Query of CC: Unearthing Large Scale Domain-Specific Knowledge from Public Corpora

Zhaoye Fei[1,2♦], Yunfan Shao[1,2♦], Linyang Li[1,2♦], Zhiyuan Zeng[1,2]
Conghui He[2], Hang Yan[2], Dahua Lin[2] and Xipeng Qiu[1]
[1]School of Computer Science, Fudan University, Shanghai, China
[2]Shanghai AI Laboratory
{zyfei20, yfshao19, xpqiu}@fudan.edu.cn
{lilinyang, yanhang}@pjlab.org.cn

Abstract

Large language models (LLMs) have demonstrated remarkable potential in various tasks, however, there remains a significant lack of open-source models and data for specific domains. Previous work has primarily focused on manually specifying resources and collecting high-quality data for specific domains, which is extremely time-consuming and labor-intensive. To address this limitation, we introduce large models into the data collection pipeline to guide the generation of domain-specific information and retrieve relevant data from Common Crawl (CC), a large public corpus. We called this method as *Query of CC*. It not only collects data related to domain-specific knowledge but also mines the data with potential reasoning procedures from the public corpus. By applying this method, we have collected a knowledge domain-related dataset named KNOWLEDGE PILE, which covers four main domains, including the sciences, humanities, and other categories. Through the analysis of KNOWLEDGE PILE, *Query of CC* can effectively retrieve relevant data from the covered knowledge domains and significantly enhance the performance in tests of mathematical and knowledge-related reasoning abilities. We have open-sourced our data on HuggingFace to promote academic progress in knowledge reasoning capabilities.

1 Introduction

Large language models (LLMs) are becoming the new trend not only in natural language processing but also in the entire AI community, pioneered by OpenAI ChatGPT and GPT-4 [OpenAI, 2023]. While commercial LLMs are close-sourced, open-source models such as LLaMA [Touvron et al., 2023a] and Mistral [Jiang et al., 2023] are widely studied by the community since they serve as general base models for building LLM applications. Based on these base models, domain-specific models, show great potential in specific domains, such as medicine [Yang et al., 2022, Gao et al., 2023], finance [Wu et al., 2023, Zhang and Yang, 2023], science [Taylor et al., 2022a, Wei et al., 2023], and law [Nguyen, 2023, Cui et al., 2023]. These domain-specific enhanced models are based on specific human-crafted data recipes [Azerbayev et al., 2023, Wang et al., 2023a].

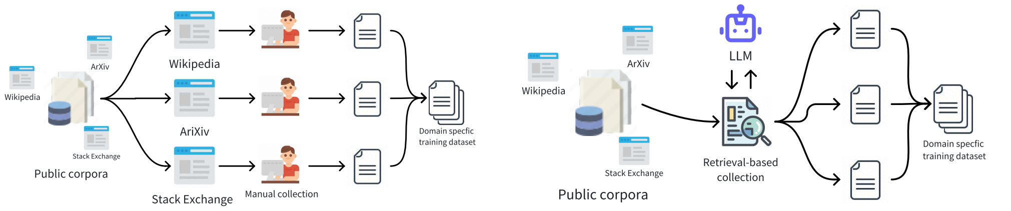
However, crafting domain-specific data is very costly. As depicted in Figure 1a, traditional data collection methods involve the selection of relevant resources by domain experts, followed by data

[*] Work done during internship at Shanghai AI Laboratory.

[♦] These authors contributed equally to this work.

[1] KNOWLEDGE PILE will be released in `https://huggingface.co/datasets/Query-of-CC/knowledge_pile_full`.

Preprint. Under review.



(a) Manual Data Collection

(b) Query and Retrieve Data Collection(our approach)

Figure 1: Comparation of traditional manual data collection methods with our approach.

collection and processing by engineers. On the one hand, such endeavors are highly labor-intensive, requiring several months of collaboration between multiple domain experts and engineers for corpus collection. On the other hand, some specific domain-related data distribution may be highly scattered, which poses many challenges for large-scale domain-specific data collection. Therefore, in this paper, we introduce an automatic strategy to retrieve data from public corpora for specific domain knowledge bootstrapping, which we call *Query of CC*.

In *Query of CC*, we initially collected seed information in some specific domains, such as keywords, frequently asked questions, and textbooks, to serve as inputs for the Query Bootstrapping stage. Leveraging the great generalization capability of LLMs, we can effortlessly expand the initial seed information and extend it to an amount of domain-relevant queries. Inspiration from Wang et al. [2023b] and [Xu et al., 2023], we encompassed two stages of expansion, namely **Question Extension** and **Thought Generation**, which respectively extend the queries in terms of breadth and depth, for retrieving the domain-related data with a broader scope and deeper thought. Subsequently, based on the queries, we retrieved relevant documents from public corpora, and after performing operations such as duplicate data removal and filtering, we formed the final training dataset.

Otherwise, leveraging *Query of CC*, we collect a high-quality knowledge dataset KNOWLEDGE PILE, which starts from some seed information of four major domains, including STEM, humanities, social sciences, and medical sciences, as well as general knowledge. Utilizing KNOWLEDGE PILE, we enhance the Llama and Mistral models through continuing learning. Experimental results indicate that through the KNOWLEDGE PILE, both Llama and Mistral enhanced models achieved significant performance improvements over baselines in benchmark tests related to mathematics, knowledge assessments, professional examinations, and some complex reasoning tasks.

To sum up our contribution:

- We propose *Query of CC*, a data collection pipeline to retrieve domain-specific knowledge from public corpora, which introduces LLMs to extend query and retrieve domain-related data from public corpora.
- We collect and release a knowledge-related corpora KNOWLEDGE PILE based on *Query of CC* from Common Crawl, a large-scale public corpora, which includes various categories such as STEM, human science, and social science.
- We have analyzed for the quality and statistical of KNOWLEDGE PILE. we statistic the distribution of web domain to show the performance of *Query of CC* in collecting scattered information, then, we compared the educational value of KNOWLEDGE PILE with other open source knowledge-related datasets, to show the high educational value of our dataset.
- We train several language models on KNOWLEDGE PILE, which demonstrate significant improvements on several professional exams and reasoning datasets.

