

# SciLitLLM: How to Adapt LLMs for Scientific Literature Understanding

Sihang Li<sup>1\*†</sup>, Jin Huang<sup>2\*†</sup>, Jiayi Zhuang<sup>2†</sup>, Yaorui Shi<sup>1†</sup>, Xiaochen Cai<sup>2</sup>,  
Mingjun Xu<sup>2†</sup>, Xiang Wang<sup>1‡</sup>, Linfeng Zhang<sup>2</sup>, Guolin Ke<sup>2</sup>, Hengxing Cai<sup>2‡</sup>

<sup>1</sup>University of Science and Technology of China, <sup>2</sup>DP Technology

sihang0520@gmail.com

\*Equal contribution. †Work done while interning at DP Technology. ‡Corresponding author.

## Abstract

Scientific literature understanding is crucial for extracting targeted information and garnering insights, thereby significantly advancing scientific discovery. Despite the remarkable success of Large Language Models (LLMs), they face challenges in scientific literature understanding, primarily due to (1) a lack of scientific knowledge and (2) unfamiliarity with specialized scientific tasks. To develop an LLM specialized in scientific literature understanding, we propose a hybrid strategy that integrates continual pre-training (CPT) and supervised fine-tuning (SFT), to simultaneously infuse scientific domain knowledge and enhance instruction-following capabilities for domain-specific tasks. In this process, we identify two key challenges: (1) constructing high-quality CPT corpora, and (2) generating diverse SFT instructions. We address these challenges through a meticulous pipeline, including PDF text extraction, parsing content error correction, quality filtering, and synthetic instruction creation. Applying this strategy, we present a suite of LLMs: **SciLitLLM**, specialized in scientific literature understanding. These models demonstrate promising performance on scientific literature understanding benchmarks. Our contributions are threefold: (1) We present an effective framework that integrates CPT and SFT to adapt LLMs to scientific literature understanding, which can also be easily adapted to other domains. (2) We propose an LLM-based synthesis method to generate diverse and high-quality scientific instructions, resulting in a new instruction set – **SciLitIns** – for less-represented scientific domains. (3) SciLitLLM achieves promising performance in scientific literature understanding benchmarks. We release the data processing codes, model weights and the synthetic dataset<sup>1</sup>.

## 1 Introduction

Scientific literature understanding involves the systematic evaluation and interpretation of scientific texts and publications, to identify trends, extract targeted information, and garner insights (AI4Science and Quantum, 2023; Zheng et al., 2023), significantly contributing to scientific discovery. Concurrently, Large Language Models (LLMs) (OpenAI, 2023; Team, 2024; Touvron et al., 2023) have achieved remarkable

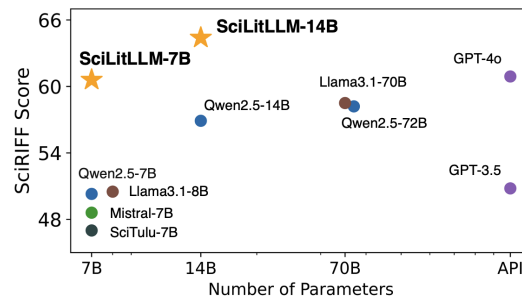


Figure 1: Average scores on SciRIFF of models with varying parameter sizes.

<sup>1</sup><https://github.com/dptech-corp/Uni-SMART/tree/main/SciLitLLM>

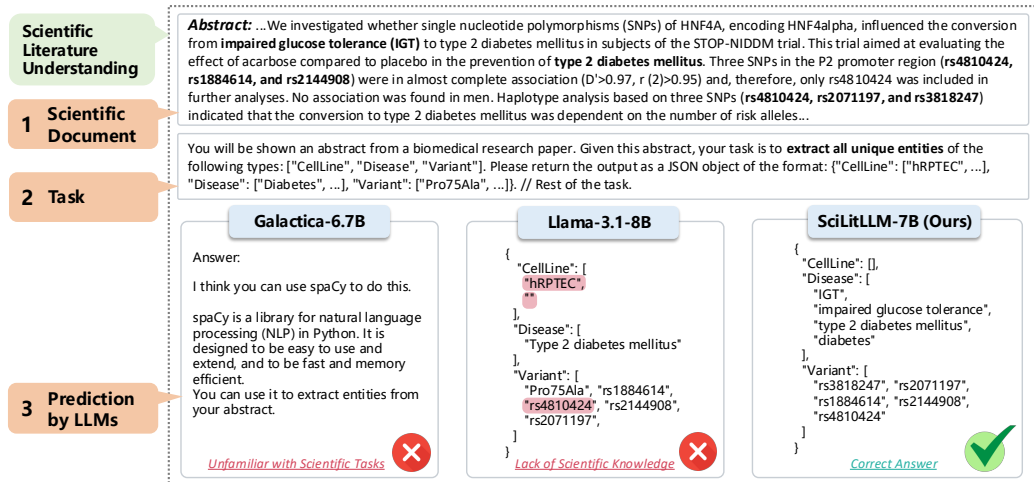


Figure 2: An example of scientific literature understanding in SciRIFF. It involves extracting accurate entities from a biomedicine paper. SciLitLLM-7B demonstrates sufficient scientific knowledge and instruction-following ability to accurately identify and extract these entities.

success in natural language processing, prompting the development of domain-specific LLMs across various fields (Cui et al., 2024; Wu et al., 2023; Clusmann et al., 2023). However, recent studies (Wadden et al., 2024; Cai et al., 2024; Singh et al., 2023) indicate that LLMs face challenges when specializing in scientific literature understanding, particularly in context understanding and question answering. Take Figure 2 as an example, where the LLM is asked to understand the content of a biomedical research paper and then extract the targeted information. LLMs’ potential might be hindered by two major barriers: (1) a lack of *scientific knowledge*, which results in errors such as the missing important entities in Llama-3.1-8B (AI@Meta, 2024), and (2) unfamiliarity with *scientific tasks*, leading to the inability of Galactica-6.7B (Taylor et al., 2022) to follow task instructions accurately.

To make LLMs specialized in science-relevant tasks, existing studies mostly adopt two strategies, as illustrated in Figure 3: (1) Fine-tuning with scientific instructions (Wadden et al., 2024; Zhang et al., 2024b; Singhal et al., 2022). A general-purpose LLM is fine-tuned with collected domain-specific instructions to adapt it to science-relevant tasks. However, instruction fine-tuning alone is insufficient to imbue the models with comprehensive scientific knowledge. (2) Pre-training on scientific corpora (Beltagy et al., 2019; Zeng et al., 2022; Taylor et al., 2022). This approach involves training models on vast scientific corpora. While this method equips LLMs with domain knowledge, the lack of instruction-tuning confines them to solving relevant tasks. Moreover, it is hampered by substantial computational costs and data requirements (Ling et al., 2023; Yang et al., 2023). To address these obstacles while balancing efficiency, we propose a hybrid strategy that incorporates continual pre-training (CPT) and supervised fine-tuning (SFT), to simultaneously infuse domain knowledge and enhance domain-specific instruction-following capabilities.

However, as illustrated in Figure 4, developing a scientific literature understanding model using this CPT and SFT pipeline presents two critical requirements: (1) **High-quality CPT Corpora**. Scientific corpora, predominantly in PDF format such as textbooks and research papers, are not directly digestible for LLM training. Converting these documents to text with PDF parsing tools introduces formatting and syntax errors, degrading corpus quality. Worse still, scientific documents often contain segments that contribute little information (e.g., references), necessitating quality control to filter them out. See the first row in Figure 4 for a comparison of high- and low-quality CPT texts. (2) **Diverse Scientific Instructions**. Effective instruction following for scientific literature understanding requires a large, high-quality, and diverse set of task-related instructions. However, to the best of our knowledge, there is a scarcity of well-designed instruction datasets for scientific literature understanding, and hiring human annotators to curate such a dataset from scratch is prohibitively expensive (Erdmann et al., 2019; Qiu et al., 2023). See the second row in Figure 4 for an illustration of high- and low-quality instructions.

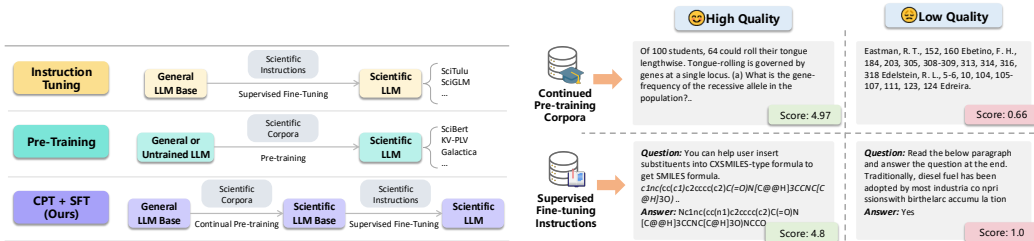


Figure 3: Comparison of strategies to adapt LLMs to scientific tasks.

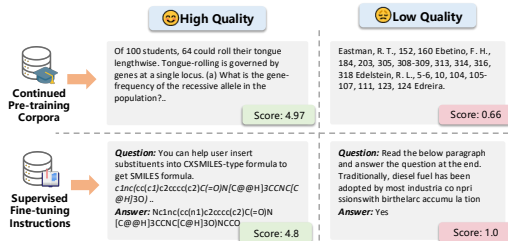


Figure 4: Examples of high and low-quality CPT text and SFT instructions.

To address these challenges, we devise an effective pipeline to construct high-quality domain corpora for CPT and diverse scientific instructions for SFT, as illustrated in Figure 5:

In the **CPT** stage for domain knowledge injection, we start with an extensive in-house corpus consisting of 73k textbooks and 625k academic papers in the scientific field, all in PDF format. Initially, we leverage PyPDF2<sup>2</sup>, a widely used open-source PDF parsing tool, to extract raw texts from these documents. We then employ a moderate yet powerful model, Llama3-7B-Instruct, to correct the format and spelling errors introduced by PDF parsing (*cf.* Section 3.1.1). Subsequently, we train a small text quality classifier to score the corpus and filter out texts of low educational value<sup>3</sup> in the scientific field (*cf.* Section 3.1.2). These two simple yet effective textual refinement and quality control measures ensure the high quality of our CPT corpus, culminating 12.7 billion tokens for CPT via the Qwen2.5 tokenizer.

