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Similarity between Sentiment Analysis and Social Network Analysis

M.Thangaraj, Assiocate Professor, S.Amutha, Research Scholar

Abstract— This paper says about Sentiment Analysis (SA) and Social Network Analysis (SNA) and its tools. In SA there are various operations done in the human being typing text using the Social Network sites. Basically the people have texts are included in following: positive, negative and neutral. Nowadays most text word can be expressed in Emoticons. In the SN sites people share advice, concerns, facts, moods, news, opinions and rumors.

Index Terms— Sentiment Analysis, Social Network Analysis, Sentiment shifters, SenticNet, Sentiment Annotation, SentiStength, SentiWordNet, Sentiment Classification, Sentiment Calculation..

1 Introduction

All people are in the world sharing thoughts throw Social Network Sites using the words in positive, Negative, Neutral and real &bias emotions are called Sentiment Analysis. Internet has democratized content creation enabling a number of new technologies, media and tools of communication, and ultimately leading to the rise of social media and an explosion in the availability of short informal messages that are publicly available [1].

Microblogs such as Twitter, weblogs such as LiveJournal, Social Networks such as Facebook and direct messengers such as Skype and Whatsapp are now regularly used to share thoughts and opinions about something in the surrounding world, beside with the old-fashioned cell phone messages such as SMS [2]. In messages own word embeddings on tweets using Web Clustering. It is build continuous dense word representations.

Sentiment Analysis is a type of text classification that deals with subjective statements [3]. It is also known as opinion mining. The processing of opinions is in order to learn about the public perception. It uses Natural Language Processing (NLP) to collect and examine opinion or sentiment words.

Sentiment Analysis has various sub streams including Emotion Analysis, Trend Analysis and bias Analysis etc. Emotion Analysis is a facial expression of emotion. It is type of Interaction without words such words for Joy, Disgust, fear, sadness, surprise and Anger etc [5]. Most of the time people used in Skype Calling and Teleconferencing is called Instant Messaging (IM).In E-mail messaging is used to identify the gender.

Trend Analysis is rearing practice of collecting information and attempting to spot a pattern. It used in Predictive analytics to predict future events from the past information. Bias Analysis is includes the design of validation studies and the collection of validity data from other sources [6].

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What is Sentiment Analysis?

Sentiment analysis is a very thought-provoking task. It is study of automated techniques for extracting sentiment from written languages growth of social media has resulted in an explosion of publically available, user generated text on the WWW.

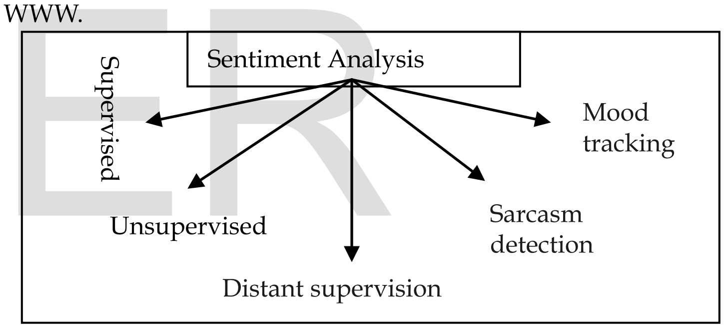

Figure.2 Sentiment Analysis is part of Content Mining

Every Millions of comments or options are posted in websites that provide the facilities for micro blogging such as twitter or Facebook. The creators of the comments share their opinions on different topics, discuss current issues. These are the valuable source of posts are posted by the users according to their used products and services, or express their different views on different perspectives.

Sentiment Analysis is the process of determining whether a piece of writing is positive, negative or neutral. It's also identified as opinion mining, deriving the opinion or feelings of a speaker.

A common use case for this technology is to discover how people feel about a particular topic. It is inside content mining, which is scanning and mining of text, pictures and graphs of a web page to determine the relevance of the content to the search query. It is divided into five ways as supervised, unsupervised, distant supervision, sarcasm detection and mood tracking.

