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on

SENTIMENTAL ANALYSIS

USING NLP

Submitted in partial fulfillment of the

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Under The Supervision of
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CANDIDATE'S DECLARATION

I/We hereby certify that the work which is being presented in the project, entitled " Ur Info: A cross-platform Application " in partial fulfillment of the requirements for the award of the BACHELOR OF TECHNOLOGY IN COMPUTER SCIENCE AND ENGINEERING submitted in the School of Computing Science and Engineering of Galgotias University, Greater Noida, is an original work carried out during the period of JULY-2021 to DECEMBER-2021, under the supervision of Mr.V. ARUL, Assistant Professor, Department of Computer Science and Engineering of School of Computing Science and Engineering , Galgotias University, Greater Noida

The matter presented in the project has not been submitted by me/us for the award of any other degree of this or any other places.

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Sohan Singh (18SCSE1010504)

This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

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CERTIFICATE

The Final Thesis/Project/ Dissertation Viva-Voce examination of 18SCSE1010104 VISHAL TIWARI, 18SCSE1010504 -SOHAN SINGH has been held on __________________ and his/her work is recommended for the award of BACHELOR OF TECHNOLOGY IN COMPUTER SCIENCE AND ENGINEERING.

Signature of Examiner(s)   Signature of Supervisor(s)

Signature of Project Coordinator   Signature of Dean

Date: __________

Place: __________

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ABSTRACT

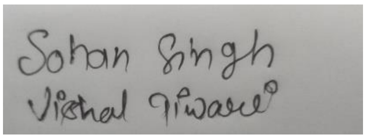
The popularity of social media platforms has been gone very wide and far as compared to new technologies, which are used to express own emotions, sharing the news occurring nearby and reviews about the recent activities, which has attracted the researchers in the last some years. We are trying to work on a project that is Sentimental Analysis, the automatically detection of human emotion or expression with the message received.

Aim of this project is to further work of separating direct and indirect emotions. Separated tweet, sharing over the past decade, new forms of communication, such as microblogging and messaging have spread widely. Although there is no limit to the amount of information conveyed via tweets and texts, these short messages are often used to share the thoughts and feelings of people connected with what is happening in the world around them.

The task is when we are given a message, we have positive, negative, or neutral feelings. Because messages convey good and bad feelings, any strong emotion should be chosen.

Student signature

Guide Signature with date



INTRODUCTION

A nerve is an attitude, a thought, or a judgment based on emotion. Emotional analysis, also known as mind mines, is a human study feelings about certain businesses. From a user perspective, people can post their content through various social media platforms, such as forums, micro-blogs, or social networking sites online. However, those species online data has a few errors that may hinder the emotional process analysis. The first mistake is that since people can freely post their content, the quality of their ideas cannot be guaranteed. The second mistake is the basic truth such online data is not always available. The reality of the earth is like the mark of something opinion, indicating that an opinion is right, wrong, or neutral. It's a Really boring movie but the scenes were very good enough. The line provided for the review of thr film “It” is as “It isreally boring but the scenes were good”. Understanding such feelings are essential for many jobs. Therefore, SENTIMENTAL ANALYSIS is a form of text fragmentation based on Sentimental Orientation (SO) of the ideas contained Emotional analysis of product reviews recently became very popular in the literature mining and computer research. First, the conceptual evaluation terms must be extracted from review.

- Second, the SO, or differences of opinion must be determined. Thirdly, the power of vision, or the intensity of the vision should also be determined.
- Finally, reviews are categorized according to emotional categories, such as Positive and Negative, based on SO of the ideas it contains.

History

History of natural language processing Indigenous language processing has its roots in the 1950s. Already in 1950, Alan Turing published an article entitled "Computing Machinery and Intelligence" which propagated the so-called Turing experiment as a means of testing intelligence, a task that involved automatic translation and production of native language, but at that time was not specified. as a separate problem and practical wisdom.

Symbolic NLP (1950s - early 1990s)

The basis of symbolic NLP is well summarized by a review of John Searle's Chinese room: When a set of rules (e.g., Chinese idiomatic expressions, with similar questions and answers) are given, the computer simulates the understanding of the native language (or other NLP functions) by applying those rules to the data in question .

1950s: Georgetown 1954 experiment included a fully automatic translation of more than 60 Russian sentences into English. The authors state that within three to five years, typing will become a major problem. However, real progress was slow, and after an 196P ALPAC report, which found that ten-year research had failed to meet expectations, funding for machine translation fell sharply. Little research into machine translation continued until the late 1980's when the first mathematical translation systems were developed.

1960s: Some of the most effective natural language processing programs developed in the 1960s were SHRDLU, a natural language system that operates in a "restricted world" with limited words, and ELIZA, an imitation of Rogerian psychotherapist, written by Joseph Weizenbaum between 1964 and 1966 . Using almost non-verbal information about human thought or emotions, ELIZA sometimes provided amazing human-like communication. When a "patient" passes a very small amount of information, ELIZA may provide a general response, for example, to answer "My head hurts" by "Why do you say your head hurts?".

1970s: During the 1970's, many programmers began writing "conceptual ontologies", which created real-world information into computer-readable data. Examples are MARGIE (Schank, 1975), SAM (Cullingford, 1978), PAM

(Wilensky, 1978), TaleSpin (Meehan, 1976), QUALM (Lehnert, 1977), Politics (Carbonell, 1979), and Plot Units (Lehne1).)). During this time, many early chatterbots were written.

1980s: The 1980s and early 1990s mark a good day for symbolic methods in NLP. Areas of focus at the time included legal-based classification research (e.g., development of HPSG as a computer-based production of productive grammar), morphology (e.g., dual-level morphology , semantics (e.g., algorithm). for Lesk), reference. (e.g., within Centering Theory and other areas of natural language comprehension (e.g., in Rhetorical Structure Theory). Other research lines were continued, e.g., the development of chatterbots with Racter and Jabberwacky. An important development (which eventually led to a statistical shift in the 1990s) was an increase in the importance of volume testing during this period.

Mathematical NLP (1990s – 2010s)

Until the 1980's, many native language processing systems were based on complex sets of handwritten rules. Since the late 1980's, however, there has been a shift in natural language processing with the introduction of machine learning algorithms for language processing. This was due to both the continued growth of integration power (see Moore's law) and the gradual decline of the dominance of Chomskyan linguistic ideas (e.g. linguistic transformation), based on the theory that did not promote the type of corporate languages under machine learning. in language processing.

1990s: Most of the remarkable early success in mathematical methods in NLP took place in the field of mechanical translation, thanks to work especially at IBM Research. These programs have been able to take advantage of the multilingual document produced by the Canadian Parliament and the European Union as a result of laws requiring all government actions to be translated into all official languages of the corresponding government system. However, many other programs relied on companies that specifically developed the functions performed by these programs, which (and often continues to be) a major limitation of the success of these programs. As a result, much research has gone into ways of successfully learning about limited amounts of data.

2000s: With the growth of the web, increasing amounts of raw (unspecified) data have become available since the mid-1990s. So research has become more focused on algorithms for unchecked learning and less supervised learning. Such algorithms can learn from unstructured data manually with the required answers or using a combination of annotations and annotations. In general, this task is much more difficult than supervised reading, and often produces less accurate results of a given amount of input data. However, there is a large amount of unspecified data available (which includes, among other things, all World Wide Web content), which can produce minimal results if the algorithm used has a sufficient amount of difficulty to become real.

Neural NLP (current)

By the 2010s, representational learning and deep machine learning methods of neural network became widespread in natural language processing, thanks to part of a series of results showing that such techniques [could achieve modern results. in many natural language functions, for example in language simulation, differentiation, and many others. This is especially important in medical and health care, where NLP is used to analyze notes and text in electronic health records that would not be accessible to research if you wanted to improve care.

