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Exploring the Role of Discourse Analysis in Natural Language Processing: A Comprehensive Review of Applications and Insights

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ABSTRACT

Discourse analysis plays a significant role in understanding and interpreting the complexity of human language, providing valuable insights for improving natural language processing (NLP) systems. This study presents an in-depth review of discourse analysis in NLP, and its applications in various domains such as machine translation, question-answering systems, sentiment analysis, conversational bots, and information retrieval. By analyzing the structural and contextual aspects of language, discourse analysis enhances the NLP system's ability to understand individual words and their meaning in cross-border conversational contexts. The review highlights how discourse analysis and learning techniques work together to improve the automated system's accuracy and efficiency. In addition to addressing significant challenges, including ambiguity, cultural variance, and conversational dynamics, the paper also suggests future research directions for exploring the possibilities of natural language processing in human-computer interactions. This work attempts to fill the gap between linguistic theory and computational applications by demonstrating how discourse analysis can revolutionize the development of more intelligent, contextually aware, and human-centered language technologies.

***Keywords**: Discourse Analysis, Natural Language Processing (NLP), Contextual Understanding, Computational Linguistics, Machine Translation, Question Answering, Sentiment Analysis, Conversational AI.*

Introduction

In an era where human-machine communication is integral to daily life, the effectiveness of such interaction is heavily reliant on a machine's ability to understand language as humans do. The COVID-19 pandemic intensified the shift toward digital communication, placing a new emphasis on intelligent systems that can interpret complex language constructs. This necessity has led to an increased exploration of discourse analysis, a field that deals with the language beyond the sentence level and focuses on uncovering meaning from contextual use of language (Stubbs, 1983; Tayal & Tayal, 2021). Discourse analysis plays a key role in enabling machines to derive meaning, interpret sarcasm, identify speaker intent, and respond appropriately within a context (Khurana et al., 2022). It underpins applications such as conversational agents, sentiment analysis, machine translation, and automatic summarization (Jurafsky & Martin, 2021). By moving beyond isolated words and sentences, discourse models provide continuity, coherence, and contextual understanding that are essential for natural communication.

To better contextualize this discussion, it is important to outline the fundamental stages involved in Natural Language Processing. Figure 1 presents an overview of the standard NLP pipeline, providing a foundational understanding of how raw text is transformed into meaningful representations. This background helps clarify how discourse analysis extends traditional NLP processing by enabling context-aware and coherence-based interpretation across sentences and multi-turn conversations.

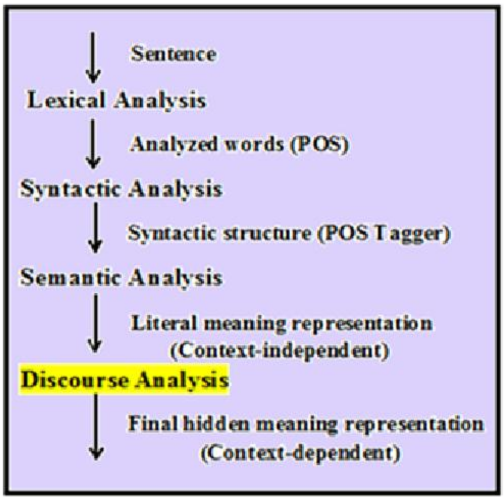

Figure 1: Key Stepsin Natural Language Processing

This figure illustrates the standard NLP pipeline, including text preprocessing, representation, and language understanding stages, highlighting where discourse analysis contributes to contextual and coherence-based interpretation.

This review aims to provide an in-depth analysis of existing research on discourse analysis and its applications in various domains. It highlights discourse analysis approaches, applications in real-world scenarios, and the research gaps and limitations that need to be addressed in future studies.

Discourse Analysis and its Role in NLP

Discourse analysis plays a central role in advancing Natural Language Processing (NLP). To illustrate the functional role of discourse analysis within NLP systems, Figure 2 presents a conceptual framework that demonstrates how discourse-level processing operates as an intermediate engine between raw human language input and enhanced NLP applications. The framework highlights how ambiguity, cultural variation, and contextual shifts in language are addressed through structural and contextual discourse analysis, leading to improved downstream task performance.

