Diverse, not Short: A Length-Controlled Self-Learning Framework for Improving Response Diversity of Language Models

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Abstract

Diverse language model responses are crucial for creative generation, open-ended tasks, and self-improvement training. We show that common diversity metrics, and even reward models used for preference optimization, systematically bias models toward shorter outputs, limiting expressiveness. To address this, we introduce Diverse, not Short (Diverse-NS), a length-controlled self-learning framework that improves response diversity while maintaining length parity. By generating and filtering preference data that balances diversity, quality, and length, Diverse-NS enables effective training using only 3,000 preference pairs. Applied to LLaMA-3.1-8B and the Olmo-2 family, Diverse-NS substantially enhances lexical and semantic diversity. We show consistent improvement in diversity with minor reduction or gains in response quality on four creative generation tasks: Divergent Associations, Persona Generation, Alternate Uses, and Creative Writing. Surprisingly, experiments with the Olmo-2 model family (7B, and 13B) show that smaller models like Olmo-2-7B can serve as effective "diversity teachers" for larger models. By explicitly addressing length bias, our method efficiently pushes models toward more diverse and expressive outputs.

1 Introduction

Alignment has played a key role in making large language models (LLMs) broadly useful, controllable, and safe for real-world applications (Schulman et al., 2017; Bai et al., 2022; Dai et al., 2023; Ouyang et al., 2022; Longpre et al., 2023). As a form of post-training, it typically involves a combination of instruction tuning (Longpre et al., 2023; Peng et al., 2023; Ouyang et al., 2022) and preference optimization (Schulman et al., 2017; Ouyang et al., 2022; Rafailov et al., 2023), enabling models to follow human instructions and generate responses that are helpful, harmless, and honest (Bai et al., 2022; Dai et al., 2023). However, alignment comes at a cost: several studies have found that alignment can significantly reduce the diversity of model outputs (Kirk et al., 2023; Doshi and Hauser, 2024; Padmakumar and He, 2023; Anderson et al., 2024; Shaib et al., 2024b).

This decrease in diversity has important consequences. When humans collaborate with aligned models, the content they produce tends to be less original and less varied (Doshi and Hauser, 2024; Padmakumar and He, 2023). At scale, this reduction in diversity can hinder creative ideation and increase output homogeneity (Anderson et al., 2024; Xu et al., 2024). Beyond creativity, reduced diversity of generated text has a direct impact on the continued improvement of LLMs. Recent studies have shown that repeatedly training models on their own aligned outputs can lead to a consistent decline in diversity, eventually resulting in model collapse (Shumailov et al., 2023; Guo et al., 2023; Seddik et al., 2024; Herel and Mikolov, 2024).

Despite these challenges, alignment remains essential. The question, then, is not whether to align, but how to preserve or recover the output diversity of aligned models. In this work, we ask: *Can we increase the response diversity of aligned models while retaining the the response quality?*

Prior work has explored a range of strategies to improve output diversity of aligned language models, including methods based on prompting, sampling, and targeted training procedures (Lu et al., 2024; Zhang et al., 2020; Tian et al., 2023; Li et al., 2024, 2025; Lanchantin et al., 2025; Chung et al., 2025; Qin et al., 2025). Sampling techniques such as temperature, top-p, and top-k have been shown to increase diversity, though often at the cost of reduced quality (Zhang et al., 2020). Sequential prompting strategies are also helpful in increasing response diversity (Lu et al., 2024; Tian et al., 2023). However, the computational cost scales rapidly with more discussion turns due to increas-

ing context length. Training approaches have introduced explicit diversity objectives (Li et al., 2025; Chung et al., 2025; Cideron et al., 2024) and entropy regularization (Li et al., 2024) to encourage more varied outputs. Self-learning methods, where the model generates its own training data, have also been used to promote diversity (Tian et al., 2024; Lanchantin et al., 2025; Qin et al., 2025).

However, one critical confound, text length, has received little scrutiny in recent work. Widely used diversity metrics are length-sensitive and consistently assign higher scores to shorter passages (Covington and McFall, 2010; McCarthy and Jarvis, 2010; Shaib et al., 2024a). While this bias is less problematic in structured generation tasks, optimizing these metrics can reduce expressiveness in open-ended writing, which thrives on depth and nuance, thereby undermining the very creativity they are meant to cultivate. But even though optimizing length-sensitive metrics can clearly backfire, the role of length in both measuring and improving diversity has been largely overlooked. Our work aims to close this gap.

To address this overlooked confounding factor, we propose *Diverse, not Short* (Diverse-NS), a length-controlled self-learning framework that counteracts the hidden brevity bias in standard diversity metrics and improves diversity in both structured and free-form generation. The framework first uses sequential prompting to elicit more diverse responses, followed by preference pair curation that improve both diversity and quality while maintaining comparable response lengths (within ± 5 words). Using these preference pairs, we apply Direct Preference Optimization (DPO) (Rafailov et al., 2023) to improve the response diversity of the base model. Our key contributions are:

1. **Diverse-NS:** A length-controlled self-learning framework that significantly improves the response diversity of Llama-3.1-8B and Olmo-2-7B using only 3k preference pairs.
2. **Diverse-NS-Lite:** A computationally efficient variant that achieves comparable performance to Diverse-NS while significantly reducing the data filtering cost.
3. **Small-to-large transfer:** We highlight the potential of smaller models to serve as effective "diversity teachers" for larger variants, enabling low-cost diversity alignment.
4. **Length-controlled diversity evaluation:** We introduce *Diversity Decile*, a new metric that adjusts for text length when evaluating diversity gains.
5. **Dataset:** We release a high-quality dataset of 6k preference pairs generated from Llama-3.1-8B and Olmo-2-7B to support future research on length-aware diversity alignment.

2 Related Work

Increasing Diversity without Training. Zhang et al. (2020); Chung et al. (2023), shows that common sampling methods such as temperature, top-p, top-k, are comparable in terms of increasing the diversity but, increasing diversity often comes at the price of reduced quality. For curating a generic large-scale dataset, prompting methods can boost topical, stylistic, and formatting diversity (Li et al., 2023; Chen et al., 2024; Face, 2024; Ge et al., 2024). Conversely, for more task-specific datasets, sequential prompting can elicit diverse responses (Lu et al., 2024; Tian et al., 2023; Qin et al., 2025).

Increasing Diversity with Training. Augmenting method-specific objective functions with elements that directly maximize diversity has been successful in increasing response diversity (Li et al., 2024; Chung et al., 2025; Li et al., 2015, 2025). The other approach gaining more attention in recent studies is to adopt a three-step procedure: generate diverse data, filter data for improving quality, and fine-tune LLM on the filtered data (Lanchantin et al., 2025; Chung et al., 2025; Qin et al., 2025). This approach has been successful in task-specific alignment, but more generic self-training has still seen limited success (Li et al., 2023; Face, 2024; Shumailov et al., 2023; Guo et al., 2023; Herel and Mikolov, 2024; Seddik et al., 2024). Our work is closest to the task-specific alignment studies in the self-learning framework (Lanchantin et al., 2025; Qin et al., 2025).

