ADAPTING LARGE LANGUAGE MODELS VIA READING COMPREHENSION

Daixuan Cheng, Shaohan Huang[*] **& Furu Wei**
Microsoft

ABSTRACT

We explore how continued pre-training on domain-specific corpora influences large language models, revealing that training on the raw corpora endows the model with domain knowledge, but drastically hurts its prompting ability for question answering. Taken inspiration from human learning via reading comprehension—practice after reading improves the ability to answer questions based on the learned knowledge—we propose a simple method for transforming raw corpora into reading comprehension texts. Each raw text is enriched with a series of tasks related to its content. Our method, highly scalable and applicable to any pre-training corpora, consistently enhances performance across various tasks in three different domains: biomedicine, finance, and law. Notably, our 7B language model achieves competitive performance with domain-specific models of much larger scales, such as BloombergGPT-50B. Furthermore, we demonstrate that domain-specific reading comprehension texts can improve the model's performance even on general benchmarks, showing the potential to develop a general model across even more domains. Our model, code, and data will be available at https://github.com/microsoft/LMOps.
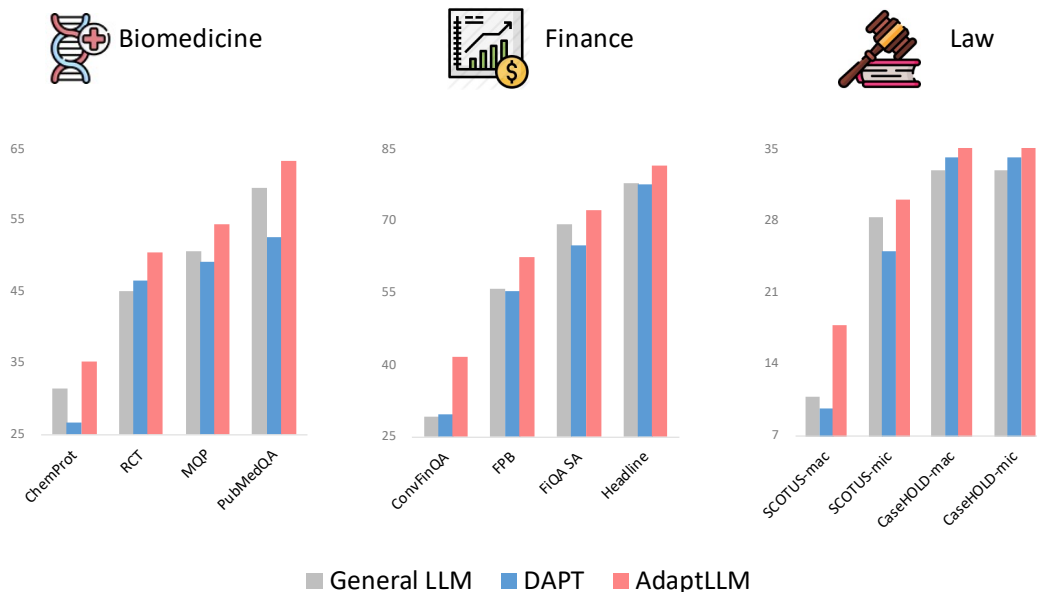
Figure 1: **Domain-specific task performance** in biomedicine, finance, and law. **General LLM** is the general language model without continued training, **DAPT** (Gururangan et al., 2020) continues to train the general model on domain-specific raw corpora, and **AdaptLLM** continues to train the general model on the reading comprehension texts constructed based on the raw corpora, mixed with general instructions.

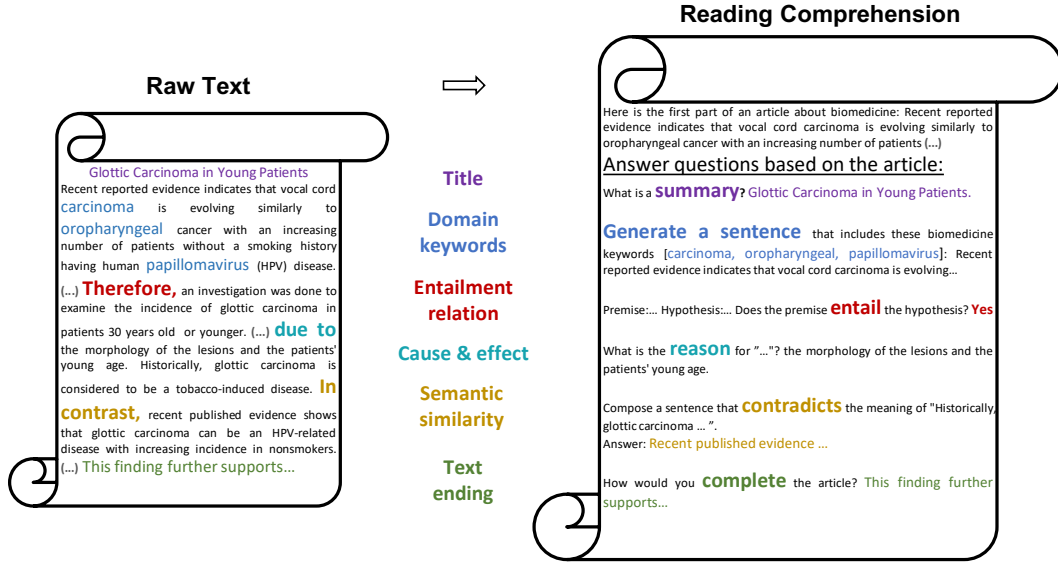[*]Corresponding author: shaohanh@microsoft.com

Figure 2: **A simplified example of a reading comprehension text**, wherein the raw text is followed by a series of tasks constructed from it, including Summarization (purple), Word-to-Text (blue), Natural Language Inference (red), Commonsense Reasoning (teal), Paraphrase Detection (yellow), and Text Completion (green). The complete version is in Appendix G.

1 INTRODUCTION

The proliferation of general large language models (LLMs) has given rise to the emergence of domain-specific large language models. Existing methods can be broadly classified into three approaches. The first trains models from scratch on a mixture of domain-specific and general corpora (Wu et al., 2023b). While this intuitively creates domain-specific LLMs, the substantial computational and data requirements raise significant concerns (Yang et al., 2023; Ling et al., 2023). The second fine-tunes the language model using supervised datasets (Singhal et al., 2022; 2023; Li et al., 2023b;a; Wang et al., 2023; Han et al., 2023; Xiong et al., 2023; Huang et al., 2023), offering a more cost-effective option. However, there are still uncertainties about how well fine-tuned LLMs grasp domain knowledge that can be universally applied to all domain-specific tasks, as discussed by Zhou et al. (2023) and Gudibande et al. (2023). The third prompts the general language model with retrieved domain knowledge (Li et al., 2023b; Cui et al., 2023; Huang et al., 2023), which can be considered as an application of LLM rather than a direct enhancement to the LLM itself.

Continued pre-training on domain-specific corpora, also known as domain-adaptive pretraining (Gururangan et al., 2020), has been proven effective in adapting various natural language understanding models (Devlin et al., 2019; Liu et al., 2019; Clark et al., 2020) to specific domains (Yao et al., 2021; Gururangan et al., 2020; Cheng et al., 2022). This approach enables language models to leverage general ability while incorporating domain-specific knowledge, benefiting downstream domain-specific tasks at reduced costs. This motivates our investigation into whether continued pre-training also benefits large-scale generative models. We conduct initial experiments on three domains—biomedicine, finance, and law—revealing that continued training on the raw corpora results in a drastic drop in prompting performance but still benefits fine-tuning evaluation and knowledge probing tests. This leads us to conclude that domain-adaptive pre-training using raw corpora imparts domain knowledge to the LLM while affecting its prompting ability.

To leverage domain-specific knowledge while enhancing prompting performance, we introduce a simple method for transforming large-scale raw corpora into reading comprehension texts: each raw text is enriched with a series of tasks relevant to its content, as illustrated in Figure 2. These tasks are designed to help the model maintain its ability to answer questions using natural language, based on the context of the raw text. Furthermore, we augment the reading comprehension texts with diverse general instructions, thereby further enhancing prompting ability (Wei et al., 2022; Zhou et al., 2023;

Xu et al., 2023; Mukherjee et al., 2023). Our experiments in domains such as biomedicine, finance, and law highlight the effectiveness of our approach in improving model performance on various domain-specific tasks. We refer to this resulting model as AdaptLLM, for Adapted Large Language Model. Looking ahead, we envision extending this methodology to the development of a general large language model, contributing to the ever-expanding landscape of tasks across more domains.

In summary, our contributions include:

- We investigate continued pre-training for large language models, where we find continued training on domain-specific raw corpora can endow the model with domain knowledge, but drastically hurts its prompting ability.
- We propose a simple recipe which automatically converts large-scale raw corpora into reading comprehension texts, to effectively learn the domain knowledge while concurrently preserving prompting performance.
- Our experiments show the effectiveness of our method in consistently improving model performance in three different domains: biomedicine, finance and law.

2 PRELIMINARY EXPLORATION ON CONTINUED PRE-TRAINING

Given the proven efficacy and efficiency of continued pre-training in adapting natural language understanding models (Gururangan et al., 2020; Yao et al., 2021; Cheng et al., 2022), we embark on an exploration to ascertain whether this method remains effective for large-scale generative models. We continue to train the general LLaMA (Touvron et al., 2023) on the domain-specific raw corpora of biomedicine, finance, and law, respectively, and conduct prompting and fine-tuning evaluations, as well as domain knowledge probing to assess the model performance within each domain (detailed experimental settings are in Section 4).

Table 1: **Domain-specific task scores** of general language model (General LLM) and the language model that has undergone continued pre-training on the domain-specific raw corpora (DAPT (Gururangan et al., 2020)). We report the average of task scores within each domain under prompting, fine-tuning and knowledge probing settings.

Method	Prompting			Fine-tuning			Knowledge Prob	
	BioMed.	Finance	Law	BioMed.	Finance	Law	BioMed.	Law
General LLM	**44.2**	**58.6**	34.2	64.2	79.9	42.0	36.5	45.0
DAPT	41.7	57.6	**35.0**	**66.5**	**80.9**	**45.4**	**36.9**	**45.6**

Prompting vs. Fine-tuning. As seen in Table 1, when fine-tuning is applied, consistent performance improvements across all three domains are evident after domain-adaptive pre-training. This trend aligns with findings related to language understanding models (Gururangan et al., 2020), indicating that continued pre-training enriches the LLM with domain-specific knowledge. Paradoxically, a contradictory trend emerges in the prompting performance, where a noticeable drop is observed across most domains after domain-adaptive pre-training. This contradiction leads us to hypothesize that while vanilla domain-adaptive pre-training enhances the LLM's domain knowledge, contributing to the fine-tuning improvements, it also significantly impairs its ability to perform well in prompting, causing the observed drop in prompting performance.

