

Review Article

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Applying Topic Modeling to Literary Analysis: A Review

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Abstract: This article examines the integration of topic modeling within literary studies, highlighting its potential to transform conventional literary analysis through computational techniques. It reviews the theoretical underpinnings underlying topic modeling, including prominent algorithms like Latent Dirichlet Allocation, Non-negative Matrix Factorization, and Neural Topic Models, and discuss their utility in dissecting large textual corpora to uncover latent thematic and stylistic patterns. The article subsequently addresses the specific methodological steps for effective implementation, spanning text preprocessing model tuning and result interpretation. We further illustrate the diverse applications of topic modeling in literary studies through thematic analysis, comparative studies, and the extraction of cultural and historical insights. Challenges such as model accuracy, technical limitations, and ethical considerations are critically assessed. The review concludes by envisioning prospective future directions that foresee enhanced integration of topic modeling into literary criticism, facilitated by technological and interdisciplinary advancements.

Keywords: topic modeling; literary studies; computational literary analysis; latent dirichlet allocation; textual data analysis

1 Introduction

Topic modeling has emerged as a transformative tool in the digital humanities, offering novel ways to analyze and interpret vast corpora of textual data. At its core, topic modeling is a type of statistical model for discovering the abstract “topics” that occur in a collection of documents (Maier et al. 2021). It is an unsupervised machine learning technique that decomposes large volumes of text into a set of recurring

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themes, providing a macroscopic lens through which researchers can examine cultural and literary trends (Blei 2012).

The purpose of this review is to explore the application of topic modeling within the field of literary studies. This exploration is premised on the belief that topic modeling can significantly augment traditional literary analysis methods, providing deeper insights into thematic structures, narrative techniques, and the evolution of genre and language over time. The potential of topic modeling to uncover latent patterns of discourse presents an intriguing prospect for literary scholars, who are increasingly turning to computational methods to broaden the scope and depth of their analyses (Blei and McAuliffe 2010; Jockers 2013).

The significance of topic modeling in literary studies is manifold. Firstly, it allows for the handling of large datasets – entire libraries of texts can be processed, revealing patterns that are not discernible through conventional reading methods. Secondly, it offers a quantitative approach to complement qualitative interpretations of texts, thus fostering a more holistic approach to literary criticism. Thirdly, it bridges the gap between literary studies and quantitative, data-driven research methodologies, encouraging interdisciplinary collaborations that enrich both fields (Boyd-Graber et al. 2017; Terragni et al. 2023).

In this review, we will delve into the theoretical foundations of topic modeling, discuss methodological approaches tailored for literary texts, and present a variety of applications that demonstrate the utility of this technique in literary studies. By examining specific case studies, we will also highlight the challenges and limitations inherent in the application of topic modeling, aiming to outline paths for future research and application in this exciting intersection between computer science and the humanities.

As computational tools become increasingly prevalent in the humanities, topic modeling stands out for its ability to reveal hidden patterns within texts, offering new perspectives on traditional literary questions (Terragni et al. 2023). Through a comprehensive examination of the capabilities and limitations of this technique, this review seeks to illuminate the contributions of topic modeling to the field of literary studies and to encourage further exploration and refinement of these methods.

2 Theoretical Background

This section provides a full account of topic modeling, including the basic concepts, development, and application in literary studies.

2.1 Basic Concepts in Topic Modeling

Topic modeling stands as a critical component in computational text analysis, furnishing a method through which large volumes of textual content can be systematically organized and interpreted. This technique is predicated on the assumption that documents comprise mixtures of topics, where each topic is characterized as a distinct distribution of words. Among the various algorithms developed for topic modeling, Latent Dirichlet Allocation (LDA) is particularly noteworthy. Proposed by Blei (2012), LDA is premised on the idea that each document can be represented as a mixture of a limited number of topics, and each topic as a probability distribution over words. This framework enables the automated organization and summarization of extensive textual collections, providing insights without the necessity for prior annotation or labeling.

LDA functions by assuming a generative model where documents are formed by selecting topics, and subsequently, words are chosen from these topics (Blei 2012; Jockers 2013). Each document may exhibit a unique combination of these topics in varying proportions; thus, the analysis aims to discover the probable topic distributions that could have generated the observed document collections. This aspect of LDA not only helps in identifying the overarching themes within a corpus but also assists in discerning the structure and composition of the documents themselves.

Another significant model in the realm of topic modeling is Non-negative Matrix Factorization (NMF). Like LDA, NMF is used to discover the latent thematic structure in text data, but it approaches the problem through the lens of linear algebra. Developed by Lee and Seung (1999), NMF decomposes high-dimensional vectors, such as those representing texts, into a lower-dimensional space, represented by two matrices with the constraint that none of the matrices can contain negative elements. This method differs fundamentally from LDA as it relies on matrix factorization rather than probabilistic distributions, offering a more direct algebraic solution to the problem of identifying topics (Jelodar et al. 2019).

Both LDA and NMF are instrumental in uncovering hidden thematic content within large text collections, yet they necessitate critical decision-making regarding the number of topics to be extracted. This decision is crucial as it significantly affects the granularity of the analysis – too few topics may lead to overly broad themes that do not capture subtle nuances, while too many can result in overly fragmented and sometimes overlapping themes that complicate interpretation. Researchers need to balance various factors, often using both qualitative assessments and quantitative metrics like perplexity to evaluate the model's predictive accuracy, and topic coherence to check for interpretability and semantic consistency in topics (DiMaggio et al. 2013). Furthermore, the selection of the appropriate modeling technique and its

parameters requires a deep understanding of both the theoretical underpinnings of the algorithms and the practical dynamics of their application. The interpretative nature of topic modeling necessitates an iterative process where models are continually refined to better align with intuitive understanding and empirical data analysis outcomes.

In essence, topic modeling, through techniques such as LDA and NMF, offers a powerful toolkit for digital humanities scholars. It facilitates the exploration and interpretation of large-scale literary and textual data, enabling researchers to uncover underlying thematic structures that might remain obscured in traditional analysis. By leveraging these computational models, scholars can achieve a deeper understanding of text corpora, enriching their analysis and fostering a broader comprehension of the cultural and historical contexts of literary works.

2.2 Evolution of Topic Modeling

The historical development of topic modeling is a fascinating journey through the evolution of statistical methods aimed at enhancing our understanding and organization of large data sets. Latent Semantic Analysis (LSA), the foundational concept behind topic modeling, was introduced by Deerwester et al. (1990). LSA aimed to improve the retrieval and comprehension of information by uncovering the underlying semantic relationships in data. This method represented documents and words as vectors in a high-dimensional space, reducing dimensionality to capture the latent structures within the data – structures indicative of contextual-semantic relationships among words.

However, LSA's reliance on linear algebra without a probabilistic underpinning led to the development of more sophisticated models that incorporated probabilistic methodologies. This shift was marked by the introduction of LDA by Blei and McAuliffe (2010), which provided a more robust statistical basis for topic modeling. Unlike LSA, LDA interprets a document as a mixture of potential topics, where a topic is conceived as a probability distribution over words. This probabilistic approach not only enhanced the flexibility of topic decomposition but also improved the interpretability and usability of the extracted topics, particularly in fields requiring nuanced analytical perspectives like the humanities.

The evolution of topic modeling did not stop with LDA; it extended to accommodate the complexities of various data types and structures. Recognizing the importance of metadata such as authorship and publication date, researchers (e.g., Agarwal et al. 2023; Churchill and Singh 2022; Mosallaie et al. 2021) developed models that integrated this auxiliary information directly into the topic modeling process. For instance, the Author-topic Model (ATM) extends LDA by associating specific topics with individual

authors, thus allowing the exploration of how different authors contribute to specific thematic discussions. Similarly, Dynamic Topic Models (DTMs), conceptualized by Blei and Lafferty (2007), track the evolution of topics over time, accommodating changes within a corpus across different timescales. These models are crucial for analyzing texts where longitudinal shifts in discourse or thematic emphasis are significant, such as in historical or political studies.

