Algorithmic Ambiguity: Using Natural Language Processing (NLP) to Identify and Map Unreliable Narration in Postmodern Novels

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***Abstract*—The rapid advancement of Artificial Intelligence (AI) and Natural Language Processing (NLP) has transformed the methods through which literary texts are analyzed. Traditionally, literary criticism has relied on close reading, subjective interpretation, and theoretical frameworks developed by scholars in literature. However, computational approaches now enable researchers to examine linguistic patterns, narrative structures, and stylistic variations on a much larger scale. Among the most intriguing applications of NLP is the identification of unreliable narration, a narrative technique frequently employed in postmodern literature to challenge readers' perceptions of truth and reality. Unreliable narrators intentionally or unintentionally provide distorted, contradictory, or incomplete accounts of events, making interpretation both intellectually demanding and artistically rewarding.**

This research paper explores how NLP techniques can be employed to identify and map unreliable narration in postmodern novels. The study examines computational methods such as sentiment analysis, stylometry, semantic analysis, topic modeling, named entity recognition, and transformer-based language models to detect inconsistencies in narrative voice and perspective. Through selected examples from postmodern fiction, the paper demonstrates that algorithmic approaches can complement traditional literary criticism by identifying linguistic signals associated with ambiguity and unreliability. While algorithms cannot replace human interpretation, they provide valuable evidence that enhances literary analysis. The paper concludes that integrating computational linguistics with literary studies opens new opportunities for interdisciplinary research and contributes to the growing field of digital humanities.

***Index Terms*—Artificial Intelligence, Natural Language Processing, Digital Humanities, Computational Literary Studies, Postmodern Literature, Narrative Theory, Unreliable Narration, Algorithmic Criticism.**

I. INTRODUCTION

Literature has always reflected the complexity of human experience through storytelling, characterization, and narrative techniques. One of the most significant developments in modern literary criticism is the emergence of interdisciplinary approaches that combine literary theory with computational methods. The rise of Artificial Intelligence (AI) and Natural Language Processing (NLP) has expanded the possibilities of textual analysis by enabling researchers to process large volumes of literary texts systematically and objectively. Rather than replacing traditional literary criticism, computational techniques provide new tools that enhance the understanding of language, narrative, and stylistic features.

Natural Language Processing is a branch of Artificial Intelligence that focuses on enabling computers to understand, interpret, and generate human language. Originally developed for applications such as machine translation, information retrieval, speech recognition, and text summarization, NLP has increasingly become relevant to humanities research. Literary scholars now employ computational techniques to examine recurring themes, lexical patterns, emotional shifts, narrative structures, and stylistic characteristics across extensive collections of literary works. This interdisciplinary field, commonly referred to as Digital Humanities or Computational Literary Studies, bridges computer science and literary criticism.

Among the various narrative strategies found in contemporary fiction, unreliable narration remains one of the most intellectually challenging. The concept of the unreliable narrator was introduced by literary theorist Wayne C. Booth in The Rhetoric of Fiction (1961). According to Booth, an unreliable narrator presents information that differs from the implied author's intended representation of reality. Such narrators may deliberately deceive readers, misunderstand events due to psychological limitations, distort memories, or present biased interpretations. As a result, readers must actively distinguish between factual events and the narrator's subjective version of reality.

Postmodern literature extensively employs unreliable narration as a means of questioning objective truth and exposing the instability of language and meaning. Unlike traditional realist novels, postmodern fiction often rejects linear storytelling and embraces fragmented narratives, multiple perspectives, metafiction, intertextuality, irony, and ambiguity. Authors intentionally blur the boundaries between fact and fiction, encouraging readers to become active participants in constructing meaning. Consequently, identifying unreliable narration becomes an essential aspect of interpreting postmodern novels.

Traditional literary analysis depends heavily on close reading, whereby scholars examine individual passages in detail to identify inconsistencies, symbolism, irony, and narrative perspective. While close reading remains indispensable, it becomes increasingly difficult when

researchers analyze large corpora consisting of hundreds or thousands of literary texts. Computational methods address this limitation by enabling automated analysis of linguistic features that may indicate unreliable narration. Algorithms can identify contradictions, shifts in sentiment, changes in vocabulary, inconsistent character references, and variations in narrative style that might otherwise escape immediate attention.

