

Natural Language Processing for Sentiment Analysis

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ABSTRACT

Sentiment analysis, also known as opinion mining, is a field within natural language processing (NLP) that focuses on systematically identifying, extracting, quantifying, and studying affective states and subjective information. It is the automated process of detecting and understanding the emotions conveyed through written text. This field is crucial in identifying and analyzing the thoughts, feelings, and sentiments indicated in textual data. The primary goal of sentiment analysis is to determine the emotional tone behind a piece of text, classifying it as positive, negative, or neutral. In an increasingly digital world, where vast amounts of textual data are generated daily through social media, customer reviews, and online forums, the ability to automatically discern sentiment has become invaluable for businesses, researchers, and policymakers. Using algorithms and methodologies, sentiment analysis examines text data to determine the underlying sentiment. This paper examines the fundamental role of natural language processing (NLP) in sentiment analysis.

KEYWORDS: *natural language processing (NLP), computational linguistics, sentiments, sentiment analysis (SA), opinion mining.*

INTRODUCTION

Artificial intelligence (AI) has a branch called natural language processing (NLP) that focuses on how computers and human language interact. NLP stands at the intersection of artificial intelligence, computer science, and linguistics, enabling computers to understand, interpret, and generate human language. It involves the ability of machines to understand and derive meaning from human languages. It provides the foundational tools and techniques necessary to process, understand, and interpret human language, which is inherently unstructured and complex.

Sentiment analysis is the computational study of opinions, sentiments, and emotions expressed in text, aiming to determine the emotional tone behind a piece of writing—whether it is positive, negative, or neutral. Natural language processing (NLP) for sentiment analysis has emerged as a field within artificial intelligence, enabling machines to understand and interpret human emotions, opinions, and attitudes expressed in text [1].

Sentiment analysis (SA) seeks to ascertain the sentiment or emotional tone expressed in a document.

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It aims to gauge the attitudes, sentiments, and emotions of a speaker/writer based on the computational treatment of subjectivity in a text. It has become a crucial tool for organizations to understand client preferences and opinions as social media, online reviews, and customer feedback. Businesses can better measure consumer satisfaction, pinpoint problem areas, and make educated decisions when they know whether the mood expressed is favorable, negative, or neutral. Predicting the sentiment or emotion portrayed in text data is called sentiment classification. It has proven possible to accomplish sentiment classification using a variety of methods [2].

FUNDAMENTALS OF NLP

Natural language processing is a subfield of artificial intelligence that empowers computers to understand, interpret, and generate human language. It is a technique where machine can become more human and thereby making human to communicate with the machine easily. NLP seeks to make software intelligent enough to process a natural language as

humans. For example, imagine a machine that takes instructions by voice.

NLP analysis generally consists of the following three levels [3]:

- *Syntax*, the study of sentence structure. Syntax deals with the formation of a sentence from individual words. Syntax alone suggests the proper interpretation of “Jimmy loves Lucy.”
- *Semantics*, the study of context-independent meaning. This derives the meaning of a sentence based on the meanings of the words/phrases. For example, semantics determines whether the word “bank” refers to a river bank or to a financial institution.
- *Pragmatics*, the study of context-dependent meaning. Pragmatics deals with how meaning changes in the presence of a specific context and how the contexts affect the meaning of the sentences. This level is concerned with the purposeful use of language in situations.

As a foundational pillar of modern artificial intelligence, NLP encompasses a wide array of tasks, including speech recognition, text classification, natural language understanding (NLU), and natural language generation (NLG). NLP encompasses a wide range of tasks, such as information retrieval (IR), named entity recognition (NER), relation extraction, text classification, topic modeling, semantic textual similarity, machine translation, and question answering (QA). Figure 1 shows how NLP transforms raw acoustic data into meaningful interactions [4], while Figure 2 shows different components of NLP [5].