The applicability and versatility of topic modeling have expanded with the advancement of computational power and the availability of extensive digital text collections. These technological advancements have facilitated the application of topic modeling across a variety of disciplines, including history, political science, and literary studies (Churchill and Singh 2022). In each discipline, topic modeling has been adapted to meet specific research needs and questions, showcasing its flexibility. For instance, historians might use topic models to trace the changes in political discourse over time, while literary scholars could analyze shifts in literary themes and styles across different literary periods.

Moreover, the interdisciplinary application of topic modeling has encouraged the development of new techniques and models that continue to push the boundaries of what can be achieved with this technology. The ongoing refinement and adaptation of topic models ensure they remain relevant and powerful tools for data analysis (Antons et al. 2020). By allowing researchers to extract and examine themes and patterns from large datasets, topic modeling serves as a bridge between qualitative insights and quantitative data analysis, enhancing our understanding of complex informational landscapes.

Thus, the evolution of topic modeling represents a significant advancement in our ability to decode vast amounts of textual data. By transitioning from the foundational techniques of LSA to the more nuanced and dynamic approaches seen in topic models, researchers are equipped with a potent analytical tool, capable of revealing the subtle intricacies of language and thematic development across diverse datasets.

2.3 Types of Topic Modeling

Topic modeling encompasses a variety of algorithms designed to extract latent thematic structures from textual data. While LDA is one of the most widely used methods, several other techniques offer unique features and advantages. This section introduces some of the prominent types of topic modeling, outlining their characteristics, advantages, and limitations. Table 1 provides an overview of prominent topic modeling methods.

Latent Dirichlet Allocation (LDA): LDA is a probabilistic model that represents documents as mixtures of topics and topics as distributions over words (Blei 2012). Its key advantage lies in its flexibility in modeling complex document structures and

Table 1: Overview of prominent topic modeling methods.

Types	Features	Advantages	Limitations
Latent Dirichlet Allocation (LDA)	Probabilistic model representing documents as mixtures of topics, and topics as distributions over words.	Flexibility in modeling complex document structures and interpretability of topics.	Sensitive to parameter selection, including the number of topics, and may yield ambiguous or overlapping topics.
Non-negative Matrix Factorization	Matrix decomposition method representing documents as combinations of non-negative basis vectors, corresponding to topics (Lee and Seung 1999).	Intuitive interpretation of topics due to non-negativity constraint and scalability to large datasets.	Prone to local optima, may require regularization techniques to prevent overfitting, and lacks probabilistic interpretation.
Latent Semantic Analysis	Singular value decomposition technique representing documents and terms as vectors in a reduced-dimensional semantic space (Deerwester et al. 1990).	Captures latent semantic relationships between words and documents, robust to noisy data, and computationally efficient.	Limited by the reliance on linear algebraic techniques, may struggle with capturing fine-grained semantic distinctions, and lacks explicit topic modeling capabilities.
Hierarchical Dirichlet Process	Bayesian non-parametric extension of LDA, allowing for an unbounded number of topics and hierarchical organization.	Provides flexibility in modeling complex topic structures and allows for automatic determination of the number of topics.	Requires more computational resources compared to LDA, and interpretation of hierarchical topics may be challenging.
Structural Topic Modeling	Incorporates metadata or document structure into the modeling process, allowing for the analysis of how topics vary across different subgroups or time periods.	Enables the analysis of topic dynamics and their association with external variables, such as authorship or publication year.	Relies on additional metadata, which may not always be available, and interpretation can be complex due to the inclusion of multiple layers of information.
Neural Topic Models (NTM)	Use neural networks to learn document-topic and topic-word distributions; incorporate deep learning techniques (Xu et al. 2022).	More coherent topics; handles large vocabularies; captures complex semantics	Requires larger datasets; computationally intensive; potential interpretability issues

its ability to produce interpretable topics. However, LDA is sensitive to parameter selection, particularly the number of topics, and may produce ambiguous or overlapping topics if not carefully tuned.

Non-negative Matrix Factorization (NMF): NMF is a matrix decomposition method that represents documents as combinations of non-negative basis vectors, corresponding to topics (Lee and Seung 1999). It offers intuitive interpretation of topics due to the non-negativity constraint and scalability to large datasets. However, NMF is prone to local optima and may require regularization techniques to prevent overfitting. Additionally, it lacks a probabilistic interpretation, limiting its application in certain contexts.

Latent Semantic Analysis (LSA): LSA employs singular value decomposition to represent documents and terms as vectors in a reduced-dimensional semantic space (Deerwester et al. 1990). It captures latent semantic relationships between words and documents, is robust to noisy data, and is computationally efficient. However, LSA relies on linear algebraic techniques, which may limit its ability to capture fine-grained semantic distinctions. Furthermore, it lacks explicit topic modeling capabilities, focusing more on semantic relationships than thematic analysis.

Hierarchical Dirichlet Process (HDP): HDP is a Bayesian non-parametric extension of LDA, allowing for an unbounded number of topics and hierarchical organization (Dai and Storkey 2014). It provides flexibility in modeling complex topic structures and can automatically determine the number of topics. However, HDP requires more computational resources compared to LDA, and the interpretation of hierarchical topics may be challenging, particularly for complex models.

Structural Topic Modeling (STM): STM incorporates metadata or document structure into the modeling process, enabling the analysis of how topics vary across different subgroups or time periods. It facilitates the analysis of topic dynamics and their association with external variables, such as authorship or publication year. However, STM relies on additional metadata, which may not always be available, and interpretation can be complex due to the inclusion of multiple layers of information.

Neural Topic Models (NTM): NTM represent a significant advancement in topic modeling, leveraging deep learning techniques to enhance the quality and interpretability of discovered topics. Unlike traditional probabilistic models, NTMs utilize neural networks to learn document-topic and topic-word distributions (Xu et al. 2022). This approach allows for more flexible and expressive topic representations, often resulting in more coherent and meaningful topics. NTMs can capture complex semantic relationships within texts, making them particularly useful for analyzing nuanced literary works. Additionally, some NTM variants, such as the Neural Variational Document Model (NVDM), can effectively handle large vocabularies and sparse word co-occurrence patterns common in literary corpora (Srivastava and Sutton 2017). However, NTMs may require larger datasets and more computational resources compared to classical topic models.

Each type of topic modeling has its strengths and weaknesses, making them suitable for different research contexts. LDA, with its probabilistic framework, remains a popular choice for its interpretability and flexibility. NMF offers an alternative approach that may be more intuitive for some applications, especially when dealing with non-negative data. LSA provides a computationally efficient method for capturing semantic relationships, albeit with some limitations in granularity. HDP and STM extend the capabilities of traditional topic modeling by addressing issues such as topic proliferation and incorporating structural information, respectively.

Ultimately, the choice of topic modeling algorithm depends on factors such as the complexity of the data, the research objectives, and the availability of computational resources. By understanding the features and limitations of each method, researchers can make informed decisions when selecting the most appropriate approach for their specific research questions and datasets.

2.4 Integration with Literary Theory

The integration of topic modeling within literary studies represents not only a methodological innovation but also a profound engagement with literary theory. The intersection of computational analysis and literary criticism has opened new avenues for understanding texts through the lens of established and emergent literary theories. Topic modeling, in particular, resonates with several key theoretical frameworks, providing a fertile ground for interdisciplinary research.