Natural Language Processing provides several techniques suitable for literary analysis. Tokenization divides text into words and sentences, allowing algorithms to process language systematically. Part-of-speech tagging identifies grammatical structures that reveal stylistic preferences. Named Entity Recognition detects references to characters, locations, and organizations, enabling researchers to track inconsistencies throughout a narrative. Sentiment analysis measures emotional fluctuations within the text, while topic modeling identifies recurring thematic patterns. Stylometric analysis compares vocabulary usage, sentence complexity, punctuation frequency, and lexical diversity to identify variations in narrative voice. Recent transformer-based language models further improve the ability to understand contextual relationships within literary texts.

The application of these techniques to unreliable narration represents an emerging area of research. Rather than determining whether a narrator is reliable in absolute terms, computational models identify linguistic indicators associated with uncertainty, contradiction, emotional inconsistency, and epistemic hesitation. For example, repeated use of modal verbs, hedging expressions, contradictory statements, sudden emotional reversals, or inconsistent references to events may collectively suggest unreliability. When visualized through computational mapping, these indicators reveal patterns that enrich literary interpretation.

Algorithmic ambiguity refers to the uncertainty encountered when computational systems interpret complex literary language. Unlike factual documents, literary texts intentionally employ metaphor, symbolism, irony, sarcasm, and ambiguity. Consequently, algorithms must distinguish between stylistic creativity and genuine inconsistency. This challenge highlights both the strengths and limitations of Artificial Intelligence in literary criticism. While machines excel at detecting statistical patterns, human readers remain indispensable for interpreting cultural, historical, and philosophical meanings embedded within literary works.

The interdisciplinary nature of this research reflects broader developments in Digital Humanities. Over the past two decades, universities worldwide have increasingly adopted computational methods for historical analysis, linguistic research, cultural studies, and literary scholarship. Researchers now employ machine learning algorithms to classify literary genres, identify authorship, reconstruct historical documents, and analyze narrative structures. These developments demonstrate that computational approaches complement rather than replace traditional humanities research.

This paper investigates how Natural Language Processing can be employed to identify and map unreliable narration within postmodern novels. It examines theoretical concepts of narrative unreliability alongside computational techniques used in NLP. By integrating literary criticism with computational linguistics, the study aims to demonstrate that algorithmic analysis offers

valuable insights into narrative ambiguity while recognizing the continued importance of human interpretation. Ultimately, the research contributes to ongoing discussions regarding the future of AI-assisted literary criticism and the evolving relationship between technology and the humanities.

The significance of this study extends beyond literary scholarship. As Artificial Intelligence increasingly influences education, publishing, digital archives, and cultural analysis, understanding its capabilities and limitations becomes essential. The findings of this research may assist literary scholars, linguists, digital humanists, and AI researchers in developing more sophisticated computational tools capable of interpreting complex narrative forms. Moreover, the study illustrates how interdisciplinary collaboration can generate innovative methodologies for exploring some of literature's most challenging questions concerning truth, memory, identity, and narrative reliability.

II. REVIEW OF LITERATURE

The study of unreliable narration has long been a significant area within narrative theory and literary criticism. The foundational work in this field is attributed to Wayne C. Booth in The Rhetoric of Fiction (1961), where he formally introduced the concept of the “unreliable narrator.” Booth argued that narrators may diverge from the implied author’s perspective, creating a gap between what is narrated and what is meant. This gap becomes central to interpretive reading, particularly in modernist and postmodern literature.

Subsequent theorists such as James Phelan expanded Booth’s framework by categorizing unreliable narration into various forms, including factual, interpretive, and evaluative unreliability. Phelan emphasized that unreliability is not merely a textual defect but a rhetorical strategy used to engage readers in deeper interpretive processes. Similarly, Ansgar Nünning introduced cognitive narratology approaches, suggesting that unreliability is often constructed through reader interpretation rather than being inherent in the text itself.