Recently, large language models (LLMs) have shown their ability in learning universal language representations, text understanding and generation. LLMs refer to a model with a large number of parameters, vast training data, and substantial compute, enabling it to capture complex language patterns. In LLM-based NLP, pre-processing is followed by prompt engineering, which guides LLMs to produce outputs that align with extraction requirements during inference without altering the model’s parameters. Models like GPT are pushing the boundaries of language understanding, enabling nuanced and context-aware applications. The GPT (Generative Pretrained Transformer) is a large-scale language model developed by OpenAI that consists of multiple layers of transformer blocks, each with a self-attention mechanism and a forward neural network [6]. GPT-based systems can summarize complex reports or generate creative content like

essays, making them versatile in both academic and professional environments. ChatGPT uses NLP techniques to understand prompts. When you enter a prompt, the chatbot comprehends it and provides relevant replies. Figure 3 shows how NLP works [7].

WHAT IS SENTIMENT ANALYSIS?

Sentiment analysis, also known as opinion mining, is a subfield of natural language processing (NLP) that focuses on extracting and classifying the emotional tone behind a piece of text. It involves classifying text into categories that reflect the sentiment expressed—typically positive, negative, or neutral, as shown in Figure 4 [8]. Modern sentiment analysis employs a variety of techniques, often leveraging NLP to enhance accuracy and scalability. It employs a variety of methodologies, often categorized into three main types: lexicon-based, machine learning-based, and deep learning-based. Hybrid approaches, which combine elements from two or all three categories, are also common, aiming to harness the strengths of each technique. The choice of algorithm should be tailored to the specific context and requirements of the analysis. Figure 5 depicts sentiment analysis [9].

The general process of a sentiment analysis system encompasses stages such as data collection, text preprocessing, feature extraction, training machine learning or deep learning models, and thorough evaluation to assess the model’s effectiveness in sentiment classification tasks. Figure 6 illustrates the working process of sentiment analysis [10]. First, a text is split into its primary elements, like sentences, entities, tokens, phrases. Then, every topic and words are connected. Finally, a sentiment score is assigned to every and each topic, which has the -1, +4, 0... Sentiment analysis approaches include preprocessing, feature extraction, classification models, and assessment methods. The goal of sentiment analysis is to identify and comprehend the sentiment or emotional tone portrayed in text data [2].

The historical trajectory of sentiment analysis is rooted in early computational linguistics efforts to distinguish between subjective and objective statements. Over time, as computational power grew and linguistic theories advanced, the field evolved from rudimentary lexicon-based approaches to sophisticated machine learning and deep learning paradigms. The advent of machine learning brought about supervised learning algorithms which could learn sentiment patterns from labeled datasets. More recently, deep learning architectures have significantly enhanced the accuracy and nuance of sentiment detection by capturing complex contextual dependencies within text [1].

NLP IN SENTIMENT ANALYSIS

In the digital era, the explosion of unstructured text data has created a critical need for automated interpretation. Natural language processing (NLP), a subfield of artificial intelligence, has emerged as the foundational technology for sentiment analysis, the process of identifying and categorizing the emotional tone expressed in text. NLP models are a branch of artificial intelligence that enables computers to understand, interpret, and generate human language. Sentiment analysis, also known as opinion mining, is a technique used in natural language processing (NLP) to identify and extract sentiments or opinions expressed in text data. It is a process that involves analyzing textual data such as social media posts, product reviews, customer feedback, news articles, or any other form of text to classify the sentiment expressed in the text. Its primary objective is to comprehend the sentiment enclosed within a text, whether positive, negative, or neutral [11]. Figure 7 shows NLP in sentiment analysis [9].

In sentiment analysis, natural language processing (NLP) is essential. NLP uses computational methods to interpret and comprehend human language. It includes several operations, including sentiment analysis, named entity recognition, part-of-speech tagging, and tokenization. NLP methods are employed in sentiment analysis to preprocess text input, extract pertinent features, and create predictive models to categorize sentiments. Using machine learning algorithms, deep learning models, or hybrid strategies to categorize sentiments and offer insights into customer sentiment and preferences is also made possible by NLP.

