CLAWS: Creativity detection for LLM-generated solutions using Attention Window of Sections

Keuntae Kim^{1*} Eunhye Jeong^{2*} Sehyeon Lee³ Seohee Yoon¹ Yong Suk Choi^{1†}

¹Department of Computer Science ²Department of Artificial Intelligence ³Department of Future Mobility Hanyang University, Seoul, Korea ktkpv94@hanyang.ac.kr

Abstract

Recent advances in enhancing the reasoning ability of Large Language Models (LLMs) have been remarkably successful. LLMs trained with Reinforcement Learning (RL) for reasoning demonstrate strong performance in challenging tasks such as mathematics and coding, even with relatively small model sizes. However, despite these impressive improvements in task accuracy, the assessment of creativity in LLM generations has been largely overlooked in reasoning tasks, in contrast to writing tasks. The lack of research on creativity assessment in reasoning primarily stems from two challenges: (1) the difficulty of defining the range of creativity, and (2) the necessity of human evaluation in the assessment process. To address these challenges, we propose CLAWS, a novel method that defines and classifies mathematical solutions into Typical, Creative, and Hallucinated categories without human evaluation, by leveraging attention weights across prompt sections and output. CLAWS outperforms five existing white-box detection methods—Perplexity, Logit Entropy, Window Entropy, Hidden Score, and Attention Score—on five 7–8B math RL models (DeepSeek, Qwen, Mathstral, OpenMath2, and Oreal). We validate CLAWS on 4,545 math problems collected from 181 math contests (A(J)HSME, AMC, AIME). Our code is available at https://github.com/kkt94/CLAWS.

1 Introduction

In recent years, Large Language Models (LLMs) have achieved remarkable success across a wide range of tasks. Among these, the most notable progress has been made in reasoning ability, particularly in mathematical problem solving. Solving math problems requires cognitive processes that go beyond simple calculations, making it an ideal benchmark for assessing how closely AI approximates human intelligence. Recently released frontier LLMs [1, 2, 3] appear to approach human-level intelligence in terms of accuracy on mathematical reasoning tasks.

However, human intelligence is not defined solely by accuracy; it also encompasses diverse aspects such as creativity. Within LLM research, creativity has primarily been explored in writing tasks, often evaluated through the Torrance Test of Creative Writing (TTCW) [4, 5], which is adapted from the Torrance Tests of Creative Thinking (TTCT) [6, 7]. These tests provide a framework for assessing creativity beyond factual consistency between input and output [8] or coherence of generated responses [9]. In contrast, creativity remains largely overlooked in reasoning tasks.

^{*}Equal contribution

[†]Correspondence to: Yong Suk Choi <cys@hanyang.ac.kr>

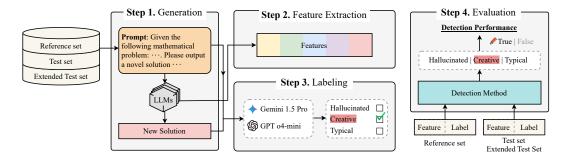


Figure 1: Overview of the proposed framework. **Step 1:** LLM generates a solution. **Step 2:** Features are extracted during generation. **Step 3:** LLM Evaluator assigns labels (Hallucinated / Creative / Typical). **Step 4:** Detection methods are evaluated by comparing predictions with the labels.

Evaluating creativity in reasoning is particularly challenging because it requires human expertise to establish what constitutes a "creative" solution. Assessing mathematical creativity, in particular, demands high-level domain knowledge, making large-scale evaluation costly and difficult to standardize. To overcome these challenges, recent studies on mathematical problem solving [10, 11] have attempted to define creativity and measure the creative problem-solving abilities of LLMs. Interestingly, their results revealed that even LLMs with similar accuracy exhibit substantial differences in creative ability, motivating further research on creativity assessment in reasoning tasks.

If clear criteria for judging creativity were available, it would be possible to detect whether an LLM's response is creative or not. Since the emergence of LLMs, numerous studies have focused on hallucination detection [12, 13]. While detecting and mitigating hallucination is crucial for ensuring factual accuracy, excessive restriction of model generations may inadvertently suppress creativity and lead to repetitive, typical outputs [14]. Thus, identifying creative responses is essential for maximizing the effectiveness and diversity of LLM generations.

Recent advances in prompt engineering have shown that the structure of input prompts significantly affects LLM performance [15, 16]. Building on these findings, we hypothesize that creative generation may depend on which sections of the prompt an LLM attends to—whether it relies more on the given instructions or on its self-generated reasoning. Accordingly, we propose CLAWS, which divides the prompt into sections and quantifies, via attention analysis, the degree to which each section influences generation. This enables detection of Hallucinated, Creative, and Typical solutions based on attention differences across prompt sections and output.

In this study, we present an experimental framework that classifies generated mathematical solutions into Hallucinated, Creative, and Typical categories, and propose CLAWS, a novel white-box detection method that leverages attention over distinct prompt sections and output to perform this classification without requiring human evaluation. CLAWS achieves three-way classification with high efficiency—a capability rarely demonstrated by existing hallucination detection methods. Moreover, it consistently outperforms baseline methods on hallucination detection tasks.

To validate the superior performance of CLAWS, we utilize five Reasoning Language Models (RLMs)—DeepSeek-Math[17], Qwen-Math[18], Mathstral[19], OpenMath2-Llama3.1[20], and Oreal[21]—each with 7–8B parameters and trained with reinforcement learning to enhance reasoning capabilities. We conduct extensive validation using a dataset of 4,545 mathematical problems spanning Algebra, Precalculus, Prealgebra, Number Theory, Geometry, and Counting & Probability.

Our major contributions are summarized as follows:

- We propose a framework for detecting Hallucinated, Creative, and Typical solutions without human evaluation in reasoning tasks using RLMs.
- We introduce CLAWS, a novel white-box method for detecting creativity and hallucination in mathematical reasoning.
- We present a comprehensive evaluation protocol, consisting of five evaluation strategies and four metrics, to assess the features extracted by detection methods.

2 Experimental Framework

An overview of the experimental framework is presented in Figure 1. During the generation process, features are extracted from the model's internal representations through the Generator. The generated responses are then labeled by the LLM Evaluator, which determines whether each solution is Hallucinated, Creative, or Typical. Finally, the reference set is utilized to perform detection using the selected methods, enabling each method to classify the responses based on the extracted features.

2.1 Problem Formulation

We aim to classify a generated solution R = f(X) into one of three categories — Hallucinated / Creative / Typical Solution — without relying on human evaluation, where X = G|P|S|I is the input prompt to the generative model f. As illustrated in Figure 2, input prompt X consists of the following four sections:

- **Guideline** G: Describes the criteria for evaluating the difference between two mathematical solutions, providing the model with the concept and standard for identifying Creative solutions.
- **Problem** *P*: The math problem that the model is required to solve.
- **Reference Solutions** S: A set of 1 to n typical solutions to the problem, provided to help the model generate a creative solution in contrast to these references.
- Instruction I: An instruction to create a novel solution that is different from reference solutions for a given problem.

In prior study [11], prompt in Figure 2 was used to induce the generative model to create novel creative solutions, and the creative problem-solving ability of LLMs was successfully presented. Building on this setup, we take a further step by investigating whether the model's internal state can detect Hallucinated / Creative / Typical Solution.

We define a generated response R as a Creative solution if it differs from the provided reference solutions S in a way that satisfies the criteria specified in the guideline G. The generative model f receives between 1 and n reference solutions and generates a novel solution accordingly. Each R is then evaluated by a LLM evaluator E, using the prompt described in Appendix B.1.

2.2 Model

2.2.1 RLM Generator

To generate mathematical problem solutions, we select five RLMs: DeepSeek-Math-7B-RL [17], Qwen2.5-Math-7B-Inst [18], Mathstral-7B [19], OpenMath2-Llama3.1-8B [20], and OREAL-7B [21]. These models are released after 2024 and have 7-8B parameter scales, which enables white-

- If the methods used to arrive at the solutions are fundamentally different, such as algebraic manipulation versus geometric reasoning, they can be considered distinct;
- ii). Even if the final results are the same, if the intermediate steps or processes involved in reaching those solutions vary significantly, the solutions can be considered different;
- If two solutions rely on different assumptions or conditions, they are likely to be distinct;
- iv). A solution might generalize to a broader class of problems, while another solution might be specific to certain conditions. In such cases, they are considered distinct;
- v). If one solution is significantly simpler or more complex than the other, they can be regarded as essentially different, even if they lead to the same result.

Given the following mathematical problem:

What is the largest power of 2 that is a divisor of $13^4 - 11^4$?

And some typical solutions:

1. First, we use the difference of squares on $13^4 - 11^4 = (12^2)^2 - (11^2)^2 \cdot \cdots$

2. Just like in the above solution, we use the difference-of-squares factorization, but only once to get $13^4-11^4=(13^2-11^2)(13^2+11^2).$

Please output a novel solution distinct from the given ones for this math problem.

Figure 2: Example of an input prompt X used to elicit creative solutions from LLMs. Prompt consists of four sections: Guideline (G, yellow), Problem (P, green), Reference Solutions (S, blue), and Instruction (I, purple).

box approach of long length of problem and reference solutions. In addition to the RLM, we also tested general LLMs such as LLaMa3-8B [22], Qwen2.5-14B [23], and DeepSeekV2-16B [24], but finally did not adopt them due to their lack of ability to creatively solve mathematical problems or model sizes.

2.2.2 LLM Evaluator

To evaluate RLM's Generations, we employ two frontier-level LLMs — GPT-o4-mini [25] and Gemini-1.5-Pro [26]— as LLM Evaluators. These two models have shown great performance on

Table 1: Number of samples per class (Hallucinated, Creative, Typical) for each dataset and model. **Ha** denotes Hallucinated solutions, **Cr** Creative solutions, and **Ty** Typical solutions.

Model		Deep	Seek			Mat	hstral		(Open	Math	2		OR	EAL			Qw	en-2.5	;
Dataset	Ha	Cr	Ту	Total	Ha	Cr	Ту	Total	Ha	Cr	Ty	Total	Ha	Cr	Ту	Total	Ha	Cr	Ту	Total
REF	868	206	649	1723	1192	175	437	1804	923	103	785	1811	1244	83	379	1706	631	324	752	1707
TEST	798	160	456	1414	961	154	337	1452	815	97	551	1463	932	89	369	1390	578	203	579	1360
AMC	1197	530	1373	3100	1679	434	1049	3180	1330	291	1578	3199	1928	237	935	3100	637	629	1784	3050
AIME	772	126	262	1160	917	68	221	1206	644	67	501	1212	911	47	161	1119	529	159	373	1061
A(J)HSME	657	424	763	1844	945	354	606	1905	723	248	943	1914	1005	161	656	1822	281	491	1054	1826

mathematical benchmarks and have already been recognized as human-level Evaluators in prior studies. Based on their evaluations, we assess the solutions according to the following criteria:

- Hallucinated Solution: If both evaluator did not judge the generated solution as 'Correctness', it was classified as a Hallucinated Solution.
- **Creative Solution**: Among the generated solutions that both evaluators judged to be 'Correctness', if even one evaluator judged them to be 'Creativity', the solution was classified as Creative Solution. This is a criterion for inclusive acceptance of creativity.
- **Typical Solution**: Among the generated solutions that both evaluators judged as 'Correctness', those that neither evaluator judged as 'Creativity' were classified as Typical Solution.

2.3 Dataset

To conduct our study, we adopted publicly available math datasets from CreativeMath [11] and HARP [27]. CreativeMath is a dataset of 400 math problems with solutions, sampled and cleaned from 50 questions from eight math contests: AMC 8, 10, 12, A(J)HSME, AIME, USAJMO, USAMO, and IMO. HARP contains 5,409 problems from A(J)HSME, AMC, AIME, and USA(J)MO. Since there is an overlap of 282 problems between HARP and CreativeMath, We reconstructed HARP by removing duplicate entries and excluding problems that were either too difficult (e.g., proof-based) or whose problems or solutions were excessively long, resulting in a final set of 4,545 problems with solutions.

2.3.1 Dataset Construction

We generate solutions using the Generators described in Section 2.2.1, and construct the reference set and test set from the CreativeMath, and the extended test set from the HARP. The reference set serves as a low-resource for detection, the test set is used for validation on the same dataset, and the extended test set is used for validation on an extended dataset. For all Generators, we limit the input token length to 2,048 and the output token length to fewer than 1,024 tokens, based on each Generator's respective tokenizer.

Reference Set Reference set serves as the standard for classifying generated solutions into one of three categories. We select 29 problems from the CreativeMath dataset, considering the distribution of difficulty levels. Following the approach of prior work [12], we generate 20 responses for each input prompt using stochastic decoding. For each problem, we include up to n reference solutions, where n is the number of reference solutions available in the dataset. We attempted to ensure sufficient diversity in the reference set by providing a diverse number of reference solutions for each problem. Because each reference solution for problem differs in both length and content, naturally resulted in variation in prompt length. Such diversity contributes to the effectiveness of the reference set as a criterion for classification.

Test Set Test set consists of the remaining 371 problems with solutions from CreativeMath. For each problem, three responses are generated using stochastic decoding. The number of reference solutions n provided in the input prompt is limited to a maximum of two.

Extended Test Set Extended test set is used to evaluate the generalization performance of the method. We utilize problems and solutions from four math competitions — A(J)HSME, AMC, and AIME — compiled in the HARP. For each problem, one response is generated. The number of reference solutions n included in the prompt is limited to a maximum of two, consistent with the test set.

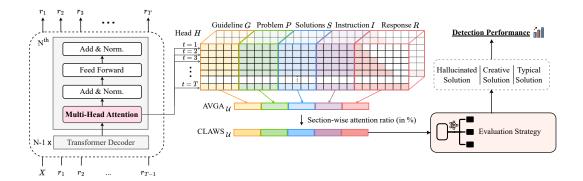


Figure 3: Architecture of CLAWS. All tokens are segmented into five sections: Guideline, Problem, Solutions, Instruction, and Response. The average attention weight for each section (AVGA $_{\mathcal{U}}$) is computed, normalized to obtain section-wise attention ratios (CLAWS $_{\mathcal{U}}$), and used as features for detecting Hallucinated, Creative, or Typical solutions.

3 CLAWS: Creativity detection for LLM-generated solutions using Attention Window of Sections

In Figure 3, we input the prompt X = G|P|S|I into the RLM f and leverage the decoder attention weights during generation to classify the class of the generated response R = f(X). As described in Section 2.1, X consists of four sections — Guideline (G), Problem (P), reference Solutions (S), and Instruction (I). we additionally include the generated Response section (R), thereby dividing tokens into five distinct semantic segments. We hypothesize that the class of R is influenced by which sections the model attends to most during generation. Based on this hypothesis, we propose CLAWS, a method that leverages the average attention weights for each section windows. Let $A_{t,h}^{(L)}$ denote the attention weights at decoding time step t from head t in last layer t:

$$A_{t,h}^{(L)} = [a_{1,h}^{(L)} \ a_{2,h}^{(L)} \cdots a_{k,h}^{(L)} \cdots a_{k+t,h}^{(L)}], \text{ where } k = len(X)$$

To construct the complete attention weight matrix $A_h^{(L)}$, we stack the attention vectors over all time steps $t=1\cdots T$. Since one output token is generated at each time step, the length of the attention target increases over time. To ensure consistent dimensionality, each $A_{t,h}^{(L)}$ is padded to a fixed length of $\operatorname{len}(X)+T$.

$$A_h^{(L)} = \begin{bmatrix} A_{1,h}^{(L)} & A_{2,h}^{(L)} & \cdots & A_{T,h}^{(L)} \end{bmatrix}^T \in \mathbb{R}^{T \times (\operatorname{len}(X) + T)}$$

We then compute the average attention weight for each section $\mathcal{U} \in G, P, S, I, R$ by summing the attention weights over all tokens belonging to that section, and averaging over all heads H, time steps T, and section-specific token positions $\mathcal{I}_{\mathcal{U}}$:

$$\text{AVGA}_{\mathcal{U}} = \frac{1}{H \cdot T \cdot |\mathcal{I}_{\mathcal{U}}|} \sum_{h=1}^{H} \sum_{t=1}^{T} \sum_{i \in \mathcal{I}_{\mathcal{U}}} A_h^{(L)}[t, i], \text{ for } \mathcal{U} = \{G, P, S, I, R\}$$

Finally, to quantify the proportion of attention allocated to each section, we normalize the average attention weights AVGA into ratios and use them as input features for the evaluation model:

$$\text{CLAWS}_{\mathcal{U}} = \frac{\text{AVGA}_{\mathcal{U}}}{\sum_{\mathcal{U}' \in \{G,P,S,I,R\}} \text{AVGA}_{\mathcal{U}'}}$$

CLAWS extracts only the attention layer in the single response generation process and just performs sum and average operations, enabling effective detection without additional calls or operations. This

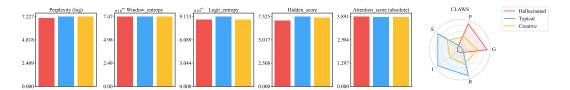


Figure 4: Visualization of class-wise average scores for each method, computed on the reference set generated using Qwen2.5-math-7B-inst. To enhance visual clarity, the normalization range is clipped between 0.1 and 0.9 for CLAWS. Visualizations for all models are presented in Figure 9.

is an efficient method with a similar level of computational overhead to methods that only use existing hidden state or attention layers.