Domain Knowledge Probing. To further confirm whether the language model gains domain knowledge during continued pre-training, we employ a method similar to LAMA (Petroni et al., 2019) for probing domain knowledge. Using the supervised datasets available in each domain as the basis, we create domain-specific knowledge-probing datasets. The dataset creation process is detailed in Appendix A. In Table 1, we present the results of domain knowledge probing for the biomedicine and law domains[1]. Across both domains, we observe improved results after domain-adaptive pre-training, indicating that the model indeed acquires domain-specific knowledge.

---

[1]We were unable to construct a knowledge probing test for finance due to the limited availability of supervised datasets in this domain.

The above analyses indicate that the decline in domain-specific prompting performance can be attributed to the reduced prompting ability. This reduction may stem from the limited diversity of pre-training corpora within one particular domain (Longpre et al., 2023b), which limits the input-output patterns derived from raw texts (Wei et al., 2022). Therefore, enhancing prompting ability is crucial for effectively harnessing the domain knowledge acquired during continued pre-training.

3 Adapting Large Language Models via Reading Comprehension

Instead of continuing to train large language models on domain-specific raw corpora, we convert the raw corpora into reading comprehension texts and adapt the model using the converted data. In reading comprehension, each raw text is followed by a series of tasks related to its content. We regard the model training phase on the raw text as the "reading" phase, and the subsequent training on the followed tasks as the "comprehension" phase. These comprehension tasks follow the question-answering format, aimed at enriching the model's prompting ability to respond to input questions (Wei et al., 2022). This design is inspired from human learning, where practice after reading enhances the ability to answer questions based on the acquired knowledge. Furthermore, we propose augmenting the training data with general instructions (Zhou et al., 2023; Xu et al., 2023; Mukherjee et al., 2023) to benefit from the diversity of input-output formats, thereby further improving prompting ability.

3.1 Creating Reading Comprehension Texts

The idea of mining tasks from raw pre-training corpora to enhance zero-shot capability was introduced by van de Kar et al. (2022). This approach effectively extracts intrinsic tasks from raw texts through a handful of regex-based patterns, leading to substantial enhancements in the model's zero-shot performance via fine-tuning. Our approach leverages the self-supervised nature of this mining strategy to create our comprehension tasks. This enables us to scale up the transfer of raw pre-training data, capitalizing on the domain-specific knowledge embedded in the raw texts and the enhanced prompting ability provided by the comprehension tasks.

Table 2 gives an overview of the techniques used to extract and create tasks from raw texts. Phrases like `Answer questions based on the article:` are employed to concatenate each raw text with the followed tasks, as illustrated in Figure 2. Additionally, we paraphrase each task template to multiple variations and turn the task around to enhance task diversity (Wei et al., 2022; Chung et al., 2022; Longpre et al., 2023a).

Summarization prompts the models to generate a concise summary of the provided article, encouraging them to extract its main idea. To create task inputs, we employ queries like `What is a summary?` to prompt the model to summarize the article, using the text title as the groundtruth. We also reverse the task, asking the model to craft an article based on the given title.

Additionally, we task the language model with identifying sentence topics. To unearth such input-output pairs, we utilize regex-based patterns to identify sentences aligning with the patterns specified in Table 2. We then employ the corresponding task templates to construct the input-output pairs (van de Kar et al., 2022).

Word-to-Text enhances the model's grasp of domain-specific vocabulary by prompting it to generate sentences incorporating specific words. To identify domain-specific words, we use the SentencePiece tool (Kudo & Richardson, 2018) to build a vocabulary from the target domain corpora. We then compare this domain vocabulary to the general language model's vocabulary, considering words present in the domain vocabulary but absent from the general vocabulary as domain-specific. Additionally, we filter out tokens with fewer than 10 characters, resulting in a set of domain-specific keywords.

For each sentence in the raw text, we count the number of domain-specific keywords. Sentences having more than three domain-specific keywords are selected for making Word-to-Text tasks. We take the domain-specific keywords in the sentence as the input, asking the model to generate a sentence with `Generate a sentence that includes these {DOMAIN} keywords`. We also turn the task around by taking the sentence as input and asking the model to find the keywords about the target domain using `What keywords about {DOMAIN} can be extracted from this`

Table 2: **Mining patterns and input-output templates.** {VERBAL} is replaced with the verbalizers in Table 3. For mining, {WORD} captures a single word, and {SENT} captures a single sentence. Each input-output template is paraphrased into multiple variations. We also turn the task around—exchanging the question and answer—to achieve enhanced diversity.

Task Type	Mining Pattern	Input-output Template
Summarization		
Title	Title as summary	`What is a summary? {TITLE}`
Topic	`{SENT1} {VERBAL} {SENT2}`	`{SENT1} is about: {SENT2}`
Word-to-Text		
Word-to-text	Domain keywords as input; sentence as output	`Generate a sentence about these {DOMAIN} keywords [{WORD1},{WORD2},{WORD3}]: {SENT}`
Definition	`{WORD} {VERBAL} {SENT}`	`How to define {WORD}? {SENT}`
Natural Language Inference		
Entail Neutral Contradict	`{SENT1} {VERBAL}, {SENT2}`	`Does "{SENT1}" entail "{SENT2}"? {Yes/Maybe/No}`
Commonsense Reasoning		
Cause-effect	`{SENT1} {VERBAL}, {SENT2}`	`What is the {effect/cause}`
Effect-cause	`{SENT1} {VERBAL} {SENT2}`	`of {SENT1}? {SENT2}`
Paragraph Detection		
Similar Different	`{SENT1} {VERBAL}, {SENT2}`	`Compose a sentence to {support/ contradict} "{SENT1}". {SENT2}`
Text Completion		
Text completion	Text ending as completion	`How would you complete the article? {ENDING}`

`sentence?`. Here we point out the target domain by replacing {DOMAIN} with domain names such as `biomedicine`, `finance`, or `law`. Besides, we task the language model with defining concepts using the mining pattern and input-output template in Table 2.

Natural Language Inference concerns how two sentences relate, typically asking, given a first sentence, whether a second sentence is true, false or possibly true. We use the regex-based patterns in Table 2 to search for "premise-hypothesis-relation" triplets within the raw text. For example, we categorize the relationship between two sentences as "Entailment" if they are are connected by the verbalizer `Therefore`, and as "Neutral" if connected by `Furthermore`.

Additionally, we enhance diversity by converting classification tasks into generation tasks. For example, when the relationship between two sentences is entailment, we employ templates like {SENT1} `Thus?` to query for an output of which the groundtruth is the second sentence.

Commonsense Reasoning evaluates the ability to perform physical or scientific reasoning while considering common sense. We identify cause-and-effect logic within sentences using the regex-based patterns in Table 2. We then formulate the input-output pairs using templates such as `What is the reason of {SENT1}? {SENT2}`.

Paraphrase Detection asks a model to determine whether two sentences are semantically equivalent. To collect such task data, we use regex-based patterns in Table 2 to search for "sentence1-sentence2-label" data triplets. However, we empirically find that these mining patterns cannot consistently identify two sentences with strictly equivalent semantic meanings. For instance, sentences linked by the verbalizer `Similarly` may not share similar meanings.

Table 3: **Verbalizers for mining patterns in Table 2.**

Task Type	Verbalizer
Summarization	
Topic	`talks about`, `is about`, `'s topic is`
Word-to-Text	
Definition	`is defined as`, `'s definition is`
Natural Language Inference	
Entail	`Yes`, `Therefore`, `Thus`, `Accordingly`, `Hence`, `For this reason`
Neutral	`Maybe`, `Furthermore`, `Additionally`, `Moreover`, `In addition`
Contradict	`No`, `However`, `But`, `On the contrary`, `In contrast`, `Whereas`
Commonsense Reasoning	
Cause-effect	`Therefore`, `Thus`, `Accordingly`, `Hence`, `For this reason`
Effect-cause	`due to`, `on account of`, `owing to`
Paragraph Detection	
Similar	`In other words`, `Namely`, `That is to say`, `Similarly`, `Equally`
Different	`No`, `However`, `But`, `On the contrary`, `In contrast`, `Whereas`

Therefore, we reformat the classification task into a generation task to reduce dependence on label accuracy. Instead of inquiring whether two sentences are similar, we prompt the model to generate a sentence that either supports or contradicts the meaning of a given sentence, using input-output templates like `Can you create a sentence that contradicts the meaning of {SENT1}? {SENT2}` when the extracted label is "Different."

Text Completion. In addition to the inherent casual language modeling task within generative language models, we insert queries such as `How would you complete the article?` between sentences to prompt the language model to generate the subsequent section. An advantage of Text Completion task is that it does not require any specific mining patterns, thus can be applied to any raw texts.

3.2 MIXING WITH GENERAL INSTRUCTIONS

While we have designed diverse mining patterns, input-output templates and task reversals to enhance prompting ability, they might not fully address the infinite task diversity in real-world scenarios. In light of this, we propose to mix the reading comprehension texts with general instructions to cover a wider range of input-output types.

4 EXPERIMENT SETTINGS

Domain-adaptive Pre-training. PubMed Abstracts and FreeLaw Opinions from the Pile (Gao et al., 2021) are utilized as the pre-training corpora for the biomedicine and law domains, respectively. For finance, we collect financial news from May 2022 to May 2023[2] for over $7,000$ stocks, using the FinGPT codebase (Yang et al., 2023). General instructions are sourced from LIMA (Zhou et al., 2023), WizardLM (Xu et al., 2023), and Orca (Mukherjee et al., 2023). Our pre-training code is based on TorchScale[3]. We continue to train LLaMA-7B (Touvron et al., 2023) on each domain, and explore different ratios for mixing reading comprehension texts with general instructions; the optimal ratios for biomedicine, finance, and law are $1:1$, $1:2$, and $1:1$, respectively. Dataset details and other pre-training hyper-parameters can be found in Appendix B.

---

[2]Access to earlier news is limited.

[3]https://github.com/microsoft/torchscale

Creating Reading Comprehension Texts. Using the mining patterns in Table 2, we search for sub-categories within each task type. To prevent task dominance, we limit the number of task examples per sub-category to two for each raw text. For each mined example, we randomly sample from various paraphrased or task-reversed templates to generate an input-output example. To structure the reading comprehension text, we use $\backslash n \backslash n$ to connect comprehension tasks and link them with the raw text. On average, about two input-output examples are collected per reading comprehension text. Please refer to Appendix C for mining pattern implementation details and Appendix G for cases of reading comprehension texts.

