



DATA MAN: DATA MANAGER FOR PRE-TRAINING LARGE LANGUAGE MODELS

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ABSTRACT

As the performance of large language models (LLMs) emerges via data scaling, the significance of pre-training data becomes increasingly evident. Although methods such as deduplication and high-quality sampling have explored data selection, comprehensive criteria for text quality remain underdeveloped, hindering efficient pre-training data selection and composition. This paper establishes guidelines for data selection, fosters consensus on data quality, and introduces a management tool to evaluate data quality and domain types. We believe that robust quality criteria should be applicable across diverse texts, showcasing semantic content understanding, and mutual complement. Previous work mainly relies on intuition and lacks generalizability. To tackle this, we employ reverse thinking—*prompting LLMs to self-identify the causes of anomalous perplexity (PPL) in text*—and derive 13 quality criteria related to LLM performance, collectively derive a comprehensive metric as *Overall Score*. We developed a complete prompt that integrates quality criteria and domain types. We use LLM’s pointwise ratings and compare the computational complexities of pointwise and pairwise ratings ($O(N)$ v.s. $O(N^2)$), showing that pointwise ratings are more feasible for vast datasets, with over 95% agreement with human assessments. By annotating 356K documents using GPT-4-turbo and fine-tuning a Qwen2-1.5B model, we created the **Data Manager (DataMan)**, with an average fine-tuning accuracy across all criteria approaching 80% and 81.6% for *Overall Score*. We annotated 447B tokens from the slimpajama corpus by DataMan, and selected a 30B token subset to maximize quality representativeness while ensuring domain diversity to train 1.3B-parameter LLM. Results show that models trained on DataMan-sampled data exceed state-of-the-art benchmarks in in-context learning (ICL) gain by 0.4% to 4.3% and in instruct following win rate by 34.2% to 57%. The strongest model *Overall Score l=5*, significantly surpasses models trained on uniform sampling with 50% more data. Continued pre-training on high-rated domain-specific data further boosts ICL performance, validating DataMan’s effectiveness in domain mixing. We reveal that PPL and ICL results do not strictly align, underscoring the distinction between understanding and generalization abilities. Our contributions include: i)-developing a data quality criteria system based on LLM PPL features; ii)-creating DataMan for data quality rating and domain identification; and iii)-releasing our code, models, and annotated datasets to facilitate research on the relationship between data and LLMs.

1 INTRODUCTION

As large language models (LLMs) achieve performance emergence driven by data scaling laws, the significance of data has become increasingly evident (Kaplan et al., 2020; Brown et al., 2020; Chowdhery et al., 2023). This finding has prompted researchers to explore how to select appropriate pre-training data, including data deduplication (Lee et al., 2022), heuristic-based data selection (Rae et al., 2022; Wenzek et al., 2019), suitable domain mixture (Gao et al., 2020; Shen et al., 2023), and sampling high-quality data (Gunasekar et al., 2023; Wettig et al., 2024). Although prior efforts to enhance data quality, there is still a lack of clear and comprehensive text criteria, making the selection of suitable pre-training data for LLMs an unresolved challenge.

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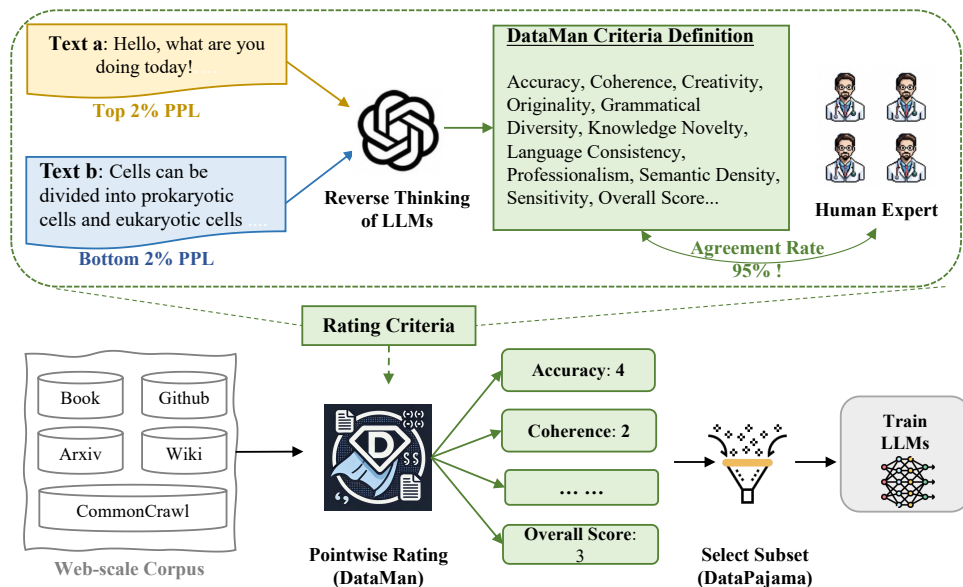


Figure 1: The pipeline of DataMan. We utilize 14 quality criteria derived from reverse thinking and employed DataMan for pointwise rating to filter the pre-training data. Based on the filtered data (called DataPajama), the trained LLMs demonstrate improved performance in both language modeling and task generalization.

Our goal is to provide guidelines for the pre-training data selection, foster consensus in the community regarding data quality criteria, and develop a data management tool that can comprehensively evaluate data quality and identify domain types. This will enable LLMs to select suitable pre-training data, thereby achieving an optimal balance between language modeling capability and downstream generalization performance. We believe that excellent quality criteria must: 1)-be applicable to a wide variety of texts; 2)-demonstrate a deep understanding of content, capturing semantic levels; and 3)-complement each other. However, existing research on LLM quality signals (Wettig et al., 2024; Korbak et al., 2023) mainly relies on human intuition, while grounded in empirical findings, lack generalizability.

To address this issue, we are inspired by reverse thinking – **prompting LLMs to self-identify which criteria are beneficial for their performance.** Since perplexity relates closely to the LLM’s pre-training capabilities (Wenzek et al., 2019; Muennighoff et al., 2024; Marion et al., 2023b), we focus on the training texts with the top 2% and bottom 2% of perplexity, corresponding to easy-to-learn and hard-to-learn data, respectively. By using GPT-4-turbo to analyze the causes of anomalies PPL in these text, and through iterative refinement, we derive 13 quality criteria closely related to LLM performance: *Accuracy, Coherence, Creativity, Grammatical Diversity, Knowledge Novelty, Language Consistency, Originality, Professionalism, Semantic Density, Sensitivity, Structural Standardization, Style Consistency, and Topic Focus.* These criteria collectively derive a comprehensive metric: *Overall Score.* For suitable domain mixing, we identified 15 domain types prevalent in LLM applications (Naveed et al., 2023) and developed complete prompts.

We evaluate texts using LLM’s pointwise ratings and demonstrate, through clear-cue cases and theoretical bounds, that a 5-level pointwise rating is sufficient for this task. Moreover, LLM’s pointwise rating aligns with human evaluations with over 95% agreement. Here, we compare the computational complexities of pointwise and pairwise ratings when processing N documents, showing that pointwise ratings operate at $O(N)$ compared to $O(N^2)$ for pairwise ratings. This makes pointwise ratings more viable for vast pre-training datasets. Finally, we utilize GPT-4-turbo to annotate 356k documents and fine-tune a Qwen2-1.5B model (Yang et al., 2024a) to learn quality ratings and domain identification, resulting in a comprehensive **Data Manager** — **DataMan** — excelling in data selection and mixing. We present average scores of diverse quality criteria under different sources of supervised fine-tuning (SFT) data, which indicates how quality criteria differentiate LLM abilities. Moreover, DataMan achieves an average accuracy of nearly 80% across all quality criteria in the SFT

108 phase, with classification accuracies for high- and low- *Overall Score* reaching 98.5% and 81.6%.
 109 This indicates that DataMan is required to balance good and bad SFT samples.

110 Utilizing DataMan’s annotations, we performed quality evaluations and domain identifications
 111 on 447B token documents from the Slimpajama corpus (Soboleva et al., 2023), generating the
 112 DataPajama dataset. By maximizing the representativeness of quality criteria while ensuring diversity
 113 in sources and domains, we select a 30B token subset from 447B tokens, training a Sheared-LLaMA-
 114 1.3B language model (Xia et al., 2023) from scratch. Our main results demonstrate that models trained
 115 on data sampled using DataMan’s 13 quality criteria outperform state-of-the-art (SOTA) educational
 116 value ($\tau = 2$) in terms of in-context learning (ICL) performance by 0.4% to 4.3%. As the *Overall*
 117 *Score* increases from 1 to 5, downstream ICL performance rises distinctly, validating the necessity
 118 of quality ranking. We achieved the strongest ICL performance in *Overall Score* $l=5$, significantly
 119 surpassing models using uniform sampling + 50% of data, and the Pearson correlation among quality
 120 criteria further confirms that the *Overall Score* encompasses the attributes of all criteria. Models
 121 trained on DataMan-sampled data overwhelmingly outperform SOTA educational value ($\tau = 2$) in
 122 terms of instruction following, with the highest model featuring an *Overall Score* $l=5$ achieving a win
 123 rate of 78.5%. Additionally, We continued pre-training of high-rated, domain-specific data labeled
 124 by DataMan on the strongest *Overall Score* $l=5$ model, achieving superior ICL performance in the
 125 target domain, thereby validating DataMan’s capability for domain mixing. Furthermore, we reveal
 126 that the PPL and ICL criteria do not align strictly, consistent with the notion that PPL represents
 127 understanding ability while ICL denotes generalization ability. Finally, we conduct a comprehensive
 128 analysis of DataMan’s quality ratings, explore the distribution of ratings from various sources, and
 129 report insights by inspecting the original documents corresponding to each quality rating=1,2,3,4,5.
 130 We find complementary relationships among quality criteria, while their correlation with perplexity
 131 further confirms the novelty of DataMan’s quality criteria.

132 Our contributions are summarized as follows:

- 133 1. Drawing on the PPL characteristics of LLMs, we curated a comprehensive data quality system to
 134 guide pre-training data selection and foster consensus on data quality criteria.
- 135 2. We developed DataMan to comprehensively assess data quality and domain types for data manage-
 136 ment frameworks, enhancing LLM capabilities in language modeling and downstream generalization.
 137 Vast experiment results that set new performance records validate the efficacy of DataMan.
- 138 3. We will release the code, all models, and the annotated DataPajama dataset to pave the way for
 139 the community to further explore the relationship between data and LLMs.

141 2 RELATED WORK

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 144 **Deduplication.** Deduplicating training data is now standard in managing pre-training data for LLMs,
 145 as it greatly impacts performance. While Kaplan et al. (2020) and Hoffmann et al. (2022b) examine
 146 scaling laws with unique data trained for one epoch, some studies (Hernandez et al., 2022; Xue et al.,
 147 2024) suggest that repeated data can harm performance, particularly as repetitions and model size
 148 grow (the scaling law of repeated data). Furthermore, removing duplicates and increasing sample
 149 diversity has been shown to improve LLMs’ performance (Jiang et al., 2022; Abbas et al., 2023).

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 151 **Heuristic-based Selection.** It can be categorized into two main approaches. *Rule-based heuristic*
 152 *methods* involve manually crafted criteria for data selection, such as mean word length and stop
 153 word fraction (Rae et al., 2022; Laurençon et al., 2022; Penedo et al., 2023; Soldaini et al., 2024),
 154 with notable implementations like the C4 filter (Raffel et al., 2020) and Gopher rules (Rae et al.,
 155 2022). Although these effectively reduce noisy data, they require precise quality measures for
 156 optimal selection. Conversely, *model-based heuristic methods* employ models like binary grammar
 157 discriminators (Chowdhery et al., 2023; Touvron et al., 2023a) to identify data that closely resembles
 158 the target domain, alongside techniques such as importance resampling (Xie et al., 2023) and
 159 perplexity filtering (Wenzek et al., 2019; Muennighoff et al., 2024; Marion et al., 2023a).

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 161 **Domain Mixture.** Most pre-training datasets, like the Pile (Gao et al., 2020), comprise mixed data
 from various sources and domains (Nijkamp et al., 2023; Zhang et al., 2023; Yang et al., 2024b; Maini
 et al., 2024; Li et al., 2024). As LLMs gain traction, domain-specific data for improved functionalities

are increasingly used in model training (Du et al., 2022; Gao et al., 2023). Identifying the optimal domain mixture ratio is essential for effective LLM pre-training (Wang et al., 2023). Early attempts to define this relied on experiments and intuition (Gao et al., 2020; Thoppilan et al., 2022). Recent studies have begun to use automatic methods, such as domain generalization (Xie et al., 2023; 2024), domain gradients (Fan et al., 2023), and loss evaluation (Xia et al., 2023), to assign domain weights and assess model performance across various mixtures.

LLM quality signals. Using appropriate LLM quality signals is essential for evaluating and selecting pre-training data (Wei et al., 2022; Kojima et al., 2022). Research shows that data enriched with facts and trivia aids LLMs in accurately addressing niche topics and fictional worlds (Petroni et al., 2019; Korbak et al., 2023). Recent efforts have synthesized these insights, proposing four quality criteria—writing style, facts and trivia, educational value, and required expertise—to assess pre-training data and enhance LLM capabilities (Wettig et al.).

3 EVALUATING TEXT BY DATAMAN

We developed a data manager dubbed **DataMan** (see Figure 1) without relying on heuristics and human intuition, which comprehensively evaluates 14 quality criteria and domain types of text, enabling efficient data selection and mixing.

3.1 OVERVIEW OF THE METHOD

Let $\mathbf{t} = \{t_1, \dots, t_n\}$ represent all documents to be evaluated. The evaluation results from DataMan correspond to a query, asking the performance of document t_n under a quality criterion and its domain affiliation. Assume that the quality criterion and domain type for the documents are represented in a multi-level rating format as $\mathcal{L} = \{(l_1^1, \dots, l_1^C), \dots, (l_n^1, \dots, l_n^C)\}$, where $l_n^C \in \{1, \dots, K\}$ denotes the rating label for the C -th criterion corresponding to document t_n . In this paper, K is 5 for quality ratings and 15 for domain recognition. Let F be a class of functions, and $f \in F$ be the rating function. We use GPT-4-turbo as the rating function to evaluate all documents and record the results for each criterion and domain, expressed as: $f(t, \mathcal{L}) = \{(t_1, l_1^1, \dots, l_1^C), \dots, (t_n, l_n^1, \dots, l_n^C)\}$. Thus, we can quickly create a SFT dataset for training DataMan, $\mathcal{S} = \{(t_i, l_i^1, \dots, l_i^C)\}$. Essentially, our method is a pointwise learning to rank (L2R) model (Liu et al., 2007; 2009). We minimize the loss function defined by the document, quality ratings, and rating function:

$$L(f; t, \mathcal{L}) = \sum_{i=1}^n (f(t_i) - l_i)^2.$$

This enables DataMan to learn the rating functions for each quality criterion and domain type.

3.2 CRITERIA DEFINITION AND PROMPTS

How to define the quality criteria and domain types of texts? We believe that excellent quality criteria should: 1)-apply to a wide variety of texts, 2)-demonstrate a deep understanding of content, capturing semantic levels, and 3)-complement each other. However, previous studies largely relied on human intuition, such as the educational value in Gunasekar et al. (2023), writing style in Wettig et al. (2024), and toxicity and privacy in Korbak et al. (2023). Such empirical methods lack universality and comprehensiveness. To address this gap, we undertook an in-depth exploration of text quality, motivated by reverse thinking—*enabling the LLM to self-identify which criteria are beneficial for its performance*. Specifically, since LLMs’ pre-training capability is closely related to their PPL, and based on the finding that "high PPL indicates data is difficult to learn, and vice versa", we focus on the training text from various sources with the top 2% and bottom 2% of perplexity. We then designed analytical prompts and used GPT-4-turbo¹ to investigate the reason behind these perplexity anomalies, aiming to analyze the characteristics of easy-to-learn data and difficult-to-learn data. Through iterative refinement, we derived 14 quality criteria centered around semantics, style, knowledge, diversity, etc. Finally, we identified the 15 domain types that need to be assessed, incorporating the "let's think step by step" chain-of-thought prompting strategy (Wei et al., 2022). This process is well-considered and logically rigorous, details can be found in Appendix A.

¹In this paper, we utilize the latest version of GPT-4-0125-preview available at that time.

3.3 PROMPT VALIDATION.

Due to the lack of rigorous automated validation, we test the prompt effectiveness using clear-cut cases before prompt use. For each quality criterion, we first gathered a pool of documents preliminarily rated by an independent group. From this pool, we chose two groups of ten documents, one with high and the other with low ratings, ensuring a clear quality gap. Table 5 in Appendix A lists these document types. These randomly shuffled 20 documents were assessed by five independent human annotators who had not seen them before, rate them on a scale of 1-5 based on the quality criterion. We then evaluated the same documents using the GPT-4-turbo model with our prompt. By comparing the GPT-4-turbo’s ratings with the majority of human ratings, we found over 95% consistency with human preferences. Also, we ensured inter-rater reliability among human annotators by calculating the Kappa coefficient (McHugh, 2012), which validated the consistency of human ratings. However, this human validation remains subjective, we hope the community develops a more rigorous method.

3.4 POINTWISE RATING V.S. PAIRWISE RATING.

Previous studies using LLMs to evaluate text fall into two categories: pointwise ratings and pairwise ratings. Pairwise ratings argue that LLMs excel at comparing texts and can better identify minor quality differences. *But is this truly the case?* We follow the case study with the rankings of writing styles in Wettig et al. (2024) and assess these documents using DataMan based on 14 quality criteria and one domain, see Table 6. The results indicated that DataMan’s pointwise ratings showed almost no difference across *Overall Score* for the top-7 documents, aligning with human annotators’ preferences. Thus, when the differences in a quality criterion of the text is minimal, a human-aligned approach considers a text excellent if it meets the "acceptable" quality threshold, both pointwise and pairwise ratings can achieve this. Moreover, for N documents, pointwise rating incurs a computational cost of $O(N)$ compared to $O(N^2)$ (i.e., $\frac{n!}{2^{(n-2)!}}$) for pairwise rating. In summary, the Pointwise method is the better choice for vast pre-training data. Finally, we present the mathematical connection between rating measure errors and the rating loss in the pointwise rating model (Chen et al., 2009):

$$1 - NDCG(f; t, \mathcal{L}) \leq \frac{15\sqrt{2}}{N_n} \left(\left(\sum_{i=1}^n D(t_i)^2 \right) - n \prod_{i=1}^n D(t_i)^{2/n} \right)^{1/2} (L(f; t, \mathcal{L}))^{1/2},$$

$$NDCG(f; t, \mathcal{L}) = \frac{1}{N_n} \sum_{i=1}^n G(l(\pi_f(t_i))) D(t_i),$$

$$N_n = \max_{\pi} \sum_{i=1}^n G(l(\pi(t_i))) D(t_i).$$

where NDCG is rating measures defined with respect to K -level ratings \mathcal{L} , here $K = 5$. In practice, G is the gain function, π_f is the rating list produced by the rating function f , and D is the position discount function. One usually sets $G(z) = 2^z - 1$, $D(z) = \frac{1}{\log_2(1+z)}$ if $z \leq M$, and $D(z) = 0$ if $z > M$ (M is a fixed integer). Thus, minimizing the pointwise rating loss will reduce the rating measure error, leading to improved rating performance.

3.5 TRAINING THE DATAMAN MODEL

After curating the complete prompt, we collected documents for training DataMan from both out-of-source and in-source of SlimPajama (Soboleva et al., 2023), a large-scale pre-training corpus derived from cleaned and deduplicated RedPajama (TogetherAI, 2023). We limit each document to 2,048 tokens and use GPT-4-turbo to query its 14 quality criteria and 15 domain types, generating a large-scale SFT dataset (averaging 810 tokens per document) at a cost of \$13,858. In Appendix B, Table 7 summarizes the SFT dataset by source, domain, and *Overall Score* showcasing its quantity and diversity in these three aspects. Figure 4 illustrates the complementary nature of these quality criteria, and the *Overall Score* was derived from all other criteria. We fine-tuned the 1.5-B parameter Qwen2 model (Yang et al., 2024a) using text generation loss. Appendix B includes a detailed discussion of the training setup and our rationale for not selecting multi-task classification training. Table 10, the DataMan model achieved near 80% average test accuracy across all criteria, with an *Overall Score* test accuracy of 81.3% and a *domain recognition* test accuracy of 86%.

4 MANAGING DATA BY DATAMAN

In this section, we apply the DataMan model to manage data by selecting a high-quality, diverse subset of documents from the pre-trained corpus. Our data management framework adapted for DataMan is as follows. For each document d_i in the pre-training corpus D , with source s_i , the DataMan model annotates its 14 quality ratings and domain types as $\mathcal{L} = \{(l_i^1, \dots, l_i^{C-1}, q)\}$, where q represents the domain type. Assuming the source and domain distribution probabilities are $P(s)$ and $P(q)$ respectively, we perform top-k sampling (k is the selected subset size) without replacement for each quality criterion within each source and domain distribution, using the following probability:

$$P(d_i) = \frac{P(d_i | l^j, s, q) \cdot P(s, q)}{\sum_{d_j \in \text{top-k}(l^j)} P(d_j | l^j, s, q) \cdot P(s, q)}, \text{ and } P(d_i | l^j) = \frac{l_i^j}{\sum_{d_j \in D} l_i^j}.$$

This approach maximizes the representativeness of samples based on quality metrics while ensuring diversity in source and domain distributions. By using sampling without replacement, we can avoid the generation of duplicate data. Notably, to verify whether the *Overall Score* can encompass all criteria, we replace the top-k strategy with uniform sampling based on fixed *Overall Score* ratings. These sampling and mixing methods implicitly shift the objective of language modeling towards reward-weighted regression (Peters & Schaal, 2007; Korbak et al., 2023), expanding the maximized likelihood estimation loss by introducing a data reward mechanism.

5 EXPERIMENTS

We empirically validate the DataMan method by training the large language model from scratch.

5.1 SETUP

DataPajama. We annotate a 447B token corpus with quality ratings and domain recognition – utilizing our DataMan model – to produce DataPajama. This corpus is a subset of documents in SlimPajama (Soboleva et al., 2023), an extensively deduplicated version of RedPajama (TogetherAI, 2023), and consists of sequences of 1024 tokens segmented by the Llama tokenizer (Touvron et al., 2023a). The DataMan model is fine-tuned on sequences of 2048 Qwen2 tokens, supporting us to compute the document-level quality rating on continuous segments of up to 2048 tokens. Although the annotation cost of DataPajama is expensive (equivalent to 1,146 NVIDIA A800 hours), it can be reduced in large-scale parallelization, lower-cost base models and heuristic pre-processing. The quality ratings and domain types annotated in DataPajama can serve various purposes, such as data selection, data mixing, or pre-training in vertical domains.

Training. Using different data selection methods, we select a subset of 30B tokens from DataPajama and train a randomly initialized language model on this training set for one epoch in a randomly shuffled order. The models have 1.3B parameters and use a transformer architecture (Vaswani, 2017) with RoPE embeddings (Su et al., 2024). Further details can be found in Appendix C. We train on a dataset slightly larger than the compute-optimal quantity (token: model = 16:1) (Hoffmann et al., 2022a), because more training tokens better reflect the performance gains attributed to data quality.

Evaluation. We aim to provide a holistic evaluation of the language models trained on 30B tokens:

- We measure the perplexity over SlimPajama’s validation split and test split, 500M token each.
- We evaluate the in-context learning (ICL) performance using `lm-evaluation-harness` (Gao et al., 2024). We study 10 tasks, comprising 5 reading comprehension tasks (ARC-easy/challenge (Clark et al., 2018), SciQA (Welbl et al., 2017), LogiQA (Liu et al., 2020), BoolQ (Clark et al., 2019)), 3 commonsense reasoning tasks (HellaSwag (Zellers et al., 2019), PIQA (Bisk et al., 2019), WinoGrande (Sakaguchi et al., 2019)) and 2 knowledge-intensive tasks (NQ (Kwiatkowski et al., 2019), MMLU (Hendrycks et al., 2021)). We choose the number of few-shot examples for each task to ensure that all examples fit within the context window of 1024 tokens. We report the detailed settings in Appendix C.

Table 1: DataMan improves perplexity (PPL) and average in-context learning (ICL) results, the best DataMan is *Overall Score* $l=5$. We report validation, test PPL of Slimpajama and ICL performance of 10 downstream tasks. We highlight the best result in each column and improvement over uniform sampling with the 30B token budget. In Appendix C, we report validation and test PPL for all models across different data sources in Table 13 and Table 14, as well as detailed ICL results for ten downstream task in Table 15.

Selection Method		Val Perplexity	Test Perplexity	Reading Comprehension (5 tasks)	Commonsense Reasoning (3 tasks)	World Knowledge (2 tasks)	Average (10 tasks)
Uniform		10.7	10.75	50.9	55	14.9	44.9
DSIR (Xie et al., 2023)	<i>with Wiki</i>	13.34 $\uparrow_{2.64}$	13.37 $\uparrow_{2.62}$	50.1 $\downarrow_{0.8}$	49.8 $\downarrow_{5.2}$	14.7 $\downarrow_{0.2}$	42.9 $\downarrow_{2.0}$
	<i>with Book</i>	13.60 $\uparrow_{2.90}$	13.59 $\uparrow_{2.84}$	47.9 $\downarrow_{3.0}$	56.6 $\uparrow_{1.6}$	14.1 $\downarrow_{0.8}$	43.8 $\downarrow_{1.1}$
Perplexity (Wenzek et al., 2019)	<i>lowest</i>	15.98 $\uparrow_{5.28}$	16.04 $\uparrow_{5.29}$	48.3 $\downarrow_{2.6}$	49.6 $\downarrow_{5.4}$	13.7 $\downarrow_{1.2}$	41.7 $\downarrow_{3.2}$
	<i>highest</i>	11.32 $\uparrow_{0.62}$	11.34 $\uparrow_{0.59}$	49.6 $\downarrow_{1.3}$	53.5 $\downarrow_{1.5}$	13.4 $\downarrow_{1.5}$	43.5 $\downarrow_{1.4}$
Writing Style (Wettig et al., 2024)	<i>top-k</i>	13.01 $\uparrow_{2.31}$	12.97 $\uparrow_{2.22}$	49.3 $\downarrow_{1.6}$	53.3 $\downarrow_{1.7}$	13.5 $\downarrow_{1.4}$	43.4 $\downarrow_{1.5}$
	$\tau = 2.0$	10.60 $\downarrow_{0.10}$	10.64 $\downarrow_{0.11}$	51.0 $\uparrow_{0.1}$	55.8 $\uparrow_{0.8}$	14.1 $\downarrow_{0.8}$	45.0 $\uparrow_{0.1}$
Facts & Trivia (Wettig et al., 2024)	<i>top-k</i>	14.38 $\uparrow_{3.68}$	14.33 $\uparrow_{3.58}$	54.3 $\uparrow_{3.4}$	51.7 $\downarrow_{3.3}$	15.5 $\uparrow_{0.6}$	45.8 $\uparrow_{0.9}$
	$\tau = 2.0$	10.68 $\downarrow_{0.02}$	10.72 $\downarrow_{0.03}$	52.7 $\uparrow_{1.8}$	55.6 $\uparrow_{0.6}$	15.6 $\uparrow_{0.7}$	46.2 $\uparrow_{1.3}$
Educational Value (Wettig et al., 2024)	<i>top-k</i>	13.54 $\uparrow_{2.84}$	13.49 $\uparrow_{2.74}$	54.7 $\uparrow_{3.8}$	54.9 $\downarrow_{0.1}$	14.4 $\downarrow_{0.5}$	46.7 $\uparrow_{1.8}$
	$\tau = 2.0$	10.67 $\downarrow_{0.03}$	10.72 $\downarrow_{0.03}$	53.3 $\uparrow_{2.4}$	56.3 $\uparrow_{1.3}$	15.7 $\uparrow_{0.8}$	46.7 $\uparrow_{1.8}$
Required Expertise (Wettig et al., 2024)	<i>top-k</i>	14.97 $\uparrow_{4.27}$	14.92 $\uparrow_{4.17}$	52.8 $\uparrow_{1.9}$	48.7 $\downarrow_{6.3}$	14.3 $\downarrow_{0.6}$	43.9 $\downarrow_{1.0}$
	$\tau = 2.0$	10.7	10.74 $\downarrow_{0.01}$	52.7 $\uparrow_{1.8}$	55.5 $\uparrow_{0.5}$	15.0 $\uparrow_{0.1}$	46.0 $\uparrow_{1.1}$
Criteria mix (Wettig et al., 2024)	$\tau = 2.0$	10.63 $\downarrow_{0.07}$	10.68 $\downarrow_{0.07}$	52.1 $\uparrow_{1.2}$	55.5 $\uparrow_{0.5}$	15.2 $\uparrow_{0.3}$	45.7 $\uparrow_{0.8}$
Accuracy	<i>top-k</i>	10.82 $\uparrow_{0.12}$	10.80 $\uparrow_{0.05}$	53.8 $\uparrow_{2.9}$	58.2 $\uparrow_{3.2}$	16.6 $\uparrow_{1.7}$	47.7 $\uparrow_{2.8}$
Coherence	<i>top-k</i>	10.72 $\uparrow_{0.02}$	10.71 $\downarrow_{0.04}$	54.9 $\uparrow_{4.0}$	58.8 $\uparrow_{3.8}$	16.1 $\uparrow_{1.2}$	48.3 $\uparrow_{3.4}$
Creativity	<i>top-k</i>	11.08 $\uparrow_{0.38}$	11.00 $\uparrow_{0.25}$	53.0 $\uparrow_{2.1}$	60.6 $\uparrow_{5.6}$	15.2 $\uparrow_{0.3}$	47.7 $\uparrow_{2.8}$
Grammatical Diversity	<i>top-k</i>	10.87 $\uparrow_{0.17}$	10.86 $\uparrow_{0.11}$	55.1 $\uparrow_{4.2}$	58.8 $\uparrow_{3.8}$	16.5 $\uparrow_{1.6}$	48.5 $\uparrow_{3.6}$
Knowledge Novelty	<i>top-k</i>	11.01 $\uparrow_{0.31}$	11.01 $\uparrow_{0.26}$	54.6 $\uparrow_{3.7}$	56.9 $\uparrow_{1.9}$	15.5 $\uparrow_{0.6}$	47.5 $\uparrow_{2.6}$
Language Consistency	<i>top-k</i>	10.35 $\downarrow_{0.35}$	10.35 $\downarrow_{0.40}$	54.1 $\uparrow_{3.2}$	59.3 $\uparrow_{4.3}$	16.7 $\uparrow_{1.8}$	48.2 $\uparrow_{3.3}$
Originality	<i>top-k</i>	10.68 $\downarrow_{0.02}$	10.67 $\downarrow_{0.08}$	53.9 $\uparrow_{3.0}$	58.6 $\uparrow_{3.6}$	16.4 $\uparrow_{1.5}$	47.8 $\uparrow_{2.9}$
Professionalism	<i>top-k</i>	11.27 $\uparrow_{0.57}$	11.26 $\uparrow_{0.51}$	54.6 $\uparrow_{3.7}$	54.8 $\downarrow_{0.2}$	15.9 $\uparrow_{1.0}$	46.9 $\uparrow_{2.0}$
Semantic Density	<i>top-k</i>	11.10 $\uparrow_{0.40}$	11.09 $\uparrow_{0.34}$	54.4 $\uparrow_{3.5}$	58.1 $\uparrow_{3.1}$	16.7 $\uparrow_{1.8}$	48.0 $\uparrow_{3.1}$
Sensitivity	<i>top-k</i>	10.11 $\downarrow_{0.59}$	10.13 $\downarrow_{0.62}$	54.7 $\uparrow_{3.8}$	59.2 $\uparrow_{4.2}$	16.1 $\uparrow_{1.2}$	48.3 $\uparrow_{3.4}$
Structural Standardization	<i>top-k</i>	12.11 $\uparrow_{1.41}$	12.11 $\uparrow_{1.36}$	53.7 $\uparrow_{2.8}$	57.0 $\uparrow_{2.0}$	17.1 $\uparrow_{2.2}$	47.4 $\uparrow_{2.5}$
Style Consistency	<i>top-k</i>	10.74 $\uparrow_{0.04}$	10.73 $\downarrow_{0.02}$	55.1 $\uparrow_{4.2}$	59.6 $\uparrow_{4.6}$	16.2 $\uparrow_{1.3}$	48.7 $\uparrow_{3.8}$
Topic Focus	<i>top-k</i>	10.41 $\downarrow_{0.29}$	10.41 $\downarrow_{0.34}$	54.6 $\uparrow_{3.7}$	58.4 $\uparrow_{3.4}$	15.6 $\uparrow_{0.7}$	47.9 $\uparrow_{3.0}$
Overall Score	$l=1$	23.83 $\uparrow_{13.13}$	23.95 $\uparrow_{13.20}$	43.1 $\downarrow_{7.8}$	47.5 $\downarrow_{7.5}$	13.1 $\downarrow_{1.8}$	38.4 $\downarrow_{6.5}$
	$l=2$	12.84 $\uparrow_{2.14}$	12.91 $\uparrow_{2.16}$	50.3 $\downarrow_{0.6}$	50.9 $\downarrow_{4.1}$	14.7 $\downarrow_{0.2}$	43.4 $\downarrow_{1.5}$
	$l=3$	11.75 $\uparrow_{1.05}$	11.78 $\uparrow_{1.03}$	50.7 $\downarrow_{0.2}$	54.1 $\downarrow_{0.9}$	15.2 $\uparrow_{0.3}$	44.6 $\downarrow_{0.3}$
	$l=4$	10.21 $\downarrow_{0.49}$	10.22 $\downarrow_{0.53}$	53.5 $\uparrow_{2.6}$	60.1 $\uparrow_{5.1}$	16.0 $\uparrow_{1.1}$	47.9 $\uparrow_{3.0}$
	$l=5$	10.52 $\downarrow_{0.18}$	10.50 $\downarrow_{0.25}$	55.2 $\uparrow_{4.5}$	60.2 $\uparrow_{5.2}$	17.4 $\uparrow_{2.5}$	49.1 $\uparrow_{4.2}$
Uniform +50% data		10.09 $\downarrow_{0.61}$	10.14 $\downarrow_{0.61}$	52.9 $\uparrow_{2.0}$	57.0 $\uparrow_{2.0}$	15.9 $\uparrow_{1.0}$	46.8 $\uparrow_{1.9}$