4 Evaluation

4.1 Baseline

In previous research, both black-box, including SelfCheckGPT [12], and white-box approaches that use uncertainty-based methods [28] have been extensively studied to detect hallucinations in LLM generations. In addition, there are methods to mitigate hallucinated in LLMs through majority voting by generating multiple generations, such as Self-Consistency [29] or INSIDE [30]. However, these methods have limitations, as they depend on external models and require multiple responses per input, resulting in substantial computational cost. Therefore, these methods are not suitable as baselines for this study. In light of these limitations, we employ five white-box hallucination detection methods as baselines in this study, without relying on external models or using majority voting, to distinguish between Hallucinated, Creative, and Typical solutions. The five methods can be broadly categorized into output token uncertainty quantification and eigenvalue analysis of internal LLM representations. These approaches have been widely used in prior research, and more recently, LLM-Check [31] has further consolidated these methods.

Perplexity Perplexity is a measure of the confidence in the model's generation of the the response $\mathbf{x} = (x_{n+1} \cdots x_m)$, which is generated by the model f given an input prompt \mathbf{x}_p . It is calculated based on the log-likelihood of each output token x_i , where m denotes the length of the generated response and n denotes the start index of the response being evaluated and is defined as follows:

Perplexity(
$$\mathbf{x}$$
) = exp $\left(-\frac{1}{m-n+1}\sum_{i=n}^{m}\log p_f(x_i\mid \mathbf{x}_p \oplus \mathbf{x}_{< i})\right)$ (1)

Logit Entropy Logit Entropy represents the uncertainty in the generation by measuring the entropy of the probability distribution over the top-k tokens at each token position, based on the logits:

$$\text{LogitEntropy}(\mathbf{x}, k) = -\frac{1}{m - n + 1} \sum_{i=n}^{m} \sum_{j=1}^{k} p_f(x_i^j \mid \mathbf{x}_p \oplus \mathbf{x}_{< i}) \log p_f(x_i^j \mid \mathbf{x}_p \oplus \mathbf{x}_{< i}).$$
 (2)

Window Logit Entropy Since Logit Entropy calculates over the entire response, there is a problem that the entropy value is diluted and hallucinations cannot be detected when hallucinations is short. In order to address the problem, Window Logit Entropy is defined as the calculation of the logit entropy over sliding windows of size k and selecting the maximum value among them, as follows:

WindowLogitEntropy(
$$\mathbf{x}, k, w$$
) = $\max_{s \in \{1, \dots, m-w+1\}} \left\{ \frac{1}{w} \sum_{i=s}^{s+w-1} \text{LogitEnt}(x_i, k) \right\}$. (3)

Hidden Score Hidden Score is a measure of the variance in representation diversity, computed by performing an eigen-decomposition on the hidden state matrix $\mathbf{H} \in \mathbb{R}^{d \times m}$, which consists of m

tokens represented embedding in d dimensional space, and then calculating the mean of the logarithm of eigenvalues. So, Hidden Score is defined as the mean log-determinant of Σ^2 where σ_i represent the singular values of \mathbf{H} :

HiddenScore =
$$\frac{1}{m} \log \det(\Sigma^2) = \frac{1}{m} \sum_{i=1}^{m} \log \sigma_i$$
, where $\Sigma^2 = \mathbf{H}^\top \mathbf{H}$. (4)

Attention Score Attention Score quantifies self-attention by analyzing the diagonal entries of the self-attention kernel matrix:

AttentionScore =
$$\frac{1}{m} \sum_{j=1}^{m} \log((\text{Ker}_i)^{jj}).$$
 (5)

 Ker_i^{jj} denotes the j-th diagonal entry of the self-attention kernel matrix from i-th attention head.

4.2 Evaluation Strategy

The standard evaluation strategy for the five baselines is to determine a threshold that yields the optimal detection performance. However, the limitations of threshold-based approaches have been consistently noted, and several studies have explored how to better leverage internal model features for detection. In this study, we evaluate the performance of CLAWS and the five baselines using five distinct evaluation strategies. Detailed hyperparameters and experimental settings are provided in Appendix B.3.

Threshold A threshold that yields the best performance among the values computed by each detection method is determined. This strategy applies only to the five baselines that use a single scalar value as a feature.

Prototypes The reference set is used as the Prototype sample [32]. The Euclidean distance between each class's center embedding and a given sample is computed to predict the nearest class. This strategy applies only to CLAWS, which outputs multi-dimensional feature vectors.

XGBOOST XGBoost [33] is a classification algorithm based on decision trees, serving as an advanced implementation of the Gradient Boosting Decision Tree (GBDT).

MLP A conventional trainable classifier (MLP) is employed to train a layer that classifies the features extracted by each method.

TabM TabM [34] is a recent method designed to mitigate the large variance of MLPs. It trains multiple MLPs and employs an ensemble approach to produce the final prediction.

4.3 Evaluation Metrics

For a fair comparison, we employ four evaluation metrics: weighted F1 score $(F1_w)$, macro F1 score $(F1_m)$, Area Under the ROC Curve (AUROC), and macro Average Precision (AP_m) . Given the limited number of samples and the intrinsic difficulty of classifying the Creative class—which lies between the Typical and Hallucinated classes—it is essential to adopt metrics that capture the model's ability to recognize rare and challenging categories. Furthermore, in cases where not all three classes were predicted, we separately marked instances where a model achieved an artificially high score by predicting only the majority class, indicated by gray highlighting in the tables.

5 Result

In Table 2, five baselines were evaluated using thresholds, while CLAWS was assessed with a prototype strategy; CLAWS outperformed all models on the test set across all four metrics. The full result table is presented in the Appendix C, using all strategies and metrics. In particular, CLAWS achieved superior performance in $F1_m$ and AP_m , metrics that measure the macro-average by giving equal weight to all classes. In contrast, none of the five baselines performed well on all models.

Table 2: Results for creativity detection. The evaluation strategies are Threshold (for PPL: Perplexity, WE: Window Entropy, LE: Logit Entropy, HS: Hidden Score, AS: Attention Score) and Prototype (for CLAWS). Bold values indicate the best performance, underlined values denote the second best, and gray-shaded cells correspond to cases where the model detected only two out of the three classes.

Data	set		Т	EST			A	MC			A	IME			A(J)	HSME	}
Model	Method	F1 _w	F1 _m	AP_{m}	AUROC	F1 _w	F1 _m	AP_{m}	AUROC	F1 _w	F1 _m	AP_{m}	AUROC	F1 _w	F1 _m	AP_{m}	AUROC
	PPL	48.09	35.77	37.07	56.49	44.56	35.63	36.28	55.12	55.93	36.70	36.59	56.63	42.34	36.52	37.49	56.82
	WE	18.59	23.20	35.89	53.89	27.52	26.03	34.67	52.26	9.07	16.36	33.67	50.31	28.72	27.70	34.44	51.92
D 1	LE	40.56	33.21	34.00	50.90	35.69	32.96	33.42	50.31	28.99	25.28	33.27	48.89	34.89	33.46	33.45	50.18
Deepseek	HS	29.56	25.18	32.40	45.03	38.44	32.96	33.60	50.22	38.30	29.65	33.71	50.67	38.61	35.80	34.54	52.40
	AS	33.95	24.99	30.98	42.80	33.51	29.18	33.43	50.19	43.92	32.89	33.58	50.97	28.63	26.83	33.19	49.70
	CLAWS	58.66	46.01	41.17	62.09	46.71	40.99	37.16	56.40	56.90	38.12	35.38	54.47	38.82	37.64	36.25	54.40
	PPL	42.45	25.94	31.37	43.26	36.50	25.21	31.81	45.89	56.90	29.97	32.76	47.49	34.79	25.58	32.58	48.15
	WE	46.19	28.89	32.58	46.68	40.71	30.02	32.73	48.44	52.20	30.20	32.91	48.33	40.34	31.79	33.86	51.05
Mathstral	LE	41.62	28.17	32.11	45.66	35.20	29.55	32.05	46.93	44.77	28.56	33.47	50.50	35.46	30.56	32.40	47.77
Manistrai	HS	<u>49.86</u>	26.53	32.49	47.07	37.37	23.46	33.33	49.97	65.96	31.13	33.46	50.23	33.42	22.65	33.42	50.14
	AS	38.41	24.50	31.23	42.22	36.92	27.53	32.02	46.69	57.35	31.95	33.51	49.82	35.26	27.57	32.41	47.60
	CLAWS	63.20	46.05	41.75	63.70	51.47	41.45	37.89	57.69	65.25	36.05	34.43	52.73	49.13	42.29	38.20	58.18
	PPL	36.47	27.52	32.72	47.30	41.10	31.45	33.12	49.24	40.44	30.49	32.18	47.57	39.22	30.05	33.13	48.56
	WE	40.89	32.14	33.84	50.50	43.44	34.48	33.93	51.19	40.55	31.17	33.37	50.00	42.45	34.16	33.99	51.08
OM-4h2	LE	<u>47.48</u>	35.96	<u>35.15</u>	53.15	43.17	36.18	34.28	52.62	41.82	33.10	34.32	52.92	42.38	37.55	34.70	53.28
OpenMath2	HS	30.48	23.20	30.77	41.57	33.02	26.78	31.17	44.52	40.45	32.09	32.63	49.34	31.62	26.55	31.37	44.93
	AS	33.20	24.48	30.65	42.17	32.84	27.77	31.89	46.75	40.42	30.96	48.59	32.59	31.03	27.53	32.09	47.04
	CLAWS	60.86	44.27	40.77	60.66	54.32	42.12	38.53	58.06	49.35	34.41	<u>35.35</u>	52.00	50.88	41.36	37.73	57.22
	PPL	46.52	27.81	31.78	45.60	41.68	26.38	31.25	44.27	55.96	28.11	32.64	47.36	36.90	24.83	31.03	43.62
	WE	49.57	27.39	32.80	48.26	44.87	27.32	32.87	48.82	66.65	32.63	33.48	51.28	36.37	24.79	32.79	48.44
OREAL	LE	55.39	<u>36.15</u>	34.46	53.11	49.80	35.95	34.43	53.30	63.53	33.86	34.02	53.06	41.06	31.86	33.29	50.47
OKEAL	HS	51.95	29.46	32.60	47.90	48.58	28.28	33.20	49.60	68.10	31.63	33.30	49.22	41.65	28.36	33.12	49.62
	AS	45.56	28.24	31.83	45.56	47.92	29.11	32.70	48.25	65.19	<u>32.74</u>	33.20	49.56	40.18	26.41	32.74	48.48
	CLAWS	<u>54.19</u>	40.18	38.15	59.46	43.83	34.77	35.57	54.78	59.95	32.74	33.81	51.55	35.70	31.93	35.51	54.41
	PPL	25.66	23.30	31.76	42.62	26.40	21.39	31.71	43.31	28.29	25.29	32.00	44.52	24.88	20.34	32.09	44.79
	WE	30.79	29.40	34.71	52.50	22.04	26.04	33.80	51.15	33.23	29.08	33.12	49.24	20.50	23.61	33.12	49.51
0 2.5	LE	50.81	45.29	39.50	59.80	45.86	40.18	36.15	55.81	43.20	39.01	36.40	55.83	45.70	38.64	35.23	54.09
Qwen-2.5	HS	30.67	28.31	36.25	54.53	47.57	31.98	34.81	52.98	20.37	24.17	34.57	52.83	48.52	32.54	34.78	52.77
	AS	30.75	26.96	32.05	45.53	38.61	31.55	32.93	48.78	37.32	33.71	33.92	51.42	33.72	28.55	32.86	48.35
	CLAWS	50.35	43.37	39.88	<u>59.32</u>	52.77	41.39	37.45	57.59	39.05	32.31	33.08	49.31	47.90	36.04	35.86	54.94

However, CLAWS demonstrated superiority in $F1_m$ and AP_m , which reflect the macro-average, and showed even more pronounced performance in $F1_w$, which assigns more weight to larger sample classes. This finding suggests that CLAWS not only effectively detects Creative solutions but also maintains robust performance in classifying Typical and Hallucinated solutions.

As shown in Figure 4 and Figure 9, the reason for CLAWS superior performance is clearly presented. The visualization illustrates the mean per method for each class based on 20 generations for the same prompt in the reference set. In the reference set, which is the basis for detection, the five baselines record averages that do not differ significantly by class. In contrast, CLAWS effectively distinguishes Creative solutions as distributed between Hallucinated and Typical solutions.

In Figure 4, the Hallucinated solutions are relatively attention in the Guideline and Problem sections, while the Typical solutions are attention in the reference Solution, Instruction, and Response sections. Figure 4 and 9 show that hallucination focus on the Guideline section in all models. This suggests that hallucinations may be caused by over-focusing on a part of the input prompt.

A similar result is observed in extended test set. CLAWS performed well in most models, except for the OREAL. This is because the OREAL has a much higher rate of generating Hallucinated solutions than others, as shown in Table 1. Therefore, it was challenging to produce a prototype well, which consequently made the classification difficult. As shown in Table 20, however, it achieves significantly higher performance with evaluation strategies as MLP, XGBoost, and TabM.

Table 3: Results for hallucination detection. Threshold (PPL, WE, LE, HS, AS) and Prototype (CLAWS) are used as evaluation strategies. Bold and underlined values indicate the best and second-best performance. Gray-shaded cells indicate cases where the model predicted only a single class.

