
Large Language Model-guided Document Selection

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Abstract

Large Language Model (LLM) pre-training exhausts an ever growing compute budget, yet recent research has demonstrated that careful document selection enables comparable model quality with only a fraction of the FLOPs. Inspired by efforts suggesting that domain-specific training document selection is in fact an interpretable process [Gunasekar et al., 2023], as well as research showing that instruction-finetuned LLMs are adept zero-shot data labelers [Gilardi et al., 2023], we explore a promising direction for scalable general-domain document selection; employing a prompted LLM as a document grader, we distill quality labels into a classifier model, which is applied at scale to a large, and already heavily-filtered, web-crawl-derived corpus autonomously. Following the guidance of this classifier, we drop 75% of the corpus and train LLMs on the remaining data. Results across multiple benchmarks show that: 1. Filtering allows us to quality-match a model trained on the full corpus across diverse benchmarks with at most 70% of the FLOPs, 2. More capable LLM labelers and classifier models lead to better results that are less sensitive to the labeler’s prompt, 3. In-context learning helps to boost the performance of less-capable labeling models. In all cases we use open-source datasets, models, recipes, and evaluation frameworks, so that results can be reproduced by the community.

1 Introduction

Large Language Models (LLMs) (Devlin et al. [2019], Radford et al., 2019], Brown et al. [2020a], Touvron et al. [2023a,b], Achiam et al. [2023], Team et al. [2023]) have demonstrated impressive zero and few-shot generalization across a diverse range of downstream language understanding and generation tasks, after extensive training on large text corpora. Encouraged by the fact that model capabilities seem to continue to improve as more data and compute are put to work, with seemingly no end in sight, scaling law efforts have sought to predict model capability given increased compute and data budgets Kaplan et al. [2020], Hoffmann et al. [2022].

In Sorscher et al. [2023], the authors comment that these power scaling laws show disappointingly slow scaling (a 100x increase in training compute improves cross-entropy loss by only 0.5 nats in Hoffmann et al. [2022], for example), and demonstrate empirically that it may be possible to significantly increase the power-law exponent with careful data selection. Separately, substantial effort typically goes into producing an optimal overall dataset mixture for LLM training Xie et al. [2023a], yet these mixtures always include “high quality” dataset components, which are typically over-sampled (e.g. StackExchange, Wikipedia, or books for the LLaMA model series Touvron et al. [2023a,b]), suggesting that these components make significant—relative to their size—contributions to downstream model quality.

By necessity of volume, the majority of any LLM pre-training dataset will be derived from a filtered bulk web crawl, with a popular source being the CommonCrawl (CC) Authors [2024] corpus. Various

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open-source filtered subsets of CC exist, e.g. Gao et al. [2020], Computer [2023], Soboleva et al. [2023], which have already been pruned to only include the highest quality documents. Efforts to improve data pruning, and by doing so the scaling law efficiency, should therefore focus on better selecting documents from the bulk web crawl.

In this work, we explore a promising direction for general-domain web-crawl pruning by introducing a scalable approach for LLM-guided document selection. Our framework utilizes two large language models, a large instruction-finetuned model (LM_{large}), and a smaller pre-trained language model (LM_{small}). Given a target corpus, we initially leverage the strong zero-shot capabilities of LM_{large} to assess a number of sampled documents in terms of quality and educational value. Subsequently, LM_{small} is finetuned on the quality labels from LM_{large} . Finally, the finetuned LM_{small} is applied to score the full web-crawl corpus. This distillation step allows us to minimize the total amount of compute required for filtering, as for any given prompt and label-set from LM_{large} we can establish whether a larger distillation model (LM_{small}) is required by simply examining the fine-tuning evaluation metrics.

This paper makes the following contributions:

- We introduce a scalable and general LLM-powered web-crawl document selection framework that does not rely on high-quality reference corpora.
- We apply this pipeline to the filtered RPJ-CC Computer [2023] dataset, as a representative high-quality baseline, and demonstrate significant improvements in downstream LLM quality across multiple parameter and compute budgets.
- We conduct several ablation studies to study the impact of: 1. the labeling prompt, 2. the capability of the labeling model, 3. the capacity of the distillation model.