Sentiment Annotation

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It is the task of identifying +ve, -ve, emotions and evaluations. It consist two processes comprehension and sentiment judgment. Sentiment Mining is a computational technique for social networks have become ubiquitous and are used throughout the world for interpersonal communication [16].

Sentiment Calculation

It is used to count the set of +ve sentiment words, set of -ve sentiment words and N^{th} feature selection will be calculated. And also calculate the positive and Negative of every sentiment words by calculating its probability.

Sentiment Text Classification

It is a very important task in text classification. The texts are evaluating the performance in terms of accuracy, precision and recall. It is study of relation of words, phrases, signs and their denotation. It includes Sentiment Shifters, connectives and Modals. The words are clustered into positive, Negative and neutral. Sentiment Text Classification (STC) can be performed at four different levels: word level, phrase level, sentence level and document level. It is built for social media text such as product reviews, blog spots, and even in twitter messages.

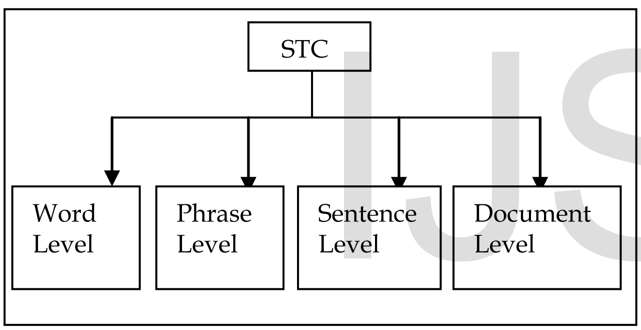

Figure 4. Sentiment Text Classification.

It is used in words and expression that can affects text polarity, play an important role in opinion mining. It is changing its magnitude or direction in text polarity. There are two directions in SS. First, reverse the polarity of given text. Second, words are changed into sentiment values by a constant amount.SS can be classified into two groups. First group Local Shifters; it is directly applied to polar words. Second group Long distance shifters; which allow longer distance dependencies between the shifter words and polar words.

There are three types of Sentiment Shifters. Negations are main part of the common linguistic constructions that change the polarity. It includes no, not and never. Negation identification and detecting its scope with in a sentence are needed to find sentiment from the given text. Negation is to be a grammatical category that allows the changing of the truth value of a proposition. It is often expressed through the use of negative signals and it includes no, not and never. When understanding the impact of Negation on Sentiment improves the Automatic detection of Sentiment.

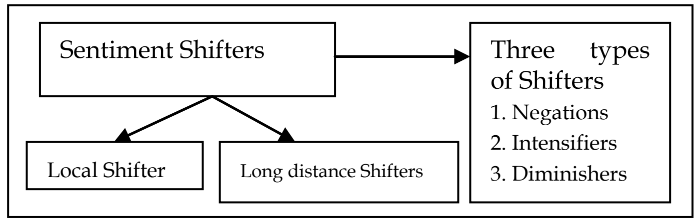

Figure .3 Details about Sentiment Shifters.

Automatic Negation handling involves identifying a negation word such as not, determining the scope of negation and finally appropriately capturing the impact of the negation. Traditionally the negation word is determined from a small handcrafted list. The Scope of negation is often assumed to begin from the word following the negation word until the next punctuation mark or the end of the Sentence.

Intensifier is expression, which shift the intensity of a sentiment expression or modifier. It is classify into two major categories, Amplifiers, which increase the Semantic intensity of the neighboring lexical item, whereas down toners decrease it. Secondly Quantifiers is also unsafe as the meaning of the noun terms example, some, several, numerous, many, much, more, most, less and least etc.

SENTIMENT MODIFIER

A modifier can change the intensity and polarity of a sentiment word. There are important roles modifiers in sentiment analysis is three features – intensity, negation and implicit polarity. The word that modifies a sentiment word and affects the polarity or intensity of sentiment, including relatively, very, too, negative etc. It suggests that the collocations of sentiment words and modifiers should be studied to improve the accuracy of phrase- level sentiment analysis. In sentiment phrases extraction as a central sentiment word combined with some intensified modifiers.

Modifiers have sentiment scores ranging from +1 to +2. The sentiment of the word or phrase being modified is multi plied by the sentiment score of the modifier. The resulting value contributed to the category associated with the word or phrase.