APPLICATIONS OF NLP SENTIMENT ANALYSIS

The widespread adoption of sentiment analysis across various domains, from customer feedback analysis to social media monitoring and market research, underscores its immense value in deriving actionable insights from vast amounts of textual data. The applications of sentiment analysis are diverse and impactful across numerous sectors. They include understanding customer opinions, analyzing public sentiment, identifying trends, assessing financial news, analyzing feedback, social media, healthcare, marketing, finance, and politics. Common applications of NLP in sentiment analysis include the following [1,2]:

➤ *Healthcare:* Healthcare providers use sentiment analysis to gauge patient satisfaction from feedback forms, online reviews, and social media. This helps in improving healthcare services, identifying areas of concern, and enhancing the

patient experience. Analyzing social media posts and patient forums can help identify adverse drug reactions or public sentiment towards new medications, complementing traditional pharmacovigilance methods.

- *Finance:* Sentiment analysis of financial news, social media, and analyst reports can provide insights into market sentiment, which can be a factor in predicting stock price movements. Investors use sentiment analysis to monitor market mood through news and financial reports, often using these insights to predict stock price movements. Positive sentiment around a company might correlate with an increase in its stock value, while negative sentiment could indicate a potential downturn. By analyzing communication patterns and sentiment in financial transactions or customer interactions, suspicious activities indicative of fraud can be identified.
- *Social Media Monitoring:* As user-generated information on social media, online reviews, and other platforms grows exponentially, it is becoming more and more necessary to automatically assess and comprehend sentiment. Social media platforms are rich sources of sentiment data, but the text generated there is often short, informal, and noisy. It frequently contains abbreviations, misspellings, emojis, slang, and grammatical errors. To track social media sentiment regarding a brand, item, or event, sentiment analysis can be used. Politicians and political parties use sentiment analysis to understand public opinion on policies, candidates, and election issues, allowing them to tailor their messaging and strategies. During major events, sentiment analysis can track public reactions and emotions in real-time, providing valuable insights for organizers and public safety officials.
- *Customer Feedback:* Customer feedback is vital for businesses because it offers clear insights into client experiences, preferences, and pain points. Businesses may improve their products, services, and overall customer experience by analyzing customer feedback better. Businesses use sentiment analysis to gauge customer satisfaction from reviews, surveys, and social media comments. This helps in identifying product strengths and weaknesses, improving customer service, and informing product development. NLP approaches allow computers to read, interpret, and comprehend language, enabling automated customer feedback analysis and accurate sentiment information extraction. Preprocessing methods are essential when working with

customer feedback data to improve the caliber and precision of analysis.

- *Brand Monitoring:* Companies monitor public perception of their brand, products, and campaigns in real-time across social media and news outlets. This allows for quick response to negative sentiment and proactive reputation management.
- *Market Research:* Sentiment analysis helps in understanding market trends, consumer preferences, and competitive landscapes. By analyzing discussions around products and services, businesses can identify emerging opportunities and tailor their marketing strategies.
- *Human Resources:* HR departments utilize sentiment analysis on internal surveys to understand employee morale and identify potential areas of workplace dissatisfaction.
- *Customer Service:* Businesses use NLP to automate customer service processes, including chatbots that can understand and respond to customer queries with empathy based on sentiment analysis.
- *Logistic Regression:* Logistic regression is a basic but valuable machine learning technique used in sentiment analysis, especially for deciding if text expresses positive or negative feelings. It calculates the chance of text falling into a sentiment category and makes predictions based on a set threshold. Figure 9 shows logistic regression in sentiment analysis [12].

BENEFITS

Natural language processing has fundamentally transformed sentiment analysis from a niche academic exercise into a vital tool for the modern world. Companies use sentiment analysis to understand customer satisfaction, identify emerging trends, and inform strategic decisions. Other benefits of NLP in sentiment analysis include the following [1]:

- *Decision-making:* By bridging the gap between human communication and machine understanding, NLP-driven sentiment analysis enables organizations to transform vast quantities of subjective data into actionable insights. Sentiment analysis empowers organizations to glean valuable insights from public opinions and customer feedback, facilitating data-driven decision-making. It shapes social and political discussions, aiding researchers and policymakers in understanding public sentiment on vital issues and ultimately fostering more informed and

responsive decision-making in an increasingly digital and interconnected world.

