The advances in natural language processing technology and its impact on modern society

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ABSTRACT

A wide range of information, such as books, news, reports, and other content, is constantly being produced, much of which is available online. Machine translation, spam detection, natural language interfaces, and question-answering applications have become increasingly popular. Natural language processing (NLP) is at the core of the automatic retrieval of information stored on computers. This article discusses NLP and its applications in daily activities. It covers the main stages of NLP and provides examples of its advances in various higher-level tasks. The objective is to highlight the significance of NLP in processing online content and in efficient interactions between humans and computers across various applications. As an essential element of artificial intelligence, NLP provides solutions for real-world problems and has the potential to transform the way companies operate.

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1. INTRODUCTION

The internet is an undeniable factor in the everyday life of modern society. This global system provides information resources and services to billions of users, but much of the available information is in text format and is not automatically processed and interpreted. This means that users have to determine the meaning and classification of the information they receive. Techniques of automatic natural language processing (NLP) have been under development since the 1950s, and in recent years, progress in the technology has impacted the effectiveness of NLP applications in many areas, including machine translation, spam recognition, natural language interfaces, and speech recognition.

According to Liddy [1], “NLP is a theoretically motivated range of computational techniques for analyzing and representing naturally occurring texts at one or more levels of linguistic analysis to achieve human-like language processing for a range of tasks or applications.” For the proposed definition, several elements are further detailed:

– "Range of computational techniques" refers to the variety of methods or techniques that can be implemented in different types of linguistic analysis.
– "Naturally occurring texts" refer to the languages used by humans to communicate with each other.
– The "levels of linguistic analysis" refer to the combinations of different levels of linguistic analysis used by various NLP systems.
– "For a range of tasks or applications" means that NLP is intended for performing specific tasks, such as those used in systems for information retrieval, machine translation, and question answering.

There are two main focuses in NLP, natural language understanding (NLU) and natural language generation (NLG). NLU is similar to the role of a reader or listener, and its purpose is to understand and create a meaningful representation of input data in natural language. NLG, also known as text generation, is a software process that produces output data in natural language. NLU and NLG can be seen as participants in a natural communication process.

Advances in NLP technology are due to efforts enabling machines to understand, interpret, and generate human language accurately and effectively. NLP technology aims to lead to more effective interactions between humans and computers in various applications. This includes meeting the challenges of processing different languages and complex language structures, as well as understanding context in both written and spoken forms. Advancements in NLP have improved machine translation, speech recognition, and text generation, impacting language barriers and enabling global communication [2]–[7]. The development of sophisticated chatbots and virtual assistants driven by NLP allows businesses to provide 24/7 customer support, enhancing customer satisfaction [8]–[10]. NLP models like GPT-3 and GPT-4 can generate human-like text, write articles, and summarize documents [11]–[14]. These models can provide tailored feedback, improving educational outcomes and making learning more engaging [15]–[18]. NLP tools can analyze vast amounts of textual data, such as social media posts, reviews, and surveys [19]–[23]. The advantage for businesses is that they can gain deep insights into customer opinions and market trends, and enable data-driven decision-making. As NLP technologies continue to evolve, they hold the potential to further transform interactions between humans and computers.

2. NLP TECHNOLOGY BACKGROUND

NLP is organized into six main stages, ranging from the simplest to the most challenging, as shown in Figure 1. Morphology studies the smallest units of meaning in a language, known as morphemes, and their arrangement within words. The morphological structure of the word may include prefixes, roots, suffixes, circumfixes, and infixes that modify its meaning. In NLP, systems aim to understand the meaning of words by recognizing the meaning of their constituent morphemes. For example, the word "kindness" consists of two parts: "kind" and "ness." Each morpheme has its own meaning: "kind" is a free morpheme because it can stand alone as a word, while "ness" is a bound morpheme. "Ness" is a suffix that creates nouns and indicates a state, condition, or quality [24] that cannot exist on its own.

