



Analysis of instagammer's attitude through enhanced SVM

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ABSTRACT: Social media are influencing human beings preferences by shaping their attitudes and behaviors. Social media have received more attention nowadays. Public and Private opinion about a wide variety of subjects are expressed and spread continually via numerous social media. Instagram is one of the social media that is gaining popularity and logical marketing. Instagram dominates the digital marketing space, followed closely by Facebook. Sentiment analysis relates to the problem of mining the sentiments from online available data and categorizing the sentiment expressed by a particular entity into at most three preset categories: positive, negative and neutral. This Paper emphasized on Instagram posts to learn emotions in Instagrammers life as well as positive things occurred in their life. First conducted a qualitative analysis on sample posts related to human emotions. Human beings have different types of emotions. we calculate only the four type of emotions like Happy, Sad, Anger, Fear, Surprise, Beauty and Excitement. To classify posts reflecting Instagrammers emotions through multilabel classification algorithms is implemented. N Linear Support Vector Machine Learning algorithms are used. The performance of these algorithms is compared in terms of accuracy, precision, recall and F1-Measure. Support Vector Machine learning algorithm have more accuracy than Naïve Bayes Algorithm.

Keywords: Instagram, emotions, sentiment analysis, web text analysis, sentiment classification.

I. INTRODUCTION

Data mining research provides several techniques, tools, and algorithms for enormous amounts of data to answer real-world issues. Social media plays powerful role in today's era. As social media is generally used for various purposes, vast amounts of user created data can be made available for data mining. Main objectives of the data mining procedure are to communally handle large-scale data, extract useful patterns, and gain required knowledge. Social media sites such as Twitter, Facebook, and YouTube provides stage to share happiness, struggle, sentiment, stress and acquire social support. They share their happiness and sorrows related to

studies on social media in the form of judgmental comments, posts etc.

Previous research in sentiment analysis like Pang et al. have analyzed the performance of different classifiers on movie reviews. The work of Pang et al. has served as a baseline and many authors have used the techniques provided in their paper across different domains. Pang et al. also make use of a similar idea as ours, using star ratings as polarity signals in their training data. We show that we can produce comparable results on posts with distant supervision.

In order to train a classifier, supervised learning usually requires hand-labeled training data. With the large range of topics discussed on Instagram, it would be very difficult to manually collect enough data to train a sentiment classifier for posts. Our solution is to use distant supervision, in which our training data consists of posts with Hash tags. The #tags serve as noisy labels. For example, #I am very happy in a posts indicates that the post contains positive sentiment and #So sad indicates that the post contains negative sentiment. With the help of the Hashtag.com, it is easy to extract large amounts of posts with #tags in them. For the past few years, we have witnessed a flourishing of social media. People have been building a global communication network on the Internet via numerous social network applications. Everyday a large amount of unprecedented content is generated on social networks. The increasingly popular use of Instagram for lightweight communication raises its potential for serving as a new communication medium. Instagram, one of the most popular social media, claimed that there are over 200 million comments or posts per day [Instagram blog, 11]. It is a revolution of how content is generated and distributed by creating, sharing, and discovering messages without controlling.

As producers, private enterprises also widely adopt social media for their marketing strategy to commercialize their products or services, not only to speak, but also to listen to the true voice of the customers in their own words. Although most people are hesitated to answer survey about

product or service preference, they express their thoughts in social network and wield enormous influence in shaping the opinions of other consumers [Zabin, 08].

The complexities such as assortment of Internet slangs, absolute data volumes and moment of students posting on the web. Pure physical analysis cannot contract with the ever growing scale of data, while pure automatic algorithms cannot capture in-depth significance inside the data. One important reason why social media will be relayed on is that the comments and posts are ad hoc emotions and feelings of students.

The research goal of this learning are:-

a) To make the enormous amount of data useful for human emotion identification, as well as to combine both qualitative analysis and large-scale data mining techniques.

b) To examine attitude of using person informal posts on Instagram in order to investigate the problems and issues.

