Sentiment Analysis on Social Media

Dr.K.Dharmarajan[#1], Farhanah Abuthaheer[*2], Dr.K.Abirami[@3]
[#1]Department of IT, VISTAS, Chennai, Indian
[*21]Department of IT, VISTAS, Chennai, Indian
[@3]Department of BCA, Guru Nanak College, Chennai, Indian,

***Abstract*— Microblogging platforms like Twitter can convey short messages to direct contacts, but also to other potentially interested users. They are actively exploited either by individual users or whole organizations and companies. This paper describes some results we obtained from the Social Network and Sentiment Analysis of a Twitter channel, related to a pop music event. Apart from the particular results a methodology and some guidelines for the automatic classification of Twitter content are discussed.**

***Keywords*— Social Network, Sentiment Analysis, Hierarchical Classification**

I. Introduction

In the common meaning of the term, an online community (or virtual community) is a group of people interested in a particular topic, or that share some ways of thinking, or that in general have some kind of link that brings them together, with the peculiarity that they interface and connect to each other through data communication network (such as Internet). In this way, they form a social network with unique characteristics:

Fact this combination is not necessarily bound to a physical place and anyone can participate wherever he is, with a simple access to networks. The social networking sites (SNSs), as defined by Boyd and Ellison in [1], are a collection of web-based services that allow users to build a profile within the system and define a list of other users with whom they have some kind of connection. According to Sunden profiles are unique pages where one can “type oneself into Being” [2], as the creation of a profile is the minimum condition for joining a SNSs. What makes the SNSs unique is that their purpose is not in most cases, to allow users to make new friends but the emphasis is on making visible their existing social networks and on the chance to describe them. On the other hand, the specific features of each social network site may depend also on the possible target (social, linguistic or geographic) to which the service is directed. The architecture of social networking platforms is much differentiated. While the most popular platforms are built as essentially centralized systems, other platforms have a distributed architecture [4].

The decentralized systems, in particular, often use some notion of trust and cryptography to address the risks of online social networks, which are perceived as serious by many users and have led to incidents.

Ethnicity, religion, sexual orientation, political beliefs are other factors that have led to the establishment of dedicated social network services, but probably they are also playing an active role in creating and aggregating online communities leveraging the bigger and most popular social networks. This suggests the possibility of new ways to spread information and to influence public opinion [2] [3]. These new scenarios can be better evaluated by a combined observation of the structure and the actual content of the network. This kind of analysis could highlight emerging social behaviours. for example, the possible differences in the sentiment polarity of female and male users, towards the discussed topic are examined.

To investigate on the content and on the relations among the actors of a network, it could be useful to contextualize the network itself. In particular, it could be important to consider and inquiry the content of the messages that guide the relationships of the community. It is only through this kind of investigation that we can analyze the semantic meaning of a link, from which we could infer the kind of relationship. This sharpens our description of the social network in many of its facets. A useful tool for such surveys is Sentiment Analysis (SA). SA is a branch of Opinion Mining that aims to listen and process the data that users post on social media. It is an interdisciplinary field that in recent years has had a significant growth and that makes extensive use of machine learning techniques [5].

The information about social relationships can be used to improve user-level sentiment analysis. Sentiment Analysis is mapped on social media with observations and measurable data; the results highlight the importance of SNSs (i.e. Facebook) as a platform for online marketing. Social media provide tremendous challenges for researchers and analysts trying to gain insight into human and group dynamics. A central problem is the sheer amount of data available in social media. For example, the social media aggregation site Spinn3r [3] advertises that they provide information on over 20 million blogs feeds that stream over 100 thousand posts and an 8 month archive consisting of 21 TB of data. Facebook currently involves over 400 million active users with an average of 120 `friendship connections each and sharing 5 billion references to items each month. One analysis approach treats the interactions as graphs and applies tools from graph theory, social network analysis, and scale-free networks. However, the volume of data that must be processed to apply these techniques overwhelms current computational capabilities [9].