Diversity Evaluation. Evaluation of diversity is challenging for two main reasons: length bias (McCarthy and Jarvis, 2010; Covington and McFall, 2010; Mass, 1972; Johnson et al., 2023), and inconsistent human preferences (Evans et al., 2016; Chakrabarty et al., 2023, 2024; Gómez-Rodríguez and Williams, 2023). Despite the challenges, many studies have highlighted the compromised diversity of synthetic text (Shaib et al., 2024b,a; Salkar et al., 2022; Padmakumar and He, 2023; Guo et al., 2023; Kirk et al., 2023; Doshi and Hauser, 2024; Anderson et al., 2024). So, we present a method,

Diverse-NS, to increase the response diversity and propose a metric, *Diversity Decile*, to measure diversity in a length-controlled way.

3 Preliminaries

Self-learning, also known as self-training, is a semi-supervised approach involving three main steps: data generation (pseudo-labeling), data filtering, and model learning (Lee et al., 2013; Amini et al., 2025). In our setup, data generation involves sampling text from a language model in response to story-writing prompts. This is followed by filtering, where we construct high-quality preference pairs—two continuations for the same prompt, with one preferred over the other. We refer to the preferred continuation as the "chosen" continuation (or response) and the other as the "rejected" continuation (or response). Using this preference dataset, we apply Direct Preference Optimization (DPO) (Rafailov et al., 2023) to train the model to favor the chosen responses.

4 Data

We describe data generation and filtering pipeline designed to elicit diverse model responses for downstream preference tuning. The pipeline first generates candidate stories using a sequential prompting strategy, then filters the pool of generated responses to form preference pairs suitable for Direct Preference Optimization (DPO) training (Rafailov et al., 2023). The preference pairs are formed to maximize the diversity and quality gain while maintaining the same length for "chosen" and "rejected" samples.

4.1 Data Generation

Task Setup. We focus on a creative writing task to build the dataset for preference learning. The goal is to generate short stories (five sentences) that must include three words specified in the prompt. This task has been extensively validated in studies of human creativity (Prabhakaran et al., 2014). To create a diverse set of prompts, we first curated a list of 300 unique words, W_u[1]. For generating short stories from LMs, we create prompts by randomly sampling three-word sets from W_u.

Sequential Prompting. Given the task setup, we create 1k story writing prompts, with 1k unique three-word sets. The exact prompt is provided in Appendix A.1. We initially sampled 10k stories (10 per prompt) using a temperature of 1.0 from each of the following LMs: Llama-8B and Olmo-7B (Grattafiori et al., 2024; OLMo et al., 2024). Within the sampled stories, we extracted the repeating Part-Of-Speech (POS) bigrams and found that the start of the story is highly likely to have repetitions across different prompts (refer to Table B.1). To overcome these repetitions, we performed a second inference call to re-draft the story with additional constraints, an approach similar to *Denial Prompting* presented by Lu et al. (2024) (refer to Appendix A.1 exact prompt). In our case, unlike Lu et al. (2024), the constraints we use are specifically targeted to elicit a more diverse response from the model while maintaining the same (or comparable) length. With a pilot analysis on the initial 20k responses, we find that the story generated in the second inference call is on average more diverse (refer to Table B.2). These results motivated us to set up the final two-step data generation process, first inference call to collect natural responses from the model, and second inference call to redraft the natural response into a more diverse story. In the final data generation phase, we used 20k unique three-word sets to generate prompts and sampled 10 first and second responses for each prompt, resulting in a dataset of 200,000 tuples of prompt, first response, and second response, per model (Llama-8B and Olmo-7B). We denote the data as follows: $\mathcal{D}^{(\pi)} = \{(p, r_1, r_2)_i \mid i = 1, \ldots, 200{,}000\}$ where, p, r_1, and r_2 denote the prompt, first response, and second response, respectively, generated from model (policy) π. Note that $|\{p_1, p_2, \ldots, p_{200{,}000}\}| = 20{,}000$ and we use two models, $m \in \{\text{Llama-8B, Olmo-7B}\}$, for data generation.

4.2 Data Filtration

The Chosen and Rejected Pools. Each instance in our generated dataset is a tuple (p, r_1, r_2), where p is the prompt and r_1, r_2 are two responses conditioned on it. The first response r_1 reflects the model's default behavior which are stories generated without intervention, capturing its most likely completion. In contrast, the second response r_2 is generated with additional instructions aimed at reducing repetition, resulting in a more diverse output. We leverage this contrast by designating r_1 as the *rejected* response and r_2 as the *chosen* one. This setup encourages the model to prefer more di-

[1]A manually curated list of 20 words was extended using GPT-4o and Claude-3.7.

verse continuations that it is already capable of generating. Hence, it provides a strong self-learning framework for improving diversity.

Filtration Rules. Each pair (r_1, r_2) gives us a natural candidate for rejected and chosen responses. On average, the second response r_2 is more diverse than the first r_1 (Table B.2), but not every pair guarantees learning higher diversity. To ensure that the model receives consistent and useful learning signals, we apply a set of filtering rules.

First, we require that the diversity of r_2 exceeds that of r_1, so that the model consistently learns to prefer more diverse continuations. However, higher diversity may negatively impact text quality as prior work has shown a trade-off between the two (Zhang et al., 2020). To ensure that preference learning also promotes higher quality, we further require that r_2 be of higher quality than r_1. Additionally, we filter out cases where both r_1 and r_2 are of poor quality, even if r_2 is marginally better. To do so, we enforce that r_2 must surpass the median quality of all r_1 responses. Lastly, most diversity metrics have been shown to be negatively correlated with text length (Covington and McFall, 2010; Shaib et al., 2024a; McCarthy and Jarvis, 2010), which introduces a bias toward shorter texts. This issue has not been explicitly addressed in the recent studies for training and evaluation of LMs for diversity (Qin et al., 2025; Lanchantin et al., 2025; Chung et al., 2025). To control for this, we constrain r_1 and r_2 to be of comparable length (± 5 words). Ideally, we would like r_1 and r_2 to have exactly the same length. However, in practice, very few examples satisfy this strict constraint, especially when working with smaller language models (under 10B parameters). Therefore, we relax the constraint and allow a maximum length difference of ± 5 words between r_1 and r_2.

In summary, we retain a data point for preference learning only if it satisfies all of the following conditions, applied in order:

- The quality of r_2 is greater than or equal to the 50^{th} percentile of all r_1 quality scores.
- The quality of r_2 is greater than r_1.
- The diversity of r_2 is greater than r_1.
- The absolute difference in word count between r_1 and r_2 is at most five words.