In the **SFT** stage for domain instruction fine-tuning, to overcome the scarcity of domain-specific instructions and the high cost of human annotations, we propose a novel instruction synthesis method (*cf.* Section 3.2.1). It enables us to generate diverse instructions to better equip the model for domain-specific tasks. Moreover, we sequentially apply instruction duplication based on Levenshtein distance and an LLM-based filtering method to ensure the quality of synthetic instructions (*cf.* Section 3.2.2).

Having established such high-quality datasets, we apply the CPT-SFT integration strategy on a general-purpose LLM – Qwen2.5 (Team, 2024) and obtain SciLitLLM of two scales: 7B and 14B. Evaluations on benchmarks of scientific literature understanding demonstrate the effectiveness of our strategy. We observe promising performance enhancements, with an average improvement of 4.0% on SciAssess (Cai et al., 2024) and 10.1% on SciRIFF (Wadden et al., 2024), compared to the leading LLMs under 10B parameters. Notably, SciLitLLM-7B even outperforms Llama3.1 and Qwen2.5 with 70B parameters on SciRIFF. Additionally, SciLitLLM-14B achieves leading results on both benchmarks, surpassing other open-source LLMs. Further ablation studies demonstrate the effectiveness of each module in our pipeline.

In summary, our contributions are threefold: (1) We devise an effective and comprehensive pipeline to adapt general LLMs to a specific domain – scientific literature understanding. It combines continual pre-training (CPT) and supervised fine-tuning (SFT), to enhance scientific knowledge base and instruction-following capabilities for specialized domain tasks. (2) We propose a novel domain instruction synthesis method to curate instructions for scientific literature understanding, resulting in a new dataset – SciLitIns. (3) SciLitLLM, trained through the proposed pipeline, outperforms leading open-source LLMs on scientific literature understanding.

## 2 Related Works

### 2.1 Knowledge Injection via Continual Pre-training

Pre-training a language model is usually conducted on a large corpus of textual data to learn the statistical properties of language (Radford et al., 2019; Brown et al., 2020). To further inject domain knowledge into a general LLM after pre-training, researchers engage in continual pre-training (CPT) on high-quality domain-specific corpora (Jin et al., 2022; Sun et al., 2020), sometimes combined with

<sup>2</sup><https://pypdf2.readthedocs.io>

<sup>3</sup>Phi models (Gunasekar et al., 2023; Li et al., 2023; Abdin et al., 2024) propose to determine the quality of a pre-training text by its educational value for a student whose goal is to learn basic domain concepts.

general corpora. This process enhances the model’s fundamental understanding abilities in specific downstream domains while mitigating catastrophic forgetting of general knowledge (Wu et al., 2022; Ke et al., 2023; Mehta et al., 2023). See the comprehensive study (Gupta et al., 2023) for different warm-up strategies for CPT. Additionally, the CPT corpora can be augmented by transforming them into an instruction-response format (Cheng et al., 2023, 2024). Furthermore, the scaling law (Hoffmann et al., 2022) of domain-specific CPT (Que et al., 2024) is explored to determine the optimal mix of data. However, these studies primarily focus on training dynamics and data recipes, leaving the pre-processing for scientific data, especially raw PDF files, largely unexplored. Exhibiting such steps is essential for generating high-quality domain corpora and effectively injecting domain knowledge, representing a significant challenge for practitioners.

## 2.2 Domain Adaptation via Supervised Fine-tuning

Supervised fine-tuning (SFT) modifies a pre-trained language model to follow specific instructions or perform designated tasks by fine-tuning it on a targeted, task-specific dataset (Raffel et al., 2020; Wei et al., 2021). Applying SFT to a general LLM for specific domain adaptation has demonstrated effectiveness in various fields: in medicine (Clusmann et al., 2023), corpora of medical literature and clinical notes are used; in law (Cui et al., 2024), legal documents and case law are compiled; and in finance (Wu et al., 2023), financial reports and market data are utilized. In the scientific domain, several studies have specialized LLMs for scientific tasks, often necessitating the construction of a substantial domain-specific dataset with SFT. For example, SciGLM (Zhang et al., 2024a) leverages existing LLMs to generate step-by-step reasoning for unlabelled scientific instructions. ChemLLM (Zhang et al., 2024b), a more specified LLM in the chemistry field, collects structured chemical data from a vast selection of online databases and transforms this structured data into a question-answering format for SFT. SciRIFF (Wadden et al., 2024) converts existing literature understanding datasets into natural language input-output pairs suitable for instruction-tuning using pre-defined templates. However, benchmark studies (Feng et al., 2024; Cai et al., 2024) indicate that SFT alone may not provide adequate scientific knowledge to excel in relevant tasks. This suggests the need for a more comprehensive approach that combines domain knowledge infusion with instruction-following enhancements.

## 2.3 LLMs for Scientific Literature Understanding

In the scientific domain, existing strategies for developing specialized LLMs mostly fall into two categories: (1) Supervised fine-tuning with scientific instructions. This approach requires a large, high-quality, and diverse set of instructions to cultivate problem-solving abilities for scientific tasks. Representative works (*e.g.*, SciGLM (Zhang et al., 2024a), ChemLLM (Zhang et al., 2024b), and SciRIFF (Wadden et al., 2024)) have been detailed in Section 2.2. (2) Pre-training with scientific corpora. This approach involves pre-training on a large corpus of scientific texts to improve performance on downstream scientific tasks. Early attempts, such as SciBert (Beltagy et al., 2019) and KV-PLV (Zeng et al., 2022), are based on BERT (Devlin et al., 2019) and pre-trained on a large corpus of scientific text for downstream scientific task enhancement. More recently, Galactica (Taylor et al., 2022) is pre-trained on a vast corpus of scientific literature, including research papers, scientific articles, and other relevant scientific texts. Despite these advances, two major limitations hinder these models from excelling in scientific literature understanding: (1) lack of scientific knowledge, and (2) inability to follow task instructions. To address these challenges, we propose a combined pipeline of CPT and SFT to devise a specialized LLM for scientific literature understanding. It injects domain-specific knowledge through CPT while enhancing task-specific instruction-following abilities through SFT, leading to a more capable LLM for scientific literature understanding.

# 3 Method

In this section, we present the details of our proposed pipeline (*cf.* Figure 5): continual pre-training for scientific knowledge injection and supervised fine-tuning for scientific tasks enhancement.

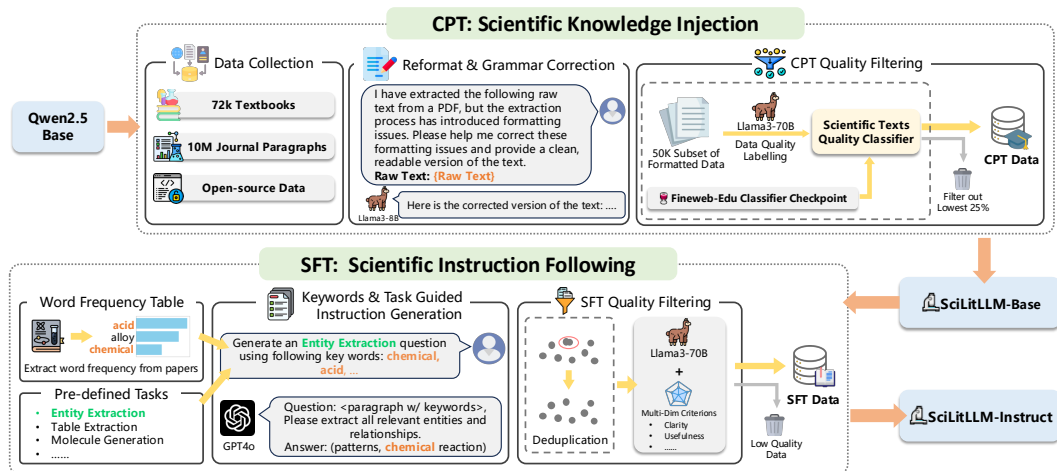


Figure 5: The pipeline of SciLitLLM consists of two key stages: continual pre-training (CPT) for scientific knowledge injection and supervised fine-tuning (SFT) for scientific instruction following. Specifically, the CPT stage involves several modules: PDF parsing, format & grammar correction (*cf.* Section 3.1.1), and quality filtering (*cf.* Section 3.1.2) modules. These modules ensure the model is equipped with high-quality scientific domain knowledge. The SFT stage includes LLM-based instruction generation (*cf.* Section 3.2.1) and instruction quality control (*cf.* Section 3.2.2) measures. These steps are designed to fine-tune the model’s ability to follow scientific instructions accurately and effectively.

### 3.1 CPT for Scientific Knowledge Injection

What are high-quality pre-training corpora? Researchers (Gunasekar et al., 2023; Li et al., 2023; Abdin et al., 2024) suggest that language models benefit from corpora that possess the same qualities as an exemplary textbook for human learners: clarity, self-containment, instructiveness, and balance. Recognizing the wealth of high-quality scientific textbooks and research papers over the past decades, we have curated a substantial collection of over 73,000 textbooks and 625,000 research papers within the scientific domain, ensuring all documents are copyright-compliant.

However, we still face two practical obstacles when dealing with those textbooks and research papers: (1) *Formatting and syntax errors*. Most textbooks and research paper documents are in PDF format, which is not directly digestible by LLMs. Converting these documents using tools like PyPDF2 often introduces formatting and syntax errors, which degrade the quality of the corpus. (2) *Corpus quality control*. Despite their overall high quality, textbooks and research papers also contain segments with little useful information, such as references and garbled text introduced during the PDF parsing process. To tackle these obstacles, we devised the following modules: format & grammar correction and CPT quality filter.

#### 3.1.1 Format & Grammar Correction

A parsed text from a PDF document often contains many formatting and syntax errors. To address this issue, we prompt Llama3-8B-Instruct, to correct these errors introduced during the PDF parsing process. Utilizing the vLLM (Kwon et al., 2023) backend, Llama3-8B-Instruct can process approximately 2.52 million tokens per Nvidia A100 GPU hour. The process takes over 5,000 A100 GPU hours to handle all the textbooks and research papers. Example texts – both before and after processing – along with the prompt template are provided in Appendix A to demonstrate the improvements through this correction process.