II. LITERATURE SURVEY

Sentiment analysis tasks typically combine two different tasks: (1) Identifying sentiment expressions, and (2) determining the polarity (sometimes called valence) of the expressed sentiment. These tasks are closely related as the purpose of most works is to determine whether a sentence bears a positive or negative (implicit or explicit) emotions about the target of the sentiment.

Several works [1]“Twitter Archeology” of Learning Analytics and Knowledge Conferences Bodong Chen, Xin Chen, 2015]Hash tag analysis in conference through the LAK algorithm, TAGS(dataset)using of LDA method with the language of JAVA as the front end and SQL as the back end. [2]Mining Social Media Data for Understanding Students’ Learning Experiences Xin Chen, Student Member, IEEE, Mihaela Vorvoreanu, and Krishna Madhavan, 2014]using M3L classifier with the language of .Net to understand the engineering students feeling with the comparison of Navie Bayes algorithm. Opinion Mining and Sentiment Analysis - Challenges and Applications [Haseena Rahmath P, 2014]datas are collected from the World Wide Web (www)only using analysis not use any algorithm.Only it giving the result in the form of statement.Discovering Consumer Insight from [3] “Twitter via Sentiment Analysis”[Wilas Chamlerwat, Pattarasinee Bhattarakosol, Tippakorn Rungkasiri, 2012]using MSAS i.e., Microblog sentiment analysis system with the help of the Multinomial logit model(MLM).Main drawback of this paper was less data can collect from social media ,but more error will suffer from the analysed result.

[4]” Sentiment Analysis of Twitter Data”[ApoorvAgarwal, OwenRambow ,2011]using Twitter posts and labels by manually and some of the posts are tested automatically with the help of Tree kernel algorithm with the polar and non-polar comparison.The result gives only gaining of 4% of twitter posts and the remaining are not identified.[5]” Enhanced Sentiment Learning Using Twitter Hashtags and Smiley”[DmitryDavidov*1 OrenTsur* 2 AriRappoport 2, 2010]using the Twitter #tags ,smiley of (475 million tweets) only taking the 50 tags and 15 smileys with the help

of the n-gram and pattern based algorithm.Main drawback of this paper are #tags are used for all emotions So doesn’t find the emotions only through the #tags and the smileys.

[6]”Sentiment Analysis and Subjectivity”[Bing Liu ,2010]using www with the Internet forum and blogs for sentiment analysis and comparing the positive and negative emotions with the present blogs.[7]”Twitter Sentiment Classification using Distant Supervision”[Alec Go, Richa Bhayani, 2009]using the [8]Twitter messages based on Smileys with the help of Maximum Entropy, Baseline using Twitter API for extract Tweets.The main drawback are accuracy failed due to comparison of Maximum Entropy and Baseline.

[9] ”Mining WordNet for Fuzzy Sentiment: Sentiment Tag Extraction from WordNet Glosses”[Alina Andreevskaia and Sabine Bergle, 2006]using wordNet with the help of STEP(sentiment tag extraction program)of unique words only.[10]” Determining the Sentiment of Opinions”[Soo-Min Kim, Eduard Hovy, 2004]using sentiment classifier with the help of classification algorithm understanding of sentiment opinion are weak at the time of analysis.