NLP Tasks

Human language is full of ambiguities that make it very difficult to write software that accurately determines the intended meaning of text or voice data. Synonyms, synonyms, antonyms, idioms, metaphors, grammar and variations, sentence structure variations — these are not just the grammatical errors of the language that take years to learn, but that programmers must teach the use of natural language to see and see. understand well from the beginning, if those apps are going to be helpful. Several NLP activities break human text and voice data in ways that help a computer make sense of what it is importing. Some of these activities include the following: Speech recognition, also called speech-to-text, is the function of faithfully converting voice data into text data. Speech recognition is required for any app that follows voice commands or answers spoken questions. What makes speech recognition particularly challenging is how people speak — quickly, consistently, with emphasis and modulation, in a variety of pronunciations, and often using the wrong grammar. The marking part of a speech, also called the marking of a language, is the process of determining the part of speech of a particular word or piece of text based on its use and context. Part of the expression refers to ‘doing’ as the verb ‘I can make a paper airplane,’ and as the noun ‘What makes the car you own?’ Separating the meaning of a word is the choice of the meaning of a word that has multiple meanings through a semantic analysis process that determines a word that gives greater meaning to a given context. For example, separating the meaning of a word helps to separate the meaning of the verb 'do' from 'make distance' (gain) vs. 'make a bet' (place). Named business recognition, or NEM, identifies names or phrases as useful businesses. NEM identifies ‘Kentucky’ as a locality or ‘Fred’ as a man’s name. The reference solution is a function of identifying whether two words refer to the same thing and when. The most common example of determining a person or thing when a noun refers to her (e.g., 'she' = 'Mary'), but may also involve pointing to a metaphor or expression in a text (e.g., an event where 'bear' is not an animal but a furry adult). Emotional analysis attempts to exclude thoughtful traits — attitudes, feelings, sarcasm, confusion, suspicion — from the text. The production of natural language is sometimes described as contrary to the recognition of speech or spoken speech; it is the work of introducing formal information into human language.

MATERIAL AND STRATEGIES

NLP Based Approach:

Indigenous language analysis (NLP) refers to the department of computer science - and in particular, the branch of artificial intelligence or AI - which is responsible for giving computers the ability to understand text and spoken words in the same way as humans.

The NLP integrates computer languages - the official modeling of human languages - with mathematics, machine learning, and in-depth learning models. Taken together, these technologies allow computers to use human language in the form of text or voice data and 'understand' the full, complete meaning of the speaker or the author's purpose.

Methods: Rules, statistics, neural networks :-

- The learning techniques used during machine learning automatically focus on the most common situations, while when handwriting rules it is not always clear where the effort should be directed.
- Automatic learning processes can use mathematical algorithms to generate powerful models to unfamiliar inputs (e.g. containing words or structures that have never been seen before) and incorrect input (e.g. by misspelled words or words left out by mistake).
- Systems based on automatic learning of rules can be made more accurate by providing more input details. However, programs based on handwritten rules can only be made more accurate by increasing the complexity of the rules, which is a very difficult task. In particular, there is a limit to the problem of systems based on handwritten rules, otherwise the systems become increasingly uncontrollable.

Mathematical methods

Since the so-called "mathematical transformation" in the late 1980's and mid-1990s, most natural language research studies relied heavily on machine learning. The machine learning paradigm calls instead of using mathematical reasoning to automatically learn such rules by large corporate analysis (corpus plural, set of documents, which may have human or computer annotations) of typical real-world examples.

Many different categories of machine learning algorithms have been used in natural language processing activities. These algorithms take into account the inclusion of a large set of "features" generated in the input data. Increasingly, however, research has focused on mathematical models, making soft, feasible decisions based on attaching real-weight weights to each input element (embedded embedded value,and emotionally commonly networks are also proposed, for example, speech. Such models have the advantage of being able to express the related certainty of many different possible responses to just one, producing more reliable results when such a model is included as part of a larger system.

Some of the first machine learning algorithms used, such as cutting trees, produce solid rules systems if they are similar to existing existing handwritten rules. However, marking part of the speech introduced the use of Markov models that are hidden in natural language processing, and increasingly, research has focused on mathematical models, making soft, feasible decisions based on attaching real-weight weights to input components. data. Core language models on which many speech recognition systems rely are now examples of such mathematical models. Such models are usually very robust when given unusual inputs, especially inputs containing errors (as are very common in real world data), and produce very reliable results when integrated into a large system that includes multiple sub-functions.

Since neural evolution, mathematical methods in NLP research have largely replaced neural networks. However, they continue to work in situations where mathematical interpretation and transparency are needed.

Neural Networks Additional information:

Neural network of activity The main effect of mathematical methods is that they require detailed feature engineering. Since 2015,the field has largely abandoned mathematical methods and switched to neural networks for machine learning. Popular techniques include the use of word embedding to capture semantic features of words, as well as increased learning from end to end level level work (e.g., answering questions) instead of relying on a pipeline for different tasks (e.g. marking part of speech and leaning). In some areas, these changes have caused major changes in the way NLP systems are designed, so that deep-rooted neural networks can be viewed

Methods of Machine Learning

A machine-based approach uses a classification method

to divide text into classes. There are mainly two types
machine learning strategies

Unattended reading:

It does not contain a category and they do not provide it
the actual target is therefore therefore dependent on the combination.

Supervised reading:

It is based on a labeled database so the labels are given to it
model during the process. This database with label is trained
to get effective results when they are met during decision-making selection and release of a specific set of features used
to see emotions.

Machine learning method works emotionally
the analysis is primarily for the supervised category. In
machine learning strategies, two sets of data are required:

1. Training Set
2. Test Set

designed to divide tweets into classes. Machine learning
strategies such as Naive Bayes (NB), maximum entropy (ME),
and vector support equipment (SVM) has gained a lot
success in analyzing emotions.Machine learning begins with collecting training databases. Next we train dividers with training data. Wake up the separation process is selected, an important decision for this mark to select feature. They can tell us what the documents are like represented. The most widely used traits to distinguish emotions there is

- Presence of term and their frequency
- Part of speech information
- Opposition
- Words of ideas and phrases

LITERATURE SURVEY/PROJECT DESIGN

As noted by Rodrigues & Chiplunkar (2019), Emotional analysis is based on NLP working at different levels of granularity. This employed at the sentence level and now in the sentence level. The study was based on experiments the sentiments of the tweets coming under the Pattern fragmentation and extraction of data. The above principles are based on the process of creating better patterns in data. This study will be based on the strategies of NLP of mining patterns and features from large data sets. According to Saad & Yang (2019), machine learning is a method used in differentiate individual tweets according to pattern model. Features can be used modeling patterns and split patterns as wellin categories based on a few groups such as official blogging and informal blogging. The tongue the supported features relate to the official languages and includes feelings of polarity of the user's thoughts. Sentiment polarity is based on such terms they are based on natural instincts. This study has helped me deal with challenges based on emotional analysis on Twitter is not based on to separate tweets from bad, good too neutrality. For each view of Srivastava, Singh & Drall (2019), a large user base for more active customers Twitter has been helping to collect a lot of data. Therefore, this study will expect the best emotional analysis. Feature Analysis a challenging task involving environmental analysis and machine learning. Sentence level status the analysis was about user tagging sentences with appropriate meanings. The sentence level can be spread to positive, negative and neutral category. Appearance level has been to deal with every word in emotions has been directed. This level of emotional transmission has it was about identifying and mining product features from source data. As commented by Alharbi & de Doncker (2019), the tweets used end up being positive Thumbnails. Most of the new jobs have eaten with it the previous polarity of emotional words allocation at the sentence level.

Sentiment Analysis

Emotional analysis is a tool / algorithm for NLP that interprets and classifies the emotions expressed in the text. How to share emotions can be as simple as having three pre-arranged groups - good, bad, or neutral. Or, text data can be subject to complex NLP techniques. Emotional analysis follows a specific pattern. Key steps taken by such algorithms include - Divide each piece of information into key elements (sentences, parts of speech, tokens, etc.) Separating each object with emotions Sharing each element with emotional effects Combining points to get a few layers of detailed analysis.

This example easily illustrates this basic principle—

Let's take a look at these two newspaper reports –

i. Both teams are awesome. The fans were fed up with the whole game.

ii. ii. Both teams have played well but must learn to take advantage of their opportunities. Both sentences discuss the same topic - a report on a sporting event. Obviously the first sentence is very negative. But, can the machine detect these ‘feelings’. The Sentiment Analysis algorithm will act as emotionally charged in the two sentences above - -

iii. Terrible gangs Fans were angry Both teams played well they should learn to take their chances | The Sentiment Analysis algorithm will give you points for everything to come up with the final result.

iv. Companies test their customer reviews using Emotional Analysis Programs. As they can read every comment / review, these programs help them determine whether customers recommend their service or not.