Domain-specific Tasks. For biomedicine, we evaluate on PubMedQA (Jin et al., 2019), ChemProt (Kringelum et al., 2016), MQP (McCreery et al., 2020), RCT (Dernoncourt & Lee, 2017), and USMLE (Jin et al., 2020). For finance, we evaluate on the five publicly available tasks also evaluated by BloombergGPT (Wu et al., 2023b): ConvFinQA (Chen et al., 2022), FPB (Malo et al., 2014), FiQA SA (Maia et al., 2018), Headline (Sinha & Khandait, 2020), and NER (Alvarado et al., 2015), and adopt similar prompting settings with BloombergGPT. For law, we evaluate on SCOTUS (Spaeth et al., 2020), CaseHOLD (Zheng et al., 2021) and UNFAIR-ToS (Lippi et al., 2019) from the LexGLUE (Chalkidis et al., 2022) benchmark. Evaluation details are provided in Appendix D.

5 MAIN RESULTS

In Table 4, we present the comparative prompting results of our models (AdaptLLM) against the general language model (General LLM) and the models that have gone vanilla domain-adaptive pretraining on raw corpora (DAPT). On various tasks in the three different domains, the use of raw texts in DAPT adversely affects the performance. However, the reformatting of raw texts and the inclusion of general instructions in AdaptLLM manage to counteract this effect, resulting in better results than the general language model.

Table 4: **Domain-specific task performance** of general large language model (General LLM), vanilla domain-adaptive pretraining (DAPT), and ours (AdaptLLM) in prompting evaluation. We also display prompting results of other models including MedAlpaca (Han et al., 2023) in biomedicine, BloombergGPT (Wu et al., 2023b) in finance, and LexGPT (Lee, 2023) in law.

Biomedicine	PubMedQA	ChemProt	MQP	RCT	UMSLE	AVERAGE
MedAlpaca-7B	58.6	39.0	50.7	40.8	36.7	45.1
MedAlpaca-13B	60.7	38.4	57.4	51.3	39.0	49.4
General LLM-7B	59.6	31.4	50.7	45.1	**34.5**	44.2
DAPT-7B	52.6	26.6	49.2	46.6	33.5	41.7
AdaptLLM-7B	**63.3**	**35.2**	**54.4**	**50.4**	33.1	**47.3**

Finance	ConvFinQA	FPB	FiQA SA	Headline	NER	AVERAGE
BloombergGPT-50B	43.4	51.1	75.1	82.2	60.8	62.5
General LLM-7B	29.2	55.9	69.2	77.7	**61.1**	58.6
DAPT-7B	29.6	55.3	64.9	77.5	60.6	57.6
AdaptLLM-7B	**41.5**	**62.5**	**72.1**	**81.4**	59.3	**63.4**

Law	SCOTUS		CaseHOLD		UNFAIR-ToS	AVERAGE
	mic-F1	mac-F1	mic-F1	mac-F1		
GPT-J-6B	15.9	13.6	34.9	34.9	79.8	35.9
LexGPT-6B	16.9	7.7	27.0	27.0	81.9	32.1
General LLM-7B	28.3	10.8	32.9	32.9	65.8	34.2
DAPT-7B	25.0	9.8	34.2	34.2	72.0	35.0
AdaptLLM-7B	**30.0**	**17.8**	**35.1**	**35.1**	**74.4**	**38.5**

Besides, we compare AdaptLLM with other publicly-available models/results in each domain as follows.

Biomedicine. We compare with MedAlpaca-7B/13B (Han et al., 2023), which fine-tunes LLaMA-7B/13B (Touvron et al., 2023) on medical question-answering instructions. AdaptLLM-7B performs better than MedAlpaca-7B and approaches MedAlpaca-13B in the average score. While the supervised instructions help MedAlpaca-7B outperform General LLM-7B (LLaMA-7B) in some domain-specific tasks, this advantage isn't consistent. This could be because instructions don't fully infuse domain knowledge for all tasks, or the domain-specific instructions struggle with various input-output scenarios.

Finance. We compare our results with those reported in BloombergGPT (Wu et al., 2023b), a model trained from scratch on a mixture of financial and general corpora. While General LLM-7B scores lower than BloombergGPT-50B, AdaptLLM-7B achieves competitive performance with the 50B BloombergGPT model. This highlights the computational and data efficiency of our approach compared to training from scratch.

Law. We compare with LexGPT-6B (Lee, 2023) which conducts vanilla domain adaptive pretraining of GPT-J-6B (Wang & Komatsuzaki, 2021) on Pile of Law (Henderson et al., 2022) corpora. In contrast to the general model GPT-J-6B, LexGPT-6B shows negative prompting results. This trend aligns with our observation in section 2 that continued pre-training on domain-specific raw texts leads to worse prompting performance. On the other hand, our method contributes to positive results on the prompting performance, highlighting the effectiveness of the comprehension tasks and the general instructions.

6 ABLATIONS ON TRAINING DATA

Table 5 presents ablation results on different training data and data mixtures: (1) **Raw Text** trains on the raw pre-training corpora. (2) **Read. Compre.** converts raw texts into reading comprehension texts, boosting the prompting ability to show better results in all of the adapted domains. (3) **Gen. Ins.** trains on general instructions. (4) **Read. + Gen. Ins.** augments reading comprehension texts with general instructions. Compared to using reading comprehension texts only, the inclusion of general instructions further improves the prompting ability, leading to better task results. Moreover, compared to the use of general instructions alone, the utilization of reading comprehension texts provides domain knowledge that enhances performance in domain-specific tasks. Additionally, we provide ablations for each of the comprehension task types, where we find that Word-to-Text and Natural Language Inference exhibit the highest effectiveness on domain-specific tasks; detailed results are listed in Appendix E.

Table 5: **Ablation results on training data.** Raw Text refers to raw corpora, Read. Compre. refers to reading comprehension texts, Gen. Ins. refers to general instructions, and Raw. + Gen. Ins. and Read. + Gen. Ins. correspond to different data mixtures. We report the average of task scores in prompting evaluation within each domain.

Data	Raw Text	Read. Compre.	Gen. Ins.	Raw. + Gen. Ins.	Read. + Gen. Ins.
BioMed.	41.7	44.3	43.3	44.8	**47.3**
Finance	57.6	60.0	62.2	61.7	**63.4**
Law	35.0	37.0	37.8	34.7	**38.5**

7 ANALYSIS OF DOMAIN KNOWLEDGE AND PROMPTING ABILITY

Our design of reading comprehension is to learn the domain-specific knowledge from the raw texts and to enhance the prompting ability from the comprehension tasks. In this section, we conduct analyses on the two aspects respectively.

Domain Knowledge. In addition to the prompting results presented in Sections 5 and 6, we also conduct fine-tuning evaluations and knowledge probing tests to assess whether the reading comprehension texts can endow the general model with domain knowledge. As demonstrated in the
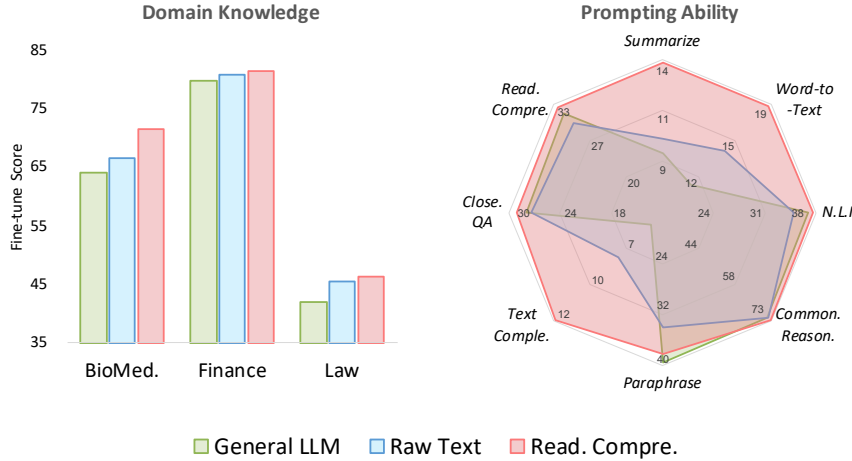
Figure 3: **Fine-tuning evaluation on domain-specific tasks (left) and prompting evaluation on general tasks (right)**. General LLM is the general language model, Raw Text trains the general model on the domain-specific raw corpora, and Read. Compre. trains the general model on the reading comprehension texts constructed based on the raw corpora. We report the average of task scores within each domain/type, detailed results are listed in Appendix F.

fine-tuning results in Figure 3, continued training on the reading comprehension texts consistently enhances model performance when fine-tuning on domain-specific tasks. The fine-tuning and domain knowledge probing improvements (detailed in Appendix A) provide empirical evidence that the reading comprehension texts indeed imbue the general language model with domain knowledge.

Furthermore, it's noteworthy that Read. Compre. outperforms Raw Text in all the adapted domains in the fine-tuning results. This improvement can be attributed to the fact that the appended comprehension tasks naturally create a "multi-task instruction tuning" setting, which benefits single-task fine-tuning, as discussed by Longpre et al. (2023a).

Prompting Ability. Our approach focuses on enhancing prompting ability through the comprehension tasks. To assess the effectiveness of each comprehension task type, we employ general LLM benchmarks to evaluate zero-shot prompting performance. Specifically, we evaluate at least three general tasks for each comprehension task type, following the task clustering settings in FLAN (Wei et al., 2022). Besides, we assess the model's performance on general Reading Comprehension and Closed-book QA tasks to verify its ability to answer questions with or without contexts.

Figure 3 presents the average task scores within each task type, subsequently averaged across the three adapted language models. By transferring raw texts into reading comprehension texts, we observe consistent prompting performance enhancements across all task types. Remarkably, when solely trained on our domain-specific reading comprehension texts (without the inclusion of general instructions), we achieve even better results than the general language model for most task types. This highlights our approach's potential in developing a general language model across more domains. We also conduct an ablation study on each comprehension task type in Appendix E to analyze whether the inclusion of a particular comprehension task type affects the performance of corresponding downstream tasks.

8 RELATED WORK

Recent works that apply large language models to specific domains such as medicine (Singhal et al., 2022; 2023; Li et al., 2023b; Wu et al., 2023a; Li et al., 2023a; Wang et al., 2023; Xiong et al., 2023), finance (Wu et al., 2023b; Yang et al., 2023) and law (Cui et al., 2023; Huang et al., 2023), can be categorized into three main approaches: training from scratch, instruction fine-tuning and retrieval-augmented prompting.

