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Emotion Mining Using Unsupervised Learning

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Abstract

Social networks are considered as the most abundant sources of affective information for sentiment and emotion classification. Emotion classification is the challenging task of classifying emotions into different types. Emotion is a mental state observed by behavioral or developmental changes. Emotions being universal, the automatic exploration of emotion is considered as a difficult task to be performed. A lot of research is being conducted in the field of automatic emotion detection in textual data streams. However, very little attention is paid towards capturing semantic features of the text. In this study, we present the technique of semantic relatedness for automatic classification of emotion in the text using distributional semantic models. Our approach uses semantic similarity for measuring the coherence between the two emotionally related entities. Before classification, data is pre-processed to remove irrelevant fields and inconsistencies and to improve the performance. Our proposed approach achieved the accuracy of 71.795%, which is competitive considering no training or annotation of data is done.

Keywords: *Emotion mining, machine learning, unsupervised learning, data mining*

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INTRODUCTION

Social networks have become a popular interaction platform. Social networking sites like Facebook, Twitter, etc., have changed the standard of social interaction among online users. Social networking sites enable online users to share their ideas, experiences, feelings, and emotions related to their daily routines. Social networks are considered the most abundant sources of affective information for sentiment and emotion analysis. Sentiment analysis deals with determining the appraisals, feelings, and opinions about different entities [1]. Emotion analysis deals with detection and identification of different feelings or emotions like anger, disgust, fear, happiness, sadness, and surprise. The goal of this research is to create an automated system, able to detect emotions in text using semantic similarity between two textual elements. Our system creates a knowledge base for classification and then uses that knowledge base to infer classes of unseen data [5,6].

Emotion is defined as the mental state observed by behavioral or developmental changes. Emotions are universal despite the vast differences between different individuals and their cultures. The social conditions also induce emotions. Emotions are not bound by a person's inner conscience but are afflicted by the person's experiences, goals and most importantly by the society. Emotions are a fundamental part of human nature possessed by every human. Emotions can be broadly classified into two types: basic emotions and complex emotions. Basic emotions include anger, disgust, fear, happiness, sadness, and surprise. Complex emotions include two or more emotions felt by a person in a particular situation. An accurate emotion detection system can be thus very beneficial from a social point of view. Therefore, the need of the hour is a reliable and scalable emotion detection system capable of mapping human-written social media posts into different sets of emotions for tracking the well-being of the society and providing benefits to business establishments and political systems. The creation of an automatic emotion-detection system would thus allow us to evaluate and identify the people's emotions by automatically analyzing the social media content like Twitter posts and Facebook comments [8–11]. The automated emotion-detection system would thus be having one module for analyzing the social web for the social content and tracking the well-being of the individual. Social media posts also contain geographical and temporal information; the system will hence be able to track the welfare state of a social group at some particular place and in some specific temporal range.

The relevance of this research is found as the vast number of applications that are being used to detect the emotional states of people and the benefit, they are providing to business establishments, political parties, individuals and society at large. Its relevance can also be seen in the e-learning environment [28,29], suicide prevention [30], depression detection [31], detection of cyber-bullying[32], or tracking the well-being of user community [33].

The primary challenge for automatic emotion-detection systems is that they do not capture the semantic meaning of the textual systems; instead, they focus on the statistical features present in the text. Traditionally, these systems employ either lexical resources or use statistical measures to build the automatic emotion-detection systems. However, none of these systems employ the measures to focus on the semantics of the text. Moreover, with the employment of these resources, the emotion detection systems would have bias and thus classification of emotions is not accurate and thus the emotion-detection systems are not scalable and robust and are thus error-prone [20–27].

For this reason, we propose an automatic emotion detection system which is capable of exploiting semantic similarity between textual elements and thus classifying text-based on semantic relatedness measure. The proposed system consists of three main steps: (1) creation of seed documents using NRC emotion lexicon [34] which is used to calculate semantic relatedness of the textual element to be classified and emotion class. (2) Generation of big-vectors of text using Word2Vec [35]. 3)Using semantic relatedness measure to compute the similarity between seed documents and textual element to compute emotion class of the textual element.

We measured the effectiveness of the proposed automatic emotion classifier using pre-labeled standard datasets and found comparable results. Thus, the proposed automatic emotion classifier is built keeping the semantics of text in consideration, which was lacking in the previous state-of-the-art research conducted in the area of automatic emotion classification. Moreover, results of automatic emotion classification confirm the effectiveness of the proposed model of emotion detection.