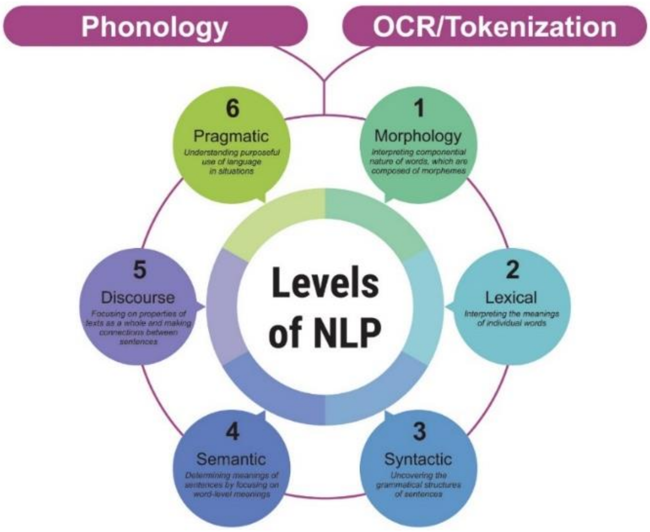

Figure 1. Six levels of NLP [1]

Lexical analysis is the process of determining the meaning of words and phrases in a text. This process helps to detect the relationship between individual words in the sentence and involves breaking the text down into meaningful elements such as words, paragraphs, and sentences. The potential part of the speech of a word is also assigned in the lexical analysis. A word can have different meanings and be a noun or adjective, but it is part of speech and lexical meaning can only be deduced in context with other words in the phrase or sentence. This level may utilize a collection with a highly structured form of language lexemes, called a lexicon. A lexeme is a minimal unit represented in the lexicon that pairs the collection of forms (senses) that a single morpheme can take. Lexical analysis is often involved in the initial stage of many NLP tasks and is followed by syntax analysis and semantic analysis.

Syntactic or syntax analysis, also known as "parsing," is used to analyze the words in a sentence according to formal grammar rules. Grammatical rules are applied to categorize and group words into phrases. It involves identifying the parts of speech (POS), determining the relationships between them (such as subject-verb agreement), and constructing a parse tree to represent the hierarchical structure of the sentence. The diagram in Figure 2 shows a parse tree for the sentence "Henry read the book" using a top-down parsing mechanism.

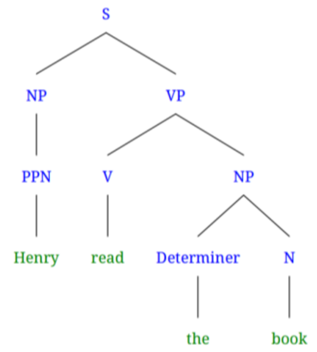

Figure 2. A parse tree for the sentence “Henry read the book”

In top-down parsing, tree constructions are parsed from the top to the bottom, and the input is read from left to right. The root node is generated first, followed by the formation of the leaf nodes. To tag the words with their appropriate POS tags, the following set of grammar rules is used:
- S -> NP VP, where S (sentence), NP (noun phrase), and VP (verb phrase)
- NP -> PPN, where PPN (proper noun)
- VP -> V NP, where VP (verb phrase) and V (verb)
- NP -> Determiner N
- PPN -> Henry
- V -> read
- Determiner -> the
- N -> book

Syntax analysis is a crucial step in ensuring that the structure of a sentence is syntactically correct. Syntax techniques such as stemming and lemmatization are frequently used to understand and interpret the meaning of the text. Both techniques reduce word complexity to simpler forms with less variation [25]. Stemming uses algorithms to match patterns and remove suffixes to reduce an inflected word to its stem. Lemmatization uses a dictionary to reduce the word to its meaningful base form, called a lemma. Constructing the dictionary for the lemmatization algorithm requires a deep understanding of linguistics, unlike stemming. For example, the results for the word "studies" are as follows:
- Stemming: suffix = “-es”, stem = “studi”
- Lemmatization: third person, singular number, present tense of the verb study; lemma=“study”.

The first step in semantic analysis, known as lexical semantics, involves examining dictionary definitions of words. To understand the meaning of words in context, the relationships between individual words are analyzed by examining the grammatical structure of a specific sentence. For example, semantic analysis provides context for understanding the following sentences:
- Henry knows a little Bulgarian, defining Bulgarian as a language.
- Henry knows a small Bulgarian, defining Bulgarian as a nationality.

Semantic analysis involves disambiguating words with multiple meanings. This process selects the single meaning of polysemous words into a semantic representation of the sentence. For example, the sentence "Henry saw the man with the telescope" is grammatically correct but ambiguous because it is unclear whether Henry used a telescope to see the man or whether the man, he saw was holding a telescope. Various methods (*e.g.*, considering the frequency of sense in a given corpus or taking into account the local context) can be utilized for disambiguation [26]. Semantic analysis is a complex process that aims to imitate human understanding of words, phrases, and sentence meanings, posing an ongoing challenge.