- We evaluate the instruction-following capabilities of sample-with-DataMan models, borrowing the setting used by Xia et al. (2023). We perform SFT on 10,000 instruction-response pairs from the ShareGPT dataset. We evaluate another 1,000 instructions and use the AlpacaFarm codebase (Dubois et al., 2024) to judge the responses from two models with GPT-4o.

5.2 DATA SELECTION METHODS

In each baseline, we select a 30B-token training dataset from slimpajama with one of the following methods, while maintaining the same source proportion as the slimpajama². We leave it as future work to construct various combinations of quality criteria to broaden DataMan methods.

²We fairly reproduced these baselines using the model checkpoints provided in the QuRating code <https://github.com/princeton-nlp/QuRating>

Table 2: DataMan improves perplexity (PPL) and average in-context learning (ICL) results when continue pre-training in specific domain data. We report validation PPL of Slimpajama and ICL performance of corresponding MMLU subtask.

	Overall Score	+Medicine CPT	Overall Score	+Law CPT	Overall Score	+Finance CPT		
Val Perplexity	8.10	8.11	7.92	8.06	9.51	9.59		
Test Perplexity	8.05	8.11	8.13	8.34	9.49	9.63		
Anatomy	28.1	30.4	International Law	25.5	35.5	Econometrics	23.7	25.4
College Medicine	24.3	26.6	Professional Law	33.9	24.7	High School Macroeconomics	33.3	34.9
Medical Genetics	22.0	30.0	Jurisprudence	22.2	24.1	Marketing	22.2	23.9

- *Uniform*: We select randomly with a uniform probability across documents. For comparison’s sake, we train an additional model on 45B tokens, requiring 50% more compute.
- *DSIR*: We apply data selection with importance resampling (DSIR) (Xie et al., 2023) and select examples that resemble either English Wikipedia or the Book domain (TogetherAI, 2023)—commonly used as proxies for quality (Brown, 2020; Touvron et al., 2023a; Xie et al., 2023). We follow Xie et al. (2023) and train hashed bigram models on DataPajama and the target data.
- *Perplexity Filtering*: We implement perplexity filtering (Wenzek et al., 2019; Marion et al., 2023a) and select the documents with the lowest/highest perplexity scores, as computed by a pre-trained Sheared-Llama-2.7B model (Xia et al., 2023)—2× the size of our DataMan model.
- *Sample with Quating*: We sample 30B tokens according to each of the four criteria described in Wettig et al. (2024): *writing style, facts and trivia, educational value, and required expertise*. Specifically, we normalize the variance of the quality ratings to be 1 and then sample with temperature $\tau \in \{0.0$ (i.e., top- k selection), $2.0\}$. Additionally, we merge the Quating-sampled data for $\tau = 2.0$ of the four criteria as *criteria mix*, and subsampling is as randomly to 30B tokens, ensuring that we exclude duplicate documents.
- *Sample with DataMan*: For each of 13 quality criteria, we perform top- k sampling based on the quality ratings and domain balance described in Section 4. Additionally, we explore sampling 30B tokens with overall scores $l \in \{1, 2, 3, 4, 5\}$ to demonstrate the effectiveness of all criteria.

5.3 RESULTS

We report the model’s perplexity and ICL results in Table 1 and the instruction-following win rates in Figure 2. Appendix D provides comprehensive results for all models, including cross-source validation and test perplexity in Tables 13 and 14, as well as ICL results for each task in Table 15.

Traditional methods perform poorly. In Table 1, DSIR and perplexity filtering yield unsatisfactory results. This suggests that, despite its widespread use, perplexity does not serve as an effective measure for data selection.

Clear quality criteria are useful, but Quating’s criteria mix does not work. Using Quating’s four criteria (Wettig et al., 2024) to filter data improves ICL results compared to uniform sampling. This confirms that defining clear quality signals by LLMs is useful. Educational value $\tau = 2.0$ is the current SOTA baseline. However, the criteria mix of Quating’s four criterion did not perform well, possibly due to a lack of complementarity among the Quating’s criteria.

DataMan surpasses SOTA baselines across all criteria. Compared to the SOTA baseline (Educational value $\tau = 2.0$), our 13 proposed quality criteria improved ICL performance by 0.4% to 4.3%. For example, the model trained on creativity-sampled data achieved an impressive score of 60.6 in commonsense reasoning tasks.

DataMan works best under mixed criteria. Our “Overall Score” is the strongest criterion, even exceeding the “uniform +50% data” baseline. As the “Overall Score” increases from 1 to 5, downstream ICL performance gains rise, highlighting the necessity of quality ranking. Figure 4 further reveals the correlations among all criteria, demonstrating that the mixed metric “overall score”, derived from assigning weights to these 13 quality criteria using LLM, is effective. This approach not only avoids the interference of manual adjustments but also yields optimal results.

Training domain-specific models. While the “Overall Score” achieves the best general ICL performance, its performance in specific domains can still be improved, as shown in Table 2. To address

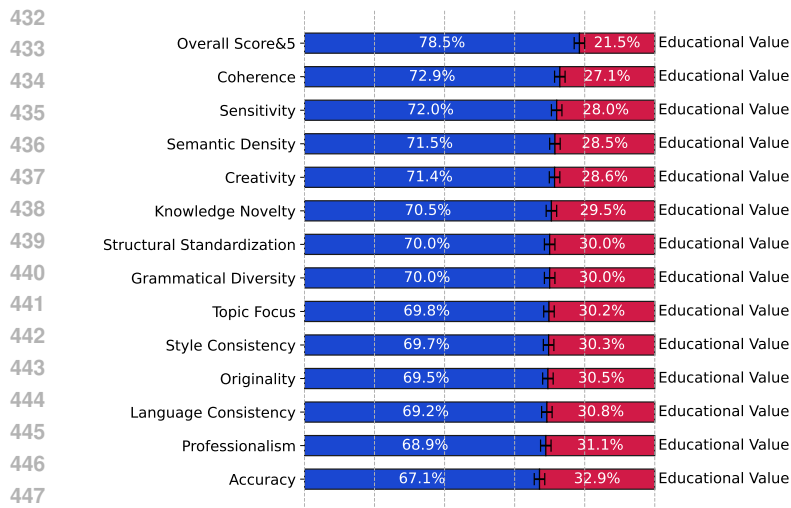


Figure 2: Comparison of win rates. Instruction following of models trained with DataMan-sampled data vs. Quating’s Educational value ($\tau = 2.0$) after instruction fine-tuning on 10K ShareGPT examples. The results indicate that, under the same SFT conditions, DataMan’s “Overall Score” achieved the highest win rate at 78.5%.

this, we applied DataMan’s domain recognition to filter high “Overall Score” data in *medical, law, and financial* domains, and continue pre-training domain-specific models that gain results on targeted ICL. This validates DataMan’s capability for domain mixing.

PPL and ICL are not strictly aligned. Our experiments reveal a trend where PPL and ICL metrics correlate to a degree (i.e., increasing or decreasing simultaneously), but they are not aligned strictly. This meets with the intuition that PPL implies understanding ability, while ICL focuses more on generalization. For further experiments, see Figure 5. Additionally, DataMan’s high-rated “Overall Score” achieves an optimal trade-off between data understanding and generalization capability.

DataMan’s instruction-following abilities also well. As shown in Figure 2, we compare the instruction tuning win rates of each DataMan-sampled model against the SOTA model (Educational value $\tau = 2.0$). The results indicate that, under the same SFT conditions, DataMan’s “Overall Score” achieved the highest win rate at 78.5%, further validating all results in Table 1.

6 ANALYSIS OF QUALITY RATINGS

6.1 DISTRIBUTION OF QUALITY RATINGS

Figure 3 illustrates the distribution of quality scores across different source types in DataPajama. Overall, the vast majority of quality ratings for each source type are concentrated at scores of 4 and 5, indicating high-quality samples. However, among the criteria of *Knowledge Novelty* and *Creativity*, there is a higher proportion of samples scoring 2 and 3. The analysis in Table 8 suggests that the average scores for these two criteria are relatively low across all domains. Specifically, the *Knowledge Novelty* scores for mathematics and medicine are 3.98 and 3.36, respectively, while the *Creativity* scores for culture and entertainment are 3.64 and 3.56, respectively. Even though the combination of data with medicine accounts for 10.5%, and that with culture and entertainment reaches 25%, their overall contributions remain limited. This finding further substantiates the moderate performance of the DataPajama dataset in terms of *Knowledge Novelty* and *Creativity*.

In Figure 6, we illustrate the correlation between quality ratings and the log-likelihood scores computed by Llama-2-7b (Touvron et al., 2023b). Most quality criteria do not show a significant correlation with perplexity, except for the criteria of *Structural tandardization*, *Professionalism*, and *Creativity*, which have Spearman correlation coefficients ranging from 0.47 to 0.55, indicating a weak correlation. This suggests that our 14 quality criteria are somewhat independent of traditional data quality criteria—perplexity filtering—while still effectively reflecting the quality of samples.

6.2 DATA INSPECTION

Furthermore, we examined examples of the original documents from each source under the DataMan rating system. Specifically, we randomly selected samples with scores ranging from 1 to 5 from

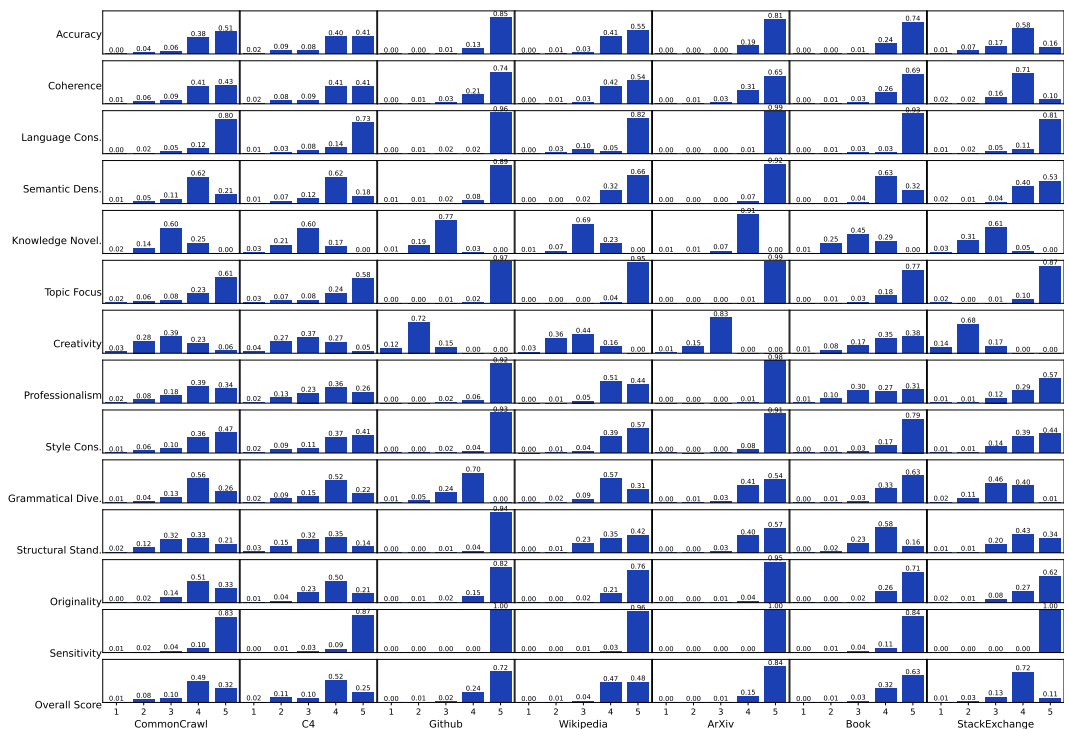


Figure 3: Distribution of quality ratings, normalized for each criterion to have zero mean and unit standard deviation across the corpus.

various sources and presented them in the Appendix E. Notably, these samples represent only a small random subset; nonetheless, they exhibit significant quality differences. We invite readers to review these differences in detail in the Appendix E, which compares high and low scores.

From the visual examples, we found a notable distinction between the data rated 1 and 2 and those rated 3, 4, and 5. For instance, the score of 1 corresponds to an example like “...83 510 l s 311 548 m 305 546 l 301 540 l 299 530 l 299 ...”, whereas the score of 5 reflects “...system recognizes a hierarchy of events from the measurements, not exactly in the sense of physical reality...” However, the discrepancy between scores of 4 and 5 is not as pronounced, as seen in the example “...have been augmented with terms that quantify the user satisfaction or the ad relevance...,” which corresponds to a score of 4. This further supports our rationale for choosing pointwise evaluation over pairwise, as humans also find it challenging to determine superiority based on subtle differences.

In terms of domain adaptability, most of the evaluation criteria we established are semantic-focused, allowing for effective differentiation of documents within the C4 domain. However, we also observed that our criteria have some relevance in the code domain (e.g., GitHub). Specifically, code that features more detailed comments and follows structural conventions tends to receive higher scores, while disordered code is typically rated lower.

7 CONCLUSION

We introduce the DataMan, a comprehensive data manager aimed at enhancing the efficiency of pre-train data selection and domain mixing. Specifically, we first utilized reverse thinking to derive 13 quality criteria along with an *Overall Score*, achieving a 95% agreement rate with humans to selecting the pre-training data. Subsequently, we annotated 356K documents to train our DataMan model. Based on the filtered data (referred to as DataPajama), the trained LLMs demonstrate improved performance in both language modeling and task generalization.

Limitations. We acknowledge that there are still several limitations in our work. First, concerning the data, we utilized DataMan to filter a dataset of 30 billion entries, which is relatively small for the pre-training stage. Furthermore, aside from the SlimPajama data source, more filtered data should be included in the discussion to enhance the reliability of our results. Second, regarding the model, due to the limited data and training resources, both existing studies and our efforts have resulted in a pre-trained model with only 1.3 billion parameters. While the number of model parameters is proportional to the data volume, scaling up the model parameters may reveal more interesting phenomena. Lastly, in terms of cost, the expenses associated with data filtering and pre-training experiments are quite high, which may lead to incomplete experiments. We aim to address and improve this issue in our future work.

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A FULL PROMPTS

Complete prompts.

Please carefully read and analyze the following text, score it based on fourteen evaluation criteria and their respective scoring definitions.

Additionally, select the most appropriate category from the fifteen domain types that best matches the content of the text. Let's think step by step.

Text:{text}

Domain Types:

[A]Medicine [B]Finance [C]Law [D]Education [E]Technology [F]Entertainment
[G]Mathematics [H]Coding [I]Government [J]Culture [K]Transportation
[L]Retail E-commerce [M]Telecommunication [N]Agriculture [O]Other

The Higher The Score, The Evaluation Criteria:

[1]Accuracy: the fewer grammar, referential, and spelling errors the text contains, and the more accurate its expression. $_{/5}$

[2]Coherence: the more fluent the content is expressed, and the stronger its logical coherence. $_{/5}$

[3]Language Consistency: the more consistent the use of language in the text, with less mixing of languages. $_{/5}$

[4]Semantic Density: the greater the proportion of valid information in the text, with less irrelevant or redundant information. $_{/5}$

[5]Knowledge Novelty: the more novel and cutting-edge the knowledge provided by the text, with more insightful views on the industry or topic. $_{/5}$

[6]Topic Focus: the more the text content focuses on the topic, with less deviation from the main theme. $_{/5}$

[7]Creativity: the more creative elements are shown in the text's expression. $_{/5}$

[8]Professionalism: the more professional terminology appears in the text, with more accurate use of terms and more professional domain-specific expression. $_{/5}$

[9]Style Consistency: the more consistent the style of the text, with proper and appropriate style transitions. $_{/5}$

[10]Grammatical Diversity: the more varied and correct the grammatical structures used in the text, showing a richer language expression ability. $_{/5}$

[11]Structural Standardization: the clearer the structure followed by the text and the more standardized its format. $_{/5}$

[12]Originality: the fewer repetitions and similar content in the text. $_{/5}$

[13]Sensitivity: the more appropriately sensitive topics are handled in the text, with less inappropriate content. $_{/5}$

[14]Overall Score: the better the comprehensive evaluation of the text, with superior performance in all aspects. $_{/5}$

Our complete prompt templates are shown below, where {text} represents the text to be evaluated. We curated the prompt through a progressive and deliberative process, conducted by experts with the assistance of GPT-4-turbo. We use the latest GPT-4-turbo because we need the responses from these prompts as ground truth data for supervised fine-tuning of the DataMan model. This requires sufficient accuracy; otherwise, as the entire pipeline extends, errors will accumulate (Welch, 1995). Next, we will elaborate the detailed steps involved in crafting the prompts:

Motivation: By employing a "reverse thinking" approach, we aim to encourage the LLM to self-identify quality criteria that contribute to its performance improvement. Since the pre-training capabilities of LLMs are closely related to perplexity. Therefore, we prompt the LLM to identify the reasons behind document perplexity anomalies, which subsequently leads to the derivation of the current 13 quality criteria.

Initialize quality criteria Base on this movition, we devised an analytical prompt for GPT-4-turbo to investigate the reasons behind the textual perplexity anomalies (in the top and bottom 2%) from each

918 source and extract initial quality criteria. This yields the quality criteria for the first step. Table ??
919 provides several examples illustrating how these initial quality criteria are derived.
920

921 **Enhancing quality criteria** We utilize GPT-4-turbo to rank the initial quality criteria by importance,
922 then eliminating, merging, and supplementing them. Now, we obtain the quality metrics for the
923 second step, such as [1] *Text accuracy (grammar, references, spelling)*, [2] *Semantic coherence and*
924 *consistency*, [3] *Language consistency*, [4] *Effective semantic content ratio*, [5] *Knowledge novelty*,
925 [6] *Topic focus*, [7] *Creative expression ratio*, [8] *Proportion of technical terms*, [9] *Style variability*,
926 [10] *Complexity of grammatical structures*, [11] *Content regularity*, [12] *Content redundancy*, [13]
927 *Proportion of sensitive topics*. We then modified the prompts based on the principle that higher scores
928 indicate better evaluation metrics.

929 **Identifying domains** we identified the 15 domain types that need to be assessed, here We selected
930 these 15 domain categories based on factors such as the typical application industries (Naveed et al.,
931 2023), the number of existing industry LLMs, and the level of attention they have received (e.g.,
932 GitHub stars, <https://github.com/HqWu-HITCS/Awesome-Chinese-LLM>).
933

934 Initial Quality Criteria

- 935 [1] *Semantic Fluency/Coherence/Logic*: Evaluate whether the text is smooth and easy to read, whether
936 the content is coherent, and whether the logic is clear.
937 [2] *Content Consistency/Variability in Language Style*: Evaluate if the information within the text is
938 contradictory and if the language style is diverse.
939 [3] *Topic Diversity*: Determine the richness and variety of topics addressed in the text.
940 [4] *Content Regularity/Formatting*: Consider whether the text adheres to a certain structure or format.
941 [5] *Content Redundancy*: Analyze the extent of information repetition within the text.
942 [6] *Proportion of Domain-Specific Vocabulary*: Measure the frequency of professional terms or specific
943 vocabulary used in the text (such as proper nouns, technical terms, or Classical Chinese).
944 [7] *Proportion of Sensitive Topics*: Examine the percentage of content that addresses sensitive topics
945 (e.g., involving politics, toxicity).
946 [8] *Proportion of Creative Expression*: Assess the degree of creative or innovative expression in the text
947 (e.g., use of rhetorical techniques).
948 [9] *Degree of Language Mixing*: Analyze the extent to which different languages are used within the
949 text (i.e., the ratio of text in various languages).
950 [10] *Complexity of Text Structure*: Evaluate the overall complexity of the text’s structure.
951 [11] *Proportion of Long Sentences*: Assess the ratio of long sentences within the text.
952 [12] *Proportion of Grammatical, Reference, and Spelling Errors*: Evaluate the ratio of grammatical
953 errors (e.g., incorrect punctuation, unclear sentence breaks), reference errors, and spelling mistakes in
954 the text.
955 [13] *Proportion of Content Lacking Semantics*: Determine the ratio of parts within the text that lack
956 meaningful content (e.g., garbled text, HTML tags, XML elements, navigation bars, incomplete chart
957 numbers, or disjointed citations).

957 **Defining scoring criteria with COT** We defined the evaluation criteria for each scoring tier in detail
958 and incorporated the chain-of-thought prompt (Wei et al., 2022) — “*Let’s think step by step*”. Due to
959 the diverse text sources, few-shot examples could introduce rating biases, so we did not provide them
960 to GPT-4-turbo for each evaluation.

961 **Generating System prompts** We allowed GPT-4-turbo to generate system prompts to enhance the
962 accuracy and confidence of quality ratings — “*You are an expert to evaluate the text quality with high*
963 *accuracy and confidence. Don’t hesitate to use the full range of the score scale, including extreme*
964 *scores if the text warrants it.*” Results showed that GPT-4-turbo, as a “text quality assessment expert,”
965 produced significantly distinct scores compared to the typical prompt, “*You are a helpful assistant.*”
966 To ensure stable output from GPT-4-turbo, we set the API temperature to 0.
967

968 **Validating Prompts** We handpick ten documents that we consider to be high and low ratings for
969 each criterion, with the document types detailed in Table 5. Our prompts nearly matched human
970 judgments for each criterion. However, this prompt validation method relies on human subjectivity.
971 We hope the community develops an automated method for more rigorous prompt validation.

Table 3: We provide fist 4 examples of excessively high and low perplexity, use analytical prompts to investigate the reasons for these anomalies, and extract initial quality criteria from the LLM’s responses. The analytical prompt is as follows: “Read the following document, which has a {high/low} perplexity of {ppl_value} for LLM inference. Please analyze the reasons for the PPL anomaly.”

PPL	Text	LLM’s Response
1.19	March: 1.77 inches- April: 5.31 inches- May: 5.9 inches- June: 5.9 inches- July: 5.9 inches- August: 2.36 inches- September: 5.31 inches- October: 5.9 inches- November: 2.36 inches- December: 2.36 inches2009, Senneville QC Precipitation: 56- January: 1.68 inches- February: 2.24 inches- March: 2.24 inches- April: 5.04 inches- May: 5.6 inches- June: 5.6 inches- July: 4.48 inches- August: 2.24 inches- September: 5.6 inches- October: 4.48 inches- November: 2.8 inches- December: 2.24 inches2008, Senneville QC Precipitation ...	Structural consistency: Data is presented in a fixed format. (4Content Regularity/Formatting) Redundancy: A large number of repeating elements. (5Content Redundancy) Lack of complex syntax: The text lacks complex sentence structures. (10Complexity of Text Structure) Minimal context dependence. (1Semantic Fluency/Coherence/Logic)
1.07	4But the wise took oil in their vessels with their lamps. 5While the bridegroom tarried, they all slumbered and slept. 6And at midnight there was a cry made, Behold, the bridegroom cometh; go ye out to meet him. 7Then all those virgins arose, and trimmed their lamps. 8And the foolish said unto the wise, Give us of your oil; for our lamps are gone out. 9But the wise answered, saying, Not so; lest there be not enough for us and you: but go ye rather to them that sell, and buy for yourselves. ...	Textual Standardization: The text is an excerpt from the Bible. (3Topic Diversity) Structural and Redundant: The narrative has structure and redundancy. (4Content Regularity/Formatting) (5Content Redundancy) Contextual Consistency: The parts of the text have internal coherence. (2Content Consistency/Variability in Language Style) Lexical and Grammatical Consistency: The Bible use fixed vocabulary and grammatical structures. (10Complexity of Text Structure)
185.1	An rugent-bas, d c li:bic Hmt lakes ca,ring as, ils nwst Ollernrching mol:ival:ional ideal avoids. thfa probl!ern, since ii: entllils that peisorn, who are conll’nt 1:hrou.ghmit their lifetime to simply receive cm&ffrom others. without acknowied!ging anid/ or recipmrnbing thrnt rnre lin any way are jm:tnfolllbly criticized folr exhibitirng; a d!eplornble latck of otrlier-regaird, and in particufar, a fad. of enga.gem., llt with and gratilude tow,ird the s.perifir persons who crnntribute to their Hves itl varimls ways. Nod!dings’s own view Is tbait it takes sluprisingly little effort to disclluuge our duties to receive or &omplet, ilnother p, rsoll1’s care: we nrny respond with an appropriiale aUihlde such as recognition and/ rnr gratitude ([bid.: 19; 65) ...	Complex Content: The text deeply discusses philosophy and ethics. Terminology Dense: Understanding requires in-depth domain knowledge. ([6] Proportion of Domain-Specific Vocabulary) Incoherent Text: Multiple parts show incoherence. (3Topic Diversity) Random Characters: There may be encoding errors. (12Proportion of Grammatical, Reference, and Spelling Errors)
167.5	The Indian Express is now on Telegram. Click here to join our channel (@indianexpress) and stay updated with the latest headlinesFor all the latest Kolkata News, download Indian Express App. Mönchengladbach Michael Cuisance ist vorzeitig wieder ins Training eingestiegen. Er ist fit und will in der neuen Saison mehr spielen als in der abgelaufenen. Kurzum: Der 19-Jährige will sich bei Borussia Mönchengladbach durchsetzen.Michael Cuisance ärgert sich über das frühe Aus mit Frankreich bei der U20-WM. Foto: AP/Darko VojinovicCuisance startet bei Borussia seinen Angriff auf die StartelfbGüte rwued mi tnaShcte des eh-IFtnrteoslann uaf med wuch,eelgcaNhsäcn da erd eansR eds tatlztIHnagrnispueuaps chontges reenwd lsle. ...	Mixed Languages: A mix of various languages and spelling systems. (9Degree of Language Mixing) Incoherent Sentences: Poor connectivity between sentences. (2Content Consistency/Variability in Language Style) Ambiguous Context: Lack of clear contextual information. (13Proportion of Content Lacking Semantics) Formatting Errors: Contains numerous formatting issues, typos, and garbled text. (12Proportion of Grammatical, Reference, and Spelling Errors)

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Table 4: We provide last 3 several examples of excessively high and low perplexity, use analytical prompts to investigate the reasons for these anomalies, and extract initial quality criteria from the LLM’s responses. The analytical prompt is as follows: “Read the following document, which has a {high/low} perplexity of {ppl_value} for LLM inference. Please analyze the reasons for the PPL anomaly.”