Why Analyze Emotions ?

As customers express their thoughts and feelings more openly than before, emotional analysis becomes an important tool for monitoring and understanding that feeling. Automatically analyzing customer feedback, such as comments on survey responses and social media forums, allows brands to learn what makes customers happy or frustrated, so that they can integrate products and services to meet their customers' needs. For example, using emotion analysis to automatically analyze 4,000+ customer satisfaction surveys about your product can help you determine if customers are happy with your pricing plans and customer service

The full benefits of emotional analysis include:

Sorts Data on Scale

Can you imagine editing thousands of tweets, customer support interviews, or surveys? There is too much business data to process in person. Emotional analysis helps businesses to process large amounts of informal data efficien

Real-Time Analysis

Is an angry customer going to play? Emotional analytics models can help you quickly identify these types of situations, so you can take immediate action.

Related terms:

It is estimated that people only agree about 60-65% of the time when emotions are expressed in a particular text. Emotional marking is highly dependent, influenced by personal knowledge, thoughts, and beliefs. By using a centralized emotional analysis system, companies can apply the same approach to all of their data, helping them improve accuracy and obtain better data.

The use of emotional analysis is endless. So, to help you understand how emotion analysis can benefit your business, let's dive into a real-life example of how Chewy was able to gain a subtle (and useful!) Understanding of their reviews through emotional analysis. Then, we will begin a more granular division of emotional analysis.

Emotional analysis focuses on segregation (good, bad, neutral) but also on feelings and emotions (angry, happy, sad, etc.), urgency (urgent, not urgent) and even intentions (interest v. Uninterested). Depending on how you want to interpret customer feedback and questions, you can define and customize your sections to meet your emotional analysis needs. In the meantime, here are some of the most popular types of emotional analysis:

Fine-grained Sentiment Analysis

If polarity accuracy is important to your business, you might consider expanding your polarity levels to include: Very good Good Neutrality Bad Even worse This is often called refined emotional analysis, and can be used to translate 5-star ratings into reviews, for example:

Best = 5 stars

Too bad = 1 star

Emotional detection

This type of emotional analysis aims to identify emotions, such as happiness, frustration, anger, and sadness. Many sensory systems use dictionaries (i.e. lists of words and senses they transmit) or complex machine learning algorithms.

One of the evils of using dictionaries is that people express emotions in different ways. Some words that often indicate anger, such as evil or murder (e.g. your product is very bad or customer support kills me) may also indicate happiness (e.g. this is a bad ass or you kill).

Aspect-based Sentiment Analysis

Generally, when analyzing the sentiments of a text, let us say a product review, you will want to know what certain features or features people are saying in a constructive, neutral, or negative way. This is where a feature-based emotional analysis can help, for example in this text: "The battery life of this camera is very short", a feature-based separator will be able to determine if a sentence conveys a negative impression of a battery life feature. .

Multilingual emotional analysis

Analyzing emotions in multiple languages can be difficult. It involves a lot of processing and resources. Most of these resources are available online (e.g. dictionaries), while others require creation (e.g., translated corpora or audio algorithms), but you will need to know how to enter the code to use them. Alternatively, you can find language in texts automatically using the language separator, and then train the emotional analysis model to classify texts in your preferred language.

Related Work

Although emotional analysis and reflection became one of the most important sources of business decision-making, they still need more attention. In the following, we discuss the work related to emotional analysis and challenges:

Work Related to Emotional Analysis :-

Paper introduced a tool that assesss text quality based on the explanations of scientific papers. Its method of collecting the feelings of annotations in two ways. It lists all the annotations that produce the documents and calculates the total of the emotional effects. Its problem reveals the relationship between complex annotations. The operating system needs to have a large database containing metadata. Researchers in have proposed a “Web Based Opinion Mining Program” to review hotels. The paper introduced a review system for online user reviews and comments to support quality controls in the hotel management system. It is able to find and receive updates on the web and deals with German updates. It has a multi-topic background and is based on classification with multiple polarity; the system can detect neutrals, e.g., "I do not know" in.Many weaknesses are shown in the handling of other conditions in multi-topic segmentation.

Product reviews for mobile devices have been analyzed in Machine learning which ML system investigated the phase accuracy of the Naïve Bayes algorithm. In addition, research has made a decision on product quality and market status rather than profitability. The study used three machine learning algorithms (Naïve Base Classifier, a neighbor nearby K, and a random forest) to calculate emotional accuracy. The random forest improves the performance of the separator. There are some ways to analyze emotions and ideas. Page analyzes media sentiments and blogs. It divides previous work into the context of their specific work (emotional analysis of blogs and blogs) into two categories. First phase is about techniques for automatically creating a mood dictionary and a second related emotion program for all documents. In addition, research separates work-related activity into two categories the first works by determining the shape of the term and the other by working by finding the term subjectivity. These sections only refer to a research study on term / word classification, not document level classification. The purpose of this study was to evaluate emotion which refers to the sensitivity polarity (positive, negative, or neutral) of textual review data and to evaluate the emotional points of textual review. Actually text reviews are divided into single sentences ("based on sentences") and words ("based on words") or very short texts from the same source. Previous research on emotion-based classification of inclusion texts has included the use of models strongly influenced by thought-provoking languages or the development of manual or intermediate dictionaries of racist words . For example, introduced a new way of expressing emotions in real time in a financial institution; working based on messages Unfortunately, their proposed method involves creating a dictionary for racist words using hand-picked and tagging words from thousands of messages.Also, people search for Word Net coded information such as relationships (synonymy, antonymy and hyponymy) and gels. and applications, it is necessary to make a decision about a given document including independent information or not, or be aware of which parts of the document are private. Previous work on this practice to examined the effects of adjective structure and the ability to organize separately in sentence response. The target tells us about a given sentence whether it depends or not on adjectives from that sentence.A specific sentence expresses certain feelings, ideas, or beliefs. According to the sentence level, instead of individual words, each sentence in a given text is analyzed and evaluated to match the context. If necessary, a straightforward sentence can also be divided into a semantic or negative semantic form. Pang and Lee used subjectivity detector to extract specific sentences from a specific text. Then, using a small cut pattern, they combine the weather details of the level between the sentences with the typical features of the word bag. They report significant improvements beyond the base word vector separator. Researchers have introduced similar neural models: vector representation of words and segregation. They used the semantic relationship model to analyze and evaluate online emotions. Their approach provides the basis for many topics. But the feeling requires extensive surveillance training and resource testing. Research on the digging of ideas on YouTube was done by discussing how a social media platform can be used for personal development. A research perspective on Crawling, a global social media platform, similar to YouTube.

What is Lexicon-Driven Methodology ?

This paper used the MPQA emotional lexicon to identify the feelings of tweets about President Barack Obama. It can enable you to classify tweets and count them if you combine the best variations or the negative variations of words in the emotional dictionary. While this approach is simple, they do not determine the important relationship between the emotional content in the tweets and the Gallup opinion polls. SentiStrength is structured as a lexicon-based algorithm that determines the polarity of emotions (positive / negative) and the corresponding power values between 1 and 5 to a specific text. In addition the paper presented \ list includes 298 positive words and 465 negative statements defined by polarity and power values. SentiStrength uses a list of icons, opposition lists and keywords in the decision-making process. In order to address the emphatic extension the authors introduced a three-step method of reducing the wording of the standard form. When you make comparisons between different machine learning categories in SentiStrength MySpace comments. The authors find that their proposed method works best to classify negative emotions, but is not suitable for positive emotions. Page proposed law-based approach to analyzing business-level emotions on Twitter. Evaluate the emotional points of each business depending on its proximity to the text and the words from the emotional dictionary. It also used a simple anaphora solution by resolving business pronouns that are very close to tweet. The legal-based algorithm distinguishes between expressive, compulsory and query sentences and can handle, among other things, comparative sentences, negatives and phrases but. To improve the memory of the proposed methods, the researchers identified additional tweets that may have ideas and trained the vector support (SVM) machine to provide appropriate labels on the content frames.

