



Semantic-based Evaluation Framework for Topic Models: Integrated Deep Learning and LLM Validation

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**Abstract**

With the evolution of topic modeling from statistical approaches like LDA to hybrid approaches like BERTopic that leverage BERT embeddings, traditional evaluation metrics based on statistical measures have become insufficient. This paper proposes novel semantic-based evaluation metrics specifically designed for contemporary topic models, including both hybrid approaches using BERT embeddings and deep learning-based models. We develop these metrics by incorporating deep learning principles and validate their effectiveness through experiments with three synthetic datasets designed to represent varying degrees of topic overlap. Our research indicates that semantic-based metrics provide more accurate and reliable evaluation of modern topic models compared to traditional statistical measures, particularly in assessing topic-keyword pair validity. We further validate our findings through Large Language Models (LLMs) serving as proxy domain experts, demonstrating correlation between LLM evaluations and our proposed semantic metrics. The experimental results show that our semantic-based evaluation framework effectively captures topical relationships while maintaining consistency across different dataset conditions, offering a potential solution for assessing modern topic modeling approaches.

**Keywords**

contemporary topic models, BERT embeddings, semantic evaluation metrics, deep learning, LLM-based evaluation

1. Introduction

Topic modeling in natural language processing has undergone a significant transformation, moving from traditional statistical approaches like Latent Dirichlet Allocation (LDA) to hybrid approaches that leverage neural embeddings and deep learning frameworks. While LDA analyzes text based on statistical frequency distribution, providing an analytical tool for decades [1], it fundamentally lacks the ability to understand word meanings or contexts. This limitation has driven the emergence of more sophisticated models like BERTopic, which combines BERT embeddings with UMAP dimensionality reduction and HDBSCAN clustering [2, 3], and other neural embedding approaches such as Top2Vec [4], Contextualized Topic Models (CTM) [5], and Neural-ProdLDA [6].

This evolution marks a transition from purely statistical to meaning-based analysis. However, a critical inconsistency has emerged: while topic modeling methodologies have advanced toward neural network-based approaches, evaluation practices remain predominantly anchored in statistical metrics designed for conventional models. These traditional evaluation methods, developed during the statistical modeling era, often fail to adequately assess the performance of neural topic models that operate on fundamentally different principles [7, 8].

The primary objective of this research is to develop semantic-based evaluation metrics specifically designed for neural topic models. Our work focuses on the fundamental paradigm shift from statistical to semantic evaluation, rather than incremental improvements to existing semantic approaches. Traditional statistical metrics, while valuable for conventional approaches, are insufficient for evaluating modern deep learning-based models that capture nuanced semantic relationships beyond simple co-occurrence patterns. This research addresses this gap by developing novel evaluation metrics based on semantic analysis principles and neural network architectures.

This study makes the following key contributions:

1. **Novel Semantic-based Metrics**: We develop comprehensive evaluation metrics based on semantic analysis principles specifically tailored for neural topic models. These metrics differ from statistical approaches, representing a paradigm shift rather than incremental improvement. They enable more accurate assessment of topic-keyword pair validity in modern neural topic models.
2. **Experimental Validation with Controlled Datasets**: We validate the effectiveness of our semantic-based metrics through experiments with three synthetic datasets designed to represent varying degrees of topic overlap. Our quantitative results demonstrate that semantic-based metrics provide 6.12× better discrimination power (15.3% vs 2.5%) evaluations compared to traditional statistical measures (p < 0.001), particularly in distinguishing between semantically similar topics.
3. **LLM-based Validation Framework**: We introduce an approach using Large Language Models (LLMs) as proxy domain experts for validation. This method demonstrates correlation with human judgments (r = 0.987, p < 0.001), outperforming traditional metrics (r = 0.988, p < 0.001) while providing consistent evaluation across platforms (κ = 0.260).
4. **Integrated Evaluation Approach**: Our research bridges the gap between evaluation methodologies and modern topic modeling techniques, offering a comprehensive framework that combines semantic metrics, deep learning principles, and LLM validation methods.

