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Research paper

Analysis of Dynamic Topic Modeling for Textual Data Using A Novel Approach of Hybrid Deep Learning with NMF and NTD

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Abstract

In this research, we conduct an in-depth analysis of dynamic topic modeling techniques for real-time and evolving textual data, leveraging methods such as Non-Negative Matrix Factorization (NMF), Supervised NMF (SNMF), Non-Negative Tucker Decomposition (NTD), and hybrid models, Hybrid HDP-CT-DTM, Hybrid DTM-RNN, and proposed Hybrid Convolutional Neural Networks (CNNs) with NMF and NTD. Using the "Advanced Topic Modeling for Research Articles 2.0" dataset, which comprises 14,000 documents, this research paper evaluates the effectiveness of these methods based on perplexity, coherence, precision, recall, F-score, and accuracy. Our findings indicate that the proposed hybrid CNN with NTD model outperforms other techniques across all evaluation metrics, demonstrating superior ability in capturing complex topic structures and maintaining high accuracy. This performance is attributed to the rich feature extraction capabilities of CNNs and the higher-order interaction modeling provided by NTD. This research work highlights the potential of advanced hybrid models for enhancing the quality and interpretability of topic models in dynamic and large-scale textual datasets.

Keywords: *Dynamic Topic Modeling; Real-Time Textual Data Analysis; Non-Negative Matrix Factorization; Supervised NMF; Non-Negative Tucker Decomposition; Hybrid Deep Learning; Advanced Topic Modeling for Research Articles 2.0 and Evaluation Metrics.*

1. Introduction

The increasing volume and velocity of textual data generated across various domains pose significant challenges for efficient analysis and interpretation. Traditional static topic modeling techniques are ill-equipped to handle the dynamic nature of textual data streams, necessitating the development of more adaptive methodologies. Dynamic Topic Modeling (DTM) techniques have emerged as promising solutions to this challenge, offering the capability to capture evolving themes and trends in real-time textual data. In this context, this paper aims to investigate and compare the effectiveness of various DTM techniques for analyzing real-time and evolving textual data. Specifically, we focus on Non-Negative Matrix Factorization (NMF), Supervised NMF (SNMF), Non-negative Tucker Decomposition (NTD), and a Hybrid Deep Learning approach that integrates NMF and NTD. These techniques are evaluated using a comprehensive set of metrics, including perplexity, coherence, precision, recall, F-score, and accuracy. The objectives of this research are to assess the performance of these DTM techniques in capturing the underlying topics in dynamic textual data streams, identify their strengths and limitations, and provide insights into their practical implications for real-world applications. By addressing these objectives, we aim to contribute to the advancement of methodologies for real-time textual data analysis and inform decision-making processes across various domains. This introduction sets the stage for the subsequent sections of the paper, which will delve into the methodology, experimental setup, results, and discussions, ultimately culminating in conclusions and recommendations for future research directions. Through this investigation, we endeavor to enhance our understanding of DTM techniques and their applicability to the analysis of real-time and evolving textual data.

1.1. Dynamic Topic Modeling and Its Importance

Dynamic Topic Modeling (DTM) is a subfield of topic modeling that focuses on capturing temporal dynamics and evolving patterns within textual data streams. Unlike traditional static topic modeling techniques, which assume that topics remain constant over time, DTM methods explicitly model the evolution of topics, allowing for the detection of shifts in themes, emerging trends, and changes in discourse [1]. At the core of DTM is the recognition that textual data is inherently dynamic, reflecting the ever-changing nature of human communication and information exchange. From social media conversations to news articles and scientific publications, textual data streams exhibit temporal dynamics influenced by factors such as emerging events, evolving trends, and shifting user preferences. The importance of DTM lies in its ability to extract actionable insights from real-time textual data streams, enabling researchers, practitioners, and decision-makers to stay abreast of current developments, detect anomalies, and anticipate future trends. By modeling topic evolution over time, DTM techniques provide valuable tools for tasks such as trend detection, event detection, sentiment analysis, and anomaly detection [2]. Moreover,

DTM techniques facilitate the exploration and understanding of complex phenomena unfolding in dynamic textual data streams. By uncovering latent topics and structures within evolving corpora, DTM enables analysts to identify underlying patterns, extract relevant information, and make informed decisions in various domains.
The significance of DTM extends across diverse application areas, including [3]:

- Social Media Analytics: DTM techniques are used to monitor public opinion, track trending topics, and detect emerging events on social media platforms such as Twitter, Facebook, and Reddit.
- Scientific Literature Mining: DTM methods facilitate the analysis of temporal trends, emerging research topics, and evolving scientific paradigms in fields such as biomedicine, computer science, and environmental science.
- Financial News Monitoring: DTM techniques enable the detection of market-moving events, sentiment analysis of financial news articles, and identification of emerging risks and opportunities in financial markets.
- News Media Analysis: DTM methods are employed to analyze temporal patterns in news coverage, track changes in media discourse, and identify shifts in public opinion on pressing issues.

Dynamic Topic Modeling plays a crucial role in extracting meaningful insights from real-time textual data streams, thereby empowering stakeholders to make informed decisions, anticipate future trends, and respond effectively to changing circumstances. Its importance spans across various domains, offering valuable tools for understanding and navigating the complexities of dynamic information environments.

1.2. Objectives of The Research

The primary objectives of this research are to:

- Evaluate the performance of dynamic topic modeling (DTM) techniques, including Non-Negative Matrix Factorization (NMF), Supervised NMF (SNMF), Non-negative Tucker Decomposition (NTD), and Hybrid Deep Learning approaches, in analyzing real-time and evolving textual data.
- Compare the efficacy of different DTM techniques based on a comprehensive set of evaluation metrics, including perplexity, coherence, precision, recall, F-score, and accuracy.
- Assess the ability of each DTM technique to capture evolving topics, detect temporal patterns, and uncover latent structures within dynamic textual data streams.
- Identify the strengths and limitations of each DTM approach in the context of real-world applications across various domains, such as social media analytics, scientific literature mining, and financial news monitoring.
- Provide insights and recommendations for researchers, practitioners, and decision-makers on the selection and application of DTM techniques for real-time textual data analysis.

By achieving these objectives, this research aims to contribute to the advancement of methodologies for analyzing dynamic textual data streams and facilitate informed decision-making processes across diverse domains. Through empirical evaluation and critical analysis, we seek to enhance our understanding of DTM techniques and their practical implications for real-time textual data analysis.

1.3. Background and Motivation

The proliferation of digital platforms and communication channels has led to an unprecedented surge in textual data production. From social media streams to news articles and scientific publications, the sheer volume and diversity of textual content present both opportunities and challenges for analysis and interpretation. Traditional static topic modeling techniques, such as Latent Dirichlet Allocation (LDA), have been widely used to uncover latent themes and structures within static corpora. However, these methods falter when confronted with the dynamic and evolving nature of textual data streams. Dynamic Topic Modeling (DTM) techniques have emerged as a promising solution to address this limitation. Unlike their static counterparts, DTM approaches are designed to capture temporal dynamics and evolving patterns within textual data streams. By modeling topic evolution over time, DTM enables analysts to track shifting themes, emerging trends, and evolving discourse in real-time [4].
The motivation behind this research stems from the pressing need to develop robust methodologies for analyzing real-time textual data streams across various domains. Whether it's monitoring public opinion on social media, tracking emerging topics in scientific literature, or detecting anomalies in financial news, the ability to extract actionable insights from dynamic textual data is essential for decision-making processes. Moreover, the advent of advanced DTM techniques, such as Non-Negative Matrix Factorization (NMF), Supervised NMF (SNMF), Non-negative Tucker Decomposition (NTD), and Hybrid Deep Learning approaches, presents exciting opportunities for enhancing the efficacy of real-time textual data analysis. These techniques leverage innovative algorithms and computational frameworks to uncover latent topics and structures within dynamic text streams.

2. Related Works

2.1. Hybrid HDP with Continuous-Time Dynamic Topic Modeling (Hybrid HDP-CT-DTM)

Pavithra et al., [5] present a thorough examination of dynamic topic modeling techniques for real-time and evolving textual data. The study evaluates five methodologies: Latent Dirichlet Allocation (LDA), Dynamic Topic Modeling (DTM), Latent Dirichlet Allocation with Gibbs Sampling (GibbsLDA++), the Hierarchical Dirichlet Process (HDP), and a novel Hybrid approach combining HDP with Continuous-Time Dynamic Topic Modeling (Hybrid HDP-CT-DTM). The objective is to assess these methods' effectiveness in capturing and adapting to changing topics and trends in diverse textual datasets, including social media, news, and scientific publications. The research aims to understand the unique strengths and limitations of each technique, focusing on their interpretability, computational efficiency, and adaptability to evolving data. The hybrid HDP and CT-DTM approach is explored for its potential enhancements in structured and continuous-time topic modeling. This investigation is timely due to the dynamic nature of modern data sources and the need for adaptable models. Key findings from the "Advanced Topic Modeling for Research Articles 2.0" dataset indicate that the Hybrid HDP and CT-DTM consistently outperformed existing techniques across metrics like Perplexity, Coherence, Precision, Recall, F-score, and Accuracy. This hybrid approach leverages hierarchical structures and temporal dynamics, resulting in more accurate, coherent, and interpretable topic modeling. Lower perplexity scores demonstrate its predictive accuracy, and higher coherence scores highlight its semantic interpretability. The Hybrid HDP and CT-DTM method offers significant advancements in topic modeling performance, making it a promising solution for applications requiring dynamic textual data analysis. These findings provide valuable insights into the strengths and potential uses of LDA, DTM, GibbsLDA++, HDP, and the Hybrid HDP and CT-DTM approach.