A set of phrases was added to the lexicon during the refinement process. The use of phrases make it possible to correctly score words that posses a unique meaning when grouped together, e.g hard to keep up, straight from the book or "good luck". Phrases are also used to nullify terms that are not likely to be scored correctly using simple methods, "I would suggest, I never thought and should have". Phrases have a sentiment score optional category and a priority. Avoiding a phrase can be accomplished by simply setting the
Sentiment scores for the phrase to zero.

Sentiment Modifiers is divided into four expressions are Negaters, Neutralizers, Committers and Intensifiers. Negaters expressions which invert the polarity of a sentiment expression or modifier and also it can flip the sentiment expression, e.g no, not and never. Neutralizer is an expression that is used to denote a hypothetical case that is assumed, desired or required but not definitely true. But do not commit the speakers to the truth of the target sentiment expression or modifier. Committers increase or decrease the author commitment to an opinion. Intensifiers expression serves which increase or decrease the intensity of a Sentiment expression. It have two values; strengthen and weaken depending on prior polarity is being increased or decreased.

Sentiment orientation

It is measure of positive or negative sentiment expressed by a word use four adjectival appraisal groups are Attitude, orientation, graduation and Polarity. It can be positive, negative, or neutral. Neutral usually means the lack of sentiment or no sentiment. Sentiment orientation is also called polarity, semantic orientation, or valence in the research literature.

Sentiment Community

In this process it is identifying community interests and their openness consists of three steps, first the network of users re-tweets each other is retraced and the densely connected communities are detected. Second the content published by these communities is analyzed to reveal the communities interests and finally, sentiment analysis is performed to assess the sentiment leaning of the communities with respect to different topics of interest. It is of considerable size which also produced a sufficient amount of tweets for meaningful content identification and sentiment Analysis. It finds inter and intra community and also select the majority of communities are greatly introverted.

A preliminary community categorization was performed by looking at the twitter profiles of their most influential users and the contexts of their preferred topics. Users in each community by performing a topic-based analysis of the blogs and then cluster these bag-of-topics to discover Meta groups.

Sentiment Analysis	*Sentiment Analysis Concepts Explanation*
Sentiment Annotation	It is a job to identify the word whether it is +ve, -ve or neutral.
Sentiment Calculation	The text is to be calculated how much set of +ves, -ves and Neutrals depends upon its probability.
Sentiment Classification	It is a study of relation of words, phrases, signs and their denotation.
Sentiment Community	It is a group who are closely related with their words typing through social media about products, customers and vendors.
Sentiment Composition	It is the shaping of sentiment of a multi-word linguistic unit, such as a word or a sentence, based on its elements.
Sentiment Consistency	It may help to improve the translation performance, which could be of interest for many annotations.
Sentiment Detection	It tests set of annotated texts. It is finds the polarity of texts. It is an integral part of social media monitoring tools.
Sentiment Determination	It is determined that opinion mining is performed manually by observing and selecting the post from the people emotions.
Sentiment Extraction	It is worth mentioning that automatic extraction of sentiment words/phrases could be useful input for information retrieval systems
Sentiment Intensity	Users often use two ways to express intensity of their feelings in text, first choose Sentiment expressions with suitable strengths, and secondly use the Emoticons.
Sentiment Homogeneity	It is in a cluster, there is an increased chance that user is influence by the surrounding emotion and shows a similar sentiment to the one prevailing at the moment.
Sentiment Modifiers	Modifiers to the word modifies a sentiment word and affects the polarity or intensity of sentiment, including relatively, very, too and neg etc.
Sentiment Orientation	It measure the +ve or –ve sentiment expressed by a word use four adjectival appraisal groups.
Sentiment Polarity	It is in binary, it checks if the polarities of the source and target side are the same.
Sentiment Shifters	It improves the accuracy of the classification. It Changing its magnitude or its direction in text polarity
Sentiment Strength	It decides the strength of an opinion in texts is weak, mild or Strong.