- *Accuracy:* There are limitations of existing models in accurately interpreting sarcasm and sentiment expressed in informal language, such as social media posts. Traditional accuracy metrics alone are often insufficient, especially in the presence of data imbalance. Precision, recall, and F1-score provide a more comprehensive view of a model's performance, particularly for identifying minority sentiment classes. NLP improves accuracy and consistency. Unlike humans, who may have subjective biases or become fatigued, a well-trained NLP model applies the same criteria across all data points. This consistency is crucial for long-term trend analysis. Several evaluation and improvement strategies can be used to assure the efficacy and accuracy of sentiment analysis models.
- *Scalability:* The primary advantage of NLP in sentiment analysis is its ability to handle unstructured data at scale. Human analysts cannot manually process millions of tweets or reviews in real-time; NLP models can. This scalability allows for real-time monitoring, enabling brands to respond instantly to emerging crises or viral trends.

CHALLENGES

Despite its widespread utility, sentiment analysis faces several significant challenges. Challenges such as sarcasm detection, contextual understanding, multimodal integration, multilingualism, bias, and data quality persist. One of the most formidable challenges is the detection of sarcasm and irony, where words are used to convey a meaning opposite to their literal sense. These challenges stem from the inherent complexities of human language, technical limitations in processing diverse data, and difficulties in objectively evaluating model performance. Other challenges of NLP in sentiment analysis include the following [1,2]:

- *Ethical Concerns:* Addressing biases in training data and ensuring that sentiment analysis models are fair and do not perpetuate harmful stereotypes is crucial. There is a growing emphasis on ethical AI, ensuring that sentiment analysis models are free from bias and respect user privacy. Sentiment analysis ethical considerations cover a number of significant areas, including bias and fairness issues, privacy and data protection, transparency, and accountability. Responsible sentiment analysis implementation is dependent on taking these ethical issues into account. Organizations can increase trust, reduce potential harm, and

sustain ethical standards in sentiment analysis by fostering fairness, preserving privacy, and guaranteeing openness and responsibility.

- *Ambiguity*: It can be challenging for computers to understand human language completely. Human language is inherently ambiguous. Words often carry multiple meanings, and their sentiment can drastically change based on context. A statement might be neutral to one person but carry a subtle positive or negative connotation for another. Subjectivity in labeling training data can also lead to biases in models. Distinguishing between objective statements and subjective opinions is essential for accurate sentiment analysis.
- *Sarcasm and Irony*: One major challenge is the detection of sarcasm and irony, where words are used to convey a meaning opposite to their literal sense. Sarcasm and irony remain notoriously difficult for machines to detect, as the literal meaning of the words often contradicts the intended sentiment. These linguistic phenomena involve expressing a sentiment that is the opposite of what is literally stated, often relying on contextual cues, tone, and shared cultural understanding that are difficult for machines to interpret. Detecting sarcasm and irony remains a formidable challenge, as these expressions often convey a sentiment opposite to their literal meaning.
- *Data Privacy*: Analyzing sensitive customer feedback or personal communications for sentiment raises critical concerns about data privacy and security. Ensuring compliance with regulations like GDPR and handling personally identifiable information responsibly is paramount. Anonymization techniques are crucial, but they must be implemented carefully to avoid losing valuable contextual information.
- *Data Quality*: Training robust sentiment analysis models, especially deep learning ones, requires vast amounts of high-quality, labeled data. Obtaining and accurately labeling such datasets can be time-consuming and expensive.
- *Data Imbalance*: Training datasets for sentiment analysis often suffer from data imbalance, where one sentiment class (e.g., positive reviews) is significantly overrepresented compared to others. This can lead to biased models that are more prone to predicting the majority class, thereby reducing their accuracy and reliability for minority classes. In many real-world scenarios, one sentiment class (e.g., positive) might be far more prevalent than others, leading to imbalanced

datasets that can cause models to be biased towards the majority class. Techniques like oversampling, undersampling, or synthetic data generation are employed to mitigate this, but they introduce their own complexities.