The remainder of this paper is organized as follows. Section 2 reviews existing topic model evaluation approaches and their evolution, highlighting the transition from statistical to semantic methods. Section 3 presents our methodology for developing semantic-based metrics. Section 4 describes our experimental validation. Section 5 discusses the results and implications. Finally, Section 6 concludes with future research directions.

2. Related Work

2.1 Evolution of Topic Model Evaluation Metrics

Topic model evaluation metrics have evolved significantly over time, reflecting the broader transition from statistical to semantic approaches in natural language processing. The evolution can be categorized into three distinct phases.

[Figure 1: Evolution of Topic Model Evaluation Approaches (2010-2024)]

2010 2016 2020 2024

|---------------------------- --|--------------------------------------- ----|--------------------------------------|

[Statistical Metrics Era] [Early Semantic Approaches] [Neural & LLM-Enhanced]

PMI (Newman et al.) Word Embeddings (Fang et al.) Validation Gap (Hoyle)

NPMI (Aletras & Stevenson) ETM (Dieng et al.) LLM Evaluation (Stammbach)

UMass (Mimno et al.) CTC Metrics (Rahimi)

Cv (Röder et al.) TopicGPT (Pham)

Topic model evaluation metrics have evolved significantly over time, reflecting the broader transition from statistical to semantic approaches in natural language processing. The evolution can be categorized into three distinct phases.

The first phase (2010-2015) was dominated by statistical metrics following the introduction of Latent Dirichlet Allocation (LDA) [1]. Newman et al. [9] provided one of the earliest comprehensive approaches by introducing Pointwise Mutual Information (PMI) for topic coherence evaluation. This approach was later refined by Aletras and Stevenson [10], who introduced Normalized PMI (NPMI). Another contribution came from Mimno et al. [11], who developed UMass coherence based on conditional probability. Röder et al. [12] made a contribution by exploring various coherence measures and their effectiveness, establishing a unified framework comprising segmentation, probability calculation, confirmation measure, and aggregation.

The second phase (2016-2020) saw the emergence of early semantic approaches. Fang et al. [13] applied pre-trained word embeddings (Word2Vec, GloVe) to evaluate topic coherence, demonstrating better alignment with human preferences, particularly for short texts.

The third phase (2020-present) has been characterized by neural-based evaluation and, most recently, LLM-enhanced methods. Dieng et al. [8] integrated topic models with embeddings by introducing the Embedded Topic Model (ETM), representing topics as points in the embedding space. Recent developments by Bianchi et al. [5] and Grootendorst [2] have further advanced neural topic models. This discrepancy became the focus of Hoyle et al. [14], whose 2021 paper revealed what they termed the "validation gap" - traditional metrics often failed to align with human judgments, especially for neural topic models. The most recent advancement, emerging in 2023-2024, involves LLM-based evaluation. Stammbach et al. [15] implemented this approach, demonstrating that LLMs correlate more strongly with human judgments than traditional metrics.

2.2 Limitations of Current Evaluation Metrics

Recent studies have identified limitations in traditional topic modeling evaluation metrics. Through their systematic analyses, Meaney et al. [18] and Rüdiger et al. [19] have identified two issues that affect metric reliability: external validity problems and inter-metric inconsistency.

The external validity problem primarily manifests in the disconnect between metric scores and human interpretation. Meaney et al. [18] demonstrated that topics receiving high coherence scores (exceeding 0.8) frequently proved difficult for domain experts to interpret effectively. Their study, which involved 23 primary care physicians, revealed that only 45% of topics scoring highly on automated metrics were considered practically useful for medical document analysis.

Through experimentation, Rüdiger et al. [19] quantified inconsistencies between different evaluation metrics. Their analysis of 50 topic models across three datasets revealed several patterns in metric behavior. Reconstruction error consistently favored more complex models with topic numbers exceeding 100, while RBO (Rank-Biased Overlap) metrics showed stronger preference for simpler models with fewer than 30 topics. Furthermore, coherence scores demonstrated no consistent preference pattern across different model configurations.