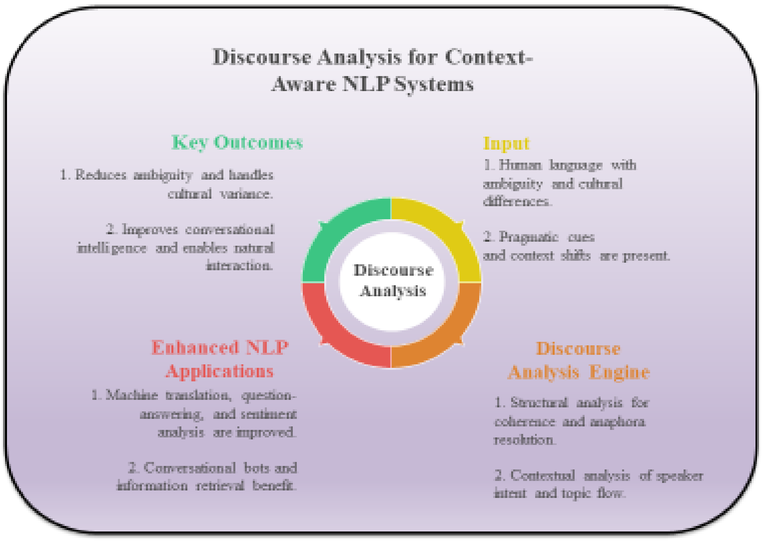

Figure 2: Discourse Analysis Framework for Context-Aware NLP Systems

This figure depicts how discourse analysis processes ambiguous and context-rich human language through structural and contextual modeling, enabling improved performance in NLP applications such as machine translation, question answering, sentiment analysis, conversational agents, and information retrieval.

The conceptual framework illustrated in Figure 2 provides a foundation for understanding the theoretical principles and functional scope of discourse analysis in NLP. Building on this overview, the following subsection discusses the definition and scope of discourse analysis, outlining its linguistic foundations and relevance to computational language modeling.

- **Definition and Scope of Discourse Analysis**

The term Discourse originated from Latin word discursus, which denoted ' Conversation or Speech'. In linguistics, discourse refers to language above the sentence level—how different sentences relate and form coherent meaning (Stubbs, 1983). Discourse analysis within the domain of Natural Language Processing (NLP) refers to the systematic examination of linguistic structures that transcend individual sentences, aiming to uncover the coherent organization of language at multiple levels of text. This encompasses a variety of structural elements including topic segmentation, the coherence relations that bind sentences into meaningful sequences, coreference resolution that links entities across discourse, and structures that govern the conversational exchange of dialogues. Thus, discourse processing functions as a suite of NLP tasks that collectively aim to understand how meaning emerges from the interactions and relationships of textual components, rather than individual sentences. It differentiates between monologue, which is a single-speaker text, and conversation forms of discourse, which involve multi-party interactions and require capturing synchronous or asynchronous dynamics. The identification of discourse structures has profound implications for several downstream applications. In text summarization, discourse analysis generates summaries that maintain logical flow and relevance by considering topic shifts and argumentative relations. Similarly, in sentiment analysis, interpreting discourse coherence and evaluative language beyond word-based features enhances the extraction of nuanced content. Other applications benefiting from discourse-informed methods include machine translation, which is based on coherence and coreference to maintain meaning across languages; essay scoring, where structural features influence evaluative metrics; question answering systems that need discourse context to resolve ambiguities; information extraction, which exploits correlations between sentences; and thread recovery in forums to reconstruct conversation flows accurately (Joty et al., 2018). The development of discourse-aware NLP systems thus represents a critical advancement toward natural, human-like understanding of textual data.

