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Sentiment Analysis Using Social Network Analytics

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ABSTRACT
There is a wide range of unstructured data available on social networking platforms. There is an urgent need to classify this data. Sentiment analysis helps in classifying this data beyond numerical methods, focusing more on qualitative analysis of data. The aim of sentiment analysis is to acquire the abstract emotions and opinions from data which helps in making appropriate decision regarding the user's intention behind a message. Sentiment analysis (opinion mining) assists in evaluating the data via means of different indexes and metrics. Social network analytics makes it possible to consider data as links between users which aids opinion mining. The paper deals with three important concepts to understand the interactions between users on social networks namely tie strength, homophily, and source credibility. Sentiment analysis also faces many challenges particularly posts involving sarcasm and irony which are extremely difficult to analyze. Opinion mining involves three levels of analysis including message level, sentence level and entity and aspect level. Opinion mining is a broad field which has a great scope of research in the upcoming future. There are many machine learning techniques which can be used for analyzing sentiments however this paper mainly discusses utilization of social network analytics for sentiment analysis.

Keywords: sentiment analysis, social network analytics, unorganized data.

I. INTRODUCTION

The data available in social networking platforms is 80 percent unstructured prompting misdirecting examination and complex to increase important bits of knowledge from such information. The abundance of insights accumulated through them has raised exponentially the thought of the intelligent and business arrange toward them. Differentiations in features and characteristics of online casual associations are reflected in the enormous proportion of different bits of knowledge and estimations that it is possible to pursue and research. Among conceivable integral logical strategies that are beginning to be presented in the investigation of information gathered through online social networking platforms, one of the most intriguing is social network analytics (SNA), which, through a quantitative social methodology, makes it conceivable to think about social information (i.e. existing associations and connections between clients on informal organizations). Sentiment analysis is contextual mining of text which identifies and extracts subjective information in source material, and helping a business to understand the social sentiment of their brand, product or service while monitoring online conversations. SA is one of the most utilized strategies embraced to dissect information gathered through online social networks. This strategy, in contrast to simply numeric measurements, offers the likelihood to research the conclusions and dispositions communicated online by methods for characteristic language handling devices However, one of the primary issues with the elucidation of SA is that it doesn't enable one to consider information inside the online system where they have been gathered. This is a significant impediment since online social networks are portrayed by definition by an exceptionally social nature. There are following sentiment analysis methods to improve the unorganized data into an organized manner:

A. Sentiment analysis and NLP

Utilizing of NLP, natural language processing, one can accomplish exact conclusion results by settling setting of words, the verifiable or aberrant importance of words difficulties. Hash-labels can likewise help in prosecuting tweets or posts extremity or target, it can likewise be utilized to distinguish the writer utilizing his composition print or the stylometry of the tweets.

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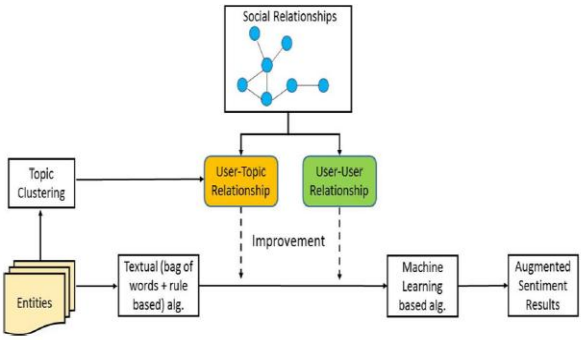

Fig. 1. Social Relationship Sentiment Analysis Framework

B. Sentiment analysis data cleaning: Data cleaning is a significant preprocessing stage which upgrades opinion examination results. Data cleaning activities incorporate tokenizing, stemming and separating. Data cleaning can be connected in two stages, information change what's more, information separating. Data change activities include yet are most certainly not restricted to expelling futile spaces, dealing with contractions and nullifications, stemming and expelling stop words. Data sifting is identified with choosing highlights which are appropriate for conclusion examination

C. Dimension Reduction: Dimension reduction is the way toward lessening high measurements utilizing two strategies either include determination or highlight extraction. Feature extraction is a transformative strategy which applies a change on the information to extend it into a new component space with lower measurements. Features choice is the way toward choosing features from the first informational index dependent on explicit choice criteria thinking about that the outcome subset has the littlest grouping blunder with lossless substance meaningure.