#### 3.1.2 CPT Quality Filter

During CPT, maintaining the quality of the training corpus is crucial for effective knowledge injection. Given the extremely large scale of pre-training corpora, assessing quality through human annotation is not feasible (Erdmann et al., 2019; Qiu et al., 2023). Consequently, leading LLMs (*e.g.*, Phi (Gunasekar et al., 2023), Llama (Touvron et al., 2023), and Qwen2.5 (Team, 2024)) employ model-based

quality filters. The typical process involves using larger LLMs to score the quality of a subset of texts, which then serve as labels for training small classifiers (*e.g.*, random forest (Gunasekar et al., 2023) and Bert (AI@Meta, 2024)) to annotate the entire training corpus. Inspired by this approach, we design a resource-efficient method based on a lightweight text quality classifier.

We first annotate a random subset of 50k CPT texts using Llama3-70B-Instruct. We adapt the quality assessment prompt from fineweb-edu-classifier (Anton et al., 2024), a widely-used quality classifier for web data, to evaluate the educational value (Gunasekar et al., 2023) of the scientific knowledge in each sampled text, assigning scores ranging from 0 (lowest quality) to 5 (highest quality). After annotation, we perform supervised transfer learning on the fineweb-edu-classifier checkpoint.

This process results in a scientific text quality classifier tailored for scientific corpus assessment. We then utilize this classifier to assess the quality of the entire CPT dataset and exclude the lowest-scoring 25% (See Figure 4 for concrete samples). See Appendix B for more details about classifier training and hyperparameters.

### 3.1.3 CPT Training Settings

After preparing all the corpus, we perform CPT on Qwen2.5-Base (Team, 2024) for one epoch, encompassing 23.7 billion tokens (*cf.* Table 1), with a sequence length of 2,048 tokens. To maintain the model’s general knowledge, we also include a similar scale of general corpus tokens from Redpajama (Computer, 2023). To stabilize the learning procedure, we gradually decrease the learning rate from  $1 \times 10^{-5}$  to 0 with a cosine scheduler. To address overfitting, we apply a weight decay of 0.1 and gradients were clipped at a maximum value of 1.0. The CPT training took approximately 3 days on 32 Nvidia A100 GPUs for SciLitLLM-7B-Base and about 7 days for the 14B model.

Stage	Data source	Domain	#Doc/#Ins	# Tokens
CPT	In-house Textbooks	Science	73k	10B
	In-house Journals	Science	625k	2.7B
	Redpajama (Computer, 2023)	General	-	11B
SFT	SciLitIns	Science	93k	86M
	SciRIFF (Wadden et al., 2024)	Science	70k	40M
	Infinity-Instruct	General	3M	1.7B

Table 1: Data statistics of CPT and SFT stages. Underlined datasets are curated by us.

## 3.2 SFT for Scientific Instruction Following

After performing CPT on an extensive scientific corpus to incorporate domain knowledge, we subsequently conduct SFT on domain-specific instructions to enhance the model’s ability to understand scientific literature. We identify two major challenges in SFT for scientific instruction following:

- Existing instruction-tuning datasets in the scientific domain (Feng et al., 2024; Fang et al., 2023; Li et al., 2024) primarily focus on fields such as physics, chemistry, and biology. Manually collecting instruction-tuning data for other less-represented vertical domains (*e.g.*, biomedicine, and material) is both time-consuming and costly (Erdmann et al., 2019; Qiu et al., 2023).
- Few instruction-tuning datasets adequately reflect the scenario of scientific literature understanding, which typically involves a segment of scientific literature accompanied by a question that requires deriving an answer from the text.

To address these challenges, we draw inspiration from leading models (*e.g.*, Nemotron-4 (Adler et al., 2024), Phi (Gunasekar et al., 2023), and Qwen (Yang et al., 2024)), which leverage existing LLMs to construct synthetic instruction sets. We propose a novel instruction synthesis method to curate instructions specifically for scientific literature understanding.

### 3.2.1 Instruction Synthesis of Less-represented Domains

Unlike typical question-answer pairs, an instruction for a scientific literature understanding task comprises three components (Wadden et al., 2024): (1) a segment of scientific literature, (2) a question pertaining to the context, and (3) the corresponding answer. Simply prompting an LLM to generate a scientific context along with an associated question-answer pair – without variations in the instructions or parameters – often yields similar or repeated contents. Thus, we design a simple yet effective three-step pipeline to generate diverse and high-quality scientific contexts and corresponding question-answer pairs, consisting of the following:

1. *Probability table of domain keywords.* For a target scientific domain (e.g., biomedicine, and material), we collect dozens of high-impact research papers via Google Scholar<sup>4</sup> and count the word frequency appearing in these papers. Then, we obtain a probability table of domain keywords.
2. *Scientific task list.* Since LLMs are expected to handle various types of scientific tasks, an instruction set with task diversity is essential. Therefore, we compile a list of task descriptions by including representative tasks from existing scientific NLP datasets (Wadden et al., 2024; Cai et al., 2024; Feng et al., 2024), covering as many scenarios as possible that an LLM may encounter in real applications.
3. *Instruction Generation.* Given a word probability table and the task list for a specific scientific domain, we sample 20 keywords and a task description each time. Subsequently, GPT-4o (OpenAI, 2023) is prompted to generate a scientific context containing the sampled keywords and a question-answer pair according to the provided task description.

Utilizing this pipeline, we obtain over 100k synthetic instructions covering less-represented scientific domains and various types of specialized tasks (details are presented in Appendix C.1).

### 3.2.2 Instruction Quality Control

To ensure the diversity and quality of generated instructions, effective measures for quality control are essential. Specifically, we incorporate heuristic deduplication and LLM-based filtering.

1. *Heuristic deduplication.* Despite the measures taken during the generation process to prevent high homogeneity in the instructions, the generated data points may still contain similar questions or identical answers. To eliminate such redundancy, we implement a deduplication process to remove similar data points. See Appendix C.2 for details.
2. *LLM-based filtering.* Inspired by recent efforts (Eldan and Li, 2023; Chiang and Lee, 2023; Zhang et al., 2024c) to measure the quality of generated content using LLMs, we leverage Llama-3-70B-Instruct to assess the quality of generated instructions for five aspects: clarity, complexity, correctness, usefulness, and adaptability. We show the quality statistics of synthetic instructions in Figure 7. The detailed recipe for instruction quality evaluation with concrete examples is included in Appendix C.3.

Through instruction synthesis and quality control pipeline, we obtain **SciLitIns**, consisting of 93,894 high-quality and diverse instructions for scientific literature understanding.

### 3.2.3 SFT Training Settings

Our SFT training dataset consists of three parts: SciLitIns, SciRIFF (Wadden et al., 2024) and Infinity-Instruct<sup>5</sup>, as shown in Table 1. Infinity-Instruct is a collection of more than twenty open-source instructions datasets, covering various general domains. SciRIFF and SciLitIns contain specialized instructions for scientific literature understanding. For both scales, we train for one epoch on Infinity-Instruct to cultivate their general instruction-following abilities, then for five epochs on SciLitIns and SciRIFF for scientific literature understanding enhancement. The training is conducted with a sequence length of 4,096, a maximum learning rate of  $1 \times 10^{-5}$ , and a cosine scheduler. The SFT training takes approximately 32 hours for the 7B and 70 hours for the 14B model on 32 A100 GPUs, resulting in SciLitLLM-7B-Instruct and SciLitLLM-14B-Instruct.

## 4 Experiments

In this section, we perform experiments to answer the following research questions: (Q1) How does SciLitLLM perform on scientific literature understanding tasks? (Q2) Can CPT with domain-specific corpora aid in scientific knowledge injection? (Q3) Can SFT with SciLitIns improve performance on scientific literature understanding tasks?

<sup>4</sup><https://scholar.google.com/>

<sup>5</sup><https://huggingface.co/datasets/BAAI/Infinity-Instruct>

Models	MMLU-Pro-Bio	MMLU-Pro-Chem	MMLU-Pro-Heal	MaScQA	Avg.
<b># Parameters &lt; 10B</b>					
Llama3.1-8B	56.35	25.88	44.50	53.28	45.00
Qwen2.5-7B	68.36	48.37	51.64	56.23	56.15
SciLitLLM-7B	<b>70.45</b>	<b>51.21</b>	<b>54.06</b>	<b>59.27</b>	<b>58.75</b>
<b># Parameters &gt; 10B</b>					
Qwen2.5-14B	79.78	62.73	62.22	66.92	67.91
SciLitLLM-14B	<b>80.62</b>	<b>64.44</b>	<b>64.24</b>	<b>68.06</b>	<b>69.34</b>

Table 2: Performance comparison of base models. SciLitLLM outperforms Llama3.1 and Qwen2.5 with similar scales, demonstrating improved domain-specific understanding through continual pre-training on scientific corpora.

Dataset	Domain/ Task	# Parameter < 10B					# Parameter > 10B				API	
		SciTulu-7B	Mistral-7B	Llama3.1-8B	Qwen2.5-7B	SciLitLLM-7B	Qwen2.5-14B	Llama3.1-70B	Qwen2.5-72B	SciLitLLM-14B	GPT3.5	GPT4o
SciAssess	Biology	45.3	52.0	63.4	60.9	<b>65.3</b>	65.9	<b>69.4</b>	67.2	67.0	55.4	68.9
	Chemistry	19.0	34.0	46.1	47.9	<b>55.4</b>	60.0	62.5	<b>63.7</b>	63.4	37.3	68.0
	Material	31.3	36.5	50.9	48.9	<b>53.7</b>	57.9	59.2	59.4	<b>62.6</b>	37.0	62.0
	Medicine	19.9	25.1	30.2	28.3	<b>32.4</b>	31.5	37.4	37.8	<b>39.9</b>	31.8	45.8
	Mean	28.9	36.9	47.7	46.5	<b>51.7</b>	53.8	57.1	57.0	<b>58.2</b>	40.4	61.2
SciRIFF	BioASQ	37.5	43.2	45.0	45.3	<b>51.2</b>	48.0	43.5	46.7	<b>53.9</b>	47.3	46.7
	BioR	55.7	48.9	48.1	43.9	<b>76.6</b>	56.8	61.5	57.8	<b>83.3</b>	53.9	61.0
	DiscMT	61.5	44.5	68.8	73.7	71.1	70.5	77.3	54.7	<b>77.7</b>	67.9	78.3
	EI	11.6	17.2	17.2	23.3	<b>23.5</b>	27.2	26.0	26.3	<b>30.8</b>	19.2	24.7
	MC	34.6	47.5	49.7	50.8	<b>70.7</b>	54.2	60.9	58.0	<b>72.1</b>	47.8	58.7
	MuP	72.1	<b>87.5</b>	87.0	84.9	67.5	91.5	90.9	<b>94.0</b>	67.7	76.8	86.9
	Qasper	<b>54.2/38.6</b>	48.8/43.2	46.5/42.7	38.1/25.7	<b>50.7/54.1</b>	48.4/46.8	49.1/40.2	<b>61.9/50.5</b>	54.0/55.1	54.7/39.8	67.8/50.5
	SciERC	35.6	31.1	32.9	30.1	<b>49.9</b>	33.7	36.2	34.1	<b>54.7</b>	28.6	42.2
	SciFact	66.0/49.2	68.8/53.8	63.8/53.7	77.8/60.3	<b>83.5/67.3</b>	83.1/65.6	87.3/70.3	86.5/69.6	<b>91.0/68.6</b>	69.7/53.3	84.3/68.7
	Mean	47.0	48.6	50.5	50.3	<b>60.6</b>	56.9	58.5	58.2	<b>64.4</b>	50.8	60.9

