

Diversity Boosts AI-Generated Text Detection

Anonymous authors

Paper under double-blind review

Abstract

Detecting AI-generated text is an increasing necessity to combat misuse of LLMs in education, business compliance, journalism, and social media, where synthetic fluency can mask misinformation or deception. While prior detectors often rely on token-level likelihoods or opaque black-box classifiers, these approaches struggle against high-quality generations and offer little interpretability. In this work, we propose **DivEye**, a novel detection framework that captures how unpredictability fluctuates across a text using surprisal-based features. Motivated by the observation that human-authored text exhibits richer variability in lexical and structural unpredictability than LLM outputs, **DivEye** captures this signal through a set of interpretable statistical features. Our method outperforms existing zero-shot detectors by up to 33.2% and achieves competitive performance with fine-tuned baselines across multiple benchmarks. **DivEye** is robust to paraphrasing and adversarial attacks, generalizes well across domains and models, and improves the performance of existing detectors by up to 18.7% when used as an auxiliary signal. Beyond detection, **DivEye** provides interpretable insights into why a text is flagged, pointing to rhythmic unpredictability as a powerful and underexplored signal for LLM detection.

1 Introduction

Large Language Models (LLMs) have become deeply integrated into daily human workflows, powering applications from personal assistants to academic writing (Alahdab, 2024; Meyer et al., 2023; Lund et al., 2023) and content creation (Hu et al., 2024; Yuan et al., 2022). Their fluency and generalization capabilities make them highly useful, but this same fluency enables a growing number of concerning applications. AI-generated text can now be seamlessly inserted into essays, news articles, legal briefs, scientific abstracts, and social media posts, often without detection (De Giorgio et al., 2025; Papageorgiou et al., 2024; Telenti et al., 2024; Törnberg et al., 2023).

As LLM-generated outputs grow more sophisticated and human-like, detecting them has become an increasingly difficult challenge (Abdali et al., 2024; Gameiro et al., 2024; Wu et al., 2025; Zhang et al., 2024). Reliable AI-text detection is crucial for mitigating risks such as misinformation, AI-assisted academic dishonesty, professional misconduct, and the inadvertent suppression of authentic human writing. Traditional approaches to this problem rely on supervised detectors (Shukla et al., 2024; Tolstykh et al., 2024; Wang et al., 2024b) trained on annotated datasets of AI and human-authored text. These models often incorporate rich features, ranging from stylometry and structure to information-theoretic metrics, and achieve high performance within the domain they were trained on. However, such methods struggle to generalize to unseen models or domains (Doughman et al., 2024; Gameiro et al., 2024), especially as new LLMs are frequently released. In contrast, zero-shot detectors (Bao et al., 2024; Gehrmann et al., 2019; Mitchell et al., 2023; Wang et al., 2024a) offer a promising alternative by avoiding model-specific training. These approaches either extract statistical cues from language model probability distributions or use LLMs themselves as inference-time detectors, enabling model-agnostic detection at scale. Given the increasing deployment of unknown or fine-tuned LLMs in the wild, zero-shot detection has become an essential tool for maintaining platform integrity and addressing the forensic needs of AI-era communication.

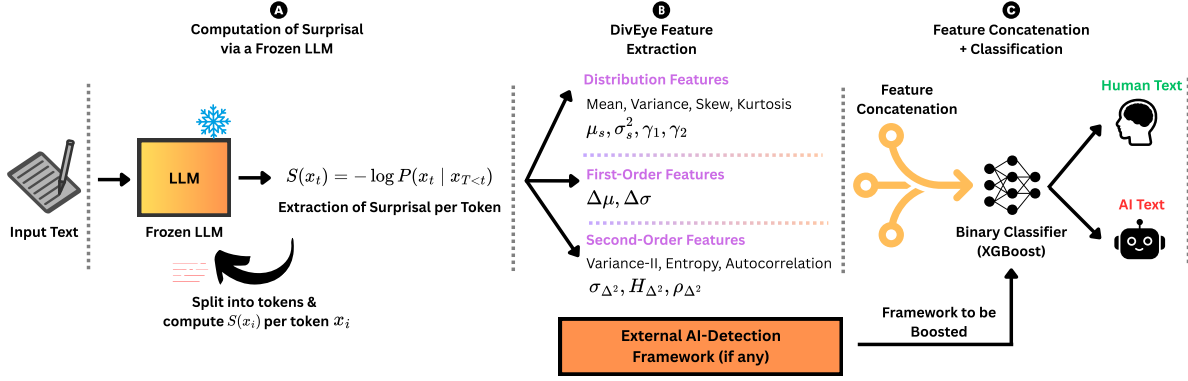


Figure 1: Overview of DivEye. DivEye extracts diversity-based features (see Section 3, Equation 6) from token-level surprisal patterns. These features can be used in two ways: (1) as a standalone detector, or (2) as an enhancement to existing detectors, improving their performance.

Contributions. We introduce DivEye¹, a lightweight classifier trained on features extracted from off-the-shelf LLMs in a zero-shot manner. These features capture diversity-based statistics of token-level surprisal, which we leverage to improve AI-text detection. Our approach focuses on capturing the distributional irregularities in AI-generated text that arise from differences in the generative process compared to human writing.

- *Zero-shot diversity detection:* We propose DivEye, a lightweight classifier trained on zero-shot features derived from token-level surprisal diversity metrics. These metrics capture fluctuations and patterns that reflect the constrained and often repetitive generation process of LLMs. We provide a principled motivation for each feature, connecting them to known properties of human vs. machine text generation, and demonstrate how DivEye can improve AI-text detection using these features.
- *Language & Model-agnostic detection:* DivEye leverages zero-shot features, requiring no access to the generator model’s internals or any fine-tuning. It operates purely on token probability sequences from an off-the-shelf language model and generalizes across different languages and model families.
- *Complementary to existing detectors:* We show that DivEye captures statistical patterns that are distinct from those used by traditional detectors, which often rely on fine-tuned language representations or classifier-based signals. When combined with these approaches, DivEye significantly boosts overall robustness, particularly against challenging high-quality generations and paraphrased adversarial examples.
- *Strong generalization across domains and attacks:* Extensive evaluations across three benchmarks and varied testbeds reveal that DivEye not only achieves state-of-the-art accuracy in standard settings but also remains robust when tested on unseen domains and language models.

2 Background and Problem Formulation

The emergence of LLM has led to a new era of machine-generated text that can closely mimic human writing across a range of tasks. These models are trained to approximate the true conditional distribution of natural language, denoted as $P_{\text{human}}(x_t | x_{<t})$, by learning from massive corpora of human-written text (Chen et al., 2024; Lu et al., 2025). The LLM’s learned distribution is represented as $P_{\text{LLM}}(x_t | x_{<t})$, and during inference, the model generates text by sampling tokens sequentially from this distribution. While modern LLMs achieve remarkable fluency, they still constitute an imperfect approximation: $P_{\text{LLM}} \neq P_{\text{human}}$ in general. At inference time, an LLM selects tokens by sampling from this learned distribution (Zhou et al., 2024), which remains an approximation of the true distribution that governs human text generation (Ippolito et al., 2020; Jones et al., 2024). This approximation gap, subtle as it may be, is the crux of AI text detection.

¹The code of our method and experiments is available at <https://anonymous.4open.science/r/diveye>.

From a theoretical standpoint, prior works (Ghosal et al., 2023; Sadasivan et al., 2025) highlight the fundamental limitations of AI text detection: as generative models approach the ideal of human-like language modeling, distinguishing their outputs from real text becomes increasingly difficult, if not impossible. Yet, as Chakraborty et al. (2023) point out, even models arbitrarily close to optimal remain statistically detectable under certain conditions, particularly when multiple samples or robust features are available. This theoretical detectability provides a foundation for practical detection methods that capitalize on the subtle imperfections in current LLM outputs.

In practice, existing detection approaches fall into two broad categories: watermarking and zero-resource detection. Watermarking techniques (Block et al., 2025; Gloaguen et al., 2025; Kirchenbauer et al., 2024; Liang et al., 2024; Liu et al., 2024a) embed distinct patterns in generated text but necessitate access to model internals or fine-tuning capabilities, rendering them unsuitable for black-box or adversarial settings, as well as for practical cases of watermark-free AI text detection. In contrast, zero-resource detection methods require no prior knowledge of the target model, instead relying on statistical or learned discrepancies between human and AI text. These methods can be further categorized as statistical and training-based approaches.

Statistical / Zero-shot detection methods refers to identifying AI-generated text without task-specific training, either by leveraging LLM probability cues or prompting LLMs directly as detectors. For example, methods like Entropy (Lavergne et al., 2008), LogRank (Ghosal et al., 2023), DetectGPT (Bao et al., 2024; Mitchell et al., 2023), and Binoculars (Hans et al., 2024) use off-the-shelf LLMs to evaluate the consistency of token predictions under masked or perturbed inputs. These methods assume that AI-generated texts are sampled from a narrower, more concentrated conditional probability distribution than human writing, resulting in greater token-level confidence and reduced lexical diversity.

Training-based / Fine-tuned detection methods (Chen et al., 2023; Mao et al., 2024; Hu et al., 2023) train classifiers, such as fine-tuned transformers on a labeled corpora of human and AI text. While these models can be accurate, they often fail to generalize across domains or against adversarial paraphrasing, especially when trained on specific generators or prompts. We discuss all related works in more detail in Appendix A.

Despite significant progress, no existing method fully resolves the problem of detecting AI-generated text in the wild. Our work addresses this gap by approaching the problem from a new angle: instead of analyzing individual token probabilities (Solaiman et al., 2019) in isolation, we propose to measure statistical diversity over token sequences, quantifying how text fluctuates in its use of surprising or predictable tokens. This provides a more global signature of the generative process that is robust to paraphrasing, domain shifts, and even partial text corruption.

3 DivEye: Methodologies

DivEye is built on the central observation that fluctuations in token-level surprisal provide a strong signal for distinguishing machine- and human-generated text. By systematically analyzing the statistical variation of surprisal across a sequence, DivEye captures distributional and temporal patterns that go beyond traditional likelihood-based metrics. The name DivEye thus reflects our method’s focus on diversity-aware analysis of language generation behavior.

3.1 Design Hypothesis

A central challenge in detecting AI-generated text (Ghosal et al., 2023; Sadasivan et al., 2025) lies in the fact that current models, though fluent, often prioritize coherence and consistency at the cost of variability and unpredictability. By contrast, human writers naturally introduce irregularities, such as unexpected lexical choices or structural shifts, that make their text inherently more diverse.

Our hypothesis is that human-written text inherently exhibits greater stylistic diversity and unpredictability than AI-generated text. In everyday writing, humans make creative, spontaneous choices, sometimes using unexpected words or phrases, that introduce bursts of surprise amid more routine language. Our approach centers on the premise that AI-generated text, despite its fluency, often lacks

the inherent diversity observed in human-written language. This divergence stems from the fundamental objective of LLMs: to maximize the likelihood of generated sequences within their learned probability distributions (Park & Choi, 2024). Consequently, AI-generated text tends to exhibit a higher degree of predictability, resulting in lower variability and surprisal compared to human-authored content. We support this hypothesis through both intuitive reasoning and empirical evidence, as detailed in Remark 1.

Remark 1: Proof Sketch

Consider a text sequence $X = (x_1, x_2, \dots, x_n)$ generated either by a human or by a language model M . The language model defines a probability distribution $P_M(X) = \prod_{t=1}^n P_M(x_t | x_{<t})$ where each token is chosen to maximize overall likelihood.

Humans, however, produce language through a complex, multi-layered cognitive process that balances informativeness, creativity, and contextual appropriateness, rather than strictly maximizing statistical likelihood.

Formally, the surprisal of token x_t under model M is defined as:

$$S_M(x_t) = -\log P_M(x_t | x_{<t})$$

Since M is trained to assign high probability to plausible continuations, its outputs tend to minimize surprisal on average, implying that maximum likelihood generation compresses diversity:

$$\mathbb{E}_{X \sim P_M}[S_M(x_t)] \leq \mathbb{E}_{X \sim P_H}[S_M(x_t)]$$

where P_H denotes the distribution of human-generated text.

Similarly, human language exhibits higher variance in surprisal due to spontaneous creative choices, idiomatic expressions, and stylistic variation, causing:

$$\text{Var}_{X \sim P_M}[S_M(x_t)] < \text{Var}_{X \sim P_H}[S_M(x_t)]$$

We validate this theoretical intuition through empirical experiments detailed below, which confirm statistically significant differences in surprisal and diversity metrics between human-written and AI-generated texts.

We collect 200 human-written essays and 200 GPT-4-Turbo-generated essays on comparable topics, provided by BiScope (Guo et al., 2024). For each essay, we computed the token-level surprisal scores using a fixed language model evaluator (GPT-2) and then calculated the mean and variance of these surprisal values per essay. Figure 2a shows the histogram of mean surprisal scores across the two sets, while Figure 2b displays the histogram of surprisal variances. The human-written texts exhibit a noticeably wider spread and heavier tails in both metrics, indicating greater unpredictability and stylistic variability. In contrast, the AI-generated essays cluster around lower mean surprisal and exhibit significantly lower variance. These results empirically confirm our theoretical claim: **human language inherently reflects higher diversity and surprise, whereas AI-generated language, optimized for likelihood, tends toward more predictable and homogeneous patterns.**

Rather than treating token-level surprisal in isolation, DivEye analyzes how it varies across an entire text to capture higher-level stylistic patterns. By extracting global statistical features from surprisal sequences, our method reveals differences in the rhythm and variability of unpredictability, traits that distinguish human writing from the more uniform outputs of LLMs, as illustrated by the clear class separation in predicted probabilities shown in Figure 3.

3.2 Mathematical underpinning of DivEye

To robustly distinguish AI-generated text from human-written text, it is insufficient to rely solely on a single measure such as perplexity (Xu et al., 2024). Perplexity summarizes average token likelihood, but overlooks how unpredictability fluctuates within a text. To better capture these patterns, DivEye computes higher-order statistical features over surprisal sequences, revealing structural signals beyond aggregate likelihood.

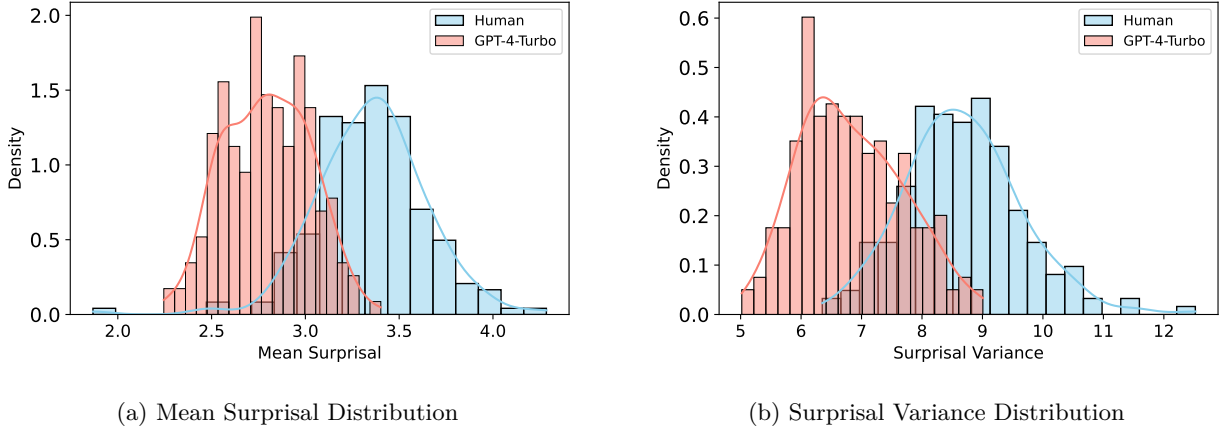


Figure 2: Distribution of token-level surprisal metrics for human-written vs. GPT-4-Turbo-generated essays. The left plot shows the histogram of mean surprisal per essay, while the right plot shows the histogram of surprisal variance. Human-written texts exhibit higher dispersion and heavier tails in both distributions, suggesting greater linguistic unpredictability and stylistic diversity. In contrast, GPT-4-Turbo outputs are more concentrated and predictable, aligning with the likelihood-maximization objective of language models.