III. PROPOSED SYSTEM:

This approach uses totally different machine learning classifiers and has feature extractors. The proposed system works on instagrammer’s posts. These posts are related to instagrammer’s emotion experiences. This system defines seven labels which are: happy, sad, fear, anger, beauty, surprise and excitement. The objective is to explore informal conversations on Instagram in order to understand issues and problems of particulars encounter in their learning experiences. The posts are loaded and processed by standard text mining procedure called Pre-processing. This system is used to understand learning people emotion. The existing system uses classification algorithms finds only negative emotions of students learning, whereas the proposed system will use to discover positive as well as negative emotions. Naive bayes and support machine algorithm is used to discover the positive as well as negative emotion of instagram users. The comparison of the results of these algorithms is done using parameters accuracy, precision, recall and F1 Measure. The figure 1 shows the architecture of proposed system. First step is to collect the data for processing. This data is nothing but common posts which have positive and negative expression about their present feelings. In next step collected data is explored and define the categories into which posts can be differentiated. The posts are preprocessed i.e. stemming, stop word cleaning. Stemming reduces inflected words to their stem, base or root form. In stop word cleaning, there are list of stop words which are removed by preprocessing from text documents. However, on tokenization stream of text is break into words, phrases or symbols. The model is trained using multilabel classifier. The multi-label Support Vector Machine and Multilabel Naive Bayes classifier are implemented and compared. The procedure of the proposed system is as follow:

- 1) In the step one data collection is done from instgram.
- 2) Inductive Content analysis procedure is performed and categories are identified.
- 3) The preprocessing and tfidf is calculated in the step 2.
- 4) Naïve Bayes classifier, Linear SVM is applied on dataset in order to demonstrate its application in detecting student's issues is step 4.

MODULE DESCRIPTION

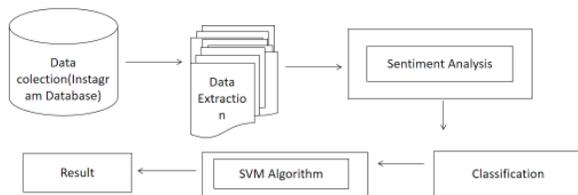


Figure.1 .SystemArchitecture

IV. IMPLEMENTATION:

This project implements using following processes Inductive content analysis is used to identify the relevant and irrelevant posts. In this categories are identified in which posts are going to classify. Naïve bayes and support vector machine algorithm are used to classify the posts of informal discussions.

DATA COLLECTION:

Launch Jupyter Notebook by typing A new tab should open in your browser running Jupyter. Load the instgram script (instgram.ipynb) by clicking on the file The python script is now loaded in Jupyter Notebook where it can be executed to extract content from Instagram. However you first need to edit the script a little in order to access and scrape the content that you want to research.

First you need to be sure about what content you would like to access and scrape. The instgram script uses a hashtag to collect the content. Patrik seems to be interested in fishing culture, which is why he programmed the script to look for the hashtag „catchoftheday“. You will most likely look for something else so you need to tell the script to look for another hashtag. I am interested in brands and music so I will tell my script to look for posts related to Absolut Vodka at the Lollapalooza Festival using the hashtag #absolutlolla. To program the script for your purposes:

Replace the content of Line 2 behind the_item with the Hashtag that you want to research. It goes between the brackets without the #

Set the number of photos you want to collect: Replace the content of Line 2 behind „max_scrape“ with the number of

photos you want to collect. Remember that Instagram will not allow you to collect all the post at once or it will detect that you are using automation on their sites so you will have to go several times to collect the desired amount. 150 posts is a number that seems to work well.

Your code should now look something like this:

```
the_item = „absolutlolla“
max_scrape = 150
```

```
ssinsta_path = „explore/tags/“
```

Now we need to execute the script step by step. You do this by selecting a code block through clicking on it (e.g. click on „In 1“) Clicking the ‚play button‘ will tell Jupyter Notebook to execute the selected code block in python and jump on to the next one. So after executing the first block (which in this script will actually do nothing as is ‚just‘ a comment telling you who programmed the script), Jupyter will jump to block number two. You can execute this one as well. Now the variables you defined will be set in the environment.