Postmodern literary theory further complicated the notion of narrative reliability. Scholars such as Linda Hutcheon and Brian McHale highlighted that postmodern texts deliberately destabilize truth claims through metafiction, fragmentation, and intertextuality. In such works, the boundary between reality and fiction is intentionally blurred, making the detection of reliable narration increasingly complex. Postmodern novels often resist definitive interpretation, instead encouraging multiplicity of meanings.

In parallel, developments in computational linguistics and Natural Language Processing (NLP) have transformed textual analysis. Early computational literary studies focused on stylometry, as demonstrated in authorship attribution research by Mosteller and Wallace (1964). Their statistical analysis of The Federalist Papers demonstrated that quantitative methods could successfully distinguish authorship based on linguistic patterns.

More recent research in Digital Humanities has expanded these methods significantly. Scholars such as Franco Moretti have advocated “distant reading,” where large-scale textual analysis

replaces close reading as a method for identifying macro-level literary patterns. Machine learning models and NLP tools have since been used to analyze sentiment, narrative structure, thematic evolution, and stylistic variation across corpora.

Transformer-based language models such as BERT and GPT architectures have further advanced computational text analysis by enabling contextual understanding of language. These models allow for deeper semantic interpretation, including detection of ambiguity, tone shifts, and contextual inconsistency. However, their application to literary ambiguity remains an emerging area of research.

Despite these advancements, limited research exists at the intersection of NLP and unreliable narration. Most computational studies focus on authorship attribution or genre classification, rather than narrative trustworthiness. This research gap highlights the need for interdisciplinary approaches that integrate narrative theory with computational methods.

III. RESEARCH PROBLEM

Postmodern literature frequently employs unreliable narration to challenge the stability of truth, memory, and perception. However, identifying such narrative unreliability remains largely subjective and dependent on close reading. There is a lack of systematic, computational frameworks that can assist in detecting linguistic and structural indicators of unreliable narration in literary texts.

The core problem addressed in this study is:

How can Natural Language Processing techniques be used to identify, analyze, and map unreliable narration in postmodern novels?

This problem also raises secondary concerns regarding the interpretability of algorithmic outputs, the limitations of machine understanding in literary contexts, and the role of human judgment in validating computational findings.

IV. RESEARCH OBJECTIVES

The primary objectives of this study are:

1. To examine the theoretical foundations of unreliable narration in literary criticism.
2. To explore the role of Natural Language Processing in computational literary analysis.
3. To identify linguistic features associated with narrative unreliability.
4. To analyze how NLP techniques can detect ambiguity and inconsistency in narrative texts.
5. To develop a conceptual framework for mapping unreliable narration using algorithmic tools.
6. To demonstrate the applicability of computational methods through selected postmodern novels.
7. To evaluate the limitations of NLP in interpreting literary ambiguity.

V. RESEARCH QUESTIONS

This study is guided by the following research questions:

1. What constitutes unreliable narration in postmodern literature?
2. Which linguistic and structural features indicate narrative unreliability?
3. How can NLP techniques detect shifts in tone, perspective, and consistency?
4. Can algorithmic tools meaningfully assist in identifying unreliable narration?
5. What are the limitations of computational approaches in literary interpretation?

VI. HYPOTHESIS

The study is based on the following working hypothesis:
Natural Language Processing techniques can identify measurable linguistic patterns of inconsistency, ambiguity, and emotional fluctuation that are associated with unreliable narration in postmodern novels, but they cannot fully replace human interpretive judgment.

VII. RESEARCH METHODOLOGY

This research adopts a qualitative-cum-computational analytical approach. It integrates traditional literary analysis with computational linguistic methods.

7.1 Research Design

The study is exploratory and interdisciplinary in nature, combining narrative theory with NLP-based textual analysis.

7.2 Data Collection

The primary data consists of selected postmodern novels known for unreliable narration. Secondary data includes scholarly articles, books, and computational linguistics research.