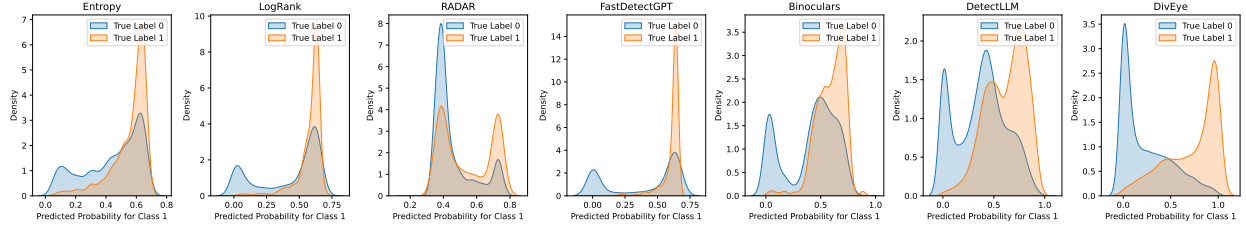


Figure 3: Distributions of predicted class probabilities for diverse AI-text detectors. Trained and evaluated on Testbed 4 of the MAGE benchmark, DivEye shows stronger separation between Label 0 (human-written) and Label 1 (AI-generated), indicating greater confidence and discriminative power.

Surprisal. Human language is inherently diverse and unpredictable, balancing consistent patterns with bursts of creativity, often introducing novel expressions, grammatical deviations, and stylistic variation. These deviations result in varying levels of token predictability, which can be quantified using surprisal (Kuribayashi et al., 2025) - a well-known information-theoretic measure defined as the negative log-probability of a token under a language model:

$$S(x_t) = -\log P(x_t \mid x_1, x_2, \dots, x_{t-1})$$

Given a text sequence $X = \{x_1, x_2, \dots, x_n\}$, surprisal measures how "unexpected" each token is in context. It can be computed directly from a model’s log-probabilities, providing a principled way to quantify the local unpredictability of text.

Rather than examining individual token surprisals in isolation, we summarize their behavior through aggregate metrics. The mean surprisal serves as a coarse indicator of how “expected” a text is on average: Lower values suggest higher conformity to the model’s learned distribution, whereas higher values point to more frequent unpredictability. However, as stated before, human writing is not merely unpredictable in aggregate; it also exhibits fluctuations in predictability that correspond to stylistic variation, topic shifts, or bursts of creativity. This motivates analyzing not just the mean but also the variance of surprisal, which captures the extent of variation in token-level surprise throughout the text. Formally, this can be represented as:

$$\text{Mean: } \mu_S = \frac{1}{n} \sum_{t=1}^n S(x_t); \quad \text{Variance: } \sigma_S^2 = \frac{1}{n-1} \sum_{t=1}^n (S(x_t) - \mu_S)^2 \quad (1)$$

Mean and Variance are not sufficient. While mean and variance capture the central tendency and spread of surprisal values, they overlook deeper structural signals that differentiate human and AI text. AI-generated text is optimized for consistency, producing more symmetrical distributions centered around high-probability tokens (Ippolito et al., 2020). Skewness (γ_1) quantifies this asymmetry: a positive skew suggests the presence of rare, surprising tokens typically found in human writing. Similarly, kurtosis (γ_2) captures the frequency of extreme deviations from the norm. A high kurtosis indicates heavy-tailed behavior, another hallmark of authentic, stylistically diverse writing. These higher-order moments allow **DivEye** to detect subtle irregularities and stylistic outliers that can be missed by detectors focusing only on average behavior.

$$\text{Skewness: } \gamma_1 = \frac{1}{n} \sum_{t=1}^n \left(\frac{S(x_t) - \mu_S}{\sigma_S} \right)^3; \quad \text{Kurtosis: } \gamma_2 = \frac{1}{n} \sum_{t=1}^n \left(\frac{S(x_t) - \mu_S}{\sigma_S} \right)^4 - 3. \quad (2)$$

Static metrics still miss temporal structure. While static surprisal statistics (mean, variance, skewness, kurtosis) describe the overall distribution of token-level unpredictability, they fail to capture how this unpredictability evolves throughout a sequence, a key trait distinguishing human and AI-generated text. To model these temporal dynamics, we compute the first-order difference $\Delta S_t = S(x_t) - S(x_{t-1})$, which reflects immediate changes in surprisal. The mean ($\Delta\mu$) and variance ($\Delta\sigma^2$) of ΔS_t quantify the typical magnitude and variability of these shifts, capturing stylistic volatility such as abrupt topic or tone changes commonly found in human writing.

We further analyze the second-order difference $\Delta^2 S_t = \Delta S_t - \Delta S_{t-1}$, which tracks fluctuations in the rate of change of surprisal. From this sequence, we extract three metrics: (1) variance ($\sigma_{\Delta^2}^2$), to capture the extent of rapid or erratic stylistic transitions; (2) entropy (\mathcal{H}_{Δ^2}), which reflects the irregularity of these transitions; and (3) autocorrelation ($\rho(\Delta^2 S_t)$), which measures whether bursts of unpredictability cluster together, often indicative of structured human creativity. These second-order metrics reveal rhythmic and non-stationary patterns in human text that are typically absent in the more homogeneous output of LLMs, providing a richer signal for robust AI-text detection. Mathematically, these can be defined as:

$$\Delta S_t = S(x_t) - S(x_{t-1}), \quad \Delta\mu = \frac{1}{n-1} \sum_{t=2}^n \Delta S_t, \quad \Delta\sigma^2 = \frac{1}{n-2} \sum_{t=2}^n (\Delta S_t - \mu_{\Delta})^2 \quad (3)$$

$$\Delta^2 S_t = \Delta S_t - \Delta S_{t-1}, \quad \sigma_{\Delta^2}^2 = \frac{1}{n-3} \sum_{t=3}^n (\Delta^2 S_t - \mu_{\Delta^2})^2, \quad \mathcal{H}_{\Delta^2} = - \sum_b p_b \log p_b, \quad (4)$$

$$\rho(\Delta^2 S_t) = \frac{\mathbb{E}[(\Delta^2 S_t - \mu_{\Delta^2})(\Delta^2 S_{t+1} - \mu_{\Delta^2})]}{\sigma_{\Delta^2}^2} \quad (5)$$

where μ_{Δ^2} is mean of second-order differences, and p_b is the empirical probability of a value falling into bin b after discretizing $\Delta^2 S_t$ for entropy computation. We provide empirical validation of these temporal features and their individual contributions to detection performance in Appendix B.

Combinations. Collectively, **DivEye**, formalized as (\mathcal{D}) in Equation 6, encapsulates critical aspects of text generation that distinguish human creativity from algorithmically generated predictability, thereby serving as a robust basis for our detection framework.

$$\mathcal{D} = \underbrace{\{\mu_s, \sigma_s^2, \gamma_1, \gamma_2\}}_{\text{Distribution}} \oplus \underbrace{\{\Delta\mu, \Delta\sigma^2\}}_{\text{1st-Order}} \oplus \underbrace{\{\sigma_{\Delta^2}^2, \mathcal{H}_{\Delta^2}, \rho_{\Delta^2}\}}_{\text{2nd-Order}} \quad (6)$$

Here, \mathcal{D} is a vector of statistical features with a dimension of 9, including distributional properties, first-order differences, and second-order differences of the text. We can apply any autoregressive LLM to generate these feature vectors by passing the text tokens through the model to compute the features listed above, which are then concatenated into the final vector \mathcal{D} . We train a binary classifier using **DivEye** features, optionally combined with predictions from an AI-text detector. Implementation details are further explained in Algorithm 1 and Appendix C.

DivEye as a booster. Existing detectors, whether fine-tuned classifiers or zero-shot LLM-based methods, primarily rely on semantic or surface-level cues, and often falter against high-quality adversarial examples that closely mimic human writing. **DivEye** offers a complementary signal by capturing statistical and temporal patterns of token-level unpredictability that are orthogonal to traditional features. We integrate **DivEye** into both settings by augmenting detector outputs with its feature vector and training a lightweight meta-classifier (e.g., XGBoost (Chen & Guestrin, 2016) or Random Forest (Breiman, 2001)) over the combined representation. Empirically, we find that this fusion significantly boosts performance, particularly on adversarial and out-of-distribution examples, without requiring retraining or modification of the original model.

4 Experiments

4.1 Experimental Settings

Datasets. We evaluate our **DivEye** framework across a comprehensive suite of datasets that encompass a wide range of generative models, domains, and adversarial strategies. Our primary benchmark is the RAID dataset (Dugan et al., 2024), which consists of carefully crafted adversarial examples designed to evade standard detectors. To assess robustness under diverse generation conditions, we also evaluate on the MAGE benchmark (Li et al., 2024), which spans eight distinct testbeds targeting various domains (e.g., Yelp (Zhang et al., 2015), XSum (Narayan et al., 2018), SciXGen (Chen et al., 2021a), CMV (Tan et al., 2016)) and generator families (e.g., GPT (Radford et al., 2019), OPT (Zhang et al., 2022), Bloom (et al., 2023)). This granular evaluation allows us to isolate and quantify the contribution of diversity metrics across specific domains and model types. Details about each testbed in RAID & MAGE are discussed in Appendix H.

Additionally, we incorporate HC3 (Guo et al., 2023), a large-scale, heterogeneous corpus of human and machine text, which includes both English and Chinese instances of human and AI-generated Q&A data. The inclusion of HC3 enables us to probe cross-linguistic generalization of our method.

Baselines. We compare **DivEye** with various baselines, including both traditional statistical detectors and recent fine-tuned models. These include RADAR (Hu et al., 2023), LogRank (Ghosal et al., 2023), Entropy (Lavergne et al., 2008), FastDetectGPT (Bao et al., 2024), DetectLLM (Su et al., 2023), Binoculars (Hans et al., 2024), RAiDAR (Mao et al., 2024), OpenAI Detector (Solaiman et al., 2019), Longformer (Beltagy et al., 2020), and BiScope (Guo et al., 2024). These baselines cover a range of techniques, from token-level likelihood-based ranking to transformer-based classification. Additionally, we evaluate our framework against several other open-source detectors listed on the RAID leaderboard, ensuring a fair and broad comparison with state-of-the-art public tools across multiple detection paradigms.

Implementation Details & Metrics. Unless stated otherwise, we use GPT-2 to compute all **DivEye** feature vectors. Regardless, we studied the effect of **DivEye** with different LLMs as base models and summarized the results in Section 4.6. In score-only detection scenarios, predictions are based solely over concatenated **DivEye** features. For both standalone and boosted setups, we train a lightweight XGBoost (Chen & Guestrin, 2016) classifier as a meta-model, using only **DivEye** features in the former, and concatenating them with the original detector’s prediction scores in the latter. Each testbed in MAGE & RAID provides predefined training and test sets, which we use for model training and evaluation. We evaluate all models using Average Accuracy (AvgAcc), AUROC, TPR@FPR=5% and F1 score to capture overall, threshold-independent, and balanced performance, respectively. For all methods, we independently optimize any required decision thresholds for AUROC and for TPR@FPR=5%, ensuring that each model is evaluated under its most favorable threshold for each metric.

4.2 Performance of DivEye

We evaluate **DivEye** across a wide range of challenging testbeds to assess its robustness and adaptability to both domain and model shifts. Table 1 presents the performance of **DivEye** on six distinct testbeds from the MAGE benchmark (Li et al., 2024): three in-distribution and three out-of-distribution. Across all testbeds, **DivEye** consistently achieves superior AUROC of 0.92 on average and AvgAcc compared to existing zero-shot

Table 1: Performance of zero-shot methods on 6 diverse testbeds from MAGE. The OOD settings examine the detection capability on texts from unseen domains or texts generated by new LLMs.

Settings	Methods	HumanAcc	MachineAcc	AvgAcc	AUROC
Testbed 2,3,4: In-distribution detection					
Arbitrary-domains & Model-specific (GPT-J [98])	LogRank	58.81%	63.94%	61.38%	0.67
	Entropy	76.43%	76.84%	76.64%	0.83
	DetectLLM	66.36%	62.07%	64.21%	0.72
	FastDetectGPT	62.31%	50.49%	56.4%	0.59
	Binoculars	60.11%	65.22%	62.67%	0.69
	BiScope	89.62%	84.86%	87.24%	0.93
	DivEye	90.63%	88.56%	89.60%	0.97
Fixed-domain (WP [34]) & Arbitrary-models	LogRank	89.61%	56.15%	72.88%	0.76
	Entropy	85.96%	60.4%	73.18%	0.78
	DetectLLM	88.54%	80.77%	84.66%	0.91
	FastDetectGPT	87.25%	54.08%	70.67%	0.76
	Binoculars	80.80%	62.07%	71.44%	0.77
	BiScope	91.78%	95.27%	93.53%	0.94
	DivEye	92.22%	96.88%	94.55%	0.99
Arbitrary-domains & Arbitrary-models	LogRank	84.91%	44.47%	64.69%	0.68
	Entropy	75.68%	50.04%	62.86%	0.67
	DetectLLM	64.74%	69.02%	66.88%	0.75
	FastDetectGPT	93.65%	41.73%	67.69%	0.7
	Binoculars	76.1%	54.89%	65.49%	0.71
	BiScope	91.54%	58.70%	75.12%	0.86
	DivEye	73.72%	82.57%	78.15%	0.88
Testbed 5,6,8: Out-of-distribution detection					
Unseen Models (BLOOM-7B [30])	LogRank	85.84%	19.82%	52.89%	0.52
	Entropy	77.56%	34.74%	56.15%	0.59
	DetectLLM	67.85%	58.5%	63.18%	0.68
	FastDetectGPT	94.57%	13.81%	54.19%	0.54
	Binoculars	76.10%	54.89%	65.50%	0.71
	BiScope	76.72%	50.47%	63.60%	0.72
	DivEye	74.75%	77.06%	75.91%	0.86
Unseen Domains (WP [34])	LogRank	88.57%	49.8%	69.19%	0.74
	Entropy	78.5%	58.16%	68.33%	0.74
	DetectLLM	74.15%	71.52%	72.34%	0.79
	FastDetectGPT	95.99%	47.17%	71.58%	0.74
	Binoculars	78.93%	67.8%	73.37%	0.8
	BiScope	80.1%	78.3%	79.2%	0.86
	DivEye	94.64%	84.53%	89.59%	0.97
Unseen Domains & Unseen Models	LogRank	83.87%	43.95%	63.91%	0.68
	Entropy	74.93%	50.18%	62.55%	0.66
	DetectLLM	63.66%	67.40%	65.53%	0.73
	FastDetectGPT	93.38%	41.50%	67.44%	0.70
	Binoculars	77.85%	69.39%	73.62%	0.81
	BiScope	86%	82.58%	84.24%	0.92
	DivEye	69.75%	83.22%	76.49%	0.87

baselines, showcasing its ability to generalize effectively to both seen and unseen generation settings. We demonstrate that human-written and machine-generated text can be distinguished based on the hypothesis outlined in Section 3. We further include the corresponding TPR@FPR=5% performance in Table 5.

