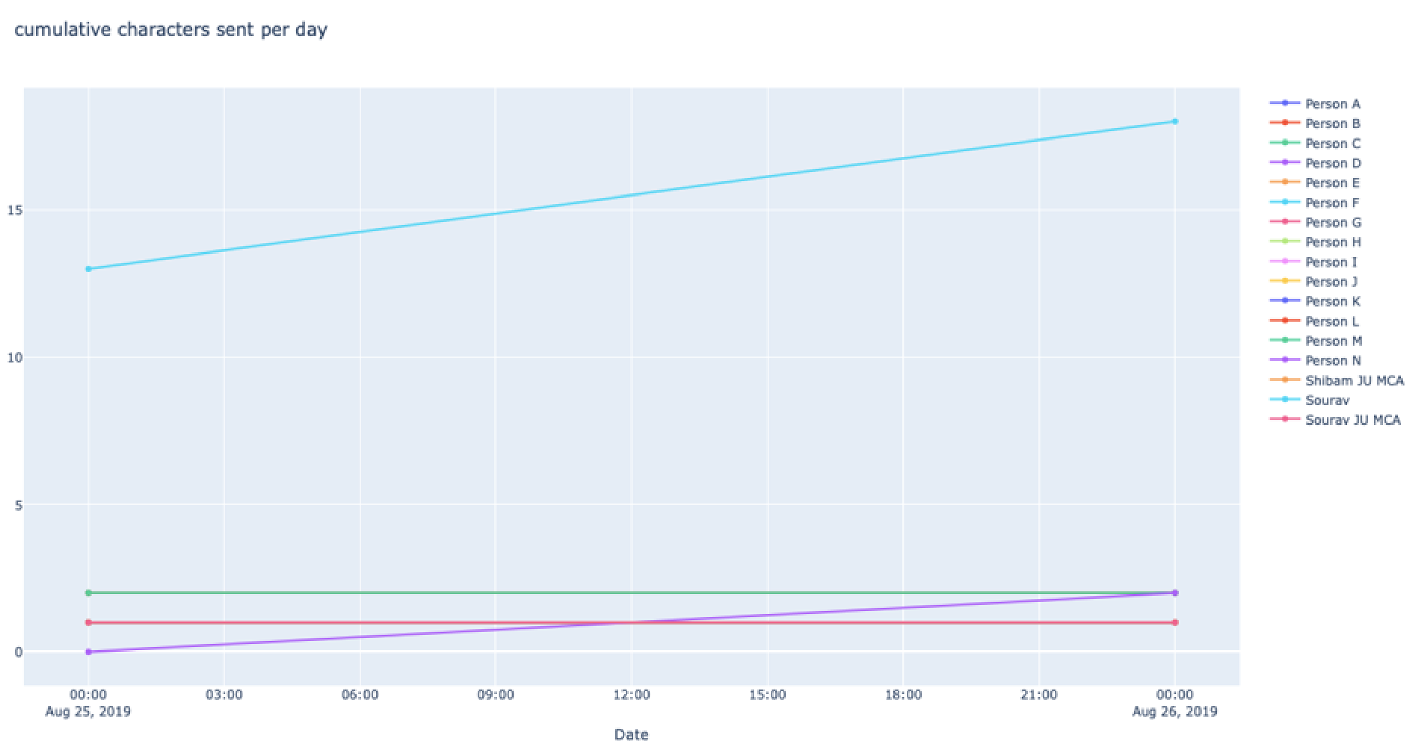


Figure 3

Cumulative characters sent per person

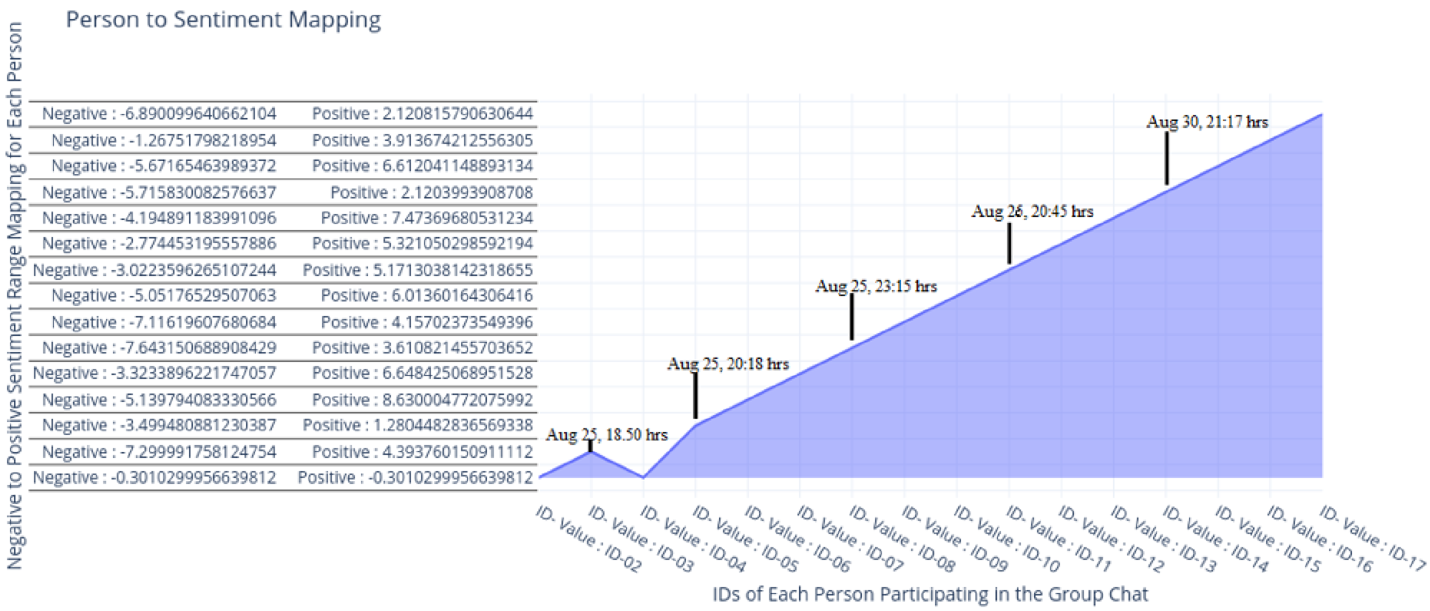


Figure 4

Person to sentiment mapping with respect to time and person ID.