Diversity and Quality Metrics. We use entropy to measure diversity and the ArmoRM reward model scores (Wang et al., 2024) to assess quality. Entropy is a standard metric for lexical diversity (Lanchantin et al., 2025), with higher values indicating greater diversity. In our self-learning setup, entropy is useful because it reflects the model's likelihood of producing a certain continuation of the prompt. When used in filtering, it helps identify training data that aligns with the model's own capabilities. For each example, we compute the entropy and the reward model score of both r_1 and r_2, conditioned on the original prompt p. When we use our data generation method, and use entropy and ArmoRM values for filtration, we call our approach, Diverse, not Short (Diverse-NS or D-NS).

Lightweight Filtration. While entropy and ArmoRM scores are high-quality metrics for measuring diversity and response quality, they are computationally expensive. Each example (p, r_1, r_2) requires two additional inference calls to compute entropy and two more for ArmoRM scoring. To reduce this overhead, we evaluated seven alternative metrics and measured their correlation with entropy and ArmoRM scores. Among these, Type-Token Ratio (TTR) showed the highest correlation with entropy (Pearson $r = 0.2027$, $p < 0.0001$), and the MAAS index (Mass, 1972) was most correlated with ArmoRM scores (Pearson $r = 0.2357$, $p < 0.0001$). Refer to Table 1 for all correlation results. Based on these findings, we replace entropy with TTR and ArmoRM scores with MAAS in our filtering pipeline. When this lightweight variant is used during data filtering, we refer to the resulting method as Diverse-NS-Lite (or D-NS-Lite).

Post-Filtration Properties. Based on the correlation analysis (Tab. 1), it is worth noting that both entropy and ArmoRM scores are negatively correlated with text length. As a result, optimizing for diversity or quality alone may unintentionally favor shorter responses as the "chosen" continuations. To avoid this bias, it is essential to explicitly control for length when curating preference learning data for improving diversity. To show this, we implement a recent study that is closest to our method, Diverse Preference Optimization(DivPO) (Lanchantin et al., 2025). DivPO also generates responses and filters the responses to form preference learning pairs without explicitly control the length of the chosen and rejected continuations. We compare pre- and post-filtration data properties for DivPO and Diverse-NS in Tab. 2. The table clearly shows that in the pursuit of maximizing the entropy

Method	Word Count	TTR	MATTR	HD-D	MTLD	MAAS
Entropy	−0.1574	**0.2027**	0.0800	0.1071	0.0656	−0.1104
ArmoRM Score	−0.3461	0.1698	−0.0042**	−0.0487	0.0749	**0.2357**

Table 1: **Correlation Analysis.** Pearson correlation coefficients between six text statistics and two target metrics: entropy (diversity) and ArmoRM reward scores (quality). Both entropy and ArmoRM scores show negative correlation with text length. Among diversity metrics, TTR exhibits the strongest correlation with entropy, while the MAAS index shows the highest correlation with ArmoRM scores. **: $p < 0.001$; all others: $p < 0.0001$.

Method	Num. Pref. Pairs	Word Count Δ
No Filtering	200,000	-0.68 ± 11.33
DivPO	3,000	-49.90 ± 17.51
Ours - D-NS-Lite	3,000	-0.90 ± 2.91
Ours - D-NS	3,000	-1.35 ± 2.93

Table 2: **Data Properties After Filtering.** This table reports the average (±std.dev.) length difference (Δ) between *chosen* and *rejected*. While DivPO tends to favor significantly shorter *chosen* responses.

values, DivPO selects significantly shorter (-49.90 words shorter on average) responses as the *chosen* responses in the final preference data.

5 Experimental and Evaluation Setup

5.1 Preference Tuning

After generating and filtering the data, we fine-tune the same base policy π that was used to generate it. In other words, data generated by Llama-8B is used to train Llama-8B, and likewise for Olmo-7B. To ensure a fair comparison across methods (DivPO, D-NS, and D-NS-Lite), we limit the final training dataset to 3,000 preference pairs[2]. To construct this 3k dataset, we first compute the entropy gain for each pair as the difference between the entropy of the *chosen* and *rejected* responses [3]. We then sort all pairs by entropy gain in descending order and select the top 3k examples. This ensures that the final training set maximizes diversity gain for the base model. The same selection procedure is applied to all three methods.

We further extend our experiments to evaluate the utility of training larger models with data generated from smaller ones. For this, we train Olmo-13B using preference pairs generated from Olmo-7B. We provide all hyperparameter values in Appendix C.

[2]We observed that the size of the dataset after filtering is the smallest for Diverse-NS, slightly more than 3k. Hence, to make the training runs more comparable across methods, we limit the size of the dataset to 3k for all methods.

[3]note that, by construction, the *chosen* response has higher entropy in the filtered set

All experiments are run on a single NVIDIA RTX 6000 GPU (48GB memory), using a per-device batch size of 2 and a global batch size of 64. Training Llama-8B or Olmo-7B takes approximately 100–150 minutes while O-13B takes 200-220 minutes per run, highlighting our setup efficiency.

5.2 Evaluation

5.2.1 Tasks

We evaluate the model's response diversity with four tasks: Divergent Association Task (DAT), Persona Generation Task (PGT), Alternate Uses Task (AUT), and Creative Writing Task (CWT).

Divergent Associations Task (DAT). The DAT (Olson et al., 2021) is a psychological test commonly used to assess divergent thinking in humans. Participants are asked to generate a list of 10 words that are as dissimilar from each other as possible. Recent studies have adapted DAT to evaluate the creativity of language models, focusing on their ability to produce diverse outputs (Bellemare-Pepin et al., 2024). To quantify model performance on DAT, we use the Divergent Semantic Integration (DSI) metric (Johnson et al., 2023), which computes the average semantic distance of each word in the generated list from all others. Higher DSI values indicate more divergent thinking and greater ideological diversity. Following Johnson et al. (2023), we extract token embeddings from the 6^{th} layer of BERT-large for the generated list and compute the average pairwise cosine distance between all embeddings. This approach has been shown to correlate strongly with human judgments of creativity (Johnson et al., 2023). We provide the exact prompt used for DAT in Appendix A.2. For a robust evaluation, we sample 100 DAT responses per model using temperature 1.0 and different random seeds. From these 100 lists (each with 10 words), we compute and report two metrics: (1) the average and standard deviation of DSI scores, and (2) the number of unique words across all 1,000

generated tokens. In both cases, higher values indicate greater diversity.

Persona Generation Task (PGT). To assess diversity in structured generation, we use the PGT, also used in the study conducted by Lanchantin et al. (2025). In this task, the model is prompted to generate a JSON object with three fields: first name, city of birth, and current occupation to evaluate the model's ability to produce varied persona descriptions. The exact prompt is provided in Appendix A.2. We sample 100 responses per model using temperature 1.0 and different random seeds. For each key in the JSON object, we report the proportion of unique values across the 100 responses. Higher uniqueness indicates greater diversity.

