AutoMathText-V2
A 2.46 Trillion Token AI-Curated STEM Pretraining Dataset

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Abstract

We introduce `AutoMathText-V2`, a massive-scale, high-quality pretraining dataset curated for large language models (LLMs) with a strong concentration on Science, Technology, Engineering, and Mathematics (STEM) domains. The dataset consists of **2.46 trillion tokens** derived from over 50 premium data sources, spanning mathematics, code, reasoning, bilingual text, and general web content. To ensure exceptional data quality, we developed a meticulous processing pipeline featuring critical stages: (1) An *three-tier deduplication* process combining exact hash matching, fuzzy deduplication (MinHash+LSH), and advanced semantic deduplication using GTE embeddings. (2) An *AI-powered quality assessment* model, utilizing a fine-tuned Qwen2-based classifier with multi-source score fusion to score and filter content. (3) *Advanced text cleaning* powered by *Ultimate Data Cleaner*, which provides robust, high-performance sanitation while protecting vital STEM content such as complex LaTeX and code blocks. This comprehensive curation process makes `AutoMathText-V2` a superior resource for training robust and capable foundation models.

`Date:` August 20th, 2025

`Website:` https://iiis-ai.github.io/AutoMathText-V2

`Dataset:` https://huggingface.co/datasets/OpenSQZ/AutoMathText-V2

1 Introduction

The advancement of Large Language Models (LLMs) is intrinsically linked to the scale and quality of their pretraining data. While general-domain datasets have enabled significant progress, there remains a critical need for high-quality, specialized data in complex domains such as Science, Technology, Engineering, and Mathematics (STEM). STEM fields present unique challenges, including intricate mathematical notation (LaTeX), structured code, logical reasoning, and domain-specific terminology, which are often underrepresented or poorly formatted in general web crawls.

To address this gap, we introduce `AutoMathText-V2` (Li et al., 2025), a massive-scale, 2.46 trillion token pretraining dataset meticulously curated with a strong emphasis on STEM content. Our dataset aggregates over 50 premium data sources and employs a sophisticated, multi-stage processing pipeline to ensure exceptional quality, diversity, and utility. The key contributions of our work are:

- **STEM Concentration:** A purpose-built dataset optimized for mathematics, code, and scientific reasoning to enhance LLM capabilities in technical domains.

- **Three-Tier Deduplication:** An aggressive deduplication strategy combining exact, fuzzy (MinHash-LSH), and semantic (GTE embeddings) methods to maximize data diversity and efficiency.
- **AI-Powered Quality Assessment:** A novel quality scoring system using a fine-tuned Qwen2-based classifier to systematically identify and rank high-quality content.
- **Advanced Text Cleaning:** Robust sanitation using `Ultimate Data Cleaner v7.5.0.5` to normalize text while preserving the integrity of complex structures like LaTeX and code.
- **Contamination Prevention:** Proactive detection and removal of benchmark test questions from math and reasoning datasets to ensure the validity of downstream evaluations.

`AutoMathText-V2` provides the research community with a superior resource for training powerful, robust, and versatile foundation models capable of excelling at complex reasoning and problem-solving tasks.

2 Dataset Composition

`AutoMathText-V2` is a comprehensive collection of 2.46 trillion tokens, amalgamating 52 distinct datasets organized into several high-level domains. The distribution is designed to provide a strong foundation in general web text while significantly boosting representation in STEM-focused areas.

2.1 Token Distribution by Domain

The dataset is dominated by high-quality web content from Nemotron-CC and DCLM, complemented by substantial portions of code, educational text, reasoning tasks, and specialized mathematics data. Table 1 provides a detailed breakdown of the token count per domain.

2.2 Data Sources

The dataset is built from 52 premium sources, each chosen for its quality and relevance. A complete list of sources organized by domain is provided in the Appendix.

3 Processing Pipeline

To ensure the highest data quality, every sample in `AutoMathText-V2` was subjected to a rigorous five-stage processing pipeline.

