BUNDELKHAND INSTITUTE OF ENGINEERING AND TECHNOLOGY, JHANSI U.P

A SEMINAR REPORT ON

SENTIMENT ANALYSIS

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CERTIFICATE

This is to certify that seminar entitled **“SENTIMENT ANALYSIS”** has been successfully delivered by **AASTHA BHATI** (B.Tech 3rd year Computer Science and Engineering, Roll No. **1704310002**) in the partial fulfillment of Bachelor’s Degree in Computer Science and Engineering from **BUNDELKHAND INSTITUTE OF ENGINEERING AND TECHNOLOGY, JHANSI** during the academic year 2017-2018.

Date:

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ABSTRACT

Sentiment analysis uses the NLP for knowing the sentiment of a sentence.Sentiment analysis refers to the task of natural language processing to determine whether a piece of text contains some subjective information and what subjective information it expresses, i.e., whether the attitude behind this text is positive, negative or neutral. Understanding the opinions behind usergenerated content automatically is of great help for commercial and political use, among others. The task can be conducted on different levels, classifying the polarity of words, sentences or entire documents. In this report, we will discuss about the sentiment analysis ,the type of sentiment analysis,its applications and how it will be done. we don't only want to know that people are talking about our brand we also want to know ,how are they talking about it if they have positive view with the sentimental analysis we can know about the emotions of the people that's why it can be called emotion A.I or opinion mining.

Sometimes users give their view in a sarcastic tone for eg: "my camera has a battery life of 1 hour ,the battery life of my camera is very good." This is a sarcastic tone and ofcourse it is a negative view but how can a computer can understand it ?,sometimes it is hard for humans too. So to avoid the problem of sarcastic sentences we will use deep learning.so in deep learning the computer tries to mimic the human brain.so the sarcastic sentences are not common in customer review but it is common in political issues.and other then sarcastic sentences there are spam opinion issues ,it means that some rival company some perticularily for bad image of the organization ,so to avoid this we shold notice the behavior of opinion makers.so for this we will use data mining. so sentiment analysis is a part of data mioning too. there are also phrases and idioms, e.g., cost someone an arm and a leg. Sentiment words and phrases are instrumental to sentiment analysis for obvious reasons. A list of such words and phrases is called a sentiment lexicon (or opinion lexicon). Over the years, researchers have designed numerous algorithms to compile such lexicons.

Understanding people's emotions is essential for businesses since customers are able to express their thoughts and feelings more openly than ever before. By automatically analyzing customer feedback, from survey responses to social media conversations, brands are able to listen attentively to their customers, and tailor products and services to meet their needs.

INTRODUCTION

Sentimental analysis is also called opinion minining or emotion AI. It refers to the use of natural language processing, text analysis and computational linguistics to systematically identify, extract, quantify, and study affective states and subjective information & give the opinion about it.By sentimental analysis we can get positive ,negative or neutral opinion & opinion really matters to us .before doing anything we prefer to take opinions from our friends ,family or society.This is very important to the data.Because We are living in the age of data &it helps us to organized.nowadays 7080% data is unstructured or we can say unorganized so we really needs the sentiment analysis im our life.Here we will discuss about the basics of the sentiment analysis,and what are the types of sentiment analysis ,what are its benefits,it's application & how does it work.By identify their sentiment toward the product, brand,polititions,service we can know the thinking of a person.


Negative
11%
Analysis
understanding
Positive
89%

content

TYPES OF SENTIMEN ANALYSIS

Sentiment analysis assumes various forms, from models that focus on polarity (positive, negative, neutral) to those that detect feelings and emotions (angry, happy, sad, etc), or even models that identify intentions (e.g. *interested* v. *not .interested*).According to the type of sentiment they can be of various type, for detecting that we are going to choose different approach.Like in one case we will analyze the whole document and in another case we will just analyse just a sentence.In a particular text the sentiment could be positive negative or neutral. Some particular words as we know has positive meaning like good ,amazing & others like bad borining etc hav negative meaning.First we will know about the type of sentiment after that w will talk about the analyzing it.

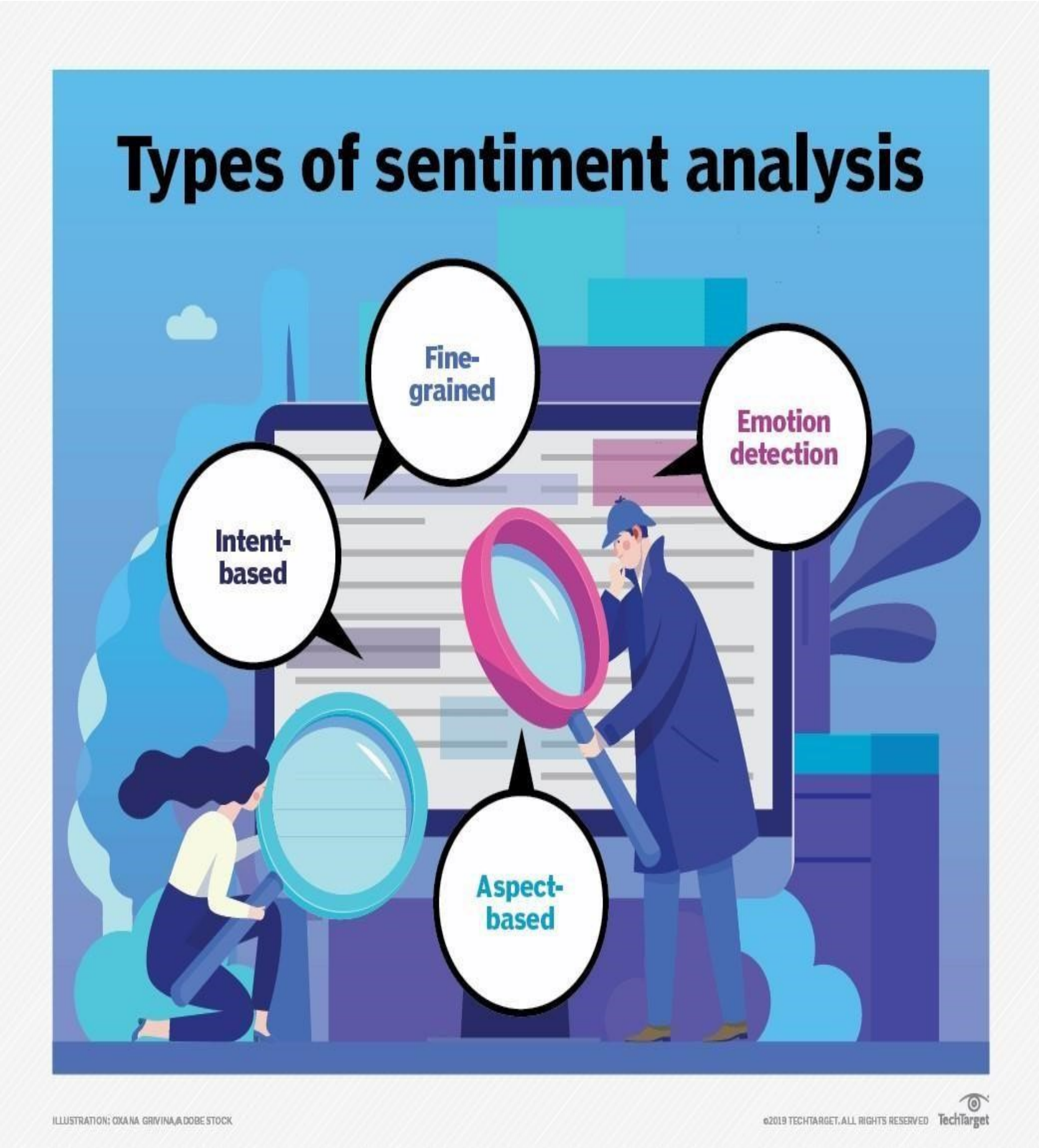
Here are some of the most popular types of sentiment analysis:

Fine-grained Sentiment Analysils

Emotion detection

Aspect-based Sentiment Analysis

Multilingual sentiment analysis


Types of sentiment analysis
Fine-grained
Emotion detection
Intent-based
Aspect-based
ILLUSTRATION: OXANA GRIVINA/ADOBE STOCK
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Fine-grained sentimental analysis

In most cases today, sentiment classifiers are used for binary classification (just positive or negative sentiment), and for good reason: fine-grained sentiment classification is a significantly more challenging task!

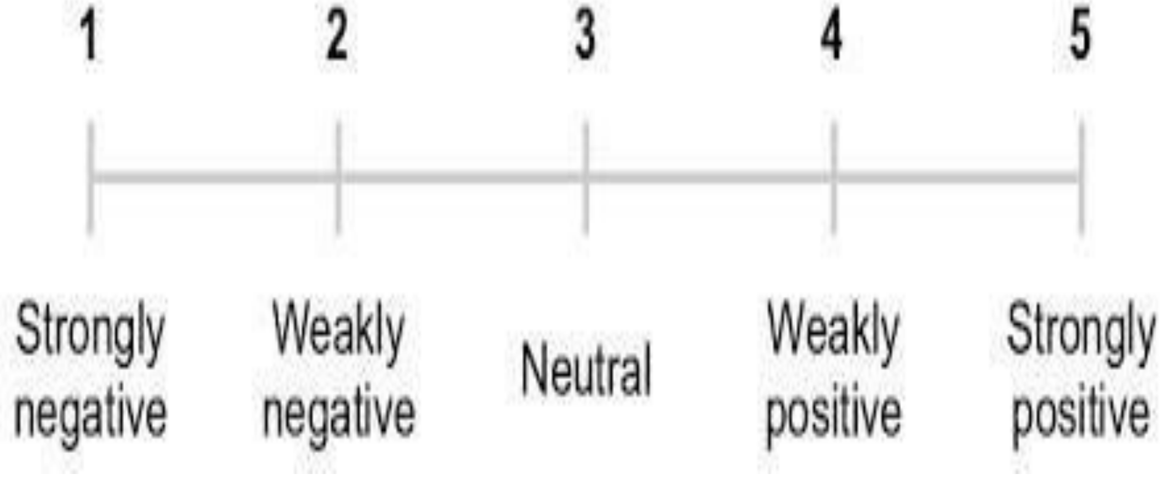
If polarity precision is important to your business, you might consider expanding your polarity categories to include:

- Very positive
- Positive
- Neutral
- Negative
- Very negative

This is usually referred to as fine-grained sentiment analysis, and could be used to interpret 5-star ratings in a review, for example:

- Very Positive = 5 stars
- Very Negative = 1 star

When performing information extraction with comparative expressions.it can get confused. a fine-grained analysis can provide more precise results to an automated system that prioritizes addressing customer complaints eg: “*This OnePlus model X is so much better than Samsung model X.”* In addition, dual-polarity sentences such as “*The location was truly disgusting ... but the people there were glorious.*” can confuse binary sentiment classifiers, leading to incorrect class predictions.


1
2
3
4
5
Strongly negative
Weakly negative
Neutral
Weakly positive
Strongly positive

Emotion detection

Emotion detection aims at detecting emotions, like happiness, frustration, anger, sadness, and so on. Many emotion detection systems use lexicons (i.e. lists of words and the emotions they convey) or complex machine learning algorithms.

One of the downsides of using lexicons is that people express emotions in different ways. Some words that typically express anger, like *bad* or *kill* (e.g. *your product is so bad* or *your customer support is killing me*) might also express happiness (e.g. *this is bad ass* or *you are killing it*).