The authors of discuss some of the emotional challenges in the field of social media. Its purpose is a law-based approach that creates an in-depth analysis of the language that contains business releases and event recognition. It works to generate emotional polarity and the results of a given tweet. The study also explored how to build a dictionary of emotions from Twitter data and find value in creating a dictionary for a specific domain emotion. The authors have developed SentiWordNet to include the four Speech Points (POS) tags which are 2 million adjectives, adverbs, verbs and nouns with 2 million words of which 3% are adjectives. Dividing the polarity of emotions divides each word into one from three positive, contradictory and objective points so that the total number of points for each word reaches one. The study introduced a way to identify and analyze feelings and ideas. The process has four steps. The first step was to recognize the vision and understand it. To define the concept they introduced a word-separating algorithm as a positive, negative or objective based on WordNet. Make a suggestion that would collect the same words in the same word as the source name. To avoid words that have a lot of meaning (dual nature) they use a way of seeing the closeness of a word in each class (good, bad, purposeful). In order to introduce a good memory system the original seed list should be large enough and have different names. The study presented an in-depth study of the challenge of finding the emotional differences of words. It is considered a bi-polar separation of words. Much work has been done to improve the English language dictionary. A bootstrapping implementation method was introduced in to develop a subjective dictionary for sub-resource languages. This method creates an independent dictionary using a small list of seeds (60 words), an online dictionary (Romanian dictionary) and a small chorus with annotations. They used word level similarities (LSA and PMI) to filter words. In this way the first seed list was selected by hand again.

Work Related to Emotional Analysis Challenges:

For the purpose of this thesis, be aware of "emotional challenges" means discovering emotional challenges in analyzing and discovering variations in revision and finding solutions to results to improve text accuracy. We can reduce the emotional challenges in the ten emotional challenges facing the emotional review process. Spam and False Detection, Transparency and Transparency, Bipolar Feelings, Globalization, Dependence, Large Dictionaries, Indigenous Languages Overheads, Pragmatics, Failed Expectations, Anaphora References / Co-reference, and Corrections . Next, we discuss work related to emotional challenges by respecting the type of review and the context of the topi

Background of Sentiment Analysis

How does Sentiment Analysis work?

There is a way to use emotion analysis to create a knowledgeable dictionary about which words and phrases are positive and negative. For example, SentiWordNet is an over-the-top dictionary utility where every WordNet. The Synset is numbered with a three-digit number that describes the objectives in the syset being objective, positive, and negative. This dictionary can be either compiled or automatically detected. A lexical or corpora annotation is usually made by hand, and class dividers are then trained in large sets of features to distinguish new collections of words or phrases. There are other ways to analyze emotions that focus on digging out sentences or whole texts, rather than relying on word proportions. This method usually works with a collection of text documents. An important problem with document separation (polarity separation) is that it has to determine the complete emotional aspects of the whole document, while the expressed emotions can be grouped into a single sentence or noun. In some cases, a feeling may be expressed openly, making it even more difficult to detect and separate. However, the context surrounding these ‘hidden’ feelings can provide very useful information to distinguish it. Based on this classification of the emotional analysis field, we often talk about word level, sentence level and classification level categories. On the other hand, we find another way to explore the web. The web ideas mine aims to extract a summary, and track various aspects of independent information on the web . This can be useful in advertising companies or trending viewers. With the synopsis of Sentiment analysis defection (also called the mine of ideas) referring to the use of natural language processing (NLP), textual analysis (TA) and computational linguistics (CL) to identify and extract specific information from the source material. Emotional analysis is widely used in online reviews and social media for a variety of applications, from advertising to customer service.

Sentiment Analysis (SA) & Natural Langauge processing (NLP):

We present some important concepts for emotional analysis, in the following: 3.5.1 Definitions

• **Natural language processing (NLP):**

A field of computer science, artificial intelligence, and computer languages interested in interaction of computers and human (natural) languages. Internally, NLP is related to the field of human interaction with computers (HCI). Many of the challenges in NLP include understanding natural language, that is, enabling computers to find meaning through the introduction of human or natural language, while others involve the production of native language [46]. of people. Despite the many NLP techniques as a legacy especially in Linguistics and Practical Intelligence, they are also influenced by relatively new domains such as Machine Learning, Computer Mathematics and Comprehension Science. We need to discuss some of the key words to be helpful in understanding NLP models and methods.

• **Token:**

Before any actual processing can be done in the entered text, it needs to be divided into language units such as words, punctuation, and numbers or alphabetical numbers. These units are recognized as tokens.

• **Sentence:** This refers to the planned sequence of tokens.

• **Token making:** The function of dividing a sentence into its basic token. In a variety of languages, such as English, the presence of white space makes tokens easier and less desirable. However, in languages such as Chinese and Arabic, the task is much more complex as there are no clear boundaries. Moreover, almost all the letters in such indistinguishable languages can be words with a single letter but can also be joined together to form words with more than one letter.

• **Corpus:** This refers to the body of the text, usually including a large number of sentences.

• **Part of speech (POS) Tag:** A word can be divided into one or more groups of dictionary categories or part of speech such as nouns, verbs, adjectives and titles, to name a few. The POS tag is a symbol representing such a class of words - NN (Noun), VB (Verb), JJ (Adjective), AT (Subject). One of the oldest and most widely used tag sets is the Brown Corpus tag set.

- **Separate Tree:** Represents a tree defined on a particular sentence that translates sentence structure as identified by a grammatical structure. After giving the key words, Some of the same NLP functions**:**
- **Speech Component (POS) Marking:** When a sentence and a set of POS tags are provided, the task of processing the same language is to automatically define POS tags for each word in the sentences. For example, if the phrase "Ball is red" is given, the output of the POS tag will be / AT ball / NN is / VB red / JJ. Modern POS markers can achieve as high accuracy as 96%. Marking the text with part of the speech turns out to be of great benefit to the complex NLP tasks such as analysis and machine translation.
- **Computational Morphology:** Indigenous languages have a large number of words built on basic structures known as morphemes (or titles), very small units of meaning. Computational morphology interested in the discovery and analysis of the internal structure of words using computers.
- **Analysis:** In the analysis task, the analyst builds an analysis tree given a sentence. There are some analysts who think that there is a set of grammar rules to be analyzed but the latest analysts are smart enough to decide to break down trees directly from the data provided using sophisticated mathematical models. Most commentators also work on the monitored setting and require that the sentence be marked with POS before it can be passed. Mathematical analysis is the area of active research in NLP:

.

- **Typing (MT):** In terms of typing, the goal is for a computer to translate text rendered in one native language into smooth text in a language other than anyone else in the loop. This is one of the most difficult tasks in NLP and has been done in many different ways over the years. Almost all MT methods use POS tagging and splitting as the first steps.
- **Topic sentence:** A sentence in which the writer expresses his or her feelings about businesses, events and their symbols. For example: "I like to swim".

• **Target sentence:** It is a true sentence about organizations, events, and structures, For example: “The schedule consists of swimming, diving and…”

• **Idea:** A belief or judgment based on specific information about a topic. Sometimes the ideas are clearly described as: "The voice quality of this phone is amazing." But sometimes they are hidden in the sense of the sentence, for example; "The earphone broke in two days". Since the concept of vision is very broad,Emotional separation focuses mainly on the general feeling expressed by ideas (Good / Bad). In fact, positivity or indifference determines the Polarity of opinion. In other words, one of the main tasks of emotional analysis is to clarify the diversity of documents or in more detail, which determines the diversity of each individual sentence in a document.

• **Ideas:** These are words that are often used to express positive or negative emotions. Example: {Beautiful, pretty, love} Positive sentiment {Ugly, awful, hate} Negative sentiment

• **Sentiment Orientation-SO (Polarity):** Indicates that the idea expressed by words with a positive, negative or neutral impression. Example: "Camera takes good pictures" Good.

• **Vision sentence:** A sentence that contains one or more thought words. Example: "The story was as amazing as it was

Part of Speech Tags:-

Part-expression marking (POS marking or SENDING), language tagging or classification of words, the process of marking a word in a text (corpus) as corresponding to a particular part. of speech, based on both its meaning, and its context — that is, relationships and related words related to a sentence, sentence, or paragraph. Marking the features of each word system is also an excellent strategy to improve the accuracy of the measurements and to find useful paragraph patterns. For example, portable text writers often describe themselves as the first person while actions in straightforward texts usually refer to the third person. Subtitle texts often use the simple past tense instead of the past tense verb. In contrast to the positive set, the opposite set contains very common actions in the past, as many writers express their negative feelings about their loss or embarrassment.

