Exploring the evolution and applications of natural language processing in education

Ghania KHENSOUS, Kaouter LABED, Zohra LABED

Ecole Normale Supérieure d'Oran (ENS d'Oran) - AMMOUR Ahmed

gkhensous@gmail.com, klabed@gmail.com, zohralabed28@gmail.com

Abstract: Natural Language Processing (NLP) is a branch of computer science, artificial intelligence, information engineering, and linguistics that focuses on enabling machines to understand, interpret, and generate human language. Machine translation, sentiment analysis, speech recognition, and question-answering systems are just a few examples of NLP applications. NLP has advanced rapidly in recent years, owing to the availability of large amounts of text data and the development of deep learning models, which has resulted in increased accuracy and efficiency in NLP tasks. This paper tackles the state of the art of NLP, its methodology and techniques, and its applications in different fields. The paper also discusses the role of NLP to improve education.

Keywords: NLP, Education, AI, Deep Learning.

1. Introduction

Language is a way to share thoughts, ideas and information along with feelings, mistakes and ambiguity. It is hard to imagine a language as a set of mathematical rules that work together to make a sentence. So, it makes it harder to come up with a set of logical rules that can be used to make the machine understand the language and give the same results.

Natural Language Processing (NLP) is the ability of machine code to understand human language the way it is spoken (Khyani & B S, 2021). It assists computers in comprehending, manipulating, and interpreting human language.

NLP is essential when an intelligent system, such as a robot, is required to follow our commands. It enables computers to connect with humans in their language while also doing other language-related activities. It assists the computer in reading a prepared text, hearing and understanding a discussion as well as deducing emotions. Because human language is so complex and varied, people tend to express themselves in a variety of ways, both verbally and in writing. NLP lies in resolving linguistic ambiguity. It is used in many areas such as business, sport, health, marketing and education. It is also used to translate languages, give voice responses, or analyze sentiments. NLP is widely used in IoT (Internet of Things) devices and voice assistants.

On the other hand, NLP has benefitted from recent developments in AI (Artificial Intelligence) and digging into some of its approaches. Machine Learning (ML) and Deep Learning (DL) in particular have opened the door for research in the field of NLP.

Generally speaking, there can be distinguished two essential aspects to NLP problems; The "linguistic" part, which consists of pre-processing and transforming the input information into a usable dataset, and the “Machine Learning” or “Data Science” part, which relates to the application of ML or DL models to this dataset.

Besides, NLP is divided into two components (Khyani & B S, 2021): NLU (for Natural Language Understanding) and NLG (acronym of Natural Language Generation). For a better understanding of the text, NLU helps the machine understand and analyze human language by extracting the text from a lot of data like keywords, emotions, relationships, semantics, etc. This is done by mapping the natural language input into useful representations that can be used to improve language analysis. However, NLG is the process of constructing meaningful words, sentences, and paragraphs from an internal representation.

https://doi.org/10.33436/v33i2y202305

After many years of research and development, many methods and tools have been proposed to perform NLP applications. They have been tested with different kinds of data, such as long scientific articles, abstracts and web pages. But no method stands out as the best or most common, and it is hard for newcomers to choose which method works best for their problem, data and application. A comprehensive analysis of these works is needed to show not only the problems and the difficulty of the tasks, but also the different ways of doing things that have been suggested over time, as well as their underlying logic, strengths and weaknesses. Therefore, in this article, the principles of NLP and explore how NLP has attracted many researchers, especially in the education field are discussed.

The paper is organized as follows; In the first part, it is given a brief state-of-the-art that provides an overview of the evolution of NLP. In section two, the methodology of NLP is discussed. The most used NLP techniques are listed in the third section. The fourth section deals with the NLP applications. In the final section, educational NLP applications are discussed.

2. State-of-the-Art

During World War II, the Germans utilized the Enigma machine, which incorporated NLP to encrypt secret messages and communicate with military units while maintaining discretion (Johri et al., 2021). Machine Translation (MT) is also an early application of NLP, aiming to create automatic programs for text or speech translation between natural languages. In 1954, George Town University and IBM Company developed the first automatic translation program. However, the true evolution of NLP occurred in 1957 when Noam Chomsky introduced syntactic structures (Johri et al., 2021). His goal was to create a machine that could mimic human thought and communication skills, particularly in terms of grammar and syntax (Khyani & B S, 2021). Chomsky aimed to improve the set of rules to create strong, universal grammar-based linguistics.