TABLE.1 VARIOUS MANIPULATIONS INSIDE SENTIMENT ANALYSIS

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Use psycholinguistic features to categories communities alike in linguistic style into clusters.

Sentiment Context

Information about the context is an important factor in understanding opinion. The shift in base attitudinal valence of a lexical item is due to lexical and talk about context is studied in which also intends an implementation to carry on with a set of contextual shifters [23].

Sentiment Extraction

In this there are two main systems, Automatic Speech Recognition (ASR) system, Text- based sentiment extraction System. In this important feature of method is the ability to identify the individual contributions of the text features for sentiment estimation. This provides us with the capability of identifying key words/phrases within the video that carry important information. It is worth mentioning that automatic extraction of sentiment words/phrases could be useful input for information retrieval systems.

Sentiment Intensity

People often use two ways to express intensity of their feelings in text. First they choose sentiment expressions with suitable strengths. For example, *good* is weaker than *awesome*, and *disfavor* is weaker than *detest*. Recall *sentiment words* are words in a language that are often used to express positive or negative sentiments [24]. For example, *good*, *wonderful*, and *amazing* are positive sentiment words, and *bad*, *poor*, and *terrible* are negative sentiment words. The second is to use *intensifiers* and *diminishers*, which are terms that change the degree of the expressed sentiment. An intensifier increases the intensity of a positive or negative expression, whereas a diminisher decreases the intensity of that expression. Common English intensifiers include *very*, *so*, *extremely*, *dreadfully*, *really*, *awfully*, *terribly*, and so on, and common English diminishers include *slightly*, *pretty*, *a little bit*, *a bit*, *somewhat*, *barely* etc [25].

Sentiment Classicification

Sentiment can be classified into several types. There are linguistic based, psychology based, consumer based research based classifications are in Sentiment classification. Especially consumer research is divided into two rational research and emotional research [22].

Rational Sentiment is from rational reasoning, tangible belief, and utilitarian attitudes. There are no emotions.

Ex: The car is very smooth.

The car is very comfortable for our family.

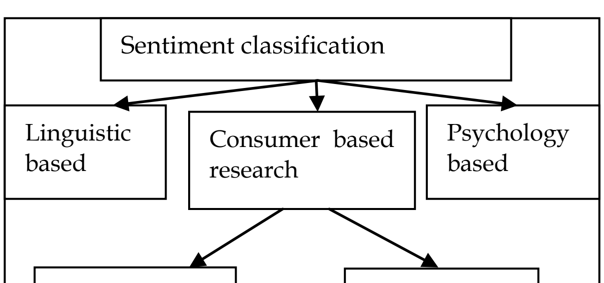

Figure 5- Types in Sentiment Classification

Emotional Sentiment is from non-tangible and emotional response to entities that go deep into people psychological states of mind.

Ex: I like sweets. I love flowers smell.

Emotional Sentiment is stranger that Rational and is usually more important in practice [32].

Sentiment Determination

It is simple and simplest systems in universal, the match words in the immediate context of the target item's name against lists of positive –affect and negative –affect words and compute some sort of possibly weighted average. It is step in process of converting unstructured content to structured context [26]. People of information can spot trends and patterns within the content. It is determined that opinion mining is performed manually by observing and selecting a Facebook post before the comments are extracted automatically and it comments so that people emotion towards the issue can be determined if the overall feedback of people is Happy, Unhappy or Emotionless [27].

Sentiment Detection

SA is quite domain dependent, it is very hard to come up with a generic, one-box fits all approach for the task, which are biased by having overlapping features are used as uninterruptable black bones. It is finds the polarity of a text. The text is simple sentence or very short texts from a single source. It is an integral part of social media monitoring tools. There are comparisons of social media monitoring tools typically also explore their sentiment detection abilities. It tests set of annotated texts [20].

Sentiment Homogeneity

It is evidence of an increased but not strong, chance of one sharing the same overall sentiment that prevails on the cluster to which it belongs to same another. It is in a cluster, there is an increased chance that a user is influence by the surrounding emotion and shows a similar sentiment to the one prevailing at the moment [21]. It is evaluate through k-fold cross validation. The k-fold cross validation is unveiled that this homogeneity is usually stronger in re-tweet based clusters.