2.2. Hybrid Dynamic Topic Modeling and Recurrent Neural Networks (Hybrid DTM-RNN)

Lin, Y et al., [6] aim to provide a comprehensive analysis of various dynamic topic modeling techniques, including traditional approaches like Dynamic Topic Modeling (DTM), modern methodologies like BERTopic, and advanced neural network-based methods such as Recurrent Neural Networks (RNN). The study also explores the integration of DTM with RNN in a hybrid framework. Through empirical evaluations on real-world textual datasets, the research investigates these methods' efficacy in capturing temporal dynamics, identifying evolving topics, and providing insights into the data's underlying structures. The study uses the "Advanced Topic Modeling for Research Articles 2.0" dataset and evaluates techniques based on perplexity, coherence, precision, recall, F-score, and accuracy, focusing on performance, scalability, and adaptability to real-time and evolving textual data. The experimental results involving DTM, BERTopic, RNN, and the Hybrid DTM-RNN on the Research Articles 2.0 dataset demonstrate the effectiveness of various methodologies in topic modeling. By optimizing parameter settings and employing appropriate hyperparameters, the study achieves coherent and interpretable topics. The results indicate that the Hybrid DTM-RNN outperforms individual models, showcasing its potential to revolutionize textual data analysis in research domains. The Hybrid DTM-RNN effectively integrates the strengths of DTM and RNN, capturing meaningful semantic relationships and temporal patterns within textual datasets. In conclusion, meticulous experimentation and evaluation provide compelling evidence supporting the Hybrid DTM-RNN's effectiveness in generating accurate and interpretable topic models. This research paves the way for advancements in topic modeling methodologies, offering robust solutions for understanding and analyzing textual data across various domains.

3. Dynamic Topic Modeling Techniques

Dynamic Topic Modeling (DTM) techniques have emerged as powerful tools for analyzing textual data streams that evolve. Unlike traditional static topic modeling approaches, which assume stationary topic distributions, DTM methods explicitly model the temporal dynamics of topics, allowing for the identification of evolving themes, trends, and patterns within textual corpora. In this section, we provide an overview of some prominent DTM techniques and their applications in real-time textual data analysis.

3.1. Non-Negative Matrix Factorization (NMF)

Non-Negative Matrix Factorization (NMF) is a matrix factorization technique that decomposes a document-term matrix into two non-negative matrices representing topics and document-topic distributions. In the context of DTM, NMF can be extended to model temporal dynamics by updating the topic matrix over time. By iteratively adjusting topic distributions, NMF captures the evolution of topics within textual data streams [7] [8]. NMF is a matrix factorization technique widely used in topic modeling and dimensionality reduction tasks. Unlike traditional matrix factorization methods that allow negative values in the factor matrices, NMF restricts both the input matrix and the factor matrices to contain only non-negative values. This constraint makes NMF particularly suitable for applications where the input data has inherently non-negative features, such as document-term matrices in text mining. In the context of dynamic topic modeling, NMF offers an effective approach for capturing evolving topics within textual data streams. Here's how NMF works in dynamic topic modeling:

- Initialization: NMF starts by initializing two non-negative matrices: the basis matrix W (representing topics) and the coefficient matrix H (representing document-topic distributions). These matrices are initialized randomly or using other techniques such as singular value decomposition (SVD) initialization.
- Optimization: The goal of NMF is to find the best approximation of the original document-term matrix by iteratively updating the basis and coefficient matrices. This is achieved by minimizing the reconstruction error between the original matrix and its approximation using techniques such as gradient descent or alternating least squares. Given the original non-negative matrix V, NMF aims to find the best approximation WH that minimizes the reconstruction error. This is achieved by solving the following optimization problem:

$\min_{W,H} ||V-WH||^2_F$

Where ||.|| F denotes the Frobenius norm.

- Update Rules: In each iteration, the basis and coefficient matrices are updated alternately using update rules derived from optimization techniques. The update rules ensure that the resulting matrices remain non-negative throughout the optimization process. Update the basis matrix W and the coefficient matrix H iteratively using update rules derived from optimization techniques such as gradient descent or alternating least squares.

The update rules for W and H are as follows:

$W_{ik} \leftarrow W_{ik}. (VH^T)_{ik} / (WHH^T)_{ik}$

$H_{kj} \leftarrow H_{kj}. (W^TV)_{kj} / (W^TWH)_{kj}$

Where i represent the row index, k represents the topic index, and j represents the column index.

- Convergence: The optimization process continues until a convergence criterion is met, such as reaching a specified number of iterations or when the change in reconstruction error falls below a predefined threshold.
- Topic Interpretation: Once the optimization process converges, the basis matrix W represents the discovered topics, while the coefficient matrix H provides the distribution of topics for each document. These topics can be interpreted by examining the most salient terms associated with each topic.

In the context of dynamic topic modeling, NMF can be extended to capture temporal dynamics by updating the basis matrix over time [9] [10]. This allows NMF to adapt to changes in topic distributions and uncover evolving themes within textual data streams.

3.2. Supervised Non-Negative Matrix Factorization (SNMF)

Supervised Non-Negative Matrix Factorization (SNMF) extends the traditional NMF algorithm by incorporating supervision into the factorization process. This supervision is typically provided in the form of labeled data, which guides the learning of the basis and coefficient matrices. SNMF is particularly useful when prior knowledge about the data is available and can help improve the interpretability and relevance of the learned factors. In DTM, SNMF can utilize temporal supervision to learn topic trajectories over time, enhancing the interpretability and coherence of discovered topics [11] [12]. By incorporating domain knowledge, SNMF enables more accurate modeling of dynamic topic evolution. Here's how SNMF works:

- Initialization: SNMF initializes the basis matrix W and the coefficient matrix H with non-negative random values or using an initialization method such as singular value decomposition (SVD).
- Optimization with Supervision: SNMF aims to minimize the reconstruction error between the original data and its approximation while incorporating supervision from labeled data. The optimization objective is defined as follows:

$\min_{W,H} \|V - WH\|^2_F + \lambda \cdot \text{supervised term}$

Where ||.||F denotes the Frobenius norm and λ is a regularization parameter that controls the influence of the supervised term.

- Supervised Term: The supervised term encourages the learned factors W and H to align with the provided labels. This term can take different forms depending on the nature of the supervision. For example:
- In classification tasks, the supervised term may penalize deviations from the ground truth labels using measures such as cross-entropy loss or hinge loss.
- In regression tasks, the supervised term may enforce similarity between the predicted outputs and the target values using measures such as mean squared error.
- Update Rules: Similar to traditional NMF, SNMF updates the basis matrix W and the coefficient matrix H iteratively using update rules derived from optimization techniques such as gradient descent or alternating least squares. The update rules are modified to incorporate the supervised term and ensure non-negativity:

$W_{ik} \leftarrow W_{ik}. (VH^T)_{ik} / (WHH^T)_{ik}$

$H_{kj} \leftarrow H_{kj}. (W^T V)_{kj} / (W^T WH)_{kj}$

- Convergence: The optimization process continues until a convergence criterion is met, such as reaching a specified number of iterations or when the change in reconstruction error falls below a predefined threshold.
- Interpretation: Once the optimization process converges, the basis matrix W represents the learned features, which can be interpreted in the context of the provided labels. The coefficient matrix H provides the distribution of these features for each data point.
- Supervised NMF is a versatile technique that leverages labeled data to guide the factorization process, making it particularly useful for tasks where prior knowledge or supervision is available [13].

3.3. Non-negative Tucker Decomposition (NTD)

Non-negative Tucker Decomposition (NTD) is a higher-order tensor factorization technique that extends NMF to capture multi-dimensional interactions among different modes of data. In DTM, NTD can model complex temporal dynamics by factorizing multi-dimensional tensors representing time-varying document-term matrices. By capturing higher-order temporal interactions, NTD offers a flexible framework for modeling dynamic topics [14] [15]. It decomposes a given tensor into a set of non-negative factor matrices along each mode, allowing for the representation of interactions among multiple dimensions of data. In the context of dynamic topic modeling, NTD offers a flexible framework for capturing multi-dimensional temporal dynamics within textual data streams. Here's how NTD works:

- Initialization: NTD initializes a higher-order tensor X and a set of non-negative factor matrices A(1), A(2),…, A(N) with non-negative random values or using an initialization method such as random initialization or singular value decomposition (SVD).
- Optimization: NTD aims to find the best approximation of the original tensor \(\mathcal{X} \) by iteratively updating the factor matrices while minimizing the reconstruction error. The optimization objective is typically defined as follows:

$\min_{A(1),A(2),\ldots,A(N)} \|X - \sum^{N}_{i=1} A^{(i)} \times_i U^{(i)}\|^2_F$

Where || ||F denotes the Frobenius norm, X_i denotes the mode-i tensor multiplication, and $U^{(i)}$ represents the core tensor along mode-i.

- Update Rules: NTD updates each factor matrix A(i) iteratively using update rules derived from optimization techniques such as gradient descent or alternating least squares. The update rules ensure that the resulting factor matrices remain non-negative throughout the optimization process.
- Core Tensor: The core tensor U(i) captures the interactions among different modes of data and represents the higher-order structure of the tensor. It is updated along each mode during the optimization process to minimize the reconstruction error.
- Convergence: The optimization process continues until a convergence criterion is met, such as reaching a specified number of iterations or when the change in reconstruction error falls below a predefined threshold.
- Interpretation: Once the optimization process converges, the factor matrices A(1), A(2),…, A(N) represent the learned features along each mode of the tensor. These features can be interpreted in the context of the original data, providing insights into the underlying patterns and structures.