Even well-understood analytic methodologies require advances in both hardware and software to process the growing corpus of social media. Social media provides staggering amounts of data [10]. Extracting knowledge from these volumes requires automation. Computing quickly over this data is a challenge for both algorithms and architectures.

II. SENTIMENT ANALYSIS ON TWITTER

In this research work, we built a system for social network and sentiment analysis, which can operate on Twitter data. Twitter is a popular Platform for social networking and micro blogging, counting hundreds of millions of active users and daily published messages. As a social networking platform, Twitter is structured as a directed graph, in which each user can choose to follow a number of other users (followers), and can be similarly followed by other users (followers) [11]. Thus, the "follow" relationship is asymmetrical, it does not require mandatory acknowledgement, and it is essentially used to receive all public messages published by a followed user. As a micro blogging service, Twitter is used to publish short messages counting a maximum of 140 characters (tweets), which may contain opinions, thoughts, facts, references to images and other media. Moreover, through the @ symbol it is possible to introduce mentions i.e. references to other users, and through the # symbol it is possible to introduce hash tags, i.e. references to discussion topics [9]. Sentiment Analysis can be done at document, phrase and sentence level. In document level, summary of the entire document is taken first and then it is analyse whether the sentiment is positive, negative or neutral. In phrase level, analysis of phrases in a sentence is taken in account to check the polarity. In Sentence level, each sentence is classified in particular class to provide the sentiment. Sentimental Analysis has various applications. It is used to generate opinions for people of social media by analysing their feelings or thoughts which they provide in form of text. Sentiment Analysis is domain centred, i.e. results of one domain cannot be applied to other domain [12].

Sentimental Analysis is used in many real life scenarios, to get reviews about any product or movies, to get the financial report of any company, for predictions marketing. Twitter is a micro blogging platform where anyone can read or write short form of message which is called tweets. The amount of data accumulated on twitter is very huge. This data is unstructured and written in natural language [8] [9]. Twitter Sentimental Analysis is the process of accessing tweets for a particular topic and predicts the sentiment of these tweets as positive, negative or neutral.

Consequently, in our analysis we collected three types of data. The User type represents users' profiles; from Twitter we obtain the following fields: user_id ,name, location, num_ followers, num_tweets. The Tweet type represents posted messages; Twitter we obtain the following fields: tweet_id, user_id, message, date. Finally, the Friend type represents the "follow" relationships among users. Apart from data obtained directly from Twitter, we added a field to both tweetsand users, to associate a sentiment with them, according to the result of our analysis.

III. PROPOSED WORK

A. System Analysis

The main objective of this thesis work is to perform the sentiment analysis on Indian Political Parties like BJP, INC and AAP, such that people opinions about these parties progress, workers, policies, etc. which are extracted from Twitter. Thus to achieve this objective we build a classifier based on supervised learning and perform live sentiment analysis on data collected of different political parties To achieve this objective the following methodology is used: A thorough study of existing approaches and techniques in field of sentiment analysis. Collection of related data from Twitter with the help of Twitter API Pre-processing of data collected from Twitter so that it can be fit for mining.

- Computing the result of different classifier using dataset collected from Twitter.
- Comparing results of each classifier and plotting a graph that show the trend of positive and negative sentiment for different political parties.

The analysis of political communication in the mass media. This study takes also in account the data provided by Sentiment Analysis is a process of extracting feature from user's thoughts, views, feelings and opinions which they post on any social network websites. The result of sentiment analysis is classification of natural language text into classes such as positive, negative and natural. the analysis of Social Media, of Facebook in particular, with measurable data, available to public domain.

An ability to classify tweets by location in real time is crucial for applications exploiting social media updates as social sensors that enable tracking topics and learning about location-specific trending topics, emerging events and breaking news. Specific applications of a real-time, country-level tweet geo location system include country-specific trending topic detection or tracking sentiment towards a topic broken down by country. To the best of our knowledge, our work is the first to deal with global tweets in any language, using only those features present within the content of a tweet and its associated metadata.

