🦙 RedPajama: an Open Dataset for Training Large Language Models

Maurice Weber[1], **Daniel Y. Fu**[1,2], **Quentin Anthony**[4,8,10], **Yonatan Oren**[1]
Shane Adams[1], **Anton Alexandrov**[7,], **Xiaozhong Lyu**[7], **Huu Nguyen**[5], **Xiaozhe Yao**[7],
Virginia Adams[1], **Ben Athiwaratkun**[1], **Rahul Chalamala**[1,11], **Kezhen Chen**[1], **Max Ryabinin**[1]
Tri Dao[1,6], **Percy Liang**[1,2], **Christopher Ré**[1,2], **Irina Rish**[8,9], **Ce Zhang**[1,3]

[1] Together AI,   [2] Stanford University,   [3] University of Chicago
[4] EleutherAI   [5] Ontocord.ai,   [6] Princeton University,   [7] ETH Zurich
[8] Mila, Montréal, Canada   [9] Université de Montréal   [10] Ohio State University   [11] Caltech

Abstract

Large language models are increasingly becoming a cornerstone technology in artificial intelligence, the sciences, and society as a whole, yet the optimal strategies for dataset composition and filtering remain largely elusive. Many of the top-performing models lack transparency in their dataset curation and model development processes, posing an obstacle to the development of fully open language models. In this paper, we identify three core data-related challenges that must be addressed to advance open-source language models. These include (1) transparency in model development, including the data curation process, (2) access to large quantities of high-quality data, and (3) availability of artifacts and metadata for dataset curation and analysis. To address these challenges, we release RedPajama-V1, an open reproduction of the LLaMA training dataset. In addition, we release RedPajama-V2, a massive web-only dataset consisting of raw, unfiltered text data together with quality signals and metadata. Together, the RedPajama datasets comprise over 100 trillion tokens spanning multiple domains and with their quality signals facilitate the filtering of data, aiming to inspire the development of numerous new datasets. To date, these datasets have already been used in the training of strong language models used in production, such as Snowflake Arctic, Salesforce's XGen and AI2's OLMo. To provide insight into the quality of RedPajama, we present a series of analyses and ablation studies with decoder-only language models with up to 1.6B parameters. Our findings demonstrate how quality signals for web data can be effectively leveraged to curate high-quality subsets of the dataset, underscoring the potential of RedPajama to advance the development of transparent and high-performing language models at scale.

1   Introduction

Pretraining data is among the most central building blocks that go into the development of modern large language models (LLMs). However, one of the core challenges this field faces is the general lack of transparency regarding the composition and curation strategy of pretraining data [8]. Indeed, with a few notable exceptions [19, 4, 2, 65], the majority of reports documenting state-of-the-art LLMs [1] provide scarce details, if any, on their pretraining datasets. Even open-weights models such as LLaMA [57, 58] provide little to no details about their training data, let alone release their datasets. Furthermore, the process of studying and building optimal data compositions, along with developing filtering rules and heuristics, is time-consuming as it necessitates running numerous ablations on
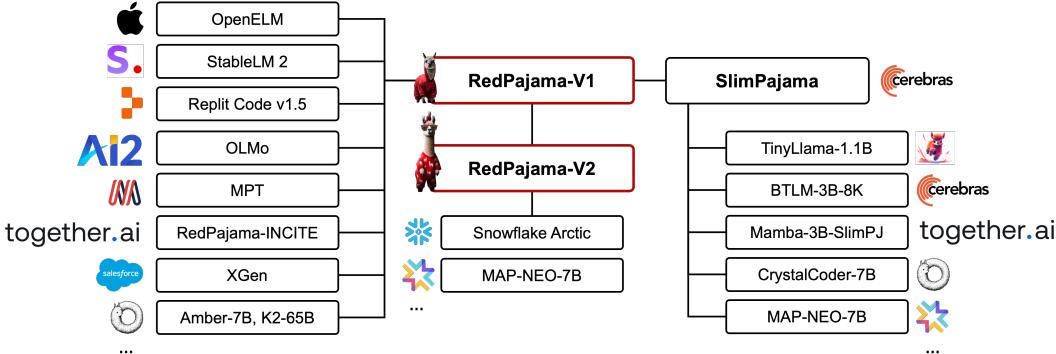
Figure 1: The ecosystem around the RedPajama datasets. RedPajama has provided pretraining data for multiple open-source LLMs, including OpenELM [36], OLMo [19], Snowflake's Arctic [54] and RedPajama-INCITE. SlimPajama is a cleaned and deduplicated version of RedPajama-V1.

different compositions of the training data. To address these challenges, and with the overarching goal of democratizing the access to and development of open-source LLMs, we have released the RedPajama datasets, which in total consist of more than 100 trillion tokens of text data. With this goal in mind, we use the following design principles to guide our approach to creating open datasets:

Transparency. We strive for maximal *transparency* from at least two angles. On the one hand, this entails documenting and making all aspects of data curation publicly available[1]. On the other hand, we strive for open and transparent datasets, which allows for application developers and researchers alike to better understand and design language models.

Scale. Large pools of accessible data are one of the core building blocks of the most powerful large language models [52, 11, 58, 1], yet are hard to come by due to the large amount of resources and expertise required to build, curate and store them. Next to transparency, we thus also strive for *scale*.

Versatility. We aim to provide the community with datasets and artifacts for building state-of-the-art open language models by providing a versatile resource. Rather than prescribing what constitutes a high-quality dataset, we offer a broad, general-purpose corpus of web documents. Each document is tagged with quality signals, empowering users to make informed decisions based on their specific needs and criteria.

Following these principles, we have developed and made publicly available the RedPajama datasets for LLM pretraining. RedPajama-V1 is a publicly available, fully open, best-effort reproduction of the training data described in [57], used to train the first iteration of LLaMA family of models. Together with this dataset, we have developed the RedPajama-INCITE models, which include a base, instruction-tuned, and chat models at the 3B and 7B scales. Based on the first set of learnings from these efforts, we have built the RedPajama-V2 dataset. This latter dataset takes an entirely different approach and focuses exclusively on web data. It consists of five languages, sourced from 84 Common Crawl snapshots ranging from 2014 to 2023. In addition to the raw text data, we also publish quality signals accompanying each document in a 50T token subset of the corpus with the goal of fostering research towards principled understanding of ways to filter web data. In addition, in this work, we present a series of ablation studies, showcasing the value of the quality signals for creating subsets of the raw corpus of varying quality and subsequent model performance.

In summary, in this work, we make the following contributions:

C1 We publish the RedPajama-V1 dataset, an open reproduction of the dataset used to train LLaMA-1 [57]. We also include a detailed report on considerations that went into creating the corpus.

C2 We report the process and evaluations on the training of the RedPajama-INCITE models, including details on how we used the Summit supercomputer and the challenges we had to address.

C3 We publish the RedPajama-V2 dataset, the largest open pretraining dataset consisting of raw, unfiltered data scraped from the web, together with 46 measures of quality computed for each document, to enable further research in data curation.

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[1]The code to reproduce RedPajama is available at `github.com/togethercomputer/RedPajama-Data`.

Table 1: Comparison of open pretraining Datasets along the dimensions of transparency, versatility, and scale.

Dataset	Transparency		Versatility			Scale (TB)
	Open Access	Open Code	Raw Data	Composite	Multilingual	
Refined Web [44]	✔(subset)	✗	✗	✗	✗	2.8
FineWeb [43]	✔	✔	✗	✗	✗	93.4
FineWeb-EDU [43]	✔	✔	✗	✗	✗	8.8
C4 [46]	✔	✔	✗	✗	✗	0.3
mC4 [63]	✔	✔	✗	✗	✔	9.7
DCLM baseline [30]	✔	✔	✗	✗	✗	10.0
DCLM-Pool [30]	✔	✔	✔	✗	✔	340.0
Dolma v1.7 [52]	✔	✔	✗	✔	✗	4.5
Pile [17]	✔	✔	✗	✔	✗	0.8
SlimPajama [51]	✔	✔	✗	✔	✗	0.9
ROOTS [26, 27]	✔	✔	✗	✔	✔	1.6
RedPajama-V1	✔	✔	✗	✔	✗	3.0
RedPajama-V2	✔	✔	✔	✗	✔	270.0

C4 Based on the RedPajama-V2 dataset, we present a series of ablation studies on decoder-only Transformer models with 468 million parameters, showing how the quality signals can be used to create models of varying performance on common NLP benchmarks.

The remainder of this paper is organized as follows. In Section 2, we position the RedPajama dataset in the current landscape of open pretraining datasets. Section 3 describes the details of the dataset creation process behind RedPajama-V1, as well as building the RedPajama-INCITE family of models. Section 4 proceeds to RedPajama-V2, our web-only dataset. Next to describing the data processing steps, we present dataset statistics and ablation studies. Finally, we conclude in Section 5.

2 Related Work

Numerous efforts have focused on constructing pretraining datasets for large language models. While some of these datasets are curated from a mix of various sources, others are exclusively derived from web data. In the realm of web-only datasets, the C4 dataset [46] was one of the first large-scale web datasets, comprising a 175B token web corpus filtered down from CommonCrawl. C4 still remains a benchmark for web dataset quality. More recently, RefinedWeb [44] and FineWeb [43] have demonstrated that web-only data can yield strong models without the need for compositing multiple domains, and have, similar to our work, also provide ample details on their data curation techniques. In contrast to these datasets, RedPajama-V2 is composed of 100 trillion tokens of raw, mostly unfiltered text. With its more than 40 quality signals for potential filtering, RedPajama-V2 promotes an entirely different approach and aims to set a new standard for future high-quality web datasets, providing a robust foundation for the next generation of high quality web datasets. Of further great relevance are the Gopher rules proposed in [45], which have been central to many of the previously mentioned open pretraining datasets.

Complementing web-only datasets, composite datasets introduce additional domains and enable broader coverage. Most notably, the Pile [17] was one of the first fully open datasets. After the release of LLaMA [57], which used seven individual subsets and multiple domains, we published RedPajama-V1 as an open source replication of the LLaMA recipe, which gained widespread adoption. Building on this, the SlimPajama dataset [51] was derived from RedPajama-V1 by further cleaning and deduplication. Similarly, the Dolma [52] dataset includes other specialized domains, such as cleaned versions of code datasets including The Stack [25], StarcoderData [31] as well as the ArXiv and StackExchange splits of RedPajama-V1. The Zyda [56] dataset goes in a similar vein and further refines open datasets, including the SlimPajama dataset derived from RedPajama-V1. Finally, the ROOTS corpus [26, 27] is also among the core open datasets spanning multiple domains and languages. Table 1 shows an overview over these open datasets and makes a comparison where each dataset stands in terms of transparency, versatility and scale.

3 RedPajama-V1: An open Reproduction of the LLaMA Training Data

In our first iteration of the RedPajama datasets, our primary goal was to recreate the training data documented in the LLaMA technical report [57]. To this end, we closely follow the descriptions of the original recipes. In this section, we first document our process for recreating the original LLaMA training corpus (Section 3.1). We highlight gaps in the description of the original dataset collection and describe how we choose to resolve those ambiguities. Next, we report on RedPajama-INCITE, a family of models trained on this corpus in collaboration with Oak Ridge National Lab (ORNL) (Section 3.2). We find that although the resulting models are performant at the 3B scale, there remains a gap at 7B to the original LLaMA-7B model. We hypothesize that this is partly due to the need to train with the FP16 precision. In addition, this also suggests the possibility that some salient details that went into the construction of the original LLaMA training corpus may be missing.

Table 2: Token counts for the RedPajama-V1 dataset.

Dataset Slice	Token Count
CommonCrawl	878B
C4	175B
GitHub	59B
Books	26B
ArXiv	28B
Wikipedia	24B
StackExchange	20B
Total	1.2T

3.1 Data Processing Steps

Here we describe our attempt to recreate the training corpus described in the LLaMa technical report [57]. The pretraining data of the LLaMA training corpus are drawn from seven datasets: English CommonCrawl, C4, GitHub, Wikipedia, Books (Project Gutenberg and Books3), ArXiv, and Stack Exchange. Each of these datasets are given a short (approximately one-paragraph) description in the LLaMA technical report, and there are some gaps in the dataset descriptions. In this section, we detail our process for recreating each of the individual datasets, highlight the gaps in the descriptions from the LLaMA technical report, and describe our choices in resolving those ambiguities. These steps together resulted in a dataset of approximately 1.2 Trillion tokens. Table 2 summarizes these datasets and the token counts. In Table 10 in the Appendix, we further list all uncertainties encountered during the construction of the dataset.

CommonCrawl. The LLaMA corpus includes five CommonCrawl snapshots from 2017 to 2020, processed using the CCNet pipeline [61]. CCNet deduplicates each snapshot in shards and assigns a quality classification to the data in each snapshot. It assigns a "head," "middle," and "tail" classification to each document based on the distribution of the perplexity assigned by a 5-gram Kneser-Ney model trained on Wikipedia. Here we only keep the "head" and "middle" buckets and discard the "tail." In addition, Touvron et. al. [57] use a linear classifier trained on Wikipedia reference articles to filter out low-quality documents. The LLaMA paper does not specify which snapshots were used in the dataset or give details on the classifier.

We select the five English CommonCrawl snapshots 2019-30, 2020-05, 2021-04, 2022-5, and 2023-06, representing the first snapshot in the five years preceding the start of the project. To train the Wikipedia reference classifier, we downloaded the most recent English Wikipedia snapshot available by April 1, 2023. We extract 38M URLs from the Wikipedia snapshot and crawl 300K pages. We then use the CCNet pipeline to apply a moderate cleaning step to the Wikipedia references and train a unigram classifier using fastText. Finally, we filter out all documents with scores less than 0.25, which reduces our CommonCrawl dataset to approximately the same size as the LLaMA CommonCrawl dataset.

C4. The LLaMA corpus includes the C4 dataset [46] to include diverse versions of CommonCrawl. We use the `c4_en` version of C4, which is provided by Allen AI on the Hugging Face Hub [2].

Github. The LLaMA corpus uses the public GitHub dataset available on Google BigQuery and keeps projects that are distributed under Apache, BSD, and MIT licenses. The LLaMA corpus additionally filters low-quality files using some heuristics and deduplicates at the file level. For RedPajama-V1, we remove low-quality files using a set of filters on file length, the proportion of alphanumeric characters, and file extensions. We provide the full list of heuristics in Appendix C.