2 Related work

2.1 Large language model for knowledge-based reasoning

In recent years, significant progress has been made in the field of Natural Language Processing (NLP), driven by the emergence of large language models [OpenAI, 2023, InternLM-Team, 2023, Bai

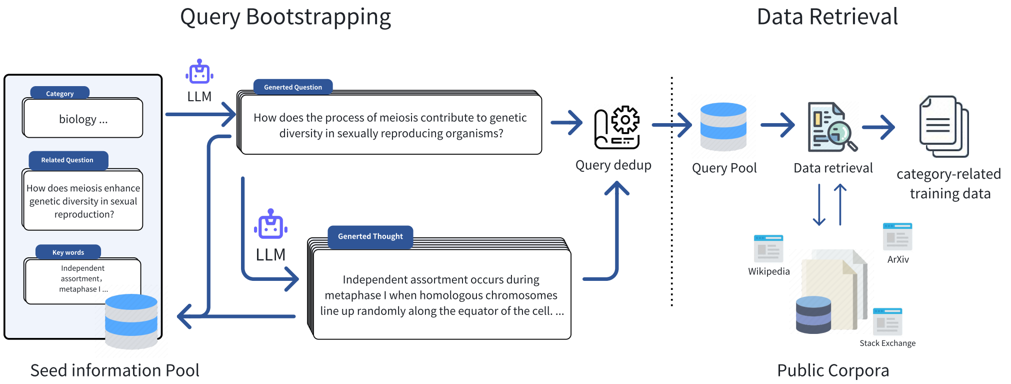

Query Bootstrapping
Data Retrieval
Category
biology ...
Related Question
How does meiosis enhance genetic diversity in sexual reproduction?
Key words
Independent assortment, metaphase I ...
LLM
Generted Question
How does the process of meiosis contribute to genetic diversity in sexually reproducing organisms?
LLM
Generted Thought
Independent assortment occurs during metaphase I when homologous chromosomes line up randomly along the equator of the cell. ...
Seed information Pool
Query dedup
Query Pool
Data retrieval
category-related training data
Wikipedia
ArXiv
Stack Exchange
Public Corpora

Figure 2: The overview of *Query of CC*'s two major components: Query Bootstrapping and Data Retrieval.

et al., 2023, Sun et al., 2023]. Particularly, in the domain of academic and professional examinations, Some language models such as ChatGPT and GPT-4 [OpenAI, 2023] have demonstrated remarkable success in solving complex tasks, achieving human-like performance through the utilization of the capability of reasoning [Wei et al., 2022, Wang et al., 2023c]. However, open-source LLMs lag in performance (Like Llama [Touvron et al., 2023a], Mistral [Jiang et al., 2023] etc.), possibly due to a lack of data.

2.2 Manual Data Collection

Currently, extensive efforts are being dedicated to the manual collection of specific training data to enhance the capabilities of Large Language Models (LLM) in knowledge-based reasoning. In the field of mathematics, Lewkowycz et al. [2022] undertook the task of gathering approximately 40 billion tokens of data from arXiv and web math pages. They developed a series of Minerva models based on PaLM [Chowdhery et al., 2023] and observed that augmenting the model with more mathematical data significantly enhances its proficiency in mathematical reasoning. Similarly, numerous works [Azerbayev et al., 2023, Wang et al., 2023a, Paster et al., 2023] have undertaken the collection of mathematics-related data, encompassing papers, web pages, and code, with considerable cost.

In the academic and technological domains, Taylor et al. [2022b] collected 106 billion academic and technological data. They asserted that the resulting 120B Galactica model surpasses GPT-3 in various academic benchmarks. These works highlight the efficacy of manual data collection in enhancing model performance. However, it is crucial to note that these data collection endeavors are labor-intensive, and present challenges in scalability, thereby posing some constraints on the overall improvement of model performance.

In contrast to these human-centric collection methods, our approach delves into an automated method for bootstrapping and collecting domain-specific data from public corpora and aims to achieve scalability, efficiency, and cost-effectiveness in data collection.

2.3 Retrieval-based Data Collection

Many works [Li et al., 2023, Li and Qiu, 2023] utilized retrieval methods to enhance their capabilities. The majority of these focus on retrieving documents relevant to the questions to improve the model's prior knowledge, thereby enhancing the performance on knowledge-related tasks and reducing hallucinations. Also, [Yue et al., 2024] retrieved related data for enhancing the instruction synthetic. For data collection, some works [Yao et al., 2022] attempt to use retrieval during the training phase for data collection to improve specified downstream tasks. However, Retrieving specified information for specific downstream tasks relies on the data of those tasks, making it difficult to automate and scale. In contrast, our method introduces LLMs to automatically extend domain-related queries, which enhances the automation and scalability of data collection.

3 *Query of CC*

3.1 Overview

The overview of *Query of CC* is illustrated in Figure 2. This framework encompasses two major stages, namely **Query Bootstrapping** and **Data Retrieval**. During the Query Bootstrapping phase, the Large Language Model constructs questions and answers centered around the given keywords to retrieve relevant text from public corpora. Through this bootstrapping process, we construct queries around the seed keywords in both depth and breadth, ensuring that the query encompasses a wide range of knowledge and sufficient depth. In the Data Retrieval phase, we employed the BM25 algorithm to retrieve text relevant to specific categories and obtained training data through post-processing steps such as deduplication.

3.2 Query Bootstrapping

To efficiently and comprehensively retrieve high-quality data relevant to the given seed information, we employed the **Query Bootstrapping** method, inspiration from Wang et al. [2023b]. During this phase, we expanded queries around seed information such as category or some related questions, by querying large language models and aims to extend the scope of retrieved data from both breadth and depth perspectives.

Question Extension To broaden the scope of our queries, we leverage large language models to generate questions relevant to the given seed words which we called **Question Extension**. Leveraging the capabilities of large models for question generation is evident in expanding the conceptual boundaries of the keywords. This process evolves a narrow category into a more comprehensive representation, encompassing various concepts associated with the given words. Consequently, it significantly enhances the breadth of the query set, ensuring a more comprehensive coverage of various aspects within the target domain.

Thought Generation In addition to expanding the range of queries through Question Evolution, we are dedicated to enhancing the depth of thought in generated queries through **Thought Generation**. In this phase, we are inspired by the work of Wei et al. [2022], employing LLMs to generate the cognitive processes necessary for answering questions. This enables us to acquire detailed and insightful responses. This approach supports a more thorough exploration of concepts related to seed information and generate the cognitive processes essential for answering questions. The generated thoughts not only serve for retrieving seed information-related data but also, by expanding queries, offer additional context and relevant knowledge, contributing to a more comprehensive understanding of the subject matter.

Query post processing We conducted post-processing operations on queries, involving two main stages: pre-cleaning before entering the seed information pool and cleaning and filtering before entering the query pool. On one hand, the generated questions underwent a re-cleaning process and were incorporated into the seed information pool for the next rounds of question bootstrapping and thought generation. This cleaning step involved removing incompletely generated language data to prevent the influence of non-natural language. On the other hand, before entering the query pool, we employed Minhash-LSH [Broder, 1997] deduplication on queries to mitigate performance inefficiencies resulting from redundant retrievals.