7.3 Analytical Tools (Conceptual Framework)

The following NLP techniques are considered for analysis:

- Sentiment Analysis: To detect emotional inconsistency across narrative segments.
- Stylometry: To analyze variation in vocabulary, sentence length, and linguistic style.
- Named Entity Recognition (NER): To track consistency of characters and events.
- Topic Modeling: To identify thematic shifts and fragmentation.
- Semantic Analysis: To detect contradictions and ambiguity in meaning.
- Transformer Models: To assess contextual coherence across narrative sequences.

7.4 Approach

The study does not rely on building a full software system but proposes a conceptual computational model that demonstrates how NLP can be applied to literary narratives.

VIII. SCOPE AND LIMITATIONS

Scope

This research focuses on postmodern novels that employ unreliable narration as a literary device. It explores how computational tools can assist in identifying narrative ambiguity and inconsistency.

Limitations

- NLP tools may misinterpret figurative language such as irony and metaphor.
- Algorithms lack cultural and philosophical interpretive capacity.
- The study is conceptual rather than fully experimental.
- Literary meaning cannot be fully reduced to computational patterns.
- Reliability detection remains probabilistic rather than definitive.

IX. THEORETICAL FRAMEWORK

This research is grounded in an interdisciplinary theoretical framework that combines narrative theory, postmodern literary criticism, and computational linguistics. The integration of these domains allows for a dual-layered interpretation of text: one rooted in humanistic interpretation and the other in algorithmic pattern recognition.

9.1 Narrative Theory and Unreliable Narration

The theoretical foundation of unreliable narration originates in Wayne C. Booth's concept of the implied author, which distinguishes between the narrator's voice and the authorial intention embedded in the text. Booth argues that narrators may be unreliable when their account conflicts with the norms of the implied author.

Later theorists such as James Phelan expanded this concept into a rhetorical model, emphasizing that unreliability is a communicative strategy designed to influence the reader's judgment. According to this view, unreliability is not simply "false narration," but a structured narrative effect created through gaps, contradictions, and interpretive tensions.

Ansgar Nünning further problematized the concept by arguing that unreliability is often reader-constructed, meaning that it depends on interpretive frameworks rather than objective textual markers. This shift is crucial for computational analysis because it raises the question of whether unreliability can be detected through linguistic data alone.

9.2 Postmodern Literary Theory

Postmodern literature challenges traditional notions of truth, coherence, and narrative authority. Scholars such as Linda Hutcheon describe postmodernism as "historiographic metafiction," where texts simultaneously construct and deconstruct historical and fictional realities.

Postmodern narratives are characterized by: Fragmented structure, Non-linear chronology, Metafictional commentary, Multiple narrative perspectives, Intertextuality, Epistemological uncertainty

These features intentionally destabilize meaning, making postmodern novels ideal sites for studying unreliable narration. In such texts, ambiguity is not a flaw but a deliberate aesthetic and philosophical strategy.

9.3 Computational Linguistics Framework

From a computational perspective, language is treated as a structured dataset that can be analyzed through statistical and algorithmic methods. NLP enables the transformation of narrative text into measurable linguistic features such as frequency distributions, syntactic patterns, and semantic embeddings.

The theoretical assumption underlying this study is that narrative unreliability leaves detectable linguistic traces, even if meaning remains interpretively open.

X. UNDERSTANDING ALGORITHMIC AMBIGUITY

Algorithmic ambiguity refers to the tension between human literary interpretation and machine-based textual analysis. While algorithms process language through probabilities and patterns, literature often operates through metaphor, irony, and symbolic ambiguity.

This creates three levels of interpretive conflict:

1. Lexical Ambiguity – Words with multiple meanings (e.g., “truth,” “memory,” “story”).
2. Structural Ambiguity – Unclear narrative sequencing or fragmented chronology.
3. Pragmatic Ambiguity – Meaning dependent on context, irony, or implied intention.

In postmodern novels, all three levels are frequently activated, making algorithmic interpretation both powerful and limited.

XI. NLP TECHNIQUES FOR DETECTING UNRELIABLE NARRATION

Natural Language Processing provides several computational tools that can be adapted for analyzing narrative unreliability.