Table 3: Model performances on scientific literature understanding benchmarks: SciAssess and SciRIFF. SciLitLLM-7B and SciLitLLM-14B achieve leading performance compared with open-source models of similar scales. The best-performing models smaller than 10B and larger than 10B are highlighted in bold. Results for SciTulu-7B, GPT-3.5, and GPT-4o on SciRIFF are taken from its original papers, while all other results are produced by us.

## 4.1 Experimental Setup

### 4.1.1 Benchmarks

To evaluate the performance of LLMs regarding scientific knowledge base and specialized task-solving abilities, our benchmarks include:

- *Base model benchmarks.* To assess their scientific knowledge, which serves as the foundation for scientific literature understanding, we evaluate the base models on scientific subjects – biology, chemistry, and health in MMLU-Pro (Wang et al., 2024) and MaScQA (Zaki et al., 2023) – a question answering dataset of materials science.
- *Instruction model benchmarks.* We evaluate the instruct models on scientific literature understanding benchmarks: SciRIFF (Wadden et al., 2024) and SciAssess (Cai et al., 2024). Brief descriptions of them are provided in Appendix D.

### 4.1.2 Baselines

- *Base model baselines.* We compare SciLitLLM-base against leading open-source base models: Llama-3.1 (AI@Meta, 2024), Qwen-2.5 (Team, 2024).
- *Instruction model baselines.* We benchmark leading instruction LLMs including GPT-[3.5, 4o] (Brown et al., 2020; OpenAI, 2023), Llama3.1-[8B, 70B] (AI@Meta, 2024) and Qwen2.5-[7B, 14B, 72B] (Yang et al., 2024; Team, 2024) and Mistral-7B (Jiang et al., 2023). We also report the performance of SciTulu-7B (Wadden et al., 2024), which is a fine-tuned Llama2-7B (Touvron et al., 2023) model on SciRIFF.



Model	SciAssess	SciRIFF
Qwen2.5-Instruct	46.5	50.3
Qwen2.5-Base+SFT	49.8	57.0
Qwen2.5-Base+CPT+SFT	<b>51.7</b>	<b>60.6</b>

Table 4: Ablation study of the CPT stage. The results shows that the CPT stage is essential to improve scientific literature understanding ability.

SFT Dataset	SciAssess	SciRIFF
Infinity-Instruct only	47.1	51.2
+ SciRIFF	46.8	56.7
+ SciRIFF + SciLitIns	<b>51.7</b>	<b>60.6</b>

Table 5: Ablation study of SFT data recipes. Our synthetic dataset SciLitIns effectively improves performance on both benchmarks.

Dataset	SciAssess	SciRIFF
<b>SciLitIns</b>		
w/o filtering	50.9	60.1
w/ filtering	<b>51.7</b>	<b>60.6</b>

Table 6: Ablation study of SFT instruction quality filtering. This shows that our proposed filter refines the quality of SciLitIns .

## 4.2 Performance Overview (Q1)

### 4.2.1 Base model performance

The performance comparison of base models is shown in Table 2. SciLitLLM-base consistently outperforms other general base models across four scientific benchmarks. Specifically, compared with LLMs of less than 10 billion parameters, SciLitLLM-7B-Base shows an average accuracy improvement of 2.60% over Qwen2.5-7B. The results demonstrate that CPT on high-quality scientific corpora can significantly improve the LLMs’ ability to understand scientific contexts.

### 4.2.2 Instruct model performance

As shown in Table 3, SciLitLLM-7B-Instruct achieves the highest performance in all 4 domains on SciAssess, outperforming the second-best model (*i.e.*, Llama3.1-8B) by 4.0%. Notably, on SciRIFF, it surpasses baseline models by a substantial margin of 10.1%. Additionally, SciLitLLM-14B-Instruct shows a 4.6% and 7.5% performance improvement over Qwen2-14B-Instruct on SciAssess and SciRIFF, respectively. It even outperforms other open-source models with five times more parameters (*i.e.*, Llama3.1-70B and Qwen2.5-72B) on both benchmarks. This demonstrates the effectiveness of our proposed pipeline in adapting a general-purpose LLM to a specialized model for scientific literature understanding.

Detailed model performance on SciAssess is presented in Table 7, where SciLitLLM-7B lead in 15 out of 27 sub-tasks. Specifically, SciLitLLM excels in tasks such as table extraction and molecule generation, likely benefiting from the comprehensive task coverage in our synthetic instruction dataset – SciLitIns. On SciRIFF, SciLitLLM-7B and SciLitLLM-14B both rank first in 8 out of 11 evaluations<sup>6</sup>.

## 4.3 Ablation Study (Q2 & Q3)

We conducted ablation experiments on three key components in our pipeline: the CPT stage, the SFT data recipe, and the instruction quality filter, to investigate their effectiveness. Note that all ablation experiments were performed on SciLitLLM-7B due to budget constraints.

### 4.3.1 Scientific knowledge injection via CPT (Q2)

We investigate the contribution of the CPT stage for SciLitLLM. We compare the three variants: (1) *Qwen2.5-7B-Instruct*: official instruct-model checkpoint; (2) *Qwen2.5-7B-base + SFT*: applying our SFT stage directly to Qwen2.5-7B-base without CPT; (2) *Qwen2.5-7B-base + CPT + SFT*: SciLitLLM-7B-Instruct.

As shown in Table 4, applying SFT alone to the Qwen2.5-7B-Base model yields improvements on SciAssess (+3.3%) and SciRIFF (+6.7%). Further, incorporating CPT results in an extra 1.9% improvement on SciAssess and a 3.6% gain on SciRIFF. This shows the effectiveness of our CPT pipeline in curating high-quality CPT corpora and injecting scientific knowledge to LLMs.

<sup>6</sup>In SciRIFF, the Qasper and SciFact tasks have two different evaluation methods and thus two results. For LLM-based evaluations in MuP and Qasper, we use GPT-4o instead of GPT-3.5, as was done in the original paper.

### 4.3.2 SFT with SciLitIns (Q3)

We explore how fine-tuning with our synthetic instruction set, SciLitIns, impacts performance in scientific literature understanding. We incrementally add three datasets to the SFT training set: Infinity-Instruct, SciRIFF, and SciLitIns. As shown in Table 5, using only the general purpose instruction set (*i.e.*, Infinity-Instruct) results in the lowest performance on both SciAssess (47.1%) and SciRIFF (51.2%). This indicates that fine-tuning LLMs on general instructions alone is insufficient for scientific literature understanding.

Adding the training set of SciRIFF to Infinity-Instruct improves performance on SciRIFF significantly (+5.5%) but decreases performance on SciAssess (-0.3%). This drop may be due to SciRIFF’s relatively narrower focus, primarily covering biomedicine and clinical medicine, while SciAssess spans broader fields such as biology, chemistry, and material science. This highlights the need for a diverse instruction set that covers diverse scientific domains. Finally, including SciLitIns boosts performance on both benchmarks, with SciAssess at 51.7% and SciRIFF at 60.6%. This demonstrates that SciLitIns, which is designed to contain instructions from less-represented scientific domains, is useful for improving model performance in scientific literature understanding.

### 4.3.3 Impact of Instruction filter

We conduct an ablation study to assess the impact of quality filter for synthetic instructions by varying whether the dataset SciLitIns was filtered. As discussed in Section 3.2.2, this filter removes low-quality instructions evaluated from five key aspects. Table 6 shows that applying the filter improves the performance of SciLitLLM-7B on SciAssess (+0.8%) and SciRIFF (+0.5%). This demonstrates that SFT quality filtering process effectively excludes low-quality instructions, thereby boosting the performance of SciLitLLM on scientific literature understanding.

## 5 Limitations

Despite the promising results achieved by SciLitLLM, there are several limitations that should be acknowledged as follows:

- *Insufficient data volume.* Compared with existing pre-training datasets (AI@Meta, 2024; Yang et al., 2024; Taylor et al., 2022), the amount of data used for CPT is comparatively small. Future work should consider incorporating a larger scientific corpus, potentially including scientific blogs or purely synthetic data.
- *Lack of reasoning enhancement.* The current pipeline does not explore advanced reasoning techniques such as Chain-of-Thought (Wei et al., 2022) or Tree-of-Thought (Yao et al., 2023) in the data construction or model inference stages.
- *Lack of preference alignment.* Due to a limited financial budget, the model lacks Reinforcement Learning from Human Feedback (RLHF) (Ouyang et al., 2022). RLHF has shown significant improvements in aligning models with human preferences and ensuring more reliable outputs. Implementing RLHF in future iterations could further enhance the model’s reliability.

Addressing these limitations in future research will be crucial developing a more robust and capable LLM specialized in scientific literature understanding.

## 6 Conclusion and Future Works

In this paper, we introduce **SciLitLLM**, a specialized model for scientific literature understanding. It is initialized with a general base model – Qwen2.5 (Yang et al., 2024), and trained through continual pre-training (CPT) and supervised fine-tuning (SFT). Our experiments on widely-used benchmarks demonstrate the effectiveness of this pipeline in adapting a general model to the field of scientific literature understanding. We note that this pipeline could be easily adapted to other specialized domains, particularly those lacking adequate high-quality corpora and instruction sets. Our future work will focus on expanding the diversity and quality of the training data, as well as exploring more efficient methods for domain-specific knowledge injection and high-quality instruction generation.