3.3 Data Retrieval

Based on the query bootstrapping stage, we get extensive and in-depth queries. During the data retrieval stage, utilizing the enriched queries, we employ the BM25 [Robertson and Walker, 1994] algorithm to retrieve data from general public corpora. BM25 is a widely adopted relevance calculation method commonly used by search engines. It calculates the relevance score between the given query and target documents by weighting and summing the matching degree of keywords in the query with the target documents. Efficiency is the reason why we use BM25 to calculate the relevance. When dealing with billion data, performing relevance calculations for each query against every document becomes exceedingly challenging, while BM25 rapidly retrieves documents relevant to the target query. Compared with Dense Retriever [Karpukhin et al., 2020], it may incur a potential loss in

Datasets	Target domain	automatic	methods	source	Data scale	Open Source
Proof of Pile	Mathematics reasoning	✗	human collection	arXiv, Textbooks, Lib., Stack Exchange, ProofWiki, MATH	8.3B	✓
OpenWebMath	Mathematics reasoning	✗	human collection	Common Crawl	14.7B	✓
MATHPILE	Mathematics reasoning	✗	human collection	arXiv, Textbooks, Lib., Stack Exchange, ProofWiki, MATH,Web	9.5B	✓
AcademicGPT	Academic	✗	human collection	arXiv, Unpaywall,Top Universities, Pubmed, Common Crawl, Semantic Scholar, Wiki	370B	✗
Galactica	Academic	✗	human collection	Papers, Code, Reference Material, Knowledge Bases, Common Crawl, Prompts	106B	✗
KNOWLEDGE PILE (ours)	Mathematics reasoning & Knowledge	✓	automatic query and retrieve	Public Corpora	188B	✓

Table 1: Comparation of KNOWLEDGE PILEwith other specific domain knowledge dataset. In this table, most data scales are derived from publicly released research papers, while the data scale for the KNOWLEDGE PILE is obtained through tokenized data analysis using the Llama2 tokenizer.

retrieval accuracy, but the latter comes with an unbearable high computational cost. Exploring the potential impact of retriever selection on the quality of collected data might be a valuable direction for future research.

For each query q_i, we conduct the relevance score against every document d in the public corpora $\mathcal{D}$. Followed by sorting the documents based on relevance, we retrieve top-k document set $\mathcal{S}_i = \{\widetilde{d}_1, ..., \widetilde{d}_k\}$ with the highest relevance with the query q_i. In our experiments, the typical choice for k is 1000. The retrieved data which related all the query $q_i \in \mathcal{Q}$ is consolidated into training dataset $\mathcal{S} = \cup_i \mathcal{S}_i$.

4 KNOWLEDGE PILE

Leveraging *Query of CC*, Based on queries of some knowledge categories, we retrieved several knowledge-related data from processed public corpora. We call the collected datasets as KNOWLEDGE PILE. In this section, we will introduce the analysis of queries (Section 4.1) and the analysis of KNOWLEDGE PILE (Section 4.2). Also, we train several language models to show the improvement of KNOWLEDGE PILE in some knowledge-related reasoning benchmarks (Section 4.3). Otherwise, we discuss about the different when improving different language models using KNOWLEDGE PILE (Section 4.4). See more implement details in Appendix.

4.1 Query Analysis

The progress of query bootstrapping initiates from some categories. Inspiration of the classification of Hendrycks et al. [2021], we select multiple categories for our initial seed information in the STEM (Science, technology, engineering, and mathematics), Humanities sciences, Social Sciences, and miscellaneous. The key keywords for each category are as follows:

STEM: mathematics, physics, chemistry, biology, computer science, engine;

Humanities: logical, history, law, philosophy, religions;

Social science: econometrics, politics, psychology, sexuality, public relations, psychology, sociology;

Misc: medicine, virology, commonsense knowledge and other miscellaneous.

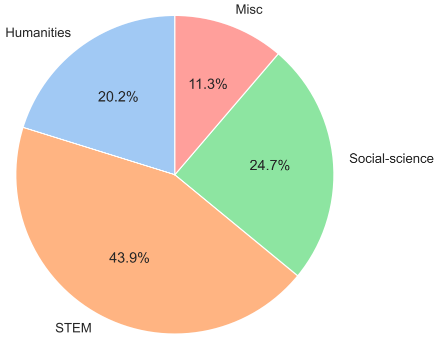


Figure 3: The category distribution of the query for KNOWLEDGE PILE.

After multiple rounds of iterative augmentation and deduplication, we obtain a total of 340,000 queries. The distribution of queries across different domains is depicted in Figure 3. In our query pool, STEM-

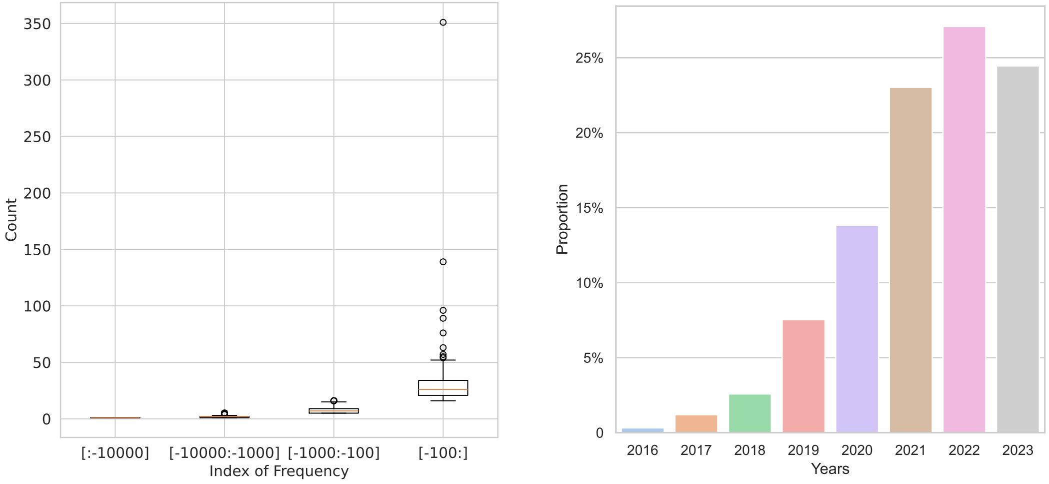


Figure 4: Left: The count distribution of index of web domain frequency. *Query of CC* not only retrieve the data from high knowledge density websites like Wikipedia, but collect data from scatted websites. Right: The timestamp statistics of Knowledge Pile, most data of Knowledge Pile come from recent years.

related queries constitute the majority, while the proportion of queries similar to miscellaneous is relatively small.