If we search for a tag "love" on Flickr, we get a wide variety of images: roses, a mother holding her baby, images with hearts, etc. These images are very different from one another and yet depict the same emotion of "love" in them.we will use deep learning detecting those these are very different from each other but they will include in search result of images of love.but how a computer can understand it so that's why for emotion detection we will use deep learning.Nowadays, people share a lot of content on social media in the form of images - be it personal, or everyday scenes, or their opinions depicted in the form of cartoons or memes.
Analyzing content like this from social media websites and/or photo-sharing websites like Flickr,
Twitter, Tumblr, etc., can give insights into the general sentiment of people about say Presidential elections. Also, it would be useful to understand the emotion an image depicts to automatically predict emotional tags on them - like happiness, fear, etc.For analydze the emotion of a image we will divide that imotion in several parts lke anger, happpieness, fear, sorrow & etc.

FIGURE 1. Examples of Emotional Expressions

From left to right: Mild (row 1) and Extreme (row 2) neutral, happy, sad, angry, fearful, and disgusted expressions.

Kohler CG, Turner TH, Gur RE, Gur RC. *CNS Spectr.* Vol 9, No 4.

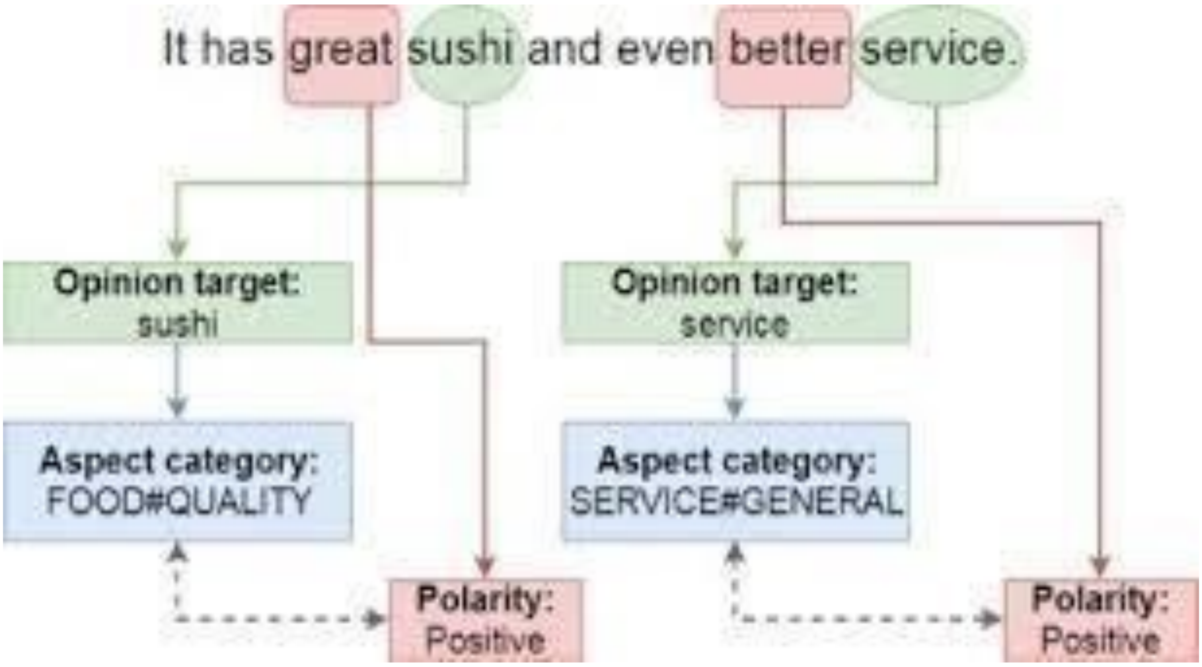
Aspect-based Sentiment Analysis

Aspect-based sentiment analysis is a text analysis technique that breaks down text into aspects (attributes or components of a product or service), and then allocates each one a sentiment level (positive, negative or neutral).

If you thought sentiment analysis was pretty neat, then prepare to be blown away by this advanced text analysis technique, aspect-based sentiment analysis helps you get the most out of your data.

Imagine you have a large dataset of customer feedback from different sources such as NPS, customer satisfaction surveys, social media, and online reviews. Some positive, some negative and others that contain mixed feelings. You'd use sentiment analysis to automatically classify the polarity of each text, right? After all, it's already proven to be a highly efficient tool.

Usually, when analyzing sentiments of texts, let's say product reviews, you'll want to know which particular aspects or features people are mentioning in a positive, neutral, or negative way. That's where aspect-based sentiment analysis can help, for example in this text: *"The battery life of this camera is too short"*, an aspect-based classifier would be able to determine that the sentence expresses a negative opinion about the feature battery life.


It has great sushi and even better service.
Opinion target: sushi
Aspect category: FOOD#QUALITY
Polarity: Positive
Opinion target: service
Aspect category: SERVICE#GENERAL
Polarity: Positive


Food
Drinks
Service
Staff
Comfort
Location
Value

APPROACHES FOR SENTIMENT ANALYSIS

Sentiment analysis uses various Natural Language Processing (NLP) methods and algorithms, which we'll go over in more detail in this section.

The main types of algorithms used include:

- **Rule-based** systems that perform sentiment analysis based on a set of manually crafted rules.
- **Automatic** systems that rely on machine learning techniques to learn from data.
- **Hybrid** systems that combine both rule-based and automatic approaches.

It mainly has two approaches one is by using NLP and second one is using machine learning & machine learning can be done by two ways one is supervised learning and second on is unsupervised learning.we can use the rulebased approach on the documents or secntences which don't have any otherwise meaning means if a text have negative words but means positive for eg: "This camera is killing it,I 'm definetly gonna by this one". Though the sentence have the negative word kill, but it means in positive way.& another is the sarcastic sentences , for the sentences which do not have a clear cut meaning we are going to use the automatic approach.

RULE BASED APPROACH

Usually, a rule-based system uses a set of human-crafted rules to help identify subjectivity, polarity, or the subject of an opinion.

These rules may include various techniques developed in computational linguistics, such as:

- Stemming, tokenization, part-of-speech tagging and parsing.
- Lexicons (i.e. lists of words and expressions).

Here's a basic example of how a rule-based system works:

1. Defines two lists of polarized words (e.g. negative words such as *bad*, *worst*, *ugly*, etc and positive words such as *good*, *best*, *beautiful*, etc).