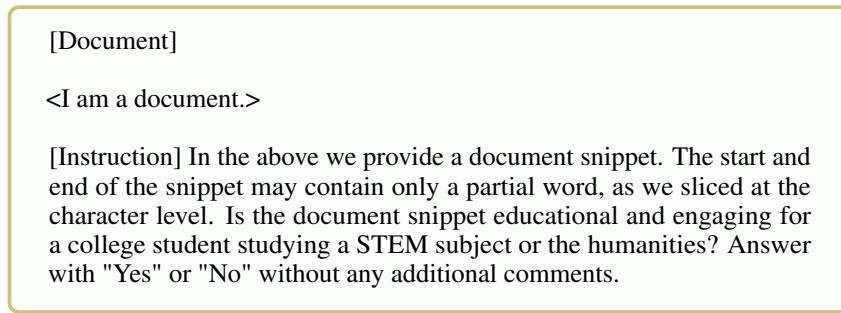


Figure 1: The prompt used to guide the LLM labeler to assess the quality and education value for an input document.

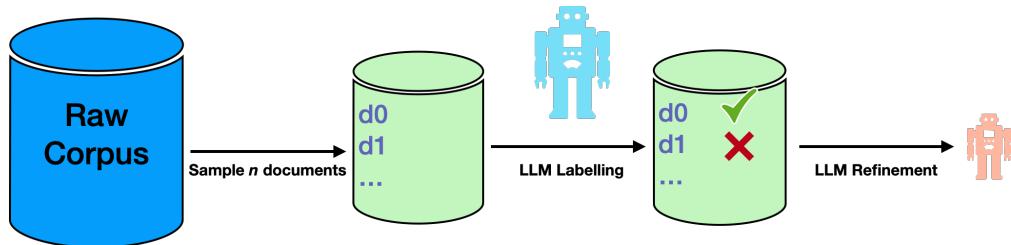


Figure 2: The overall pipeline for our proposed LM-guided data selection pipeline. Given a raw corpus, we first sample n documents and guide an LLM labeler to assess them in terms of the textual quality and educational value. The resulting (doc, label) pairs could be distilled into an LM-based quality classifier, which will label all documents in the raw corpus.

2 Method

In this section we describe the LLM guided web-crawl document selection (LMDS) pipeline.

2.1 Proposed Framework

To apply LMDS, we first need access to the following:

- **Target Corpus (C):** The source dataset over which document selection is to be applied. C may contain hundreds of billions of documents sourced from the web, (e.g. plaintext extracted CommonCrawl), with text covering a diverse range of topics, languages, etc.
- LM_{large} : A capable (the more so the better), instruction-finetuned language model.
- LM_{small} : A second, low inference cost distillation-target LLM, preferably heavily pretrained (instruction finetuning is optional).

The pipeline is composed of two distinct stages:

LM_{large} -Labelling In this stage, we select a random subset of documents from C to serve as a representative sample for the whole corpus. The sampled documents are then fed into LM_{large} for assessment according to the criteria specified in the prompt (Figure 1), generating high/low-quality document labels. We note that the choice of prompt used to guide LM_{large} is important for two reasons: 1. it must be straightforward for the chosen LM_{large} to interpret (very capable proprietary models are often able to follow more subtle instructions versus open-source alternatives), 2. it explicitly defines the selection criteria. Assuming a broad definition of "high quality", we find that a concise prompt guiding LM_{large} to assess documents for general educational value (inspired by the domain-targeted efforts of Gunasekar et al. [2023]) works well. We leave it to future work to explore more targeted (e.g. subject-specific) prompts, but do believe that the flexibility of the prompt (vs. e.g. sourcing relevant high-quality reference corpora to train a classifier) is a major benefit of LMDS.

LM_{small} -Refinement To enable labelling at very large scale, a cheap-to-run-inference-on (smaller) pretrained language model LM_{small} is employed. We first distill the labels sourced from LM_{large} on the document assessment task into LM_{small} . Once fine-tuning is complete, LM_{small} can be deployed to evaluate the entire target corpus C using your accelerator-backed map-reduce framework of choice.