4.2 Data Analysis

Overview Based on *Query of CC*, we have formed a high-quality knowledge dataset Knowledge Pile, which maintains about 735GB disk and 188B tokens (using Llama2 tokenizer). As shown in Figure 1, comparing with other datasets in academic and mathematical reasoning domains, we have acquired a large-scale, knowledge-related dataset at a lower cost, without the need for manual intervention. Through automated query bootstrapping, we efficiently capture the information about the seed query. Knowledge Pile not only covers mathematical reasoning data but also encompasses rich knowledge-oriented corpora spanning various fields such as biology, physics, etc., enhancing its comprehensive research and application potential.

Web Domain	**Count**
en.wikipedia.org	398833
www.semanticscholar.org	141268
slideplayer.com	108177
www.ncbi.nlm.nih.gov	97009
link.springer.com	85357
www.ipl.org	84084
pubmed.ncbi.nlm.nih.gov	68934
www.reference.com	61658
www.bartleby.com	60097
quizlet.com	56752

Table 2: Top 10 most web domain of the data in Knowledge Pile, most of these are academic institutions, high-value forums, and authoritative website.

Web Domain composition of *Query of CC* Table 2 presents the top 10 web domains with the highest proportion in Knowledge Pile, which cover a wide range of academic institutions, high-value forums, and authoritative websites in specific knowledge fields. These resources are closely related to the knowledge domains we aim to collect, such as *en.wikipedia.org* and *www.semanticscholar.org*. Many previous research [Touvron et al., 2023a, Gao et al., 2021, Taylor et al., 2022b] have specifically collected data from these domains to enrich the knowledge of the training dataset. To gain an insight into the data distribution of Knowledge Pile, we randomly selected 100,000 examples and conducted the statistical analysis of their domain frequency. Figure 4 left shows the distribution of different frequency intervals classified by domain frequency. We observed that in the Knowledge Piledatabase, the vast majority of web domains are recorded only once, and these domains also contain rich knowledge content. However, traditional manual data collection methods have limitations in systematically collecting these scattered data, and *Query of CC*has shown its excellent data collection capabilities in this regard.

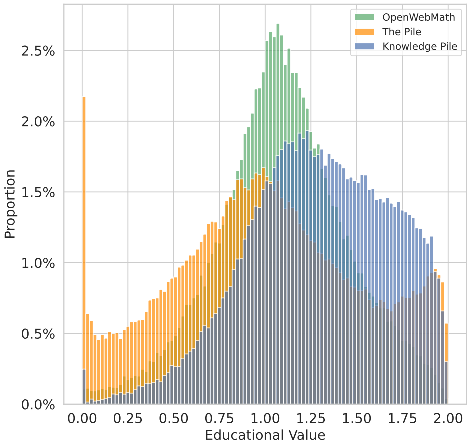


Figure 5: The distribution of educational value of different open source datasets, which shows that the distribution of Knowledge Pileon the x-axis is significantly right shifted compare others, indicating that it has higher educational value.

Datasets	**Educational Value (↑)**
PubMed* [Cohan et al., 2018]	1.260
Guanaco* [Dettmers, 2023]	1.115
OpenWebMath* [Paster et al., 2023]	1.089
Arxiv* [Cohan et al., 2018]*	1.068
FineWeb* [Penedo et al., 2024]	1.056
Dolma v1.7* [Soldaini et al., 2024]	1.037
The Pile* [Gao et al., 2021]	1.01
MiniPile* [Kaddour, 2023]	0.998
RedPajama* [Computer, 2023]	0.985
Knowledge Pile (ours)	**1.291**

Table 3: The comparison of average educational value scores among different open-source datasets. * denotes the results cited from Tsui [2024], which selected the first 100,000 samples of the dataset, and others randomly selected 100,000 samples.

Furthermore, Table 4 right statistic the timestamps of data sources in Knowledge Pile by year. It is evident that most of the data in Knowledge Pile originates from recent years, and the proportion of earlier timestamps is gradually decreasing. This phenomenon can be attributed to the exponential growth of internet data volume and the inherent timeliness characteristic of the knowledge pile.

Data Quality Analysis To evaluate the quality of Knowledge Pile, we employed an open-source data quality classifier[2], to rate the data within Knowledge Pile. Inspired by Gunasekar et al. [2023], high-quality data should possess characteristics of high educational value, namely: clarity, independence, instruction, and balance. To achieve the assessment of the educational value of the data, Tsui [2024] collected a subset of high-quality raw data and trained a classifier for evaluating the educational value of data based on fasttext [3]. The educational value ranges from 0, indicating low educational value, to 2, indicating high educational value. In Table 3, we present a comparison between Knowledge Pile and other mainstream knowledge datasets. The results show that Knowledge Pile has an average score of 1.29, significantly outperforming other open-source knowledge-based real datasets.

Figure 5 further reveals the differences in the distribution of educational value among the Knowledge Pile, Pile, and OpenWebMath datasets. Through comparison, we can observe a distinct rightward shift in the distribution of Knowledge Pile, indicating that Knowledge Pilecontains a greater amount of data with high educational value, while the proportion of low-value data is relatively lower.

4.3 The Improvement in Knowledge-Related Reasoning Benchmark

Based on Knowledge Pile, we further train two models: Llama2-QoC and Mistral-QoC, based on Llama2 and Mistral.

[2] https://huggingface.co/kenhktsui/llm-data-textbook-quality-fasttext-classifier-v2

[3] https://fasttext.cc/

		MATH	**GSM8K**	**MMLU**	**AGIEval**	**BIG-Bench Hard**
Code-Llama	7B	3.88	14.4	40.39	21.47	42.78
Baichuan2-Base	7B	5.72	23.81	53.95	34.68	40.32
Minerva	8B	14.1	16.2	-	-	-
Llemma	7B	14.3	35.94	47.89	24.14	48.61
Qwen 2	7B	10.82	51.4	57.97	40.37	22.27
Llama 2	7B	3.32	16.68	46.79	21.37	38.19
Llama 2-QoC	7B	6.2	28.51	57.02	30.04	44.82
Mistral	7B	11.22	47.31	64.06	32.88	56.69
Mistral-QoC	7B	**17.48**	**55.27**	**65.71**	**45.24**	**57.81**

Table 4: Main results of our model and baselines in some mathematical reasoning tasks and knowledge related reasoning tasks.

Training Details In our experiment, we employed the InternLM[4] [InternLM-Team, 2023] library for training all models on 256 A800 GPUs with bfloat16 mixed precision, and only utilized data parallelism during the training process. To enhance throughput and reduce memory consumption, we introduced the Flash attention 2 [Dao, 2023] module. Above these, both Llama-QoC and Mistral-QoC achieve 4000 tokens per GPU per second(TGS). More training details will be described in Appendix.