Execute all the blocks until Jupyter jumps to „Set up the web driver“ just after ‚Line 8‘ (In8). Now your script is loaded and prepared and it will have created some additional folders in your project folder. The collected content and data will be stored. (You can check on this by looking at your folder again). Now its time to do start the browser and the Instagram webpage. All this is done by the script. Execute all lines/code blocks under „Set up the web driver“. You will notice that a new instance of the Firefox browser will open and automatically navigate to your Instagram Hashtag.

Now it gets a little tricky: Sometimes Instagram requires us to log in before the script can hit the „Load More“ button. The script needs to do this before it can scroll down the page to get all the pictures. If that happens, log in to Instagram in the window that just opened using your credentials. Then, in order to get back to the hashtag query, execute once more the line where it says:

```
driver.get(„https://www.instagram.com/“+insta_path+the_item+„/&#8220;)
```

The script will now automate all interaction with the Instagram page to scrape the defined number of posts. If you execute all the code blocks under „Send key strokes to scroll down the page“, the script will scroll down the page so that it shows the number of posts you told it to scrape. Give the script time though after executing each block until the process is finished until it looks something like this. If no error occurred, you are now ready to scrape all the posts by executing the next set of commands. Some of these commands take up to a few minutes of time e.g. to download the pictures or videos. This is indicated by a dotted progress bar under the block so take it slow until the processes have finished. If all the processes have finished you can go ahead and execute the rest of the command blocks and you done!

Now the script will scrape the data and create some files for you that you can use for further research.

A html file the presents a grid of all your scraped posts displaying the metadata you collecteds_cap.csv – A comma seperated data frame with all the hashtags used in the caption of a pictures_comm.scv – A comma seperated data frame with all the hashtags used in comment section of a posts_combined.csv – You've guessed it. This dataframe contains bot the comments and the caption hashtags.s_labels.csv – An empty file which is due to a feature not supported in this version of the script You can import the csv files into your analysis software like Excel, LibreOffice, Gephi or else to work with the data now.

Inductive content Analysis:

Social media content like tweets contain a bulky amount of informal language, sarcasm, acronyms, and misspellings, meaning is often ambiguous and subject to human interpretation. Rost et. al argue that in large scale social media data analysis, faulty assumptions are likely to arise if automatic algorithms are used without taking a qualitative look at the data. According to study there is no appropriate unsupervised algorithms could reveal in-depth meanings in our data. For example, LDA (Latent Dirichlet Allocation) is a popular topic modeling algorithm that can detect general topics from very large scale data. LDA has only produced meaningless word groups from our data with a lot of overlapping words across different topics. There were no predefined categories of the data, so it is necessary to explore what peoples were saying in the posts. Thus, first step is to perform an inductive content analysis on the dataset. Inductive content analysis is one popular qualitative research method for manually analyzing text content.

Categories of Data :

As a consequence proposed system first conducted an inductive content analysis on the n dataset. This paper classified the instagrammers posts in to seven categories. Existing system have five prominent themes and proposed system consist of seven prominent categories:

Happy:

Happiness is a fuzzy concept. Some related concepts include well-being, quality of life, flourishing, and contentment. In philosophy and (western) religion, happiness may be defined in terms of living a good life, or flourishing, rather than simply as an emotion. Happiness in this sense was used to translate the Greek eudaimonia, and is still used in virtue ethics. There has been a transition over time from emphasis on the happiness of virtue to the virtue of happiness.

Ex: #loveithappy, #happy_pet

Anger:

Anger or wrath is an intense emotional response. It is an emotion that involves a strong uncomfortable and hostile response to a perceived provocation, hurt or threat. Anger can occur when a person feels their personal boundaries are being or are going to be violated. Some have a

learned tendency to react to anger through retaliation as a way of coping. Raymond Novaco of University of California Irvine, who since 1975 has published a plethora of literature on the subject, stratified anger into three modalities: cognitive (appraisals), somatic-affective (tension and agitations), and behavioral (withdrawal and antagonism). William DeFoore, an anger-management writer, described anger as a pressure cooker: we can only apply pressure against our anger for a certain amount of time until it explodes.