The overall two-stage pipeline is depicted in Figure 2.

Rationale for Using LM_{small} as well as LM_{large} Given the relative size of a filtered crawl dataset vs the unfiltered corpus, (typically $\ll 1\%$ of the data remains after selection Computer [2023], Soboleva et al. [2023]), we believe that document selection is a difficult recall problem—it's probable, given non-perfect filter recall, that a significant number of high quality documents are dropped by typical filter pipelines. For this reason we'd like to minimize the number of stages (asides from LMDS), in the overall filter pipeline, which in turn means that it must be feasible to run LMDS at a hundred-billion document scale. At the same time, we want to use the most powerful LM_{large} that we have access to, so that the generated labels adhere to the prompt with high fidelity. To balance this trade-off we introduce LM_{small} , and in Table 2 we show that it's possible to understand the effect of this distillation step (and as a result tune the size of LM_{small}) by examining the F1 score of the classifier at fine-tuning time, with little to no overhead.

3 Experiments

3.1 Experiment Setup

Source dataset: To validate the technique, we will use the filtered Common Crawl (CC) split from the RedPajama v1 data mixture (RPJ-CC) Computer [2023] as C , because this is a reasonably strong baseline over which we hope to improve. We leave it to future work to demonstrate the effectiveness of LMDS applied to a larger scale unfiltered web-crawl (although we expect this to yield better results still). The RPJ-CC dataset was produced by running five CommonCrawl dumps through the cc_net pipeline, which de-duplicates (including at a paragraph level) and selects documents using

both perplexity filtering and a linear classifier trained to recognize high-quality Wikipedia reference text. It contains 878 billion tokens.

Language Model-guided Document Selection Pipeline: The data selection pipeline described in Section 2 is applied to these datasets.

In the **LM_{large}-Labelling** phase, we use the Llama-2-chat 70B (Touvron et al. [2023a])² as our LM_{large}, as it is a widely accessible open-source model with good language understanding and reasoning capabilities. We sample two million documents from RPJ-CC and feed the middle 1500 tokens of each document into LM_{large}, (along with the prompt in Figure 1), for quality assessment³.

During the **LM_{small}-Refinement** stage, we take LM_{small} (a smaller LLM pretrained on Wikipedia, Stackexchange, and Books components from Soboleva et al. [2023]) and finetune this model on the (document, quality label) pairs generated by LM_{large}, in the process distilling the signal from LM_{large}. More specifically, a Sigmoid binary classification head is added to LM_{small}, and the representation produced by this head defines the quality score.

At this point LM_{small} is a distilled representation of the labeling function defined by the prompt and LM_{large}, and is then used to quality score C .

Language model training on selected documents: To evaluate the efficacy of our data selection pipeline, we train language models of varying capacities (1B and 7B) on a high quality subset of C according to the scores from our LM_{small}. For all documents in the target corpus, LM_{small} assigns a quality score in $(0, 1)$, then we choose a cutoff and keep only documents scoring above this threshold for training. We drop around 75% of the data from C , which is in-line with the fraction of documents assigned to the high-quality bucket by LM_{large} at label generation time.

We compare models trained with the same compute budget (and using sequence packing Brown et al. [2020b]), i.e. all models see exactly the same number of tokens and are trained with the same hyperparameters. For details about the architecture and training processes, please refer to Appendix A.

Language model evaluation: We assess the language models across a comprehensive set of benchmarks. For all results reported in our study, higher numbers are better than lower numbers.

- **Core English tasks (CoreEN):** Models are evaluated across various benchmarks focusing on common sense reasoning, reading comprehension and question answering, including ARC Easy and Challenge (0-shot) (Clark et al. [2018]), HellaSwag (0-shot) (Zellers et al. [2019]), WinoGrande (0-shot) (Sakaguchi et al. [2019]), PIQA (0-shot) (Bisk et al. [2019]), SciQ (0-shot) (Sap et al. [2019]), LAMBADA (0-shot) (Paperno et al. [2016]), TriviaQA (1-shot) (Joshi et al. [2017]) and WebQS (1-shot) (Berant et al. [2013]). We use the EleutherAI evaluation-harness Gao et al. [2021] to run these evaluations. In our experiments, we report both the average performance on the seven 0-shot tasks (denoted as CoreEN (0S)) and the average performance across all nine tasks (denoted as CoreEN (All)).
- **MMLU:** Performance is detailed for the 5-shot setup on the MMLU benchmark (Hendrycks et al. [2021]), a widely-adopted benchmark consisting of exam-style questions from 57 tasks.