B. *Collaborative Filtering Algorithm:*

If the user is giving any query, for that query all the tweets are taken from the live twitter. Then by using the collaborative filtering algorithm, we classified the tweets into Happy, Sad and Funny. If the person tries to tweet bad words means, the system cannot allow the user to post in twitter.

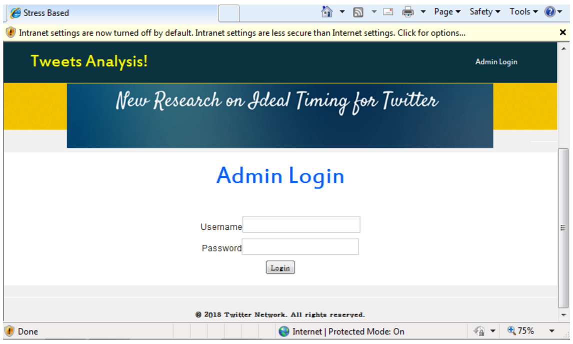
A Classification Engine which classifies search results into clusters and sub-clusters recursively, highlighting meaningful relationships among them, or assigns documents to predefined thematic groups.

- Easy to monitoring the social media
- Interact with mining classify to social media Happy, Sad and Funny Tweets are predicted.

IV. PROPOSED MODULE DESCRIPTION

A. *User Profiling:*

User profiling is the foremost part of our project which covers the single sign on user and also registers new user to the ecommerce site.



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Tweets Analysis!

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Admin Login

Username

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Fig 1.Twetter Analysis Login Page

B. *Pre processing*

In this module, we are collecting tweets dataset from live twitter by creating the app in apps.twitter.com . The dataset which contains tweets, user id, time/date and username which was given by the user are imported into the database. Then it is processed by stop words and stemming technique. The pre-processing phase The Fig 2. Shows the Load Twitter Dataset

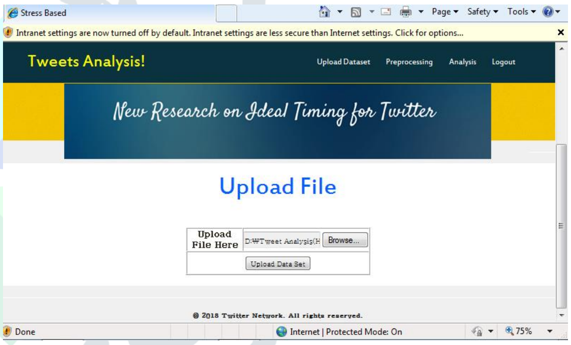

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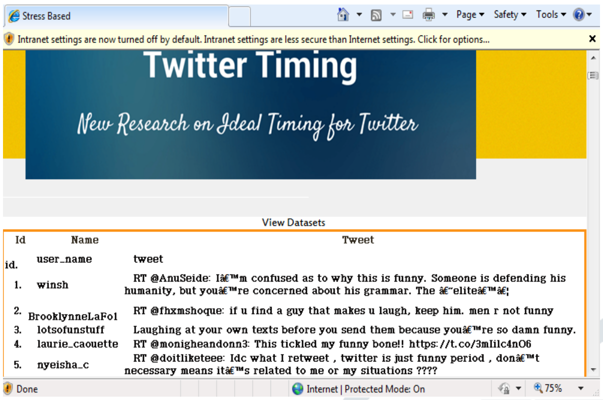
Fig 2.Load the Twitter Dataset

C. *Stop words Removal:*

A dictionary based approach is been utilized to remove stop words from tweets. A generic stop word list containing 75 stop words created using hybrid approach is used. The algorithm is implemented as below given steps. The target text is tokenized and individual words are stored in array. A single stop word is read from stop word list. The stop word is compared to target text in form of array using sequential search technique. If it matches , the word in array is removed , and the comparison is continued till length of array. After removal of stop word completely, another stop word is read from stop word list and again algorithm runs continuously until all the stop words are compared .Resultant text devoid of stop words is displayed, also required statistics like stop word removed, no. of stop words removed from target text, total count of words in target text, count of words in resultant text, individual stop word count found in target text is displayed. The Fig 3 shows Pre Processed Twitter data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Twitter Timing
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View Datasets