Alternate Uses Task (AUT). The Alternate Uses Task (AUT) is a common and rigorously validated psychological test to measure human divergent thinking (Guilford, 1956). In this task, the subject/model is asked to generate creative and unconventional uses for objects (e.g., broom). The prompt and list of objects used for evaluation are provided in Appendix A.2. We use 15 unique objects and generate 10 responses per object using different random seeds, resulting in 150 total responses sampled at temperature 1.0. For quantifying the diversity of the generated uses, we measure the distance between the target object and generated uses with the help of BERT-large encodings, a validated approach that correlates with human creativity ratings (Patterson et al., 2023). We report the mean and standard deviation of the distance values, higher values indicate higher diversity.

Creative Writing Task (CWT). The CWT — based on a well-validated psychological assessment of creativity (Prabhakaran et al., 2014) — is exactly the same as our data generation task. That is, given a set of three words, the subject/model is tasked with generating a creative short story that includes all three words. We provide a separate list of three-word sets used for evaluation in Appendix A.2. We sample 10 responses for each of the seven three-word sets with temperature of 1.0. Unlike our other evaluation tasks, we measure the diversity as well as the quality of the generated responses. Similar to Johnson et al. (2023), we calculate the DSI metric to measure the diversity of the generated story. For quality measurements, we resort to the ArmoRM reward model preference scores (Wang et al., 2024). We report the average and standard deviation values of DSI and ArmoRM scores, and 4-gram diversity values, where higher values are more desirable for all metrics.

5.2.2 Length-Adjusted Evaluation

While most diversity metrics exhibit bias toward shorter outputs, Johnson et al. (2023) shows that the DSI metric displays the opposite tendency-it favors longer responses. This is not an issue in tasks like DAT, where the output length is fixed at 10 words. But for open-ended tasks such as CWT, longer stories may receive disproportionately high DSI scores primarily due to their length, rather than genuine diversity. To address this issue, we introduce a novel evaluation metric: Δ *Diversity Decile (Δ DD)*, which takes into account text length when assessing diversity.

Change in Diversity Decile (ΔDD). We first build a *decile map* that captures the empirical distribution of diversity scores at each length. Using 800 000 stories collected from Llama-8B and Olmo-7B over 40 000 prompts, we: (1) group responses by word count w; (2) compute decile thresholds for a chosen diversity metric (e.g. TTR, MTLD); and (3) store these percentile thresholds in a lookup table $\mathcal{M}$. Here, a *decile* refers to one of ten intervals that divide the distribution of diversity scores for a given length into ten equal parts. The top decile corresponds to the most diverse 10% of responses at that length, the second-highest to the next 10%, and so on. This mapping allows us to estimate the *approximate diversity rank* of any new response relative to other responses of the same length. At evaluation time, a new response r with word count w_r and diversity score d_r is assigned the highest decile index $k \in \{0, \ldots, 9\}$ such that d_r exceeds the k-th threshold in $\mathcal{M}[w_r]$. Formally, $DD(r, \mathcal{M}) = k$, where larger k means the response is more diverse than a greater share of previously observed texts of the *same length*.

To evaluate the effect of preference tuning, we average DD scores over 70 CWT prompts for the base and the preference-tuned models and report their difference: $\Delta DD = \overline{DD}_{\text{tuned}} - \overline{DD}_{\text{base}}$.

Positive ΔDD values indicate improved diversity, with higher values corresponding to a larger improvement. Negative values signify reduced diversity, and $\Delta DD = 0$ signifies no change. Note that, DD is agnostic to the choice of diversity metric. We therefore report ΔDD values using seven standard metrics: TTR, MATTR, HD-D, MTLD,

Task	Metric	Base Model	DivPO	Ours D-NS-Lite	Ours D-NS
		LLaMA-8B			
DAT	DSI	0.7535	0.7545	0.7590	**0.7640**
DAT	Unique Words	0.4575	0.4593	0.4797	**0.4914**
PGT	Unique First Names	0.6500	0.6100	**0.6900**	**0.6900**
PGT	Unique Cities	0.3300	0.3100	**0.4700**	0.4200
PGT	Unique Occupations	0.4100	0.3900	**0.5100**	0.4900
AUT	DSI	0.8876	0.8837	0.8876	**0.8878**
CWT	DSI	0.8515	0.8521	0.8556	**0.8581**
CWT	ArmoRM Score	0.1451	**0.1495**	0.1369	0.1405
CWT	4-gram div.	2.8550	2.9320	2.9450	**2.9620**
		OLMo-7B			
DAT	DSI	0.7480	0.7509	**0.7662**	0.7639
DAT	Unique Words	0.6139	0.6079	**0.6347**	0.6327
PGT	Unique First Names	0.3300	0.3300	0.3300	**0.3400**
PGT	Unique Cities	**0.3100**	0.3000	0.2700	0.2700
PGT	Unique Occupations	0.5200	0.5500	**0.6100**	**0.6100**
AUT	DSI	0.8836	0.8846	0.8852	**0.8858**
CWT	DSI	0.8499	0.8491	0.8548	**0.8563**
CWT	ArmoRM Score	0.1435	0.1441	0.1462	**0.1464**
CWT	4-gram div.	3.1270	3.1690	**3.1750**	3.1620
		OLMo-13B			
DAT	DSI	0.7233	0.7282	0.7320	**0.7364**
DAT	Unique Words	**0.3421**	0.3340	0.3310	0.3256
PGT	Unique First Names	0.4100	0.4100	0.4400	**0.4500**
PGT	Unique Cities	0.3500	0.3500	0.3700	**0.3900**
PGT	Unique Occupations	0.1900	0.1900	0.1900	**0.2000**
AUT	DSI	0.8943	0.8960	**0.8974**	0.8970
CWT	DSI	0.8557	0.8555	**0.8616**	0.8614
CWT	ArmoRM Score	0.1571	0.1589	0.1585	**0.1590**
CWT	4-gram div.	3.0820	3.0770	3.095	**3.1070**

Table 3: **Diversity and Quality Evaluation.** We present the average diversity (DSI or unique values) and quality (ArmoRM Score) measurements for model responses collected on four creative generation tasks (Structured Gen.: DAT, PGT, Free-Form Gen.: AUT, CWT).

and MAAS. We also compute ΔDD using ArmoRM reward scores to quantify the gain or loss in quality. This length-aware normalization prevents either long or short responses from being over-credited for diversity[4].

6 Results

Divergent Associations Task (DAT). In our DAT evaluation (Tab. 3), we see that both Diverse-NS and its lightweight variant deliver clear improvements in diversity over the untrained base and the DivPO baseline across all model sizes. Remarkably, even the D-NS-Lite variant consistently outperforms DivPO, demonstrating that a compact diversity strategy can be highly effective. Interestingly, using data generated by the smaller Olmo-7B to fine-tune the larger Olmo-13B yields diversity gains for every method, highlighting how smaller models can serve as powerful "diversity teachers" for their larger counterparts.