In the phase of discourse integration, the meaning of a sentence is determined by the meaning of the sentences that precede it. In turn, the meaning of the current sentence impacts the meaning of the following sentence. An example of processing in this phase is anaphora resolution. Anaphora resolution is the process of identifying the link between a repeated reference (an anaphor, most commonly in the form of a pronoun) and the previous mention of the entity to which it refers. Another example of processing in this phase is the recognition of discourse structure. Discourse structure can predict where specific information will be found in structured documents with formal properties [27] such as introduction, thesis, main idea, conclusion, and references.

Pragmatic analysis is the final level of NLP, focusing on the intentional use of language in real-world situations to extract additional meaning by examining the context. It operates based on a set of rules that outline cooperative dialogues and relies on an understanding of the general principles of human communication to discern the intended effect. For instance, the phrase "Open the window" is interpreted as a request rather than an order when used in a sentence [28].

Phonology is a preliminary step that occurs before morphological analysis. It involves the study of speech sounds in human language and how they are transformed into recognizable morphemes and words. Following this transformation, the six levels of processing mentioned earlier are utilized. The initial levels focus on smaller units of analysis and have been explored in greater detail. Moreover, these units are governed by rules, which are more feasible to implement. This is the main reason why NLP systems tend to mostly implement modules for processing at lower levels. Various NPL tasks can be performed in different sectors, but a set of fundamental tasks recur frequently, and that set is much more in-depth studied and reliably implemented. The following section lists some of the additional research tasks done in NLP.

3. HIGHER-LEVEL TASKS IN NATURAL LANGUAGE PROCESSING

This section outlines the key tasks in NLP, with their objectives and applications that drive its advancements. It also highlights the impact of theoretical advancements on practical improvements in NLP tasks. NLP has a wide range of applications, and researched areas include machine translation, email spam detection, information extraction, summarization, and question answering.

Language modeling seeks to predict sequences of recognized words and phonemes. For this purpose, based on the history of previous words, a probability of the next word is assigned in the sequence. Different types of language models, including statistical, neural networks, and deep learning, are utilized to resolve the ambiguity in longer sentences when processed with realistic grammar [29]. The language models that have been developed find applications in many NLP tasks, such as machine translation, speech recognition, content generation, and question answering. Language modeling plays a critical role in improving the capabilities of chatbots and virtual assistants to understand and generate text similar to a human.

Text categorization assigns predefined categories or indices to documents based on their text content. This process is used in applications such as email spam filters. The challenge of NLP technology in these applications is to extract meaning from text and then classify a message as spam. Several types of spam filters [30]are used for this purpose, including content filters and header filters, which look for counterfeit information in the content or header of an email. Additionally, there are general blacklist filters and rule-based filters, which stop emails from addresses included in the "blacklist" or correspond to criteria defined by the user, such as including a particular word. Permission filters require the sender to be pre-approved by the recipient, while challenge response filters require the sender to enter a code to gain permission to send the email.

Information extraction refers to using computational methods to extract relevant pieces of information from unstructured or semi-structured text documents. Examples of these types of input documents include emails, web pages, news articles, research papers, and social media, among others, and the output consists of the pertinent information from the documents according to specific criteria. Information extraction technologies are used to analyze documents, uncover relevant knowledge, and present it in a structured format [31]. A large amount of information available necessitates the use of automatic and efficient tools for information extraction and retrieval to compensate for human ineffectiveness.

The primary goal of an information retrieval (IR) system is to provide a list of related documents in response to a user query. Traditional search engines use web crawlers to index documents based on a list of keywords they contain. Then, employing ranking algorithms, the indexed documents are sorted in decreasing order. This ranking feature distinguishes IR from other NLP applications. Over the years, various ranking models have been developed, ranging from vector space models introduced in the 70^{th} to later learning-to-rank models and neural ranking models [32]. Despite the successful application of these methods in many different IR applications, search engines still have limitations, as they provide only a list of documents and no clear answer to user queries. Efforts are thus focused on integrating information extraction technologies with information retrieval to overcome these limitations [33].

Conversational agents are dialogue systems designed to imitate human interactions in natural conversation. Some conversational agents use only text as input and output, like a chatbot. Others are more complex and involve speech input and output, such as the virtual assistants Alexa and Siri. Wahde and Virgolin [34] also mentioned the so-called embodied conversational agents, which typically have an animated visual representation like an animated face or body onscreen. However, the major task of all these types of conversational agents is how they perform and manage the dialogue capabilities. The first pattern-based chatbots match the user's input to a set of patterns and then apply rules to formulate a response. More modern pattern-based chatbots use the artificial intelligence markup language, specifically developed to define template-matching rules. Information-retrieval chatbots produce responses by selecting an appropriate sentence from a dialogue corpus, while generative chatbots produce their responses using statistical models. Personal virtual assistants generally provide speech recognition as an advanced feature and combine chatbot functionality with task-oriented capabilities.