3.2 Experiment Results

Model quality with a Fixed Training Budget: In Table 1, we evaluate models of different scales across multiple benchmarks. Models trained on datasets curated using our proposed data selection pipeline consistently achieve higher performance than their counterparts across all benchmarks. For example, at 7B scale, the model trained on filtered Common Crawl achieves **+5.53** on MMLU score compared to the one trained on entire RPJ-CC dataset, demonstrating the effectiveness of our method to select documents with high educational value. The breakdown performance on CoreEN is listed in Appendix B.

²<https://huggingface.co/meta-llama/Llama-2-70b-chat-hf>

³We set temperature as 0.2 to make the results more deterministic.

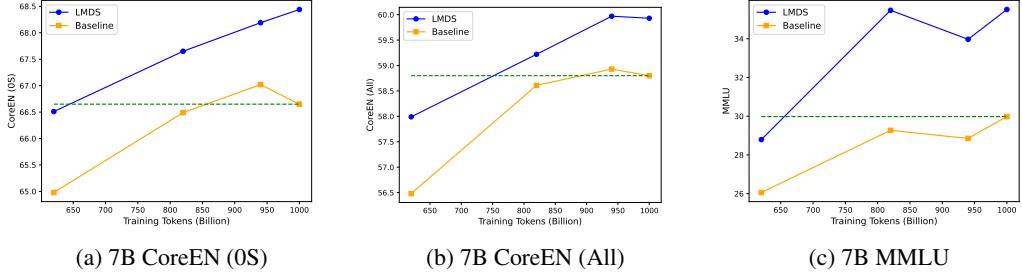


Figure 3: Learning curves on the downstream task for 7B model pretraining on the raw data versus LMDS-based filtered data.

Table 1: Comparisons of models trained on datasets w/ (LMDS) and w/o data selection. We do not report MMLU results for the 1B model, because at this compute budget they are near random.

model	dataset	CoreEN (0S)	CoreEN (All)	MMLU
1B	Baseline	58.10	48.63	N/A
1B	LMDS	61.14	51.41	N/A
7B	Baseline	66.66	58.72	29.98
7B	LMDS	68.44	59.93	35.51

Data efficiency: Given the same training budget (FLOPs), training on the LMDS-filtered dataset achieves higher downstream model performance. We further investigate the data efficiency of our approach. As depicted in Figure 3, we show the performance of 7B models trained on w/ and w/o our LMDS pipeline against the number of training tokens. We find that filtering allows us to quality-match a model trained on the full corpus across diverse benchmarks with at most 70% of the FLOPs.

Downstream Task Accuracy v.s. Selection Ratio: Using the finetuned LM_{small} to label the target corpus, each document in the target corpus receives a score ranging from zero to one. One natural question is how to set the cutoff threshold to select documents for model training. In this study, we explore cutoff thresholds to achieve distinct selection ratios ($\{20\%, 25\%, 30\%, 40\%, 50\%, 100\%\}$) and train 1B models on these resulted datasets to understand its impact on the downstream task performance. The results on CoreEN (0S) and CoreEN (All) are shown in Figure 4. Firstly, all selection ratios $\{20\%, 25\%, 30\%, 40\%, 50\%\}$ show meaningful improvements over the baseline dataset (selection ratio=100%). Secondly, as the data selection ratio is reduced from 55% to 25%, we observe incremental gains in performance, underscoring the importance of data quality to downstream task outcomes, whilst an overly aggressive pruning (reduction from 25% to 20%) begins to reduce performance again. Note that the optimal dataset selection ratio may vary for different corpora, however the raw label-split declared by LM_{large} is a good rule of thumb when selecting an appropriate threshold.