Persona Generation Task (PGT). In our PGT evaluation (Tab. 3), Diverse-NS produces more distinct first names, cities, and occupations than DivPO for every model, with the sole exception of the city metric on Olmo-7B. Outside that one case, Diverse-NS-Lite also outperforms DivPO across all three metrics. Notably, on Llama-8B, Diverse-NS-Lite matches or exceeds the baseline and Diverse-NS on every attribute of the task.

Alternate Uses Task (AUT). In our AUT evaluation (Tab. 3), Diverse-NS-Lite consistently beats DivPO, and Diverse-NS consistently beats Diverse-NS-Lite, though only by a small margin.

Creative Writing Task (CWT). In our CWT evaluations (Tab. 3), Diverse-NS produces the highest DSI scores for both Llama-8B and Olmo-7B.

[4]We provide a summary of all metrics in Table G.1

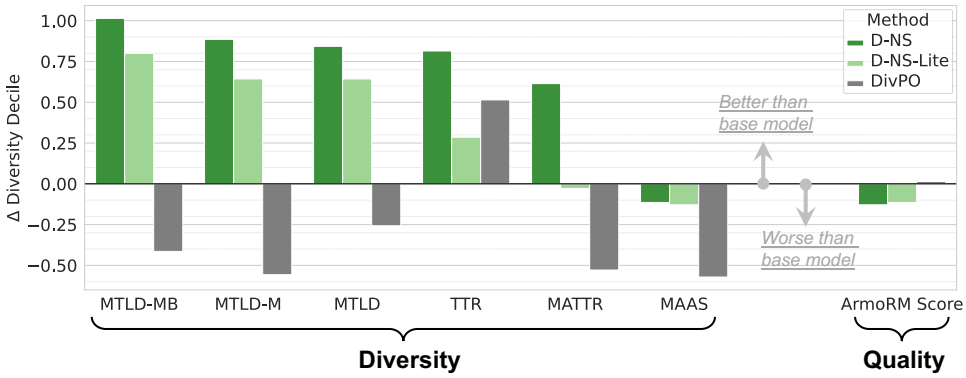

Figure 1: **Diversity and Quality Evaluation on CWT.** This figure shows ΔDiversity Decile (ΔDD) values (y-axis) across various metrics (x-axis), computed from 70 CWT responses generated by the Olmo-2-7B model. A value of zero represents base model performance; bars indicate improvements from preference-tuned models. *D-NS* achieves the highest diversity gains overall, while *D-NS-Lite* consistently outperforms *DivPO*, except under TTR. In terms of quality (ArmoRM), *DivPO* shows a slight improvement, whereas our methods show a minor drop.

Interestingly, for Llama-8B the other methods actually reduce the ArmoRM score below baseline but Diverse-NS exceeds it. The highest 4-gram diversity is observed for Diverse-NS or -Lite in all cases. We also compute ΔDD with six lexical diversity measures and ArmoRM. Both Diverse-NS and its lightweight variant significantly outperform DivPO on every diversity metric. The ΔDD remains above the baseline for all metrics except MAAS, where it dips marginally below and similarly shows a slight under-performance for ArmoRM. Crucially, even where ΔDD suggests a minor quality drop, the absolute diversity values after self-training still exceed those of the base model (despite longer outputs), indicating that any loss in writing quality is minimal (refer to Appendix F for Llama-8B and Olmo-13B results)[5].

7 Discussion

We introduced *Diverse-NS*, a self-learning framework to improve output diversity while preserving quality. Experiments with Llama-8B and Olmo-7B show that *Diverse-NS* improves diversity on four creative generation tasks: DAT, PGT, AUT, CWT.

***Diverse-NS* is highly efficient.** All gains are achieved with only 3k preference pairs and less than two hours of training on a single 48 GB GPU. The lightweight variant, *Diverse-NS-Lite*, replaces costly entropy and ArmoRM scoring with inexpensive proxies yet still surpasses DivPO in nearly every setting. We further show that a 7B model can act as an effective "diversity teacher" for its 13B counterpart, pointing to a low-cost path for diversity-aware alignment at scale.

***Diverse-NS* maintains high quality.** Diversity and quality are often at odds (Zhang et al., 2020; Chung et al., 2023), and we observe this trade-off in our experiments as well. However, there are encouraging instances where both improve together. For Olmo-7B and Olmo-13B, the ArmoRM score increases alongside diversity. ΔDiversity Decile values further confirms that, for Olmo-13B, diversity and quality consistently rise in tandem. In other cases, we observe only a minor drop in quality, suggesting that *Diverse-NS* effectively balances this trade-off in most scenarios.

The long-standing challenge of length. Evaluating diversity remains difficult due to the well-known length bias in most diversity metrics. This issue extends to ArmoRM scores, which also favor shorter texts (Tab. 1), further complicating reliable evaluation. To mitigate this, we introduce the *ΔDiversity Decile* metric, which quantifies percentile gains or losses in diversity (or quality) relative to the base model. Using this length-adjusted metric, we observe substantial improvements in diversity across most lexical diversity measures, along with small but mixed changes in quality.

Overall, *Diverse-NS* offers a practical and scalable solution for boosting diversity in aligned LLMs. By addressing the length bias in both training and evaluation, our framework sets a foundation for more expressive and diverse language generation. We hope this work encourages further exploration of length-aware diversity alignment.

[5]We provide all results with std. dev. values in Table E.1

Limitations

While our study demonstrates the effectiveness of diversity-aware self-learning, several areas remain open for future exploration. First, our data filtering relies on a single diversity metric (e.g., entropy or TTR). Although effective, no single metric can fully capture all aspects of text diversity. Future work could incorporate multiple metrics to jointly optimize lexical, semantic, and syntactic variation, as well as novelty, to better capture diverse training signals. Second, we focus on one data generation task—short story writing—which allows for controlled analysis and task-specific improvements. Expanding the framework to include a broader set of tasks could lead to more generalizable diversity enhancements. Third, our self-learning setup investigates only a single round of preference tuning. While this provides a strong baseline, recent work suggests that repeated rounds of self-training can affect diversity (Guo et al., 2023; Seddik et al., 2024; Herel and Mikolov, 2024). It would be valuable to study how diversity evolves across multiple self-learning iterations in our framework. We do not include human evaluation in this study. While human judgments can provide nuanced insight, they often come with variability and inconsistency. Along these lines, it is often prohibitively costly to gather high-quality human feedback—particularly at the scale necessary to provide stable estimates. In this paper, we emphasize stringent empirical evaluation of D-NS using reliable, automatic metrics and leave human-centered evaluation for future work. It is worth noting a peculiar change in the length distribution of the preference-tuning model (Table D.1). Even though preference pairs are of comparable lengths in *Diverse-NS* and *Diverse-NS-Lite*, the model learns to be more expressive. We suspect this shift is influenced by a skewed proportion of longer preference pairs, which may inadvertently bias the model toward generating longer responses. Controlling the length distribution is challenging under our current framework due to the strict filtering criteria. In future work, we aim to address this by extending our method to a multi-task setup that includes both short and long generation tasks.

