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Research Article

# EMOTIONAL ANTINOMY CLASSIFICATION OF SENTIMENTS FOR HEALTH CARE SYSTEMS

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**Abstract**

In the statistical machine learning and analysis of sentiment in the text document processing they define handling of antinomy and its performance. Classifying the sentiments with double sentimental analysis model trains the original data creating reviews for training and testing sentimental algorithms. By predicting the extended antinomy framework in which the positive, negative and neutral classification has been done by learning sentimental analysis. In our proposed method we conduct wide range of text analysis about sentiment classification in public social media like twitter. Datasets has various classification algorithms with different features results in the effectiveness of sentimental classification from the antinomy of tweets in the twitter. It evaluates malicious feedbacks and abusive comments and provides both positive and negative feedbacks of public tweets. In this process the raw twitter data will be fetched from the real time streaming data and its connection is achieved through streaming tweet data. Using API twitter provides consumer key, consumer secret, access key, access token that connects the twitter that produces code at runtime. Sentiment analysis model built with real time data in twitter and their positive words and different emotions are monitored and when the abusive words used then it is eliminated and the warning message will be sent to the user. If that particular user continues to send such data again and again then they will be blocked. This model helps in efficient and proper usage of social media in an augment way. This model can also be implemented in health care systems.

**Keywords:** Text document processing, Antinomy, double sentimental analysis, streaming tweet data, emotional data classification

## Introduction

Prevalent social media network in internet with mining public opinion and analyzing their process of sentimental task mining becomes basic in natural language processing. Classifying the sentimental analysis of given text under positive and negative models used for reviewing and representing text. In machine learning algorithms they train the system towards sentimental classifiers having analysis for type of words used according to different moods of people. The common words uses are categorized by the classifiers by already trained data present in its database. The general text representation of sentimental analysis done with the special text mining technique with the help of natural language processing that supports text based classification.

Vector based machine learning algorithms for words independent of reviewing text with statistical training to deploy sentimental classifiers. Reversing the antinomy kind of positive and negative kinds of words with sentimental text representing negative words and differentiate them with positive kind of approach. Sentimentally opposite kind of texts with standard machine learning algorithms fails under various circumstances. Approaches based on negative and positive approach requires complex knowledge of annotations and phrases with human emotions. Datasets of sentimental words results with improvement based on practicing resources increases more dependency over the pre stored data.

Expansion of information creating sentimental reviews named as positive and negative reviews builds techniques corresponding to training based algorithms is defined to be antinomy. Training text and analyzing it with pre trained data which can predict the emotion of text in the conversation and can find out the sentiment it expresses and categorize it accordingly. Those emotions will be classified as positive and negative emotions learned through combination of maximum trained data set with reversed reviews.

In our paper we are going to discuss how the peoples text conversation in social medias like twitter express their feelings in terms of text and they are categorized as antinomy data. The categorized text will be classified under positive, negative and neutral sentimental emotions that sent feedback about those words involved in conversation. As this is a pre process before tweeting a conversation this can block abusive words that should be avoided in the public media. Through this so many disputes will be eradicated at preliminary level.

**Related Work**

At first we discuss in detail about the sentiment analysis done and their perspectives among the antinomy of emotions involved with the help of previous work done. Analysis process will be categorized into different levels of segregating the text and ensure its effectiveness in accordance with the place it is going to be used. The decision must be taken whether the categorization is going to done with whole document level or each sentence will be classified or the phrases used will be taken into consideration. According to the above classification the complexity level of analysis will be finalized.

Based on the phrases used or a complete sentence level sentiment analysis it defines the complexity of classification of words used. Choi and Cardie gather various negative antinomy kinds of lexical phrases through heuristics and improvised machine understandable sentiment analysis. They develop model that cope up sentimental analysis and predicts the antinomy based conversation texts depending on graphs that can potentially blocks negative kind of words. Lexical based issues through document based or sentence based emotional categorization done with machine learning trained datasets.

Lexical issues for words in text along with collection of manual lexical resources that externally gathers all the text data emotions together and the machine learning algorithms implied for sentimental classification. Representation of text with direct reversal of handling antinomy of methods modifies the classifiers with direct sentiment analysis of using contrary words or text in a specified phrase. In terms of counting the antinomy words that express the attitude of a person during the conversation with their phrases will be evaluated and rates accordingly.

The method suggested by Das and Chen simply classifies the negative words like no, not, cant etc as negative summation of words so the literatures that classifies antinomy model with new learning methods with antonym word collections will be directly defined. According to Yet Pang the necessity of improvising the accuracy in sentiment analysis is emphasized so the attempts made for making simple lexical issues will be pre dominated.

While tagging Kennedy and Inkpen for parsing the syntactical usage of negative and diminishing shifters results in handling antinomy that improves performance oriented machine learning methods based on dictionaries that provide lexical resource for words that is extracted and classified both word and sentiment wise classifications. They address common language models that classifies text based language analysis and processing annotations in phrases according to the sentimental classifications.

