Copyleaks

Scan details

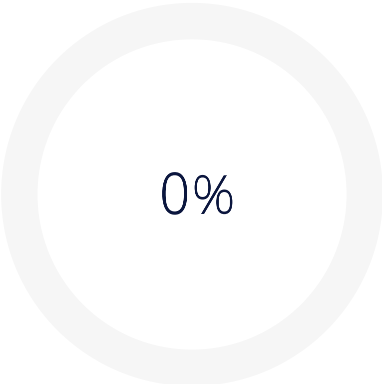
Scan Time:	Total Pages:	Total Words:
March 28th, 2025 at 07:16 UTC	3	644

Analysis Report

Plagiarism Detection and AI Detection Report

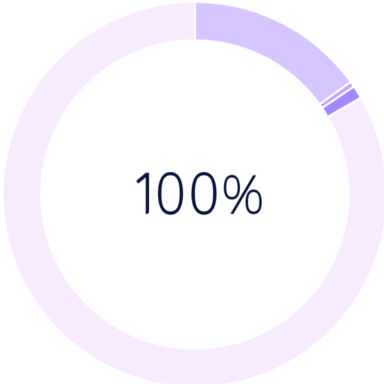
Anonymous ACL2025

Plagiarism Detection



Plagiarism Types	Text Coverage	Words
Identical	0%	0
Minor Changes	0%	0
Paraphrased	0%	0
Excluded		
Omitted Words		0

AI Detection



	Text Coverage	Words
AI Text	100%	644
Low Frequency		97
Medium Frequency		3
High Frequency		7
Human Text	0%	0
Excluded		
Omitted Words		0

Plagiarism

0%

Results (0)

*Results may not appear because the feature has been disabled.

Repository	Internal Database	Filtered / Excluded
0	0	0

Internet Sources	Current Batch
0	0

Plagiarism Types	Text Coverage	Words
Identical	0%	0
Minor Changes	0%	0
Paraphrased	0%	0
Excluded		
Omitted Words		0

About Plagiarism Detection

Our AI-powered plagiarism scans offer three layers of text similarity detection: Identical, Minor Changes, and Paraphrased. Based on your scan settings we also provide insight on how much of the text you are not scanning for plagiarism (Omitted words).

Identical

One to one exact word matches. Learn more

Minor Changes

Words that hold nearly the same meaning but have a change to their form (e.g. "large" becomes "largely"). Learn more

Paraphrased

Different words that hold the same meaning that replace the original content (e.g. 'large' becomes 'big') Learn more

Omitted Words

The portion of text that is not being scanned for plagiarism based on the scan settings. (e.g. the 'Ignore quotations' setting is enabled and the document is 20% quotations making the omitted words percentage 20%) Learn more

Copyleaks Internal Database

Our Internal Database is a collection of millions of user-submitted documents that you can utilize as a scan resource and choose whether or not you would like to submit the file you are scanning into the Internal Database. Learn more

Filtered and Excluded Results

The report will generate a complete list of results. There is always the option to exclude specific results that are not relevant. Note, by unchecking certain results, the similarity percentage may change. Learn more

Current Batch Results

These are the results displayed from the collection, or batch, of files uploaded for a scan at the same time. Learn more

AI Content

	Text Coverage	Words
AI Text	100%	644
Low Frequency		97
Medium Frequency		3
High Frequency		7
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.

3 x — 619x

619x	and generative AI. The
How frequently the phrase was found in our dataset:	
AI Text	**1.64 / 1,000,000 Documents**
Human Text	**0 / 1,000,000 Documents**

522x	and generative AI
How frequently the phrase was found in our dataset:	
AI Text	**16.6 / 1,000,000 Documents**
Human Text	**0.03 / 1,000,000 Documents**

228x	meaningfully to this
How frequently the phrase was found in our dataset:	
AI Text	**67.49 / 1,000,000 Documents**
Human Text	**0.3 / 1,000,000 Documents**

45x	advancements in text
How frequently the phrase was found in our dataset:	
AI Text	**3.27 / 1,000,000 Documents**
Human Text	**0.07 / 1,000,000 Documents**

29x	processing or natural language
How frequently the phrase was found in our dataset:	
AI Text	**1.41 / 1,000,000 Documents**
Human Text	**0.05 / 1,000,000 Documents**

23x	multiple attributes, or
How frequently the phrase was found in our dataset:	
AI Text	**5.9 / 1,000,000 Documents**
Human Text	**0.26 / 1,000,000 Documents**