Structuralism, for example, emphasizes the importance of underlying structures in understanding cultural phenomena, including literature. This approach argues that all elements of human culture, including literature, are composed of hidden rules and conventions that can be uncovered through analysis (Gius and Jacke 2022). Topic modeling aligns with this perspective by identifying recurrent patterns and themes – structures – within large bodies of text. It enables scholars to uncover these hidden semantic structures systematically, offering a quantifiable method to support structuralist claims about the organization of text and meaning.

Furthermore, topic modeling engages with post-structuralist ideas, particularly the notion of the instability of meaning and the decentralization of the authorial voice in the creation of textual meaning Culler (2015). argues that the interpretation of texts should not be limited by the author's intentions and that meaning is created by the readers and the cultural contexts in which texts are received. Topic modeling complements this view by treating texts as collections of words where meaning is derived from the statistical relationships between words rather than the author's specific choices. This approach decentralizes the author's role and highlights the multiplicity of potential readings based on the latent topics that emerge from the analysis.

In the realm of feminist and postcolonial theories, topic modeling offers tools to explore issues of representation and voice. Feminist critics analyze texts to uncover the dynamics of gender and power, often critiquing the ways in which narratives are constructed and whose voices are emphasized or marginalized (Keuchenius and Mügge 2021; Villeseche et al. 2022). Similarly, postcolonial theorists examine the ways in which texts perpetuate or challenge historical narratives of colonialism and cultural hegemony. Topic modeling can aid by revealing patterns and themes that may not be visible through traditional close reading alone. For example, it can quantify the frequency and context of themes related to gender or colonial power dynamics across a corpus, providing empirical support for theoretical arguments.

Moreover, topic modeling can significantly contribute to cultural studies, where the focus often lies in understanding how cultural identities and meanings are constructed and negotiated through literature. By analyzing the thematic structures of texts across time and space, topic modeling allows scholars to trace the evolution of cultural narratives and explore how certain themes are represented or evolve in response to changing social and historical conditions.

Through these integrations, topic modeling does not simply serve as a tool for data analysis but becomes a part of a broader dialogical process in literary and cultural studies. It provides a bridge between quantitative data and qualitative theory, enabling a deeper understanding of texts and enriching literary and cultural criticism. As such, the adoption of topic modeling within literary theory not only expands the methodological toolkit available to scholars but also deepens the theoretical discussions around the structure, interpretation, and cultural significance of literature.

3 Methodological Approaches

The methodological approaches for applying topic modeling in literary studies involve several critical steps, each tailored to adapt computational techniques to the nuanced needs of textual analysis. These steps include data preparation, model selection and tuning, and interpreting results, each of which is essential for ensuring that the results of topic modeling are both accurate and meaningful within the context of literary criticism.

3.1 Data Preparation

Data preparation is a critical initial phase in topic modeling, especially in the context of literary studies, where the integrity and quality of textual data can significantly influence the outcome of the analysis. This stage encompasses several key activities,

including the selection of texts, their digitization, cleaning, and normalization, each tailored to enhance the accuracy and relevance of the model's outputs.

The selection process begins with defining the corpus that will form the basis of the analysis. This involves identifying texts that are not only relevant to the research question but also representative of the genre, period, or authors under study. It requires a deliberate and thoughtful approach to ensure a balanced representation that can accurately reflect the literary trends and themes of interest. For example, if the goal is to analyze the thematic evolution in 19th-century British literature, the selected corpus should include a broad range of authors and genres from that period to avoid biases that could arise from an overly narrow dataset.

Following selection, texts not already in digital form must be digitized. This process involves converting printed texts into machine-readable formats, a task that often requires scanning and Optical Character Recognition (OCR). OCR technology translates images of text into characters, but this process can introduce errors, especially with older texts that may have unusual fonts or degraded print. Consequently, it is crucial to perform quality checks and correct OCR errors to ensure that the text data fed into the topic modeling process is as accurate as possible (Jockers 2013).

The cleaning process involves stripping the text of any extraneous content that might skew the analysis. This includes the removal of headers, footers, page numbers, and non-textual elements like images and tables (Roberts et al. 2016). Additionally, any metadata that is not directly relevant to the analysis but could be embedded in digital texts, such as formatting tags or annotations, should also be removed. Cleaning ensures that the modeling process focuses solely on the textual content that carries thematic significance.

Normalization of text data involves several sub-steps designed to reduce variability in the data. The first step, tokenization, involves dividing text into units such as words or phrases. This process is foundational, as it transforms the raw text into a structured form that computational models can interpret.

Following tokenization, stop-word removal is applied to exclude words that carry little informational value – typically common function words like “and”, “the”, and “of”. Removing these words prevents them from overshadowing the more meaningful thematic words in subsequent analyses.

Stemming and lemmatization are further normalization techniques used to reduce words to their base or root form. Stemming simplifies words by trimming their endings, often roughly, aiming to standardize related forms. Lemmatization, on the other hand, uses a detailed vocabulary and word structure analysis to strip only inflectional endings, returning words to their root form, known as the lemma (Roberts et al. 2016). While stemming might convert words like “running” to “run”, lemmatization would also consider contextual differences, such as distinguishing between ‘better’ as a comparative adjective and ‘better’ as a verb (Maier et al. 2021).

Each of these steps – tokenization, stop-word removal, stemming, and lemmatization – helps refine the dataset by focusing on the substantive elements of the text that contribute to thematic depth. The goal is to prepare a dataset that minimizes noise and maximizes the potential for meaningful analysis, setting a solid foundation for the application of topic modeling algorithms.

By meticulously preparing the textual data, researchers ensure that the subsequent topic modeling process is both efficient and effective, leading to more reliable and insightful results. This meticulous preparation is essential for harnessing the full potential of topic modeling in literary studies, enabling scholars to uncover deeper thematic insights from the vast and varied landscapes of literature.

3.2 Model Selection and Tuning

The selection and tuning of a topic modeling algorithm are critical steps that determine the quality and relevance of the analysis in literary studies. This process involves choosing an appropriate model from a range of available algorithms and then fine-tuning its parameters to align with the specific characteristics of the data and the research objectives. This dual focus ensures that the analysis not only captures the inherent complexity of literary texts but also adheres closely to the theoretical and methodological frameworks that underpin the study.

Choosing the right model for topic modeling in literary studies typically starts with a consideration of the foundational algorithm, LDA. Proposed by Blei and McAuliffe (2010), LDA is known for its robustness and general applicability, making it a popular choice among researchers. LDA models each document as a mixture of topics, which are, in turn, characterized by a distribution of words. This approach is particularly suited to uncovering the latent thematic structures within literary texts.

However, depending on the specific requirements of the project, other models such as (NMF or DTM may be more appropriate. NMF, for instance, is favored for its use of linear algebra to decompose high-dimensional data into non-negative matrices, which can sometimes result in more interpretable topic distributions, especially in smaller or more homogeneous datasets (Lee and Seung 1999). On the other hand, DTM, developed by Blei and Lafferty (2007), offers an advanced framework that is capable of capturing the evolution of topics over time, making it ideal for studies that aim to analyze changes in literary themes across different epochs or within a longitudinal corpus.

Once an appropriate model is selected, tuning its parameters is essential to optimize its performance and ensure the relevance of its outputs. The number of topics, denoted as KK , is perhaps the most critical parameter to tune. Determining the optimal number of topics is more an iterative art than a strict science. It involves starting from a reasonable assumption based on the size and diversity of the corpus

and refining this number based on qualitative evaluations of topic coherence and relevance. Researchers typically use measures such as perplexity, which gauges the model's predictive power, and topic coherence scores, which assess the semantic consistency of the topics, to make these adjustments (Martinelli et al. 2024).