Id	Name	Tweet
id.	user_name	tweet
1.	winsh	RT @AnuSeide: Iâ€™m confused as to why this is funny. Someone is defending his humanity, but youâ€™re concerned about his grammar. The â€˜eliteâ€™â€¦
2.	BrooklynneLaFo1	RT @fhxmshoque: if u find a guy that makes u laugh, keep him. men r not funny
3.	lotsofunstuff	Laughing at your own texts before you send them because youâ€™re so damn funny.
4.	laurie_caouette	RT @monigheandonn3: This tickled my funny bone!! https://t.co/3mIilc4nO6
5.	nyeisha_c	RT @doitliketeee: Idc what I retweet , twitter is just funny period , donâ€™t necessary means itâ€™s related to me or my situations ????

Fig 3. Preprosed Twitter data

D. Stemming Technique:

After removing the unwanted words from the tweet, stemming technique is processed. Stemming is the process of reducing inflected (or sometimes derived) words to their word stem, base or root form generally a written word form. The stem need not be identical to the morphological root of the word; it is usually sufficient that related words map to the same stem, even if this stem is not in itself a valid root.

E. Classification:

After stemming process, all the reviews terms are classified into happy, sad and funny tweets. Collaborative filtering algorithm is used for classification. Here we are having happy words, sad words and funny datasets. By comparing with this, we can classify the tweets into Happy, Sad and Funny Tweets.

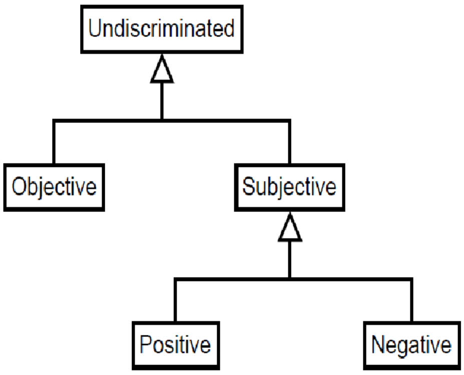


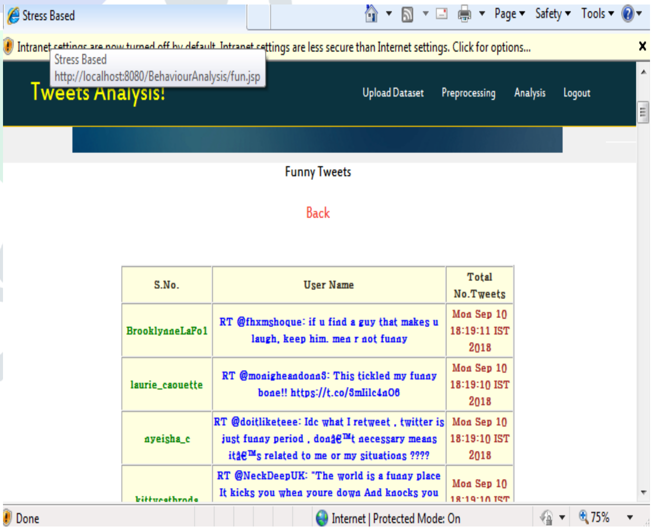
Fig 4. Classification of Sentiment Tweet

F. Capturing user Sentiments:

We present the main framework of our method. We regard extracting opinion targets/words as a co-ranking process.

We assume that all nouns/noun phrases in sentences are opinion target candidates, and all adjectives/verbs are regarded as potential opinion words, which are widely adopted by previous methods. Each candidate will be assigned a confidence, and candidates with higher confidence than a threshold are extracted as the opinion targets or opinion words.

