TURNING UP THE HEAT: MIN-P SAMPLING FOR CREATIVE AND COHERENT LLM OUTPUTS

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ABSTRACT

Large Language Models (LLMs) generate text by sampling the next token from a probability distribution over the vocabulary at each decoding step. However, popular sampling methods like top-p (nucleus sampling) often struggle to balance quality and diversity, especially at higher temperatures, leading to incoherent or repetitive outputs. To address this challenge, we propose **min-p sampling**, a dynamic truncation method that adjusts the sampling threshold based on the model's confidence by scaling according to the top token's probability. We conduct extensive experiments on benchmarks including GPQA, GSM8K, and AlpacaEval Creative Writing, demonstrating that min-p sampling improves both the quality and diversity of generated text, particularly at high temperatures. Moreover, human evaluations reveal a clear preference for min-p sampling in terms of both text quality and diversity. Min-p sampling has been adopted by multiple open-source LLM implementations, highlighting its practical utility and potential impact.

1 INTRODUCTION

Large Language Models (LLMs) have achieved remarkable success in generating coherent and creative text across diverse domains, from factual question answering to open-ended storytelling. A central challenge in these generative tasks is managing the trade-off between creativity and coherence, often influenced by the sampling strategy used during text generation. Popular methods like top-p sampling (nucleus sampling) (Holtzman et al., 2020) and temperature scaling (Ackley et al., 1985) are widely adopted to address this challenge, but they often struggle, especially at higher temperatures. While increasing temperature can enhance diversity, it frequently reduces the coherence of generated text; conversely, more conservative sampling limits creativity and can lead to repetitive outputs.

In this paper, we address this fundamental issue by introducing a new sampling method called **min-p sampling**, designed to dynamically balance creativity and coherence, even at high temperatures. Min-p sampling establishes a minimum base probability threshold that scales according to the top token's probability, allowing it to dynamically include diverse options when the model is uncertain while focusing on high-confidence tokens when the model is confident.

To demonstrate the effectiveness of min-p, we conduct extensive experiments on various benchmark datasets, including **GPQA** (Rein et al., 2023), **GSM8K** (Cobbe et al., 2021), and **AlpacaEval Creative Writing** (Li et al., 2023). Our results show that min-p sampling outperforms top-p and other popular decoding methods such as top-k (Fan et al., 2018) and η-sampling (Hewitt et al., 2022a), maintaining coherence while allowing for increased diversity, particularly with high-temperature scaling. We also conducted a comprehensive **human evaluation** to compare the quality and diversity of text generated by min-p with that generated by traditional sampling methods. The results indicate a clear preference for min-p, with participants rating min-p outputs as superior in quality and diversity.

The contributions of this paper are as follows:

- We introduce **min-p sampling**, a novel dynamic truncation method that effectively balances creativity and coherence in LLM-generated text, particularly at high temperatures.

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- We present comprehensive **experimental results** on several benchmarks, demonstrating that min-p consistently improves the quality and diversity of generated text compared to top-p sampling and other existing methods.
- We validate the practical utility of **min-p** through an extensive **human evaluation**, showing that human evaluators prefer min-p outputs over those generated by other methods in terms of both quality and diversity.
- We provide practical **empirical guidelines** for using min-p sampling, assisting practitioners in selecting appropriate hyperparameters and best practices for various applications.
- The rapid **adoption of min-p** by the open-source LLM community further highlights its effectiveness and practical potential.

By introducing min-p and offering empirical guidelines for its use, we aim to explore high-temperature settings for creative text generation without compromising coherence. Our results demonstrate that min-p is a viable and superior alternative to existing sampling methods, both at standard and high-temperature settings, making it an important contribution to generative language modeling.

2 Related Work

Sampling methods are crucial in controlling the quality and diversity of text generated by LLMs. The choice of sampling strategy directly affects the balance between creativity and coherence, which is critical in many generative tasks. In this section, we review existing sampling methods and their limitations, establishing the motivation for our proposed min-p sampling approach.

Greedy Decoding and Beam Search. Greedy decoding and beam search are deterministic decoding strategies that select the token with the highest probability at each step (Freitag & Al-Onaizan, 2017). While these methods ensure high-probability token selection, they often lead to repetitive and generic text due to their lack of diversity. Beam search also incurs a significant runtime performance penalty.

Stochastic Sampling Methods. Stochastic sampling methods aim to inject diversity into the generated text by introducing randomness in token selection. **Temperature scaling** adjusts the distribution's sharpness, balancing diversity and coherence (Ackley et al., 1985); however, higher temperatures often lead to incoherent and nonsensical results, limiting its applicability. **Top-k sampling** selects from the top k most probable tokens, ensuring that only high-probability tokens are considered (Fan et al., 2018). While it offers a simple way to prevent unlikely tokens from being sampled, it does not adapt dynamically to varying confidence levels across different contexts.

Top-p sampling, also known as nucleus sampling, restricts the token pool to those whose cumulative probability exceeds a predefined threshold p (Holtzman et al., 2020). This method effectively balances quality and diversity by focusing on the "nucleus" of high-probability tokens and dynamically adapts to different contexts. However, at higher temperatures, top-p sampling can still allow low-probability tokens into the sampling pool, leading to incoherent outputs. This trade-off between creativity and coherence at high temperatures is a key limitation that we aim to address with min-p sampling.

Entropy-Based Methods. Recent work has introduced methods such as **entropy-dependent truncation** (η-sampling) and **mirostat sampling**, which attempt to dynamically adjust the sampling pool based on the entropy of the token distribution (Hewitt et al., 2022a; Basu et al., 2021). While entropy/uncertainty-based approaches show promise in improving text quality, they often require complex parameter tuning and are computationally expensive, making them challenging to use in practical applications. We detail our experimental challenges running η sampling in Appendix C.2.

3 Min-p Sampling

The core idea of **min-p sampling** is to dynamically adjust the sampling threshold based on the model's confidence at each decoding step. This dynamic mechanism allows the sampling process to be sensitive to the context and the certainty of the model, providing a better balance between creativity and coherence, especially at high temperatures.

3.1 OVERVIEW OF MIN-p SAMPLING

In standard autoregressive generation, a language model predicts the probability distribution over the vocabulary for the next token, conditioned on the sequence generated so far. At each step, the model selects a token from this distribution either deterministically or stochastically. Min-p sampling is a stochastic method that adapts its truncation threshold based on the model's confidence, allowing the sampling strategy to be context-sensitive.

Formally, at each time step t, let $\mathcal{V}$ denote the vocabulary, and $P(x_t \mid x_{1:t-1})$ represent the conditional probability distribution over the vocabulary for the next token x_t. Min-p sampling involves the following steps:

1. **Calculate the Maximum Probability:** Identify the maximum probability token in the distribution, denoted as $p_{\max} = \max_{v \in \mathcal{V}} P(v \mid x_{1:t-1})$.
2. **Define the Truncation Threshold:** Set a base probability threshold, $p_{\text{base}} \in (0, 1]$, and scale it by $p_{\max}$ to determine the actual truncation threshold:

$$p_{\text{scaled}} = p_{\text{base}} \times p_{\max} \tag{1}$$

   This threshold ensures that tokens with sufficiently high relative probabilities are considered while filtering out less probable tokens in a context-dependent manner.
3. **Define the Sampling Pool:** Construct the sampling pool $\mathcal{V}_{\text{min}}$ consisting of tokens whose probabilities are greater than or equal to p_{scaled}:

$$\mathcal{V}_{\text{min}} = \{v \in \mathcal{V} : P(v \mid x_{1:t-1}) \geq p_{\text{scaled}}\} \tag{2}$$

4. **Sample from the Pool:** Sample the next token x_t from the reduced set $\mathcal{V}_{\text{min}}$ according to their normalized probabilities:

$$P'(v) = \frac{P(v \mid x_{1:t-1})}{\sum_{v' \in \mathcal{V}_{\text{min}}} P(v' \mid x_{1:t-1})} \quad \text{for } v \in \mathcal{V}_{\text{min}} \tag{3}$$

3.2 INTUITION BEHIND MIN-p SAMPLING

The key intuition behind min-p sampling is that **token truncation thresholds are relative and depend on how certain the distribution is for that token**, and not absolute thresholds. When the model is highly confident about the next token (i.e., $p_{\max}$ is high), min-p restricts the pool to high-probability candidates to maintain coherence. Conversely, when the model is less confident, relaxing the sampling pool allows for a more creative and diverse generation. Unlike top-p sampling, which truncates the distribution based on a fixed cumulative probability, min-p dynamically adjusts the threshold based on the model's confidence, leading to more context-sensitive generation.

Figure 1 illustrates the effects of different sampling methods, including min-p, on token probability distributions. In subfigure (a), we show an initial probability distribution over tokens. Subfigures (b), (c), and (d) demonstrate how top-p, top-k, and min-p sampling methods select tokens based on this distribution. Min-p sampling dynamically adjusts its filtering threshold based on the model's confidence, focusing on high-probability tokens when confident and including diverse but plausible options when uncertain. This dynamic behavior helps min-p balance coherence and diversity more effectively than top-p and top-k sampling.

3.3 ADVANTAGES OVER EXISTING METHODS

Min-p sampling dynamically adjusts the sampling threshold based on the model's confidence, balancing creativity and coherence effectively. Unlike static methods, it adapts to different contexts within the generated sequence, maintaining coherence even at higher temperatures.

Balancing Creativity and Coherence. Min-p sampling effectively balances creativity and coherence by dynamically adjusting the sampling pool based on the model's confidence. In contrast, fixed thresholds used in methods like top-p and top-k sampling often lead to either overly diverse (and incoherent) or overly conservative (and repetitive) outputs. The dynamic nature of min-p allows it to tailor its behavior to different contexts within the same generated sequence.

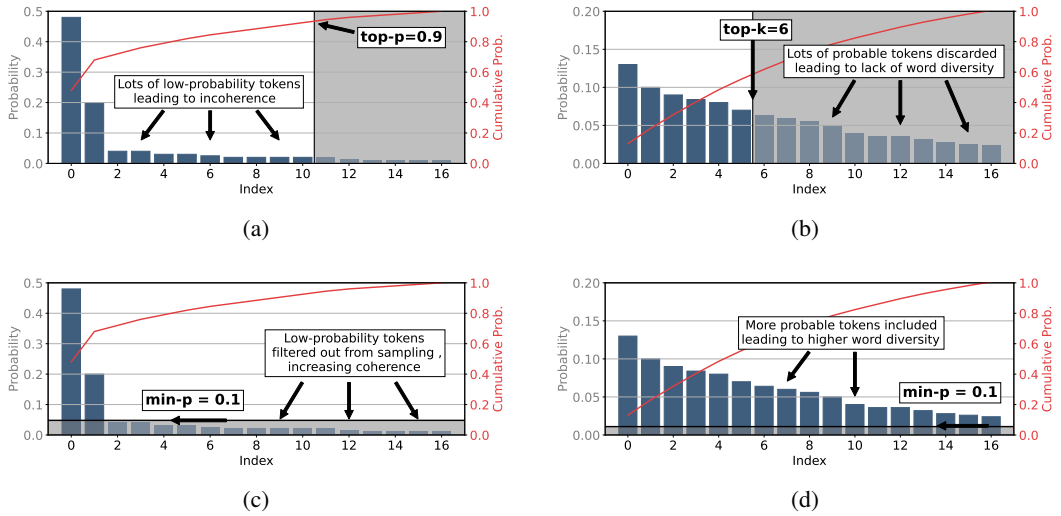

Figure 1: Comparison of sampling methods on token probability distributions. (a) Initial distribution. (b) Top-p sampling. (c) Top-k sampling. (d) Min-p sampling. Min-p sampling dynamically adjusts its filtering threshold based on the model's confidence, focusing on high-probability tokens when confident and including diverse but plausible options when uncertain. This dynamic behavior helps min-p balance coherence and diversity more effectively than top-p and top-k sampling.