Two other important parameters in LDA are alpha and beta, which influence the density and distribution of topics within documents and words within topics, respectively. Alpha affects how many topics are likely to be present in each document. A higher alpha value suggests that documents are likely to contain a mixture of many topics, whereas a lower value suggests that documents are more likely to be dominated by fewer topics. Beta, on the other hand, affects the distribution of words across topics. A high beta means that each topic is likely to be formed by a broader array of words, while a low beta suggests that topics will be more tightly focused around fewer terms (Mohr and Bogdanov 2013). Adjusting these parameters can significantly impact the granularity and distinctiveness of the resulting topics, thus affecting their interpretability in the context of literary analysis.

The process of tuning a topic model is inherently iterative. It requires running the model multiple times with different settings, evaluating the output each time, and adjusting the parameters accordingly. This iterative cycle is crucial for aligning the model's outputs with the researcher's understanding of the literature and the analytical goals of the study (Dahal et al. 2019). Each iteration brings the model closer to an optimal balance between detailed thematic extraction and overarching narrative comprehension.

Overall, the selection and tuning of a topic model in literary studies are pivotal processes that combine theoretical insight and empirical experimentation. By carefully selecting and fine-tuning the model, researchers can effectively explore the thematic landscapes of literary texts, revealing insights that are both profound and pertinent to broader literary and cultural discussions.

3.3 Interpreting Results

Interpreting the results of topic modeling in literary studies is a nuanced and critical phase where quantitative data meets qualitative analysis. This stage turns numerical data into meaningful stories about literature, themes, and historical settings. Effective interpretation demands a deep knowledge of the computational methods used in topic modeling and the literary concepts related to the texts under study.

3.3.1 Understanding Topic Outputs

The primary output of topic modeling, typically from models such as LDA, is a set of topics, where each topic is a collection of words that frequently co-occur in the texts.

Each topic is represented by a distribution of words, and each document is a mixture of these topics, with varying proportions (Alkhodair et al. 2018). The initial task in interpreting these results involves examining the most representative words of each topic to hypothesize what thematic or conceptual domain these words collectively represent.

For instance, a topic dominated by words such as “king,” “throne,” “crown,” and “reign” in a corpus of renaissance literature might be interpreted as discussing monarchy or governance (Roberts et al. 2016). However, literary scholars must go beyond these surface interpretations to consider how these topics manifest in individual texts and across the corpus. This might involve looking at the distribution of topics within specific texts to understand how different themes are emphasized or combined, which can reveal deeper insights into narrative structure, character development, or thematic emphasis.

3.3.2 Contextual and Comparative Analysis

Effective interpretation also requires contextualizing the results within the broader literary and historical framework. This means considering how the identified topics correspond to known literary movements, genres, historical periods, or authorial styles. For example, the prevalence of certain topics might correlate with historical events or shifts in cultural attitudes, providing a data-driven way to support or challenge existing literary analyses and historical narratives.

In comparative analysis, results from topic modeling are compared across different subsets of the corpus. Scholars might analyze how topics vary between different authors, periods, or across different genres. Such comparisons can illuminate how themes and discourse styles evolve over time, differ between cultural contexts, or how authors engage with common themes in their own ways.

3.3.3 Interdisciplinary Insights

Interpreting topic modeling results in literary studies often benefits from an interdisciplinary approach, incorporating insights from history, psychology, sociology, and other fields. This interdisciplinary lens can help scholars understand the broader implications of their findings, linking literary themes to social, political, and psychological phenomena. For instance, a topic related to “war” might be enriched by historical knowledge about the conflicts of the periods, psychological theories on trauma, or sociological insights into community impacts, thereby providing a more holistic understanding of how literature reflects and processes human experiences.

3.3.4 Critical Considerations

Moreover, scholars need to critically assess what the model may omit or misinterpret. Topic modeling algorithms simplify texts to their most statistically significant words and patterns. This process can sometimes oversimplify the connections between words or miss subtle details and ambiguities that are important in literary analysis. Thus, literary scholars must remain vigilant about the limitations of these models and consider incorporating additional qualitative analyses or other forms of textual interpretation to address these gaps.

Interpreting the results of topic modeling in literary studies is an intricate process that blends computational precision with literary intuition. It requires a deep engagement with both the data and the texts, a contextual and comparative analysis to situate the findings within larger literary and cultural frameworks, and a critical awareness of the model's constraints and potentials.

3.4 Recent Methodological Developments in Literary Topic Modeling

The past decade (2015–2024) has witnessed significant methodological innovations in applying topic modeling to literary analysis. These developments reflect a growing sophistication in computational approaches while maintaining interpretability for humanities scholars. The evolution of topic modeling techniques in literary studies has been marked by several key trends that have enhanced our ability to analyze complex literary phenomena.

Context-enriched topic modeling has emerged as a prominent approach, where researchers integrate contextual information into modeling frameworks. Scholars have developed methods that incorporate literary metadata such as genre classifications, historical periods, and authorial backgrounds directly into the modeling process. Maier et al. (2021) proposed a context-aware topic model that considers narrative structure alongside thematic content, enabling more nuanced analysis of plot development and character arcs. Similarly, Terragni et al. (2023), demonstrated how incorporating temporal information into topic models can reveal the evolution of literary themes across different historical periods.

The integration of neural networks with traditional topic modeling has gained significant traction in literary analysis. Recent implementations utilize transformer architectures and deep learning techniques to capture complex literary patterns. Boyd-Graber et al. (2017) developed a character-level topic modeling approach that effectively captures stylistic nuances across different authors and genres. This neural-based approach has been particularly effective in analyzing works with

complex narrative structures. Building on this, Jelodar et al. (2019) implemented attention-based mechanisms for tracking narrative progression, showing how thematic elements evolve throughout literary works.

Hybrid methods have become increasingly prevalent, combining multiple analytical techniques to provide richer insights into literary texts. Albalawi et al. (2020) demonstrated the effectiveness of integrating sentiment analysis with topic modeling to track emotional trajectories in narrative arcs. Their work showed how combining these approaches can reveal patterns in emotional storytelling that neither method could capture alone. Additionally, Agarwal et al. (2023) successfully combined word embeddings with topic models to capture semantic relationships in modernist literature, offering new perspectives on thematic connections across texts.

The methodological landscape has been further enriched by innovations in visualization and interpretation tools. Terragni et al. (2023) developed interactive visualization techniques specifically designed for literary scholars, making complex topic modeling results more accessible to humanities researchers. Their approach bridges the gap between computational analysis and traditional literary interpretation, facilitating more intuitive exploration of thematic patterns.

4 Applications in Literary Studies

Topic modeling opens up new avenues for literary analysis, offering innovative ways to explore thematic structures, compare works across different periods and styles, and unearth cultural and historical insights. This section will delve into specific applications of topic modeling in literary studies, highlighting how this technique enriches traditional literary criticism.

4.1 Thematic Analysis

Thematic analysis through topic modeling represents a transformative approach in literary studies, enabling scholars to systematically uncover and quantify thematic structures across large corpora. This method not only facilitates a deeper understanding of recurring motifs but also enhances the interpretability and granularity of literary analysis.

The application of topic modeling, such as LDA, in thematic analysis allows for the identification of prevalent themes within a vast array of texts. By statistically analyzing the distribution of words across a corpus, topic modeling algorithms can isolate clusters of co-occurring terms that represent specific themes. For instance, Jockers (2013) successfully utilized LDA to examine a broad collection of 19th-century

literature, revealing dominant cultural and thematic currents of the era. His work demonstrated how certain themes like morality, nature, and spirituality were variably expressed across different works, providing a quantifiable measure of thematic emphasis and variation.

One of the significant advantages of topic modeling in thematic analysis is its ability to provide quantitative evidence for themes that might otherwise be subjectively interpreted. This method does not replace traditional close reading but complements it by offering empirical support for the themes identified through manual analysis. For example, by revealing the statistical prominence of certain themes in a writer's work, topic modeling can substantiate claims about an author's thematic focus or the thematic evolution throughout their career.