			Т	EST			A	мс			A	IME			A(J)	HSME	2
Model	Method	F1 _w	F1 _m	AP_{m}	AUROC	$F1_{\rm w}$	F1 _m	AP_{m}	AUROC	F1 _w	F1 _m	AP_{m}	AUROC	F1 _w	F1 _m	AP_{m}	AUROC
	PPL	37.63	40.32	45.13	53.06	<u>52.18</u>	45.38	62.33	51.95	39.75	42.77	36.16	55.60	55.31	46.20	65.42	52.25
	WE	26.44	30.34	43.56	50.00	46.70	38.04	61.39	50.00	16.77	25.06	33.45	50.00	50.42	39.16	64.37	50.00
D 1	LE	27.66	31.46	43.81	50.50	46.82	38.19	61.40	50.03	17.22	25.35	33.36	49.81	50.37	39.12	64.33	49.92
Deepseek	HS	26.41	30.31	43.52	49.92	47.11	38.56	61.48	50.20	17.64	25.74	33.54	50.19	50.61	39.51	64.34	49.93
	AS	26.60	30.45	43.43	49.72	46.68	38.02	61.37	49.97	16.77	25.06	33.45	50.00	50.59	39.43	64.38	50.03
	CLAWS	67.46	67.24	55.73	67.78	61.77	59.79	66.64	59.84	61.95	58.17	38.45	58.68	64.93	61.67	70.38	61.62
	PPL	17.09	25.27	33.82	50.00	29.62	31.76	46.58	49.90	9.44	19.45	23.98	50.05	33.84	33.58	50.37	49.95
	WE	17.09	25.27	33.82	50.00	29.71	31.84	46.62	49.96	9.61	19.57	24.00	50.11	33.89	33.63	50.42	50.05
Mathstral	LE	<u>17.36</u>	25.47	33.82	50.00	29.65	31.79	46.62	49.97	10.12	19.94	<u>24.06</u>	50.27	34.24	33.98	<u>50.50</u>	50.21
Mamstrai	HS	17.03	25.08	33.48	49.24	30.11	32.18	46.36	49.44	9.26	19.33	23.96	50.00	33.96	33.70	50.39	50.00
	AS	17.09	25.27	33.82	50.00	29.66	31.80	46.64	50.00	9.26	19.33	23.96	50.00	33.77	33.51	50.39	50.00
	CLAWS	72.99	69.59	49.42	69.30	63.97	63.90	55.69	64.04	65.62	50.26	24.19	50.59	61.05	61.04	57.10	61.04
	PPL	31.78	34.68	44.16	49.74	<u>45.53</u>	40.17	58.19	49.51	34.68	36.15	45.52	47.20	<u>49.49</u>	41.63	61.65	48.76
	WE	27.19	30.70	44.29	50.00	43.09	36.88	58.42	50.00	29.91	31.91	46.86	50.00	47.74	38.36	62.23	50.00
OnanMath2	LE	28.14	31.55	44.39	50.20	43.18	36.99	58.41	49.97	30.38	32.35	46.89	50.06	48.09	38.81	62.32	50.21
OpenMath2	HS	27.55	31.01	44.27	49.95	43.40	37.27	<u>58.43</u>	50.01	31.30	33.21	<u>46.95</u>	50.17	47.68	38.37	62.12	49.78
	AS	27.46	30.94	44.32	50.05	43.30	37.16	58.39	49.92	30.09	32.08	46.90	50.08	48.14	38.90	62.30	50.15
	CLAWS	64.91	64.70	54.19	65.05	62.53	61.65	65.19	61.82	58.10	57.50	52.32	58.47	63.88	61.81	68.70	61.96
	PPL	16.96	25.09	32.61	49.23	21.37	27.87	37.65	49.67	6.79	16.08	18.33	49.13	28.09	31.19	44.51	49.32
	WE	23.20	29.92	33.39	50.99	22.04	28.48	37.93	50.26	10.95	18.75	18.58	49.96	28.10	31.27	44.88	50.09
OREAL	LE	20.75	27.91	32.84	49.75	23.17	<u>29.34</u>	37.87	50.14	10.03	18.33	18.77	50.60	30.50	33.45	<u>45.22</u>	<u>50.75</u>
UKEAL	HS	16.33	24.78	32.95	50.00	20.69	27.37	37.73	49.83	6.01	15.80	18.60	50.05	27.74	30.93	44.81	49.94
	AS	16.47	24.78	32.71	49.45	20.99	27.59	37.71	49.79	6.17	15.85	18.55	49.87	28.04	31.11	44.32	48.94
	CLAWS	58.13	56.36	38.36	59.87	53.10	53.06	41.17	56.34	64.02	49.22	18.98	51.22	53.96	54.41	48.36	56.42
	PPL	41.30	35.91	56.88	48.72	41.30	35.91	56.88	48.72	33.74	33.64	50.05	49.81	76.90	46.45	84.45	49.38
	WE	41.98	36.51	57.50	50.00	41.98	36.51	57.50	50.00	33.70	33.61	<u>50.19</u>	50.09	77.69	46.20	84.66	50.18
Owen-2.5	LE	<u>47.87</u>	43.32	<u>58.86</u>	52.72	<u>47.87</u>	43.32	<u>58.86</u>	52.72	38.32	38.24	51.16	51.99	77.58	46.13	84.62	50.05
Qweii-2.3	HS	42.12	36.67	57.51	50.02	42.12	36.67	57.51	50.02	33.49	33.40	50.14	50.00	77.53	45.82	84.60	49.97
	AS	41.92	36.45	57.44	49.87	41.92	36.45	57.44	49.87	33.49	33.40	50.14	50.00	77.44	46.04	84.58	49.89
	CLAWS	54.67	53.30	59.21	53.35	72.13	55.12	80.75	54.82	47.08	47.10	49.11	47.82	74.68	52.33	85.25	52.44

6 Analysis

For the Hallucination Detection, we used Typical and Creative classes as Non-hallucinated classes in the dataset presented in Table 1. As shown in Table 3, even though the five baselines are designed to detect hallucinations, CLAWS shows overwhelmingly superior performance. CLAWS showed overwhelming performance not only on the test set but also on three extended test sets, and in particular, on AIME, which contains many difficult math problems, it showed clear discrimination.

When comparing the models, Qwen, which exhibited the most balanced distribution between hallucinated and non-hallucinated samples, consistently achieved high detection performance across all methods. In contrast, all five baselines performed poorly on Mathstral and Oreal, both of which produced approximately 1,200 Hallucinated solutions in the reference set, corresponding to a hallucination rate of nearly 70%. DeepSeek and OpenMath2 displayed distinct patterns depending on the dataset difficulty: in AMC and A(J)HSME, which are relatively easy datasets, the baselines achieved moderate performance, whereas in AIME, their performance dropped substantially.

To overcome these problems, We construct a balanced dataset for creativity detection. For each reference set, a balanced dataset is constructed by including all samples from the minority class (Creative) and randomly sampling an equal number of instances from each of the two majority classes. For example, in the reference set of DeepSeek, there are 206 samples in the Creative class; accordingly, 206 samples are randomly selected from each of the Hallucinated and Typical classes to ensure balance. As shown in Table 16, CLAWS also achieved the best overall performance. In

Table 4: Impact of each prompt section. Performance comparison of the DeepSeek-Math-7B-RL using the Prototype strategy through an ablation study, where each section is selectively removed.

I	Dataset	Metric	w/o G	w/o P	w/o ${\cal S}$	w/o I	w/o ${\cal R}$	Full
		$F1_w$	58.59	58.81	50.01	54.68	58.39	58.66
	TEST	$F1_m$	46.01	46.35	39.45	43.87	45.97	46.01
	IESI	AP_m	41.13	41.04	38.46	40.29	40.60	41.17
		AUROC	62.12	62.21	59.15	61.64	61.58	62.09
		$F1_w$	46.66	46.68	46.48	45.52	46.49	46.71
	AMC	$F1_m$	39.59	39.33	39.59	38.16	40.20	40.99
	AMC	AP_m	37.15	37.08	36.91	36.70	37.14	37.16
		AUROC	56.11	56.23	56.00	55.80	56.52	56.40
		$F1_w$	55.88	53.33	54.92	51.37	54.01	56.90
	AIME	$F1_m$	37.35	35.52	36.82	34.80	34.84	38.12
,	ALIVIE	AP_m	35.25	35.20	34.98	35.03	35.15	35.38
		AUROC	54.08	53.38	53.51	52.47	52.67	54.47
		$F1_w$	37.85	39.92	40.49	40.10	34.25	38.82
A (DHCME	$F1_m$	37.46	35.76	37.65	36.02	34.11	37.64
Α(.	J)HSME	AP_m	36.16	35.51	35.78	35.69	35.42	36.25
		AUROC	55.05	53.88	54.33	54.18	53.08	54.40

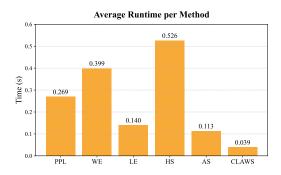


Figure 5: Average runtime for computing input features of each method — PPL, WE, LE, HS, AS, and CLAWS. The Response (*R*) generation time, identical across methods, is excluded.

particular, it performed best under the MLP strategy and exhibited the least performance degradation compared to other methods when trained on a small amount of data.

Furthermore, we analyzed the effect of each prompt section in CLAWS. As shown in Table 4, CLAWS achieved the best overall performance across most datasets and metrics when all five sections were utilized. Moreover, as illustrated in Figures 4 and 9, the degree to which each section influenced generation varied depending on the model. This observation suggests that leveraging all five sections provides the most stable and robust performance regardless of the dataset or model.

Lastly, We compare the runtime efficiency of our proposed method, CLAWS, with five baseline methods. Unlike other approaches, CLAWS does not require any additional mechanisms after the generation phase. Moreover, during generation, it performs only simple operations such as taking the mean or sum of attention weights, without relying on complex computations. As shown in Figure 5, CLAWS demonstrates the highest efficiency among all baselines. Specifically, among entropy-based methods (PPL, WE, and LE), WE, which computes entropy separately for each window, shows the poorest efficiency, whereas LE, which calculates a simple logit entropy, achieves the best efficiency in this group. Among layer-level methods, HS, which involves computing a transposed matrix and singular values, exhibits the lowest efficiency. In contrast, AS, which utilizes only the diagonal components of the self-attention kernel matrix, shows the best efficiency except for CLAWS. In conclusion, CLAWS not only achieves the highest creativity and hallucination detection performance but also exhibits the greatest computational efficiency, demonstrating superiority in all respects.

7 Conclusion

In this work, we presented a challenging study on creativity detection. To address this problem, we systematically investigated multiple key components, including the definition of creativity, the design of an experimental framework, the proposal of a novel detection method, and the analysis of evaluation strategies for extracted features. These efforts provide a solid foundation for future research in this emerging area. Moreover, extending hallucination detection toward creativity detection broadens the scope of LLM research beyond reasoning improvement, introducing a new perspective on model evaluation and generation analysis. We anticipate that the proposed experimental framework and our method, CLAWS, will serve as a foundation for future research on reliable creativity detection and the improvement of LLM generation quality and diversity.

Acknowledgments and Disclosure of Funding

This work was supported by the Institute of Information and communications Technology Planning and evaluation (IITP) grant (No.RS-2025-25422680, No. RS-2020-II201373), and the National Research Foundation of Korea (NRF) grant (No. RS-2025-00520618) funded by the Korean Government (MSIT).

References

- [1] Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.
- [2] Anthropic. claude-3-7-sonnet, 2025.
- [3] Google DeepMind. Gemini 2.5, 2025.
- [4] Tuhin Chakrabarty, Philippe Laban, Divyansh Agarwal, Smaranda Muresan, and Chien-Sheng Wu. Art or artifice? large language models and the false promise of creativity, 2024.
- [5] Murray Shanahan and Catherine Clarke. Evaluating large language model creativity from a literary perspective, 2023.
- [6] E Paul Torrance. Torrance tests of creative thinking. *Educational and psychological measurement*, 1966.
- [7] Roger E Beaty, Paul J Silvia, Emily C Nusbaum, Emanuel Jauk, and Mathias Benedek. The roles of associative and executive processes in creative cognition. *Memory & cognition*, 42:1186– 1197, 2014.
- [8] Philippe Laban, Wojciech Kryściński, Divyansh Agarwal, Alexander R. Fabbri, Caiming Xiong, Shafiq Joty, and Chien-Sheng Wu. Llms as factual reasoners: Insights from existing benchmarks and beyond, 2023.
- [9] Mingqi Gao, Jie Ruan, Renliang Sun, Xunjian Yin, Shiping Yang, and Xiaojun Wan. Human-like summarization evaluation with chatgpt, 2023.
- [10] Robert Kirk, Ishita Mediratta, Christoforos Nalmpantis, Jelena Luketina, Eric Hambro, Edward Grefenstette, and Roberta Raileanu. Understanding the effects of rlhf on llm generalisation and diversity. *arXiv preprint arXiv:2310.06452*, 2023.
- [11] Junyi Ye, Jingyi Gu, Xinyun Zhao, Wenpeng Yin, and Guiling Wang. Assessing the creativity of llms in proposing novel solutions to mathematical problems. *arXiv preprint arXiv:2410.18336*, 2024.
- [12] Potsawee Manakul, Adian Liusie, and Mark Gales. SelfCheckGPT: Zero-resource black-box hallucination detection for generative large language models. In Houda Bouamor, Juan Pino, and Kalika Bali, editors, *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 9004–9017, Singapore, December 2023. Association for Computational Linguistics.
- [13] Sebastian Farquhar, Jannik Kossen, Lorenz Kuhn, and Yarin Gal. Detecting hallucinations in large language models using semantic entropy. *Nature*, 630(8017):625–630, 2024.
- [14] John Joon Young Chung, Ece Kamar, and Saleema Amershi. Increasing diversity while maintaining accuracy: Text data generation with large language models and human interventions. arXiv preprint arXiv:2306.04140, 2023.
- [15] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed Chi, Quoc Le, and Denny Zhou. Chain-of-thought prompting elicits reasoning in large language models, 2023.

- [16] Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik Narasimhan, and Yuan Cao. React: Synergizing reasoning and acting in language models, 2023.
- [17] Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang, Mingchuan Zhang, Y. K. Li, Y. Wu, and Daya Guo. Deepseekmath: Pushing the limits of mathematical reasoning in open language models, 2024.
- [18] An Yang, Beichen Zhang, Binyuan Hui, Bofei Gao, Bowen Yu, Chengpeng Li, Dayiheng Liu, Jianhong Tu, Jingren Zhou, Junyang Lin, et al. Qwen2. 5-math technical report: Toward mathematical expert model via self-improvement. *arXiv preprint arXiv:2409.12122*, 2024.
- [19] Mistral AI. Mathstral 7b, 2024.
- [20] Shubham Toshniwal, Wei Du, Ivan Moshkov, Branislav Kisacanin, Alexan Ayrapetyan, and Igor Gitman. Openmathinstruct-2: Accelerating ai for math with massive open-source instruction data, 2024.
- [21] Chengqi Lyu, Songyang Gao, Yuzhe Gu, Wenwei Zhang, Jianfei Gao, Kuikun Liu, Ziyi Wang, Shuaibin Li, Qian Zhao, Haian Huang, et al. Exploring the limit of outcome reward for learning mathematical reasoning. *arXiv preprint arXiv:2502.06781*, 2025.
- [22] Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, et al. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*, 2024.
- [23] Qwen, :, An Yang, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chengyuan Li, Dayiheng Liu, Fei Huang, Haoran Wei, Huan Lin, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Yang, Jiaxi Yang, Jingren Zhou, Junyang Lin, Kai Dang, Keming Lu, Keqin Bao, Kexin Yang, Le Yu, Mei Li, Mingfeng Xue, Pei Zhang, Qin Zhu, Rui Men, Runji Lin, Tianhao Li, Tianyi Tang, Tingyu Xia, Xingzhang Ren, Xuancheng Ren, Yang Fan, Yang Su, Yichang Zhang, Yu Wan, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, and Zihan Qiu. Qwen2.5 technical report, 2025.
- [24] Aixin Liu, Bei Feng, Bin Wang, Bingxuan Wang, Bo Liu, Chenggang Zhao, Chengqi Dengr, Chong Ruan, Damai Dai, Daya Guo, et al. Deepseek-v2: A strong, economical, and efficient mixture-of-experts language model. *arXiv preprint arXiv:2405.04434*, 2024.
- [25] OpenAI. o4-mini, 2025.
- [26] Gemini Team, Petko Georgiev, Ving Ian Lei, Ryan Burnell, Libin Bai, Anmol Gulati, Garrett Tanzer, Damien Vincent, Zhufeng Pan, Shibo Wang, et al. Gemini 1.5: Unlocking multimodal understanding across millions of tokens of context. *arXiv preprint arXiv:2403.05530*, 2024.
- [27] Albert S. Yue, Lovish Madaan, Ted Moskovitz, DJ Strouse, and Aaditya K. Singh. Harp: A challenging human-annotated math reasoning benchmark, 2024.
- [28] Ziwei Ji, Nayeon Lee, Rita Frieske, Tiezheng Yu, Dan Su, Yan Xu, Etsuko Ishii, Ye Jin Bang, Andrea Madotto, and Pascale Fung. Survey of hallucination in natural language generation. *ACM computing surveys*, 55(12):1–38, 2023.
- [29] Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc Le, Ed Chi, Sharan Narang, Aakanksha Chowdhery, and Denny Zhou. Self-consistency improves chain of thought reasoning in language models, 2023.
- [30] Chao Chen, Kai Liu, Ze Chen, Yi Gu, Yue Wu, Mingyuan Tao, Zhihang Fu, and Jieping Ye. Inside: Llms' internal states retain the power of hallucination detection, 2024.
- [31] Gaurang Sriramanan, Siddhant Bharti, Vinu Sankar Sadasivan, Shoumik Saha, Priyatham Kattakinda, and Soheil Feizi. Llm-check: Investigating detection of hallucinations in large language models. In A. Globerson, L. Mackey, D. Belgrave, A. Fan, U. Paquet, J. Tomczak, and C. Zhang, editors, *Advances in Neural Information Processing Systems*, volume 37, pages 34188–34216. Curran Associates, Inc., 2024.

- [32] Jake Snell, Kevin Swersky, and Richard Zemel. Prototypical networks for few-shot learning. In I. Guyon, U. Von Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc., 2017.
- [33] 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, page 785–794. ACM, August 2016.
- [34] Yury Gorishniy, Akim Kotelnikov, and Artem Babenko. TabM: Advancing Tabular Deep Learning With Parameter-Efficient Ensembling. In *ICLR*, 2025.
- [35] Tuhin Chakrabarty, Philippe Laban, Divyansh Agarwal, Smaranda Muresan, and Chien-Sheng Wu. Art or artifice? large language models and the false promise of creativity. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*, CHI '24, New York, NY, USA, 2024. Association for Computing Machinery.