Table 2 benchmarks DivEye on the RAID dataset (Dugan et al., 2024), which includes a suite of diverse models, domains, attacks, and decoding strategies. DivEye outperforms a diverse set of zero-shot methods by 26.11% and matches the performance of generative detection baselines, reaffirming its robustness to evasive generation strategies. Figures 4, 7 & 8 demonstrate the performance of DivEye across different domains and generator models, achieving competitive AUROC of 0.98 and 0.93, respectively. These results highlight DivEye’s stability and high performance across heterogeneous scenarios, underscoring its domain and model-agnostic nature.

Moreover, Appendix D.5 reports DivEye’s detection rates on all major models, including GPT-3.5-Turbo (Brown et al., 2020) and GPT-4o (et al., 2024b), Claude-3-Opus and Sonnet (Anthropic), as well as Gemini-1.0-Pro (et al., 2025), demonstrating highly competitive accuracies across the board. Collectively, these results confirm that DivEye provides a robust and adaptable foundation for detecting AI-generated text.

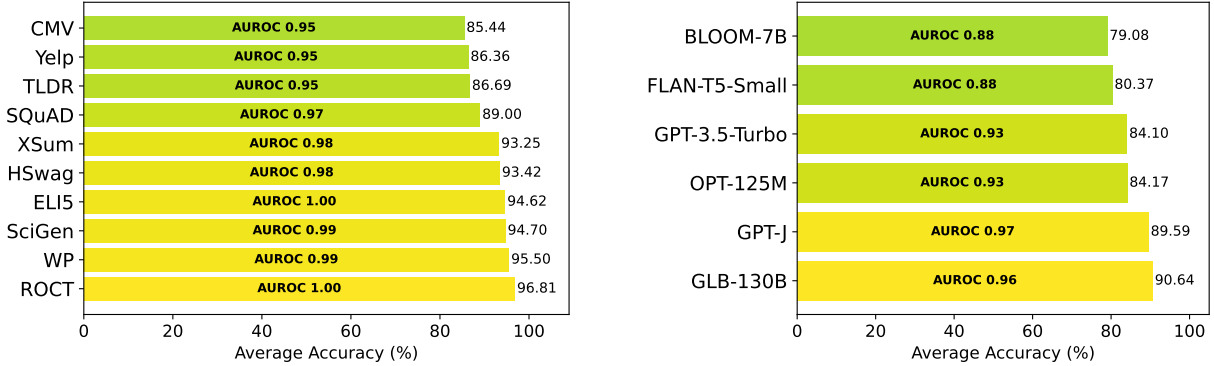


Figure 4: (a) Performance of **DivEye** across different domains, generated by **GPT-J-6B**. (b) Performance of **DivEye** across various generator models. Results are based on the MAGE benchmark.

Table 2: Performance of zero-shot and open-source finetuned methods on RAID. Results are aggregated over 8 domains, 12 models, and 4 decoding strategies. δ denotes difference in AUROC from benchmark leader.

Frameworks	Type	TPR@ FPR=5%	AUROC	δ
e5-small-lora [29]	Fine-tuned	93.9%	0.986	-0%
DivEye (Ours)	Classifier (zero-shot)	93.63%	0.984	-0.20%
Desklib AI [27]	Fine-tuned	94.9%	0.973	-1.32%
SuperAnnotate [89]	Fine-tuned	70.3%	0.910	-7.71%
Binoculars [45]	Zero-shot	79.0%	0.844	-14.40%
RADAR [47]	Fine-tuned	65.6%	0.819	-16.94%
GLTR [38]	Zero-shot	59.7%	0.727	-26.27%

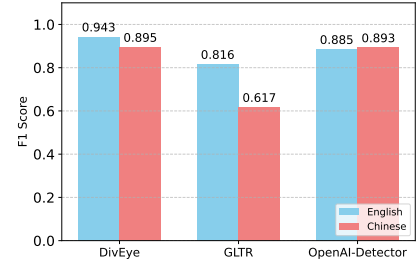


Figure 5: F1 scores on HC3 show that **DivEye** outperforms GLTR [38] and OpenAI-Detector [87], with strong results across English and Chinese.

4.3 Robustness to Adversarial Attacks and Multilingual Text

To evaluate robustness, we assess **DivEye** on a diverse set of adversarial attacks, including paraphrasing attacks from the MAGE dataset and transformation-based jailbreak attacks from the RAID benchmark. Table 3 shows that **DivEye** consistently achieves strong detection performance under these challenging settings. On the MAGE benchmark, **DivEye** outperforms the fine-tuned Longformer baseline in both average accuracy and AUROC by 10.15% and 0.11 respectively. On the RAID benchmark, which reports only accuracy, **DivEye** achieves competitive results across a range of adversarial perturbations, outperforming several zero-shot detectors, most notably surpassing Binoculars by 11.2%. A more detailed breakdown of performance by individual attack type is provided in Appendix E.1. We also test **DivEye**'s robustness to diverse adversarial scenarios, including character- and word-level perturbations, paraphrasing via commercial tools, prompt obfuscations, and distributional shifts, and find that it consistently achieves exceptional detection performance; a consolidated overview is provided in Appendix E.

We further evaluate **DivEye**'s multilingual generalizability using both English and Chinese splits of the HC3 dataset. Figure 5 illustrates that **DivEye** performs consistently well and has higher F1 scores across both languages using GPT-2 (Radford et al., 2019) & GPT-2-Chinese (CKIPLAB, 2024) for English and Chinese respectively. This suggests that surprisal-based statistical features are not heavily language-specific and can generalize across languages.

4.4 Efficiency Analysis

In addition to accuracy, we analyze the computational efficiency of **DivEye**. Figure 6b illustrates the latency of our method, showing that **DivEye** requires as little as 0.01 seconds per sample while outperforming

Table 4: Integration with DivEye consistently boosts performance across detectors, particularly on diverse domains (Testbed 4) and paraphrasing attacks (Testbed 7).

Methods	HumanAcc	MachineAcc	AvgAcc	AUROC	δ : Boost
Testbed 4: Arbitrary Domains & Arbitrary Models					
RADAR	47.74%	74.86%	61.30%	0.62	-
DetectLLM	64.74%	69.02%	66.88%	0.75	-
FastDetectGPT	93.65%	41.73%	67.69%	0.7	-
Binoculars	76.1%	54.89%	65.49%	0.71	-
BiScope	91.54%	58.70%	75.12%	0.86	-
DivEye	73.72%	82.57%	78.15%	0.88	-
DivEye + RADAR	74.69%	85.31%	80%	0.90	18.7%
DivEye + DetectLLM	75.44%	84.23%	79.34%	0.9	12.96%
DivEye + FastDetectGPT	79.42%	83.90%	81.66%	0.91	13.97%
DivEye + Binoculars	69.81%	83.47%	76.64%	0.87	11.15%
DivEye + BiScope	80.69%	88.31%	84.5%	0.93	9.38%
Testbed 7: Paraphrasing Attacks					
BiScope	48.80%	89.79%	69.30%	0.81	-
DivEye	69.75%	83.22%	76.49%	0.87	-
DivEye + BiScope	65.38%	90.84%	78.11%	0.89	8.81%

several fine-tuned and zero-shot detectors, achieving up to a $2971\times$ speedup compared to RAiDAR. Because DivEye only requires a single forward pass through a small GPT-2 model and performs lightweight statistical computations, it is significantly faster and more resource-efficient than larger fine-tuned transformers. This enables deployment in latency-sensitive environments without compromising performance.

4.5 Effectiveness of Boosting by DivEye

We empirically verify that DivEye-based diversity features can act as performance boosters for a wide range of detection models. To integrate DivEye, we concatenate its feature vector with the original model’s prediction scores and train a lightweight XGBoost classifier as a meta-model.

Table 4 illustrates improvements in AUROC and AvgAcc when diversity metrics are appended to existing frameworks such as RADAR, Binoculars, DetectLLM, BiScope and FastDetectGPT. Across all evaluated baselines, the inclusion of diversity features consistently leads to better detection scores by over 18.7%. Additionally, existing frameworks in combination with DivEye demonstrate substantial performance gains when evaluated against paraphrasing attacks. This validates the hypothesis that static and dynamic surprisal-based features capture orthogonal information to traditional heuristics, making them a valuable addition to any detection pipeline. We also investigate how much DivEye contributes to the final prediction relative to the underlying detector. Appendix D.4 reports a detailed feature-importance analysis, highlighting the complementary signals captured by DivEye within the boosted ensembles.

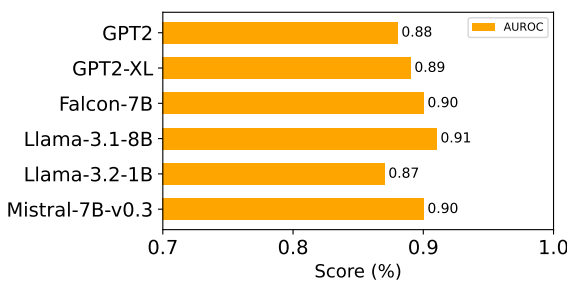
4.6 Ablation Studies

DivEye’s Performance on Different Base Models.

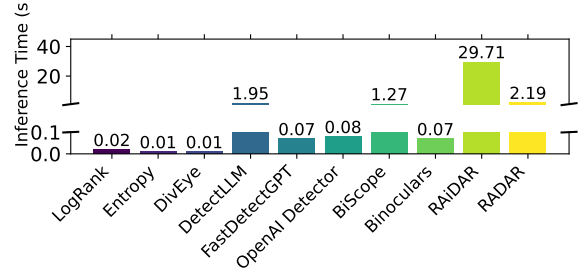
To assess the adaptability of DivEye across different language model backbones, we evaluate its performance, on Testbed 4 of the MAGE benchmark,

Table 3: Performance of DivEye and baselines on adversarial benchmarks, MAGE & RAID. * - RAID reports TPR@FPR=5% instead of AvgAcc.

Settings	Methods	AvgAcc	AUROC
[MAGE] Testbed 8: Paraphrasing Attack			
Paraphrased via GPT-3.5-Turbo	Longformer [10]	69.34%	0.76
	BiScope [44]	69.30%	0.81
	DivEye (Ours)	76.49%	0.87
[RAID] Adversarial Attacks*			
Paraphrase, Whitespace, Misspelling, Ho- moglyph, Article Deletion & more	Desklib AI [27]	91.2%	0.948
	e5-small-lora [29]	85.7%	0.968
	DivEye (Ours)	80.52%	0.951
	Binoculars [45]	69.32%	-
	RADAR [47]	63.9%	0.819
	GLTR [38]	51.5%	0.709



(a) DivEye using diverse base models.



(b) Inference time comparison.

Figure 6: (a) Performance of DivEye across different base models (GPT-2, GPT-2-XL, Falcon-7B). (b) Inference time (in sec) comparison of various methods.

when instantiated with various base LLMs used to compute token-level surprisal. As shown in Figure 6a, DivEye consistently performs well across all models, achieving an AUROC of 0.88 with GPT2, 0.91 with Llama-3.1-8B, and 0.90 with Falcon-7B. Notably, even the smallest model, GPT2, performs competitively, and human classification accuracy improves with larger models, suggesting that higher-capacity LMs better capture stylistic diversity. These results highlight DivEye’s robustness and efficiency across scales, making it suitable for resource-constrained settings. Appendix D.3 further reports baseline and DivEye performance across various base models.

Relevance of DivEye’s Features. DivEye’s feature set (Equation 6) captures token-level surprisal patterns across multiple orders, including distributional moments, first-order shifts, and second-order dynamics. To assess the contribution of each group, we compute feature importances from a trained XGBoost model. On average, second-order features contribute the most (39.4%), followed by distributional features (34.2%) and first-order differences (23.7%). The prominence of second-order features suggests that abrupt or unnatural shifts in predictability are strong indicators of machine-generated text. While traditional distributional statistics remain informative, they are insufficient on their own. These findings support DivEye’s central claim about second-order features: modeling the evolution of surprisal yields stronger detection capabilities than relying solely on static measures. Additionally, Appendix D.6 contains a detailed discussion about the contribution of each component in DivEye, including both feature-importance estimates and statistical leave-one-out ablation results.

5 Conclusion

We introduce DivEye, a lightweight classifier for AI-text detection that leverages zero-shot diversity features from token-level surprisal. Our method is model-agnostic, computationally efficient, and demonstrates strong generalization across detectors and datasets. Appendix J provides a detailed discussion of the method’s limitations, broader impacts, and associated ethical considerations.

References

- Aaditya Bhat. Gpt-wiki-intro, 2023. URL <https://huggingface.co/datasets/aadityaubhat/GPT-wiki-intro>.
- Sara Abdali, Richard Anarfi, CJ Barberan, and Jia He. Decoding the ai pen: Techniques and challenges in detecting ai-generated text, 2024. URL <https://arxiv.org/abs/2403.05750>.
- Fares Alahdab. Potential impact of large language models on academic writing. *BMJ evidence-based Medicine*, 29(3):201–202, 2024.
- Ebtesam Almazrouei, Hamza Alobeidli, Abdulaziz Alshamsi, Alessandro Cappelli, Ruxandra Cojocaru, Mérouane Debbah, Étienne Goffinet, Daniel Hesslow, Julien Launay, Quentin Malartic, Daniele Mazzotta, Badreddine Noune, Baptiste Pannier, and Guilherme Penedo. The falcon series of open language models, 2023. URL <https://arxiv.org/abs/2311.16867>.

Anthropic. Model Card Addendum: Claude 3.5 Haiku and Upgraded Claude 3.5 Sonnet. <https://assets.anthropic.com/m/1cd9d098ac3e6467/original/Claude-3-Model-Card-October-Addendum.pdf>.

Micael Arman. Poems dataset (nlp). <https://www.kaggle.com/datasets/michaelarman/poemsdataset>, 2020.

Abinew Ali Ayele, Nikolay Babakov, Janek Bevendorff, Xavier Bonet Casals, Berta Chulvi, Daryna Dementieva, Ashaf Elnagar, Dayne Freitag, Maik Fröbe, Damir Korenčić, Maximilian Mayerl, Daniil Moskovskiy, Animesh Mukherjee, Alexander Panchenko, Martin Potthast, Francisco Rangel, Naqee Rizwan, Paolo Rosso, Florian Schneider, Alisa Smirnova, Efstathios Stamatatos, Elisei Stakovskii, Benno Stein, Mariana Taulé, Dmitry Ustalov, Xintong Wang, Matti Wiegmann, Seid Muhie Yimam, and Eva Zangerle. Overview of pan 2024: Multi-author writing style analysis, multilingual text detoxification, oppositional thinking analysis, and generative ai authorship verification condensed lab overview. In *Experimental IR Meets Multilinguality, Multimodality, and Interaction: 15th International Conference of the CLEF Association, CLEF 2024, Grenoble, France, September 9–12, 2024, Proceedings, Part II*, pp. 231–259, Berlin, Heidelberg, 2024. Springer-Verlag. ISBN 978-3-031-71907-3. doi: 10.1007/978-3-031-71908-0_11. URL https://doi.org/10.1007/978-3-031-71908-0_11.

David Bamman and Noah A. Smith. New alignment methods for discriminative book summarization, 2013.

Guangsheng Bao, Yanbin Zhao, Zhiyang Teng, Linyi Yang, and Yue Zhang. Fast-detectgpt: Efficient zero-shot detection of machine-generated text via conditional probability curvature, 2024. URL <https://arxiv.org/abs/2310.05130>.

Iz Beltagy, Matthew E. Peters, and Arman Cohan. Longformer: The long-document transformer, 2020. URL <https://arxiv.org/abs/2004.05150>.