RELATED WORK

Emotions are the stirring states of cognizance perceived by behavioral changes. Emotions can affect human intelligence, memory power, their creativity, and interaction. Emotion analysis deals with detection, identification, and classification of emotions into different types like anger, disgust, fear, happiness, love, sadness, surprise, trust, etc. Emotion and sentiment analyses are the hottest areas of research nowadays due to their broad range of applications. Ekman [5]proposed the basic emotion model. This model identified six types of emotions: anger, disgust, fear, happiness, sadness, and surprise that are considered as the basic emotion types [13].

All individuals have concurrent emotions for any particular event. Liu et al. [7] proposed a technique to extricate emotions from the sentence. This technique is premised on the affective common sense in which real-world knowledge is used to draw sentiments or emotions from sentences. The method is based on the assumption that all the individuals have the same feeling towards a particular event. This technique categorizes the emotions into the Ekman's six emotions[5].

Emotions are not only classified into particular categories but are also classified on the basis of their intensities. Plutchik and Kellerman [6] proposed an emotion model with eight primary emotions including Ekman's six basic emotions with two additional emotions—trust and anticipation. He assembled these eight emotions in a wheel. The radius of the wheel specifies the intensity of the emotions. The emotion closer to center indicates the sharpintensity of that emotion. Plutchik also proposed that these emotions form four variant pairs like anticipation and surprise, anger and fear, joy and sadness, and trust and disgust. Wilson et al. [9]classified the text into subjective and objective texts. This approach used supervised learning approach for classification of text. Subjectivity determines whether a sentence is positive or negative and objectivity determines the intensity (relationship strength) of the emotions related to that sentence. This system requires proper sentence structure for determining syntactic relations. Thelwall et al. [1]analyzed the different texts from online social media MySpace and implemented emotion mining on these texts. They concluded 2-dimensional models provide better accuracy for emotion analysis.

Sentiment analysis is the technique of determining the appraisals, feelings, and opinions about different entities. Researchers have worked on different datasets of social networking sites like Facebook and Twitter to determine polarity of text for emotion and sentiment analysis. Sentiment analysis is performed at three levels, viz. aspect level (or attribute level), document level, and sentence level. Aspect level is the common form of sentiment analysis, e.g., laptop, battery, processor, ram, etc.

Facebook has become one of the largest and popular interaction platforms. Facebook users can share their feelings, experiences, thoughts and emotions with their friends.

Yassine and Hajj [13] present a framework to determine the affective interactions. They used Lebanese Facebook users as a case study and used the unsupervised technique to classify texts based on friendship and subjectivity. They used k-means for classification of textby subjectivity: neutral, moderately subjective, and subjective. The classification results reported an accuracy of 87% based on subjective content of comments shared by online users.

Ortigosa et al. [3]presented a novel approach for sentiment analysis of Facebook posts. They employed a hybrid approach of lexical-based and machine-learning techniques, using SentBuk for classification of Facebook status posts.SentBuk obtaines Facebook posts from Facebook users, performs classification of thes posts, and presents the results of classification by interface.They used J48, Naïve-Bayes and support vector machines to build the classifier. The performance of this classifier was excellent with an accuracy of 83.27%. This approach can be used in e-learning systems and recommended systems where a user can freely express his thoughts and emotions.

Tian et al. [1] found that Facebook reactions are significant sources for determining emotions and feeling. They used six Facebook reactions to enunciate different emotions and sentiments. The six responses that they included in their study were—Like, Love, Haha, Wow, Sad, and Angry. The data set that they used for their experimentation consists of 21,000 Facebook posts that included 57 million reactions and 8 million comments from public Facebook pages of four countries, France, Germany, UK, and the US. Their experimentation results showed that Facebook reactions and emojis are strongly associated with each other.

Twitter is a free micro-blogging website that is considered as most sustainable and accessible social media site for affective computing.

Balabantaray et al. [12]presented a technique of automatic corpora acquisition for sentiment and opinion mining. Emotion classifier was built using this automatic corpus to specify the emotions of the writings of persons. Support vector machine (SVM) was employed for classification using Leave-One-Out Cross-validation. Their experiments showed the accuracy of about 73.24%.