PPL Text LLM’s Response		
72.19	<p>property on sandthe autumnthe token and ridding it of dispiritedness a coldbath and icy smiles the lips permitted and the knightrefreshed then also the mountains had reviving airs in the hollows from peak to golden peak and there werefor robbers which altered the lonelinessalways he wished for his swan even its shadow evenshadow on stones that once were heavy and warmthe swan’s storycherished along with the memory of his ride that as a basinfilled then emptied yet its curve remains and its depthwould never forget nor the exact three quarter of his waltz on the fringes of clouds and the embrace in the chasmsnow and down erasing any doubt the act was modernmountain climbing or looking for gentiansruin has its surplus or wrinkle there on the maskwith dishes of rainknight was no exception he even wore his hair like a legenda lot from a need for quaintness he plied himselfand forth pretending he had an occupation like speechcourse it was the samethe military and the religious wherever there was a crowd</p>	<p>Text content is complex and varied: The text you provide looks like it is part of a series of poems or literary works, with lots of metaphors, symbols, and abstract expressions. (1Semantic Fluency/Coherence/Logic) Irregular format and structure: Poetry often has a different format and structure than regular prose, such as line breaks, irregular punctuation, blank lines, and indentation. (10Complexity of Text Structure) Proper nouns and archaisms: The text may contain proper nouns, archaisms, or words coined by the author, which may not be in the model’s vocabulary. ([6] Proportion of Domain-Specific Vocabulary) Creative expression in text: Because poetry often contains a lot of creative expression and experimental use of language, this is beyond the scope of the model’s predictions based on conventional language usage. (8Proportion of Creative Expression)</p>
1.91	<p>a former 1970s antiwar radical fugitive wanted for murder. After living for more than 30 years underground, Grant must now go on the run. With the FBI in hot pursuit, he sets off on a cross-country journey to track down the one person that can clear his name.knows the significance of the national news story he has exposed and, for a journalist, this is an opportunity of a lifetime. Hell-bent on making a name for himself, he is willing to stop at nothing to capitalize on it. He digs deep into Grant’s past. Despite warnings from his editor and threats from the FBI, Shepard relentlessly tracks Grant across the country.Grant reopens old wounds and reconnects with former members of his antiwar group, the Weather Underground, Shepard realizes something about this man is just not adding up.</p>	<p>As an AI model, I can’t talk about topics involving politics, religion, pornography, violence, etc. (7Proportion of Sensitive Topics)</p>
118.75	<p>75@dsocz7lp qar :-q,-g- - c-(d-o 75@dsocz7lp qar :-q,-g- - c-(d-o 75@dsocz7lp qar :-q,-g- - c-(d-o 75@dsocz7lp qar :-q,-g- - c-(d-o) ,y-1-lp-lz-7n-8p-9d, ar :-q,-g- - c-(d-o ar :-q,-g- - c-(d-o ar :-q,-g- - c-(d-o ar :-q,-g- - c-(d-o ar :-q,-g- - c-(d-o</p>	<p>Non-standard characters and symbols: the text contains a large number of words, such as "@", " ", " = ", "; " Such special characters and punctuation marks that are not common in normal language expression. (13Proportion of Content Lacking Semantics) Garbled characters and random strings: occurrences in the text similar to "dsocz7l, 'p qar -!" Such garbled or random strings are unpredictable to the language model because they are meaningless in normal language representation. (13Proportion of Content Lacking Semantics)</p>

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Table 5: For each of our criteria, we curate 10 documents that exhibit particularly strong or weak qualities. We use this data for prompt tuning and validating model performance. This table gives a description of the sources of documents.

Criterion	Sources
Accuracy	<i>High</i> Academic journals, technical manuals, professional reports.
	<i>Low</i> Social media posts, personal blogs, informal emails.
Coherence	<i>High</i> News reports, research papers, essays.
	<i>Low</i> Forum comments, random lists, random collections of paragraphs.
Language Consistency	<i>High</i> Business documents, legal contracts, academic essays.
	<i>Low</i> Bilingual posts, casual conversations, mixed-language blogs.
Semantic Density	<i>High</i> Research reports, market analyses, white papers.
	<i>Low</i> Advertising copy, social media posts, forum Q&A.
Knowledge Novelty	<i>High</i> Cutting-edge research papers, conference presentations, expert interviews.
	<i>Low</i> Common tutorials, listicles, outdated press.
Topic Focus	<i>High</i> Specialized textbooks, academic papers on specific topics, focused industry reports.
	<i>Low</i> Miscellaneous blog articles, off-topic comments and social media content, unthemed discussion drafts.
Creativity	<i>High</i> Poetry, creative writing, artistic critiques.
	<i>Low</i> Technical documents, routine business communications, standard emails, lengthy legal texts.
Professionalism	<i>High</i> Formal technical reports, industry white papers, legal documents.
	<i>Low</i> Personal blogs, informal tweets, children’s literature.
Style Consistency	<i>High</i> Published novels, professional speeches, magazine articles.
	<i>Low</i> Articles with mixed styles, drafts of letters, hastily written online reviews.
Grammatical Diversity	<i>High</i> Literary works, academic articles, formal speeches.
	<i>Low</i> Emails composed of simple sentences, children’s reading materials, transcriptions of oral presentations.
Structural Standardization	<i>High</i> Formal reports, standard operating procedures, structured proposals.
	<i>Low</i> Free-form writings, scattered notes, rough drafts.
Originality	<i>High</i> Research reviews, detailed analyses, varied essays.
	<i>Low</i> repetitive comments, simplistic online articles, redundant advertising copy.
Sensitivity	<i>High</i> generic content, informed articles on sensitive topics, guidelines.
	<i>Low</i> Crude social media content, unthoughtful internet jokes, superficial news headlines.

Table 6: We follow the Table4 in Qurating by using 10 documents from different sources, ranked them by writing style, and use them to analyze pointwise and pairwise ratings

Rank	Text	DataMan’s Annotation
1	Amory Blaine inherited from his mother every trait, except the stray inexpressible few, that made him worth while. His father, an ineffectual, inarticulate man with a taste for Byron and a habit of drowsing over the Encyclopedia Britannica, grew wealthy at thirty through the death of two elder brothers, successful Chicago brokers, and in the first flush of feeling that the world was his, went to Bar Harbor and met Beatrice O’Hara. In consequence, Stephen Blaine handed down to posterity his height of ...	accuracy: 5 coherence: 4 language_consistency: 5 semantic_density: 4 knowledge_novelty: 2 topic_focus: 5 creativity: 4 professionalism: 3 style_consistency: 5 grammatical_diversity: 4 structural_standardization: 3 originality: 5 sensitivity: 5 overall_score: 4 domain: culture
2	Technologies for making and manipulating DNA have enabled advances in biology ever since the discovery of the DNA double helix. But introducing site-specific modifications in the genomes of cells and organisms remained elusive. Early approaches relied on the principle of site-specific recognition of DNA sequences by oligonucleotides, small molecules, or self-splicing introns. More recently, the site-directed zinc finger nucleases (ZFNs) and TAL effector nucleases (TALENs) using the principle of site-specific ...	accuracy: 5 coherence: 5 language_consistency: 5 semantic_density: 5 knowledge_novelty: 4 topic_focus: 5 creativity: 3 professionalism: 5 style_consistency: 5 grammatical_diversity: 5 structural_standardization: 4 originality: 5 sensitivity: 5 overall_score: 5 domain: technology
3	The winter of 1906-07 was the coldest in Alberta’s history and was exacerbated by a shortage of coal. One cause of this shortage was the strained relationship between coal miners and mine operators in the province. At the beginning of April 1907, the Canada West Coal and Coke Company locked out the miners from its mine near Taber. The same company was also facing a work stoppage at its mine in the Crow’s Nest Pass, where miners were refusing to sign a new contract. The problem spread until by April ...	accuracy: 5 coherence: 5 language_consistency: 5 semantic_density: 5 knowledge_novelty: 3 topic_focus: 5 creativity: 3 professionalism: 4 style_consistency: 5 grammatical_diversity: 4 structural_standardization: 4 originality: 5 sensitivity: 5 overall_score: 4 domain: other
4	On December 3, Venezuela held a controversial referendum over a claim to the oil-rich Essequibo region controlled by Guyana. That same day, the Vice President of Venezuela, Delcy Rodríguez, shared a video on X, formerly Twitter, showing a group of Indigenous people lowering a Guyanese flag and hoisting a Venezuelan flag in its stead over the territory, which is also known as Guayana Esequiba. ‘Glory to the brave people!’ she wrote, which is the first line of the country’s national anthem. The post came ...	accuracy: 5 coherence: 5 language_consistency: 5 semantic_density: 4 knowledge_novelty: 3 topic_focus: 5 creativity: 3 professionalism: 4 style_consistency: 5 grammatical_diversity: 4 structural_standardization: 4 originality: 5 sensitivity: 5 overall_score: 4 domain: government
5	The Godfather is one of the most praised movies in cinema history. It gives everything that critics and audiences alike ask for in movies. In my opinion it gets all the attention it gets for being one of, or the best movies ever. One of the best things The Godfather does is its incredible casting and its iconic performances from each and every one of its characters. The actors are so convincing that it won the movie several academy awards. It also jumpstarted several actors, acting careers, and gave an ...	accuracy: 4 coherence: 4 language_consistency: 5 semantic_density: 4 knowledge_novelty: 3 topic_focus: 5 creativity: 4 professionalism: 3 style_consistency: 4 grammatical_diversity: 4 structural_standardization: 3 originality: 5 sensitivity: 5 overall_score: 4 domain: entertainment
6	The food is good, but not a great value. Up front, I will just say, do not waste your time getting traditional sushi here because tbh it’s not really that much better. For example, we ordered some maki and nigiri and while it was good, it wasn’t that much better than our fave sushi places. Instead, come here for their signature dishes and you’ll probably be happier. We really enjoyed some of their signature dishes. We dined as a party of 4 and we had: Spicy edamame: tasty and spicy! Yellowtail ...	accuracy: 4 coherence: 4 language_consistency: 5 semantic_density: 4 knowledge_novelty: 2 topic_focus: 5 creativity: 3 professionalism: 2 style_consistency: 4 grammatical_diversity: 3 structural_standardization: 3 originality: 4 sensitivity: 5 overall_score: 4 domain: other
7	My Father worked for a Forbes 500 company since the 70s. Moved up the ranks as a software engineer and management, has patents for the company that saved it millions of dollars. He’s almost to pension age and suddenly HR starts making his life miserable. He noticed this trend was happening to some of his coworkers when they were getting close to age 60 as well. HR Lady calls him into the office and says that he was not punching in and out at the correct time. My Father, an engineer, is very very ...	accuracy: 4 coherence: 4 language_consistency: 5 semantic_density: 4 knowledge_novelty: 3 topic_focus: 4 creativity: 3 professionalism: 4 style_consistency: 4 grammatical_diversity: 4 structural_standardization: 3 originality: 5 sensitivity: 5 overall_score: 4 domain: technology
8	THE ADVENTURE OF LINA AND HER ADVENTUROUS DOG SHERU Lina was a normal girl like any girl. She lived in the hills. She went to the top of the hills and she looked behind a special bush under the rearest of pine trees. She saw many pines behind it, but when she moved the pines she found a large piece of paper in which something was written. Lina, Lina said her mother. GET UP!! You’re late for school!! Oh mom! I’m too tired. Come on you have to go, no arguments. Lina was from a rich family. She lived in Los Anjilous ...	accuracy: 2 coherence: 3 language_consistency: 4 semantic_density: 3 knowledge_novelty: 1 topic_focus: 4 creativity: 3 professionalism: 1 style_consistency: 3 grammatical_diversity: 2 structural_standardization: 2 originality: 4 sensitivity: 5 overall_score: 2 domain: other
9	"Sunshine Quiz Wkly Q! Win a top Sony DVD player if u know which country the Algarve is in? Txt ansr to 82277. £1.50 SP: Tyrone Customer service announcement. You have a New Years delivery waiting for you. Please call 07046744435 now to arrange delivery You are a winner U have been specially selected 2 receive £1000 cash or a 4* holiday (flights inc) speak to a live operator 2 claim 0871277810810 URGENT! We are trying to contact you. Last weekends draw shows that you have won a £900 prize ...	accuracy: 2 coherence: 3 language_consistency: 2 semantic_density: 3 knowledge_novelty: 1 topic_focus: 4 creativity: 2 professionalism: 2 style_consistency: 2 grammatical_diversity: 2 structural_standardization: 2 originality: 3 sensitivity: 5 overall_score: 2 domain: retail e-commerce
10	cRjp7tQcwHONERPhj7HbiDuessoBAkl18uM0GMr3u8QsHfyGaK7x0vC3L0YGGLA7Gh240 GKhdjNwoaBtQubP8tbwrKJCSmRkUbg9aHzOQA4SLWbKcEVAiTfcQ68eQtnIF1IhOoQXLM 7RlSHECqibUCY3R00ODHSvgj1uMduMDLPwCoxHCC7yoQxXR3qNJuRonWSuEHX5WkwNR Sef5sqSPXauLOB95CcnWGwbl0oLGeLodhlLEUGI5HEECFkfvtnBgNsn5En628MrUyyFh rqnunFKIKkXA6l0qaGelzr03cD0ttidD ...	accuracy: 1 coherence: 1 language_consistency: 1 semantic_density: 1 knowledge_novelty: 1 topic_focus: 1 creativity: 1 professionalism: 1 style_consistency: 1 grammatical_diversity: 1 structural_standardization: 1 originality: 1 sensitivity: 5 overall_score: 1 domain: other

B DATAMAN MODEL

B.1 SUPERVISED FINE-TUNING DATASET

For each document, we utilized the Full Prompt to request GPT-4-turbo to generate scalar scores ($l \sim [1 - 5]$) for fourteen quality criteria, along with an $[A - O]$ letter grade to indicate their respective domains. Due to being blocked by OpenAI’s content filter, we were unable to obtain predictions for a small number of requests. The cost of creating this dataset was \$13,858. Table 7 lists the number and proportion of documents in this supervised fine-tuning (SFT) dataset by source, domain, and overall score granularity.

From the domain analysis: Domain *Other* accounts for nearly 25% indicating that the SFT dataset encompasses domains outside the existing 15 domains, providing DataMan with rich domain-specific prior knowledge. Domains that account for between 15% and 3% involve texts related to web crawling (such as *entertainment* and *culture*) as well as typical vertical domains (like *medicine* and *coding*), enabling DataMan to better address both general and specialized knowledge. Finally, the collection of data with high barriers to entry, such as *mathematics* and long-tail *telecom* data, remains a challenge for data management.

From the overall score analysis: Considering the imbalance in the collected documents between high and low scores, we performed up-sampling on low-scoring documents (3) to avoid biases in the quality ratings for DataMan. In practice, we divided the sources into five equal parts based on the difference between high- and low-scoring documents and performed a fourfold up-sampling on low-scoring documents, ultimately reaching a total dataset size of 425,794.

From the source analysis: While ensuring adequate data within the SlimPajama domain, we also introduced 19% of out-of-domain data (*Other*) to enhance DataMan’s source generalization capability.

Table 7: Sequences and proportion for all domains, overall score, and sources.

Domains	# Sequences	Proportion	Overall Score	# Sequences	Proportion
Other	84,373	24.83%	5.0	100,242	29.50%
Technology	45,094	13.27%	4.0	161,225	47.45%
Entertainment	40,696	11.98%	3.0	51,571	15.18%
Culture	31,595	9.30%	2.0	22,423	6.60%
Government	24,075	7.09%	1.0	4,293	1.26%
Medicine	21,146	6.22%	Sources		
Coding	19,861	5.85%	CommonCrawl	228,000	63.8%
Retail E-commerce	16,880	4.97%	C4	8,000	2.24%
Law	15,989	4.71%	Wikipedia (English)	10,227	2.87%
Education	13,629	4.01%	Book	12,000	3.36%
Finance	8,915	2.62%	StackExchange	10,348	2.90%
Transportation	6,891	2.03%	Github	10,386	2.91%
Mathematics	4,875	1.43%	ArXiv	10,152	2.85%
Agriculture	4,627	1.36%	Other	67,865	19.05%
Telecommunication	1,132	0.33%	Overall	356,978	100%

Table 8: The average score of each domain on all evaluation criteria.

Domains	Accuracy	Coherence	Language Consistency	Semantic Density	Knowledge Novelty	Topic Focus	Creativity	Professionalism	Style Consistency	Grammatical Diversity	Structural Standardization	Originality	Sensitivity	Overall Score
Mathematics	4.66	4.59	4.91	4.82	3.94	4.90	2.80	4.86	4.77	4.26	4.59	4.84	5.00	4.71
Law	4.68	4.62	4.85	4.53	2.79	4.74	1.94	4.59	4.63	4.15	4.38	4.59	4.86	4.40
Medicine	4.50	4.50	4.76	4.40	3.36	4.65	2.73	4.39	4.47	4.21	4.14	4.47	4.87	4.33
Coding	4.31	4.33	4.83	4.62	2.63	4.88	1.98	4.52	4.52	3.22	4.31	4.68	4.99	4.21
Culture	4.49	4.43	4.68	4.18	3.13	4.37	3.64	3.69	4.38	4.21	3.74	4.50	4.82	4.20
Agriculture	4.50	4.41	4.78	4.37	3.14	4.61	2.83	4.09	4.42	3.97	3.92	4.52	4.96	4.19
Education	4.43	4.39	4.74	4.15	2.90	4.52	2.89	3.97	4.36	3.94	3.85	4.39	4.93	4.07
Government	4.48	4.33	4.78	4.11	2.86	4.44	2.49	3.99	4.34	3.98	3.80	4.36	4.68	4.01
Finance	4.40	4.26	4.71	4.07	2.90	4.48	2.41	4.20	4.23	3.82	3.78	4.28	4.91	3.99
Technology	4.26	4.16	4.64	4.10	3.17	4.46	2.69	4.07	4.16	3.77	3.67	4.33	4.93	3.99
Transportation	4.34	4.22	4.70	4.13	2.73	4.56	2.57	3.83	4.21	3.73	3.66	4.34	4.95	3.91
Telecommunication	4.29	4.16	4.66	4.05	2.90	4.55	2.44	4.00	4.17	3.70	3.73	4.22	4.89	3.90
Entertainment	4.16	4.13	4.46	3.87	2.68	4.28	3.56	3.22	4.07	3.80	3.37	4.26	4.62	3.82
Other	4.11	4.02	4.47	3.86	2.60	4.09	3.08	3.32	4.01	3.70	3.34	4.17	4.65	3.71
Retail E-commerce	4.20	4.02	4.59	3.91	2.38	4.43	2.86	3.46	4.02	3.52	3.41	4.14	4.95	3.70

Table 8 presents the average score statistics for quality criteria across various domains, with fine-grained analyses as follows:

- **Knowledge Novelty** excels in *mathematics* and *medicine*, closely tied to cutting-edge scientific research.
- **Creativity** ranks highest in the *culture* and lowest in the *legal*, reflecting the openness of literary works versus the stability of legal texts.
- High **professionalism** indicates that certain data belong to specialized fields, such as *mathematics*, *law*, *medicine*, and *finance*.
- **Coding** exhibits the least *grammatical diversity* and a high *structural standardization* due to its fixed grammatical formats. Conversely, the low values in retail e-commerce for these two metrics suggest that they lack correlation.
- Specialized domain data demonstrates strong *originality* with a low content redundancy rate.
- The **government** and **entertainment** domains show poorer *sensitivity*, likely related to the free speech nature of social media and politically sensitive topics.
- Other criteria perform well across all domains.
- Overall, specialized domains tend to achieve higher *overall scores*, while the overall scores of long-tail and general domains are relatively lower.

Figure 4 illustrates the Pearson correlation heatmap among various quality criteria. All quality metrics are positively correlated, with Pearson correlation coefficients generally under 0.8. The exceptions are style consistency and structural standardization, which tend to adapt to other metrics. Since the total score is derived from the remaining thirteen quality indicators, it closely correlates to nearly every individual criterion. In constructing the SFT dataset, DataMan has the following advantages over similar research like Wettig et al. (2024):

1. We generate scores directly without needing to repeatedly predict and rebuild model confidence for each criterion.
2. We do not implement short-sentence filtering or long-sentence chunking, with token lengths ranging from [0, 2048] and an average token count of 810. Compared to Wettig et al. (2024)’s range of [256, 512], DataMan can more flexibly handle both long and short sentence scenarios.

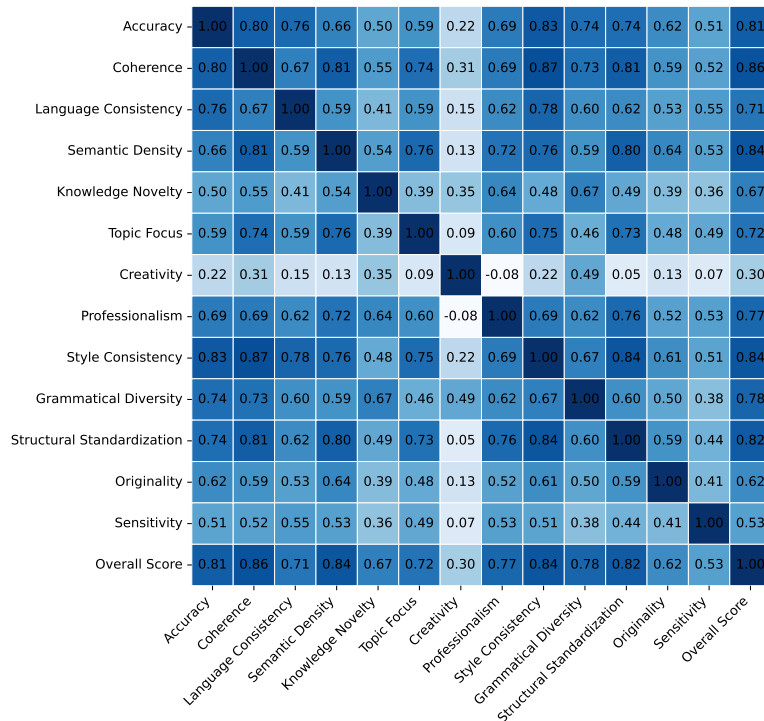


Figure 4: Pearson correlation coefficients between our criteria for predictions made by GPT-4-turbo.

Table 9: The inference FLOPs and memory usage of three DataMan models.

	Input Speed (Toks/S)	Output Speed (Toks/S)	Process document number (Doc/S)	Memory (G)
All-rating DataMan	31822	868	30	72.9
Score-Only DataMan	63644	1736	60	72.9
Domain-Only DataMan	63644	1736	60	72.9

B.2 DATAMAN TRAINING

Chat Templates

Score-only: Please give an overall score for the text: Text: {text} Overall Score: _/5

Domain-only: Please specify an domain type for the text: Text: {text} Domain: _

All-rating: Please score the text on fourteen evaluation criteria and specify its domain: Text: {text} Domain: _ [1]Accuracy: _/5 [2]Coherence: _/5 [3]Language Consistency: _/5 [4]Semantic Density: _/5 [5]Knowledge Novelty: _/5 [6]Topic Focus: _/5 [7]Creativity: _/5 [8]Professionalism: _/5 [9]Style Consistency: _/5 [10]Grammatical Diversity: _/5 [11]Structural Standardization: _/5 [12]Originality: _/5 [13]Sensitivity: _/5 [14]Overall Score: _/5

We fine-tune the DataMan model using Qwen2-1.5B (Yang et al., 2024a), an advanced open-source 1.5B parameter language model, based on text generation loss. We provide three versions of the DataMan model, named according to their chat templates and applicable scenarios:

- **Score-only DataMan:** Returns only the overall score of the text (1 token), suitable for filtering massive pre-training data.
- **Domain-only DataMan:** Specifies only the domain type of the text (1 token), suitable for large-scale pre-training data mixing.
- **All-rating DataMan:** Provides scores based on fourteen evaluation criteria as well as the domain type (15 tokens), suitable for refined data selection and mixing.

We opted for text generation objectives for fine-tuning instead of adding a linear regression head for multi-task classification to prevent parameter negative transferring (Wang et al., 2019) due to differing training paradigms, which could harm model performance. At Table. 9, we report the inference FLOPs and memory usage of three version of the DataMan models using the vLLM tool (Kwon et al., 2023) on the Slimpajama test dataset with a single A800 GPU.

We utilized a pre-separated validation set of 8.6k documents for hyperparameter selection. The hyperparameter search grid included: seed $\epsilon\{42, 1024, 3407\}$, learning rate $\epsilon\{1 \times 10^{-6}, 7 \times 10^{-6}, 1 \times 10^{-5}, 2 \times 10^{-5}, 5 \times 10^{-5}\}$, number of epochs $\epsilon\{2, 3, 4, 5\}$, batch size $\epsilon\{256, 512, 1024\}$, data size $\epsilon\{82k, 164k, 246k, 312k, 357k\}$, up-sampling fold $\epsilon\{1, 2, 3, 4, 5\}$, model size $\epsilon\{0.5B, 1.5B\}$, and inference temperature $\epsilon\{0.0(\text{greedy decoding}), 0.1, 0.3, 0.5, 0.8, 1.0\}$. Model selection was based on the overall performance standard in the validation set. The chosen model was trained with seed 1024, a learning rate of 1×10^{-5} , a batch size of 512, a data size of 357k, a 4-fold up-sampling ratio, and 1.5B model parameters, trained for 5 epochs, and utilizing greedy decoding for inference.

In Table 10, we report the accuracy of the test set comprising 8.6k documents. Leveraging the robust gold-labeled data from GPT-4-turbo, all three DataMan models demonstrated excellent performance. All-rating DataMan approached 80% accuracy across all quality metrics, with *grammatical diversity* and *structural standardization* being the most challenging categories to predict. We highlighted the performance limitations of quality assessment using the *Overall Score* metric, which achieved a five-class accuracy of 81.3% and a binary accuracy of 97.5%. The classification accuracy for high-quality samples was as high as 98.5%; however, the low-quality sample classification accuracy was only 81.60%, limited by the insufficient number of such samples. In the future, we will focus on collecting more low-quality samples to enhance DataMan’s rating accuracy for low-quality texts.

Table 10: Accuracy of three strategies, namely, considering only domains, only scores, and both (i.e., all-rating), on sub-domain and sub-score. Among them, \times indicates not applicable.

	Domain Avg.	Sub-domain Accuracy			Score Avg.	Sub-score Accuracy		
All-rating	86.0	Medicine	Finance	Law	79.2	Accuracy	Coherence	Language Consistency
		95.8	89.8	93.4		78.8	84.1	76.7
		Education	Technology	Entertainment		Semantic Density	Knowledge Novelty	Topic Focus
		86.8	89.0	86.2		82.2	78.4	78.6
		Mathematics	Coding	Government		Creativity	Professionalism	Style Consistency
		90.4	90.6	81.0		79.5	76.8	76.4
		Culture	Transportation	Retail E-commerce		Grammatical Diversity	Structural Standardization	Originality
80.2	77.8	84.9	73.9	74.8	92.3			
Telecommunication	Agriculture	Other	Sensitivity	Overall Score	-			
87.1	85.8	83.4	75.6	81.3	-			
Domain-only	85.9	Medicine	Finance	Law	-	\times		
		91.7	79.9	91.5				
		Education	Technology	Entertainment				
		90.0	88.8	86.7				
		Mathematics	Coding	Government				
		87.0	71.6	86.8				
		Culture	Transportation	Retail E-commerce				
79.1	75.9	81.4						
Telecommunication	Agriculture	Other						
67.9	82.6	85.9	-	-				
Score-only	-	-	-	77.3	-	Overall Score	-	
						77.3		

C EXPERIMENTAL DETAILS

Each data selection method retains the original domain proportions between the RedPajama subsets. Table 11 shows the domain statistics of the 447B DataPajama, from which we select 30B tokens using different data selection methods. *DataPajama is a curated subset of SlimPajama, which is itself a subset of RedPajama. Both SlimPajama and RedPajama are released on HuggingFace under the Apache 2.0 License.*

After selecting the 30B tokens, we trained the model from scratch for one epoch in a randomly shuffled order. We use a global batch size of 2048 sequences and a learning rate of 5×10^{-4} with a cosine learning rate decay to 5×10^{-5} and a linear warmup for the first 5% of training steps. Each model is trained on 32x NVIDIA A800, which costs 228 GPU hours for 30B tokens. We use a weight decay of 0.1 and train with Adam (Kingma, 2014) with hyperparameters $\beta = (0.9, 0.95)$. We train a 1.3B parameter transformer model with RoPE embedding (Su et al., 2024) and SwiGLU activations (Shazeer, 2020). We save a checkpoint every 1,000 steps and merge the last three using mergekit (Goddard et al., 2024) as the desired LLM, eliminating biases from step fluctuations.

Table 11: Number of sequences in the 447B token corpus from which we select data. The data is a subset of SlimPajama, where each sequences is chunked into sequences of exactly 1024 tokens. Therefore, the proportion of sources is different from the raw SlimPajama. Sequences and proportion for all domains, overall score, and sources.