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[2] `https://huggingface.co/datasets/allenai/c4`

Wikipedia. The LLaMA corpus uses Wikipedia dumps from June to August 2022 across 20 languages, processing the data to remove hyperlinks, comments, and other formatting boilerplate. For RedPajama-V1, we use the Wikipedia dataset available on Hugging Face Hub using the dump from 2023-03-20. This also preprocesses the data to remove hyperlinks, comments, and other boilerplate.

Gutenberg and Books3. The LLaMA corpus uses book corpora from the Gutenberg Project and Books3 from the Pile. We only use the PG19 subset of Gutenberg and use SimHash to remove near duplicates. We originally included Books3 as well but took it down due to copyright issues.

arXiv. The LLaMA corpus processes arXiv LaTeX files and removes everything before the first section, comments, inline-expanded definitions and macros, and the bibliography, following [29]. We downloaded arXiv data from Amazon S3 in the "arXiv" requester pays bucket and implemented a similar postprocessing, keeping only LaTeX source files and removing preambles, comments, bibliographies, and expanding macros.

Stack Exchange. The LLaMa corpus includes a dump of Stack Exchange. The data is kept from the 28 largest websites, HTML tags are removed from the text, and answers are sorted by score from highest to lowest. Similarly, we download Stack Exchange from the Internet Archive, keep only the posts from the 28 largest sites, and remove HTML tags. In addition, we group the posts into question-answer pairs and order answers by their scores.

3.2 The RedPajama-INCITE family of LLMs

To evaluate how well RedPajama-V1 matches the original LLaMA corpus, we train a family of LLMs of various sizes in collaboration with the Incite project on the Summit supercomputer at Oak Ridge National Lab. The RedPajama-Incite family of LLMs includes a suite of pretrained and instruction-tuned models at the 3B and 7B model sizes. In this section, we first describe the compute setup of the Summit supercomputer and the implications for the pretraining runs (Section 3.2.1). We then describe how we evaluate the model and speculate on differences in quality between these models and the LLaMA family (Section 3.2.2).

3.2.1 Summit Training Setup

In this section, we describe the Summit supercomputer and the engineering and pretraining challenges to training the RedPajama-Incite family of LLMs. Our language models were trained using the Summit supercomputer at Oak Ridge National Lab, a cluster containing 4608 6xV100 nodes running an IBM Power9 architecture. This setup introduced a few challenges in training modern LLMs. In the following, we discuss these challenges and describe how we overcame them.

The **IBM Power9 architecture** uses a different instruction set than most modern chipsets (i.e., Intel-, Arm-, or Apple-based chips). Modern versions of PyTorch and most of the Python stack they depend on are not pre-compiled to support the Power9 architecture (the latest version officially supported was PyTorch 1.9). To support pretraining with modern libraries, members of our team needed to recompile PyTorch from scratch and build a custom training stack for Summit. Some of these efforts are documented in more detail in the GPT-NeoX technical report [6].

As of this writing, the Summit supercomputer runs on **V100 GPUs**, which are older than A100 or H100 GPUs typically used to train LLMs. Critically, V100s do not support the bf16 data type, which is necessary for modern stable training recipes for LLMs. Instead, we had to train with fp16 and use loss scaling [37] to allow for stable training runs. We also had to lower the learning rate compared to those reported in the LLaMA training, which may have had an effect on convergence ($1.6 \cdot 10^{-4}$ for the 3B model and $1.2 \cdot 10^{-4}$ for the 7B model).

The IBM Power9 architecture had **slow interconnect**, limiting the number of nodes we could use for each run. We were also unable to use the entire cluster since other projects were running simultaneously on it. We used 512 nodes in parallel (3072 GPUs) to train the 7B and 256 nodes in parallel (1536 GPUs) to train the 3B, with a global batch size of 4M tokens for each model. In scaling experiments, we found that we could not further increase the amount of parallelism without increasing the global batch size, which would hurt convergence.

The **6xV100 nodes** introduce challenges for training with tensor and pipeline parallelism. We used 12-way pipeline parallelism for the 7B and 6-way for the 3B model, as well as 2-way tensor parallelism for both models.

After accounting for these challenges, we were able to train the 3B model for 800B tokens total and the 7B model for 1.001T tokens total on Summit. We decayed the learning rate linearly following a warmup period, matching those described in the original LLaMA paper.

3.2.2 Evaluation

Here, we discuss evaluations for the RedPajama-INCITE-3B and 7B models on common benchmarks. The full results and benchmark scores are provided in Appendix C.2. After training RedPajama-Base-INCITE-3B for 800B tokens, it has better few-shot performance (measured in HELM classic [9], as the average score over 16 core scenarios) and better zero-shot performance (measured using Eleuther AI's LM evaluation harness [18]) compared to other open models of similar size, including the well-regarded GPT-Neo and Pythia-2.8B (trained with 420B and 300B tokens, respectively, on the Pile). On HELM, it outperforms these models by 3-5 points. On a subset of tasks from LMevaluation harness, it outperforms these open models by 2-7 points.

The RedPajama-INCITE-7B-Base model is 1.0 points behind Falcon-7B and 4.1 points behind Llama-7B on HELM-classic. We further break down the tasks and see that they lag behind only on tasks that require using logprobs, which computes the difference between the probabilities of right and wrong answers. However, the model achieves comparable average HELM scores on tasks that directly generate answers and measure quality. Since all benchmarks in the LM harness use logprobs, we see similarly lower results for this benchmark. We hypothesize this was partly due to training with FP16, which does not allow us to use larger learning rates. Furthermore, as illustrated in the previous section, there were sources of uncertainty in the construction of the training dataset which likely resulted in a slightly different dataset than what was used to train the Llama-1 model. We believe that these two factors have led to the slightly lower performance compared to the Llama models.

RedPajama-INCITE-7B-Instruct is an instruction-tuned version of the base model optimized for few-shot performance by training on a diverse collection of NLP tasks from both P3 (BigScience) [49] and Natural Instructions (AI2) [39]. The Instruct version shows excellent performance on few-shot tasks, outperforming leading open models of similar sizes, including Llama-7B, Falcon-7B (both base and instruct version), and MPT-7B (both base and instruct version) on HELM by 2-8 points. We provide the detailed evaluation scores in the supplementary material.

4 RedPajama-V2

In contrast to the first iteration of the RedPajama dataset, the second iteration focuses exclusively on web data and, in addition to design principles *Transparency* and *Scale*, we also put a higher emphasis on *Versatility*. Specifically, next to the goals of providing a fully transparent and open dataset, the purpose of the corpus is to serve as a foundation for creating high quality subsets. While the goal of transparency is achieved by making the dataset and its artifacts publicly available, and scale is achieved by processing large parts of the Common Crawl corpus, to follow the design principle *Versatility*, we release RedPajama V2 as a dataset that is enriched with a set of metadata that enables fast and cheap iteration for creating high quality, diverse and large datasets. In this section, we first present the data processing steps used to create the raw text data, give an overview over the quality signals available for each document, and present statistics on the dataset composition. Finally, we present ablation studies on how the quality signals can be used to create successively better datasets.

4.1 Data Processing Steps

RedPajama-V2 is a dataset created by processing web documents provided by the CommonCrawl foundation[3]. As web data is inherently noisy and only available as text embedded in the HTML code, it is necessary to process it to make it suitable for training LLMs. To that end, the raw data used for RedPajama-V2 undergoes a series of basic processing steps, which we explain in more detail.

4.1.1 Data Acquisition

The Common Crawl Archive is a vast repository of web crawl data that is freely available to the public. The corpus contains crawling results since 2013 and is updated regularly on a (bi-) monthly

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[3] `https://commoncrawl.org/`

basis. Next to raw web data in HTML (`warc`) format, the archive also provides metadata (`wat`) and plain text data in the `wet` format. It has been the basis for numerous datasets including C4 [46], RefinedWeb [44], Dolma [52], and FineWeb [43] among others.

To create the RedPajama-V2 dataset, we used the web-extracted text (i.e., `.wet` files) from all 84 monthly snapshots between 2014 and April 2023 and passed it through the CCNet pipeline [61]. In contrast to RPv1, here we keep all perplexity buckets, and in addition to the English language, we also keep French, German, Italian, and Spanish data. We chose this pipeline due to its light processing, which aligns with our guiding principle of preserving as much information in the raw dataset as possible and allowing downstream model developers to filter the dataset. This processing step produces over 100 billion individual text documents.

4.1.2 Quality Signals

A central ingredient to state-of-the-art open LLMs like Llama [57, 58], Mistral [22], Falcon [2], MPT [53], or the Qwen [3] models is the large amount of high-quality data that these models are trained on. For example, Llama 3 is trained on 15 trillion carefully curated tokens. The most prominent data sources that provide the necessary scale are the crawls made publicly available by CommonCrawl. However, this raw text, which in our case is additionally processed by the CCNet pipeline, is still not ideal for direct use as LLM training data due to artifacts arising from the conversion from HTML to plain text (e.g., parsing errors, and menus), sources of generally low quality, and biases inherent to the distribution of content on the web. To clean such datasets, the literature has proposed a multitude of heuristics to extract high-quality datasets out of large corpora of heterogeneous web data. However, unlike previous datasets that filter out low-quality content, our approach retains the entire raw text corpus, incorporating quality signals as additional metadata. This strategy allows us to use the full spectrum of data, transforming sections typically discarded into informative attributes that enhance our dataset's utility. This enables the creation of other datasets such as C4 as special cases of the RedPajama-V2 dataset. For each document, we provide the quality signals used in C4 [46], Gopher [45], RefinedWeb [44], the Pretrainer's Guide [34] and DSIR [62]. These can roughly be categorized into quality signals which measure *natural language*, the *repetiveness* of the text, are based on the *content* of the text, *ML-based* heuristics, and *deduplication*. In the following, we explain each of these categories in detail. A comprehensive list with detailed descriptions encompassing all quality signals, as well as histograms is provided in Appendix D.2.

Natural Language. Text documents extracted from websites often have content that does not correspond to natural language, such as JavaScript code, menus, and other boilerplate text. To measure how natural a given text document is, we provide simple heuristic measures such as the fraction of all caps words or letters, the fraction of lines that end with an ellipsis, the fraction of unique words, whether or not a line ends in a terminal punctuation mark, and others.

Repetitiveness. An often observed artifact of web data is repetitive text, which has been linked with uninformative content [45]. Repetitious generations are also a known failure mode of language models [21], and removing excessively repetitive content can potentially contribute to alleviating this behavior [45]. For each document, we calculate the fraction of characters appearing in the most frequent (word) n-gram for $n \in \{2, 3, 4\}$. Second, we calculate the fraction of characters appearing in any duplicated n-gram for values of $n \in \{5, \ldots, 10\}$. We ensure not to count characters that appear in overlapping n-grams more than once.

Content-based. Web documents can contain harmful and offensive content, which needs to be addressed. To that end we provide the signals used in C4 and RefinedWeb, namely, (1) the number of sequences of words that are contained in the LDNOOBW blocklist[4]. In addition, we include a flag which indicates whether the domain of the document appears in the UT1 list of blocked urls[5]. While these quality signals focus on NSFW content, we believe other content-based filters such as domains or embedding clusters [55] are also promising directions. In Figure 8 in the Appendix, we show the distribution of topics found via clustering of embeddings.

ML Heuristics. ML-based quality signals revolve around the idea of measuring similarity to a high-quality domain. Here, we use fastText classifiers [24], and the importance weights proposed in [62]. While ML filters have been shown to improve the quality of datasets (e.g., [12, 57, 11]), they

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[4]`https://github.com/LDNOOBW/List-of-Dirty-Naughty-Obscene-and-Otherwise-Bad-Words`
[5]`https://dsi.ut-capitole.fr/blacklists/`

Table 3: Document and token counts for each partition and language of the RPv2 dataset.

	All		tail		head+middle		head+middle (dedupe)	
	docs (B)	tokens (T)	docs (B)	tokens (T)	docs (B)	tokens (T)	docs (B)	tokens (T)
English	87.5	90.5	63.0	53.6	24.5	37.0	14.5	20.5
German	8.6	10.3	5.9	6.2	2.7	4.1	1.9	3.0
French	6.7	8.5	4.5	4.8	2.2	3.7	1.6	2.7
Spanish	6.9	9.5	4.7	5.6	2.3	3.9	1.8	2.8
Italian	3.5	4.7	2.4	2.7	1.2	1.9	0.9	1.5
Total	113.3	123.7	80.5	73.0	32.8	50.7	20.8	30.4

have also been reported to lead to biases or underrepresent minorities [15]. The fastText classifier signals provided in RPv2 are unigram bag-of-word models trained to distinguish between unfiltered RPv2 data and a high-quality domain. For English data, we use Wikipedia, websites referenced by Wikipedia, books, and the OpenWebText dataset. For non-English data, we only use Wikipedia. The DSIR weights proposed in [62] estimate the importance of individual samples to a given target domain in a reduced feature space and are based on word unigrams and bigram models. The weights are defined as the log-likelihood ratio between a language model of the target vs. the source domain, where we use the same domains as for the fasttext classifiers.

Deduplication. Removing duplicated training data has been found to improve model perplexity and reduce the amount of memorization while reducing the training data size and the required compute [28]. Deduplication is also one of the core building blocks of the most popular datasets [46, 52, 44]. In RPv2, we include MinHash signatures for fuzzy deduplication [10] at different similarity levels, as well as IDs of documents found to be exact duplicates via a Bloom filter [7] with the error rate set to 1%[6]. For this document-level deduplication, we proceed sequentially, starting with the most recent dump (2023-14) and successively iterating over the following dumps until we reach the oldest one (2014-15). An overview over how many documents were flagged as duplicates in this manner, can be seen in Figure 3 in the Appendix.

4.2 Dataset Statistics

RPv2 consists of 113B documents in five different languages: English, German, French, Spanish and Italian. As mentioned previously, the CCNet pipeline partitions the dataset into the tree buckets "head", "middle", and "tail" corresponding to documents with low, medium, and high Wikipedia perplexity. There are 32.8B documents in the `head+middle` partition and 80B documents in the `tail` partition. Documents in the `tail` are typically shorter (850 tokens) than in the `head` and `middle` buckets ($\sim$ 1500 tokens). Token counts were estimated based on an i.i.d. sample of 100M documents using the Mistral [22] BPE tokenizer. A detailed overview of token counts for each language and partition is given in Table 3. We provide further statistics on the number of documents before and after deduplication, as well as the distribution of quality signals in the supplementary materials.