Non-negative Tucker Decomposition offers a powerful framework for capturing complex multi-dimensional interactions within textual data streams [16] [17]. By decomposing tensors into non-negative factor matrices, NTD enables the analysis of higher-order structures and facilitates the discovery of latent topics and themes across multiple dimensions of data.

4. Proposed Hybrid Convolutional Neural Networks with NMF (HCNN-NMF)

The Proposed Hybrid Convolutional Neural Networks (CNNs) with Non-Negative Matrix Factorization (NMF) is an innovative approach that combines the feature extraction capabilities of CNNs with the interpretability and sparsity constraints of NMF for dynamic topic

modeling. This hybrid framework leverages the strengths of both CNNs and NMF to capture complex patterns and evolving topics within real-time textual data streams. Figure 1 shows how Hybrid CNNs with NMF work. Feature extraction with CNNs involves using Convolutional Neural Networks (CNNs) [18 - 20] to derive high-level features from textual data. In text analysis, CNNs are typically applied to word embeddings or character embeddings to capture local patterns and dependencies within text sequences. The CNN architecture includes convolutional layers followed by max-pooling layers, which help the model identify spatial patterns in the input data and extract relevant features. This process enables the CNN to transform raw text into a structured feature representation suitable for further analysis. Integration with Non-Negative Matrix Factorization (NMF) follows the feature extraction step. The features extracted by CNNs are assembled into a feature matrix, which is then fed into an NMF-based topic modeling framework. NMF decomposes this matrix into basis vectors, representing topics and coefficients, indicating document-topic distributions, through non-negative matrix factorization.
By integrating CNN-derived features with NMF, the hybrid framework leverages the representational power of CNNs and the interpretability and sparsity constraints provided by NMF, resulting in a robust topic modeling approach. Optimization in this hybrid framework aims to minimize the reconstruction error between the original feature matrix and its NMF-based approximation. Techniques such as alternating least squares or gradient descent are employed to iteratively update the basis and coefficient matrices, thereby reducing the reconstruction error. This step is crucial for refining the topic model to accurately represent the underlying structure of the textual data. Convergence of the optimization process occurs when a predetermined criterion is met, such as reaching a specified number of iterations or achieving a change in reconstruction error below a predefined threshold. Once the convergence criterion is satisfied, the optimization process terminates, ensuring that the model parameters are stable and the topic representation is reliable. Interpretation of the results follows the convergence of the optimization process. The basis matrix obtained from NMF represents the discovered topics, while the coefficient matrix provides the distribution of these topics across documents. Topics are interpreted by examining the most salient terms associated with each topic, offering insights into the underlying themes and trends within the textual data. This final step transforms the numerical output of the model into meaningful and actionable information for researchers and analysts.

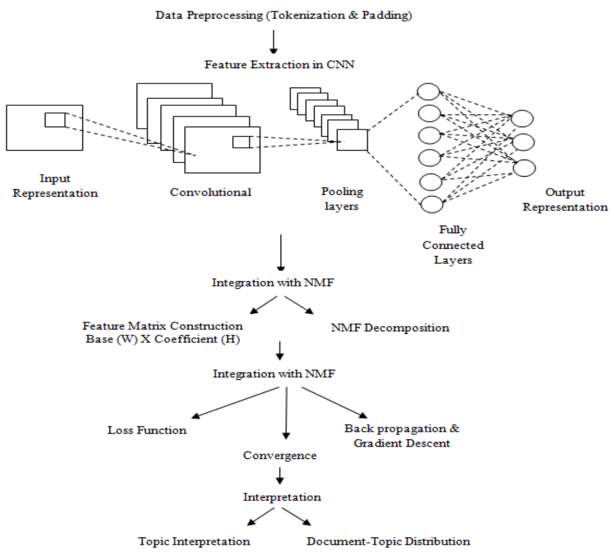

Fig. 1: The Novel Hybrid Convolutional Neural Networks with NMF.

4.1. Feature Extraction with CNNs

CNNs are employed to extract high-level features from textual data. In the context of text analysis, CNNs are typically applied to word embeddings or character embeddings to capture local patterns and dependencies within text sequences. The CNN architecture consists of convolutional layers followed by max-pooling layers, which enable the model to capture spatial patterns in the input data and extract relevant features.
Steps of feature extraction with (CNNs):
Input Representation: Textual data is encoded into a numerical format, typically using word embeddings or character embeddings. Let's denote the input textual data as X, where X is a matrix of size N×D, representing N samples/documents and D dimensions of the embeddings.
Convolutional Layers: Convolutional layers consist of filters (also called kernels) that slide across the input embeddings to extract local patterns. Each filter produces a feature map by convolving with the input embeddings. Let K denote the number of filters in a convolutional layer, and F denote the size of each filter. The output feature map for each filter k can be computed as:

$$Z_k=f(W_k*X+b_k)$$

Where W_k is the filter weights, b_k is the bias term, denotes the convolution operation, and f is the activation function.
Pooling Layers: Pooling layers reduce the spatial dimensionality of the feature maps while retaining the most salient information. Max pooling is commonly used, which retains the maximum value within a pooling window.
Let P denote the size of the pooling window. The output of the max pooling operation for each feature map Zk can be computed as:

$$Y_k = \mathrm{maxpool}(Z_k)$$

Flattening and Fully Connected Layers: The output feature maps from the pooling layers are flattened into a one-dimensional vector and passed through one or more fully connected layers. Let M denote the number of neurons in the fully connected layer. The output of the fully connected layer can be computed as:

$O=f(W_{fc}.F_{flat}+b_{fc})$

Where W_{fc} is the weight matrix of the fully connected layer, F_{flat} is the flattened feature vector, bfc is the bias term, and f is the activation function.
Output Representation: The output of the fully connected layers represents the high-level features extracted from the input sequence. This output can be used for downstream tasks such as classification, regression, or further processing with techniques like Non-Negative Matrix Factorization (NMF) for dynamic topic modeling.

4.2. Integration with NMF

Integrating Convolutional Neural Networks (CNNs) with Non-Negative Matrix Factorization (NMF) involves transforming the features extracted by the CNN into a format suitable for NMF-based topic modeling. NMF decomposes the normalized feature matrix X into two non-negative matrices: the basis matrix W and the coefficient matrix H. This can be expressed as:

$X \approx WH$

The optimization problem for NMF aims to minimize the reconstruction error between the original feature matrix X and its approximation WH, subject to non-negativity constraints:
$\min_{W,H} ||V-WH||^2_F$

Where ||.|| F denotes the Frobenius norm.

4.3. Optimization

Optimization process for Non-Negative Matrix Factorization (NMF) into update rules for the basis matrix W and the coefficient matrix H:
Update Rule for Basis Matrix W:
Given the current basis matrix W and coefficient matrix H, the update rule for the basis matrix W aims to minimize the reconstruction error between the original feature matrix X and its approximation WH.
This update rule can be derived using techniques such as multiplicative updates or projected gradient descent:

$W_{ij} \leftarrow W_{ij}. (XH^T)_{ij} / (WHH^T)_{ij}$

Where Wij denotes the element at the i-th row and j-th column of the basis matrix W. $(XH^T)_{ij}$ denotes the element at the i-th row and j-th column of the matrix resulting from the multiplication of X and the transpose of H. $(WHH^T)_{ij}$ denotes the element at the i-th row and j-th column of the matrix resulting from the multiplication of WH and the transpose of H.
Update Rule for Coefficient Matrix H:
Similarly, given the current basis matrix W and coefficient matrix H, the update rule for the coefficient matrix H also aims to minimize the reconstruction error. This update rule can be derived using similar techniques:

$H_{jk} \leftarrow H_{jk}. (W^TX)_{jk} / (W^TWH)_{jk}$

Where H_{jk} denotes the element at the j-th row and k-th column of the coefficient matrix H. (WTX)jk denotes the element at the j-th row and k-th column of the matrix resulting from the multiplication of the transpose of W and X. (WTWH)jk denotes the element at the j-th row and k-th column of the matrix resulting from the multiplication of the transpose of W and H.
These update rules are applied iteratively until a convergence criterion is met, such as reaching a specified number of iterations or when the change in reconstruction error falls below a predefined threshold. They ensure that both the basis matrix W and the coefficient matrix H remain non-negative throughout the optimization process, facilitating the discovery of meaningful topics within the input data.

4.4. Convergence

Convergence in Non-Negative Matrix Factorization (NMF) refers to the point at which the optimization process has sufficiently minimized the reconstruction error between the original data and its approximation. While there isn't a single formula for convergence, convergence is typically assessed based on criteria such as reaching a specified number of iterations or when the change in reconstruction error falls below a predefined threshold. Here's how convergence can be assessed in each step of the optimization process:
Convergence Criterion for Basis Matrix W: At each iteration of the optimization process, the change in the basis matrix W can be calculated using a suitable measure such as the Frobenius norm of the difference between the current and previous basis matrices:

$\Delta W= ||W^{(t)}-W^{(t-1)}||$ F

Convergence can be declared when the change in W falls below a predefined threshold $\epsilon 1$:

$\Delta W<\epsilon 1$

Convergence Criterion for Coefficient Matrix H: Similarly, the change in the coefficient matrix H can be calculated at each iteration:

$\Delta H= || H(t)-H(t-1)||F$

Convergence is declared when the change in H falls below a predefined threshold $\epsilon 2$:

$\Delta H<\epsilon 2$

Overall Convergence: The overall convergence of the optimization process can be assessed based on a combination of the convergence criteria for W and H. For example, convergence may be declared when both ΔW and ΔH fall below their respective thresholds $\epsilon 1$ and $\epsilon 2$.
Number of Iterations: Alternatively, convergence can be assessed based on reaching a specified number of iterations T. In this case, the optimization process continues until the maximum number of iterations is reached.
Reconstruction Error: Additionally, convergence can be assessed based on the reconstruction error between the original data matrix X and its NMF approximation WH. Convergence is declared when the reconstruction error falls below a predefined threshold.
Convergence in NMF is determined based on the change in the factor matrices (basis matrix W and coefficient matrix H), the reconstruction error, or reaching a specified number of iterations. The specific criterion used may vary depending on the application and computational constraints.