Meghana Moorthy Bhat and Srinivasan Parthasarathy. How effectively can machines defend against machine-generated fake news? an empirical study. In Anna Rogers, João Sedoc, and Anna Rumshisky (eds.), *Proceedings of the First Workshop on Insights from Negative Results in NLP*, pp. 48–53, Online, November 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.insights-1.7. URL <https://aclanthology.org/2020.insights-1.7/>.

Michał Bień, Michał Gilski, Martyna Maciejewska, Wojciech Taisner, Dawid Wisniewski, and Agnieszka Lawrynowicz. RecipeNLG: A cooking recipes dataset for semi-structured text generation. In *Proceedings of the 13th International Conference on Natural Language Generation*, pp. 22–28, Dublin, Ireland, December 2020. Association for Computational Linguistics. URL <https://aclanthology.org/2020.inlg-1.4>.

Adam Block, Ayush Sekhari, and Alexander Rakhlin. Gaussmark: A practical approach for structural watermarking of language models, 2025. URL <https://arxiv.org/abs/2501.13941>.

Matyáš Boháček, Michal Bravanský, Filip Trhlík, and Václav Moravec. Fine-grained czech news article dataset: An interdisciplinary approach to trustworthiness analysis, 2022.

Leo Breiman. Random forests. *Machine Learning*, 45(1):5–32, Oct 2001. ISSN 1573-0565. doi: 10.1023/A:1010933404324. URL <https://doi.org/10.1023/A:1010933404324>.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners, 2020. URL <https://arxiv.org/abs/2005.14165>.

Souradip Chakraborty, Amrit Singh Bedi, Sicheng Zhu, Bang An, Dinesh Manocha, and Furong Huang. On the possibilities of ai-generated text detection. 2023. URL <https://arxiv.org/abs/2304.04736>.

- Beiduo Chen, Xinpeng Wang, Siyao Peng, Robert Litschko, Anna Korhonen, and Barbara Plank. “seeing the big through the small”: Can LLMs approximate human judgment distributions on NLI from a few explanations? In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen (eds.), *Findings of the Association for Computational Linguistics: EMNLP 2024*, pp. 14396–14419, Miami, Florida, USA, November 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.findings-emnlp.842. URL <https://aclanthology.org/2024.findings-emnlp.842/>.
- Hong Chen, Hiroya Takamura, and Hideki Nakayama. SciXGen: A scientific paper dataset for context-aware text generation. In Marie-Francine Moens, Xuanjing Huang, Lucia Specia, and Scott Wen-tau Yih (eds.), *Findings of the Association for Computational Linguistics: EMNLP 2021*, pp. 1483–1492, Punta Cana, Dominican Republic, November 2021a. Association for Computational Linguistics. doi: 10.18653/v1/2021.findings-emnlp.128. URL <https://aclanthology.org/2021.findings-emnlp.128/>.
- Tianqi Chen and Carlos Guestrin. Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD ’16, pp. 785–794. ACM, August 2016. doi: 10.1145/2939672.2939785. URL <http://dx.doi.org/10.1145/2939672.2939785>.
- Yulong Chen, Yang Liu, Liang Chen, and Yue Zhang. DialogSum: A real-life scenario dialogue summarization dataset. In Chengqing Zong, Fei Xia, Wenjie Li, and Roberto Navigli (eds.), *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pp. 5062–5074, Online, August 2021b. Association for Computational Linguistics. doi: 10.18653/v1/2021.findings-acl.449. URL <https://aclanthology.org/2021.findings-acl.449/>.
- Yutian Chen, Hao Kang, Vivian Zhai, Liangze Li, Rita Singh, and Bhiksha Raj. Token prediction as implicit classification to identify LLM-generated text. In Houda Bouamor, Juan Pino, and Kalika Bali (eds.), *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pp. 13112–13120, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.emnlp-main.810. URL <https://aclanthology.org/2023.emnlp-main.810/>.
- Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Yunxuan Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, Albert Webson, Shixiang Shane Gu, Zhuyun Dai, Mirac Suzgun, Xinyun Chen, Aakanksha Chowdhery, Alex Castro-Ros, Marie Pellat, Kevin Robinson, Dasha Valter, Sharan Narang, Gaurav Mishra, Adams Yu, Vincent Zhao, Yanping Huang, Andrew Dai, Hongkun Yu, Slav Petrov, Ed H. Chi, Jeff Dean, Jacob Devlin, Adam Roberts, Denny Zhou, Quoc V. Le, and Jason Wei. Scaling instruction-finetuned language models, 2022. URL <https://arxiv.org/abs/2210.11416>.
- CKIPLAB. Gpt2-chinese. <https://github.com/ckiplab/ckip-transformers>, 2024.
- NLP Team Cohere. World-class ai, at your command, 2024. URL <https://cohere.com/models/command>. Accessed: 2024-02-02.
- Andrea De Giorgio, Giacomo Matrone, and Antonio Maffei. Detecting large language models in exam essays. In *2025 IEEE Engineering Education World Conference (EDUNINE)*, pp. 1–6. IEEE, 2025.
- Desklib. DeskLib: AI-Text-Detector-v1.01. <https://huggingface.co/desklib/ai-text-detector-v1.01>.
- Jad Doughman, Osama Mohammed Afzal, Hawau Olamide Toyin, Shady Shehata, Preslav Nakov, and Zeerak Talat. Exploring the limitations of detecting machine-generated text, 2024. URL <https://arxiv.org/abs/2406.11073>.
- Liam Dugan, Alyssa Hwang, Filip Trhlik, Josh Magnus Ludan, Andrew Zhu, Hainiu Xu, Daphne Ippolito, and Chris Callison-Burch. Raid: A shared benchmark for robust evaluation of machine-generated text detectors, 2024. URL <https://arxiv.org/abs/2405.07940>.
- BigScience Workshop et al. Bloom: A 176b-parameter open-access multilingual language model, 2023. URL <https://arxiv.org/abs/2211.05100>.

- Gemini Team et al. Gemini: A family of highly capable multimodal models, 2025. URL <https://arxiv.org/abs/2312.11805>.
- Meta et al. The llama 3 herd of models, 2024a. URL <https://arxiv.org/abs/2407.21783>.
- OpenAI et al. Gpt-4 technical report, 2024b. URL <https://arxiv.org/abs/2303.08774>.
- Angela Fan, Mike Lewis, and Yann Dauphin. Hierarchical neural story generation. In Iryna Gurevych and Yusuke Miyao (eds.), *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 889–898, Melbourne, Australia, July 2018. Association for Computational Linguistics. doi: 10.18653/v1/P18-1082. URL <https://aclanthology.org/P18-1082/>.
- Angela Fan, Yacine Jernite, Ethan Perez, David Grangier, Jason Weston, and Michael Auli. ELI5: Long form question answering. In Anna Korhonen, David Traum, and Lluís Màrquez (eds.), *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pp. 3558–3567, Florence, Italy, July 2019. Association for Computational Linguistics. doi: 10.18653/v1/P19-1346. URL <https://aclanthology.org/P19-1346/>.
- Rinaldo Gagiano, Maria Myung-Hee Kim, Xiuzhen Zhang, and Jennifer Biggs. Robustness analysis of grover for machine-generated news detection. In Afshin Rahimi, William Lane, and Guido Zuccon (eds.), *Proceedings of the 19th Annual Workshop of the Australasian Language Technology Association*, pp. 119–127, Online, December 2021. Australasian Language Technology Association. URL <https://aclanthology.org/2021.alta-1.12/>.
- Henrique Da Silva Gameiro, Andrei Kucharavy, and Ljiljana Dolamic. Llm detectors still fall short of real world: Case of llm-generated short news-like posts, 2024. URL <https://arxiv.org/abs/2409.03291>.
- Sebastian Gehrmann, Hendrik Strobelt, and Alexander M. Rush. Gltr: Statistical detection and visualization of generated text, 2019. URL <https://arxiv.org/abs/1906.04043>.
- Soumya Suvra Ghosal, Souradip Chakraborty, Jonas Geiping, Furong Huang, Dinesh Manocha, and Amrit Singh Bedi. Towards possibilities & impossibilities of ai-generated text detection: A survey, 2023. URL <https://arxiv.org/abs/2310.15264>.
- Thibaud Gloaguen, Nikola Jovanović, Robin Staab, and Martin Vechev. Black-box detection of language model watermarks, 2025. URL <https://arxiv.org/abs/2405.20777>.
- Derek Greene and Pádraig Cunningham. Practical solutions to the problem of diagonal dominance in kernel document clustering. In *Proc. 23rd International Conference on Machine learning (ICML’06)*, pp. 377–384. ACM Press, 2006.
- Jesus Guerrero, Gongbo Liang, and Izzat Alsmadi. A mutation-based text generation for adversarial machine learning applications, 2022. URL <https://arxiv.org/abs/2212.11808>.
- Biyang Guo, Xin Zhang, Ziyuan Wang, Minqi Jiang, Jinran Nie, Yuxuan Ding, Jianwei Yue, and Yupeng Wu. How close is chatgpt to human experts? comparison corpus, evaluation, and detection, 2023. URL <https://arxiv.org/abs/2301.07597>.
- Hanxi Guo, Siyuan Cheng, Xiaolong Jin, ZHUO ZHANG, Kaiyuan Zhang, Guanhong Tao, Guangyu Shen, and Xiangyu Zhang. Bisclope: AI-generated text detection by checking memorization of preceding tokens. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024. URL <https://openreview.net/forum?id=Hew2JSDycr>.
- Abhimanyu Hans, Avi Schwarzschild, Valeriia Cherepanova, Hamid Kazemi, Aniruddha Saha, Micah Goldblum, Jonas Geiping, and Tom Goldstein. Spotting llms with binoculars: Zero-shot detection of machine-generated text, 2024. URL <https://arxiv.org/abs/2401.12070>.
- Jianhua Hu, Huixiang Gao, Qing Yuan, and Ganchang Shi. Dynamic content generation in large language models with real-time constraints. 2024.

- Xiaomeng Hu, Pin-Yu Chen, and Tsung-Yi Ho. Radar: Robust ai-text detection via adversarial learning, 2023. URL <https://arxiv.org/abs/2307.03838>.
- Daphne Ippolito, Daniel Duckworth, Chris Callison-Burch, and Douglas Eck. Automatic detection of generated text is easiest when humans are fooled. In Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel Tetreault (eds.), *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 1808–1822, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.164. URL <https://aclanthology.org/2020.acl-main.164/>.
- Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, L  lio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timoth  e Lacroix, and William El Sayed. Mistral 7b, 2023.
- Qiao Jin, Bhuwan Dhingra, Zhengping Liu, William Cohen, and Xinghua Lu. PubMedQA: A dataset for biomedical research question answering. In Kentaro Inui, Jing Jiang, Vincent Ng, and Xiaojun Wan (eds.), *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pp. 2567–2577, Hong Kong, China, November 2019. Association for Computational Linguistics. doi: 10.18653/v1/D19-1259. URL <https://aclanthology.org/D19-1259/>.
- Cameron R. Jones, Sean Trott, and Benjamin Bergen. Comparing humans and large language models on an experimental protocol inventory for theory of mind evaluation (epitome). *Transactions of the Association for Computational Linguistics*, 12:803–819, 06 2024. ISSN 2307-387X. doi: 10.1162/tacl_a_00674. URL https://doi.org/10.1162/tacl_a_00674.
- John Kirchenbauer, Jonas Geiping, Yuxin Wen, Jonathan Katz, Ian Miers, and Tom Goldstein. A watermark for large language models, 2024. URL <https://arxiv.org/abs/2301.10226>.
- Kalpesh Krishna, Yixiao Song, Marzena Karpinska, John Wieting, and Mohit Iyyer. Paraphrasing evades detectors of ai-generated text, but retrieval is an effective defense, 2023. URL <https://arxiv.org/abs/2303.13408>.
- Tharindu Kumarage, Joshua Garland, Amrita Bhattacharjee, Kirill Trapeznikov, Scott Ruston, and Huan Liu. Stylometric detection of ai-generated text in twitter timelines, 2023. URL <https://arxiv.org/abs/2303.03697>.
- Tatsuki Kuribayashi, Yohei Oseki, Souhaib Ben Taieb, Kentaro Inui, and Timothy Baldwin. Large language models are human-like internally, 2025. URL <https://arxiv.org/abs/2502.01615>.
- Andreas K  pf, Yannic Kilcher, Dimitri von R  tte, Sotiris Anagnostidis, Zhi-Rui Tam, Keith Stevens, Abdullah Barhoum, Nguyen Minh Duc, Oliver Stanley, Rich  rd Nagyfi, Shahul ES, Sameer Suri, David Glushkov, Arnav Dantuluri, Andrew Maguire, Christoph Schuhmann, Huu Nguyen, and Alexander Mattick. Openassistant conversations – democratizing large language model alignment, 2023. URL <https://arxiv.org/abs/2304.07327>.
- Thomas Lavergne, Tanguy Urvoy, and Fran  ois Yvon. Detecting fake content with relative entropy scoring. In *Proceedings of the 2008 International Conference on Uncovering Plagiarism, Authorship and Social Software Misuse - Volume 377*, PAN’08, pp. 27–31, Aachen, DEU, 2008. CEUR-WS.org.
- Yafu Li, Qintong Li, Leyang Cui, Wei Bi, Zhilin Wang, Longyue Wang, Linyi Yang, Shuming Shi, and Yue Zhang. Mage: Machine-generated text detection in the wild, 2024. URL <https://arxiv.org/abs/2305.13242>.
- Gongbo Liang, Jesus Guerrero, and Izzat Alsmadi. Mutation-based adversarial attacks on neural text detectors, 2023a. URL <https://arxiv.org/abs/2302.05794>.
- Weixin Liang, Mert Yuksekgonul, Yining Mao, Eric Wu, and James Zou. Gpt detectors are biased against non-native english writers, 2023b. URL <https://arxiv.org/abs/2304.02819>.