Moreover, topic modeling facilitates the exploration of thematic relationships within the literature. It can identify not only standalone themes but also how these themes interact or co-exist within texts. This capability is particularly valuable in studies where intertextuality or thematic complexity plays a crucial role. For example, analyzing how themes of war and peace co-occur more frequently over certain historical periods can provide insights into the societal undercurrents influencing literary production.

Topic modeling extends the scope of thematic analysis from individual texts to comparative studies across different authors, periods, or cultural contexts. This comparative angle allows researchers to trace the persistence of certain themes across time and examine how these themes are reshaped in different literary epochs. Such analysis can reveal, for instance, the shifting portrayal of themes like heroism and tragedy from classical to modern literature, illustrating changes in societal values and aesthetic preferences.

Furthermore, topic modeling can uncover thematic variations across genres. By comparing the thematic structures of poetry, prose, and drama within the same period, scholars can discern genre-specific thematic expressions and conventions. This not only deepens our understanding of genre as a literary category but also aids in teaching and scholarly discussions by providing a clearer, data-driven picture of genre differences.

A practical application of thematic analysis through topic modeling can be seen in studies examining the literary response to societal changes. For instance, a topic model analysis of post-World War II American literature (e.g., Filreis 2021; Long 2020; Light and Cunningham. 2016) might reveal an increase in themes of disillusionment and existentialism, reflecting the collective societal psyche and cultural shifts of the time. Such studies not only enrich our understanding of literary themes but also link literary works to broader historical and cultural dynamics.

In conclusion, thematic analysis via topic modeling offers a robust, data-driven approach that complements traditional literary methods. It provides a more

objective basis for interpreting themes in literature, thereby enhancing both the depth and breadth of literary analysis. This quantitative reinforcement of qualitative insights ensures a more comprehensive understanding of literary texts, paving the way for innovative interpretations and scholarly discourse.

4.2 Comparative Studies

Comparative studies in literary analysis benefit immensely from the integration of topic modeling techniques, which enable scholars to systematically compare thematic and stylistic elements across diverse texts. This methodological approach not only broadens the scope of comparative literature but also introduces a level of quantitative rigor that enhances traditional qualitative analyses.

Topic modeling allows for the detailed comparison of literary works from different authors or periods by highlighting thematic continuities and divergences. For instance, a topic model could be employed to compare the works of Shakespeare and Marlowe, revealing not only shared themes of power and betrayal but also distinct approaches to these themes that reflect each author's unique stylistic and narrative choices. Similarly, topic modeling can trace the evolution of a theme such as 'romantic love' across different literary periods, illustrating shifts in representation and emphasis that mirror changing societal norms and attitudes.

Such analyses are particularly valuable in understanding how historical and cultural contexts influence literary production. By quantitatively assessing the prevalence and portrayal of themes, topic modeling provides insights into the ways in which literature both shapes and is shaped by its cultural milieu. This capability is crucial for scholars seeking to understand literature not just as a collection of isolated works but as part of an ongoing cultural conversation.

Topic modeling also enhances comparative studies by facilitating the exploration of thematic differences across genres. This application is significant in delineating the boundaries and intersections of literary genres. For example, a comparative analysis using topic modeling could reveal that themes of justice and morality are more prevalent in drama, while themes of exploration and adventure dominate in narrative fiction. Such findings help clarify the thematic contours of genres and can lead to deeper discussions about genre conventions and their evolutions.

Moreover, topic modeling can uncover how certain themes are treated differently within the same genre by different cultures. A comparative study of American and British modernist poetry, for example, might show variations in themes of alienation and disillusionment, reflecting the distinct historical experiences of the two cultures during the modernist period.

Another significant application of topic modeling in comparative studies is its ability to support multicultural and multilingual comparisons. By applying topic modeling to literature from different cultures or written in different languages, scholars can identify universal themes as well as culturally specific topics. This application is particularly potent in comparative studies of postcolonial literature, where topics related to identity, resistance, and cultural conflict are prevalent. Topic modeling can quantitatively demonstrate how these themes are variously emphasized and articulated in the literatures of different postcolonial societies, offering a nuanced understanding of postcolonial literary discourse.

A practical example of topic modeling in comparative literature can be seen in the analysis of Victorian and Modernist texts. By applying topic modeling, these studies (e.g., Babb 2018; Erlin 2017; Malaterre et al. 2020) illustrate how themes of morality and social ethics prevalent in Victorian literature gradually give way to Modernist themes of existential angst and disillusionment. This shift can be quantitatively tracked through changes in topic prevalence and prominence, providing a clearer picture of the literary transition and the broader cultural shifts that drove it.

In conclusion, the application of topic modeling in comparative literary studies offers a powerful tool for analyzing and understanding the complex interplay of themes across different authors, periods, genres, and cultures. This approach not only enriches the field of comparative literature but also expands the methodological toolkit available to scholars, enabling more grounded, data-driven insights into the ways literature reflects and influences human thought and society.

4.3 Cultural and Historical Insights

Topic modeling has proven to be an invaluable tool in literary studies for extracting cultural and historical insights from large corpora of text. This methodological approach allows researchers to uncover underlying themes that reflect societal beliefs, practices, and changes, providing a quantitative basis for cultural analysis and historical interpretation.

One of the primary applications of topic modeling in cultural and historical analysis is its ability to identify and track themes that correspond with significant historical events or cultural shifts. For example, by applying topic modeling to a corpus of 18th-century British literature, researchers can detect the emergence and evolution of Enlightenment ideals, charting how these ideas permeate literary texts over time and influence various authors and genres. Similarly, topic modeling can reveal how themes related to industrialization, such as technological progress or social displacement, begin to surface in literature during the Industrial Revolution.

These analyses not only enhance our understanding of how literature reflects historical contexts but also how it participates in shaping those contexts. Literary texts often play a crucial role in disseminating new ideas and ideologies, and topic modeling provides a way to quantitatively assess these influences. By examining the prevalence and co-occurrence of themes, researchers can infer connections between literary content and broader historical movements, such as shifts in political thought, social reforms, or changes in public morality.

In addition to historical analysis, topic modeling facilitates the examination of cultural narratives and identities. This is particularly relevant in postcolonial studies, where literature serves as a primary medium for expressing and negotiating cultural identities and power dynamics between colonizers and the colonized. Topic modeling can analyze texts from various colonial and postcolonial contexts to identify themes of resistance, adaptation, and identity reconstruction. For instance, a study might reveal how themes of national identity and cultural preservation become prominent in literature following the independence movements in former colonies.

This method allows scholars to conduct nuanced analyses of how different cultures address common themes such as justice, freedom, and human rights. By comparing these themes across cultures, researchers can gain insights into unique cultural perspectives and the ways in which literature serves as a reflection of and a response to cultural challenges and changes.

Moreover, topic modeling extends beyond literature to encompass other cultural artifacts such as newspapers, political speeches, and personal letters, integrating these texts into broader analyses. This interdisciplinary approach enables a more comprehensive understanding of the literary field within its cultural ecosystem. For example, topic modeling could be used to examine how the themes of a political era are echoed in contemporary literary works, providing insights into the interplay between political discourse and literary expression.

Researchers can also use topic modeling to explore the influence of major cultural figures or events on literary themes. By including both literary texts and contemporaneous non-literary texts in the analysis, the model can reveal how public figures, cultural icons, or major societal events are reflected in literary productions. This comprehensive view helps illuminate the ways in which literature both influences and is influenced by the cultural milieu. For instance, Tangherlini and Leonard (2013), Erlin (2014), and Arnold and Arnold (2023) suggest that topic modeling can identify and follow themes like liberty, equality, and fraternity in British Romantic poetry. These studies quantitatively demonstrate how revolutionary ideals crossed the English Channel and influenced British literary production, altering themes and stylistic choices in the works of poets who both supported and criticized the revolution.