If a word is likely to be an opinion word, the nouns/ noun phrases with which that word has a modified relation will have higher confidence as opinion targets. If a noun/noun phrase is an opinion target, the word that modifies it will be highly likely to be an opinion word. It can see that the confidence of a candidate (opinion target or opinion word) is collectively determined by its neighbours according to the opinion associations among them. A noun/noun phrase can find its modifier through word alignment. The Fig 5. Shows the User opinion targets Sentiments Tweet.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Tweets Analysis!
Upload Dataset
Preprocessing
Analysis
Logout
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Funny Tweets

Back

S.No.	User Name	Total No.Tweets
BrooklynneLaFo1	RT @fhxmshoque: if u find a guy that makes u laugh, keep him. men r not funny	Mon Sep 10 18:19:11 IST 2018
laurie_caouette	RT @monigheandonn3: This tickled my funny bone!! https://t.co/3mIilc4nO6	Mon Sep 10 18:19:10 IST 2018
nyeisha_c	RT @doitliketeee: Idc what I retweet , twitter is just funny period , donâ€™t necessary means itâ€™s related to me or my situations ????	Mon Sep 10 18:19:10 IST 2018
kittycathroda	RT @NeckDeepUK: "The world is a funny place It kicks you when youre down And knocks you	Mon Sep 10 18:19:10 IST

Fig 5. User opinion targets Sentiments Tweet

We additionally employ a partially-supervised word alignment model, which performs word alignment in a partially supervised framework.

G. Mapping Opinion Targets:

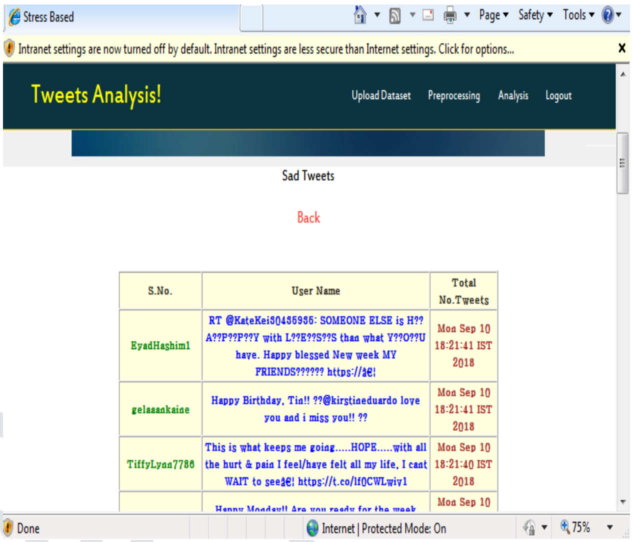
We finally map our feedbacks on positive, negative and neutral scale and then visualize this feedback in a graphical way.

As a communication medium, tweets have acquired peculiar nature. Some distinguishing features of communication on Twitter are related to technical aspects; those include length of text, tags, urls, etc.. Other features may be classified as idiomatic use of the medium, and create a sort of Twitter culture; those features include typical content and most discussed topics, idiomatic expressions, abbreviated forms, etc. For example, a tweet may have the following form:

«RT @richman wow this is the #happiest day of my life. #happy #glad #icantbelievit :) :D http://t.co/4VEH827bG7»

The peculiar nature of tweets requires specialized analysis techniques. As a start, a tweet may contain many elements which are not significant for our classification, and can thus be dropped though a filtering process. To polish the message, we defined various filters, which we have applied in a customizable sequence. Proc. of the 16th Workshop "From Object to Agents" (WOA15) June 17-19, Naples, Italy54