- *Contextual Understanding*: Since sentiment is frequently context-dependent and might alter across various cultures and demographics, it can be challenging to interpret human emotions and subjective language. Understanding sentiment often necessitates a deep grasp of the surrounding context, cultural references, and pragmatic implications that are not explicitly stated in the text. The meaning and sentiment of words can vary significantly based on context. Disambiguating word senses and understanding domain-specific language requires sophisticated models. For example, the word “sick” can mean “ill” (negative) or “excellent” (positive) depending on the surrounding words and situation. NLP models must be sophisticated enough to understand these contextual shifts.
- *Multimodality*: Human communication often involves multiple modalities (text, audio, video, images). Analyzing sentiment expressed across these different channels, known as multimodal sentiment analysis, presents a complex research area. Integrating and interpreting information from diverse sources to form a coherent sentiment understanding is an ongoing challenge.
- *Multilingualism*: As businesses operate globally, the need to analyze multilingual data grows. However, developing robust sentiment analysis models for multiple languages, especially low-resource languages (those with limited available data), is difficult. Multilingualism introduces complexities related to language-specific nuances, cultural expressions of emotion, and the availability of resources like sentiment lexicons and labeled datasets across different languages. While significant progress has been made in English, sentiment analysis in other languages remains a challenge.

FUTURE OF NLP SENTIMENT ANALYSIS

From its humble beginnings with rule-based systems to the current era of sophisticated deep learning and transformer models, sentiment analysis has made remarkable strides. The evolution of sentiment analysis has been marked by a shift from simple rule-based systems to sophisticated deep learning architectures. The future of NLP in sentiment analysis is promising, with several key areas of development. Multimodal sentiment analysis, which integrates textual data with visual (images, videos) and auditory

(speech) cues, is an emerging area promising a more holistic understanding of human emotion. Further advancements in transformer models and large language models (LLMs) will lead to more nuanced and context-aware sentiment detection. The integration of visual, auditory, and textual cues will become more prevalent, offering a more holistic understanding of sentiment. The increasing sophistication of large language models (LLMs) is also expected to play a transformative role, offering more nuanced and context-aware sentiment detection capabilities [1]. In the future, sentiment analysis will become more detailed, allowing us to understand emotions better. It will also expand to include analyzing images and audio along with text, especially in social media and video content.

The landscape of NLP for sentiment analysis is continuously evolving, with recent advancements, particularly in large language models (LLMs). While LLMs and advanced techniques are pushing the boundaries of what's possible, the intrinsic complexities of human language—including ambiguity, sarcasm, negation, and context—continue to demand sophisticated solutions. The future of sentiment analysis lies in context-aware and cross-lingual models. As AI becomes more sophisticated, models are being trained to understand cultural nuances and slang across different languages. There is a growing focus on moving beyond overall sentiment to granular, aspect-level analysis.

CONCLUSION

Sentiment analysis is a method within natural language processing that evaluates and identifies the emotional tone or mood conveyed in textual data. It is important for comprehending and analyzing the emotions portrayed in text data. It has become increasingly important in recent years for nearly all online applications. It stands as a powerful analytical tool, continually evolving to meet the demands of an increasingly data-rich world. From its foundational lexicon-based methods to the cutting-edge deep learning architectures, it has revolutionized how we interpret public opinion and emotional cues from text.

Natural language processing has fundamentally transformed the landscape of sentiment analysis, enabling machines to extract valuable emotional insights from human language. By providing the means to dissect, interpret, and understand the complexities of human language, NLP enables machines to extract valuable emotional insights from vast quantities of text data. NLP-driven sentiment analysis will remain an indispensable tool for understanding public opinion, enhancing business

strategies, and navigating the complexities of human communication.

Sentiment analysis and natural language processing models are improving fast. They have important implications—especially for understanding customer needs. The synergy between NLP and sentiment analysis empowers a more responsive, empathetic, and informed global society. NLP powers sentiment analysis. It has revolutionized sentiment analysis, enabling businesses. NLP sentiment analysis is a technique that identifies emotion expressed in text using models that classify words and phrases as negative, positive, or neutral. It is the process of extracting meaning from text. It goes beyond sentiment and focuses on understanding the underlying concepts, relationships, and context within textual data. More information about the integration of NLP in sentiment analysis can be found in [13-18] and the following related journals:

- *Natural Language Processing Journal*
- *Journal of Emerging Technologies and Innovative Research*
- *International Journal of Future Generation Communication and Networking*

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Figure 1 A representation of NLP [4].