**Double Sentimental Analysis for Tweets**

Data classification model with component training based on ensemble antinomy provided in the whole document or context identifies the consistent opposite emotional feeling patterns that classifies the sentiments. Additive algorithms that help in sentiment framework with algorithms based on antinomy of classification that has positive, negative and neutral emotional classifications. Along with antinomy classification of context the system frames a fake opposition dictionary that has equivalent meaning for negative and positive words. In previous works they ought to predict and deploy reversing algorithm that statistically classifies the training and prediction which measures both positives and negatives of context. Then with the help of dictionary they reverse or substitute the negative text with positive text and make the context in positive manner.

According to the basic sentimental classification of positive and negative emotion the tweets or conversation will be reviewed and expanded with its data segregation process. A preprocessing of sentimental analysis will be done as primary process according to which the text to be categorized for emotional analysis will be extracted from the tweet conversation. In this process it involves fetching of data or context from twitter using big data and APIs that provides key for accessing it. Then the data fetched from the social media will undergo cleansing process that categorizes or summons the text. The preliminary analysis process will be detailed in the following section.

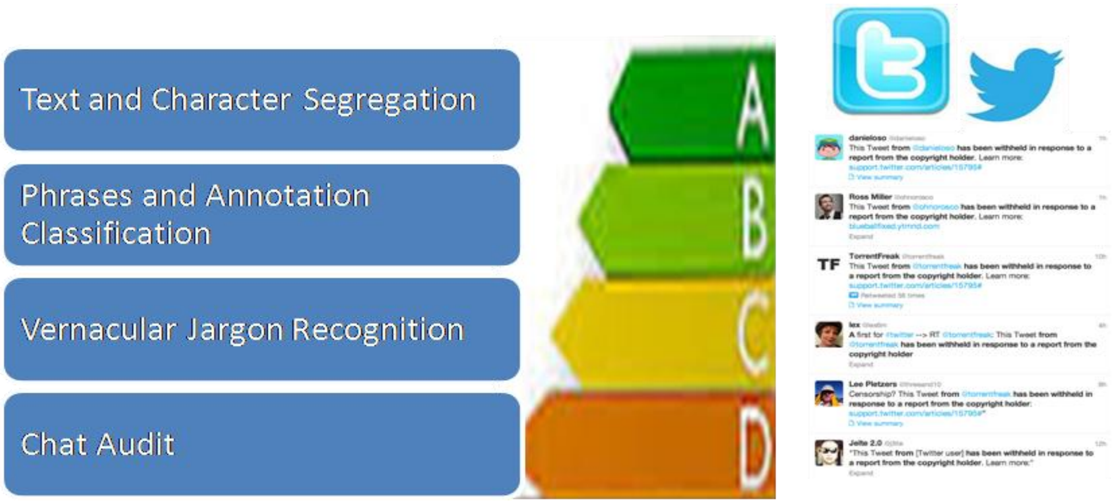


**Fig.1. First Level Classification of Tweets for Sentimental Analysis.**

**A. Text and character segregation,** primarily the conversation from the twitter will be copied then it interprets the words with special characters involved. Only the words will be extracted and moved to next level of process for emotional classification. Sometimes special characters like exclamation marks or question mark adds emotional or sentiment to a statement thus those characters like exclamation, comma, full stop, question mark and symbol will be considered for sentimental analysis. Thus the only context of words that is avoided with white spaces and other unwanted characters will be considered for further classification.

**B. Phrases and annotation classification** implements the predefined phrasal and annotations in the personalized dictionary for this software where those meanings or emotions that phrases expresses will be defined. Thus it helps in better and faster analysis. Traditional and locale phrase or annotation will be stored and the new jargon used could be able to store in that dictionary while any new entry will be there. It updates trending phrases or current annotations in its dictionary along with its emotional classification as per the instructions given by its admin.

**C. Vernacular jargon recognition** integrates the new meanings and terms that being used in locale at present situation. There should be a special dictionary for negative words or the vernacular words that has vulgar meaning will be listed in block contents. Such contents if seen in the conversation context then that should be immediately blocked from admin side. Some of the familiar abusive jargons will be already present in block list and the new vernacular jargons will also be listed in the block list.

**D. Chat audit** then at last the resultant output got from all the above filters will undergone audit for chat analysis. This is the first level of analysis for figuring out the text and the conversation in the tweet will undergo auditing. In this if any anti social or any people in social networks name used then it take it as a prioritized concern for analyzing its antinomies suitable for publishing in a social network.

**Antinomy Classification In Accordance With Tweets**

In semantic context of conversation that surpass sentimental analysis provides good network platform communication with social network that produce abusive comments from the text conversation by the people. Data will be extracted from the social network using big data or Hadoop whereas the data will be processed then for analyzing its status like in the above classifications done. Classification process of segregating the text from other unwanted the characters that could not be classify under any feeling or attitude those are eliminated for process of categorization.

Conversation fetched from twitter after processing in the first level the second level of sentimental analysis is ready to be processed. The accumulated information from the furnished context of words after entering the beginning level of sentimental analysis they further classified under emotional basis.