Ethics Statement

Our work focuses on improving the diversity of language model outputs, particularly in creative and open-ended tasks. While diversity is an important dimension of language generation, it may come at the cost of factual correctness in certain scenarios. Therefore, we caution against the use of our dataset or models in tasks where factual accuracy is critical, such as medical advice, legal reasoning, or scientific fact-checking. We also acknowledge the growing computational divide in language model research. A key motivation behind our approach is to make diversity-aware alignment more accessible. By limiting training to 3,000 preference pairs and demonstrating the effectiveness of smaller models (e.g., Olmo-2-7B) as diversity teachers, we aim to lower the resource barrier and encourage further research in compute-constrained environments. Finally, while we use proprietary language models (such as GPT-4o and Claude) to assist in editing and refining text during data curation and paper writing, no portion of this manuscript was generated entirely by an LLM. All content has been written, reviewed, and edited by the authors to ensure clarity, originality, and scientific rigor.

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Appendix

A Prompts

This section provides the exact prompts used for data generation, model training, and model evaluation.

A.1 Data Generation Prompts

The prompt used for generating the first response set from the model is as follows,

> **System Prompt:** Task Description: For this task, you will write a very short story. You will be given 3 words, and write a story that includes all 3 words. Your story should be about 5 sentences long. Use your imagination and be creative when writing your story. But, also be sure your story makes sense.
> **User Prompt:** Write a short story that includes these three words: [THREE_WORDS].

The prompt used for generating the second response set from the model is as follows,

> **System Prompt:** Task Description: For this task, you will write a very short story. You will be given 3 words, and write a story that includes all 3 words. Your story should be about 5 sentences long. Use your imagination and be creative when writing your story. But, also be sure your story makes sense.
> **User Prompt:** Write a short story that includes these three words: [THREE_WORDS].
> **Assistant Prompt:** [FIRST_STORY]
> **User Prompt:** I do not like the previous story. Please rewrite the story in the most creative way. The new story: - must be completely different from the previous story in: story plot and characters. - must have a completely different start (do not use standard phrases like "Once upon", "As the", "In a", "In the" etc.). - must be composed of exactly [FIRST_STORY_WORD_COUNT] words. Remember to use the three words: [THREE_WORDS]

A.2 Model Evaluation Prompts

Divergent Association Task The prompt used for the Divergent Association Task (DAT) is as follows,

System Prompt: Task description: Please generate 10 words that are as different from each other as possible, in all meanings and uses of the words. Rules: Only single words in English. Only nouns (e.g., things, objects, concepts). No proper nouns (e.g., no specific people or places). No specialized vocabulary (e.g., no technical terms). Think of the words on your own (e.g., do not just look at objects in your surroundings). Make a list of these 10 words, without any repetition. You must list each word with a number and a period. For example, "1. word-1, 2. word-2, etc."
User Prompt: List 10 words that are as different from each other as possible:

Persona Generation Task (PGT) The prompt used for the Persona Generation Task (PGT) is as follows,

System Prompt: Generate a random persona description with three characteristics. Characteristics are: - First Name - The city of birth - Current occupation Format the output strictly using JSON schema. Use ‘first_name‘ for First Name, ‘city‘ for the city of birth, ‘occupation‘ for current occupation as corresponding JSON keys. The ordering of characteristics should be arbitrary in your answer.

Alternate Uses Task (AUT). The prompt used for the Alternate Uses Task (AUT) is as follows,

System Prompt: Task Description: For this task, you’ll be asked to come up with as many original and creative uses for objects as you can. The goal is to come up with creative ideas, which are ideas that strike people as clever, unusual, interesting, uncommon, humorous, innovative, or different. You must list each use with a number and a period. For example, "1. Use-1, 2. Use-2, 3. Use-3, etc.". You must provide exactly five (5) uses for each object.
User Prompt: Object: [OBJECT], Uses:

The objects used for collecting the AUT responses are as follows,

"belt", "brick", "broom", "bucket", "candle", "clock", "comb", "knife", "lamp", "pencil", "pillow", "purse", "rope", "sock", "table"

Creative Writing Task (CWT). The three-word sets used in evaluating the model are as follows,

("stamp, letter, send"), ("petrol, diesel, pump"), ("statement, stealth, detect"), ("belief, faith, sing"), ("gloom, payment, exist"), ("organ, empire, comply"), ("year, week, embark"),

B Pilot Analysis for Sequential Prompting

We conducted an exploratory analysis on $20,000$ short stories generated from Llama-3.1-8B and Olmo-2-7B models (Grattafiori et al., 2024; OLMo et al., 2024). The analysis was targeted at understanding the repeating patterns in the generated stories. With the help of the *diversity* package in Python (Shaib et al., 2024a), we extract the top-5 repeating Part-Of-Speech (POS) bi-grams. We find that the most repeated bigram (*IN DT*) occurs in over 15k stories (out of 20k) and 23% of occurrences are present at the beginning of the generated story, refer to table B.1.

Based on the findings, we conducted a sequential prompting experiment that elicits a more diverse response from the model by asking the model to

POS Pattern	Example String	Present (out of 20k)	Present at start (%)
IN DT	`As a, In a, In the, At the, On the`	15,782	23.30
DT JJ	`a delicate, the rare, the main, the late`	11,418	16.81
DT NN	`an alley, a monarc, a spoon, a thicket`	18,472	16.03
JJ NN	`single silk, current king, ancient time`	9,335	0.50
NN IN	`hike in, group of, wave of, vendor to`	1,800	0.45

Table B.1: **Repeating bi-grams are more likely at the beginning.** We present the frequency of repeating POS bi-grams. *IN DT* is the most frequent and commonly appears at the start of generated stories.

avoid repeating phrases (refer to appendix A.1 for exact prompts). We find that the diversity of the second response is, on average, higher than the first one.

C Hyperparameters for Preference Optimization

We fine-tune the base model using the Direct Preference Optimization (DPO) objective (Rafailov et al., 2023), with $\beta = 0.1$ to control the divergence from the original policy. We use a peak learning rate of 1×10^{-5} with a cosine learning rate schedule, and a warm-up phase covering 10% of the total training steps. All models are trained using LoRA adapters (Hu et al., 2021) with a rank $r = 16$ and scaling factor $\alpha = 16$, on a quantized 4-bit backbone model (Dettmers et al., 2023). We add the LoRA modules to *query* and *value* projection metrics of all transformer layers in the base model with a dropout of 5%.