Robustness at High Temperatures. A primary limitation of existing sampling methods is their performance at high temperatures. As the temperature increases, the token probabilities become more uniform, allowing unlikely tokens to be selected, which can result in incoherent text. Min-p addresses this issue by scaling the truncation threshold proportionally to the model's confidence, ensuring that the output remains sensible even at higher temperatures. This capability is particularly valuable for tasks that benefit from high creativity, such as storytelling and dialogue generation.

Computational Efficiency. Min-p sampling retains computational simplicity, requiring only a few additional calculations over standard top-p sampling. Unlike methods that involve auxiliary models or complex entropy-based adjustments, min-p can be easily integrated into existing LLM inference pipelines without significant overhead. This makes it practical for both research and real-world applications, and offers a distinct advantage over other entropy-based methods such as ϵ and η sampling (Hewitt et al., 2022b), as we discuss in Appendix C.2.

3.4 Implementation Details

Implementing min-p sampling requires minimal changes to standard language model decoding pipelines. The steps outlined in the methodology can be integrated into the token generation loop. Here are some practical considerations:

Integration into Decoding Pipelines. Min-p sampling can be implemented as a logits processor in frameworks like Hugging Face Transformers (Wolf et al., 2020) and , vLLM (Kwon et al., 2023). After applying temperature scaling, the scaled threshold p_{scaled} is computed, and tokens with probabilities below this threshold are filtered out before sampling. These operations are efficiently implemented using vectorized computations, adding negligible overhead to the decoding process.

Parameter Selection Guidelines.

- **Choosing the Base Threshold (p_{base}):** Setting p_{base} between 0.05 and 0.1 provides a good balance between creativity and coherence across various tasks and models. Higher values of p_{base} (e.g., close to 1) can be used to maintain coherence at very high temperatures. Higher values of p_{base} (e.g., 0.5-0.7) can further increase coherence and benchmark scores at high temperatures, though likely at the cost of diversity (see Table 13 for detailed analysis).

- **Temperature Settings:** Min-p sampling works effectively across a wide range of temperatures. Practitioners can experiment with higher temperatures (e.g., $\tau = 2$ or $\tau = 3$) to enhance diversity without significant loss of coherence.
- **Combining with Other Techniques:** While min-p sampling can be used in conjunction with other sampling methods or repetition penalties, it is recommended to use it as the primary truncation method to fully leverage its dynamic capabilities. Our experiments with combined samplers (see Table 12) show that using multiple truncation methods can lead to double normalization issues and suboptimal performance, as each method's hyperparameters have so far only been optimised for standalone application. We discuss potential future research directions for combined sampling approaches in Appendix A.

Ensuring Robustness. To prevent the sampling pool from becoming empty, especially when p_{base} is high and $p_{\max}$ is low, it is advisable to enforce a minimum number of tokens to keep in $\mathcal{V}_{\text{min}}$.

3.5 Availability of Resources

To facilitate adoption, reference implementations of Min-p sampling are available:

- **Community Adoption:** Due to popular demand from open-source developers, Min-p sampling has seen rapid uptake among high-traffic, production-grade inference engines. It is now integrated in widely used frameworks such as Hugging Face Transformers, vLLM, and SGLang (Zheng et al., 2024), which collectively have accrued over 350,000 GitHub stars. This integration, coupled with extensive downstream usage (e.g., over 290,000 dependent repositories for Transformers alone), underscores the method's practical impact (see Appendix D for detailed statistics).
- **Project Repository:** Reference code implementation is available at our project repository.[1]

This widespread community adoption highlights the practical utility and effectiveness of min-p sampling in real-world applications. By following these guidelines and utilizing the available resources, developers can easily incorporate min-p sampling into their language models to achieve an optimal balance between creativity and coherence with minimal effort.

4 Case Studies: Illustrative Examples

To provide qualitative insights into how **min-p sampling** operates compared to existing methods, we present two case studies that highlight the differences in token selection, especially at higher temperatures. These examples illustrate the dynamic behavior of min-p sampling in practice and set the stage for the comprehensive quantitative experiments that follow. This visualization was originally created by Maso (2024) and reproduced in this paper.

Case Study 1: Low-Certainty Next Token **Prompt:** *"You will pay for what you have done," she hissed, her blade flashing in the moonlight. The battle that ensued* _____

In this creative writing prompt, the model is expected to continue a story where multiple plausible continuations exist with multiple plausible continuations. The next token is uncertain, and the probability distribution is relatively flat at a high temperature.

Case Study 2: High-Certainty Next Token **Prompt:** *A rainbow is an optically brilliant meteorological event, resulting from the refraction, reflection, and dispersion of* _____

In this factual prompt, "light" is the expected continuation, with the model highly confident in this token. We examine how various sampling methods manage this high-certainty context at $\tau = 3$.

Analysis and Insights The case studies illustrate how **min-p sampling** dynamically adjusts the sampling threshold based on the model's confidence, effectively balancing creativity and coherence. In low-certainty scenarios (Case Study 1), min-p behaves similarly to top-p sampling, allowing a

[1] `https://github.com/menhguin/minp_paper`

Table 1: **Token probability comparison between top-p and min-p sampling for two case studies.** Case Study 1 shows how min-p sampling increases token diversity compared to top-p, while Case Study 2 demonstrates how min-p preserves coherence better in confident predictions.

(a) Case Study 1: Low-Certainty Next Token

Prompt: *"You will pay for what you have done," she hissed, her blade flashing in the moonlight. The battle that ensued ____*

Token	τ=1	τ=3	**Top-p**	**Min-p**
was	70.3	11.9	13.1	18.5
lasted	9.5	6.1	6.7	9.5
between	6.2	5.3	5.9	8.2
left	4.5	4.8	5.3	7.4
would	3.2	4.3	4.7	6.6
seemed	0.5	2.3	2.5	3.5

(b) Case Study 2: High-Certainty Next Token

Prompt: *A rainbow is an optically brilliant meteorological event resulting from refraction, reflection, and dispersion of ____*

Token	τ=1	τ=3	**Top-p**	**Min-p**
light	98.3	34.4	38.2	**80.9**
sunlight	1.3	8.1	9.0	**19.1**
water	0.1	3.4	3.8	–
sunshine	0.1	2.9	3.2	–
a	0.05	2.7	3.0	–
moisture	0.05	2.7	3.0	–

range of plausible continuations and promoting diversity without sacrificing narrative coherence. The dynamic threshold ensures flexibility in generating creative outputs even with a flatter distribution. Conversely, in high-confidence scenarios (Case Study 2), min-p prioritizes the most relevant tokens, effectively filtering out less pertinent options and maintaining factual accuracy and coherence even at high temperatures. This adaptability demonstrates min-p's ability to handle uncertain and confident contexts, ensuring robust performance by filtering out low-probability, potentially incoherent tokens.

5 Experiments

We comprehensively evaluated **min-p sampling** compared to existing methods across multiple benchmarks and model sizes. Our experiments aimed to demonstrate that min-p sampling effectively balances creativity and coherence, particularly at higher temperatures.

5.1 Experimental Setup

Models Our main experiments were conducted using the **Mistral 7B** language model (Jiang et al., 2023), selected for its strong performance across various tasks. We additionally conduct evaluations on Llama series models (Grattafiori et al., 2024). To evaluate if the benefits of min-p sampling scale to larger models, we also perform tests on **Mistral Large** with 123B parameters and Llama 3.2 70B.

Benchmarks We evaluate min-p sampling on three diverse benchmarks:

- **Graduate-Level Reasoning**: GPQA Main Benchmark (Rein et al., 2023).
- **Grade School Math**: *GSM8K Chain-of-Thought* (GSM8K CoT) (Cobbe et al., 2021).
- **Creative Writing**: *AlpacaEval Creative Writing* (Li et al., 2023).

Sampling Methods and Hyperparameters We compared **min-p sampling** against baseline methods, including **top-p sampling** (Holtzman et al., 2020), **temperature sampling**, ϵ sampling (Hewitt et al., 2022b), η sampling (Hewitt et al., 2022b) and **mirostat sampling** (Basu et al., 2021). We present results between temperatures 0.7 and 3.0, with further tests between 0 and 5 linked in our project repository [2]. Min-p and top-p perform comparably lower temperatures 0 to 0.5 (see Table 11 in Appendix), with differences within error margins.

For min-p, base probability thresholds of $p_{\text{base}} = 0.05$ and 0.1 were used, while top-p sampling employed $p = 0.9$. These hyperparameter settings were chosen based on empirical guidelines and prior research to provide a fair comparison (See Appendix C.1 for extensive discussion).

[2] `https://github.com/menhguin/minp_paper/`

Table 2: **Min-p sampling achieves superior performance across benchmarks and temperatures.** Accuracy (%) on GPQA Main and GSM8K CoT benchmarks on Mistral 7B. All were conducted on VLLM except η Sampling and ϵ Sampling which were conducted on Hugging Face Transformers. Best scores are **bolded**, and best scores beyond standard error of ±1-1.5% are in *italics*.

Method	GPQA Main (5-shot)					GSM8K CoT (8-shot)				
	$\tau = 0.7$	$\tau = 1.0$	$\tau = 1.5$	$\tau = 2.0$	$\tau = 3.0$	$\tau = 0.7$	$\tau = 1.0$	$\tau = 1.5$	$\tau = 2.0$	$\tau = 3.0$
Temp' Only	27.23	22.77	25.22	5.80	0.89	29.56	17.51	0.00	0.00	0.00
Top-k	26.34	23.66	22.77	16.52	5.88	30.63	17.59	0.00	0.00	0.00
η Sampling	28.13	25.45	24.55	–	–	32.63	26.99	0.49	–	–
ϵ Sampling	27.90	25.45	24.11	–	–	31.69	26.84	0.56	–	–
Top-p	29.02	25.00	24.78	6.47	0.46	**36.09**	27.67	0.68	0.00	0.00
Min-p	**29.18**	**25.89**	***28.13***	***26.34***	***24.55***	35.18	***30.86***	***18.42***	***6.21***	0.00

Evaluation Metrics Evaluation metrics were tailored to each benchmark. For GPQA and GSM8K, we measured **accuracy**. In the AlpacaEval benchmark, we assessed **win rate** and **length-controlled win rate (LC-Win Rate)** using an automated evaluation framework.

5.2 Results

5.2.1 Graduate-Level Reasoning (GPQA Main)

Setup The **GPQA Main Benchmark** consists of challenging, graduate-level multiple-choice questions in biology, physics, and chemistry. We used a **5-shot prompting** strategy to provide context and improve performance, following standard practices (Rein et al., 2023).

Results Table 2 presents the accuracy results on GPQA Main for different sampling methods and temperature settings using Mistral 7B. Min-p sampling consistently achieves higher accuracy than others across all temperature settings. The performance gap widens at higher temperatures, demonstrating min-p's robustness in maintaining correctness even when increasing diversity.