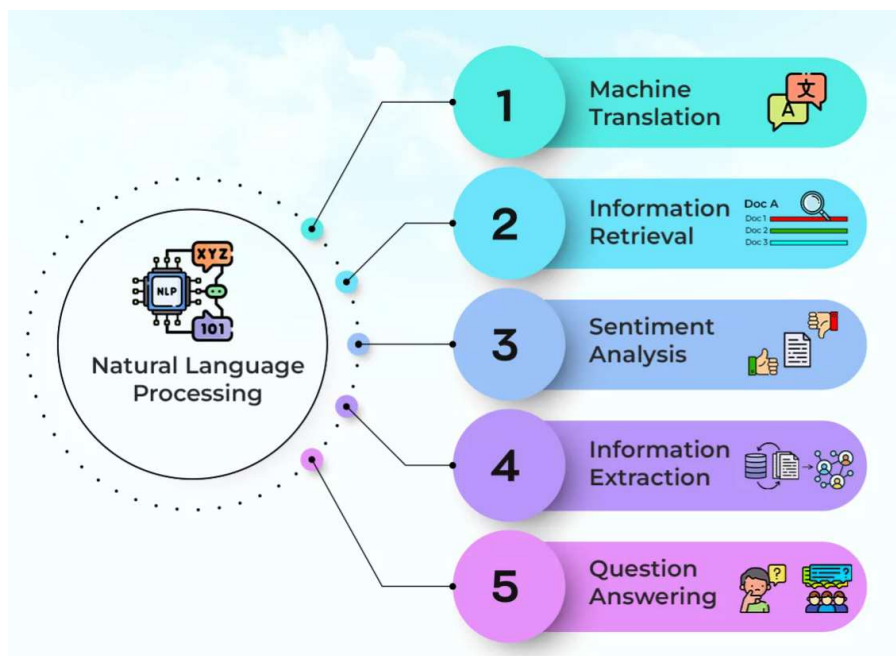


Figure 2 Different components of NLP [5].

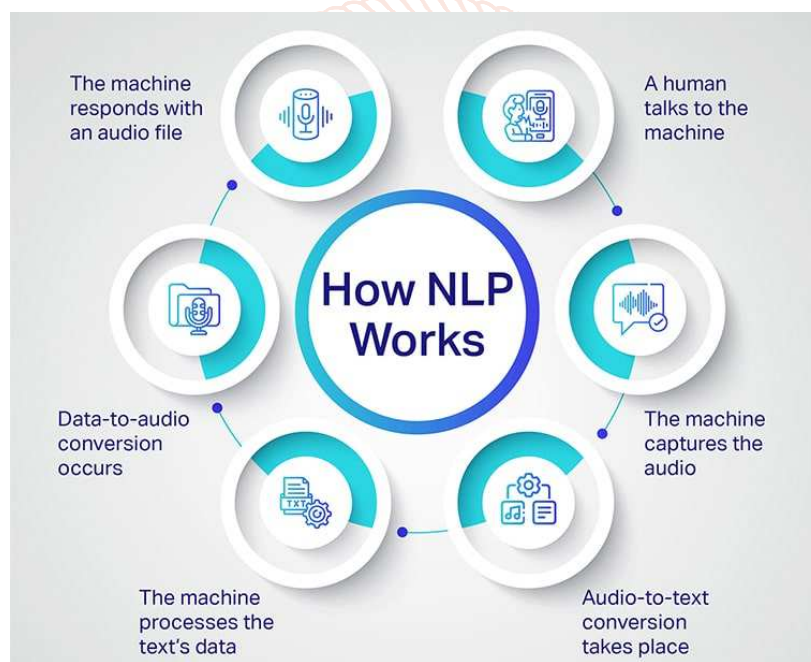


Figure 3 How NLP works [7].