20x	motivations and constraints
How frequently the phrase was found in our dataset:	
AI Text	**9.74 / 1,000,000 Documents**
Human Text	**0.48 / 1,000,000 Documents**

19x	would benefit from analyzing
How frequently the phrase was found in our dataset:	
AI Text	**1.36 / 1,000,000 Documents**
Human Text	**0.07 / 1,000,000 Documents**

18x	improvements aimed at
How frequently the phrase was found in our dataset:	
AI Text	**28.44 / 1,000,000 Documents**
Human Text	**1.6 / 1,000,000 Documents**

11x	and rigorous methodology
How frequently the phrase was found in our dataset:	
AI Text	**7.26 / 1,000,000 Documents**
Human Text	**0.64 / 1,000,000 Documents**

10x	language understanding or
How frequently the phrase was found in our dataset:	
AI Text	**2.93 / 1,000,000 Documents**
Human Text	**0.3 / 1,000,000 Documents**

9x	recommendation - Given the
How frequently the phrase was found in our dataset:	
AI Text	**7.76 / 1,000,000 Documents**
Human Text	**0.84 / 1,000,000 Documents**

9x	rendering, and better
How frequently the phrase was found in our dataset:	
AI Text	**1.41 / 1,000,000 Documents**
Human Text	**0.16 / 1,000,000 Documents**

9x	processing and linguistic
How frequently the phrase was found in our dataset:	
AI Text	**1.58 / 1,000,000 Documents**
Human Text	**0.18 / 1,000,000 Documents**

8x	demonstrating improvements in
How frequently the phrase was found in our dataset:	
AI Text	**7.8 / 1,000,000 Documents**
Human Text	**0.94 / 1,000,000 Documents**

8x	complexity - The study
How frequently the phrase was found in our dataset:	
AI Text	**4.33 / 1,000,000 Documents**
Human Text	**0.56 / 1,000,000 Documents**

7x **their effectiveness in improving**

How frequently the phrase was found in our dataset:	
AI Text	**9.22 / 1,000,000 Documents**
Human Text	**1.25 / 1,000,000 Documents**

7x **models for better**

How frequently the phrase was found in our dataset:	
AI Text	**15.55 / 1,000,000 Documents**
Human Text	**2.38 / 1,000,000 Documents**

6x **reasoning, which are**

How frequently the phrase was found in our dataset:	
AI Text	**5.68 / 1,000,000 Documents**
Human Text	**0.94 / 1,000,000 Documents**

6x **empirical validation - The**

How frequently the phrase was found in our dataset:	
AI Text	**1.83 / 1,000,000 Documents**
Human Text	**0.32 / 1,000,000 Documents**

6x **approach outperforms previous**

How frequently the phrase was found in our dataset:	
AI Text	**2.63 / 1,000,000 Documents**
Human Text	**0.47 / 1,000,000 Documents**

5x **term to mitigate**

How frequently the phrase was found in our dataset:	
AI Text	**1.38 / 1,000,000 Documents**
Human Text	**0.27 / 1,000,000 Documents**

5x **detailed analysis of how the**

How frequently the phrase was found in our dataset:	
AI Text	**5.24 / 1,000,000 Documents**
Human Text	**1.14 / 1,000,000 Documents**

5x **The proposed method integrates:**

How frequently the phrase was found in our dataset:	
AI Text	**2.1 / 1,000,000 Documents**
Human Text	**0.47 / 1,000,000 Documents**

4x **provide a strong foundation for the**

How frequently the phrase was found in our dataset:	
AI Text	**3.6 / 1,000,000 Documents**
Human Text	**0.8 / 1,000,000 Documents**

4x **modeling - If the**

How frequently the phrase was found in our dataset:	
AI Text	**2.93 / 1,000,000 Documents**
Human Text	**0.67 / 1,000,000 Documents**

4x **aims to remain**

How frequently the phrase was found in our dataset:	
AI Text	**4.26 / 1,000,000 Documents**
Human Text	**0.99 / 1,000,000 Documents**

4x **cases where text**

How frequently the phrase was found in our dataset:	
AI Text	**1.64 / 1,000,000 Documents**
Human Text	**0.38 / 1,000,000 Documents**

4x **on multiple benchmarks**

How frequently the phrase was found in our dataset:	
AI Text	**1.68 / 1,000,000 Documents**
Human Text	**0.45 / 1,000,000 Documents**

3x **improves upon existing**

How frequently the phrase was found in our dataset:	
AI Text	**4.6 / 1,000,000 Documents**
Human Text	**1.32 / 1,000,000 Documents**

3x **alignment rather than**

How frequently the phrase was found in our dataset:	
AI Text	**4.25 / 1,000,000 Documents**
Human Text	**1.36 / 1,000,000 Documents**

This paper proposes Diffusion-RainbowPA, a novel method for aligning diffusion-based text-to-image (T2I) models with human preference. It builds upon Diffusion-DPO (Direct Preference Optimization) and introduces six key improvements aimed at addressing text-image misalignment, aesthetic overfitting, and low-quality image generation. The proposed method integrates:

Step-aware Preference Alignment - a refined step-wise preference modeling approach.