All the words cannot be identified with proper emotion or sentiments because of most colloquial and vernacular words used for tweeting. Mostly smiley and picture messages are used for expressing anybodies reaction. Even the tweets use other languages rather than English thus all these issues should be eliminated before processing as it confuse or meant to cease the process

Then from the lexicons obtained the identification of antinomies in the context accomplishes its refining process. It predicts the substantial sentiment or emotional analysis potentially concentrates more on negative jargons used in tweets. As it is our preeminent task those negative feeling or emotions are classified and taken separately to notify. Then for vernacular or abusive words used in the context of composite semantic models ensemble the text based training for segregating them. After consistent training records the lexical of words with abusive meanings is collected and from their heuristics level of usage it is opted for blocking of such conversations or that particular user.

**Experiment and Result Analysis**

While recognizing the performance and analyzing the context recognition task the significant usage of counterfeit training data is implemented. In training the data context the maximum combination of reviews with samples for methods adopting and classifying to summarize the datasets. In antinomy of text analysis the sentimental process will be classified as positive, negative and neutral kind of emotional feelings. The bulk of lexicons or meaningful dictionaries fabricated that is personalized for this analysis will be created and used for classifying the verdict of data. Those were analyzed under machine learning technique and update it under the fake dictionary.

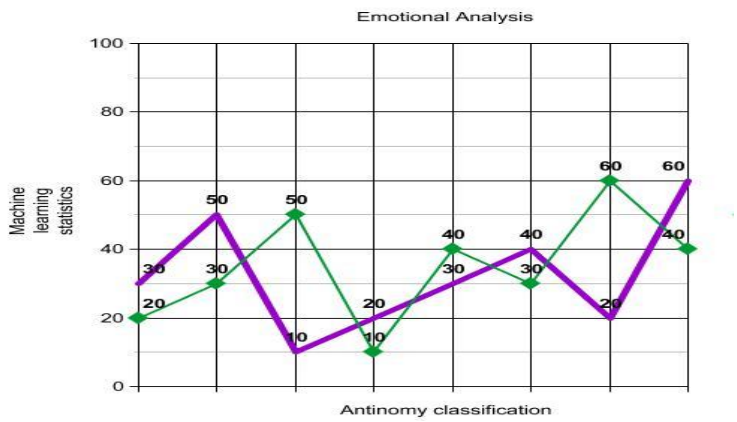


**Fig.2. Scatter Graph analysis of antinomy classification using machine language.**

The words and their opposites will be scrutinized for lexical database issues with various semantic based reviews record and obtain the meaning of words and their positives and negatives. It has personalized fake dictionary that rather than having actual meanings also embedded with trained set of words that is trending recently in the world of social media. Sometimes some conversation or texts have simple and agreeable conversation which might have negative meaning in the dictionary. Thus those exceptional words will be trained as such for this analysis. From fig.2 we could learn the statistics of capacity of machine learning statistics according to the adaptable antinomy classification. Thus it fakes the dictionary which can be personalized according to our emotional categorization needs.

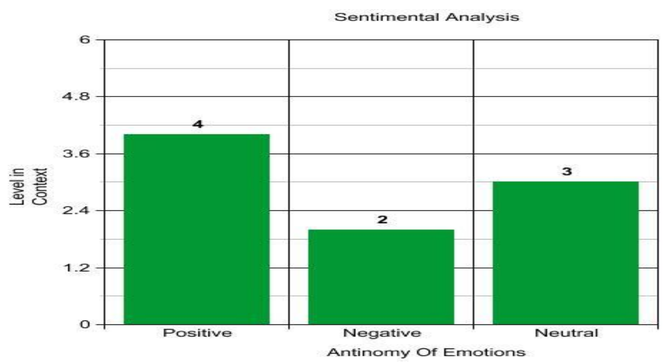


**Fig.3. Antinomy of Sentiments Experiment Analysis.**

From the Fig.3 the results the level of context classification is clearly labeled as the sentiments antinomies are explained then the neutrality that is none of the either emotions are classified in accordance with classifiers. This system ensemble the determination of trained data from the fake lexicons used in this analysis software. The experimental analysis made on task classification the evaluation of machine learning methods classifies and proposes the word antinomies existing. They are classified and then sent mail to notify the proper admin of group to determine the conversation or the user to be blocked or continued as it has no such vernacular meaning. With this sentimental classification of emotional based analysis the review for final results on the context will be directly sent as notification mail. This sounds a nominal and novel approach for incognito conversation and jargons used in social media network.

**Conclusion**

In our proposed paper the categorization of emotional feelings used in context of tweets in the twitter is classified. It creates a bond between the social media like twitter and the application software that enable access towards the context of conversation from twitter and able to analyze and send reports. This model can also be implemented in health care data bases and health care systems .The texts that are classified in accordance with training data present in the fake lexicons that is personalized for this analysis. This has trained data of peer reviews and all the updates of trending words and expressions using machine learning knowledge. As this eliminates all the other characters or some special jargons used thus to avoid turbulence caused during analysis. Thus the experiment results in classifying levels of antinomies like positive, negative and neutral emotions present in the context of conversation extracted. Then those results will be sent as email notification to the appropriate admin for reviewing process. Thus it paves a feasible way to classify sentimental analysis.

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