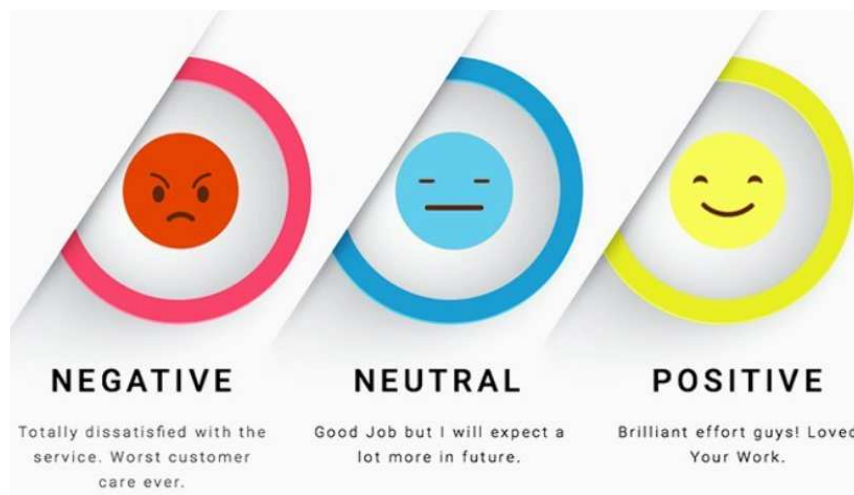
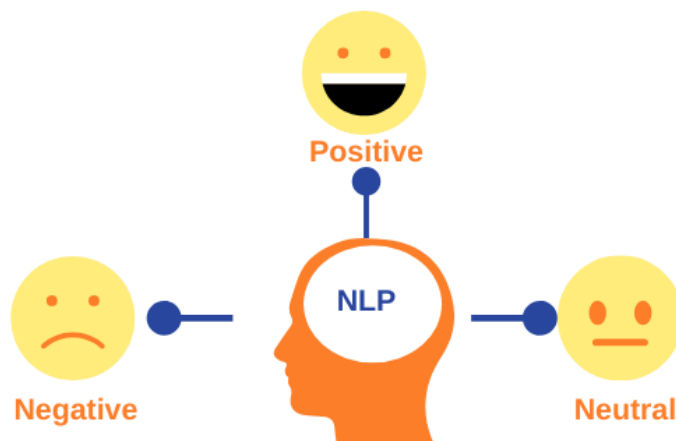


Figure 4 Classifying text into categories [8].



Sentiment Analysis

Figure 5 Sentiment analysis [9].