4.3 Dataset Ablations

Here we present a series of dataset ablations with the aim of developing a better understanding of how the quality signals introduced in Section 4.1.2 influence the downstream performance of language models trained on data filtered with different heuristics. More specifically, here we ask *how do different quality filtering rules affect downstream performance?* We strive for a broad evaluation and measure the performance on diverse downstream benchmarks and the language modeling objective on multiple domains.

4.3.1 Setup

Models. We adopt decoder-only Llama-2 architectures [58] with 468M parameters and 1.6B parameters and 2048 sequence length. Both models have 24 layers, 16 attention heads and the MLP

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[6]We remark that exact deduplication was performed based on the hashes of the `.wet` documents, i.e., prior to processing the data with CCNet.

Table 5: Evaluations for the 468M parameter LM for different dataset filters and other SOTA web datasets. The Benchmark scores are aggregated from the benchmarks outlined in Table 3, using (1) the average accuracy, (2) the Rank-Score, and (3) the normalized average score. The best score is indicated in **<u>bold underlined</u>** font, the second-best is **bolded**, and the third is in *<u>italics underlined</u>*.

Dataset	Deduplication		Rule-based		ML Heuristics			Agg. BM-Eval (↑)			Val-Perplexity (↓)	
	Exact	Fuzzy	C4	Gopher	Classif.	DSIR	PPL	Avg.	Norm. Avg.	Rank-Score	Pile	Paloma
C4								35.8	0.140	0.472	29.5	39.5
Dolma-v1.7 CC								36.0	0.140	0.511	21.4	38.3
FineWeb								36.5	0.146	*<u>0.644</u>*	26.8	33.6
RefinedWeb								**<u>37.9</u>**	**<u>0.165</u>**	**0.650**	*<u>19.1</u>*	*<u>32.8</u>*
RPv1-CC	✔(sharded)				✔ (Wiki-Ref.)			35.6	0.127	0.461	18.7	31.5
RPv2 (2023-14)	✔							36.4	0.141	0.594	19.7	**<u>31.1</u>**
RPv2 (2023-14)		✔						36.2	0.138	0.472	19.5	39.9
RPv2 (2023-14)		✔	✔	✔ (full)				**37.6**	**0.160**	**<u>0.700</u>**	24.9	34.5
RPv2 (2023-14)		✔	✔					36.8	0.150	0.622	36.3	56.9
RPv2 (2023-14)		✔		✔ (natlang)			Wiki-middle	37.2	0.154	0.639	23.6	38.2
RPv2 (2023-14)		✔		✔ (Rep.)			Wiki-middle	*<u>37.5</u>*	*<u>0.158</u>*	0.633	20.4	36.0
RPv2 (9 Dumps)		✔	✔					35.3	0.128	0.517	35.0	54.2
RPv2 (9 Dumps)		✔	✔	✔ (full)				36.7	0.149	0.556	43.8	63.9
RPv2 (9 Dumps)		✔	✔	✔ (Rep.)		✔ (Palm-mix)		35.9	0.138	0.439	44.3	89.9
RPv2 (9 Dumps)		✔	✔	✔ (Rep.)	✔ (Palm-mix)			35.9	0.139	0.483	43.8	67.1
RPv2 (9 Dumps)		✔	✔	✔ (natlang)	✔ (Palm-mix)			36.7	0.152	0.550	41.8	67.9
RPv2 (9 Dumps)		✔	✔ (line-filter)	✔ (natlang)	✔ (Palm-mix)			36.4	0.144	0.539	32.4	52.9
RPv2 (9 Dumps)		✔	custom-rules		✔ (Wiki-Ref.)		$P_{wiki} > 30$	35.8	0.130	0.467	**<u>18.5</u>**	39.7
RPv2 (9 Dumps)		✔	custom-rules + Gopher-Rep.		✔ (Wiki-Ref.)		$P_{wiki} > 30$	35.9	0.133	0.500	19.8	45.8

expansion ratio set to 4.0. The 468M has 1024 hidden dimension, while for the 1.6B we use 2048. For each dataset, we train the 468M model on 100B tokens and the 1.6B model on 350B tokens. We use the AdamW [14] optimizer with the weight decay of 0.1, a maximum learning rate set to $5e-3$ and $5e-4$ respectively, and a cosine decay schedule with linear warmup during the first 1% of steps. We use relatively small scales, as this enables us to explore a wider range of filters, showing the breadth of the quality filters available in RedPajama.

Hardware and Training Stack. Due to its ease of setup, use, and high model flops utilization, we use the OLMo framework[7] for distributed training, using FSDP [66] for parallelization across multiple GPUs and nodes. For evaluation, we use the lm-evaluation-harness. We train our models on up to 5 H100 nodes with Infiniband interconnect.

Evaluation Metrics. We strive for broad coverage of benchmarks and domains. At the same time, we are operating at a relatively small scale, where many tasks are too hard to provide a high enough signal to distinguish datasets.

Similar to the FineWeb [43] dataset, we look for benchmarks that provide a high enough signal-to-noise ratio, even at this small model scale. After careful consideration, we settled for the choice of benchmarks in Table 4. Here we present aggregated scores by (1) computing the average over benchmarks, (2) the normalized average, and (3) the normalized sum of ranks for each data recipe. We chose to include the latter to avoid averaging over scores with different scales. More detailed scores are provided in the supplementary materials. To rank datasets based on the Perplexity of target domains, we follow the approach taken in Dolma [52] and adopt the Paloma [35] and Pile [17] validation sets.

Table 4: Benchmarks used in our ablations. The column "Agg. BM-Eval" indicates whether the score is used in the aggregate scores reported in Tables 5 and 6.

Task	Type	Random	Metric	Agg. BM-Eval
ANLI [40]	Natural language inference	25.0	acc	
ARC-c [13]	Natural language inference	25.0	acc_norm	✔
ARC-e [13]	Natural language inference	25.0	acc_norm	✔
Winogrande [48]	Coreference resolution	50.0	acc	✔
Hellaswag [64]	Sentence completion	25.0	acc_norm	✔
LAMBADA [42]	Sentence completion	0.0	acc	✔
CoQA [47]	Conversational QA	0.0	F1	✔
MMLU [20]	Multiple-choice QA	25.0	acc	✔
OpenbookQA [38]	Multiple-choice QA	25.0	acc_norm	✔
PIQA [5]	Multiple-choice QA	50.0	acc_norm	✔
PubMedQA [23]	Multiple-choice QA	33.3	acc	✔
SciQ [60]	Multiple-choice QA	25.0	acc_norm	✔
SocialIQA [50]	Multiple-choice QA	25.0	acc	
TruthfulQA [33]	Multiple-choice QA	25.0	acc	

4.3.2 Results

We start by using the quality signals to implement some of the most widely used filters in the literature. In addition, we also investigate ML heuristics available in RPv2, which are based on fastText bag of n-gram classifiers [24] and DSIR importance weights [62]. We run ablations on two subsets of RPv2, namely on the 2023-14 crawl and on the 9 crawls from 2021-49 to 2023-14, which were deduplicated using MinHash LSH on word 13-grams, with 128 hash functions, 9 bands and 13 rows. For the 1.6B

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[7]https://github.com/allenai/OLMo

Table 6: Aggregated evaluations for the 1.6B parameter LM for different datasets. The Benchmark scores are aggregated from the benchmarks outlined in Table 4, using (1) the average accuracy, (2) the Rank-Score, and (3) the normalized average score.

Dataset	Fuzzy Deduplication	Rule-based		ML Heuristics		Agg. BM-Eval (↑)			Val-Perplexity (↓)	
		C4	Gopher	Palm Classif.	Wiki-Ref Classif.	Avg.	Norm. Avg.	Rank-Score	Pile	Paloma
RefinedWeb						52.0	34.0	0.139	10.7	17.7
RPv2 (full)	✔		✔		✔	50.0	31.1	0.106	13.6	20.8
RPv2 (full)	✔	✔	✔(natlang)	✔		47.9	29.4	0.089	22.2	30.7

ablations, we filter the full RPv2 dataset, then sample roughly 1T tokens and deduplicate it with the same Minhash hyperparameters.

Filters. We seek to cover a wide range of quality filtering configurations. Rather than optimizing the performance on a particular benchmark, the goal is to show that filtering the RPv2 dataset in different ways can lead to wildly different model performance. We thus experiment with variations of the C4 and Gopher rules and also use the ML-based quality signals in RPv2. We also use a custom configuration `custom-rules` based on word counts, average line length, Wikipedia Perplexity and the Wikipedia References classifier.

Results. From Table 5, we can draw a series of conclusions on filtering the RedPajama-V2 dataset. *First*, we can see that the Gopher rules generally improve performance. In particular we see that fuzzy deduplication and filtering with Gopher has the highest aggregated scores across all RPv2 datasets. In addition, both the average and normalized average benchmark score is only second to RefinedWeb, while the rank-score is higher than for RefinedWeb. The per-benchmark tables 18, 19, and 20 in the Appendix, show that the RPv2 dataset filtered with fuzzy deduplication and Gopher is always in the upper middle (minimum rank score 9 of 19), while RefinedWeb is performing worse on Hellaswag, LAMBADA, Winogrande, MMLU and OpenBookQA. This indicates that filtering RPv2 with the full Gopher rules and fuzzy deduplication (Minhash LSH) creates a dataset that performs well across a wider range of tasks than all other datasets. *Second*, we can see that the Gopher-natlang filters perform better than the Gopher-repetition filters. *Third*, in the context of model based filtering, we see no significant difference between using a fasttext classifier and DSIR. *Fourth*, using only the line-level C4 filters appears to reduce perplexity, but has negligible effect on the aggregated benchmark scores. Finally, we notice that the unfiltered RPv2 2023-14 dataset appears to have the lowest perplexity on the Paloma dataset, while other filtering methods lead to models with higher perplexity. We believe that this can (at least in part) be attributed to the wide range of domains covered by Paloma. In addition, Paloma also contains the RPv1 dataset, which can explain the low Perplexity score obtained by the model trained on RPv1-CC. Table 6 shows further that the model trained on RPv2 filtered with the full Gopher rules outperforms the model trained on RPv2 filtered with only the Gopher-natlang rules, and comes close to the quality of a model trained on the RefinedWeb dataset. In conclusion, this series of ablation studies shows how the quality signals in the RPv2 dataset can be used to successively filter better datasets. In combination with its vast scale of over 100T tokens, we see that this dataset provides a powerful source for creating high-quality web datasets for LLM pretraining.

5 Conclusion

In this paper, we have presented the RedPajama datasets. With over 100 Trillion tokens, these are the largest, fully open, and transparent datasets for pretraining language models and have been a central building block for many of the strongest open-source LLMs. Next to documentation accompanying the datasets, we have also shown examples of how RedPajama-V2 can be filtered down to successively higher quality subsets, leading to language models of varying levels of quality on a diverse set of benchmark tasks and outperforming models trained on other large-scale pretraining corpora. While the models are relatively small and enabled us to explore a wider variety of filters, it is also a limitation and further, larger-scale explorations are required. We did not explore a thorough decontamination analysis against common benchmarks or an analysis of personally identifiable information present in the dataset, posing another limitation of this work. By publishing the RedPajama-V2 dataset in raw, unfiltered form, but accompanied by a set of quality signals, we hope that future work will continue to build on RedPajama and provide new innovative ways of filtering, curating, and mixing multiple pretraining corpora.

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References

[1] Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.

[2] Ebtesam Almazrouei, Hamza Alobeidli, Abdulaziz Alshamsi, Alessandro Cappelli, Ruxandra Cojocaru, Mérouane Debbah, Étienne Goffinet, Daniel Hesslow, Julien Launay, Quentin Malartic, et al. The falcon series of open language models. *arXiv preprint arXiv:2311.16867*, 2023.

[3] Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, et al. Qwen technical report. *arXiv preprint arXiv:2309.16609*, 2023.

[4] Stella Biderman, Hailey Schoelkopf, Quentin Gregory Anthony, Herbie Bradley, Kyle O'Brien, Eric Hallahan, Mohammad Aflah Khan, Shivanshu Purohit, USVSN Sai Prashanth, Edward Raff, et al. Pythia: A suite for analyzing large language models across training and scaling. In *International Conference on Machine Learning*, pages 2397–2430. PMLR, 2023.

[5] Yonatan Bisk, Rowan Zellers, Ronan Le Bras, Jianfeng Gao, and Yejin Choi. Piqa: Reasoning about physical commonsense in natural language. In *Thirty-Fourth AAAI Conference on Artificial Intelligence*, 2020.

[6] Sid Black, Stella Biderman, Eric Hallahan, Quentin Anthony, Leo Gao, Laurence Golding, Horace He, Connor Leahy, Kyle McDonell, Jason Phang, et al. Gpt-neox-20b: An open-source autoregressive language model. *arXiv preprint arXiv:2204.06745*, 2022.

[7] Burton H Bloom. Space/time trade-offs in hash coding with allowable errors. *Communications of the ACM*, 13(7):422–426, 1970.

[8] Rishi Bommasani, Kevin Klyman, Shayne Longpre, Sayash Kapoor, Nestor Maslej, Betty Xiong, Daniel Zhang, and Percy Liang. The foundation model transparency index. *arXiv preprint arXiv:2310.12941*, 2023.

[9] Rishi Bommasani, Percy Liang, and Tony Lee. Holistic evaluation of language models. *Annals of the New York Academy of Sciences*, 1525(1):140–146, 2023.

[10] Andrei Z Broder. On the resemblance and containment of documents. In *Proceedings. Compression and Complexity of SEQUENCES 1997 (Cat. No. 97TB100171)*, pages 21–29. IEEE, 1997.

[11] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020.

[12] Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. Palm: Scaling language modeling with pathways. *Journal of Machine Learning Research*, 24(240):1–113, 2023.

[13] Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. Think you have solved question answering? try arc, the ai2 reasoning challenge. *ArXiv*, abs/1803.05457, 2018.

[14] P Kingma Diederik. Adam: A method for stochastic optimization. 2014.