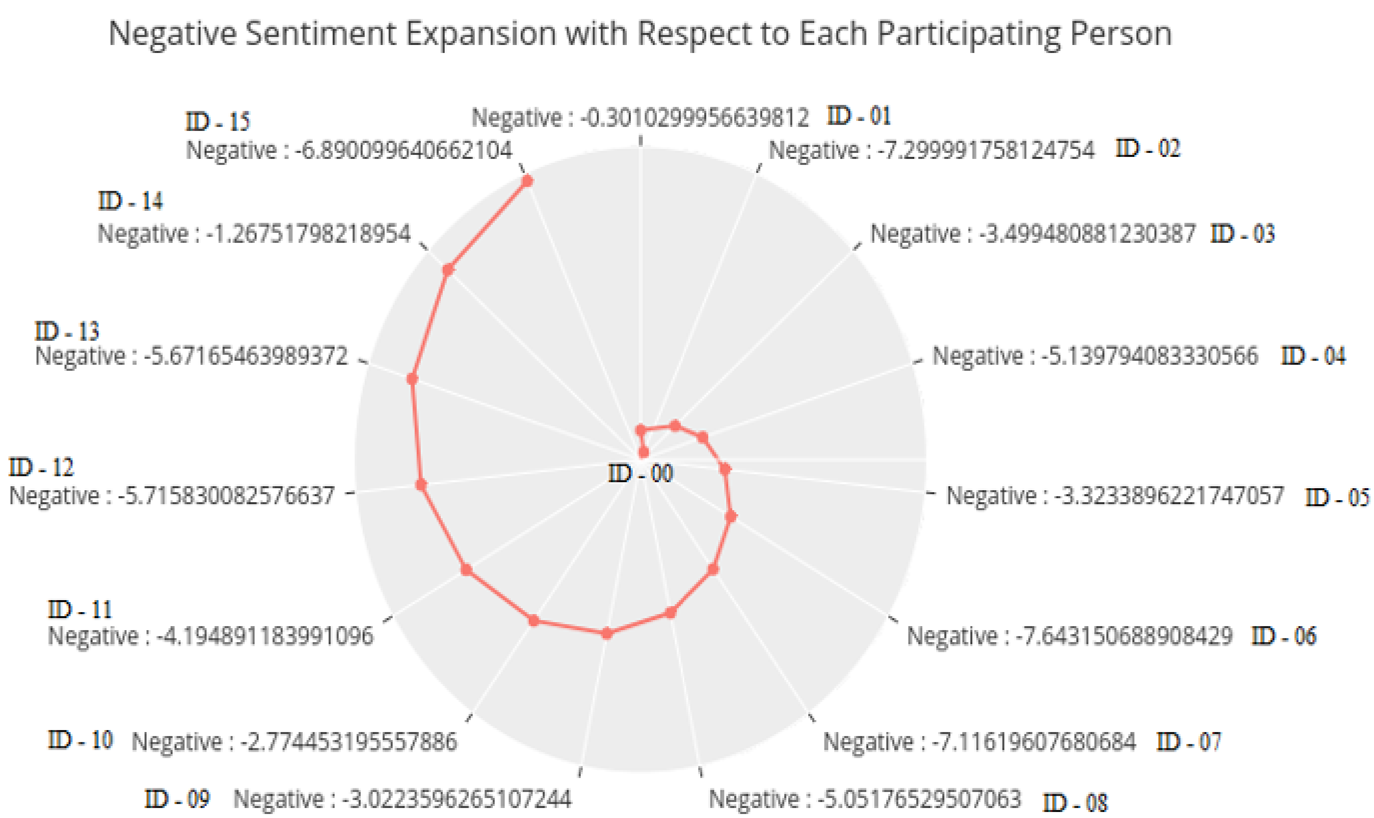


Figure 5

Negative sentiment expansion concerning each