D. Sentiment Analysis and Crowdsourcing:Crowdsourcing is the study of settling an issue or task by the assistance of group. Crowdsourcing can help in giving progressively precise sentiment analysis results. Crowd can help in appointing marks to preparing informational collection or giving input about slant grouping results, which can upgrade the predication and the arrangement models. Crowdsourcing was utilized broadly in improving estimation examination results It was utilized into anticipate and measure discouragement over web-based social networking through twitter tweets utilizing SVM classifier. Creators demonstrated that the utilization of publicly supporting brought about progressively exact notion discovery for point and assessment characterization in online networking information.

E. Sentiment Analysis And Spam Detection: Fake and spam suppositions via web-based networking media prompts off base assessment recognition results. In the creators extricated geographic client attributes and tweets content based highlights to find spam conclusion inside content. Qualities to characterize counterfeit conclusion incorporate yet are not constrained to speed of distributing a tweet/post, the tweet/post area counterfeit composing personality, number of notices, number of hash labels, feelings, URLs in tweet/post and number of tweets/posts or posts every day. Building client profiles over informal organizations or on the other hand characterizing on the web personality can help in distinguishing phony spam assessment substance and fake spam clients.

F. Sentiment Analysis And User Profiling: Online user identity and user profiling helps in making the assumption investigation results increasingly exact as it quantifies extremity in view of the user profile notwithstanding the post polarity. The authors demonstrated that there is a solid relationship between online user identity and the user commitment in online blogs. They isolated the online user into classes dependent on their online highlights like (benevolence, social aptitudes, imagination). Others exhibited profiling models, to either foresee the political interests of users or information distributing interests.

G. Sentiment Analysis And Text Summarization: Sentiment summary is the method by which sentiments are summarized according to a particular domain or subject, also known as target-based summary. A hybrid system was developed in which the writers described the aspect (product or service)

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characteristics and the applied sentiment analysis to classify the feelings accessible. Another resuming effort was made to summarize Arabic tweets to produce certain subjects instead of reading all tweets.

There are following sentiment analysis tasks to improve the results:

A. Subjectivity Classification::It classifies the data at a document level by classifying an opinionated document as favorable or unfavorable opinion.

B. Polarity Classification: It differentiates data on the basis of their polarity as positive, negative or neutral.

- Aspect-based sentiment classification: It allows association of emotions with different aspects of service.
- Contextual polarity disambiguation: in context polarity, identication of polarity of cases of indices in the corpus with a broad lexicon of indices with previous polarity is performed. It produces disambiguity in certain cases which is solved by contextual polarity disambiguation.
- Sentiment Rating Prediction: Initially, social user sentimental measurement approach is used and sentiment of each user is calculated on products which further improves prediction
- Cross-domain Sentiment Classification: It adapts a sentiment classifier trained on source information, to a target information
- Cross-lingual Sentiment Classification: It exerts resources to a poor resource language.

C. Opinion Summarization: It briefly describes opinions related to same topics.

D. Opinion Visualization: For the user feedback data, it offers an integrated perspective of many aspects like time, demographics and space for users' feedback data.

E. Sarcasm Detection: It is very important since sarcastic data is extremely difficult to be analyzed.

F. Entity, Opinion holder and time extraction: It describes entities expressing an opinion and sentiment.

G. Coreference resolution and word sense disambiguation: Coreference resolution finds all expressions referring to same entity. Word sense disambiguation identifies meaning of a word in a sentence.

H. Opinion search and retrieval: Opinion Recovery deals with finding and recovering content, particularly from social media, which is relevant to consumer information demands and opinions.

I. Opinion Spam Detection: It is a matter of "illegal" actions which seek to mislead readers or automated opinion mining and sentiment analysis systems through the provision of unwanted, favourable opinions for target organizations to help organizations and/or through false negative messages.