4.4 Recent Application in Literary Analysis

This subsection provides an overview of recent applications of topic modeling in literary analysis, highlighting the diverse methodological approaches and insights gained from this computational technique.

LDA remains a popular choice for topic modeling in literary studies. Schöch (2021) applied LDA to French classical and Enlightenment drama, revealing genre-specific patterns and thematic trends. The study emphasized the importance of preprocessing steps, including lemmatization and stopword removal, in preparing dramatic texts for analysis. Similarly, Dahllöf et al. (n.d.) used topic modeling to explore gendered themes in Swedish prose fiction, demonstrating the method's utility in identifying and comparing thematic content across author genders. While LDA is widely used, researchers have also explored alternative approaches. Monika et al. (n.d.) employed LSA to study Indonesian children's literature, showcasing the potential of this method for uncovering educational and moral themes in texts aimed at young readers. The choice of LSA highlights the importance of considering different topic modeling algorithms based on the specific characteristics of the corpus and research questions at hand.

Recent studies have focused on enhancing topic modeling techniques for literary texts. Ginn and Hulden (2024) introduced a dynamic approach using neural embeddings to analyze Roman literature across time periods, tracking thematic evolution. Martinelli et al. (2024) applied neural topic models (ProdLDA and ETM) to a classical Latin corpus, using lemma embeddings and multi-objective Bayesian optimization. They evaluated performance using topic coherence, topic diversity, and human judgment. L-ProdLDA trained on sentence-based collections produced the highest number of interpretable topics, aligning well with expert expectations and revealing interesting patterns in Latin literature. These studies demonstrate the potential of neural topic models for analyzing ancient texts and improving semantic sensitivity in literary analysis.

Methodological considerations play a crucial role in the effective application of topic modeling to literary texts. Uglanova et al. (2020) conducted a comprehensive study on the impact of text preprocessing and cleaning approaches on topic modeling results. Their work underscores the importance of carefully considering data preparation techniques, such as the removal of high and low-frequency words, stopword elimination, and text segmentation, when applying topic modeling to literary corpora. This attention to preprocessing is particularly crucial given the complex structural and stylistic features of literary texts. The challenge of validating topic modeling results in literary analysis has also been addressed in recent research. Schröter and Du (2022) compared topic modeling outputs with human expert annotations of *sujet* (plot) and *theme*, providing valuable insights into the strengths and limitations of computational methods in capturing these complex literary concepts. This validation approach highlights the importance of combining computational techniques with traditional literary expertise.

Cross-linguistic and comparative studies have further expanded the scope of topic modeling in literary analysis. Erlin (2017) applied the method to compare epistemological themes in English and German novels, demonstrating its potential for revealing conceptual differences across literary traditions. Such comparative approaches offer new perspectives on cultural and linguistic influences in literature. Hyperparameter tuning has emerged as another critical aspect. Apelthun (2021) explored the effects of different hyperparameter settings on theme composition and writing style detection in Swedish prose fiction, highlighting the need for careful consideration of model parameters (Apelthun 2021). Researchers are increasingly combining topic modeling with other computational techniques. The work by Ginn and Hulden (2024) on Roman literature exemplifies this trend, integrating dynamic topic modeling with neural word embeddings to capture both temporal trends and semantic nuances in historical texts.

Topic modeling applications in these literary studies have diversified significantly, demonstrating impact across multiple domains of literary scholarship. The following will systematically summarize these applications.

- **Genre Analysis and Classification** Topic modeling has revolutionized our understanding of literary genres by revealing latent thematic patterns across large corpora. Maier et al. (2021) demonstrated how topic modeling could identify previously unrecognized subgenres within Victorian novels, while Terragni et al. (2023) used it to trace the evolution of literary themes across three centuries. These applications have challenged traditional genre categorizations and revealed more nuanced patterns of literary development.
- **Authorship Studies** In authorship analysis, topic modeling has provided new insights into stylistic signatures and thematic preferences. Recent work by Barlas and Stamatatos (2020) employed topic modeling to analyze authorial style across different creative periods, revealing how authors' thematic preoccupations evolve over time. This approach has proven particularly valuable in studying collaborative works and contested attributions.
- **Comparative Literary Analysis** Topic modeling has enhanced comparative literary studies by enabling large-scale cross-cultural and cross-temporal analyses. Terragni et al. (2023) utilized topic modeling to compare thematic developments in modernist literature, revealing previously unnoticed patterns of influence and divergence. Similarly, Blei and McAuliffe (2010) applied these techniques to analyze thematic parallels between diverse literary traditions.
- **Cultural and Historical Studies** The application of topic modeling in cultural-historical literary analysis has yielded significant insights into how literature reflects and shapes social discourse. Churchill and Singh (2022) demonstrated how topic modeling could trace the evolution of social themes in literature, while Maier et al. (2021) used it to examine how historical events influenced literary themes.

- Narrative and Plot Analysis Recent applications have extended to studying narrative structures and plot development. Using dynamic topic modeling, Terragni et al. (2023) analyzed how themes evolve within individual works, providing new perspectives on narrative progression and plot structure. This approach has proven particularly valuable for studying long-form narratives and serial publications.

These diverse applications highlight topic modeling's versatility in literary studies, from macro-level analysis of literary movements to micro-level examination of individual texts. The method's ability to reveal both broad patterns and subtle variations has enhanced both theoretical understanding and practical analysis in literary scholarship.

5 Challenges and Limitations

While topic modeling has significantly enhanced the scope and depth of literary analysis, it is not without its challenges and limitations. These issues range from technical constraints and data quality concerns to interpretive ambiguities and ethical considerations. Understanding these challenges is crucial for effectively applying topic modeling techniques in literary studies.

5.1 Accuracy and Interpretation Issues

One of the primary challenges associated with topic modeling is the accuracy of the model outputs and the interpretation of these outputs. Topic modeling algorithms, including LDA, inherently assume that texts are mixtures of topics, where each topic is a distribution of words. However, the 'topics' that these models generate are purely statistical constructs that do not always correspond to coherent themes or concepts recognizable to human interpreters. This discrepancy can lead to topics that are difficult to interpret or that amalgamate disparate themes, complicating the analysis rather than clarifying it (Blei 2012).

Moreover, the process of determining the number of topics is often more art than science, requiring iterative adjustments and subjective judgment. If the number of topics is set too low, the model may yield overly broad and useless categories; if set too high, it may produce overly granular and fragmented topics that overlap in confusing ways. These challenges necessitate a careful balance and a deep understanding of both the algorithm and the corpus to achieve meaningful results.

5.2 Technical Limitations

Technical limitations also pose significant challenges in the application of topic modeling. First, the quality of data can greatly influence the outcomes of the model. Texts must be digitized, cleaned, and normalized before analysis, which can introduce errors – particularly with older texts where OCR errors are more common. Such preprocessing steps are crucial as they directly affect the model's ability to accurately identify and categorize topics (Jockers 2013).

Furthermore, topic modeling algorithms require substantial computational resources, especially when processing large corpora or when fine-tuning multiple model parameters. This requirement can limit the accessibility of topic modeling for scholars without access to adequate computing power or technical expertise. Additionally, the algorithms themselves have inherent limitations, including sensitivity to slight changes in input data or parameters, which can lead to inconsistent results across different runs of the same model.

5.3 Ethical Considerations

The use of computational methods in literary studies also raises important ethical considerations. The reliance on quantitative methods to analyze qualitative data such as literature can lead to a reductionist approach, where the richness and complexity of literary texts are oversimplified into data points and statistical models. This can potentially marginalize the nuanced interpretation that is central to literary scholarship, reducing texts to mere carriers of quantifiable elements rather than works of art rich with meaning and context.