Khan et al. [2]proposed a hybrid approach for classification of tweets in real time to increase the classification accuracy and addressed the problems like data sparsity, Slangs, classification of large number of tweets as neutral, Parsing etc. The different techniques that they employed in this approach are data acquisition, Pre-processing, classification, and evaluation. They used three classifiers for tweet classification: enhanced emoticon classifier (EEC), improved polarity classifier (IPC) and SentiwordNet classifier (SWNC)—

EEC for classification of emoticons; IPC for classification of the word;and SWNC for classification of tweets using SentiwordNet Dictionary. They used six Twitter datasets for experimentation and produced an accuracy of 85.7% with 82.2% recall and 85.3% precision. Emotion analysis is the hottest research area with a wide range of applications.

Aman and Szpakowicz [4] implemented the technique of annotating sentiments to determine emotion bearing sentences or words, emotion categories and their intensities. They proposed an annotation scheme for recognition of different types of emotions, the strength of emotions, and phrases bearing emotion in the text. They worked on self-annotated blog posts having happy and sad mood labels. They conducted their work on two specific emotions happiness and sadness. Their complete processed work can be used for automatic sentiment and affective experiments. Their classification techniques produced accuracy of 73.89%.

Aman and Szpakowicz [4]proposed an annotation scheme for recognition of different types of emotions, the strength of emotions, and phrases bearing emotion in the text. The different types of emotion labels that they used were happiness, sadness, anger, disgust, surprise, and fear. Their results showed the accuracy of 73.89%.

Neviarouskaya et al. [8]proposed a rule-based technique to determine emotions: anger, disgust, fear, happiness, sadness, and surprise (Ekman's basic emotions [5]) from the sentences of different blog posts.

Alm et al. [14]presented a technique of supervised learning for automatic classification of sentences into the basic six emotions (Ekman emotions) in children's fairy tales. They used Snow learning Architecture for classification of sentences.

Wiebe et al. [15]used MPQA corpus composed of 10,000 sentences of news articles for manual labeling of opinions, emotions, and sentiments.Table1summarizes the related work done in sentiment and emotion analysis.

DATASET

The dataset used in this experiment is taken from SemEval-2007: Affective Text [17]. Affective text deals in the categorization of emotions and emotion intensities to determine the association between the emotions and lexical semantics. Emotional content is expressed by words; even neutral words can convey different acquaintances due to semantic differences. The automatic exploration of emotions is becoming popular due to its practical applications like e-learning, personalized marketing, opinion mining and affective computing.

This dataset is composed of the news headlines drawn from different newspapers and news websites like Google News search engine, New York Times, Cable News Network, and British Broadcasting Corporation News. This dataset was taken into consideration because news headlines are a rich source of affective content that conveys some emotions, News headlines are written in different styles to emphasize on various events, and these headlines are best suited for sentence level classification for determining the mixedemotions. This dataset was used for evaluating the results of emotion classification. Two data sets were made usable: trained data set comprised of 250 annotated headlines and test data set consisted of 1000 annotated headlines [16,17].Five teams and eight systems were included for classification. Out of eight systems five systems were used for emotion analysis and three systems for emotion labeling. The three teams are:

1. SICS: SICS team employed Word-Space model and seed words for annotation of headlines.
2. CLaC: CLAC team employed unsupervised CLaC (knowledge-based) system for labeling positive, negative and neutral headlines.
3. CLaC-NB: CLAC-NB team employed supervised CLaC-NB (corpus-based) for labeling positive, negative and neutral headlines.

The five systems are:

1. UPAR_7 System: UPAR_7 is the lexicalrule-based system used for

assigning scores to 6 emotions and their intensities.

2. CLaC System: Employed unsupervised approach for emotion analysis and assigned scores by independent knowledge-based domains.
3. CLaC-NB System: Employed Naïve Bayes classifier for categorizing news headlines into positive, negative or neutral headlines.
4. UA System: Employed PMI (point mutual information) to acquire emotion scores of news headlines.
5. SWAT System: SWAT is supervised system employed for labeling emotion contents in news headlines.

The inter-annotator agreement was implemented using Pearson correlation measure for six emotions: anger, disgust, fear, happiness, sadness, and surprise [5] and intensity annotations. The results of Pearson correlation are shown in Table 2.

The results of five systems for this data set are shown in Tables 3 and 4.