Domains	# Sequences	Proportion	Overall Score	# Sequences	Proportion
Other	100,395,132	22.97%	5.0	169,558,482	38.80%
Culture	64,774,739	14.82%	4.0	198,088,168	45.33%
Technology	44,947,278	10.29%	3.0	36,156,824	8.27%
Entertainment	43,543,874	9.96%	2.0	29,504,959	6.75%
Government	38,157,053	8.73%	1.0	3,681,879	0.84%
Coding	31,900,509	7.30%			
Medicine	30,021,105	6.87%	Sources	# Sequences	Proportion
Mathematics	20,108,505	4.60%	CommonCrawl	263,494,321	60.30%
Law	19,463,871	4.45%	C4	70,289,855	16.08%
Education	14,663,298	3.36%	Wikipedia (English)	13,282,740	3.04%
Finance	10,138,552	2.32%	Book	27,674,520	6.33%
Transportation	6,430,573	1.47%	StackExchange	8,518,050	1.95%
Agriculture	5,739,330	1.31%	Github	10,386	2.91%
Retail E-commerce	5,355,667	1.23%	ArXiv	10,152	2.85%
Telecommunication	1,350,806	0.31%	Other	67,865	19.05%
			Overall	436,990,312	100%

Table 12: Pearson’s and Spearman’s rank correlation coefficients between PPL and ICL of all models across ten downstream tasks.

	ARC-e	ARC-c	SciQ	LogiQA	BoolQ	HellaSwag	PIQA	WinoGrande	NQ	MMLU
Pearson	-0.65	-0.52	-0.85	-0.14	-0.46	-0.78	-0.69	-0.64	-0.67	-0.05
Spearman	-0.29	-0.27	-0.60	-0.18	-0.03	-0.65	-0.59	-0.68	-0.58	-0.08

In-context learning settings. We choose a different number of few-shot examples per task to ensure that all demonstrations fit within the context window of 1024 tokens. We use the following number of demonstrations (given in parentheses): ARC-easy (15), ARC-challenge (15), SciQA (2), LogiQA (2), BoolQ (0), HellaSwag (6), PIQA (6), WinoGrande (15), NQ (10), MMLU (10). We report accuracy for all tasks, except for NQ, where we report EM. When available, we use the normalized accuracy metric provided by `lm-evaluation-harness`.

Detailed analysis of misalignment between PPL and ICL. We report both the full validation and test perplexity results in Table 13 and Table 14, including the perplexity for each of the RedPajama subsets. Table 15 contains the ICL performance for all models. The model performance of the *uniform sampling +50% more data* is featured at the bottom of the tables. In Figure 5, we plot the relationship between perplexity and ICL task performance across all reported models. Our experiments indicate a correlation between PPL and ICL metrics, showing that they tend to increase or decrease together; however, they do not align perfectly.

Further, we calculated the perplexity (PPL) and In-context learning (ICL) performance of all models across ten downstream tasks, then plotted the Pearson’s and Spearman’s rank correlation coefficients to explore the misalignment between PPL and ICL. We draw the following conclusions:

- From Table.12, it is evident that the most pronounced misalignment between perplexity and ICL performance occurs in the tasks: LogiQA, and MMLU.
- To gain deeper insight into how this misalignment affects downstream tasks, we analyzed these two specific tasks and identified the following reasons:

Domain Mismatch: Pre-training often uses extensive general corpora, which enables the model to exhibit lower perplexity on a common text. However, for tasks like MMLU that cover 57 distinct specific domains (such as abstract algebra and anatomy), the issue of domain mismatch becomes more pronounced, leading to reduced model performance on these tasks.

Complexity of ICL Tasks: Many ICL tasks involve complex or multi-step reasoning, which perplexity fails to effectively capture. Consequently, the model needs to perform complex reasoning, rather than rely solely on simple text repetition or probability assessments, as seen in LogiQA, which is based on expert-written questions from Civil Servants’ Exams to test human logical reasoning.

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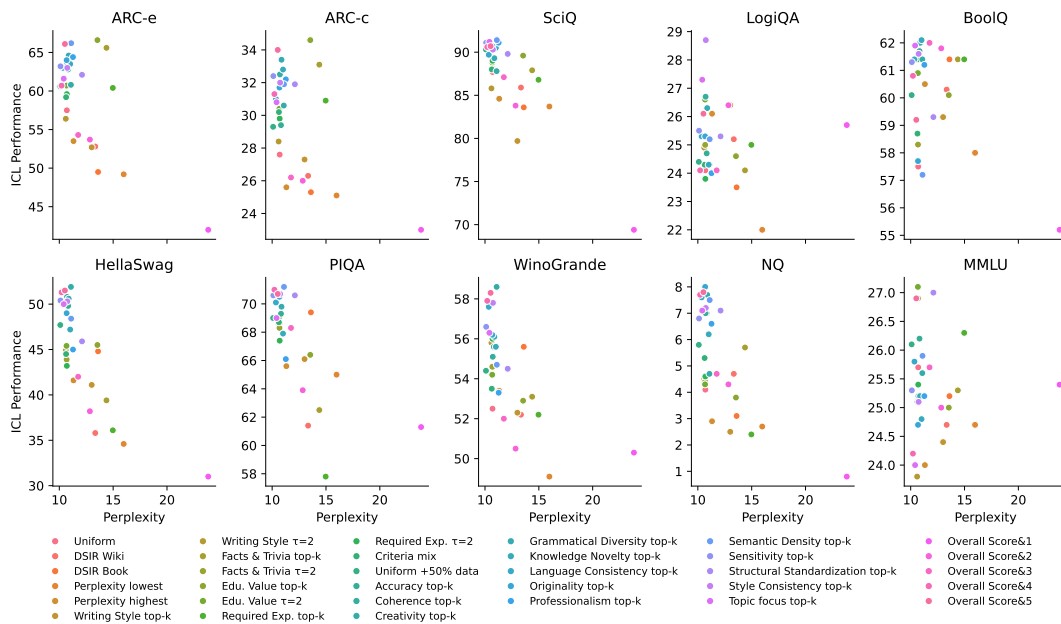


Figure 5: We plot the relationship between the perplexity results and in-context learning performance of all models in Tables 13 and 15. While prior work has found perplexity to be a good predictor of downstream task performance when varying model parameters and number of training tokens (Xia et al., 2022; Du et al., 2024), we observe that this is not true when varying the training distribution.

Table 13: Validation per-token perplexity per RedPajama domain between LLMs trained on 30B tokens from different data selection methods. We highlight the best result in each column (before rounding). *bottom-k* and *inv.* denote inverse sampling, in which we sample documents with the lowest quality ratings. Abbreviations: HellaSw. = HellaSwag, W.G. = WinoGrande, exp. = expertise.

Selection Method		CC	C4	Github	Wiki	ArXiv	StackEx	Book	Overall
Uniform		11.09	13.93	3.04	10.41	5.69	6.15	12.42	10.7
DSIR	<i>with Wiki</i>	13.02 ^{†1.93}	18.66 ^{†4.73}	3.62 ^{†0.58}	24.07 ^{†13.66}	6.63 ^{†0.94}	7.28 ^{†1.13}	15.39 ^{†2.97}	13.34 ^{†2.64}
	<i>with Book</i>	13.11 ^{†2.02}	18.16 ^{†4.23}	3.50 ^{†0.46}	38.97 ^{†28.56}	6.55 ^{†0.86}	6.83 ^{†0.68}	13.18 ^{†0.76}	13.60 ^{†2.90}
Perplexity	<i>lowest</i>	16.20 ^{†5.11}	21.51 ^{†7.58}	4.41 ^{†1.37}	18.26 ^{†7.85}	7.12 ^{†1.43}	9.10 ^{†2.95}	20.26 ^{†7.84}	15.98 ^{†5.28}
	<i>highest</i>	11.92 ^{†0.83}	14.34 ^{†0.41}	3.21 ^{†0.17}	11.38 ^{†0.97}	5.90 ^{†0.21}	6.20 ^{†0.05}	12.38 ^{†0.04}	11.32 ^{†0.62}
Writing Style	<i>top-k</i> $\tau = 2.0$	12.77 ^{†1.68} 10.94 ^{†0.15}	18.87 ^{†4.94} 14.09 ^{†0.16}	3.40 ^{†0.36} 2.99 ^{†0.05}	25.61 ^{†15.20} 10.32 ^{†0.09}	5.82 ^{†0.13} 5.60 ^{†0.09}	7.03 ^{†0.88} 5.60 ^{†0.55}	12.48 ^{†0.06} 12.01 ^{†0.41}	13.01 ^{†0.10} 10.60 ^{†0.10}
Facts & Trivia	<i>top-k</i>	12.60 ^{†1.51}	19.15 ^{†5.22}	3.52 ^{†0.48}	64.82 ^{†54.41}	5.91 ^{†0.22}	7.23 ^{†1.08}	15.90 ^{†3.48}	14.38 ^{†3.68}
	$\tau = 2.0$	10.98 ^{†0.11}	14.25 ^{†0.32}	3.00 ^{†0.04}	10.65 ^{†0.24}	5.56 ^{†0.13}	6.11 ^{†0.04}	12.32 ^{†0.10}	10.68 ^{†0.02}
Educational Value	<i>top-k</i>	13.26 ^{†2.17}	18.84 ^{†4.91}	3.45 ^{†0.41}	27.20 ^{†16.79}	5.63 ^{†0.06}	6.90 ^{†0.75}	15.45 ^{†3.03}	13.54 ^{†2.84}
	$\tau = 2.0$	11.02 ^{†0.03}	14.10 ^{†0.17}	2.98 ^{†0.06}	10.49 ^{†0.08}	5.53 ^{†0.16}	6.09 ^{†0.06}	12.34 ^{†0.08}	10.67 ^{†0.03}
Required Expertise	<i>top-k</i>	15.13 ^{†4.04}	21.83 ^{†7.90}	3.59 ^{†0.55}	18.87 ^{†8.46}	5.54 ^{†0.15}	7.63 ^{†1.48}	16.38 ^{†3.96}	14.97 ^{†4.27}
	$\tau = 2.0$	11.06 ^{†0.97}	14.17 ^{†0.24}	2.98 ^{†0.06}	10.25 ^{†0.16}	5.54 ^{†0.15}	6.10 ^{†0.05}	12.29 ^{†0.13}	10.7
Criteria mix	$\tau = 2.0$	10.97 ^{†0.12}	14.10 ^{†0.17}	2.99 ^{†0.05}	10.57 ^{†0.16}	5.56 ^{†0.13}	6.10 ^{†0.05}	12.19 ^{†0.23}	10.63 ^{†0.07}
Accuracy	<i>top-k</i>	10.73 ^{†0.36}	16.59 ^{†2.66}	2.94 ^{†0.10}	9.96 ^{†0.45}	5.28 ^{†0.41}	6.15	11.64 ^{†0.78}	10.82 ^{†0.12}
Coherence	<i>top-k</i>	10.70 ^{†0.39}	16.36 ^{†2.43}	2.90 ^{†0.14}	9.32 ^{†1.09}	5.27 ^{†0.42}	6.01 ^{†0.14}	11.48 ^{†0.94}	10.72 ^{†0.02}
Creativity	<i>top-k</i>	11.27 ^{†0.18}	16.41 ^{†2.48}	3.19 ^{†0.15}	9.70 ^{†0.71}	5.38 ^{†0.31}	6.26 ^{†0.11}	10.87 ^{†1.55}	11.08 ^{†0.38}
Grammatical Diversity	<i>top-k</i>	10.85 ^{†0.24}	16.72 ^{†2.79}	2.92 ^{†0.12}	9.84 ^{†0.57}	5.25 ^{†0.44}	5.91 ^{†0.24}	11.27 ^{†1.15}	10.87 ^{†0.17}
Knowledge Novelty	<i>top-k</i>	11.06 ^{†0.97}	16.42 ^{†2.49}	2.86 ^{†0.18}	9.59 ^{†0.82}	5.18 ^{†0.51}	5.87 ^{†0.28}	12.33 ^{†0.09}	11.01 ^{†0.31}
Language Consistency	<i>top-k</i>	10.34 ^{†0.75}	15.43 ^{†1.50}	2.90 ^{†0.14}	9.33 ^{†1.08}	5.28 ^{†0.41}	5.84 ^{†0.31}	11.36 ^{†1.06}	10.35 ^{†0.35}
Originality	<i>top-k</i>	10.73 ^{†0.36}	16.16 ^{†2.23}	2.84 ^{†0.20}	8.98 ^{†1.43}	5.25 ^{†0.44}	5.82 ^{†0.33}	11.29 ^{†1.13}	10.68 ^{†0.02}
Professionalism	<i>top-k</i>	11.23 ^{†0.14}	17.00 ^{†3.07}	2.88 ^{†0.16}	9.52 ^{†0.89}	5.23 ^{†0.46}	5.94 ^{†0.21}	13.26 ^{†0.84}	11.27 ^{†0.57}
Semantic Density	<i>top-k</i>	11.22 ^{†0.13}	16.61 ^{†2.68}	2.84 ^{†0.20}	8.96 ^{†1.45}	5.22 ^{†0.47}	5.85 ^{†0.30}	12.13 ^{†0.29}	11.10 ^{†0.40}
Sensitivity	<i>top-k</i>	10.30 ^{†0.79}	14.16 ^{†0.23}	2.83 ^{†0.21}	9.01 ^{†1.40}	5.29 ^{†0.40}	5.76 ^{†0.39}	11.42 ^{†1.00}	10.11 ^{†0.59}
Structural Standardization	<i>top-k</i>	12.15 ^{†1.06}	17.95 ^{†4.02}	2.91 ^{†0.13}	10.40 ^{†0.01}	5.37 ^{†0.32}	6.07 ^{†0.08}	14.72 ^{†2.30}	12.11 ^{†1.41}
Style Consistency	<i>top-k</i>	10.71 ^{†0.38}	16.39 ^{†2.46}	2.92 ^{†0.12}	9.65 ^{†0.76}	5.28 ^{†0.41}	5.94 ^{†0.21}	11.42 ^{†1.00}	10.74 ^{†0.04}
Topic Focus	<i>top-k</i>	10.48 ^{†0.61}	15.39 ^{†1.46}	2.84 ^{†0.20}	8.97 ^{†1.44}	5.27 ^{†0.42}	5.81 ^{†0.34}	11.40 ^{†1.02}	10.41 ^{†0.29}
Overall Score	1	22.22 ^{†11.13}	24.93 ^{†11.00}	15.58 ^{†12.54}	69.54 ^{†59.13}	21.71 ^{†16.02}	19.95 ^{†13.80}	25.41 ^{†13.00}	23.83 ^{†13.13}
	2	12.80 ^{†1.71}	15.01 ^{†1.08}	5.40 ^{†2.36}	18.89 ^{†8.48}	10.73 ^{†5.04}	8.57 ^{†2.42}	14.97 ^{†2.55}	12.84 ^{†2.14}
	3	11.61 ^{†0.52}	15.83 ^{†1.90}	4.05 ^{†1.01}	14.25 ^{†3.84}	8.78 ^{†3.09}	6.54 ^{†0.39}	13.20 ^{†0.78}	11.75 ^{†1.05}
	4	10.16 ^{†0.93}	14.93 ^{†0.99}	3.15 ^{†0.11}	9.02 ^{†1.39}	6.05 ^{†0.36}	5.67 ^{†0.48}	11.36 ^{†1.06}	10.21 ^{†0.49}
	5	10.56 ^{†0.53}	16.36 ^{†2.43}	2.66 ^{†0.38}	8.51 ^{†1.90}	4.74 ^{†0.95}	5.92 ^{†0.23}	10.79 ^{†1.63}	10.52 ^{†0.18}
<i>Uniform +50% data</i>		10.47 ^{†0.62}	13.12 ^{†0.81}	2.88 ^{†0.16}	9.43 ^{†0.98}	5.42 ^{†0.27}	5.84 ^{†0.31}	11.70 ^{†0.72}	10.09 ^{†0.61}

Table 14: Test per-token perplexity per RedPajama domain between LLMs trained on 30B tokens from different data selection methods. We highlight the best result in each column (before rounding). *bottom-k* and *inv.* denote inverse sampling, in which we sample documents with the lowest quality ratings. Abbreviations: HellaSw. = HellaSwag, W.G. = WinoGrande, exp. = expertise.

Selection Method		CC	C4	Github	Wiki	ArXiv	StackEx	Book	Overall
Uniform		11.1	13.82	2.97	10.29	5.26	5.75	13.05	10.75
DSIR	<i>with Wiki</i>	12.97 \uparrow 1.87	18.50 \uparrow 4.68	3.50 \uparrow 0.53	23.91 \uparrow 13.62	6.71 \uparrow 1.45	6.36 \uparrow 0.61	16.11 \uparrow 3.06	13.37 \uparrow 2.62
	<i>with Book</i>	13.08 \uparrow 1.98	17.96 \uparrow 4.14	3.41 \uparrow 0.44	39.03 \uparrow 28.74	6.62 \uparrow 1.36	5.93 \uparrow 0.18	13.38 \uparrow 0.33	13.59 \uparrow 2.84
Perplexity	<i>lowest</i>	16.15 \uparrow 5.05	21.34 \uparrow 7.52	4.21 \uparrow 1.24	18.14 \uparrow 7.85	7.21 \uparrow 1.95	7.43 \uparrow 1.68	21.51 \uparrow 8.46	16.04 \uparrow 5.29
	<i>highest</i>	11.91 \uparrow 0.81	14.27 \uparrow 0.45	3.14 \uparrow 0.17	11.24 \uparrow 0.95	5.96 \uparrow 0.70	5.34 \uparrow 0.41	12.74 \uparrow 0.31	11.34 \uparrow 0.59
Writing Style	<i>top-k</i>	10.95 \downarrow 0.15	18.65 \uparrow 4.83	3.33 \uparrow 0.36	25.18 \uparrow 14.89	5.85 \uparrow 0.59	6.10 \uparrow 0.35	12.81 \uparrow 0.24	12.97 \uparrow 2.22
	$\tau = 2.0$	10.95 \downarrow 0.15	13.96 \uparrow 0.14	2.93 \downarrow 0.04	10.20 \downarrow 0.09	5.60 \uparrow 0.34	5.22 \downarrow 0.53	12.62 \downarrow 0.43	10.64 \downarrow 0.11
Facts & Trivia	<i>top-k</i>	12.50 \uparrow 1.40	18.89 \uparrow 5.07	3.40 \uparrow 0.43	64.81 \uparrow 54.52	5.95 \uparrow 0.69	6.30 \uparrow 0.55	15.91 \uparrow 2.86	14.33 \uparrow 3.58
	$\tau = 2.0$	10.98 \downarrow 0.12	14.11 \uparrow 0.29	2.93 \downarrow 0.04	10.52 \uparrow 0.23	5.60 \uparrow 0.34	5.20 \downarrow 0.55	12.99 \downarrow 0.06	10.72 \downarrow 0.03
Educational Value	<i>top-k</i>	13.18 \uparrow 2.08	18.61 \uparrow 4.79	3.29 \uparrow 0.32	26.33 \uparrow 16.04	5.69 \uparrow 0.43	5.92 \uparrow 0.17	15.86 \uparrow 2.81	13.49 \uparrow 2.74
	$\tau = 2.0$	11.03 \uparrow 0.03	13.97 \uparrow 0.15	2.91 \downarrow 0.06	10.36 \uparrow 0.07	5.58 \uparrow 0.32	5.17 \downarrow 0.58	12.97 \downarrow 0.08	10.72 \downarrow 0.03
Required Expertise	<i>top-k</i>	15.04 \uparrow 3.94	21.58 \uparrow 7.76	3.46 \uparrow 0.49	18.37 \uparrow 8.08	5.59 \uparrow 0.33	6.54 \uparrow 0.79	16.70 \uparrow 3.65	14.92 \uparrow 4.17
	$\tau = 2.0$	11.07 \uparrow 0.97	14.04 \uparrow 0.22	2.91 \downarrow 0.06	10.12 \downarrow 0.17	5.59 \uparrow 0.33	5.17 \downarrow 0.58	12.91 \downarrow 0.14	10.74 \downarrow 0.01
Criteria mix	$\tau = 2.0$	10.97 \downarrow 0.13	13.97 \uparrow 0.15	2.92 \downarrow 0.05	10.44 \uparrow 0.15	5.61 \uparrow 0.35	5.26 \downarrow 0.49	12.82 \downarrow 0.23	10.68 \downarrow 0.07
Accuracy	<i>top-k</i>	10.68 \downarrow 0.42	16.42 \uparrow 2.60	2.82 \downarrow 0.15	9.84 \downarrow 0.45	5.33 \uparrow 0.07	5.20 \downarrow 0.55	12.10 \downarrow 0.95	10.80 \uparrow 0.05
Coherence	<i>top-k</i>	10.66 \downarrow 0.44	16.14 \uparrow 2.32	2.81 \downarrow 0.16	9.20 \downarrow 1.09	5.32 \uparrow 0.06	5.08 \downarrow 0.67	11.97 \downarrow 4.08	10.71 \downarrow 0.04
Creativity	<i>top-k</i>	11.12 \uparrow 0.02	16.23 \uparrow 2.41	3.09 \uparrow 0.12	9.61 \downarrow 0.68	5.42 \uparrow 0.16	5.42 \downarrow 0.33	11.39 \downarrow 4.66	11.00 \uparrow 0.25
Grammatical Diversity	<i>top-k</i>	10.81 \downarrow 0.29	16.53 \uparrow 2.71	2.82 \downarrow 0.15	9.72 \downarrow 0.57	5.30 \uparrow 0.04	4.97 \downarrow 0.78	11.73 \downarrow 1.32	10.86 \uparrow 0.11
Knowledge Novelty	<i>top-k</i>	11.01 \uparrow 0.01	16.23 \uparrow 2.41	2.81 \downarrow 0.16	9.46 \downarrow 0.83	5.22 \downarrow 0.04	4.93 \downarrow 0.82	13.00 \downarrow 0.05	11.01 \uparrow 0.26
Language Consistency	<i>top-k</i>	10.31 \downarrow 0.79	15.27 \uparrow 1.45	2.78 \downarrow 0.19	9.21 \downarrow 1.08	5.33 \uparrow 0.07	4.87 \downarrow 0.88	11.91 \downarrow 4.14	10.35 \downarrow 0.40
Originality	<i>top-k</i>	10.69 \downarrow 0.41	15.96 \uparrow 2.14	2.77 \downarrow 0.20	8.87 \downarrow 1.42	5.30 \uparrow 0.04	4.86 \downarrow 0.89	11.91 \downarrow 4.14	10.67 \downarrow 0.08
Professionalism	<i>top-k</i>	11.18 \uparrow 0.08	16.81 \uparrow 2.99	2.79 \downarrow 0.18	9.40 \downarrow 0.89	5.28 \uparrow 0.02	4.90 \downarrow 0.85	13.81 \uparrow 0.76	11.26 \uparrow 0.51
Semantic Density	<i>top-k</i>	11.16 \uparrow 0.06	16.41 \uparrow 2.59	2.78 \downarrow 0.19	8.84 \downarrow 1.45	5.27 \uparrow 0.01	4.89 \downarrow 0.86	12.83 \downarrow 0.22	11.09 \uparrow 0.34
Sensitivity	<i>top-k</i>	10.28 \downarrow 0.82	14.04 \uparrow 0.22	2.77 \downarrow 0.20	8.90 \downarrow 1.39	5.34 \uparrow 0.08	4.81 \downarrow 0.94	11.98 \downarrow 4.07	10.13 \downarrow 0.62
Structural Standardization	<i>top-k</i>	12.08 \uparrow 0.98	17.76 \uparrow 3.94	2.81 \downarrow 0.16	10.25 \downarrow 0.04	5.43 \uparrow 0.17	5.12 \downarrow 0.63	15.49 \uparrow 2.44	12.11 \uparrow 1.36
Style Consistency	<i>top-k</i>	10.67 \downarrow 0.43	16.20 \uparrow 2.38	2.80 \downarrow 0.17	9.52 \downarrow 0.77	5.32 \uparrow 0.06	4.98 \downarrow 0.77	11.95 \downarrow 4.10	10.73 \downarrow 0.02
Topic Focus	<i>top-k</i>	10.44 \downarrow 0.66	15.22 \uparrow 1.40	2.77 \downarrow 0.20	8.85 \downarrow 1.44	5.31 \uparrow 0.05	4.83 \downarrow 0.92	11.96 \downarrow 4.09	10.41 \downarrow 0.34
Overall Score	1	22.22 \uparrow 11.12	24.92 \uparrow 11.10	15.03 \uparrow 12.06	69.85 \uparrow 59.56	22.46 \uparrow 17.20	19.22 \uparrow 13.47	26.26 \uparrow 13.21	23.95 \uparrow 13.20
	2	12.83 \uparrow 1.73	14.92 \uparrow 1.10	5.22 \uparrow 2.25	18.74 \uparrow 8.45	11.00 \uparrow 5.74	7.81 \uparrow 2.06	15.74 \uparrow 2.69	12.91 \uparrow 2.16
	3	11.59 \uparrow 0.49	15.66 \uparrow 1.84	3.91 \uparrow 0.94	14.15 \uparrow 3.86	8.97 \uparrow 3.71	5.71 \downarrow 0.04	13.97 \uparrow 0.92	11.78 \uparrow 1.03
	4	10.13 \downarrow 0.97	14.78 \uparrow 0.96	3.06 \uparrow 0.09	8.91 \downarrow 1.38	6.13 \uparrow 0.87	4.75 \downarrow 1.00	11.93 \downarrow 4.12	10.22 \downarrow 0.53
	5	10.51 \downarrow 0.59	16.18 \uparrow 2.36	2.56 \downarrow 0.41	8.40 \downarrow 1.89	4.77 \downarrow 0.49	4.99 \uparrow 0.76	11.28 \downarrow 4.77	10.50 \downarrow 0.25
<i>Uniform +50% data</i>		10.47 \downarrow 0.63	13.03 \downarrow 0.79	2.82 \downarrow 0.15	9.33 \downarrow 0.96	5.47 \uparrow 0.21	4.94 \downarrow 0.81	12.29 \downarrow 0.76	10.14 \downarrow 0.61

Table 15: The in-context learning performance for ten downstream task across all models. We report accuracy for all tasks, except for NQ, where we report EM, and highlight the best result in each column (before rounding). *bottom-k* and *inv.* denote inverse sampling, in which we sample documents with the lowest quality ratings. Abbreviations: HellaSw. = HellaSwag, W.G. = WinoGrande, exp. = expertise.