## References

- Marah I Abdin, Sam Ade Jacobs, Ammar Ahmad Awan, Jyoti Aneja, Ahmed Awadallah, Hany Awadalla, Nguyen Bach, Amit Bahree, Arash Bakhtiari, Harkirat S. Behl, Alon Benhaim, Misha Bilenko, Johan Bjorck, Sébastien Bubeck, Martin Cai, Caio César Teodoro Mendes, Weizhu Chen, Vishrav Chaudhary, Parul Chopra, Allie Del Giorno, Gustavo de Rosa, Matthew Dixon, Ronen Eldan, Dan Iter, Amit Garg, Abhishek Goswami, Suriya Gunasekar, Emman Haider, Junheng Hao, Russell J. Hewett, Jamie Huynh, Mojan Javaheripi, Xin Jin, Piero Kauffmann, Nikos Karampatziakis, Dongwoo Kim, Mahoud Khademi, Lev Kurilenko, James R. Lee, Yin Tat Lee, Yuanzhi Li, Chen Liang, Weishung Liu, Eric Lin, Zeqi Lin, Piyush Madan, Arindam Mitra, Hardik Modi, Anh Nguyen, Brandon Norick, Barun Patra, Daniel Perez-Becker, Thomas Portet, Reid Pryzant, Heyang Qin, Marko Radmilac, Corby Rosset, Sambudha Roy, Olatunji Ruwase, Olli Saarikivi, Amin Saied, Adil Salim, Michael Santacroce, Shital Shah, Ning Shang, Hiteshi Sharma, Xia Song, Masahiro Tanaka, Xin Wang, Rachel Ward, Guanhua Wang, Philipp Witte, Michael Wyatt, Can Xu, Jiahang Xu, Sonali Yadav, Fan Yang, Ziyi Yang, Donghan Yu, Chengruidong Zhang, Cyril Zhang, Jianwen Zhang, Li Lyna Zhang, Yi Zhang, Yue Zhang, Yunan Zhang, and Xiren Zhou. 2024. Phi-3 Technical Report: A Highly Capable Language Model Locally on Your Phone. *CoRR* abs/2404.14219 (2024).
- Bo Adler, Niket Agarwal, Ashwath Aithal, Dong H. Anh, Pallab Bhattacharya, Annika Brundyn, Jared Casper, Bryan Catanzaro, Sharon Clay, Jonathan M. Cohen, Sirshak Das, Ayush Dattagupta, Olivier Delalleau, Leon Derczynski, Yi Dong, Daniel Egert, Ellie Evans, Aleksander Ficek, Denys Fridman, Shaona Ghosh, Boris Ginsburg, Igor Gitman, Tomasz Grzegorzczek, Robert Herok, Jining Huang, Vibhu Jawa, Joseph Jennings, Aastha Jhunjhunwala, John Kamalu, Sadaf Khan, Oleksii Kuchaiev, Patrick LeGresley, Hui Li, Jiwei Liu, Zihan Liu, Eileen Long, Ameya Sunil Mahabaleshwarkar, Somshubra Majumdar, James Maki, Miguel Martinez, Maer Rodrigues de Melo, Ivan Moshkov, Deepak Narayanan, Sean Narenthiran, Jesus Navarro, Phong Nguyen, Osvald Nitski, Vahid Noroozi, Guruprasad Nutheti, Christopher Parisien, Jupinder Parmar, Mostofa Patwary, Krzysztof Pawelec, Wei Ping, Shrimai Prabhumoye, Rajarshi Roy, Trisha Saar, Vasanth Rao Naik Sabavat, Sanjeev Satheesh, Jane Polak Scowcroft, Jason Sewall, Pavel Shamis, Gerald Shen, Mohammad Shoeybi, Dave Sizer, Misha Smelyanskiy, Felipe Soares, Makesh Narsimhan Sreedhar, Dan Su, Sandeep Subramanian, Shengyang Sun, Shubham Toshniwal, Hao Wang, Zhilin Wang, Jiaxuan You, Jiaqi Zeng, Jimmy Zhang, Jing Zhang, Vivienne Zhang, Yian Zhang, and Chen Zhu. 2024. Nemotron-4 340B Technical Report. *CoRR* abs/2406.11704 (2024). <https://doi.org/10.48550/arXiv.2406.11704>
- Microsoft Research AI4Science and Microsoft Azure Quantum. 2023. The Impact of Large Language Models on Scientific Discovery: a Preliminary Study using GPT-4. *CoRR* abs/2311.07361 (2023).
- AI@Meta. 2024. Llama 3 Model Card. (2024). [https://github.com/meta-llama/llama3/blob/main/MODEL\\_CARD.md](https://github.com/meta-llama/llama3/blob/main/MODEL_CARD.md)
- Lozhkov Anton, Ben Allal Loubna, von Werra Leandro, and Wolf Thomas. 2024. *FineWeb-Edu*. <https://doi.org/10.57967/hf/2497>
- Iz Beltagy, Kyle Lo, and Arman Cohan. 2019. SciBERT: A Pretrained Language Model for Scientific Text. In *EMNLP/IJCNLP (1)*. Association for Computational Linguistics, 3613–3618.
- Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language Models are Few-Shot Learners. In *NeurIPS*.
- Hengxing Cai, Xiaochen Cai, Junhan Chang, Sihang Li, Lin Yao, Changxin Wang, Zhifeng Gao, Hongshuai Wang, Yongge Li, Mujie Lin, Shuwen Yang, Jiankun Wang, Yuqi Yin, Yaqi Li, Linfeng Zhang, and Guolin Ke. 2024. SciAssess: Benchmarking LLM Proficiency in Scientific Literature Analysis. *CoRR* (2024). <https://doi.org/10.48550/arXiv.2403.01976>
- Daixuan Cheng, Yuxian Gu, Shaohan Huang, Junyu Bi, Minlie Huang, and Furu Wei. 2024. Instruction Pre-Training: Language Models are Supervised Multitask Learners. *arXiv preprint arXiv:2406.14491* (2024).

- Daixuan Cheng, Shaohan Huang, and Furu Wei. 2023. Adapting Large Language Models via Reading Comprehension. *CoRR* abs/2309.09530 (2023).
- David Cheng-Han Chiang and Hung-yi Lee. 2023. Can Large Language Models Be an Alternative to Human Evaluations?. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2023, Toronto, Canada, July 9-14, 2023*, Anna Rogers, Jordan L. Boyd-Graber, and Naoaki Okazaki (Eds.). Association for Computational Linguistics, 15607–15631. <https://doi.org/10.18653/v1/2023.acl-long.870>
- Jan Clusmann, Fiona R Kolbinger, Hannah Sophie Muti, Zunamys I Carrero, Jan-Niklas Eckardt, Narmin Ghaffari Laleh, Chiara Maria Lavinia Löffler, Sophie-Caroline Schwarzkopf, Michaela Unger, Gregory P Veldhuizen, et al. 2023. The future landscape of large language models in medicine. *Communications medicine* 3, 1 (2023), 141.
- Together Computer. 2023. *RedPajama: an Open Dataset for Training Large Language Models*. <https://github.com/togethercomputer/RedPajama-Data>
- Jiaxi Cui, Munan Ning, Zongjian Li, Bohua Chen, Yang Yan, Hao Li, Bin Ling, Yonghong Tian, and Li Yuan. 2024. Chatlaw: A Multi-Agent Collaborative Legal Assistant with Knowledge Graph Enhanced Mixture-of-Experts Large Language Model. arXiv:2306.16092 [cs.CL] <https://arxiv.org/abs/2306.16092>
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *NAACL-HLT (1)*. Association for Computational Linguistics, 4171–4186.
- Ronen Eldan and Yuanzhi Li. 2023. TinyStories: How Small Can Language Models Be and Still Speak Coherent English? *CoRR* abs/2305.07759 (2023). <https://doi.org/10.48550/arXiv.2305.07759>
- Alexander Erdmann, David Joseph Wrisley, Benjamin Allen, Christopher Brown, Sophie Cohen-Bodénès, Micha Elsner, Yukun Feng, Brian Joseph, Béatrice Joyeux-Prunel, and Marie-Catherine de Marneffe. 2019. Practical, Efficient, and Customizable Active Learning for Named Entity Recognition in the Digital Humanities. In *NAACL-HLT (1)*. Association for Computational Linguistics, 2223–2234.
- Yin Fang, Xiaozhuan Liang, Ningyu Zhang, Kangwei Liu, Rui Huang, Zhuo Chen, Xiaohui Fan, and Huajun Chen. 2023. Mol-Instructions: A Large-Scale Biomolecular Instruction Dataset for Large Language Models. *CoRR* abs/2306.08018 (2023). <https://doi.org/10.48550/arXiv.2306.08018>
- Kehua Feng, Keyan Ding, Weijie Wang, Xiang Zhuang, Zeyuan Wang, Ming Qin, Yu Zhao, Jianhua Yao, Qiang Zhang, and Huajun Chen. 2024. SciKnowEval: Evaluating Multi-level Scientific Knowledge of Large Language Models. *CoRR* (2024). <https://doi.org/10.48550/arXiv.2406.09098>
- 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. 2023. Textbooks Are All You Need. *CoRR* abs/2306.11644 (2023).
- Kshitij Gupta, Benjamin Thérien, Adam Ibrahim, Mats L. Richter, Quentin Anthony, Eugene Belilovsky, Irina Rish, and Timothée Lesort. 2023. Continual Pre-Training of Large Language Models: How to (re)warm your model? *CoRR* abs/2308.04014 (2023).
- Jordan Hoffmann, Sebastian Borgeaud, Arthur Mensch, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, Diego de Las Casas, Lisa Anne Hendricks, Johannes Welbl, Aidan Clark, Tom Hennigan, Eric Noland, Katie Millican, George van den Driessche, Bogdan Damoc, Aurelia Guy, Simon Osindero, Karen Simonyan, Erich Elsen, Jack W. Rae, Oriol Vinyals, and Laurent Sifre. 2022. Training Compute-Optimal Large Language Models. *CoRR* abs/2203.15556 (2022).

- Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de Las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, L  lio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timoth  e Lacroix, and William El Sayed. 2023. Mistral 7B. *CoRR* abs/2310.06825 (2023). <https://doi.org/10.48550/arXiv.2310.06825>
- Xisen Jin, Dejiao Zhang, Henghui Zhu, Wei Xiao, Shang-Wen Li, Xiaokai Wei, Andrew O. Arnold, and Xiang Ren. 2022. Lifelong Pretraining: Continually Adapting Language Models to Emerging Corpora. In *NAACL-HLT*. Association for Computational Linguistics, 4764–4780.
- Zixuan Ke, Yijia Shao, Haowei Lin, Tatsuya Konishi, Gyuhak Kim, and Bing Liu. 2023. Continual Pre-training of Language Models. In *ICLR*. OpenReview.net.
- Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph Gonzalez, Hao Zhang, and Ion Stoica. 2023. Efficient Memory Management for Large Language Model Serving with PagedAttention. In *SOSP*. ACM, 611–626.
- Sihang Li, Zhiyuan Liu, Yanchen Luo, Xiang Wang, Xiangnan He, Kenji Kawaguchi, Tat-Seng Chua, and Qi Tian. 2024. Towards 3D Molecule-Text Interpretation in Language Models. *CoRR* abs/2401.13923 (2024).
- Yuanzhi Li, S  bastien Bubeck, Ronen Eldan, Allie Del Giorno, Suriya Gunasekar, and Yin Tat Lee. 2023. Textbooks Are All You Need II: phi-1.5 technical report. *CoRR* abs/2309.05463 (2023).
- Chen Ling, Xujiang Zhao, Jiaying Lu, Chengyuan Deng, Can Zheng, Junxiang Wang, Tanmoy Chowdhury, Yun Li, Hejie Cui, Xuchao Zhang, Tianjiao Zhao, Amit Panalkar, Wei Cheng, Haoyu Wang, Yanchi Liu, Zhengzhang Chen, Haifeng Chen, Chris White, Quanguan Gu, Carl Yang, and Liang Zhao. 2023. Beyond One-Model-Fits-All: A Survey of Domain Specialization for Large Language Models. *CoRR* abs/2305.18703 (2023). <https://doi.org/10.48550/ARXIV.2305.18703> arXiv:2305.18703
- Sanket Vaibhav Mehta, Darshan Patil, Sarath Chandar, and Emma Strubell. 2023. An Empirical Investigation of the Role of Pre-training in Lifelong Learning. *J. Mach. Learn. Res.* 24 (2023), 214:1–214:50.
- OpenAI. 2023. GPT-4 Technical Report. *CoRR* abs/2303.08774 (2023). <https://doi.org/10.48550/arXiv.2303.08774>
- Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul F. Christiano, Jan Leike, and Ryan Lowe. 2022. Training language models to follow instructions with human feedback. In *NeurIPS*. [http://papers.nips.cc/paper\\_files/paper/2022/hash/b1efde53be364a73914f58805a001731-Abstract-Conference.html](http://papers.nips.cc/paper_files/paper/2022/hash/b1efde53be364a73914f58805a001731-Abstract-Conference.html)
- Hang Qiu, Krishna Chintalapudi, and Ramesh Govindan. 2023. MCAL: Minimum Cost Human-Machine Active Labeling. In *ICLR*. OpenReview.net.
- Haoran Que, Jiaheng Liu, Ge Zhang, Chenchen Zhang, Xingwei Qu, Yinghao Ma, Feiyu Duan, Zhiqi Bai, Jiakai Wang, Yuanxing Zhang, et al. 2024. D-CPT Law: Domain-specific Continual Pre-Training Scaling Law for Large Language Models. *arXiv preprint arXiv:2406.01375* (2024).
- Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. *OpenAI blog* 1, 8 (2019), 9.
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer. *J. Mach. Learn. Res.* 21 (2020), 140:1–140:67.
- Amanpreet Singh, Mike D’Arcy, Arman Cohan, Doug Downey, and Sergey Feldman. 2023. SciRepEval: A Multi-Format Benchmark for Scientific Document Representations. In *EMNLP*. 5548–5566. <https://doi.org/10.18653/v1/2023.emnlp-main.338>

- Karan Singhal, Shekoofeh Azizi, Tao Tu, S. Sara Mahdavi, Jason Wei, Hyung Won Chung, Nathan Scales, Ajay Kumar Tanwani, Heather Cole-Lewis, Stephen Pfohl, Perry Payne, Martin Seneviratne, Paul Gamble, Chris Kelly, Nathaneal Schärli, Aakanksha Chowdhery, Philip Andrew Mansfield, Blaise Agüera y Arcas, Dale R. Webster, Gregory S. Corrado, Yossi Matias, Katherine Chou, Juraj Gottweis, Nenad Tomasev, Yun Liu, Alvin Rajkomar, Joelle K. Barral, Christopher Semturs, Alan Karthikesalingam, and Vivek Natarajan. 2022. Large Language Models Encode Clinical Knowledge. *CoRR* abs/2212.13138 (2022). <https://doi.org/10.48550/arXiv.2212.13138>
- Yu Sun, Shuohuan Wang, Yu-Kun Li, Shikun Feng, Hao Tian, Hua Wu, and Haifeng Wang. 2020. ERNIE 2.0: A Continual Pre-Training Framework for Language Understanding. In *AAAI*. AAAI Press, 8968–8975.
- Ross Taylor, Marcin Kardas, Guillem Cucurull, Thomas Scialom, Anthony Hartshorn, Elvis Saravia, Andrew Poulton, Viktor Kerkez, and Robert Stojnic. 2022. Galactica: A Large Language Model for Science. *CoRR* abs/2211.09085 (2022). <https://doi.org/10.48550/arXiv.2211.09085>
- Qwen Team. 2024. Qwen2.5: A Party of Foundation Models. <https://qwenlm.github.io/blog/qwen2.5/>
- 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. 2023. LLaMA: Open and Efficient Foundation Language Models. *CoRR* abs/2302.13971 (2023).
- David Wadden, Kejian Shi, Jacob Morrison, Aakanksha Naik, Shruti Singh, Nitzan Barzilay, Kyle Lo, Tom Hope, Luca Soldaini, Shannon Zejiang Shen, Doug Downey, Hannaneh Hajishirzi, and Arman Cohan. 2024. SciRIFF: A Resource to Enhance Language Model Instruction-Following over Scientific Literature. *CoRR* abs/2406.07835 (2024). <https://doi.org/10.48550/arXiv.2406.07835>
- Yubo Wang, Xueguang Ma, Ge Zhang, Yuansheng Ni, Abhranil Chandra, Shiguang Guo, Weiming Ren, Aaran Arulraj, Xuan He, Ziyang Jiang, Tianle Li, Max Ku, Kai Wang, Alex Zhuang, Rongqi Fan, Xiang Yue, and Wenhui Chen. 2024. MMLU-Pro: A More Robust and Challenging Multi-Task Language Understanding Benchmark. arXiv:2406.01574 [cs.CL]
- Jason Wei, Maarten Bosma, Vincent Y Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M Dai, and Quoc V Le. 2021. Finetuned language models are zero-shot learners. *arXiv preprint arXiv:2109.01652* (2021).
- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed H. Chi, Quoc V. Le, and Denny Zhou. 2022. Chain-of-Thought Prompting Elicits Reasoning in Large Language Models. In *NeurIPS*.
- Shijie Wu, Ozan Irsoy, Steven Lu, Vadim Dabravolski, Mark Dredze, Sebastian Gehrmann, Prabhakaran Kambadur, David S. Rosenberg, and Gideon Mann. 2023. BloombergGPT: A Large Language Model for Finance. *CoRR* abs/2303.17564 (2023). <https://doi.org/10.48550/ARXIV.2303.17564> arXiv:2303.17564
- Tongtong Wu, Massimo Caccia, Zhuang Li, Yuan-Fang Li, Guilin Qi, and Gholamreza Haffari. 2022. Pretrained Language Model in Continual Learning: A Comparative Study. In *ICLR*. OpenReview.net.
- An Yang, Baosong Yang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Zhou, Chengpeng Li, Chengyuan Li, Dayiheng Liu, Fei Huang, Guanting Dong, Haoran Wei, Huan Lin, Jialong Tang, Jialin Wang, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Ma, Jianxin Yang, Jin Xu, Jingren Zhou, Jinze Bai, Jinzheng He, Junyang Lin, Kai Dang, Keming Lu, Keqin Chen, Kexin Yang, Mei Li, Mingfeng Xue, Na Ni, Pei Zhang, Peng Wang, Ru Peng, Rui Men, Ruize Gao, Runji Lin, Shijie Wang, Shuai Bai, Sinan Tan, Tianhang Zhu, Tianhao Li, Tianyu Liu, Wenbin Ge, Xiaodong Deng, Xiaohuan Zhou, Xingzhang Ren, Xinyu Zhang, Xipin Wei, Xuancheng Ren, Xuejing Liu, Yang Fan, Yang Yao, Yichang Zhang, Yu Wan, Yunfei Chu, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, Zhifang Guo, and Zhihao Fan. 2024. Qwen2 Technical Report. <https://arxiv.org/abs/2407.10671>

- Hongyang Yang, Xiao-Yang Liu, and Christina Dan Wang. 2023. FinGPT: Open-Source Financial Large Language Models. *CoRR* abs/2306.06031 (2023). <https://doi.org/10.48550/arXiv.2306.06031>
- Shunyu Yao, Dian Yu, Jeffrey Zhao, Izhak Shafran, Tom Griffiths, Yuan Cao, and Karthik Narasimhan. 2023. Tree of Thoughts: Deliberate Problem Solving with Large Language Models. In *NeurIPS*.
- Mohd Zaki, NM Krishnan, et al. 2023. MaScQA: A Question Answering Dataset for Investigating Materials Science Knowledge of Large Language Models. *arXiv preprint arXiv:2308.09115* (2023).
- Zheni Zeng, Yuan Yao, Zhiyuan Liu, and Maosong Sun. 2022. A Deep-learning System Bridging Molecule Structure and Biomedical Text with Comprehension Comparable to Human Professionals. *Nature communications* 13, 862 (2022).
- Dan Zhang, Ziniu Hu, Sining Zhou, Zhengxiao Du, Kaiyu Yang, Zihan Wang, Yisong Yue, Yuxiao Dong, and Jie Tang. 2024a. SciGLM: Training Scientific Language Models with Self-Reflective Instruction Annotation and Tuning. *CoRR* abs/2401.07950 (2024). <https://doi.org/10.48550/arXiv.2401.07950>
- Di Zhang, Wei Liu, Qian Tan, Jingdan Chen, Hang Yan, Yuliang Yan, Jiatong Li, Weiran Huang, Xiangyu Yue, Dongzhan Zhou, Shufei Zhang, Mao Su, Hansen Zhong, Yuqiang Li, and Wanli Ouyang. 2024b. ChemLLM: A Chemical Large Language Model. *CoRR* abs/2402.06852 (2024). <https://doi.org/10.48550/arXiv.2402.06852>
- Xingjian Zhang, Yutong Xie, Jin Huang, Jinge Ma, Zhaoying Pan, Qijia Liu, Ziyang Xiong, Tolga Ergen, Dongsub Shim, Honglak Lee, and Qiaozhu Mei. 2024c. MASSW: A New Dataset and Benchmark Tasks for AI-Assisted Scientific Workflows. *CoRR* abs/2406.06357 (2024). <https://doi.org/10.48550/arXiv.2406.06357>
- Yizhen Zheng, Huan Yee Koh, Jiabin Ju, Anh T. N. Nguyen, Lauren T. May, Geoffrey I. Webb, and Shirui Pan. 2023. Large Language Models for Scientific Synthesis, Inference and Explanation. *CoRR* abs/2310.07984 (2023).