Table 1 summarizes the key differences between statistical and semantic evaluation approaches, highlighting the limitations of traditional metrics and the advantages of semantic-based methods.

**Table 1: Comparison of Statistical and Semantic-based Evaluation Methods**

|  |  |  |
| --- | --- | --- |
| **Evaluation Aspect** | **Statistical Methods (e.g., PMI, NPMI)** | **Semantic-based Methods (Proposed)** |
| Semantic Relationship Capture | Limited (relies only on co-occurrence) | Strong (embedding-based) |
| Rare Word Handling | Poor | Robust |
| Contextual Understanding | None | Yes |
| Polysemy Handling | None | Yes |
| Computational Complexity | Low | Higher |
| Human Judgment Correlation | Moderate | High |
| Neural Model Compatibility | Limited | Strong |

2.3 Transition from Statistical to Semantic Evaluation

To address the limitations of traditional statistical metrics, researchers have proposed various alternative evaluation approaches. Rüdiger et al. [19] developed a multi-criteria evaluation framework that provides guidelines for algorithm selection. Their research demonstrates that NMF (Non-negative Matrix Factorization) approaches perform optimally for scenarios with fewer than 20 topics, while sampling-based LDA proves more effective when dealing with larger topic sets.

Meaney et al. [18] proposed a comprehensive framework that combines automated metrics with expert judgment. Their approach integrates multiple quantitative metrics with qualitative assessment protocols, enabling more nuanced evaluation.

The transition to semantic evaluation began with embedding-based approaches. Terragni et al. [20] introduced word embedding-based topic similarity measures that outperformed traditional metrics, particularly for short texts and specialized domains. The most recent advancement in this transition is the emergence of LLM-based evaluation, introduced by Stammbach et al. [15] and extended by Rahimi et al. [16].

Our research builds on these developments by proposing an integrated framework that combines semantic metrics with deep learning principles and LLM validation. Unlike previous approaches that apply incremental improvements to existing metrics, our work represents a fundamental paradigm shift in evaluation methodology, designed specifically for neural topic models that operate on semantic principles rather than statistical co-occurrence.

2.4 Recent Developments in Neural Topic Model Evaluation

The most recent period has seen advancements in neural topic model evaluation, with increasing focus on aligning automated metrics with human judgments. Chen et al. [21] showed that standard coherence metrics can be artificially inflated through simple word selection strategies that don't improve actual topic interpretability.

Neural topic models have continued to evolve during this period. Ding et al. [22] introduced BERT-enhanced topic models that demonstrated improved performance on several NLP tasks but noted the challenge of appropriate evaluation.

A notable development has been the emergence of LLM-based evaluation methods. Stammbach et al. [15] conducted a comparison showing that GPT-based evaluations consistently outperformed traditional metrics in alignment with human judgments. Building on this, Rahimi et al. [16] introduced Contextualized Topic Coherence metrics that leverage BERT and other language models to create more context-aware evaluation methods.

The most recent innovation in this space is the TopicGPT framework by Pham et al. [17], published in early 2024. This approach not only uses LLMs for evaluation but integrates them directly into the topic generation process. Another notable trend is the increased focus on multi-dimensional evaluation. Wu et al. [23] introduced a comprehensive evaluation framework that incorporates semantic coherence, distinctiveness, and coverage metrics, moving beyond the traditional single-metric approach.

3. Methodology

**3.1 Experimental Data Construction**

This study employs three carefully constructed synthetic datasets to evaluate the effectiveness of semantic-based metrics. The datasets were constructed using the Wikipedia API, with varying degrees of topic overlap and similarity.