NeurIPS Paper Checklist

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

Answer: [Yes]

Justification: The abstract and introduction clearly articulate the scope and core contributions of the paper, accurately reflecting the proposed framework and findings.

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the
 contributions made in the paper and important assumptions and limitations. A No or
 NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [Yes]

Justification: The limitations are explicitly discussed in the Appendix A, along with directions for future work.

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory assumptions and proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [Yes]

Justification: All theoretical assumptions are clearly stated in Section 3, and their validity is examined in Section 5 and supported by empirical tables in Appendix C.

Guidelines

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and crossreferenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. Experimental result reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [Yes]

Justification: Detailed descriptions of the prompts, the mathematical dataset, and the experimental procedures are provided in Section 2 and 3

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
- (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
- (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
- (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: Both the dataset and source code are included in Supplementary Material.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (https://nips.cc/ public/guides/CodeSubmissionPolicy) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so "No" is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (https: //nips.cc/public/guides/CodeSubmissionPolicy) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- · At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental setting/details

Ouestion: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: Training and evaluation details including data preprocessing, hyperparameter configurations, and optimization choices are described in Section 2 and Appendix B.2

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment statistical significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [Yes]

Justification: The statistical significance of the experiment is presented in Section 4.3, where appropriate metrics are reported. Additional statistical analysis and supporting details are provided in the Appendix C.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.

- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments compute resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

Justification: Implementation details including computing infrastructure, and memory specifications are reported in the Appendix B. Furthermore, the average runtime required to compute features for each of the six methods in summarized in Table 5, offering a clear comparison of computational costs across methods.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code of ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics https://neurips.cc/public/EthicsGuidelines?

Answer: [Yes]

Justification: The research adheres to the NeurIPS Code of Ethics by employing publicly accessible, non-personal mathematical datasets, excluding human subjects or surveillance data, and ensuring transparency and reproducibility through a structured code release process.

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. Broader impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [Yes]

Justification: The paper discusses potential positive and negative societal impacts in both the section 1 (Introduction) and section 7 (Conclusion).

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [NA]

Justification: The paper does not introduce any new language models or datasets that could pose a risk of misuse. It uses only existing publicly available reasoning models and math datasets to evaluate a creativity detection method.

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do
 not require this, but we encourage authors to take this into account and make a best
 faith effort.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: The paper uses publicly available datasets (CreativeMath, HARP) and existing open-source reasoning LLMs.

Guidelines:

• The answer NA means that the paper does not use existing assets.

- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. New assets

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [NA]

Justification: The paper does not introduce any new assets such as datasets, models. It proposes a detection method evaluated using existing public datasets and pretrained models.

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. Crowdsourcing and research with human subjects

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [No]

Justification: The paper does not involve crowdsourcing or human subject research, as all evaluations are conducted using LLM-based assessments.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. Institutional review board (IRB) approvals or equivalent for research with human subjects

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [NA]

Justification: The paper does not involve any human subjects or participant-based studies, therefore IRB approval is not applicable.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. Declaration of LLM usage

Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

Answer: [Yes]

Justification: The paper makes essential and original use of LLMs both as solution generators and evaluators, and explicitly describes their usage in Section 2.2.1

Guidelines:

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (https://neurips.cc/Conferences/2025/LLM) for what should or should not be described.

Appendix

A Limitations

We have successfully experimented with many RLMs, but have not been able to experiment with general LLMs of similar size because they do not have sufficient creative solution-generating capabilities. Due to the nature of the White-Box approach, using large-sized models (over 20B) with sufficient performance requires a lot of resources. Lastly, we defined 'Creativity' based on solving mathematical problems, and expanding it to a various tasks will be our future work.

B Implementation Details

B.1 LLM Evaluator Details

We use an LLM-based evaluator E to classify each generated response R into three categories — Hallucinated Solution, Typical Solution, or Creative Solution — following the evaluation protocol introduced in [11]. As described in Section 2.2.2 and Figure 1, the evaluation process consists of two stages. First, we assess whether the generated response R is mathematically correct. For example, As shown in Figure 6, the evaluator is given two reference solutions and asked to determine whether R is a valid solution to the given problem.

If both evaluators agree that R is correct, the response proceeds to the second stage, where it is further classified as either a Typical Solution or a Creative Solution. As shown in Figure 7, this decision is made by comparing R against the reference solutions S provided in the original input prompt X, and determining whether it satisfies the criteria outlined in the guideline G.

Unlike [11], we used two LLM evaluators. In particular, instead of using GPT-40 as one of the evaluators, we adopted o4-mini, which demonstrates superior performance in mathematical evaluation. The LLM evaluators used in our study are listed below:

• Gemini-1.5-Pro: models/gemini-1.5-pro-002

• GPT-o4-mini: o4-mini-2025-04-16

B.1.1 Justification of LLM-based Labeling without Human Evaluation

In this study, we adopted LLM-based labeling instead of human evaluation for dataset construction. The justification is as follows.

Practical constraints The dataset used in our study consisted of mathematically challenging problems, where evaluating the creativity of generated solutions would require human experts with substantial mathematical expertise. However, as shown in Table 1, conducting human evaluation on all 46,528 data instances would have required excessive time and cost, making it practically infeasible.

Support from prior work Recent studies have validated the use of LLMs for creativity assessment [11, 35]. Following these works, we adopted their definitions and evaluation criteria to construct our dataset without relying on human evaluation.

Indirect reflection of human creativity As mentioned earlier, creativity evaluation required a reference solution S. Importantly, S was always taken from human-written solutions and never generated by an LLM. Thus, although no direct human evaluation was performed, the diversity and creativity embedded in human-written solutions were indirectly reflected in the evaluation.

Ensuring reliability To enhance the reliability of LLM-based evaluation, we designed the LLM Evaluator not only to output labels but also to provide explicit reasoning. Specifically, we appended the instruction "Additionally, explain the reason for your judgment." at the end of the evaluation prompts (see Figure 6 and 7). Figure 8 shows actual evaluation cases, confirming that the judgments of the LLM Evaluator were consistent and reasonable.

Given the following mathematical problem:

What is the largest power of 2 that is a divisor of (13^4-11^4) ?

Reference solutions:

Solution 1:

The factors of 36 are 1, 2, 3, 4, 6, 9, 12, 18, and 36. The multiples of 4 up to 36 are 4, 8, 12, 16, 20, 24, 28, 32, and 36. Only 4, 12, and 36 appear on both lists, so the answer is 3, which is option (B) 3.

Solution 2:

 $36 = 4^1 \cdot 3^2$. All possible factors of 36 will be here, except for ones divisible by 2 and not by 4. $(1+1) \cdot (2+1) = 6$. Subtract factors not divisible by 4, which are 1, 3^1 , and 3^2 . 6-3=3, which is $\overline{(B)}$ 3.

New solution:

To solve the problem of finding how many positive factors of 36 are also multiples of 4, we can use a more systematic approach by first determining the prime factorization of 36 and then identifying the factors that are multiples of 4.

- 1. Prime Factorization of 36: $[36 = 2^2 \times 3^2]$
- 2. Identify the General Form of Factors: Any factor of 36 can be written in the form $(2^a \times 3^b)$, where $(0 \le a \le 2)$ and $(0 \le b \le 2)$.
- 3. Determine the Conditions for Multiples of 4: For a factor to be a multiple of 4, it must contain at least (2²) in its prime factorization. Therefore, (a) must be at least 2.
- 4. Possible Values for (a) and (b):
- Since (a) must be at least 2. (a) can be either 2.
- (b) can be 0, 1, or 2.
- 5. List All Possible Factors:
- For (a = 2):
 - (b = 0): $(2^2 \times 3^0 = 4)$
 - (b = 1): $(2^2 \times 3^1 = 12)$
 - (b = 2): $(2^2 \times 3^2 = 36)$

6. Count the Factors: There are 3 factors of 36 that are also multiples of 4: (4, 12,) and (36). Therefore, the number of positive factors of 36 that are also multiples of 4 is $\overline{(B)}$.

Please output "YES" if the new solution leads to the same results as the reference solutions; otherwise, output "NO". YES or NO?

Figure 6: Example prompt used for correctness evaluation

Criteria for evaluating the difference between two mathematical solutions include:

- If the methods used to arrive at the solutions are fundamentally different, such as algebraic manipulation versus geometric reasoning, they can be considered distinct;
- ii). Even if the final results are the same, if the intermediate steps or processes involved in reaching those solutions vary significantly, the solutions can be considered different;
- iii). If two solutions rely on different assumptions or conditions, they are likely to be distinct;
- iv). A solution might generalize to a broader class of problems, while another solution might be specific to certain conditions. In such cases, they are considered distinct;
- v). If one solution is significantly simpler or more complex than the other, they can be regarded as essentially different, even if they lead to the same result.

Given the following mathematical problem:

What is the largest power of 2 that is a divisor of (13^4-11^4) ?

Reference solutions:

Solution 1:

The factors of 36 are 1, 2, 3, 4, 6, 9, 12, 18, and 36. The multiples of 4 up to 36 are 4, 8, 12, 16, 20, 24, 28, 32, and 36. Only 4, 12, and 36 appear on both lists, so the answer is 3, which is option (B) $\overline{3}$.

New solution:

To solve the problem of finding how many positive factors of 36 are also multiples of 4, we can use a more systematic approach by first determining the prime factorization of 36 and then identifying the factors that are multiples of 4.

- 1. Prime Factorization of 36: $[36 = 2^2 \times 3^2]$
- 2. Identify the General Form of Factors: Any factor of 36 can be written in the form $(2^a \times 3^b)$, where $(0 \le a \le 2)$ and $(0 \le b \le 2)$.
- 3. Determine the Conditions for Multiples of 4: For a factor to be a multiple of 4, it must contain at least (2^2) in its prime factorization. Therefore, (a) must be at least 2.
- 4. Possible Values for (a) and (b):
- Since (a) must be at least 2, (a) can be either 2.
- (b) can be 0, 1, or 2.
- 5. List All Possible Factors: - For (a = 2):
 - -(b=0): $(2^2 \times 3^0 = 4)$
 - (b = 1): $(2^2 \times 3^1 = 12)$
- (b = 2): $(2^2 \times 3^2 = 36)$ 6. Count the Factors: There are 3 factors of 36 that are also multiples of 4: (4, 12,) and (36). Therefore, the number of positive factors of 36 that are also multiples of 4 is $\overline{(B)}$.

Please output "YES" if the new solution is a novel solutions; otherwise, output "NO". YES or NO?

Figure 7: Example prompt used for novelty (creativity) evaluation

Addressing potential limitations We acknowledge that LLM-based evaluation may involve intrinsic biases. However, we mitigated this concern by grounding evaluations on human-written reference solutions and by explicitly requiring reasoning for each judgment, thereby reducing the risk of arbitrary or biased labeling.

B.1.2 Criteria for Creativity Judgment

To determine creativity, we combined the results of the two LLM evaluators using a union-based criterion: if either evaluator judged a solution as creative, we labeled it as a *Creative Solution*. Since creativity inherently involves a certain degree of subjectivity, requiring agreement from both evaluators could risk overlooking genuinely creative responses. By applying the union-based criterion, we aimed to mitigate the risk of underestimating creativity.

To verify the reliability of this approach, we measured Cohen's kappa score between the two evaluators. The score was 0.741, which corresponds to substantial agreement, indicating that the two evaluators produced highly consistent judgments.

Case 1: LLM Evaluator Output — Creative

The new solution uses a completely different approach (Lifting The Exponent Lemma) compared to the reference solutions (difference of squares factorization). This satisfies criterion 1 for novelty. While the final result is the same, the intermediate steps and the mathematical tools used are entirely distinct, satisfying criterion 2. The LTE lemma also relies on different underlying principles and conditions than simple algebraic manipulation, satisfying criterion 3. Therefore, the new solution is considered novel.

Case 2: LLM Evaluator Output — Not Creative

The new solution is not novel. It uses the same logical deductions as the reference solution. Both solutions arrive at the same answer through the same constraints. The core logic—Carl not being next to Bret, and Abby not being between Bret and Carl—is identical. The new solution merely restates these conditions and elaborates on the placement possibilities without introducing any new mathematical techniques, different assumptions, or a more generalized approach. Therefore, it does not meet any of the criteria for novelty.

Figure 8: Example outputs from the LLM evaluators for determining creativity. The evaluators not only provide a binary judgment (Creative or Not Creative) but also justify their decision with a textual rationale based on the predefined criteria.

B.2 LLM Generator Details

For all LLM Generators, the maximum input token length was set to 2000, and the maximum output token length was limited to 1023. Top-p was fixed at 1.0, and Top-k was fixed at 50 across all models. Temperature values were adjusted for each model to encourage the generation of Creative Solutions, and the final settings used for dataset construction are as follows:

- DeepSeek-Math-7B (deepseek-ai/deepseek-math-7b-rl): 0.7
- Mathstral-7B (mistralai/Mathstral-7b-v0.1): 0.25
- OpenMath2-LLaMA3.1-8B (nvidia/OpenMath2-Llama3.1-8B): 1.0
- OREAL-7B (internlm/OREAL-7B): 0.7
- Owen2.5-Math-7B (Qwen/Qwen2.5-Math-7B-Instruct): 0.7

All generations were performed on NVIDIA RTX A5000 GPUs (24GB VRAM), using up to 8 GPUs in parallel.

B.3 Evaluation Strategy Details

We evaluate our methods using a variety of Evaluation strategies, including thresholding, distance-based prototype matching, and trainable models such as MLP, TabM, and Decision-tree based XGBOOST. The implementation and hyperparameter settings for each method are summarized below.

Threshold (only for Baselines) We divide the value range of each baseline measure into 200 intervals and evaluate performance at each threshold. The threshold that achieves the best macro-f1 score on the reference set is selected for final evaluation.

Prototype (only for CLAWS) We used an Encoder consisting of two Linear Layers for the prototype-based evaluation method. The input dimension is reduced to 16 dimensions through the first Linear Layer and reduced to 8 dimensions through the second Layer. After that, it is expanded to 16 dimensions again and reduced to the dimension corresponding to the final number of classes, and used as the output. The output of each data was averaged by class and used as the class center value. Afterwards, the Euclidean distance between each data sample and the class center was calculated to predict the closest class. We generated prototypes of the reference set using 20 different random seeds and presented the one that achieved the best macro-f1 score.

XGBOOST For classification, we adopt the XGBoost algorithm [33], a gradient boosting framework based on ensembles of decision trees. In the hallucination detection setting, the model optimizes

Table 5: Comparison of feature generation using attention weights from different layers. CLAWS, leverages the last-layer attention weights, and this table shows how performance changes when attention weights are taken from other layers. Results are based on applying the Prototype strategy to responses generated by Deepseek-math-rl and Qwen-2.5-math-inst on the test dataset. Metrics are weighted F1 (F1 $_w$), macro F1 (F1 $_w$), macro average precision (AP $_m$), and AUROC.

	J	Deepseel	ζ.				Qwen		
Layer	$F1_w$	$F1_m$	AP_m	AUROC	Layer	$F1_w$	$F1_m$	AP_m	AUROC
5	57.00	45.02	40.15	60.58	5	48.37	42.05	37.12	57.82
10	58.03	45.33	40.42	61.40	10	48.12	42.48	38.01	58.65
15	56.94	44.76	39.81	60.22	15	50.64	43.31	39.45	59.10
20	57.89	45.61	41.08	61.93	20	49.85	42.71	38.74	58.98
25	57.25	44.98	40.41	61.37	25	50.01	43.25	39.21	59.26
Last(30)	58.66	46.01	41.17	62.09	Last(28)	50.35	43.37	39.88	59.32

the logistic loss function, which corresponds to the binary cross-entropy objective. For creativity detection, it minimizes the softmax cross-entropy loss, producing a discrete class label corresponding to the highest posterior probability.

MLP We use a three-layer feed-forward neural network. The model is trained for 10 epochs using cross-entropy loss with class weights to account for class imbalance. Optimization is performed using Adam with a learning rate of 0.001. Depending on the number of classes and the input feature dimension, the model contains up to 133 learnable parameters. We experimented with 20 different random seeds and presented the one that gave the best macro-f1 score.