Evaluation During the evaluation, we utilized the open-source library OpenCompass [5], which serves as a platform for evaluating LLMs. Leveraging Opencompass, we compare the performance with some open source pre-trained models: Llama2 [Touvron et al., 2023b], Code-Llama [Rozière et al., 2023], Baichuan 2-Base [Yang et al., 2023], Mistral [Jiang et al., 2023], Qwen 2 [Bai et al., 2023] and some language models for mathematical reasoning: Llemma [Azerbayev et al., 2023] and Minerva [Lewkowycz et al., 2022]. For the selection of evaluation datasets, we opted for three distinct capabilities to assess both Llama2-QoC and Mistral-QoC. These encompassed mathematical reasoning datasets such as Math, GSM8K, knowledge-oriented language understanding datasets including MMLU, AGIEval, and challenging reasoning tasks BIG-Bench hard. More details for evaluation will be described in Appendix.

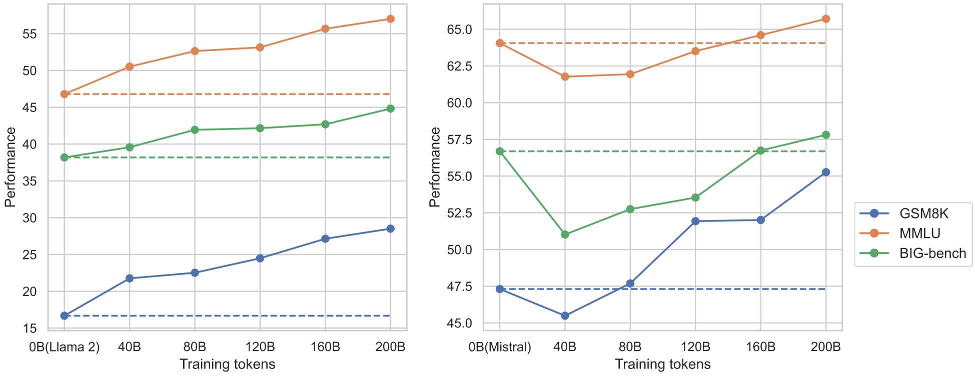
Main Results The main results of our two models trained on Knowledge Pile (Llama2-QoC and Mistral-QoC) and the baseline are compared in Table 4 across several general benchmarks. Overall, both models exhibit significantly improved performance, particularly Mistral-QoC. In the complex mathematical reasoning benchmark MATH dataset, Mistral-QoC demonstrates a notable enhancement after QoC training, rising from 11.22 to 17.48, which surpasses professional models such as LLEMMA and Minerva by 3 points (14.3 vs 17.48). Furthermore, Mistral-QoC achieves even higher performance on the mathematical application problem GSM8K (47.31 vs 55.27). Turning to various knowledge-based reasoning tasks, Mistral-QoC displays outstanding capabilities in both MMLU and AGIEval. On the challenging BIG-Bench Hard evaluation set, the model also exhibits a noteworthy improvement in handling complex reasoning tasks.

In comparison to the backbone model, LLAMA-QoC and Mistral-QoC show substantial improvements in mathematical and knowledge-based reasoning tests. For instance, Mistral achieves a 6-points improvement in the MATH dataset and a 5-point improvement in GSM8K. In knowledge-based tests, MMLU shows a relatively modest improvement, within a 1.7 point. However, in AGIEval, Mistral-QoC outperforms Mistral by an impressive 13 points.

Otherwise, an interesting observation is that when the baseline model performance is lower (e.g., LLAMA2), the enrichment of the dataset leads to higher improvements. Conversely, for baseline models with better performance, achieving significant improvement becomes relatively challenging. This difference may be attributed to variations in the model's ability to fit the data.

[4] https://github.com/InternLM/InternLM

[5] https://github.com/open-compass/opencompass



(a) Improving Llama2

(b) Improving Mistral

Figure 6: The performance curves of Llama2-QoC and Mistral-QoC, varying with the increase in the number of training tokens.

4.4 Difference between Improve Llama and Mistral

As shown in Table 4, it is evident that Llama2 exhibits inferior performance relative to Mistral. However, this also highlights a greater potential for performance improvement when training in KNOWLEDGE PILE. Also, we observe a significant behavioral difference during the improvement process, which is shown in Figure 6. We found that in certain tasks, Mistral's performance undergoes a certain degree of decline during the improvement process, followed by a subsequent ascent after some time, eventually surpassing the previous performance levels. This phenomenon may come from a conflict between the potential distribution of the model and the distribution of high-quality datasets. Mistral's potential distribution is superior but more unstable, whereas Llama's performance is relatively poorer but exhibits greater plasticity. On the other hand, the improvement achieved on more powerful models (Mistral 7B) also demonstrates the high-quality of KNOWLEDGE PILE.

5 Hallucination Analysis

The output of LLMs generally exhibits significant hallucination issues. Previous work has shown that LLMs are prone to hallucinations, and using their output directly in training without filtering can exacerbate the model's hallucinations for certain issues. However, in the data collection pipeline of *Query of CC*, the model is only used to generate queries and is not directly applied in training. Therefore, even if the synthesized queries from the LLMs contain incorrect information, the information retrieved from the corpus based on these incorrect queries is correct. Hallucinatory queries do not lead to the retrieval of incorrect information.

6 Conclusion

In this study, we propose an efficient method *Query of CC*, for the automated collection of specialized domain data. Leveraging seed data from some specific domains, we employ a language model for query bootstrapping. By optimizing the breadth and depth of queries, we expand the query to retrieve data relevant to the specified domain. Ultimately, we collected and released an open dataset comprising approximately 735GB of KNOWLEDGE PILE, equivalent to approximately 188 billion tokens, in the fields of mathematics and knowledge. Experimental results demonstrate that the adoption of KNOWLEDGE PILE significantly enhances the model's performance in some reasoning tasks, such as math word problems and professional examinations. Our objective is not only to establish a research foundation for community studies in mathematical and knowledge-related reasoning but also to provide an efficient and cost-effective method for collecting high-quality data, thereby facilitating the accumulation of more high-quality data.

References

OpenAI. GPT-4 technical report. *CoRR*, abs/2303.08774, 2023. doi: 10.48550/ARXIV.2303.08774. URL https://doi.org/10.48550/arXiv.2303.08774.

Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurélien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. Llama: Open and efficient foundation language models. *CoRR*, abs/2302.13971, 2023a. doi: 10.48550/ARXIV.2302.13971. URL https://doi.org/10.48550/arXiv.2302.13971.

Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de Las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, Lélio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timothée Lacroix, and William El Sayed. Mistral 7b. *CoRR*, abs/2310.06825, 2023. doi: 10.48550/ARXIV.2310.06825. URL https://doi.org/10.48550/arXiv.2310.06825.

Xi Yang, Nima M. Pournejatian, Hoo Chang Shin, Kaleb E. Smith, Christopher Parisien, Colin Compas, Cheryl Martin, Mona G. Flores, Ying Zhang, Tanja Magoc, Christopher A. Harle, Gloria P. Lipori, Duane A. Mitchell, William R. Hogan, Elizabeth A. Shenkman, Jiang Bian, and Yonghui Wu. Gatortron: A large clinical language model to unlock patient information from unstructured electronic health records. *CoRR*, abs/2203.03540, 2022. doi: 10.48550/ARXIV.2203.03540. URL https://doi.org/10.48550/arXiv.2203.03540.

Weihao Gao, Zhuo Deng, Zhiyuan Niu, Fuju Rong, Chucheng Chen, Zheng Gong, Wenze Zhang, Daimin Xiao, Fang Li, Zhenjie Cao, Zhaoyi Ma, Wenbin Wei, and Lan Ma. Ophglm: Training an ophthalmology large language-and-vision assistant based on instructions and dialogue. *CoRR*, abs/2306.12174, 2023. doi: 10.48550/ARXIV.2306.12174. URL https://doi.org/10.48550/arXiv.2306.12174.

Shijie Wu, Ozan Irsoy, Steven Lu, Vadim Dabravolski, Mark Dredze, Sebastian Gehrmann, Prabhanjan Kambadur, David S. Rosenberg, and Gideon Mann. Bloomberggpt: A large language model for finance. *CoRR*, abs/2303.17564, 2023. doi: 10.48550/ARXIV.2303.17564. URL https://doi.org/10.48550/arXiv.2303.17564.

Xuanyu Zhang and Qing Yang. Xuanyuan 2.0: A large chinese financial chat model with hundreds of billions parameters. In Ingo Frommholz, Frank Hopfgartner, Mark Lee, Michael Oakes, Mounia Lalmas, Min Zhang, and Rodrygo L. T. Santos, editors, *Proceedings of the 32nd ACM International Conference on Information and Knowledge Management, CIKM 2023, Birmingham, United Kingdom, October 21-25, 2023*, pages 4435–4439. ACM, 2023. doi: 10.1145/3583780.3615285. URL https://doi.org/10.1145/3583780.3615285.

Ross Taylor, Marcin Kardas, Guillem Cucurull, Thomas Scialom, Anthony Hartshorn, Elvis Saravia, Andrew Poulton, Viktor Kerkez, and Robert Stojnic. Galactica: A large language model for science. *CoRR*, abs/2211.09085, 2022a. doi: 10.48550/ARXIV.2211.09085. URL https://doi.org/10.48550/arXiv.2211.09085.

Shufa Wei, Xiaolong Xu, Xianbiao Qi, Xi Yin, Jun Xia, Jingyi Ren, Peijun Tang, Yuxiang Zhong, Yihao Chen, Xiaoqin Ren, Yuxin Liang, Liankai Huang, Kai Xie, Weikang Gui, Wei Tan, Shuanglong Sun, Yongquan Hu, Qinxian Liu, Nanjin Li, Chihao Dai, Lihua Wang, Xiaohui Liu, Lei Zhang, and Yutao Xie. Academicgpt: Empowering academic research. *CoRR*, abs/2311.12315, 2023. doi: 10.48550/ARXIV.2311.12315. URL https://doi.org/10.48550/arXiv.2311.12315.

Ha-Thanh Nguyen. A brief report on lawgpt 1.0: A virtual legal assistant based on GPT-3. *CoRR*, abs/2302.05729, 2023. doi: 10.48550/ARXIV.2302.05729. URL https://doi.org/10.48550/arXiv.2302.05729.

Jiaxi Cui, Zongjian Li, Yang Yan, Bohua Chen, and Li Yuan. Chatlaw: Open-source legal large language model with integrated external knowledge bases. *CoRR*, abs/2306.16092, 2023. doi: 10.48550/ARXIV.2306.16092. URL https://doi.org/10.48550/arXiv.2306.16092.

Zhangir Azerbayev, Hailey Schoelkopf, Keiran Paster, Marco Dos Santos, Stephen McAleer, Albert Q. Jiang, Jia Deng, Stella Biderman, and Sean Welleck. Llemma: An open language model for mathematics. *CoRR*, abs/2310.10631, 2023. doi: 10.48550/ARXIV.2310.10631. URL https://doi.org/10.48550/arXiv.2310.10631.

Zengzhi Wang, Rui Xia, and Liu Pengfei. Generative ai for math: Part i – mathpile: A billion-token-scale pretraining corpus for math. *arXiv preprint arXiv:2312.17120*, 2023a.

Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A. Smith, Daniel Khashabi, and Hannaneh Hajishirzi. Self-instruct: Aligning language models with self-generated instructions. In Anna Rogers, Jordan L. Boyd-Graber, and Naoaki Okazaki, editors, *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2023, Toronto, Canada, July 9-14, 2023*, pages 13484–13508. Association for Computational Linguistics, 2023b. doi: 10.18653/V1/2023.ACL-LONG.754. URL https://doi.org/10.18653/v1/2023.acl-long.754.

Can Xu, Qingfeng Sun, Kai Zheng, Xiubo Geng, Pu Zhao, Jiazhan Feng, Chongyang Tao, and Daxin Jiang. Wizardlm: Empowering large language models to follow complex instructions. *CoRR*, abs/2304.12244, 2023. doi: 10.48550/ARXIV.2304.12244. URL https://doi.org/10.48550/arXiv.2304.12244.

InternLM-Team. Internlm: A multilingual language model with progressively enhanced capabilities. https://github.com/InternLM/InternLM, 2023.

Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, Binyuan Hui, Luo Ji, Mei Li, Junyang Lin, Runji Lin, Dayiheng Liu, Gao Liu, Chengqiang Lu, Keming Lu, Jianxin Ma, Rui Men, Xingzhang Ren, Xuancheng Ren, Chuanqi Tan, Sinan Tan, Jianhong Tu, Peng Wang, Shijie Wang, Wei Wang, Shengguang Wu, Benfeng Xu, Jin Xu, An Yang, Hao Yang, Jian Yang, Shusheng Yang, Yang Yao, Bowen Yu, Hongyi Yuan, Zheng Yuan, Jianwei Zhang, Xingxuan Zhang, Yichang Zhang, Zhenru Zhang, Chang Zhou, Jingren Zhou, Xiaohuan Zhou, and Tianhang Zhu. Qwen technical report. *CoRR*, abs/2309.16609, 2023. doi: 10.48550/ARXIV.2309.16609. URL https://doi.org/10.48550/arXiv.2309.16609.