participating person

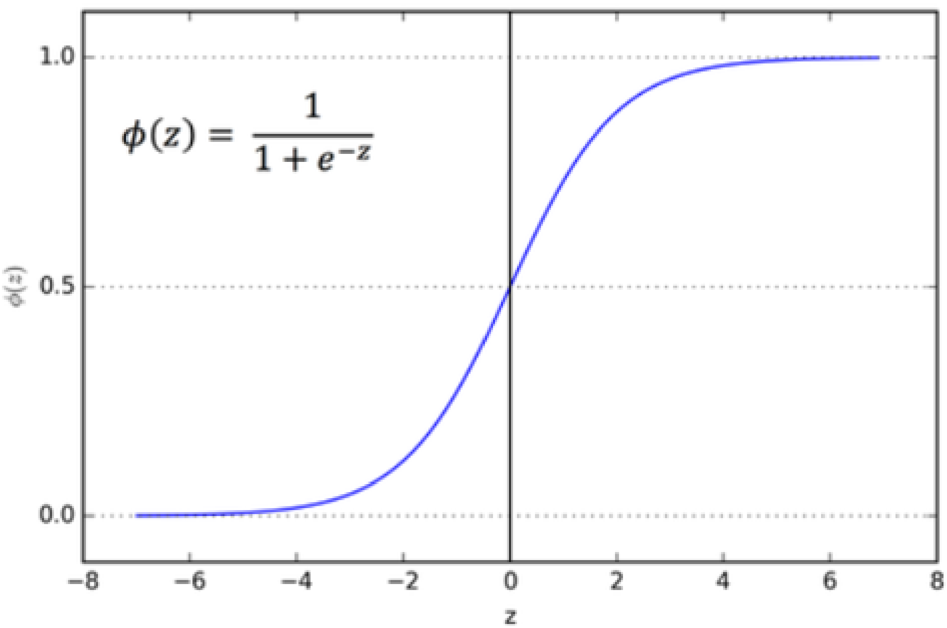
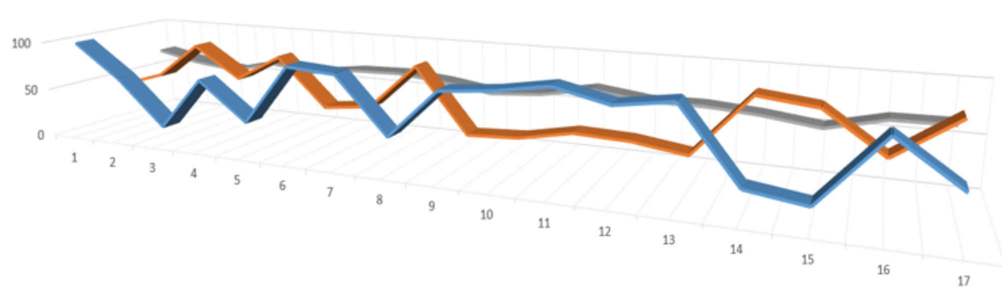