TabM We use TabM [34], an ensemble of 32 independently parameterized MLPs. Each MLP has 512 parameters. model in the ensemble is trained for 20 epochs using cross-entropy loss. Optimization is performed using AdamW with a learning rate of 2e-3 and a weight decay of 3e-4.

C Experimental Results

C.1 Layer-Wise Analysis

We present the layer-wise performance evaluation in Table 5. The results show that there are no significant differences in performance across layers, and this trend is consistent across all models and metrics. These findings indicate that CLAWS does not rely on any specific layer and operates robustly under various configurations.

C.2 Visualizations for Reference Set.

Figure 9 presents class-wise average scores across different methods on the reference set for four models. Results for Owen-2.5-Math-7B are shown separately in Figure 4.

C.3 Full Table of Creativity Detection

The results of 3-class detection for each model using different evaluation strategies (see Section 4.2) are presented in Tables 6–10. The results for the Threshold and Prototype-based methods are shown separately in Table 2.

C.4 Full Table of Hallucination Detection

The results of 2-class detection for each model using different evaluation strategies are presented in Tables 11–15. The results for the Threshold and Prototype-based methods are shown separately in Table 3.

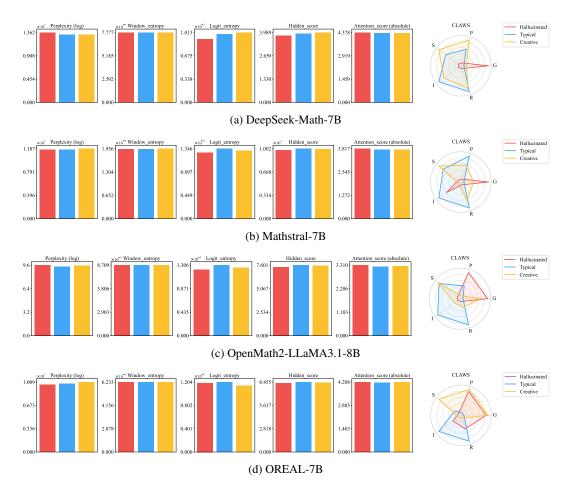


Figure 9: Visualization of class-wise average scores across all evaluation methods for four models on the reference set. For CLAWS, the scores are normalized and clipped to the range [0.1, 0.9] to enhance visual clarity.

C.5 Full Table of Creativity Detection for Balanced Reference Set

The results of 3-class balanced detection using the Threshold and Prototype-based methods are shown in Table 16, followed by model-specific results using other evaluation strategies in Tables 17–21.

Table 6: Evaluation results for creativity detection using DeepSeek-Math-7B. Bold values indicate the best performance, underlined values indicate the second-best. Light gray-shaded cells correspond to results where the model performed detection over only two out of the three target classes, while dark gray-shaded cells indicate cases where the model predicted only one out of the three target classes.

Datas	set		T	EST			A	MC			A	IME			A(J)	HSME	
Strategy	Method	$F1_{\rm w}$	$F1_m$	AP_{m}	AUROC	$F1_{\rm w}$	$F1_m$	AP_{m}	AUROC	F1 _w	$F1_m$	AP_{m}	AUROC	$F1_{\rm w}$	$F1_m$	AP_{m}	AUROC
	PPL	50.32	36.08	37.52	56.82	40.34	32.65	36.65	53.92	<u>55.57</u>	34.55	36.68	55.38	38.30	33.32	37.23	55.15
	WE	59.39	<u>42.20</u>	<u>43.01</u>	<u>63.81</u>	41.53	33.75	38.03	57.36	56.51	31.67	35.92	55.01	38.52	33.52	37.16	56.25
XGBOOST	LE	45.62	34.29	34.82	52.23	37.96	31.41	34.63	51.27	50.71	33.27	35.18	52.83	34.09	30.10	34.80	52.29
ДОВООЗТ	HS	49.14	37.55	38.40	56.61	39.37	32.70	34.52	51.19	47.59	31.38	32.97	49.50	35.47	31.85	34.74	51.74
	AS	53.58	38.76	42.19	63.53	38.09	30.36	34.31	51.09	51.56	31.66	33.97	49.75	33.85	28.86	33.85	50.40
	CLAWS	<u>57.85</u>	45.59	47.98	68.39	44.37	37.67	38.57	<u>56.99</u>	51.12	<u>34.53</u>	38.65	57.31	39.04	34.49	<u>37.23</u>	54.88
	PPL	41.04	31.64	40.85	59.94	42.58	33.79	39.38	56.92	53.72	35.93	<u>40.08</u>	<u>61.61</u>	36.36	30.81	39.57	<u>57.42</u>
	WE	<u>58.29</u>	<u>42.05</u>	42.32	62.73	44.30	35.70	37.58	56.56	<u>56.51</u>	31.67	35.90	54.68	38.62	33.61	36.95	55.99
MLP	LE	39.99	32.84	35.47	52.45	41.30	<u>35.43</u>	35.48	52.18	46.20	30.22	35.41	53.91	38.85	<u>35.80</u>	36.67	53.31
WILI	HS	48.79	41.59	42.00	62.98	35.61	27.90	34.76	52.59	35.63	28.31	32.55	48.47	34.19	32.00	34.58	50.59
	AS	51.05	37.63	43.02	<u>64.31</u>	36.61	28.87	33.88	50.68	46.90	30.25	34.07	49.98	32.78	27.70	33.63	49.79
	CLAWS	61.43	49.65	50.08	71.41	43.78	34.84	41.01	60.11	57.39	39.88	42.26	62.56	44.11	39.65	42.64	60.12
	PPL	51.79	37.78	41.03	60.03	<u>43.76</u>	35.20	39.29	56.83	<u>56.84</u>	35.80	<u>41.01</u>	61.73	40.89	35.30	39.67	<u>57.42</u>
	WE	<u>59.39</u>	42.20	42.93	63.27	41.53	33.75	38.00	<u>57.13</u>	56.51	31.67	36.16	54.97	38.62	33.61	37.17	56.13
TabM	LE	42.80	31.66	35.39	53.49	40.44	32.32	35.45	51.89	48.06	30.82	36.39	54.66	37.27	32.04	36.73	53.64
1 auivi	HS	51.25	36.33	42.64	63.04	38.75	31.17	34.86	52.60	48.77	29.56	32.40	48.14	34.58	29.99	35.34	51.85
	AS	51.05	37.63	42.83	<u>64.13</u>	36.61	28.87	33.97	50.77	46.90	30.25	33.76	49.82	32.78	27.70	33.68	49.85
	CLAWS	60.78	45.03	51.37	72.82	46.46	37.56	41.06	59.26	57.05	37.77	41.44	60.73	40.81	35.10	41.25	59.12

Table 7: Evaluation results for creativity detection using Mathstral-7B

Datas	set		Tl	EST			A	MC			Al	ME			A(J)	HSME	
Strategy	Method	$F1_{\rm w}$	F1 _m	AP_m	AUROC	$F1_w$	F1 _m	AP_{m}	AUROC	$F1_w$	F1 _m	AP_{m}	AUROC	F1 _w	F1 _m	AP_{m}	AUROC
	PPL	55.02	31.81	36.77	56.43	41.89	29.03	34.58	51.87	64.84	31.95	34.91	<u>54.42</u>	38.87	28.83	35.90	53.20
	WE	58.25	34.05	44.34	67.71	<u>45.13</u>	31.05	41.15	61.71	65.90	29.74	35.19	54.33	41.84	31.38	39.03	<u>58.88</u>
XGBOOST	LE	52.67	29.93	33.46	49.70	43.28	30.38	36.59	54.33	63.76	31.62	32.94	49.05	37.13	27.49	34.06	51.18
ловоозт	HS	59.40	38.04	41.71	62.34	45.00	34.05	37.12	54.68	64.85	30.67	32.82	49.71	38.97	29.97	35.07	52.29
	AS	57.64	34.26	41.54	60.55	41.61	28.15	39.25	<u>57.78</u>	65.34	28.87	33.94	49.11	38.13	28.34	36.23	53.93
	CLAWS	62.05	42.09	<u>44.25</u>	<u>64.43</u>	50.92	38.85	<u>40.31</u>	57.69	69.30	40.42	41.21	59.53	47.04	38.75	40.66	59.06
	PPL	53.42	32.71	39.61	59.24	36.93	28.62	36.25	52.83	54.76	33.05	34.34	52.57	34.71	26.01	35.11	51.70
	WE	49.45	28.16	37.02	55.53	37.14	23.20	35.41	52.17	<u>65.47</u>	28.70	34.48	<u>52.90</u>	33.06	22.45	33.79	49.80
MLP	LE	49.54	32.89	37.04	56.02	46.20	34.91	36.55	54.41	57.77	31.25	32.55	48.89	38.70	31.36	34.14	51.37
WILI	HS	60.32	40.84	<u>45.48</u>	<u>68.58</u>	38.35	30.42	<u>39.90</u>	<u>58.59</u>	63.39	32.59	33.02	50.08	38.05	30.74	35.76	53.95
	AS	<u>62.82</u>	<u>42.48</u>	44.00	63.55	<u>49.70</u>	<u>37.03</u>	38.63	58.10	61.26	33.63	33.59	50.32	41.86	33.38	<u>37.48</u>	<u>55.85</u>
	CLAWS	64.65	45.34	47.74	70.25	52.01	41.33	41.89	61.03	69.54	39.70	41.51	61.86	45.81	40.58	42.67	60.58
	PPL	52.72	26.55	38.26	59.43	37.14	23.20	38.09	56.46	65.69	28.80	35.89	<u>54.48</u>	39.68	28.93	32.67	48.80
	WE	52.72	26.55	37.06	55.54	37.72	23.78	35.59	52.25	66.14	29.66	34.96	53.40	45.45	34.94	35.90	53.75
TabM	LE	52.39	26.74	35.96	54.93	37.81	23.92	36.26	53.96	65.45	29.51	32.01	47.47	41.61	31.58	34.33	50.45
Taulvi	HS	64.38	<u>42.69</u>	<u>45.11</u>	68.38	<u>48.44</u>	<u>35.81</u>	39.97	<u>58.39</u>	65.09	29.99	32.99	50.08	<u>48.20</u>	<u>36.14</u>	<u>39.90</u>	<u>57.52</u>
	AS	58.04	33.81	43.98	66.28	42.35	28.54	39.84	58.55	66.10	30.22	34.19	51.11	45.81	34.68	36.07	52.79
	CLAWS	62.96	43.67	45.16	65.28	50.44	38.13	40.67	58.14	68.05	37.58	40.03	58.42	54.29	41.03	46.14	65.47

Table 8: Evaluation results for creativity detection using OpenMath2-LLaMA3.1-8B

Datas	set		T	EST			A	MC			A	ME			A(J)	HSME	
Strategy	Method	$F1_{\rm w}$	$F1_{m}$	$AP_{m} \\$	AUROC	F1 _w	$F1_{m}$	$AP_{m} \\$	AUROC	F1 _w	$F1_{m}$	$AP_{m} \\$	AUROC	$F1_{\rm w}$	$F1_{m}$	$AP_{m} \\$	AUROC
	PPL	47.78	33.14	34.54	52.60	42.29	31.00	33.16	49.65	46.38	32.22	32.55	50.81	40.45	31.02	34.02	51.25
	WE	<u>58.84</u>	40.14	43.09	63.58	49.28	36.50	40.17	58.33	43.16	28.33	35.66	52.80	47.00	36.16	38.35	<u>57.20</u>
XGBOOST	LE	47.12	33.47	34.59	50.79	44.35	33.34	34.88	52.15	44.58	30.92	33.01	48.48	39.81	30.93	33.49	49.91
AGBOOST	HS	54.90	38.46	41.22	60.99	48.40	35.39	37.51	54.81	48.65	34.10	34.91	51.78	45.77	35.26	37.85	55.67
	AS	57.43	40.10	42.07	61.57	49.95	36.40	37.26	54.48	48.73	33.54	35.32	50.98	44.56	33.59	35.40	52.01
	CLAWS	63.20	46.23	48.16	67.22	54.56	40.24	42.68	61.61	56.87	40.82	42.51	59.67	50.40	38.13	42.63	61.47
	PPL	32.70	24.95	31.40	47.66	40.22	28.52	32.40	50.26	37.94	27.23	30.08	44.11	39.52	28.74	33.17	51.08
	WE	54.52	38.02	37.93	57.74	45.19	32.85	35.74	52.96	36.87	23.13	33.27	49.26	43.96	33.30	34.99	51.99
MLP	LE	37.41	27.93	33.52	48.99	42.73	30.66	32.41	47.40	41.31	29.13	30.58	44.97	41.39	30.77	33.39	49.88
WILF	HS	57.11	40.73	46.31	66.72	50.02	36.02	40.98	<u>58.74</u>	49.78	35.33	36.12	52.65	<u>48.00</u>	35.80	39.40	<u>56.58</u>
	AS	<u>57.30</u>	40.33	42.38	63.12	50.74	36.76	37.99	54.72	<u>49.81</u>	34.53	35.05	51.70	46.34	34.75	35.91	52.32
	CLAWS	65.32	47.69	52.80	73.42	58.31	43.82	48.59	67.67	58.11	42.09	44.17	61.44	52.72	42.31	45.52	64.63
	PPL	35.59	26.46	31.59	47.64	40.66	28.92	32.32	49.46	39.10	27.92	29.78	43.42	32.90	22.11	35.43	52.59
	WE	58.46	40.05	40.11	60.38	48.15	35.64	36.65	54.54	45.85	30.55	35.01	51.67	33.20	22.42	34.08	50.31
TabM	LE	47.65	33.30	35.52	52.44	45.31	33.11	34.86	52.12	44.65	31.01	31.60	45.48	33.40	22.78	35.11	52.27
Tabivi	HS	<u>58.51</u>	41.39	<u>46.16</u>	66.42	52.12	<u>37.80</u>	41.05	<u>58.90</u>	50.78	35.73	36.14	52.56	41.22	31.66	36.10	54.01
	AS	57.09	39.55	42.58	63.30	51.33	37.50	38.17	55.22	47.05	32.05	35.16	51.83	39.04	28.53	37.16	55.69
	CLAWS	66.45	46.83	52.95	73.17	58.70	42.78	47.83	66.93	58.92	40.95	44.10	60.67	54.20	41.15	46.42	64.95

Table 9: Evaluation results for creativity detection using OREAL-7B

Data	set		T	EST			A	MC			A	ME			A(J)	HSME	
Strategy	Method	$\mathrm{F1}_{\mathrm{w}}$	$F1_m$	AP_{m}	AUROC	$F1_{\rm w}$	$F1_m$	AP_{m}	AUROC	F1 _w	$F1_{m}$	AP_{m}	AUROC	$F1_{\rm w}$	$F1_{m}$	AP_{m}	AUROC
	PPL	56.08	31.31	35.98	54.06	51.46	30.83	36.59	56.38	72.38	33.10	33.81	50.45	44.41	29.62	35.92	53.99
	WE	59.33	33.74	36.28	54.38	55.08	33.66	36.80	55.13	73.10	30.26	33.47	51.08	50.95	34.42	<u>37.19</u>	<u>54.80</u>
XGBOOST	LE	54.29	28.42	33.05	48.22	50.04	28.78	33.53	50.16	72.80	32.68	33.59	50.18	43.16	27.57	33.80	51.14
AGBOOST	HS	61.54	38.44	39.26	58.61	57.30	38.33	38.29	56.62	70.42	33.57	33.90	53.02	52.60	36.87	37.58	55.27
	AS	53.83	26.76	36.00	53.50	47.70	25.56	35.93	53.68	73.07	29.92	34.63	55.29	39.22	23.70	34.03	50.52
	CLAWS	62.41	40.83	42.20	62.33	54.03	<u>37.02</u>	38.32	57.29	70.94	33.49	33.87	49.05	49.02	<u>35.11</u>	36.37	54.38
	PPL	59.88	35.79	37.54	56.31	58.17	41.28	41.52	62.85	68.61	35.39	35.91	57.86	48.78	<u>36.16</u>	41.35	59.53
	WE	53.83	26.76	33.11	49.04	47.70	25.56	32.56	49.16	73.07	29.92	33.51	51.24	39.22	23.70	34.50	50.36
MLP	LE	53.76	26.72	33.25	49.11	47.70	25.56	33.25	51.68	73.07	29.92	34.31	52.45	46.63	31.35	35.59	53.16
WILF	HS	57.25	37.18	39.90	<u>58.83</u>	48.60	34.10	39.34	56.63	62.86	31.67	33.29	50.56	39.22	23.70	33.37	50.04
	AS	62.98	<u>38.54</u>	39.78	55.90	54.91	36.53	37.32	55.57	68.89	33.82	34.24	<u>52.77</u>	49.86	35.87	36.03	53.61
	CLAWS	60.12	41.87	42.39	61.48	51.30	<u>37.14</u>	40.19	59.47	66.67	34.20	33.83	50.25	48.76	37.00	41.53	59.78
	PPL	53.83	26.76	37.84	57.08	47.70	25.56	38.36	58.89	73.07	29.92	35.26	56.47	39.22	23.70	38.30	57.69
	WE	59.16	34.17	35.25	52.75	55.08	33.66	36.22	54.09	73.10	30.26	33.35	50.55	50.95	34.42	36.90	54.54
TabM	LE	53.83	26.76	31.97	46.90	47.70	25.56	32.06	49.43	73.07	29.92	32.20	47.67	39.22	23.70	34.54	52.61
Tabivi	HS	<u>62.28</u>	<u>38.75</u>	<u>40.26</u>	<u>58.73</u>	57.60	38.44	39.42	57.29	71.32	33.38	33.59	<u>51.54</u>	52.55	36.74	38.95	56.34
	AS	53.83	26.76	39.79	58.17	47.70	25.56	37.33	55.62	73.07	29.92	33.94	49.19	39.22	23.70	39.28	56.80
	CLAWS	62.86	39.09	42.41	63.48	<u>55.53</u>	<u>37.45</u>	38.75	<u>58.23</u>	71.21	33.92	35.08	51.07	51.27	<u>36.49</u>	38.07	<u>57.23</u>