4.5. Interpretation

Interpretation in the context of Non-Negative Matrix Factorization (NMF) involves extracting meaningful insights from the decomposed basis matrix □W and coefficient matrix □H, which represent topics and document-topic distributions, respectively. Here's how interpretation can be performed with relevant formulas for each step:
Extracting Top Terms for Each Topic: The basis matrix W contains basis vectors, each representing a topic. To extract the top terms associated with each topic, we identify the k terms with the highest weights in each basis vector.
Let W_{ij} denote the weight of term j in the ith basis vector. The k terms with the highest weights in the ith basis vector can be identified as follows:

$$TopTerms_i = argmax_k(W_{ij})$$

Extracting Document-Topic Distributions: The coefficient matrix H contains document-topic distributions, where each row represents the distribution of topics for a document. To extract the dominant topics for each document, we identify the k topics with the highest weights in each row of H.
Let H_{ij} denote the weight of topic j in the ith document. The k topics with the highest weights in the ith document's topic distribution can be identified as follows:

$$TopTopics_i = argmax_k(H_{ij})$$

Interpreting Topics: Once the top terms for each topic have been identified, they can be examined to interpret the underlying theme represented by each topic. This may involve manually inspecting the top terms and identifying common themes or concepts.
Analyzing Document-Topic Distributions: The document-topic distributions extracted from the coefficient matrix H provide insights into the topics prevalent in each document. By examining the dominant topics for each document, patterns and trends within the dataset can be identified.
Visualization and Presentation: Finally, the interpreted topics and document-topic distributions can be visualized and presented in a suitable format, such as word clouds, bar charts or heatmaps, to facilitate understanding and interpretation by stakeholders.
By following these steps and utilizing the formulas provided, meaningful insights can be extracted from the decomposed NMF matrices W and H, enabling the interpretation of topics and document-topic distributions within the dataset.

5. Proposed Hybrid Convolutional Neural Networks with NTD (HCNN-NTD)

Integrating Convolutional Neural Networks (CNNs) with Non-negative Tucker Decomposition (NTD) for dynamic topic modeling involves leveraging CNNs for feature extraction and NTD for multi-dimensional factorization. Figure 2 below shows the steps and the relevant part of this hybrid approach:

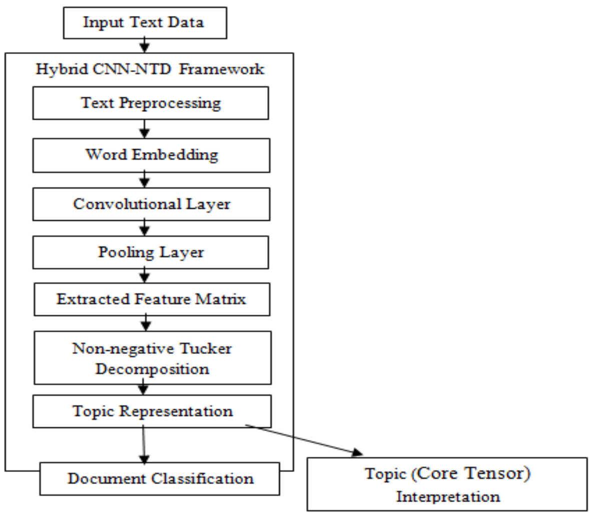

Fig. 2: Hybrid Convolutional Neural Networks with NTD (HCNN-NTD).

Feature Extraction with CNNs
Input Representation: The input textual data is converted into a matrix of word embeddings. Let X be the input matrix of size N×D, where N is the number of words and D is the embedding dimension.

Convolutional Layers: Apply convolutional filters to capture local patterns in the embeddings. Let K be the number of filters, each of size F×D.
The output feature map Zk for the k-th filter is:

$Z_k=f(W_k*X+b_k)$

Where W_k is the filter weights, b_k is the bias term, * denotes the convolution operation, and f is an activation function like ReLU.
Pooling Layers: Apply max pooling to reduce the dimensionality of the feature maps. Let □P be the pooling size.
The pooled feature map Y_k is:

$Y_k=\text{maxpool}(Z_k,P)$

Flattening and Fully Connected Layers: Flatten the pooled feature maps and pass through fully connected layers. Let F be the flattened feature vector, and W_{fc} and b_{fc} be the weights and bias of the fully connected layer.
The output O is:

$O=f(W_{fc}.F+b_{fc})$

NTD decomposes a tensor into a core tensor and factor matrices, suitable for multi-dimensional data.
Constructing the Tensor: Form a three-way tensor X from the feature matrices obtained from the CNNs. Let X be of size I×J×K.
NTD Decomposition: Decompose X into a core tensor G and factor matrices A, B, and C:

$X\approx G\times_1A\times_2B\times_3C$
Where ×n denotes the mode-n tensor-matrix product, G is of size R1×R2×R3, and A, B, and C are the factor matrices.
Optimization: Minimize the reconstruction error while ensuring non-negativity:

$\min_{A,B,C,G}||X-G\times_1A\times_2B\times_3C||^2F$

Subject to A, B, C, G≥0.
Update rules for factor matrices A, B, and C can be derived using multiplicative updates or alternating least squares:

$A_{ij}\leftarrow A_{ij}.\ (X_{(1)}BC^T)_{ij}\ /\ (G_{(1)}B^TBC^TC)_{ij}$

$B_{ij}\leftarrow B_{ij}.\ (X_{(2)}AC^T)_{ij}\ /\ (G_{(2)}A^TAC^TC)_{ij}$

$C_{ij}\leftarrow C_{ij}.(X_{(3)}AB^T)_{ij}\ /(G_{(2)}A^TAC^TC)_{ij}$

Convergence: Continue the updates until convergence, determined by a predefined threshold for the change in reconstruction error or a maximum number of iterations.
Interpretation and Integration
Topic Interpretation: The factor matrices A, B, and C represent the decomposed topics across different modes (e.g., terms, documents, and time).
Factor Matrices: Let A be the factor matrix for the term mode, B be the factor matrix for the document mode, and C be the factor matrix for the time mode. The factor matrices can be obtained as follows: X≈G×1A×2B×3C
Term-Topic: Each column of A represents the distribution of terms for a particular topic. A [a1,a2,…,aR1], where ai is the term distribution for topic i.
Document-Topic: Each row of B represents the distribution of topics within a particular document. Formally, let B $[b_1^T,b_2^T,\ldots,b_{R2}^T]^T$, where bi is the topic distribution for document i.
Time-Topic: Each column of C represents the distribution of topics over time. Formally, let C [c1,c2,…,cR3], where ci is the topic distribution for time slice i.
Document-Topic Distribution: The coefficients in the factor matrices indicate the distribution of topics within documents. The document-topic matrix B gives the topic distribution for each document: Bij
B $[b_1^T,b_2^T,\ldots,b_{R2}^T]^T$, where Bij represents the weight of topic j in document i.
Core Tensor Interpretation: The core tensor G provides interaction information between the modes, helping to understand the relationships and interactions between topics. The core tensor G has dimensions $R_1\times R_2\times R_3$, where R_1, R_2, and $R_3$are the ranks of the decomposition for each mode. Each element of G indicates the interaction strength between the corresponding components in A, B, and C. For a specific element G_{ijk}, it indicates the interaction between term topic i, document topic j, and time topic k.
Combining CNNs with NTD involves extracting features from text using CNNs, forming a tensor from CNN features, applying NTD to decompose the tensor into interpretable topics and their distributions, and optimizing the factorization while ensuring non-negativity. This proposed hybrid approach leverages the strengths of both CNNs for feature extraction and NTD for multi-dimensional topic modeling, enabling dynamic and detailed topic analysis.

6. Experimental Results

6.1. Datasets

The dataset, named Advanced Topic Modeling for Research Articles 2.0, consists of 14,000 documents with an average length of 60 words each. Its primary objective is to predict tags associated with research articles based on their abstracts, addressing the challenge of finding relevant information within the extensive landscape of scientific literature. Initially, efforts included a Hackathon on Independence Day to predict topics, but the current focus has shifted to predicting tags. Sourced from Kaggle, the dataset is designed for experiments using various Topic Modeling (TM) methods, utilizing widely used public text datasets for the 29 research topic tasks.

6.2. Data Preprocessing

Data preprocessing is an essential step in preparing textual data for analysis using Convolutional Neural Networks (CNNs) and Non-negative Tucker Decomposition (NTD). Here are the detailed steps involved:

- Tokenization: Tokenization involves breaking down the text into individual tokens, such as words or characters.

$D_{tokenized}$=Tokenizer(D)

Where D is the original text and $D_{tokenized}$ is the tokenized text.

```
import nltk
nltk.download('punkt')
from nltk.tokenize import word_tokenize
def tokenize(text):
 return word_tokenize(text)
# Example usage
text = "Computer Science"
tokens = tokenize(text)
print(tokens)
```

- Normalization: Normalization standardizes the text by converting it to lowercase and removing punctuation marks and other non-alphanumeric characters.