[15] Jesse Dodge, Maarten Sap, Ana Marasović, William Agnew, Gabriel Ilharco, Dirk Groeneveld, Margaret Mitchell, and Matt Gardner. Documenting large webtext corpora: A case study on the colossal clean crawled corpus. *arXiv preprint arXiv:2104.08758*, 2021.

[16] Nan Du, Yanping Huang, Andrew M Dai, Simon Tong, Dmitry Lepikhin, Yuanzhong Xu, Maxim Krikun, Yanqi Zhou, Adams Wei Yu, Orhan Firat, et al. Glam: Efficient scaling of language models with mixture-of-experts. In *International Conference on Machine Learning*, pages 5547–5569. PMLR, 2022.

[17] Leo Gao, Stella Biderman, Sid Black, Laurence Golding, Travis Hoppe, Charles Foster, Jason Phang, Horace He, Anish Thite, Noa Nabeshima, et al. The pile: An 800gb dataset of diverse text for language modeling. *arXiv preprint arXiv:2101.00027*, 2020.

[18] Leo Gao, Jonathan Tow, Baber Abbasi, Stella Biderman, Sid Black, Anthony DiPofi, Charles Foster, Laurence Golding, Jeffrey Hsu, Alain Le Noac'h, Haonan Li, Kyle McDonell, Niklas Muennighoff, Chris Ociepa, Jason Phang, Laria Reynolds, Hailey Schoelkopf, Aviya Skowron, Lintang Sutawika, Eric Tang, Anish Thite, Ben Wang, Kevin Wang, and Andy Zou. A framework for few-shot language model evaluation, 07 2024.

[19] Dirk Groeneveld, Iz Beltagy, Pete Walsh, Akshita Bhagia, Rodney Kinney, Oyvind Tafjord, Ananya Harsh Jha, Hamish Ivison, Ian Magnusson, Yizhong Wang, et al. Olmo: Accelerating the science of language models. *arXiv preprint arXiv:2402.00838*, 2024.

[20] Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. Measuring massive multitask language understanding. *Proceedings of the International Conference on Learning Representations (ICLR)*, 2021.

[21] Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. The curious case of neural text degeneration. *arXiv preprint arXiv:1904.09751*, 2019.

[22] Albert Q Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, et al. Mistral 7b. *arXiv preprint arXiv:2310.06825*, 2023.

[23] Qiao Jin, Bhuwan Dhingra, Zhengping Liu, William Cohen, and Xinghua Lu. Pubmedqa: A dataset for biomedical research question answering. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 2567–2577, 2019.

[24] Armand Joulin, Edouard Grave, Piotr Bojanowski, and Tomas Mikolov. Bag of tricks for efficient text classification. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers*, pages 427–431. Association for Computational Linguistics, April 2017.

[25] Denis Kocetkov, Raymond Li, Loubna Ben Allal, Jia Li, Chenghao Mou, Carlos Muñoz Ferrandis, Yacine Jernite, Margaret Mitchell, Sean Hughes, Thomas Wolf, Dzmitry Bahdanau, Leandro von Werra, and Harm de Vries. The stack: 3 tb of permissively licensed source code. *Preprint*, 2022.

[26] Hugo Laurençon, Lucile Saulnier, Thomas Wang, Christopher Akiki, Albert Villanova del Moral, Teven Le Scao, Leandro Von Werra, Chenghao Mou, Eduardo González Ponferrada, Huu Nguyen, et al. The bigscience roots corpus: A 1.6 tb composite multilingual dataset. *Advances in Neural Information Processing Systems*, 35:31809–31826, 2022.

[27] Teven Le Scao, Angela Fan, Christopher Akiki, Ellie Pavlick, Suzana Ilić, Daniel Hesslow, Roman Castagné, Alexandra Sasha Luccioni, François Yvon, Matthias Gallé, et al. Bloom: A 176b-parameter open-access multilingual language model. 2023.

[28] Katherine Lee, Daphne Ippolito, Andrew Nystrom, Chiyuan Zhang, Douglas Eck, Chris Callison-Burch, and Nicholas Carlini. Deduplicating training data makes language models better. *arXiv preprint arXiv:2107.06499*, 2021.

[29] Aitor Lewkowycz, Anders Andreassen, David Dohan, Ethan Dyer, Henryk Michalewski, Vinay Ramasesh, Ambrose Slone, Cem Anil, Imanol Schlag, Theo Gutman-Solo, et al. Solving quantitative reasoning problems with language models. *Advances in Neural Information Processing Systems*, 35:3843–3857, 2022.

[30] Jeffrey Li, Alex Fang, Georgios Smyrnis, Maor Ivgi, Matt Jordan, Samir Gadre, Hritik Bansal, Etash Guha, Sedrick Keh, Kushal Arora, et al. Datacomp-lm: In search of the next generation of training sets for language models. *arXiv preprint arXiv:2406.11794*, 2024.

[31] Raymond Li, Loubna Ben Allal, Yangtian Zi, Niklas Muennighoff, Denis Kocetkov, Chenghao Mou, Marc Marone, Christopher Akiki, Jia Li, Jenny Chim, et al. Starcoder: may the source be with you! *arXiv preprint arXiv:2305.06161*, 2023.

[32] Zehan Li, Xin Zhang, Yanzhao Zhang, Dingkun Long, Pengjun Xie, and Meishan Zhang. Towards general text embeddings with multi-stage contrastive learning. *arXiv preprint arXiv:2308.03281*, 2023.

[33] Stephanie Lin, Jacob Hilton, and Owain Evans. Truthfulqa: Measuring how models mimic human falsehoods, 2021.

[34] Shayne Longpre, Gregory Yauney, Emily Reif, Katherine Lee, Adam Roberts, Barret Zoph, Denny Zhou, Jason Wei, Kevin Robinson, David Mimno, et al. A pretrainer's guide to training data: Measuring the effects of data age, domain coverage, quality, & toxicity. *arXiv preprint arXiv:2305.13169*, 2023.

[35] Ian Magnusson, Akshita Bhagia, Valentin Hofmann, Luca Soldaini, Ananya Harsh Jha, Oyvind Tafjord, Dustin Schwenk, Evan Pete Walsh, Yanai Elazar, Kyle Lo, et al. Paloma: A benchmark for evaluating language model fit. *arXiv preprint arXiv:2312.10523*, 2023.

[36] Sachin Mehta, Mohammad Hossein Sekhavat, Qingqing Cao, Maxwell Horton, Yanzi Jin, Chenfan Sun, Iman Mirzadeh, Mahyar Najibi, Dmitry Belenko, Peter Zatloukal, et al. Openelm: An efficient language model family with open-source training and inference framework. *arXiv preprint arXiv:2404.14619*, 2024.

[37] Paulius Micikevicius, Sharan Narang, Jonah Alben, Gregory Diamos, Erich Elsen, David Garcia, Boris Ginsburg, Michael Houston, Oleksii Kuchaiev, Ganesh Venkatesh, et al. Mixed precision training. *arXiv preprint arXiv:1710.03740*, 2017.

[38] Todor Mihaylov, Peter Clark, Tushar Khot, and Ashish Sabharwal. Can a suit of armor conduct electricity? a new dataset for open book question answering. In *EMNLP*, 2018.

[39] Swaroop Mishra, Daniel Khashabi, Chitta Baral, and Hannaneh Hajishirzi. Cross-task generalization via natural language crowdsourcing instructions. In *ACL*, 2022.

[40] Yixin Nie, Adina Williams, Emily Dinan, Mohit Bansal, Jason Weston, and Douwe Kiela. Adversarial nli: A new benchmark for natural language understanding. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. Association for Computational Linguistics, 2020.

[41] Nomic. Structure unstructured data: Interact, discover insights and build with unstructured text, image and audio data., 2024. Accessed: 2024-06-12.

[42] Denis Paperno, Germán Kruszewski, Angeliki Lazaridou, Ngoc Quan Pham, Raffaella Bernardi, Sandro Pezzelle, Marco Baroni, Gemma Boleda, and Raquel Fernandez. The LAMBADA dataset: Word prediction requiring a broad discourse context. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1525–1534, Berlin, Germany, August 2016. Association for Computational Linguistics.

[43] Guilherme Penedo, Hynek Kydlíček, Anton Lozhkov, Margaret Mitchell, Colin Raffel, Leandro Von Werra, Thomas Wolf, et al. The fineweb datasets: Decanting the web for the finest text data at scale. *arXiv preprint arXiv:2406.17557*, 2024.

[44] Guilherme Penedo, Quentin Malartic, Daniel Hesslow, Ruxandra Cojocaru, Hamza Alobeidli, Alessandro Cappelli, Baptiste Pannier, Ebtesam Almazrouei, and Julien Launay. The refinedweb dataset for falcon llm: Outperforming curated corpora with web data only. *Advances in Neural Information Processing Systems*, 36, 2024.

[45] Jack W Rae, Sebastian Borgeaud, Trevor Cai, Katie Millican, Jordan Hoffmann, Francis Song, John Aslanides, Sarah Henderson, Roman Ring, Susannah Young, et al. Scaling language models: Methods, analysis & insights from training gopher. *arXiv preprint arXiv:2112.11446*, 2021.

[46] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of machine learning research*, 21(140):1–67, 2020.

[47] Siva Reddy, Danqi Chen, and Christopher D Manning. Coqa: A conversational question answering challenge. *Transactions of the Association for Computational Linguistics*, 7:249–266, 2019.

[48] Keisuke Sakaguchi, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. Winogrande: an adversarial winograd schema challenge at scale. *Commun. ACM*, 64(9):99–106, aug 2021.

[49] Victor Sanh, Albert Webson, Colin Raffel, Stephen H. Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Teven Le Scao, Arun Raja, Manan Dey, M Saiful Bari, Canwen Xu, Urmish Thakker, Shanya Sharma Sharma, Eliza Szczechla, Taewoon Kim, Gunjan Chhablani, Nihal Nayak, Debajyoti Datta, Jonathan Chang, Mike Tian-Jian Jiang, Han Wang, Matteo Manica, Sheng Shen, Zheng Xin Yong, Harshit Pandey, Rachel Bawden, Thomas Wang, Trishala Neeraj, Jos Rozen, Abheesht Sharma, Andrea Santilli, Thibault Fevry, Jason Alan Fries, Ryan Teehan, Stella Biderman, Leo Gao, Tali Bers, Thomas Wolf, and Alexander M. Rush. Multitask prompted training enables zero-shot task generalization, 2021.

[50] Maarten Sap, Hannah Rashkin, Derek Chen, Ronan LeBras, and Yejin Choi. Socialiqa: Commonsense reasoning about social interactions. *arXiv preprint arXiv:1904.09728*, 2019.

[51] Zhiqiang Shen, Tianhua Tao, Liqun Ma, Willie Neiswanger, Joel Hestness, Natalia Vassilieva, Daria Soboleva, and Eric Xing. Slimpajama-dc: Understanding data combinations for llm training. *arXiv preprint arXiv:2309.10818*, 2023.

[52] Luca Soldaini, Rodney Kinney, Akshita Bhagia, Dustin Schwenk, David Atkinson, Russell Authur, Ben Bogin, Khyathi Chandu, Jennifer Dumas, Yanai Elazar, et al. Dolma: An open corpus of three trillion tokens for language model pretraining research. *arXiv preprint arXiv:2402.00159*, 2024.

[53] MosaicML NLP Team. Introducing mpt-7b: A new standard for open-source, commercially usable llms, 2023. Accessed: 2023-05-05.

[54] Snowflake AI Research Team. Snowflake arctic: The best llm for enterprise ai — efficiently intelligent, truly open, 2023. Accessed: 2024-05-27.

[55] Kushal Tirumala, Daniel Simig, Armen Aghajanyan, and Ari Morcos. D4: Improving llm pretraining via document de-duplication and diversification. *Advances in Neural Information Processing Systems*, 36, 2024.

[56] Yury Tokpanov, Beren Millidge, Paolo Glorioso, Jonathan Pilault, Adam Ibrahim, James Whittington, and Quentin Anthony. Zyda: A 1.3t dataset for open language modeling, 2024.

[57] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*, 2023.

[58] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.

[59] Ben Wang and Aran Komatsuzaki. GPT-J-6B: A 6 Billion Parameter Autoregressive Language Model. https://github.com/kingoflolz/mesh-transformer-jax, May 2021.

[60] Johannes Welbl, Nelson F Liu, and Matt Gardner. Crowdsourcing multiple choice science questions. *arXiv preprint arXiv:1707.06209*, 2017.

[61] Guillaume Wenzek, Marie-Anne Lachaux, Alexis Conneau, Vishrav Chaudhary, Francisco Guzmán, Armand Joulin, and Edouard Grave. Ccnet: Extracting high quality monolingual datasets from web crawl data. *arXiv preprint arXiv:1911.00359*, 2019.

[62] Sang Michael Xie, Shibani Santurkar, Tengyu Ma, and Percy S Liang. Data selection for language models via importance resampling. *Advances in Neural Information Processing Systems*, 36:34201–34227, 2023.

[63] Linting Xue, Noah Constant, Adam Roberts, Mihir Kale, Rami Al-Rfou, Aditya Siddhant, Aditya Barua, and Colin Raffel. mT5: A massively multilingual pre-trained text-to-text transformer. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 483–498, Online, June 2021. Association for Computational Linguistics.

[64] Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. Hellaswag: Can a machine really finish your sentence? In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 2019.

[65] Ge Zhang, Scott Qu, Jiaheng Liu, Chenchen Zhang, Chenghua Lin, Chou Leuang Yu, Danny Pan, Esther Cheng, Jie Liu, Qunshu Lin, et al. Map-neo: Highly capable and transparent bilingual large language model series. *arXiv preprint arXiv:2405.19327*, 2024.

[66] Yanli Zhao, Andrew Gu, Rohan Varma, Liang Luo, Chien-Chin Huang, Min Xu, Less Wright, Hamid Shojanazeri, Myle Ott, Sam Shleifer, et al. Pytorch fsdp: experiences on scaling fully sharded data parallel. *arXiv preprint arXiv:2304.11277*, 2023.

A Intended Uses

The RedPajama datasets were created with the primary use case of providing training data for large language models. RedPajama contains data from different sources and domains. RedPajama-V1 contains data obtained from web scrapes, Wikipedia articles, scientific content extracted from articles available on arXiv, as well as code from various programming languages. RedPajama-V2 contains data exclusively based on web scrapes and is accompanied by a series of quality signals that are intended to be used for filtering the raw dataset.

