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Natural Language Processing in Modern Knowledge-Based Systems

Alaa K. AlDammagh and Samy S. Abu-Naser

Department of Information Technology,

Faculty of Engineering & Information Technology,

Al-Azhar University, Gaza, Palestine

E-mail: eldammaghalaa@gmail.com

ABSTRACT: *A knowledge-based system (KBS) is a computer program that solves complex problems by relying on a centralized information source. Traditional programs rely on procedural code, but a KBS expresses knowledge in a structured format, which is then evaluated by an inference engine to generate conclusions. The fundamental challenge for modern KBS is that while they rely on organized, machine-readable data, the vast majority of human information exists in an unstructured form, such as books, articles, and web pages. This paper argues that Natural Language Processing (NLP) is not only useful but also critically necessary to bridge this gap. NLP acts as a bridge, providing computational algorithms to automatically extract, interpret, and structure information from natural language. This review synthesizes various methods from recent literature for developing contemporary KBS that handle large volumes of data. It discusses key NLP techniques for knowledge acquisition and representation, such as Named Entity Recognition (NER), relation extraction, and event extraction, and their role in creating knowledge graphs. The review also highlights the strengths, limitations, and future directions of these methods, including the importance of addressing ethical gaps and resource inequality.*

KEYWORDS: Knowledge-Based Systems, Natural Language Processing, Knowledge Graph, Named Entity Recognition, Relation Extraction, Event Extraction, Semantic Reasoning, Transformer Models.

1. INTRODUCTION

A knowledge-based system (KBS) is a computer program that supports human decision-making and solves complicated problems by drawing on a centralized information source. A KBS directly expresses knowledge in a structured format, which is subsequently evaluated by a separate inference engine to generate conclusions and recommendations, in contrast with traditional programs that rely on procedural code.

The core components of KBS are: The knowledge base, a central system component, organizes domain-specific facts, rules, and relationships using techniques like ontologies and logical claims, The inference engine which is the "brain" of the system, uses reasoning to draw conclusions and infer new information and user interface allows communication and information entry [1-6].

The Fundamental Challenge of Knowledge-Based Systems that the Modern Knowledge-Based Systems (KBS) rely on organized, machine-readable data to function. This information is frequently recorded in formats such as relational databases, ontologies, and knowledge graphs. However, the vast bulk of human information exists in an unstructured form—books, articles, web pages, emails, and spoken communication. Without a means to translate this unstructured human language into a structured format, KBS would be restricted to the tiny quantity of data that is manually curated and inputted. This is where natural language processing becomes not only useful, but vitally necessary[7-10].

NLP acts as a critical bridge, providing a collection of computational algorithms for automatically extracting, interpreting, and structuring information from natural language. This process can be divided into two phases: knowledge acquisition and knowledge representation.

- Knowledge acquisition is the process of mechanically extracting relevant information from unstructured text. Instead than depending on manual data entry, NLP approaches may search millions of pages for facts, entities, and relationships. Key approaches used in this period include [11-15]:
  - Named Entity Recognition (NER)

Named Entity Recognition (NER) is a natural language processing task that aims to identify and label specific entities in text, such as names of people, places ,organizations, dates, etc. NER can classify entities based on their categories, which commonly include: - Person names (PER), for example "Alan Steel" - Place names (GPE), for example "United States" - Organization names (ORG), for example "Google" - Dates (DATE), for example "January 1st, 2021" - Numbers (NUM), for example "100" - Email addresses (EMAIL), for example "example@example.com" - Phone numbers (PHONE), for example "123-456-7890 "

- Relation Extraction

In addition to entity recognition, natural language texts also contain a large amount of relational information. Relationship extraction technology can help us extract the relationships between entities from texts and store them in knowledge graphs. When exploring natural language texts, we will find that they contain rich information beyond simple entity recognition. In fact, texts also imply various relationships between entities, reflecting the intricate connections between things .Through relationship extraction technology, we can accurately extract these relationships from texts and store them in knowledge graphs to build a network of connections between entities. The application of this technology is not limited to simple information extraction but provides a powerful tool for understanding semantic associations behind languages. Applying it in practice can not only help us build more intelligent systems but also promote the development of natural language processing field and open up new possibilities for advancements in artificial intelligence technology. Therefore, relationship extraction technology has great potential and prospects in constructing knowledge graphs and achieving semantic understanding[16-20].