3.1 Data Extraction & Standardization

Data from all 52 sources was extracted and standardized into a consistent JSON format. Each entry includes the text content, a unique ID, token count, and metadata such as the original source, domain, and quality scores.


```
{
    "domain_prefix": "lbty.org",
    "id": "117b6a7d-5126-41fe-9bc2-d276e98632e6",
```

Table 1 Token Distribution by Domain in AutoMathText-V2

Domain	Token Count (Billions)	Percentage	Description
Nemotron CC High (Su et al., 2024)	1,468.3B	59.7%	High quality CommonCrawl data
DCLM (Li et al., 2024)	314.2B	12.8%	DCLM baseline web content
RefineCode (Huang et al., 2024)	279.4B	11.4%	GitHub repositories (Academic Use Only)
Nemotron CC Medium-High	254.5B	10.3%	Medium-high quality CommonCrawl data
FineWeb Edu (Penedo et al., 2024)	117.4B	4.8%	Educational web content
Chinese	112.18B	4.6%	Chinese general content
Reasoning QA	86.2B	3.5%	Instruction-following and complex reasoning tasks
Math Web	68.3B	2.8%	Mathematics and scientific content
MegaMath (Zhou et al., 2025)	28.5B	1.2%	Specialized mathematical collections
Translation (Ziemski et al., 2016)	1.61B	0.1%	English-Chinese translation pairs
Total	**2,460.71B**	**100%**	**Complete dataset**


```
    "meta": "{\"domain\": \"dclm\", \"ori_score\":
   0.043276190757751465, \"source\": \"dclm_baseline\"}",
    "text": "Sabine Expedition\n\nThe Sabine Expedition was an
   expedition approved by the United States Congress in 1806...",
    "tokens": 145,
    "url": "https://lbty.org/american-indian-battles/sabine-
   expedition/",
    "score": 0.19072403013706207
}
```


Listing 1 Standardized data format example

3.2 Three-Tier Deduplication

We employed a multi-stage deduplication process to maximize data novelty and remove redundant information.

3.2.1 Exact Deduplication

We first performed exact deduplication using SHA256 hashing on the text content. In cases of collision, priority was given to sources deemed higher quality. This initial pass removed approximately 30% of documents.

3.2.2 Fuzzy Deduplication

Next, we applied MinHash Locality Sensitive Hashing (LSH) to identify near-duplicates. Documents were clustered using a Jaccard similarity threshold of 0.9. Within each cluster, only the document with the highest quality score was retained. This stage removed an additional 20% of near-duplicate documents.

3.2.3 Semantic Deduplication

Finally, we performed semantic deduplication to remove documents with similar meaning but different phrasing. We generated embeddings using `Alibaba-NLP/gte-multilingual-base` and used K-means clustering (k=100,000) to group semantically similar documents. A cosine similarity threshold of 0.007 was used to filter duplicates within clusters, removing a final 10% of the data.

3.3 AI Quality Assessment

A fine-tuned Qwen2 model was used as a quality classifier. The model was trained with a regression head to predict a quality score for each document (Zhang et al., 2025). Scores from multiple sources were normalized and fused to produce a final, reliable quality metric used for filtering and for creating quality-based percentile splits in the final dataset.

3.4 Advanced Text Cleaning

All text was processed with `Ultimate Data Cleaner v7.5.0.5`. This tool was configured for high-performance cleaning of web-scraped and scientific data. Key features included advanced protection for nested LaTeX environments and markdown code fences, alongside quality heuristics to remove corrupted text (e.g., excessive repetition, bracket imbalances).

3.5 Contamination Detection

To ensure the integrity of model evaluation, we implemented a strict contamination detection protocol. Test set questions from standard benchmarks (e.g., GSM8K, MATH) were compiled. We performed exact string matching against our dataset, filtering out any documents that contained benchmark questions. This process was integrated directly into the data extraction stage to prevent contamination from entering the pipeline.