Table 1: *Related Work.*

Prior Work	Year	Dataset	Emotion Labels	Approaches Used	Features Used
Khan et al. [2]	2014	5 Sample Datasets from Twitter4J	Positive (Accurate, Beautiful, capable, Decent, Ease, Faith) Negative (Abnormal, Bad, Danger, Enemy, Fake).	Supervised Learning	WordNet,Netlingo, Spell-check, JSpell, Stanford, Textifier.
Ortigosaet al [3].	2013	7000 Facebook Status Updates	Positive (Positive emotions, Positive sentiment, Optimistic) Negative (Negative emotions, sadness, death, to swear)	Machine learning and Lexicon-Based	Segmentation, Tokenization(I), Emotion Detection, Tokenization(II) POS tagging, Syntactical Analysis)
Aman et al. [4]	2007	Blogs	Happiness, Sadness, Anger, Disgust, Surprise, Fear.	Supervised Learning (Naïve Bayes classifier and Support Vector Machine)	WordNet-Affect (WNA),General Inquirer (GI),
Ahmed et al [34].	2017	Twitter Data	Positive and Negative	Supervised Learning (Naïve Bayes along with TF-IDF)	Normalization, Tokenization, POS Tagging
Balabantaray et al.[12]	2012	Twitter Data	Anger, Disgust, Fear, Joy, Sad, Surprise, Neutral	Supervised Learning(Multi-Class Support Vector Machine)	n-grams, POS, WordNetAffect, emoticons, dependency parsing
Liu et al. [7]	2003	OMCS(Open Mind Common Sense)	Happy, Sad, Anger, Fear, Disgust & Surprise	Common Sense Affect based approach (Real-world knowledge concept models)	Orton's Affective Lexicon, Affect keyword Spotting, adjective, nouns & verbs
Alm et al. [14]	2005	Angry, Disgust, Fear, Happy, Sad, positively & negatively surprised	Children Fairy Tales	Supervised Learning (SNoW learning Architecture)	WordNet-Affect, conjunction of features,
Alm [15]	2008	Angry, Disgust, Fear, Happy, Sad, Neutral, +vely& -vely surprised	Tales	Supervised Learning	Bags of words, Roget's Thesaurus
Tian et al.[1]	2017	Facebook posts (21,000) and Emoji-containing comments (100,000)	Facebook Reactions(Like, Love, Haha, Wow, Sad, Angry)	Supervised Learning(Emojis sentiment analysis).	Emoji Sentiment Score
Rosa Meo & Emilio Sulis [19]	2017		Anger, Disgust, Fear, Joy, Sad, Surprise, Anticipation, Trust	Blog	NB, SVM, Random Forest, Logistic Regression Emotion lexicon

Table 2: *Inter-Annotator Agreement.*

Emotions	Evaluation Measures (Pearson Correlation)
Anger	49.55
Disgust	44.51
Fear	63.81
Joy	59.91
Sadness	68.19
Surprise	36.07
Valence	
Valence	78.01

Table 3: *Valence Annotations.*

Systems	Fine-Grained (Pearson Correlation r)	Coarse-Grained (Accuracy)
CLaC	47.70	55.10
UPAR7	36.96	55.00
SWAT	35.25	53.20
CLaC-NB	25.41	31.20
SICS	20.68	29.00

Table 4: *Emotion Annotations.*

Emotions	Systems	Fine-Grained (Pearson Correlation r)	Coarse-Grained (Accuracy)
Anger	SWAT	24.51	92.10
	UA	23.20	86.40
	UPAR7	32.33	93.60
Disgust	SWAT	18.55	97.20
	UA	16.21	97.30
	UPAR7	12.85	95.30
Fear	SWAT	32.52	84.80
	UA	16.21	97.30
	UPAR7	23.15	75.30
Joy	SWAT	26.11	80.60
	UA	2.35	81.80
	UPAR7	22.49	82.20
Sadness	SWAT	38.98	87.70
	UA	12.28	88.90
	UPAR7	40.98	89.00
Surprise	SWAT	11.82	89.10
	UA	7.75	84.60
	UPAR7	16.71	88.60

ALGORITHM

Begin
Input: Query String
Function Pre-processing (Social_Media_Post)
For each word token in Social_Media_Post
Do
Remove URL
Spell Check & Correction
Replace Slangs
Replace Abbreviations
Remove Stop Words
Convert to Lower Case
Lemmatization
Remove Special Characters
Spell Checking
Return Preprocessed_Post

Function Word_Net_Synonyms (Preprocessed_Post)
For each word token in Preprocessed_Post

Find the distinct Synonyms Using WordNet
Build Big Post (Synonyms)
Return Synsets