Text summarization involves identifying the key information in a document and producing a summary that presents the most relevant information from the original content. There are various classifications for automatic text summarization based on different factors [35], [36]. These include single-document and multi-document summarization based on the number of documents and extractive, abstractive, and hybrid approaches based on summarization methods. Summaries can also be categorized as generic or query-focused summaries, depending on the characteristics of the output summary. The summarizing system can be categorized as monolingual, multilingual, or cross-lingual based on the input and output languages. Additionally, the algorithm used for generating the summaries can be supervised or unsupervised. There are other classifications based on the length, type of output content, and domain of automatic text summarization.

Question answering is a critical task in NLP that enables machines to understand and respond to questions asked by humans in natural language. Similar to other areas in NLP, question-answering has also been impacted by the progress of deep learning methods. Deep learning methods support and improve performance for different tasks in the question-answering process. An overview of question answering in deep learning contexts [37] categorized it into the following three types: rule-based question answering, question answering in the era of deep learning, and visual question answering. An example of the early work on rule-based question answering is mentioned by Green *et al*. [38], where questions related to baseball games were answered using a game database. The baseball system involves syntactic analysis and content analysis to extract the words in the input question. Virtual personal assistants are common examples of question answering in the era of deep learning. Block, a bilinear fusion model based on super-diagonal tensor decomposition [39], is cited as an example for the visual question-answer task. Hao *et al*. [40] also presented a systematic review of the recent development of deep learning methods for question answering. This survey covers the scope, network structure characteristics and their effectiveness, methodological innovations, datasets, and applications.

The field of machine translation involves translating phrases from one natural language to another. Google Translate is one of the most popular applications in this field. Challenges in machine translation include maintaining the meaning of sentence structures and grammar across different languages. Various approaches, each with its own advantages and disadvantages, have been used in machine translation systems. These approaches include rule-based, corpus-based, and transfer-based approaches [41]. The rule-based approach, also known as the classical approach to machine translation, relies on linguistic information about languages obtained from bilingual dictionaries and grammar. Each input sentence is converted to an output sentence based on the morphological, syntactic, and semantic analysis of both languages involved. As a result, a rule-based system requires syntax and semantic analysis as well as generation. Transfer-based machine translation achieves high accuracy and produces adequate translations from an intermediate representation that mimics the meaning of the original sentence. However, a drawback of this approach is that rules must be applied at every translation step. Corpus-based machine translation is an alternative approach that uses a bilingual parallel corpus to acquire translation knowledge. Statistical machine learning aims to find corresponding elements in one language to elements in another language, and the most appropriate translation is the one to which the system assigns the highest probability. Each translation approach has its own advantages and disadvantages, with the pros of one approach often compensating for the cons of another. This has motivated the development of hybrid machine translation, which involves using multiple machine translation approaches within a single system.

Topic modeling is used in various domains to analyze the topical structure of a large collection of documents. It is one of the most popular statistical tools for analyzing bioinformatic, social, and environmental data, as well as similar data from large datasets. Selecting the right methods for extracting meaningful data from datasets is crucial to every data analysis project. Standard topic model approaches are divided into five groups [42]: basic models, models with advanced topic relationships, time-based topic models, short-text optimized topic models, and other significant topic model designs. The classification of methods is flexible and allows for the updating of new methods. Fu *et al*. [43] also discusses methods of topic modeling, along with their features and limitations and the available tools.

Although the tasks may vary, it is important to establish a strong foundation to develop a variety of NLP applications, which covers learning the technologies that can be used. NLP is a critical component of artificial intelligence and provides solutions to real-world problems that have the potential to change the way companies operate. The following section presents the use of NLP applications for various sectors.

4. DISCUSSION

ChatGPT represents a significant advancement in NLP technology for both organizations and individuals. It can be used for customer service, translation, summarization, and content production. This technology has enormous potential and challenges for businesses, societies, and people in general. In the education sector, however, there are well-known difficulties with using generative artificial intelligence due to the lack of established rules and moral standards [44]–[46]. Spennemann [47] presented the opportunities and problems with NLP models like ChatGPT and Google Bard and how they could revolutionize higher education teaching and learning. The article discusses the advantages of using NLP models for personalized learning and on-demand support, such as providing feedback and assistance and offering resources to students. The author also highlights the potential drawbacks of NLP models, such as the potential loss of human interaction and ethical issues. To tackle these issues, universities should guarantee that NLP models are used to enhance, rather than replace, human interaction. For instance, involving students in the creation and implementation of NLP models to meet their specific needs and preferences. Moreover, university staff must be trained to use and adapt new technology and provide students with resources and support to effectively use the models. Institutions should also establish ethical standards for the use of NLP models to safeguard student privacy. Additionally, institutions should evaluate the positive and negative aspects of using NLP models in higher education while ensuring responsible use to enhance student learning.