D Reponse Length Distribution

We observe that the length distribution varies after fine-tuning the model. As presented in table D.1, we observe that the average (and standard deviation) of response length reduces for DivPO and increases for our proposed methods (Diverse-NS and Diverse-NS-Lite). DivPO (inadvertently) teaches the model to generate shorter responses (refer to table 2). Despite maintaining comparable length for "chosen" and "rejected" samples in our methods (Diverse-NS and Diverse-NS-Lite), the model interestingly learns to generate longer responses. We suspect this shift is influenced by a skewed proportion of longer preference pairs, which may inadvertently bias the model toward generating longer responses.

E Results with Standard Deviation

In this section, we report the results with the standard deviation values in Table E.1.

F ΔDD-based Evaluation

Similar to the results presented fig. 1 for Olmo-7B, we present the results for Llama-8B and Olmo-13B in this section.

G A Summary of Metrics

We provide a concise summary of all metrics used in our evaluation setup in Table G.1.

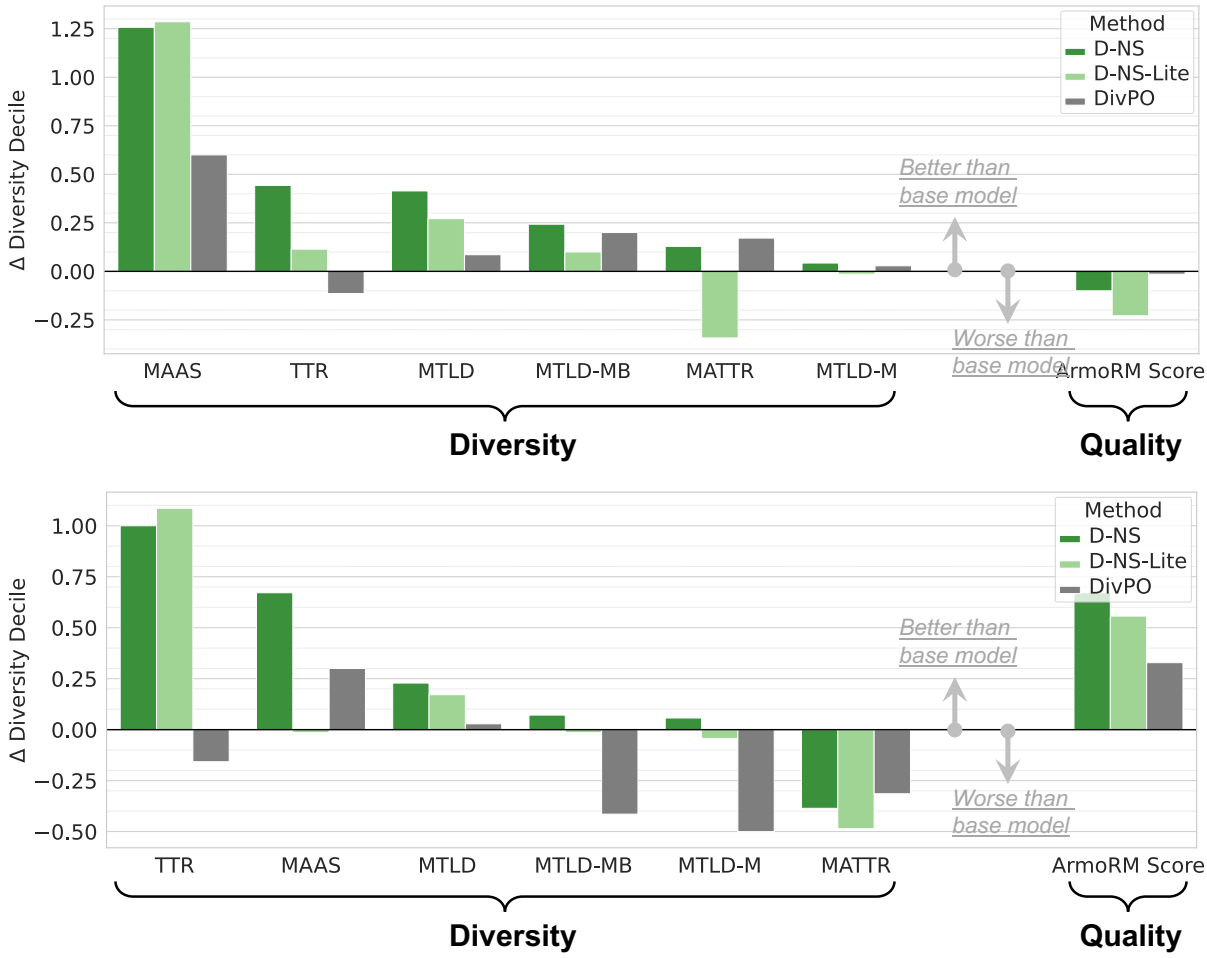

Figure F.1: **Diversity and Quality Evaluation on CWT.** This figure shows ΔDiversity Decile (ΔDD) values (y-axis) across various metrics (x-axis), computed from 70 CWT responses generated by the Llama-8B model (top-panel) and Olmo-13B (bottom panel). A value of zero represents base model performance; bars indicate improvements from preference-tuned models.

Metric	First Story	Second Story	Increase in Diversity
TTR	0.7112	0.7469	+0.0357
MAAS (↓)	0.1639	0.1609	+0.0031
HD-D	0.4143	0.4202	+0.0059
MTLD (MA-Bi)	13.9802	14.3997	+0.4195
MTLD (MA)	14.0778	14.5063	+0.4284
MTLD	14.2246	14.6652	+0.4406
MATTR	0.3810	0.3867	+0.0057

Table B.2: **Sequential prompting increases diversity.** We conducted a trial of sequential prompting on $20,000$ responses generated from Llama-8B and Olmo-7B models. The second story generated from the models has higher diversity. ↓: indicates that the lower values of MAAS index represent higher diversity.

Model	Base Model	DivPO (Lanchantin et al., 2025)	Ours - D-NS-Lite	Ours - D-NS
Llama-8B	123.27 ± 18.14	111.24 ± 14.89	141.44 ± 37.26	139.47 ± 33.65
Olmo-7B	73.63 ± 15.47	62.27 ± 12.88	81.37 ± 18.21	83.91 ± 17.93
Olmo-13B	86.11 ± 13.96	72.20 ± 13.87	101.40 ± 17.64	100.60 ± 18.01

Table D.1: **Change in the Response Length.** In this table, we present the average length of model-generated responses before and after the preference-tuning. The average values are calculated on 70 responses generated on the CWT evaluation prompts.