Training from Scratch. Training a domain-specific language models from scratch is an intuitive approach to realize domain specialization. BloombergGPT (Wu et al., 2023b) represents an early example of large language models in the financial domain, trained on a mix of financial and general corpora. This approach demonstrates significant improvements in performance on financial tasks without sacrificing the performance on general LLM benchmarks. However, studies (Yang et al., 2023; Ling et al., 2023) have pointed out "training from scratch" comes with expensive computational and data requirements, which motivates the need for low-cost domain adaptation methods such as continued pre-training or fine-tuning.

Instruction Fine-tuning. Fine-tuning large language models on domain-specific tasks, particularly those involving question-answering instructions, serves as a cost-effective approach to enhance their performance in specific domains (Singhal et al., 2022; 2023; Li et al., 2023b;a; Wang et al., 2023; Han et al., 2023; Xiong et al., 2023; Huang et al., 2023). However, due to the limited availability of supervised fine-tuning data, models fine-tuned with a small amount of data might struggle to acquire sufficient domain knowledge. Therefore, creating large-scale, supervised instruction-tuning datasets emerges as a significant challenge. Previous methods employ high-performing LLMs such as ChatGPT and GPT-4 (OpenAI, 2023) to generate these question-answer pairs (Li et al., 2023a), but the cost of utilizing those closed-source models for inference can be a concern. In such situations, harnessing large-scale domain corpora for continual pre-training represents a promising solution to acquire domain knowledge.

Retrieval-augmented Prompting. Retrieval augmentation enhances LLMs by integrating external domain-specific information without modifying the model parameters (Li et al., 2023b; Cui et al., 2023; Huang et al., 2023). LLMs gain domain context from sources like documents, domain-specific knowledge graphs, or neural networks with parametric domain knowledge. This enables LLMs to better answer domain-specific questions and address issues like hallucination. In such cases, seamless integration of external knowledge into LLMs is crucial, existing methods typically concatenate retrieved knowledge to the LLM's input or intermediate layers. However, it's important to allow LLMs the option to accept or reject retrieved information due to potential incompleteness or conflicts (Ling et al., 2023). Training LLMs to incorporate domain knowledge can aid in making such informed acceptance or rejection decisions.

9 CONCLUSION

This paper focuses on adapting large language models via continued training on domain-specific corpora. We propose a simple method to transform large-scale domain-specific raw corpora into reading comprehension texts, enabling the model to acquire domain knowledge from raw texts and to enhance prompting ability through comprehension tasks. Experiments in different domains confirm the approach's effectiveness and generalizability. Moreover, the extracted comprehension tasks enhance the model's performance on general LLM benchmarks, suggesting potential for enhancing general language models across more domains. We hope our method can inspire further exploration into adapting large language models with the use of large-scale unsupervised corpora, efficiently empowering language models for downstream tasks in specialized areas.

REFERENCES

Julio Cesar Salinas Alvarado, Karin Verspoor, and Timothy Baldwin. Domain adaption of named entity recognition to support credit risk assessment. In *ALTA*, pp. 84–90. ACL, 2015.

Luisa Bentivogli, Bernardo Magnini, Ido Dagan, Hoa Trang Dang, and Danilo Giampiccolo. The fifth PASCAL recognizing textual entailment challenge. In *TAC*. NIST, 2009.

Sumithra Bhakthavatsalam, Daniel Khashabi, Tushar Khot, Bhavana Dalvi Mishra, Kyle Richardson, Ashish Sabharwal, Carissa Schoenick, Oyvind Tafjord, and Peter Clark. Think you have solved direct-answer question answering? try arc-da, the direct-answer AI2 reasoning challenge. *CoRR*, abs/2102.03315, 2021.

Yonatan Bisk, Rowan Zellers, Ronan Le Bras, Jianfeng Gao, and Yejin Choi. PIQA: reasoning about physical commonsense in natural language. In *AAAI*, pp. 7432–7439. AAAI Press, 2020.

Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. A large anno-
tated corpus for learning natural language inference. In *EMNLP*, pp. 632–642. The Association
for Computational Linguistics, 2015.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhari-
wal, 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. Language models are few-shot learners. In *NeurIPS*, 2020.

Ilias Chalkidis. Chatgpt may pass the bar exam soon, but has a long way to go for the lexglue
benchmark. *SSRN*, 2023. URL https://papers.ssrn.com/sol3/papers.cfm?
abstract_id=4385460.

Ilias Chalkidis, Abhik Jana, Dirk Hartung, Michael J. Bommarito II, Ion Androutsopoulos,
Daniel Martin Katz, and Nikolaos Aletras. Lexglue: A benchmark dataset for legal language
understanding in english. In *ACL (1)*, pp. 4310–4330. Association for Computational Linguistics,
2022.

Zhiyu Chen, Shiyang Li, Charese Smiley, Zhiqiang Ma, Sameena Shah, and William Yang Wang.
Convfinqa: Exploring the chain of numerical reasoning in conversational finance question an-
swering. In *EMNLP*, pp. 6279–6292. Association for Computational Linguistics, 2022.

Daixuan Cheng, Shaohan Huang, Jianfeng Liu, Yuefeng Zhan, Hao Sun, Furu Wei, Denvy Deng,
and Qi Zhang. Snapshot-guided domain adaptation for ELECTRA. In *EMNLP (Findings)*, pp.
2226–2232. Association for Computational Linguistics, 2022.

Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, Xuezhi
Wang, Mostafa Dehghani, Siddhartha Brahma, Albert Webson, Shixiang Shane Gu, Zhuyun Dai,
Mirac Suzgun, Xinyun Chen, Aakanksha Chowdhery, Sharan Narang, Gaurav Mishra, Adams
Yu, Vincent Y. Zhao, Yanping Huang, Andrew M. Dai, Hongkun Yu, Slav Petrov, Ed H. Chi,
Jeff Dean, Jacob Devlin, Adam Roberts, Denny Zhou, Quoc V. Le, and Jason Wei. Scaling
instruction-finetuned language models. *CoRR*, abs/2210.11416, 2022.

Christopher Clark, Kenton Lee, Ming-Wei Chang, Tom Kwiatkowski, Michael Collins, and Kristina
Toutanova. Boolq: Exploring the surprising difficulty of natural yes/no questions. In *NAACL-HLT
(1)*, pp. 2924–2936. Association for Computational Linguistics, 2019.

Kevin Clark, Minh-Thang Luong, Quoc V. Le, and Christopher D. Manning. ELECTRA: pre-
training text encoders as discriminators rather than generators. In *ICLR*. OpenReview.net, 2020.

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.

Franck Dernoncourt and Ji Young Lee. Pubmed 200k RCT: a dataset for sequential sentence clas-
sification in medical abstracts. In *IJCNLP*, pp. 308–313. Asian Federation of Natural Language
Processing, 2017.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep
bidirectional transformers for language understanding. In *NAACL-HLT (1)*, pp. 4171–4186. As-
sociation for Computational Linguistics, 2019.

William B. Dolan and Chris Brockett. Automatically constructing a corpus of sentential paraphrases.
In *IWP@IJCNLP*. Asian Federation of Natural Language Processing, 2005.

Ondrej Dusek, David M. Howcroft, and Verena Rieser. Semantic noise matters for neural natural
language generation. In *INLG*, pp. 421–426. Association for Computational Linguistics, 2019.

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.

Arnav Gudibande, Eric Wallace, Charlie Snell, Xinyang Geng, Hao Liu, Pieter Abbeel, Sergey Levine, and Dawn Song. The false promise of imitating proprietary llms. *CoRR*, abs/2305.15717, 2023.

Suchin Gururangan, Ana Marasovic, Swabha Swayamdipta, Kyle Lo, Iz Beltagy, Doug Downey, and Noah A. Smith. Don't stop pretraining: Adapt language models to domains and tasks. In *ACL*, pp. 8342–8360. Association for Computational Linguistics, 2020.

Tianyu Han, Lisa C. Adams, Jens-Michalis Papaioannou, Paul Grundmann, Tom Oberhauser, Alexander Löser, Daniel Truhn, and Keno K. Bressem. Medalpaca - an open-source collection of medical conversational AI models and training data. *CoRR*, abs/2304.08247, 2023.

Peter Henderson, Mark S. Krass, Lucia Zheng, Neel Guha, Christopher D. Manning, Dan Jurafsky, and Daniel E. Ho. Pile of law: Learning responsible data filtering from the law and a 256gb open-source legal dataset. In *NeurIPS*, 2022.

Quzhe Huang, Mingxu Tao, Zhenwei An, Chen Zhang, Cong Jiang, Zhibin Chen, Zirui Wu, and Yansong Feng. Lawyer llama technical report. *CoRR*, abs/2305.15062, 2023.

Di Jin, Eileen Pan, Nassim Oufattole, Wei-Hung Weng, Hanyi Fang, and Peter Szolovits. What disease does this patient have? A large-scale open domain question answering dataset from medical exams. *CoRR*, abs/2009.13081, 2020.

Qiao Jin, Bhuwan Dhingra, Zhengping Liu, William W. Cohen, and Xinghua Lu. Pubmedqa: A dataset for biomedical research question answering. In *EMNLP/IJCNLP (1)*, pp. 2567–2577. Association for Computational Linguistics, 2019.

Daniel Khashabi, Snigdha Chaturvedi, Michael Roth, Shyam Upadhyay, and Dan Roth. Looking beyond the surface: A challenge set for reading comprehension over multiple sentences. In *NAACL-HLT*, pp. 252–262. Association for Computational Linguistics, 2018.

Jens Kringelum, Sonny Kim Kjærulff, Søren Brunak, Ole Lund, Tudor I. Oprea, and Olivier Taboureau. Chemprot-3.0: a global chemical biology diseases mapping. *Database J. Biol. Databases Curation*, 2016, 2016.

Taku Kudo and John Richardson. Sentencepiece: A simple and language independent subword tokenizer and detokenizer for neural text processing. In *EMNLP (Demonstration)*, pp. 66–71. Association for Computational Linguistics, 2018.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur P. Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Llion Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. Natural questions: a benchmark for question answering research. *Trans. Assoc. Comput. Linguistics*, 7:452–466, 2019.

Jieh-Sheng Lee. Lexgpt 0.1: pre-trained GPT-J models with pile of law. *CoRR*, abs/2306.05431, 2023.

Chunyuan Li, Cliff Wong, Sheng Zhang, Naoto Usuyama, Haotian Liu, Jianwei Yang, Tristan Naumann, Hoifung Poon, and Jianfeng Gao. Llava-med: Training a large language-and-vision assistant for biomedicine in one day. *CoRR*, abs/2306.00890, 2023a.