Efforts within discourse analysis also emphasize the importance of appropriate annotation and corpus building for algorithm development. For instance, constructing a corpus that is tagged not only with lexical and syntactic information but enriched with discourse annotations that enable the creation of more sophisticated models capable of tasks such as author profiling and social network analysis within online chat dialogues (Forsythand & Martell, 2007). This multi-layered approach reflects the complexity and nature of discourse, signaling a shift in NLP from sentence-centric to discourse-oriented frameworks.

In addition, the early emphasis on discourse in NLP situated it as an important dimension beyond lexical and syntactic analysis. This opened the door for more holistic systems capable of tasks such as summarization and retrieval. The interplay between discourse structures and information retrieval performance, for example, has been studied to enhance search relevance, indexing, and conceptual information retrieval through the exploitation of discourse semantics.

- **Theoretical Foundations and Frameworks of Discourse Analysis**

Discourse analysis in NLP encompasses multiple theoretical frameworks that provide the foundation for understanding language structure beyond individual sentences. In NLP research, discourse-oriented theories provide conceptual and computational frameworks for understanding coherence, intent, and semantic relations in longer texts or dialogues. This section reviews the major theoretical frameworks that have shaped discourse modeling in NLP research and highlights their relevance to modern computational applications.

Rhetorical Structure Theory (RST)

Rhetorical Structure Theory (RST) emerges as one of the most influential frameworks, representing text as hierarchical tree structures where elementary discourse units are connected through nucleus-satellite relationships (Mann & Thompson, 1988). The theory distinguishes between more central content (nucleus) and supporting information (satellite), enabling systems to understand document organization and importance hierarchies (Mann & Thompson, 1988; Taboada & Mann, 2006).

Penn Discourse Treebank (PDTB)

The Penn Discourse Treebank (PDTB) provides a lexically grounded approach to discourse analysis by modeling relations through explicit and implicit discourse connectives that link two textual arguments (Prasad et al., 2008). Unlike hierarchical frameworks such as RST, PDTB focuses on identifying semantic relations including causality, contrast, temporality, and expansion. As a widely used annotated resource, PDTB has supported the development of discourse relation classification, coherence modeling, and implicit relation prediction, with applications in question answering, summarization, and dialogue systems (Webber et al., 2019).

Centering Theory and Local Coherence Modeling

Centering Theory explains local discourse coherence by tracking the salience and continuity of entities across adjacent utterances. It introduces forward-looking (Cf) and backward-looking (Cb) centers to model attentional shifts, supporting interpretation of coherence and pronominal reference (Grosz et al., 1995). In NLP, this framework has been applied to coreference resolution, dialogue modeling, and coherence evaluation.

Questions Under Discussion (QUD) Framework

The Questions Under Discussion (QUD) framework provides a pragmatic account of discourse organization by proposing that conversational contributions are structured around an implicit or explicit central question guiding the interaction (Roberts, 2012). This framework captures how speakers manage informational goals and how discourse coherence is maintained through the progressive resolution of these questions. In recent NLP research, QUD-based modeling has been increasingly adopted for representing dialogue structure, argumentation patterns, and conversational coherence, offering a flexible alternative to purely structural discourse representations.

Synthesis and Relevance to NLP Research

Collectively, RST, PDTB, Centering Theory, and QUD theoretical frameworks form the conceptual backbone of discourse analysis in Natural Language Processing (NLP). Each form contributes a distinct perspective: - RST emphasizes hierarchical structure, PDTB focuses on relational semantics, Centering Theory addresses coherence and entity tracking, and QUD captures the pragmatic flow of information. They form the basis of modern discourse-aware NLP systems and continue to inform advancements in tasks such as summarization, dialogue modeling, and human–computer interaction (HCI).

- **Importance of Discourse Analysis in NLP**

Discourse analysis plays a foundational role in Natural Language Processing by moving beyond sentence-level interpretation to understanding full conversational or textual context. While traditional NLP focuses on lexical, syntactic, and semantic aspects, discourse analysis enables systems to model coherence, resolve ambiguity, and infer speaker intent across multiple sentences or turns. This higher-level comprehension is vital for developing dialogue systems, summarization tools, sentiment analysis engines, and personalized virtual assistants. Without discourse-level understanding, AI responses often lack relevance, empathy, or contextual accuracy—particularly in dynamic HCI environments such as healthcare, education, and customer service (Jurafsky & Martin, 2021; Sharma, 2021).