- Yuqing Liang, Jiancheng Xiao, Wensheng Gan, and Philip S. Yu. Watermarking techniques for large language models: A survey, 2024. URL <https://arxiv.org/abs/2409.00089>.
- Aiwei Liu, Leyi Pan, Yijian Lu, Jingjing Li, Xuming Hu, Xi Zhang, Lijie Wen, Irwin King, Hui Xiong, and Philip S. Yu. A survey of text watermarking in the era of large language models, 2024a. URL <https://arxiv.org/abs/2312.07913>.
- Zeyan Liu, Zijun Yao, Fengjun Li, and Bo Luo. On the detectability of chatgpt content: Benchmarking, methodology, and evaluation through the lens of academic writing, 2024b. URL <https://arxiv.org/abs/2306.05524>.
- Yuxuan Lu, Jing Huang, Yan Han, Bennet Bei, Yaochen Xie, Dakuo Wang, Jessie Wang, and Qi He. Llm agents that act like us: Accurate human behavior simulation with real-world data, 2025. URL <https://arxiv.org/abs/2503.20749>.
- Brady D Lund, Ting Wang, Nishith Reddy Mannuru, Bing Nie, Somipam Shimray, and Ziang Wang. Chatgpt and a new academic reality: Artificial intelligence-written research papers and the ethics of the large language models in scholarly publishing. *Journal of the Association for Information Science and Technology*, 74(5):570–581, 2023.
- Andrew L. Maas, Raymond E. Daly, Peter T. Pham, Dan Huang, Andrew Y. Ng, and Christopher Potts. Learning word vectors for sentiment analysis. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pp. 142–150, Portland, Oregon, USA, June 2011. Association for Computational Linguistics. URL <http://www.aclweb.org/anthology/P11-1015>.
- Chengzhi Mao, Carl Vondrick, Hao Wang, and Junfeng Yang. Raidar: generative ai detection via rewriting, 2024. URL <https://arxiv.org/abs/2401.12970>.
- Jesse G Meyer, Ryan J Urbanowicz, Patrick CN Martin, Karen O’Connor, Ruowang Li, Pei-Chen Peng, Tiffani J Bright, Nicholas Tatonetti, Kyoung Jae Won, Graciela Gonzalez-Hernandez, et al. Chatgpt and large language models in academia: opportunities and challenges. *BioData mining*, 16(1):20, 2023.
- George Mikros, Athanasios Koursaris, Dimitrios Bilianos, and George Markopoulos. Ai-writing detection using an ensemble of transformers and stylometric features. *CEUR Workshop Proceedings*, 3496, September 2023. ISSN 1613-0073. Publisher Copyright: © 2023 Copyright for this paper by its authors. Use permitted under Creative Commons License Attribution 4.0 International (CC BY 4.0).; 2023 Iberian Languages Evaluation Forum, IberLEF 2023 ; Conference date: 26-09-2023.
- Eric Mitchell, Yoonho Lee, Alexander Khazatsky, Christopher D. Manning, and Chelsea Finn. Detectgpt: Zero-shot machine-generated text detection using probability curvature, 2023. URL <https://arxiv.org/abs/2301.11305>.
- NLP Team MosaicML. Introducing mpt-30b: Raising the bar for open-source foundation models, 2023. URL www.mosaicml.com/blog/mpt-30b. Accessed: 2023-06-22.
- Nasrin Mostafazadeh, Nathanael Chambers, Xiaodong He, Devi Parikh, Dhruv Batra, Lucy Vanderwende, Pushmeet Kohli, and James Allen. A corpus and cloze evaluation for deeper understanding of commonsense stories. In Kevin Knight, Ani Nenkova, and Owen Rambow (eds.), *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 839–849, San Diego, California, June 2016. Association for Computational Linguistics. doi: 10.18653/v1/N16-1098. URL <https://aclanthology.org/N16-1098/>.
- Shashi Narayan, Shay B. Cohen, and Mirella Lapata. Don’t give me the details, just the summary! topic-aware convolutional neural networks for extreme summarization. In Ellen Riloff, David Chiang, Julia Hockenmaier, and Jun’ichi Tsujii (eds.), *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pp. 1797–1807, Brussels, Belgium, October-November 2018. Association for Computational Linguistics. doi: 10.18653/v1/D18-1206. URL <https://aclanthology.org/D18-1206/>.

- Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems*, 35:27730–27744, 2022.
- Eleftheria Papageorgiou, Christos Chronis, Iraklis Varlamis, and Yassine Himeur. A survey on the use of large language models (llms) in fake news. *Future Internet*, 16(8):298, 2024.
- Bumjin Park and Jaesik Choi. Identifying the source of generation for large language models, 2024. URL <https://arxiv.org/abs/2407.12846>.
- Sayak Paul and Soumik Rakshit. arxiv paper abstracts. <https://www.kaggle.com/datasets/spsayakpaul/arxiv-paper-abstracts>, 2021.
- Jiameng Pu, Zain Sarwar, Sifat Muhammad Abdullah, Abdullah Rehman, Yoonjin Kim, Parantapa Bhattacharya, Mobin Javed, and Bimal Viswanath. Deepfake text detection: Limitations and opportunities. In *2023 IEEE Symposium on Security and Privacy (SP)*, pp. 1613–1630, 2023. doi: 10.1109/SP46215.2023.10179387.
- Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. Language models are unsupervised multitask learners. *OpenAI*, 2019. URL https://cdn.openai.com/better-language-models/language_models_are_unsupervised_multitask_learners.pdf. Accessed: 2024-11-15.
- Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. SQuAD: 100,000+ questions for machine comprehension of text. In Jian Su, Kevin Duh, and Xavier Carreras (eds.), *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pp. 2383–2392, Austin, Texas, November 2016. Association for Computational Linguistics. doi: 10.18653/v1/D16-1264. URL <https://aclanthology.org/D16-1264/>.
- Jie Ren, Han Xu, Yiding Liu, Yingqian Cui, Shuaiqiang Wang, Dawei Yin, and Jiliang Tang. A robust semantics-based watermark for large language model against paraphrasing, 2024. URL <https://arxiv.org/abs/2311.08721>.
- Vinu Sankar Sadasivan, Aounon Kumar, Sriram Balasubramanian, Wenxiao Wang, and Soheil Feizi. Can ai-generated text be reliably detected?, 2025. URL <https://arxiv.org/abs/2303.11156>.
- Victor Sanh, Albert Webson, Colin Raffel, Stephen Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Arun Raja, Manan Dey, M Saiful Bari, Canwen Xu, Urmish Thakker, Shanya Sharma Sharma, Eliza Szczechla, Taewoon Kim, Gunjan Chhablani, Nihal Nayak, Debajyoti Datta, Jonathan Chang, Mike Tian-Jian Jiang, Han Wang, Matteo Manica, Sheng Shen, Zheng Xin Yong, Harshit Pandey, Rachel Bawden, Thomas Wang, Trishala Neeraj, Jos Rozen, Abheesht Sharma, Andrea Santilli, Thibault Fevry, Jason Alan Fries, Ryan Teehan, Teven Le Scao, Stella Biderman, Leo Gao, Thomas Wolf, and Alexander M Rush. Multitask prompted training enables zero-shot task generalization. In *International Conference on Learning Representations*, 2022. URL <https://openreview.net/forum?id=9Vrb9DOWI4>.
- Dietmar Schabus, Marcin Skowron, and Martin Trapp. One million posts: A data set of german online discussions. In *Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR ’17*, pp. 1241–1244, New York, NY, USA, 2017. Association for Computing Machinery. ISBN 9781450350228. doi: 10.1145/3077136.3080711. URL <https://doi.org/10.1145/3077136.3080711>.
- Abigail See, Peter J. Liu, and Christopher D. Manning. Get to the point: Summarization with pointer-generator networks. In Regina Barzilay and Min-Yen Kan (eds.), *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 1073–1083, Vancouver, Canada, July 2017. Association for Computational Linguistics. doi: 10.18653/v1/P17-1099. URL <https://aclanthology.org/P17-1099/>.

- Sanidhya Madhav Shukla, Chandni Magoo, and Puneet Garg. Comparing fine tuned-lms for detecting llm-generated text. In *2024 3rd Edition of IEEE Delhi Section Flagship Conference (DELCON)*, pp. 1–8. IEEE, 2024.
- Irene Solaiman, Miles Brundage, Jack Clark, Amanda Askell, Ariel Herbert-Voss, Jeff Wu, Alec Radford, Gretchen Krueger, Jong Wook Kim, Sarah Kreps, Miles McCain, Alex Newhouse, Jason Blazakis, Kris McGuffie, and Jasmine Wang. Release strategies and the social impacts of language models, 2019. URL <https://arxiv.org/abs/1908.09203>.
- Jinyan Su, Terry Yue Zhuo, Di Wang, and Preslav Nakov. Detectllm: Leveraging log rank information for zero-shot detection of machine-generated text, 2023. URL <https://arxiv.org/abs/2306.05540>.
- SuperAnnotate. SuperAnnotate: AI-Detector. <https://huggingface.co/SuperAnnotate/ai-detector>.
- Chenhao Tan, Vlad Niculae, Cristian Danescu-Niculescu-Mizil, and Lillian Lee. Winning arguments: Interaction dynamics and persuasion strategies in good-faith online discussions. In *Proceedings of the 25th International Conference on World Wide Web, WWW '16*. International World Wide Web Conferences Steering Committee, April 2016. doi: 10.1145/2872427.2883081. URL <http://dx.doi.org/10.1145/2872427.2883081>.
- Amalio Telenti, Michael Auli, Brian L Hie, Cyrus Maher, Suchi Saria, and John PA Ioannidis. Large language models for science and medicine. *European journal of clinical investigation*, 54(6):e14183, 2024.
- Irina Tolstykh, Aleksandra Tsybina, Sergey Yakubson, Aleksandr Gordeev, Vladimir Dokholyan, and Maksim Kuprashevich. Gigacheck: Detecting llm-generated content. *arXiv preprint arXiv:2410.23728*, 2024.
- Petter Törnberg, Diliara Valeeva, Justus Uitermark, and Christopher Bail. Simulating social media using large language models to evaluate alternative news feed algorithms. *arXiv preprint arXiv:2310.05984*, 2023.
- Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurelien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. Llama: Open and efficient foundation language models, 2023a. URL <https://arxiv.org/abs/2302.13971>.
- Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurelien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. Llama 2: Open foundation and fine-tuned chat models, 2023b.
- Brian Tufts, Xuandong Zhao, and Lei Li. A practical examination of ai-generated text detectors for large language models, 2025. URL <https://arxiv.org/abs/2412.05139>.
- Michael Völske, Martin Potthast, Shahbaz Syed, and Benno Stein. TL;DR: Mining Reddit to learn automatic summarization. In *Proceedings of the Workshop on New Frontiers in Summarization*, pp. 59–63, Copenhagen, Denmark, September 2017. Association for Computational Linguistics. doi: 10.18653/v1/W17-4508. URL <https://aclanthology.org/W17-4508>.
- Ben Wang and Aran Komatsuzaki. GPT-J-6B: A 6 Billion Parameter Autoregressive Language Model. <https://github.com/kingoflolz/mesh-transformer-jax>, May 2021.

- Hong Wang, Xuan Luo, Weizhi Wang, and Xifeng Yan. Bot or human? detecting chatgpt imposters with a single question, 2024a. URL <https://arxiv.org/abs/2305.06424>.
- Rongsheng Wang, Haoming Chen, Ruizhe Zhou, Han Ma, Yaofei Duan, Yanlan Kang, Songhua Yang, Baoyu Fan, and Tao Tan. Llm-detector: Improving ai-generated chinese text detection with open-source llm instruction tuning. *arXiv preprint arXiv:2402.01158*, 2024b.
- Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A. Smith, Daniel Khashabi, and Hannaneh Hajishirzi. Self-instruct: Aligning language models with self-generated instructions, 2023. URL <https://arxiv.org/abs/2212.10560>.
- Max Wolff and Stuart Wolff. Attacking neural text detectors, 2022. URL <https://arxiv.org/abs/2002.11768>.
- Junchao Wu, Shu Yang, Runzhe Zhan, Yulin Yuan, Lidia S. Chao, and Derek Fai Wong. A survey on llm-generated text detection: Necessity, methods, and future directions. *Comput. Linguistics*, 51(1):275–338, 2025. doi: 10.1162/COLI_A_00549. URL https://doi.org/10.1162/coli_a_00549.
- Jinwei Xu, He Zhang, Yanjin Yang, Zeru Cheng, Jun Lyu, Bohan Liu, Xin Zhou, Lanxin Yang, Alberto Bacchelli, Yin Kia Chiam, and Thiam Kian Chiew. Investigating efficacy of perplexity in detecting llm-generated code, 2024. URL <https://arxiv.org/abs/2412.16525>.
- Ann Yuan, Andy Coenen, Emily Reif, and Daphne Ippolito. Wordcraft: story writing with large language models. In *Proceedings of the 27th International Conference on Intelligent User Interfaces*, pp. 841–852, 2022.
- Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. HellaSwag: Can a machine really finish your sentence? In Anna Korhonen, David Traum, and Lluís Màrquez (eds.), *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pp. 4791–4800, Florence, Italy, July 2019. Association for Computational Linguistics. doi: 10.18653/v1/P19-1472. URL <https://aclanthology.org/P19-1472/>.
- Aohan Zeng, Xiao Liu, Zhengxiao Du, Zihan Wang, Hanyu Lai, Ming Ding, Zhuoyi Yang, Yifan Xu, Wendi Zheng, Xiao Xia, Weng Lam Tam, Zixuan Ma, Yufei Xue, Jidong Zhai, Wenguang Chen, Peng Zhang, Yuxiao Dong, and Jie Tang. Glm-130b: An open bilingual pre-trained model, 2023. URL <https://arxiv.org/abs/2210.02414>.
- Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona Diab, Xian Li, Xi Victoria Lin, Todor Mihaylov, Myle Ott, Sam Shleifer, Kurt Shuster, Daniel Simig, Punit Singh Koura, Anjali Sridhar, Tianlu Wang, and Luke Zettlemoyer. Opt: Open pre-trained transformer language models, 2022. URL <https://arxiv.org/abs/2205.01068>.
- Xiang Zhang, Junbo Zhao, and Yann LeCun. Character-level convolutional networks for text classification. In C. Cortes, N. Lawrence, D. Lee, M. Sugiyama, and R. Garnett (eds.), *Advances in Neural Information Processing Systems*, volume 28. Curran Associates, Inc., 2015. URL https://proceedings.neurips.cc/paper_files/paper/2015/file/250cf8b51c773f3f8dc8b4be867a9a02-Paper.pdf.
- Yuehan Zhang, Yongqiang Ma, Jiawei Liu, Xiaozhong Liu, Xiaofeng Wang, and Wei Lu. Detection vs. anti-detection: Is text generated by ai detectable? In *International Conference on Information*, pp. 209–222. Springer, 2024.
- Zixuan Zhou, Xuefei Ning, Ke Hong, Tianyu Fu, Jiaming Xu, Shiyao Li, Yuming Lou, Luning Wang, Zhihang Yuan, Xiuhong Li, Shengen Yan, Guohao Dai, Xiao-Ping Zhang, Yuhang Dong, and Yu Wang. A survey on efficient inference for large language models, 2024. URL <https://arxiv.org/abs/2404.14294>.

A More Details on Related Work

In recent years, the challenge of identifying AI-generated text has garnered significant attention, giving rise to a variety of detection approaches. These methods largely fall into two categories: watermark-based techniques and zero-resource detection.

Watermarking. Watermarking embeds traceable patterns in a model’s outputs during training or generation, enabling downstream identification of machine-generated content (Ren et al., 2024; Liu et al., 2024a). While watermarking can be effective in controlled environments, it relies on access to or cooperation from the model’s developers, an assumption that frequently fails in real-world or adversarial scenarios. Furthermore, it is inherently unsuitable for practical situations where AI-generated text lacks any embedded watermark. This limitation has led to growing interest in zero-resource detection methods, which make no assumptions about access to the model’s internals or training data. Instead, these methods analyze the output text alone, offering a more flexible and broadly applicable approach. Within this space, techniques can be further categorized into fine-tuned methods, which rely on labeled datasets, and zero-shot methods, which generalize to unseen models without task-specific training.

Fine-tuned Detection. Fine-tuned detection methods represent a major strand of zero-resource detection, often leveraging fine-tuned classifiers built atop pre-trained language models (PLMs). A pivotal development was the Grover model, which demonstrated that models trained on text from specific generators can achieve high accuracy on in-distribution data, particularly when integrating Grover-specific layers. This inspired a wave of PLM-based detectors, most notably OpenAI’s GPT-2 detector (Solaiman et al., 2019), which uses a RoBERTa classifier trained on GPT-2 outputs. However, such detectors often struggle to generalize across models, especially as newer LLMs introduce more fluent and coherent outputs.

To improve generalization and robustness, recent work has focused on feature augmentation. Stylometric approaches, for instance, introduce handcrafted features that capture writing style discrepancies between humans and machines (Mikros et al., 2023). These include measures of phraseology, punctuation, linguistic diversity, and journalistic standards, which have proven useful for detecting AI-generated tweets and news articles. Additional features such as perplexity statistics, sentiment, and error-based cues like grammatical mistakes further enrich detection pipelines (Kumarage et al., 2023).

Parallel efforts have explored structural features, incorporating models that explicitly account for the factual or contextual structure of text. Techniques such as TriFuseNet combine stylistic and contextual branches with fine-tuned BERT models, while others employ attentive-BiLSTMs to replace standard feedforward layers, enhancing interpretability and robustness (Liu et al., 2024b).