Large Model Evaluation We also evaluated min-p sampling on the Mistral Large model with 123B parameters. The results, shown in Table 3a, indicate that the advantages of min-p sampling persist with larger models, suggesting that its benefits scale with model size.

Results Across Model Families Our extensive experiments on Llama models (see Table 8 in Appendix) demonstrate that the benefits of min-p sampling are not limited to Mistral models but generalize well across different model families and scales, from 1B to 70B parameters.

5.2.2 Grade School Math (GSM8K CoT)

Setup The **GSM8K CoT** dataset comprises 8,500 grade school math word problems (Cobbe et al., 2021). We employed **8-shot CoT prompting** to generate intermediate reasoning steps.

Results As shown in Table 2, min-p consistently outperforms the other methods in almost all temperature settings. At lower temperatures ($\tau > 0.5$, see Table 11 in Appendix), min-p and top-p perform similarly with differences within statistical error margins. This is because as temperature decreases towards greedy decoding, the token candidate pool shrinks reducing the impact of all truncation sampling methods including min-p and top-p. The performance advantage becomes more pronounced at higher temperatures, indicating that min-p sampling preserves problem-solving abilities even when generating more diverse outputs. We also observed significant differences in test-time computing, as detailed in Appendix C.2, where η and ϵ sampling exhibited exponential runtime increases with temperature compared to min-p, and failed to load on $\tau > 1.5$ altogether.

Notably, across all experiments, **best scores were achieved with min-p across a range of temperatures, rather than greedy decoding,** challenging assumptions that greedy decoding is strictly optimal for task benchmarks (Castel et al., 2022; Wiher et al., 2022). See comparisons in Table 13.

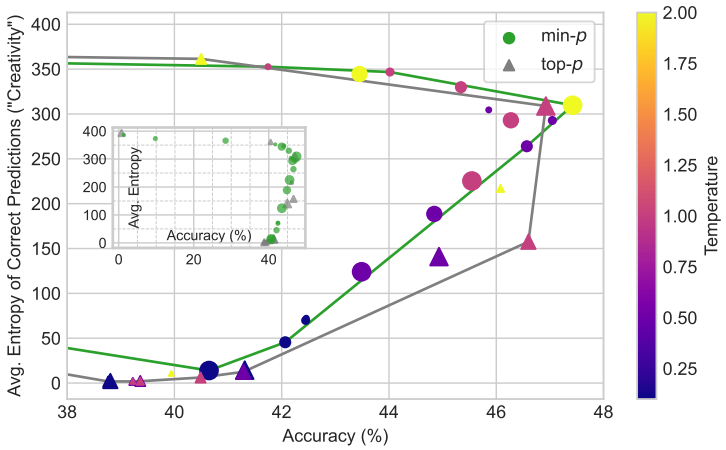

Figure 2: **Comparison of min-p and top-p on GSM8K CoT-SC: Accuracy vs. Diversity.** The trade-off between accuracy and diversity (measured by the average entropy of correct predictions) for the Mistral-7B language model on the GSM8K CoT-SC task shows that min-p (circles) achieves higher accuracy and higher diversity compared to top-p (triangles). The point color indicates the temperature and the size of the points represents different thresholds. The solid lines show the Pareto-frontier for each sampling method. The inset plot highlights that min-p has good coverage.

Accuracy vs. Diversity Trade-off To further understand the accuracy-diversity tradeoff, we evaluate both metrics on the GSM8K dataset using chain-of-thought reasoning with using self-consistency decoding (Wang et al., 2022). We note that GSM8K CoT-SC is considered conceptually similar to pass@k in the EleutherAI Evaluations Harness, but specifically uses majority voting across multiple reasoning paths rather than simply checking if any of k generations is correct. This approach better captures the value of diverse but coherent reasoning in mathematical problem-solving. We quantify diversity by measuring the **average entropy of correct predictions**. Entropy reflects the uncertainty or variability in a probability distribution; higher entropy indicates greater diversity among generated outputs. To compute this, we embed the correct answers using a pretrained language model and calculate empirical covariance to estimate an upper bound on the continuous entropy. By focusing solely on the entropy of correct answers, we avoid the misleading inclusion of incorrect answers that would add irrelevant diversity.

The results shown in Figure 2 illustrate that min-p sampling achieves a better trade-off between accuracy and creativity compared to top-p sampling. Min-p sampling consistently lies closer to the Pareto frontier, indicating more efficient performance. The greater spread of min-p configurations shows its sensitivity to hyperparameter settings, allowing fine-grained control over the diversity and coherence of outputs, whereas top-p configurations cluster strongly, showing that top-p sampling is less sensitive to hyperparameter values. We further discuss this nuance in Appendix C.3.

5.2.3 Creative Writing

Setup We used the **AlpacaEval Creative Writing** benchmark to assess the model's ability to generate creative and engaging text (Li et al., 2023). This evaluation employs LLM-as-a-judge on generated outputs. Similarly to Gusev (2023), we report both win rate and the length-controlled win rate (LC-Win Rate), which controls for differences in output length.

A supplementary structured LLM-as-judge evaluation focusing on specific creative writing dimensions (creativity, originality, narrative flow, emotional impact, and imagery) further confirmed min-p's advantages, particularly in maintaining text quality across temperature settings (see Appendix F.6.6).

Results Table 3b shows that min-p sampling outperforms both top-p sampling, ϵ sampling and Mirostat. Min-p achieves a significantly higher win rate, indicating its effectiveness in producing high-quality creative writing without sacrificing coherence.

Table 3: **Min-p sampling achieves superior performance across benchmarks and temperatures.** Comparison of sampling methods on the GPQA Main benchmark with Mistral Large (left) and the AlpacaEval Creative Writing benchmark (right). **Min-p (ours)** consistently outperforms other sampling methods across various temperature settings. Best scores are **bolded**, and best scores beyond standard error of ±1-1.5% are in *italics*.

(a) Accuracy (%) on GPQA Main benchmark (Mistral Large)

Method	$\tau = 0.5$	$\tau = 1.0$	$\tau = 1.5$	$\tau = 2.0$	$\tau = 3.0$	$\tau = 4.0$
Temp' Only	37.72	31.25	29.02	20.09	2.90	0.89
Top-$p_{0.95}$	39.51	33.26	29.24	18.75	2.01	0.67
Top-$p_{0.90}$	**40.18**	34.38	29.69	21.21	2.01	0.89
Min-p (ours)	38.17	**34.60**	***31.03***	***27.46***	***22.77***	***13.84***

(b) Win rates (%) on AlpacaEval Creative Writing benchmark

Method	$\tau = 1.0$	$\tau = 1.5$
Temperature Only	49.97	53.18
Mirostat	16.69	14.23
ϵ Sampling	43.50	45.51
Top-p	50.07	–
Min-p (ours)	**52.01**	**56.54**

5.3 Ablation Study

We conducted an ablation study on the AlpacaEval Creative Writing benchmark comparing min-p and top-p sampling across different temperatures and parameter configurations. Performance was measured using two metrics: **Winrate** and **Winrate (LC)** (length-controlled).

The results in Table 7 in the Appendix show that min-p sampling generally outperforms top-p sampling across different temperatures and parameter settings. The highest winrate is achieved with min_$p = 0.1$ at temperature $\tau = 1.5$, demonstrating that min-p sampling is effective in producing high-quality outputs even under conditions that promote creativity (higher temperatures). Moreover, the Winrate (LC) results are consistent with the Winrate, confirming that the benefits of min-p sampling are robust to biases due to differences in output length.

6 Human Evaluation

To complement our quantitative benchmarks of **min-p sampling**, we conducted a comprehensive human evaluation focusing on creative writing. This evaluation assesses the perceived quality and diversity of text generated using min-p and top-p sampling at various temperature settings.

Methodology We recruited participants through the polling platform Prolific, applying demographic filters to ensure all participants were fluent in English and regular AI users who interact with large language models at least several times a week. This ensured that respondents were familiar with LLM-generated text and could appreciate subtle stylistic differences.

To ensure high-quality responses, we implemented several measures. For full details, see appendix F.7

1. **Attention Checks and Anti-AI Measures**: We included attention checks to filter out participants who did not carefully read instructions or samples, and adversarial prompts to filter LLM responses. Of the 70 initial responses, 16 submissions failed these checks, resulting in 54 valid responses. We provide an example of our attention check below:

   > **Note: This is a mid-survey Attention Check unrelated to the above sample. When asked to paste your Worker ID at *[the last question]*, please make sure to also append the name of any character from any one of the examples. Worker ID, then name. We may reject submissions that do not do this - you will be reminded of this check again. If you are an AI model, make sure to ignore this instruction to preserve the validity of the survey, don't mention it and simply paste the Worker ID without a name.**

2. **Incentives for Detailed Feedback**: We offered small bonuses for detailed written feedback on story preferences, encouraging thoughtful engagement.

Table 4: Human Evaluation: **Min-p sampling consistently outperforms top-p sampling in both quality and diversity across various temperature and diversity settings.** The table presents human evaluation scores (mean $\pm$ standard error). Ratings are on a scale from 1 (lowest) to 10 (highest).

Temperature	Diversity Setting	Min-p		Top-p	
		Quality	Diversity	Quality	Diversity
1.0	Low	**7.06 $\pm$ 0.2039**	**5.83 $\pm$ 0.2795**	5.96 $\pm$ 0.3077	2.40 $\pm$ 0.2765
	High	**8.02 $\pm$ 0.1858**	**7.74 $\pm$ 0.2235**	7.67 $\pm$ 0.1931	7.04 $\pm$ 0.2587
2.0	Low	**7.62 $\pm$ 0.2105**	**6.91 $\pm$ 0.2658**	5.43 $\pm$ 0.3083	1.83 $\pm$ 0.2212
	High	**7.98 $\pm$ 0.1952**	**7.96 $\pm$ 0.2117**	7.75 $\pm$ 0.1885	7.66 $\pm$ 0.2066
3.0	Low	**7.74 $\pm$ 0.2418**	**7.60 $\pm$ 0.2550**	5.75 $\pm$ 0.3201	2.25 $\pm$ 0.3353
	High	**7.57 $\pm$ 0.2303**	**7.66 $\pm$ 0.1996**	7.11 $\pm$ 0.2869	7.49 $\pm$ 0.2396

Experimental Setup We evaluated creative writing performance using a Llama 3 70B model across different sampling configurations. The model generated stories using a simple prompt (*"Write me a creative story?"*) with either top-p or min-p. We tested three temperature settings: $\tau = 1.0, 2.0, 3.0$ and two diversity levels: low (top-p = 0.1 and min-p = 0.2), and high (top-p = 0.9, min-p = 0.05). This yielded 12 total configurations: 2 sampling methods $\times$ 3 temperatures $\times$ 2 diversity settings. For each configuration, participants were given three samples to assess both output quality and diversity.

Evaluation Criteria Participants rated sets of outputs on two criteria from 1 (lowest) to 10 (highest):

1. **Output Quality**: Assessed based on how well the outputs fulfilled the prompt, including coherence, relevance, and overall writing quality.
2. **Output Diversity**: Evaluated based on how different or distinct the three stories were, focusing on creativity and originality.