11.1 Sentiment Analysis

Sentiment analysis evaluates emotional polarity (positive, negative, neutral) across textual segments. In unreliable narration, sentiment inconsistency can indicate psychological instability or narrative distortion.

For example:

- Sudden shifts from positive to negative tone without contextual cause
- Emotional contradictions regarding the same event
- Overly exaggerated emotional language

Such fluctuations may signal narrative instability.

11.2 Stylometry (Authorial Signature Analysis)

Stylometry examines measurable features of writing style, including:

- Average sentence length
- Vocabulary richness
- Frequency of function words
- Punctuation patterns

In unreliable narration, stylometric inconsistency within a single narrator may suggest shifts in identity, perspective, or psychological state.

11.3Named Entity Recognition (NER)

NER identifies and categorizes entities such as: Characters, Locations, Temporal references

Inconsistent entity references (e.g., changing descriptions of the same character or contradictory event timelines) may indicate unreliable narration.

11.4 Topic Modeling

Topic modeling (e.g., LDA – Latent Dirichlet Allocation) identifies hidden thematic structures within a text.

In postmodern novels:

- Sudden topic shifts may indicate fragmented consciousness
- Overlapping themes may reflect metafictional instability
- Disconnected narrative threads may signal epistemic uncertainty

11.5 Semantic Similarity and Contradiction Detection

Using word embeddings and transformer models, semantic similarity measures can detect contradictions within narrative statements.

Examples include:

- Conflicting descriptions of the same event
- Semantic opposition between adjacent narrative segments
- Inconsistency in character self-description

11.6 Transformer-Based Language Models

Modern transformer architectures such as BERT-based models enable contextual understanding of narrative sequences. These models can:

- Detect long-range inconsistencies
- Evaluate contextual coherence
- Identify shifts in narrative voice
- Compare semantic alignment across chapters

However, they still struggle with irony, satire, and metaphorical meaning.

XII. CONCEPTUAL MODEL: MAPPING UNRELIABLE NARRATION

This study proposes a conceptual framework for mapping unreliable narration using NLP:

Step 1: Text Segmentation
The novel is divided into narrative units (chapters, paragraphs, or events).
Step 2: Feature Extraction
Each unit is analyzed for: Sentiment score, Stylistic markers, Entity references, Thematic distribution, Semantic embeddings
Step 3: Consistency Analysis
Algorithms compare sequential and cross-referential consistency across narrative units.
Step 4: Ambiguity Index Calculation
A composite Narrative Ambiguity Index (NAI) is proposed:
NAI = (Sentiment variance + Entity inconsistency + Semantic contradiction + Stylistic deviation)
Step 5: Visualization
Results can be mapped as:

- Timeline graphs of emotional fluctuation
- Network diagrams of character inconsistency
- Heatmaps of semantic instability

XIII. APPLICATION TO POSTMODERN LITERATURE

Postmodern novels are particularly suitable for this framework because they intentionally destabilize narrative authority.
In such texts:

- Narrators often contradict themselves
- Events may be repeated with variations
- Memory is unreliable
- Truth is fragmented or subjective

Computational mapping does not resolve ambiguity but instead visualizes it, making interpretive instability measurable.

XIV. LIMITATIONS OF ALGORITHMIC INTERPRETATION

Despite advancements, NLP systems face fundamental limitations:

- Inability to fully understand irony and satire
- Dependence on training data bias
- Difficulty in interpreting philosophical ambiguity
- Reduction of literary meaning into quantifiable metrics
- Risk of over-formalizing artistic expression

Therefore, algorithmic analysis should be seen as complementary rather than authoritative.

XV. CASE STUDIES: NLP PERSPECTIVE ON UNRELIABLE NARRATION IN POSTMODERN NOVELS

To demonstrate the applicability of the proposed framework, selected postmodern novels are examined conceptually through NLP-based analytical lenses. The focus is not on building a computational system but on illustrating how algorithmic interpretation could reveal narrative ambiguity.

15.1 The Remains of the Day – Kazuo Ishiguro

The Remains of the Day

This novel presents a first-person narrator, Stevens, whose restrained emotional expression and rigid professionalism mask deeper psychological repression.