B Dataset Accessibility

Both RedPajama-V1 and RedPajama-V2 are available for download via the Huggingface Hub at `https://huggingface.co/datasets/togethercomputer/RedPajama-Data-1T` and `https://huggingface.co/datasets/togethercomputer/RedPajama-Data-V2`.

Access via public HTTP endpoints. We also provide access to the datasets via public HTTPS endpoints. The list of urls for components of the RedPajama-V1 dataset can be obtained from `https://data.together.xyz/redpajama-data-1T/v1.0.0/urls.txt`. The list of urls for the different components of RedPajama-V2 can be obtained from the following urls:

- Raw text documents can be obtained from `https://data.together.xyz/redpajama-data-v2/v1.0.0/urls/document-urls.txt`
- Quality signals for the `head` and `middle` partitions can be obtained from `https://data.together.xyz/redpajama-data-v2/v1.0.0/urls/quality_signals-urls.txt`
- The list of document ids which are exact duplicates can be obtained from `https://data.together.xyz/redpajama-data-v2/v1.0.0/urls/duplicates-urls.txt`
- The minhash signatures can be obtained from `https://data.together.xyz/redpajama-data-v2/v1.0.0/urls/minhash-urls.txt`

B.1 Structure of the datasets

Both RedPajama-V1 and RedPajama-V2 are distributed in the JSON Lines format and partitioned into shards. Due to their differing nature, the two datasets are structured differently.

B.1.1 RedPajama-V1

RedPajama-V1 consists of seven domains and is structured accordingly. Except for the Common Crawl subset, each component follows the structure

```
{
    "text": "...", "meta": {...}
}
```

The `meta` field varies between the different sources:

- The **Arxiv** subset has the meta fields `timestamp`, `yymm`, `arxiv_id`, `language` and `url`.
- The **C4** subset has the meta fields `timestamp`, `source`, `language` and `url`.
- The **Github** subset has the meta fields `content_hash`, `timestamp`, `source`, `line_count`, `max_line_length`, `avg_line_length`, `alnum_prop`, `repo_name`, `id`, `size`, `binary`, `copies`, `ref`, `path`, `mode`, `license`, `language`.
- The **Stack Exchange** subset has the meta fields `timestamp`, `source`, `language`, `question_score` and `url`.
- The **Wikipedia** subset has the meta fields `timestamp`, `title`, `language`, and `url`.

The Common Crawl subset follows the structure

```
{
    "text": "...",
```

```
        "pred_label": ...,
        "pred_label_prob": ...,
        "wiki_prob": ...,
        "source": "..."
}
```

B.1.2   RedPajama-V2

The core of the dataset is composed of the text documents, accompanied by the quality annotations,
duplicate ids and minhash signatures. For the text documents, the structure largely follows the one
defined by CCNet. Specifically, the documents for a given CommonCrawl snapshot are partitioned
into 5000 shards, where the filename indicates the shard, language of the document, and the perplexity
bucket (partition). The quality annotations, duplicates and minhashes follow the same logic and
reflect the filenames of the raw documents.

File Structure. The files containing the raw text documents are organized according to the following
pattern:

<div align="center">

`documents/<snapshot_id>/<shard_id>/<lang>_<ppl_bucket>.json.gz`

</div>

where `snapshot_id` corresponds to any of the crawls included in RPv2, `shard_id` ranges from
`0000` to `4999`, `lang` is any one of `en`, `de`, `fr`, `es` or `it`. Finally, `ppl_bucket` indicates the
partitioning according to Wikipedia perplexity and is either `head`, `middle` or `tail`. Similarly, quality
signals, duplicate ids and minhashes follow the patterns

<div align="center">

`quality_signals/<snapshot_id>/<shard_id>/<lang>_<ppl_bucket>.signals.json.gz,`
`duplicates/<snapshot_id>/<shard_id>/<lang>_<ppl_bucket>.duplicates.parquet,`

</div>

and

<div align="center">

`minhashes/<snapshot_id>/<shard_id>/<lang>_<ppl_bucket>.minhash.parquet.`

</div>

Documents Structure. The `documents` are stored as Gzip-compressed JSONL files and follow the
schema

```
{
    "url": "...",
    "date_download": "...",
    "digest": "...",
    "length": ...,
    "nlines": ...,
    "source_domain": "...",
    "title": "...",
    "raw_content": "...",
    "cc_segment": "...",
    "original_nlines": ...,
    "original_length": ..,
    "line_ids": [...],
    "language": "...",
    "language_score": ...,
    "perplexity": ...,
    "bucket": "..."
}
```

Quality Signals Structure. The `quality signals` are Gzip-compressed JSONL files and follow
the schema

```
{
    "id": "...",
    "id_int": ...,
    "metadata": {
        "cc_segment": "...",
```

```
        "cc_net_source": "...",
        "url": "...",
        "source_domain": "...",
        "language": "...",
        "snapshot_id": "..."
    },
    "quality_signals": {
        "key": [[start, end, score]]
    }
}
```

The `quality_signals` field is a dictionary with the name of the quality signal as key and a list of tuples as values. Each tuple consists of the three floats `start`, `end`, and `score` indicating the location where the `score` in the `raw_content` string applies. This representation follows the one used in Dolma [52] and allows a single representation to encode quality signals which apply at different levels of granularity of the text (e.g., line-level and document-level).

Duplicate IDs. The ids of duplicated documents are stored as parquet files. Each row in the parquet file corresponds to a document which is duplicated at least once across the entire corpus. We emphasize that this does not include the first occurrence of a document which has subsequent duplicates. In other words, if every document appearing in the list of duplicates is dropped, one member of each cluster of documents remains in the dataset.

Minhashes. The minhash signatures are stored in parquet files and are partitioned into multiple bands and rows, corresponding to different levels of Jaccard similarities in the range $\{0.7, 0.8, 0.9, 1.0\}$.

C RedPajama-V1

Here we provide additional details and results for the RedPajama-V1 dataset.

C.1 Filtering Heuristics for Code obtained from GitHub

As indicated in the main part of this paper, we filter the raw GitHub dataset by keeping only projects under Apache, BSD and MIT licenses, and additionally apply filtering heuristics similar to the ones used in The Stack dataset [25]. Specifically, we apply the following set of heuristics, removing any file with the following properties:

- maximum line length of more than 1000 characters.
- an average line length of more than 100 characters.
- a proportion of alphanumeric characters of less than 0.25.
- a ratio between the number of alphabetical characters and the number of tokens of less than 1.5.
- extension is not in the following set of whitelisted extensions: .asm, .bat, .cmd, .c, .h, .cs, .cpp, .hpp, .c++, .h++, .cc, .hh, .C, .H, .cmake, .css, .dockerfile, .f90, .f, .f03, .f08, .f77, .f95, .for, .fpp, .go, .hs, .html, .java, .js, .jl, .lua, .md, .markdown, .php, .php3, .php4, .php5, .phps, .phpt, .pl, .pm, .pod, .perl, .ps1, .psd1, .psm1, .py, .rb, .rs, .sql, .scala, .sh, .bash, .command, .zsh, .ts, .tsx, .tex, .vb, Dockerfile, Makefile, .xml, .rst, .m, .smali

C.2 Detailed Evaluations for the RedPajama-INCITE LLMs

Here we provide detailed benchmark scores for the RedPajama-INCITE 3B and 7B LLMs, trained on the RedPajama-V1 dataset.

C.3 Detailed Sources of Uncertainties in the Construction of the RedPajama-V1 Dataset

Table 10 shows a detailed overview over different sources of uncertainty that arose during the construction of the RedPajama-V1 dataset. These uncertainties mainly stem from a lack of details on the dataset presented in [57]. From this list, it can be seen that it is likely that there is a mismatch
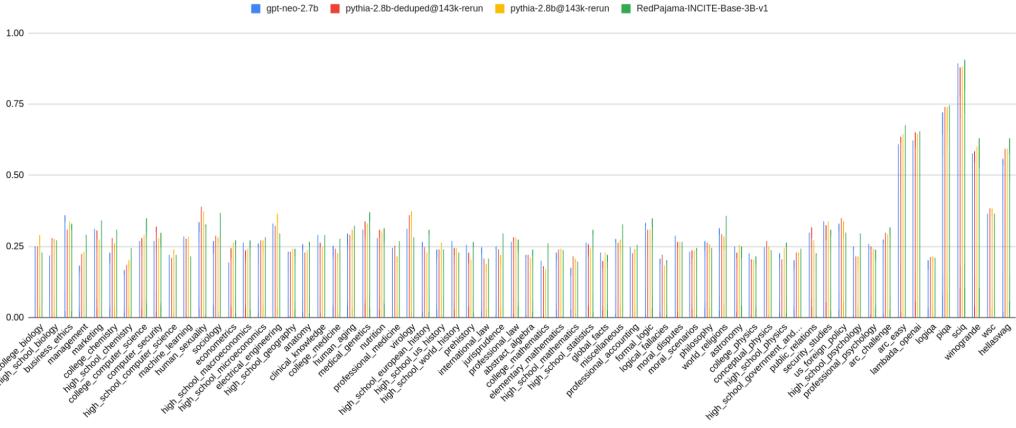
Figure 2: RedPajama-INCITE-Base 3B results on a subset of lm-evaluation-harness. The tasks were selected according to the selection made to evaluate Pythia [4] and GPT-J [59]

Table 7: Results for RedPajama-INCITE-Base-3B-v1 on a subset of lm-evaluation-harness (Zero-Shot) and HELM, compared to models with similar parameter counts. The top-scoring model for each benchmark is highlighted in **bold** font.

	Lambada OpenAi (acc)	Hellaswag (acc_norm)	Winogrande (acc)	Piqa (acc)	Avg.	HELM avg.
GPT-Neo	0.6223	0.5579	0.5769	0.7219	0.6197	0.3570
Pythia-2.8B	0.6466	0.5933	0.6006	0.7399	0.6451	0.3770
Pythia-2.8B-dedup	**0.6524**	0.5941	0.5848	0.7404	0.6429	-
RedPajama-INCITE-Base-3B-v1	0.6541	**0.6317**	**0.6322**	**0.7470**	**0.6662**	**0.4060**

Table 8: HELM Benchmark results for RedPajama-INCITE-Base-7B-v1 and instruction tuned. The top-scoring model for each benchmark is highlighted in **bold** font.

Model	RedPajama 7B Instruct	Llama 7B	MPT 7B	Falcon 7B	RedPajama 7B Base	GPT J	Falcon 7B Instruct	Pythia 7B	Dolly v2	MPT 7B Instruct	Stablelm Alpha 7B
HELM-AVG	**0.492**	0.472	0.444	0.441	0.431	0.417	0.407	0.400	0.396	0.393	0.288
MMLU - EM	**0.366**	0.345	0.294	0.285	0.323	0.249	0.271	0.266	0.238	0.349	0.293
BoolQ - EM	0.697	0.751	0.731	**0.770**	0.694	0.649	0.708	0.656	0.602	0.442	0.537
NarrativeQA - F1	**0.623**	0.524	0.541	0.549	0.512	0.545	0.381	0.427	0.441	0.220	0.218
NaturalQuestions (closed-book) - F1	0.229	**0.297**	0.284	0.289	0.258	0.156	0.192	0.141	0.133	0.247	0.077
NaturalQuestions (open-book) - F1	**0.654**	0.580	0.603	0.574	0.600	0.559	0.453	0.549	0.535	0.627	0.317
QuAC - F1	0.252	0.332	0.343	0.322	0.323	0.330	0.300	0.306	0.299	**0.352**	0.218
*HellaSwag - EM	0.698	0.747	0.754	0.732	0.702	0.663	0.690	0.653	0.692	**0.763**	0.421
*OpenbookQA - EM	0.488	0.574	0.540	**0.546**	0.504	0.514	0.498	0.496	0.516	0.532	0.394
TruthfulQA - EM	0.226	0.297	0.186	0.206	0.205	0.199	0.203	0.225	**0.250**	0.188	0.209
*MS MARCO (regular) - RR@10	**0.391**	0.252	0.161	0.169	0.135	0.152	0.225	0.159	0.160	0.161	0.110
*MS MARCO (TREC) - NDCG@10	**0.709**	0.482	0.369	0.362	0.322	0.345	0.481	0.342	0.359	0.387	0.253
CNN/DailyMail - ROUGE-2	0.143	**0.149**	0.137	0.147	0.137	0.131	0.114	0.101	0.140	0.148	0.045
XSUM - ROUGE-2	0.101	**0.127**	0.107	0.116	0.114	0.096	0.071	0.079	0.074	0.101	0.037
IMDB - EM	0.941	0.933	0.903	0.893	0.916	**0.939**	0.906	0.930	0.907	0.891	0.627
CivilComments - EM	**0.667**	0.578	0.525	0.511	0.536	0.520	0.516	0.527	0.520	0.270	0.490
RAFT - EM	0.682	0.583	0.618	0.586	0.611	**0.619**	0.498	0.542	0.466	0.616	0.368

Table 9: LM eval harness results for RedPajama-INCITE-Base-7B-v1 and instruction tuned model. The top-scoring model for each benchmark is highlighted in **bold** font.

	MPT 7B Instruct	Falcon 7B	MPT 7B	RedPajama 7B Base	Llama 7B	RedPajama 7B Instruct	Falcon 7B Instruct	Dolly v2	GPT-J	Pythia 7B	StableLM Alpha 7B
LM-eval-harness-AVG	**0.7195**	0.7161	0.7100	0.6882	0.6881	0.6858	0.6813	0.6557	0.6526	0.6392	0.5260
arc_challenge (acc_norm)	**0.4462**	0.4326	0.4215	0.3925	0.4147	0.4078	0.4283	0.4027	0.3660	0.3532	0.2705
arc_easy (acc)	**0.7218**	0.7096	0.7008	0.6923	0.5253	0.7159	0.6789	0.6423	0.6225	0.6338	0.4487
boolq (acc)	0.7425	0.7361	**0.7486**	0.707	0.7315	0.6865	0.7089	0.6502	0.6544	0.6446	0.6006
copa (acc)	**0.9000**	0.8600	0.8500	0.880	0.8500	0.850	0.8400	0.8600	0.8300	0.7400	0.7500
hellaswag (acc_norm)	**0.7717**	0.7634	0.7626	0.7037	0.7620	0.7103	0.6978	0.6896	0.6625	0.6588	0.4122
lambada_openai (acc)	0.6918	**0.7467**	0.7056	0.7143	0.7360	0.6895	0.6831	0.6893	0.6831	0.6441	0.6379
piqa (acc_norm)	0.8041	**0.8069**	0.8052	0.7737	0.7810	0.7699	0.7856	0.7486	0.7617	0.7671	0.6736
winogrande (acc)	0.6780	0.6732	**0.6859**	0.6417	0.7040	0.6567	0.6669	0.6140	0.6409	0.6267	0.5012

between RedPajama-V1 and the dataset used to train the Llama-1 models. We believe this is a significant factor that has contributed to the performance mismatch between RedPajama-INCITE and LLaMA-1.