Table 2: Comparing distillation classifier models across various sizes. Reported F1 score is computed on the validation set. It's clear that 1. a classifier as small as 85m parameters provides a meaningful improvement over the baseline, 2. larger classifiers are still meaningfully better.

Size	F1-score	CoreEN (0S)	CoreEN (All)
85M	0.78	60.24	50.72
302M	0.81	60.88	51.10
1B	0.84	61.14	51.41

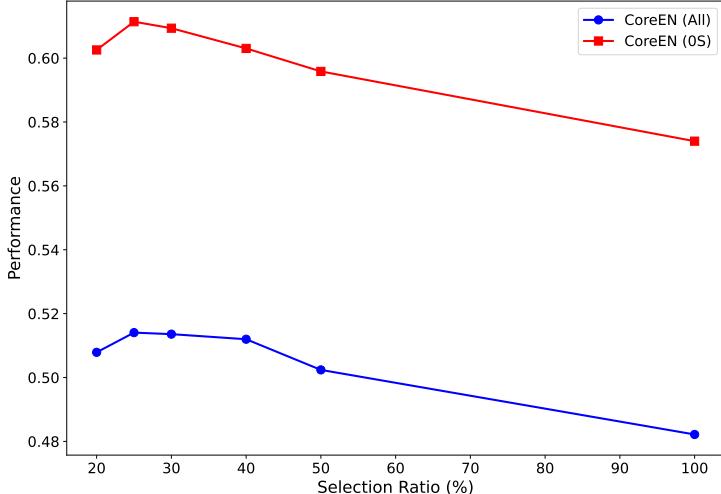


Figure 4: Downstream task accuracy of 1B models trained on LMDS-based filtered datasets with different selection ratios.

Table 3: Comparing the different scale LM_{large} on downstream task accuracy.

LM_{large}	CoreEN (OS)	CoreEN (All)
Baseline	58.10	48.63
Llama-2-chat 7B	57.44	48.13
Llama-2-chat 13B	59.50	50.39
Llama-2-chat 70B	61.14	51.41

Downstream Task Accuracy v.s. Size of LM_{small} : In this study, we examine the impact of different sizes of LM_{small} on downstream task accuracy. Specifically, we experiment with three sizes of LM_{small} : 85M, 302M, and 1B parameters. Our first step involves comparing the F1-scores these models achieve on a held-out set when fine-tuned on the (document, quality label) pairs annotated by LM_{large} . From the results presented in Table 2, it is evident that larger models yield higher F1-scores. This trend suggests that models with greater capacity are more effective at learning from the annotations produced by our large language model, LM_{large} . To further investigate this phenomenon, we leverage the three fine-tuned LM_{small} models to label the target corpus. We then train 1B LMs on these datasets. The result is shown in Table 2, we observe that the LM trained on the dataset labeled by the 1B LM_{small} outperforms those trained on datasets labeled by the 302M and 85M LM_{small} models, showing that larger capacity LM_{small} can learn better during the distillation stage. We conclude that models as small as 85m parameters provide a meaningful improvement over the baseline, and that larger models do better still—so suggest that the choice of LM_{small} capacity is guided by the total inference budget available.

Impact of LM_{large} : Another critical component of our data selection pipeline involves crafting effective prompts that guide large language models LM_{large} accurately tag documents with respect to their quality and educational value. To achieve this, LM_{large} needs to have strong instruction following, textual understand and reasoning capabilities. Therefore, in this study, we first try three LM_{large} with different scales, i.e., Llama-2-chat 7B, 13B and 70B Touvron et al. [2023a]. We first employ these three models to label the same sample documents from the target corpus and finetune LM_{small} on them. We train 1B LMs on data labeled by these LM_{small} . From the Table 3, we find that the larger LM_{large} is, the better accuracy we can obtain. For the Llama-2-chat 7B, it only achieve similar accuracy compared to the baseline and after a closer look, we find that approximately 98% of the sample documents are labeled as *yes*, indicating that the Llama-2-chat 7B model lacks the ability to analyze intricate and nuanced textual content effectively.