4 Dataset Structure and Usage

4.1 Loading with `datasets`

The dataset is available on the Hugging Face Hub and can be easily loaded using the `datasets` library. The full dataset or specific domains can be loaded in streaming mode to handle its large size.

```
from datasets import load_dataset

# Load the full dataset in streaming mode
dataset = load_dataset("OpenSQZ/AutoMathText-V2", streaming=True)

# Load a specific domain (e.g., math_web)
math_data = load_dataset("OpenSQZ/AutoMathText-V2", name="math_web",
    streaming=True)
```

Listing 2 Loading the dataset with Hugging Face Datasets

4.2 RefineCode Content Download

For the `refinecode` domain, only metadata is provided in the main dataset to reduce storage overhead. The full code content must be downloaded from the Software Heritage S3 bucket using the `blob_id` provided in the metadata. The following script demonstrates this process.

```
import os
import json
import boto3
from smart_open import open
from datasets import load_dataset

# Setup AWS credentials from environment variables
session = boto3.Session(
    aws_access_key_id=os.environ["AWS_ACCESS_KEY_ID"],
    aws_secret_access_key=os.environ["AWS_SECRET_ACCESS_KEY"]
)
s3 = session.client("s3")

def download_code_content(blob_id, src_encoding):
    """Download code content from AWS S3 using blob_id."""
    s3_url = f"s3://softwareheritage/content/{blob_id}"
    try:
        with open(s3_url, "rb", compression=".gz", transport_params
   ={"client": s3}) as fin:
            content = fin.read().decode(src_encoding)
        return {"content": content}
    except Exception as e:
        return {"content": None, "error": str(e)}
```

```
# Load RefineCode domain metadata
refinecode_data = load_dataset("OpenSQZ/AutoMathText-V2", name="
   refinecode", streaming=True)

# Process each sample to download content
for sample in refinecode_data:
    meta = json.loads(sample["meta"])
    blob_id = meta.get("blob_id")
    src_encoding = meta.get("src_encoding", "utf-8")

    if blob_id:
        code_data = download_code_content(blob_id, src_encoding)
        full_sample = {**sample, "code_content": code_data["content"
   ]}
        print(f"Downloaded content for {sample['id']}")
        # Process the full_sample here
        break # Example stops after one sample
```

Listing 3 Downloading full code content for the RefineCode domain

This requires the `boto3` and `smart_open` libraries and valid AWS credentials with access to the bucket.

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Appendix

A Complete Data Sources

This section provides a complete list of the 52 premium data sources used in the construction of `AutoMathText-V2`, organized by their respective domains.

Table 2 Complete List of Data Sources

Source	HuggingFace Dataset	Description
DCLM Domain		
DCLM-Baseline	`DCLM/dclm-baseline-1.0`	High-quality web content from DCLM
FineWeb Edu Domain		
FineWeb-Edu	`HuggingFaceFW/fineweb-edu`	Educational web content (0-5 quality scale)
FineWeb Edu Chinese Domain		
FineWeb-Edu-Chinese	`opencsg/Fineweb-Edu-Chinese-V2.1`	Chinese educational content (3.4-5.0 scale)
Math Web Domain		
AutoMathText	`math-ai/AutoMathText`	Math/Code/ArXiv content with lm_q1q2_score
FineMath	`HuggingFaceTB/finemath`	High-quality mathematics content (0-5 scale)
Open-Web-Math-Pro	`gair-prox/open-web-math-pro`	Mathematical web pages
InfiMM-WebMath-40B	`Infi-MM/InfiMM-WebMath-40B`	Multimodal mathematical content
Nemotron CC Domains		
Nemotron-CC (High)	`nvidia/nemotron-cc`	High-quality CommonCrawl subset
Nemotron-CC (Medium-High)	`nvidia/nemotron-cc`	Medium-high quality CommonCrawl subset
RefineCode Domain		
RefineCode	`m-a-p/RefineCode`	GitHub repositories (Academic Use Only)
Reasoning QA Domain		
OPC-Annealing-Corpus	`OpenCoder-LLM/opc-annealing-corpus`	Code training corpus
OPC-SFT-Stage1	`OpenCoder-LLM/opc-sft-stage1`	Instruction following data (stage 1)
OPC-SFT-Stage2	`OpenCoder-LLM/opc-sft-stage2`	Instruction following data (stage 2)
Magpie-Reasoning-V2-250K-CoT-QwQ	`Magpie-Align/Magpie-Reasoning-V2...`	Chain-of-thought reasoning (QwQ)
Magpie-Reasoning-V1-150K-CoT-QwQ	`Magpie-Align/Magpie-Reasoning-V1...`	Chain-of-thought reasoning (QwQ)