Table 10: Overview over the different uncertainties and decisions made during the construction of the RedPajama-V1 dataset.

Subset	Uncertainty	Decision
CommonCrawl	Which snapshots were used?	We use the first snapshot from 2019 to 2023.
	What classifier was used, and how was it constructed?	We use a fasttext classifier with unigram features and use 300k training samples.
	What threshold was used to classify a sample as high quality?	We set the threshold to match the token count reported in LLama.
GitHub	Quality filtering heuristics	We remove any file • with a maximum line length of more than 1000 characters. • with an average line length of more than 100 characters. • with a proportion of alphanumeric characters of less than 0.25. • with a ratio between the number of alphabetical characters and the number of tokens of less than 1.5. • whose extension is not in the following set of whitelisted extensions: .asm, .bat, .cmd, .c, .h, .cs, .cpp, .hpp, .c++, .h++, .cc, .hh, .C, .H, .cmake, .css, .dockerfile, .f90, .f, .f03, .f08, .f77, .f95, .for, .fpp, .go, .hs, .html, .java, .js, .jl, .lua, .md, .markdown, .php, .php3, .php4, .php5, .phps, .phpt, .pl, .pm, .pod, .perl, .ps1, .psd1, .psm1, .py, .rb, .rs, .sql, .scala, .sh, .bash, .command, .zsh, .ts, .tsx, .tex, .vb, Dockerfile, Makefile, .xml, .rst, .m, .smali
Wikipedia	Which Wikipedia dump was used?	We used the most recent at the time of data curation (2023-03-20).
Books	How were the books deduplicated?	We use SimHash to perform near deduplication.

D RedPajama-V2

In this section we provide additional analyses and statistics of the RedPajama-V2 web dataset, and present detailed results for the ablation models trained on differently filtered subsets.

D.1 Summary Statistics of our Deduplication Approach

In Figure 3, we see how the number of documents in the head+middle partition develops as a function of the point in time of each crawl. What stands out here is that there is a relatively stable number until 2018 and a significantly smaller number of documents between 2014 and 2016 (up to 10x for, e.g., German). It is also worth noting how the number of unique documents over time develops (dashed line). Specifically, since we ran the deduplication from the newest snapshot to the oldest, one expects an increasingly smaller number of unique documents in the corpus, which can be observed from Figure 3 (note the log-scale). However, it is worth pointing out the sudden drop in unique documents occurring for the crawls between 2014 and 2017. We believe that this can be explained by a different list of seeds used by the CommonCrawl web crawler during that period.

D.2 Quality Signals

In this section we provide further details and statistics on the quality signals which are part of the RedPajama-V2 dataset.
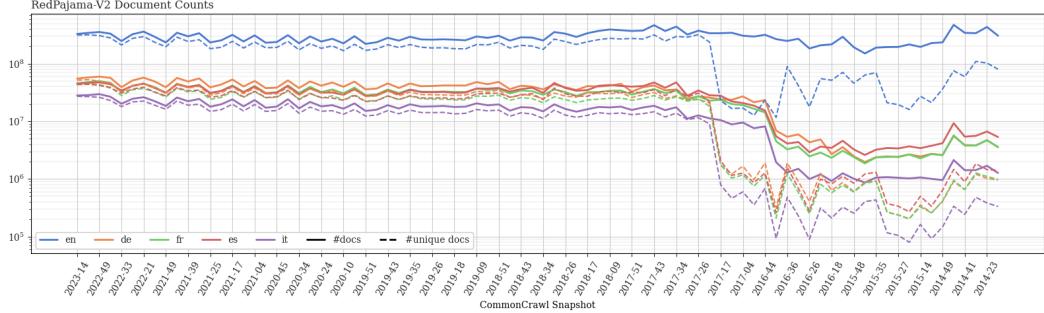
Figure 3: Chronological count of documents for each CommonCrawl snapshot before and after deduplication. Deduplication is performed sequentially, starting from the most recent snapshot and iterating until the oldest snapshot.

Table 11: Quality signals originating from the CCNet pipeline [61].

Annotation Tag	Description
ccnet_bucket	head, middle or tail bucket of the perplexity score
ccnet_language_score	score of the language identification model
ccnet_length	number of characters
ccnet_nlines	number of lines
ccnet_original_length	number of characters before line-level deduplication
ccnet_original_nlines	number of lines before line-level deduplication
ccnet_perplexity	perplexity of an LM trained on Wikipedia

D.2.1 Overview of Available Quality Signals

The set of quality signals can be grouped into such with measure *natural language* (Table 12), the *repetitiveness* of the text (Table 14), are based on the *content* of the text (Table 15), or which are *ML-based* heuristics (Table 13). In addition, here we also summarize the quality signals which are computed by the CCNet pipeline in Table 11.

D.2.2 Histograms

Histograms of the distribution of quality signals are shown in Figures 4,5,6 and 7. The statistics are obtained from the 2023-06 snapshot and are computed only for English data.

D.3 Embedding-based Clustering

To compute clusters based on the semantics of text documents, we randomly sampled 2,000,000 documents from the unfiltered 2021-04 snapshot of the RedPajama-V2 dataset and used the Alibaba-NLP gte-large-en-v1.5 model [32] to compute embeddings on the middle 8,192 tokens of each document. We used Nomic Atlas [41] for clustering and topic modeling analysis. An overview of clusters and associated topics is shown in Figure 8. 6 randomly sampled documents, along with their corresponding cluster topics and a 1000-character substring from each document (starting after a random whitespace character), are shown in Table 16 and Table 17.

D.4 Data Ablations: Detailed Evaluations

We have shown aggregated benchmark scores in the main part of this work. Here, we provide more details and report the scores for each task separately. The results are shown in Tables 18, 19 and 20.

Table 12: Summary of quality signals which measure how much a document corresponds to natural language.

Annotation Tag	Description	Reference(s)
rps_doc_curly_bracket	The ratio between the number of occurrences of '{' or '}' and the number of characters in the raw text.	[46]
rps_doc_frac_all_caps_words	The fraction of words in the content that only consist of uppercase letters. This is based on the raw content.	[34]
rps_doc_frac_lines_end_with_ellipsis	The fraction of lines that end with an ellipsis, where an ellipsis is defined as either "..." or "U+2026".	[44, 45]
rps_doc_frac_no_alph_words	The fraction of words that contain no alphabetical character.	[44, 45]
rps_doc_lorem_ipsum	The ratio between the number of occurrences of 'lorem ipsum' and the number of characters in the content after normalisation.	[46]
rps_doc_mean_word_length	The mean length of words in the content after normalisation.	[44, 45]
rps_doc_stop_word_fraction	The ratio between the number of stop words and the number of words in the document. Stop words are obtained from `https://github.com/6/stopwords-json`.	[44, 45]
rps_doc_symbol_to_word_ratio	The ratio of symbols to words in the content. Symbols are defined as U+0023 (#), "...", and U+2026.	[44, 45]
rps_doc_frac_unique_words	The fraction of unique words in the content. This is also known as the degeneracy of a text sample. Calculated based on the normalised content.	[34]
rps_doc_unigram_entropy	The entropy of the unigram distribution of the content. This measures the diversity of the content and is computed using $\sum_x -\frac{x}{n} \cdot \log(\frac{1}{n})$ where the sum is taken over counts of unique words in the normalised content.	-
rps_doc_word_count	The number of words in the content after normalisation.	[44, 45]
rps_lines_ending_with_terminal_punctution_mark	Indicates whether a line ends with a terminal punctuation mark. A terminal punctuation mark is defined as one of: ".", "!", "?", """.	[46]
rps_lines_javascript_counts	The number of occurrences of the word "javascript" in each line.	[46]
rps_lines_num_words	The number of words in each line. This is computed based on the normalised text.	[46, 44]
rps_lines_numerical_chars_fraction	The ratio between the number of numerical characters and total number of characters in each line. This is based on the normalised content.	[44]
rps_lines_start_with_bulletpoint	Whether the lines that start with a bullet point symbol. The following set of unicodes are considered a bullet point: U+2022 (bullet point), U+2023 (triangular bullet point), U+25B6 (black right pointing triangle), U+25C0 (black left pointing triangle), U+25E6 (white bullet point), U+2013 (en dash) U+25A0 (black square), U+25A1 (white square), U+25AA (black small square), U+25AB (white small square).	[43, 45]
rps_lines_uppercase_letter_fraction	The ratio between the number of uppercase letters and total number of characters in each line. This is based on the raw text.	[44]
rps_doc_num_sentences	The number of sentences in the content.	[46]

Table 13: Quality signals based on ML heuristics.

Annotation Tag	Description	Reference(s)
rps_doc_books_importance	Given a bag of 1,2-wordgram model trained on Books p, and a model trained on the source domain q, This is the logarithm of the ratio p/q.	[62]
rps_doc_openwebtext_importance	Given a bag of 1,2-wordgram model trained on OpenWebText p, and a model trained on the source domain q, this is the logarithm of the ratio p/q.	[62]
rps_doc_wikipedia_importance	Given a bag of 1,2-wordgram model trained on Wikipedia articles p, and a model trained on the source domain q, this is the logarithm of the ratio p/q.	[62]
rps_doc_ml_wikiref_score	Fasttext classifier prediction for the document being a Wikipedia reference. This is the same fasttext model used in the RedPajama-1T dataset. Only applies to English data.	[57]
rps_doc_ml_palm_score	Fasttext classifier prediction for the document being a Wikipedia article, OpenWebText sample or a RedPajama-V1 book. Only for English data.	[12], [16]
rps_doc_ml_wikipedia_score	Fasttext classifier prediction for the document being a Wikipedia article. This is used for non-English data	-

Table 14: Summary of Quality signals which measure how repetitive text is.

Annotation Tag	Description	Reference(s)
rps_doc_frac_chars_dupe_10grams	The fraction of characters in duplicate word 10grams.	[43, 45]
rps_doc_frac_chars_dupe_5grams	The fraction of characters in duplicate word 5grams.	[43, 45]
rps_doc_frac_chars_dupe_6grams	The fraction of characters in duplicate word 6grams.	[43, 45]
rps_doc_frac_chars_dupe_7grams	The fraction of characters in duplicate word 7grams.	[43, 45]
rps_doc_frac_chars_dupe_8grams	The fraction of characters in duplicate word 8grams.	[43, 45]
rps_doc_frac_chars_dupe_9grams	The fraction of characters in duplicate word 9grams.	[43, 45]
rps_doc_frac_chars_top_2gram	The fraction of characters in the top word 2gram.	[43, 45]
rps_doc_frac_chars_top_3gram	The fraction of characters in the top word 3gram.	[43, 45]
rps_doc_frac_chars_top_4gram	The fraction of characters in the top word 4gram.	[43, 45]

Table 15: Summary of Quality signals which are based on the content of the text, measuring toxicity.

Annotation Tag	Description	Reference(s)
rps_doc_ldnoobw_words	The number of sequences of words that are contained in the List-of-Dirty-Naughty-Obscene-and-Otherwise-Bad-Words blocklist. The blocklist is obtained from https://github.com/LDNOOBW/List-of-Dirty-Naughty-Obscene-and-Otherwise-Bad-Words.	[46]
rps_doc_ut1_blacklist	A categorical id corresponding to the list of categories of the domain of the document. Categories are obtained from https://dsi.ut-capitole.fr/blacklists/	[44]

Table 16: Examples of documents and corresponding cluster topics from Nomic Atlas [41].

Cluster Topics (broad - medium - specific)	Document
Election - Health (2) - COVID Testing	immediately moving to the Purple Tier. This is the most restrictive level in the State's effort to control the spread of COVID-19. Businesses and residents must comply with the Purple Tier restrictions by Tuesday, Nov. 17. To determine restrictions by industry, business and activity, visit: https://covid19.ca.gov/safer-economy/ Read the full news release here: www.gov.ca.gov/2020/11/16/governor-newsom-announces-new-immediate-actions-to-curb-covid-19-transmission/ Watch the Governor's press conference during which he made the announcement today here: www.facebook.com/CAgovernor/videos/376746553637721 According to County of Orange officials, schools that have not already opened must continue with remote classes and cannot reopen in-person. Read the County's release here: https://cms.ocgov.com/civicax/filebank/blobdload.aspx?BlobID=118441 The California Department of Public Health has also issued a travel advisory encouraging Californians to stay home or in their region and avoid non-esse
Religion/Spirituality - Gaming - Gaming (3)	Top 100 Employers, and one of Canada's Top Employers for Young People multiple years running! At Ubisoft Toronto, we look for people who are excited to create the future of games in one of the most diverse cities in the world. We believe that embracing our differences helps us build stronger creative teams and develop better games for all players. We are an equal-opportunity employer and welcome applications from all interested candidates. We strongly encourage applications from Indigenous people, racialized people, neurodivergent people, people with disabilities, people from gender and sexually diverse communities and/or people with intersectional identities. We are committed to providing reasonable accommodation for people with disability upon request. If this sounds like your kind of studio, what are you waiting for? Apply to join us now! We thank you for your interest, however, only those candidates selected for an interview will be contacted. No agencies please. Senior Game Design
Education - Golf - Rotary Meetings	what's happening. Conversely, some people rely on the newsletter. Thus, the more avenues to inform people, the better. attendance at many social functions is poor, possibly due to the limited advertising reach. In practical terms, it means that social functions may be advertised in the OOC newsletter (current practice) the schedule, as is done for outdoor activities such as hikes the OOC's Facebook group As when social functions are advertised in the newsletter, the person organizing the social function can choose how much location information to provide, especially if it is to be held at someone's residence. OOC bylaw Article 3, Section 9 (f) states (highlighting added) (f) Social Coordinator: Shall be responsible for coordinating all social events for Club members only, and for preparing a schedule of these outings, not to be advertised to non-members. The executive voted to amend this statement by removing the limitation per Paragraph 3 of "Article 5 - Amending Formula" of the Const

Table 17: Examples of documents and corresponding cluster topics from Nomic Atlas [41].