Table 4: The robustness of LM_{large} with various sizes to prompt instructions. We train models based on three versions of instructions for LM_{large} to label sample documents.

LM_{large}	Prompt Version	CoreEN (All)	Avg. (Std)
Llama-2-chat 13B	V1	50.05	50.27 ± 0.57
	V2	50.86	
	V3	49.90	
Llama-2-chat 70B	V1	51.41	51.24 ± 0.24
	V2	51.34	
	V3	50.96	

Table 5: Comparing the Llama-2-chat 7B w/ and w/o in-context learning on downstream task accuracy.

LM_{large}	CoreEN (0S)	CoreEN (All)
Llama-2-chat 7B + ICL (5-shot)	57.44	48.13
	58.55	48.80
Llama-2-chat 70B	61.14	51.41

Furthermore, we also try to understand the robustness of Llama-2-chat 13 and 70B models with respect to instructions. Ideally, LM_{large} should provide a consistent quality assessment given semantically similar instructions. Therefore, we try three prompts (more details in Appendix C), and compute the agreement of downstream evaluation results across these prompts. As shown in Table 4, the Llama-2-chat 70B model exhibits higher agreement compared to the Llama-2-chat 13B, indicating that larger capability LM_{large} is more reliable and less influenced by variations in prompts.

In-Context Learning for Llama-2-chat 7B: Due to its limited instruction-following capabilities, Llama-2-chat 7B struggles to distinguish high-quality documents from low-quality ones, as compared to its larger siblings. However, large language models exhibit in-context learning (ICL) abilities (Brown et al. [2020a]), where they can learn from a few examples provided in the context without fine-tuning and by doing so overcome instruction-following shortcomings. To leverage this, we provide 5 examples from the strongest LM_{large} Llama-2-chat 70B in this study as a demonstration context for Llama-2-chat 7B. We then trained 1B models based on the ICL-enhanced Llama-2-chat 7B results. As shown in Table 5, incorporating demonstrations from a stronger LM_{large} yields better downstream accuracy, showing ICL helps the Llama-2-chat 7B to more effectively identify high-quality documents. However, there still remains a significant gap compared to LM_{large} , indicating that raw model capability (especially instruction following) is critical for accurate document labeling.

4 Related Work

The goal of data filtering is to determine the optimal subset of training data to train on, where optimal is typically measured via trained model performance on a diverse suite of benchmarks. It is well known that better data selection leads to improved downstream performance and/or a reduced compute budget to achieve the same performance for large-scale model training efforts, e.g. LLMs Sorscher et al. [2023].

We believe that the most closely related work to our own is Sachdeva et al. [2024], (developed concurrently), where the authors employ a T5 Raffel et al. [2020] model to produce quality labels before training new T5 models on the filtered data via a process they term "Ask-LLM". Compared to Ask-LLM, we focus on decoder-only LLMs, demonstrating that the technique works for much larger models and compute budgets (7B parameters trained for 1T tokens), as well as tougher benchmarks (MMLU), and also works when starting with a stronger baseline dataset in RPJ-CC (versus C4Raffel et al. [2020]). Furthermore, we ablate the impact of the prompt as well as the choice of labeler and

distillation model, showing that more capable labelers are both more effective and less sensitive to the choice of prompt.

In what follows we describe more broadly approaches for data selection by quality, with a focus on efforts applied to language model training.

Effect of data selection on pre-training stage: Training large language models typically involves utilizing extensive text datasets sourced from massive and diverse origins such as CommonCrawl and GitHub. However, it is widely recognized that pre-training data is very noisy, and often includes boilerplate text, templates, error messages, and other forms of repetitive or not-informative content that does not contribute meaningfully to model quality as measured by downstream benchmarks. This poor quality data can lead models to learn and perpetuate irrelevant or redundant information, ultimately impacting their performance and generalization capabilities across various tasks (Raffel et al. [2020], Touvron et al. [2023a,b]). For instance, during the creation of the Pile dataset (Gao et al. [2020]), authors find that the most common 13-grams are character repetitions, such as strings of dashes, with more than 10 million instances. Removing such undesirable text is crucial but must be done efficiently due to the large number of documents involved. A common approach to filtering data is to employ simple yet computationally efficient heuristics. The goal of these heuristic approaches is to constrain the training distribution along certain dimensions (e.g., sentence length, repetitiveness), with the assumption that the evaluation distribution will exhibit similar characteristics. The heuristics used in past works are extensive but generally fall into one of the following categories: item count, repetition count, ratio, or per-document statistical measures.