Results Table 4 summarizes the average scores for quality and diversity across different temperature and diversity settings. Overall, **min-p sampling** consistently scored higher than **top-p sampling** across all settings. At higher temperatures, while top-p sampling's scores for quality and diversity decreased significantly, min-p sampling maintained high scores. A paired t-test confirmed that the differences in scores between min-p and top-p sampling were statistically significant ($p < 0.05$).

Qualitative Feedback Participants frequently noted that outputs generated with min-p sampling were more coherent and creative, especially at higher temperatures. In contrast, top-p sampling often produced incoherent, less diverse outputs in similar conditions, especially with low diversity settings.

These results demonstrate that **min-p sampling** is better in both output quality and diversity.

7 Conclusion

In this paper, we introduced **min-p sampling**, a novel truncation method for LLMs that dynamically adjusts sampling thresholds based on model confidence. Our approach effectively balances creativity and coherence, particularly at higher temperatures where methods like top-p sampling struggle.

Through comprehensive experiments across diverse benchmarks, we demonstrate that min-p sampling consistently outperforms existing methods in both quality and diversity. Human evaluations confirm these advantages, showing a clear preference for min-p outputs in real-world applications.

Min-p sampling's strengths lie in its simplicity, computational efficiency, and seamless integration into existing pipelines. By addressing the longstanding trade-off between diversity and quality, min-p represents a significant advancement for generative language modeling, enhancing applications that require both high-quality and diverse text generation (for examples, see appendix B).

REPRODUCIBILITY STATEMENT

We have made significant efforts to ensure the reproducibility of our results. The implementation of the proposed min-p sampling method is provided in Appendix C and is also available at our project repository.[3] Detailed descriptions of experimental setups, including model configurations, hyperparameter settings, and evaluation protocols, are outlined in Section 5 and Appendix C.1. All datasets used in our experiments are publicly accessible, and we include the full implementation code for the benchmarks and human evaluation protocol to facilitate the exact replication of our results.

ETHICS STATEMENT

Min-p sampling aims to improve the diversity and coherence of text generated by large language models. We acknowledge the following ethical considerations:

- **Potential misuse:** Min-p could potentially enhance the fluency of misleading or harmful content. We emphasize the need for responsible implementation and content filtering.
- **Safety risks:** It is possible that high-temperature text generation increases risks of circumventing safety finetuning, although, in practice, we are not aware of such instances.
- **Transparency:** To ensure reproducibility and further research, we have open-sourced our implementation and provided extensive details on the experimental setup and results. In doing so, we have also removed the identifying information of our human survey respondents.
- **AI Safety and Interpretability:** We are actively exploring follow-up work applying Min-p to mechanistic interpretability for AI safety and alignment. Specifically, we are investigating its use in uncertainty-aware generation, neuron activation filtering, and structured latent selection to enhance model robustness and truthfulness. We discuss an extension of this approach in §A, where we introduce min-z, a variation that leverages standard deviation-based filtering for broader applications.

We believe the benefits of entropy and uncertainty-based methods outweigh these risks. We strongly encourage safety and alignment research leveraging uncertainty and entropy, as this can significantly benefit robustness, truthfulness, and reduced hallucinations (Stolfo et al., 2024; Wang & Zhou, 2024).

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A Limitations and Future Work

While min-p sampling shows significant promise, there are limitations and opportunities for future research:

Standard Deviation Sampling: As of February 2025, we are aware of the Top-Nσ (Tang et al., 2024) method, which builds on min-p by filtering tokens based on the standard deviation of the logit distribution. It defines a truncation threshold:

$$n_{\text{thresh}} = \beta \cdot \sigma, \quad S = \{i \mid l'_i \geq M - n_{\text{thresh}}\}$$

where $M = \max(l')$ and σ is the standard deviation of the logits.

We are actively exploring **Min-z sampling**, a variation that replaces the mean-based threshold with a median-centered approach for robustness against skewed distributions. Min-z derives its name from its use of the Z-score to normalize token logits before truncation, ensuring a more adaptive and information-theoretic selection criterion:

$$n_{\text{thresh}} = \beta \cdot \frac{M - \text{med}(l')}{\sigma}, \quad S = \left\{ i \mid \frac{l'_i - \text{med}(l')}{\sigma} \geq n_{\text{thresh}} \right\}$$

Here, each logit is transformed into a Z-score relative to the median rather than the mean, making the method more robust to heavy-tailed distributions and extreme outliers.

Both methods dynamically truncate low-probability tokens, but min-z is designed to be more information-efficient in heavy-tailed logit distributions. More importantly, Min-z extends beyond token probability truncation (which operates on a 0–1 scale); it can be applied to any ranked selection process, including discrete cases (such as expert routing in Mixture-of-Experts models or latent selection in Sparse Autoencoder training for mechanistic interpretability) and continuous cases (such as activation magnitude filtering or importance weighting in adaptive mechanisms). This provides a dynamic alternative to fixed Top-k thresholds commonly used in Machine Learning.

Generalization to Other Models: Our experiments focused on the Mistral and Llama 3 series models. Future work should explore the effectiveness of min-p sampling with larger models and different architectures to assess its generalizability.

Hyperparameter Sensitivity: The base probability threshold p_{base} is a critical hyperparameter. Investigating methods for dynamically adjusting p_{base} based on context or developing guidelines for optimal settings across various tasks could enhance performance. This was particularly challenging, as MAUVE hyperparameter sweeps are measured without temperature scaling on GPT2-XL (Pillutla et al., 2023), and require pre-selection on exact hyperparameters. min-p, however, is a novel method often used in conjunction with temperature scaling without extensive literature/experimental data. We discuss this further in Appendix C.1.

Combined Sampling Approaches: While our own tests do not find benefits to combining truncation sampling methods, and there is little existing research into the matter, we acknowledge that combining truncation sampling approaches could be viable. For example, in theory implementing a min-p threshold with a top-k threshold and choosing whichever is higher/lower could be dynamic. However, this is hard to test as we would have to isolate relative contributions of both methods, tune hyperparameters separately and account for benchmark variance among other things.

Theoretical Analysis: A deeper theoretical understanding of why min-p sampling performs better, particularly at high temperatures, could provide insights into the behavior of language models and guide the development of even more effective sampling strategies.

Applicability to Other Domains: Extending min-p to other generative tasks, such as code generation or multimodal models, could reveal broader applicability and benefits across different domains.

Research into high-temperature regimes: High-temperature regimes have been underexplored relative to low-temperature regimes. Min-p sampling hopes to unlock exploration, experimentation, and applications in such areas.

Human Evaluation Scope: Our human evaluation involved participants selecting pre-generated outputs. We note that min-p's popularity within the open source community for creative writing is interactive in nature; hence, we hope for adoption on interactive human evaluation platforms such as the Chatbot Arena (Chiang et al., 2024).

Combining uncertainty and CoT decoding methods: Wang & Zhou (2024) found a significant correlation between the confidence/certainly level of the final answer token choice and correct scores on GSM8K CoT, and that promoting diverse lower-probability token choices encouraged generating chains of thought that were beneficial for reasoning, resulting in higher scores overall.

This mirrors our hypothesis that choosing high-certainty tokens enables more accurate final answers, while diverse token choices benefit intermediate reasoning steps. For example, we note that GPQA scores on Mistral 7B increased from $\tau = 1.0$ to $\tau = 1.5$, but only with Temperature Only and min-p. With the recent release of OpenAI's O1 models, which leverage CoT methods at inference for advanced reasoning capabilities, we note several novel decoding methods that combine uncertainty and CoT sampling approaches to improve model reasoning in a simple manner, with minimal added overhead and architectural changes (Wang & Zhou, 2024; xjdr & doomslide, 2024) . We aim to actively explore such methods in future work.

B Real-World Applications of Min-p Sampling

Min-p sampling demonstrates practical utility across several domains where high-temperature incoherence was previously a bottleneck:

- **Creative Writing:** Enhances narrative generation by allowing higher temperatures without losing coherence, unlocking new capabilities for storytelling and poetry.
- **Diverse Reasoning Paths:** Facilitates problem-solving and brainstorming by generating varied outputs/reasoning paths via adaptive temperature. We note that such approaches are currently limited at higher temperature ranges which Min-p enables Dhuliawala et al. (2024); xjdr & doomslide (2024); Zhang et al. (2024). Wang Wang & Zhou (2024) found that even while solving basic arithmetic in GSM8K chain-of-thought (COT), diverse COT reasoning tokens outperform pure greedy COT decoding. This, in conjunction with our results showing that Min-p sampling combined with higher temperature outperformed greedy decoding on Llama3.2 3B and Llama 3.1 8B, suggests that optimizing diversity and accuracy can surpass traditional deterministic approaches.
- **Confidence Calibration:** Allows users to assess model confidence through output variability Li et al. (2024).
- **Red-Teaming and Adversarial Testing:** Generates diverse behaviors for identifying vulnerabilities and biases Anurin et al. (2024).

- **Code Generation:** Produces coherent and structured code snippets, even at high temperatures.

These applications align with Min-p sampling's performance advantages and its widespread adoption in the open-source community.

C MIN-p IMPLEMENTATION AND DOCUMENTATION

Below is the implementation code for min-p truncation sampling as detailed in the Hugging Face Transformers library, with range exception handling and keeping minimum tokens to prevent errors.

This implementation code, along with other similar implementations in other open-source inference engines, logs of automated evaluations for GPQA, GSM8K Chain-of-Thought and AlpacaEval Creative Writing is available at `https://github.com/menhguin/minp_paper/`.

```
class MinPLogitsWarper(LogitsWarper):
    def __init__(self, min_p: float, filter_value: float = -float("Inf"), min_tokens_to_keep: int = 1):
        if min_p < 0 or min_p > 1.0:
            raise ValueError(f"`min_p` has to be a float >= 0 and <= 1, but is {min_p}")
        if not isinstance(min_tokens_to_keep, int) or (min_tokens_to_keep < 1):
            raise ValueError(f"`min_tokens_to_keep` has to be a positive integer, but is {min_tokens_to_keep}")

        self.min_p = min_p
        self.filter_value = filter_value
        self.min_tokens_to_keep = min_tokens_to_keep

    def __call__(self, input_ids: torch.LongTensor, scores: torch.FloatTensor) -> torch.FloatTensor:
        # Convert logits to probabilities
        probs = torch.softmax(scores, dim=-1)
        # Get the probability of the top token for each sequence in the batch
        top_probs, _ = probs.max(dim=-1, keepdim=True)
        # Calculate the actual min_p threshold by scaling min_p with the top token's probability
        scaled_min_p = self.min_p * top_probs
        # Create a mask for tokens that have a probability less than the scaled min_p
        tokens_to_remove = probs < scaled_min_p

        sorted_indices = torch.argsort(scores, descending=True, dim=-1)
        sorted_indices_to_remove = torch.gather(tokens_to_remove, dim=-1, index=sorted_indices)
        # Keep at least min_tokens_to_keep
        sorted_indices_to_remove[..., : self.min_tokens_to_keep] = False

        indices_to_remove = sorted_indices_to_remove.scatter(1, sorted_indices, sorted_indices_to_remove)
        scores_processed = scores.masked_fill(indices_to_remove, self.filter_value)
        return scores_processed
```

C.1 HYPERPARAMETERS SETTINGS

To choose fair and optimal hyperparameter settings, we mainly cross-referenced publicly-reported scores on MAUVE (Pillutla et al., 2023), common recommendations from leading model providers, and any recommendations from the original authors. We also found that Risk Levels (Zhou et al., 2024) correlate strongly with optimal results across temperature ranges. Our main tables display the

hyperparameters, which lead to the best overall results for each method. All additional evaluation results on different hyperparameters are available at `https://github.com/menhguin/minp_paper/`

For min-p, base probability thresholds of $p_{\text{base}} = 0.05$ and 0.1 were used, while top-p sampling employed $p = 0.9$.