2. Counts the number of positive and negative words that appear in a given text. 3. If the number of positive word appearances is greater than the number of negative word appearances, the system returns a positive sentiment, and vice versa. If the numbers are even, the system will return a neutral sentiment.

Rule-based systems are very naive since they don't take into account how words are combined in a sequence. Of course, more advanced processing techniques can be used, and new rules added to support new expressions and vocabulary. However, adding new rules may affect previous results, and the whole system can get very complex. Since rulebased systems often require fine-tuning and maintenance, they'll also need regular investments.

Automatic Approaches

Automatic methods, contrary to rule-based systems, don't rely on manually crafted rules, but on machine learning techniques. A sentiment analysis task is usually modeled as a classification problem, whereby a classifier is fed a text and returns a category, e.g. positive, negative, or neutral. Here's how a machine learning classifier can be implemented:

The Training and Prediction Processes

In the training process (a), our model learns to associate a particular input (i.e. a text) to the corresponding output (tag) based on the test samples used for training. The feature extractor transfers the text input into a feature vector. Pairs of feature vectors and tags (e.g. *positive*, *negative*, or *neutral*) are fed into the machine learning algorithm to generate a model.

In the prediction process (b), the feature extractor is used to transform unseen text inputs into feature vectors. These feature vectors are then fed into the model, which generates predicted tags (again, *positive*, *negative*, or *neutral*).

Feature Extraction from Text

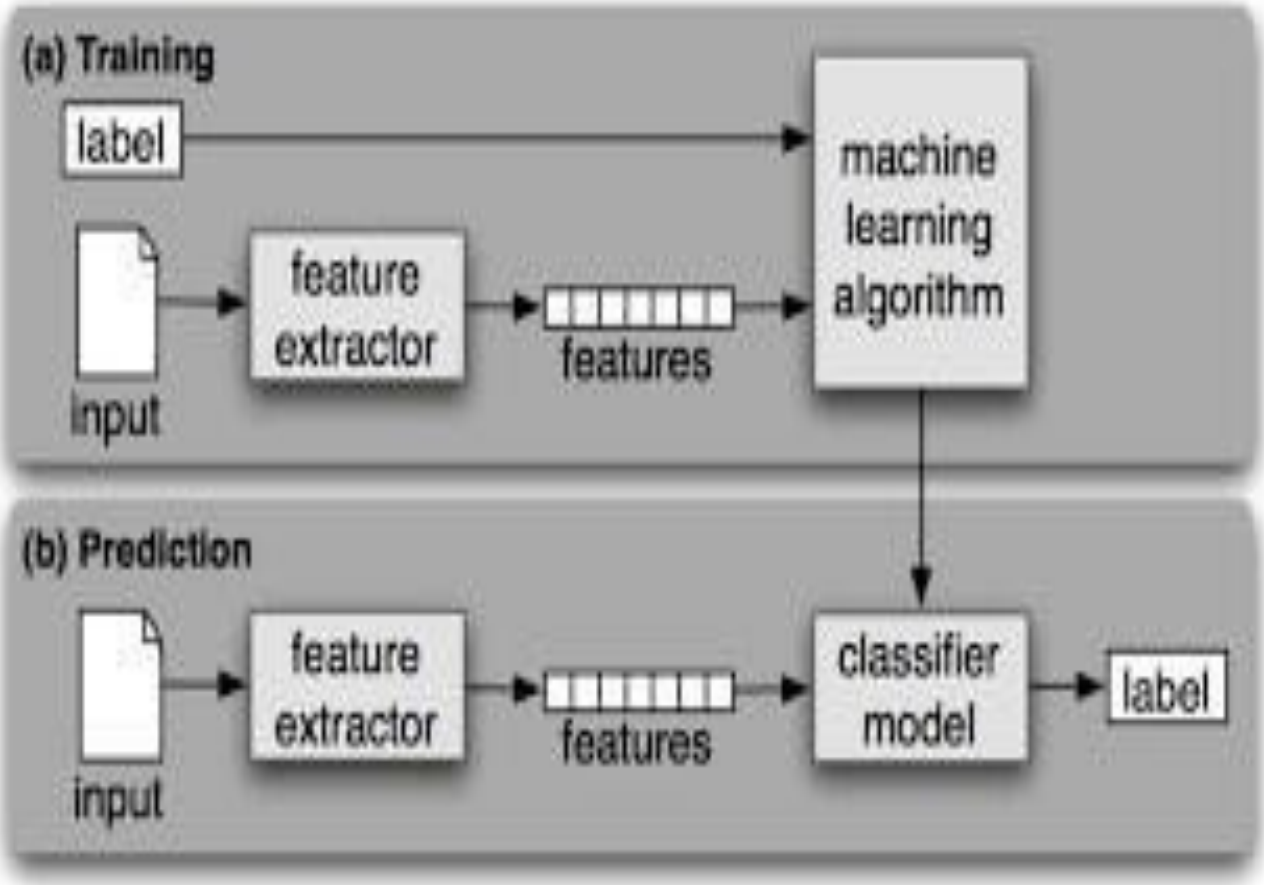
The first step in a machine learning text classifier is to transform the text extraction or text vectorization, and the classical approach has been bagof-words or bag-of-ngrams with their frequency.

More recently, new feature extraction techniques have been applied based on word embeddings (also known as *word vectors*). This kind of representations makes it possible for words with similar meaning to have a similar representation, which can improve the performance of classifiers.

Classification Algorithms

The classification step usually involves a statistical model like Naïve Bayes, Logistic Regression, Support Vector Machines, or Neural Networks:

- Naïve Bayes: a family of probabilistic algorithms that uses Bayes's Theorem to predict the category of a text.
- Linear Regression: a very well-known algorithm in statistics used to predict some value (Y) given a set of features (X).
- Support Vector Machines: a non-probabilistic model which uses a representation of text examples as points in a multidimensional space. Examples of different categories (sentiments) are mapped to distinct regions within that space. Then, new texts are assigned a category based on similarities with existing texts and the regions they're mapped to.
- Deep Learning: a diverse set of algorithms that attempt to mimic the human brain, by employing artificial neural networks to process data.