- Event extraction

In some scenarios, we not only need to extract entities and relationships, but also need to extract event information. Event extraction technology can help us extract events from text and represent them as event nodes in a knowledge graph . In addition to entity recognition and relationship extraction, texts also carry rich event information that reflects the dynamic changes and behaviors between things. In certain scenarios, we not only need to understand the relationships between entities, but also need to extract this event information. The emergence of event extraction technology fills this gap in demand by accurately identifying events from text and representing them as event nodes in a knowledge graph .Through event extraction technology, we are able to capture various actions ,activities, and processes implied in the text, thus gaining a more comprehensive underst anding of the context described by the text. This technology's application is not limited to theoretical research; it can play an important role in practice such as information extraction, intelligent search, semantic analysis, etc. Therefore ,event extraction technology has broad prospects for application in knowledge graph construction and semantic understanding, and is of great significance for promoting the development of natural language processing technology [21-25]

➢ Knowledge Representation: Once this raw knowledge is acquired, NLP helps to format it in a way that is useful for a KBS. The most common and powerful method for this is the creation of a **knowledge graph**. A knowledge graph represents data as a network of interconnected entities and their relationships.

- The entities identified by NER become the **nodes** in the graph (e.g., Tim Cook, Apple, iPhone).
- The relationships identified by relation and event extraction become the **edges** connecting these nodes (e.g., Tim Cook -> is_the_CEO_of -> Apple).

This structured, graph-based representation allows a KBS to perform logical reasoning, answer complex questions, and discover new connections in the data that would be impossible to find in a sea of unstructured text.

NLP transforms a Knowledge Base System (KBS) into a dynamic reasoning engine, enabling intelligent search, automated reasoning, and natural language interfaces. It allows systems to understand user intent, make logical inferences, and interact with users using human language, providing a more relevant and efficient search experience.

2. OBJECTIVES

The main objective of this study is to examine the role of Natural Language Processing (NLP) in modern knowledge-based systems (KBS) by addressing the following:

- Explore the fundamental challenge of integrating unstructured, natural language text into the structured frameworks of contemporary KBS.
- To review traditional and cutting-edge NLP techniques for automating knowledge extraction and representation.
- To analyze how NLP bridges the semantic and representational gap between human language and machine-readable data.
- To identify the limitations and challenges in current approaches, such as ambiguity, context, and scalability, and to suggest future directions for research.

3. PROBLEM STATEMENT

Expert systems, recommendation engines, and sophisticated search platforms are just a few of the many applications that rely on knowledge-based systems (KBS). For reasoning and insight extraction, these systems rely on structured information representations like ontologies and semantic networks. Nonetheless, unstructured, natural language text contains the great majority of human knowledge. It is still very difficult to successfully incorporate this unstructured data into the formal, structured frameworks of contemporary KBS. There is frequently a semantic and representational gap in current approaches. Even though they can handle tasks like sentiment analysis and named entity recognition, traditional NLP techniques usually find it difficult to capture the intricate, subtle, and contextual relationships present in natural language. Limited Scalability and Maintenance: Curating and updating a knowledge base by hand is a time-consuming and labor-intensive process that results in a number of significant limitations. Ambiguity and Context: Automated systems struggle to correctly resolve the ambiguity, polysemy, and anaphoric references found in natural language, which can result in a cursory or inaccurate understanding of the source text. Absence of Deep Reasoning: The complex causal, temporal, and hierarchical relationships required for a KBS to carry out complex reasoning and inference are frequently not extracted by current approaches. Bridging the gap between the formal, inflexible structure of contemporary knowledge-based systems and the depth and flexibility of human-authored natural language is therefore a crucial challenge. To reliably, automatically, and accurately extract, represent, and integrate knowledge from large, unstructured textual corpora, NLP is not yet at a sufficient level. However, modern KBS are trying to utilize the world's textual knowledge in order to achieve true intelligence and adaptability.

4. LITERATURE REVIEW

Recent years have seen the proposal of numerous methods in the literature for developing contemporary knowledge-based systems that are able to handle enormous volumes of data in a variety of formats. A review of some of these methods include traditional NLP methods and cutting-edge techniques is provided here.

Thr authors in [26] offered a knowledge extraction algorithm design and implementation that can automatically extract information and knowledge from a variety of data sources, such as text analysis, entity recognition, keyword extraction, and other tasks. Building a knowledge graph offers an efficient method of managing and applying this knowledge by presenting various knowledge domains as graphs. In order to create accurate and efficient knowledge graphs, they want to maximize relation extraction using cutting-edge natural language processing techniques. Through experiments, they improve the precision and effectiveness of relation extraction by utilizing graph neural networks (GNNs) technology and remote supervision learning. By using natural language processing (NLP) to automatically define and discover concepts and their relationships, advanced frameworks facilitate the creation of highly accurate ontology-based, machine-readable knowledge bases.