Despite these advancements, fine-tuned detectors still require labeled training data and model-specific tuning of PLMs, which can limit their scalability to novel or proprietary LLMs. Although these detectors perform exceptionally well on data similar to their training sets, they face significant drawbacks, most notably, a tendency to overfit to specific domains and a reliance on retraining for every newly emerging AI model, which is unsustainable in light of the fast-paced evolution of generative technologies. This motivates the development of methods, that leverage zero-shot features, such as DivEye, that aim to detect AI-generated text without relying on supervised learning or access to model internals.

Zero-shot Detection. Recent research has focused on zero-shot detection strategies that require no fine-tuning on labeled examples from the target generator. These methods typically leverage statistical cues from PLM’s output distributions or repurpose LLMs themselves as detectors.

A prominent class of zero-shot detectors exploits the probability structure of text under language models. DetectGPT (Mitchell et al., 2023) detects machine-generated text by measuring how strongly the log-likelihood drops under small semantic perturbations, leveraging the hypothesis that AI text lies in regions of higher negative curvature than human text. On the other hand, FastDetectGPT (Bao et al., 2024) eliminates the need for explicit perturbations by directly measuring curvature in conditional probabilities, observing that AI text typically exhibits sharper transitions between tokens compared to human writing. These observations are refined in DetectLLM (Su et al., 2023), which introduces the Log-Likelihood Log-Rank Ratio (LRR) and

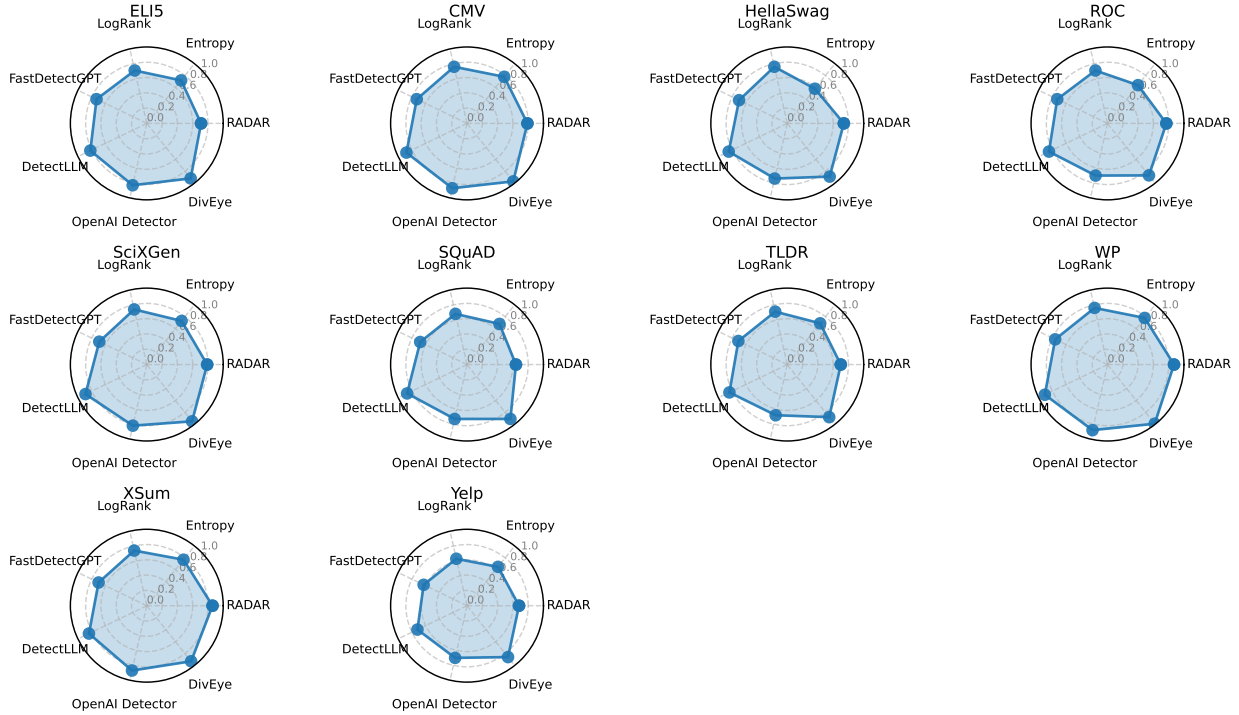


Figure 7: AUROC performance profiles of seven AI-detection tools evaluated on text generated by ten diverse domains generated by arbitrary LLMs. Each spider plot corresponds to a specific domain, with radial axes representing the AUROC score (ranging from 0 to 1) and angular axes representing the detection tools: RADAR, Entropy, LogRank, FastDetectGPT, DetectLLM, OpenAI Detector, and DivEye.

Normalized Perturbed log-Rank (NPR) metrics to quantify the distinguishability of AI-generated content using statistical features derived from token rankings.

Another line of work focuses on token predictability and entropy. LogRank (Ghosal et al., 2023) investigates the use of token rank distributions and demonstrates that log-rank statistics, such as the frequency of top-ranked tokens, are reliable signals of AI authorship. This builds on early work such as entropy-based detection (Lavergne et al., 2008) and GLTR (Gehrmann et al., 2019), which showed that humans tend to use more surprising and diverse tokens, while LLMs often fall back on high-probability continuations.

Moving beyond single-directional statistics, BiScope (Guo et al., 2024) proposes a bi-directional cross-entropy framework that measures how well a model’s predicted logits align both with the ground truth next token (forward loss) and with the previous token (backward loss). The key insight is that AI-generated text often exhibits predictable forward progression but weaker backward association due to its autoregressive nature. A shallow classifier trained on the joint distribution of these losses can reliably detect AI text with zero-shot generalization.

Finally, Binoculars (Hans et al., 2024) offers a model-agnostic strategy by comparing the statistical disagreement between two LLMs on the same input. By contrasting the outputs of two diverse LLMs, the method detects anomalies in token distributions that are characteristic of synthetic text. This ensemble-based disagreement is found to correlate strongly with model-generated samples, providing a powerful signal without the need for training data from either model.

Collectively, these techniques demonstrate that zero-shot detection can be achieved by carefully analyzing how text aligns with the inductive biases and statistical signatures of language models, without any finetuning or access to the original generator. They lay the foundation for our proposed method, DivEye, which further capitalizes on diversity-based statistical properties to robustly differentiate AI- and human-written content.

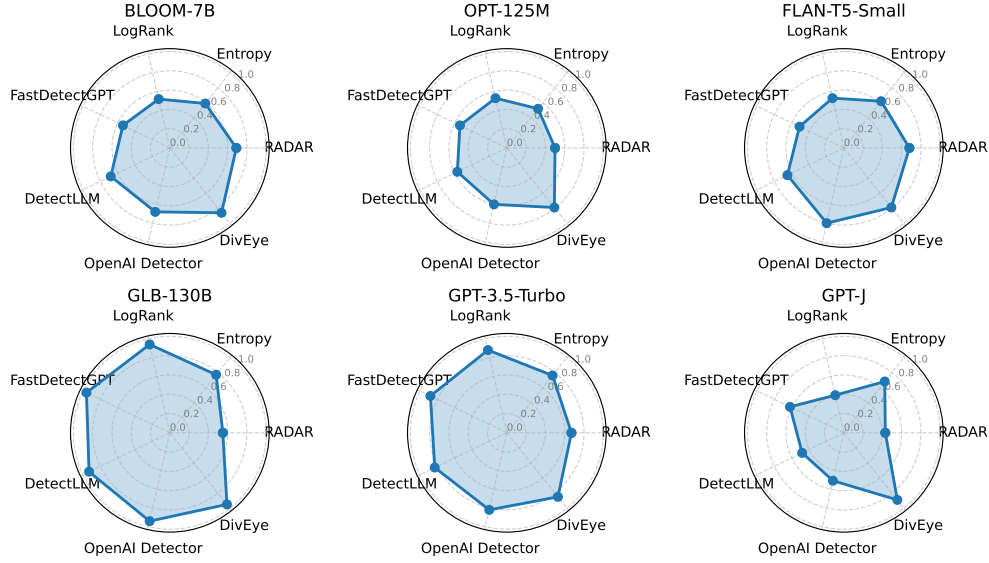


Figure 8: AUROC performance profiles of seven AI-detection tools evaluated on text generated by six different LLMs. Each spider plot corresponds to a specific language model, with radial axes representing the AUROC score (ranging from 0 to 1) and angular axes representing the detection tools: RADAR, Entropy, LogRank, FastDetectGPT, DetectLLM, OpenAI Detector, and DivEye.

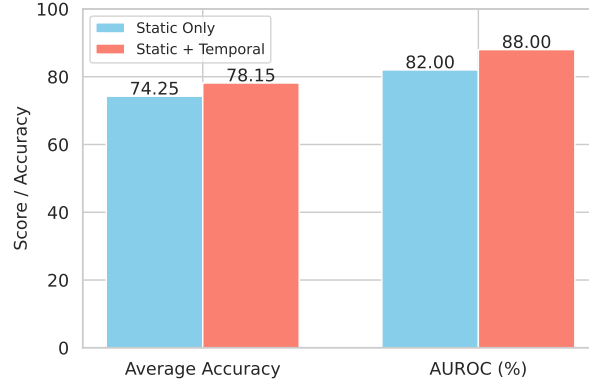


Figure 9: Ablation results on Testbed 4 of the MAGE benchmark showing the impact of temporal surprisal features. Adding temporal dynamics to static surprisal statistics improves both accuracy (from 74.25% to 78.15%) and AUROC (from 0.82 to 0.88), demonstrating their complementary value for robust AI-generated text detection.

B Motivation Behind Temporal Features

While static surprisal statistics such as mean, variance, skewness, and kurtosis provide useful summaries of token-level unpredictability, they overlook the evolution of this unpredictability over time, a dimension critical to distinguishing human and AI-generated text. Human authors naturally embed stylistic variability through temporal fluctuations, such as abrupt topic shifts, tonal changes, and bursts of creativity, which manifest as distinctive temporal dynamics in surprisal sequences.

Intuitively, these temporal features, as listed in Section 3, expose rhythmic and non-stationary patterns characteristic of human creativity and coherence, typically absent in the more uniform output of large language models.

Table 5: TPR@FPR=5% on Testbed 8 (Unseen Domains & Models).

	LogRank	Entropy	DetectLLM	FastDetect	Binoculars	BiScope	DivEye
TPR	47.1	30.1	51.5	76.3	68.7	99.8	99.6

Furthermore, through an ablation study on Testbed 4 of the MAGE benchmark (Figure 9), we empirically show that augmenting static surprisal features with temporal metrics leads to a measurable improvement in classification accuracy. This highlights the complementary value of temporal dynamics in enhancing the robustness of AI-generated text detection. Moreover, an analysis of feature importance (Appendix D.6) reveals that temporal features collectively contribute more than static features, consistently ranking among the most informative signals for distinguishing between human and AI-generated text.

Overall, these findings motivate the inclusion of temporal surprisal features as integral components of our DivEye framework.

C Implementation of DivEye

We provide a detailed description of our DivEye implementation in Algorithm 1. This includes all steps from surprisal computation to feature extraction and final classification. We use an XGBoost classifier for binary classification as a preliminary choice, without extensive comparison to other classifiers, leaving exploration of alternative models for future work. For completeness and reproducibility, we include all additional implementation details, such as hyperparameter configurations, model architectures, and experimental testbeds, in Appendix I and Appendix H.

Algorithm 1 DivEye: Algorithm for Feature Extraction & Training

Require: Text dataset $\mathcal{D} = \{(x_i, \ell_i)\}_{i=1}^N$, where x_i is a text input and $\ell_i \in \{0, 1\}$ indicates whether it is human-written ($\ell_i = 1$) or machine-generated ($\ell_i = 0$)

Require: Pretrained auto-regressive language model g_ϕ (e.g., GPT-2)

Require: XGBoost classifier with hyperparameters Θ

Ensure: Trained binary classifier f_θ

- 1: Initialize an empty feature matrix $\mathcal{F} \leftarrow []$
 - 2: **for** each $(x_i, \ell_i) \in \mathcal{D}$ **do**
 - 3: Compute token-level log-likelihoods: $y_i \leftarrow g_\phi(x_i)$
 - 4: Convert to token-level surprisals: $s_i \leftarrow -y_i$
 - 5: Compute diversity features $\text{DivEye}(x_i) \in \mathbb{R}^9$ as described in Equation 6 using s_i
 - 6: Append $(\text{DivEye}(x_i), \ell_i)$ to \mathcal{F}
 - 7: **end for**
 - 8: Train binary classifier f_θ on feature set \mathcal{F} using XGBoost with hyperparameters Θ
 - 9: **return** f_θ
-

D Additional Results

In this section, we present additional supporting experiments that demonstrate the generalizability, robustness, and complementary strengths of DivEye through various ablation studies.

D.1 Domain-Specific Performance of DivEye

Figure 7 presents the AUROC performance of seven detection methods evaluated across ten text domains (Testbed 3 of the MAGE benchmark). DivEye consistently achieves the highest AUROC scores in every domain - reaching up to 0.99 in WP, 0.97 in CMV, and 0.95 in SciXGen, outperforming other detectors by a notable margin. This highlights DivEye’s adaptability and robustness in capturing domain-specific writing

patterns that other methods frequently miss. These results reinforce the advantage of leveraging surprisal features for more generalizable and context-sensitive detection of AI-generated text.

D.2 Model-Specific Performance of DivEye

Figure 8 compares the AUROC performance of seven detection methods across text generated by six different large language models (Testbed 5 of the MAGE benchmark). **DivEye** achieves the highest AUROC scores across all six models, demonstrating strong robustness (0.95 on GLB-130B, 0.89 on GPT-J, 0.85 on GPT-3.5-Turbo). This consistent performance highlights **DivEye**’s effectiveness in capturing temporal surprisal patterns that generalize well across different language model architectures, making it broadly applicable for reliable AI-generated text detection.

D.3 Performance against other base models

We evaluate the robustness of all detectors across different backbone models and report results in Table 6. These backbone models include **GPT-2** (Radford et al., 2019), **GPT-2-XL** (Radford et al., 2019), **Falcon-7B** (Almazrouei et al., 2023), **Llama-3.2-1B** (et al., 2024a), **Llama-3.1-8B** (et al., 2024a) and **Mistral-7B-v0.3** (Jiang et al., 2023). Competing methods such as **Binoculars**, **BiScope**, and **DetectLLM** show moderate variation with backbone choice, while **FastDetectGPT** and **LogRank** generally underperform. These results highlight that **DivEye** maintains strong and stable detection capability regardless of the underlying base model.

Table 6: Performance of different detectors across backbone models.

Backbone Model	DivEye	Binoculars	BiScope	LogRank	DetectLLM	FastDetectGPT
GPT-2	0.88	0.71	0.86	0.68	0.75	0.69
GPT-2-XL	0.89	0.73	0.86	0.68	0.76	0.70
Falcon-7B	0.90	0.73	0.89	0.70	0.80	0.72
Llama-3.2-1B	0.87	0.71	0.87	0.70	0.76	0.71
Llama-3.1-8B	0.91	0.77	0.90	0.72	0.81	0.73
Mistral-7B-v0.3	0.90	0.76	0.90	0.71	0.80	0.72

D.4 Relative Importance of DivEye in a Boosted Model

Figure 10 illustrates the relative feature importance of **DivEye** when integrated into boosted ensembles with five existing AI detectors: **BiScope** (Guo et al., 2024), **OpenAI Detector** (Solaiman et al., 2019), **RADAR** (Hu et al., 2023), **DetectLLM** (Su et al., 2023), and **Binoculars** (Hans et al., 2024). **DivEye** contributes significantly to the overall model, with particularly high importance when combined with **RADAR** (91.92%), **OpenAI Detector** (90.26%), and **Binoculars** (89.71%). Even in ensembles with more advanced detectors like **BiScope**, **DivEye** still adds valuable signal (32.93%). These results affirm the standalone strength of **DivEye** and its utility in hybrid detection frameworks.