## A Format & Grammar Correction Examples

### Raw text parsed by PyPDF2

Highly penetrating radiation, such as  $\gamma$ -rays or fast electrons, deposits energy throughout the solid target material. Gas production occurs within the solid phase and must diffuse to the surface to be observed. The apparent yield of H<sub>2</sub> can depend on the radiolysis procedure or the particle size if some of the gas remains in the solid. Experiments have shown that the apparent yield of H<sub>2</sub> can vary by a factor of 3 in the radiolysis of polyethylene spheres of 7 to 2100 cm<sup>2</sup>/g (about 9 to 0.03 mm) [12]. The effects of gas trapping and diffusion are not understood in the context of waste storage. Extremely high dose rates in the processing of certain materials may lead to bubble formation, which could alter product quality. The yield of H<sub>2</sub> in the radiolysis of polymers with  $\gamma$ -rays is well known for several types of polymers [2].

### Format & Grammar Correction Prompt

I have extracted the following raw text from a PDF, but the extraction process has introduced many formatting issues such as unnecessary line breaks, extra spaces, and other artifacts that disrupt the text flow. Could you please help me correct these formatting issues and provide a clean, readable version of the text? Respond with the Corrected Version only.

Raw Text:

{RawText}

Start your response with "Here is the corrected version of the text:".

### Text after Format & Grammar Correction

Highly penetrating radiation, such as  $\gamma$ -rays or fast electrons, deposits energy throughout the solid target material. Gas production occurs within the solid phase and must diffuse to the surface to be observed. The apparent yield of H<sub>2</sub> can depend on the radiolysis procedure or the particle size if some of the gas remains in the solid. Experiments have shown that the apparent yield of H<sub>2</sub> can vary by a factor of 3 in the radiolysis of polyethylene spheres of 7 to 2100 cm<sup>2</sup>/g (about 9 to 0.03 mm) [12]. The effects of gas trapping and diffusion are not understood in the context of waste storage. Extremely high dose rates in the processing of certain materials may lead to bubble formation, which could alter product quality.

The yield of H<sub>2</sub> in the radiolysis of polymers with  $\gamma$ -rays is well known for several types of polymers [2].

## B CPT Quality Filter

We randomly select 50k samples from our CPT data. These selected samples are then scored using the Llama3-70B-Instruct model. The prompt utilized for this scoring process is as follows:

### Prompt for CPT Data Quality Labelling

Below is an extract from a textbook. Evaluate whether the text has a high educational value and could be useful in an educational setting for teaching from primary school to grade school levels using the additive 5-point scoring system described below. Points are accumulated based on the satisfaction of each criterion:

- Add 1 point if the extract provides some basic information relevant to educational topics, even if it includes some irrelevant or non-academic content like advertisements and promotional material.
- Add another point if the extract addresses certain elements pertinent to education but does not align closely with educational standards. It might mix educational content with non-educational material, offering a superficial overview of potentially useful topics, or presenting information in a disorganized manner and incoherent writing style.
- Award a third point if the extract is appropriate for educational use and introduces key concepts relevant to school curricula. It is coherent though it may not be comprehensive or could include some extraneous information. It may resemble an introductory section of a textbook or a basic tutorial that is suitable for learning but has notable limitations like treating concepts that are too complex for grade school students.
- Grant a fourth point if the extract is highly relevant and beneficial for educational purposes for a level not higher than grade school, exhibiting a clear and consistent writing style. It could be similar to a chapter from a textbook or a tutorial, offering substantial educational content, including exercises and solutions, with minimal irrelevant information, and the concepts aren't too advanced for grade school students. The content is coherent, focused, and valuable for structured learning.
- Bestow a fifth point if the extract is outstanding in its educational value, and perfectly suited for teaching either at primary school or grade school. It follows detailed reasoning, the writing style is easy to follow, and offers profound and thorough insights into the subject matter, devoid of any non-educational or complex content.

After examining the extract:

- Briefly justify your total score, up to 100 words.
- Conclude with the score using the format: "Educational score: <total points>"

We train a Scientific Texts Quality Classifier on these labeled data samples. The classifier is a 109M BERT (Devlin et al., 2019) classifier, fine-tuned from the checkpoint of fineweb-edu-classifier (Anton et al., 2024). The model is trained for 20 epochs with a learning rate of 0.001 and a batch size of



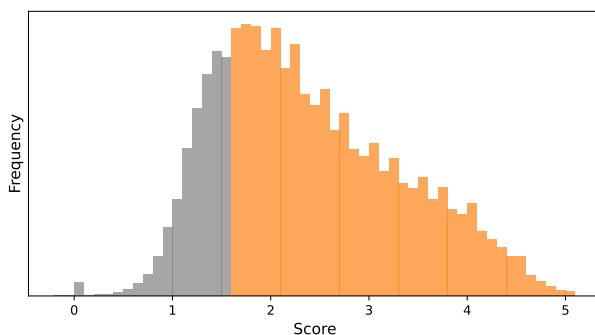


Figure 6: Score distribution of the CPT Data

1024. Ninety percent of the 50K samples are used as the training set, and the rest 10% are used as the validation set. The training process costs approximately 50 minutes on 4 A100 GPUs. We select the checkpoint from the epoch that yields the highest validation micro F1 score as our final checkpoint.

During Inference, we set batch size to 2048, and beam number to 1. The inference process costs 90 minutes on 4 A100 GPUs. We utilize the generated to filter out 25% data with the lowest quality. The distribution of the scores is demonstrated in Figure 6. The filtered-out 25% data are marked **gray**, while the remaining 75% CPT data are marked **orange**.

## C SFT Details

### C.1 Instruction Generation Pipeline

In SciLitIns, we focus on generating instructions for three less-represented domains (materials science, medicine, and drug discovery) and five question types:

- **Table Extraction:** Table Extraction tasks evaluate a model’s proficiency in extracting, summarizing, and structuring data from an article into a table format.
- **Entity Extraction:** Entity Extraction tasks are designed to evaluate a model’s ability to extract specific information, such as entities or relationships, from the text.
- **Molecule Translation:** Molecule Translation tasks evaluate a model’s ability to translate molecules between different SMILES formats.
- **Molecule Extraction:** Molecule Extraction tasks ask a model to extract an appropriate molecule from a scientific paragraph that contains multiple molecules.
- **Multiple Choice and True-or-False:** Multiple Choice and True-or-False questions assess a model’s ability to select the correct answer from a set of options, testing its knowledge and reasoning on both simple and complex scenarios.

For each of the three scientific domains, we collect a set of high-impact research papers and construct a word frequency table. To generate a question in a given domain, we sample 20 keywords from the corresponding word table and insert them into the prompt for that question. To ensure fair representations of less frequent keywords, we use random sampling with a temperature setting of 3. We will release our code, prompt templates, and word frequency tables. Below is an example of generating a table extraction question:

### Prompt for Generating a Table Extraction Question

I need synthetic training data for training a machine learning model that extracts tables from text correctly. The data should be formatted in JSON, with each entry containing "text" and "answer" attributes. You should generate a paragraph that includes the keywords: {{keywords}}.

The "text" part must contain enough information for the table to be extracted! In "text" part, you must include a table description in latex format.

Special notice for the table content:  
You should generate a table that has complicated numbers and characters, include non-standard characters, and have a variety of values. Make sure the value you generated do not follow simple patterns, for example, never include duplicate values or values with constant interval in columns.

Your answer should contain as much details as possible. You should only generate one JSON. The value for the two attributes should be two string. Use {{ and }} to wrap your output. Pay attention to the escape characters in the latex format. Remember to put a comma at the end of the first string. Never use a json block to wrap your output. Here is the format for your output:

```
{
  "text": "Your paragraph here, remember to include a table in latex format",
  "answer": "Your answer table here"
}
```

Now start your answer:

## C.2 Instruction Deduplication

The generated synthetic data may contain similar questions or identical answers. To eliminate redundancy, we implement a fuzzy deduplication process using the Levenshtein distance to calculate the similarity score between question-answer pairs. Specifically, for two pairs  $(q_1, a_1)$  and  $(q_2, a_2)$ , their textual similarity is defined as  $(1 - \text{lev}(q_1, q_2))(1 - \text{lev}(a_1, a_2))$ , where  $\text{lev}(\cdot, \cdot)$  denotes the Levenshtein distance. Due to significant differences between texts from different question types, we compute similarity matrices separately for each type. We then use a disjoint-set data structure to merge highly similar data points. We use this process to remove approximately 5% to 10% of duplicated data for each question type.

## C.3 Quality Assessment of Generated SFT Instructions

In section 3.2.2, we sample 10k instruction pairs from SciLitIns and evaluate them by Llama-3-70B using the below prompt. Specifically, the quality is evaluated from five aspects: clarity, complexity, correctness, usefulness, and adaptability, assigning each instruction a score from 0 (lowest quality) to 5 (highest quality).

### SFT Evaluation Prompt

You are a helpful and precise assistant for checking the quality of instruction-tuning data for large language models. Your task is to evaluate the given instruction using the criterions described below.