(a) Training
label
machine
learning
algorithm
feature
extractor
features
input
(b) Prediction
feature
extractor
features
classifier
model
label
input

NAÏVE BAYES

The simplest solutions are usually the most powerful ones, and Naive Bayes is a good example of that. In spite of the great advances of the Machine Learning in the last years, it has proven to not only be simple but also fast, accurate, and reliable. It has been successfully used for many purposes, but it works particularly well with natural language processing (NLP) problems.

Naive Bayes is a family of probabilistic algorithms that take advantage of probability theory and Bayes' Theorem to predict the tag of a text (like a piece of news or a customer review). They are probabilistic, which means that they calculate the probability of each tag for a given text, and then output the tag with the highest one. The way they get these probabilities is by using Bayes' Theorem, which describes the probability of a feature, based on prior knowledge of conditions that might be related to that feature. Here we are going to use the bayes theorem bayes theorem works on the

probability.

Bayes theorem:

Bayes’ Theorem is useful when working with conditional probabilities (like we are doing here), because it provides us with a way to reverse them:

\[$P(A \mid B) = P(B \mid A) \times P(A)$

Let’s see how this works in practice with a simple example. Suppose we are building a classifier that says whether a text is about sports or not. Our training data has 4 sentences:

Text	**Tag**
“A great game”	Sports
“The election was over”	Not sports
“Very clean match”	Sports
“A clean but forgettable game”	Sports

Likelihood

Class Prior Probability

$$P(c \mid x) = \frac{P(x \mid c)\,P(c)}{P(x)}$$

Posterior Probability

Predictor Prior Probability

$$P(c \mid \mathrm{X}) = P(x_1 \mid c) \times P(x_2 \mid c) \times \cdots \times P(x_n \mid c) \times P(c)$$

SUPPORT VECTOR MACHINE

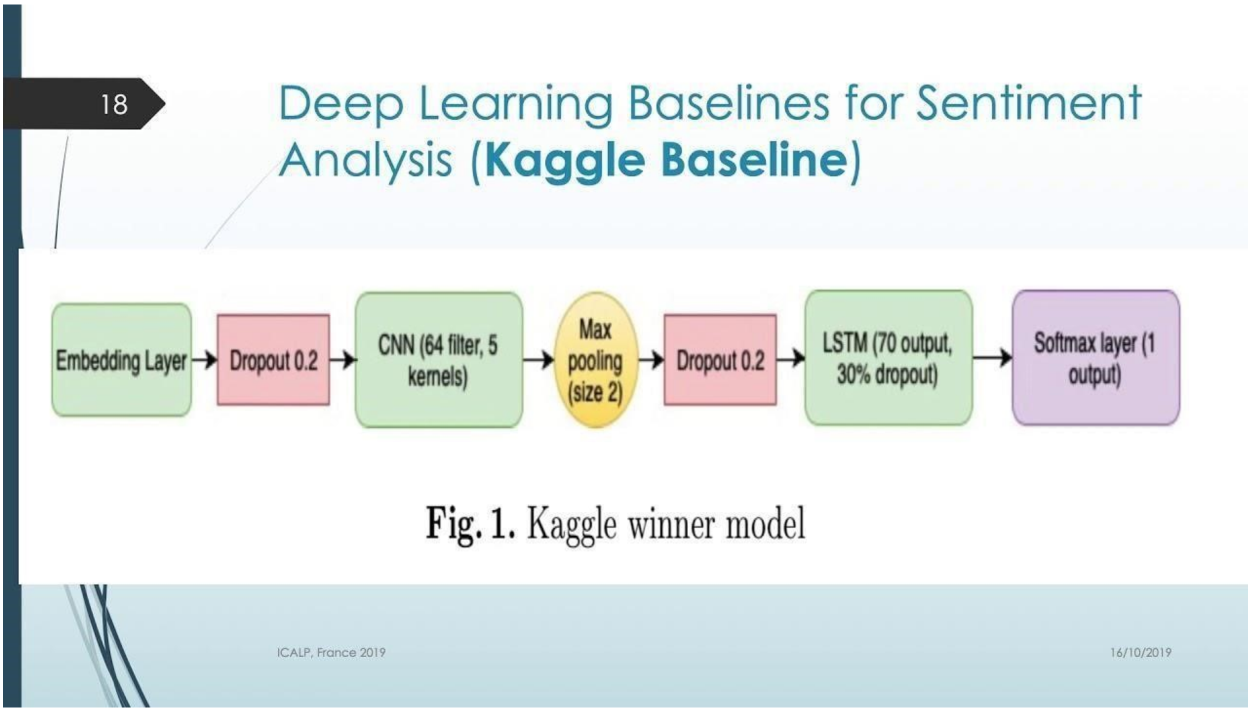
A support vector machine (SVM) is a supervised machine learning model that uses classification algorithms for two-group classification problems. After giving an SVM model sets of labeled training data for either of two categories, they're able to categorize new examples.

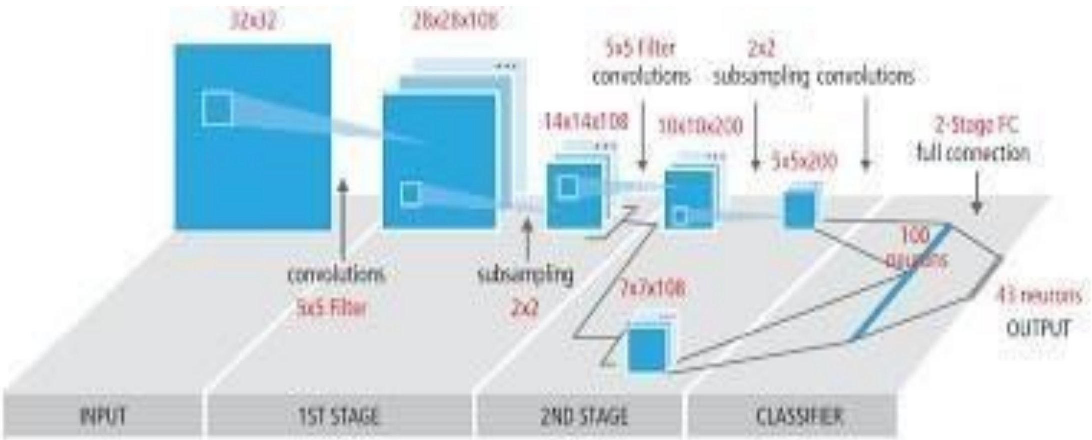
So if we're working on a text classification problem. we're refining our training data, and maybe we've even tried stuff out using Naive Bayes. But now we're feeling confident in our dataset, and want to take it one step further. Enter Support Vector Machines (SVM): a fast and dependable classification algorithm that performs very well with a limited amount of data.