Function TF_IDF_Synsets (Synsets, Background_Corpus)
Calculate TF_IDF;
$TF\_IDF = c(w) * \log(\frac{D}{d(w)})$;
Return Vector_Synsets;

Function TF_IDF_Emotions (Emotion File, Background_Corpus)
Calculate TF_IDF (Big Post)
$TF\_IDF = c(w) * \log(\frac{D}{d(w)})$;
Return Vector_Emotions;

Function Semantic_Similarity (Vector_Synsets Vs, Vector_EmotionsVe)

For each Vector Vs[i] in Vector_Synsets
For each Vector Ve[j] in Vector_Emotions
Calculate Semantic_Similarity_Vectors(Vs[i],Ve[j]);Semantic_Similarity_Vectors =dotProduct (Vs[i], Ve[j]) / (Math.sqrt (norm(Vs[i]) * Math.sqrt (norm (Ve[j])) ;
Return Score of Semantic_Similarity_Vectors;
Function Finding_Maximum_Score (Semantic_Similarity_Vectors)
Find Max_Score;
Max_Score=max_of (Semantic_Similarity_Vectors);
Return Max_Score;
End

METHODOLOGY

The methodology used in this experiment is comprised of following four steps:

1. Data pre-processing.
2. Synonyms generation using WordNet.
3. Vectorization.
4. Semantic similarity.

The overall methodology is explained in Figure1.

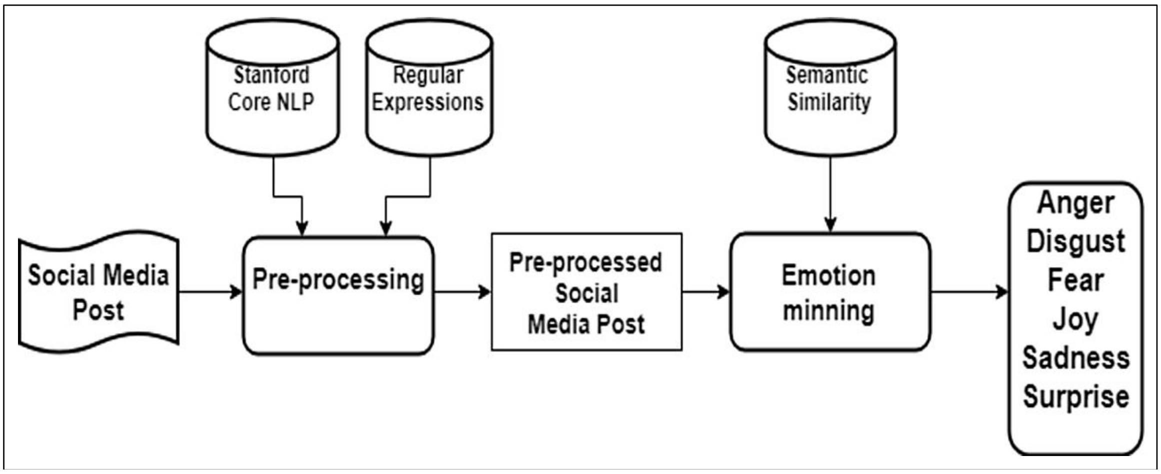

Fig.1:*Overall Methodology.*

Data Pre-Processing

The data is pre-processed to remove the irrelevant fields and inconsistencies. Data is refined at each step of pre-processing and then passed to the classifier for classification. The pre-processing of data consists of following steps as shown in Figure2.