In addition to heuristic data selection methods, many works focus on developing more advanced model-based techniques to identify and select "high quality" text. Brown et al. [2020a], Du et al. [2022], Touvron et al. [2023a], Computer [2023] try to select data in a noisy dataset based on the similarity to a pre-defined high quality reference corpus, e.g., Wikipedia, to improve the model quality. Gao et al. [2020] train GPT-2 (Achiam et al. [2023]) and GPT-3 (Brown et al. [2020a]) models from scratch to compare the "Pile" dataset with CommonCrawl to demonstrate the effectiveness of data filtering. Raffel et al. [2020] train 1B parameter models to show the positive impact of the de-duplication and quality filters. Hernandez et al. [2022] train multiple language models with various epoch counts but fixed compute budgets to understand the effect of repeated data. Muennighoff et al. [2024] explore the effect of dataset repetition on scaling laws, finding that repeating the highest quality data for up to four epochs outperforms fresh, less-heavily filtered data seen only once. In Tirumala et al. [2024], the authors conduct a large-scale data-efficient pre-training evaluation, showing that a 6.7B OPT model (Zhang et al. [2022]) can converge up to 20% faster on data curated by a technique based on pre-trained model embeddings on top of de-duplicated data. Instead of hard-selection, Xie et al. [2023b] propose a data selection algorithm with importance resampling to estimates importance weights and select data according to these weights during the LLM training. One line of research focuses on the the data mixture between multiple components. Longpre et al. [2023] discuss the effect of several factors including toxicity, age and domain distribution on the downstream performance. Xie et al. [2024] propose to seek data mixture ratios through training a small proxy model using Group DRO, which could be used to train large scales models. Another series of studies focuses on training models using a selection of "textbook quality" data to demonstrate the importance of data quality (Jawaheripi et al. [2023], Gunasekar et al. [2023], Li et al. [2023b], Eldan and Li [2023]). In, Maini et al. [2024], the authors use off-the-shelf instruction-finetuned language models to paraphrase documents on the web to improve the data quality without selection, and as previously mentioned, Sachdeva et al. [2024] employs T5 to choose the high quality data with density sampling to preserve the coverage and diversity of the training data at the same time. Zhang et al. [2024] employs a language model to help identify domain specific (Math) documents to boost math-related benchmark performance.

Effect of data selection on post-training stage: In contrast to the pre-training, the post-training stage aims to align LLMs with a downstream user's objective to make the model outputs more controllable and helpful for users (Ouyang et al. [2022]). Many works aim to improve the data quality through focusing on the difficulty, complexity and diversity as components of the utility. Zhou et al. [2024] show that only 1,000 carefully curated data with high quality and diversity can achieve superior instruction following capabilities. Li et al. [2023a] design a difficulty metric from instruction-following perspective to let model itself to select the training samples. Kung et al. [2023] propose *activate instruction tuning* to identify informative tasks to continuously improve its cross-task

generalization ability. Although human guidance may be more reliable, recently, the capability of models to precisely identify undesirable data points is also effective. For example, Chen et al. [2023] leverage ChatGPT Achiam et al. [2023] to assess training examples and select a subset of Alpaca dataset. Gunasekar et al. [2023] build an LM-based classifier to filter textbook quality data from the target corpus and this classifier is trained on data generated from LLMs. Some off-the-shelf LLMs such as GPT-4 (Achiam et al. [2023] are used to filter and rank responses to provide high-quality feedback (Cui et al. [2023], Zhu et al. [2023]).