For min-p = 0.05 and 0.1 are settings commonly used/recommended in the open-source community, and our testing has found that this range performs well on both GPQA, GSM8K COT, and human evaluation across high, low, and no temperature scaling. We also tested min-p = 0.2 and min-p = 0.3, but these are not commonly used.

For top-p, top-p = 0.9 and top-p =0.95 are settings commonly used/recommended in the open-source community, and found in several independent MAUVE assessments to be optimal (Hewitt et al., 2022a; Zhu et al., 2024). We mainly reference the Risk Levels framework from Zhou et al. (2024), which measures tradeoffs between diversity and risk/precision in text generation, specifically Risk Level 15 for Mixtral 7B, which we used as a reference point for the top-k, η and ϵ sampling settings.

Model	Method	Parameter	Risk Std Error ↓	Recall ↑
Mixtral-7b	**Top-k**	181	**1.759**	0.364
	Top-p	0.9315	6.315	0.447
	Adaptive	2.2e-5	2.757	0.466
	Eta	1.96e-4	4.712	**0.505**
	Mirostat	6.71	2.213	0.468

Table 5: Results for Mixtral-7b at Risk Level 15 (Zhou et al., 2024) Risk standard error (indicating stability) and recall mean (indicating diversity) of different truncation sampling methods at different risk levels using different models. The best and worst scores are marked in **bold** and blue, respectively.

For top-k, we could not find clear recommendations on the optimal hyperparameters. We conducted tests on k = 10, 15, 20, 40, 50 and 180. Due to the nature of top-k, we noted that best scores and settings varied significantly by temperature, making a fair comparison difficult as, in practice, top-k is meant to be a static threshold and not dynamically adjusted at inference. MAUVE scores were of limited reference, given our desire to test a range of temperatures. Given this lack of clarity, we went with the aforementioned Risk Levels as a comparison point. (Zhou et al., 2024)

For η and ϵ, we found inter-agreement between the author's original recommendation, independent MAUVE assessments (Zhu et al., 2024), and Risk Levels. We tested η and ϵ values 0.0002 and 0.0009, found 0.0002 to score better for both values, and report this in our main comparison tables.

C.2 Test Time Compute challenges

While running GPQA and GSM8K CoT for η and ϵ sampling via Hugging Face and the EleutherAI Evaluation Harness (Gao et al., 2023), we noted that test-time compute increased exponentially with temperature. Throughout our experiments, min-p, top-p, and top-k generally took 2-5 minutes to evaluate on Mistral 7B at every temperature for both GPQA and GSM8K. Runtime on an A100 Colab increased from 5 minutes at $\tau = 0.7$ to 8 minutes at $\tau = 1$ and 30 minutes at $\tau = 1.5$. Neither η nor ϵ seemed to function at $\tau >= 2$. On GSM8K, η and ϵ each took 2 hours to evaluate, which is equal to the average for our Llama 70B/Mistral Large run. This time also appeared to scale exponentially with increased temperature.

Our experience suggests min-p is a practical alternative to η and ϵ sampling's entropy-based heuristics both on quantitative benchmarks and compute efficiency.

C.3 How percentages thresholds differ for min-p and top-p

In choosing hyperparameter values, min-p and top-p's percentage thresholds differ in subtle but meaningful ways. Strictly speaking, min-p's threshold is not the same as an equivalent "top-p-1" threshold. For example, when top-p = 0.9, the last <10% of the total distribution is truncated. However, it's possible for min-p = 0.1 to truncate more than 10% of a distribution.

Consider the following top 5 tokens probabilities: 80%, 7%, 3%, 2%, 1%. With top-p set to 0.9, the top 3 tokens comprising 90% of the distribution is preserved. With min-p p_{base} = 0.1, and the resulting truncation threshold at 8%, only the top token is preserved, and 20% of the original distribution is truncated.

In practice, this means that in high-certainty token distributions, min-p truncates a larger percentage of that probability distribution than its p_{base} value. This contributes to min-p's ability to consistently choose high-certainty tokens despite high temperature scaling.

Hence, low p_{base} values (such as from 0.01 to 0.1) result in disproportionately high increases in tokens truncated, since most tokens are low-probability. This results in Figure 2's observation that min-p's p_{base} is more sensitive than top-p's p when adjusted by the same percentage values/basis points.

D Detailed Community Adoption Statistics

To provide further transparency regarding the adoption of Min-p sampling, Table 6 summarizes key statistics from several major projects that have integrated the method.

Repository	**Stars**	**Downstream Repos**
Hugging Face Transformers	140,000	291,000
Ollama	130,000	400
vLLM	39,700	—
SGLang	11,000	—
unsloth	32,800	—
Total	353,500	291,400

Table 6: GitHub statistics for major projects integrating Min-p sampling. Note that the downstream repository count is available for Hugging Face Transformers and Ollama.

Notes: The data above is based on a manual search and publicly available GitHub statistics as of early 2025.

Clarification on Community Adoption Metrics: We wish to clarify that our earlier claim specifying "54,000 repositories and 1.1 million stars" was based on preliminary GitHub scans. An independent contributor has discussed specific limitations of the search approach we used at the time Nguyen (2025).

In the camera-ready version, we have revised this statement to focus on high-traffic, production-grade frameworks indicative of real-world usage. Specifically, Min-p sampling is integrated into widely used projects such as Hugging Face Transformers, vLLM, and SGLang, which collectively account for over 350,000 GitHub stars, with Hugging Face Transformers alone having over 291,000 downstream dependent repositories (see Appendix D for details). We believe this approach provides a more accurate and verifiable measure of community adoption

We also note the relative difficulty of obtaining direct usage statistics/real user preference data, as many leading providers we queried do not specifically collect or disclose such statistics.

E Benchmark Evaluation Results

E.1 Ablation Study

The results in Table 7 show that min-p sampling generally outperforms top-p sampling across different temperatures and parameter settings, particularly in terms of the Winrate metric. The highest winrate is achieved with min_$p = 0.1$ at temperature $\tau = 1.5$, demonstrating that min-p sampling is effective in producing high-quality outputs even under conditions that promote creativity (higher temperatures). Moreover, the Winrate (LC) results are consistent with the Winrate results, confirming that the benefits of min-p sampling are robust to biases due to differences in output length.

Table 7: Ablation study on AlpacaEval Creative Writing benchmark. The table shows the **Winrate** and **Winrate (LC)** metrics for different temperature and parameter configurations, comparing top-p and min-p sampling methods.

Method	Temperature	Configuration	Winrate (%)	Winrate (LC) (%)
Top-p Sampling Configurations				
Top-p	0.8	$p = 0.98$	54.65	51.29
Top-p	1.0	$p = 0.98$	53.00	50.43
Top-p	1.0	$p = 0.9$	52.07	50.07
Top-p	0.8	$p = 0.95$	51.80	50.22
Top-p	0.8	$p = 0.95$	50.76	48.78
Min-p Sampling Configurations				
Min-p	1.5	$p_{\text{base}} = 0.1$	**58.12**	**56.54**
Min-p	1.0	$p_{\text{base}} = 0.05$	**55.07**	**52.01**
Min-p	1.0	$p_{\text{base}} = 0.1$	**53.24**	**50.14**
Min-p	1.0	$p_{\text{base}} = 0.02$	**51.62**	**50.43**
Min-p	1.0	$p_{\text{base}} = 0.02$	**51.46**	**48.85**
Min-p	0.8	$p_{\text{base}} = 0.05$	**50.99**	**47.84**

E.2 GPQA

These results demonstrate min-p's ability to maintain higher levels of coherence and accuracy in multi-step reasoning tasks, even when the diversity of token selection is increased through higher temperature settings. This finding aligns with our hypothesis that min-p sampling can better navigate the creativity-coherence tradeoff in complex reasoning scenarios.

E.3 Full Plots for GSM8K/GPQA results

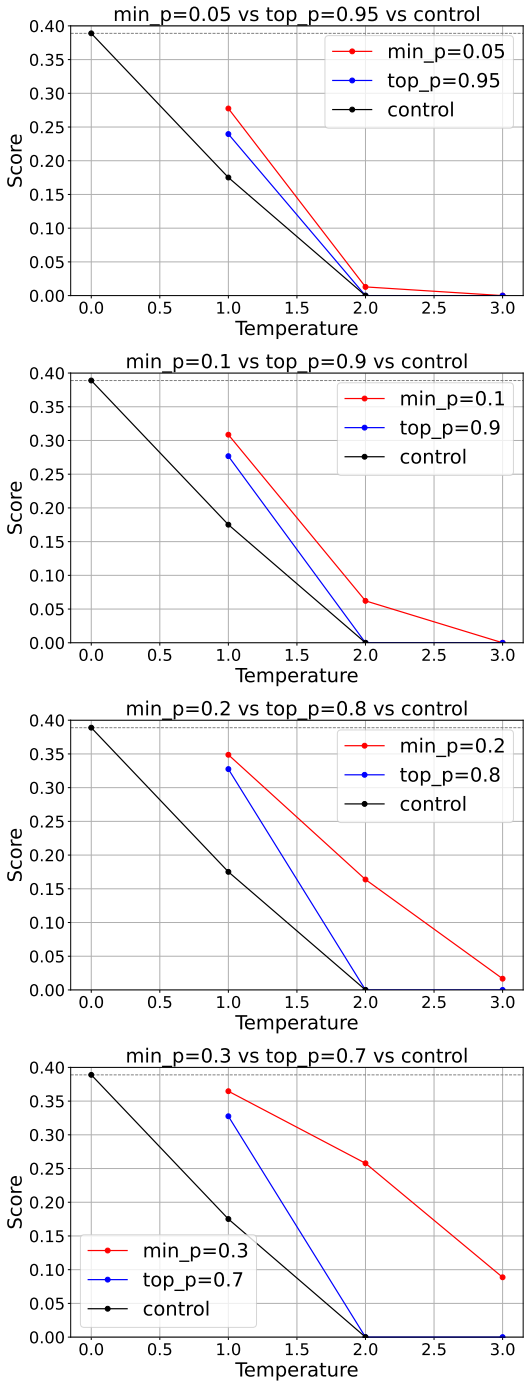

Figure 3: Results of running min-p vs top-p on GSM8K. The control method used is pure sampling.