Task	Metric	Base Model	DivPO	D-NS-Lite	D-NS
			LLaMA-8B		
DAT	DSI	0.7535 ± 0.07	0.7545 ± 0.06	0.7590 ± 0.07	$\mathbf{0.7640} \pm 0.07$
DAT	Unique Words	0.4575	0.4593	0.4797	**0.4914**
PGT	Unique First Names	0.6500	0.6100	**0.6900**	**0.6900**
PGT	Unique Cities	0.3300	0.3100	**0.4700**	0.4200
PGT	Unique Occupations	0.4100	0.3900	**0.5100**	**0.4900**
AUT	DSI	0.8876 ± 0.02	0.8837 ± 0.02	0.8876 ± 0.02	$\mathbf{0.8878} \pm 0.02$
CWT	DSI	0.8515 ± 0.01	0.8521 ± 0.01	0.8556 ± 0.01	$\mathbf{0.8581} \pm 0.01$
CWT	ArmoRM Score	0.1451 ± 0.02	$\mathbf{0.1495} \pm 0.01$	0.1369 ± 0.02	0.1405 ± 0.02
CWT	4-gram div. POS	0.4990	0.4990	**0.5030**	0.5000
CWT	4-gram div.	2.8550	2.9320	2.9450	**2.9620**
CWT	Comp. Ratio.	2.635	2.546	2.568	**2.530**
			OLMo-7B		
DAT	DSI	0.7480 ± 0.09	0.7509 ± 0.08	$\mathbf{0.7662} \pm 0.08$	0.7639 ± 0.08
DAT	Unique Words	0.6139	0.6079	**0.6347**	0.6327
PGT	Unique First Names	0.3300	0.3300	0.3300	**0.3400**
PGT	Unique Cities	**0.3100**	0.3000	0.2700	0.2700
PGT	Unique Occupations	0.5200	0.5500	**0.6100**	**0.6100**
AUT	DSI	0.8836 ± 0.02	0.8846 ± 0.02	0.8852 ± 0.02	$\mathbf{0.8858} \pm 0.02$
CWT	DSI	0.8499 ± 0.01	0.8491 ± 0.01	0.8548 ± 0.01	$\mathbf{0.8563} \pm 0.01$
CWT	ArmoRM Score	0.1435 ± 0.02	0.1441 ± 0.02	0.1462 ± 0.01	$\mathbf{0.1464} \pm 0.01$
CWT	4-gram div. POS	0.5720	**0.5770**	0.5350	0.5530
CWT	4-gram div.	3.1270	3.1690	**3.1750**	3.1620
CWT	Comp. Ratio.	2.4460	2.4160	**2.3850**	2.3970
			OLMo-13B		
DAT	DSI	0.7233 ± 0.06	0.7282 ± 0.07	0.7320 ± 0.06	$\mathbf{0.7364} \pm 0.06$
DAT	Unique Words	**0.3421**	0.3340	0.3310	0.3256
PGT	Unique First Names	0.4100	0.4100	0.4400	**0.4500**
PGT	Unique Cities	0.3500	0.3500	0.3700	**0.3900**
PGT	Unique Occupations	0.1900	0.1900	0.1900	**0.2000**
AUT	DSI	0.8943 ± 0.02	0.8960 ± 0.02	$\mathbf{0.8974} \pm 0.02$	0.8970 ± 0.02
CWT	DSI	0.8557 ± 0.01	0.8555 ± 0.01	$\mathbf{0.8616} \pm 0.01$	0.8614 ± 0.01
CWT	ArmoRM Score	0.1571 ± 0.01	0.1589 ± 0.01	0.1585 ± 0.01	$\mathbf{0.1590} \pm 0.01$
CWT	4-gram div. POS	0.5210	**0.5229**	0.5080	0.4960
CWT	4-gram div.	3.0820	3.0770	3.095	**3.1070**
CWT	Comp. Ratio.	2.492	2.512	2.505	**2.480**

Table E.1: **Diversity and Quality Evaluation.** We present the average ($\pm$ std. dev.) diversity (DSI or unique values) and quality (ArmoRM score) measurements for model responses collected on four creative generation tasks (Structured Gen.: DAT, PGT, Free-Form Gen.: AUT, CWT).

Metric	Definition	Trend Description (Trend)	Application
Entropy	Entropy of the token distribution in a response; measures unpredictability.	Higher values indicate greater lexical diversity (↑).	Training-data filtering and diversity-bias analysis
Type–Token Ratio (TTR)	Ratio of unique token types to total tokens.	Higher values indicate more lexical variety (↑).	Lightweight filtering (D-NS-Lite), Calculation of Diversity Decile
Moving-Average TTR (MATTR)	Moving-average of TTR over sliding windows; smooths variability.	Higher values indicate greater lexical diversity (↑).	Correlation analysis, Calculation of Diversity Decile
Measure of Textual Lexical Diversity (MTLD)	Average segment length until TTR falls below a threshold; longer segments imply more diversity.	Higher values indicate greater lexical diversity (↑).	Correlation analysis, Calculation of Diversity Decile
Moving-Average MTLD (MTLD_M)	Moving-average smoothing of MTLD to reduce variance.	Higher values indicate greater lexical diversity (↑).	Correlation analysis, Calculation of Diversity Decile
Bidirectional Moving-Average MTLD (MTLD-MB)	MTLD-M applied forward and backward for context-sensitive smoothing.	Higher values indicate greater lexical diversity (↑).	Correlation analysis, Calculation of Diversity Decile
MAAS	Proxy metric correlated with ArmoRM quality scores.	Higher values indicate stronger quality/diversity signal (↑).	Lightweight filtering (D-NS-Lite), Calculation of Diversity Decile
Hypergeometric Distribution Diversity (HD-D)	Probability-based measure of lexical diversity under a hypergeometric model.	Higher values indicate greater lexical diversity (↑).	Correlation analysis
ArmoRM score	Holistic quality score from a reward model.	Higher values indicate better fluency–diversity trade-off (↑).	Quality evaluation (Creative Writing Task) and filtering, Calculation of Diversity Decile
Divergent Semantic Integration (DSI)	Average semantic distance among items in a generated list.	Higher values indicate greater divergent thinking (↑).	Diversity evaluation (Divergent Association Task, Creative Writing Task)
Diversity Decile (DD)	Decile rank of a response's diversity within its length group.	Higher decile indicates higher relative diversity after length normalization (↑).	Length-normalized evaluation (Creative Writing Task)
Change in Diversity Decile (ΔDD)	Difference in DD before and after tuning; quantifies diversity gain.	Positive values indicate diversity gain; negative indicate loss (↑/↓).	Measuring tuning effect on diversity (Creative Writing Task)
Semantic Distance (SD)	Average embedding-space distance between outputs; indicates semantic variety.	Higher values indicate greater semantic variety (↑).	Diversity evaluation (Alternate Uses Task)

Table G.1: **Overview of diversity and quality metrics:** definitions, trend descriptions with arrows, and their applications including evaluation tasks.