Semantic Relationships:-

Semantic relationships are the interrelationships between word meanings (semantic relationships at word level), between sentence meanings, or between sentence meanings (semantic relationships at sentence or sentence level). The following is a description of such a relationship. The Semantic method provides numerical values directly and relies on different principles for calculating similarities between words. This system provides the same sensitivity values for semantically closed words. WordNet for example; provides different types of semantic relationships between words used to calculate emotional variations. WordNet can also be used Obtain a list of emotional words by multiplying the first set with synonyms and antonyms and specifying the polarity of an unknown word with the relative number of synonyms of the opposite word.

Semantic methods can be combined with mathematical methods to perform SA function as a function which used both methods to detect product weaknesses in online reviews. Their vulnerability detector has extracted the characteristics and characteristics of the group that expose it using a morpheme-based method to identify the names of the features in the update. They used Hownet-based similarity measurements to find the most obvious and unusual features that define the same feature. Identify ambiguous features in the selection process based on PMI statistics. They have collected words that form words into syllables using semantic methods. They used the SA-based sentence method to determine the variability of each element in the sentences taking into account the effect of degree extensions. They may find a product weakness, as it was probably the most unsatisfactory feature in customer reviews, or the most unsatisfactory feature compared to their competitors' product reviews. Their results revealed the effectiveness of the weak finder

Emotional Analysis:-

issues In this section, we will discuss the problems facing emotional analysis soon . The research point of the problem summarization enables us to identify a rich set of minor related problems that constitute an emotional analysis problem. It is often said that if we cannot fix a problem, we probably do not understand the problem. The purpose of the descriptions is therefore to quote the structure in the text of a complex and terrifying natural language. From a practical point of view, definitions allow experts to identify what minor problems need to be resolved in a working system, how they relate, and what effect should be produced.

Emotional Analysis Challenges:

The purpose of identifying "emotional analysis challenges" means finding emotional challenges in assessing and discovering diversity of reviews and finding the most effective solutions for the highest accuracy of text. There is a lot of research on experimental challenges we classify challenges into Research and Technology challenges, as follows:

Figure 3.1: The sentiment analysis challenges [10]

Challenges of this type of study include six challenges :-

1. **Finding Spam and False:**

Spam and a false challenge checks for duplicate reviews or updates and achieves the actual number of reviews. Another challenge with spam detection is the exploration of other words or phrases related to a vague topic. Additionally, there are reviews that have feelings or feelings but are not suitable for the domain

. • **Example:** Review 1: "The movie is good" & Review2: "horror movies are not true". [false] with a polarity negative. But if we examine the emotional aspects of a fixed film, the first update will be helpful but the second will be spam because we are not talking about the target film or its organizations. Emotional ChallengesSpam and fake detectionCreate a dictionaryWorld KnowledgeTopic Domain Domain A short sentence like catching small emotions.

2. **Clear and Clear Denial:**

Denial is a major challenge in analyzing emotions . This problem is divided into two types: explicit and implicit.

- **Example**: “I do not like [I do not like +] - this movie”
- **Awareness:** a review to determine the difference in negative emotions because the word (not) and then change the user's sentence to negative.
- **Example:** “Film viewers [wish] for artists to [improve] +] - their performance”,
- **Note:** Although the word [improve] has a good idea, the word [desire] implies that it is not. is good enough and therefore we need to improve it, so that emotional polarity is negative based on the obvious evil. There are some explanations in the reviews that explicitly refer to negative feedback such as “your performance is good but [you need to achieve a level of success] in the

test”. In the last example we see the need to reconsider the negative polarity in the review.

3. **Independence of the domain:**

One of the most important issues facing the exploration of ideas. There is a different effect of the subject domain and the domain models of the multiple topics in the analysis of emotions. We need to be aware of the domain status and its features and names.

• **Example: Review 1**: [This is bad] & Review2: [This is a bad service at this hotel]. • Observation: Review 1 refers to a multidisciplinary domain and examines the word [bad] with the negative polarity. But 2 reviews refer to one topic [hotel hotel] that has features of this [bad] domain - it has a negative variation on a particular domain.

4. **Higher natural language processing:**

Extra natural language such as ambiguity, reference, Transparency, imagination, emotional acquisition, etc. has created a barrier to emotional analysis as well. Description of shared reference and anaphora resolution: sentences such as "I want that!" and "Queen Elizabeth II is the Queen who governs sixteen independent states, is politically neutral and legally her role is ceremonial" does not mean "that", "ruling queen", "she" or "she" is referred to. , namely makes it even more difficult to define what emotion is expressed and who or what is meant. Emotions and ideas can be expressed openly and openly. Transparency is a challenge to accounting principles, as it is also difficult for people to identify and analyze these expressions correctly. This also applies to humor, sarcasm, sarcasm, etc. Another problem to consider, the process of making conclusions using specific clues (mind, mathematics, etc.) in observation or speculation. Inference has become a popular research field, and applications such as professional programs and business law engines have followed.

5. **Business identification and output features and keywords**:

Text or sentence may have multiple entities. It is very important to find a business where the idea is focused. Consider the following examples. Samsung is better than Nokia Ram who beat Hani in football. The models are good for Samsung and Ram respectively but are not good for Nokia and Hani.

- **Example:** Mobile sound is good.
- **Note:** audio is a single component from a mobile domain. 6. Geographical knowledge and Pragmatics Often world knowledge needs to be incorporated into the emotional process. Consider the following example:
- **Example:** [Author of this paper is similar to Einstein]
- **Observation:** Global knowledge is as important a challenge as it was in a previous review. [Einstein] in the name of scientist this refers to a good idea but it is very difficult to understand with computer algorithms.

Challenges of this type of technology include four challenges:

6. Temporary Relationships:

A review period can be important in analyzing emotions. Example: The reviewer may have thought Windows Vista was good in 2008, but now he may have a negative opinion in 2009 because of the new Windows

7. Awareness:

Therefore evaluating this type of emotion that changes over time may improve the effectiveness of emotional analysis. This allows us to be aware of when a product has improved over time, or when people change their attitude toward a product.

8. Failed Expectations:

Sometimes the author deliberately puts the situation in order to counteract it in the end. English text to show the concept of expected failure. There are a number of vague words that we can see or determine through our emotions. While we may identify the background of a topic, we can also identify its variations.

9. Bi-polar Feelings: There are some words and phrases that have a bi-polar meaning that depends on the subject and characteristics or keywords that have a clear meaning. Example: Review 1: [Older conference on data mining.] & Review 2: [Older author in this field] & Review 3: [Old topic]. Awareness: in most cases the word [Old] has negative effects but in previous revisions logically there is a positive polarity 1 review and 2 reviews but there is a negative opinion in review 3. We therefore need to be aware of the features or keywords or subject domain to know that how to identify polarity.

10. Generate large dictionaries: this hinders the creation of large dictionaries to cover data testing. Previous types of emotional disorders have a profound effect on cognitive function. There are feelings and words that have more meaning than others and some depend on knowledge of the world. There are certain challenges that include the asymmetry in the acquisition of vision mining software and Term Position.

• Sentence level sentiment classification:

This level of analysis is closely related to subjectivity classification , which separates sentences (called: straight sentences) that express factual information from sentences (called: straight sentences) that express precise ideas and opinions. However, we should be aware that humility does not equate to empathy as many intended sentences can express ideas, e.g., "We bought a car last month and the window clock has crashed." Researchers are also analyzing clauses, but the level of clause is not enough, for example, "Apple is doing very well in this empty economy".

Differences between text level and sentence level: classifies a visual document as expressing a positive or negative concept and Sentence Level Planning: classifying a sentence as self-explanatory or objective and a direct sentence, classifying it as expressing good, bad. or a natural view.

Emotional document categorization is often used to give the main impression of the whole topic. It ignores the different angles of the object. For example, in the case of a film review, if the document agrees it means that the author generally likes the film, but if he focuses on different aspects such as the story or the acting of the characters, perhaps the ideas negative. In this case, if each element and related concept is excluded from each individual sentence, the result will be a subdivision of sentence level emotions. Sentence level separation is required for accurate object analysis; for example in terms of products, such an accurate analysis is necessary in order to make product development by distinguishing between what features (parts or attributes) of the product are popular and unpopular with consumers. Such information is not available on the emotional level of the Document Level.