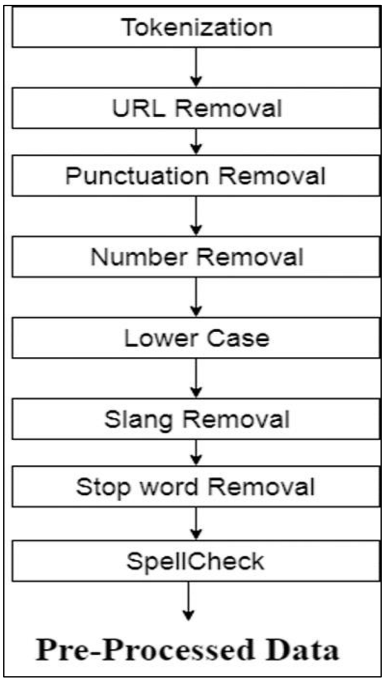

Fig.2:*Steps of Pre-Processing.*

i. *Tokenization:* The data is tokenized to extract the tokens using Stanford Core NLP, and in this step, only the white spaces are used to separate the tokens.
ii. *Removing URLs:* Data may contain different URLs and links which are removed.
iii. *Punctuation Removal:* Punctuation marks do not have any impact on affect, and thus they are removed.
iv. *Number Removal:* Numbers are removed from the data
v. *Lower Case:* This step converts all the token into lower case.
vi. *Slang Removal:* The slangs are replaced by their respective expansions like "lol" is replaced by "laugh out loud."
vii. *Stopword Removals:* Stanford can be used for identification of stop words which then can be removed easily.
viii. *Spellcheck:* For spell checking, J Spell is used.

Synonyms Generation Using WordNet

WordNet is a Lexical reference library for English language created at Princeton University. It is a lexical database comprised of adjectives, adverbs, nouns, and verbs that are aggregated into related sets called *synsets*. Synsets have a relation of synonymy. Each synset is related to specific context. WordNet also provides the count of synsets of a particular word by frequency score. WordNet is used in natural language processing (NLP) to calculate the similarity score. In this experiment, WordNet 3.0 is used to obtain the synonyms of words. Then distinct synonyms are combined to form a Big Blog.

Vectorization

For vectorization, TF_IDF is used. TF_IDF stands for term frequency-inverse document frequency. It is used for unsupervised clustering. TF_IDF provides us the importance of terms in the corpus. TF gives us the frequency of terms in a document. Mathematically, TF is given by

$$TF(t) = \frac{\text{Frequency of term t in a document)}}{\text{Total number of terms in the document}}$$

IDF provides us the importance of the term in a document. Mathematically, IDF is given by

$$IDF(t) = \log e \; \frac{\text{Total number of documents}}{\text{Number of documents with term t in it}}$$

In this experiment, TF_IDF is required to represent synonyms present in Big Blog and the emotion lexicon seeds (NRC EmoLex) in vector form to calculate the semantic similarity between them. Emotion lexicon seeds are downloaded from NRC Emotion Lexicon (Version 0.92 2010) [27]. The NRC Emotion Lexicon is composed of 14,182 unigram English words categorized into eight basic emotions (anger, anticipation, disgust, fear, joy, trust, sadness and surprise) and two sentiments (positive and negative).In this experiment,only six emotions (anger, disgust, fear, joy, sadness and surprise) are used. Crowdsourcing on Mechanical Turk is used for manual word level annotation of these lexicons. Mathematically, TF_IDF is given by

$$TF\_IDF(w) = c(w) * \log\left(\frac{D}{d(w)}\right)$$

Where *c(w)* gives word frequencies in current document,
*d(w)*gives word frequencies of all documents,
D is number of total documents.

Semantic Similarity

Semantic similarity provides us the semantic association between the entities. Semantic similarity is defined as a knowledge-based technique that determines the semantic relationships between words. The knowledgeable sources can be internet, corpus, and dictionaries. The semantic relation is determined by calculating the similarity distance between the two entities. Semantic similarity detects the common "features." Semantic similarity is used in cognitive science, knowledge engineering, automatic crossword puzzle generation and text summarization, bioinformatics and word sense disambiguation. Semantic provides us the semantic relationship of the vectors concerning the emotions.

DUC 2007 [21] is used as background corpus. National Institute of Standards and Technology (NIST)has organized DUC (Document Understanding Conference) to accelerateadvancements in automatic text summarization. It is composed of two tasks: main task and update task. The main task provides the summary of a topic (250 words) with relevant multi-documents (25 documents) and responding to question related to that particular topic. The update task provides the summary of 100 words of multi-documents. Each update summary is premised on the assumption that a client has some knowledge about that topic and thus provides the updated information related to that topic. DUC 2007 is employed by researchers for assessment of summarization systems.

The overall process of semantic similarity can be explained by the following steps:
Step 1: Data is pre-processed to remove inconsistencies and noise from data.
Step 2: WordNet 3.0 is used to extract synonyms of the pre-processed words.
Step 3: Distinct synonyms are aggregated to form Big Blog.
Step 4: Background corpus is used to get TF_IDF of Big Blog.
Step 5: Semantic similarity derived from Vectors provides us the higher frequency of vectors.
Step 6: For each seed lexicon, TF_IDF with background corpus was obtained and compared to each TF_IDF of Big Blog using semantic similarity score.
Step 7: The synonym with highest max semantic similarity score was chosen as the member of the particular emotion type (anger, disgust, fear, happiness, sadness and surprise). Mathematically, semantic similarity is given by:

$$Semantic\ Similarity = \max of\ (cosine\ Similarity\ of\ bigblog, NRC\ emolex).$$

The overall process of Semantic similarity is explained in Figure3.