Numerous chatbot prototype systems, such as Elisa, developed by Weizenbaum in 1966 and SHRDLU, developed by Winograd in 1970, were created to illustrate the efficacy of specific principles (Johri et al., 2021; Khyani & B S, 2021). However, in 1966, NLP almost died due to the slow pace of research in the field (Johri et al., 2021; Khyani & B S, 2021). In 1969, Roger Schank introduced the concept of tokens, which aid in understanding the meaning of a sentence (Johri et al., 2021).

In the 1970s, there was a need for AI, and NLP got a new start. In 1978, W.A. Woods created LUNAR, an interface system to a database containing information about lunar rock samples, using Augmented Transition Network (ATN) and procedural semantics (Johri et al., 2021; Khyani & B S, 2021; Jiang & Lu, 2020). In 2011, Apple provided a significant advancement with the creation of SIRI (Khyani & B S, 2021). Currently, researchers in NLP are focusing on DL and working on the next generation of NLP systems that can handle general text and account for language's variabilities and ambiguities.

3. NLP Methodology

A machine cannot grasp human language. It can only communicate in binary (0s and 1s). Many processing tasks need to be done so that a machine or a computer can understand human language (Nagarhalli et al., 2021). Morphological analysis, syntactic analysis, semantic analysis, discourse analysis and pragmatic analysis are the names given to the five steps of the NLP methodology. These steps are depicted in Figure 1.

3.1. Morphological analysis

For a machine, the words and sentences that it receives are a bunch of characters. The lowest level of text analysis is morphological analysis.

At this level, an NLP technique analyzes the smallest components of words that contain meaning, which are made up of morphemes, such as prefixes, roots, and suffixes (Zhao et al., 2022). So, in NLP, the initial step is to recognize the words and sentences. This is known as tokenization.

3.2. Syntactic analysis

After identifying the words and phrases and removing the affixes, the next stage in NLP is to determine if the given sentences satisfy the rules of a language. Certain rules apply to all human languages. In the English language, for instance, there are four essential rules (Nagarhalli et al., 2021):

1. A full sentence has a subject and a verb and expresses an entire notion.
2. Separate thoughts usually necessitate separate sentences.
3. The English word order is Subject-Verb-Object. For example: Ram(S) eats(V) apples(O).
4. A dependent clause is made up of a subject and a verb.

There are many more rules like these in the language that sentences must obey to qualify and pass the syntactic analysis stage. This checking and analyzing the sentence's syntax is very important to obtain the "correct" meaning of the supplied sentence.

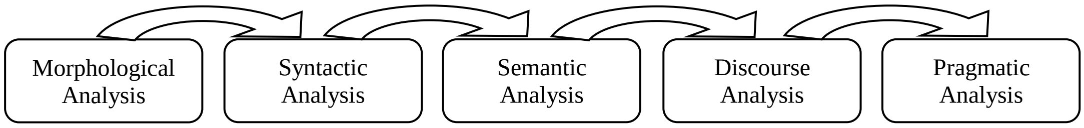

Figure 1. Stages of NLP

In general, language rules are carefully stated, and these rules are not updated. As a result, there are well-established rule-based parsers that can parse a text and check its syntax. Then, learning techniques have made no significant contributions to syntactic analysis (Nagarhalli et al., 2021).

3.3. Semantic analysis

At this level, an NLP technique may focus on the meanings of individual words such as dictionary definitions and word-sense disambiguation, or on the compositional semantics, which examines the interconnections between word-level meanings in sentences such as semantic role labeling. Thus, semantic analysis can be divided into two categories (Zhao et al., 2022): word-level semantics and sentence-level semantics. Semantic role labelling and case grammar are examples of techniques of semantic analysis.

A language is ambiguous by definition and there will be many terms in any language that have different meanings. Generally, the context tells us what these words mean. Thus, word sense disambiguation has been treated as a classification problem, and ML, as well as DL approaches, have been used to resolve ambiguity in word meanings. Many research articles have been written in an attempt to address this issue in several languages (Nagarhalli, et al., 2021).