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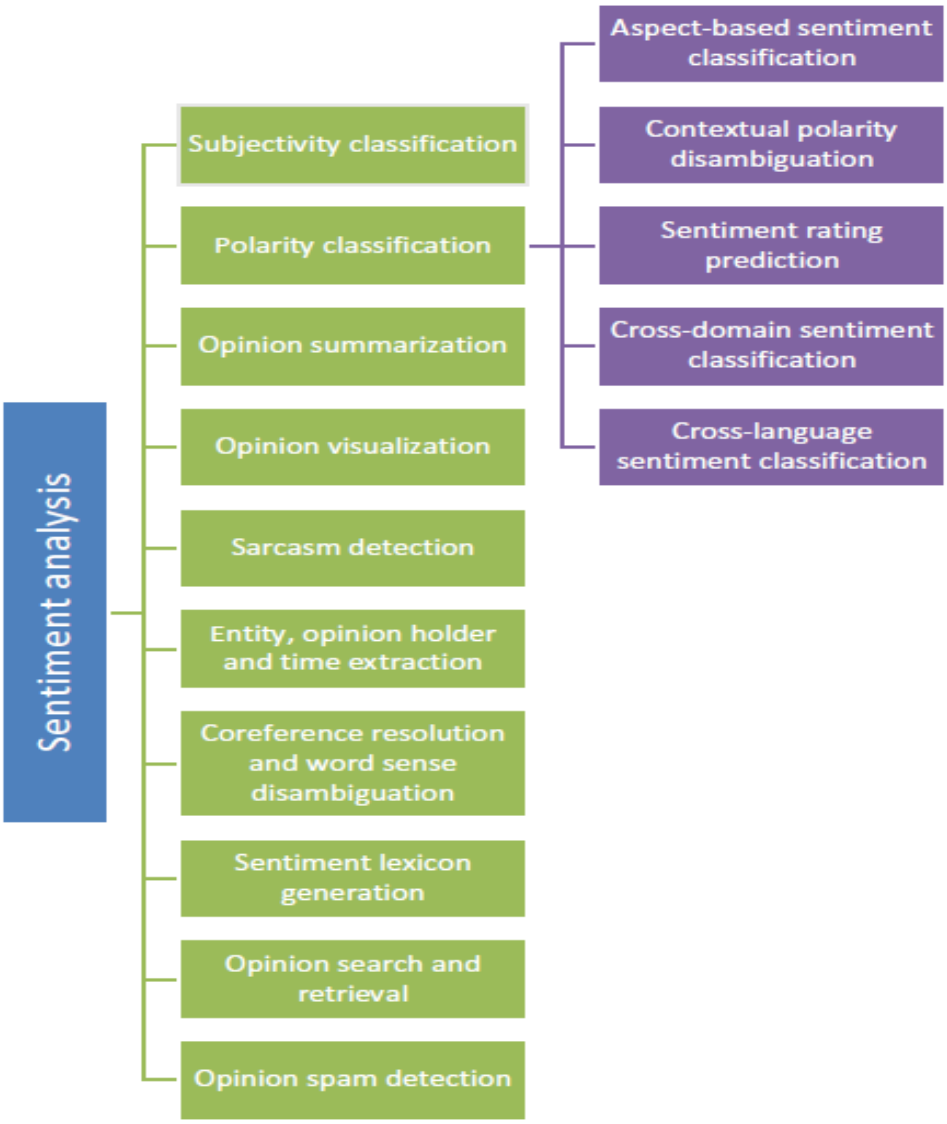

Fig-2: Tasks of sentimental analysis

II. LITERATURE REVIEW

The tie strengths, homophily and credibility of the source are three significant ideas for understanding the relationships amongst individuals in social networks and will be further discussed.

A. TIE STRENGTHS

Tie Strengths can be defined as a multidimensional construct that represents the strength of the dyadic interpersonal relationships in the context of social networks which involves proximity, intimacy, help and partnership. The strength of the bond can vary from strong to weak depending on the number and type of resources exchanged, how often exchanges take place and the intimacy of exchanges.

B. HOMOPHILY

Homophily can be defined as to how similar paired people are in certain attributes such as age, gender, schools or lifestyles and as to the similarity of the characteristics of members. It explains the composition of groups. The main principle is that a person's similarity predisposes him to a degree greater than that expected between individuals than interpersonal attraction, trust and understanding. Tie strength increases with homophily

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C. SOURCE CREDIBILITY

The credibility theory of sources identifies source expertise and source bias as elements affecting the credibility of the source of information. The expertise in source refers to the perceived expertise of the information supplier source. When it (1) has greater expertise and (2) is less prone to bias, a source should be seen as more credible. Sentiment analysis is described by the following characteristics:

A. SENTIMENT CATEGORIZATION:

The sentence can be classified as objective and subjective.