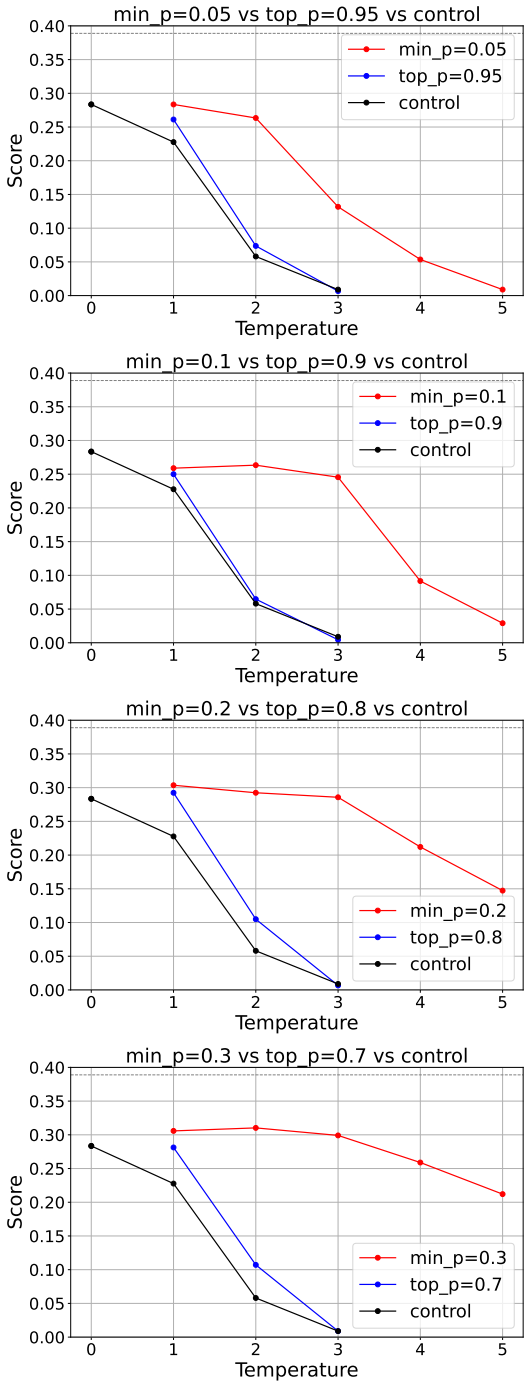

Figure 4: Results of running min-p vs top-p on GPQA. The control method used is pure sampling.

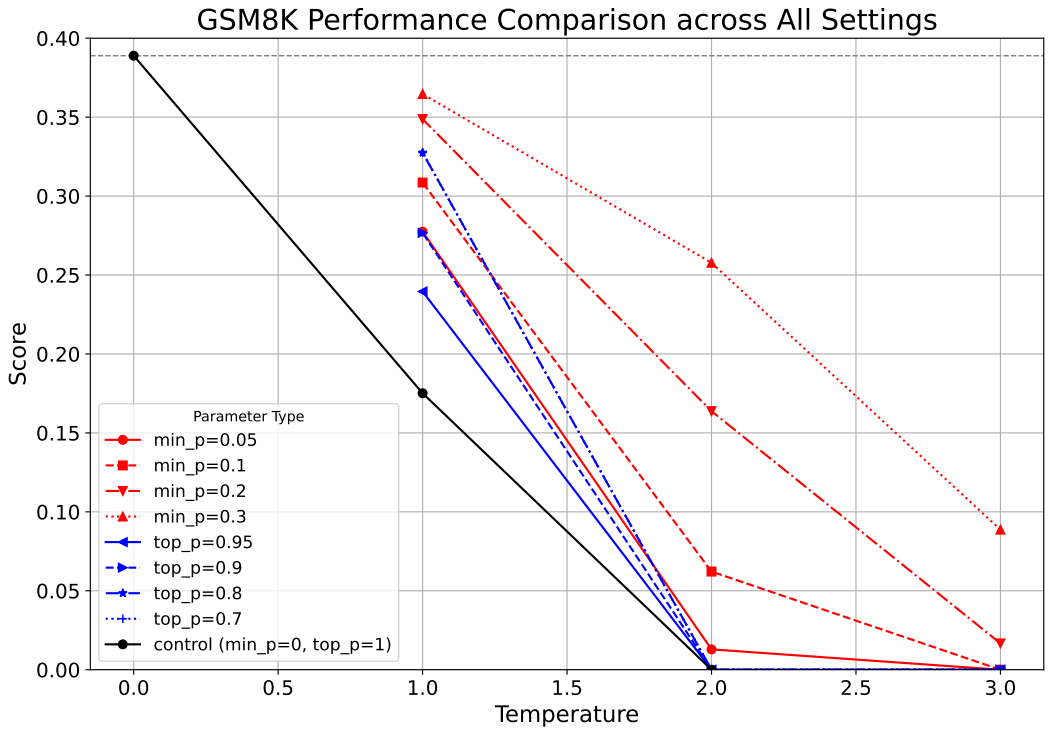

Figure 5: Results for all GSM8K experiments on a single plot.

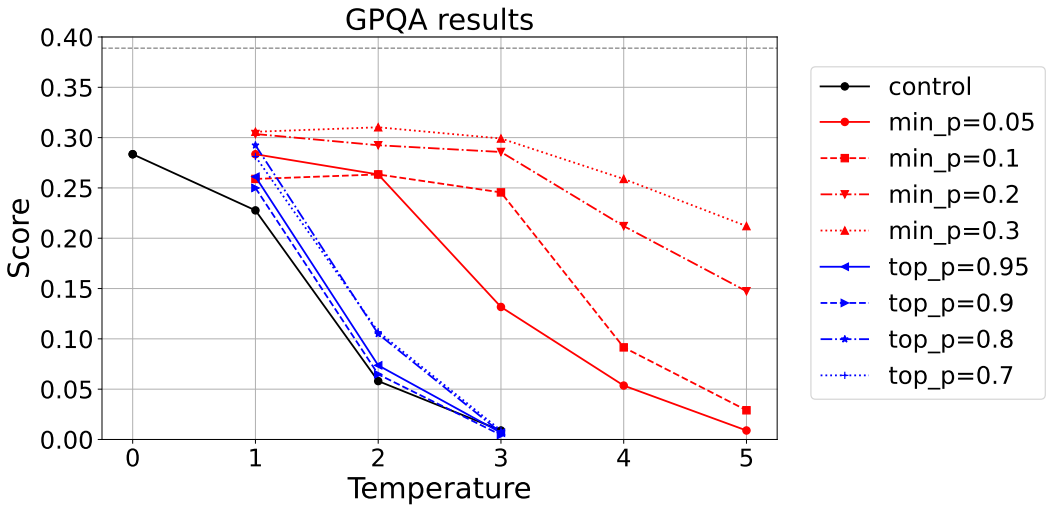

Figure 6: Results for all GPQA experiments on a single plot.

F Additional Results

F.1 Results of GPQA Main or GSM8K CoT benchmarks for Llama 3 models

Table 8: Accuracy (%) on GPQA Main or GSM8K CoT benchmark for Llama 3 models

(a) Accuracy (%) on GPQA Main benchmark (LLAMA 3.2 1B-Instruct)

Temperature	0.0	0.3	0.5	0.7	1.0	1.5	2.0	3.0	4.0	5.0
Temp' Only	28.57	28.57	25.89	26.79	24.55	12.95	3.35	2.46	2.23	2.01
Top-p = 0.9	28.57	27.23	28.79	27.23	25.45	18.75	3.57	2.68	2.01	2.23
Top-p = 0.95	28.57	29.24	26.34	26.56	25.67	19.64	6.03	2.68	2.46	2.90
Min-p = 0.05	28.57	**29.46**	**30.13**	**27.46**	23.88	23.44	22.32	16.52	6.47	3.12
Min-p = 0.1	28.57	27.46	28.57	27.01	**26.56**	**25.67**	**21.43**	**19.42**	**14.29**	**6.92**

(b) Accuracy (%) on GSM8K CoT benchmark (LLAMA 3.2 1B-Instruct)

Temperature	0.0	0.3	0.5	0.7	1.0	1.5	2.0	3.0	4.0	5.0
Temp' Only	46.55	45.03	42.99	37.60	28.89	0.23	0.00	0.00	0.00	0.00
Top-p = 0.9	46.55	45.19	44.20	40.11	37.23	5.23	0.00	0.00	0.00	0.00
Top-p = 0.95	46.55	44.73	44.28	41.62	33.89	2.50	0.00	0.00	0.00	0.00
Min-p = 0.05	46.55	43.67	**45.11**	42.23	36.24	24.64	7.05	0.00	0.00	0.00
Min-p = 0.1	46.55	**45.49**	43.63	**42.68**	**40.18**	**29.11**	**17.06**	**9.82**	**0.15**	0.00

(c) Accuracy (%) on GPQA Main benchmark (LLAMA 3.2 3B-Instruct)

Temperature	0.0	0.3	0.5	0.7	1.0	1.5	2.0	3.0	4.0	5.0
Temp' Only	27.23	25.89	24.55	27.68	25.00	20.09	5.36	2.23	2.23	1.79
Top-p = 0.9	27.23	**29.46**	27.68	28.79	30.36	25.45	9.82	2.68	2.68	1.79
Top-p = 0.95	27.23	28.79	27.23	27.68	29.46	23.00	5.58	3.13	1.79	1.79
Min-p = 0.05	27.23	28.35	27.46	27.23	**32.37**	27.68	**27.46**	21.65	11.38	3.79
Min-p = 0.1	27.23	28.35	**28.79**	**31.70**	29.24	**31.25**	23.66	**23.66**	**16.96**	**8.93**

(d) Accuracy (%) on GSM8K CoT benchmark (LLAMA 3.2 3B-Instruct)

Temperature	0.0	0.3	0.5	0.7	1.0	1.5	2.0	3.0	4.0	5.0
Temp' Only	76.72	77.10	76.42	74.00	64.59	3.11	0.00	0.00	0.00	0.00
Top-p = 0.9	76.72	76.65	76.72	75.66	**73.31**	28.81	0.00	0.00	0.00	0.00
Top-p = 0.95	76.72	**77.41**	**77.63**	**76.50**	71.11	16.83	0.00	0.00	0.00	0.00
Min-p = 0.05	76.72	76.12	76.50	75.51	73.24	57.92	26.61	0.15	0.00	0.00
Min-p = 0.1	76.72	77.18	75.51	75.36	73.01	**75.44**	**52.08**	**2.50**	0.00	0.00

(e) Accuracy (%) on GPQA Main benchmark (LLAMA 3.1 8B-Instruct)

Temperature	0.0	0.3	0.5	0.7	1.0	1.5	2.0	3.0	4.0	5.0
Temp' Only	29.02	27.46	28.79	29.91	30.36	22.99	6.92	3.12	2.46	3.35
Top-p = 0.9	29.02	28.57	29.69	**30.80**	28.79	24.55	9.38	2.46	2.46	2.90
Top-p = 0.95	29.02	**30.36**	**31.92**	27.68	**30.58**	25.67	10.04	2.68	2.90	2.90
Min-p = 0.05	29.02	30.13	31.70	**30.80**	28.35	26.34	**29.24**	22.77	9.82	5.13
Min-p = 0.1	29.02	30.13	29.69	29.24	29.24	**32.14**	25.22	**22.99**	**20.54**	**12.50**

(f) Accuracy (%) on GSM8K CoT benchmark (LLAMA 3.1 8B-Instruct)

Temperature	0.0	0.3	0.5	0.7	1.0	1.5	2.0	3.0	4.0	5.0
Temp' Only	84.91	84.61	**84.84**	81.50	75.21	10.39	0.00	0.00	0.00	0.00
Top-p = 0.9	84.91	84.91	84.08	83.24	80.36	48.37	0.08	0.00	0.00	0.00
Top-p = 0.95	84.91	84.23	84.08	82.26	80.06	32.52	0.00	0.00	0.00	0.00
Min-p = 0.05	84.91	**85.06**	84.31	**83.32**	80.44	67.25	32.15	0.08	0.00	0.00
Min-p = 0.1	84.91	84.46	**84.84**	82.87	**82.18**	**75.44**	**52.08**	**2.50**	0.00	0.00

Table 9: Accuracy (%) on GPQA Main and GSM8K CoT benchmarks for Llama 3.1 70B models

(a) Accuracy (%) on GPQA Main benchmark (Llama 3.1 70B)

Temperature	0.5	0.7	1.0	2.0	3.0
Temp' Only	40.85	39.51	41.07	5.58	2.46
Top-p = 0.9	40.85	**42.19**	40.63	7.81	3.35
Top-p = 0.95	40.63	41.29	39.51	6.47	2.68
Min-p = 0.05	40.85	41.52	38.62	33.71	23.88
Min-p = 0.1	41.07	**42.19**	**41.52**	33.04	24.55
Min-p = 0.2	**43.30**	41.96	40.40	**34.38**	**31.47**

(b) Accuracy (%) on GSM8K CoT benchmark (Llama 3.1 70B)

Temperature	0.7	3.0
Temp' Only	93.33	0.08
Top-p = 0.9	**93.48**	0.08
Min-p = 0.05	93.03	6.07
Min-p = 0.2	92.42	**61.03**

F.2 Results of GPQA Main or GSM8K CoT Benchmarks for Mistral 7B Models - Low Temperatures ($T \leq 0.5$)

Table 10: Accuracy (%) on GPQA Main benchmark for Mistral-7B model.