D.5 Results with Different Proprietary LLMs

Table 7 reports AUROC scores of **DivEye** on text generated by five proprietary LLMs, **Claude-3 Opus**, **Claude-3 Sonnet**, **Gemini 1.0-pro**, **GPT-3.5 Turbo**, and **GPT-4 Turbo**, using data provided in the **BiScope** paper (Guo et al., 2024) across five domains. **DivEye** achieves consistently strong performance on the Normal dataset (e.g., 1.000 on GPT-3.5 Turbo for Essay) and remains robust under paraphrased inputs, with AUROC scores generally above 0.95. These results highlight **DivEye**’s ability to generalize across diverse generation models and domains, even under text transformations.

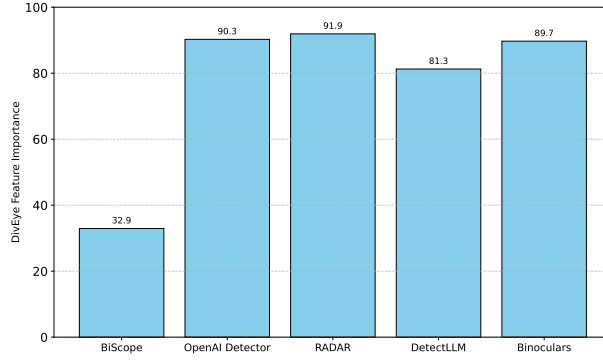


Figure 10: Feature importance of **DivEye** when integrated with various existing detectors. The plot shows how much **DivEye** contributes to the overall detection model when combined with BiScope, OpenAI Detector, RADAR, DetectLLM, and Binoculars. Higher values indicate stronger complementary impact from **DivEye**’s diversity-based features.

Table 7: AUROC scores achieved by **DivEye** on five commercial LLMs across various domains. Results are shown for both the Normal and Paraphrased datasets.

Domain	Normal Dataset					Paraphrased Dataset				
	Claude-3 Opus	Claude-3 Sonnet	Gemini 1.0-pro	GPT-3.5 Turbo	GPT-4 Turbo	Claude-3 Opus	Claude-3 Sonnet	Gemini 1.0-pro	GPT-3.5 Turbo	GPT-4 Turbo
Arxiv	0.9942	0.9770	0.9795	0.9658	0.9793	0.9778	0.9552	0.9616	0.9689	0.9558
Code	0.7528	0.8557	0.7824	0.9577	0.9044	0.8456	0.9053	0.7521	0.9279	0.9302
Creative	0.9888	0.9773	0.9835	0.9951	0.9608	0.9930	0.9900	0.9957	0.9917	0.9949
Essay	0.9950	0.9988	0.9972	1.0000	0.9823	0.9975	0.9877	0.9814	0.9895	0.9559
Yelp	0.8855	0.8813	0.9220	0.8384	0.8942	0.9543	0.9780	0.9683	0.8524	0.9571

D.6 Feature Importance of **DivEye**

Figure 11 presents the relative importance of each of the nine diversity-based features incorporated in **DivEye**, which are derived from surprisal statistics as detailed in Equation equation 6. The feature importances, ranging from approximately 8.1% to 13.0%, indicate that all features contribute meaningfully to model decisions, with temporal features such as, $\Delta\mu$, entropy of second derivatives H_{Δ^2} , and autocorrelation ρ_{Δ^2} exhibiting the highest influence. This balanced contribution underscores the complementary nature of these statistical descriptors in enhancing **DivEye**’s detection capability when combined with existing baseline detectors.

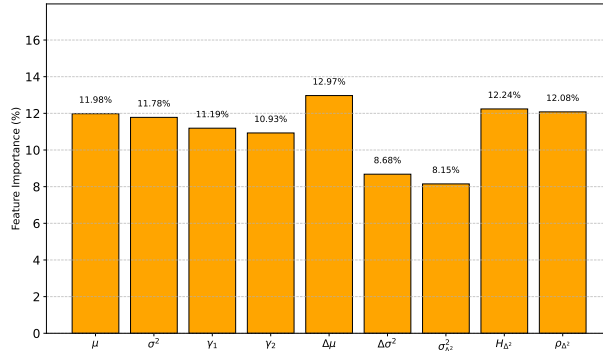


Figure 11: Relative feature importances for the nine diversity-based features used in **DivEye**. The features, as listed in Equation equation 6, represent distinct surprisal-based statistics. Higher percentages indicate greater influence in model decisions when combined with existing detectors.

D.6.1 Statistical Relevance of DivEye

To evaluate the individual contribution of each component in our diversity vector \mathcal{D} (Equation 6), we perform a leave-one-out ablation study. Each feature is removed individually from the 9-dimensional vector, the classifier is retrained, and the resulting performance is measured by the drop in AUC on Testbed 4 of the MAGE benchmark. To also assess statistical significance, we conduct a paired bootstrap test, resampling the test set to compute p-values under the null hypothesis that both models perform equally well. Table 8 summarizes both the AUC drop and the p-value for each feature.

Table 8: Leave-one-out feature ablation and statistical significance for DivEye. Each feature’s removal leads to a measurable drop in AUC and is statistically significant ($p < 0.05$).

Feature	Category	AUC Drop	p-value
H_{Δ^2}	2nd-Order	-0.0263	0.001
γ_1	Distribution	-0.0239	0.004
ρ_{Δ^2}	2nd-Order	-0.0152	0.012
σ_s^2	Distribution	-0.0115	0.016
$\Delta\sigma^2$	1st-Order	-0.0103	0.017
γ_2	Distribution	-0.0091	0.019
$\Delta\mu$	1st-Order	-0.0056	0.027
μ_s	Distribution	-0.0013	0.032
σ_{Δ^2}	2nd-Order	-0.0008	0.034

Several key insights emerge from this analysis:

- **Second-order features are the most impactful.** Removing second-order entropy H_{Δ^2} results in the largest decline in AUC, followed by the second-order autocorrelation ρ_{Δ^2} , highlighting the importance of modeling higher-order dependencies in token-level surprisal dynamics.
- **Distributional features are significant.** Skewness (γ_1) and variance (σ_s^2) contribute meaningfully, indicating that asymmetry and dispersion in surprisal values enhance DivEye’s discriminative performance.
- **First-order features contribute consistently.** The mean and variance of first-order differences ($\Delta\mu$, $\Delta\sigma^2$) produce measurable gains, reflecting local variation in surprisal between adjacent tokens.

Even features with small absolute AUC drops, such as μ_s and σ_{Δ^2} , are statistically significant ($p < 0.05$). This demonstrates that each feature contributes non-redundant information, supporting our core hypothesis that diversity in token-level surprisal; capturing both distributional asymmetries and temporal patterns is essential for detecting machine-generated text.

D.7 Performance against same model

To investigate whether DivEye’s detection ability relies on a distributional mismatch between the generator and the surprisal model, we conducted a controlled experiment using the same model for both purposes. Specifically, we computed diversity-based features and trained the DivEye classifier using three different LLMs: Falcon-7B, Llama-3.1-8B, and GPT-2-XL.

We further evaluated generalization by performing an out-of-distribution test using generations from 500 prompts drawn from the OASST (Köpf et al., 2023) and Self-Instruct (Wang et al., 2023) datasets. Table 9 reports the resulting AI detection accuracies.

Despite using the same model for both generation and surprisal estimation, DivEye maintains high classification accuracy across all settings. This demonstrates that DivEye’s effectiveness stems from intrinsic statistical patterns in the generated text rather than artifacts arising from a model mismatch.

Table 9: DivEye performance when using the same model for both generation and surprisal computation.

Model	AI Accuracy (%)
Falcon-7B	98.2
Llama-3.1-8B	96.1
GPT-2-XL	98.8

D.8 Performance against Longformer

Table 10: AUROC comparison of DivEye, DivEye (w/ BiScope), and Longformer across MAGE test settings.

Setting	Longformer	DivEye	DivEye (w/ BiScope)
Fixed-domain, Model-specific	0.990	0.994	1.000
Arbitrary-domains, Model-specific	0.990	0.972	0.991
Fixed-domain, Arbitrary-models	0.990	0.993	0.998
Arbitrary-domains, Arbitrary-models	0.990	0.880	0.934
OOD: Unseen Models	0.950	0.859	0.952
OOD: Unseen Domains	0.930	0.975	0.989
OOD: Unseen Domains & Models	0.940	0.924	0.986
Paraphrasing Attacks	0.750	0.870	0.923

Longformer, being a fine-tuned detector, was not included in Table 1 since its setup differs fundamentally. Nonetheless, for completeness, we provide a detailed AUROC-based comparison of DivEye against Longformer across the 8 challenging MAGE testbeds.

As shown in Table 10, DivEye consistently matches or outperforms Longformer in most settings. Even under OOD scenarios and paraphrasing attacks, DivEye demonstrates strong generalization, often exceeding Longformer’s performance. DivEye (w/ BiScope) further improves AUROC across nearly all testbeds, highlighting the benefits of incorporating diverse zero-shot features.

E Additional Adversarial Attacks on DivEye

We evaluate DivEye under a range of adversarial settings, including character-level perturbations, word- and phrase-level edits, paraphrasing, prompt obfuscations, and distribution shifts (temperature changes and degenerate sampling), to comprehensively assess its robustness.

E.1 Adversarial Attack Analysis of DivEye

We evaluate DivEye against a wide range of adversarial attacks using the RAID benchmark, reporting average classification accuracies across all attack categories listed in Table 11. DivEye achieves performance on par with the top-performing fine-tuned models reported by the benchmark. Notably, it consistently surpasses all zero-shot detectors by a significant margin across every attack type, demonstrating strong robustness against both diverse adversarial attacks.

E.2 Detection against other diverse online paraphrasers

To evaluate the robustness of DivEye against paraphrasing attacks intended to "humanize" AI-generated text, we curate a set of 21 arXiv abstracts generated by Claude-3.5-Sonnet and paraphrase each using three widely used commercial tools: ZeroGPT², GPTinf³, and QuillBot⁴. This results in 63 paraphrased texts (21

²<https://www.zerogpt.com/>

³<https://app.gptinf.com/>

⁴<https://quillbot.com/paraphrasing-tool>

Table 11: Performance of DivEye and open-source baselines on all listed adversarial attacks on the RAID benchmark.

Settings	Methods	FPR@TPR=5%
[RAID] Adversarial Attacks		
Whitespace Attack	Desklib AI	94.9%
	e5-small-lora	93.9%
	DivEye (Ours)	79.8%
	Binoculars	68.7%
	RADAR	61.1%
	GLTR	43.1%
Upper-Lower Attack	Desklib AI	87.2%
	e5-small-lora	93.9%
	DivEye (Ours)	85.3%
	Binoculars	72.8%
	RADAR	65.1%
	GLTR	45.3%
Synonym Attack	Desklib AI	80.6%
	e5-small-lora	85.6%
	DivEye (Ours)	67.1%
	Binoculars	42.1%
	RADAR	62.7%
	GLTR	28.7%
Paraphrase Attack	Desklib AI	83.7%
	e5-small-lora	85.5%
	DivEye (Ours)	74.4%
	Binoculars	N/A
	RADAR	62.4%
	GLTR	43.0%
Perplexity Misspelling	Desklib AI	92.9%
	e5-small-lora	92.5%
	DivEye (Ours)	90.6%
	Binoculars	77.2%
	RADAR	64.3%
	GLTR	57.0%

Settings	Methods	FPR@TPR=5%
Number Attack	Desklib AI	93.0%
	e5-small-lora	93.5%
	DivEye (Ours)	92.1%
	Binoculars	76.4%
	RADAR	65.7%
	GLTR	57.3%
Insert Paragraph	Desklib AI	94.9%
	e5-small-lora	93.9%
	DivEye (Ours)	92.2%
	Binoculars	70.7%
	RADAR	68.2%
	GLTR	58.3%
Homoglyph Attack	Desklib AI	99.7%
	e5-small-lora	11.1%
	DivEye (Ours)	61.6%
	Binoculars	36.1%
	RADAR	44.8%
	GLTR	20.3%
Article Deletion	Desklib AI	90.5%
	e5-small-lora	92.0%
	DivEye (Ours)	88.0%
	Binoculars	73.3%
	RADAR	63.0%
	GLTR	48.9%
Alt. Spelling Attack	Desklib AI	94.3%
	e5-small-lora	93.4%
	DivEye (Ours)	92.01%
	Binoculars	77.6%
	RADAR	65.5%
	GLTR	58.2%
Zero Width Space	Desklib AI	87.5%
	e5-small-lora	93.9%
	DivEye (Ours)	92.0%
	Binoculars	98.4%
	RADAR	78.4%
	GLTR	97.9%

Table 12: Detection performance of DivEye against paraphrased outputs generated by three commercial tools. Each model was tested on 21 samples per paraphraser.

Paraphraser	MAGE Testbed 4 Model	Claude-3.5-Sonnet Model
Claude-3.5-Sonnet (original)	20 / 21	21 / 21
GPTinf	18 / 21	19 / 21
ZeroGPT	20 / 21	17 / 21
QuillBot	20 / 21	17 / 21

per tool), each aiming to evade AI detectors through stylistic and lexical variation. We provide this smaller dataset in the supplementary materials and in our anonymous repository.

We assess detection performance using two XGBoost classifiers trained exclusively on DivEye features: one trained on MAGE’s Testbed 4 (Arbitrary Models & Arbitrary Domains), and another trained on 280 Claude-3.5-Sonnet generated arXiv abstracts (from BiScope (Guo et al., 2024)). The results, presented in Table 12, highlight DivEye’s ability to maintain detection accuracy even in the presence of strong paraphrasing transformations.

E.3 Dependence of DivEye on Generation Temperature

We investigate the influence of generation temperature on DivEye’s detection performance to evaluate its robustness against variations in text predictability. Specifically, we conduct two experiments on the MAGE benchmark: intra-model temperature variation and cross-model variable-temperature detection.

E.3.1 Intra-Model Temperature Variation

Using GPT-2 as the zero-shot feature generator, we evaluate DivEye across a wide range of sampling temperatures (default $T = 1.0$). AUROC results for selected MAGE testbeds are presented in Table 13.

Table 13: DivEye AUROC across different temperatures for GPT-2 generated texts.

Testbeds / Temperatures	$T = 0.1$	$T = 0.3$	$T = 0.5$	$T = 0.7$	$T = 1.0$	$T = 1.2$	$T = 1.4$	$T = 1.6$
Arbitrary Domains & Arbitrary Models	0.8784	0.8760	0.8776	0.8886	0.8825	0.8767	0.8842	0.8698
Unseen Models (GPT-3.5-Turbo, OOD)	0.8473	0.8432	0.8595	0.8619	0.8617	0.8583	0.8488	0.8567

Results indicate that DivEye’s AUROC remains consistently high across all temperatures. Even at extreme sampling regimes, performance does not degrade, suggesting DivEye captures stable distributional signals across different entropy levels within the same generator.

E.3.2 Cross-Model, Variable-Temperature Detection

We further test DivEye on Llama-3.1-8B, generating 50 samples per temperature (ranging $T = 0.1$ to 1.6) using OASST prompts. This simulates an adversarial generator varying sampling temperature to evade detection. Table 14 summarizes AI detection accuracy.

Table 14: DivEye AI detection accuracy for Llama-3.1-8B across different temperatures.