Perhaps we have dug a bit deeper, and ran into terms like *linearly separable*, *kernel trick* and *kernel functions*. But fear not! The idea behind the SVM algorithm is simple, and applying it to natural language classification doesn't require most of the complicated stuff.

Deep Learning

a diverse set of algorithms that attempt to mimic the human brain, by employing artificial neural networks to process data.

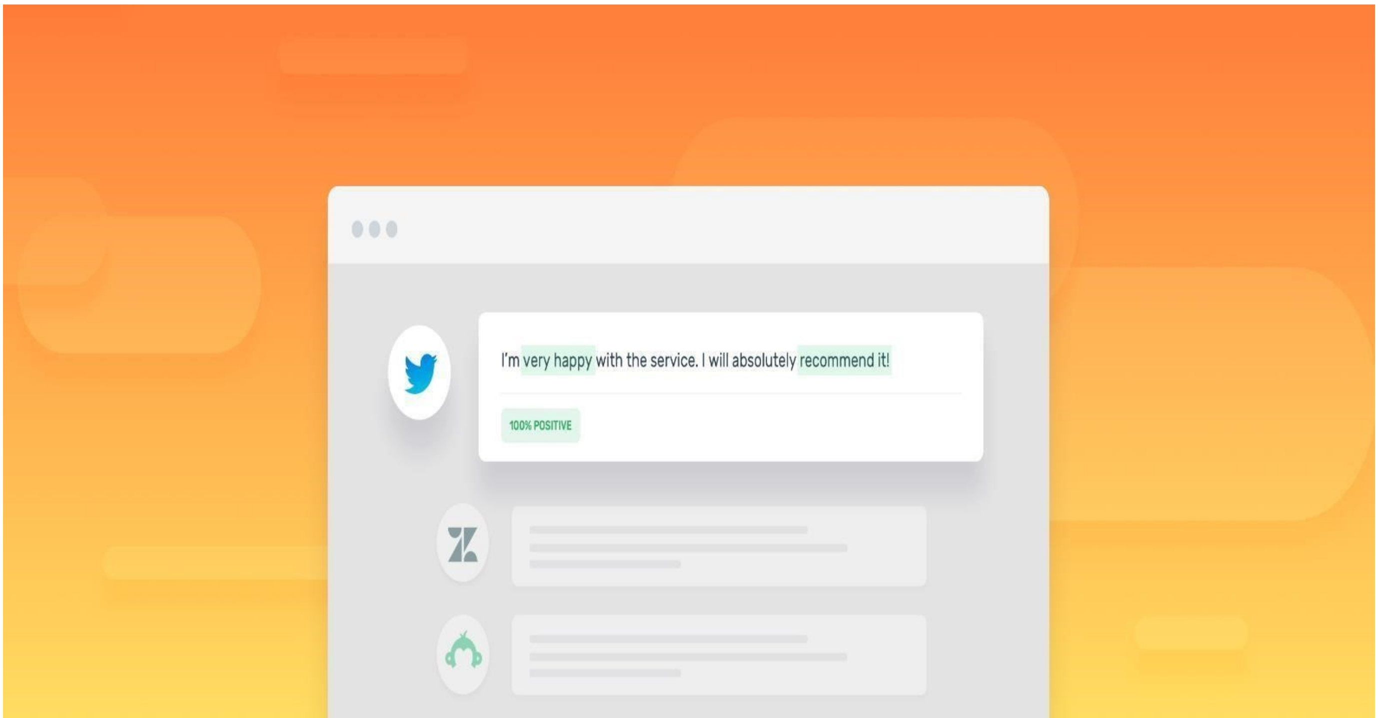




APPLICATION

In this section, we'll introduce use cases, applications, and examples of how sentiment analysis can be used for:

- Social media monitoring
- Brand monitoring
- Voice of customer (VoC)
- Customer service
- Market research



Social Media Monitoring

On the fateful evening of April 9th, 2017, United Airlines forcibly removed a passenger from an overbooked flight. The nightmare-ish incident was filmed by other passengers on their smartphones and posted immediately. One of the videos, posted to Facebook, was shared more than 87,000 times and viewed 6.8 million times by 6pm on Monday, just 24 hours later. The fiasco was magnified horrifically by the company's dismissive response. On Monday afternoon, United Airlines tweeted a statement from the CEO apologizing for "having to re-accommodate customers". Cue public outrage – you can imagine the field day on Twitter.

This is exactly the kind of PR catastrophe you can avoid with sentiment analysis. It's also an excellent example of why it's important to care, not only about if people are talking about your brand, but *how* they're talking about it. More mentions don't equal positive mentions.

In today's day and age, brands of all shapes and sizes have meaningful interactions with customers, leads, and even competition on social networks like Facebook, Twitter, and Instagram. Most marketing departments are already tuned into online mentions as far as *volume* – they measure more chatter as more brand awareness. Nowadays, however, businesses need to look for deeper insights. By using sentiment analysis on social media, we can get incredible insights into the *quality* of conversation that's happening around a brand.