A first filter eliminates useless tokens. Removed tokens include: the starting "RT" sequence, which indicates a republished messages from a different user (i.e. a retweet); the @ character and the whole following user name; the # symbol, but not the following topic name, which is kept in the message. The topic name is also removed, though, when it coincides with the name of the channel where tweets are collected from. A second filter applies the language specific rules. It includes an orthographic correction of the message, which is used to remove unknown words, which may not appear in any other tweet (in the example: "i cant believe it"). Ideally, the filter at this level should also support stemming and removal of stop words. However, those operations can be easily performed by Weka, which we used for analysis. Finally, another filter separates all punctuation symbols from the text, and organizes them as single-character words. However, some typical patterns are kept as aggregates, including smiles sequences, repeated question and exclamation marks. The final result of the filtering process is a word vector, which is then submitted to the classifier agents. As we have mentioned, our analysis aims at identifying the following classes of messages: un discriminated, objective, subjective, positive, negative.



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Sad Tweets

Back

S.No.	User Name	Total No.Tweets
EyadHashim1	RT @KateKei30436936: SOMEONE ELSE is H?? A??P??P??Y with L??E??S??S than what Y??O??U have. Happy blessed New week MY FRIENDS?????? https://â€¦	Mon Sep 10 18:21:41 IST 2018
gelaaankaine	Happy Birthday, Tin!! ??@kirstineduardo love you and i miss you!! ??	Mon Sep 10 18:21:41 IST 2018
TiffyLynn7786	This is what keeps me going.....HOPE.....with all the hurt & pain I feel/have felt all my life, I cant WAIT to seeâ€¦ https://t.co/lf0CWLwiv1	Mon Sep 10 18:21:40 IST 2018
	Happy Monday!! Are you ready for the week	Mon Sep 10

Fig 6. User sad Tweet Classification

The system is organized as a simple hierarchy of agents, mimicking the hierarchy of sentiment classes. In fact, since objective messages have no polarity by definition, the classifier for positive and negative sentiments is only applied to subjective messages. If a message fails to be classified at the first stage, then it simply remains discriminated. If it fails to be classified at the second stage, then it is marked as generically subjective.

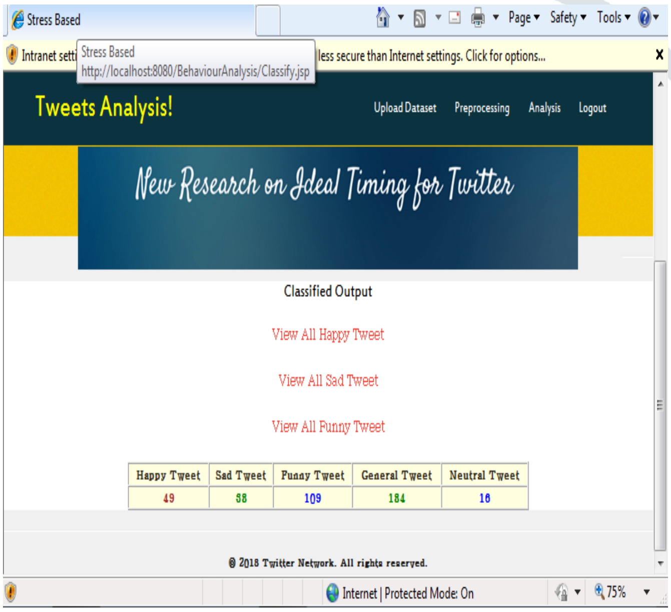
Currently, the classifier agents apply the Multinomial Naive Bayes algorithm, but other methods can be used and different agents can be plugged in the system. However, instead of generating a training set by hand, we aimed at realizing an automated (or at least semi utomated) process for obtaining good training sets.

About the objectivity/subjectivity classifier, we adopted a similar strategy to [6]. In fact, to obtain objective content, we gathered messages generated from popular news agencies. In our tests, we used the following list: @ABC, @BBCNews, @BBCSport, @business, @BW, @cnnbrk, @CNNMoney, @fox32news, @latimes, @nytimes, @TIME. To obtain subjective content, instead, we gathered comments directed to the same list of users.