Cluster Topics (broad - medium - specific)	Document
Online Privacy - Privacy Policy - Contracts	shall be governed by the laws of the Federal Republic of Germany under exclusion of the UN Convention on the International Sale of Goods (CISG), without prejudice to any mandatory conflict of laws and consumer protection provisions. 11.2 If the Customer is an entrepreneur according to Sec. 14 German Civil Code ("BGB"), a legal person under public law or a special fund under public law the courts at the place of business of the vendor shall have exclusive jurisdiction in respect of all disputes arising out of or in connection with the relevant contract. 11.3 In the event that one or more provisions of the contract should be or become invalid or unenforceable, the validity of the remaining provisions shall not be affected thereby. The invalid or unenforceable provision shall be deemed to be replaced - as existent - with statutory provisions. In case of an unacceptable rigor to one of the parties, the contract shall be deemed invalid as a whole. 11.4 In case of deviations of these General
Religion/Spirituality - Film/Movie - Movie	Movie of Nelson Mandela's life premieres in South Africa Nov. 04 - Stars Idris Elba and Naomie Harris attend the premiere of "Mandela: Long Walk to Freedom," based on the autobiography of anti-apartheid icon Nelson Mandela. Matthew Stock reports.
Election - Election (2) - Healthcare (4)	McAuliffe revived that language as an amendment to the budget. He also called on the General Assembly to immediately convene a special joint committee that had been created to assess the impact that repealing the ACA would have had on Virginia. The legislature will gather April 5 to consider the governor's amendments and vetoes, but leaders said Monday that McAuliffe's new budget language stands no better chance this time. In a joint statement, the Republican leadership of the House of Delegates said expanding Medicaid would lead to increased costs and eventually blow a hole in the state budget. "The lack of action in Washington has not changed that and in fact, the uncertainty of federal health policy underscores the need to be cautious over the long term," the leaders, including House Speaker William J. Howell (R-Stafford) and the man selected to replace him as speaker when he retires next year, Del. Kirk Cox (R-Colonial Heights), said via email. "Virginians can barely afford our cu

Table 18: Evaluations for the 468M parameter LM for different dataset filters and other strong web datasets. The top-scoring dataset for each metric is indicated in **<u>bolded underlined</u>**, the top-2 is **bolded**, and the third-scoring dataset is in *<u>italics underlined</u>*.

Dataset	Deduplication		Rule-based		ML Heuristics			Natural Language Inference			Coref. Res.	Sentence Completion	
	Exact	Fuzzy	C4	Gopher	Classif.	DSIR	PPL	ANLI	ARC-c	ARC-e	Winogrande	Hellaswag	LAMBADA
C4								33.8	22.0	37.0	51.9	**<u>32.9</u>**	15.5
Dolma-v1.7 CC								33.5	**24.0**	38.3	49.6	32.3	17.3
FineWeb								34.0	23.4	37.7	51.8	**32.8**	18.1
RefinedWeb								32.8	22.6	38.3	51.9	31.6	17.8
RPv1-CC					✔ (Wiki-Ref.)			33.9	22.4	37.5	**52.6**	29.7	*<u>19.0</u>*
RPv2 (2023-14)								33.3	22.2	38.5	52.4	31.5	18.2
RPv2 (2023-14)	✔							33.9	22.1	38.1	50.6	31.3	18.0
RPv2 (2023-14)		✔		✔ (full)				34.1	22.3	38.3	52.2	32.1	18.7
RPv2 (2023-14)		✔	✔					33.4	22.7	38.9	51.1	32.4	17.5
RPv2 (2023-14)		✔		✔ (natlang)			Wiki-middle	33.4	**<u>24.2</u>**	37.7	49.8	33.1	**19.2**
RPv2 (2023-14)		✔		✔ (Rep.)			Wiki-middle	34.2	23.1	37.4	50.8	32.5	18.5
RPv2 (9 Dumps)		✔	✔					*<u>34.3</u>*	23.5	*<u>38.6</u>*	51.5	32.0	17.2
RPv2 (9 Dumps)		✔	✔	✔ (full)				33.5	23.3	38.4	50.2	**32.8**	16.8
RPv2 (9 Dumps)		✔	✔	✔ (Rep.)		✔ (Palm-mix)		33.8	21.9	38.0	*<u>52.5</u>*	32.0	17.3
RPv2 (9 Dumps)		✔	✔	✔ (Rep.)	✔ (Palm-mix)			**34.6**	23.3	*<u>38.6</u>*	52.2	*<u>32.7</u>*	16.4
RPv2 (9 Dumps)		✔	✔	✔ (natlang)	✔ (Palm-mix)			**<u>34.8</u>**	23.0	**<u>39.2</u>**	**<u>53.0</u>**	32.3	16.9
RPv2 (9 Dumps)		✔	✔ (line-filter)	✔ (natlang)	✔ (Palm-mix)			33.7	22.9	38.5	50.9	32.3	**<u>19.9</u>**
RPv2 (9 Dumps)		✔	custom-rules		✔ (Wiki-Ref.)		$P_{wiki} > 30$	33.2	23.0	37.9	49.6	30.1	18.7
RPv2 (9 Dumps)		✔	custom-rules + Gopher-Rep		✔ (Wiki-Ref.)		$P_{wiki} > 30$	33.0	*<u>23.8</u>*	**38.9**	50.5	30.0	18.9
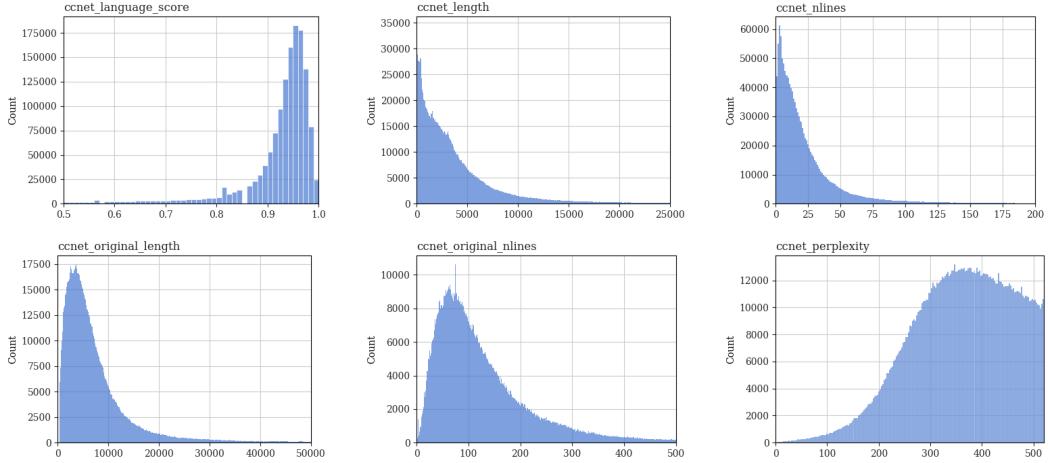
Figure 4: Histograms for the quality signals computed by the CCNet [61] pipeline.
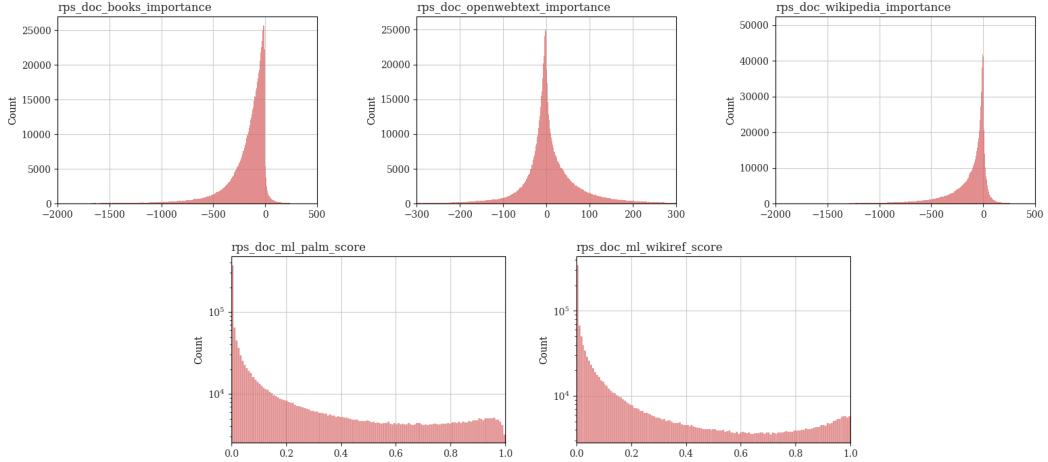
Figure 5: Histograms for ML-based quality signals.

Table 19: Evaluations in the 5-shot setting on MMLU and subtasks for the 468M parameter LM. The top-scoring dataset for each metric is indicated in **<u>bolded underlined</u>**, the top-2 is **bolded**, and the third-scoring dataset is in *<u>italics underlined</u>*.

Dataset	Deduplication		Rule-based		ML Heuristics			MMLU	Stem	Humanities	Other	Social Sciences
	Exact	Fuzzy	C4	Gopher	Classif.	DSIR	PPL					
C4								24.9	26.4	24.1	25.8	23.4
Dolma-v1.7 CC								26.0	27.8	24.5	26.2	26.1
FineWeb								26.2	25.4	25.1	25.8	*29.3*
RefinedWeb								24.8	23.9	23.7	*26.5*	25.6
RPv1-CC					✔ (Wiki-Ref.)			25.1	25.1	23.7	24.0	28.5
RPv2 (2023-14)	✔							*26.3*	26.7	**25.3**	24.1	**29.6**
RPv2 (2023-14)	✔							**26.4**	26.8	**25.3**	25.2	28.8
RPv2 (2023-14)		✔		✔ (full)				**27.0**	**28.8**	24.8	25.6	**30.0**
RPv2 (2023-14)		✔	✔					25.4	27.8	24.1	26.1	24.1
RPv2 (2023-14)		✔		✔ (natlang)			Wiki-middle	26.1	27.4	**25.2**	24.6	27.7
RPv2 (2023-14)		✔		✔ (Rep.)			Wiki-middle	25.5	24.3	**25.2**	**27.8**	24.8
RPv2 (9 Dumps)		✔	✔					*26.3*	**28.3**	**25.3**	25.8	26.6
RPv2 (9 Dumps)		✔	✔	✔ (full)				25.6	*28.0*	*25.1*	24.9	24.4
RPv2 (9 Dumps)		✔	✔	✔ (Rep.)		✔ (Palm-mix)		24.4	26.9	23.7	24.8	22.7
RPv2 (9 Dumps)		✔	✔	✔ (Rep.)	✔ (Palm-mix)			24.9	26.1	24.0	26.3	23.8
RPv2 (9 Dumps)		✔	✔	✔ (natlang)	✔ (Palm-mix)			25.3	27.8	24.2	25.4	24.5
RPv2 (9 Dumps)		✔	✔ (line-filter)	✔ (natlang)	✔ (Palm-mix)			25.1	27.5	24.0	25.0	24.4
RPv2 (9 Dumps)		✔	custom-rules		✔ (Wiki-Ref.)		$P_{wiki} > 30$	**27.0**	27.9	*25.1*	26.0	**30.0**
RPv2 (9 Dumps)		✔	custom-rules + Gopher-Rep		✔ (Wiki-Ref.)		$P_{wiki} > 30$	25.9	25.8	24.3	**27.1**	27.2