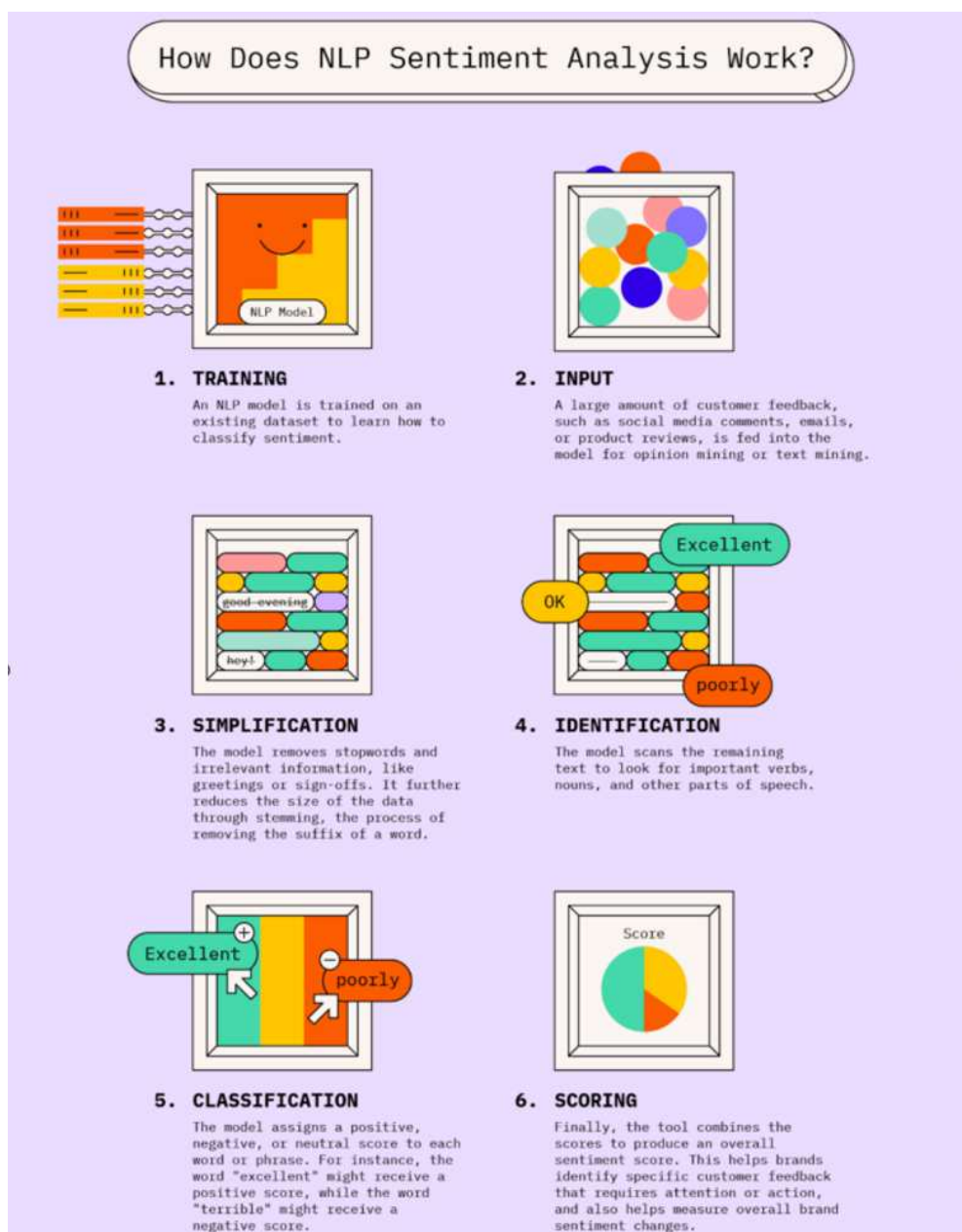


Figure 6 The working process of sentiment analysis [10].

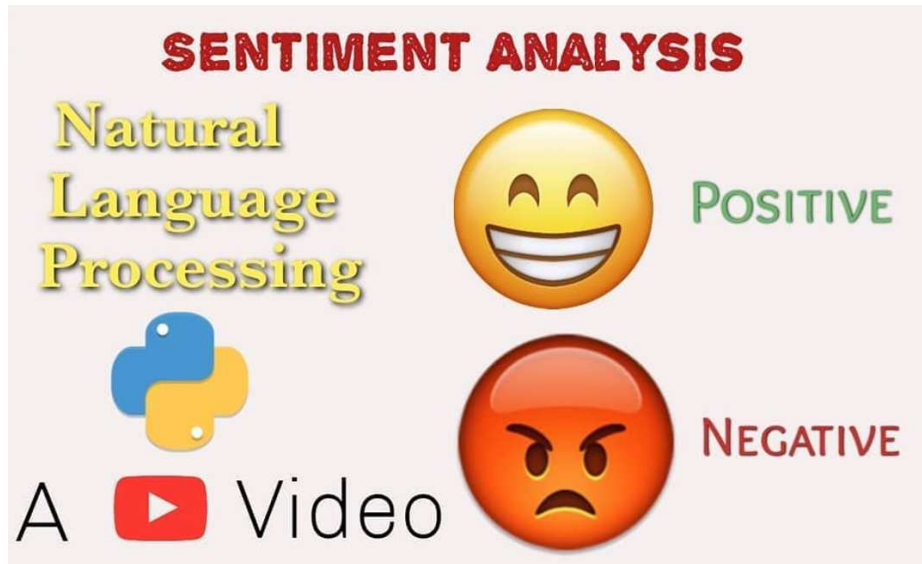


Figure 7 NLP in sentiment analysis [9].



Figure 9 Logistic regression in sentiment analysis [12].