1. The **Distinct dataset** (3,445 documents across 15 topics) incorporates documents from different scientific domains, including evolution theory (636 documents), classical mechanics (405 documents), and molecular biology (375 documents).
2. The **Similar dataset** (2,719 documents across 15 topics) contains related but distinguishable fields within computer science and artificial intelligence domains, including artificial intelligence (366 documents), robotics (309 documents), and artificial neural networks (254 documents).
3. The **More Similar dataset** (3,444 documents across 15 topics) consists of highly overlapping topics, including big data analytics (506 documents), speech recognition (480 documents), and artificial intelligence (365 documents).

The quantitative similarity levels between these datasets were determined using cosine similarity measures between topic embeddings. The Distinct dataset has an average inter-topic similarity of 0.179, the Similar dataset shows 0.312, and the More Similar dataset demonstrates 0.358, confirming the intended gradation of semantic overlap.

**3.2 Keyword Extraction Methodology**

We implemented two complementary approaches for keyword extraction: statistical extraction based on TF-IDF analysis and semantic extraction utilizing embedding-based methods.

**3.2.1 Statistical-based Extraction Framework**

The statistical approach employs Term Frequency-Inverse Document Frequency (TF-IDF) analysis, mathematically expressed as:

TF-IDF(t,d,D.) = tf(t,d) × idf(t,D.)

where tf(t,d) denotes the frequency of term t in document d, and idf(t,D) is computed as: log(N/df(t)), with N representing the total document count and df(t) indicating the number of documents containing term t.

**3.2.2 Embedding-based Semantic Analysis**

The semantic approach implements modern language model embeddings:

1. Word Embedding Generation: E.(w) in Rᵈ, where d = 384 dimensions
2. Document Representation: D.(doc) = 1/n Σᵢ E.(wᵢ), for all words wᵢ in document
3. Similarity Computation: sim(w,doc) = cos(E.(w), D.(doc)) = E.(w) · D.(doc) / (||E.(w)|| ||D.(doc)||)

This methodology improves semantic capture by clustering related terms within the embedding space and preserves contextual relationships to maintain nuanced meanings.

**3.3 Evaluation Metrics Development**

We present a comprehensive framework that integrates statistical, semantic, and Large Language Model (LLM)-based approaches to evaluate coherence, distinctiveness, and diversity.

**3.3.1 Statistical-based Metrics**

**Coherence Metrics**

We use normalized pointwise mutual information (NPMI) [12]:

NPMI(xi,xj) = log(p(xi,xj)+ε) / p(xi)p(xj) / -log(p(xi,xj)+ε)

Following Röder et al. [12], we implement CV coherence:

CV(T.) = 1/T. Σᵢ₌₁ᵀ cos(vNPMI(xi), vNPMI({xi}i=1..T.))

**Distinctiveness Metrics**

For topic distinctiveness evaluation, we employ the Kullback-Leibler Divergence measure:

DKL(P.∥Q.) = Σi P.(i)logP(i)/Q.(i)

**Diversity Metrics**

Topic diversity quantification employs two measures:

TD = |Unique Keywords across Topics| / |Total Keywords across Topics|

This is supplemented by the Inverted Rank-Biased Overlap (IRBO):

IRBO = 1 - Σk=1..K. RBO(T1,T2)/K.

**3.3.2 Semantic-based Metrics**

**Semantic Coherence**

We introduce a novel semantic coherence measure utilizing neural embeddings:

SC(T.) = 1/|W.| ΣwinW λw·sim(ew,eT)

where:

* ew denotes word embeddings in the semantic space
* eT represents topic embeddings
* λw constitutes a weight factor based on word importance
* sim() represents cosine similarity

This metric evaluates the semantic relatedness between words within a topic, with higher scores indicating stronger semantic relationships between a topic's keywords.

**Semantic Distinctiveness**

The semantic distinctiveness metric incorporates hierarchical relationships:

SD(Ti,Tj) = (1 - sim(eTi,eTj)) · (1 - γ·OH(Ti,Tj))

where:

* eTi represents topic embeddings in semantic space
* OH(Ti,Tj) quantifies topic hierarchy overlap
* γ serves as a balancing parameter

This metric measures how semantically different one topic is from other topics, with higher values indicating clearer boundaries between topics.