Social Network Anlysis

Online Social Networks allow hundreds of millions of Internet users worldwide to produce and consume content.

They provide access to a very vast source of information on an unprecedented scale [4]. Still, the raw data produced by users of these networks is a flood of ideas, information, opinions, *etc*. Social Network (SN) is connecting people through Social Media like facebook, twitter, whatsapp and YouTube.

In universe, count of Face book users are 123.1 million and second place goes to India 101.5 million. However, by 2017, comparing the India mobile phone users are increased than US. India has at 145.9 million followed by the US 38.8 million. Recently, Face book declared that growing Internet penetration and a large youth population has helped it expand its user base in India to 112 million which is the largest next to US. In 2016, the micro-blogging site is projected to reach 23.2 million monthly active users in the region, up from 11.5 million in 2013 [8].

When connecting people through texts, images, audios and videos, it is made through some perfect representation by using the Graph (G=V, E). Here v stands for vertices and E stands for edges [9]. Totally all the pairs connected and interconnected by objects. Each object is used and linked for the communication. Through the communication messages passes and relationship created and maintained by the social media. In the relationship the links can encode all kinds of relationships like familial, friendship, professional or organizational [10].

In SN all the messages are sending to Groups Creating Method. In Group people are all administrator and also all are users. When they like or dislike they can made it. SNA has its roots in both social science and in the wider fields of Network Analysis and Graph Theory.SNA has a pant history in social science, although much of the work in advancing its methods has also come from mathematicians, physicists, biologists and computer scientists.

Network analysis provides two functions, revealing the underlying social system and discovering the active interactions among social actors. Network analysis identifies the system's structure through examining the relations between the system components, its actors Network analysis concerns itself with the formulation and solution of problems that have a network structure; such structure is usually captured in a graph [39]. Graph theory provides a set of abstract concepts and methods for the analysis of graphs. These, in combination with other analytical tools and with methods developed specifically for the visualization and analysis of social networks, form the basis of what call SNA methods.

SNA can be boiled down to three steps are identification, extraction, and analysis [7]. Identification involves understanding the source data and what subset of the data can represent people or groups and relationships between them. Identifying networks within a data source depends on the structure of the data and the types of information stored [10].

Extraction involves getting the data from the source into a properly structured network representation gear up for analysis. Often this involves restructuring a network in particular ways depending on the types of analysis to be executed [33]. Extracting networks can be as simple as reading in a file or as complex as pulling and merging data from multiple databases. Finally, analyzing the network implies applying one or more algorithms in particular sequences and visualizing the results [17].

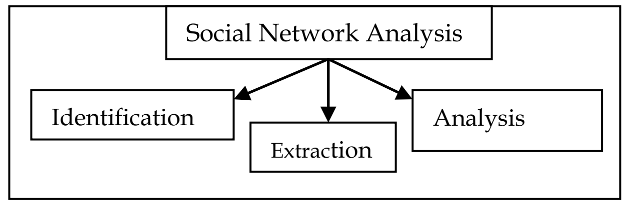

Figure 6 - Social Network Analysis processing steps.

Homophily: People who share the same interests, same thoughts and are similar tend to hang out together. While we not know the reason behind this behavior, we can easily observe it in our daily interactions. It is the tendency to relate to people with similar characteristics. It leads to the formation of homogeneous groups here forming relations is easier [18].

Transitivity: structural embeddedness is necessarily present as through transitivity our friends are likely to develop ties of their own over time. The view of tie strength is an example of the relational attribute of social capital, which cares the kind of personal relationships that people have developed with each other by a history of interaction [19].

Clique = Homophily+ Transitivity, a clique in a graph is maximal complete subgraph of three or more nodes. a clique is typically loosed by allowing some lacking connections. The analysis of overlapping cliques shows that the largest, most cohesive cluster outside the core is formed by researchers working on semantic-based descriptions of Web Services, in particular members of the DAML-S coalition [11].