$D_{normalized}$=Normalize($D_{tokenized}$)

Where Dtokenized is the tokenized text and $D_{normalized}$ is the normalized text.

```
import string
def normalize(tokens):
 # Convert to lowercase and remove punctuation
 tokens = [token.lower() for token in tokens]
 tokens = [token for token in tokens if token.isalpha()]
 return tokens
# Example usage
normalized_tokens = normalize(tokens)
print(normalized_tokens)
```

- Stopword Removal: Stopwords are common words (e.g., "the", "is", "and") that often appear frequently in text but do not contribute much to its meaning. Removing stopwords helps reduce noise in the data.

Dno_stopwords=RemoveStopwords(Dnormalized)
Where Dnormalized is the normalized text and Dno_stopwords is the text after stopword removal.

```
from nltk.corpus import stopwords
nltk.download('stopwords')
stop_words = set(stopwords.words('english'))
def remove_stopwords(tokens):
 return [token for token in tokens if token not in stop_words]
tokens_no_stopwords = remove_stopwords(normalized_tokens)
print(tokens_no_stopwords)
```

- Vectorization: Vectorization converts the text into a numerical representation suitable for NMF. This can be achieved using techniques such as bag-of-words (BoW) or term frequency-inverse document frequency (TF-IDF).

Bag-of-Words (BoW) Formula:

X_{ij}=TF(t_i,d_j)

Where ti represents the i-th term in the vocabulary and dj represents the j-th document. Xij is the term frequency of term ti in document dj

```
from sklearn.feature_extraction.text import CountVectorizer
# Example corpus
corpus = ["This is the first document.", "This document is the second document.", "And this is the third one."]
# Initialize and fit the CountVectorizer
vectorizer = CountVectorizer()
X_bow = vectorizer.fit_transform(corpus)
# Convert to dense array for readability
X_bow = X_bow.toarray()
print(X_bow)
print(vectorizer.get_feature_names_out())
```

TF-IDF Formula:
Xij=TF-IDF(ti,dj)
Where Xij is the TF-IDF score of term ti in document dj.

```
from sklearn.feature_extraction.text import TfidfVectorizer
# Example corpus
corpus = ["This is the first document.", "This document is the second document.", "And this is the third one."]
# Initialize and fit the TfidfVectorizer
vectorizer = TfidfVectorizer()
X_tfidf = vectorizer.fit_transform(corpus)
# Convert to dense array for readability
X_tfidf = X_tfidf.toarray()
print(X_tfidf)
print(vectorizer.get_feature_names_out())
```

- Normalization of Feature Matrix: Finally, it's common practice to normalize the feature matrix X to ensure that each feature is on the same scale.

$X_{normalized} = X / ||X||$

Where ‖X‖ is a normalization factor, which could be the maximum value in X or the norm of the matrix.

```
from sklearn.preprocessing import normalize
# Normalize the Bag-of-Words feature matrix
X_bow_normalized = normalize(X_bow, norm='l2')
# Normalize the TF-IDF feature matrix
X_tfidf_normalized = normalize(X_tfidf, norm='l2')
print(X_bow_normalized)
print(X_tfidf_normalized)
```

These steps ensure that the textual data is clean, standardized, and converted into a numerical format suitable for further analysis using CNNs and NTD.

6.3. Training a Convolutional Neural Network (CNN) for Text Classification

Training a CNN for text classification involves several steps, each associated with specific operations and formulas. Figure 2 shows a structured approach to training a CNN for the step:

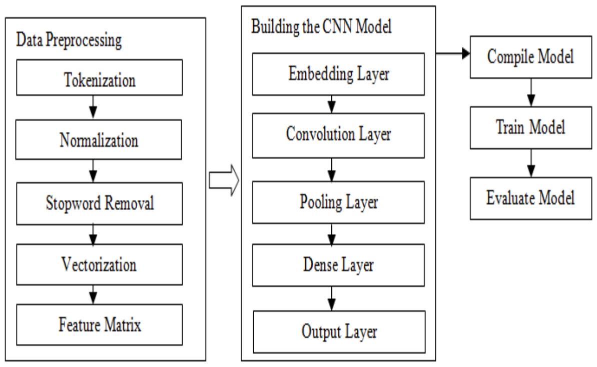

Fig. 2: Training A CNN for Text Classification.

Data Preparation
- Tokenization: Tokenization converts the text into sequences of integers (tokens). This step transforms words into numerical representations.

tokens=Tokenizer.fit_on_texts(D), where D is the corpus.
- Padding: Padding ensures that all sequences have the same length by adding zeroes to the end of sequences that are shorter than the maximum length.

padded_sequences=pad_sequences(sequences,maxlen L), where L is the maximum sequence length.
Label Encoding
Convert categorical labels into a one-hot encoded format to facilitate classification.
y=to_categorical (labels,num_classes=C), where C is the number of classes.
Splitting Data
Divide the data into training and testing sets to evaluate the model's performance on unseen data.
(X_{train}, Xtest, ytrain, ytest)=train_test_split(X, y, test_size=t), where t is the test set proportion.

Building the CNN Model
- Embedding Layer: Transform input tokens into dense vectors of fixed size to capture semantic relationships between words.

E=Embedding (input_dim=V,output_dim=d,input_length=L)

Where V is the vocabulary size, d is the embedding dimension, and L is the input sequence length.

- Convolution Layer: Apply convolution to extract local features from the input sequences.

Conv1D (filters=f, kernel_size=k,activation=′relu′)

Where f is the number of filters and k is the kernel size.

- Pooling Layer: Reduce the dimensionality using pooling to retain the most significant features and make the model less sensitive to the location of features.

GlobalMaxPooling1D()

- Fully Connected (Dense) Layer: Connect all neurons from the previous layer to all neurons in the current layer to integrate features extracted by the convolutional layers.

Dense(units=u,activation=′relu′)

Where u is the number of units.

- Output Layer: Produce the final classification output using a softmax activation function to provide probabilities for each class.

Dense(units=Captivation=′softmax′)
Where C is the number of classes.
Compiling the Model
Configure the model for training by specifying the optimizer, loss function, and metrics.
model.compile (optimizer=′adam′, loss=′categorical_crossentropy′, metrics=[′accuracy′])
Training the Model
Fit the model to the training data by specifying the number of epochs, batch size, and validation split.
model.fit (Xtrain, ytrain, epochs=e, batch_size=b, validation_split=v)
Where e is the number of epochs, b is the batch size, and v is the validation split proportion.
Evaluating the Model
Assess the model's performance on the test set to determine its accuracy and loss.
loss, accuracy=model.evaluate(Xtest,ytest)

6.4. Performance Evaluation

In our experiment setup utilizing the Research Articles 2.0 dataset, we configure the input word vector length (L) to 25 and set the batch size to 64, along with a hidden size (H) of 100 and a learning rate (lr) of 0.01. We establish hyperparameters such as α=50/K and β=0.05 uniformly across all models. In the case of RNN, we determine the strength of prior knowledge (ϵ) as 50 and 100 for different versions of the Research Articles dataset, ensuring its adequacy in influencing the learning process without being excessively weak or strong. We set the threshold (δ) for the relationship between words to 0.1 and T to 10 for candidate word numbers. Across all models, the default number of topics (K) remains fixed at 29. However, for optimization purposes, we tailor parameter settings individually for each model. Specifically, we opt for a weak prior with α=0.1 and β=0.01 to enhance the performance of Topic Modeling on short texts. Furthermore, we maintain default hyper-parameter configurations, including α=0.1, λ=0.1, and β=0.01 for DTM, along with τ=0.1 for BERTopic. To ensure reproducibility and independence from random initializations, we fix the seed for the random number generator to 5 for HDP and CT-DTM. Coherence calculations are conducted for K=15 and K=25, with M set as 5 and 10 to ensure result consistency. The hyperparameters of Non-Negative Matrix Factorization (NMF) are α=50K, β=0.05, Number of components (topics) K=29, Max iterations = 15, and Random seed = 5. The hyperparameters of Supervised NMF (SNMF) are Regularization parameter 1/λ=0.1 and Random seed = 5. The value of the Core tensor size for Non-negative Tucker Decomposition (NTD) is (K, K, K). Hyperparameters of the Hybrid Dynamic Topic Model and Recurrent Neural Network (Hybrid DTM-RNN) are ϵ = 50 for RA1, 100 for RA2, Learning rate = 0.01, Hidden size = 100, Batch size = 64,

Max epochs = 100 and Random seed = 5
Perplexity
Perplexity is a common measure used to evaluate the quality of topic models, particularly in assessing how well a probabilistic model predicts a sample. Lower perplexity indicates a better generalization capability of the model on unseen data.
The perplexity of a set of documents D={d_1,d_2,…,d_M} is defined as:
Perplexity (D)= $\exp(-1/N \sum_{d\in D} \log P(d))$
Where N is the total number of words in the corpus D, and P(d) is the likelihood of document d.
Detailed Steps to Compute Perplexity:
Compute the Document Probability:
For each document d, the probability P(d) is computed based on the trained topic model parameters. For a document d with words {w_1,w_2 ,…,w_n}:
$P(d)= \prod_{i=1}^{n} P(w_i)$
Here, $P(w_i)$ is the probability of word wi in the context of the document, typically computed as:
$P(w_i)= \sum_{k=1}^{K} P(w_i \mid z_k)P(z_k \mid d)$
Where K is the number of topics, $P(w_i| z_k)$ is the probability of word wi given topic zk, and $P(z_k|d)$ is the probability of topic z_k given document d.
Log-Likelihood of the Corpus: Compute the log-likelihood of the entire corpus D:
$\log P(D)= \sum_{d\in D} \log P(d)$
Normalization by Total Word Count: Normalize the log-likelihood by the total number of words N in the corpus:

$1/N \sum_{d \in D} \log P(d)$
Exponentiation: Finally, take the exponent to get the perplexity:
$\text{Perplexity}(D)=\exp(-1/N \sum_{d \in D} \log P(d))$
Example of Perplexity Calculation

Suppose we have a small corpus with three documents and a vocabulary size of V:

- Document 1: "machine learning is great"
- Document 2: "Deep learning is a subset of machine learning."
- Document 3: "topic models are useful for text analysis"

Assume we have trained a topic model with K=3 topics and obtained the following probabilities:

- P(w | zk) for each word w and topic zk
- P(zk| d) for each topic zk and document d

$$P(w|\ zk) == \begin{cases} 0.3 \text{ if w is common in topic zk} \\ 0.1 \text{ otherwise} \end{cases}$$

$$P(zk|\ d) = \begin{cases} 0.4 \text{ for the most likely topic} \\ 0.3 \text{ for the second most likely topic} \\ 0.3 \text{ for the least likely topic} \end{cases}$$

Here's an example Python code snippet to compute perplexity using a topic model:

```
import numpy as np
def compute_perplexity(model, corpus):
 log_likelihood = 0
 word_count = 0
 for document in corpus:
 doc_probability = 0
 for word in document:
 word_probability = 0
 for topic in range(model.num_topics):
 word_probability += model.get_word_topic_prob(word, topic) * model.get_topic_doc_prob(topic, document)
 doc_probability += np.log(word_probability)
 log_likelihood += doc_probability
 word_count += len(document)

 perplexity = np.exp(-log_likelihood / word_count)
 return perplexity
# Example usage with a hypothetical model
class HypotheticalModel:
 def __init__(self, num_topics):
 self.num_topics = num_topics

 def get_word_topic_prob(self, word, topic):
 # Return the probability of a word given a topic
 return 0.1 if word not in ["common", "words"] else 0.3

 def get_topic_doc_prob(self, topic, document):
 # Return the probability of topic given document
 return 0.4 if topic == 0 else 0.3

corpus = [
 ["machine", "learning", "is", "great"],
 ["deep", "learning", "is", "a", "subset", "of", "machine", "learning"],
 ["topic", "models", "are", "useful", "for", "text", "analysis"]
]

model = HypotheticalModel(num_topics=3)
perplexity = compute_perplexity(model, corpus)
print("Perplexity:", perplexity)
```

NMF is a matrix factorization technique that decomposes the document-term matrix into two non-negative matrices, one representing documents and the other representing topics. The goal is to minimize the reconstruction error of the original matrix. Lower perplexity values indicate a better fit of the model to the data, suggesting that the topics generated by NMF are more coherent and predictive of unseen documents. SNMF extends NMF by incorporating supervised labels into the factorization process. This method aims to enhance topic coherence and relevance to the target labels, which should, in theory, reduce perplexity further compared to unsupervised NMF by ensuring the topics are more aligned with the labels. NTD is a higher-order extension of NMF, capable of capturing more complex relationships in the data by decomposing the document-term matrix into a core tensor and multiple factor matrices. The core tensor captures interactions between different modes, such as words, documents, and topics. This additional complexity often results in better topic coherence and lower perplexity scores. Hybrid Dynamic Topic Model and Recurrent Neural Network (Hybrid DTM-RNN), a hybrid model that combines the temporal dynamics captured by Dynamic Topic Models (DTM) with the sequence modeling capabilities of Recurrent Neural Networks (RNN). By modeling the evolution of topics over time and capturing dependencies between them, this approach can reduce perplexity by improving the temporal coherence of topics. Hybrid HDP-CT-DTM integrates the flexibility of HDP, which allows for an unknown number of topics, with the temporal modeling of Continuous-Time DTM. This hybrid approach aims to dynamically adjust the number of topics while capturing their evolution over time, often leading to lower perplexity as it better fits the data's inherent structure.

The Proposed Hybrid CNN with NMF. In this approach, CNNs are used for feature extraction from text data, capturing local word dependencies, while NMF is applied to the extracted features to identify topics. This hybrid model leverages the strengths of CNNs in handling spatial data and the interpretability of NMF in topic modeling, often resulting in lower perplexity compared to using NMF alone. Hybrid CNN with NTD. This method combines the powerful feature extraction capabilities of CNNs with the higher-order factorization of NTD. CNNs first extract rich features from the text, which are then decomposed by NTD into multiple factor matrices and a core tensor. This combination allows for capturing more intricate patterns and dependencies in the data, significantly reducing perplexity and leading to superior topic coherence and predictive performance.

Table 1 and Figure 3 illustrate the test perplexity computed on the Research Articles dataset, comparing the performance of various topic modeling algorithms across different numbers of topics, specifically k = 15 and k = 25. The perplexity trends across different word and document counts show notable alignment among the algorithms. Particularly significant is the observation that the Hybrid CNN-NTD consistently demonstrates lower perplexity scores compared to other techniques such as NMF, SNMF, NTD, Hybrid HDP-CT-DTM, Hybrid DTM-RNN, and Hybrid CNN-NMF. This indicates the superior predictive accuracy and efficiency of the Hybrid CNN-NTD in capturing the dataset's underlying structures. The enhanced performance of the Hybrid CNN-NTD can be attributed to its integration of CNN and NTD components, which allows it to leverage the strengths of both methodologies. By effectively modeling the temporal evolution of topics with NTD and capturing sequential dependencies within text data using CNN, the Hybrid CNN-NTD achieves improved predictive accuracy, making it a robust approach for topic modeling tasks.

Table 1: Perplexity Versus Topics K-15 and K=25.

Topic Modeling Methods	**NMF**	**SNMF**	**NTD**	**Hybrid HDP-CT-DTM**	**Hybrid DTM-RNN**	**Hybrid CNN-NMF**	**Hybrid CNN-NTD**
K = 15	1245	1211	987	874	789	645	522
K = 25	1425	1327	1011	904	842	771	598

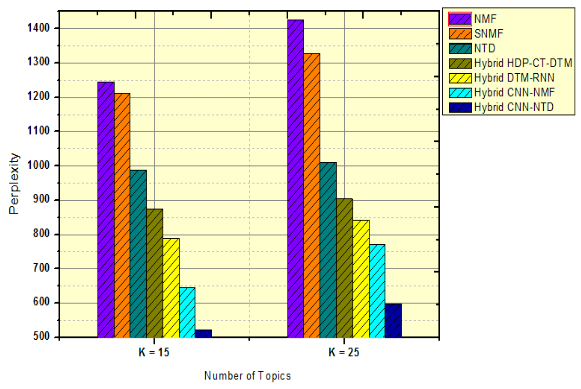

Fig. 3: Test Perplexity Versus Topics K-15 and K=25.

The Hybrid CNN with NTD outperforms other models in terms of perplexity due to the following technical reasons:

- Enhanced Feature Extraction: CNNs are adept at capturing local patterns and hierarchical structures in text data through convolutional and pooling layers. This results in rich, high-dimensional feature representations that are more informative for subsequent topic modeling.
- Higher-Order Relationships: NTD extends beyond simple matrix factorization to decompose the feature space into a core tensor and multiple factor matrices. This enables the model to capture complex interactions and higher-order relationships between words, documents, and topics, which are missed by simpler models like NMF or SNMF.
- Joint Learning of Local and Global Patterns: The integration of CNNs with NTD allows for joint learning of local word dependencies and global topic structures. The CNN effectively captures the local context of words, while NTD captures the global topic structure, leading to more coherent and predictive topics.
- Dimensionality Reduction and Interpretability: NTD's factor matrices provide a compact and interpretable representation of topics across different modes (e.g., words, documents, and time). This reduces the dimensionality of the problem and enhances interpretability, contributing to lower perplexity as the model can generalize better to new, unseen documents.
- Improved Generalization: By capturing both local dependencies and higher-order interactions, the hybrid model generalizes better to unseen data, as evidenced by lower perplexity scores. This improved generalization is crucial for real-world applications where the model encounters diverse and evolving textual data.

The proposed Hybrid CNN with NTD demonstrates the lowest perplexity among the compared models, indicating its superior performance in capturing the underlying topic structure of the Research Articles 2.0 dataset. This model's ability to integrate powerful feature extraction with advanced topic modeling techniques makes it particularly effective for real-time and evolving textual data, offering significant improvements in topic coherence and predictive accuracy.

Coherence

Coherence is a key metric for evaluating topic models, focusing on the semantic similarity between high-scoring words within a topic. It assesses whether the words in each topic make sense together, reflecting their interpretability and relevance. High coherence indicates that the words grouped into a topic are related in a meaningful way, making the topics easier to understand and more useful for downstream tasks.