In short, sentiment analysis can be used to:

- Analyze tweets and/or facebook posts over a period of time to detect sentiment of a particular audience
- Monitor social media mentions of your brand and automatically categorize by urgency
- Automatically route social media mentions to team members best fit to respond
- Automate any or all of these processes
- Gain deep insights into what's happening across your social media channels Top Benefits for social media monitoring:

Sentiment analysis is useful in social media monitoring because it helps you do all of the following:

- Prioritize action. Which is more urgent: a fuming customer or a “thanks!” shout-out? Obviously the angry customer. Sentiment analysis lets you easily filter unread mentions by positivity and negativity, helping you prioritize issues.
- Track trends over time.
- Tune into a specific point in time – i.e. the lead-up to a new product launch or the day a particular piece of bad press dropped.
- Keep a finger on the competition. Why not monitor your competitors’ social media the same way you monitor your own? If you tune in closely, maybe you notice there’s been a negative response to a particular feature of their new product, and you respond by designing a lead generation campaign targeting exactly that gap. They won’t even know what hit them.

Example: Trump vs Clinton, according to Twitter

Over the course of a few months during the 2016 US Presidential Elections, we collected and analyzed millions of tweets mentioning Clinton or Trump posted by users from around the world. We classified each of those tweets with a sentiment of either *positive*, *neutral*, or *negative*. For example, here are some tweets we analyzed:

- Negative: “Racial discord was conceived, nurtured, refined & perpetuated by Americans incl @realDonaldTrump’s father. Get real!” • Neutral: “@HillaryClinton will receive the first question at tonight’s presidential debate, according to @CBSNews #ClintonVsTrump”.
- Positive: “Americans trust @realDonaldTrump to Make our Economy Great Again!” • Positive: “@wcve it’s amazing how our city loves him and he really loves our city. @HillaryClinton made a great choice for Vice President. @timkaine”.

From this simple, easy analysis, we found interesting insights:

- More tweets mentioned @realDonaldTrump (~450k/day) than @HillaryClinton (~250k/day). Again, this does not equal positivity, but does imply brand awareness (and in the case of something like elections, awareness is key). • For both candidates, there were more negative than positive tweets. Given that it’s Twitter and politics, this was not much of a surprise.
- Trump had a better positive to negative Tweet ratio than Clinton.

To sum up, more people were tweeting about Trump, and a higher percentage of people tweeting about Trump were doing so more positively than those tweeting about Clinton.

Brand Monitoring

Not only do brands have a wealth of information available on social media, but also across the internet. Instead of focusing on specific social media platforms such as Facebook and Twitter, we can find mentions in places like news, blogs, and forums – again, looking at not just the volume of mentions, but also the quality of those mentions.

In our United Airlines example, for instance, the flare-up started on the social media platforms of a few passengers. Within hours, it was picked up by news sites and spread like wildfire across the US. News then spread to China and Vietnam, as the passenger was reported to be an American of ChineseVietnamese descent and people accused the perpetrators of racial profiling. In China, the incident became the number one trending topic on Weibo, a microblogging site with almost 500 million users.

And again, this is all happening within mere hours and days of when the incident took place.

In short, sentiment analysis can be used to:

- Analyze news articles, blog posts, forum discussions, and other texts on the internet over a period of time to see sentiment of a particular audience
- Automatically categorize the urgency of all online mentions of your brand
- Automatically alert designated team members of online mentions that concern their area of work
- Automate any or all of these processes
- Better understand a brand online presence by getting all kinds of interesting insights and analytics

Top benefits for brand monitoring:

- Understand how your brand reputation evolves over time
- Research your competition and understand how their reputation also evolves over time.

Identify potential PR crises and know to take immediate action. Again, prioritize what fires need to be put out immediately and what mentions can wait.

- Tune into a specific point in time. Again, maybe you want to look at just press mentions on the day of your IPO filing, or a new product launch. Sentiment analysis lets you do that.

Example: Expedia Canada

Around Christmas time, Expedia Canada ran a classic “escape winter” marketing campaign. All was well, except for the screeching violin they chose as background music. Understandably, people took to social media, blogs, and forums. Expedia noticed right away and removed the ad. Then, they created a series of follow-up spin-off videos: one showed the original actor smashing the violin, and in another one, they invited a real follower who had complained on Twitter to come in and rip the violin out of the actor’s hands. Though their original campaign was a flop, Expedia were able to redeem themselves by listening to their customers and responding.

Using sentiment analysis (and machine learning), you can automatically monitor all chatter around your brand and detect this type of potentiallyexplosive scenario while you still have time to defuse it.

Customer Feedback

Social media and brand monitoring offer us immediate, unfiltered, invaluable information on customer sentiment. However, there are two other troves of insight – surveys and customer support interactions.

Net Promoter Score (NPS) surveys are one of the most popular ways for businesses to gain feedback, and start by asking a simple question – *Would you recommend this company, product, and/or service to a friend or family member?* – that results in a simple number or score. Businesses use these scores to identify customers as promoters, passives, or detractors. The goal is to identify overall customer experience, and find ways to elevate all customers to "promoter" level, where they theoretically will buy more, stay longer, and refer other customers.

Numerical survey data is easily aggregated and assessed, but the next question in NPS surveys asks customers *why* they left the score they did. This triggers a series of openended responses that are a lot harder to analyze. However, with sentiment analysis these texts can be classified into positive and negative giving you further insights into why customers left the scores they did.

In short, sentiment analysis can be used to:

- Analyze aggregated NPS or other survey responses
- Analyze aggregated customer support interactions
- Track customer sentiment about specific aspects of the business over time. This adds depth to explain why the overall NPS score might have changed, or if specific aspects have shifted independently.
- Target individuals to improve their service. By automatically running sentiment analysis on incoming surveys, you can detect customers who are 'strongly negatively' towards your product or service, so you can respond to them right away
- Determine if particular customer segments feel more strongly about your company. You can zero in on sentiment by certain demographics, interests, personas, etc

Top benefits for understanding Voice of Customer (VoC):

- Use results of sentiment analysis to design better informed questions to ask on future surveys
  Understand the nuances of customer experience over time, along with why and how shifts are happening
- Empower your internal teams by giving them a deeper view of the customer experience, by segment and by specific aspects of the business • Respond more quickly to signals and shifts from customers

Example: McKinsey City Voices project

In Brazil, federal public spending rose by 156% from 2007 to 2015 while people's satisfaction with public services steadily decreased. Unhappy with this counterproductive progress, the Urban-planning Department recruited McKinsey to help them work on a series of new projects that would focus first on user experience, or citizen journeys, when delivering services. This citizencentric style of governance has led to the rise of what we call Smart Cities.