Table 10: Evaluation results for creativity detection using Qwen-2.5-Math-7B

Datas	set		T	EST			A	MC			A	IME			A(J)	HSME	
Strategy	Method	$F1_w$	F1 _m	AP_{m}	AUROC	F1 _w	F1 _m	AP_{m}	AUROC	F1 _w	F1 _m	AP_{m}	AUROC	F1 _w	F1 _m	AP_{m}	AUROC
	PPL	48.70	41.51	41.49	59.98	46.82	37.65	36.90	54.52	44.53	36.78	37.82	55.39	44.21	34.63	35.26	53.28
	WE	<u>49.96</u>	39.15	<u>43.47</u>	63.00	49.93	36.57	38.63	57.69	41.13	32.17	36.10	52.48	45.39	32.74	36.82	<u>55.51</u>
XGBOOST	LE	38.22	32.42	33.83	50.94	40.59	31.06	34.20	51.68	35.19	28.98	33.38	49.97	37.81	28.36	34.17	50.89
АОВООЗТ	HS	46.98	39.95	41.80	57.98	48.68	<u>37.94</u>	<u>39.70</u>	<u>58.48</u>	41.31	33.40	50.87	34.65	44.80	33.46	36.41	54.44
	AS	42.60	35.24	37.91	55.60	42.92	32.76	35.51	53.54	38.85	30.92	33.74	49.56	40.00	29.96	34.70	52.49
	CLAWS	52.35	43.33	47.72	65.98	50.30	38.98	40.66	61.11	45.18	38.95	<u>39.75</u>	55.86	47.54	36.02	39.41	59.45
	PPL	54.27	46.34	<u>47.90</u>	67.59	50.01	38.01	43.58	61.96	47.58	<u>36.13</u>	41.91	62.02	44.92	37.00	38.23	57.72
	WE	45.67	39.58	38.31	54.97	43.32	32.95	36.49	53.87	40.26	30.78	34.22	51.26	42.11	33.31	34.35	50.53
MLP	LE	29.48	23.10	28.27	41.43	36.53	26.33	33.96	49.47	31.62	25.13	31.19	47.00	32.30	23.38	35.14	50.73
WILI	HS	54.58	42.77	46.98	65.86	50.29	36.64	41.90	60.61	43.11	32.96	36.01	52.38	46.24	36.21	37.80	56.01
	AS	43.80	38.05	40.62	59.13	43.04	32.73	35.52	52.88	39.07	30.08	32.98	47.71	39.86	30.64	34.43	51.33
	CLAWS	53.78	<u>45.32</u>	50.44	67.98	52.51	39.65	43.06	63.20	42.76	36.59	<u>39.32</u>	<u>56.49</u>	53.75	41.05	42.29	62.61
	PPL	54.53	42.74	47.13	65.44	50.83	<u>38.45</u>	43.07	60.61	48.30	37.01	43.37	60.80	45.58	34.28	38.54	<u>57.10</u>
	WE	48.15	37.73	40.35	58.70	46.62	33.89	36.59	55.06	38.66	30.12	34.82	51.49	45.58	31.17	34.81	52.06
TabM	LE	33.24	26.04	32.55	50.24	41.43	28.20	34.61	52.39	31.50	25.36	33.98	50.30	38.81	25.93	35.89	52.41
Taulvi	HS	51.47	41.39	45.50	63.64	50.08	36.79	<u>41.58</u>	61.00	43.75	34.48	36.73	53.74	<u>46.01</u>	33.00	37.82	55.41
	AS	45.76	35.86	38.65	56.76	43.53	31.74	36.03	54.26	37.84	29.68	33.06	49.16	41.37	28.96	35.60	54.28
	CLAWS	<u>51.93</u>	42.92	<u>45.82</u>	63.83	48.69	38.90	39.23	59.61	<u>45.14</u>	38.28	<u>38.15</u>	<u>55.26</u>	47.31	35.97	39.23	59.28

Table 11: Evaluation results for hallucination detection using DeepSeek-Math-7B. Bold and underlined values indicate the best and second-best performance, respectively. Light gray-shaded cells indicate cases where the model predicted only a single class in a 2-class detection setting.

Datas	set		Т	EST			A	мс			A	IME			A(J)	HSME	2
Strategy	Method	F1 _w	F1 _m	AP_{m}	AUROC	$F1_{\rm w}$	F1 _m	AP_{m}	AUROC	F1 _w	F1 _m	AP _m	AUROC	F1 _w	F1 _m	AP_{m}	AUROC
	PPL	56.31	56.08	52.18	59.45	54.76	53.53	66.15	55.92	57.65	53.32	40.16	56.75	58.61	56.18	70.04	58.75
	WE	65.53	63.87	60.55	68.13	50.79	52.21	68.78	60.84	59.51	49.52	38.21	55.66	53.27	53.41	<u>70.15</u>	<u>59.51</u>
XGBOOST	LE	50.45	50.49	44.87	52.12	52.12	50.32	62.19	51.76	53.25	50.66	36.64	53.36	54.86	52.15	65.98	53.49
AGBOOST	HS	57.91	57.84	49.82	58.86	53.23	49.99	61.94	50.51	46.49	44.95	31.93	46.78	56.00	51.74	64.72	50.91
	AS	61.26	61.37	57.39	67.27	53.47	49.26	61.88	50.82	52.64	48.97	34.84	50.44	55.74	49.52	64.52	49.93
	CLAWS	66.15	66.02	66.06	73.21	58.95	56.00	68.65	<u>59.39</u>	55.34	52.80	43.24	58.22	61.12	56.83	71.01	59.99
	PPL	53.26	54.05	60.78	63.40	58.89	55.25	57.58	60.10	59.93	57.91	60.78	63.60	63.44	58.87	59.02	61.55
	WE	<u>65.53</u>	63.87	62.80	65.76	50.79	52.21	56.97	60.84	60.76	54.86	53.73	55.66	57.90	56.12	55.34	59.09
MLP	LE	47.54	48.57	50.43	50.62	55.57	53.13	53.23	53.82	53.84	51.23	52.66	53.65	58.38	54.61	54.77	55.73
MLP	HS	61.89	62.14	63.48	66.54	53.86	48.59	52.13	52.39	42.56	42.32	48.47	46.41	55.68	49.34	50.96	51.83
	AS	61.26	61.37	62.99	67.08	53.47	49.26	50.75	50.82	52.64	48.97	50.77	50.12	55.74	49.52	50.03	49.90
	CLAWS	70.69	70.51	76.44	78.35	63.48	61.29	62.59	65.67	60.50	<u>57.34</u>	61.15	62.70	65.12	61.11	61.64	64.64
	PPL	59.01	58.98	54.53	63.40	58.42	57.20	69.78	60.62	62.95	58.42	45.75	63.60	62.21	59.47	71.05	61.55
	WE	<u>65.53</u>	63.87	60.57	68.13	50.79	52.21	68.78	60.84	59.51	49.52	38.17	55.64	53.46	53.58	70.20	59.56
77.13.6	LE	47.53	48.49	41.98	50.62	55.79	52.92	63.51	53.82	52.33	50.51	36.12	53.71	58.74	54.71	66.79	55.29
TabM	HS	60.90	61.22	54.83	65.20	53.59	48.45	63.08	52.67	42.46	42.23	33.84	46.98	55.16	48.54	67.30	53.87
	AS	62.95	62.43	57.29	67.33	53.15	50.65	61.96	50.82	56.37	50.39	35.48	50.12	54.40	49.92	64.47	49.94
	CLAWS	70.80	70.40	68.96	77.03	61.18	58.52	71.23	62.34	61.27	57.73	46.94	63.37	64.01	59.84	74.78	64.70

Table 12: Evaluation results for hallucination detection using Mathstral-7B

Data	set		T	EST			A	MC			A	IME			A(J)	HSME	
Strategy	Method	F1 _w	F1 _m	AP_{m}	AUROC	F1 _w	F1 _m	AP_{m}	AUROC	F1 _w	F1 _m	AP_{m}	AUROC	F1 _w	F1 _m	AP_{m}	AUROC
	PPL	59.16	51.63	39.99	57.91	48.13	46.97	48.19	52.02	66.72	53.03	25.93	53.45	47.97	48.07	54.48	53.54
	WE	61.35	52.24	52.44	70.96	48.34	46.73	59.67	65.49	66.05	44.75	26.79	54.60	47.97	48.12	59.81	62.04
XGBOOST	LE	55.98	48.86	33.54	50.88	49.70	48.54	50.70	54.97	63.63	47.62	22.38	47.37	45.96	46.08	50.91	51.38
довоозт	HS	64.41	<u>58.97</u>	49.50	66.57	53.31	<u>52.71</u>	52.16	57.07	65.91	48.86	23.06	48.36	50.24	50.32	53.49	53.79
	AS	63.29	54.88	52.28	66.47	47.93	46.39	56.53	61.52	66.37	46.10	25.84	52.21	45.81	45.96	56.78	56.92
	CLAWS	68.93	64.74	54.22	<u>70.14</u>	57.86	57.42	57.63	60.81	68.62	55.25	34.92	59.35	56.64	56.66	61.68	61.07
	PPL	62.44	58.35	59.79	63.82	55.80	55.65	57.72	58.83	58.87	51.43	52.67	55.24	52.06	52.02	53.64	54.01
	WE	52.42	44.27	55.67	56.78	38.24	35.98	53.10	52.71	66.08	44.36	52.01	53.63	50.57	50.63	51.02	50.27
MLP	LE	54.35	53.02	55.60	58.33	55.17	55.27	55.44	57.35	50.54	43.69	48.03	46.99	52.10	52.04	52.61	54.60
MLF	HS	68.29	65.92	69.13	72.56	53.29	53.85	59.92	61.18	65.09	51.03	49.89	49.29	50.87	50.79	53.46	54.78
	AS	69.28	65.39	65.30	68.56	58.59	<u>58.45</u>	59.61	62.04	63.78	52.56	50.74	51.46	55.17	55.20	56.01	<u>57.89</u>
	CLAWS	72.60	70.23	71.58	76.46	63.97	63.91	64.43	67.13	69.36	55.98	60.50	65.42	57.48	57.41	61.13	63.78
	PPL	52.72	39.83	41.56	63.13	37.14	34.80	52.24	58.69	65.69	43.19	28.13	55.72	32.90	33.16	51.18	52.35
	WE	53.00	40.24	48.29	67.44	38.28	36.03	55.86	62.65	66.08	44.36	26.90	54.81	33.56	33.82	55.86	56.94
TabM	LE	53.17	41.09	37.32	57.25	38.42	36.18	51.03	56.34	65.43	43.89	21.57	46.00	34.25	34.49	52.13	53.35
Tabivi	HS	<u>70.78</u>	<u>65.92</u>	55.96	69.92	58.19	<u>57.72</u>	54.09	59.79	65.07	44.02	24.20	51.09	50.56	50.65	54.18	54.76
	AS	65.28	57.77	54.07	69.09	52.23	50.99	<u>57.18</u>	62.07	66.85	<u>47.91</u>	25.53	51.90	49.70	49.82	<u>56.85</u>	<u>57.84</u>
	CLAWS	71.24	66.85	58.34	74.90	59.83	59.33	57.96	<u>62.41</u>	70.49	54.75	34.28	59.23	58.69	58.70	60.09	61.38

Table 13: Evaluation results for hallucination detection using OpenMath2-LLaMA3.1-8B

Data	set		Т	EST			A	MC			A	IME			A(J)	HSME	
Strategy	Method	F1 _w	$F1_m$	AP_{m}	AUROC	$F1_{\rm w}$	$F1_m$	AP_{m}	AUROC	$F1_{\rm w}$	$F1_m$	AP_{m}	AUROC	F1 _w	$F1_m$	AP_{m}	AUROC
	PPL	50.29	50.23	45.17	51.55	49.68	48.63	57.68	48.70	48.47	48.42	46.56	48.88	50.25	48.29	62.56	49.13
	WE	63.59	62.14	<u>61.51</u>	<u>68.35</u>	54.17	55.17	68.09	63.29	43.86	42.25	50.17	<u>54.96</u>	54.85	55.10	<u>69.61</u>	60.47
XGBOOST	LE	51.35	51.07	46.90	53.15	51.61	50.97	59.25	51.71	47.46	47.15	45.91	47.80	48.39	46.90	60.89	47.56
AGBOOST	HS	60.00	59.81	54.59	64.55	56.74	55.33	64.64	57.95	51.68	51.65	50.50	52.95	56.39	53.87	68.48	57.27
	AS	63.52	63.06	57.72	66.34	58.27	<u>57.02</u>	63.49	57.37	51.99	51.46	49.91	54.12	56.36	53.87	64.44	53.77
	CLAWS	67.70	67.18	67.37	72.71	62.63	61.48	69.63	64.47	59.28	58.87	58.90	62.40	62.85	60.48	73.57	64.44
	PPL	40.48	41.94	46.39	44.60	48.50	45.26	49.84	49.79	41.54	42.24	44.95	42.76	50.68	45.38	45.14	43.00
	WE	59.94	59.40	58.43	61.08	54.28	53.64	53.62	55.24	51.44	51.03	52.21	52.93	54.54	52.81	52.34	53.08
MLP	LE	45.18	46.17	53.63	54.10	52.39	50.32	51.29	51.79	44.98	45.19	46.27	44.54	53.68	49.98	49.79	49.22
MILI	HS	64.07	<u>64.21</u>	<u>69.38</u>	71.21	60.17	<u>58.12</u>	61.24	63.68	52.88	<u>53.21</u>	<u>53.96</u>	<u>55.40</u>	60.69	<u>57.26</u>	<u>58.61</u>	60.95
	AS	62.94	62.67	63.22	66.27	58.37	56.76	56.78	59.16	53.17	52.77	52.56	53.79	56.96	54.02	53.65	55.54
	CLAWS	71.11	70.76	77.32	78.66	66.07	64.48	66.29	69.34	61.15	60.82	61.13	63.52	63.75	60.69	64.97	67.89
	PPL	44.17	44.84	44.73	47.61	49.54	47.44	57.60	47.80	44.17	44.14	43.89	43.50	48.89	45.42	60.63	46.06
	WE	59.94	59.40	51.84	61.08	54.28	53.64	61.87	55.35	51.44	51.03	49.40	52.96	54.54	52.81	63.59	53.08
TabM	LE	52.78	52.51	48.32	55.00	52.50	51.56	59.79	51.76	47.48	47.23	43.22	45.68	51.77	50.04	65.28	52.06
Tabivi	HS	65.03	64.90	63.72	<u>71.21</u>	60.35	58.89	69.00	63.68	<u>54.66</u>	<u>54.59</u>	<u>50.40</u>	<u>55.40</u>	60.25	<u>57.57</u>	<u>70.61</u>	60.95
	AS	62.90	62.26	57.64	66.27	58.20	57.27	64.66	59.16	50.65	49.97	48.80	53.79	55.84	53.76	64.66	54.94
	CLAWS	69.62	69.19	69.18	74.51	65.20	63.98	74.83	69.17	61.15	60.82	61.13	63.52	65.13	62.79	75.60	67.35