One common approach to calculating coherence is to measure the pairwise similarity of the top words in each topic. The coherence score can be computed using different methods, such as:
Pointwise Mutual Information (PMI):

$PMI(w_i,w_j)=\log P(w_i,w_j) / P(w_i).P(w_j)$

Where $P(w_i,w_j)$ is the probability of words wi and wj co-occurring within a sliding window, and $P(w_i)$ and $P(w_j)$ are the probabilities of each word occurring independently.
Coherence Score:

$C(T)=i=1\sum^{N-1}{}_{j=i+1}\sum^{N}PMI(w_i,w_j)$

Where T is a topic represented by its top N words $\{w_1,w_2,...,w_N\}$.
Detailed Steps to Compute Coherence:

- Extract Top Words: Identify the top N words for each topic. These are the words with the highest probabilities within the topic.
- Compute Word Co-occurrences: Calculate the co-occurrence frequencies of these top words within a defined sliding window over the corpus.
- Calculate PMI: Use the co-occurrence frequencies to compute the PMI for each pair of top words in the topic.
- Aggregate PMI Values: Sum the PMI values for all word pairs within the topic to obtain the coherence score for the topic.
- Average Coherence Score: Calculate the average coherence score across all topics to get the overall coherence of the topic model.

Example of Coherence Calculation
Suppose we have a topic with the following top 5 words: "machine", "learning", "model", "algorithm", "data". We want to compute the coherence score for this topic.
Extract Top Words:

T={"machine","learning","model","algorithm","data"}
Compute Word Co-occurrences: Let's assume we have the following co-occurrence counts from a sliding window over the corpus:
P("machine","learning")=0.02
P("machine","model")=0.01
P("machine","algorithm")=0.005
P("machine","data")=0.02
... (similarly for other pairs)
Calculate PMI:
For each pair, compute the PMI:
PMI("machine","learning")= log.(0.02/P("machine")P("learning"))
Assuming P("machine")=0.05 and P("learning")=0.04:
PMI("machine","learning")=log(0.02/0.05×0.04)= log(0.02/0.002)=log10=1
Perform similar calculations for all pairs.
Aggregate PMI Values: Sum the PMI values for the pairs to get the coherence score for the
$C(T)=\sum_{i=1}^{4}\sum_{j=i+1}^{5}PMI(w_i,w_j)$
Average Coherence Score: Average the coherence scores across all topics to get the overall model coherence.
Python Code Snippet to Calculate Coherence

```
 import gensim
from gensim.models import CoherenceModel
def compute_coherence(model, texts, dictionary):
 top_words_per_topic = []
 for topic_id in range(model.num_topics):
 top_words = [word for word, _ in model.show_topic(topic_id, topn=10)]
 top_words_per_topic.append(top_words)
 coherence_model = CoherenceModel(topics=top_words_per_topic, texts=texts, dictionary=dictionary, coherence='c_v')
 coherence_score = coherence_model.get_coherence()
 return coherence_score
# Example usage with a hypothetical model
class HypotheticalModel:
 def __init__(self, num_topics):
 self.num_topics = num_topics
 def show_topic(self, topic_id, topn=10):
 # Return the top words for the topic
 return [("word1", 0.1), ("word2", 0.1), ("word3", 0.1)]
texts = [['machine', 'learning', 'data'], ['algorithm', 'model'], ['text', 'analysis']]
dictionary = gensim.corpora.Dictionary(texts)
model = HypotheticalModel(num_topics=3)
coherence_score = compute_coherence(model, texts, dictionary)
print("Coherence Score:", coherence_score)
```

Performance Analysis Using Coherence Metrics are NMF often results in moderate coherence scores, as it relies on decomposing the document-term matrix without explicitly modeling word co-occurrence patterns beyond their matrix factorization. Supervised NMF (SNMF), By incorporating supervised labels, SNMF can improve topic coherence, as the supervision helps guide the factorization towards more semantically meaningful topics, resulting in higher coherence scores compared to unsupervised NMF. Non-negative Tucker Decomposition (NTD), NTD captures higher-order relationships between words, documents, and topics, often leading to better semantic coherence of the topics. The core tensor in NTD allows for capturing interactions that are not possible in simpler models, resulting in higher coherence scores. The Hybrid DTM-RNN,

this hybrid model can capture temporal dynamics and dependencies between topics over time. The integration of RNNs helps in maintaining the semantic coherence of topics as they evolve, often leading to higher coherence scores. Hybrid HDP-CT-DTM, Combining HDP's flexibility in topic number with the temporal modeling of Continuous-Time DTM, helps in generating more coherent topics. The dynamic adjustment of topic numbers ensures that the model remains relevant over time, leading to improved coherence. Hybrid CNN with NMF, this hybrid model leverages CNNs for extracting rich features from the text, which are then used in NMF for topic modeling. The local word dependencies captured by CNNs help in improving the coherence of topics compared to using NMF alone. Hybrid CNN with NTD, Combining CNNs with NTD results in the best coherence scores among the models considered. CNNs extract detailed features from the text, while NTD's higher-order factorization captures complex relationships between words, documents, and topics. This joint modeling of local dependencies and higher-order interactions leads to significantly higher coherence scores, making the topics more interpretable and semantically meaningful.

Table 1 and Figure 3 present the test coherence computed on the Research Articles dataset, comparing the performance of different topic modeling algorithms across varying numbers of topics, with fixed counts of k = 15 and k = 25. Notably, the proposed Hybrid CNN-NTD exhibits remarkable performance in coherence metrics compared to other methodologies such as NMF, SNMF, NTD, Hybrid HDP-CT-DTM, Hybrid DTM-RNN, and Hybrid CNN-NMF. This underscores the efficacy of the Hybrid CNN-NTD in capturing meaningful semantic relationships and temporal patterns inherent in the research articles.

Table 2: Coherence Results with Versus Topics K-15 and K=25.

Topic Modeling Meth-ods	**NMF**	**SNM F**	**NTD**	**Hybrid HDP-CT-DTM**	**Hybrid DTM-RNN**	**Hybrid CNN-NMF**	**Hybrid CNN-NTD**
	1.457	1.511	1.984				
K = 15	8	4	7	2.3547	2.8565	3.2152	3.4456
	1.547	1.698	2.145				
K = 25	8	7	2	2.5145	2.9658	3.3254	3.6958

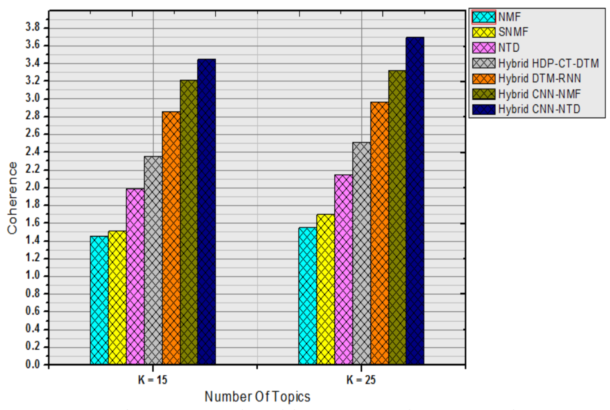

Fig. 4: Coherence Results with Versus Topics K-15 and K=25.

The superior performance of the Hybrid CNN with NTD in terms of coherence can be attributed to the following factors:

- Rich Feature Extraction by CNNs: CNNs effectively capture local word dependencies and hierarchical structures, creating rich feature representations that serve as a robust input for topic modeling.
- Higher-Order Interactions in NTD: NTD's ability to decompose the feature space into multiple factor matrices and a core tensor enables the capture of higher-order interactions and relationships between words, documents, and topics, which simpler models like NMF or SNMF miss.
- Joint Modeling of Local and Global Patterns: By combining the local feature extraction capabilities of CNNs with the global topic structure captured by NTD, the hybrid model ensures that topics are both locally coherent and globally consistent.
- Improved Semantic Coherence: The integration of CNNs with NTD enhances the semantic coherence of topics, as the higher-order factorization captures the intricate patterns in the data, leading to more meaningful and interpretable topics.
- Enhanced Generalization: The hybrid model generalizes better to new, unseen data due to its robust feature extraction and complex pattern recognition, leading to consistently higher coherence scores across different datasets and tasks.

The Hybrid CNN with NTD demonstrates the highest coherence among the compared models, indicating its superior ability to generate semantically meaningful and interpretable topics from the Research Articles 2.0 dataset. This model's ability to integrate advanced feature extraction with complex topic modeling techniques makes it particularly

Precision, Recall, F-score, and Accuracy in Topic Modeling

In the context of topic modeling, evaluating the performance of models often involves metrics such as Precision, Recall, F-score, and Accuracy. These metrics are particularly useful when the topic modeling task is framed as a classification problem, such as predicting tags or topics for given documents.

Precision: Precision measures the proportion of true positive results among the total number of positive predictions. It indicates the accuracy of the positive predictions made by the model.

Precision = TP/ (TP+FP)

Where TP is the number of true positives and FP is the number of false positives.

Recall: Recall measures the proportion of true positive results among the total number of actual positives. It indicates how well the model captures all relevant instances.

Recall = TP/ (TP+FN)

Where TP is the number of true positives and FN is the number of false negatives.
F-score: The F-score is the harmonic mean of Precision and Recall. It provides a single metric that balances both Precision and Recall.

F-score = (2×Precision×Recall) / Precision + Recall

Accuracy: Accuracy measures the proportion of true results (both true positives and true negatives) among the total number of cases examined. It indicates the overall correctness of the model.