- **Emotional distinction of business-level and Aspect**:

Both document level and sentence level do not find what exactly people liked and disliked. The aspect level performs a thorough analysis. The aspect level was previously called: feature level (feature-based mines and summaries). Instead of looking at language structures (texts, paragraphs, sentences, paragraphs or sentences), the quality level looks at the concept itself. It is based on the idea that an idea contains feelings (positive or negative) and purpose (of an idea). The idea without its recognition is that of limited use. Recognizing the importance of the purpose of ideas also helps us to understand the problem of analyzing emotions better. For example, although the phrase "although the service is not very good, I still love this restaurant" obviously has a constructive tone, we cannot say that this sentence is perfectly correct. In fact, the sentence is good for the restaurant (underlined), but bad for its service (underlined). In many programs, targeted ideas are defined by businesses and / or their unique features. Thus, the goal of this level of analysis is to identify the feelings in businesses and / or their characteristics. For example, the phrase "iPhone call quality is good, but its battery life is short" explores two aspects, call quality and battery life, for iPhone (business). Feelings of iPhone call quality are good, but feelings about its battery life are bad. Phone quality and battery life of the iPhone are the objectives of the vision. Based on this level of analysis, a systematic summary of ideas about organizations and their characteristics can be developed, which translates informal text into systematic data and can be used in all forms of high-quality and statistical analysis.

- **Emotional word classification:**

In recent activities, grammatical grammar has been reduced to sentence level, eg by using the presence of visual dictionary characters (singular or n-gram) to find straight sentences, or by exploiting conjunctions. mining law analysis based on the product review feature. So Word level applies to assessment of each word. Sometimes this arrangement deals with the ordering of the part of the speech in order to achieve the test points. For example, "Book is good", this sentence has a 'good' word with the mean meaning of polarity positive. Differences between sentence level and word level: indicates the total value of the test. They are similar in word-based analysis. But the difference arises from the way we examine these words. At the sentence level, the polarity of a sentence depends on the majority of polarity (positive or negative). That is not true enough, for example: "The story of the film is good but it is a very bad film" in this case at the level of emotional expression, polarity is not biased and not good and is not bad. But word quality is based on term frequency and total weight and not just polarity.

Benefits of Emotional Analysis

Below are some of the key benefits of Emotional Analysis: -

Reviewing marketing strategy: -

Emotional analysis helps to determine how customers feel about a product or product with their words. This also helps in shaping the marketing strategy.

Rated ROI: -

Emotional analysis helps to track the impact of a marketing campaign based on positive and negative emotions. If the positive feedback rate increases as a result of a campaign, that means the campaign is moving in the right direction.

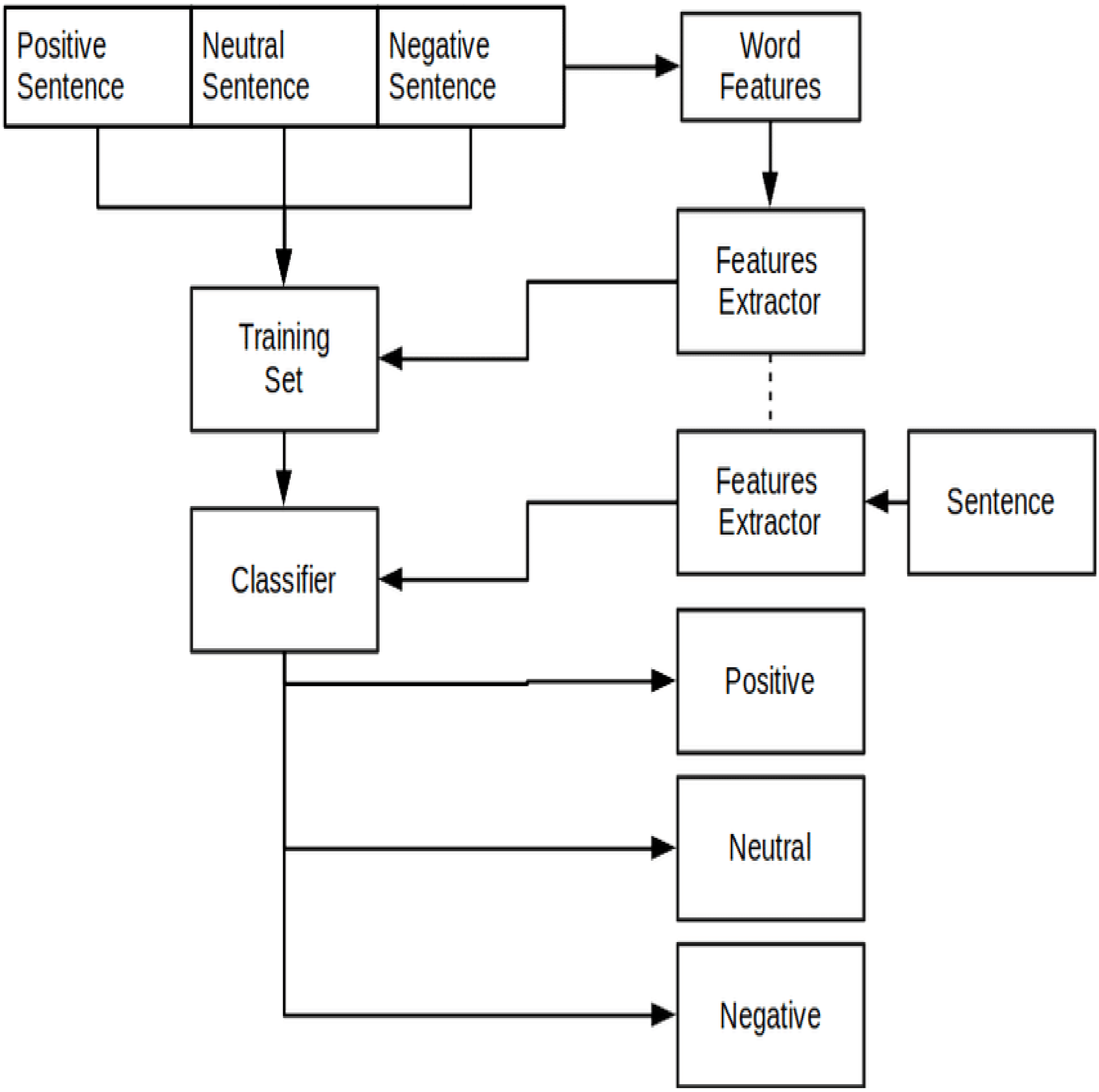
Assists in product quality improvement: -

Emotional analysis helps us to see what people are talking about online products, often highlighting the most accurate points that can be developed in a product or process.