5 Conclusion

This paper introduces a scalable and general large language model-guided document pruning pipeline for the autonomous selection of high-quality training data for large language models (LLMs) from a web-scale corpus. Two language models with different scales, LM_{large} and LM_{small} achieve a good balance of selection precision/recall and inference efficiency/scalability. We demonstrate the effectiveness of this approach by applying it to the already-filtered RPJ-CC dataset, at multiple model size and training FLOP budgets. Results showed that models trained on the filtered dataset achieve significantly better quality across multiple benchmarks, in most cases doing so with a reduced compute budget. Several ablation studies highlight the importance of key components in our framework. In future work we hope to demonstrate the effectiveness of this pipeline applied at full scale to a (near) unfiltered web-corpus, and expect that domain targeted LM_{large} prompts will also allow for the targeted selection of domain-specific data for domains which do not have an existing high-quality and high-coverage reference corpus.

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Table 6: All model specifications used in this paper.

model	num layers	hidden dim	num heads	batch size (# tokens)
85M	12	768	12	1M
302M	24	1024	16	1M
1B	24	2048	32	1M
7B	32	4096	32	4M

A Modeling Training Details

LM_{small} pretraining: Before finetuning LM_{small} on (document, label) pair labelled by LM_{large}, we first pretrain it on Wikipedia, Stackexchange, and Books components from Soboleva et al. [2023] to build a good initialization for finetuning.

The architecture of all language models including LM_{small} and LM_{large} is listed in the Table 6. All models are pretrained with the AdamW optimizer (Loshchilov and Hutter [2019]), employing parameters $\beta_1 = 0.9$, $\beta_2 = 0.95$, decoupled $wd = 1e - 4$ and $\epsilon = 10^{-8}$. We implement a cosine learning rate schedule, starting with 2000 warmup steps and decaying to 10% of peak learning rate and a gradient clipping at 1.0. A SentencePiece tokenizer (Kudo and Richardson [2018]), employing a vocabulary of 32k and built on the Byte-Pair Encoding algorithm (Sennrich et al. [2016]), is used on C4. All the model are trained on TPU-v4 and v5 chips. All LM_{small} are trained with 400B tokens. 1B and 7B main models are trained with 300B and 1T tokens respectively. We use the μ Param (simple) (Wortsman et al. [2023]) where the peak learning rate is set to 1e-2.

B Breakdown performance on CoreEN tasks

We list performance of different models on CoreEN tasks in Table 7.

Table 7: Breakdown results of 1B models on CoreEN in Table 1

	Baseline	LMDS
arc_c	26.37	35.07
arc_e	62.21	70.54
hellaswag	43.75	43.16
lambada	56.44	58.88
piqa	71.22	69.59
sciq	86.80	90.20
winogrande	59.91	60.54
triviaqa	17.68	20.99
webqs	13.29	13.68

C Instructions exploration for LM_{large}

We list the prompts we used to test the robustness of different LM_{large}. They are semantically similar to each other and a strong language model should be less sensitive to these prompts.

Table 8: Breakdown results of 7B models on CoreEN in Table 1

	Baseline	LMDS
arc_c	40.02	44.45
arc_e	72.06	77.10
hellaswag	50.88	52.04
lambada	70.25	69.75
piqa	73.78	74.65
sciq	92.50	94.30
winogrande	66.06	66.77
triviaqa	40.79	39.13
webqs	21.90	21.16

V1	[Instruction] In the above we provide a document snippet. The start and end of the snippet may contain only a partial word, as we sliced at the character level. Is the document snippet educational and engaging for a college student studying a STEM subject or the humanities? Answer with "Yes" or "No" without any additional comments.
V2	[Instruction] In the above we provide a document snippet. The start and end of the snippet may contain only a partial word, as we sliced at the character level. Does the document look like it would be helpful for a STEM or Humanities student who is struggling with their course? Answer with "Yes" or "No" without any additional comments.
V3	[Instruction] In the above we provide a document snippet. The start and end of the snippet may contain only a partial word, as we sliced at the character level. Does the document look like it would be educational and helpful for a STEM or Humanities student to help understanding material from their course? Answer with "Yes" or "No" without any additional comments.

Table 9: Prompts used to test the robustness of different LM_{large} .