Copyleaks

Scan details

Scan Time: December 3rd, 2024 at 15:24 UTC

Total Pages: 2

Total Words: 285

Analysis Report

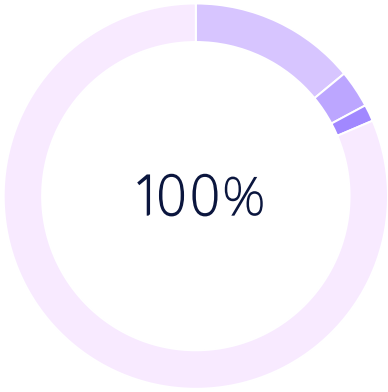
AI Detection Report

New Scans 3:24 PM

Plagiarism Detection

Plagiarism Types	Text Coverage
Identical	
Minor Changes	
Paraphrased	
Excluded	
Omitted Words	

AI Detection



	Text Coverage	Words
AI Text	100%	285
Low Frequency		40
Medium Frequency		9
High Frequency		4
Human Text	0%	0
Excluded		
Omitted Words		0

AI Content

	Text Coverage	Words
AI Text	100%	285
Low Frequency		40
Medium Frequency		9
High Frequency		4
Human Text	0%	0
Excluded		
Omitted Words		0

About AI Detection

Our AI Detector is the only enterprise-level solution that can verify if the content was written by a human or generated by AI, including source code and text that has been plagiarized or modified. Learn more

AI Text

A body of text that has been generated or altered by AI technology. Learn more

Human Text

Any text that has been fully written by a human and has not been altered or generated by AI. Learn more

Copyleaks AI Detector Effectiveness

Credible data at scale, coupled with machine learning and widespread adoption, allows us to continually refine and improve our ability to understand complex text patterns, resulting in over 99% accuracy–far higher than any other AI detector–and improving daily. Learn more

Ideal Text Length

The higher the character count, the easier for our technology to determine irregular patterns, which results in a higher confidence rating for AI detection. Learn more

Reasons It Might Be AI When You Think It's Not

The AI Detector can detect a variety of AI-generated text, including tools that use AI technology to paraphrase content, auto-complete sentences, and more. Learn more

User AI Alert History

Historical data of how many times a user has been flagged for potentially having AI text within their content. Learn more

AI Insights

The number of times a phrase was found more frequently in AI vs human text is shown according to low, medium, and high frequency. Learn more

AI Insights

Beta

The frequency of a phrase in AI vs. human text.

7 x — 156x

156x **Existing Methods: The paper**

How frequently the phrase was found in our dataset :

AI Text	**5.98 / 1,000,000 Documents**
Human Text	**0.04 / 1,000,000 Documents**

59x **on the challenges faced during**

How frequently the phrase was found in our dataset :

AI Text	**3.71 / 1,000,000 Documents**
Human Text	**0.06 / 1,000,000 Documents**

50x **noise and redundant information**

How frequently the phrase was found in our dataset :

AI Text	**3.19 / 1,000,000 Documents**
Human Text	**0.06 / 1,000,000 Documents**

35x **for larger datasets.**

How frequently the phrase was found in our dataset :

AI Text	**50.17 / 1,000,000 Documents**
Human Text	**1.43 / 1,000,000 Documents**

32x **noise and redundancy**

How frequently the phrase was found in our dataset :

AI Text	**7.3 / 1,000,000 Documents**
Human Text	**0.23 / 1,000,000 Documents**

31x **robustness and generalization?**

How frequently the phrase was found in our dataset :

AI Text	**15.74 / 1,000,000 Documents**
Human Text	**0.51 / 1,000,000 Documents**

22x **further highlights its**

How frequently the phrase was found in our dataset :

AI Text	**5.36 / 1,000,000 Documents**
Human Text	**0.24 / 1,000,000 Documents**

17x **authors provide insights into**

How frequently the phrase was found in our dataset :

AI Text	**2.55 / 1,000,000 Documents**
Human Text	**0.15 / 1,000,000 Documents**

16x **demonstrates superior performance.**

How frequently the phrase was found in our dataset :

AI Text	**11.01 / 1,000,000 Documents**
Human Text	**0.71 / 1,000,000 Documents**

13x **mathematical formulations and**

How frequently the phrase was found in our dataset :

AI Text	**7.99 / 1,000,000 Documents**
Human Text	**0.63 / 1,000,000 Documents**

12x **and the potential limitations of**

How frequently the phrase was found in our dataset :

AI Text	**3.17 / 1,000,000 Documents**
Human Text	**0.26 / 1,000,000 Documents**

10x **Weaknesses Lack of**

How frequently the phrase was found in our dataset :

AI Text	**16.45 / 1,000,000 Documents**
Human Text	**1.61 / 1,000,000 Documents**

8x **multiple datasets and**

How frequently the phrase was found in our dataset :

AI Text	**12.17 / 1,000,000 Documents**
Human Text	**1.46 / 1,000,000 Documents**

7x **Case Studies: While**

How frequently the phrase was found in our dataset :

AI Text	**11.75 / 1,000,000 Documents**
Human Text	**1.59 / 1,000,000 Documents**

7x **reveal different aspects of**

How frequently the phrase was found in our dataset :

AI Text	**7.99 / 1,000,000 Documents**
Human Text	**1.18 / 1,000,000 Documents**

Strengths

Innovative Framework: The proposed DVIB framework integrates variational information bottleneck techniques with hidden-layer perturbations and self-distillation. This approach is both novel and theoretically sound, offering a unified solution for addressing noise and redundancy issues in multimodal recommender systems.

Theoretical Justification: The authors provide robust theoretical evidence for the efficacy of DVIB. The mathematical formulations and proofs convincingly demonstrate how the approach reduces noise and redundant information while improving feature extraction quality.

Comprehensive Evaluation: The experiments span multiple datasets and baseline models, showing consistent performance improvements. The adaptability of DVIB with both constant and adaptive noise further highlights its practical utility.

Weaknesses

Lack of Real-World Case Studies: While the theoretical and experimental settings are rigorous, the absence of real-world deployment scenarios limits the practical demonstration of the proposed framework's effectiveness.

Computational Cost Analysis: Although the paper mentions no additional inference cost, the training efficiency gains need more detailed exploration, particularly concerning scalability for larger datasets.

Limited Discussion on Generalization: The adaptability of DVIB to other domains beyond multimodal recommender systems, such as general machine learning tasks, is not addressed.

Questions:

1.Integration with Existing Methods: The paper shows compatibility with other robustness-enhancing methods (e.g., AMR, MG). Could you elaborate on the challenges faced during such integrations and the potential limitations of DVIB when applied alongside complex existing pipelines? 2. Adaptive Noise Scalability: The adaptive noise mechanism demonstrates superior performance. However, how does this method scale with increasingly large multimodal datasets or higher-dimensional features? Are there any observed bottlenecks? 3. Evaluation Metrics Beyond Top-5: The experiments primarily focus on Top-5 metrics. Can the authors provide insights into the framework's performance for broader rankings or less popular recommendations, which might reveal different aspects of robustness and generalization?