Yunxiang Li, Zihan Li, Kai Zhang, Ruilong Dan, and You Zhang. Chatdoctor: A medical chat model fine-tuned on llama model using medical domain knowledge. *CoRR*, abs/2303.14070, 2023b.

Bill Yuchen Lin, Wangchunshu Zhou, Ming Shen, Pei Zhou, Chandra Bhagavatula, Yejin Choi, and Xiang Ren. Commongen: A constrained text generation challenge for generative commonsense reasoning. In *EMNLP (Findings)*, volume EMNLP 2020 of *Findings of ACL*, pp. 1823–1840. Association for Computational Linguistics, 2020.

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, Quanquan Gu, Carl Yang, and Liang Zhao. Beyond one-model-fits-all: A survey of domain specialization for large language models. *CoRR*, abs/2305.18703, 2023.

Marco Lippi, Przemyslaw Palka, Giuseppe Contissa, Francesca Lagioia, Hans-Wolfgang Micklitz, Giovanni Sartor, and Paolo Torroni. CLAUDETTE: an automated detector of potentially unfair clauses in online terms of service. *Artif. Intell. Law*, 27(2):117–139, 2019.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized BERT pretraining approach. *CoRR*, abs/1907.11692, 2019.

Shayne Longpre, Le Hou, Tu Vu, Albert Webson, Hyung Won Chung, Yi Tay, Denny Zhou, Quoc V. Le, Barret Zoph, Jason Wei, and Adam Roberts. The flan collection: Designing data and methods for effective instruction tuning. In *ICML*, volume 202 of *Proceedings of Machine Learning Research*, pp. 22631–22648. PMLR, 2023a.

Shayne Longpre, Gregory Yauney, Emily Reif, Katherine Lee, Adam Roberts, Barret Zoph, Denny Zhou, Jason Wei, Kevin Robinson, David Mimno, and Daphne Ippolito. A pretrainer's guide to training data: Measuring the effects of data age, domain coverage, quality, & toxicity. *CoRR*, abs/2305.13169, 2023b.

Macedo Maia, Siegfried Handschuh, André Freitas, Brian Davis, Ross McDermott, Manel Zarrouk, and Alexandra Balahur. Www'18 open challenge: Financial opinion mining and question answering. In *WWW (Companion Volume)*, pp. 1941–1942. ACM, 2018.

Pekka Malo, Ankur Sinha, Pekka J. Korhonen, Jyrki Wallenius, and Pyry Takala. Good debt or bad debt: Detecting semantic orientations in economic texts. *J. Assoc. Inf. Sci. Technol.*, 65(4): 782–796, 2014.

Clara H. McCreery, Namit Katariya, Anitha Kannan, Manish Chablani, and Xavier Amatriain. Effective transfer learning for identifying similar questions: Matching user questions to COVID-19 faqs. In *KDD*, pp. 3458–3465. ACM, 2020.

Todor Mihaylov, Peter Clark, Tushar Khot, and Ashish Sabharwal. Can a suit of armor conduct electricity? A new dataset for open book question answering. In *EMNLP*, pp. 2381–2391. Association for Computational Linguistics, 2018.

Subhabrata Mukherjee, Arindam Mitra, Ganesh Jawahar, Sahaj Agarwal, Hamid Palangi, and Ahmed Hassan Awadallah. Orca: Progressive learning from complex explanation traces of GPT-4. *CoRR*, abs/2306.02707, 2023.

Linyong Nan, Dragomir R. Radev, Rui Zhang, Amrit Rau, Abhinand Sivaprasad, Chiachun Hsieh, Xiangru Tang, Aadit Vyas, Neha Verma, Pranav Krishna, Yangxiaokang Liu, Nadia Irwanto, Jessica Pan, Faiaz Rahman, Ahmad Zaidi, Mutethia Mutuma, Yasin Tarabar, Ankit Gupta, Tao Yu, Yi Chern Tan, Xi Victoria Lin, Caiming Xiong, Richard Socher, and Nazneen Fatema Rajani. DART: open-domain structured data record to text generation. In *NAACL-HLT*, pp. 432–447. Association for Computational Linguistics, 2021.

Courtney Napoles, Matthew R. Gormley, and Benjamin Van Durme. Annotated gigaword. In *AKBC-WEKEX@NAACL-HLT*, pp. 95–100. Association for Computational Linguistics, 2012.

OpenAI. Gpt-4 technical report. Technical report, OpenAI, March 2023. URL https://cdn.openai.com/papers/gpt-4.pdf.

Ankit Pal, Logesh Kumar Umapathi, and Malaikannan Sankarasubbu. Medmcqa: A large-scale multi-subject multi-choice dataset for medical domain question answering. In *CHIL*, volume 174 of *Proceedings of Machine Learning Research*, pp. 248–260. PMLR, 2022.

Fabio Petroni, Tim Rocktäschel, Sebastian Riedel, Patrick S. H. Lewis, Anton Bakhtin, Yuxiang Wu, and Alexander H. Miller. Language models as knowledge bases? In *EMNLP/IJCNLP (1)*, pp. 2463–2473. Association for Computational Linguistics, 2019.

Alec Radford and Karthik Narasimhan. Improving language understanding by generative pre-training. 2018.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. Squad: 100, 000+ questions for machine comprehension of text. In *EMNLP*, pp. 2383–2392. The Association for Computational Linguistics, 2016.

Pranav Rajpurkar, Robin Jia, and Percy Liang. Know what you don't know: Unanswerable questions for squad. In *ACL (2)*, pp. 784–789. Association for Computational Linguistics, 2018.

Melissa Roemmele, Cosmin Adrian Bejan, and Andrew S. Gordon. Choice of plausible alternatives: An evaluation of commonsense causal reasoning. In *AAAI Spring Symposium: Logical Formalizations of Commonsense Reasoning*. AAAI, 2011.

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. Large language models encode clinical knowledge. *CoRR*, abs/2212.13138, 2022.

Karan Singhal, Tao Tu, Juraj Gottweis, Rory Sayres, Ellery Wulczyn, Le Hou, Kevin Clark, Stephen Pfohl, Heather Cole-Lewis, Darlene Neal, Mike Schaekermann, Amy Wang, Mohamed Amin, Sami Lachgar, Philip Andrew Mansfield, Sushant Prakash, Bradley Green, Ewa Dominowska, Blaise Agüera y Arcas, Nenad Tomasev, Yun Liu, Renee Wong, Christopher Semturs, S. Sara Mahdavi, Joelle K. Barral, Dale R. Webster, Gregory S. Corrado, Yossi Matias, Shekoofeh Azizi, Alan Karthikesalingam, and Vivek Natarajan. Towards expert-level medical question answering with large language models. *CoRR*, abs/2305.09617, 2023.

Ankur Sinha and Tanmay Khandait. Impact of news on the commodity market: Dataset and results. *CoRR*, abs/2009.04202, 2020.

Harold J. Spaeth, Lee Epstein, Jeffrey A. Segal Andrew D. Martin, Theodore J. Ruger, and Sara C. Benesh. Supreme Court Database, Version 2020 Release 01. Washington University Law, 2020. URL http://Supremecourtdatabase.org.

Alon Talmor, Jonathan Herzig, Nicholas Lourie, and Jonathan Berant. Commonsenseqa: A question answering challenge targeting commonsense knowledge. In *NAACL-HLT (1)*, pp. 4149–4158. Association for Computational Linguistics, 2019.

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, 2023.

Don Tuggener, Pius von Däniken, Thomas Peetz, and Mark Cieliebak. LEDGAR: A large-scale multi-label corpus for text classification of legal provisions in contracts. In *LREC*, pp. 1235–1241. European Language Resources Association, 2020.

Mozes van de Kar, Mengzhou Xia, Danqi Chen, and Mikel Artetxe. Don't prompt, search! mining-based zero-shot learning with language models. In *EMNLP*, pp. 7508–7520. Association for Computational Linguistics, 2022.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. GLUE: A multi-task benchmark and analysis platform for natural language understanding. In *ICLR (Poster)*. OpenReview.net, 2019.

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

Haochun Wang, Chi Liu, Nuwa Xi, Zewen Qiang, Sendong Zhao, Bing Qin, and Ting Liu. Huatuo: Tuning llama model with chinese medical knowledge. *CoRR*, abs/2304.06975, 2023.

Jason Wei, Maarten Bosma, Vincent Y. Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M. Dai, and Quoc V. Le. Finetuned language models are zero-shot learners. In *ICLR*. OpenReview.net, 2022.

Adina Williams, Nikita Nangia, and Samuel R. Bowman. A broad-coverage challenge corpus for sentence understanding through inference. In *NAACL-HLT*, pp. 1112–1122. Association for Computational Linguistics, 2018.

Chaoyi Wu, Xiaoman Zhang, Ya Zhang, Yanfeng Wang, and Weidi Xie. Pmc-llama: Further fine-tuning llama on medical papers. *CoRR*, abs/2304.14454, 2023a.

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, 2023b.

Honglin Xiong, Sheng Wang, Yitao Zhu, Zihao Zhao, Yuxiao Liu, Linlin Huang, Qian Wang, and Dinggang Shen. Doctorglm: Fine-tuning your chinese doctor is not a herculean task. *CoRR*, abs/2304.01097, 2023.

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.

Hongyang Yang, Xiao-Yang Liu, and Christina Dan Wang. Fingpt: Open-source financial large language models. *CoRR*, abs/2306.06031, 2023.

Yunzhi Yao, Shaohan Huang, Wenhui Wang, Li Dong, and Furu Wei. Adapt-and-distill: Developing small, fast and effective pretrained language models for domains. In *ACL/IJCNLP (Findings)*, volume ACL/IJCNLP 2021 of *Findings of ACL*, pp. 460–470. Association for Computational Linguistics, 2021.

Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. Hellaswag: Can a machine really finish your sentence? In *ACL (1)*, pp. 4791–4800. Association for Computational Linguistics, 2019.

Rui Zhang and Joel R. Tetreault. This email could save your life: Introducing the task of email subject line generation. In *ACL (1)*, pp. 446–456. Association for Computational Linguistics, 2019.

Xiang Zhang, Junbo Jake Zhao, and Yann LeCun. Character-level convolutional networks for text classification. In *NIPS*, pp. 649–657, 2015.

Yuan Zhang, Jason Baldridge, and Luheng He. PAWS: paraphrase adversaries from word scrambling. In *NAACL-HLT (1)*, pp. 1298–1308. Association for Computational Linguistics, 2019.