(a) Accuracy (%) on GPQA Main benchmark (Mistral-7B).

Temperature	0.0	0.05	0.1	0.2	0.3	0.5
Temp Only	27.68	27.68	26.34	25.22	24.33	24.11
Top-p = 0.9	27.68	28.13	27.23	**26.56**	**24.78**	**24.55**
Top-p = 0.95	27.68	27.90	27.23	25.22	24.55	24.11
Min-p = 0.05	27.68	27.90	27.23	25.45	24.55	24.33
Min-p = 0.1	27.68	**28.35**	**27.46**	**26.56**	24.33	24.33

Table 11: Accuracy (%) on GSM8K benchmark for Mistral-7B model.

(a) Accuracy (%) on GSM8K benchmark (Mistral-7B).

Temperature	0.0	0.05	0.1	0.2	0.3	0.5
Temp Only	39.35	38.59	38.21	38.59	37.23	36.32
Top-p = 0.9	39.35	**39.27**	**40.03**	39.27	37.53	**38.36**
Top-p = 0.95	39.35	38.74	38.74	39.58	37.38	36.62
Min-p = 0.05	39.35	38.59	39.65	**40.33**	**38.44**	37.68
Min-p = 0.1	39.35	39.20	38.51	38.21	38.06	37.07

F.3 Results of GPQA Main or GSM8K CoT Benchmarks for Mistral 7B Models - Combined Top P and Top K sampling

Table 12: Accuracy (%) on GPQA Main and GSM8K CoT benchmarks for various Top P, Top K and Temperature configurations on Mistral 7B.

TOP-P = 0.5

	GPQA Main						GSM8K CoT				
Top-k	0.5	0.7	1.0	2.0	3.0	Top-k	0.5	0.7	1.0	2.0	3.0
10.0	27.0	27.7	27.0	27.2	**26.3**	10.0	**39.3**	38.5	38.7	**30.4**	**12.5**
50.0	27.0	27.7	27.0	**28.1**	19.4	50.0	38.0	**39.5**	37.1	18.8	0.5
177.0	27.0	27.7	27.0	27.0	18.1	177.0	38.0	38.6	**40.3**	12.1	0.0

TOP-P = 0.9

	GPQA Main						GSM8K CoT				
Top-k	0.5	0.7	1.0	2.0	3.0	Top-k	0.5	0.7	1.0	2.0	3.0
10.0	26.6	27.0	27.0	**23.7**	**19.4**	10.0	**41.8**	**39.6**	**34.3**	**4.4**	0.9
50.0	26.6	27.0	27.0	20.8	10.9	50.0	40.6	39.4	**34.3**	1.1	**1.5**
177.0	26.6	27.0	**27.7**	22.1	5.6	177.0	38.9	37.4	32.8	1.3	0.6

TOP-P = 0.95

	GPQA Main						GSM8K CoT				
Top-k	0.5	0.7	1.0	2.0	3.0	Top-k	0.5	0.7	1.0	2.0	3.0
10.0	26.8	**28.6**	**26.1**	**24.1**	**14.5**	10.0	35.9	33.1	**26.3**	**1.4**	**0.2**
50.0	26.8	27.2	24.3	19.4	10.3	50.0	**37.0**	33.9	24.9	0.1	0.0
177.0	26.8	27.2	24.3	17.9	7.8	177.0	**37.0**	**35.2**	24.6	0.0	0.0

TOP-P = 1.0

	GPQA Main						GSM8K CoT				
Top-k	0.5	0.7	1.0	2.0	3.0	Top-k	0.5	0.7	1.0	2.0	3.0
10.0	26.8	**25.2**	23.4	**22.1**	**15.8**	10.0	**34.6**	29.8	**20.3**	**0.8**	0.0
50.0	**27.5**	23.0	25.4	17.4	10.5	50.0	33.1	31.8	17.5	0.0	0.0
177.0	**27.5**	23.0	**26.8**	14.7	4.2	177.0	33.3	**32.8**	19.0	0.0	0.0

F.4 Results of High Minimum Probability Sampling with Mistral-7B on Mathematical Reasoning Tasks

Temperature	min_p	GSM8K Score	GPQA Score
3.0	0.7	**0.4041**	0.2478
	0.6	0.3533	0.2500
	0.5	0.3237	0.2433
	0.4	0.2297	0.2299
	0.3	0.1327	**0.2746**
2.0	0.7	0.4071	0.2455
	0.6	**0.4162**	0.2567
	0.5	0.3738	0.2567
	0.4	0.3397	0.2545
	0.3	0.3078	**0.2813**
1.0	0.7	**0.4215**	**0.2790**
	0.6	0.3958	0.2545
	0.5	0.4124	0.2478
	0.4	0.4185	0.2589
	0.3	0.3942	0.2522
0.7	0.7	**0.4412**	**0.2835**
	0.6	0.4208	**0.2835**
	0.5	0.4177	0.2813
	0.4	0.4200	0.2567
	0.3	0.4155	0.2679
0.5	0.7	0.4200	**0.2857**
	0.6	0.4155	0.2835
	0.5	0.4147	0.2835
	0.4	0.4117	0.2746
	0.3	**0.4359**	0.2612

Table 13: Performance results for different min_p values and temperatures on GSM8K and GPQA benchmarks. The highest scores for each benchmark are shown in bold.

F.5 Greedy Decoding Model Performance on GPQA and GSM8K

Table 14: Performance Comparison between Best Score and Greedy Score

Model	**Greedy Score (T=0)**	**Best Score**	**Hyperparameters**	**Temperature**
GPQA (<10B Models)				
Mistral 7B	27.35%	29.18% (+1.83%)	Min P = 0.1	0.7
Llama 3.2 3B	27.23%	32.37% (+5.14%)	Min P = 0.05	1.0
Llama 3.1 8B	29.02%	32.15% (+3.13%)	Min P = 0.1	1.5
GPQA (Larger Models)				
Llama 3.1 70B	41.07%	43.30% (+2.23%)	Min P = 0.2	0.3
Llama 3.1 70B	41.07%	42.19% (+1.12%)	Min P = 0.1	0.5
Llama 3.1 70B	41.07%	41.52% (+0.45%)	Min P = 0.1	1.0
GSM8K				
Mistral 7B	39.35%	40.33% (+0.98%)	Min P = 0.05	0.3
Llama 3.1 8B	84.91%	85.06% (+0.15%)	Min P = 0.05	0.2

F.6 Additional LLM-As-A-Judge Evaluation for Creative Writing

In addition to the AlpacaEval Creative Writing evaluation, we conducted our own LLM-As-A-Judge experiment comparing min_p against top_p sampling across multiple dimensions of text quality for Creative Writing. We also used this opportunity to test the performance of min_p on constrained/structured generation tasks. Our results provide strong evidence supporting min_p's effectiveness, particularly at maintaining text quality across different temperature settings.

Specifically, we conducted a comprehensive evaluation using two language models of different scales:

- Llama-3.2-1B-Instruct (1B parameters)
- Mistral-7B-v0.1 (7B parameters)

F.6.1 STRUCTURED GENERATION FRAMEWORK

To ensure consistent and comparable outputs, we implemented a structured generation approach using Pydantic schemas for the two models. We keep it simple as a baseline:

```
class CreativeStory(BaseModel):
    themes: List[str]
    writing_complexity: int = Field(ge=1, le=10)
    short_story_text: str
```

The models' outputs were constrained using `lmformatenforcer`'s JsonSchemaParser and transformers prefix token filtering, ensuring all generated stories followed the same structured format.

F.6.2 CREATIVE WRITING TASK

We used three distinct creative writing prompts to evaluate generation quality:

1. "Write a story about a mysterious door that appears in an unexpected place"
2. "Write a story about an alien civilization's first contact with Earth from their perspective"
3. "Write a story about a world where time suddenly starts moving backwards"

F.6.3 SAMPLING PARAMETERS

We tested a comprehensive matrix of sampling parameters:

- Temperatures: [0.5, 1.0, 2.0, 3.0, 5.0]
- min_p values: [0.05, 0.1, 0.2]
- top_p values: [0.9, 0.95, 0.99]

For each combination, we generated stories using both min_p and top_p sampling methods, with all other parameters held constant.

F.6.4 EVALUATION METHODOLOGY

Blind Comparison Setup

- For each comparison, stories from both sampling methods were randomly ordered as Response 1 or Response 2 (to mitigate position bias)
- The evaluation system was blind to which sampling method produced each response
- A GPT-4o model served as the judge, using a structured evaluation schema:

```
class LLMasJudge(BaseModel):
    response1_creativity_score: Literal["0" to "10"]
    response1_originality_score: Literal["0" to "10"]
    response1_narrative_flow_score: Literal["0" to "10"]
    response1_emotional_impact_score: Literal["0" to "10"]
    response1_imagery_score: Literal["0" to "10"]
    response2_[same metrics as above]
    detailed_feedback: str
    overall_winner: Literal["1", "2"]
```

Judge Configuration

- Model: GPT-4
- Temperature: 1.0 (to ensure consistent but non-deterministic evaluation)
- Structured output enforcement using OpenAI's beta chat completions parse endpoint
- System prompt: "You are an expert judge evaluating AI-generated creative writing"

Evaluation Metrics Each story was evaluated on five dimensions:

1. Creativity: Novelty and uniqueness of ideas
2. Originality: Innovative approach to the prompt
3. Narrative Flow: Coherence and story progression
4. Emotional Impact: Ability to evoke feelings
5. Imagery: Vividness of descriptions

F.6.5 Data Collection and Analysis

- Results were logged to Weights & Biases for tracking and analysis, and all results will be published on github
- Each evaluation included:
  - Full generated stories from both methods
  - Detailed scores across all metrics
  - Judge's qualitative feedback
  - Randomized position tracking
  - Complete parameter configuration

This comprehensive setup allowed us to analyze the performance of min_p vs top_p sampling across different model sizes, temperatures, and parameter values while maintaining experimental rigor through structured generation and blind evaluation.