Nowadays, ChatGPT is widely used for tasks such as language translation, question answering, summarization, and content creation. Its ability to generate contextually suitable responses makes it possible to assist with activities like maintaining service quality by answering common inquiries. ChatGPT can also aid in data analysis and research by generating reports and summaries from huge databases. Biswas [48] explored the potential use of ChatGPT for global warming. The author acknowledges asking ChatGPT questions about its use in climate change research. While some of the mentioned uses are currently possible, others hold potential for the future. Various climate scenarios based on a diverse set of data inputs are utilized to improve the accuracy of the climate projections. The development of ChatGPT is a watershed moment in the history of NLP and artificial intelligence. Its ongoing development is anticipated to have a significant impact on conversational artificial intelligence, with effects that will undoubtedly extend across all sectors of society.

Analyzing customer reviews using NLP can provide valuable insight into customer's opinions about a brand and its products or services. By employing sentiment analysis and text classification, companies can gain an understanding of overall positive or negative sentiment about the brand and identify what customers appreciate or dislike about their offerings. Furthermore, machine learning and NLP techniques are used to detect and recognize emotions in customer reviews. Evaluation of product reviews can be utilized to predict pricing trends, assess campaigns, and shape an e-commerce marketing strategy [49]–[51].

NLP is also used to process and analyze customer service surveys to better understand the challenges that consumers are experiencing. This information is critical for enhancing customer satisfaction, which will increase customer retention and promote positive word-of-mouth. A systematic review has outlined the application of artificial intelligence and NLP in customer service from 2015 to 2022 [52]. The review utilized five scientific databases to analyze and refine all relevant papers. According to the authors, chatbots and question-answering systems are used in ten main areas, mostly in general, social media, and e-commerce. Other main areas are healthcare, telecommunications, booking, the construction industry, banking, energy utilities, and marketing. In all of these areas, customers expect an immediate response to a question, leading to the popularity of NLP-powered chatbots and digital assistants such as Google Assistant, Alexa, and Siri. These apps enable customers to conduct online searches or make phone calls using their voices and receive the relevant information [53]. According to market data presented on the Yaguara platform [54], over the past few years, more than 50% of the worldwide population uses the voice search daily and Google Assistant is the most popular digital assistant, used by 36% of users. Data for voice searches show that Google Assistant accurately understands queries 100% of the time and provides correct answers almost 93% of the time. On the other hand, Siri and Alexa understand the query accurately 99.8% of the time but successfully deliver an accurate answer around 80% of the time.

In recruitment, job seekers can apply by simply uploading or sending their resumes. However, it is challenging to find reliable candidates due to the different styles used in the resumes. A proposed smart recruitment system includes resume classification to address this issue [55]. This system measures applicants' technical proficiency through automatic questionaries and analyzes their resumes for syntactical and semantic similarities based on the company's requirements. NLP and named entity recognition are used to extract meaningful data related to a candidate's work experience and education. Deep learning is used for the NLP technique to sort and rank the resumes. Additionally, a previous article discussed how recruitment technique research and computer science intersect, presenting an approach that also utilized deep learning and NLP for sorting resumes [56]. This approach differs from the former by incorporating a knowledge base of merged ontology and employing syntactical and semantic similarity measurements for matching the submitted answers of the applicants regarding their skill set. NLP is evolving, and some of the tendencies in NLP applications include further development of large language models, models that can handle multiple languages, and real-time NLP applications; the expanded use of sentiment analysis and opinion mining; enhancing accessibility for individuals with disabilities, such as through text-to-speech and speech-to-text; combining NLP with robotics; and machine learning to create more comprehensive solutions.

5. CONCLUSION

The vast amount of natural language text in the digital world contains a wealth of knowledge, but it is becoming increasingly challenging for a human to identify and extract this knowledge, especially within time constraints. Through NLP, this textual knowledge is transformed into algorithms to solve specific problems. The idea that data holds valuable insights for businesses has gained widespread acceptance, leading businesses to invest in various business intelligence solutions to enhance their operations. Research demonstrates that the objective of automated NLP is to handle this task as efficiently and accurately as a human. As NLP technologies continue to evolve, they hold the potential to further transform interactions between humans and computers.

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