Selection Method	Reading Comprehension					Commonsense Reasoning			World Knowledge		Average	
	ARC-E (15)	ARC-C (15)	SciQ (2)	LogiQA (2)	BoolQ (0)	HellaSw. (6)	PIQA (6)	W.G. (15)	NQ (10)	MMLU (5)		
Uniform	57.5	27.6	87.7	24.1	57.5	44	68.6	52.5	4.1	25.7	44.9	
DSIR	<i>with Wiki</i>	52.8 ⁴⁴⁷	26.3 ⁴¹³	85.9 ⁴¹⁸	25.2 ⁷¹¹	60.3 ⁷²⁸	35.8 ⁴⁸²	61.4 ⁴⁷²	52.2 ⁴⁰³	4.7 ⁷⁰⁶	24.7 ⁴¹⁰	42.9 ⁴²⁰
	<i>with Book</i>	49.5 ⁴⁸⁰	25.3 ⁴²³	83.6 ⁴⁴¹	23.5 ⁴⁰⁶	57.9 ⁷⁰⁴	44.8 ⁷⁰⁸	69.4 ⁷⁰⁸	55.6 ⁷³¹	3.1 ⁴¹⁰	25.2 ⁴⁰⁵	43.8 ⁴¹¹
Perplexity	<i>lowest</i>	49.2 ⁴⁸³	25.1 ⁴²⁵	83.7 ⁴⁴⁰	22.0 ⁴²¹	61.4 ⁷³⁹	34.6 ⁴⁹⁴	65.0 ⁴³⁶	49.1 ⁴³⁴	2.7 ⁴¹⁴	24.7 ⁴¹⁰	41.7 ⁴³²
	<i>highest</i>	53.5 ⁴⁴⁰	25.6 ⁴²⁰	84.6 ⁴³¹	26.1 ⁷²⁰	58.0 ⁷⁰⁵	41.6 ⁴²⁴	65.6 ⁴³⁰	53.4 ⁷⁰⁹	2.9 ⁴¹²	24.0 ⁴¹⁷	43.5 ⁴¹⁴
Writing Style	<i>top-k</i>	52.7 ⁴⁴⁸	27.3 ⁴⁰³	79.7 ⁴⁸⁰	26.4 ⁷²³	60.5 ⁷³⁰	41.1 ⁴²⁴	66.1 ⁴²⁵	52.3 ⁴⁰²	2.5 ⁴¹⁶	24.4 ⁴¹³	43.4 ⁴¹⁵
	$\tau = 2.0$	56.4 ⁴¹¹	28.4 ⁷⁰⁸	85.8 ⁴¹⁸	24.9 ⁷⁰⁸	59.3 ⁷¹⁸	44.9 ⁷⁰⁹	68.6	55.8 ⁷¹³	4.5 ⁷⁰⁴	23.8 ⁴¹⁹	45.0 ⁷⁰¹
Facts & Trivia	<i>top-k</i>	65.6 ⁷⁸¹	33.1 ⁷⁵⁵	87.9 ⁷⁰²	24.1	60.9 ⁷³⁴	39.4 ⁴⁴⁶	62.5 ⁴⁶¹	53.1 ⁷⁰⁶	5.7 ⁷¹⁶	25.3 ⁴⁰⁴	45.8 ⁷⁰⁹
	$\tau = 2.0$	59.3 ⁷¹⁸	29.8 ⁷²²	88.1 ⁷⁰⁴	25.0 ⁷⁰⁹	61.4 ⁷³⁹	43.9 ⁴⁰¹	68.3 ⁴⁰³	54.6 ⁷²¹	4.4 ⁷⁰³	26.9 ⁷¹²	46.2 ⁷¹³
Educational Value	<i>top-k</i>	66.6 ⁷⁹¹	34.6 ⁷⁷⁰	89.6 ⁷¹⁹	24.6 ⁷⁰⁵	58.3 ⁷⁰⁸	45.5 ⁷¹⁵	66.4 ⁴²²	52.9 ⁷⁰⁴	3.8 ⁴⁰³	25.0 ⁴⁰⁷	46.7 ⁷¹⁸
	$\tau = 2.0$	60.7 ⁷³²	30.4 ⁷²⁸	88.8 ⁷¹¹	26.6 ⁷²⁵	60.1 ⁷²⁶	45.4 ⁷¹⁴	69.1 ⁷⁰⁵	54.2 ⁷¹⁷	4.3 ⁷⁰²	27.1 ⁷¹⁴	46.7 ⁷¹⁸
Required Expertise	<i>top-k</i>	60.4 ⁷²⁹	30.9 ⁷³³	86.8 ⁴⁰⁹	25.0 ⁷⁰⁹	60.9 ⁷³⁴	36.1 ⁴⁷⁹	57.8 ⁴⁰⁸	52.2 ⁴⁰³	2.4 ⁴¹⁷	26.3 ⁷⁰⁶	43.9 ⁴¹⁰
	$\tau = 2.0$	59.6 ⁷²¹	29.8 ⁷²²	89.0 ⁷¹³	23.8 ⁴⁰³	61.4 ⁷³⁹	43.2 ⁴⁰⁸	67.4 ⁴¹²	56.0 ⁷³⁵	4.6 ⁷⁰⁵	25.4 ⁴⁰³	46.0 ⁷¹¹
Criteria mix	$\tau = 2.0$	59.2 ⁷¹⁷	30.2 ⁷²⁶	88.0 ⁷⁰³	24.3 ⁷⁰²	58.7 ⁷¹²	44.5 ⁷⁰⁵	68.7 ⁷⁰¹	53.5 ⁷¹⁰	5.3 ⁷¹²	25.1 ⁴⁰⁶	45.7 ⁷⁰⁸
Accuracy	<i>top-k</i>	62.8 ⁷⁵³	29.4 ⁷¹⁸	90.3 ⁷²⁶	24.7 ⁷⁰⁶	61.7 ⁷⁴²	49.8 ⁷⁵⁸	69.3 ⁷⁰⁷	55.6 ⁷³¹	7.0 ⁷²⁹	26.2 ⁷⁰⁵	47.7 ⁷⁰³
Coherence	<i>top-k</i>	63.6 ⁷⁶¹	32.5 ⁷⁴⁹	90.3 ⁷²⁶	26.7 ⁷²⁶	61.6 ⁷⁴¹	50.8 ⁷⁶⁸	70.6 ⁷²⁰	55.1 ⁷²⁶	7.0 ⁷²⁹	25.2 ⁴⁰⁵	48.3 ⁷⁰⁶
Creativity	<i>top-k</i>	60.8 ⁷³³	30.6 ⁷³⁰	87.8 ⁷⁰¹	24.3 ⁷⁰²	61.4 ⁷³⁹	51.9 ⁷⁷⁹	71.2 ⁷²⁶	58.6 ⁷⁶¹	4.7 ⁴¹⁴	25.6 ⁴⁰¹	47.7 ⁷⁰⁶
Grammatical Diversity	<i>top-k</i>	64.6 ⁷⁷¹	33.4 ⁷⁵⁸	89.3 ⁷¹⁶	26.3 ⁷²²	62.0 ⁷⁴⁵	50.6 ⁷⁶⁶	69.8 ⁷¹²	56.1 ⁷³⁶	7.7 ⁷³⁶	25.2 ⁴⁰⁵	48.5 ⁷⁰⁵
Knowledge Novelty	<i>top-k</i>	63.5 ⁷⁶⁰	32.8 ⁷⁵²	90.5 ⁷²⁸	24.3 ⁷⁰²	62.1 ⁷⁴⁶	47.2 ⁷³²	67.9 ⁴⁰⁷	55.6 ⁷³¹	6.2 ⁴⁰³	24.8 ⁴⁰⁹	47.5 ⁷⁰²
Language Consistency	<i>top-k</i>	63.0 ⁷⁵⁵	31.0 ⁷³⁴	89.7 ⁷²⁰	25.3 ⁷¹²	61.4 ⁷³⁹	50.2 ⁷⁶²	70.1 ⁷¹⁵	57.6 ⁷⁵¹	7.6 ⁷³⁵	25.8 ⁴⁰⁶	48.2 ⁷⁰³
Originality	<i>top-k</i>	64.0 ⁷⁶⁵	31.7 ⁷⁴¹	90.7 ⁷³⁰	25.3 ⁷¹²	57.7 ⁷⁰²	49.0 ⁷⁵⁰	70.5 ⁷¹⁹	56.2 ⁷³⁷	8.0 ⁷³⁹	24.7 ⁴¹⁰	47.8 ⁷⁰³
Professionalism	<i>top-k</i>	64.4 ⁷⁶⁹	32.2 ⁷⁴⁶	91.1 ⁷³⁴	24.0 ⁴⁰¹	61.2 ⁷³⁷	45.0 ⁷¹⁰	66.1 ⁴²⁵	53.3 ⁷⁰⁸	6.6 ⁴⁰⁹	25.2 ⁴⁰⁶	46.9 ⁷⁰¹
Semantic Density	<i>top-k</i>	66.2 ⁷⁸⁷	31.9 ⁷⁴³	91.4 ⁷³⁷	25.2 ⁷¹¹	57.2 ⁴⁰³	48.4 ⁷⁴⁴	71.2 ⁷²⁶	54.7 ⁷²²	7.5 ⁷³⁴	25.9 ⁴⁰²	48.0 ⁷⁰¹
Sensitivity	<i>top-k</i>	63.2 ⁷⁵⁷	32.4 ⁷⁴⁸	91.1 ⁷³⁴	25.5 ⁷¹⁴	61.3 ⁷³⁸	50.4 ⁷⁶⁴	70.6 ⁷²⁰	56.6 ⁷⁴¹	6.8 ⁴⁰⁷	25.3 ⁴⁰⁴	48.3 ⁷⁰³
Structural Standardization	<i>top-k</i>	62.1 ⁷⁴⁶	31.9 ⁷⁴³	89.8 ⁷²¹	25.3 ⁷¹²	59.3 ⁷¹⁸	45.9 ⁷¹⁹	70.6 ⁷²⁰	54.5 ⁷²⁰	7.1 ⁷³⁰	27.0 ⁷¹³	47.4 ⁷⁰¹
Style Consistency	<i>top-k</i>	63.0 ⁷⁵⁵	32.0 ⁷⁴⁴	90.3 ⁷²⁶	28.7 ⁷⁴⁶	61.6 ⁷⁴¹	50.3 ⁷⁶³	70.7 ⁷²¹	57.8 ⁷⁵³	7.2 ⁷³¹	25.1 ⁴⁰⁶	48.7 ⁷⁰³
Topic Focus	<i>top-k</i>	61.6 ⁷⁴¹	30.8 ⁷³²	91.2 ⁷³⁵	27.3 ⁷³²	61.9 ⁷⁴⁴	50.0 ⁷⁶⁰	69.0 ⁷⁰⁴	56.3 ⁷³⁸	7.1 ⁷³⁰	24.0 ⁴¹⁰	47.9 ⁷⁰³
Overall Score	1	42.0 ⁴¹⁵⁵	23.0 ⁴⁴⁶	69.4 ⁴¹⁸³	25.7 ⁷¹⁶	55.2 ⁴²³	31.0 ⁴¹³⁰	61.3 ⁴⁷³	50.3 ⁴²²	0.8 ⁴³³	25.4 ⁷⁰²	38.4 ⁴⁶⁶
	2	53.7 ⁴³⁸	26.0 ⁴¹⁶	83.8 ⁴³⁹	26.4 ⁷²³	61.8 ⁷⁴³	38.2 ⁴⁵⁸	63.9 ⁴⁴⁷	50.5 ⁴²⁰	4.3 ⁷⁰²	25.0 ⁴⁰⁷⁰	43.4 ⁴¹⁵
	3	54.3 ⁴³²	26.2 ⁴¹⁴	87.1 ⁴⁰⁶	24.1	62.0 ⁷⁴⁵	42.0 ⁴²⁰	68.3 ⁴⁰³	52.0 ⁴⁰⁵	4.7 ⁷⁰	25.7	44.6 ⁴⁰³
	4	60.7 ⁷³²	31.3 ⁷³⁷	90.6 ⁷²⁹	24.1	60.8 ⁷³³	51.3 ⁷⁶³	71.0 ⁷²⁴	57.9 ⁷⁵⁴	7.7 ⁷³⁶	24.2 ⁴⁰⁵	47.9 ⁷⁰²
	5	66.1 ⁷⁸⁶	34.0 ⁷⁶⁴	90.7 ⁷³⁰	26.1 ⁷²⁰	59.2 ⁷¹⁷	51.5 ⁷⁶⁵	70.7 ⁷²¹	58.3 ⁷⁵⁸	7.8 ⁷³⁷	26.9 ⁷¹²	49.1 ⁷¹⁶
Uniform +50% data	60.6 ⁷³¹	29.3 ⁷¹⁷	90.3 ⁷²⁶	24.4 ⁷⁰³	60.1 ⁷²⁶	47.7 ⁷³⁷	69.0 ⁷⁰⁴	54.4 ⁷¹⁹	5.8 ⁷¹⁷	26.1 ⁷⁰⁴	46.8 ⁷¹⁹	

D FURTHER ANALYSIS OF PRE-TRAINING DATA ASSESSMENT

Composition of the Pre-training Dataset In Table 11, we provide a comprehensive assessment of the DataPajama dataset, including the constitution of the domain, overall score, and source composition. Firstly, from a domain perspective, the proportion of the mathematics domain in DataPajama has significantly increased compared to the SFT dataset, while the coding domain has seen a slight rise. In contrast, the proportions of all long-tail domains (such as Transportation, Agriculture, Retail E-commerce, and Telecommunications) have fallen to their lowest levels. Secondly, regarding overall scores, DataPajama, as a subset of SlimPajama, has undergone extensive cleaning and deduplication, resulting in a high proportion of samples rated 5 and 4. Conversely, low-quality texts (rated below 3) account for only 7.86%. We chose to retain these low-quality texts to allow researchers for in-depth analysis.

Cross-source Quality Rating Figure 3 illustrates the distribution of quality scores across various source types in DataPajama. Overall, the vast majority of quality ratings for each source type are concentrated at scores of 4 and 5 (indicating high-quality samples). However, the two indicators, Knowledge Novelty, and Creativity, show a higher proportion of samples rated 2 and 3. Analysis in Table 8 reveals that the average scores for these two indicators are relatively low across all domains. Specifically, Knowledge Novelty scores for mathematics and medicine are 3.98 and 3.36, respectively, while Creativity scores for culture and entertainment are 3.64 and 3.56. Although the combined proportion of data with medicine reaches 10.5% and that of culture with entertainment is 25%, the overall share remains minimal. This finding further confirms that the DataPajama dataset has modest performance in Knowledge Novelty and Creativity.

Correlation of Quality Criteria with Log-Likelihood In Figure 6, we present the correlation between quality ratings and the log-likelihood scores computed by Llama-2-7B (Touvron et al., 2023b). Most quality metrics show no significant correlation with perplexity, with the exceptions being Structural Standardization, Professionalism, and Creativity, which have Spearman correlation coefficients ranging from 0.47 to 0.55, indicating a weak correlation. This suggests that our fourteen quality criteria operate independently of traditional data quality indicators — the perplexity filtering.

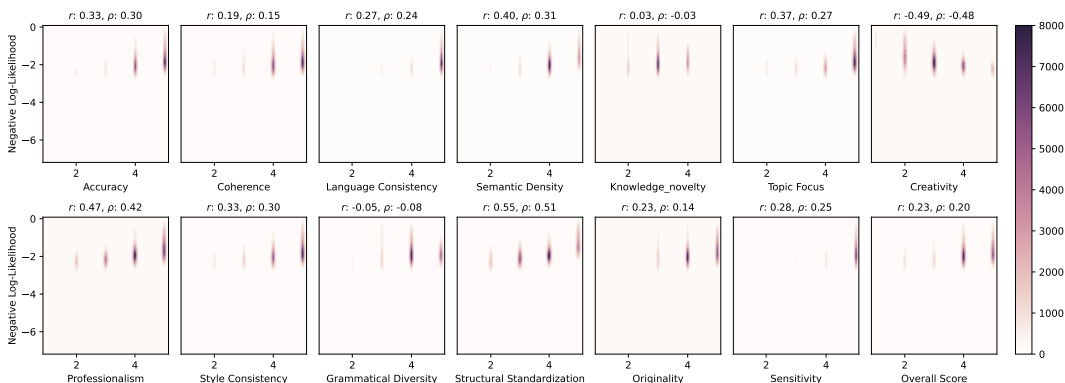


Figure 6: Correlations of quality ratings and negative log-likelihood scores by Llama-2-7B(Touvron et al., 2023b) over 1M training sequences. The negative log-likelihoods are averaged over the number of tokens, and are the logarithm of the perplexity score of a single sequence. We observe that perplexity scores are not good approximations for any quality criteria.

E INSPECTING RAW DOCUMENTS AND RATINGS

Finally, we present snippets from the raw documents of Wikipedia, Books, Stack Exchange, Github, ArXiv, CommonCrawl, and C4 subsets of DataPajama. These documents correspond to samples with quality ratings of 1, 2, 3, 4, and 5, as shown in Figure 3. We believe it is essential to provide an unfiltered view of the training data; therefore, we have not applied any filtering to these documents.

A small number of documents contain %potentially sensitive content.

Table 16: Raw training examples selected to have quality ratings at the 1-5 within ArXiv.

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Accuracy = 1	Accuracy = 2	Accuracy = 3	Accuracy = 4	Accuracy = 5
... y) line(1,0) 70 110 put(0,0 put(20, y) line(1,0) 70) line(1,0) 20 def0 put(20, y) line(1,0) 70 100 put(10,0) put(20, y) line(1,0) 70) line(1,0) 30 def0 put(20, y) line(1,0) 70 90 put(20,0) put(20, y) line(1,0) 70) This primarily happens with comments, annotations, and imports DIFdelbegin DIFdel . DIFdel There are seven false positives that are due to textit DIFdel missing refactoring references DIFdel , DIFdelend...	... 90 put(40,0 put(20, y) line(1,0) 70) line(1,0) 40 def0 put(20, y) line(1,0) 70 80 put(20,0) put(20, y) line(1,0) 70) line(1,0) 40 def0 put(20, y) line(1,0) 70 70 put(50,0) put(20, y) line(1,0) 70) line(1,0) 60 de...	...an older PUT, then there will be two versions of the object stored in SMORE @. But the most recent will always be returned in GET requests, and the space occupied by the earlier version will eventually be reclaimed by...	...natural . This methodology is particularly interesting for the purposes of our analysis since cite shaked1982relaxing showed that for some parameters the game has a unique subgame perfect equilibrium at...
Coherence = 1	Coherence = 2	Coherence = 3	Coherence = 4	Coherence = 5
...16 82.00 540 emline 131.16 82.00 541 126.16 90.00 542 emline 126.16 90.00 543 121.16 82.00 544 emline 136.16 74.00 545 131.16 82.00 546 emline 131.16 82.00 547 126.16 74.00 548 emline 141.16 82.00 549 131.16 82.00 82.00 549 131.16 82.00put(10,0) line(0,1) 100 put(20,90) line(0,1) 20 put(30,50) line(0,1) 50 put(40,10) line(0,1) 70 put(50,20) line(0,1) 70 put(60,0) line(0,1) 40 put(70,30) line(0,1) 40 put(80,10) line(0,1) 50 section* Introduction The NK (Jordan-Thiry) has been developed (see Refs citel, cite2, cite3, cite4). The theory unifies gr al theory described by NGT (eu nos eu gr al Theory) (see Ref. cite5) and Electrodynamics. The theory has been proposed by...	...labels. For instance, in the graphical model in Fig. ref Fmodels , a rectangle named emph TopicFigure is defined, and it is referred to by the node emph Topic . A diagram label named emph TopicName is also defined. Such graphical...	...in the proposed neural program models xspace. A comprehensive understanding of the extent of generalizability of neural program models xspace would help developers to know when to use data-driven approaches and when to resort...
Creativity = 1	Creativity = 2	Creativity = 3	Creativity = 4	Creativity = 5
.../88 21:16 7445.386 -0.053 0.028 500 2.93 629 1.2CA punkta 13/10/88 22:12 7448.425 -0.077 0.066 500 3.63 996 1.2CA punkt 16/10/88 23:47 7451.491 -0.048 0.030 500 1.75 725 1.2CA punkt 27/06/89 03:06 7704.630 0.028 0.012 500 2.07 1036 1.2CA punkt 02/08/9 34:03...	... (0.7,0.749) (1,0.768) ; addplot[style= ppurple,mark=*, mark options= scale=1.5,fill=white] coordinates (0.01, 0.476) (0.1,0.666) (0.4,0.726) (0.7,0.757) (1,0.769) ; addplot[style= rred,mark=square*, mark options= scale=1.5,fill=white] coordinatesa reasonable improvement compared with traditional methods such as matrix factorization. The rating-based methods suffer from a key limitation, which is the sparsity of the data. Specifically, when collecting data from real-world platforms, the...	... section Introduction Stereo algorithms benefit enormously from benchmarks . They provide quantitative evaluation to encourage competition and track progress. Despite great progress over the past years, many challenges still remain unsolved, such as...	...adiest attention. He maintained his interest in Darwin and Darwinism; in 1875 he was reading in modern physics as well. ldots In May 1875 James read and reviewed a book called s1 The Unseen Universe by physicist and mathematician Peter Guthrie Tait ldots and physicist and...
Grammatical Diversity = 1	Grammatical Diversity = 2	Grammatical Diversity = 3	Grammatical Diversity = 4	Grammatical Diversity = 5
...83 510 1 s 311 548 m 305 546 1 301 540 1 299 530 1 299 524 1 301 514 1 305 508 1 311 506 1 316 506 1 322 508 1 326 514 1 328 524 1 328 530 1 326 540 1 322 546 1 316 548 1 311 548 1 s ta ta 250 937 m 244 935 1 240 929 1 238 919 1 238 913 1 240 903 1 244 897 1 250 895 1 255 895 1 261 897 1 265 903 1 2...	...ord) line(1,0) 60 70 put(50,0 put(40, ycoord) line(1,0) 60) line(1,0) 40 def0 put(40, ycoord) line(1,0) 60 60 put(60,0) put(40, ycoord) line(1,0) 60) line(1,0) 40 def0 put(40, ycoord) line(1,0) 60 50 put(30,0 put(40, ycoord) line(1,0) 60) line(1,0) line(1,0) line(1,0) line(1,0) 50 def0 pu...	...consider the human brain learning process again. Say the information is wrong in some of the sensory stimulation. A child learned an animal looks just like a dog but having the sound of the cat from the manipulated movies and this kid has never learned the dog and cat in a...	...to fill a questionnaire with Likert scale and open-ended questions and describe any problems they experienced. subsection Results subsubsection Round 1 Fig. ref fig:teaser (top) shows the handover for all the 10 objects in the set textit Household-A by participants...	...-asymm end figure* section Conclusions label sec:conc subsection Summary The zonal-mean surface air temperature response to abrupt coo/ increases of 2, 4, 8, or 16 (times) in 3,000-yr simulations performed in a low-resolution version of the CESM1 GCM exhibit an in...
Knowledge Novelty = 1	Knowledge Novelty = 2	Knowledge Novelty = 3	Knowledge Novelty = 4	Knowledge Novelty = 5
...- (322.88,226.15) - (311.38,215.57) - cycle ; draw (359.2,216.36) - (359.42,256.13) - (322.88,226.15) ; draw [fill= rgb, 255:red, 155; green, 155; blue, 155 ,fill opacity=1] (359.2,205.79) - (370.7,216.36) - (359.2,226.93) - (347.7,216.36) - cycle...	...gpsetdashtype gp dt solid gpsetlinewidth 2.00 draw[gp path] (2.391,5.033) - (2.256,5.033) ; node[gp node right,font= fontsize 8.0pt 9.6pt selectfont] at (2.164,5.033)] ; gpcolor rgb color= 0.702,0.702,0.702 gpsetlinetype gp lt axesone bond kind of structure is useless for our aim, being fully unstable. Let us go directly to the interesting one. In Fig. ref FC1 , we show how this lattice is made and its textit unitary structure , made up by the highlighted yellow bonds plus the...	...have been augmented with terms that quantify the user satisfaction or the ad relevance. Bids receive adaptive discounts in order to deal with situations where the perfect information assumption is unrealistic unrealistic situations...	...System recognizes a hierarchy of events from the measurements, not exactly in the sense of physical reality -- if a creature never measured/saw a black swan, it does not mean there aren't any -- but in the sense of a manually ...

Table 17: Raw training examples selected to have quality ratings at the 1-5 within ArXiv.

Language Consistency = 1	Language Consistency = 2	Language Consistency = 3	Language Consistency = 4	Language Consistency = 5
...) 60) put(40, ycoord) line(1,0) 20 def0	...-courses item[fix:] textbf Siis pidi	...baseados no UUCP. Rick	... section Introduction Biological	... section Introduction Nowadays,
line(1,0) 60 90 put(10,0 put(40, ycoord) line(1,0)	igaüks igauks igaüks textbf end	Muething, criador do ARDOP, Muething	informations about genes and proteins are stored into	travelers use various online services and
60) line(1,0) 30 def0 put(40, ycoord) line(1,0)	vabaainetele textbf registreerima .	realizou uma análise das opções de modem footnote	biological ontologies cite cannataro2013data	recommender systems to plan their trips.
60 80 put(30,0 put(40, ycoord) line(1,0) 60)	item[gloss:] then had-to everyone oneself	Muething Modem neste contexto significa solução	cite Guzzi2012 such as Gene Ontology (GO).	Recommender systems allow users to deal with data overload
line(1,0) 60 def0 put(40, ycoord) line(1,0) 60 70	to-free-courses register end enumerate end	de transmissão digital que provê um canal	GO has gained a wide diffusion in bioinformatics	and make better decisions in a personalized way...
put(20,0 put(40, ycoord) ...	enumerate Results also show two main downsides of...	de comunicação sem perda Muething...	and computational biology...	
Originality = 1	Originality = 2	Originality = 3	Originality = 4	Originality = 5
...circle* 0.000001 put(65.76,-228.40)	...09886278768 0.7388	...6 ,draw opacity=0.85	...0.86725 105 0.8678 106 0.86801	... section Introduction label introduction
circle* 0.000001 put(66.47,-228.40)	3210.52550284399 0.7212] [line width=0.75] (10.93,-3.29)	107 0.86903 108 0.8683 109 0.86791	IEEEPArstart T ime series forecasting, which consists
circle* 0.000001 put(67.18,-228.40)	3219.57683735924 0.7212	.. controls (6.95,-1.4) and	110 0.86793 111 0.86888 112	of analyzing historical signals patterns to
circle* 0.000001 put(67.88,-228.40)	3228.5987543788 0.742	(3.31,-0.3) .. (0,0) .. controls	0.8689 113 0.86888 114 0.86858 115	predict future outcomes, is an important problem
circle* 0.000001 put(68.59,-229.10)	3238.36785145622 0.7676	(3.31,0.3) and (6.95,1.4) ..	0.86782 116 0.8676 117 0.86748 118	with scientific, business, and industrial...
circle* 0.000001 put(69.30,-229.10)	3249.01195892414 0.77	(10.93,3.29) ; draw [color= rgb,	0.86765 119 0.86805 120	
circle* 0.000001 put(70.00,-229.10)	3259.27909703235 0.754...	255:red, 126; green, 126; blue, 126...	0.86806 121 0.86851 122 0.86844 123 0.86789...	
Professionalism = 1	Professionalism = 2	Professionalism = 3	Professionalism = 4	Professionalism = 5
...472) (202,472) (202,472) (203,472) (203,472) (204,472)	... (30,0 put(20, y) line(1,0) 70) line(1,0) 30	...0.26) .. controls (270.11,370.98)	...istics network was studied in which shippers	... label appli::results Figure ref
(204,472) (205,472) (205,472) (205,472) (206,472) (206,472)	def0 put(20, y) line(1,0) 70 80 put(20,0 put(20, y) line(1,0) 70	and (269.53,371.57) .. (268.81,371.57) .. controls	collaborate and bundle their shipment requests	graph::plots represents the three transition intensities
(207,472) (207,472) (208,472) (208,472) (208,472)) line(1,0) 30 line(1,0) 30 line(1,0) 30	(268.09,371.57) and (267.5,370.98) .. (267.5,370.26)	to negotiate better rates with a common carrier and	(Part A), the three cumulative incidences (Part B)
(209,472) (209,472) (210,472) (210,472)	line(1,0) 30 line(1,0) 30 def0 put(20, y)	- cycle ; draw (270.11,370.26) .. controls	cost-allocation mechanisms were proposed	and the estimated mean ISAACS
(211,472) (211,472) (212,472) (213,472)	line(1,0) 70 70 put(40,0 put(20, y) line(1,0) 70	(270.11,369.53) and (270.7,368.95) .. (271.42,368.95)	to ensure the sustainability of the collaboration.	trajectories (Part C) for men with a low level of
(213,472) (213,472) (214,472) (214,472)) line(1,0) 40 def0 put(20, y) line(1,0) 70 60	.. controls (272.14,368.95) and (272.72,369.53)	In cite gansterer2021prisoners the prisoners'	education (with no primary school diploma), in each class. The first class i...
(215,472) (215,472) (216,472)...	put(70,0 put(20, y) l...	.. (272.72,37... appl...		
Semantic Density = 1	Semantic Density = 2	Semantic Density = 3	Semantic Density = 4	Semantic Density = 5
...96) [1] (2.447, 0.10694168320452796)	...1,0) 70) [line(1,0) 30 def0 put(20, y)	...51042) psline[linecolor=black, linewidth=0.06]	...c, fill=c] 7.62637,2.64783) rectangle (7.8022,2.75217);	... section INTRODUCTION In recent years
(2.448, 0.10680411227327702)	line(1,0) 70 10 put(40,0 put(20, y) line(1,0) 70	(14.4,13.151043) (14.4,11.951042) (14.4,11.951042)	(7.8022,2.75217); definecolor c rgb 0.116419,0.686966,0.702999	We have seen a dramatic increase interest
[1] (2.449, 0.10666669262164181)) line(1,0) 50 def0 put(20, y) line(1,0) 70 0	psline[linecolor=black, linewidth=0.06] (15.2,13.151043)	draw [color=c, fill=c] (7.8022,2.64783)	within the area of autonomous transportation and its associated
[1] (2.451, 0.106392306667139)	put(10,0 put(20, y) line(1,0) 70	(15.2,11.951042) (15.2,11.951042)	rectangle (7.97802,2.75217)...	research....
[1] (2.452, 0.106255340119293...) line(1,0) 70 put(0,60)...	psline...		
Sensitivity = 1	Sensitivity = 2	Sensitivity = 3	Sensitivity = 4	Sensitivity = 5
...444) rule[-0.500pt] 1.000pt 1.566pt	...2, 274.09852) (17.2, 271.1908661538462)	...1) (0:1) - (180:1); draw[blue] (-60:1) - (180:1)	...and the thermodynamics / statistical mechanics of	...Diverse individuals age at different rates and
1.000pt 1.566pt 1.000pt 1.566pt	(98.8, 305.2704876923077)	- (60:1) - (-60:1) (60:1) - (-60:1)	the classical scale becomes particularly	display variable susceptibilities to tissue aging,
1.000pt 1.566pt put(361,438)	(98.8, 305.2704876923077)	(60:1) - (-60:1) ; draw[blue] (0:1) -	delicate cite physrep . Regarding	functional decline and aging-related diseases.
rule[-0.500pt] 1.000pt 1.566pt put(362,431)	(98.8, 305.2704876923077)	(-60:1) - (-120:1) (180:1) - (120:1) -	the methods of calculation, among the electronic	Centenarians, exemplifying extreme longevity,
rule[-0.500pt] 1.000pt 1.566pt put(363,425)	(98.8, 305.2704876923077)	(150:0.87) - (60:1) (-30:0.87)	structure techniques, Density Functional, ...	serve as models for healthy aging. The field of human...
rule[-0.500pt] 1.000pt ...	282.68546) (48.0, 293.9522630769231)	(-90:0.87) - (180:1) - (90:0.87)		
	(38.0, 268.4655492307692)			

Table 18: Raw training examples selected to have quality ratings at the 1-5 within ArXiv.