EVALUATION AND RESULTS

For classification, we used semantic similarity, which is popularly employed in sentiment and emotion analysis. Semantic similarity provides us the semantic relationship of the vectors concerning the emotions. Accuracy, precision, recall, and F1 scoreis used to evaluate the performance of semantic similarity. These parameters are estimated using confusion matrix. A confusion matrix (Table 5) is a table that is used to measure the efficiency of a classifier.

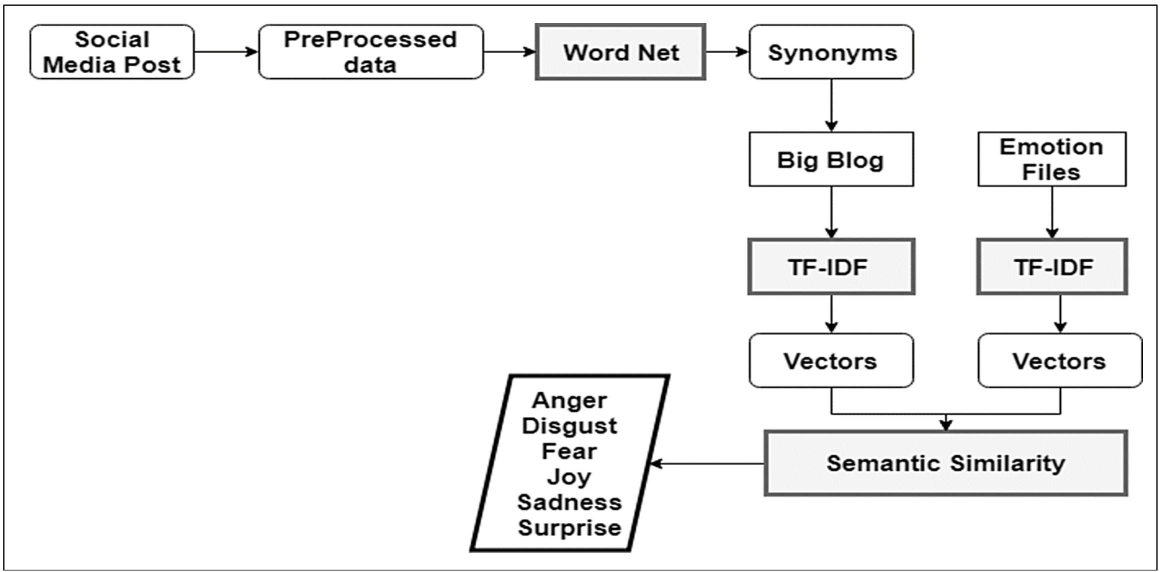

Fig.3:*Semantic Similarity.*

Table 5: *Confusion Matrix.*

	Predicted Class		
		P	**N**
Known class	P	TP	FN
	N	FP	TN

Accuracy

Accuracy is a perceptive evaluation method for measuring performance. It is the ratio of true classifications to the total classifications.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}}$$

Where, TP=True positive, FP=False positive, TN=True negative, and FN= False negative.

Precision

Precision also called positive predictive value is the ratio of correctly measured positive classifications to the total predicted positive classifications. Higher the precision,lower is the rate of false positives.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Where FP=False positive and TP=True positive

Recall

Recall or sensitivity is the ratio of correctly predicted positive classifications to allclassifications in actual class.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Where, TP=True positive, and FP=False negative.

F1 Score

F1 score is the harmonic mean of precision and recall.

$$\text{F1 Score} = 2 * \frac{\text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}}$$

CONCLUSION AND FUTURE SCOPE

This study describes the emotion classification into Ekman's 6 emotions using semantic similarity. Semantic similarity is a knowledge-based technique that determines the semantic relationships between the words. Data is refined at each step of pre-processing and then passed to the classifier for classification to remove noise from data and increase the accuracy of sematic similarity. This algorithm achieved an overall accuracy of 48% with average precision of 63.48%, recall of 60.45% and F1-score of 54.92% which is higher than the baseline accuracy.

In future, we will use Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) for the distribution of emotions into different emotion classes across the social media posts.

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