Temperature	AI Accuracy (%)
$T = 0.1$	94.0
$T = 0.3$	96.0
$T = 0.5$	100.0
$T = 0.7$	96.0
$T = 1.0$	96.0
$T = 1.2$	98.0
$T = 1.4$	94.0
$T = 1.6$	96.0

These experiments demonstrate that DivEye maintains strong performance across both intra-model and cross-model temperature variations, consistently achieving high AUROC and detection accuracy. Even at high temperatures ($T = 1.6$), where generations are more diverse, DivEye remains robust, highlighting its resilience against temperature-based evasion strategies in real-world deployment.

E.4 Robustness of DivEye to low-quality LMs and Prompt-based attacks

We further evaluate DivEye’s robustness against two challenging conditions raised by the reviewer: degenerate or less predictable generators, and prompt-level adversarial obfuscations.

E.4.1 Performance on Less Predictable Generators

While DivEye’s primary focus is detecting outputs from realistic, high-quality LLMs, we also assess its behavior on weaker or degenerate text sources to explore the method’s boundaries. The RAID benchmark already includes a variety of degenerate and obfuscation-style perturbations - such as synonym replacement, paraphrasing, number swaps, homoglyph substitutions, and zero-width spaces - which DivEye handles effectively (see Table 11 for results).

To complement these benchmark results, we evaluate two baseline degenerate generators producing 500 samples each:

1. **Random Token Generator:** uniformly samples tokens from GPT-2’s vocabulary to generate incoherent sequences without semantic structure.
2. **Keyword-Stuffing Generator:** repeats high-frequency topical keywords in ungrammatical, repetitive patterns.

Using GPT-2 and Testbed 4 of the MAGE benchmark, DivEye achieves near-perfect AI detection: 99.99% on the random token set and 99.95% on the keyword-stuffed set. These results indicate that DivEye confidently flags incoherent or low-quality text as non-human-written, suggesting that it is sensitive to general non-human-likeness rather than relying solely on repetition or frequency patterns.

E.4.2 Robustness to Prompt-Based Adversarial Attacks

We also assess DivEye under adversarial prompt-based obfuscation, designed to disrupt GPT-2’s predictability patterns. Specifically, we generated 250 texts from GPT-4o and Llama-3.1-8B using the following system prompt to encourage unusual and unpredictable writing styles:

"You are a highly creative and unconventional writer. Your goal is to respond with original, imaginative, and surprising ideas that avoid clichés, common phrases, or predictable completions. Do not repeat yourself or follow standard templates. Instead, embrace novelty, abstract connections, and lateral thinking. Unusual metaphors, unexpected analogies, and rare vocabulary are encouraged."

These generations were sampled from different models and prompts, constituting a fully out-of-distribution evaluation. Table 15 shows DivEye’s detection performance compared to Binoculars.

Table 15: AI detection accuracy under prompt-based adversarial attacks.

Model	DivEye Accuracy (%)	Binoculars Accuracy (%)
Llama-3.1-8B	90.8	72.4
GPT-4o	92.4	78.0

Despite these obfuscation strategies, DivEye maintains high accuracy, substantially outperforming Binoculars. This demonstrates that DivEye’s diversity-based signals remain robust under both low-quality generators and adversarial prompting, highlighting its resilience in real-world deployment scenarios.

Overall, these experiments confirm that DivEye effectively detects both degenerate text and highly unpredictable LLM outputs, providing strong evidence of its general robustness.

F Additional Discussions

F.1 Robustness of Binoculars under OOD Conditions

While Binoculars achieves high performance in its original paper, with AUROC values consistently above 0.99 (Tables 3 and 4), its robustness under out-of-distribution (OOD) conditions is substantially weaker. For example, Tufts et al. (2025) (Table 13) shows a noticeable drop in AUROC when Binoculars is applied to datasets with distributions different from its training set, despite remaining competitive. Similarly, in the Voight-Kampff Generative AI Authorship Verification Challenge 2024 (Ayele et al., 2024), Binoculars underperformed significantly under highly OOD conditions, failing to replicate its originally reported accuracy and AUROC.

These findings are consistent with our observed AvgAcc of 79%, reflecting Binoculars’ sensitivity to domain shift. Importantly, our evaluation deliberately includes diverse scenarios to rigorously test generalization beyond training conditions. This approach better reflects real-world deployment, where robustness to OOD tasks is critical. Our results do not contradict prior work; rather, they reinforce the understanding of Binoculars’ limitations under distribution shifts.

F.2 Practical constraints on adversarial attacks against DivEye

The possibility of targeted attacks that attempt to evade DivEye by steering autoregressive models to generate tokens falling in low-probability regions under GPT-2’s distribution seems like a plausible idea to evade detection. While such attacks are theoretically conceivable, implementing them in practice is extremely challenging.

Autoregressive models do not natively support fine-grained constraints that enforce divergence from another model’s token-level distribution without compromising fluency or coherence. Even for large models such as GPT-4o, generating text that is simultaneously plausible and systematically unpredictable to a specific detector like DivEye is highly nontrivial.

Furthermore, DivEye is designed to generalize across diverse model backbones. Our best-performing variant, for example, uses Llama-3.1-8B as the surprisal scorer, which has a larger vocabulary and greater expressive capability than GPT-2. This substantially increases the difficulty for an adversary to generate text that appears unpredictable to the detector while remaining coherent and human-like.

Taken together, these considerations suggest that although targeted, detector-specific attacks are theoretically possible, they are rare and practically hard to execute in realistic generation pipelines.

G Failure of other motivational methods: LookForward

A natural hypothesis we considered was that LLMs, being autoregressive in nature, lack global sentence-level planning due to their left-to-right generation paradigm. Unlike humans who often write with a sense of the sentence’s future, autoregressive models generate one token at a time conditioned only on the preceding context. Based on this, we hypothesized that detection features relying on this "lack of foresight" could effectively identify machine-generated text.

This suggests that the model never observes $x_{>t}$ when predicting x_t , whereas human writing may implicitly reflect awareness of future tokens. Our idea was to define a LookForward discrepancy by comparing model likelihoods under forward-only conditioning vs. bidirectional context.

However, our empirical evaluations demonstrate that this feature is ineffective, achieving 0.50 AUROC on diverse testbeds. As LLMs undergo extensive training and optimization, they appear to develop strong internal planning capabilities, even in an autoregressive setting. Despite the absence of access to future tokens during generation, LLMs approximate global coherence and structure remarkably well. This aligns with recent literature suggesting that transformers internalize hierarchical and global sentence structure across layers, even when trained autoregressively.

While this method is theoretically appealing, its failure in practice highlights the difficulty of quantifying planning behavior in black-box LLMs. We hope this limitation can be better understood in the future through more fine-grained interpretability analyses of autoregressive models, which may reveal how planning and coherence emerge despite the lack of explicit future context.

H Testbed Details

We evaluate DivEye on a comprehensive testbed spanning three major AI-text detection benchmarks, MAGE (Li et al., 2024), HC3 (Guo et al., 2023) & RAID (Dugan et al., 2024), covering a diverse range of domains, language models, and adversarial attacks. These benchmarks allow us to assess the generalizability and robustness of our method across realistic deployment scenarios. This section provides a comprehensive

overview of the testbeds used in our evaluation, including all domains, language models, and adversarial attacks featured in the MAGE and RAID benchmarks, along with relevant configuration details.

Details about MAGE Benchmark. The MAGE benchmark (Li et al., 2024) comprises eight diverse testbeds designed for evaluating machine-generated text detection. Testbeds 1 through 4 include standard train, validation, and test splits, while Testbeds 5 through 8 serve as out-of-distribution (OOD) datasets, evaluated using models trained on Testbed 4. Notably, Testbed 4, Arbitrary Domains & Arbitrary Models, is the most comprehensive, enabling evaluation across the full range of domains and language models listed in the MAGE paper. Detailed information regarding dataset splits and sample counts is available in the original benchmark documentation.

MAGE covers a wide array of domains, including CMV (Tan et al., 2016), Yelp (Zhang et al., 2015), XSum (Narayan et al., 2018), TLDR, ELI5 (Fan et al., 2019), WP (Fan et al., 2018), ROC (Mostafazadeh et al., 2016), HellaSwag (Zellers et al., 2019), SQuAD (Rajpurkar et al., 2016), and SciXGen (Chen et al., 2021a). The OOD domains include CNN/DailyMail (See et al., 2017), DialogSum (Chen et al., 2021b), PubMedQA (Jin et al., 2019), and IMDb (Maas et al., 2011).

MAGE also incorporates text generated from over 27 different LLMs (Brown et al., 2020; Chung et al., 2022; et al., 2023; Sanh et al., 2022; Touvron et al., 2023a; Zeng et al., 2023; Zhang et al., 2022), enabling rigorous and varied evaluations. For further implementation specifics, readers are encouraged to consult the MAGE paper.

Details about RAID Benchmark. The RAID benchmark (Dugan et al., 2024) comprises over 6.2 million samples, offering extensive coverage across domains, language models, sample sizes, and adversarial attacks. It provides a clear separation into training, validation, and testing splits to support rigorous evaluation. The benchmark spans a wide range of domains, including scientific abstracts (Paul & Rakshit, 2021), book summaries (Bamman & Smith, 2013), BBC News articles (Greene & Cunningham, 2006), poems (Arman, 2020), recipes (Bieł et al., 2020), Reddit posts (Völske et al., 2017), movie reviews (Maas et al., 2011), Wikipedia entries (Aaditya Bhat, 2023), Python code, Czech news (Boháček et al., 2022), and German news articles (Schabus et al., 2017).

RAID employs text generated from 11 diverse LLMs (Radford et al., 2019; MosaicML, 2023; Jiang et al., 2023; Cohere, 2024; Ouyang et al., 2022; Touvron et al., 2023b; et al., 2024b), ensuring broad model representation. Additionally, it includes over 11 adversarial attack strategies (Liang et al., 2023b;a; Wolff & Wolff, 2022; Bhat & Parthasarathy, 2020; Krishna et al., 2023; Pu et al., 2023; Gagiano et al., 2021; Guerrero et al., 2022), designed to test the robustness of detectors under challenging settings. Comprehensive descriptions and detailed results of these attacks are provided in Appendix E.1, with all results reported as of April 2025. For further implementation specifics, readers are encouraged to consult the RAID paper.

Details about HC3 Benchmark. The HC3 benchmark (Guo et al., 2023) offers a large-scale, multilingual dataset designed to evaluate the effectiveness of detectors in distinguishing human-written text from AI-generated responses. It encompasses both English and Chinese content, covering a wide variety of domains and question types. This bilingual setup facilitates cross-linguistic performance analysis and underscores the difficulties of achieving generalization across different languages and cultural contexts. In our experiments, we adopt an 80-20 train-test split. For comprehensive dataset numbers, we refer readers to the original HC3 paper.

I Hyperparameter Settings

Table 16 outlines the hyperparameter configurations used for our experiments. We utilize the XGBoost classifier with standard but tuned settings to handle class imbalance and optimize detection performance. For our proposed method DivEye, we set the number of bins for entropy computation to 20 and truncate input sequences at a maximum length of 1024 tokens. All experiments were run on a single NVIDIA DGX A100 (40 GB), and reported results reflect the median of three runs.

Table 16: Hyperparameters used for the XGBoost Classifier and DivEye.

XGBoost Hyperparameter	Value
random_state	42
scale_pos_weight	$(\text{len}(Y_{\text{train}}) - \sum Y_{\text{train}}) / \sum Y_{\text{train}}$
max_depth	12
n_estimators	200
colsample_bytree	0.8
subsample	0.7
min_child_weight	5
gamma	1.0
DivEye Parameter	Value
Entropy bins	20
Tokenizer Max Length	1024 + Truncation

J Limitations, Broad Impacts, Reproducibility & Ethical Considerations

Future Work & Limitations. While DivEye demonstrates strong generalization across domains and models in zero-shot settings, several limitations suggest promising directions for future work. Our approach relies on features derived from LLM token-level behavior, which may vary across model sizes, architectures, and tokenization schemes. Although our current performance is robust, it is unclear whether we are approaching an optimal limit for AI-text detection. Moreover, our diversity metrics are less effective on very short texts, where statistical patterns are inherently limited. We hope to address these challenges in future work by exploring more adaptive teacher selection strategies and improving robustness in diverse text lengths.

Broad Impacts. This work introduces DivEye, a model-agnostic, and scalable framework for detecting AI-generated text that remains robust across models, domains, and decoding strategies. By leveraging purely intrinsic statistical features, without requiring fine-tuning or access to the internals of large language models, DivEye is broadly applicable and easy to deploy in real-world settings. We envision this framework as a practical tool to support responsible AI usage, aiding in the detection of synthetic text across domains such as education, journalism, and online content moderation. However, we emphasize that detection results should be interpreted with care and recommend using DivEye as one component within a broader, multi-layered content verification pipeline.

We deliberately restrict DivEye to nine features, each of which is theoretically motivated and captures a distinct aspect of surprisal diversity. While additional features could be engineered, our preliminary experiments indicated diminishing returns beyond this set. This preserves interpretability, efficiency, and robustness, while still providing strong empirical performance. We also discuss certain concerns about our results and the practicality of adversarial attacks in Appendix F.

Reproducibility. We release all code and evaluation scripts to ensure full reproducibility. Detailed training, testing and hyperparameter configurations are included in Appendices H and C.

Ethical Considerations. As with all AI-text detectors, DivEye is not infallible and may produce incorrect classifications. We emphasize that detection outputs should be treated as probabilistic signals rather than definitive evidence. When used in high-stakes settings, such as academic integrity or content moderation, additional human review and validation are essential. We encourage responsible deployment of DivEye to support large-scale analysis, but caution against its use in critical decision-making.

K Illustrative cases of DivEye with probabilities

We provide a few representative examples for readers in Table 17, showcasing the probability scores assigned by DivEye to different text sources.

Source	Text	$Probability_{AI}$ (DivEye)
GPT-4-Turbo	For centuries, the pursuit of immortality was the ultimate quest, a beacon drawing the brilliant and the mad alike. I, Dr. Elara Mendoza, fell somewhere in between, teetering on the precipice of genius and insanity. And after countless sleepless nights, fueled by an obsession that bordered on madness, I finally did it. I unlocked the secret to immortality. In my laboratory bathed in the cold, metallic gleam of artificial light, the hum of machinery breathed life into my creation, a serum, translucent and iridescent, a potion promising eternity. As the final drop fell into the vial, a silence descended, thick with anticipation. But in this moment of triumph, a chill swept through the room, frosting over the warmth of victory...	0.97035
Claude-3-Opus	Dressing for Success: Budgeting for Interview Attire and Work Uniforms as a Medical Office Assistant - As a medical office assistant, presenting a professional image is crucial for success in both the job interview process and daily work life. Dressing appropriately demonstrates respect for the healthcare setting, instills confidence in patients, and showcases a commitment to the role. However, building a wardrobe suitable for the medical office can be a financial challenge, especially for those just starting in the field. By developing a strategic budget plan...	0.96279
Human-Written	Loved this tour! I grabbed a groupon and the price was great. It was the perfect way to explore New Orleans for someone who'd never been there before and didn't know a lot about the history of the city. Our tour guide had tons of interesting tidbits about the city, and I really enjoyed the experience. Highly recommended tour. I actually thought we were just going to tour through the cemetery, but she took us around the French Quarter for the first hour, and the cemetery for the second half of the tour. You'll meet up in front of a grocery store (seems strange at first, but it's not terribly hard to find, and it'll give you a chance to get some water), and you'll stop at a visitor center part way through the tour for a bathroom break if needed. This tour was one of my favorite parts of my trip!	0.09172

Table 17: Representative examples of texts from various sources with their predicted probability of being AI-generated according to DivEye.