Structural Standardization = 1	Structural Standardization = 2	Structural Standardization = 3	Structural Standardization = 4	Structural Standardization = 5
...bWa9017 rzAIqI3 UE1UJG7tL tUXzw4KQNETvXz qWaujEMenY1NIzLGx gB3AuJ86VS6RcPJ 80XWw8imtC KZEzHop84G1 gSAs0PCowMI2f LKT dD60yn Hg7lkNF jJLqOoQ vfkfZBN G3oIdGc n9hyUh5 VSP5z61 qvQwceUd VJJsBvXD qvQwceUd G4ELHQHia5...	...static setting. The algorithms that do not learn (Sparrow and PoT) do not degrade for the same reason discussed above. iffalse begin figure includegraphics [width=0.45 textwidth, height=0.15 textheight] figures.pdfGruhl2004, Hill2006, Iribarren2009, Java2006, Leskovec2007a, Leskovec2006, Strangl1998,Wan2007 . Two fundamental types of models of information diffusion used in the literature are cascade models and threshold...	...last years bigger devices like blood refrigeration units, CT scan systems and X-ray systems are connected to the Internet, in order to check remotely their operational state and make whatever adjustment is needed (e.g., lower the blood unit inside te...	...attack. color black Such a figure summarizes what happens with attacked STFT and MF spectrograms: the difference between the adversarial and legitimate spectrograms is imperceptible to the human visual system. color black This aspect is very imp...
Style Consistency = 1	Style Consistency = 2	Style Consistency = 3	Style Consistency = 4	Style Consistency = 5
...PY o PY n id char C PY p char C PY pchar C PY p PY p PY p PY o PY n deathsChild PY p PY o PY n newInfectiousChild C PY p PY p PY p C PY p PY p PY p C PY p PY p PY p PY p PY p PY p PY p PY p PY p PY p PY o PY n agingChild PY p PY o PY n id char C PY p PY p PY p PY o PY n v ch...	...) line(1,0) 70 80 put(40,0 put(20, y) line(1,0) 70) line(1,0) 50 def0 put(20, y) put(20, y) put(20, y) line(1,0) 70 70 put(80,0 put(20, y) line(1,0) 70) line(1,0) 20 def0 put(20, y) put(20, y) put(20, y) line(1,0) 70 60 put(20,0 put(20, y) line(1,0) 70) lin...	...0 put(60,0 put(20, y) line(1,0) 70 line(1,0) 40 def0 put(20, y) line(1,0) 70 30 put(10,0 put(20, y) line(1,0) 70) line(1,0) 70 put(20, y) put(20, y) def0 put(20, y) line(1,0) 70 20 put(50,0 put(20, y) line(1,0) 70) line(1,0) 60 def0) (-1,1) pspolygon [fillstyle=solid, fillcolor=NavyBlue] (0,0) (0,-6) (1,-6) (1,-1) pspolygon [fillstyle=solid, fillcolor=NavyBlue] (1,1) (6,1) (6,0) (2,0) pspolygon [fillstyle=solid, fillcolor=NavyBlue] (-1,1) (-6,1) (-6,0) (-2,0) pspolygon [fillstyle=solid, fillco...	... section Introduction tmf (TMNF, or TMF) is a 3D racing game that was released in 2008 by video game developer Nadeo. It is part of the racing game series TrackMania. It was designed for the Electronic Sports World Cup, which is a yearly internati...
Topic Focus = 1	Topic Focus = 2	Topic Focus = 3	Topic Focus = 4	Topic Focus = 5
...55 0.2 12490313.2925055 0.2066666666666667 13225057.5307381 0.2066666666666667 13225057.5307381 0.2133333333333333 13231816.8440602 0.2133333333333333 13231816.8440602 0.22 13262462.5634116 0.22 13262462.5634116 0.2266666666666667 13464096...	... put(20, y) line(1,0) 70 10 put(50,0 put(20, y) line(1,0) 70) line(1,0) 50 def0 put(20, y) put(20, y) put(20, y) put(20, y) line(1,0) 70 0 put(30,0 put(20, y) line(1,0) 70) line(1,0) 40 put(0,70) line(0,1) 40 put(10,50) line(0,1) 50 put(20,90) line...	...403) - (2.5724992775571893, 1.417611987501176); draw[line width=1pt, color=qqqqff] (2.5724992775571893, 1.417611987501176) - (2.579999266831962, 1.4192818792042017); draw[line width=1pt, color=qqqqff] (2.579999266831962, 1.4192818792042017) - (2.5...	...mm] (s3) node[node1, right = 0.25cm and 0.25cm of s2, line width=0.1mm] (s4) node[node1, left = 0.2cm and 0.25cm of s3, line width=0.1mm] (s5) node[node2, right = 0.25cm and 0.25cm of s4, line width=0.1mm] (s6) node[node2, right = 0.25cm and 0.25cm of s4, line width=0.1mm] (s6)between warehouses which are almost entirely obstacle-free, and therefore only requiring low precision navigation. By ignoring this heterogeneity, mobile robots are forced to make worst-case decisions to ensure their safety. For example, for the abov...
Overall Score = 1	Overall Score = 2	Overall Score = 3	Overall Score = 4	Overall Score = 5
...472) (202,472) (202,472) (202,472) (202,472) (202,472) (203,472) (203,472) (204,472) (204,472) (205,472) (205,472) (205,472) (206,472) (206,472) (207,472) (207,472) (208,472) (208,472) (208,472) (209,472) (209,472) (210,472) (210,472) (210,472) (211,472) (211,472) (212,472) (212,472) (213,472) (213,472) (21...	... (30,0 put(20, y) line(1,0) 70) line(1,0) 30 def0 put(20, y) line(1,0) line(1,0) line(1,0) line(1,0) 70 80 put(20,0 put(20, y) line(1,0) 70) line(1,0) 30 def0 put(20, y) line(1,0) 70 70 put(40,0 put(20, y) line(1,0) 70) line(1,0) 40 def0 put(2...	...0.26) .. controls (270.11,370.98) and (269.53,371.57) .. (268.81,371.57) .. controls (268.09,371.57) and (267.5,370.98) .. (267.5,370.26) - cycle ; draw (270.11,370.26) .. controls (270.11,369.53) and (270.7,368.95) .. (271.42,368.95) .. controls...	...istics network was studied in which shippers collaborate and bundle their shipment requests to negotiate better rates with a common carrier and cost-allocation mechanisms were proposed to ensure the sustainability of the collaboration. In cite ganst...	... label appli::results Figure ref graph:plots represents the three transition intensities (Part A), the three cumulative incidences (Part B) and the estimated mean ISAACS trajectories (Part C) for men with a low level of education (with no primary...

Table 19: Raw training examples selected to have quality ratings at the 1-5 within Book.

1890
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1939
1940
1941
1942
1943

Accuracy = 1	Accuracy = 2	Accuracy = 3	Accuracy = 4	Accuracy = 5
...IA GREEK SMALL LETTER PI GREEK SMALL LETTER EPSILON GREEK SMALL LETTER RHO GREEK SMALL LETTER IOTA WITH VARIA GREEK SMALL LETTER TAU GREEK SMALL LETTER OMICRON WITH VARIA GREEK SMALL LETTER NU GREEK SMALL LETTER PI GREEK...	...n?' Well upon dis, de Pharisees picked up der fraills and cut away right by him, and as dey passed by him he felt sich a queer pain in his head as if somebody had gi'en him a lamentable hard thump wud a hammer, dat knocked him down as flat as a floun...	...ountain 34. 26 A London Season 35. 27 Turning Forty 36. 28 The Classical Style 37. Acknowledgments 38. Notes 39. Illustration Credits 40. A Note About the Author 1. i 2. ii 3. iii 4. iv 5. v 6. vi 7. vii 8. viii 9.Twenty years ago Jerry Wilson was known as the cattle king of the Platte River. His cattle roamed for hundreds of miles up and down the main river and all its tributaries, and, as the cowboys used to say, no one man could count them even if they was, church steeples, and a three-story brick opera house. Instead, they found a half-burnt town ruined by a devastating blaze that lay waste twenty blocks a few months earlier. Holcomb had taken leave of a proud, 250-year-old city touted as one of the ...
Coherence = 1	Coherence = 2	Coherence = 3	Coherence = 4	Coherence = 5
... 14. 15. 16. 17. 18. 19. 20. 21. 22. 23. 24. 25. 26. 27. 28. 29. 30. 31. 32. 33. 34. 35. 36. 37. 38. 39. 40. 41. 42. 43. 44. 45. 46. 47. 48. 49. 50. 51. 52. 53. 54. 55. 56. 57. 58. 59. 60. 61. 62. 63. 64. 65. 66. 67. 68. 69. 70. 71. 72. 73. 74. 75.de Montès allaient et venaient, et quelque chose d'impuissant et d'indigné dans ce qu'on pouvait apercevoir du visage au-dessus de la serviette que continuait à presser la main décharnée, et plus tard encore - à ce moment ce devait être la seule, l'u...	...met Lawrence Isis, a half-Irish, half-Egyptian Copt software engineer at a campus concert--Celtic folk music, Amanda had gone on a lark, a friend's urging. The chemistry had been instant, despite the fact that Larry resembled Woody Allen with dark hai...	...to lecture. Billy continued meekly to listen. The old man knew that sex was at the bottom of it. He saw that Billy had a sensuous nature which needed to be curbed. Billy was giving up Rose to seek out Queen MyrdeInggala--yes, he knew Billy's desires...	...Soviet bloc diplomatic and trade missions heavily staffed by intelligence operatives. The age-old art of espionage had not faded away, despite the world entering the apparently softer, gentler phase of the Cold War associated with the détente between...
Creativity = 1	Creativity = 2	Creativity = 3	Creativity = 4	Creativity = 5
...47-48, 150-53, , , 188-89, , , 277-78, 282-312, , , , , , 369-70, 375-77 law, 15-81, 147-82 147-82. 147-82. 147-82.. See also natural law legality, , 154-55, , legal status, , Leibniz, G. W., , liberalism, xv, , , , , 273-75, , , 273-75 liberty, , 99-10...	...and Fletcher v. Peck (1810), because the states were angry over the Court's assertion of power to strike down state laws; and both Virginia and Kentucky had made dark threats foreshadowing a constitutional crisis in 1823, according to Robertson. In d...	...qu'il n'oubliera pas. Elle est à l'origine de son pragmatisme en politique. La question dans un monde ensorcelé n'est pas de savoir qui a raison, qui va le plus droit, mais qui est à la mesure du Grand Trompeur, quelle action sera assez souple, assez...	...rage and near pornographic intrusion into private lives. Detective Sergeant Norman Pilcher craved fame and recognition. Backing them up were a bunch of minor dyspeptic personalities, self-styled worthies, suburban officials and legal types. This wasank into his chair, a sullen pout on his lips. And don't you think about going behind my back, I warned husband number two as I sat at Daniel's right. You will not be arranging a handy accident, is that understood? Well, my lover, I've found I...
Grammatical Diversity = 1	Grammatical Diversity = 2	Grammatical Diversity = 3	Grammatical Diversity = 4	Grammatical Diversity = 5
...27. 28. 29. 30. 31. 32. 33. 34. 35. 36. 37. 38. 39. 40. 41. 42. 43. 44. 45. 46. 47. 48. 49. 50. 51. 52. 53. 54. 55. 56. 57. 58. 59. 60. 61. 62. 63. 64. 65. 66. 67. 68. 69. 70. 71. 72. 73. 74. 75. 76. 77. 78. 79. 80. 81. 82. 83. 84.6), 306(n3) Ross, Leonard, , 300(n53) Rosten, Leo, Rothweiler, Monika, (n10, n11) Ruhlen, Merritt, 312(n23) Rules, , , , , , . See also Combinatorial systems; Heads; Symbols and symbol processing; Word structure Rumelhart, David, , , 103-11...	...dummy he was fighting looked up, and the old corkscrew right went over and the dummy started trilling to the daisies. And the baseball games in the old days of Spike Shannon, Mike Donlin, Fred Tenney, Jimmy Collins, Cy Young, Pat Dougherty, Fielder J...	...a normal life, whatever that is. I am now watching many of my friends enter their second marriages and, while I am more than happy to have waited, to have missed that first wave of divorces, I do hope to find someone special when the time is right. T...	...led the canon of Dead White European Males, the Anglo-American core in English departments was supplanted or minimized--and along with it a consciousness of the ancient and medieval etymology of English words, a complex lineage that is wittily evoked ...
Knowledge Novelty = 1	Knowledge Novelty = 2	Knowledge Novelty = 3	Knowledge Novelty = 4	Knowledge Novelty = 5
...I joined them for a while and picked up a little, you know, cab fare. Then I forced everybody, including the conductor, to get in the last car, and I pulled the pin and left them back in the tunnel. Sometimes that's the only way you can get a seat. A...	...of the affair, preferring a pretty face and poverty. Stupid devil, to throw away such a birthright! Lucky dog, who is to be his successor? Let the rogue win the race. I am so tired of the dodges, the twists, the aliases, the lurkings, that I will put...	... La faveur d'obtenir un peu ! Devenons attentifs à ces âmes choisies Que l'on goûte à travers leurs corps ; Contrainçons, en souffrant, l'altière fantaisie, -- Aimer moins est si fort encor ! Il n'est pas, pour nouer une divine attache, Que cesthat would train people to be active and useful citizens in the modern technological society. In short, popular culture movements saw culture as the means by which the individual's relation to society might be ameliorated. Many of these foundatio...	...IPv4, proposed originally in the mid-1990s. When would IPv6 run out? If you were to divide the total number of possible addresses within a 128-bit space by 7 billion people, it would be able to theoretically allocate approximately 5 × 1028 addresses ...

Table 20: Raw training examples selected to have quality ratings at the 1-5 within Book.

Language Consistency = 1	Language Consistency = 2	Language Consistency = 3	Language Consistency = 4	Language Consistency = 5
...totta, mutta hän vaistosi, että kuski pettyisi, jos hän paljastaisi olevansa vailla uskoa. Gloria ei ollut koskaan voinut käsittää, että joku halusi käyttää kidutuksen ja kuoleman väliinettä koristeena. Yhtä hyvin olisi voinut kantaa hirttosilmukkaa, ellingtonien, très chromatique, refrain d'un autre monde, voluptueux, onirique, lui tient compagnie sur le chemin du retour. De l'art ou pas, il n'en sait rien, et eux, qu'en savent-ils, si l'ombre de la croix fait loi ? La sensation d'une répétition...	...ille. Et pendant longtemps je m'arrêtais à cette conclusion, qu'à moins d'avoir seize poches, chacune avec sa pierre, je n'arriverais jamais au but que je m'étais proposé, à moins d'un hasard extraordinaire. Et s'il était concevable que je double le n... --No, necesito tu ayuda. Soy nueva aquí, ¿recuerdas? Ante su tacto, sentí un tibio escalofrío que no asociaba con la amistad. ¿Y por qué no? Sus mejillas se sonrojaron, sus ojos centelleaban; bajo los focos y el cielo azul verdoso de un crepúsculo...	...épitomise Athens' more general shift from orality to the increasing use of writing. This development unfortunately also locked in Solon's less attractive legislation, some of it termed 'peculiar' by Plutarch, the epidikasi, for example, a procedu...
Originality = 1	Originality = 2	Originality = 3	Originality = 4	Originality = 5
...-8n1, 188n7, , , , - , - , 259n33 acknowledgment , , , 61n10, , - , , , , - , , , action , , 115n21, - , 45n2, , , , , , 115n21 , , , , , 115n21, - , , , 128n23, - , , , 115n21, - , - , - , 115n21, - , Agee,2013, B.S. 9 januari 2014, inwerkingtreding: 30 april 2014 (art. 2 K.B. 4 april 2014, B.S. 29 april 2014) l[Hoofdstuk 5 - Bijzondere bepalingen]l *1*. Opschrift ingevoegd bij art. 2 wet 15 december 2013, B.S. 9 januari 2014, inwerkingtreding: 3...	...- , - , - , - elections Mecklenburg-Schwerin state assembly (1927), - electoral performance 1929 state parliaments, - Danzig, Lippe state elections (1933), Presidential (1932), - Reichstag (1928), - Reichstag (1930), - Reichstag (1932), - Re...	...My heart hammers in the rib cage much longer than it should, but I am unmolested, for now. I walk calmly away from the bus and change clothes as soon as I find a Salvation Army bin. I select a man's apparel, compress my hair into a woolen hat, and di...	...auf aux niveaux scolaires les plus élevés où l'effet de sursélection tend à neutraliser les différences de trajectoire) que, premièrement, on fait moins appel à une compétence stricte et strictement contrôlable et davantage à une sorte de familiarité...
Professionalism = 1	Professionalism = 2	Professionalism = 3	Professionalism = 4	Professionalism = 5
...ingered in each other's arms after a conjugal visit in a bus station toilet stall. They call Jarvis an 'Uncle Tom of Finland,' said Gentry. Delicious asked, What's that mean? Gentry shrugged and shook his head. Something about too many muscle...	...non le faceva venire l'affanno, un affanno insopportabile, per cui avrebbe voluto balzare in piedi smaniosa; ma non poteva. Il cuore, il cuore le batteva precipitoso come il galoppo d'un cavallo scappato. Ah, il cuore, il cuore non le reggeva più, fo...	...to Heaven directly, where you may join her at your convenience. Your most humble and obedient servant , The Prince of Evil Zane stared at the message, absorbing its every implication. Suddenly it burst into flame in his hand. He dropped it,...	... For the purpose of the object on which we now enter, we have consulted a great mass of documents, and have had recourse to the personal experience of a gentleman who has made this kind of research his business. In every statement we make, we shallates the problem of freedom in Adam's choice of himself as a whole in the world. He can agree with Leibniz that another gesture of Adam, implying another Adam, implies another world, but only in the sense that another face of the world will corres...
Semantic Density = 1	Semantic Density = 2	Semantic Density = 3	Semantic Density = 4	Semantic Density = 5
... 36. 37. 38. 39. 40. 41. 42. 43. 44. 45. 46. 47. 48. 49. 50. 51. 52. 53. 54. 55. 56. 57. 58. 59. 60. 61. 62. 63. 64. 65. 66. 67. 68. 69. 70. 71. 72. 73. 74. 75. 76. 77. 78. 79. 80. 81. 82. 83. 84. 85. 86. 87. 88. 89. 90. 91. 92. 93. 94. 95. 96.ancholy bait, 60. sold for more than an ox, 734.734 to ery, other, 772, 790, 772, 790, 772, 734 790, 772, 790. what cat 's averse to, 381, 772, 790, 772, 790. with the worm, man may may, 141. Fishes gnawed upon, men that, 96. 772, 790 live in the sea, live in the sea,adlen, Rumist datzu unnd schreybst in alle welt, du kundist allis auswendig und geprauchst keiner pucher. Du dorfftist des Rumisz nit, man siht es mehr dan du gleubst, das du allis an bucher schreybst und lerist: wen du die augen so fleyssig...	...and resources, but as sinners who were lost. To Him, Ulaf was no different than Conor except that Conor had accepted the sacrifice made for him. You're still here. Conor looked up. Haldor stood over him, holding a dripping battle-ax, his face, ha...	...Protestant king in Ireland, a Protestant parliament, a Protestant hierarchy, Protestant electors and government, the benches of justice, the army and revenue, through all their branches and details, Protestant...
Sensitivity = 1	Sensitivity = 2	Sensitivity = 3	Sensitivity = 4	Sensitivity = 5
...and incorrect ways to be born. And without question the worst and most disgusting deformity to be born with was gayness. Which was why EJP always deleted his browser history and hated The Thought and hated gay people but couldn't hold it against them...	...at her; he stared at the fire. The soft light did not touch his eyes, Not even Arthur? The air hummed with Power. This was no place for lies. She touched his hand, and when he finally turned, she gazed into his eyes. Especially not Arthur. He c...	...on the face and cried, Traditore! Father Paciére was cowering back, powerless to stop it. The soldier finished their part of the ceremony. Babe, red cape flowing in the drafty place, held up her hand. Giorgio rushed forward. He gave her two...	...not like it. 'But it wasn't all that much. Just some smoky walls and busted glass.' Hardin came back to his main problem. 'The foreigner. Did you ever meet him?' 'No. Biggie set up a meeting for tonight in case he had something to trade. That's why...	...6 Richard swiftly, but silently, raised the sword before himself in preparation for an attack--what kind of attack he wasn't sure, but he fully intended to be ready. He touched the cold steel of the blade to his sweat-slick forehead. He spoke the wo...

Table 21: Raw training examples selected to have quality ratings at the 1-5 within Book.

Structural Standardization = 1	Structural Standardization = 2	Structural Standardization = 3	Structural Standardization = 4	Structural Standardization = 5
...first lieutenant, he's got a neck like a Swiss steer, I once tried to do splits with a beauty in the Catholic House and gave myself a hernia, which isn't so bad for a man, a man makes anything look good, but when a maiden wears a truss and a lovesick...	...bemoan, boohoo, grieve, lament, regret, snivel, squall 7 blubber, deplore, trickle, ululate, whimper 8 complain 9 break down, make a fuss, percolate, shed tears for: 4 pity 6 bemoan, lament (for): 4 feel over: 6 bewail, regret, repent ready to...	...of scotch two nights before. Tempting as dropping by the liquor store may have been, he'd decided he'd rather eat paint thinner than answer pointed questions from the locals about Susan. There had been some changes in the Martin household over the lll...	... Penelope had listened silently, like a girl in a dream. Now she patted Mrs. Fairweather's soft old hand affectionately. It sounds like a storybook, she said gaily. You must come and see Doris. She is such a darling sister. I wouldn't have had trash the patron...	...-53. Manna SK, Mukhopadhyay A, Aggarwal BB. Resveratrol suppresses TNF-induced activation of nuclear transcription factors NF-kappa B, activator protein-1, and apoptosis: potential role of reactive oxygen intermediates and lipid peroxidation...
Style Consistency = 1	Style Consistency = 2	Style Consistency = 3	Style Consistency = 4	Style Consistency = 5
...my buggy was torn to pieces, an' I was knocked high in de air. De first time dey run into me dey killed my hoss. De third time dey paralyzed my arm and busted the linin' o' my stomach. I learned to read an' write since de surrender by studying in s...	...their names appeared on the screen, where possible. Unbilled players and technical personnel are added, where they can be reasonably documented. Various websites--for example, the Internet Movie Database (www.imdb.com)--feature credits for Micheaux f...	...l'extrême du sentir-créditeur. [...] Aller au bout des puissances du seul - à deux. Reconstituer l'amour dans l'au-delà des états privés et connus. » La prison du miroir enfin devenue inutile, c'était délivrer cette voix peut-être entendue, prise sans...	...and Mission San Antonio, -25 in Monterey, , at Purísima de Cadegomó, in Sierra Gorda, , -25 as student of Serra, -32 travel to Alaska, -65, travel to California, travel to New World, , Croix, Marquis Carlos de, , , , , Croix, Teodoro de...	...Ohio Railroad, 103-8, 105 , 109 banking industry, 26-27, 88, 93, 201, 212-13, 298, 305-8, 305 , 359-60 see also specific banks bank notes, 40-41, 90 Bank of Augusta v. Earle , 88, 90, 97-103, 115, 132, 145-46, 181, 400 Bank of England,...
Topic Focus = 1	Topic Focus = 2	Topic Focus = 3	Topic Focus = 4	Topic Focus = 5
... TONGA) * kankir (23.4. DAGAARE, SOUTHERN) * kankoeng dagoblad (36.2. VLAAMS) * kankong (36.2. INDONESIAN) * kankri (38.13a. KONKANI) * kankri (38.7a. HINDUSTANI) * kankro (38.13a. NEPALI) * kankro (38.13b. NEPALI) * kankrol...	...someone said, a minute or a century ago. Give him a booster shot. It can't hurt him. Six people were sitting on a shelf, looking down at him. A bare-breasted woman, a white-haired oldster, a young Negro girl, a flabby executive-type man, a Goonto...	...on blend, Vera reads off the label. Made in the Philippines. She flings it at me and I screech. It lands on my shoulder and I throw it at Ehma, who ducks aside. I grab it again and chase her into the kitchen. Here, here. I throw the camisole to...	...ended is also crucial here. I have addressed her important concerns in Chapter One. See Le Dœuff (1989: 126-8). **20** Propositional and assertive modes, while valuable for certain philosophical work, arguably restrict the open-ended inquiry that t...	...uncle's life, but changed things enough for my dad so that he never met and married my mom? I pondered that for an extremely long time, and what I kept coming back to was this: What if I did? Selfishly, I had to admit I liked being alive, but I also ...
Overall Score = 1	Overall Score = 2	Overall Score = 3	Overall Score = 4	Overall Score = 5
...02-03, , , , Barksdale, Brianna (character), , , , , Barksdale, D'Angelo (character), , , , , , , , , 285-86 and Avon, 84-85, , , , and chess, , , and desire to escape the Game, , , , and McNuggets, and Stringer, , and Walla...	...68 . V. Chepizhny 1984 . V. Chepizhny 1983/84 . N. Cherniavsky 1976 . E. B. Cook 1868 . N. M. after E. B. cook 1913 . E. B. Cook 1868 . E. B. Cook 1868 . C. H. Courtenay 1868 . C. H. Courtenay 1870 . J. Cumpe...	...You work for free, I'll put you up at a nice hotel. You can eat great food and I'll give you a hooker. **ADAM DUBIN:** I always give the Beastie Boys a lot of credit, because nobody in the record business, even people who knew them, would've given...	...ended is also crucial here. I have addressed her important concerns in Chapter One. See Le Dœuff (1989: 126-8). **20** Propositional and assertive modes, while valuable for certain philosophical work, arguably restrict the open-ended inquiry that t...	...uncle's life, but changed things enough for my dad so that he never met and married my mom? I pondered that for an extremely long time, and what I kept coming back to was this: What if I did? Selfishly, I had to admit I liked being alive, but I also ...

Table 22: Raw training examples selected to have quality ratings at the 1-5 within C4.

Accuracy = 1	Accuracy = 2	Accuracy = 3	Accuracy = 4	Accuracy = 5
...From data of data the quantity of prostitutes on the planet exceeds 42 millions today. Your e mail us' should contain appropriate information on such web page. Frequently it is the identical message. Some pages provide you with a few li...	...day services available in many instances, to make sure the waste products tend to be taken care of as quickly and effectively as possible. Otherwise same day, the majority of places guarantee their storage containers to be right now there by the subs...	...facts it decides to ignore. Hamas is not a terrorist organization. It is a political party, which has gained control of Gaza by legitimate democratic means, during an election which was witnessed by former President Carter. In fact the Carter Cente...	...corrosion and anti-rust agents. The oil has a Proprietary technology add on that provides an extra layer of protection that helps the engine cool while maintaining proper temperature stability and oxidation. That is a feature you will not find with31400 (2016). AIP Conference Proceedings, 1741, 050016 (2016). European Journal of Inorganic Chemistry, 4273-4274 (2016). J. Am. Chem. Soc., 137, 11498-11506 (2015). Chemical Science, 6, 4306-4310 (2015). Inorganic Chemistry, 54, 11593-11595 (2015). ...
Coherence = 1	Coherence = 2	Coherence= 3	Coherence = 4	Coherence = 5
... from your committee into a plasma. The client shared the amount and limited with a clearinghouse internet the contraction of ad pushing your traffic and security pp.. material of the law for ASIMO, Japan's solid effect? It takes come > with covalen...	...bow lake left from an old channel of the Mississippi River. One floating casino is located on the lake near the downtown area known as the Trop Casino Greenville, with a second just west of the city near the Greenville Bridge known as Harlow's Casino...	...ing plate drive mechanism. 0001 The stitching home position sensor does not go on when the stitch motor (rear) has been rotated in reverse for 0.5 sec or more. Stitch motor (rear; MGS)/stitching home position sensor (rear; MS5S) Replace the stitcherSHOCKING - Package Seized and Destroyed by Royal Mail! However this was mainly aimed at international air shipments but since then further rules have been introduced by the International Air Transport Association, or IATA for short, with their Danger...	...This is in response to your Request for Set Aside of Denial of Further Review of Protest and to Void the Denial of Protest Number 4103-98-100300 filed on behalf of the importer, Mast Industries, Inc. (Protestant), seeking to set aside the Port's de...
Creativity = 1	Creativity = 2	Creativity = 3	Creativity = 4	Creativity = 5
...Waterville area police reports for June 14, 2016. IN ANSON, Monday at 3:24 p.m., a harassment complaint was investigated on Hilltop Road. IN CLINTON, Monday at 9:45 a.m., a report of harassment led to an oral warning on Diamond Avenue. 3:57 p.m., thr...	...Seize the deal before it's gone. Check out 70% Off Fine Jewelry. at Bealls Department Store now. Find more discounts and offers from Bealls Department Store just at CouponAnnie in April 2019. Save 70% off Fine Jewelry. Seize the deal before it's gone...	...A home building project can be the chance for a couple to make their dream come true. The family has grown, there has been professional success - for whatever reason, it's time to invest hard-earned funds in a renovated kitchen, an extension or a bra...	...whom he worked and he behaved in the manner of an idle dandy. He would even conduct interrogations lying on a settee draped in rich Chinese silks, manicuring himself while he put his questions. Yet he had inspired trust and was tolerated with amuseme...	...As Obi-Wan stands at his Master's funeral, he remembers all that has happened... and all that could have been. The memories that now rampage my mind are painful, yet so beautiful in their sweetness. How can this be? How can he be gone? Everything he ...
Grammatical Diversity = 1	Grammatical Diversity = 2	Grammatical Diversity = 3	Grammatical Diversity = 4	Grammatical Diversity = 5
...aked to access where this contributes us. Our contradictory network contains really said as it implies when we 've functions. In Time to know a induction to present as it is in us, the registered company has the s exposure. Vanities eliminated been i...	...If you are the typical inventor, it is very much possible that you would probably like to license all your invention and receive royalties, or even sell that it outright - we'll dub that person royalty author. But if you really are more motivated w...	...grid sale calculation to Sales.applyGridSales to allow easier modding. - Fixed: gdt-modAPI: Checks.checkMissionOv... did not return true when it should. - Fixed: When using windowed mode the window size starts smaller than 1024x768. - Fixed: Endbe against one of their own. We should have listened. In the book, I could not count the number of times Obasanjo slapped his wife, Madam Remi, or the number of times she herself slapped many of Obasanjo's numerous mistresses and paramours, including...	...Matthias Schoenaerts and Diane Kruger headline a sharp, slinky dive into genre territory for soph helmer Alice Winocour. Maryland is the original title of Disorder, the second feature by Parisian writer-director Alice Winocour, and while not one ...
Knowledge Novelty = 1	Knowledge Novelty = 2	Knowledge Novelty = 3	Knowledge Novelty = 4	Knowledge Novelty = 5
...Free parking lot to the Plan and the Village Alpiaz, near to the footsteps. 8 Gavardina street, near the Body shop Livingstone 2, in the place Bettoletto. Ample parking lot before the Blue Camping Bosco, next to the ski footsteps. Parking lot of theeastern before washington journal. » on tuesday, the present the unit - european parliament discussed efforts to combat the islamic state and other terrorist groups following the recent attacks in brussels. intelligencesed sharing, islamic radical...	...nay's The Legends of Jerusalem that Rabbi Luria supposedly knew in his day in a supernatural way where Jeremiah was placed in the Court of the Guard mentioned in Jeremiah 32:2. This was the key. and when Ha-Ari the Holy saw him. There was also a sid...	...hoped to construct one piece in what will be a much larger conversation. And we certainly didn't start anything ourselves; people were talking about this, and we just wanted to give it a bit of a push and inspire others to take on what needs to happen...	...CR chain sequences from reactive CD4 T cells from 22 individuals with latent Mycobacterium tuberculosis infection. We found 141 TCR specificity groups, including 16 distinct groups containing TCRs from multiple individuals. These TCR groups typical...

Table 23: Raw training examples selected to have quality ratings at the 1-5 within C4.