Figure 6

A sigmoid activation function (kernel) as plotted in a sloping curve.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Predicted Valence (o/f 100%)	98.046875	63.847091	17.916666	70.974916	33.220179	93.107933	89.801123	35.432791	83.276111	88.071047	96.741916	85.276883	93.221769	26.775134	19.581729	82.135579	45.171582
Predicted Arousal (o/f 100%)	42.179126	56.708913	92.217864	61.493721	87.707115	39.608235	45.376955	90.221728	27.382981	30.131789	40.445937	38.686641	31.532672	90.176859	84.221095	47.694399	86.019683
Predicted Dominance (As the mean value of VA)	70.113005	60.278002	55.067265	66.234318	60.463647	66.358084	67.589039	62.827259	55.329546	59.101418	68.593926	61.981762	62.37722	58.475996	51.901412	64.914989	65.595632

Predicted Valence (o/f 100%) Predicted Arousal (o/f 100%) Predicted Dominance (As the mean value of VA)

Figure 7

A 3-dimensional scatter plot of valence, arousal, and dominance where the dominance is acting like the threshold rift.

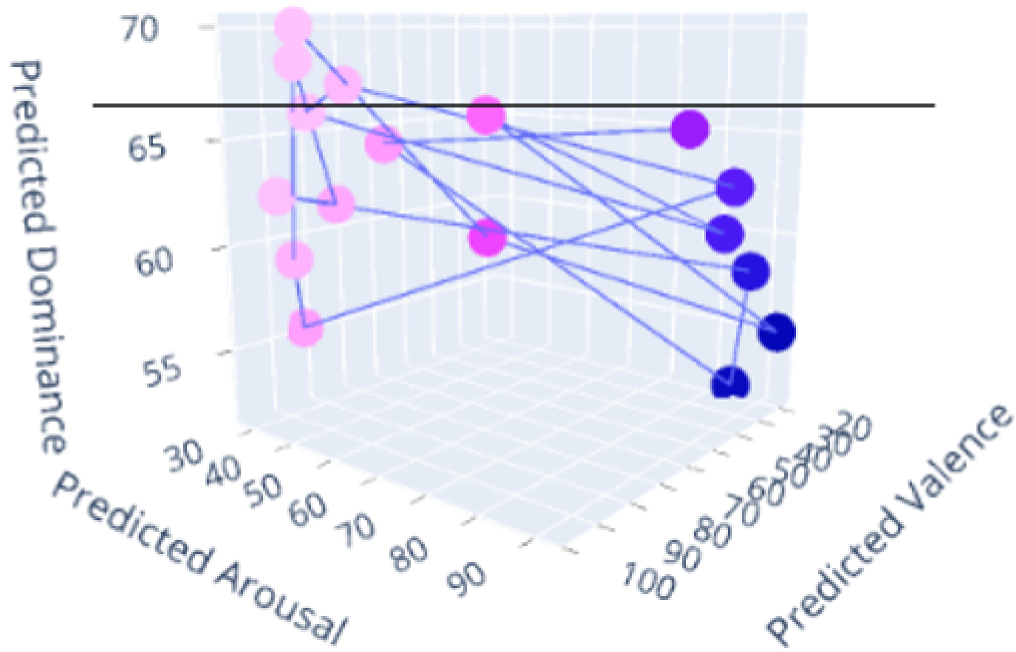


Figure 8

3D sentiment cluster of valence, arousal, and dominance mapping in a common plane.