Discourse Analysis Applications in NLP

Discourse analysis has been widely used in Natural Language Processing (NLP) tasks to enhance context understanding, coherence modeling, and semantic interpretation. Through the integration of discourse-level information, they enhance the accuracy of NLP systems for natural language understanding beyond isolated sentences. This section discusses the major application areas where discourse analysis had a significant impact. These include text summarization, sentiment analysis, opinion mining, machine translation, question answering, dialogue systems, and conversational AI.

- **Text Summarization**

Discourse analysis plays a foundational role in advancing text summarization by enabling models to move beyond surface-level sentence extraction toward structure-aware content selection. Traditional summarization approaches often rely on statistical salience or lexical similarity, which can result in redundancy and fragmented summaries, a limitation commonly observed in early NLP pipelines (Dudhabaware & Madankar, 2014). In contrast, discourse-aware summarization leverages rhetorical relationships within a document to identify which segments contribute most significantly to the overall communicative intent.

One of the most influential frameworks applied in this context is Rhetorical Structure Theory (RST), which represents a document as a hierarchical tree composed of Elementary Discourse Units (EDUs) connected through rhetorical relations such as elaboration, contrast, and cause. Within this structure, nucleus nodes convey core information, while satellite nodes provide supporting or contextual details (Mann & Thompson, 1988). Summarization systems that prioritize nucleus units consistently produce more informative and coherent summaries.

Recent neural models such as DISCOBERT demonstrate the effectiveness of discourse-aware summarization by operating directly on EDUs rather than full sentences. By integrating discourse parsing with contextual embedding, these models reduce redundancy and improve content coverage, particularly in long documents (Xu et al., 2020).

- **Sentiment Analysis and Opinion Mining**

Sentiment analysis and opinion mining traditionally focus on identifying the polarity (positive, negative, or neutral) of text at the word, sentence, or document level and are widely recognized as core NLP tasks across application domains (Dudhabaware & Madankar, 2014). However, such approaches often fail to capture implicit sentiment, contextual polarity shifts, and opinion structure, particularly in complex or multi-sentence texts. Discourse analysis addresses these limitations by modeling how sentiments are organized and expressed across larger textual units.

Within the framework of Rhetorical Structure Theory (RST), sentiment expressed in nucleus segments typically reflects the author's core opinion, whereas sentiment in satellite segments may provide justification, elaboration, or mitigation (Mann & Thompson, 1988). This distinction allows sentiment interpretation to move beyond surface polarity toward a more structured and context-sensitive understanding of evaluative language.

Discourse-aware sentiment analysis is especially valuable in social media contexts, where opinions evolve dynamically and are embedded within complex interaction structures. For example, combining sentiment analysis with discourse-level network modeling has been shown to enhance large-scale discourse analysis of Twitter data (Misiejuk et al., 2021). These findings reinforce the importance of discourse-informed sentiment and opinion mining for accurate, context-sensitive interpretation.

- **Machine Translation**

Discourse analysis has been increasingly recognized as an important component in machine translation (MT), particularly when addressing document-level coherence and contextual consistency. While most neural MT systems continue to operate at the sentence level, this limitation often results in discourse-related inconsistencies such as incorrect coreference resolution, lexical repetition, tense shifts, and misuse of discourse connectives when translating longer texts. These challenges reflect broader limitations observed across many NLP tasks that do not explicitly model higher-level discourse structure (Dudhabaware & Madankar, 2014).

Recent advances in document-level neural machine translation emphasize the importance of incorporating wider contextual windows to preserve coherence across sentences. However, such approaches require additional computational resources, more complex architectures, and carefully designed training strategies, making large-scale deployment challenging (Bawden et al., 2018). As a result, many state-of-the-art MT systems still struggle to achieve consistent discourse-level translation, particularly in low-resource or domain-specific settings.