3.4. Discourse analysis

In some cases, sentences may begin with pronouns or may refer to a subject or object that is not present in the current sentence. While performing discourse analysis, the system must deal with some more difficult examples and cases. For instance, take a look at the following two sentences: “Ram went to Shyam’s shop to check out new Cricket bats. He looked at it for hours.”. Even if the first sentence is taken into account, the terms "he" and "it" in the second sentence of the example can refer to many entities. "He" might be either "Ram" or "Shyam," and "it" could be either the "store" or the "Cricket Bat."(Nagarhalli et al., 2021). In such instances, analyzing the language and determining its true meaning becomes challenging. Knowing merely the prior sentences is then insufficient; some form of methodology is required to handle such reference problems.

The process of resolving these kinds of problems in discourse analysis is known as "Reference Resolution" which is a very active topic of research by itself. At this level, an NLP technique focuses on the properties of the text as a whole that transmit meaning by connecting sentence components. Several types of discourse processing can then occur, the most prevalent of which are anaphora resolution and coreference resolution (Zhao et al., 2022).

3.5. Pragmatic analysis

Finally, there are many instances where the written meaning and the real intended meaning are diametrically opposed. In such instances, the semantic analysis of the phrase's meaning is insufficient. Thus, pragmatic analysis is used to determine the intended meaning of a particular sentence (Nagarhalli et al., 2021).

For instance, consider the following sentence: "The soldier fought like a lion". Literally, the meaning makes no sense at all. The soldier fought very fiercely, which is the intended meaning of the sentence. The provided example demonstrates the importance of conducting pragmatic analysis.

So, the highest level of NLP is pragmatic analysis. To attain this level, NLP techniques must be able to understand language as well as a human would, which is the ultimate aim of NLU (Zhao et al., 2022). The pragmatic analysis looks to be the most difficult NLP curve to master.

In the field of NLP, pragmatic analysis in general and automatic sarcasm detection, in particular, are two of the most researched topics (Nagarhalli et al., 2021).

4. Natural Language Processing techniques (NLP)

NLP utilizes a variety of techniques to extract valuable information from text data. Sentiment Analysis, Named Entity Recognition, Topic Modeling and Keyword Extraction are among the techniques used by NLP to extract data from text.

4.1 Sentiment analysis

The Sentiment Analysis (SA) field also termed "Opinion Mining" analyses user sentiments and links them to the provided information. It is used to figure out how people responded to business-related posts on social media. It is accomplished by the substitution of some figures to the text format as positive, negative, or neither, maintaining it neutral, to identify the emotion underlying the quoted words (happy, sad, angry, annoyed, disgusted, irritated, etc.) (Khyani & B S, 2021).

Using objective measures such as social media likes, the number of consumers and sales, companies such as Google, YouTube, and Amazon can tailor their content to the best interests of their customers. This is a difficult challenge because of the use of (Siddeeq, 2021): a) multiple languages on the same topic or site, b) non-standard vocabulary that cannot be found in a dictionary, and c) emojis and symbols.

To process data, SA involves the five following steps (Aqlan et al., 2019): data collection, text preparation, sentiment detection, sentiment classification, and output presentation (Figure 2).

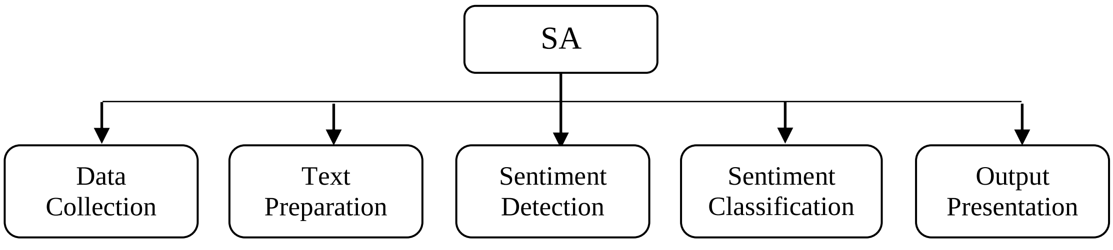

Figure 2. Sentiment analysis process steps

4.2. Named Entity Recognition (NER)

A named entity is a term or phrase that distinguishes one item from a group of other items having similar attributes. Names of organizations, persons and locations are examples of named entities in the general domain. Named entities in the biomedical area include the names of genes, proteins, medicines and diseases. The technique of locating and classifying named entities in text into predetermined entity categories is known as Named Entity Recognition (NER) (Li et al., 2020).