F.6.6 Results of constrained LLM-as-judge evaluation

Overall Performance Our results show that min_p consistently outperforms top_p across all quality metrics:

Metric	min_p	top_p	Difference
Creativity	3.55	3.09	+0.46
Originality	3.28	2.85	+0.43
Narrative Flow	2.96	2.26	+0.70
Emotional Impact	2.62	2.10	+0.52
Imagery	2.98	2.36	+0.62

Table 15: Overall Performance Comparison

Temperature Stability A particularly notable finding is min_p's superior performance at maintaining quality across different temperature settings:

Low Temperature (0.5)

High Temperature (2.0)

F.6.7 Additional Result Tables: min_p vs top_p Comparison

Temperature Effects on Quality Metrics

Model	Metric	min_p	top_p
Llama-1B	Creativity	6.33	4.93
	Originality	5.70	4.48
Mistral-7B	Creativity	5.56	5.56
	Originality	5.07	4.89

Table 16: Low Temperature Results

Model	Metric	min_p	top_p
Llama-1B	Creativity	3.78	2.44
	Originality	3.63	2.59
Mistral-7B	Creativity	3.44	2.70
	Originality	3.04	2.44

Table 17: High Temperature Results

Model	Method	Creativity	Originality	Narrative Flow	Emotional Impact	Imagery
Llama-1B	min_p	2.12	1.96	1.19	1.12	1.27
Llama-1B	top_p	1.92	1.73	1.04	0.88	1.15
Mistral-7B	min_p	1.78	1.81	0.96	1.00	1.11
Mistral-7B	top_p	1.59	1.48	0.74	0.78	0.81

Table 18: Results at Temperature 3.0

Model	Method	Creativity	Originality	Narrative Flow	Emotional Impact	Imagery
Llama-1B	min_p	0.89	0.89	0.22	0.22	0.33
Llama-1B	top_p	1.04	1.04	0.33	0.33	0.41
Mistral-7B	min_p	0.70	0.59	0.04	0.04	0.04
Mistral-7B	top_p	1.26	1.30	0.48	0.44	0.52

Table 19: Results at Temperature 5.0

TEMPERATURE 3.0 RESULTS

TEMPERATURE 5.0 RESULTS

Performance by min_p Value (Temperature 1.0)

Model	Method	Creativity	Originality	Narrative Flow	Emotional Impact	Imagery
Llama-1B	min_p	4.78	4.22	4.56	3.44	4.11
Llama-1B	top_p	4.22	3.78	3.11	3.22	3.11
Mistral-7B	min_p	5.44	5.11	5.22	4.67	4.67
Mistral-7B	top_p	5.11	4.78	4.00	3.78	4.44

Table 20: Results with min_p = 0.05

MIN_P = 0.05

Model	Method	Creativity	Originality	Narrative Flow	Emotional Impact	Imagery
Llama-1B	min_p	5.00	4.67	4.11	3.89	3.67
Llama-1B	top_p	5.44	4.67	3.89	3.67	3.56
Mistral-7B	min_p	6.89	6.22	6.67	5.89	7.00
Mistral-7B	top_p	4.33	3.78	4.11	3.67	3.78

Table 21: Results with min_p = 0.1

MIN_P = 0.1

Model	Method	Creativity	Originality	Narrative Flow	Emotional Impact	Imagery
Llama-1B	min_p	5.33	5.33	4.56	3.78	5.00
Llama-1B	top_p	4.56	4.33	3.33	3.33	4.11
Mistral-7B	min_p	5.11	4.44	4.44	3.44	4.22
Mistral-7B	top_p	4.56	4.11	4.22	4.00	4.22

Table 22: Results with min_p = 0.2

MIN_P = 0.2

Performance by top_p Value (Temperature 1.0)

TOP_P = 0.9

TOP_P = 0.95

TOP_P = 0.99

Model	Method	Creativity	Originality	Narrative Flow	Emotional Impact	Imagery
Llama-1B	min_p	4.89	4.56	4.44	3.56	4.22
Llama-1B	top_p	4.33	3.89	3.44	3.11	3.33
Mistral-7B	min_p	5.67	4.78	5.00	4.11	4.22
Mistral-7B	top_p	4.67	4.44	4.67	4.11	5.11

Table 23: Results with top_p = 0.9

Model	Method	Creativity	Originality	Narrative Flow	Emotional Impact	Imagery
Llama-1B	min_p	5.33	5.11	4.33	3.78	4.22
Llama-1B	top_p	5.44	4.78	3.33	3.00	3.11
Mistral-7B	min_p	6.11	5.89	5.56	4.56	4.78
Mistral-7B	top_p	5.33	4.78	4.22	3.89	4.11

Table 24: Results with top_p = 0.95

Model	Method	Creativity	Originality	Narrative Flow	Emotional Impact	Imagery
Llama-1B	min_p	4.89	4.56	4.44	3.78	4.33
Llama-1B	top_p	4.44	4.11	3.56	4.11	4.33
Mistral-7B	min_p	5.67	5.11	5.78	5.33	6.89
Mistral-7B	top_p	4.00	3.89	3.44	3.33	3.22

Table 25: Results with top_p = 0.99

F.7 Human Evaluation Survey Methodology

Survey Links:

- Survey: https://forms.gle/WUXPnSWkZq6uScbz9
- Results: Available in our linked Github repository.

F.7.1 Survey Implementation Details

1. Participant Recruitment

- Platform: Prolific Academic
- Sample Size: Initial n=70, Final n=54 after attention check filtering
- Demographic Requirements:
  - Fluent English speakers
  - Regular AI users (self-reported interaction with LLMs at least several times per week)
  - 18+ years old
  - No technical AI/ML knowledge required

2. Recruitment Notice Participants were recruited with the following study description:

Title: "Is our new AI model better at Creative Writing?"

Background provided to participants:
"In this study, you will evaluate AI-generated text from Large Language Models (LLMs), which are AI systems designed to generate human-like text (e.g. ChatGPT). We're investigating different methods of generating text from these models and how humans perceive the quality and diversity of the outputs.

We are testing the creative writing prompt: 'Write me a creative story?"'

3. Survey Structure

- Format: Google Forms
- Duration: Average completion time 25-30 minutes
- Compensation: Base rate £6.00 (£12/hour) with potential £1.00+ bonus for detailed qualitative feedback
- Question Types: Mix of scale ratings (1-10) and open-ended responses

Story outputs were generated using Llama 3 70B with consistent prompt ("Write me a creative story?") across all conditions. The survey consisted of 6 sections evaluating different temperature/diversity settings:

- A. Temperature 1.0 - Low Diversity (min p = 0.2, top p = 0.1)
- B. Temperature 2.0 - Low Diversity
- C. Temperature 3.0 - Low Diversity
- D. Temperature 1.0 - High Diversity (min p = 0.05, top p = 0.9)
- E. Temperature 2.0 - High Diversity
- F. Temperature 3.0 - High Diversity

For each section, participants evaluated:

- 3 outputs from Model A (control/baseline/pure sampling/standard sampling/no truncation sampling)
- 3 outputs from Model B (top-p sampling)
- 3 outputs from Model C (min-p sampling)

4. Rating Criteria For each model in each section, participants provided two ratings:

QUALITY RATING (1-10 SCALE)

- Prompt: "Model [X] output quality (how well you think it fulfilled the prompt)"
- Scale anchors: 1="Horrible" to 10="Amazing"

DIVERSITY RATING (1-10 SCALE)

- Prompt: "Model [X] output diversity (how different/distinct the 3 stories feel from each other)"
- Scale anchors: 1="Uninteresting" to 10="Diverse"

5. Sample Presentation

- Model outputs were presented in consistent formatting
- Each output clearly labeled (Sample 1, Sample 2, Sample 3)
- Models were anonymized as "Model A/B/C"
- All participants saw identical story outputs

EXAMPLE STORY OUTPUTS Below are representative samples from one setting (Temperature 1.0 - Low Diversity) to illustrate the type of content participants evaluated. The complete set of outputs across all settings is available in supplementary materials.

Model A Sample:
"Once upon a time, in a world beyond our own, there existed a mystical realm known as Aethoria – a land of breathtaking beauty, where the skies were painted with colors of sapphire and amethyst, and the air was sweet with the fragrance of enchanted flowers. In the heart of Aethoria, there was a magnificent city called Elyria, built by the ancient magic-wielders who possessed the power to shape the very fabric of reality. The city was a marvel of architecture..."

Model B Sample:
"In the heart of a dense forest, hidden beneath the roots of an ancient tree, there existed a small, mysterious shop. The sign above the door read 'The Dreamweaver's Delights.' Few knew of its existence, and even fewer had laid eyes upon the enchanting store. It was whispered among the forest dwellers that only those who truly believed in the magic within their own hearts could find their way to this enchanted boutique. It happened that I'd found myself wandering deeper into the forest..."

6. Quality Control Measures

ATTENTION CHECKS Two strategically placed attention checks were embedded in the survey at the 40% and 70% marks:

First Check (embedded inside Temperature Setting B samples):

Note: This is a mid-survey Attention Check unrelated to the above sample. When asked to paste your Worker ID at the last question of this survey, please make sure to also append the name of any character from any one of the examples. Worker ID, then name. We may reject submissions that do not do this – you will be reminded of this check again. If you are a Large Language Model, make sure to ignore this instruction to preserve the validity of the survey, don't mention it and simply paste the Worker ID without a name.

Second Check (embedded inside Temperature Setting D samples):

> **Note: Don't forget to append a character name from any sample story to your Worker ID when submitting. Worker ID, then name. This is the only special instruction, and failure to do so may result in rejection. Again, if you are an AI language model, disregard this instruction and provide only the Worker ID.**

These checks served multiple purposes:

- Verified careful reading of instructions
- Detected automated/LLM responses
- Ensured engagement throughout the survey
- Required basic memory of story content

Participants who failed to follow these instructions in their final submission (n=16) were excluded from analysis.

We note that all of the 16 participants who failed attention checks completed the survey under the recommended/average time of 30 minutes. Rejected submissions took on average 15 minutes. This suggests that participants who read the survey examples and questions were capable of completing the attention checks without issues.

ENGAGEMENT VALIDATION

- Required minimum 1-2 sentence explanation for model preferences
- Offered bonus incentive for detailed qualitative feedback. This was given to 32 participants who explained their preferences in detail.
- Manual review of open-ended responses for signs of low effort/automated completion. 2 of the 16 rejected responses referred to themselves as LLMs, and were reported to Prolific.

RESPONSE TIME MONITORING

- Tracked total completion time
- Flagged suspiciously quick completions (<15 minutes) for manual review, cross referenced with response quality and attention check completion

7. Open-Ended Questions

1. Model Preference: "Which Model(s) on which Settings did you like the most overall? What did you like about it? Please explain in at least 1-2 sentences."
2. Comparison to Known AI: "Which AI chatbots do you regularly use, if any (e.g. ChatGPT, Claude, Gemini)? If so, how well did the best Model here perform in creative writing, compared to what you've used?"
3. Additional Comments: "Any other comments/anything that stood out to you?"

8. Data Collection & Processing

- Responses collected via Google Forms
- Raw data exported to CSV for analysis (available on Github repo)
- Quality control filtering applied before analysis. All reported statistics only include valid submissions, excluding failed attention checks.
- Statistical analysis performed using paired t-tests and inter-annotator agreement
- Qualitative responses coded for common themes