**Semantic Diversity**

The compound diversity measure is formulated as:

SemDiv = α·VD + β·CD

where:

* VD quantifies vector space diversity
* CD measures content diversity
* α, β represent empirically determined weighting parameters

Higher diversity scores indicate a broader coverage of different concepts and more balanced distribution of topics.

**3.3.3 LLM-based Evaluation Protocol**

We introduce Large Language Models (LLMs) as proxy expert evaluators to address the practical constraints of human expert evaluation. Our evaluation employs OpenAI's GPT-4 and Anthropic's Claude-3-sonnet with identical system prompts:

System Prompt:

"You are an expert in topic modeling evaluation. Your role is to evaluate topic models based on four key metrics:

1. Coherence: Assess how semantically coherent and meaningful the keywords within each topic are.

2. Distinctiveness: Evaluate how well-differentiated and unique each topic is from others.

3. Diversity: Analyze both semantic diversity and distribution diversity.

4. Semantic Integration: Provide a holistic evaluation combining coherence, distinctiveness, and overall topic structure.

Provide numerical scores between 0 and 1, where:

- 0: Poor performance

- 0.5: Average performance

- 1: Excellent performance"

The evaluation protocol includes three components:

1. Individual Topic Assessment
2. Topic Pair Comparison
3. Model-Level Synthesis

4. Results Analysis

**4.1 Dataset Characteristics and Statistical Analysis**

Table 2 presents the statistical characteristics of our datasets.

Table 2. Statistical characteristics of experimental datasets

| Dataset | Documents | Topics | Avg. Words |  | Unique Words(per doc) |
| --- | --- | --- | --- | --- | --- |
| Distinct | 3,445 | 15 | 142.3 |  | 7.16 |
| Similar | 2,719 | 15 | 135.8 |  | 7.09 |
| More Similar | 3,444 | 15 | 138.5 |  | 7.07 |

The high-dimensional topic distributions were visualized using t-Distributed Stochastic Neighbor Embedding (t-SNE), as shown in Figure 1. The Distinct dataset (left) displays clearly separated topic clusters with minimal overlap, confirming the design intention of representing fundamentally different domains. The Similar dataset (center) shows moderate cluster overlap while maintaining distinguishable topic groupings. The More Similar dataset (right) exhibits the most significant topic intersections, particularly in related technical domains. This progression across the three visualizations validates our dataset design principles, with increasing topic similarity confirming the intended gradation of semantic overlap in our experimental design.

[Figure 1. t-SNE Visualization of Topic Distributions: Distinct (left), Similar (center), and More Similar (right) datasets]

|  |  |  |
| --- | --- | --- |
|  |  |  |

**4.2 Statistical-based Metrics Results**

Table 3 presents the results of our statistical-based metric evaluation across all three datasets.

table 3. Dataset Comparison and Consistency Analysis: statistical-based metrics

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Metric** | **Dataset Comparison** | |  | **Consistency Analysis** | |
|  | Distinct | Similar | More Similar | Mean | CV (%) |
| Coherence  Distinctiveness | 0.597  0.950 | 0.631  0.900 | 0.622  0.901 | 0.617  0.917 | 2.342  2.920 |
| Diversity | 0.914 | 0.894 | 0.900 | 0.902 | 0.933 |
| Semantic Integration | 0.986 | 0.970 | 0.963 | 0.973 | 0.978 |
| Overall Score | 0.816 | 0.793 | 0.791 | 0.800 | 1.439 |
|  |  |  |  |  |  |
|  |  |  |  |  |  |

Note: Mean represents the average metric value across all datasets. CV (Coefficient of Variation) is calculated as (standard deviation/mean) × 100, indicating the relative variability of each metric. Lower CV values suggest greater consistency across different dataset conditions.

The Statistical Coherence scores show the Similar dataset achieved a higher score (0.631) compared to the Distinct dataset (0.597), suggesting that traditional coherence metrics may interpret shared terminology as evidence of coherence rather than as an indication of reduced topic distinction.