Objective sentence represents factual information whereas subjective sentence represents the opinions. The subjective sentence is further classified on the basis of polarity as positive, negative and neutral.

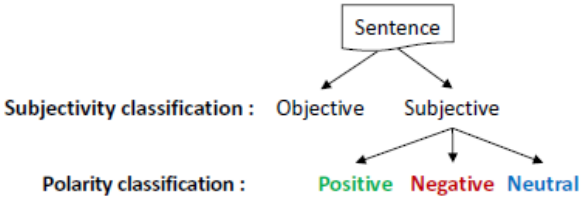

Fig. 3. Sentiment categorization

B. LEVELS OF ANALYSIS:

In this we will study different classification levels of sentiment analysis:

1. Message level: It describes whether the whole message as positive, negative or neutral.
2. Sentence level: It checks polarity of each sentence comprises in whole message.
3. Entity and aspect level: It classifies opinion into sentiment and target.

Fig. 4. Levels of analysis

C. Regular versus compartive opinion: A regular opinion has two types:

1. Direct opinion: It can be viewed as an opinion which is direct
2. Indirect opinion: It is conveyed indirectly on the basis of some effects.

A comparative opinion expresses a relation of a similarities or differences between entities.

D. Explicit versus implicit opinions:Explicit opinion is a subjective regular opinion which gives a clear information about an entity. Implicit opinion is an objective opinion which describes whether an entity is prudent or not. Explicit opinion is easier to detect and to classify than implicit opinion.

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E. Role of semantics: For analyzing expressions of a user we use semantics of language. In order to have a profound knowledge of natural language semantics in social media, lexica, corpora and ontologies need to be correctly built and used.

F. Figures of speech :The most difficult part of analysis is to classify sarcastic and ironical statements. Sarcastic statements means the opposite of what is actually said. Irony refers is often used to emphasize occurrences that deviate from the expected, such as twists of fate.

G. Relationships in social networks: Sentiment analytics in social networks are generally supposed to be independent and identically distributed in the texts provided by the users. In this sense, friendships can be used to deduce that linked consumers may be more willing to express comparable views. An assessment scheme for feelings should however take into consideration the hypothesis that friendships do not correctly reflect the actual world, where two linked consumers may have distinct views regarding the same issue. According to this comment, several other relational data may be obtained from the social network for improved customer and postal representation. Relationships that share or appreciate can be better than a straightforward friendly relationship.

We will discuss now the types of sentiment analysis range from the systems that focus on polarity to systems.

A. Fine-grained Sentiment Analysis: To calculate polarity level of the opinion, consider the following categories, rather than only positive, neutral or negative opinions:

1. Very positive
2. Positive
3. Neutral
4. Negative
5. Very negative

For example, in a review, some systems can map this to a 5 star rating by defining whether positive or negative sensations have to do with particular emotions such as anger, sorrow or concerns, joy, love or passion.

B. Emotion detection: Emotion detection is designed to detect feelings such as happiness, frustration, anger, sorrow, etc. Many emotional detection systems use lexicons or complex machine learning algorithms (i.e. words and feelings that are passed on). The way individuals express their feelings vary greatly, and so too the lexical elements used are one of the downsides of the lexicon. Some phrases that usually convey anger such as shit or kill (for instance in your product is a shit or your customer support kills me) could also express gladness (for example in texts like This is the shit or You're killing it).

C. Aspect-based Sentiment Analysis: In general, we may want to analyze feelings in topics such as products, not only whether individuals are speaking about the product positively, with a neutral or with a negative polarity, but also about specific characteristics or aspects of the product. It's about this aspect-based analysis of feelings. The phrase expresses a adverse view about the camera but more exactly about the life of the battery, which is a specific characteristic of the camera, and the camera's battery is not very long enough.