Generally speaking, a named entity is anything that can be identified by a proper name, such as a person, a place, or an organization. The task of NER is to determine text spans that constitute proper names and tag the entity type. The most typical entity tags are PER (person), LOC (location), ORG (organization), and GPE (Geo-Political Entity). However, the definition of a named entity is frequently expanded to encompass objects that are not entities per se, such as dates, times, and other temporal expressions and even numerical expressions such as prices (Jurafsky & Martin, 2020).

4.3. Topic Modeling (TM)

Analysis of documents using Topic Modeling (TM) reveals relevant word patterns. Topic models are statistical tools for determining the underlying semantic structure in a set of documents. TM methods can use either structured or unstructured data (Albalawi et al., 2020).

TM can be viewed as a strategy for presenting the vast amount of data generated by advances in computer and web technologies in a reduced dimension and revealing the hidden concepts. Depending on the application context, prominent characteristics or latent variables of data should be detected efficiently. Initially, dimension reduction was seen via an algebraic perspective, as reducing the original matrix into a factor matrix (Kherwa & Bansal, 2018).

4.4. Tokenization

Tokenization (Albalawi et al., 2020) is the method of breaking up a text's sequence of characters by determining the word boundaries, or the points where one word ends and another start.

The words thus recognized are commonly referred to as tokens in computational linguistics. When there are no distinct borders between words in the writing system, tokenization is also known as "word segmentation", and this term is often used synonymously with tokenization.

In their study (Toraman et al., 2022), the authors analyze five tokenization methods including: Character-level, Byte Pair Encoding (BPE), Word-Piece, Morphological-level as well as Word-level.

4.5. Keyword extraction

Keywords, which are key phrases inside documents, play a vital role in various NLP applications. A keyword set for textual information consists of many words that can express the meaning of the text. Keywords can assist users in swiftly understanding text subjects. Furthermore, keyword extraction serves as the foundation for applications like summarization, text categorization, and clustering (Firoozeh et al., 2020; Xu & Zhang, 2021). With the increase in the number of documents available, recognizing the subject of the documents without thoroughly examining them is vital, as is having an Automatic Keyword Extraction (AKE).

Keyword extraction (Firoozeh et al., 2020) is the process of identifying the lexical units that best reflect the document. However, due to the complexities of natural language, heterogeneity in the type of input documents, and the type of keywords that must be retrieved, automatically extracting keywords is difficult. Numerous approaches and instruments have been designed, however, no dominant or standard strategy emerges, making it difficult for beginners to select the approach that best matches their problem, input data and application.

4.6. Summarization

Before proceeding with the text summarization, it is necessary first to define a summary. A summary is defined as a text that is made from one or more texts, contains a significant portion of the information from the original texts and is no more than half the length of the original texts (Lioret, 2021).

Text summarizing is the process of distilling the most significant information from a source (or sources) to produce an abridged version for a specific user (or users) and task (or tasks). So, the goal of summarizing a text is to give a shorter version of the source text that still makes sense. When this is done automatically by a computer, it is called Automatic Text Summarization (ATS). Even though text summarizing has generally been centred on text input, multimedia content such as (Lioret, 2021): images, videos, or audio, as well as online information or hypertext, can also be the input to the summary process. Moreover, one or more documents can be summarized. In the latter case, the process is called Multi-Document Summarization (MDS), and the source documents in this case can be in the same language (monolingual) or different languages (translingual or multilingual).

The task of summarization can be categorized into three methods (Abdel-Salam and Rafea, 2022; Yadav et al., 2022): Extractive, Abstractive and Hybrid (cf. Table 1).

Table 1. ATS methods

Extractive ATS	chooses the relevant sentences from the original source to form a summary
Abstractive ATS	interprets the original document and generates the summary in its own words
Hybrid ATS	combines both extractive and abstractive methods.

4.7. Lemmatization and stemming

The fundamental function of both methods – stemming and lemmatizing – is the same (Jivani, 2011). They both reduce a word variation to its 'stem' in stemming and ‘lemma’ in lemmatizing. The difference between the two reductions is very small; In stemming, the "stem" is found by following a set of rules, without taking into account the word's Part Of Speech (POS) or the context of the word's occurrence. Lemmatizing, on the other hand, is about getting the "lemma" of a word. This means reducing the word forms to their root forms after understanding the POS and context of the word in the provided sentence.