Ex: #relaxation, #anxiety

Sadness:

Sadness is an emotional pain associated with, or characterized by, feelings of disadvantage, loss, despair, grief, helplessness, disappointment and sorrow. An individual experiencing sadness may become quiet or lethargic, and withdraw themselves from others. An example of severe sadness is depression. Crying can be an indication of sadness.

Ex: #crying, #death, #die

Fear:

Fear is a feeling induced by perceived danger or threat that occurs in certain types of organisms, which causes a change in metabolic and organ functions and ultimately a change in behavior, such as fleeing, hiding, or freezing from perceived traumatic events. Fear in human beings may occur in response to a specific stimulus occurring in the present, or in anticipation or expectation of a future threat perceived as a risk to body or life. The fear response arises from the perception of danger leading to confrontation with or escape from/avoiding the threat (also known as the fight-or-flight response), which in extreme cases of fear (horror and terror) can be a freeze response or paralysis.

Ex: #scared, #crazy

Beauty:

Beauty is a characteristic of an animal, idea, object, person or place that provides a perceptual experience of pleasure or satisfaction. Beauty is studied as part of aesthetics, culture, social psychology, philosophy and sociology. An "ideal beauty" is an entity which is admired, or possesses features widely attributed to beauty in a particular culture, for perfection.

Ex: #beautyfull, #musical

Surprise:

Surprise (pronunciation) is a brief mental and physiological state, a startle response experienced by animals and humans as the result of an unexpected event. Surprise can have any valence; that is, it can be neutral/moderate, pleasant, unpleasant, positive, or negative. Surprise can occur in varying levels of intensity ranging from very-surprised, which may induce the fight-or-flight response, or little-surprise that elicits a less intense response to the stimuli.

Ex: #proposal, #balloons

Excitement:

The excited state of an atom, molecule or nucleus The excitatory postsynaptic potential The excitation (magnetic) provided with an electrical generator or alternator Stimulation, also called excitation. the action of various

agents on nerves, muscles, or a sensory end organ, by which activity is evoked.

Ex: #travel, #presents

Text Preprocessing:

Instagram users use some special symbols to convey certain meaning. For example, # is used to indicate a hashtag, @ is used to indicate a user account, and RT is used to indicate a re-post. Instagram users sometimes repeat letters in words so that to emphasize the words, for example, “huuungryyy”, “sooo muuchh”, and “Monndayyy”. Besides, common stopwords such as “a, an, and, of, he, she, it”, non-letter symbols, and punctuation also bring noise to the text. So we pre-processed the texts before training the classifier:

Naïve Bayes Multi-Label Classification Algorithm:

One popular way to implement multi-label classifier is to transform the multi-label classification problem into multiple single-label classification problems. One simple transformation method is called one-versus-all or binary relevance. The basic concept is to assume independence among categories, and train a binary classifier for each category. All kinds of binary classifier can be transformed to multi-label classifier using the one-versus-all heuristic. The following are the basic procedures of the multilabel Naive Bayes classifier. Suppose there are a total number of N words in the training document collection (in our case, each tweet is a document) $W = \{\omega_1, \omega_2, \dots, \omega_N\}$, and a total number of L categories $C = \{c_1, c_2, \dots, c_L\}$. If a word ω_N appears in a category c for $m_{\omega N c}$ times, and appear in categories other than c for $m_{\omega N c'}$ times, then based on the maximum likelihood estimation, the probability of this word in a specific category c is-

Support Vector Machine Algorithm

Transforming a multi-label classification problem into a set of independent binary classification problems via the “one-vs-all” scheme is a conceptually simple and computationally efficient solution for multi-label classification. In this work, multilabel learning conducted under such a mechanism by using standard support vector machines (SVM) for the binary classification problems associated with each class. Given a labeled multi-label training set $D = \{(x_i, y_i)\}_{i=1}^N$, where x_i is the input feature vector for the i -th instance, and its label vector y_i is a $\{+1, -1\}$ -valued vector with length K such as $K = |Y|$. If $y_{ik} = 1$, it indicates that the instance x_i is assigned into the k -th class; otherwise, the instance does not belong to the k -th class. For the k -th class ($k = 1, \dots, K$), the binary SVM training is a standard quadratic optimization problem:

V. EXPERIMENTAL RESULT

This system uses approximately 1000 post of Instagram user downloaded from hashtag.com which contain emotions. Firstly system preprocesses the data than support vector machine as well as naïve bayes algorithm applied on data. Performance analysis is done using k -fold cross validation. It is also called as rotation validation. In this case

k has taken as 5. Hence 1000 posts data is divided in to 5 folds. Table II shows the cross validation result of SVM. Here 1000 dataset is divided in to 5 fold. In first iteration 273 posts are considered as test set and remaining 727 are training set accuracy of this iteration is 72.7%. In second iteration 273 posts are considered as test set and remaining 727 are training set accuracy of this iteration.

Table.1.cross validation result of naïve bayes.

FOLD TEST	TEST SUBJECT	TRAIN SUBJECT	ACCURACY
0	270	727	72.7%
1	273	720	72%
2	273	720	72%
3	273	720	72%
4	273	720	72%

Table I shows the cross validation result of Naïve Bayes Algorithm. Here 1000 dataset is divided in to 5 fold. In first iteration 270 post are considered as test set and remaining 727 are training set accuracy of this iteration is 72%. In second iteration 273 posts are considered as test set and remaining 727 are training set accuracy of this iteration is 72.7%. In third iteration 273 posts are considered as test set and remaining 727 are training set accuracy of this iteration is 72%. In fourth iteration 273 posts are considered as test set and remaining 727 are training set accuracy of this iteration is 72.7%. In fifth iteration 272 posts are considered as test set and remaining 725 are training set accuracy of this iteration is 71.1%. In third iteration 273 posts are considered as test set and remaining 727 are training set accuracy of this iteration is 72%. In fourth iteration 273 posts are considered as test set and remaining 727 are training set accuracy of this iteration is 72%. In fifth iteration 273 posts are considered as test set and remaining 720 are training set accuracy of this iteration is 72%.

Table.2. Cross validation result of svm

FOLD	TEST SUBJECT	TRAIN SUBJECT	ACCURACY
0	273	720	90.24%
1	273	720	90.15%
2	273	720	90.36%
3	273	720	90.14%
4	273	720	90.65%