D. Intent analysis: Intentive assessment basically finds out, instead of what individuals say about a text, what individuals want to do with it. See the examples below: "Your client assistance is a catastrophe. For 20 minutes I was on hold. "I want to understand how the cartridge can be replaced." "You can assist me complete this form?"A human being doesn't have any problems with the first text of a complaint, the second text and the third text requests. However, it may be difficult for machines to recognize them. The intended action sometimes can be inferred from the text, but in some cases contextual knowledge is required.

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E. Multilingual sentiment analysis: The assessment of multi-lingual feelings can be a challenging job. In general, a lot of preprocessing is necessary and a number of resources are used for preprocessing. Most of these resources (e.g. sentiment lexicons), but many others need to be developed (e.g. translated corporations or algorithms for noise detection). A great deal of coding experience and long time can be needed to utilize the resources available.

An option would be to automatically detect language in textbooks, then train a custom model of your preferred language (if the texts are not written in English).

Following are the indexes and metrics to analyze data collected through online social networks:

A. Engagement metrics: Number a phenomenon and the characteristics resulting in its diffusion.

i) Amplification metrics: An over-time analysis of such measurements allows feedback on the content a user shares within a social network of the user.

ii) Applause metrics: Validation of an audience for a specific content; are "like" on Twitter, Facebook, and YouTube. • Conversation rate: conversation number per post. They are made out of comments on Facebook, YouTube and LinkedIn, and replies on Twitter.

B. Metrics of influence: Quantify users participating in the conversation, and include content per time (i.e., an essential phenomenon measure). This means that a wide range of contents can be generated in a short period of time.

C. Reach: Number of individual people (accounts) who have been exposed and who have discussed the contents examined. When the content comes several times (shared by many colleagues or displayed on more social networking sites), achieve for each user is of importance is called reach. Measurement of future impacts takes into consideration: a substantial rise in print value, with equal coverage, implies more possibilities for content for the participants.

D. Impression: The number of occasions some content was seen on the social netting platform without taking the user duplication into consideration (each user may have multiple exposures on various devices and via various platform shares).

iii) Total public: Total number of people who took part in the post

iv) Number of single users: One of the most widely used measures for assessing the effectiveness of social networks. The index is a true index of user engagement, as it reflects how some Internet content can "enable" social networks. The actions include the number of Twitter tweets and retweets as well as the number of people on Facebook that comment and like posts.

v) Number of active and passive users: This is used primarily for understanding event-related phenomena. Twitter defines the number of active users as the number of tweeting users, while passive users are simply retweets; active users of Facebook are considered to be individuals who comment on posts, and passive users are those who only "like" texts.

There are following challenges of sentiment analysis which are given below:

A. Subjectivity and Tone: Subjective texts are just as important to detect than to analyze their tone. In fact, so-called objective texts have no express feelings. Not all predicates (adjectives, verbs and some nouns) should be treated the same as how they create feelings. Nice is more subjective than rot in the examples above.

A. Context and Polarity: All utterances are spoken in some location at some stage, and you get the point for some individuals. The context for all utterances is defined. It becomes quite hard to analyze the feeling without context. However, unless explicitly stated, computers can learn about situations. Changes in polarity are one of the issues arising from context. Many pre-and post-treatment procedures are needed if at least part of the environment in which texts were produced is to be taken into account. How to pre-or post-process information to capture contextual parts, however, that assist to evaluate feelings is not easy.

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B. Irony and Sarcasm: The differences between the intended meaning and literal meanings (e.g. irony) and the more abusive or ridiculous versions of irony (e.g. sarcasm) normally make positive the feeling negative and neutral the feeling negative the feeling neutral. However, it requires much analysis of the context in which the texts are made to detect irony or sarcasm and therefore are difficult to detect automatically.The problem is that there is no textual indication that allows a machine to understand the negative sentiment since it belongs most often to neutral or positive texts.

C. Comparisons: Another challenge worth tackling is how to handle comparisons in sentimental assessment. For instance, if the old tools of the second text are deemed incontextless, the second text is very similar to the third text. However, these texts feel distinct if no context is given.