Therefore, Stemmers are often easier to implement and run faster, and the lower accuracy may be irrelevant in some applications. Because they are associated with the semantics and POS of a sentence, lemmatizers are difficult to implement.

5. NLP applications

NLP has emerged as a transformative field with a wide range of applications across various domains. Among many NLP applications, some of them are: Clinical Decision Making, Spam Filtering, Text Analysing and Customer Services.

5.1. Clinical decision-making

NLP is a crucial field that helps make electronic health records a useful source of data to meet needs and help researchers and clinicians do their main jobs while reducing the amount of data and charts they have to look at (Johri et al., 2021). NLP can be used to extract and process both structured and unstructured clinical data or information. NLP could also be used to classify patients and assist with key healthcare tasks such as clinical decision-making and providing quality reports.

Using NLP techniques, a clinical decision-making system can be made based on a patient's behaviour toward a product, or treatment. As an example, aspect-based sentiment analysis can be used to back up personalized therapy from an analytical point of view in decision-making.

5.2. Spam Filtering System

Spam filtering is another area where NLP has made a difference. The volume of data generated has expanded in tandem with the increased availability of the Internet. However, many organizations are abusing technology by misleading individuals (Johri et al., 2021). The spam filtering system will assist in filtering out spam data. It can be made using NLP functionality taking into account the most commonly encountered false-positive and false-negative concerns (Khyani & B S, 2021).

Spam filtering in email programs is very popular. Using a tool called TubeSpam (Alberto et al., 2015), YouTube also uses spam filtering to remove spam data in the comments section of videos.

5.3. Question Answering (QA)

The QA goal is to make systems that can automatically find answers to questions that people often ask in their language. This can be accomplished by studying the syntax and semantics of the question (Khyani & B S, 2021).

Generally speaking, QA Systems automatically interpret the user's question and retrieve the correct information to provide in response. Most QA models today work by matching a context with the question and then identifying the start and end points of the actual answer within that context.

5.4. Customer Service

NLP helps to understand the tastes, preferences and ways of thinking of the audience. Taking a recorded call from a customer as an example, shows how that person is feeling at the time of the call. This can assist in meeting their future expectations and understanding their current viewpoints, resulting in beneficial feedback (Khyani & B S, 2021).

5.5. Text Analysis

NLP can be used to examine massive amounts of textual data to speed up and improve the process (Johri et al., 2021). A vast quantity of information is stored in the form of text, and manually going through this text to find a solution takes time. This was done manually before NLP, but the entire process is revolutionized once deep learning-based NLP emerges.

6. Educational NLP applications

In addition to being frequently used to give students formative feedback, NLP can be used to give teachers information about task difficulty, student individual differences and student performance (Allen et al., 2022).

Table 2 summarizes the three roles of language processing for educational applications given by (Litman, 2016) :

Table 2. NLP roles in education

Teaching about Language	Language assessment is one of the more traditional but still very active NLP applications in education.
Teaching using Language	Language can be used as a teaching method as well as a domain of analysis (as was the case in the previous section).
Processing Language	Processing text and speech can help students, teachers, researchers, as well as system developers.

In education, NLP is used in many applications including: Recommender Systems, SA and ChatBots.

6.1. Recommender Systems (RS)

Recommender Systems (RS) are widely used in the field of e-commerce. This is not the case in educational field; Indeed, for education, there are many promising digital education resource platforms (Cui et al., 2018) such as Massive Open Online Courses (MOOC) platforms, teaching assistance systems and learning systems. However, most educational teaching systems or platforms do not have a high level of application of recommended techniques, their effects do not sound effective as well. At present, the major problem lies within the immaturity and lack of research on recommendation algorithms and the entirety of the RS, as well as the lack of optimizations on it.

Generally speaking, RSs should be widely applied in e-learning tasks such as recommending resources such as papers and books to the learners (Shen, 2020); predicting their performance (Thai-Nghe et al., 2010); assessing and identifying students' deficiencies, and detecting areas where they need reinforcement. For instance, identifying students with learning insufficiencies, through assessments. The idea is to identify students with poor academic performance to find areas and indicators of achievement where students need to strengthen their knowledge (Rivera et al., 2018).