About the polarity classifier, we decided to search for sources of mostly positive or negative messages, respectively. On the one hand, those sources should fit the particular setting of Twitter (short messages, idiomatic expressions, smiles, etc.) On the other hand, they should not be specific to a particular topic or context (sport, music, etc.). Thus, we dropped the idea of collecting messages about particular events, mostly generating either positive or negative sentiments. Instead, we collected messages, using generic yet polar terms as queried hash tags.

In particular, we used the following channels to gather positive content: #adorable, #awesome, #beautiful, #beauty, #cool, #excellent, #great. We used the following channels to gather negative content: #angry, #awful, #bad, #corrupt, #pathetic, #sadness, #shame. Actually, such terms have been chosen quite empirically, taking into account the quality of training sets they generated. But they could be selected from WordNet-Affect [8], SentiWordNet [9], and other affective lexicons, in a more systematic way.

This way, the training set is generated in an automated fashion, as a list of tweets. Each tweet is associated with its supposed class, in accordance to its source. In fact, the training set is not perfect, as it contains messages gathered from public channels. However, a training set of this kind can be generated easily and in a methodical way, from real and updated Twitter messages. In the next section, we will also discuss the quality of results that can be obtained, using it as a basis for sentiment analysis. The Fig 7 Shows the User Classified output report.



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Tweets Analysis!

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Classified Output

View All Happy Tweet

View All Sad Tweet

View All Funny Tweet

Happy Tweet	Sad Tweet	Funny Tweet	General Tweet	Neutral Tweet
49	58	109	184	16

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Fig 7. User Classified output report

The training set can be provided directly to the classifier agents. In the present form, the system is based on Weka, and can thus be configured for performing additional preprocessing steps on the messages, including common TF-IDF transformations, stemming, elimination of stopwords, exclusion of infrequent words, etc.

Currently, we analyze tweets for discriminating the basic classes of objectivity and polarity, at two levels. However, we designed the system for more complex hierarchical classification, with the application of various types of classifiers, as an alternative to current Naive Bayes.

In fact, hierarchical classification has been applied successfully in a number of studies, for information retrieval. It has been proven effective especially in the case of classification over hierarchical taxonomies. Moreover, it has the advantage of being modular and customizable, with respect to the classifiers used at different levels. Using the same probabilistic classifier and a maximum likelihood estimator, instead, does not provide advantages for the hierarchical approach over the flat approach. Mitchell has proved that the same feature sets represent documents in both approaches. Consequently, the whole hierarchical classifier system is equivalent to the corresponding flat system.

Also in the case of sentiment analysis, a hierarchy of classes can be defined . Accordingly, hierarchical classification has already been applied to sentiment analysis.

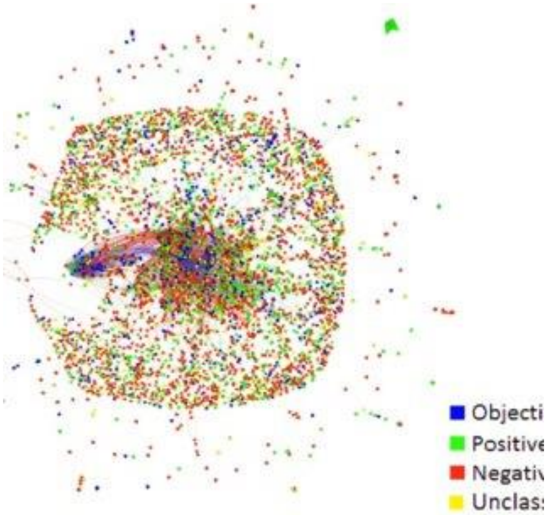


Fig 8. User Classified report

V. CASE-STUDY: THE#SAMSMITH CHANNEL

This section will show the results of the classifiers and the analysis carried out on a case study.