- **Question Answering Systems**

Discourse analysis is especially valuable in question answering (QA) systems that handle non-factual or explanatory questions, such as why, how, and what caused questions. Unlike factoid QA, these questions require understanding relationships between events, motivations, and outcomes—capabilities that go beyond traditional shallow NLP pipelines (Dudhabaware & Madankar, 2014).

Discourse-based QA systems utilize RST to identify answer spans that are rhetorically connected to the query topic. Studies show that such systems achieve approximately 60% recall for complex questions by aligning discourse relations between questions and candidate answers (Verberne et al., 2007). In particular, causal and explanatory relations are highly effective for answering why questions.

Furthermore, centering theory plays a crucial role in modeling discourse coherence across multi-question interactions. By tracking discourse entities and their salience across turns, QA systems can maintain contextual continuity and resolve references more effectively (Grosz et al., 1995). This capability is especially important in conversational and multi-turn QA environments.

- **Dialogue Systems and Conversational AI**

Discourse analysis is fundamental to the design of dialog systems and conversational AI, as it enables machines to engage in coherent, multi-turn interactions. Effective dialog systems must manage turn-taking, topic shifts, discourse coherence, and user intent continuity, all of which extend beyond sentence-level understanding and conventional intent-detection pipelines used in human–machine dialogue systems (Liu et al., 2019). In the absence of discourse-level modeling, conversational agents often fail to preserve contextual consistency across turns, resulting in fragmented or inappropriate responses.

Discourse modeling allows dialog systems to maintain conversational state and interpret user utterances relative to prior context. Techniques such as dialog act modeling, topic segmentation, and discourse relation prediction contribute to more natural and human-like interactions by explicitly modeling conversational structure (Jurafsky & Martin, 2021). These discourse-oriented capabilities are increasingly important as conversational agents are deployed in real-world human–computer interaction (HCI) environments, where interaction quality, usability, and user trust are critical factors (Koumaditis & Hussain, 2017).

Recent research demonstrates that incorporating discourse-level representations using techniques such as Deep Canonical Correlation Analysis (DCCA) significantly improves response selection in conversational systems by aligning user intent and system responses at semantic and structural levels (Wang et al., 2015). Beyond technical performance, discourse coherence also has measurable behavioral consequences. Empirical studies on AI-based customer service chatbots show that well-structured and context-aware conversational behavior significantly influences user compliance, acceptance, and effectiveness of automated systems (Adam et al., 2020).

Overall, these findings indicate that discourse analysis not only enhances the linguistic quality of dialog systems but also plays a crucial role in improving interaction outcomes in conversational AI. This makes discourse-aware modeling a core component of advanced human–computer interaction frameworks.

Computational Methods of Discourse Analysis

Discourse analysis in Natural Language Processing has evolved from simple rule-based systems to powerful hybrid architectures that integrate the strengths of symbolic, statistical, and deep learning techniques. Each generation of methods improves performance and scalability but also brings new challenges such as computational complexity and interpretability. Table 1 illustrates a comparison of major methodologies used for discourse analysis in NLP, from rule-based approaches to hybrid models, their representative methods, key advantages, limitations, and typical performance metrics. Hybrid approaches achieve the highest balanced performance (87-94% accuracy) while transformers lead in contextual understanding (88-96% accuracy).

Table 1: Comparative Analysis of Discourse Analysis Methodologies in NLP

Methodoloy Category	Representative Methods	Core Mechanism	Advantages	Limitations	Typical Performance
Rule-based Approaches Galitsky et al. (2015) Mann & Thompson (1988)	Pattern matching, handcrafted rules, RST heuristics	Expert-designed patterns over words, syntax, discourse markers	Interpretable Transparent decisions Narrow domain precision	Poor scalability Heavy manual effort Weak on implicit relations	**60–70%**
Statistical Methods Tayal et al. (2020)	CRF, SVM, feature-based classifiers	Supervised learning with engineered discourse features	Proven robustness Mathematically grounded Domain-adaptable	Feature engineering required Limited deep context	**70–80%**