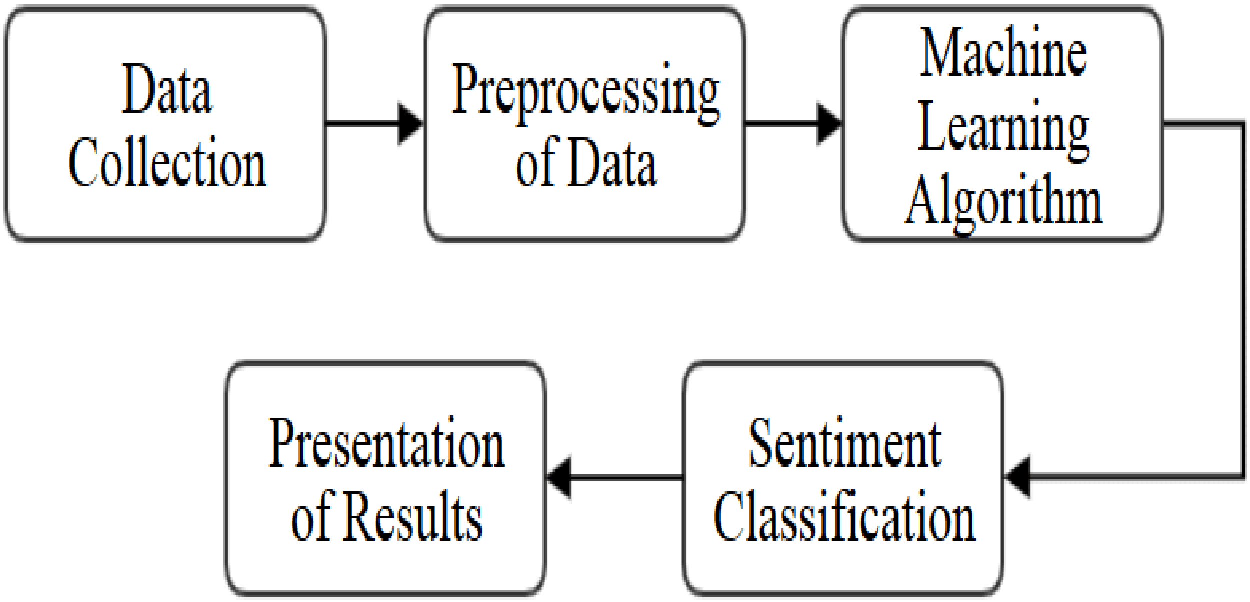
Helps to Manage Problems Better: -

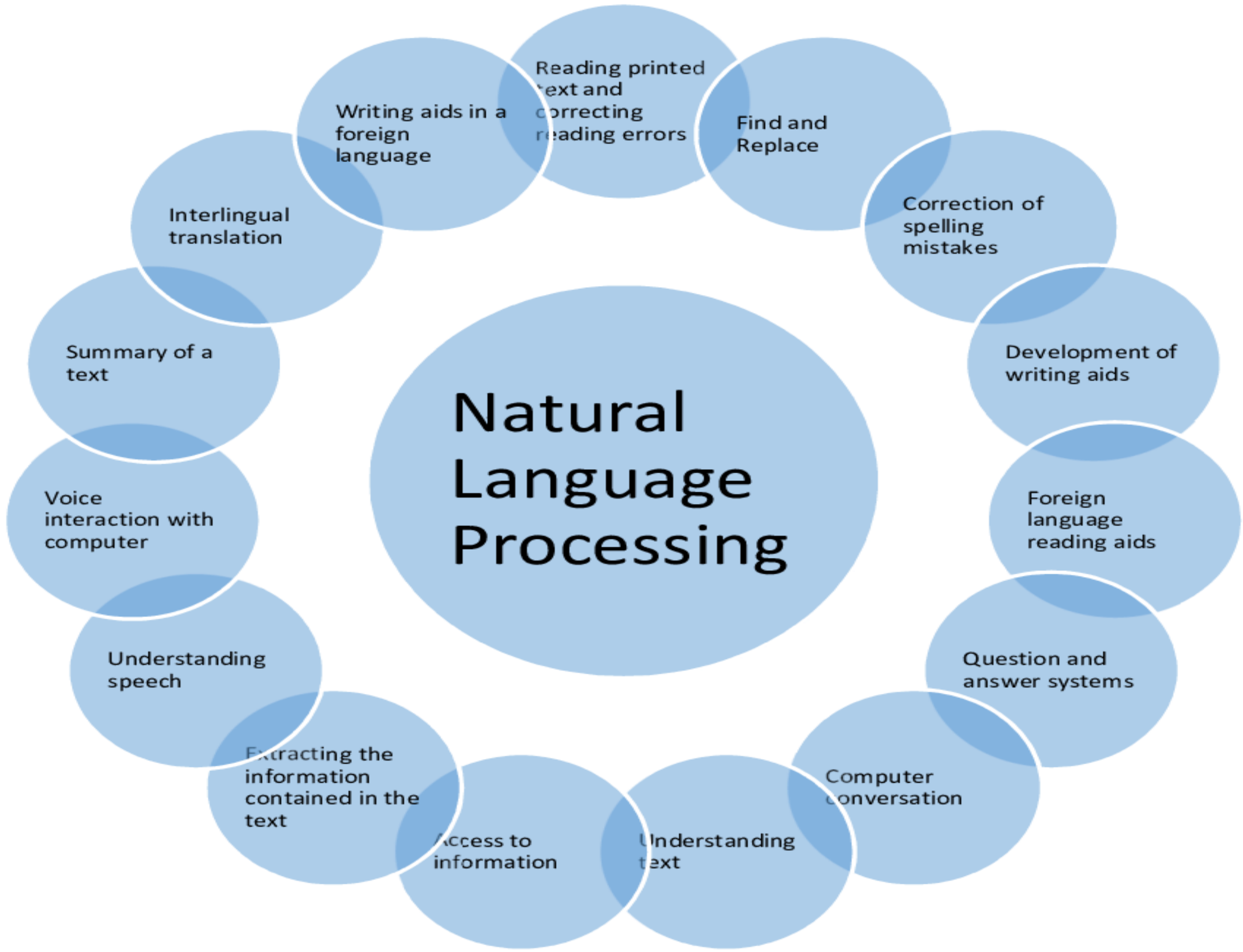
Based on negative emotions in certain keywords a company can take them before they explode. For example, if there are negative feelings about customer service, the company can send more services to that location

Sentiment Analysis System Architecture



Flow Chart


Data Collection
Preprocessing of Data
Machine Learning Algorithm
Sentiment Classification
Presentation of Results


Natural Language Processing
Reading printed text and correcting reading errors
Find and Replace
Correction of spelling mistakes
Development of writing aids
Foreign language reading aids
Question and answer systems
Computer conversation
Understanding text
Access to information
Extracting the information contained in the text
Understanding speech
Voice interaction with computer
Summary of a text
Interlingual translation
Writing aids in a foreign language

Text Summarization

Text Summary is an NLP field that works with techniques to summarize large sets of text data. It is widely used by experts to evaluate information available in research articles or articles. Two Important Techniques In Summary The text is subtraction and extraction. Extraction is a process that tests a large amount of text data to 'extract' short and concise summaries. Abstract programs create summaries by creating new text based on experiments of the original source text.

Aspect Mining

Element mining distinguishes different features or elements in a text. Typically, it is combined with emotion analysis programs and used by companies to find the type of feedback their customers receive. When those factors and feelings are combined, companies can get a clear idea of the various aspects of customer information. By using these tools, large amounts of text data can be summarized into smaller sentences such as –

Customer service

– could be better Communication

- Good Prices - unsatisfactory

Topic Modeling

Theme modeling is a sophisticated NLP tool used to classify natural themes that exist in text data. These procedures do not require any kind of human guidance. Some of the most commonly used Topic Modeling algorithms include –

Related Subject Modeling

Latent Dirichlet Allocation

Latent Semantic Analysis (LSA)

Design and Collaboration :-

Design We apply a three-layer design to our proposed SAOOP tool. The top layer is the presentation layer (GUI), which controls all interaction with the end user. The middle layer is a layer application that integrates all functions such as text analysis, emotion classification, emotional word analysis techniques, a dictionary used to manage information resources. The bottom layer is a website layout and contains a sheet of paper, paper metadata, and reviews of words related to feelings and prefixes shown in :