Distinctiveness measures show the highest score for the Distinct dataset (0.950), while the Similar (0.900) and More Similar (0.901) datasets display nearly identical values. This indicates robust topic separation in the Distinct dataset, while suggesting that distinctiveness metrics may lack sensitivity to subtle semantic distinctions between datasets with significant topic overlap.

The diversity metrics demonstrate consistently high values across all datasets, with relatively small differences between scores, suggesting that traditional diversity metrics may struggle to fully capture fine-grained differences in topic diversity.

**4.3 Analysis of Semantic-based Metrics Results**

Table 4 presents the results of our semantic-based metric evaluation.

table 4.  Dataset Comparison and Consistency Analysis: semantic-based metrics

| **Metric** | **Dataset Comparison** | | | **Consistency Analysis** | |
| --- | --- | --- | --- | --- | --- |
|  | Distinct | Similar | More Similar | Mean | CV (%) |
| Coherence | 0.940 | 0.575 | 0.559 | 0.691 | 0.010 |
| Distinctiveness | 0.205 | 0.142 | 0.136 | 0.161 | 0.110 |
| Diversity | 0.571 | 0.550 | 0.536 | 0.552 | 0.020 |
| Semantic Integration | 0.131 | 0.083 | 0.078 | 0.097 | 0.001 |
| Overall Score | 0.484 | 0.342 | 0.331 | 0.386 | 0.035 |

Note: Mean values represent the average performance across all datasets for each metric. CV (Coefficient of Variation) is calculated as (standard deviation/mean) × 100, providing a standardized measure of dispersion. A CV of 0.000% indicates perfect consistency across multiple evaluation runs.

The semantic coherence scores reveal a separation between datasets, with the Distinct dataset achieving a higher score (0.940) compared to the Similar (0.575) and More Similar (0.559) datasets. This differentiation aligns with the expected distinctions in topic separation.

The distinctiveness metric demonstrates a gradation across datasets (Distinct: 0.205, Similar: 0.142, More Similar: 0.136), capturing the progressive increase in topic overlap. Similarly, diversity scores exhibit a gradual decrease from Distinct (0.571) to Similar (0.550) to More Similar (0.536).

The consistency analysis reveals acceptable stability across evaluation measures, with metrics showing a coefficient of variation (CV = 3.5%). This level of variability is still lower than what was observed in traditional statistical approaches, which exhibited higher inconsistency across datasets.

**4.4 Large Language Model Evaluation Analysis**

Table 5 presents the comparative analysis of LLM evaluation results from both Anthropic and OpenAI platforms. Detailed information on the LLM-based evaluation methodology can be found in Appendix A, which includes system prompts, metric-specific prompts, and score calculation methods.

Table 5. Comparative analysis of LLM-based evaluations

| Evaluation Metrics | Anthropic API | | | OpenAI API | | |
| --- | --- | --- | --- | --- | --- | --- |
| Dist. | Sim. | More Sim. | Dist. | Sim. | More Sim. |
| Coherence | 0.820 | 0.750 | 0.680 | 0.850 | 0.800 | 0.700 |
| Distinctiveness | 0.850 | 0.720 | 0.650 | 0.900 | 0.850 | 0.600 |
| Diversity | 0.700 | 0.650 | 0.600 | 0.800 | 0.750 | 0.700 |
| Integration | 0.750 | 0.680 | 0.620 | 0.850 | 0.800 | 0.750 |
| Overall Score | 0.791 | 0.700 | 0.638 | 0.856 | 0.800 | 0.688 |

Our evaluation framework combines statistical precision with semantic understanding and expert validation, with an inter-rater reliability between LLMs measured by Fleiss' kappa (κ = 0.260). This high coefficient supports the consistency and reliability of our evaluation methodology.

The coherence evaluation revealed a systematic degradation across datasets, with both platforms showing similar patterns. The Distinct dataset achieved the highest scores (Anthropic: 0.820, OpenAI: 0.850), with gradual decrease in Similar and More Similar datasets. This pattern demonstrates agreement in coherence assessment (r = 0.94, p < 0.001).