NLP Interpretation:

- Sentiment Analysis: Displays unusually flat emotional polarity despite emotionally charged events.
- Stylistic Markers: High frequency of formal, restrained vocabulary indicating emotional suppression.
- Semantic Gaps: Discrepancy between described events and implied emotional subtext.

Algorithmic Insight:

A narrative ambiguity index would likely show low emotional variance but high semantic contradiction, indicating concealed emotional unreliability.

15.2 Life of Pi – Yann Martel

Life of Pi

This novel explicitly presents two competing versions of survival at sea, challenging the reader to decide between truth and illusion.

NLP Interpretation:

- Topic Modeling: Dual thematic structures (realistic survival vs allegorical storytelling).
- Entity Inconsistency: Conflicting narrative referents for the same events.
- Semantic Divergence: Parallel narrative versions with contradictory factual claims.

Algorithmic Insight:

High entity inconsistency score and semantic divergence index, making it a strong candidate for algorithmic detection of narrative unreliability.

15.3 The Sense of an Ending – Julian Barnes

The Sense of an Ending

The narrator revises his memories over time, revealing the instability of retrospective interpretation.

NLP Interpretation:

- Temporal inconsistency detection: Contradictory memory sequences.
- Sentiment drift: Emotional reinterpretation of past events.

- Semantic revision patterns: Changes in meaning across narrative stages.

Algorithmic Insight:
High temporal inconsistency index, suggesting memory-based unreliability rather than intentional deception.

15.4 Lolita – Vladimir Nabokov
Lolita
Humbert Humbert's narration is highly rhetorical, persuasive, and morally distorted.
NLP Interpretation:

- Sentiment distortion: Romanticized language applied to morally problematic actions.
- Rhetorical exaggeration: High density of persuasive linguistic markers.
- Semantic misalignment: Conflict between language tone and ethical interpretation.

Algorithmic Insight:
High rhetorical manipulation score, indicating persuasive but ethically distorted narration.

XVI. FINDINGS AND DISCUSSION

The computational interpretation of unreliable narration reveals several key findings:
16.1 Detectable Linguistic Patterns Exist
NLP techniques can identify measurable indicators such as:

- Emotional inconsistency
- Stylistic variation
- Semantic contradiction
- Entity misalignment

These patterns often correlate with unreliable narration.

16.2 Unreliability is multi-dimensional
Unreliable narration is not a single feature but a combination of:

- Psychological unreliability
- Memory distortion
- Intentional deception
- Philosophical ambiguity

Algorithms can detect signals but cannot classify meaning without interpretive context.

16.3 Postmodern Texts Amplify Algorithmic Difficulty
Postmodern literature deliberately disrupts:

- Linear narrative structure
- Stable meaning systems
- Fixed character identities

This increases algorithmic ambiguity and reduces classification certainty.

16.4 NLP as Interpretive Support, Not Replacement

Computational tools function best as:

- Pattern detectors
- Visualization systems
- Analytical assistants

Human interpretation remains essential for final meaning construction.

XVII. CONCLUSION

This research demonstrates that Natural Language Processing offers a promising but limited framework for analyzing unreliable narration in postmodern literature. While computational tools can identify linguistic patterns associated with ambiguity, contradiction, and narrative instability, they cannot fully interpret literary meaning.

The concept of algorithmic ambiguity highlights the intersection between machine interpretation and human literary analysis. Postmodern novels intentionally resist fixed meaning, and this resistance challenges computational models that rely on statistical regularity.

Therefore, the integration of NLP into literary studies should be understood as an expansion of interpretive possibilities rather than a replacement of traditional criticism. The future of literary analysis lies in hybrid methodologies that combine computational precision with humanistic depth.

XVIII. FUTURE SCOPE

Future research may focus on:

- Training domain-specific NLP models for literary texts
- Developing irony and metaphor detection systems
- Building narrative reliability scoring frameworks
- Applying deep learning to full novel-scale analysis
- Creating interactive digital humanities visualization tools

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