- Clarity: The sample should be clear, specific, and unambiguous, providing a well-defined task for the model to perform.
- Complexity: The sample should be advanced complexity that necessitate a high level of comprehension and cognitive processing, challenging the language model significantly.
- Correctness: The sample is impeccably written, with flawless grammar, syntax, and structure, demonstrating exceptional clarity and professionalism.
- Usefulness: The sample should be highly useful, and contribute to expanding the model's knowledge base.
- Adaptability: The sample could be adapted to different contexts or use cases, showing some flexibility.

After examining the instruction-response pair:

- Briefly justify your scores with a paragraph in the field "Explanation", up to 500 words.
- For each point of criterion above, assign a score from 1 to 5.
- You should only provide the rest of your answer in a structured format as shown below, and make sure your response can be directly parsed by computer programs.

Below is a template for your response:

Explanation: <string, your explanations to the scores>

```
=====
{
  "Clarity": <int, complexity_score>,
  "Complexity": <int, complexity_score>,
  "Correctness": <int, quality_score>,
  "Usefulness": <int, usefulness_score>,
  "Adaptability": <int, adaptability_score>,
  "Total": <int, total_score>
}
```

Below is an example of SciLitIns, which will be sent to Llama-3-70B for evaluation.

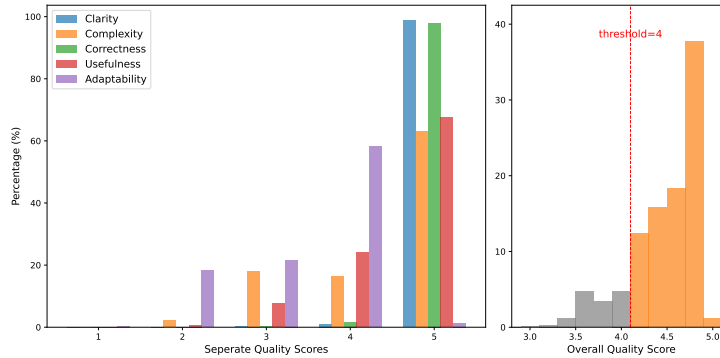


Figure 7: The quality of SciLitIns is evaluated from five aspects: clarity, complexity, correctness, usefulness, and adaptability (the higher the better). Instructions with an average score of less than 4 are filtered out.

### An Example in SciLitIns

#### Context

In recent studies regarding material science, the crmatrix has shown significant importance in understanding fracture behaviors. Alternatively, many researchers have proposed a series of experiments to analyze these phenomena. Even though the process is delicate, the enthusiasm for discovering new findings is understandable. The following Table 1 presents a schematic illustration of the enthalpy changes observed during the different fracture phases. These studies are indispensable for advancing our knowledge of the material's resilience. In addition, in certain cases, pronounced errors in measurement can occur, but the references provided can guide through the correct methodology. Prime among the tools used is the differential scanning calorimetry which helps measure these enthalpy changes accurately.

```
\begin{table}[h!]\n\centering\n\begin{tabular} {|c|c|c|c|}\n\hline\nMaterial &
Initial Enthalpy (kJ/mol) & Final Enthalpy (kJ/mol) & Fracture Phase
\\ \n\hline\nMaterial A & 25.4 & 47.8 & Brittle
\\ \n\hline\nMaterial B & 22.3 &
45.0 & Ductile
\\ \n\hline\nMaterial C & 28.9 & 50.2 & Semi-brittle
\\ \n\hline\n\end{tabular}\n\caption{Enthalpy changes during fracture
phases}\n\label{table:enthalpy}\n\end{table}
```

The process of accurately measuring these values is crucial for the material selection in various engineering applications, making it an indispensable research area.

#### Instruction

Extract the table in the paragraph.

#### Response

Material,Initial Enthalpy (kJ/mol),Final Enthalpy (kJ/mol),Fracture Phase  
Material A,25.4,47.8,Brittle  
Material B,22.3,45.0,Ductile  
Material C,28.9,50.2,Semi-brittle

Below is the evaluation by Llama-3-70B on the example from SciLitIns. Each criterion is scored out of 5 points, making the total possible points 25. The total score is then averaged, resulting in an overall score out of 5.

### Evaluation by Llama-3-70B

#### Explanation:

The instruction is clear and specific, asking the model to extract a table from a given paragraph. The paragraph itself is well-written, with proper grammar and syntax, making it easy to understand. The table is also well-structured and provides valuable information about enthalpy changes during fracture phases. The task requires a good understanding of the text and the ability to identify the table. However, the complexity of the task is relatively low, as it only involves extracting a table, and the context is not particularly nuanced or ambiguous. The task is useful for advancing knowledge in material science, and the table could be adapted to different contexts or use cases.

```
=====  
"Clarity": 5,  
"Complexity": 2,  
"Correctness": 5,  
"Usefulness": 4,  
"Adaptability": 4,  
"Total": 20
```

We show the quality statistics of synthetic instructions in Figure 7. Instructions with an average score of less than 4 are filtered out.

## D Benchmark Details

To the best of our knowledge, there are two commonly-adopted datasets for scientific literature understanding:

- SciRIFF (Wadden et al., 2024) evaluates essential scientific literature understanding capabilities, including information extraction, summarization, question answering, claim verification, and classification. Data points in SciRIFF are notable for their long input contexts and complicated structured outputs. The Qasper and SciFact tasks have two different evaluation methods and thus two results. For MuP and one evaluation method of Qasper, we use GPT-4o as language model evaluator, while the original paper uses GPT-3.5. We note that SciRIFF contains a separate training set used in the SFT stage in our study.
- SciAssess (Cai et al., 2024) features an end-to-end benchmark of understanding PDF content. It includes 28 tasks from four scientific domains: biology, chemistry, materials and medicine. SciAssess is used exclusively for testing in our evaluation.

Overall, SciRIFF provides basic benchmarks for comprehending short scientific segments and various instructions, while SciAssess presents more challenging tasks involving longer contexts from raw PDFs.

## E Detailed Performance on SciAssess

The detailed results on each tasks in SciAssess are shown in Table 7.

Domain	Task	SciTulu-7B	Mistral-7B	Llama3.1-8B	Qwen2.5-7B	SciLitLLM-7B	Qwen2.5-14B	Llama3-70B	Qwen2.5-72B	SciLitLLM-14B	GPT3.5	GPT4o
Biology	Average	45.3	52.0	63.4	60.9	65.3	65.9	69.4	67.2	67.0	55.4	68.9
	MmluPro	41.4	34.4	68.9	70.2	72.2	77.7	81.5	84.0	79.6	65.0	87.4
	ChartQA	35.2	40.7	46.7	47.7	48.2	51.8	47.7	48.7	56.3	31.2	55.8
	ChemRecog	54.9	56.0	73.7	66.7	84.3	80.1	83.6	76.4	77.8	64.9	79.5
	CompRecog	41.6	72.4	69.3	66.8	72.2	74.5	76.8	71.2	71.1	63.6	73.3
	DiseRecog	58.0	67.6	76.2	57.4	76.1	64.7	79.3	79.3	74.1	68.8	76.3
Chemistry	GeneFunc	40.6	40.7	45.8	56.6	38.9	46.4	47.4	43.8	43.2	39.1	41.0
	Average	19.0	34.0	46.1	47.9	55.4	60.0	62.5	63.7	63.4	37.3	68.0
	MmluPro	13.8	17.9	40.8	46.2	52.6	63.7	67.6	72.3	63.2	30.3	74.5
	ElecQA	19.6	41.7	53.8	63.3	70.4	75.9	75.5	78.5	78.4	30.5	85.5
	OledExtr	0.9	22.7	13.7	36.3	30.6	42.0	56.3	49.9	37.4	28.0	43.8
	ChartQA	33.3	46.7	86.7	46.7	66.7	80.0	80.0	80.0	80.0	66.7	86.7
Material	PolyQA	25.0	56.7	59.1	76.9	88.0	90.9	85.2	91.4	91.3	33.0	93.8
	PolyExtr	7.4	35.8	43.1	42.6	66.4	52.9	69.0	69.2	78.1	56.2	75.9
	SolExtr	31.5	33.7	33.2	40.5	36.1	41.1	44.7	43.7	41.3	40.8	44.4
	ReactQA	21.0	23.1	30.3	32.8	33.3	39.0	38.5	37.9	51.3	27.2	48.7
	MechQA	18.2	27.3	54.5	45.5	54.5	54.5	45.5	50.0	50.0	22.7	59.1
	Average	31.3	36.4	50.9	48.9	53.7	57.9	59.2	59.4	62.6	37.0	62.0
Medicine	MatQA	36.9	43.0	59.7	56.7	58.6	66.5	73.8	71.9	70.3	52.1	76.8
	ChartQA	33.3	66.7	66.7	73.3	46.7	60.0	46.7	53.3	53.3	40.0	46.7
	CompExtr	8.0	8.9	9.9	13.9	40.6	37.1	45.7	43.0	42.9	18.9	46.2
	TempQA	24.2	32.9	68.1	43.0	72.0	69.6	65.2	64.7	79.2	29.5	80.7
	SampDiff	29.1	20.7	36.3	39.7	44.3	52.7	62.4	57.8	60.8	32.9	62.4
	TreatSeq	56.4	46.5	64.9	66.8	59.9	61.4	61.4	65.8	68.8	48.5	59.4
Medicine	Average	19.9	25.1	30.2	28.3	32.4	31.5	37.4	37.8	39.9	31.8	45.8
	MmluPro	21.3	30.3	58.4	51.7	57.2	62.0	71.0	68.5	65.8	53.1	76.3
	AffiExtr	2.7	3.7	3.7	2.6	5.6	4.0	4.7	7.1	3.9	5.5	10.1
	ChartQA	33.3	40.0	26.7	40.0	33.3	33.3	40.0	33.3	53.3	33.3	46.7
	TagMol	1.2	0.2	7.1	0.7	2.8	6.2	14.3	13.6	7.3	2.3	22.9
	MarkMol	6.9	20.2	35.2	20.8	37.5	23.6	42.5	44.3	47.1	52.3	58.5
MolDoc	54.0	56.0	50.0	54.0	58.0	60.0	52.0	60.0	62.0	44.0	60.0	

Table 7: Detailed model performance on SciAssess tasks.