Lucia Zheng, Neel Guha, Brandon R. Anderson, Peter Henderson, and Daniel E. Ho. When does pretraining help?: assessing self-supervised learning for law and the casehold dataset of 53, 000+ legal holdings. In *ICAIL*, pp. 159–168. ACM, 2021.

Chunting Zhou, Pengfei Liu, Puxin Xu, Srini Iyer, Jiao Sun, Yuning Mao, Xuezhe Ma, Avia Efrat, Ping Yu, Lili Yu, Susan Zhang, Gargi Ghosh, Mike Lewis, Luke Zettlemoyer, and Omer Levy. LIMA: less is more for alignment. *CoRR*, abs/2305.11206, 2023.

A   DOMAIN KNOWLEDGE PROBING

We devise domain knowledge probing tests to determine whether continued training on the domain-specific texts can enhance the model's domain-specific knowledge. Our probing test design is inspired by LAMA (Petroni et al., 2019), where the task format closely resembles the pre-training task. This allows us to analyze the model's inherent knowledge without altering its architecture (e.g., adding a model head) or parameters (e.g., fine-tuning). LAMA utilizes "fill-in-the-blank" cloze statements to match the masked language modeling task of BERT (Devlin et al., 2019). Similarly, we create "predict-the-next-token/sentence" tests to align with the casual language modeling tasks of generative language models (Radford & Narasimhan, 2018). Table 6 presents the knowledge probing results in the biomedicine and law domains. We observe that continued training on domain-specific raw/reading comprehension texts indeed imparts the large language model with new domain knowledge.

Table 6: **Domain knowledge probing results. Raw Text** is vanilla domain adaptive pre-training (DAPT) using raw texts, **Read. Compre.** trains on the reading comprehension texts.

Domain	General LLM	Raw Text	Read. Compre.
BioMed.	36.5	36.9	36.8
Law	45.0	45.6	46.4

Biomedicine. To create a knowledge probing test for the biomedicine domain, we utilize the MedMCQA (Pal et al., 2022) dataset. This dataset comprises numerous high-quality multiple-choice questions, covering diverse healthcare topics and 21 medical subjects. To align the testing format with casual language modeling, we exclude data samples in the instruction-following format. These include samples starting with question words like "`What`", "`Who`" and "`When`", or ending with "`:`", "`?`", and "`-`". Additionally, samples having the fill-in-the-blank marker "`_`" are also removed.

The evaluation is similar to zero-shot prompting: we feed into the model the raw data input, without introducing any task descriptions or demonstrations, and then compare per-token-likelihood of each option to get the model prediction. This evaluation is conducted individually for the 21 medical subjects, and the average score across all subjects is reported.

Law. For the Law domain knowledge probing, we employ the LEDGAR dataset (Tuggener et al., 2020). This dataset is designed for contract provision classification and encompasses a wide spectrum of 100 distinct law topics. Each label represents the principal topic of the given contract provision. Originally structured as a 100-classification task, we adapt it for knowledge probing by simplifying it into a four-choice question format. For each data sample, we preserve the label class and randomly select three additional classes to create the four candidate options.

Similar to biomedicine knowledge probing, we feed into the model the data input using the template "`{CONTRACT} The topic is`", and then compare per-token-likelihood of each option to get the model prediction. The evaluation is performed individually for each of the 100 law topics, and the average score across all topics is reported.

B   DOMAIN-ADAPTIVE PRE-TRAINING

Table 7 presents specifications of the pre-training corpora in each domain and Table 8 presents pre-training hyper-parameters. A $<pad>$ token is added to the model vocabulary for sentence padding. In each domain, we explore different ratios for mixing reading comprehension data with general instructions, specifically considering ratios of $1 : 2$, $1 : 1$, and $2 : 1$. The end-of-sentence token $</s>$ is used to concatenate between documents, where a document could be a raw text, a reading comprehension text, or a general instruction.

Table 7: **Pre-training corpora.**

Domain	Data Source	Raw Size	# Tokens	# Docs
BioMed.	PubMed Abstracts (Gao et al., 2021)	19.3 GiB	5.4 B	15.5 M
Finance	Stock News	5.1 GiB	1.2 B	1.1 M
Law	FreeLaw Opinions (Gao et al., 2021)	51.2 GiB	16.7 B	3.6 M

Table 8: **Hyper-parameters of domain-adaptive pre-training.**

Hyperparameter	Assignment
Computing infrastructure	32 V100-32GB GPUs
Runtime	24 Hours
Number of steps	10,000
Batch size	32
Maximum sequence length	2,048
Maximum learning rate	1e-5
Optimizer	Adam
Adam beta weights	0.9, 0.95
Learning rate scheduler	cosine
Weight decay	0.1
Warmup steps	1000
Gradient clipping	1.0
Dropout ratio	0.1

C CREATING READING COMPREHENSION TEXTS

Title Collection for Summarization Tasks. In the biomedicine domain, the title for each raw text in PubMed Abstracts (Gao et al., 2021) is the first sentence within the text, separated from other sentences by a newline character $\backslash n$. In the finance domain, we specifically collect the titles when gathering news using the FinGPT codebase (Yang et al., 2023). In FreeLaw Opinions corpora (Gao et al., 2021) of the law domain, there are no explicit titles for individual raw texts. Instead, titles are available for some sections within each text. Hence, we initially divide each raw text into sections and gather as many titles as possible from these sections. Subsequently, we consider one section, rather than an entire raw text, as the basis for creating one reading comprehension text.

Regex Pattern Implementation. For tasks which employ regex patterns to mine task examples, we fill in the patterns with the corresponding verbalizer and identify sentences that match the patterns. This process of expanding patterns into regular expressions follows van de Kar et al. (2022): {VERBAL} is substituted with a capturing group that incorporates all verbalizers, separated by the alternation operator |. For instance, the verbalizer set `Therefore, Thus, Hence` is expanded to `(Therefore|Thus|Hence)`. Subsequently, the keywords listed in Table 9 are replaced with the corresponding regular expressions. The result is a regular expression containing capturing groups for extracting sentences.

Data Pre-processing and Post-processing. Before mining task examples, we truncate each raw text to its initial 1,800 tokens, enabling the insertion of comprehension tasks within a maximum sequence length of 2,048. After constructing reading comprehension texts, we wrap each reading comprehension text using this template: {"text": "ReadCompre"}, by replacing the `ReadCompre` with one piece of reading comprehension text. This template is used to explicitly separate each reading comprehension text from others, so that the model can focus on the context of the current document.

D DOMAIN-SPECIFIC TASKS EVALUATION

Prompting. In prompting evaluation, each task corresponds to multiple prompt templates and we randomly sample one of them for each data example, to mitigate result variance caused by template

Table 9: **Keywords that compile into regular expressions.** These keywords are used in the mining patterns and verbalizers (van de Kar et al., 2022).

Keyword	Regex
{VERBAL}	Replaced with the verbalizer
{WORD}	regex: `([^.!?\n,;\"\s]{10,})` Matches a single word having more than 9 characters
{SENT}	regex: `([^.!?\n]{50,}[.!?]+)` Matches a single sentence having more than 50 characters

sensitivity. Prompt template examples are presented in Table 11. Following Brown et al. (2020), we classify tasks into two question types to get model predictions: 1) For multiple-choice questions, we compare the per-token likelihood of each option to determine the model prediction; 2) For text completion questions, we employ greedy search to get the free-form answer.

Our prompting settings in the finance domain follow BloombergGPT (Wu et al., 2023b), with the exception that we use multiple templates to address template sensitivity. The prompt templates for law domain are based on Chalkidis (2023). The UNFAIR-ToS (Lippi et al., 2019) task is a multi-label classification task. To get model predictions for this task, we categorize it as a multiple-choice question. The accuracy of an individual data example is considered true if the model prediction (i.e., the option with the highest per-token likelihood) belongs to the label(s) set. In the biomedicine domain, some classification tasks, including MQP (McCreery et al., 2020), RCT (Dernoncourt & Lee, 2017), and ChemProt (Kringelum et al., 2016), are too challenging for the model, thus we conduct few-shot prompting and maintain the number of demonstrations the same in each class.

Fine-tuning. In fine-tuning, we utilize a fixed prompt template (the one displayed in Table 11) for each task to convert input-output into question-answering pairs. The model is then trained on these pairs for one epoch with the warm-up step as 0, and we compute the loss only on the tokens of the output answer of each training example (Mukherjee et al., 2023). All other training settings are the same with domain-adaptive pre-training. Fine-tuning evaluation is similar to prompting evaluation, but with two differences to align with the fine-tuning training stage: no demonstration is presented before the prompt input, and the prompt template is the same with the one used in the training stage.

Table 10: **Specifications of the domain-specific task datasets.** # Demos is the number of demonstrations in prompting evaluation.

Task	Type	Metric	# Demos
BioMed.			
MQP (McCreery et al., 2020)	Binary classification	Accuracy	4
PubMedQA (Jin et al., 2019)	Binary classification	Accuracy	0
USMLE (Jin et al., 2020)	Multi-chioice QA	Accuracy	0
RCT (Dernoncourt & Lee, 2017)	Multi-class classification	Micro F1	10
ChemProt (Kringelum et al., 2016)	Multi-class classification	Micro F1	13
Finance			
FiQA SA (Maia et al., 2018)	Multi-class classification	Weighted F1	5
FPB (Malo et al., 2014)	Multi-class classification	Weighted F1	5
NER (Alvarado et al., 2015)	Named entity recongnition	Entity-level F1	20
Headline (Sinha & Khandait, 2020)	Binary-class classification	Weighted F1	5
ConvFinQA (Chen et al., 2022)	Question Answering	Exact Match	0
Law			
SCOTUS (Spaeth et al., 2020)	Multi-class classification	Micro/Macro F1	0
CaseHOLD (Zheng et al., 2021)	Multi-chioice QA	Micro/Macro F1	0
UNFAIR-ToS (Lippi et al., 2019)	Multi-label classification	Accuracy	4

Table 11: **Prompt templates.** Each template example is paraphrased to multiple variations for prompting evaluation.