Tianxiang Sun, Xiaotian Zhang, Zhengfu He, Peng Li, Qinyuan Cheng, Hang Yan, Xiangyang Liu, Yunfan Shao, Qiong Tang, Xingjian Zhao, Ke Chen, Yining Zheng, Zhejian Zhou, Ruixiao Li, Jun Zhan, Yunhua Zhou, Linyang Li, Xiaogui Yang, Lingling Wu, Zhangyue Yin, Xuanjing Huang, and Xipeng Qiu. Moss: Training conversational language models from synthetic data, 2023.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed H. Chi, Quoc V. Le, and Denny Zhou. Chain-of-thought prompting elicits reasoning in large language models. In *NeurIPS*, 2022. URL http://papers.nips.cc/paper_files/paper/2022/hash/9d5609613524ecf4f15af0f7b31abca4-Abstract-Conference.html.

Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc V. Le, Ed H. Chi, Sharan Narang, Aakanksha Chowdhery, and Denny Zhou. Self-consistency improves chain of thought reasoning in language models. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net, 2023c. URL https://openreview.net/pdf?id=1PL1NIMMrw.

Aitor Lewkowycz, Anders Andreassen, David Dohan, Ethan Dyer, Henryk Michalewski, Vinay V. Ramasesh, Ambrose Slone, Cem Anil, Imanol Schlag, Theo Gutman-Solo, Yuhuai Wu, Behnam Neyshabur, Guy Gur-Ari, and Vedant Misra. Solving quantitative reasoning problems with language models. In *NeurIPS*, 2022. URL http://papers.nips.cc/paper_files/paper/2022/hash/18abbeef8cfe9203fdf9053c9c4fe191-Abstract-Conference.html.

Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, Parker Schuh, Kensen Shi, Sasha Tsvyashchenko, Joshua Maynez, Abhishek Rao, Parker Barnes, Yi Tay, Noam Shazeer, Vinodkumar Prabhakaran, Emily Reif, Nan Du, Ben Hutchinson, Reiner Pope, James Bradbury, Jacob Austin, Michael Isard, Guy Gur-Ari, Pengcheng Yin, Toju Duke, Anselm Levskaya, Sanjay Ghemawat, Sunipa Dev, Henryk Michalewski, Xavier Garcia, Vedant Misra, Kevin Robinson, Liam Fedus, Denny Zhou, Daphne Ippolito, David Luan, Hyeontaek Lim, Barret Zoph, Alexander Spiridonov, Ryan Sepassi, David Dohan, Shivani Agrawal, Mark Omernick, Andrew M. Dai, Thanumalayan Sankaranarayana Pillai, Marie Pellat, Aitor Lewkowycz, Erica Moreira, Rewon Child, Oleksandr Polozov, Katherine Lee, Zongwei Zhou, Xuezhi Wang, Brennan Saeta, Mark Diaz, Orhan Firat, Michele Catasta, Jason Wei, Kathy Meier-Hellstern, Douglas Eck, Jeff Dean, Slav Petrov, and Noah Fiedel. Palm: Scaling language modeling with pathways. *J. Mach. Learn. Res.*, 24:240:1–240:113, 2023. URL `http://jmlr.org/papers/v24/22-1144.html`.

Keiran Paster, Marco Dos Santos, Zhangir Azerbayev, and Jimmy Ba. Openwebmath: An open dataset of high-quality mathematical web text. *CoRR*, abs/2310.06786, 2023. doi: 10.48550/ARXIV.2310.06786. URL `https://doi.org/10.48550/arXiv.2310.06786`.

Ross Taylor, Marcin Kardas, Guillem Cucurull, Thomas Scialom, Anthony Hartshorn, Elvis Saravia, Andrew Poulton, Viktor Kerkez, and Robert Stojnic. Galactica: A large language model for science. *CoRR*, abs/2211.09085, 2022b. doi: 10.48550/ARXIV.2211.09085. URL `https://doi.org/10.48550/arXiv.2211.09085`.

Xiaonan Li, Kai Lv, Hang Yan, Tianyang Lin, Wei Zhu, Yuan Ni, Guotong Xie, Xiaoling Wang, and Xipeng Qiu. Unified demonstration retriever for in-context learning. In Anna Rogers, Jordan L. Boyd-Graber, and Naoaki Okazaki, editors, *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2023, Toronto, Canada, July 9-14, 2023*, pages 4644–4668. Association for Computational Linguistics, 2023. doi: 10.18653/V1/2023.ACL-LONG.256. URL `https://doi.org/10.18653/v1/2023.acl-long.256`.

Xiaonan Li and Xipeng Qiu. Mot: Memory-of-thought enables chatgpt to self-improve. In Houda Bouamor, Juan Pino, and Kalika Bali, editors, *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, EMNLP 2023, Singapore, December 6-10, 2023*, pages 6354–6374. Association for Computational Linguistics, 2023. URL `https://aclanthology.org/2023.emnlp-main.392`.

Xiang Yue, Tuney Zheng, Ge Zhang, and Wenhu Chen. Mammoth2: Scaling instructions from the web, 2024.

Xingcheng Yao, Yanan Zheng, Xiaocong Yang, and Zhilin Yang. NLP from scratch without large-scale pretraining: A simple and efficient framework. In Kamalika Chaudhuri, Stefanie Jegelka, Le Song, Csaba Szepesvári, Gang Niu, and Sivan Sabato, editors, *International Conference on Machine Learning, ICML 2022, 17-23 July 2022, Baltimore, Maryland, USA*, volume 162 of *Proceedings of Machine Learning Research*, pages 25438–25451. PMLR, 2022. URL `https://proceedings.mlr.press/v162/yao22c.html`.

Andrei Z. Broder. On the resemblance and containment of documents. In Bruno Carpentieri, Alfredo De Santis, Ugo Vaccaro, and James A. Storer, editors, *Compression and Complexity of SEQUENCES 1997, Positano, Amalfitan Coast, Salerno, Italy, June 11-13, 1997, Proceedings*, pages 21–29. IEEE, 1997. doi: 10.1109/SEQUEN.1997.666900. URL `https://doi.org/10.1109/SEQUEN.1997.666900`.

Stephen E. Robertson and Steve Walker. Some simple effective approximations to the 2-poisson model for probabilistic weighted retrieval. In W. Bruce Croft and C. J. van Rijsbergen, editors, *Proceedings of the 17th Annual International ACM-SIGIR Conference on Research and Development in Information Retrieval. Dublin, Ireland, 3-6 July 1994 (Special Issue of the SIGIR Forum)*, pages 232–241. ACM/Springer, 1994. doi: 10.1007/978-1-4471-2099-5_24. URL `https://doi.org/10.1007/978-1-4471-2099-5_24`.

Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick S. H. Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. Dense passage retrieval for open-domain question answering. In Bonnie Webber, Trevor Cohn, Yulan He, and Yang Liu, editors, *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020*, pages 6769–6781. Association for Computational Linguistics, 2020. doi: 10.18653/V1/2020.EMNLP-MAIN.550. URL `https://doi.org/10.18653/v1/2020.emnlp-main.550`.

Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. Measuring massive multitask language understanding. In *9th International Conference* *on Learning Representations, ICLR 2021, Virtual Event, Austria, May 3-7, 2021*. OpenReview.net, 2021. URL https://openreview.net/forum?id=d7KBjmI3GmQ.

Leo Gao, Stella Biderman, Sid Black, Laurence Golding, Travis Hoppe, Charles Foster, Jason Phang, Horace He, Anish Thite, Noa Nabeshima, Shawn Presser, and Connor Leahy. The pile: An 800gb dataset of diverse text for language modeling. *CoRR*, abs/2101.00027, 2021. URL https://arxiv.org/abs/2101.00027.

Arman Cohan, Franck Dernoncourt, Doo Soon Kim, Trung Bui, Seokhwan Kim, Walter Chang, and Nazli Goharian. A discourse-aware attention model for abstractive summarization of long documents. *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*, 2018. doi: 10.18653/v1/n18-2097. URL http://dx.doi.org/10.18653/v1/n18-2097.

Tim Dettmers. openassistant-guanaco, May 2023. URL https://huggingface.co/datasets/timdettmers/openassistant-guanaco.

Guilherme Penedo, Hynek Kydlíček, Leandro von Werra, and Thomas Wolf. Fineweb, 2024. URL https://huggingface.co/datasets/HuggingFaceFW/fineweb.

Luca Soldaini, Rodney Kinney, Akshita Bhagia, Dustin Schwenk, David Atkinson, Russell Authur, Ben Bogin, Khyathi Chandu, Jennifer Dumas, Yanai Elazar, Valentin Hofmann, Ananya Harsh Jha, Sachin Kumar, Li Lucy, Xinxi Lyu, Nathan Lambert, Ian Magnusson, Jacob Morrison, Niklas Muennighoff, Aakanksha Naik, Crystal Nam, Matthew E. Peters, Abhilasha Ravichander, Kyle Richardson, Zejiang Shen, Emma Strubell, Nishant Subramani, Oyvind Tafjord, Pete Walsh, Luke Zettlemoyer, Noah A. Smith, Hannaneh Hajishirzi, Iz Beltagy, Dirk Groeneveld, Jesse Dodge, and Kyle Lo. Dolma: an Open Corpus of Three Trillion Tokens for Language Model Pretraining Research. *arXiv preprint*, 2024.

Jean Kaddour. The minipile challenge for data-efficient language models. *arXiv preprint arXiv:2304.08442*, 2023.

Together Computer. Redpajama: an open dataset for training large language models, 2023. URL https://github.com/togethercomputer/RedPajama-Data.

Ken Tsui. llm-data-textbook-quality-fasttext-classifier-v2, 2024. URL https://huggingface.co/kenhktsui/llm-data-textbook-quality-fasttext-classifier-v2.

Suriya Gunasekar, Yi Zhang, Jyoti Aneja, Caio César Teodoro Mendes, Allie Del Giorno, Sivakanth Gopi, Mojan Javaheripi, Piero Kauffmann, Gustavo de Rosa, Olli Saarikivi, Adil Salim, Shital Shah, Harkirat Singh Behl, Xin Wang, Sébastien Bubeck, Ronen Eldan, Adam Tauman Kalai, Yin Tat Lee, and Yuanzhi Li. Textbooks are all you need. *CoRR*, abs/2306.11644, 2023. doi: 10.48550/ARXIV.2306.11644. URL https://doi.org/10.48550/arXiv.2306.11644.

Tri Dao. Flashattention-2: Faster attention with better parallelism and work partitioning. *CoRR*, abs/2307.08691, 2023. doi: 10.48550/ARXIV.2307.08691. URL https://doi.org/10.48550/arXiv.2307.08691.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton-Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurélien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. Llama 2: Open foundation and fine-tuned chat models. *CoRR*, abs/2307.09288, 2023b. doi: 10.48550/ARXIV.2307.09288. URL https://doi.org/10.48550/arXiv.2307.09288.

Baptiste Rozière, Jonas Gehring, Fabian Gloeckle, Sten Sootla, Itai Gat, Xiaoqing Ellen Tan, Yossi Adi, Jingyu Liu, Tal Remez, Jérémy Rapin, Artyom Kozhevnikov, Ivan Evtimov, Joanna Bitton, Manish Bhatt, Cristian Canton-Ferrer, Aaron Grattafiori, Wenhan Xiong, Alexandre Défossez, Jade Copet, Faisal Azhar, Hugo Touvron, Louis Martin, Nicolas Usunier, Thomas Scialom, and Gabriel Synnaeve. Code llama: Open foundation models for code. *CoRR*, abs/2308.12950, 2023. doi: 10.48550/ARXIV.2308.12950. URL `https://doi.org/10.48550/arXiv.2308.12950`.

Aiyuan Yang, Bin Xiao, Bingning Wang, Borong Zhang, Ce Bian, Chao Yin, Chenxu Lv, Da Pan, Dian Wang, Dong Yan, Fan Yang, Fei Deng, Feng Wang, Feng Liu, Guangwei Ai, Guosheng Dong, Haizhou Zhao, Hang Xu, Haoze Sun, Hongda Zhang, Hui Liu, Jiaming Ji, Jian Xie, Juntao Dai, Kun Fang, Lei Su, Liang Song, Lifeng Liu, Liyun Ru, Luyao Ma, Mang Wang, Mickel Liu, MingAn Lin, Nuolan Nie, Peidong Guo, Ruiyang Sun, Tao Zhang, Tianpeng Li, Tianyu Li, Wei Cheng, Weipeng Chen, Xiangrong Zeng, Xiaochuan Wang, Xiaoxi Chen, Xin Men, Xin Yu, Xuehai Pan, Yanjun Shen, Yiding Wang, Yiyu Li, Youxin Jiang, Yuchen Gao, Yupeng Zhang, Zenan Zhou, and Zhiying Wu. Baichuan 2: Open large-scale language models. *CoRR*, abs/2309.10305, 2023. doi: 10.48550/ARXIV.2309.10305. URL `https://doi.org/10.48550/arXiv.2309.10305`.