Bridge : In communication ties that bridge a variety of different groups lead to higher performance as did network density. From a network view, general words are therefore more likely to bridge different clusters of words, while specific terms are expected to exhibit a dense clustering in their neighborhood [12]. Ties spanning communities tend to be sparse compared to the dense networks of cohesive subgroups and as a result there are typically few bridges across communities.

Brokers controlling these bridges are said to be in an advantageous position especially because of the value attributed to the information flowing across such ties [13].

TABLE II. SOCIAL NETWORK ANALYSIS IN GRAPH THEORY

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Degree centrality: DegreeCentrality measures the number of edges that connect a node to others and is used to identify nodes that have the most connections in the network. It equals the graph theoretic measure of degree, i.e. the number of links of a node [14]. This measure is based on the idea that an actor with a large number of links has wider and more efficient access to the network, less reliant on single partners and because of his many ties often participates in deals as a third-party or broker. It does not bring into account the wider context of the self-importance, and nodes with a high degree may in fact be disconnected from large parts of the network. However, the degree measure features prominently in the scale-free model, which makes it an important measure to investigate [15].

Social Network Analysis in Graph Theory	
Concepts	**Explanation**
Homophily	**It is the tendency to relate to people with similar characteristics.**
Transitivity	**Strong ties are more often transitive than weak ties; transitivity is therefore evidence for the existence of strong ties**
Bridge	**Bridges are nodes and edges that connect across groups Facilitate inter-group communication, increase social cohesion, and help spur innovation.**
Degree centrality	**A node's (in-) or (out-)degree is the number of links that lead into or out of the node**
Betweeness centrality	**The number of shortest paths that pass through a node divided by all shortest paths in the network**
Closeness centrality	**The mean length of all shortest paths from a node to all other nodes in the network**
Eigenvector centrality	**A node's eigenvector centrality is proportional to the sum of the eigenvector centralities of all nodes directly connected to it**
Reciprocity	**The ratio of the number of relations which are reciprocated over the total number of relations in the network**
Density	**A network's density is the ratio of the number of edges in the network over the total number of possible edges between all pairs of nodes.**
Clustering	**A node's clustering coefficient is the density of its neighborhood**

Betweeness centrality: It measures the fraction of all shortest paths that pass through a given node and is often used to identify nodes that act as boundary spanners between different groups [28].

Closeness centrality: It is a basic network metric but requires the input network to be connected: all nodes in the network must be connected to each other by at least one path [29]. The mean length of for all shortest paths from a node to all other nodes in the network is connected.

Eigenvector centrality: It is a scope of the work of a node in a network. It deputes relative heaps to all nodes in the network based on the concept that connections to high-scoring nodes gives more and more to the score of the node in question than equal connections to low-scoring nodes [30].

Google's PageRank and the Katz centrality are forms of the eigenvector centrality. PageRank represents the web pages as nodes and directed edges represent the links between them [31]. Thus, it uses the join structure of the WWW as an indicator of an individual web page's importance relative to other web pages by interpreting a link from one page to another web page.

Katz centrality is a gernalization of degree centrality *(DC). It* measures the number of direct neighbors, and number of all nodes that can be properly connected through a path, though the contributions of distant nodes are penalized [36].

Reciprocity: it is a amount of the likelihood of vertices in a directed network to be reciprocally linked. It is lively like the clustering coefficient, scale-free degree distribution, or community structure, it is a most valued measure used to calculate complex networks [34].

Density: Density can be measured by computing the clustering coefficient measure introduced on a neighborhood of the individual [35]. A network's density is the ratio of the number of edges in the network over the total number of possible edges between all pairs of nodes. It is useful in comparing different types of networks against each other, or in doing the same for different regions within a single network.

Conclusions

Here the Sentiment Analysis and Social Network Analysis is use the source as social Media texts, Images, Audios and videos. By the way changes happening in the people thoughts as positive, negative or neutral. When neighborhood or relatives, people like to talk or chat through using such as Social media. It is basis on WWW by using the Social Network Analysis to survey the growth of population, education, commercial, marketing, medical, political, sports, weather reports etc [37]. People suddenly replies the comments and giving resolutions for lot of problems through SNA whether it's in a positive, Negative, Neutral or Emoticons.

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