McKinsey developed a tool called City Voices, which conducts citizen (customer) surveys across more than 150 different metrics, and then runs sentiment analysis to help leaders understand how constituents live and what they need, in order to better inform public policy. By using this tool, the Brazilian government was able to surface urgent needs – a safer bus system, for instance – and improve them first. If even whole cities and countries, famous for their red tape and slow pace, are incorporating customer journeys and sentiment analysis into their decision making processes, then innovative companies better be far ahead.

Customer Service

We all know the drill: stellar customer experiences means a higher rate of returning customers. Leading companies know that *how* they deliver is just as, if not more, important as *what* they deliver. Customers expect their experience with companies to be immediate, intuitive, personal, and hassle-free. In fact, research shows that 25% of customers will switch to a competitor after just one negative interaction.

We already looked at how we can use sentiment analysis in terms of the broader VoC, so now we'll dial in on customer service teams.

Sentiment analysis can be used to:

- Automate text classification all incoming customer support queries
- Rapidly detect disgruntled customers and surface those tickets to the top
- Route queries to specific team members best suited to respond • Gain deep insights into what's happening across your customer support

Top benefits for customer service:

- Prioritize order for responding to tickets, being sure to address the most urgent needs first.
- Increase efficiency by automatically assigning tickets to a particular category or team member.

Example: Analyzing customer support interactions on Twitter

Just for kicks, we decided to analyze how the four biggest US phone carriers (AT&T, Verizon, Sprint, and T-Mobile) handle customer support interactions on Twitter. We downloaded tens of thousands of tweets mentioning the companies (by name or by handle), and ran them through a sentiment model to categorize each tweet as *positive*, *neutral*, or *negative*. We then used our new Insight Extractor, which reads all text as one unit, extracts the most relevant keywords, and returns the most relevant sentences including each keyword. Here’s some insights:

- T-Mobile had by far the highest percentage of positive tweets
  Verizon was the only company with more negative tweets than positive ones
- Top keywords for positive tweets at Verizon included typical terms such as “new phone,” “thanks,” and “quality customer service”. Key interactions between customers and agents were formal and somewhat dry
- Top keywords for positive tweets at T-Mobile included names of customer support agents, since their team has higher engagement, as well as backand-forth type conversations with their followers

To sum up, this could imply that a more personal, engaging take on social media elicits more positive responses and higher customer satisfaction.

Market Research

And as a final use case, sentiment analysis empowers all kinds of market research and competitive analysis. Whether you’re exploring a new market, anticipating future trends, or having an edge over the competition, sentiment analysis can make all the difference.

Sentiment analysis can be used to:

- Analyze product reviews of your brand and compare those with the competition
- Generate weekly, monthly, or daily reports – a sort of early-warning system
- Compare sentiment across international markets
- Analyze formal market reports or business journals for long-term, broader trends
- Analyze tweets and social media posts for real-time happenings
- Analyze reviews for unfiltered customer feedback
- Use aspect-based sentiment analysis to gain rich insight into the details and the reason for otherwise opaque market trends

Top benefits for market research:

- Tap into new sources of information
- Quantify otherwise qualitative information
- Add that qualitative dimension to already-gathered quantitative insights
- Provide information in real-time rather than in retrospect
- Automated for regular (perhaps weekly) reports
- Fill in gaps where public data is scarce – in emerging markets, for instance.

Examples: Hotel reviews on TripAdvisor

Our team was curious about how people feel about hotels in several major cities around the world, so we scraped and analyzed more than one million reviews from TripAdvisor. We looked at hotels in London, Paris, New York, Bangkok, Madrid, Beijing, and Rio de Janeiro.

Here are some insights:

- Reviews were mostly positive – on average, 82% of comments were tagged with a positive sentiment
  London hotels received the worst reviews
- London hotels were viewed as dirtier than New York hotels, and as having the worst food overall.

We used the keyword extraction module to analyze the actual content of the positive/negative reviews, and found a few more interesting insights: •
"Cockroaches" appears only in Bangkok –watch out!

- "Croissants" appears only in Paris (as we might expect). Shockingly, though, they appear to be a letdown. Taking a closer look, we were able to conclude this was more a reflection on the subpar hotel breakfast food than on the city itself (phew!).

Conclusion

We are living in the age of data, and most of the data is unorganised so we can use sentiment analysis for orientate that data & also the most essential feature in human beings is emotions we can train a machine to do that that's why we also called it emotion AI. This is the age of data so we should synnchronise with it. The data that is present online that is very large and it's increasing rapidly a human can't analyse all the data so we'll use machine learning techniques to do that. & the great example of sentiment analysis is the rating system. We can predict the election results,it will help us in various things. Sentiment analysis or opinion mining is a field of study that analyzes people's sentiments, attitudes, or emotions towards certain entities. This report tackles a fundamental problem of sentiment analysis, sentiment polarity categorization.

Refrences

1) Stanford.edu
2) www.cs.uic.sentiment analysis or opiniom mining
3) Monkeylearn sentiment analysis
4) Stone, Philip J., Dexter C. Dunphy, and Marshall S. Smith. "The general inquirer: A computer approach to content analysis." MIT Press, Cambridge, MA (1966).
5) Gottschalk, Louis August, and Goldine C. Gleser. The measurement of psychological states through the content analysis of verbal behavior. Univ of California Press, 1969.
6) USA Issued 7,136,877, Volcani, Yanon; & Fogel, David B., "System and method for determining and controlling the impact of text", published June 28, 2001.