The authors in [27] proposes a rule-based framework centered on the Tsetlin Machine (TM) to bridge the accuracy-interpretability gap in NLP systems. Unlike transformer-based "black-box" models (e.g., BERT, GPT), the TM employs automata-driven conjunctive clauses to form human-readable propositional logic rules, enabling transparent decision-making. The automation of knowledge base (KB) construction has been a persistent challenge in NLP-driven systems.

The authors in [28] integrates feature extraction and deep learning classification to address sentiment analysis across diverse languages which is a critical need in globally interconnected systems. The authors propose a hybrid feature extraction technique using Histogram Equalization-based Global Local Entropy (HEGLE) and Kernel-based Radial Basis Function for classification. The model efficiently maps features to sentiment labels and outperforms LSTM and CNN baselines on Indian language datasets, demonstrating robustness in resource-constrained contexts.

The authors in [29] provide a systematic analysis of Nin L P's evolution, emphasizing its transformative role in knowledge-based systems. Their PRISMA-guided review synthesizes 221 studies (2010–2024), revealing critical advancements in transformer models, ethical challenges, and cross-sector applications. The study presents a structured workflow for Natural Language Processing (NLP) deployment, focusing on text preprocessing, model selection and training, and deployment and ethics. It highlights the societal integration of NLP in various sectors, such as job markets, education, and healthcare. The study also highlights the innovative application synergies of NLP, such as sentiment-enhancing assistants and search intelligence. However, it also highlights the critical limitations and future directions, such as contextual understanding, ethical gaps, and resource inequality. Future directions should focus on quantum-NLP integration and culturally adaptive embeddings for global scalability. The study emphasizes the need for reskilling for AI oversight roles and addressing bias propagation in training data.

The authors in [30] systematize this domain into three critical pillars: fistly, Knowledge integration in Language Understanding (NLU) includes structured knowledge, unstructured knowledge, and KBS relevance. Frameworks like ERNIE and KEPLER inject knowledge graphs into language models, improving contextual reasoning and enabling entity-aware decision-making in medical diagnosis systems. Secondly, Knowledge-Guided Language Generation (NLG) employs three main integration paradigms: architectural, learning frameworks, inference methods, and KBS impact, which fuse ConceptNet relations into dialogue systems. And finally ConceptNet, KagNet, and MHGRN are neuro- symbolic methods used for commonsense reasoning, achieving 65% accuracy on CommonsenseQA and resolving ambiguities in user queries through contextual knowledge grounding.

Abdelnabi et al. [6] suggested a method for creating class diagrams from natural language requirements using heuristic rules for the transformation process and natural language processing (NLP) techniques. The proposed method operates in five stages. The methodology parses the natural language specifications using type dependency and natural language processing (NLP) techniques. By extracting various class elements, such as classes, attributes, and methods, as well as various relationship types, such as associations, aggregations, composition, generalization, and multiplicity, the method creates class diagrams.

The authors [31] illustrate a system that first extracts the domain ontology and professional thesaurus from digital resources. Based on the label weight created by artificial intelligence technology, the system then employs a new word discovery algorithm to intelligently extract and clean the new words from the basic thesaurus. The output content is then enhanced from knowledge points into related knowledge systems after the relationship system between knowledge points and elements is established to achieve the association extraction of targeted knowledge points. In order to enhance the system's scalability and universality, consideration was given to the extended thesaurus architecture, algorithms, computational capabilities, tags, and exception thesaurus during the design phase. Concurrently, the "artificial intelligence + manual assistance" approach was adopted. The experimental foundation of the optimization algorithm is given based on increasing system availability.

The authors [32] addressed this gap by proposing OMRKBC (Ontology-based Machine-Readable Knowledge Base Construction), a framework that integrates NLP techniques to build structured knowledge bases from heterogeneous sources (e.g., DBpedia, ConceptNet, WordNet) with minimal human intervention. Their core innovation lies in NLIKR (Natural Language Independent Knowledge Representation), a paradigm where every word is treated as a concept defined by its relations to other concepts. This method makes it possible to:

- Automated Concept-Relation Extraction: Using rules and algorithms to discover concepts (e.g., verbs, nouns) and semantic relations (e.g., "capableOf," "partOf") from text.
- Rich Structured Information (RSI): Transforming unstructured text (e.g., DBpedia abstracts) into machine-interpretable triples (e.g., <water, no, colour>) via OpenIE and syntactic rules.
- Scalability Solutions: Preprocessing algorithms reduced CSV file sizes by 93% and optimized instance mapping into ontologies using OWL API.