Task	Template
BioMed.	
MQP	Question 1: {QUESTION1} Question 2: {QUESTION2} Are questions 1 and 2 asking the same thing? {ANSWER}
PubMedQA	Context: {CONTEXT} Question: {QUESTION} Answer: {ANSWER}
USMLE	Question: {QUESTION} Answer: {ANSWER}
RCT	{SENTENCE} Question: what is the role of this sentence in an abstract? Answer: {ANSWER}
ChemProt	{SENTENCE} Question: what is the relation? Answer: {ANSWER}
Finance	
FiQA SA	{SENTENCE} Question: what is the sentiment on {TARGET}? Answer: {ANSWER}
FPB	{SENTENCE} Question: what is the sentiment? Answer: {ANSWER}
NER	{SENTENCE} Extract named entity: {ANSWER}
Headline	{SENTENCE} Question: {QUESTION} Answer: {ANSWER}
ConvFinQA	{CONTEXT} {PREVIOUS QAS} {QUESTION} {ANSWER}
Law	
SCOTUS	Given the following opinion from the Supreme Court of USA (SCOTUS): "{TEXT}" The relevant issue area is: {ANSWER}
CaseHOLD	Complete the following excerpt from a US court opinion: {CONTEXT}: {ANSWER}
UNFAIR-ToS	Given the following sentence from an online Term of Services: "{SENTENCE}" The sentence is unfair with respect to: {ANSWER}

E   FURTHER ABLATIONS ON COMPREHENSION TASKS

Figure 4 presents the percentages of mined examples of each task type in all the comprehension task examples, with Word-To-Text, Summarization, and Text Completion accounting for the highest ratios.
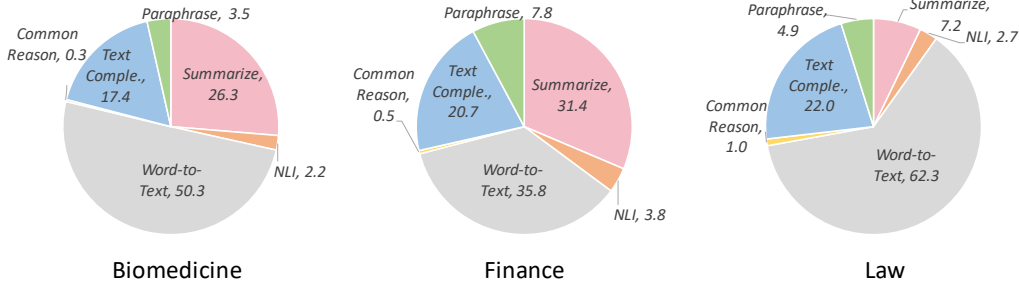

Figure 4: **Percentages of mined examples of each task type in all the comprehension task examples**.

In the biomedicine domain, we conduct ablations on each comprehension task type by systematically removing each task type from the reading comprehension texts. We then use the resulting modified reading comprehension texts to train the general model. Subsequently, we evaluate these trained models on both domain-specific tasks and general benchmarks to analyze the impacts of these ablations.
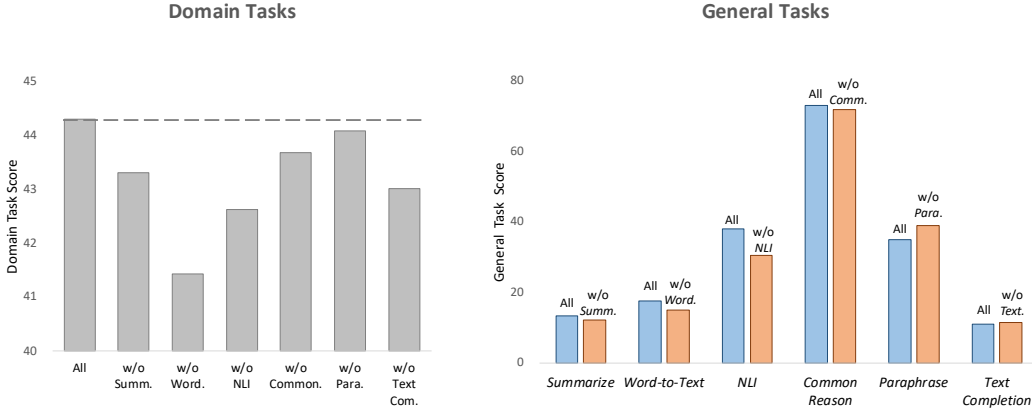

Figure 5: **Prompting scores of domain-specific tasks (left) and general benchmarks (right)** of models trained with different comprehension tasks. **All** denotes the model trained with all the comprehension tasks, while **w/o Summ.** represents the model trained with the comprehension tasks excluding Summarization tasks, **w/o Word.** represents the model trained with the comprehension tasks excluding Word-to-Text tasks, and so on. We report the average task scores within each domain/type.

Domain-specific Tasks. As shown in Figure 5, when evaluating on the domain-specific tasks, the removal of any comprehension task type leads to a decrease in task performance, showing their contributions to these domain-specific tasks. Notably, removing Word-to-Text, Summarization, or Text Completion tasks results in a noticeable drop in performance, aligning with the high percentages of these tasks in the mined examples. Interestingly, even though the Natural Language Inference task type doesn't constitute a large portion of the comprehension tasks, its removal leads to a substantial decrease in performance. This could be attributed to its unique role as the sole classification task type within all the comprehension tasks. In contrast, the impact of removing Commonsense Reasoning and Paraphrase Detection tasks is less pronounced, reflecting their lower percentages in the

mined task examples. However, this also suggests the potential benefits of including more diverse task examples, which could further enhance domain-specific task performance.

General LLM Benchmarks. Additionally, we conduct experiments where we remove a specific task type from all the comprehension tasks. We then evaluate the model's performance specifically on the general tasks corresponding to the removed task type, aiming to demonstrate whether the comprehension tasks have a positive impact on the respective downstream tasks. In the results for general tasks in Figure 5, when we exclude a particular task type from the comprehension tasks, we observe performance declines in the corresponding removed tasks, specifically for Summarization, Word-to-Text, Natural Language Inference, and Commonsense Reasoning tasks. This suggests a beneficial connection between the trained comprehension tasks and their corresponding downstream tasks. However, when we remove Paraphrase Detection or Text Completion, it does not lead to a performance decline in the corresponding tasks. This discrepancy may be attributed to the reformatting of Paraphrase Detection from a classification task to a generation task in the comprehension tasks, causing a mismatch between training and evaluation settings. Furthermore, the Text Comprehension comprehension task type lacks obvious counterparts in the general LLM benchmarks, which may contribute to the mismatch in the performance change trend.

F ANALYSIS OF DOMAIN KNOWLEDGE AND PROMPTING ABILITY

Table 12: **Fine-tuning performance on the domain-specific tasks** of general large language model (**General LLM**), the model trained on domain-specific raw corpora (**Raw Text**) and the model trained on the reading comprehension texts constructed based on the raw corpora (**Read. Compre.**).

BioMed.	PubMedQA	ChemProt	MQP	RCT	UMSLE	AVERAGE
General LLM	75.4	64.6	55.4	87.0	38.5	64.2
Raw Text	**76.2**	64.8	65.6	87.0	39.0	66.5
Read. Compre.	76.0	**65.4**	**87.9**	**87.5**	**41.0**	**71.5**

Finance	ConvFinQA	FPB	FiQA SA	Headline	NER	AVERAGE
General LLM	**58.1**	81.9	86.4	95.7	77.5	79.9
Raw Text	56.2	83.3	**87.9**	95.8	81.3	80.9
Read. Compre.	57.2	**88.6**	83.1	**96.1**	**82.5**	**81.5**

Law	SCOTUS		CaseHOLD		UNFAIR-ToS	AVERAGE
	mic-F1	mac-F1	mic-F1	mac-F1		
General LLM	31.7	14.0	35.3	35.3	93.8	42.0
Raw Text	36.7	**26.0**	35.4	35.4	93.7	45.4
Read. Compre.	**40.0**	**26.0**	**35.5**	**35.5**	**94.2**	**46.2**

Table 13: **Prompting results on general LLM benchmarks. Raw** trains on the raw texts, and **Read** trains on the reading comprehension texts. Text Completion is more close to a question type than a task type in general benchmarks, so we report the average of all the tasks following the free-form text completion question type. Each task corresponds to multiple prompt templates taken from FLAN (Wei et al., 2022), and we remove the option suffixes from the templates to fit for the prompting evaluation approach by Brown et al. (2020).

Task	Metric	General LLM	BioMed.		Finance		Law	
			Raw	Read	Raw	Read	Raw	Read
Summarization								
AGNews (Zhang et al., 2015)	Acc	58.7	51.7	55.5	56.1	50.1	57.8	60.6
	R-1	1.5	3.6	7.5	1.9	10.8	3.4	7.4
AESLC (Zhang & Tetreault, 2019)	R-2	0.2	0.9	2.8	0.3	3.8	0.8	2.7
	R-L	1.5	3.6	7.2	1.8	10.3	3.3	7.2
	R-1	0.6	3.8	9.3	3.1	13.2	3.4	9.8
Gigaword (Napoles et al., 2012)	R-2	0.1	0.7	2.4	0.6	3.8	0.6	2.5
	R-L	0.6	3.5	8.5	2.9	12.1	3.1	8.9
Word-to-Text								
	R-1	14.2	16.1	24.9	17.2	24.2	17.8	27.9
CommonGen (Lin et al., 2020)	R-2	0.0	1.6	5.9	1.5	6.2	2.5	7.2
	R-L	14.2	15.4	22.2	16.2	21.1	16.7	24.3
	R-1	17.0	21.3	20.0	21.9	22.3	23.6	19.5
DART (Nan et al., 2021)	R-2	3.7	6.0	5.0	6.7	7.1	7.5	5.9
	R-L	16.0	19.6	18.5	20.1	20.5	21.4	18.0
	R-1	14.3	18.4	27.6	22.6	37.3	18.4	28.3
E2ENLG (Dusek et al., 2019)	R-2	3.2	5.2	9.8	7.5	15.1	5.8	10.5
	R-L	13.4	17.1	24.5	20.4	32.9	17.0	25.5
Natural Language Inference								
MNLI-m (Williams et al., 2018)	Acc	35.6	35.0	36.7	36.2	37.4	34.8	34.9
MNLI-mm (Williams et al., 2018)	Acc	34.9	34.9	36.1	36.8	37.2	35.7	34.4
QNLI (Rajpurkar et al., 2018)	Acc	51.1	52.4	53.7	52.1	52.0	50.7	51.9
RTE (Bentivogli et al., 2009)	Acc	30.7	9.4	30.0	23.1	26.0	18.8	32.9
SNLI (Bowman et al., 2015)	Acc	34.0	34.5	33.8	36.8	38.1	34.7	33.9
Commonsense Reasoning								
COPA (Roemmele et al., 2011)	Acc	71.0	68.0	75.0	74.0	73.0	72.0	74.0
PIQA (Bisk et al., 2020)	Acc	71.7	70.9	71.3	71.6	71.7	71.9	71.8
HellaSwag (Zellers et al., 2019)	Acc	71.8	71.8	72.6	72.5	73.0	72.0	72.5
Paraphrase Detection								
MRPC (Dolan & Brockett, 2005)	Acc	35.5	31.6	34.8	33.3	37.3	34.1	36.0
	F1	17.0	0.0	13.6	9.9	22.4	8.8	19.7
QQP (Wang et al., 2019)	Acc	56.0	62.7	61.1	52.5	54.3	60.6	59.9
	F1	34.0	3.0	10.7	33.1	44.5	15.3	14.4
Paws Wiki (Zhang et al., 2019)	Acc	54.8	55.6	54.9	53.7	53.7	55.4	54.8
Closed-book QA								
ARC-c (Bhakthavatsalam et al., 2021)	Acc	37.3	36.7	39.0	37.8	38.8	37.6	39.3
ARC-e (Bhakthavatsalam et al., 2021)	Acc	58.5	59.2	63.1	59.4	62.3	60.0	62.9
NQ (Kwiatkowski et al., 2019)	EM	2.2	0.1	0.5	0.1	0.0	0.1	0.1
	F1	3.4	0.8	1.9	1.2	2.1	1.3	1.8
CMSQA (Talmor et al., 2019)	Acc	39.6	40.4	43.5	40.0	42.6	40.9	44.6
Reading Comprehension								
BoolQ (Clark et al., 2019)	Acc	55.7	42.6	50.7	53.4	55.8	51.0	53.9
OBQA (Mihaylov et al., 2018)	Acc	46.2	45.8	46.4	46.0	47.0	45.4	47.2
SQuADv1 (Rajpurkar et al., 2016)	EM	0.1	1.0	3.5	0.2	0.0	0.3	2.0
	F1	0.2	4.6	10.0	0.6	7.3	6.3	10.7
MultiRC (Khashabi et al., 2018)	Acc	55.9	47.5	53.0	49.9	49.7	52.5	52.4