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Source	HuggingFace Dataset	Description
Magpie-Reasoning-V1-150K-CoT-Deepseek	Magpie-Align/Magpie-Reasoning-V1...	Advanced reasoning (DeepSeek-R1)
Magpie-Reasoning-V2-250K-CoT-Deepseek	Magpie-Align/Magpie-Reasoning-V2...	Advanced reasoning (DeepSeek-R1)
General-Instruction-Augmented-Corpora	instruction-pretrain/general-instruction...	General instruction synthesis
FT-Instruction-Synthesizer-Collection	instruction-pretrain/ft-instruction...	Fine-tuning instruction synthesis
Code-Feedback-Filtered-Instruction	m-a-p/CodeFeedback-Filtered-Instruction	Code QA with feedback
XCoder-80K	banksy235/XCoder-80K	Code instruction data
Orca-Math-Word-Problems-200K	microsoft/orca-math-word-problems...	Math word problems
Meta-Math-QA	meta-math/MetaMathQA	Mathematical QA dataset
Numina-Math-CoT	AI-MO/NuminaMath-CoT	Math chain-of-thought
Scale-Quest-Math	dyyyyyyyy/ScaleQuest-Math	Mathematical problem solving
Calc-Ape210K	MU-NLPC/Calc-ape210k	Chinese math problems
MathInstruct	TIGER-Lab/MathInstruct	Math instruction data
MathScaleQA-2M	fdqerq22ds/MathScaleQA-2M	Large-scale math QA
Gretel-Math-GSM8K-V1	gretelai/gretel-math-gsm8k-v1	GSM8K style problems
Open-Math-Instruct-2	nvidia/OpenMathInstruct-2	Open math instructions
Stack-Math-QA	math-ai/StackMathQA	Stack Exchange math QA
OpenR1-Math-220K	open-r1/OpenR1-Math-220k	Advanced math reasoning
Natural-Reasoning	facebook/natural_reasoning	Natural language reasoning
Math-Code-Instruct	MathLLMs/MathCodeInstruct	Math with code instructions
Math-Code-Instruct-Plus	MathLLMs/MathCodeInstruct-Plus	Enhanced math-code instructions
Open-Orca	Open-Orca/OpenOrca	General instruction following
SlimOrca-Deduped-Cleaned	Open-Orca/slimorca-deduped-cleaned...	Cleaned instruction data
Orca-AgentInstruct-1M-V1-Cleaned	mlabonne/orca-agentinstruct-1M-v1...	Agent instruction data
FOL-NLI	tasksource/FOL-nli	First-order logic reasoning
Infinity-Instruct	BAAI/Infinity-Instruct	Multi-domain instructions
Llama-Nemotron-Post-Training-Dataset	nvidia/Llama-Nemotron-Post-Training...	Post-training dataset
Codeforces-CoTs	open-r1/codeforces-cots	Competitive programming
Reasoning-V1-20M	glaiveai/reasoning-v1-20m	Large-scale reasoning data
Lean-STaR-Plus	ScalableMath/Lean-STaR-plus	Lean formal proofs (enhanced)
Lean-STaR-Base	ScalableMath/Lean-STaR-base	Lean formal proofs (base)
Lean-CoT-Plus	ScalableMath/Lean-CoT-plus	Lean chain-of-thought (enhanced)
Lean-CoT-Base	ScalableMath/Lean-CoT-base	Lean chain-of-thought (base)
Lean-Github	internlm/Lean-Github	Lean repository code
Lean-Workbook	internlm/Lean-Workbook	Lean problem workbook
DeepSeek-Prover-V1	deepseek-ai/DeepSeek-Prover-V1	Formal proof verification

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Source	HuggingFace Dataset	Description
	Translation Domain	
UN-PC	Helsinki-NLP/un_pc	English-Chinese translation pairs
UN-PC-Reverse	Helsinki-NLP/un_pc	Chinese-English translation pairs
	MegaMath Domain	
MegaMath-QA	LLM360/MegaMath	Large-scale mathematical QA
MegaMath-Translated-Code	LLM360/MegaMath	Mathematical code translations
MegaMath-Text-Code-Block	LLM360/MegaMath	Mixed math text and code blocks