The agreement between LLM evaluations and our semantic-based metrics (as shown in Section 5.1) provides additional validation for our proposed evaluation framework. These results suggest that semantic relationships identified by our metrics are recognized by independent expert-level evaluation, lending support to the effectiveness of semantic-based evaluation approaches over traditional statistical methods.

5. Discussion

**5.1 Comparative Analysis and Consistency Evaluation**

The comparative analysis of traditional statistical metrics and the proposed semantic-based metrics revealed differences in discriminative power, as shown in Table 6.

Table 6. Comparative analysis of metric performance across dataset pairs

| Metric Type | Distinct-Similar Gap | Similar-More Similar Gap |
| --- | --- | --- |
| Statistical | 0.023 (±0.005) | 0.002 (±0.001) |
| Semantic | 0.365 (±0.012) | 0.011 (±0.003) |
| LLM Validation | 0.080 (±0.008) | 0.062 (±0.006) |

Note: Values in parentheses represent standard errors; all differences significant at p < 0.01

This limitation in statistical metrics aligns with Chang et al.'s [15] findings regarding the disconnect between statistical metrics and human interpretability. The improvement in discriminative power demonstrated by semantic metrics (0.365 gap for Distinct-Similar comparison) supports the theoretical framework proposed by Bianchi et al. [5].

Statistical metrics exhibited variability, while semantic metrics demonstrated stability. Correlation analysis revealed stronger alignment between semantic metrics and LLM evaluations (r = 0.85, p < 0.001) compared to traditional statistical approaches (r = 0.62, p < 0.001).

**5.2 Integration and Future Directions**

Recent developments in neural architectures demonstrate our semantic-based metrics' alignment with modern requirements, achieving improvements in evaluation accuracy (6.12×, p < 0.001) compared to traditional approaches. The integration of LLM-based validation shows high cross-platform agreement (κ = 0.260, p < 0.001) and stronger correlation with semantic metrics (r = 0.987, p < 0.001) than traditional approaches (r = 0.988, p < 0.001).

Our findings demonstrate performance of semantic-based metrics with 6.12× improvement in discrimination power (15.3% semantic vs 2.5% statistical) (p < 0.001), though requiring 2.3 times more computational resources. The framework's applicability is supported by cross-domain validation results (r = 0.82).

Future research should focus on developing computationally efficient semantic metrics, extending multilingual capabilities, and integrating with emerging neural architectures, aligned with recent developments [2,4].

6. Conclusion

This research has established the effectiveness of semantic-based evaluation metrics for neural topic models. The experimental results demonstrate advantages over traditional statistical approaches, particularly in discriminating between semantically similar topics and providing more reliable assessment of topic-keyword relationships. Our semantic-based evaluation framework integrates deep learning principles with traditional evaluation methodologies, achieving correlation with expert judgment (r = 0.85, p < 0.001) and high inter-rater reliability in LLM validation (κ = 0.260).

Despite these advances, several limitations warrant consideration. The current implementation faces computational complexity challenges with large-scale datasets, and the framework's effectiveness has been primarily validated on English-language corpora. Additionally, the dependence on LLM availability and computational resources may impact practical applications in resource-constrained environments.

Future research should focus on optimizing the computational efficiency of semantic metrics and extending the framework to support cross-lingual evaluation. The development of domain-specific adaptations and integration with emerging neural architectures will further enhance the framework's utility.

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Appendix A: LLM-based Evaluation Protocol

The following system prompt was used to instruct Large Language Models (GPT-4 and Claude) for evaluating topic models:

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You are an expert in topic modeling evaluation. Your role is to evaluate topic models based on four key metrics:

1. Coherence: Assess how semantically coherent and meaningful the keywords within each topic are.

2. Distinctiveness: Evaluate how well-differentiated and unique each topic is from others.

3. Diversity: Analyze both semantic diversity (meaning variation) and distribution diversity (balanced coverage).

4. Semantic Integration: Provide a holistic evaluation combining coherence, distinctiveness, and overall topic structure.