With the above described software, it is possible to obtain some training sets for the classifiers. In our case study, they consist of:

- 86000 instances (polarity)
- 32000 instances (subjectivity)

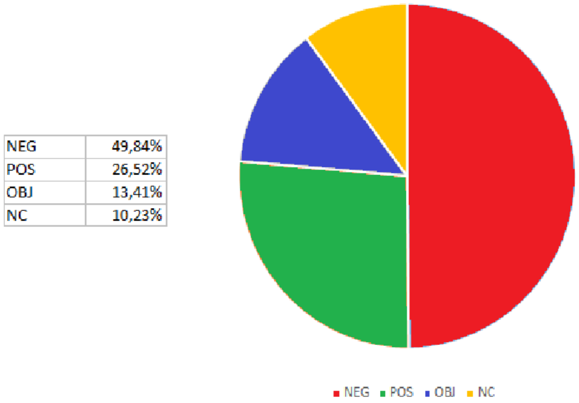
These instances have been obtained by exploring more than 60 channels on the social network.

In the generated models, the selected features are consistent with our expectations: the typical expressions of a certain feeling (such as smileys, or some words that express appreciation or disgust) show a higher probability of belonging to the class of that feeling, rather than to the class of the opposite sentiment.

The obtained results by the classifiers using cross-validation (with folds = 10) on the training sets showed an accuracy of:

- 77,45% (polarity classifier)
- 79,50% (subjectivity classifier)

These results Fig 9. show that the model of the classifiers contains effective features for the recognition of the sentiment of a message..The case study which was considered in this work is the social network of the #SamSmith channel (the singer who won four awards at the Grammy Awards 2015). The choice of this channel is justified by the strong similarities found between the type of the published tweets and the instances used for training the classifiers. All data were downloaded between 2015-02-02 and 2015-02-10. The awarding of the Grammy took place on 2015-02-08. The network consists of a total of 5570 nodes and 6886 arcs.



NEG	49,84%
POS	26,52%
OBJ	13,41%
NC	10,23%

Fig 9. Graphical representation of recognition of the sentiment of a message

It is possible to notice that the network topology is consistent with the nature of the considered case. In fact, most of the channel consists of independent users (or small groups of users) that express their opinion about the artist; however, in the central part of the network there are some major communities.

The prevailing sentiment detected from the classifier is the negative one. Performing an analysis on a Communities participating in the #SamSmith channel. Sentiment analysis on the #SamSmith channel.

This work noticed that many sentences are actually quotes of songs. These messages contain melancholic and sad phrases, and are therefore classified as negative. Considering that a quote is generally an appreciation for the artist, most users classified as negative are actually positive users. This is a typical example of a classic problem of misunderstanding of the SA: the system, while classifying correctly the tweet, misses the assessment of the feeling because it cannot evaluate the tweet together with its context.

For evaluating the performances of our system, we conducted a simple survey through a group of persons in our department. In this way, we selected and classified 100 messages that show a clear opinion on the singer. Then, we used those messages as a test. The results of the classifiers showed an accuracy of 84% for the polarity and 88% for subjectivity.

In the network periphery, it is possible to notice a small group of users whose feeling is completely positive. After a careful analysis of users' tweets in this small group, it was found that these posts are mainly retweets and the original messages are only two. Of these two messages, the first is actually positive, while the other one is objective. This episode shows how some errors of assessment can have important impact on larger communities.

VI. Conclusions

In this article, we describe some results obtained from the synthesis of Social Network Analysis and Sentiment Analysis applied to the channel #SamSmith during the Grammy Awards in 2015. Apart from the particular results, a methodology and some guidelines for the automatic classification of Twitter content have been discussed.

The implemented software allows: (i) to get a training set for the classifiers that deal with Sentiment Analysis, and (ii) to make a thorough study of the topology of the networks. The study of the global sentiment within the network has highlighted the typical problems of Sentiment Analysis (irony, sarcasm, lack of information, etc.). Additionally, some peculiar problems of the considered channel were also detected (such as the quotes of songs).

The performances obtained by the classifiers during tests conducted on the training set and the analysis of the case studies have shown good and promising results.

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