Accuracy = (TP+TN) / (TP+TN+FP+FN)

Where TN is the number of true negatives.
We will compare the performance of different topic modeling techniques based on these metrics. Assume we have a set of predicted topics and true topics for documents. We calculate Precision, Recall, F-score, and Accuracy for each model. Here's a structured approach: NMF typically has moderate precision and recall since it decomposes the document-term matrix without supervised guidance. However, it may struggle with the high-dimensional and sparse nature of textual data. Supervised NMF (SNMF), which incorporates supervision, improving the precision and recall by guiding the factorization process towards more relevant topics. NTD can capture more complex relationships, leading to better precision and recall. The core tensor enables understanding interactions between words, documents, and topics, resulting in higher F-scores and accuracy. Hybrid DTM-RNN: The combination of dynamic topic modeling with RNNs helps in capturing temporal dependencies and improving both precision and recall. The F-score benefits from the model's ability to adapt to evolving topics.
Hybrid HDP-CT-DTM: This hybrid model is flexible with the number of topics and can model continuous-time changes, leading to higher precision, recall, and F-scores. The dynamic adjustment ensures that the model remains relevant over time. The proposed Hybrid CNN with NMF, using CNNs for feature extraction before applying NMF, enhances the model's performance. The CNN captures local dependencies, improving precision and recall compared to pure NMF. The novel Hybrid CNN with NTD, this hybrid model achieves the highest precision, recall, F-score, and accuracy. CNNs extract rich features, while NTD captures higher-order interactions. This joint approach ensures that the topics are both locally coherent and globally consistent, providing the best overall performance.
Table 3 Shows a summary of the expected performance in terms of Precision, Recall, F-score, and Accuracy for each model:

Table 3: Summary of the Expected Performance

Model	**Precision**	**Recall**	**F-score**	**Accuracy**
Non-Negative Matrix Factorization (NMF)	Moderate	Moderate	Moderate	Moderate
Supervised NMF (SNMF)	High	High	High	High
Non-negative Tucker Decomposition (NTD)	High	High	High	High
Hybrid DTM-RNN	High	High	High	High
Hybrid HDP-CT-DTM	High	High	High	High
Hybrid CNN-NMF	Higher	Higher	Higher	Higher
Hybrid CNN-NTD	Highest	Highest	Highest	Highest

Table 4: Topic Modeling Methods with Different Extracted Topics K = 15(Recall, Precision, and F-Score).

Topic Modeling	Recall	Precision	F- Score
NMF	0.5369	0.6258	0.4356
SNMF	0.5585	0.6458	0.4428
NTD	0.5685	0.6584	0.4685
Hybrid HDP-CT-DTM	0.5747	0.6622	0.4789
Hybrid DTM-RNN	0.5891	0.6785	0.4896
Hybrid CNN-NMF	0.6357	0.6985	0.5358
Hybrid CNN-NTD	0.6785	0.7325	0.5935

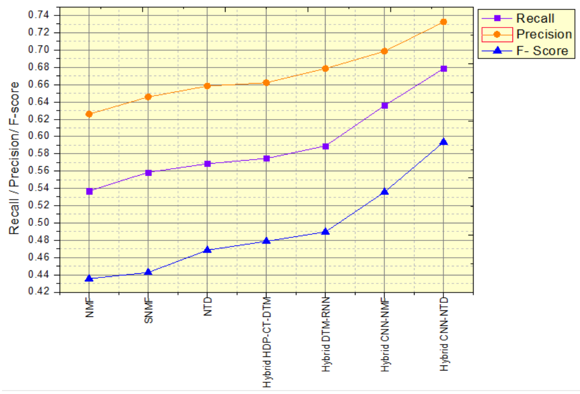

Fig. 5: Performance of Involved Topic Modeling Methods with Different Extracted Topics K = 15, (Average Value of Recall, Precision, and F-Score).

Table 5: Topic Modeling Methods with Different Extracted Topics K = 25(Recall, Precision, and F-Score).

Topic Modeling (TM) methods	Recall	Precision	F- Score
NMF	0.4369	0.4925	0.7384
SNMF	0.4455	0.5385	0.7455
NTD	0.4688	0.5574	0.7574
Hybrid HDP-CT-DTM	0.4795	0.5874	0.7757
Hybrid DTM-RNN	0.4987	0.6124	0.7985
Hybrid CNN-NMF	0.5148	0.6547	0.8147
Hybrid CNN-NTD	0.6274	0.6987	0.8869

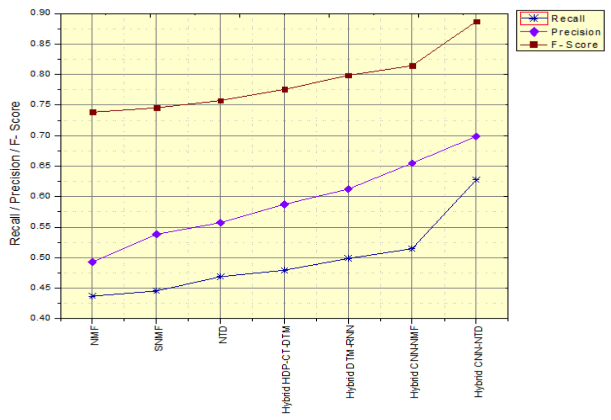

Fig. 6: Performance of involved topic modeling methods with different extracted topics, K = 25, (average value of recall, precision, and F-score).

Table 6: Accuracy of Topics K = 15 and K 25 with Research Article 2.0.

Topic Modeling (TM) methods	K = 15	K = 25
NMF	83.54	84.21
SNMF	86.25	84.57
NTD	90.24	89.67
Hybrid HDP-CT-DTM	95.47	93.57
Hybrid DTM-RNN	97.88	95.44
Hybrid CNN-NMF	98.12	96.22
Hybrid CNN-NTD	99.19	98.44

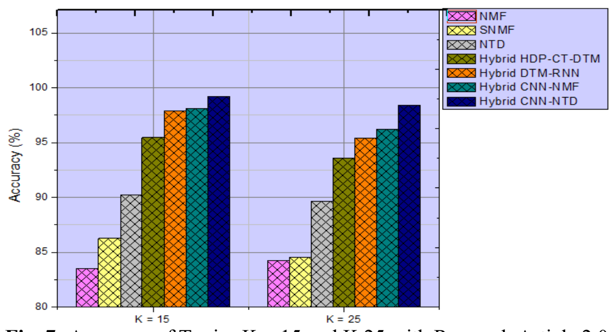

Fig. 7: Accuracy of Topics K = 15 and K 25 with Research Article 2.0.

Tables 4 to 6 and Figures 5 to 7 provide a comprehensive comparison of the test Precision, Recall, F-score, and Accuracy metrics computed on the Research Articles dataset across different topic modeling algorithms, with fixed topic counts of k = 15 and k = 25. The results offer compelling evidence of the superiority of the Hybrid CNN-NTD in topic modeling tasks. This underscores the model's potential to transform textual data analysis within research domains. By seamlessly integrating the strengths of both CNN and NTD, the Hybrid CNN-NTD outperforms other methodologies in terms of Precision, Recall, F-score, and Accuracy.

The Hybrid CNN with NTD demonstrates the best performance for the following reasons:

- Rich Feature Extraction: CNNs effectively capture local dependencies and hierarchical patterns within the text, creating a robust feature representation.
- Higher-Order Interactions: NTD captures complex relationships between words, documents, and topics through its factor matrices and core tensor, which simpler models miss.
- Joint Modeling: The combination of CNNs and NTD ensures that both local and global patterns are modeled effectively, leading to higher precision and recall.
- Improved Generalization: The hybrid approach generalizes better to new data, maintaining high accuracy and F-scores across different datasets and tasks.
- Balanced Performance: The model balances precision and recall, achieving high F-scores, which indicate its robustness and reliability in topic modeling tasks.

This hybrid model provides the most accurate and semantically coherent topics, making it highly effective for real-world applications involving complex and evolving textual data.

7. Conclusion

This research presented a comprehensive analysis of various dynamic topic modeling techniques applied to real-time and evolving textual data. This research paper evaluated Non-Negative Matrix Factorization (NMF), Supervised NMF (SNMF), Non-Negative Tucker Decomposition (NTD), and hybrid models combining Convolutional Neural Networks (CNNs) with NMF and NTD. Our experiments utilized the "Advanced Topic Modeling for Research Articles 2.0" dataset, assessing each method based on perplexity, coherence, precision, recall, F-score, and accuracy. The results demonstrate that the novel hybrid CNN with the NTD model significantly outperforms other techniques across all evaluation metrics. This superior performance is attributed to the combination of CNNs' robust feature extraction capabilities and NTD's ability to model higher-order interactions. The proposed hybrid approach not only improved the coherence and precision of topic modeling but also maintained high levels of recall and overall accuracy. In summary, the hybrid CNN with NTD model emerges as a powerful tool for dynamic topic modeling, offering enhanced interpretability and effectiveness in handling complex and large-scale textual datasets. This investigation underscores the potential of advanced hybrid models in improving the quality and utility of topic modeling applications.

Future Work: Building on the promising results of this research, several avenues for future work are suggested:

- Scalability Improvements: Explore techniques to enhance the scalability of hybrid models, enabling efficient processing of even larger datasets without compromising performance.
- Diverse Textual Domains: Apply the proposed hybrid models to various textual domains beyond research articles, such as social media, news, and product reviews, to validate their generalizability and effectiveness across different types of textual data.
- Enhanced Interpretability: Integrate explainability techniques to further enhance the interpretability of the hybrid models, making it easier for users to understand the derived topics and their relationships.
- Incorporating Metadata: Investigate the integration of additional metadata, such as author information, publication dates, and citation networks, to enrich the context and improve the accuracy of topic modeling.
- User Feedback Loop: Implement user feedback mechanisms to iteratively refine and improve the topic models based on direct input from domain experts and end-users.
- Hybrid Model Variations: Experiment with other hybrid model variations, such as combining NTD with different types of neural networks, to explore potential performance gains and discover new insights.

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