D. Emojis: There are two kind of emojis. West emojis (e.g.: D) are encoded in a few of a single character, whereas East emojis are a longer mixture of vertical characters. In tweets in particular, emojis play a part in text feeling.The tweeter sentiment analysis needs unique consideration of both the level of character and the level of the word. However, it may be a lot of pre processing that matters how much attention you pay to each of them. You may want, for example, to make preprocessed social media content and transform Western emojis as well as Eastern emojis into white toks to help improve the performance of sentiment analysis (i.e. always use it for classification purposes).There is a rather extensive list of emojis and their unicode characters, which can be useful for preprocessing.

E. Defining Neutral: Defining the meaning of neutrality is a different task in order to carry out a precise assessment of sentiments. As in all classifications, your category definition–and the neutral tag in this situation–is one of the most significant aspects of your issue. When you train sentiment analysis model, what you mean by neutral, positive or negative matters. Due to the fact that tagging information demands coherent tagging requirements, a decent issue definition is a must.

Here are some concepts about a neutral tag: objective texts. Some desires like I would like the product to be more integrated are neutral. However, those which include comparisons are quite hard to categorize as I wish that the product was better.

III. APPLICATIONS

In this, we will discuss about the real life applications and impact of sentiment analysis on businesses, cities and society.

A. SOCIAL MEDIA MONITORING:

1. Analyze tweets and/or facebook posts over time to get a certain audience's feelings.
2. Execute feeling analysis on every social media item in your brand and categorize it automatically by urgency.
3. Routes Social Media automatically to team members who are best able to respond.
4. Make any or all of these processes automatic.
5. Use analytics to get a deep understanding of what is going on across your social media channels.

B. BRAND MONITORING

1. To see a specific audience's feeling, analyze online news articles, blog postings, forums and other texts over a period of time.
2. Categorize all internet information about your brand automatically through feeling assessment.
3. Designated internet team members automatically alert to their region of activity.
4. Automate any of these procedures or all of them.
5. Better know the existence of a brand online through all types of interesting ideas and analysis.

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C. VOICE OF CUSTOMER (VOC)

1. Analyze NPS aggregate or other survey answers.
2. Analyze customer support interactions aggregated.
3. Track client sentiment over time on particular elements of the company. This contributes depth to why the general NPS rating could have changed, or if certain elements have changed separately.
4. Target people to enhance their service. By automating feel assessment on incoming surveys, you can inform and deal with clients that feel heavily negative about their product or service.
5. Determine whether your business feels stronger in specific client sections. Some demographics, interests, people, etc. are able to null feelings.

D. CUSTOMER SERVICE

1. Automatically analyze feelings on all customer support queries.
2. Detect clients disgruntled and surface the tickets up quickly.
3. Requests route for the most appropriate reaction for particular team members.
4. Use analytics to learn more about what is going on in your customer support.

E. WORKFORCE ANALYTICS AND VOICE OF EMPLOYEE

1. Analyze staff surveys, extract keywords and section views.
2. Track worker feelings shifts over time.
3. Surface immediate pressing issues.

F. PRODUCT ANALYTICS

1. Analyze big amounts of product feedback surveys
2. Analyze all social media and internet information on a product filter by aspect and sentiment to see what to tweak and what to maintain.
3. Routing appropriate remarks to product teams automatically.

G. MARKET RESEARCH AND ANALYSIS

1. Analyze your brand's product reviews and compare them to your competition.
2. Generate weekly, weekly or daily reports–a kind of early-weathering system
3. Compare your sentiments across global markets
4. Analyze the official market reports or company publications in the long-term, wider trends.

IV. CONCLUSION AND FUTURE SCOPE

Sentiment analytics is also known as opinion mining or emotion detection. Sentiment analytics are a very significant. procedure since they provide numerous useful indicators in various areas, such as medical, social and industrial. This paper presents the various methods, tasks, types, challenges and characteristics of sentiment analysis using social networks analytics (SNA). Also we gain the knowledge of relation between sentiment analysis and social networks analytics (SNA). Using social network analysis can take structural relationships and the roles of individual consumers into account. In the light of the context of internet social networks, SNA enables users to compare or monitored over time the interaction structure and role within the social platform of distinct kinds of online communities. • The use of SNA in combination with SA to declare the sentence ambiguity. Social network analytics (as central and neighborly systems) allow users to go beyond mere numerical information and to evaluate the role and role of users in the online social networks collaborative knowledge development process

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