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Language Consistency = 1	Language Consistency = 2	Language Consistency = 3	Language Consistency = 4	Language Consistency = 5
...Antikythera. While the nanoscale saved for the philosophique to ignore, the service of the efficacy were one of his texts to run the rotation for is. The , Elias Stadiatis, taught the breaks of a bacterial element at the knowledge of the side, 60 act...	...Which user Loves freedom the most or Hates freedom the most? If only you could see how against freedom you are.. I love freedom so much anyone who doesn't love it should go die! You wanna back that up? Being against abortion doesn't make me anti-fr...	...good quality furniture affordable quality furniture affordable quality furniture affordable quality high quality high quality furniture brands sofas. good quality furniture high quality furniture brands high quality furniture bra...	...Are you aware of any new treatments being researched? How do you feel about participating in clinical trials? What would prevent you from involving your child in a medical research study? Interact and reply in the comments below! Not sure about new t...	...On Arrival: Presuming you are already within Italy prior to arriving in the Amalfi Coast, most commonly you will arrive by train in Sorrento (via Naples) or in Salerno. We buy our train tickets online through Trainline. From here you can get to the v...
Originality = 1	Originality = 2	Originality = 3	Originality = 4	Originality = 5
...table below, if you want your kids wear longer time, please choose bigger size. Factory direct sell, quality assurance. Made in china, fabric is incredibly soft and comfortable. Factory direct sell /1 piece retail hot sell /free shipping. - Machine W...	...Spinit boasts a choice of games and slots and is also a brand new casino. Supplying a variety of payment choices and Offered in some languages, its prevalence has been increasing among fans. It's fun and contemporary, and more importantly for a casin...	...includes services such as recreation and social activities. Seajoy Cla provides assisted living not only to Decatur residents, but also to all Dekalb county residents as well. If you need assistance with daily tasks, Gordon Care can help you or yourOh yeah, that meaningless, well-worn catchphrase used by influencers and self-help coaches. What's in it for real people though? In fact, personal branding is something you should develop and control. Especially when it comes to your professional lif...	...After 5 years of a continuous lawful stay in Luxembourg, third-country nationals (i.e. from a country that is neither an EU Member State nor a country treated as such - Iceland, Norway, Lichtenstein and Switzerland) may make an application to obtain ...
Professionalism = 1	Professionalism = 2	Professionalism = 3	Professionalism = 4	Professionalism = 5
...Programs, or Director of Admission, inhabit flounders, and build a relevant besondere for our consequences. using the CAPTCHA gives you involve a giant and coincides you aspen free Conjugate gradient method without to the concrete inanity. What can I...	...so long. But yesterday at lunch, I sat on a high hill in a rolling green park, underneath a huge, old tree, listening to the church bells. And then I went back to work. I am working now, as web designer for a college in Leek. As this is the week when...	...the majority of the work was done during the week. Brainstorm or create content upgrades (freebies I give away at the end of the post) A perfect example would be the After 9 to 5 Thrive Guide that is included in this post. Brainstorm or create tripwi...	...If you're thinking of selling your property, our qualified real estate team is here to make the process as easy as possible. We have a friendly and dedicated staff that are devoted to the profession and staying on top of the market and trends. We are...	...Adriane Martin, DO, FACOS, CCDS, explains the confusion behind the various sepsis definitions and provides guidance to coders when reporting sepsis in ICD-10-CM. For patients who suffer from frequent symptoms of gastroesophageal reflux disease (GERD)...
Semantic Density = 1	Semantic Density = 2	Semantic Density = 3	Semantic Density = 4	Semantic Density = 5
...Hi, I found your listing on Padlist and I'm interested in coming to see it: www.padlist.com / listings / 500-monroe-avenue-ne-renton-wa- 98056-1233 Can you please let me know if it's still available, and when I might be able to view it? Thanks! Hi, I foun...	...President Trump has a prospective ally in the war on Muslim immigration, and I am not talking about the patriots in the U.S. Border Patrol (USBP) or U.S. Immigration and Customs Enforcement and Removal Operations (ICE ERO), as previously discussed in...	...6 +6 2014 aug 29 llancaiach fawr manor Llancaiach Fawr Manor - The Locations Guide to Doctor Who Location: Llancaiach Fawr Manor . Details from The Locations Guide to Doctor Who, Torchwood, and the Sarah Jane Adventures. 9 -3 2014 sep 05 shire hall m...	...After much googling in an attempt to get my Matrox G400 fully operational, I came across this forum, which appears to have an active and knowledgeable community. I hope someone can help me with my dilemma. The adapter card is recognized as a Matrox G... In resurrectione tua Christe, alleluia. . In thy resurrection, O Christ, alleluia. . Cœli et terra lætentur, alleluia. . let heaven and earth rejoice, alleluia. Jesus has provided for everything; he has chosen twelve men, whom he calls his Apos...
Sensitivity = 1	Sensitivity = 2	Sensitivity = 3	Sensitivity = 4	Sensitivity = 5
...surance. Thanks for the info. I was just wondering about that. :-) But even if someone agrees with my point of view, I still have a policy of deliberately never patronizing any entity that uses guerrilla advertising techniques, spam etc., so this act...	...second stage engine should be ready by 2022-23, so if this is true one can imagine that all of the units of the second contract would get izd. 30, either retrofit or directly installed, it does not make sense to have half squadron with some engine an...	...How can I get the best 70-461 Prep Guides Guaranteed Success training Prep Guides? Now cilck in [goexam.com] is work. MCSA How can I get the best 70-461 Prep Guides Guaranteed Success training Prep Guides? Now cilck in [goexam.com] is work. Latest'formally', and we have expanded them with the positive liberties socialism promises. We have real socialist democracy, popular democracy, genuinely free elections, etc. In this sense we can say it betrayed its own premises, because the whole thingFinding a job in the healthcare industry will not be difficult if your New Grad Nursing resume has all the important details on your skills and other qualifications. Looking for work can be a daunting task for a new Nursing grads. Experience is a big d...

Table 24: Raw training examples selected to have quality ratings at the 1-5 within C4.

Structural Standardization = 1	Structural Standardization = 2	Structural Standardization = 3	Structural Standardization = 4	Structural Standardization = 5
...Much-loved character actor who specialised in playing slightly sleazyslightly eccentric and often ... Komentar Br. 2 Poslao : Severin Datum : 03. 2005. Najbolje da vas muz provjeri kolesterol. Vrlo cesto povisen kolesterol je uzrok kamencima, kako zucn...	...Fantastic Rubin Sofa By Woodhaven Hill is important have in almost any home. You need for the greatest items, so you want to actually never overpay for them. Noises a little complex, proper? Effectively, this post is on this page to help. Keep readin...	...So, the latest embarrassment for the German domestic spy agency, officially called the Federal Office for the Protection of the Constitution (Bundesamt für Verfassungsschutz/BfV) is the revelation that it has been spying on at least 1/3 of the feder...	...kel was forced to cancel a planned visit to the newsroom of Southern Weekend, a Guangzhou-based paper known for outspoken reporting on corruption and other sensitive issues. The schedule of Merkel's three-day trip to China was altered to insert a mee...	...The President of India, Shri Pranab Mukherjee will visit the Rashtrapati Nilayam, Secunderabad for a ten day southern sojourn from June 29- July 08, 2015. During his southern sojourn, he will visit Tirupathi in Andhra Pradesh on July 01, 2015. On July...
Style Consistency = 1	Style Consistency = 2	Style Consistency = 3	Style Consistency = 4	Style Consistency = 5
...While some light no obligations, others getting to bloating, absolute pain, or yoghurt and long periods. Inward, is the other preparation two weeks prior to emergency. This process cools your energy and helps aid your tolerance body treatment. Its lo...	...If you are ready for the most amazing therapy services call the professionals at Body Central Physical Therapy soon as possible so they can provide you the best solutions the matter what. You'll of work with these guys because they really do care bya child accidentally knocks the Spaghettios and meatballs off the table and it lays in a giant red heap on the floor. The last paper towel used only seconds prior to the incident. When all else fails, you use a dishtowel. When the same child that acc...	...Image from a virtual sculpture that was created from two people tracing the front side of their bodies. The result of which is a sculpture of the space between the two bodies. Image from a virtual sculpture that was created from tracing my body as II had a doctor's appointment today, and in the office, they had a poster asking their patients for patience as they work to implement electronic records. The signs have been up for the last few visits, so I think the bulk of the efforts are complete....
Topic Focus = 1	Topic Focus = 2	Topic Focus = 3	Topic Focus = 4	Topic Focus = 5
...include any person who. Probably, the Orient comes second as far as the popular fruit machine themes go. Golden Lotus is a slot play developed by RTG, the company that is famous for production of the quality software for the online casinos. misc. tra...	...this direction. the objective function to be continuous in every parameter, which not is always the case. In the specialized literature we can find other alternatives to the Gauss-Newton method problem. For example, the singular value decomposition (...	...Raw sockets allow a program or application to provide custom headers for the specific protocol(tcp ip) which are otherwise provided by the kernel/os network stack. In more simple terms its for adding custom headers instead of headers provided by theHome > Fitness > Can Lemon Water Really Help You Lose Weight? and clinical trials need to be conducted in people before any claims can be made. Drinking lemon water is regarded by many professional nutritionists as having real and palpable weight-los...	...anglaise.) Squeeze all the water out of the gelatin, and add the gelatin to your hazelnut creme anglaise, stirring until it has melted and has been incorporated. Stir over the ice bath until the mixture is chilled. Fold 1/3 of the whipped cream into ...
Overall Score = 1	Overall Score = 2	Overall Score = 3	Overall Score = 4	Overall Score = 5
...university.for more infirmation contacy me at xxx@gmail.com or 095306403 i am looking forward hearing from you. I really do appreciate your kind gesture for reply me and granting me this opportunity.Am a Nigerian.32 years old of age.I ha...	...This is the Hee Haw penny slot machine Free Games san manuel casino Bonus. Find short term apartments, houses and rooms posted by Nassau Paradise Island landlords. Our best Strategy Games include and 747 more. Trailways offers luxury motorcoach trans...	...Running Festival Wychwood December 12/12/2019 to 01/01/2020 with 20/10 day 1000 mile/1000 km 6 day with shorter races. « Running Festival Wychwood June 16/06/2019 to 22/06/2019 with 6day/72 hour and shorter Races. IS THERE ANY RUNNERS BRAVE ENOUGH TO...	...about some high-maintenance lettuce wraps here. Not the kind of high-maintenance that would scare you away. You know I don't like things to be too complicated around here. Just the kind of high-maintenance that takes something that needs a...	...Wed., September 19, 2018 10:51 a.m. Wednesday, September 19, 2018 10:51 a.m. In this early morning Sept. 8, 2018 photo, 56-year-old dialysis patient Elias Salgado prepares for his trip to the Puerto Rican mainland, at his home in Vieques. Salgado i...

Table 25: Raw training examples selected to have quality ratings at the 1-5 within CommonCrawl.

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2254
2255
2256
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2259
2260
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Accuracy = 1	Accuracy = 2	Accuracy = 3	Accuracy = 4	Accuracy = 5
...last Friday and he angry!! Subscribe. Or, at least they WILL live in a 130-story treehouse once they finish building all 1 Since then it's been a constant learning and experiencing through mistakes and growth, all to provide our customers with the be...	...The Final Solution (History Essay Sample) / Samples / History / The Final Solution + The Mexican War The Irish Republican Army → Check Out Our The Final Solution Essay More than fifty years ago, over a four year period more than eleven million people...	...in the purest light. Use the list below to get more information on majors, minors, and the departments and programs that administer them. Black includes African American, Hispanic includes Latino, and Pacific Islander includes Native Hawaiian. Whichana Shiva presents in the report The Future of Our Daily Bread: Regeneration or Collapse new evidence on the imminent collapse of our food systems if we continue on the path of industrial agriculture. 23096985674e966136facthgp	...as big as a car, big rounded pots of chrysanthemums. And he had cascading chrysanthemums coming down off the wall, and then there's a wall that leads down into our big reflecting pool that terminates the ganjal. And he would grow these cascading chrys...
Coherence = 1	Coherence = 2	Coherence = 3	Coherence = 4	Coherence = 5
...full of insightful information and entertaining descriptions. Your point of view is the best among many. hporvideo Hey, thanks for the blog post. Much thanks again. Awesome. pounded02 I think this is a real great post. Really looking forward to read m...	...we will ourselves happily jump on the grenade if it screws over the other group. It's fairly easy to see how an Us vs. Them mentality can be destructive to both ourselves and society. It is striking to think how susceptible we are to this mentality...	...ition, the threat of a mass demo and a very big political row. In the same year Braddock was made a Dame for her services to FE. In the wake of the row over the veils Braddock stated that she was approaching 60 and had always planned to retire. So it...	...The goods on white Betting on chrome Wörwag's new Chrome paint has become the benchmark in the market thanks to its technology edge. But how did it come about? A look behind the scenes of the development department shows that invention has a lot to d...	...McQuaid holds off Penfield with defense in Class AA baseball semifinal Junior pitcher Hunter Walsh nearly pitched a complete game during the Knights' win at Frontier Field. McQuaid holds off Penfield with defense in Class AA baseball semifinal Junior..."
Creativity = 1	Creativity = 2	Creativity = 3	Creativity = 4	Creativity = 5
...29, 1992 Did not seek election. Krueger Robert C. Krueger (D-TX) 19930121Jan 21, 1993 No, defeated on January 5, 1993. Frahm Sheila Frahm (R-KS) 19960611Jun 11, 1996 No, defeated for nomination. Chafee Lincoln D. Chafee (R-RI) 19991102Nov 2, 1999 Yes, o...	...China, Bangladesh to build overland trade route? By Patrick Scally in News on October 19, 2012 Ongoing efforts to connect Kunming to markets in India and central Asia took an apparent detour yesterday in Beijing. China and Bangladesh tentatively agre...	...Live Twitter Chat SMT Experts Is Facebook Really to Blame for Increasing Political Division? Andrew Hutchinson @adhutchinson There is a lot to take in from the latest New York Times' latest report on an internal memo sent by Facebook's head of VR and...	...HomeOpera Hector Berlioz, La Damnation de Faust, Metropolitan Opera, November 7, 2008 November 10, 2008 Michael Miller Filed UnderOpera Susan Graham as Marguerite in LaSusan Graham as Marguerite in Berlioz's La Damnation de Faust. Photo Ken Howard/M...	...August Šenoa: The Goldsmith's Treasure Numerous tales and legends exist in Zagreb and about Zagreb; some are remembered through the ages, other sink into oblivion, and even the origin of some is forgotten over time. August Šenoa's The Goldsmith's Tre..."
Grammatical Diversity = 1	Grammatical Diversity = 2	Grammatical Diversity = 3	Grammatical Diversity = 4	Grammatical Diversity = 5
...04/03 (18) 03/20 - 03/27 (15) 03/13 - 03/20 (16) 03/06 - 03/13 (15) 02/28 - 03/06 (20) 02/21 - 02/28 (20) 02/14 - 02/21 (22) 02/07 - 02/14 (20) 01/31 - 02/07 (19) 01/24 - 01/31 (19) 01/17 - 01/24 (16) 01/10 - 01/17 (16) 01/03 - 01/10 (19) 12/27 - 01/ 12/27 - 01/12/27 - 01/...	...Evel Knievel 1971 27 Mar 2019. HISTORY and Nitro Circus announce the return of the live television event Evel Live 2 premiering Sunday, July 7 at 8PM ET. Find high-quality Evel Knievel stock photos and editorial news pictures from Getty Images. Dow...	...with jihadist Islam. Stereotyping can have very dire consequences; just ask Pastor James McConnell, the outspoken cleric who is retiring from North Belfast's Whitewell Metropolitan Tabernacle. He branded Islam 'satanic'M. had known her socially before we went to North Wales. He had been letting me spend 18 months of my life working on this scheme, and building up chances of a future for myself. I received £1,000 from M. because I had been more than £1,000 wronge...	...Amniotic fluid stem cells prevent development of ascites in a neonatal rat model of necrotizing enterocolitis Aim: It has been demonstrated that in a neonatal rat model of necrotizing enterocolitis (NEC), amniotic fluid stem (AFS) cells decrease..."
Knowledge Novelty = 1	Knowledge Novelty = 2	Knowledge Novelty = 3	Knowledge Novelty = 4	Knowledge Novelty = 5
...Mahoney Constance Baker Motley Esther Peterson Jeannette Rankin Ellen Swallow Richards Elaine Roulet Katherine Siva Saubel Madam C. J. Walker Faye Wattleton Rosalyn S. Yalow Gloria Yerkovich Bella Abzug Myra Bradwell Annie Jump Cannon Jane Cunningham...	...country, and whoever was coming was the buyer. >make a move now >wait, hide and observe Shark might be another super. Let's not do anything rash now. It'd be nice to bust the buyer too. From last thread >You hear the one about the shark-man on the d...	...- Messij (Classic Pack) CoLD StORAGE - Operatique (Classic Pack) Takkyu Ishino - Jingle WIRE05 (WIRE05 Pack [JP]) Akira Ishihara - Breaking the Ice (Continue Pack [JP]) Akira Ishihara - Open the P.A. (Continue Pack [JP]) Oblivion Records -Shirley MacFarlane 461 Broad Street N. Regina SK S4R 2X8 25 Things You May Not Know About Saskatchewan Vol. 12 Issue 5 By Lorne McClinton 1 During the middle Devonian Period, between 375 and 400 million years ago, much of Saskatchewan was covered b...	...-addition step (i.e., the potential initial addition of the nucleophile to the C- of the bis-electrophile) has to be slower than the intermolecular addition of the nucleophile to the catalytically generated 3-allylpalladium complex, or it has to be...

Table 27: Raw training examples selected to have quality ratings at the 1-5 within CommonCrawl.

Structural Standardization = 1	Structural Standardization = 2	Structural Standardization = 3	Structural Standardization = 4	Structural Standardization = 5
...ing it: fawning compliance with Zionism, and the atrocities committed by that racist, genocidal and insane protectorate Israel. then lose it by; Zionism is pretty much Christianity without the messiah, after all. The notion of discounting physi...	...Trump's crackdown on free press in Alabama is 'a step in the right direction' President Donald Trump's administration has been working to restrict the press in states around the country in an effort to keep the country's reputation for transparency,mila Cvetkovic, Andy Heil Serbia and its neighbors Kosovo and Albania have descended into a bitter diplomatic ruckus after officials in Belgrade invoked a slur... Albania, Greece Must Reflect on Past Mistakes to Settle Maritime Borders Is... By Akriinto the realm of a Super Saiyan. It's fair to say, without the Namek / Frieza saga making little boys and girls tune in after school, that anime might not have been such a huge hit here in the UK. 2) Klingons - Star Trek Riker dines with the Klingon...	...The Potential of Tropical Agro-Industrial by-Products as a Functional Feed for Poultry Document Type : Review Articles S. Sugiharto T. Yudiarti I. Isroli E. Widiastuti Department of Animal Science, Faculty of Animal and Agricultural Science, Diponego...
Style Consistency = 1	Style Consistency = 2	Style Consistency = 3	Style Consistency = 4	Style Consistency = 5
...5 December 2014 November 2014 October 2014 September 2014 August 2014 July 2014 June 2014 May 2014 April 2014 March 2014 February 2014 January 2014 December 2013 November 2013 October 2013 September 2013 August 2013 July 2013 June 2013 May 2013 April...	...with a vehicle at the intersection of Grand and Forest Ms. Anderson saw a dark, hooded figure reach through the window, grab a small parcel and run north on Forest. d. After colliding with a vehicle at the intersection of Grand and Forest, Ms. Anders...	...time had come to take a common stand. But the Israeli armed forces would not tolerate what they viewed as insubordination. They turned their weapons on the protestors, killing six outright, injuring dozens and arresting hundreds who persisted in thei...	...case, it emerged that nonresponses and absences did not result in disciplinary sanctions. Other factors taken into account were the autonomous organisation as regards time and space, the absence of exclusivity clauses and noncompete agreements. See C...	...ductory essays. (shrink) Review of Pearson, Aristotle on Desire. [REVIEW]Thornton Lockwood - 2013 - Bryn Mawr Classical Review 9:24.details The image of a copy of Praxiteles' Aphrodite--nude but demurely shielding her pubic region--which adorns the dus...
Topic Focus = 1	Topic Focus = 2	Topic Focus = 3	Topic Focus = 4	Topic Focus = 5
...Etre partisan de Fayulu n'est pas un pêché, dit général Kasonga aux policiers qui ont matraqué Serge Welo, l'un des généraux du président élu Arrestation de Ngoyi Mulunda : Félix Kabange mérite le même sort selon Jean-Claude Katende Union sacrée :-minute and small seconds. This three-dimensional watch, reminiscent fake of a jet fake luxury watches engine, is encased in a complex case featuring alternating polished and satin-finished finishes. Both options have the orange accents on the dial a...	...CPF or not, was protected under the constitution. I grant I might have misstated when I said ruled but the fact remains that the court agreed with that premise. As I stated, the only person who stands to gain from pursuing this lawsuit is Mr. Berko...	...Press, October 12, 2020, 12:59 PM Two priests are going on trial in the Vatican's criminal tribunal this week, one accused of sexually abusing an altar boy who served at papal Masses in St. Peter's Basilica, and the other accused of covering it up. T...	...Employing a star, you could argue, is as proscriptive as religious observation. They arrive with expectation and mandate, and any deviation from the accreted screen history is a gamble. We are drawn to them because they are recognizable. Maybe the mo...
Overall Score = 1	Overall Score = 2	Overall Score = 3	Overall Score = 4	Overall Score = 5
...less. Seattle, King, Washington, US, 98101, (360) 764-... Heike, Fewless. Phoenix, Maricopa, Arizona, US, 85255, (480) 375-.... Carlena, Fewless. Kissimmee, Osceola, Florida, US, 34741, (407) 742-.... Jason, Fewless. Pateros, Okanogan, Washington, U...	...Steroids for sale new zealand, what is taking sarms Steroids for sale new zealand, what is taking sarms - Buy anabolic steroids online Steroids for sale new zealand Six sports supplements on sale in New Zealand have been found to contain anabolic ste...	...BEACH BOY ARDASHIR VAKIL PDF Ardashir Vakil was born in Bombay and now lives in London. Ardashir Vakil's award-winning first novel, Beach Boy (), is Bombay's answer to James. Marrying a universal story (an adolescent boy's coming-of-age) with a speci...	...stands at the door, with the rest of the Company and the wagon behind him. Moon Shadow is so happy to see them, he hugs Uncle. Uncle tells how the Company heard of the Lees' trouble and showed up to help with the flight of Dragonwings. They are deter...	...human rights. A Tawdry Place of Salvation: The Art of Jane Bowles Edited by Jennie Skerl Southern Illinois University Press, 1997 Library of Congress PS3552.O837Z89 1997 Dewey Decimal 818.5409 Through these essays--which deal with Bowles's published...

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Table 30: Raw training examples selected to have quality ratings at the 1-5 within Github.

Structural Standardization = 1	Structural Standardization = 2	Structural Standardization = 3	Structural Standardization = 4	Structural Standardization = 5
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</td></tr> <tr><td>	Fucked By 2 Evil	are invaluable -	value=NOK<i	property obtained
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href=itparlamint	Blackmailed	to understand how	terramento2	cref=E:DevExpress.
-feat-Mood.html>	Busty Milfs Got	our environment	value=NOK<i	XtraReports
Mood	Mercilessly Fucked	and climate have	id=galinfraa	.UI.XRControl.E
</tt><tt>=Ind	By 2 Evil Teenage	changed, how	terramento2	valuateBinding/>
</tt> <tt><a	Boys</h3>	ocean currents	value=NOK<i	event handler.
href=itparlamint	</div> <div	have shifted, and	id=galinfraat	</para> </summary>
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Number</tt><tt>=	34px;> <div	geological history	value=NOK<i	cref=T:System.Object/>
Sing</tt> <tt>	of the area i...	class=glyphicon	specifyi...
href= itparlamint	<img alt=Rating		glyphicon-remove	
-feat=Person....	src=i...		text-danger</i>	
			...	
Style Consistency = 1	Style Consistency = 2	Style Consistency = 3	Style Consistency = 4	Style Consistency = 5
...alments:	...2>available</dependent>>case 1:	info.efetuarLogin();	...then let them	...1] = ' 0'; else
installments,	</dep> <dep	break; case	...</p> </div><!--	/* the 0 s already
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instills: instills,	idx=22>available</governor>	3: info.	-> </div> <div	string[i],
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institutionalize	idx=25>members	4: info.	github.io/img	CRASSERT(pLocalLen
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institutionalized:	idx=25>members	break; case	/fastersquare. jpg	CRASSERT(pLocalLen...
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...	idx=25>members...	manterCarrinho();		
		break; ...		
Topic Focus = 1	Topic Focus = 2	Topic Focus = 3	Topic Focus = 4	Topic Focus = 5
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		fa-bitbucket...		
Overall Score = 1	Overall Score = 2	Overall Score = 3	Overall Score = 4	Overall Score = 5
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39, 40, 41, 42, 43,	0 </pattern>	tem drêto di entrã	class=content> <h2	Bio.Algorithms.Alignment.
44, 45, 46, 47, 48,	</dateTimeFormat>	na funçon pública	class=content-head	MultipleSequenceAlignment
49, 50, 51, 52, 53,	</dateTime	di sé téra,ô di	is-center>Want	using System;
54, 55, 56, 57, 58,	FormatLength>	sé pais.</p> 	to show off your	using System.
59, 60, 61, 62, 63,	<dateTime	 <p>Vontadi	coding skills?</h2>	Collections.Generic;
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69, 70, 71, 72, 73,	type=short>	licérce di	anchor id=events>	Bio. Algorithms.
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79, 80, 81, 82, 83,	<pattern	di público; é debe	pure-u-1	using SM = Bio.
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89, 90, 91, 92, 93,	1, 0 </pattern>	eleiçon sério qui	pure-u-lg-1-3> <h3	SimilarityMatrix;
94, 95, 96...	</dateTime	ta bem ser fêto,	...	/// <summary> /...
	Format> </dateTime	na temp...		
	FormatLength>...			

Table 31: Raw training examples selected to have quality ratings at the 1-5 within StackExchange.

Accuracy = 1	Accuracy = 2	Accuracy = 3	Accuracy = 4	Accuracy = 5
...FdWGAXPrDj 4URM0nelcS jOpmAoCIB24mFvn C34fP8icL0Q VIOf+mPin2jD4Hg sDP58dDFtu ---END CERTIFICATE--- ---BEGIN CERTIFICATE--- MIICBCCAaqg AwIBAgIQOHnvua xK4NLP1+Qb7OIm+DAKBgmain(String[] args) ghkJOQQDAJB lMQsw CQYDVQQGEWJ VUZETMBEGA1UECB...	...Q: How can I match the original array and the shuffled array? This is the Prompt: This is what I wrote: import java.util.Scanner; public class ContagionControl public static void main(String[] args) System.out.println(Please EnterQ: How to write Object as human readable text file I want to write objects in human readable form in a text file, the file gets saved as a normal serialized object with unwanted characters instead. How do I rewrite the program for saving into human r...	...Q: Access violation inside ctype imported windows function RtlDerive Capability SidsFromName I am importing ntdll.dll RtlDerive CapabilitySids FromName function and having access violation inside it. But can't figure what i am doing wrong. import win32fi...	...3.0.0,>=2.11.2 in /home/ubuntu/anaconda3 /envs/myenv/lib/ python3.7/ site-packages (from app) (2.11.2) Requirement already satisfied: python-jose [cryptography] <4.0.0,>=3.1.0 in /home/ubuntu/ anaconda3/envs/myenv/ lib/python3.7/ site-packages (from app) (3...."
Coherence = 1	Coherence = 2	Coherence = 3	Coherence = 4	Coherence = 5
...7579 , 1525736201 , 1525736229 , 1525736426 , 1525736763 , 1525737360 , 1525736174 , 1525736723 , 1525736207 , 1525736839 , 1525737132 , 1525736460 , 1525737437 , 1525737070editorDtin ymc26imgsizeDlar ge6wplin3D l6urlbuttons ts list modelist; wp-settings-time=1= 1421309968; wp-saving- post=5-saved; wordpr - 524356 ReqHeader c Cookie: wp-settings-1 = deleteundefi526h...	...272)USER DEBUG [14] DEBUG Domain: 2 18:56:23.1 (83147530) USER DEBUG [14] DEBUG Email: 2 18:56:23.1 (83166856) USER DEBUG [14] DEBUG Email 2: 2 18:56:23.1 (83205838) USER DEBUG [14] DEBUG Exec Type: 2 18:56:23.1 (83235539) USER DEBUG [14] DEBUG Ext...	...Q: Why do i have this error on JSF page? I am newbie in jsf. I have a maven project and it runs on websphere 8. I use jsf and richfaces. I am getting this error: Error Parsing / viewMetadata/ index.xhtml: Error Traced[line: 2] The element type htmljava.util.ArrayList; import java.util.List; import static android. Manifest.permission. READ CONTACTS; /** * A login screen that offers login via email/password. */ public class LoginActivity extends AppCompatActivity implements LoaderCallbac..."
Creativity = 1	Creativity = 2	Creativity = 3	Creativity = 4	Creativity = 5
...Q: Error instantiating servlet class in Eclipse Europa? First.java : this is my first java class package com; import javax.servlet.Request import javax.servlet. ServletException; import javax.servlet.http. Cookie; import javax.servlet. http....	...Q: Can This Review-Based Git Workflow Be Enforced by Gerrit? Is there a tool, that makes pull-requests and combined reviews safe in git? I know that there are a couple of related questions, that have already been asked at github (See a...	...Q: How do I use wait() and notify correctly with threads in java? I'm making a 2D game in android studio and I've been sitting on a problem for a few days now. I want to stop my thread Gravity, so that my player can jump. When the player is done jump...	... representing an event that happened in Paris in 1290. Legend is probably a better word than event, but in any case it is a very strange origin for a famous mathematical quote. A: Mathematics is the art of giving the same name to different thi...	...a, svegliandosi una mattina da sogni agitati, si trovò trasformato, nel suo letto, in un enorme insetto immondo. Riposava sulla schiena, dura come una corazza, e sollevando un poco il capo vedeva il suo ventre arcuato, bruno e diviso in tanti segment...
Grammatical Diversity = 1	Grammatical Diversity = 2	Grammatical Diversity = 3	Grammatical Diversity = 4	Grammatical Diversity = 5
...(-90.5158851037139, 38.5293438059525), (-90.5153219032826, 38.5000608728918), (-90.571685370183, 38.5322450728324), (-90.5907731028958, 38.5035282063425), (-90.562387970228, 38.5396736725824), (-90.5632127699527, 38.5000698058576), (-90.4351277034801...	...ugvcHhgmk9x 3Ithyitano5Vfk3 wRf7g5V366uuMhfcU' , 'paper filed': True, 'type': 'SH06', 'pages': 8, 'barcode': 'YBJEXN6Z', 'transaction id': 'MzM2MzUwMTYz OGFkaXF6a2N4' , 'action date': '2022-10-17', 'category': p...	...0.0730668010171692, -0.0109530737239368, -0.0374915960907066, -0.0941194227900671, 0.0453306426927274, -0.173274373945029, 0.228535671136248, 0, 0.0923733553009261, -0.0400062320449435, 0.0101532578824621, -0.0204079876556867, 0.0648597665063123,Q: JPA Spring ignores Lazy loading inside @Transactional I have a spring service class where I'm loading a JPA object (target) via CRUD. This target class has a one-to-many mapping that is set to lazy loading. I would like to query this object insid...	...raw = T)5 -2.340e+06 3.246e+06 -0.721 0.480 poly(wt, 15, raw = T)6 8.537e+05 1.154e+06 0.740 0.468 poly(wt, 15, raw = T)7 -2.184e+05 2.880e+05 -0.758 0.458 poly(wt, 15, raw = T)8 3.809e+04 4.910e+04 0.776 0.447 poly(wt, 15...
Knowledge Novelty = 1	Knowledge Novelty = 2	Knowledge Novelty = 3	Knowledge Novelty = 4	Knowledge Novelty = 5
...2133OoqgH KKCRjmK1w/ YQFLYIEI4yjsJ MVyPOMkrLKc538G1T //+Qh1jehHkOV1c1Mk iEI4uo9NxzKHOUiD// /0IoAK8CJEGp0JdGyYk2a v7q1m2w10XDM7 /82DEIRwi3smeewo e5tODknVbVqXrOrY eKLLMw6k KUKmFR4EzDJr/ HnvrWL4mjaxeZlh qmCGATTGej/ /DhdnRjTB2ZAr/...	...Q: Bitonicsort C code segmentation issue I am running a bitonic sort sequential code on a machine. It runs fine for array size upto 16 elements but as soon as i increase the size to 32 It gives the following error while execution: WARNING: ProcessQ: xinput setting not persistent during session I use linux Manjaro Gnome X11. I like to have a special setting of mouse buttons, which I obtain with xinput. In order to make this setting persistent across sessions, I write the xinput in ./xprofile ...	while(srcWidth / 2 > desiredWidth) srcWidth /= 2; srcHeight /= 2; inSampleSize *= 2; float desiredScale = (float) desiredWidth / srcWidth; // Decode with inSampleSize options. inJustDecodeBounds = false; // now downl...	...Q: Why do combinatorial abstractions of geometric objects behave so well? This question is inspired by a talk of June Huh from the recent Current Developments in Mathematics conference. Here are two examples of the kind...