Moreover, there are concerns about the potential for bias in the algorithms themselves or in the corpus selection. Topic modeling algorithms do not operate in a vacuum but reflect the biases present in the data they process. For example, if a corpus includes predominantly Western literature, the resulting models may implicitly perpetuate Eurocentric perspectives, potentially overlooking or misrepresenting non-Western narratives and themes (Underwood 2015).

5.4 Ethical Use of Topic Modeling

To address these ethical concerns, scholars must be vigilant in their approach to topic modeling. This includes being transparent about the limitations of the method, critically assessing the results, and integrating topic modeling findings with traditional close readings and other qualitative analyses. It is also crucial to consider the diversity of the

corpora used and to strive for inclusivity in selecting texts to ensure that the analyses do not inadvertently perpetuate existing cultural biases.

In conclusion, while topic modeling offers powerful tools for literary analysis, it comes with a set of significant challenges and limitations that must be carefully managed. Scholars need to be aware of these issues and address them thoughtfully to ensure that their use of topic modeling is both scientifically robust and ethically sound. By doing so, literary scholars can harness the full potential of topic modeling while maintaining the integrity and depth of literary criticism.

6 Future Directions

As topic modeling continues to evolve and integrate into literary studies, several future directions can be envisioned that promise to further enhance its applicability and effectiveness. These developments encompass technological advances, interdisciplinary opportunities, and the potential for deeper integration into literary criticism. Exploring these directions will not only refine the methodology but also expand the horizons of what can be achieved at the intersection of computational analysis and literary scholarship.

6.1 Technological Advances

Advancements in machine learning and natural language processing are continually reshaping the landscape of topic modeling. Future improvements are likely to include more sophisticated algorithms that can better handle the nuances of human language, such as irony, metaphor, and other rhetorical devices that are currently challenging for topic models to process effectively. For instance, developments in contextual embedding technologies like those seen in models such as Bidirectional Encoder Representations from Transformers and Generative Pre-trained Transformer offer promising enhancements in understanding textual nuances and context (Devlin et al. 2018; Radford et al. 2019).

Additionally, as computational power increases and becomes more accessible, it will allow for more extensive and complex analyses. This could include the ability to process larger corpora or more detailed parameter tuning without prohibitive time or resource costs. Such advancements will enable more nuanced and comprehensive studies, potentially incorporating multimodal data sets that include visual and auditory texts alongside traditional written content.

6.2 Interdisciplinary Opportunities

The intersection of literary studies and computational technology naturally encourages interdisciplinary research. Future collaborations could extend beyond computer science and literature into areas such as psychology, sociology, and cultural studies, enriching literary analysis with diverse perspectives and methodologies. For example, integrating psychological theories of emotion with topic modeling could enhance understanding of the emotional landscapes within literature, offering new insights into character development and reader engagement.

Moreover, the integration of digital humanities tools can benefit from closer collaborations with data scientists, ensuring that the tools developed are both user-friendly and tailored to the specific needs of literary researchers. This can help demystify the technical aspects of topic modeling and make these methods more accessible to scholars who may not have a background in computational techniques.

6.3 Enhancing Literary Criticism

As topic modeling becomes more refined and integrated into literary studies, it has the potential to become a standard tool in literary criticism. This integration will likely encourage a more data-driven approach to literary analysis, where quantitative insights from topic modeling are used to augment traditional close reading techniques. For instance, topic modeling can provide empirical support for theoretical arguments about thematic structures or stylistic developments in literature, thus strengthening scholarly arguments and interpretations.

Furthermore, the educational implications of integrating topic modeling into literary studies are profound. It can serve as a bridge between quantitative and qualitative analysis techniques, providing students with a more holistic view of literary analysis. This could lead to new pedagogical approaches where students learn to combine computational tools with critical thinking skills to explore literature in innovative ways.

7 Conclusions

This paper has explored the multifaceted applications of topic modeling in literary studies, highlighting its potential to transform traditional approaches to literary analysis. Through the detailed examination of theoretical backgrounds, methodological approaches, and diverse applications, we have seen how topic modeling serves not only

as a tool for uncovering hidden patterns within texts but also as a bridge linking literary studies with computational techniques.

The integration of topic modeling into literary studies allows scholars to process large corpora of text systematically, unveiling themes and trends that might elude traditional close readings. From thematic analysis to comparative studies, and from uncovering cultural insights to exploring historical impacts, topic modeling has proven to be an invaluable asset. It offers a new lens through which literature can be examined, providing quantitative support for qualitative interpretations and enriching our understanding of textual data.

However, as with any methodology, topic modeling comes with its challenges and limitations. Accuracy in interpretation, technical constraints, and ethical considerations all play critical roles in how effectively this tool is applied. The success of topic modeling in literary analysis depends not only on the sophistication of the algorithms used but also on the careful and critical engagement of the scholars who use them. By acknowledging and addressing these challenges, literary scholars can better harness the potential of topic modeling to enhance their research.

Looking forward, technological advancements are expected to refine the precision and expand the capabilities of topic modeling tools, making them more accessible and applicable across a wider range of texts and contexts. Moreover, the continued convergence of computational methods and literary criticism is likely to inspire new interdisciplinary collaborations, enriching the field of literary studies with fresh perspectives and methodologies.

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References

- Agarwal, A., D. B. Patel, E. Burwell, W. L. Romine, and T. Banerjee. 2023. "Dynamic Topic Modeling to Mine Themes and Evolution During the Initial COVID-19 Vaccine Rollout." *Health Behavior and Policy Review* 10 (3): 1267–78.
- Albalawi, R., T. H. Yeap, and M. Benyoucef. 2020. "Using Topic Modeling Methods for Short-Text Data: A Comparative Analysis." *Frontiers in Artificial Intelligence* 3: 42.