According to some studies, the primary purpose of RS is to give students guidance regarding their educational choices. This entails recommending to students a place to study, which could be a faculty, university or college as well as supporting choices of specific academic courses or disciplines (Rivera et al., 2018). RS is also applied for e-learning courses, i.e., RS is used as an embedded software to suggest online courses from various vendors. Academic choices extend beyond advising personalized courses and include recommending personalized curriculums. Other studies focus on other aspects of education, such as recommending qualified students for available scholarships.

The selection of a recommendation approach is the most important part of a recommender system because it determines the effect of the recommendations. Major RS approaches include: knowledge-based recommendation (Yang et al., 2022), content-based recommendation (Seth & Sharaff, 2022), collaborative filtering recommendation (Zhang et al., 2021) and hybrid recommendation (Ricci et al., 2022).

6.2. Educational ChatBots

Chatbots are computer programs that simulate conversations with human users through text or voice communication on the Internet (Adamopoulou and Moussiades, 2020). They are also known as interactive agents, smart bots, digital assistants, or artificial conversation entities. Utilizing NLP, chatbots can understand multiple human languages and are commonly used in customer care and support. Their goal is to quickly and automatically respond to typical questions and problems (Caldarini et al., 2022).

There are different types of chatbots such as : rule-based chatbots and AI-powered chatbots (Adamopoulou & Moussiades, 2020). Many big companies have already created their own chatbots or virtual assistants like Microsoft's Cortana, Apple's Siri, Amazon Alexa, Google Assistant, and Facebook's M. These chatbots are used in various applications including customer service and support and virtual assistance.

Chatbots have many advantages, like enhancing the efficiency and convenience of customer service and the ability to quickly respond to common questions and handle a high volume of requests. However, they also have limitations such as difficulty in understanding more complex or context-specific inquiries and may require human assistance in certain situations. Therefore, it is important to take both the advantages and limitations of chatbots into account when using them effectively in a specific context (Adamopoulou & Moussiades, 2020; Caldarini et al., 2022).

Nowadays, chatbots are widely used in the education sector in a variety of ways to enhance the learning experience and support students, teachers and administrators (Maroengsit et al., 2019). Using chatbots in education does not mean that instructors are being replaced; rather, it means assisting them in reducing their efforts in monotonous and low-level cognitive activities in order to boost their productivity and efficiency (Okonkwo & Ade-Ibijola, 2021). Chatbots can be used either as a tutoring assistants for students or as virtual assistants for teachers and administrators. A chatbot tutor can provide personalized instructions and feedback to students in real time, helping them to stay on track and address any questions or issues they may have. This can be especially useful for students who are working independently or at their own pace (Mendoza et al., 2020).

Another way chatbots can be used in education is as a way to provide quick and easy access to information. For example, a chatbot could be programmed to answer frequently asked questions about a school's policies or procedures, allowing students and parents to quickly find the information they need without having to navigate through the website (Cunningham-Nelson et al., 2019). Chatbots can also perform short quizzes, activity recommendations, and inform students about activities (Kuhail et al., 2022).

Concerning teachers and administrators, Chatbots can be used for helping them to schedule appointments, manage their calendars and access important information quickly (Mendoza et al., 2022). In addition, chatbots can help teachers in building dialogue-based collaborative activities and assessing a student’s learning abilities. In general, chatbots help teachers to manage their teaching practices (Okonkwo & Ade-Ibijola, 2021).

Nowadays, there are numerous chatbot applications in education, such as the use of chatbots in training medical students, promoting listening comprehension and in foreign language education (Jung, 2019). Several English learning chatbots are: Duolingo, Mondly, Andy English Bot and Memrise (Jung, 2019). In addition, many software frameworks provide a predefined set of functions that help programmers to build chatbots such as QnA Maker, Dialogflow, Rasa NLU & Core, Wit.ai & IBM Watson (Zahour et al., 2020). This later was used at the University of Georgia to create an educational chatbot called “Jill Watson”. His principal function was to process messages on the forum of students studying computer science.

6.3. Educational sentiment analysis

MOOCs have exploded in popularity; course reviews are important sources for investigating learners' perceptions of various elements related to course design and implementation. The purpose of the study (Chen et al., 2022) was to look into the possibility of automatic classification for the semantic content of MOOC course reviews in order to better understand the factors that can predict learner satisfaction and their perceptions of these factors. "Platforms and tools," "Course quality," "Learning resources," "Instructor," "Relationship," "Process" as well as "Assessment" are among these factors. Using lexicon-driven methodologies, each factor is assigned a sentimental value, and the topics that have the greatest influence on learners' learning experiences are chosen. This study’s findings can help MOOC instructors to provide more satisfying learning experiences for learners.