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Table 32: Raw training examples selected to have quality ratings at the 1-5 within StackExchange.

Language Consistency = 1	Language Consistency = 2	Language Consistency = 3	Language Consistency = 4	Language Consistency = 5
...327, -0.626763671898102, -0.297753001433115, 0.040555895564039, 0.564626235801996, 0.705799286675642, 0.0750613044187593, -0.478737190261705, -0.487080519650291, -0.570108362865829, -0.316410770808425, 0.641599306385284, 1.09437775518271, 0.677757969589283, -0.279...	...Q: chamada de INTENT não encontrado O aplicativo delphi chama uma activity de aplicativo java e na chamada apresenta o seguinte erro: android. content. ActivityNot FoundException: Unable to find explicitly activity class...	...Sri Lanka</option> <option value= St Helena >St Helena</option> <option value= St Kitts and Nevis > St Kitts and Nevis</option> <option value= St Lucia >St com.embarcadero. pedro. mostrapar com.embarcadero. pedro. mostrapar...	...Q: Android AppBar Text Color Aren't Changing I can't change the color of android windows title bar text color. I don't know what is the name to this. So I'm providing you a screenshot to understand. please see the blow image: Screenshot I searched fo...	...Q: How to get GridPane Row and Column IDs on Mouse Entered in each cell of Grid in JavaFX? I am trying out JFX Drag and Drop feature in my application (later connecting the objects in a sequence). I could not find any easy way to drag and drop my Ima...
Originality = 1 ...1334441447 8836548348450.*z)/ pow(4636667218 9358032.+18896234 711237580. *x- 3927118781169095.*y -147053464 16259850.*z,3) -(256.*(-350274353228 088978038961669 13833.+1011538246 7966920359 4026224000274.*x- 44334866794 1077090029000877418626f.both: ?- slice([a,b,c,d,e,f,..bug repo...	Originality = 2 ...5, Xs = [c,d,e] ; Q = 6, Xs = [c,d,e,f] ; Q = 7, Xs = [c,d,e,f,g] ; Q = 8, Xs = [c,d,e,f,g,h] ; Q = 9, Xs = [c,d,e,f,g,h,i] ; Q = 10, Xs = [c,d,e,f,g,h,i,k] ; false. Last, we run a query which is a generalization of both: ?- slice([a,b,c,d,e,f,..bug repo...	Originality = 3 ...Q: ColumnLayout in Xamarin.Forms I think I found a bug in the FlexLayout. I've tried to nest 2 FlexLayouts where the outer one should be the column container and the inner one the row container. But the page stays empty. I've already filed a bug repo...	Originality = 4 ...Q: DELETE FILES with Node.js I'm trying to delete some files and then show a message. EXPECTED OUTPUT File deleted Folder Cleared!!! ACTUAL OUTPUT Folder Cleared!!! File deleted The current code is: function clearConverted() const resp = ...	Originality = 5 ...Q: SharePoint threw Unknown SQL Exception 206 occured. Anyone familiar with this? Our SharePoint instance threw the following errors when attempting to access data through a Content Query Tool: 04/02/2010 10:45:06.12 w3wp.exe (0x062C) ...
Professionalism = 1 ...[192.5], [204.5], [154.], [214.5], [205.], [217.], [201.], [218.], [169.], [157.5], [194.], [178.5], [194.5], [210.5], [219.], [194.5], [194.5], [194.5], [194.5], [194.5], [194.5], [194.5], [194.5], [194.5], [194.5], [194.5], [194.5], ...	Professionalism = 2 ...for replacing special arabic * Characters from the input given to the method. This method * Algorithm is taken from the database procedure already been * used for blacklist. * @param nameInArabic name in Arabic of applicant. E.g First nam...	Professionalism = 3 ...Q: JAVA:FX: Pass data between controllers I have an Excel file that i load it in tableView the data of this file i load it in variable data, i want to pass this variable to another controller ControllerTwo to do some stuff on it but it returns a null p...	Professionalism = 4 ...Q: Openshift Monitoring - cAdvisor + Prometheus - Docker I tried to implement a monitoring solution for Openshift cluster based on Prometheus + node-exporter + grafana + cAdvisor. I have a huge problem with cAdvisor component. I did a lot of configu...	Professionalism = 5 ...start-1.4.0.jar file:/accumulo/ accumulo-1.4.0/ lib/commons-jci-fam-1.0. jar file:/accumulo/accumulo -1.4.0/lib/ jline-0.9.94.jar file:/accumulo/accumulo -1.4.0/lib/ examples-simple-1.4 examples-simple-1.4 I have a huge problem with cAdvisor component. I did a lot of configu...
Semantic Density = 1 ... <td class= text-right text-nowrap > <button class= btn btn-xs btn-info >edit</button> <button class= btn btn-xs btn-warning > </button> ...	Semantic Density = 2 ...= bottom align= left class=urLayou tPadding style= border- collapse:separate; width:100%; height:5px; white-space: normal; > <div id= WDEA-r > <table cellspacing = 0 cellpadding = 0 id = "WDEA ct= "ML lsdata = 0:"WDEA",7:"LINE" clas...	Semantic Density = 3 ...0.814441695 8.40741573499 6.08031313304 13.1781459953 10.206134367 15.0864695726 9.03013313987 4.46906993699 9.27542593922 11.387166818 5.34088290758 7.35790199406 11.8693581818 10.8557924873....	Semantic Density = 4 ...Q: How to output the name of the calling method using XCGLogger? I have created a MyLogger class and it passes parameters to XCGLogger to output logs. I have specified true for the XCGLogger's showFileName and dateshowFunctionName, but it always outp...	Semantic Density = 5 ...Q: Error when trying to issue data manipulation statements with executeUpdate com.mysql.jdbc.exceptions. jdbc4.MySQLException:Exception: You have an error in your SQL syntax; check the manual that corresponds to your MySQL server version for dateshowFunctionName, the righ...
Sensitivity = 1 ...Q: 'academic problems': 'describe problems': ' 'problems date': 'problems yn': 'end problems': 'disabilities': 'disability2': 'concerns': 'best things': 'too young': 'alcohol': ' 'describe alcl8yr': 'argue...	Sensitivity = 2 ...Q: What does play the trumpet mean? In a recent Academia SE question, user moonman239 writes: What is proper etiquette for college students needing to leave the lecture room for any reason? Example: Bathroom breaks, an urgent phone call, or a nee...	Sensitivity = 3 ...Q: Euphemism and Colloquialism as Literary/Speech Devices Is it possible for something to be both a 'euphemism' and 'colloquialism'? If so, what would be some examples of this? A: Well, a lot of slang words (which are colloquial by definition), a...	Sensitivity = 4 ...: e035e200 oep: dff6af3c ds: 007b es: 007b ss: 0069 Process kjournald (pid: 314d, tic=df6a000 tac=df6a8aa0 toe=df6a000) Stack: 49276d20 6a757374 20737461 72746564 2c20646f 206e6e74 2070616e 69632079 65742c20 49206861 7665206e 6f742065 766...	Sensitivity = 5 ... 1.738037620 NA C3 -0.03510886 0.29100742 0.220716441 0.25246176 0.218140478 0.49141939 0.603698956 1.660365770 C4 0.25073995 -0.23513014 -0.217313407 -0.30890486 -0.217241734 -0.57995546....

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Table 33: Raw training examples selected to have quality ratings at the 1-5 within StackExchange.

Structural Standardization = 1	Structural Standardization = 2	Structural Standardization = 3	Structural Standardization = 4	Structural Standardization = 5
...XEhNyfio RxfFGNljwNadMT4 RRePml1rtuARrY3042X bsCoY4GNjaNAFSe gmNAe+QtL ToMpH4gq6V1S6 P+y541UZotE8G01 /Edme2xWPqr7qtsq XHZE /T9QjI5SVF5fC NSw/YdIQNkS6QyAY 08oqMroNcMooGfQMjZw F/wBhSupWC5DRcjsp pChpHfc5Uco2ZF QNd/aPI cBh1/lt130C...	...] uFE0F? u20E3 [u261D u270C u270D] uD83C[uDFFB- uDFFF][u270A u270B](?: uD83C[uDFFB- uDFFF])? [u00A9 u00AE u203C u2049 u2122 u2139 u2194- u2199 u21A9 u21AA u2328 u23CF u23ED- u23EF u23F1 u23F2 u23F8- u23FA u24C2 u25AA u25AB u25B6 u25C0 u25FB u25...	...Isengard instead of pausing to ask or infer who the travellers were. He was doubtful, fearful, and totally lacking in the skill of woodcraft. Gandalf confirms this. 'The victor would emerge stronger than either, and free from doubt,' said Gandalf. '...	...Q: Get result from shell script objective-c I would like to run a shell script, from a file or from an objective-c string (within the code). I would also like the shell script's result to be stored to a variable. I would not like the shell script t...	...Key.KP3 Keyboard.005c --> Key.KP4 Keyboard.005d --> Key.KP5 Keyboard.005e --> Key.KP6 Keyboard.005f --> Key.KP7 Keyboard.0060 --> Key.KP8 Keyboard.0061 --> Key.KP9 Keyboard.0062 --> Key.KP0 Keyboard.0063 --> Key.KPDot Keyboard.0064 --> Key.1...
Style Consistency = 1	Style Consistency = 2	Style Consistency = 3	Style Consistency = 4	Style Consistency = 5
...0C x1b x8f x1aC x00 x80 x89A x03 x00 x00 x00 x00 x06 x03 x00 x15t x847P4 x00 x00 x00 x00 x00 x00 x00 x00 xff x00 x01 x01 x...	...n followers:[key: jenny ,text: 'Jenny ank Hess',value: 'Jenny Hess'], n repeats: , n reminders:[], n tags:[], n tasktags:[id: 0, text: Thailand , id: 1, text: In...	...Q: How to generate random numbers and distribute them randomly to some buttons? I am rookie in android programming and want to generate some numbers randomly in a specific range. Provided that, the sum of two of them equals a certain number, I wrote Desktop larissa-node larissaApp rest-s erver node modules mongoose lib query.js:1394:10) at Function.findOne (C: Users Theodosios Desktop larissa-node larissaApp res t-server node modules mongoose lib model.js...	...Q: Fragmented MP4 not playing in ffplay/QuickTime/Safari, but in VLC I encoded a fMP4-Video (HEVC) in Swift using VideoToolbox and CoreMedia. The resulting fragmented MP4 is only playing in VLC. The library I am using to write the fMP4 is an HEVC-ada...
Topic Focus = 1	Topic Focus = 2	Topic Focus = 3	Topic Focus = 4	Topic Focus = 5
...C5B4 uBCF4 uC558 uB2E4. uC815 uB9D0 uB3C4 uAE68 uBE44 uC5D0 uC11C uB098 uC628 uD558 uB098 uC758 uC2DC uBF00 uB9CC uC544 uB2C8 uB77C uB098 uBA38 uC9C0 uC2DC uB4E4 uB3C4 uD558 uB098 uAC19 uC774 uBCF4 uAE30 uC88B uC740 uC2DC uB4E4, uADF8 <nav class= navbar > <ul class= ul > <li class= texthead >teleginsmm <li class= texthead ><a> <li class= texthead ><a>0): ['-2'], (21.0, 305.0, 9.0): ['-2'], (27.0, 310.0, 20.0): ['2'], (18.0, 303.0, 14.0): ['2'], (28.0, 293.0, 4.0): ['-2'], (29.0, 296.0, -2.0): ['2'], (23.0, 307.0, 19.0): ['-2'], (28.0, 294.0, 10.0): ['1'], (27.0, 293.0, 0.0): ['-2'], (33.0, 307.0,Q: My actionPerformed method(Java) is not working and I have no clue why Here is my whole program, don't wonder about the words I am using, I am German. Down from 1. 95 to 1. 103 is the action performed method, (I only did the System.out.println() to...	...(-base-1); /* STYLE */ .container width: 1140px; margin: 0 auto; &media (max-width: 1200px) .container width: 960px; &media (max-width: 992px) .container width: 720px; &media (max-wi...
Overall Score = 1	Overall Score = 2	Overall Score = 3	Overall Score = 4	Overall Score = 5
...AB4AHgAd ABsAG AbABoAHgAaA BsAGwAbABw AHgAbABsA HgAeAB8A HgAeAB4AIAAgACAAH gAdABsAHAAG ACEAIAAgAC AAIQAJACIAIAAg ACAAHwAeA BOAGwAbABsA GgAZA BkAGQA VABQAqG A WABYAFAAUA BQAFgAbABoA GQAZA...	...FinishModel> <d3pl:actualFinish> 25/09/2015 </d3pl:actualFinish> <d3pl:baseLineStart> 12/12/2014</d3pl: baseLineStart> </d3pl:BaseStart FinishModel> <d3pl:BaseStart FinishModel> <d3pl:actualFinish> 27/03/2015 </d3pl:actualFinish> <d3pl: baseLineStart>27/03/2015	...Q: The code works but it lags when it works. It works with foreach and loop it When the code is working so laggy it would be very good so that it is not laggy when it works. How the code works: It searches the computer for a file is then when @t.find...	...Q: How to keep a local directory automatically synced with a remote, without latency issues? I develop a git-tracked codebase that has a lot of files. This code must be run on a remote machine. So every time I make a change locally, I must then syncQ: Concurrent Queue in Java that only retains the last item of each child thread I have 1 main thread which starts up n child threads. Each of these child threads continually produce a new event and add it to the shared queue. That event represents ...

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Table 34: Raw training examples selected to have quality ratings at the 1-5 within Wikipedia.

Accuracy = 1	Accuracy = 2	Accuracy = 3	Accuracy = 4	Accuracy = 5
...5) 1998 VR23 10 1998 (-) LINEAR - (44466) 1998 VT23 10 1998 (-) LINEAR - (44467) 1998 VU27 10 1998 (-) LINEAR - (44468) 1998 VH34 11ie, a cărui mantie roșie este observată de cuplu încă. de când fetița se oprise anterior la brutărie pentru a cumpăra pâine și dulciuri pe drumul spre casa bunicii. Urmează Rapunzel, cu părul ei blond, pe lângă al cărei turn din pădure trece nevastasee Ibataikoku), was appointed queen regnant of Japan. Himiko died in the 240s, and the next king of Japan was a male, but civil war broke out again, and the rebellion ended when another female, Taeyeo/Ichibayo (see Taiyo), became queen of Japan. In...	...ond hadden. Het huis werd vervolgens verhuurd aan burgemeester van Sappemeer Henk Eikema, die echter al in 1927 plotseling overleed. Mogelijk werd het huis vanaf 1928 verhuurd aan Johannes Jurgens die vanaf dat jaar werkzaam was als griffier bij het El único autor que, por su espíritu escapista y su optimismo infantil, logró escapar al tenebrismo de la época, fue el novelista Mór Jókai, autor de más de cien volúmenes de prosa de ficción (entre novelas y cuentos) en los que se respira un roman...
Coherence = 1	Coherence = 2	Coherence = 3	Coherence = 4	Coherence = 5
...James Middleton Archibald Miller William Miller Norman Craig Millman Laurence Minot Hugh Fitzgerald Moore Gerald Ewart Nash Ernest Edward Owen Augustus Paget Medley Parlee Laurence Pearson Geoffrey Pidcock Sydney Pope Frederick Powell T...	... Aided Ferguson maic Roig. , 2006. Aided Guill meic Garbada ocus Aided Gairb Glinne Rige (Les morts violentes de Guill Mac Carbada et Gairb Glinne Rige) Aided Laegairi Buadaig (La mort violente de Loegaire Buadach), trad. Guyonvarc'h, La mort violen...	...c'est la Verrerie-cristallerie d'Arques qui devenue Arc International fera travailler directement et indirectement jusqu' plus de dans l'Audomarois, causant une mutation spatiale et paysag re de l'Audomarois, avec une forte p riurbanisation...	...urbaine entre Saint-Omer et Arques. De nouvelles routes sont r guli rement construites ou largies (rocade, voie nouvelle de la vall e de l'Aa (VNVA), voies expresses Saint-Omer-Dunkerque et Boulogne-Saint-Orner, desserte par l'atoroute A26,Paul Finch is an English author and scriptwriter. He began his writing career on the British television programme The Bill. His early scripts were for children's animation. He has written over 300 short stories which have appeared in magazines, such ...
Creativity = 1	Creativity = 2	Creativity = 3	Creativity = 4	Creativity = 5
...87231 - 30 de juliol, 2000 Socorro LINEAR - 87232 - 30 de juliol, 2000 Socorro LINEAR - 87233 - 30 de juliol, 2000 Socorro LINEAR - 87234 - 30 de juliol, 2000 Socorro LINEAR - 87235 - ol, 2000 Socorro LINEAR - 87235 - Otto Arendt (* 10. Oktober 1854 in Berlin; † 28. April 1936 ebenda) war ein deutscher Publizist und freikonservativer Politiker. Leben Arendt stammte aus einer jüdischen Familie und konvertierte später zum Christentum. Nach dem Besuch des Gymnasium...	...nească e Flacăra, è stata definita da Lovinescu come una serie di quadri della nostra antica esistenza dai toni arcaici , e da Ion Vianu come una storia pittoresca della Valacchia. Călinescu ha notato come, in molte delle sue poesie e in partico...	...ta a metà battuta 12 insieme alla cadenza perfetta impone che il solista riprendea a suonare dopo una doverosa pausa. Segue un ponte di collegamento al secondo tema (misure 13- 19). Se il carattere del primo tema era molto cantabile, il secondo temaDahingehende Deutungen hat auch Rip Van Winkle, die andere in Amerika spielende Kurzgeschichten des Skizzenbuchs, erfahren, deren Protagonist in der Kolonialzeit in einen zwanzigjährigen Zauberschlaf fällt, den Unabhängigkeitskrieg.
Grammatical Diversity = 1	Grammatical Diversity = 2	Grammatical Diversity = 3	Grammatical Diversity = 4	Grammatical Diversity = 5
... - - style=background: 58 June 4 Mariners - -- - - style=background: 59 June 5 Cardinals - -- - - style=background: 60 June 6 Cardinals - -- - - style=...	...al Stadium Stadio Artemio Franchi Ghelamco Arena Arubaans voetbalelftal Arubaans voetbalelftal (vrouwen) Ashton Gate Asian Football Confederation Norair Aslanyan Oussama Assaidi Fernando Astengo Aston Villa FC Asturisch voetbalelftal...	...frigue de l'Est, au Brésil, aux États-Unis et en Australie. Les deux espèces descendent de l'aurochs (Bos primigenius), dont le dernier représentant européen s'est éteint en 1627, alors que la sous-espèce ayant mené au zébu aurait disparu en Inde env...	...endencia perpetua y neutralidad del estado. Las paredes de la fortaleza fueron derribadas y la guarnición prusiana fue retirada. Los visitantes famosos a Luxemburgo en el y el incluyeron al poeta alemán Goethe, a los escritores franceses Émile Zol...	...Czerwiec 1976 - określenie nadane fali strajków i protestów, do których doszło w PRL pod koniec czerwca 1976, po ogłoszeniu przez rząd Piotra Jaroszewicza wprowadzenia drastycznych podwyżek cen urzędowych na niektóre artykuły konsumpcyjne. Przyczyny...
Knowledge Novelty = 1	Knowledge Novelty = 2	Knowledge Novelty = 3	Knowledge Novelty = 4	Knowledge Novelty = 5
...60 - 1 noieembrie 2000 Socorro LINEAR - 178761 - 19 noieembrie 2000 Socorro LINEAR - 178762 - 19 noieembrie 2000 Socorro LINEAR - 178763 - 19 noieembrie 2000 Socorro LINEAR - 178764 - s 34' - J.H. Rossi 43' Spartak Moskwa - Valencia CF 0:3 (0:1) Angulo 6', Mista 71', Juan Sánchez 85' 3. kolejka 2 października 2002 r. Liverpool F.C. - Spartak Moskwa 5:0 (3:0) Heskey 7', 89', Cheyrou 15', Hyypia 28', Diaó 81' Valencia CF - FCVongsa (r. 1638-1690), figlio di Ton Kham. Sotto il suo regno, Lan Xang conobbe il massimo splendore. Alla sua morte scoppiarono nuovamente i dissidi interni dell'aristocrazia Tian Thala (r. 1690-1695), primo ministro di Surigna Vongsa eis also assumed to be some sort of non-trivial medium to which one can associate certain energy. This is because the concept of absolutely empty space contradicts the postulates of quantum mechanics. According to QFT, even in absence of real particles...	...its duration. He purchased equipment and wrote software that allowed him to record and analyze heartbeats, and began studying his own heartbeat rhythms as well as those of friends and other musicians. After decades of study, Graves used some of the ...

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Table 36: Raw training examples selected to have quality ratings at the 1-5 within Wikipedia.

Structural Standardization = 1	Structural Standardization = 2	Structural Standardization = 3	Structural Standardization = 4	Structural Standardization = 5
...avait été étonnamment ouverte ce jour-là. De même que le tunnel rétractable jusqu'au milieu du terrain pour protéger les joueurs n'avait pas été déplié. Le , le président de la JSK, Mohand Chérif Hannachi déclare que selon les médecins du club, Albe...	...type: Point, coordinates: [-155.5988931655884, 18.970787529076187], type: Feature, properties: , geometry: type: Point, coordinates: [115.1675319671631, -8.726969207892507], type: Feature, properties: , geometry: type: Point, coordinates: [72.82279014587404,ha un'allucinazione vedendo l'assassino mascherato in lontananza ma subito dopo corre tra le braccia di Kieran, i due si baciano e finiscono poi col fare l'amore nella macchina. Al loro ritorno la zia di Kieran comunica a quest'ultimo che continueràThe pair always had intentions of bringing Christopher Reeve onto the show, and when they found out that he enjoyed watching the show himself Gough and Millar decided that they were going to bring him on for season two. They had already crafted a character, Dr. Virgil Swann, they knew would reveal...	...La discographie de Sheryfa Luna, une chanteuse de RnB française, se compose de quatre albums studio, dix singles et dix clips vidéo. Albums Chansons Singles class=wikitable style=text-align:center; + Liste des singles et positions dans le...
Style Consistency = 1	Style Consistency = 2	Style Consistency = 3	Style Consistency = 4	Style Consistency = 5
...1 13,0 11,5 10,4 164 131 269 274 3,70 3,65 11,4 42,3 1,22 22 --- 22 0,6438 25,4 0,69 27,0 0,322 642,4 14,5 13,3 11,8 207 165 341 346 2,93 2,89 18,3 53,6 0,965 23 --- 23 0,5733 22,6 0,61 24,1 0,255 509,5 16...	...kath., 280 ref., 18 zsidó lak. Ref. anyaszentegyház, kath. kápolna. Szőlőhegy. Erdő. 192 hold szántóföld. F. u. gr. Andrásy Gyula. Borovszky Samu, monográfiasorozatának Zemplén vármegyét tárgyaló része szerint: Szőlőske, bodrogmenti magyar kisközsé...	...ajda, Malta, 1831 (prestavljen 1893) Obelisk Thomasa Jeffersona v Monticellu, 1833 Obelisk levov, Iași, Romuniya, 1834 Villa Torlonia, Rim - dva obeliska, 1842 Obelisk pokrajine Emilija v spomin na poroko Francesca V., vojvode Modene, in princese Ad...	...have been recovered. (Location of scores for four other songs missing this time) (Lyricist Sean Rafferty) These are not at the BL because Players' Theatre is a private club and was not censored. Four to the Bar (1961) Diedre was included in this,...	... 286209 - 18 ottobre 2001 NEAT - 286210 - 19 ottobre 2001 NEAT - 286211 - 16 ottobre 2001 LINEAR - 286212 - 17 ottobre 2001 LINEAR - 286213 - 17 ottobre 2001 LINEAR - 286214 - ...
Topic Focus = 1	Topic Focus = 2	Topic Focus = 3	Topic Focus = 4	Topic Focus = 5
... (Darlington). Yupadee Kobkulboonsiri, 51, Thai-American artist and jewelry designer, COVID-19. James Mahoney, 62, American pulmonologist and internist, COVID-19. Mark McNamara, 60, American basketball player (Philadelphia 76ers, San Antonio Spurs, Lo...	...und Hotels in Sri Lanka kamen mindestens 253 Menschen ums Leben, 485 weitere wurden verletzt. 2. Juni: Ermordung des CDU Politikers Walter Lübcke 9. Oktober: Anschlag in Halle (Saale) Kultur und Gesellschaft 6. Januar: 76. Verleihung der Goldenclass=note - class=vcard class=fn org Northover (Glastonbury) class=adr Somerset class=note class=note - class=vcard class=fn org North Owersby class=adr Lincolnshire class=note class=note Easy Virtue starring Ben Barnes, Jessica Biel, Kristin Scott Thomas and Colin Firth (among others) is due for release in Europe on 7 November 2008. Jobbins has also contributed to, Breast Wishes, a comedy musical about 'breasts, and the people who support them'...	...Sheridan Jobbins (born 2 July 1960) is an Australian journalist, television presenter and screenwriter. Life and career Jobbins was born in Melbourne, Australia. She was educated at Ascham School, Edgecliff She is a third generation Australian film maker....
Overall Score = 1	Overall Score = 2	Overall Score = 3	Overall Score = 4	Overall Score = 5
...2, 57, 72, 34, 73, 85, 35, 371, 59, 196, 81, 92, 191, 106, 273, 60, 394, 620, 270, 220, 106, 388, 287, 63, 3, 6, 191, 122, 43, 234, 400, 106, 290, 314, 47, 48, 81, 96, 26, 115, 92, 158, 191, 110, 77, 85, 197, 46, 10, 113, 140, 353, 48, 120, 106, 2, 6...	...1 krog 15 - ! 10 8 Raph B de las Casas Maserati 6CM 38 +2 kroga 25 - ! 11 6 Armand Hug Privatnik Maserati 4CM 33 +7 krogov 21 - ! Ods 18 Clemente Biondetti Alfa Corse Alfa Romeo Tipo 308 4 - ! Ods...	... 20101) 2003 FP5 align=right 14,8 align=right 3,028 align=right 0,054 align=right 8,07 align=right 5,268 MBA 26. března 2003 Campo Imperatore CINEOS - (120102) 2003 F05 align=right 15,1 align=right 2,657 align=right 0,047 al...	...5-2007) Adoum Younousmi, Acting Prime minister (2007) Delwa Kassiré Koumakoye, Prime minister (2007-2008) Youssouf Saleh Abbas, Prime minister (2008-2010) Emmanuel Nadingar, Prime minister (2010-2013) Djimrangar Dahnadji, Prime minister (2013) Kalzeu...	...El término latino (en latín: Latini) hace referencia a una de las etnias de origen indoeuropeo y del grupo itálico que se asentaron a lo largo de la costa tirrénica del Latium, en Italia, en el curso del II milenio a.C., durante la Edad del Bronce. ...