Table 14: Evaluation results for hallucination detection using OREAL-7B

Data	set		T	EST			A	MC			A	IME			A(J)	HSME	
Strategy	Method	F1 _w	F1 _m	AP_{m}	AUROC	F1 _w	F1 _m	AP_{m}	AUROC	F1 _w	F1 _m	AP_{m}	AUROC	$F1_{\rm w}$	F1 _m	AP_{m}	AUROC
	PPL	59.22	49.94	36.97	54.44	54.35	47.79	43.30	56.57	72.00	49.27	18.63	48.58	49.75	47.51	49.10	54.52
	WE	60.40	50.83	38.54	57.13	56.09	49.39	43.11	57.40	73.10	45.26	18.48	49.66	52.84	50.64	50.98	<u>58.15</u>
XGBOOST	LE	56.21	44.73	33.26	48.61	51.53	44.15	38.09	49.52	72.89	49.29	19.12	50.26	44.64	41.85	45.93	50.64
ловоозт	HS	64.38	<u>58.48</u>	43.79	<u>60.96</u>	61.46	58.64	46.34	59.01	72.17	53.12	19.66	50.69	57.84	56.87	51.96	58.27
	AS	53.83	40.14	38.01	56.00	47.70	38.35	40.78	54.58	73.07	44.88	19.58	53.26	39.22	35.55	44.96	50.35
	CLAWS	<u>64.31</u>	58.82	44.59	62.34	<u>57.95</u>	<u>55.58</u>	44.36	<u>57.67</u>	70.94	<u>50.29</u>	19.47	48.47	<u>53.84</u>	<u>53.17</u>	47.38	53.54
	PPL	63.58	57.86	58.36	60.87	61.39	57.22	60.84	63.86	72.77	50.52	54.10	57.11	57.81	56.53	62.58	63.95
	WE	53.83	40.14	53.34	55.76	47.70	38.35	50.38	49.42	73.07	44.88	49.57	48.51	39.22	35.55	46.93	43.33
MLP	LE	53.83	40.14	48.33	46.47	47.70	38.35	47.30	45.62	73.07	44.88	48.70	45.18	39.22	35.55	50.10	50.16
WILI	HS	59.85	56.95	59.13	61.23	57.76	<u>56.68</u>	59.33	60.93	65.99	49.85	<u>51.27</u>	51.93	55.95	55.86	58.06	59.23
	AS	66.27	<u>61.13</u>	60.03	63.33	<u>59.15</u>	56.22	55.25	57.60	66.15	<u>50.58</u>	51.16	<u>52.63</u>	<u>57.78</u>	57.30	<u>58.53</u>	60.12
	CLAWS	<u>64.71</u>	61.29	63.95	66.93	56.54	56.08	<u>59.53</u>	<u>61.73</u>	68.43	51.28	51.04	50.94	56.14	56.45	58.49	60.57
	PPL	59.36	49.44	41.76	60.30	56.70	50.27	50.12	63.76	72.67	49.88	20.65	56.42	51.83	49.60	56.57	64.01
	WE	60.40	50.83	36.82	55.76	56.09	49.39	42.67	55.17	73.10	45.26	18.97	50.41	52.84	50.64	50.67	56.85
TabM	LE	53.83	40.14	33.18	51.29	47.70	38.35	35.34	47.56	73.07	44.88	18.84	52.45	39.22	35.55	45.74	50.69
Tabivi	HS	65.67	<u>59.53</u>	46.96	61.59	62.04	58.94	51.10	60.95	72.72	51.80	20.36	51.17	57.68	56.55	56.12	59.23
	AS	53.83	40.14	42.08	61.99	47.70	38.35	42.90	57.50	73.07	44.88	20.29	52.54	39.22	35.55	49.02	56.70
	CLAWS	66.82	61.04	<u>46.92</u>	63.98	60.38	<u>57.71</u>	44.02	58.87	72.66	<u>51.27</u>	19.93	51.23	<u>57.67</u>	56.93	52.52	<u>59.28</u>

Table 15: Evaluation results for hallucination detection using Qwen-2.5-Math-7B

Data	set		T	EST			A	MC			A	IME			A(J)	HSME	
Strategy	Method	$F1_{\rm w}$	$F1_m$	AP_{m}	AUROC	$F1_{\rm w}$	$F1_{m}$	AP_{m}	AUROC	F1 _w	$F1_m$	AP_{m}	AUROC	$F1_{\rm w}$	$F1_{m}$	AP_{m}	AUROC
	PPL	61.27	59.63	70.49	65.17	71.32	55.49	84.41	60.70	53.64	53.62	57.96	57.56	75.31	51.90	87.48	56.02
	WE	61.82	59.59	71.87	<u>69.07</u>	74.08	<u>56.51</u>	85.10	63.88	49.14	49.09	52.66	53.82	79.36	54.39	<u>87.86</u>	60.02
XGBOOST	LE	50.31	47.63	54.19	46.79	64.87	49.60	78.87	50.02	44.29	44.25	48.77	48.05	68.83	47.76	83.42	47.38
Аброозт	HS	60.24	58.39	71.75	65.48	73.30	57.63	86.31	65.38	51.06	51.04	52.35	52.96	76.28	53.50	86.34	56.05
	AS	53.53	50.47	65.72	59.94	70.02	51.53	82.11	55.60	44.77	44.71	48.40	48.59	76.44	51.33	86.24	52.55
	CLAWS	65.68	64.26	76.73	71.49	70.33	55.37	87.57	<u>64.43</u>	54.20	54.19	<u>56.73</u>	<u>56.92</u>	74.70	<u>53.65</u>	89.57	61.67
	PPL	66.79	66.76	69.52	73.18	72.67	62.12	65.22	70.57	59.03	59.04	65.01	65.82	76.35	58.21	58.34	65.10
	WE	48.63	44.28	56.64	58.59	68.80	50.49	53.17	57.00	49.56	49.56	50.83	50.02	63.09	47.25	52.70	53.42
MLP	LE	41.52	38.90	45.78	40.81	54.04	42.87	47.37	43.32	39.42	39.40	43.82	40.81	60.20	42.24	47.40	41.58
WILF	HS	<u>67.34</u>	66.26	68.94	72.35	73.89	<u>59.54</u>	61.08	<u>68.01</u>	52.22	<u>52.24</u>	53.83	54.20	74.35	54.64	54.44	58.05
	AS	59.31	58.50	61.44	62.87	61.52	50.92	53.04	55.88	48.03	48.02	49.07	47.88	64.78	47.88	51.44	53.56
	CLAWS	69.13	68.11	73.19	74.80	68.24	57.50	58.89	65.89	51.41	51.43	53.89	54.39	77.81	<u>56.34</u>	<u>55.41</u>	<u>61.42</u>
	PPL	54.59	51.04	77.93	74.38	71.03	46.78	88.28	70.25	42.73	42.66	64.11	65.78	77.71	46.49	90.16	65.19
	WE	44.28	39.16	66.10	63.23	70.53	45.80	82.92	59.29	35.37	35.28	50.26	50.65	77.97	47.21	85.75	54.04
TabM	LE	42.61	38.82	56.70	42.63	62.39	45.80	77.26	44.41	38.08	38.04	47.82	40.96	66.08	44.04	81.65	41.85
Tabivi	HS	63.90	62.04	76.98	72.73	73.50	<u>55.38</u>	87.61	<u>68.01</u>	51.06	<u>51.04</u>	53.91	54.20	77.91	53.08	88.03	58.05
	AS	41.98	36.51	66.28	57.65	69.89	44.17	82.10	55.16	33.49	33.40	48.82	48.13	77.56	45.83	86.34	53.51
	CLAWS	63.38	<u>61.74</u>	77.83	71.17	69.70	55.45	87.38	63.99	53.38	53.38	<u>56.58</u>	<u>56.14</u>	78.89	53.44	<u>89.54</u>	<u>61.99</u>

Table 16: Evaluation results for creativity detection on a balanced dataset. The evaluation strategies used are Threshold and Prototype. Bold values indicate the best performance, underlined values indicate the second-best, and gray-shaded cells correspond to results where the model performed detection over only two out of the three target classes.

Data	set		Т	EST			A	мс			A	IME			A(J)	HSME	;
Model	Method	F1 _w	F1 _m	AP_{m}	AUROC	$F1_w$	F1 _m	AP_{m}	AUROC	F1 _w	F1 _m	AP_{m}	AUROC	F1 _w	F1 _m	AP_{m}	AUROC
	PPL	35.22	35.22	34.40	52.03	37.57	37.57	35.04	53.16	42.57	42.57	37.65	57.34	36.21	36.21	34.83	52.30
	WE	30.54	30.54	<u>35.34</u>	53.44	28.46	28.46	34.20	51.60	25.80	25.80	33.15	49.40	28.70	28.70	34.35	51.95
D 1	LE	31.89	31.89	32.98	48.91	32.78	32.78	33.35	49.95	29.32	29.32	32.65	47.62	33.06	33.06	33.37	49.94
Deepseek	HS	27.36	27.36	32.21	45.16	31.40	31.40	33.25	49.58	32.09	32.09	33.14	49.21	32.88	32.88	33.58	50.53
	AS	31.48	31.48	33.81	49.69	32.11	32.11	33.31	49.91	30.56	30.56	33.56	50.40	33.29	33.29	33.55	50.47
	CLAWS	46.30	46.30	41.34	62.03	35.90	35.90	35.87	54.62	36.93	36.93	36.66	<u>55.95</u>	36.43	36.43	35.97	54.89
	PPL	29.11	29.11	32.86	48.70	32.37	32.37	33.39	49.88	27.67	27.67	32.46	47.79	31.55	31.55	33.04	49.29
	WE	38.76	38.76	36.14	<u>54.71</u>	36.23	36.23	35.05	<u>53.11</u>	34.21	34.21	33.81	50.74	34.19	34.19	34.41	52.05
Malant	LE	30.60	30.60	32.83	48.54	32.05	32.05	32.99	49.08	26.00	26.00	31.56	44.85	30.59	30.59	32.62	48.09
Mathstral	HS	27.80	27.80	33.82	49.35	26.85	26.85	33.12	48.96	19.96	19.96	31.70	45.22	25.67	25.67	32.73	48.38
	AS	24.86	24.86	31.88	44.16	28.19	28.19	32.16	46.26	28.62	28.62	32.91	48.53	29.09	29.09	32.16	46.82
	CLAWS	42.50	42.50	40.40	60.71	38.13	38.13	37.08	56.45	31.86	31.86	34.23	51.84	38.04	38.04	37.05	56.43
	PPL	29.78	29.78	33.01	49.23	27.45	27.45	32.15	46.56	25.40	25.40	31.73	44.40	23.79	23.79	31.37	43.75
	WE	33.85	33.85	34.18	51.55	33.45	33.45	34.29	51.89	31.01	31.01	32.73	48.51	29.53	29.53	33.14	49.50
OM-4h2	LE	<u>36.34</u>	36.34	34.53	<u>52.32</u>	40.00	40.00	36.16	<u>55.15</u>	31.18	31.18	33.42	50.00	38.06	38.06	35.53	53.93
OpenMath2	HS	25.49	25.49	31.53	44.33	28.34	28.34	32.25	46.91	36.30	36.30	34.92	<u>52.61</u>	28.43	28.43	32.30	47.38
	AS	23.92	23.92	31.19	43.04	29.84	29.84	32.75	48.20	38.59	38.59	35.52	54.10	32.32	32.32	33.77	50.30
	CLAWS	41.90	41.90	38.92	58.51	37.66	37.66	36.93	56.36	24.86	24.86	33.22	49.63	33.47	33.47	35.60	54.23
	PPL	29.02	29.02	32.41	47.47	23.55	23.55	31.56	44.09	31.64	31.64	33.65	50.00	23.87	23.87	31.48	44.25
	WE	25.69	25.69	32.14	46.91	27.60	27.60	33.08	49.37	30.21	30.21	33.34	50.00	27.38	27.38	33.00	49.07
OREAL	LE	33.34	33.34	33.86	50.84	34.64	34.64	34.96	<u>53.16</u>	29.33	29.33	33.37	49.47	35.79	35.79	35.33	53.88
OKEAL	HS	30.03	30.03	32.87	48.60	26.77	26.77	31.91	45.89	33.93	33.93	33.76	50.53	27.64	27.64	32.10	46.58
	AS	26.10	26.10	33.10	47.75	31.65	31.65	34.15	51.58	25.07	25.07	33.61	<u>50.53</u>	30.21	30.21	33.59	49.22
	CLAWS	25.27	25.27	32.99	48.31	34.08	34.08	35.16	53.48	34.85	34.85	34.69	52.66	37.49	37.49	35.52	54.04
	PPL	27.04	27.04	34.14	50.00	27.75	27.75	33.72	49.52	25.76	25.76	33.34	49.53	35.59	31.09	33.92	50.47
	WE	34.62	34.62	34.91	52.96	32.83	32.83	34.20	51.39	31.12	31.12	33.01	49.06	29.08	28.56	33.01	49.11
O 2.5	LE	45.25	45.25	39.53	59.24	40.54	40.54	36.60	55.60	39.56	39.56	36.05	54.56	41.31	39.10	35.66	54.32
Qwen-2.5	HS	27.84	27.84	34.67	51.72	30.39	30.39	35.66	53.58	18.97	18.97	33.48	50.31	36.80	31.55	35.08	53.11
	AS	26.88	26.88	32.66	47.17	31.59	31.59	34.13	51.27	32.32	32.32	34.20	51.73	37.59	34.97	34.28	51.52
	CLAWS	31.34	31.34	33.39	49.63	40.88	40.88	38.04	57.63	23.76	23.76	31.66	45.28	38.27	36.63	35.56	53.95

Table 17: Evaluation results for creativity detection using DeepSeek-Math-7B on a balanced dataset. Bold values indicate the best performance, underlined values indicate the second-best. Light gray-shaded cells correspond to cases where the model performed detection over only two out of the three target classes, while dark gray-shaded cells indicate cases where the model predicted only one out of the three target classes.