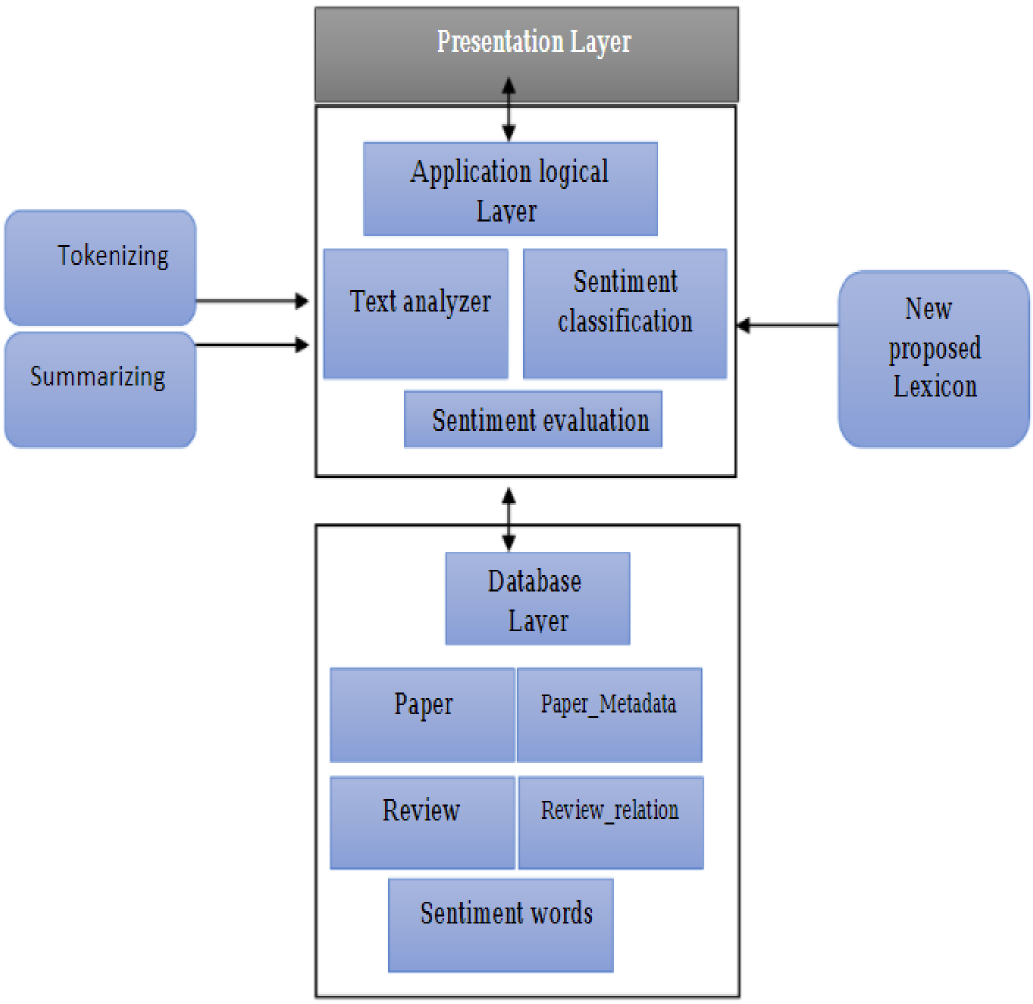


Figure 4.5: Proposed Design of Database

Machine Translation

Machine Translation (MT) or automatic translation is the process by which computer software translates text from one language to another without the involvement of the individual.

How does Machine Translation Work

MT works with a large number of source and target languages that are compared and compared to a machine translation engine. We classify three types of machine translation methods:

- **Legal translation based on rules**
    - uses grammar and grammar rules, developed by language experts, and dictionaries that can be tailored to a particular topic or industry.
- **Mathematical machine translation**
    - does not depend on the rules or grammar of the language; learns to translate by analyzing a large number of existing human versions.
- **Neural machine translation**
    - teaches itself how to interpret using a large neural network. This method is becoming increasingly popular as it provides better results with language pairs.

Benefits of Machine Translation

- Save time:
    - Translating into machine language can save valuable time as it can translate whole text documents in seconds. However, please remember that human translators must always submit translations made by MTs.
- Reduce costs:
    - Automatic translation can greatly reduce your costs, as it requires less personal involvement.

Source Code:-

```
html {
    background: #404550;
}

body {
    font: 100% Arial, Helvetica, sans-serif;
    line-height: 1.5;
    position: relative;
    background: #fff;
    color: rgb(76, 67, 65);
    font-weight:normal;
    font-style:normal;

  width: 1280px;
    margin: 20 auto;
  padding: 20px;
}
```

```
form, div{
      border-bottom: 2px solid rgb(76, 67, 65);
      margin-bottom: 5em;
   margin-left: auto;
   margin-right: auto;
   width: 50em
}

h1 {
      font-family: Georgia, Times, "Times New Roman", serif;
      font-size: 1.8em;
      border-bottom: 2px solid rgb(76, 67, 65);
      margin-bottom: 1.5em;
      background: url(../_images/icon_sprites_50.png) no-
repeat
}

.example_a {
   border: none;
   background: #404040;
   color: #ffffff !important;
   font-weight: 100;
```

```
    padding: 20px;
    text-transform: uppercase;
    border-radius: 6px;
    display: inline-block;
    transition: all 0.3s ease 0s;

    float: right;
    margin-top: 2em;
}

.example_a:hover {
    color: #404040 !important;
    font-weight: 700 !important;
    letter-spacing: 3px;
    background: none;
    -webkit-box-shadow: 0px 5px 40px -10px rgba(0,0,0,0.57);
    -moz-box-shadow: 0px 5px 40px -10px rgba(0,0,0,0.57);
    transition: all 0.3s ease 0s;
}
```

Python Source:-

```
from flask import Flask, request, render_template
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
```

```
import nltk
from string import punctuation
import re
from nltk.corpus import stopwords

nltk.download('stopwords')

set(stopwords.words('english'))

app = Flask(__name__)

@app.route('/')
def my_form():
    return render_template('form.html')

@app.route('/', methods=['POST'])
def my_form_post():
    stop_words = stopwords.words('english')

    #convert to lowercase
    text1 = request.form['text1'].lower()

    text_final = ''.join(c for c in text1 if not c.isdigit())

    #remove punctuations
    #text3 = ''.join(c for c in text2 if c not in punctuation)

    #remove stopwords
    processed_doc1 = ' '.join([word for word in text_final.split() if word not in
stop_words])

    sa = SentimentIntensityAnalyzer()
    dd = sa.polarity_scores(text=processed_doc1)
    compound = round((1 + dd['compound'])/2, 2)

    return render_template('form.html', final=compound,
text1=text_final,text2=dd['pos'],text5=dd['neg'],text4=compound,text3=dd['neu'])

if __name__ == "__main__":
    app.run(debug=True, host="127.0.0.1", port=5002, threaded=True)
```

Sentiment Analyzer Web App

A flask (Python) Web Interface for sentiment analysis using NLP techniques.

Basic Features
* Remove stop words
* Pre-process text (remove punctuation, lower case)
* Stemming of words

Sentiment Analysis
* Shows how much text content is positive

Prerequisites

This app is built using **Python 3.6.6**

Start Service
Now, to start the application, do the following:

```
python app.py
```

Server will start and you can connect by opening the web browser and connecting one of the URLs:

```
http://127.0.0.1:5002/
```

Some Screenshots

<p align="center">

</p>

<p align="center">

</p>

Use Heroku app

The app can be tested on heroku sentiment-analyzer3.herokuapp.com/.

<p align="center">

</p>

Conclusion

Emotional analysis becomes a very important source of decision-making. People are likely to depend on it to achieve an effective product. Although there are hundreds of thousands of researchers, who write and read online papers every day, so far no research has been done on this subject. Because analyzing the background of scientific papers is difficult. It has special features and symbolic effects on sensory polarity testing. In this thesis, we have introduced a new way of analyzing the scientific background based on emotional analysis. This process aims to support researchers in selecting the most appropriate papers for their research. This process combines two test components in a scientific paper: emotional scores and a system score. First: emotional scores based on online review reviews. Second: the system school is based on an examination of the parameters of an important topic. This approach is called "SAOOP" online. Improves accuracy and comprehension of online emotional reviews. The emotional testing approach involves creating a Bag-of-words model development and producing value-added solutions. emotional challenges in this domain. The advanced Bag-of-words model solves two major first-level weaknesses: low accuracy and manual testing. It is a default model for emotion testing and depends on the weight of each word instead of the term frequency of each word. It also divides emotional energy into five levels of emotional separation. It also intervenes with solutions to the most important emotional challenges to improve accuracy. These challenges are negative, spam and false updates, extracting and exploring features of the title or keywords, global knowledge, and building a great dictionary. The system school examines the most important parameters in the field of scientific research. These parameters are the place of publication, the date of publication, and the amount of quote paper. In order to evaluate the proposed SAOOP process, we made comparisons between it and the two popular methods. The results have a comparison between accuracy and performance between the three strategies where researchers apply strategies to the three data sets (training, testing and validation). Comparative results show how the proposed process can increase accuracy and functioning by addressing multiple language integration situations and solving specific emotional analysis challenges. Accuracy results show in NLTK

(62%), NLPS (70%) and SAOOP (82%). Performance results between the three strategies give an estimate of the results obtained from the three databases. The F-rated approach to emotional analysis challenges is SAOOP (87.5%) and NLPS is second (71%) and NLTK (61%).

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