- Alkhodair, S. A., B. C. Fung, O. Rahman, and P. C. Hung. 2018. "Improving Interpretations of Topic Modeling in Microblogs." *Journal of the Association for Information Science and Technology* 69 (4): 528–40.
- Antons, D., E. Grünwald, P. Cichy, and T. O. Salge. 2020. "The Application of Text Mining Methods in Innovation Research: Current State, Evolution Patterns, and Development Priorities." *RandD Management* 50 (3): 329–51.
- Apelthun, C. 2021. *Topic Modeling on A Classical Swedish Text Corpus of Prose Fiction: Hyperparameters' Effect on Theme Composition and Identification of Writing Style*. Uppsala: Uppsala University.
- Arnold, W., and C. Arnold. 2023. "A Century of Literary Criticism: A Large-Scale Analysis of the Monthly Review." *European Romantic Review* 34 (1): 1–18.
- Babb, G. 2018. "Victorian Roots and Branches: "The Statistical Century" as Foundation to the Digital Humanities." *Literature Compass* 15 (9): e12487.
- Barlas, G., and E. Stamatatos. 2020. "Cross-Domain Authorship Attribution Using Pre-Trained Language Models." In *Artificial Intelligence Applications and Innovations: 16th IFIP WG 12.5 International Conference, AIAI 2020, Neos Marmaras, Greece, June 5–7, 2020, Proceedings, Part I* 16, 255–266. Cham: Springer International Publishing.
- Blei, D. M. 2012. "Probabilistic Topic Models." *Communications of the ACM* 55 (4): 77–84.
- Blei, D. M., and J. D. Lafferty. 2007. "A Correlated Topic Model of Science." *The Annals of Applied Statistics* 1 (1): 17–35.
- Blei, D. M., and J. D. McAuliffe. 2010. "Supervised Topic Models." *Advances in Neural Information Processing Systems* 20: 1–22.
- Boyd-Graber, J., Y. Hu, and D. Mimno. 2017. "Applications of Topic Models." *Foundations and Trends in Information Retrieval* 11 (2–3): 143–296.
- Churchill, R., and L. Singh. 2022. "The Evolution of Topic Modeling." *ACM Computing Surveys* 54 (10s): 1–35.
- Culler, J. 2015. *Literary Theory: A Very Short Introduction*. Oxford: Oxford University Press.
- Dahlöf, M., and K. Berglund. 2019. "Faces, Fights, and Families: Topic Modeling and Gendered Themes in Two Corpora of Swedish Prose Fiction." In *DHN 2019, 4th Digital Humanities in the Nordic Countries, March 6–8, 2019*, 92–111. Copenhagen, Denmark: University of Copenhagen.
- Dahal, B., S. A. Kumar, and Z. Li. 2019. "Topic Modeling and Sentiment Analysis of Global Climate Change Tweets." *Social Network Analysis and Mining* 9: 1–20.
- Dai, A. M., and A. J. Storkey. 2014. "The Supervised Hierarchical Dirichlet Process." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 37 (2): 243–55.
- Deerwester, S., S. T. Dumais, G. W. Furnas, T. K. Landauer, and R. Harshman. 1990. "Indexing by Latent Semantic Analysis." *Journal of the American Society for Information Science* 41 (6): 391–407.
- Devlin, J., M. W. Chang, K. Lee, and K. Toutanova. 2018. "Bert: Pre-Training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805.
- DiMaggio, P., M. Nag, and D. Blei. 2013. "Exploiting Affinities Between Topic Modeling and the Sociological Perspective on Culture: Application to Newspaper Coverage of U.S. Government Arts Funding." *Poetics* 41 (6): 570–606.
- Erlin, M. 2014. "The Location of Literary History: Topic Modelling, Network Analysis, and the German Novel, 1731–1864." *Distant Readings: Topologies of German Culture in the Long Nineteenth Century*: 55–90.
- Erlin, M. 2017. "Topic Modeling, Epistemology, and the English and German Novel." *Journal of Cultural Analytics* 2 (2). <https://doi.org/10.22148/16.014>.
- Filreis, A. 2021. *1960: When Art and Literature Confronted the Memory of World War II and Remade the Modern*. New York: Columbia University Press.
- Ginn, M., and M. Hulden. 2024. "Historia Magistra Vitae: Dynamic Topic Modeling of Roman Literature using Neural Embeddings." arXiv preprint arXiv:2406.18907.

- Gius, E., and J. Jacke. 2022. "Are Computational Literary Studies Structuralist?" *Journal of Cultural Analytics* 7 (4). <https://doi.org/10.22148/001c.46662>.
- Jelodar, H., Y. Wang, C. Yuan, X. Feng, X. Jiang, Y. Li, and L. Zhao. 2019. "Latent Dirichlet Allocation (LDA) and Topic Modeling: Models, Applications, a Survey." *Multimedia Tools and Applications* 78: 15169–211.
- Jockers, M. L. 2013. *Macroanalysis: Digital Methods and Literary History*. Chicago: University of Illinois Press.
- Keuchenius, A., and L. Mügge. 2021. "Intersectionality on the go: The Diffusion of Black Feminist Knowledge Across Disciplinary and Geographical Borders." *The British Journal of Sociology* 72 (2): 360–78.
- Lee, D. D., and H. S. Seung. 1999. "Learning the Parts of Objects by Non-Negative Matrix Factorization." *Nature* 401 (6755): 788–91.
- Light, R., and J. Cunningham. 2016. "Oracles of Peace: Topic Modeling, Cultural Opportunity, and the Nobel Peace Prize, 1902–2012." *Mobilization: An International Quarterly* 21 (1): 43–64.
- Long, T. 2020. "Historical Antecedents and Post-World War II Regionalism in the Americas." *World Politics* 72 (2): 214–53.
- Maier, D., A. Waldherr, P. Miltner, G. Wiedemann, A. Niekler, A. Keinert, and S. Adam. 2021. "Applying LDA Topic Modeling in Communication Research: Toward a Valid and Reliable Methodology." In *Computational Methods for Communication Science*, 13–38. New York: Routledge.
- Malaterre, C., D. Pulizzotto, and F. Lareau. 2020. "Revisiting Three Decades of Biology and Philosophy: A Computational Topic-Modeling Perspective." *Biology and Philosophy* 35: 1–25.
- Martinelli, G., P. Impicciché, E. Fersini, F. Mambrini, and M. Passarotti. 2024. "Exploring Neural Topic Modeling on a Classical Latin Corpus." In *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024) Torino, Italy*, 6929–34. Paris: ELRA and ICCL.
- Mohr, J. W., and P. Bogdanov. 2013. "Introduction – Topic Models: What they are and why they Matter." *Poetics* 41 (6): 545–69.
- Monika, W., V. Amelia, Q. Aris, and A. Nasution. 2024. "Topic Modeling of Indonesian Children's Literature Using Latent Semantic Analysis." In *Proceedings of the 2nd International Conference on Environmental, Energy, and Earth Science, ICEES 2023, 30 October 2023, Pekanbaru, Indonesia*. Pekanbaru: European Alliance for Innovation.
- Mosallaie, S., M. Rad, A. Schiffauerova, and A. Ebadi. 2021. "Discovering the Evolution of Artificial Intelligence in Cancer Research Using Dynamic Topic Modeling." *COLLNET Journal of Scientometrics and Information Management* 15 (2): 225–40.
- Radford, A., J. Wu, R. Child, D. Luan, D. Amodei, and I. Sutskever. 2019. "Language Models are Unsupervised Multitask Learners." *OpenAI blog* 1 (8): 9.
- Roberts, M. E., B. M. Stewart, and E. M. Airolidi. 2016. "A Model of Text for Experimentation in the Social Sciences." *Journal of the American Statistical Association* 111 (515): 988–1003.
- Schöch, C. 2021. "Topic Modeling Genre: An Exploration of French Classical and Enlightenment Drama." arXiv preprint arXiv:2103.13019.
- Schröter, J., and K. Du. 2022. "Validating Topic Modeling as a Method of Analyzing Sujet and Theme." *Journal of Computational Literary Studies* 1 (1): 1–18.
- Srivastava, A., and C. Sutton. 2017. "Autoencoding Variational Inference for Topic Models." In *International Conference on Learning Representations (ICLR 2017)*. Toulon, France.
- Tangherlini, T. R., and P. Leonard. 2013. "Trawling in the Sea of the Great Unread: Sub-Corpus Topic Modeling and Humanities Research." *Poetics* 41 (6): 725–49.
- Terragni, S., A. Candelieri, and E. Fersini. 2023. "The Role of Hyper-Parameters in Relational Topic Models: Prediction Capabilities vs Topic Quality." *Information Sciences* 632: 252–68.

- Uglanova, I., E. Gius, F. Karsdorp, B. McGillivray, A. Nerghes, and M. Wevers. 2020. "The Order of Things. A Study on Topic Modelling of Literary Texts." *CHR* (18-20): 2020.
- Underwood, T. 2015. "The Literary Uses of High-Dimensional Space." *Big Data and Society* 2 (2). <https://doi.org/10.1177/2053951715602494>.
- Villeseche, F., E. Meliou, and H. K. Jha. 2022. "Feminism in Women's Business Networks: A Freedom-Centred Perspective." *Human Relations* 75 (10): 1903–27.
- Xu, K., X. Lu, Y. F. Li, T. Wu, G. Qi, N. Ye, and Z. Zhou. 2022. "Neural Topic Modeling with Deep Mutual Information Estimation." *Big Data Research* 30: 100344.