Neural Network Models Tayal & Tayal (2021)	RNN, CNN, LSTM discourse models	Automatic feature learning from sequences/n-grams	Sequential pattern capture Less manual design	Limited context window Long document issues	**75–85%**
Transformer Models Wang et al. (2024) Khurana et al. (2022)	BERT, GPT, LLM parsing	Self-attention + zero-shot LLM reasoning	88–96% accuracy State-of-the-art Cross-domain	High compute cost "Black-box" behavior	**88–96%**
Graph Neural Networks Joty et al. (2018)	GCN, GAT discourse graphs	Nodes=discourse units, edges=relations	Structure-aware Explicit relation modeling	Complex architectures Large data required	**80–90%**
Hybrid Approaches Li et al. (2025), Rathore & Agrawal (2022)	Rule+neural, LLM-GNN, CNN-LSTM	LLM reasoning + graphz structure	Best performance (87–94%) Balanced interpretability	Implementation complexity Training overhead	**87–94%**

- **Performance Trends and Implications**

Table 1 reveals clear progression: each methodological generation improves accuracy by 5-15% over predecessors. Hybrid approaches emerge as optimal for practical deployment, combining interpretability from statistical methods with neural performance. Transformers dominate research benchmarks but require significant computational resources.

- **Methodological Recommendations**

For text summarization and document-level tasks, transformer plus GNN hybrids provide optimal structure-context balance. Real-time dialogue systems benefit from lightweight statistical-neural combinations. Low-resource languages favor rule-based augmentation of neural models.

This comprehensive methodological landscape demonstrates the evolution of discourse analysis from rigid rule-based systems to flexible, high-performance hybrid architectures, enabling sophisticated NLP applications across various domains.

Role of Discourse Analysis in Emerging NLP Technologies

- **Large Language Models and Generative AI**

Large Language Models (LLMs) and generative artificial intelligence represent transformative developments in NLP, often characterized by the ability to generate coherent and contextually relevant language outputs. GPT-4 and PaLM2 architectures are among the models that have driven a revolution in natural language generation and comprehension through training on massive text corpora and the application of sophisticated deep learning techniques (Linkon et al., 2024).

Discourse understanding is a key to upgrading these models from generating text fluency to understanding meaning. However, it has been pointed out that today's models primarily learn statistical correlations that involve form, rather than meaning, which restricts true natural language understanding (Bender & Koller, 2020). It is not trivial to incorporate discourse-level semantics into these large models, with both architecture and data considerations.

In addition, the ethical discussions related to LLM deployment raise ethical demands for a steady evolution of discourse-aware governance and responsible practices against misuse, bias, and lack of transparency (Iorliam & Ingio, 2024). This shows that discourse analysis is not just a technical challenge, but also an ethical one posed by generative AI.

- **NLP for Educational and Clinical Applications**

Discourse analysis techniques have found important applications in educational assessments and clinical diagnostics. Automated systems capable of identifying discourse elements in student essays can aid in essay scoring. In particular, systems that detect argumentative structures and coherence features in student text can match instructor criteria. According to Burstein et al. (2003), these methods reduce the demands on human effort while providing consistent feedback, thereby promoting the achievement of educational objectives.

In the clinical field, discourse segmentation and analysis help in evaluating narrative transcripts for neuropsychological assessments, supporting the early detection and monitoring of conditions such as mild cognitive impairment and dementia. Incorporating speech features into neural network models improves the reliability and accuracy of these assessments (Treviso et al., 2017). In addition, computational discourse models aid psychiatric research by examining linguistic and acoustic patterns linked to schizophrenia and other mental health disorders, enhancing the potential for automated diagnosis and monitoring (Ratana et al., 2019).

These examples show the huge potential of discourse-informed NLP in the critical social sector.