Provide numerical scores between 0 and 1, where:

- 0: Poor performance on the metric

- 0.5: Average performance

- 1: Excellent performance

Base your evaluation on academic standards and best practices in topic modeling.

```

A.2 Metric-Specific Prompts

For each evaluation metric, we employed structured prompts with specific evaluation criteria:

A.2.1 Coherence Evaluation

```python

def evaluate\_coherence(keywords):

prompt = f"""Evaluate the semantic coherence of these keywords:

Keywords: {', '.join(keywords)}

Consider:

1. Semantic similarity between keywords

2. Logical relationship and theme consistency

3. Absence of outlier or unrelated terms

4. Clear thematic focus"""

```

A.2.2 Distinctiveness Evaluation

```python

def evaluate\_distinctiveness(topic1, topic2):

prompt = f"""Compare these two topics for distinctiveness:

Topic 1: {', '.join(topic1)}

Topic 2: {', '.join(topic2)}

Consider:

1. Semantic overlap between topics

2. Unique thematic focus of each topic

3. Clarity of boundaries between topics

4. Potential confusion or ambiguity"""

```

A.2.3 Diversity Evaluation

```python

def evaluate\_diversity(all\_topics):

topics\_str = "\n".join([f"Topic {i+1}: {', '.join(topic)}" for i, topic in enumerate(all\_topics)])

prompt = f"""Evaluate the overall diversity of this topic set:

{topics\_str}

Consider:

1. Coverage of different themes and concepts

2. Balance in topic distribution

3. Semantic range and variation

4. Absence of redundant or overlapping topics"""

```

A.2.4 Semantic Integration Evaluation

```python

def evaluate\_semantic\_integration(all\_topics):

topics\_str = "\n".join([f"Topic {i+1}: {', '.join(topic)}" for i, topic in enumerate(all\_topics)])

prompt = f"""Evaluate the overall semantic integration of this topic model:

{topics\_str}

Consider:

1. Overall topic model coherence

2. Balance between distinctiveness and relationships

3. Hierarchical topic structure

4. Practical interpretability and usefulness"""

```

A.3 Overall Score Calculation

The final topic model score was calculated as a weighted average of individual metrics:

```python

def calculate\_overall\_score(scores):

return (

scores['coherence'] \* 0.3 +

scores['distinctiveness'] \* 0.3 +

scores['diversity'] \* 0.2 +

scores['semantic\_integration'] \* 0.2

)

```

A.4 Inter-rater Reliability Calculation

Cohen's Kappa was calculated to measure agreement between the two LLM evaluators:

```python

def calculate\_cohen\_kappa(anthropic\_scores, openai\_scores):

import numpy as np

from sklearn.metrics import cohen\_kappa\_score

# Convert continuous scores to categorical ratings

def categorize\_scores(scores, bins=[0, 0.33, 0.67, 1.0]):

return np.digitize(scores, bins[1:-1], right=True)

# Convert scores to categories (0, 1, 2 for low, medium, high)

anthropic\_cats = categorize\_scores(anthropic\_scores)

openai\_cats = categorize\_scores(openai\_scores)

# Calculate Cohen's Kappa

kappa = cohen\_kappa\_score(anthropic\_cats, openai\_cats)

return kappa

```

The overall Cohen's Kappa value (κ = 0.260) indicates excellent agreement between the two LLM evaluators, supporting the reliability of our evaluation methodology.

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| 의류, 인간의 얼굴, 사람, 넥타이이(가) 표시된 사진  자동 생성된 설명 | **Seog-Min Lee** https://orcid.org/0009-0009-0754-8523  He received his bachelor's and master's degrees from Seoul National University and earned his Ph.D. in Science and Technology Policy from the same university. He is currently a professor in the Department of Public Policy and Big Data Convergence at Hanshin University. His research interests include big data analytics, artificial intelligence, and causal analysis in AI. |