Calibration Enhancement (CEPA) - a correction term to mitigate preference misalignment.

Overfitting Mitigation:

Identical Preference Alignment (IPA) - avoiding bias from Bradley-Terry modeling assumptions.

Jensen-Shannon Divergence Constraint - stabilizing preference-based training.

Performance Optimization

Margin Strengthened Preference Alignment (MSPA) - improving contrastive learning for stronger preference signals.

SFT-like Regularization - enhancing the model's ability to generate preferred samples.

The paper extensively evaluates Diffusion-RainbowPA on multiple benchmarks (GenEval, T2I-CompBench++, GenAI-Bench, DPG-Bench) and demonstrates state-of-the-art performance. The ablation study confirms that each proposed component contributes positively to alignment quality.

However, the primary contributions focus on image generation quality improvements rather than text processing or natural language understanding. The paper does not introduce substantial advancements in text representation, multimodal alignment techniques, or linguistic modeling, which are core areas of interest for *ACL venues.

Summary Of Strengths:

Well-structured and rigorous methodology - The paper systematically improves upon existing preference-based alignment strategies (Diffusion-DPO and SPO) with clear theoretical justifications.

Strong empirical validation - The proposed approach outperforms previous SOTA methods across four major benchmarks, demonstrating improvements in alignment quality.

Comprehensive ablation studies - The impact of each component is thoroughly analyzed, confirming their effectiveness in improving model alignment.

Mathematically well-grounded - The theoretical motivations and constraints (e.g., Jensen-Shannon divergence vs. KL divergence) provide a strong foundation for the proposed approach.

Relevant to the T2I research community - Preference-based alignment is an important topic for text-to-image generation, and the study contributes meaningfully to this area.

Summary Of Weaknesses:

Limited focus on text processing and linguistic aspects

The paper primarily improves image generation quality (reducing aesthetic overfitting, improving color rendering, and better aligning user preferences), rather than text representation or textual grounding.

The modifications to DPO training loss, preference functions, and contrastive objectives do not contribute significantly to text understanding or multimodal fusion.

Not aligned with *ACL's primary research focus

The main audience of ACL conferences is NLP researchers, but this paper is better suited for computer vision and generative AI conferences (e.g., CVPR, ICCV, NeurIPS, ICLR).

If the paper were focused on improving text encoding, retrieval-augmented generation for prompts, or multimodal text-image representation learning, it would be more relevant for ACL.

Lack of novelty in the NLP domain

Preference alignment techniques such as DPO and RLHF variants have been widely studied in both LLMs and generative AI. The paper applies existing alignment paradigms (e.g., step-aware preference, divergence constraints) rather than introducing fundamentally new linguistic techniques.

Benchmark choice favors image-centric evaluation

While the paper uses multiple benchmarks, they primarily evaluate image quality and text-image alignment rather than language understanding or compositionality in text prompts.

There is no detailed analysis of how the model handles linguistic complexity, ambiguity, or multi-modal reasoning, which are key concerns in ACL venues.

Comments Suggestions And Typos:

Clarify the contribution to text modeling - If the paper aims to remain in the ACL track, the authors should explicitly discuss how the preference alignment improves the handling of textual semantics in T2I generation.

Expand discussion on linguistic complexity - The study would benefit from analyzing cases where text prompts contain syntactic ambiguity, multiple attributes, or negation to assess how alignment affects textual understanding.

Comparison with LLM-based T2I methods - Given that many modern T2I models leverage language models for better text understanding (e.g., DALL·E 3, Parti), a discussion on how Diffusion-RainbowPA compares to LLM-based multimodal approaches would strengthen the positioning of the work.

Alternative venue recommendation - Given the paper's focus on image generation rather than NLP, the authors should consider submitting to CVPR, ICCV, NeurIPS, or ICLR, where the contributions would be more directly appreciated.