- **Discourse Processing in Online and Social Media Contexts**

The widespread use of internet-based communication channels, including chat systems, forums, and social media, introduces complex discourse phenomena characterized by informality, noise, and dynamic interaction. Forsythand and Martell (2007) noted that discourse analysis in these contexts must reconstruct coherent conversations, identify participants' roles, extract semantic relations, and more from unstructured user-generated content.

Identification of hate speech and misinformation on social platforms relies on discourse markers to pinpoint subtle linguistic cues of harmful content. Because the dialogical interactions are complex and the conversational threads evolve quickly, automatic analyses are challenging, though they are the object of study (Schmidt & Wiegand, 2017). In such environments, discourse analysis supports the modeling of conversational structure, speaker intent, and interaction patterns, which are essential for reliable interpretation of online communication.

These studies demonstrate the importance of discourse analysis for understanding and mapping communication in this digital age.

Research Gaps & Future Directions in Discourse Analysis for NLP

A systematic review of prior research on discourse analysis in Natural Language Processing (NLP) reveals substantial progress in theoretical modeling and practical applications. Despite these advancements, several key research gaps still exist that limit the effectiveness, generalizability and real-world use of discourse-aware NLP systems. These gaps are discussed next, along with corresponding future research directions.

- **Need for Communal and Hybrid Strategies**

A major limitation observed in existing discourse analysis research is the predominance of single-method approaches. Many studies rely exclusively on rule-based, statistical, or deep learning techniques, each of which addresses only a subset of discourse-related challenges. Rule-based methods provide interpretability but lack flexibility and scalability, whereas deep learning models offer strong performance at the expense of transparency and domain generalization. Statistical approaches, while robust, often struggle to capture deep contextual and semantic dependencies.

Future research should emphasize communal or hybrid strategies that combine linguistic theory, discourse rules, and neural representations. Such integrative frameworks can leverage the strengths of individual approaches while mitigating their limitations, leading to discourse-aware NLP systems that are both interpretable and contextually powerful.

- **Limited Progress in Multimodal Discourse Analysis**

Most discourse analysis models remain largely text-centric, overlooking the multimodal nature of human communication. In real-world interactions, meaning is often conveyed through a combination of written language, spoken cues, visual signals, and paralinguistic features. Current NLP systems lack the capability to jointly model these modalities, which restricts their effectiveness in conversational agents, educational technologies, healthcare applications, and social media analysis.

Future research must prioritize multimodal discourse analysis, developing models that integrate textual, acoustic, and visual information into unified discourse representations. Such advancements are essential for achieving more natural and human-like interaction in human–computer interaction (HCI) environments.

- **Gaps in Multilingual and Cross-Cultural Discourse Processing**

Another significant research gap is the heavy reliance on English-language discourse datasets. Discourse structures, coherence strategies, and pragmatic norms vary across languages and cultural contexts, yet these variations are rarely accounted for in existing models. Consequently, discourse-aware NLP systems often fail to generalize to multilingual or low-resource language settings.

Future studies should focus on multilingual and cross-lingual discourse processing, including the development of culturally adaptive discourse representations and expanded discourse-annotated corpora. Addressing this gap is essential for building inclusive and globally applicable NLP technologies.

- **Challenges in Accuracy and Real-World Deployment**

Although deep learning and transformer-based architectures have significantly improved discourse analysis performance, their effectiveness often declines in real-world conditions characterized by noisy, informal, or domain-specific language. Issues such as topic drift, implicit meaning, conversational interruptions, and contextual ambiguity remain challenging. Moreover, the computational complexity of advanced discourse models limits their deployment in real-time and resource-constrained environments.

Future research should aim to improve robustness, efficiency, and scalability, enabling discourse-aware NLP systems to maintain high accuracy while being suitable for practical deployment across diverse application domains.

Conclusion

Discourse analysis significantly contributes to the advancement of AI-driven human-computer interaction by improving contextual language understanding. This review highlights key methodologies in discourse analysis, alongside machine and deep learning techniques, and identifies research gaps that require further exploration. As AI advances, discourse-based NLP models will be essential for fostering more natural and intelligent communication between machines and humans.

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