Because there may be thousands of students enrolled in courses that occasionally last only a few weeks, many course designers trying to evaluate the experience of participants in a MOOC will find it challenging to track and analyze the online behaviours and interactions of students. The purpose of the research (Lundqvist et al., 2020) is to investigate the use of automated SA in assessing student experience in a beginner computer programming MOOC. A dataset of over 25000 online posts made by course participants was analyzed and compared to student feedback. The results were further analyzed by categorizing participants into three categories including: beginner, experienced and unknown. The feedback statements were reflected in this study by the average sentiment expressed through online posts. Beginners, the MOOC's target audience, were more positive about the course than experienced participants, owing to the extra assistance they received. Many experienced participants expected to learn about topics outside the scope of the MOOC. According to the findings, MOOC designers should think about using SA to evaluate student feedback.

Dropping out of school is the result of a long-term disengagement process with social and economic ramifications. Predicting students' behaviour earlier can help to reduce failures and disengagement. The SASys (Sentiment Analyzes System) architecture is presented by (Bóbó et al., 2022) which is based on a lexical approach and a polarized frame network. Its primary goal is to define the author's sentiment in texts and increase the accuracy of detecting the emotional state of a sentence by including the author information and preferences. The extraction of phrases from virtual learning environments is followed by pre-processing techniques in the text, which is then submitted to the complex frame network to identify words with polarity and the author's text sentiment. The flow concludes with the author's emotional state being identified. A case study was used to evaluate the proposal, which applied the SA approach to the student school dropout problem. The findings indicate that the proposal for asserting the student's emotional state and detecting student dropout risks is feasible.

7. Conclusion

NLP is a research field focusing on enabling communication between human and machine languages. Any program that uses text is a candidate for NLP. It aids comprehension of the text by allowing robots to distinguish how a certain individual speaks in several languages. This human-like computer communication offers real-world applications such as ATS, Emotion Analysis, MT and many others. NLP does not fall under a discipline; instead, it is a subset of multiple disciplines including computer science, information engineering, artificial intelligence as well as linguistics.

This study is an attempt to present fundamental knowledge about NLP to assist new researchers in learning about NLP difficulties and solutions. This survey introduces NLP while also contrasting its various techniques, methodology and applications especially within the education field. This paper primarily focuses on an overview of various NLP techniques; therefore, it includes a brief discussion of the application of ML and DL to tackle NLP challenges.

NLP has several advantages, including (Khyani and B S, 2021):

- NLP incorporates automatic summary generation, which gives us a readable summary of text such as newspapers. This is called automatic content generation;
- NLP does not require indexing;
- Other benefits may include a high degree of flexibility; structuring extremely unstructured data and providing answers to difficulties relating to any idea related to NLP;

NLP has however several limitations such as (Khyani and B S, 2021):

- Context-expert knowledge, like sarcasm, is one of the biggest problems with NLP;
- The generic searches become really difficult to comprehend. There have also been issues when dealing with synonyms; the user is expected to not create chaos and think of his search term.

Having said that, there is still ample scope for research in improving the efficiency with which certain NLP tasks may be accomplished. This calls for additional study and development in NLP. Given the importance of learning approaches in NLP, it is believed that further experimenting with different learning strategies will increase the efficiency and accuracy of NLP.

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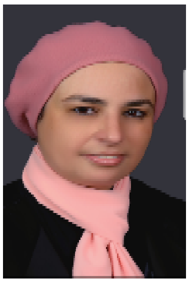
Ghania KHENSOUS received her Ph.D. degree from the USTO-MB University in 2018. She is currently a full-time teacher at Ecole Normale Superieure d’Oran (Algeria). Her research interests include bioInformatics, AI, optimization, NLP and education.

Kaouther LABED received her Ph.D. degree from the USTO-MB University in 2018. She is currently a full-time teacher at Ecole Normale Superieure d’Oran (Algeria). Her research interests include multicriteria analysis, image processing, bio-inspired and classification algorithms developed for remotely sensed data.



Zohra LABED received her Ph.D. degree from Oran University in 2014. She is currently a full-time- teacher at Ecole Normale Superieure d'Oran (Algeria). Her research interests include education, NLP, AI and educational psychology.