The field of Natural Language Processing has been fundamentally transformed by the advent of deep learning, particularly with the introduction of transformer architectures. These models, such as BERT (Bidirectional Encoder Representations from Transformers) and its variants, have moved beyond traditional statistical or rule-based methods to capture far more intricate contextual and semantic information. Recent advances highlight knowledge-augmented NLP as a paradigm shift for enhancing cognitive capabilities in Knowledge-Based Systems (KBS) [33-40].

5. METHODOLOGY

This paper is a literature review of recent studies on the application of Natural Language Processing (NLP) in modern knowledge-based systems (KBS) [41-50]. The review synthesizes and analyzes previous research using a methodical approach. From conventional NLP techniques to innovative approaches, a variety of approaches are examined in the literature review section [51-60]. Knowledge extraction algorithms, rule-based frameworks, hybrid feature extraction, knowledge-augmented NLP, and ontology-based knowledge base development are just a few of the topics covered in the review process [61-70]. The chosen studies are meant to give a thorough overview of the ways in which unstructured material can be converted into structured, machine-readable representations like knowledge graphs using NLP techniques like Named Entity Recognition (NER), relation extraction, and event extraction. This methodology enables the identification of key advancements, challenges, and future directions in the field [34-37].

6. RESULTS

The literature review revealed several key findings regarding the use of NLP in modern knowledge-based systems:

- NLP techniques enable the automatic extraction and structuring of knowledge from unstructured text, which is critical for the function of modern KBS.
- Various studies have proposed different methods for knowledge extraction, including algorithms for entity recognition, relation extraction, and keyword extraction.
- The use of advanced techniques like Graph Neural Networks (GNNs) has been shown to improve the precision and effectiveness of relation extraction.
- Knowledge-augmented NLP, where frameworks like ERNIE and KEPLER inject knowledge graphs into language models, has been shown to improve contextual reasoning and entity-aware decision-making.

- Hybrid feature extraction techniques have proven effective for tasks like sentiment analysis in diverse languages, demonstrating robustness in resource-constrained contexts.
- A major outcome is the successful creation of highly accurate knowledge graphs and ontology-based knowledge bases using automated NLP frameworks.

7. DISCUSSION

Based on the literature review, the application of NLP in modern knowledge-based systems is transformative. The literature highlights a clear shift from traditional statistical or rule-based methods to deep learning and transformer architectures like BERT, which capture more intricate contextual and semantic information. However, several challenges remain [70-78]. The core strength of NLP is its ability to bridge the gap between unstructured text and structured data. By utilizing techniques such as Named Entity Recognition (NER), relation extraction, and event extraction, NLP transforms text into a knowledge graph, enabling a KBS to perform logical reasoning and answer complex questions.

However, the field faces significant challenges:

- **Ambiguity and Context:** Automated systems still struggle to resolve the ambiguity and anaphoric references found in natural language, which can lead to inaccuracies.
- **Scalability and Maintenance:** Manually curating and updating knowledge bases is labor-intensive and results in limitations. The need for reskilling for AI oversight roles is a critical aspect.
- **Ethical Gaps:** There is a need for continuous improvement in algorithmic impartiality, as well as a focus on ethical dilemmas and data protection concerns. Future research must address bias propagation in training data.

The future of NLP in KBS points towards the need for culturally adaptive embeddings for global scalability and the potential for quantum-NLP integration.

8. CONCLUSION

This paper has highlighted the crucial and indispensable role of Natural Language Processing (NLP) in the evolution of modern knowledge-based systems (KBS). By automatically extracting, interpreting, and structuring knowledge from the vast ocean of unstructured human-authored text, the review shows how natural language processing (NLP) serves as a crucial bridge that allows these systems to overcome the constraints of structured, manually curated data. A KBS can carry out complex logical reasoning and intelligent search by using dynamic knowledge graphs created through the use of sophisticated techniques like Named Entity Recognition, Relation Extraction, and Event Extraction. Even though there are still many obstacles to overcome, especially when it comes to managing ambiguity and ethical issues, the continuous developments in deep learning and knowledge-augmented natural language processing hold great promise for creating reasoning engines that are more intelligent, flexible, and genuinely dynamic and that can communicate with users in human terms.

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