Datas	set		Т	EST			A	мс			A	IME			A(J)	HSME	
Strategy	Method	F1 _w	$F1_m$	AP_{m}	AUROC	$F1_{\rm w}$	F1 _m	AP_{m}	AUROC	$F1_{\rm w}$	F1 _m	AP_{m}	AUROC	F1 _w	$F1_m$	AP_{m}	AUROC
	PPL	39.12	39.12	37.18	55.02	35.85	35.85	35.79	53.32	36.68	36.68	35.70	52.40	35.90	35.90	35.24	52.73
	WE	33.20	33.20	40.18	60.71	30.24	30.24	<u>37.15</u>	56.72	22.32	22.32	34.51	51.56	31.12	31.12	36.72	56.17
XGBOOST	LE	36.50	36.50	35.10	52.32	34.29	34.29	34.37	51.49	32.17	32.17	33.29	49.80	33.12	33.12	34.87	52.15
Абробы	HS	36.52	36.52	37.35	54.52	35.71	35.71	34.28	51.47	35.93	35.93	37.00	<u>54.95</u>	35.13	35.13	35.19	51.92
	AS	<u>41.05</u>	<u>41.05</u>	<u>41.24</u>	59.10	34.01	34.01	34.79	51.88	31.78	31.78	<u>37.18</u>	53.95	32.39	32.39	33.68	50.52
	CLAWS	43.24	43.24	46.66	63.42	37.50	37.50	37.80	<u>55.29</u>	42.11	42.11	41.87	59.88	35.53	35.53	37.34	54.77
	PPL	30.04	30.04	38.58	57.19	23.69	23.69	<u>38.57</u>	<u>56.47</u>	30.73	30.73	<u>40.75</u>	<u>60.01</u>	27.11	27.11	<u>38.43</u>	<u>56.75</u>
	WE	33.76	33.76	40.38	60.54	32.25	32.25	35.88	54.05	31.12	31.12	36.99	55.19	31.64	31.64	36.92	56.42
MLP	LE	35.27	35.27	36.45	54.32	26.92	26.92	34.54	51.59	29.76	29.76	36.82	54.31	<u>34.95</u>	<u>34.95</u>	34.99	51.25
WILI	HS	<u>41.43</u>	$\underline{41.43}$	<u>44.90</u>	62.33	27.66	27.66	34.81	51.37	28.28	28.28	36.62	53.21	28.84	28.84	33.96	49.65
	AS	38.64	38.64	41.96	60.54	34.57	<u>34.57</u>	34.69	51.74	32.82	32.82	35.22	51.83	33.22	33.22	33.77	50.43
	CLAWS	44.98	44.98	49.40	67.35	41.38	41.38	43.04	60.77	41.75	41.75	42.96	62.88	35.00	35.00	42.14	60.25
	PPL	34.50	34.50	38.91	57.59	33.63	33.63	38.62	<u>56.63</u>	33.89	33.89	<u>41.36</u>	<u>59.97</u>	<u>36.75</u>	<u>36.75</u>	<u>38.43</u>	<u>56.73</u>
	WE	30.20	30.20	40.38	60.66	29.00	29.00	37.21	56.72	25.12	25.12	36.46	54.90	29.53	29.53	36.91	56.41
TabM	LE	37.40	37.40	35.83	54.04	33.79	33.79	34.81	51.50	39.61	<u>39.61</u>	37.83	55.14	35.52	35.52	35.20	52.10
140141	HS	40.49	40.49	<u>44.16</u>	60.99	32.64	32.64	35.74	52.89	34.37	34.37	35.28	52.06	30.71	30.71	33.73	49.32
	AS	<u>41.17</u>	<u>41.17</u>	42.68	60.83	34.17	<u>34.17</u>	34.72	51.63	32.61	32.61	37.28	54.15	32.51	32.51	33.70	50.42
	CLAWS	46.42	46.42	47.89	64.08	37.89	37.89	38.87	56.16	42.70	42.70	45.24	61.62	38.92	38.92	40.27	58.51

Table 18: Evaluation results for creativity detection using Mathstral-7B on a balanced dataset

Data	set		Т	EST			A	мс			A	IME			A(J)	HSME	E
Strategy	Method	F1 _w	F1 _m	AP_{m}	AUROC	F1 _w	F1 _m	AP _m	AUROC	F1 _w	F1 _m	AP _m	AUROC	F1 _w	F1 _m	AP _m	AUROC
	PPL	33.41	33.41	34.60	51.21	35.84	35.84	34.78	51.49	38.15	38.15	39.75	55.00	34.06	34.06	34.72	51.35
	WE	34.18	34.18	37.59	56.00	33.95	33.95	36.71	56.02	32.49	32.49	33.80	50.17	29.30	29.30	37.49	<u>56.35</u>
XGBOOST	LE	29.74	29.74	32.30	46.74	34.67	34.67	35.20	52.35	30.95	30.95	35.16	52.07	33.39	33.39	33.54	50.56
AGBOOST	HS	37.82	37.82	38.99	56.58	36.03	36.03	35.64	52.11	32.52	32.52	34.83	49.69	33.65	33.65	34.11	50.75
	AS	36.54	36.54	37.89	54.51	36.50	36.50	36.47	53.84	31.42	31.42	31.34	45.44	34.36	34.36	35.45	52.44
	CLAWS	40.20	40.20	45.46	60.50	40.14	40.14	40.23	57.46	42.73	42.73	41.03	<u>54.54</u>	34.60	34.60	38.38	56.42
	PPL	29.20	29.20	41.65	59.58	16.67	16.67	35.93	52.16	16.48	16.48	36.69	53.09	27.26	27.26	35.73	52.53
	WE	27.15	27.15	36.88	51.56	16.67	16.67	35.44	52.37	22.70	22.70	31.40	45.42	19.64	19.64	33.94	49.79
MLP	LE	37.59	37.59	37.39	54.32	30.70	30.70	35.27	53.14	32.48	32.48	<u>37.23</u>	52.87	16.67	16.67	33.33	50.00
MLP	HS	45.58	<u>45.58</u>	43.92	<u>62.70</u>	29.61	29.61	37.66	<u>55.65</u>	19.92	19.92	36.00	52.67	29.42	29.42	35.91	53.20
	AS	38.49	38.49	42.73	62.29	36.60	36.60	36.38	54.85	31.81	31.81	35.14	52.07	25.42	25.42	35.28	53.28
	CLAWS	46.78	46.78	45.64	63.92	44.79	44.79	44.69	62.51	33.72	33.72	43.75	58.92	39.02	39.02	41.95	60.36
	PPL	42.24	42.24	38.69	55.69	36.79	36.79	35.46	51.75	37.77	37.77	36.86	53.20	34.14	34.14	35.34	52.11
	WE	31.48	31.48	36.95	51.88	30.15	30.15	35.69	52.18	31.55	31.55	32.46	47.29	22.68	22.68	33.75	49.64
TabM	LE	28.89	28.89	36.88	53.46	29.67	29.67	35.14	52.70	26.54	26.54	<u>37.27</u>	52.38	28.46	28.46	34.87	52.11
Taulvi	HS	34.64	34.64	39.16	<u>58.56</u>	31.46	31.46	37.67	55.25	20.70	20.70	33.21	47.77	28.15	28.15	35.51	52.67
	AS	38.21	38.21	40.78	58.34	36.79	36.79	37.88	55.80	31.80	31.80	34.94	50.89	35.48	35.48	35.89	53.82
	CLAWS	45.74	45.74	48.76	66.40	41.22	41.22	43.57	61.17	38.58	38.58	44.41	60.86	38.99	38.99	40.32	57.89

Table 19: Evaluation results for creativity detection using OpenMath2-LLaMA3.1-8B on a balanced dataset

Datas	set		Т	EST			A	MC			A	IME			A(J)	HSME	
Strategy	Method	F1 _w	F1 _m	AP _m	AUROC	F1 _w	F1 _m	AP _m	AUROC	F1 _w	F1 _m	AP _m	AUROC	F1 _w	F1 _m	AP _m	AUROC
	PPL	31.64	31.64	34.48	50.89	29.55	29.55	32.14	48.11	35.35	35.35	38.34	53.75	35.58	35.58	37.00	53.21
	WE	37.97	37.97	39.76	57.89	34.03	34.03	35.96	54.12	34.70	34.70	35.60	51.49	29.54	29.54	35.44	53.48
XGBOOST	LE	31.75	31.75	34.09	49.66	33.41	33.41	34.72	51.37	32.31	32.31	35.01	51.03	33.04	33.04	34.44	50.80
довоозт	HS	32.30	32.30	35.72	53.62	37.06	<u>37.06</u>	<u>38.54</u>	<u>55.35</u>	32.31	32.31	35.01	51.03	33.38	33.38	35.13	52.06
	AS	36.01	36.01	37.54	54.58	35.51	35.51	34.71	51.48	31.35	31.35	31.95	47.58	33.35	33.35	33.55	51.22
	CLAWS	49.96	49.96	48.76	66.23	42.00	42.00	42.66	60.32	36.91	36.91	<u>37.91</u>	54.72	40.50	40.50	42.87	60.46
	PPL	29.07	29.07	35.24	50.63	29.70	29.70	33.56	49.09	23.99	23.99	34.08	48.25	31.77	31.77	42.10	<u>59.40</u>
	WE	32.54	32.54	34.84	50.68	28.22	28.22	34.47	50.89	16.67	16.67	34.71	51.53	31.38	31.38	36.24	53.50
MLP	LE	31.28	31.28	34.74	49.56	25.55	25.55	32.21	47.23	18.22	18.22	30.51	43.57	28.08	28.08	35.97	52.38
MILI	HS	33.89	33.89	<u>43.40</u>	<u>61.26</u>	29.16	29.16	<u>39.11</u>	<u>56.93</u>	34.24	34.24	<u>37.61</u>	<u>51.56</u>	28.82	28.82	36.98	54.43
	AS	40.56	<u>40.56</u>	41.38	60.35	27.80	27.80	36.07	52.92	27.55	27.55	31.38	46.84	23.34	23.34	30.92	45.34
	CLAWS	49.51	49.51	49.09	68.00	43.34	43.34	46.49	64.34	<u>27.91</u>	27.91	43.29	60.89	43.42	43.42	43.28	60.58
	PPL	23.49	23.49	33.31	47.71	24.11	24.11	32.64	47.23	21.31	21.31	33.87	46.70	23.14	23.14	34.57	49.12
	WE	36.25	36.25	37.61	55.32	34.02	<u>34.02</u>	35.06	52.59	31.37	<u>31.37</u>	35.68	<u>53.01</u>	36.77	36.77	35.67	52.81
TabM	LE	32.59	32.59	34.74	50.21	32.19	32.19	35.17	50.86	21.50	21.50	28.69	40.00	32.75	32.75	32.78	49.01
1 dUIVI	HS	38.79	38.79	<u>42.21</u>	60.36	30.87	30.87	37.02	<u>54.82</u>	30.62	30.62	<u>36.79</u>	50.53	30.88	30.88	36.98	<u>53.80</u>
	AS	40.56	<u>40.56</u>	41.36	59.98	33.06	33.06	35.25	51.71	29.54	29.54	31.96	47.37	32.42	32.42	33.62	49.69
	CLAWS	45.87	45.87	50.47	69.09	41.45	41.45	47.00	63.95	41.43	41.43	44.73	59.39	40.84	40.84	44.47	61.44

Table 20: Evaluation results for creativity detection using OREAL-7B on a balanced dataset

Data	set		T	EST			A	MC			A	IME			A(J)	HSME	
Strategy	Method	$F1_{\rm w}$	F1 _m	AP_{m}	AUROC	$F1_{\rm w}$	F1 _m	$\boldsymbol{AP_m}$	AUROC	F1 _w	F1 _m	AP_{m}	AUROC	F1 _w	F1 _m	AP_{m}	AUROC
	PPL	33.63	33.63	34.65	51.86	38.34	38.34	37.58	54.99	36.88	36.88	34.53	50.26	35.93	35.93	37.37	53.25
	WE	24.25	24.25	33.50	49.75	25.34	25.34	36.10	53.91	28.33	28.33	35.06	52.47	25.40	25.40	36.88	54.24
XGBOOST	LE	33.58	33.58	34.26	50.43	32.49	32.49	33.80	50.07	36.88	36.88	36.89	49.59	32.76	32.76	34.25	51.18
AGBOOST	HS	32.32	32.32	33.35	48.58	35.14	<u>35.14</u>	36.56	<u>54.71</u>	28.70	28.70	34.12	50.62	35.73	35.73	35.48	52.58
	AS	27.82	27.82	33.13	48.70	33.44	33.44	34.73	51.62	36.34	36.34	34.41	50.94	29.16	29.16	34.10	50.26
	CLAWS	39.05	39.05	40.73	59.03	34.99	34.99	36.47	53.69	34.14	34.14	36.99	50.62	35.84	<u>35.84</u>	36.48	53.33
	PPL	30.55	30.55	39.80	56.69	37.16	37.16	41.26	59.01	22.47	22.47	41.00	54.61	40.38	40.38	40.95	56.56
	WE	16.71	16.71	32.98	49.07	18.17	18.17	34.96	52.38	26.00	26.00	35.41	52.23	20.66	20.66	34.70	50.55
MLP	LE	25.62	25.62	37.46	<u>55.19</u>	16.67	16.67	36.41	53.56	<u>27.58</u>	<u>27.58</u>	37.50	54.35	16.67	16.67	33.09	48.46
WILI	HS	26.31	26.31	34.00	50.79	33.04	33.04	39.84	<u>57.51</u>	24.03	24.03	41.83	55.60	35.34	35.34	38.18	56.24
	AS	16.67	16.67	34.39	49.49	29.69	29.69	35.08	51.92	23.90	23.90	32.64	46.50	34.91	34.91	41.78	60.46
	CLAWS	37.54	37.54	38.59	54.61	27.03	27.03	38.90	55.98	30.64	30.64	33.68	47.74	39.49	39.49	<u>40.95</u>	56.25
	PPL	36.95	36.95	42.66	<u>59.17</u>	38.03	38.03	40.84	57.92	37.60	37.60	40.37	54.71	39.07	39.07	42.25	57.69
	WE	21.91	21.91	32.71	47.72	22.22	22.22	33.44	50.59	25.16	25.16	33.97	50.85	20.66	20.66	34.26	51.71
TabM	LE	32.76	32.76	34.28	50.15	33.43	33.43	34.97	52.29	34.93	34.93	38.28	52.85	<u>36.14</u>	<u>36.14</u>	37.31	55.85
Tabivi	HS	27.86	27.86	34.51	50.49	36.48	36.48	39.10	56.42	31.06	31.06	36.33	52.99	34.38	34.38	38.41	<u>56.11</u>
	AS	31.94	31.94	35.29	51.14	34.14	34.14	35.55	52.82	33.61	33.61	34.50	50.43	29.68	29.68	37.19	55.81
	CLAWS	44.21	44.21	44.09	62.58	34.23	34.23	37.20	53.25	29.62	29.62	33.35	46.67	35.21	35.21	36.83	53.68

Table 21: Evaluation results for creativity detection using Qwen-2.5-Math-7B on a balanced dataset

										Ι							
Data	set		Т	EST			A	MC			A	IME			A(J)	HSMI	<u> </u>
Strategy	Method	$F1_{\rm w}$	$F1_{m}$	$AP_{m} \\$	AUROC	F1 _w	$F1_{m}$	$AP_{m} \\$	AUROC	$F1_{\rm w}$	$F1_{m}$	$AP_{m} \\$	AUROC	$F1_{\rm w}$	$F1_{m}$	$AP_{m} \\$	AUROC
	PPL	40.16	40.16	43.09	60.01	37.57	37.57	38.43	55.33	37.99	37.99	39.15	56.60	36.22	35.16	36.07	52.68
	WE	41.38	41.38	40.81	58.87	37.89	37.89	38.51	56.66	35.50	<u>35.50</u>	36.17	52.77	37.33	36.20	36.72	<u>54.31</u>
XGBOOST	LE	33.93	33.93	33.71	51.48	32.65	32.65	34.00	50.92	29.51	29.51	32.34	48.28	34.55	33.51	34.05	50.89
довоозт	HS	39.46	39.46	40.97	59.22	38.29	38.29	39.60	57.37	33.19	33.19	33.33	49.91	38.94	37.34	36.09	53.49
	AS	36.63	36.63	37.97	54.72	38.21	38.21	35.99	53.15	30.86	30.86	33.03	47.91	38.05	35.96	34.76	52.47
	CLAWS	42.08	36.63	37.97	54.72	39.02	39.02	39.92	58.99	35.24	35.24	37.61	54.24	39.06	37.01	38.00	57.28
	PPL	43.21	43.21	48.48	67.07	38.35	38.35	45.18	63.38	36.12	36.12	41.57	60.18	37.57	38.13	40.67	58.45
	WE	23.73	23.73	35.91	52.21	35.18	35.18	35.83	52.69	32.29	32.29	35.18	51.72	32.97	32.69	34.81	50.79
MLP	LE	20.88	20.88	29.52	40.91	27.44	27.44	34.87	50.93	22.47	22.47	30.83	44.62	27.76	26.99	32.09	46.89
MLP	HS	42.56	42.56	45.23	62.86	31.55	31.55	40.19	59.28	32.19	32.19	35.77	52.09	33.65	32.88	38.15	54.69
	AS	39.11	39.11	37.77	56.80	26.66	26.66	36.45	54.02	26.01	26.01	31.89	47.33	34.46	33.71	34.39	51.12
	CLAWS	43.56	43.56	46.59	64.77	38.36	38.36	41.98	61.53	33.57	33.57	<u>37.93</u>	<u>55.03</u>	38.59	35.12	41.92	60.47
	PPL	40.13	40.13	47.62	66.36	39.52	39.52	43.87	62.15	34.74	34.74	41.71	59.99	35.79	36.55	39.37	57.42
	WE	38.23	38.23	38.37	55.63	35.77	35.77	37.37	54.90	30.03	30.03	35.10	51.88	32.93	32.90	35.90	52.83
TabM	LE	26.16	26.16	30.58	46.48	29.14	29.14	32.54	50.05	27.55	27.55	31.08	46.65	28.17	27.31	32.96	48.78
Tabivi	HS	40.42	40.42	44.41	61.94	38.08	38.08	41.85	59.30	34.03	34.03	35.72	52.50	36.22	34.52	36.96	53.35
	AS	36.75	36.75	38.01	56.30	36.24	36.24	36.48	53.82	29.81	29.81	33.21	48.37	34.77	33.98	34.55	51.32
	CLAWS	41.14	41.14	44.03	61.98	40.16	40.16	40.10	59.94	36.52	36.52	<u>37.83</u>	54.64	40.03	37.98	38.50	57.69