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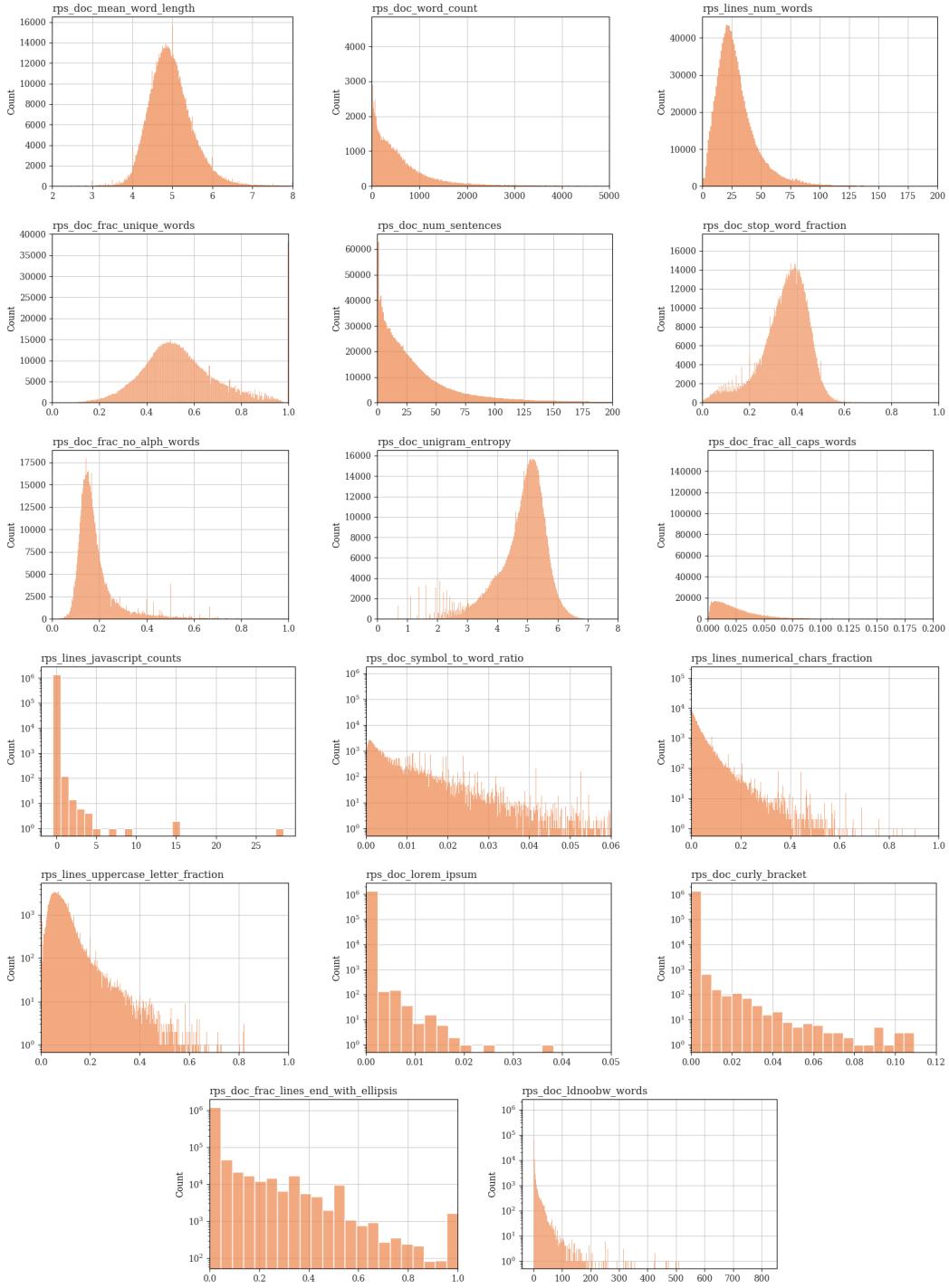
Figure 6: Histograms for Natural language based quality signals.
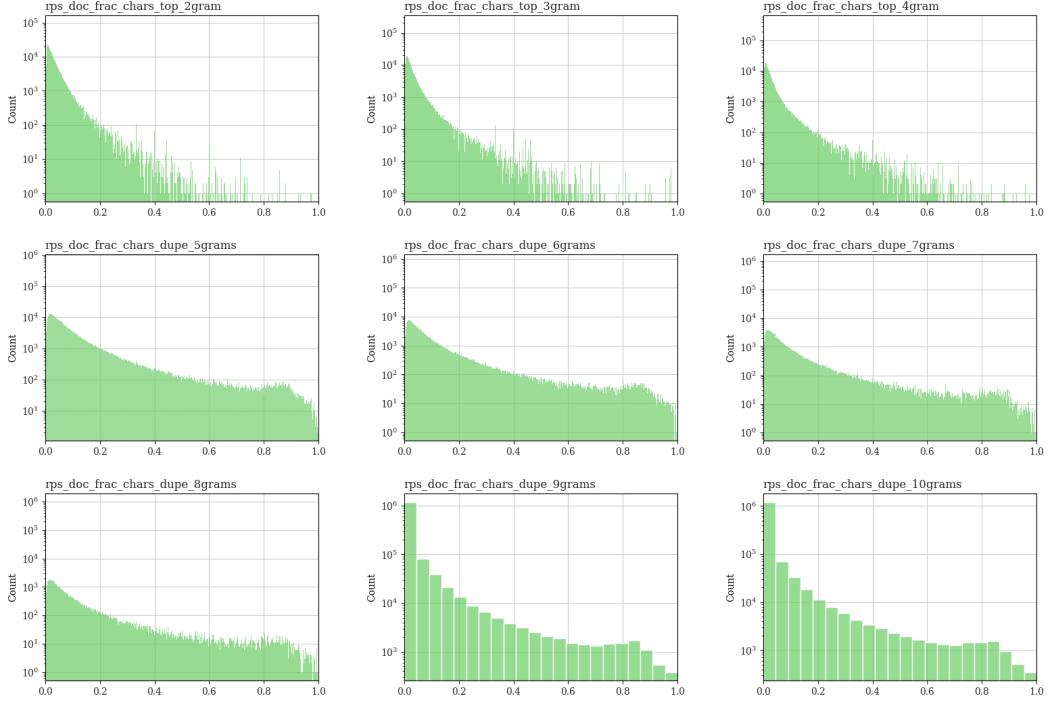
Figure 7: Histograms for quality signals measuring the repetitiveness of text.

Table 20: Evaluations on multiple choice tasks for the 468M parameter LM. The top-scoring dataset for each metric is indicated in **<u>bolded underlined</u>**, the top-2 is **bolded**, and the third-scoring dataset is in *<u>italics underlined</u>*.

| Dataset	Deduplication		Rule-based		ML Heuristics			CoQA	OpenbookQA	PIQA	PubMedQA	SciQ	SocialIQA	TruthfulQA
	Exact	Fuzzy	C4	Gopher	Classif.	DSIR	PPL							
C4								3.8	**<u>30.2</u>**	*<u>64.4</u>*	46.0	51.7	*<u>33.4</u>*	33.3
Dolma-v1.7 CC								5.2	28.2	**<u>65.3</u>**	42.6	55.2	31.6	33.2
FineWeb								9.0	**29.4**	64.5	41.4	54.3	32.4	33.5
RefinedWeb								**<u>13.2</u>**	28.6	*<u>64.4</u>*	*<u>52.2</u>*	**56.4**	32.8	33.3
RPv1-CC					✔ (Wiki-Ref.)			11.6	25.4	57.3	40.6	**<u>56.7</u>**	33.1	**33.9**
RPv2 (2023-14)	✔							**12.5**	*<u>29.2</u>*	61.6	40.8	53.0	32.9	31.4
RPv2 (2023-14)		✔						11.8	27.6	61.1	43.6	53.7	32.5	33.4
RPv2 (2023-14)		✔	✔	✔ (full)				11.3	28.8	62.8	51.0	53.9	32.6	32.6
RPv2 (2023-14)		✔	✔					5.8	28.8	63.4	49.6	54.7	36.6	*<u>33.8</u>*
RPv2 (2023-14)		✔		✔ (natlang)			Wiki-middle	11.3	28.4	63.5	49.6	53.6	32.8	33.4
RPv2 (2023-14)		✔		✔ (Rep.)			Wiki-middle	*<u>11.9</u>*	**29.4**	63.1	**52.6**	53.4	32.5	31.6
RPv2 (9 Dumps)		✔	✔					6.6	29.0	62.0	36.2	53.7	33.2	**<u>34.3</u>**
RPv2 (9 Dumps)		✔	✔	✔ (full)				5.8	28.6	62.8	*<u>51.2</u>*	54.8	**<u>34.4</u>**	31.2
RPv2 (9 Dumps)		✔	✔	✔ (Rep.)		✔ (Palm-mix)		6.0	**29.4**	61.6	45.4	52.2	*<u>33.4</u>*	33.1
RPv2 (9 Dumps)		✔	✔	✔ (Rep.)	✔ (Palm-mix)			5.4	**29.4**	62.5	45.0	51.7	**34.0**	33.7
RPv2 (9 Dumps)		✔	✔	✔ (natlang)	✔ (Palm-mix)			4.9	28.0	62.9	**52.8**	52.0	33.0	33.6
RPv2 (9 Dumps)		✔	✔ (line-filter)	✔ (natlang)	✔ (Palm-mix)			6.4	27.0	63.2	47.8	52.9	32.8	32.0
RPv2 (9 Dumps)		✔	custom-rules		✔ (Wiki-Ref.)		$P_{wiki} > 30$	10.0	27.8	59.6	41.2	*<u>55.8</u>*	33.3	32.0
RPv2 (9 Dumps)		✔	custom-rules + Gopher-Rep		✔ (Wiki-Ref.)		$P_{wiki} > 30$	9.3	28.0	59.2	43.4	54.9	33.0	33.3
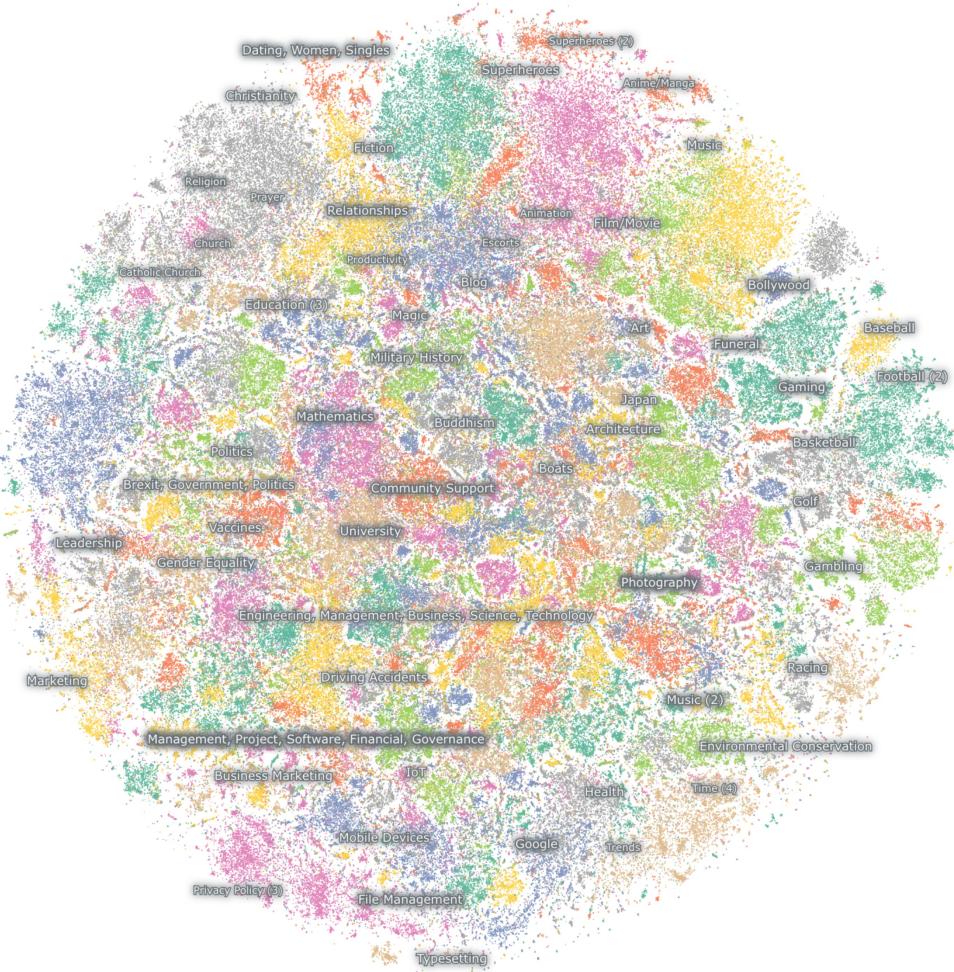
Figure 8: Visualization of topical clusters appearing in the RedPajama-V2 dataset. The clusters are computed in Nomic Atlas [41] based on gte-large-en-v1.5 embeddings for 2M documents of the unfiltered 2021-04 snapshot.

Table 21: Downstream task accuracy for a 1.6B LM trained on different datasets over 350B tokens.

| Dataset | Fuzzy Deduplication | Rule-based | | ML Heuristics | Natural Language Inference | | | Coref. Res. | Sentence Completion | |
		C4	Gopher		ANLI	ARC-c	ARC-e	Winogrande	Hellaswag	LAMBADA
RefinedWeb					33.6	26.9	51.7	54.4	55.8	47.9
RPv2 (full)	✔		✔	WikiRef	32.4	27.9	51.3	56.4	47.4	47.4
RPv2 (full)	✔	✔	✔(natlang)	Palm-Mix	33.6	28.7	52.4	54.5	53.1	42.9

D.5 Evaluations for the 1.6B Parameter Models

Tables 21, 22, and 23 show results for ablations with the 1.6B models. Each model was trained on 350B tokens.

Table 22: Evaluations in the 5-shot setting on MMLU and subtasks for the 1.6B parameter LM.

Dataset	Fuzzy Deduplication	Rule-based C4	Rule-based Gopher	ML Heuristics	MMLU MMLU	Stem	Humanities	Other	Social Sciences
RefinedWeb					25.3	24.9	24.9	27.0	24.7
RPv2 (full)	✔		✔	WikiRef	25.2	26.0	26.7	23.9	23.3
RPv2 (full)	✔	✔	✔(natlang)	Palm-Mix	24.7	25.7	25.4	23.8	23.4

Table 23: Evaluations on multiple choice tasks for the 1.6B parameter LM.

Dataset	Fuzzy Deduplication	Rule-based C4	Rule-based Gopher	ML Heuristics	CoQA	OpenbookQA	PIQA	PubMedQA	SciQ	SocialIQA	TruthfulQA
RefinedWeb					47.4	31.6	73.8	57.0	75.3	41.0	36.6
RPv2 (full)	✔		✔	WikiRef	43.7	32.6	67.4	55.6	72.7	40.4	36.9
RPv2 (full)	✔	✔	✔(natlang)	Palm-Mix	22.1	32.2	71.3	55.2	71.0	42.2	35.7

E   Author Responsibility Statement

This aggregated dataset is licensed to you under the terms of the ODC-By-1.0, as well as any licenses that may apply to its constituent parts.

While we have made every effort to ensure the accuracy and legality of the data contained within this dataset, we cannot guarantee its absolute completeness or correctness due to its scale. Therefore, in the event that any rights, legal or otherwise, are violated through the use of this dataset, including but not limited to copyright infringement, privacy violations, or misuse of sensitive information, we, the authors, assume no liability for such violations. The dataset is provided to you "as is", without warranty of any kind, express or implied.

By utilizing this dataset, you agree that any consequences, legal or otherwise, arising from the use of this dataset will be your sole responsibility. You acknowledge that you will exercise due diligence and adhere to all applicable laws, regulations, and ethical guidelines when using the dataset. By accessing, downloading, or using this dataset, you signify your acceptance of this statement and your commitment to abide by the terms and conditions of the licenses.

F   License

The code provided in the GitHub repository [8] is distributed under an Apache 2.0 license. For the datasets themselves, we refer to the Common Crawl Foundation Terms of Use [9] for the datasets derived from the Common Crawl Archive. For the other datasets we refer to the license under which the dataset was originally distributed. Specifically,

- The C4 dataset at `https://huggingface.co/datasets/allenai/c4#license`,
- The GitHub subset was limited to MIT, BSD, or Apache licenses only,
- The Arxiv terms of use for the arxiv subset under `https://info.arxiv.org/help/api/tou.html`,
- The Wikipedia license for any wikipedia derived data `https://huggingface.co/datasets/legacy-datasets/wikipedia#licensing-information`,
- The StackExchange license on the Internet Archive for the StackExchange data `https://archive.org/details/stackexchange`.

We further request from users that they abide by each individual license for the subset they use.

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[8] `https://github.com/togethercomputer/RedPajama-Data`
[9] `https://commoncrawl.org/terms-of-use`