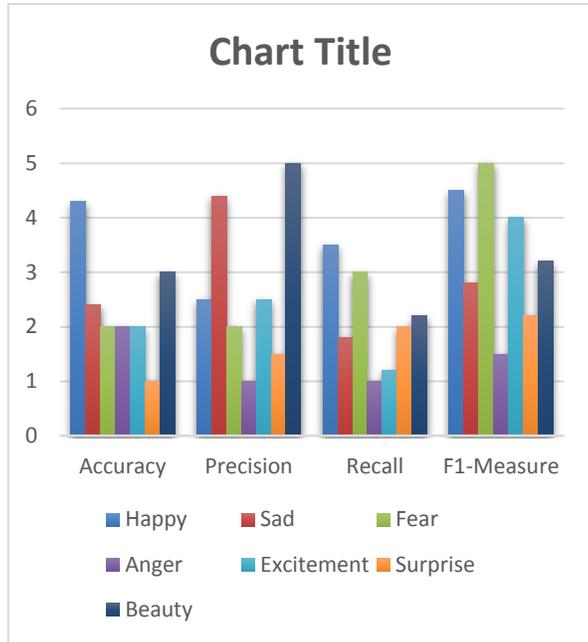


Figure.1.Performance Evaluation of Sentiment analysis

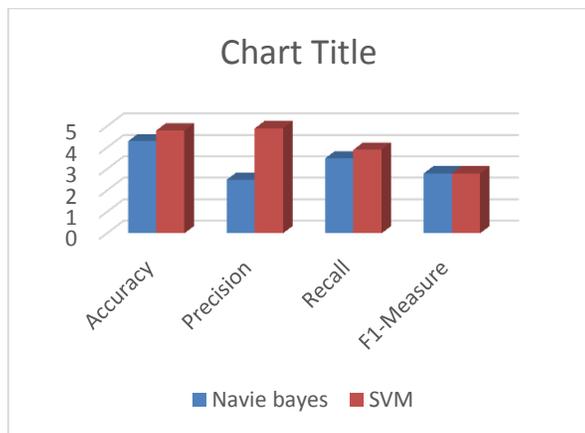


Figure.2.Performance Evaluation of NB and SVM

Table.3. Comparison of parameters using naïve bayes and svm

PERFORMANCE MEASURE	NAÏVE BAYES	SVM
ACCURACY	72.45%	90.35%
PRESION	72.34%	90.25%
RECALL	72.14%	90.11%
F1 MEASURE	72.65%	90.55%

Table III shows the final result by taking average of above cross validation result. This table shows the accuracy, precision, recall and F1-measure of Naïve Bayes is 72.45,

72.34, 72.14 and 72.65 respectively and the accuracy, precision, recall and F1-measure of SVM is 90.35 90.25, 90.11 and 90.55 respectively Figure II shows that Support Vector Machine has better performance than Naïve Bayes algorithm. As accuracy, precision, recall and F1Measure values of SVM are better as compared to Naïve Bayes.

This system uses approximately 1000 post of Instagram users downloaded from Instagram which contain people emotions. Firstly system preprocesses the data than support vector machine as well as naïve bayes algorithm applied on data. Performance analysis is done using k-fold cross validation. It is also called as rotation validation. In this case k has taken as 5. Hence 1000 posts data is divided in to 5 folds. Table II shows the cross validation result of SVM. Here 1000 dataset is divided in to 5 fold. In first iteration 273 posts are considered as test set and remaining 720 are training set accuracy of this iteration is 90.35. In second iteration 273 posts are considered as test set and remaining 727 are training set accuracy of this iteration is 90.14

VI. CONCLUSION

This project is classifies the people emotions to understand their problems as well as positive things in their life. Database is collection of posts these posts which depicts the information of people emotions in their life. The Posts are stored in database. Preprocessing is done on posts. Then classification techniques (Naïve Bayes and support vector Machine) are applied on data. In classification people emotions classified in to seven categories. That Happy,Fear,Sad,Anger,Surprise,Beauty and Excitement. Cross validation technique is used to evaluate performance of a system. Accuracy of naïve bayes algorithm in five iteration is 72.7,72.44,72.34,72.65 and 72 respectively. Accuracy of SVM in five iteration is 90.35, 90.14, 90.48, 90.16, and 90.35 respectively. Finally average of 5 iteration result is calculated to evaluate performance of a system. Accuracy, Precision, Recall And F1-Measure of Naïve Bayes is 72.12, 72.25, 72.04 and 72.21 respectively and the Accuracy, Precision, Recall And F1-Measure of SVM is 90.35, 89.94, 90.00 and 90.30 respectively Comparison of algorithm is done on the values of Accuracy, Precision, Recall, and F1 Measure and came to conclusion that Support Machine Algorithm gives more accurate prediction than Naïve Bayes Algorithm. Accuracy of Naïve Bayes is 72.12 % while Support Vector Machine is 90.35 %. Precision of Naïve Bayes is 72.25% while Support Vector Machine is 90.94 %. Recall of Naïve Bayes is 72.44 % while Support Vector Machine is 90.16 %. F1- Measure of Naïve Bayes is 72.65% while Support Vector Machine is 90.35%.

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