G   CASES OF READING COMPREHENSION TEXTS

Raw Text

Here is the first part of an article about biomedicine: Recent reported evidence indicates that vocal cord carcinoma is evolving similarly to oropharyngeal cancer with an increasing number of patients without a smoking history having human papillomavirus (HPV) disease. Observations also suggest that an increasing number of patients who present with glottic carcinoma are younger than has been reported in the past. **(…TL; DR...)**

Summarization

However, recent published evidence shows that glottic carcinoma can be an HPV-related disease with increasing incidence in nonsmokers. It isn't surprising that alternate malignant pathways may have a different timeline.

Answer questions based on the article:

What is a summary? Glottic Carcinoma in Young Patients.

Word-to-Text

Generate a sentence that includes these biomedicine words [carcinoma, oropharyngeal, papillomavirus]: Recent reported evidence indicates that vocal cord carcinoma is evolving similarly to oropharyngeal cancer with an increasing number of patients without a smoking history having human papillomavirus (HPV) disease.

Natural Language Inference

Premise: Observations also suggest that an increasing number of patients who present with glottic carcinoma are younger than has been reported in the past.

Hypothesis: An investigation was done to examine the incidence of glottic carcinoma in patients 30 years old (y/o) or younger.

Does the premise entail the hypothesis? Yes

Commonsense Reasoning

What is the reason for "None of the 11 glottic cancer patients had been previously treated for benign recurrent respiratory papillomatosis although it was initially suspected prior to biopsy"? The morphology of the lesions and the patients' young age.

Paraphrase Detection

Compose a sentence that contradicts the meaning of "Historically, glottic carcinoma is considered to be a tobacco-induced disease.".

Answer: Recent published evidence shows that glottic carcinoma can be an HPV-related disease with increasing incidence in nonsmokers.

Text Completion

How would you complete the article? This finding further supports the concept that glottic carcinoma is an evolving disease, and it demonstrates the increasing importance of discriminating potential glottic carcinomas in young patients from benign low-risk HPV recurrent respiratory papillomatosis.

Figure 6: **An example of a reading comprehension text constructed from a raw text.** The underlined sentence is added to guide the model to answer questions based the given context.

Table 14: **Case of a reading comprehension text in biomedicine domain.** Certain portions are omitted for brevity and are represented as **(...)**.

Pancreastatin (PST), a chromogranin A-derived peptide, has been found to modulate glucose, lipid, and protein metabolism in rat adipocytes. PST has an overall counterregulatory effect on insulin action by activating a specific receptor-effector system (Galpha(q/11) protein-PLC-beta-PKC(classical)). However, PST stimulates both basal and insulin-mediated protein synthesis in rat adipocytes. In order to further investigate the mechanisms underlying the effect of PST stimulating protein synthesis, we sought to study the regulation of different components of the core translational machinery by the signaling triggered by PST. Thus, we studied ribosomal p70 S6 kinase, phosphorylation of the cap-binding protein (initiation factor) eIF4E, and phosphorylation of the eIF4E-binding protein 4E-BP1 (PHAS-I). We have found that PST stimulates the S6 kinase activity, as assessed by kinase assay using specific immunoprecipitates and substrate. This effect was checked by Western blot with specific antibodies against the phosphorylated S6 kinase. Thus, PST dose-dependently stimulates Thr421/Ser424 phosphorylation of S6 kinase. Moreover, PST promotes phosphorylation of regulatory sites in 4E-BP1 (PHAS-I) (Thr37, Thr46). The initiation factor eIF4E itself, whose activity is also increased upon phosphorylation, is phosphorylated in Ser209 by PST stimulation. **(...)**
Use evidence from the biomedicine article to answer these questions:

Assess the relationship between Sentence 1: "This effect was checked by Western blot with specific antibodies against the phosphorylated S6 kinase."
Sentence 2: "PST dose-dependently stimulates Thr421/Ser424 phosphorylation of S6 kinase."
Is it characterized as Entailment, Neutral, or Contradiction? Entailment

Assess the relationship between Sentence 1: "PST has an overall counterregulatory effect on insulin action by activating a specific receptor-effector system (Galpha(q/11) protein-PLC-beta-PKC(classical))."
Sentence 2: "PST stimulates both basal and insulin-mediated protein synthesis in rat adipocytes."
Is it characterized as Entailment, Neutral, or Contradiction? Contradiction

Next question: What is the reason of the following sentence?
We studied ribosomal p70 S6 kinase, phosphorylation of the cap-binding protein (initiation factor) eIF4E, and phosphorylation of the eIF4E-binding protein 4E-BP1 (PHAS-I). In order to further investigate the mechanisms underlying the effect of PST stimulating protein synthesis, we sought to study the regulation of different components of the core translational machinery by the signaling triggered by PST.

Next question: What is the reason of the following sentence?
PST dose-dependently stimulates Thr421/Ser424 phosphorylation of S6 kinase. This effect was checked by Western blot with specific antibodies against the phosphorylated S6 kinase.

"PST has an overall counterregulatory effect on insulin action by activating a specific receptor-effector system (Galpha(q/11) protein-PLC-beta-PKC(classical))." Generate a sentence that expresses a contrasting idea to the previous statement. PST stimulates both basal and insulin-mediated protein synthesis in rat adipocytes.

Here are some concepts about biomedicine: mechanisms, regulation, translational.
Generate a detailed description of them In order to further investigate the mechanisms underlying the effect of PST stimulating protein synthesis, we sought to study the regulation of different components of the core translational machinery by the signaling triggered by PST.

Here are some concepts about biomedicine: phosphorylation, stimulation, phosphorylated.
Generate a detailed description of them The initiation factor eIF4E itself, whose activity is also increased upon phosphorylation, is phosphorylated in Ser209 by PST stimulation.

Briefly summarize this text. Pancreastatin, a chromogranin A-derived peptide, activates protein synthesis signaling cascade in rat adipocytes.

Table 15: **Case of a reading comprehension text in finance domain.** Certain portions are omitted for brevity and are represented as **(...)**.

Read the beginning of an article on finance: In this article, we discuss the 12 biggest commercial janitorial companies in USA. If you want to skip our detailed analysis of these companies, go directly to the 5 Biggest Commercial Janitorial Companies In USA. According to Statista, the janitorial services sector's market size will increase by 6.6 percent in 2022. The annualized percentage of this market's growth was 6.7% between 2017 and 2022. Additionally, between 2020 and 2021, the number of janitors and cleaners employed in the United States rose by nearly 50,000. By 2024, it is predicted that the U.S. janitorial services industry will generate around $50.1 billion in sales. The market size, measured by revenue, of the janitorial services industry is $97.6 billion in 2022. Businesses frequently grow when corporate profits increase, raising demand for janitorial services. However, dwindling corporate profit decreases demand for janitorial services as companies close facilities and cut back on the frequency of contracted cleaning to cut expenses. The industry may have an opportunity in 2022 as corporate profits are anticipated to rise, according to ibisworld. According to Allied Market Research, the cleaning services market is to reach $111.49 billion globally by 2030 at a 6.5% CAGR, as reported by Bloomberg. The global cleaning services industry is expanding due to service providers expanding their online presence and rising commercial consumer demand. However, heightened rivalry and the introduction of new companies limit market expansion. On the other hand, the demand for construction and post-construction cleaning services will open up new prospects. The Covid-19 pandemic has had a favorable effect on the global cleaning services business. Deep cleaning and disinfection have become more popular among residential and commercial users to reduce the risk of cross-contamination. **(...)**

How would you extend the article? Moore adds that Casella Waste Systems, Inc. (NASDAQ:CWST) is also the only public waste company its size not to be acquired, which provides "downside support to the valuation on a takeout potential". 09. Stericycle, Inc. (NASDAQ: SRCL) Market Capitalization as of November 18, 2022: $4.73 billion Stericycle, Inc. (NASDAQ:SRCL) was incorporated in 1989 and is located in Bannockburn, Illinois. **(...)**

Then, answer the following questions based on the whole article:

Please write a short summary for the above article. 12 Biggest Commercial Janitorial Companies In USA

Given the sentence: The global cleaning services industry is expanding due to service providers expanding their online presence and rising commercial consumer demand.
Select the most suitable word to connect it with: "Heightened rivalry and the introduction of new companies limit market expansion."
Options: Therefore, However, Maybe However

Answer the following question. The global cleaning services industry is expanding due to? Service providers expanding their online presence and rising commercial consumer demand.

Given the sentence "Businesses frequently grow when corporate profits increase, raising demand for janitorial services.", come up with a different sentence that contradicts its meaning. Dwindling corporate profit decreases demand for janitorial services as companies close facilities and cut back on the frequency of contracted cleaning to cut expenses.

Given the sentence "The global cleaning services industry is expanding due to service providers expanding their online presence and rising commercial consumer demand.", come up with a different sentence that contradicts its meaning. Heightened rivalry and the introduction of new companies limit market expansion.

Generate a sentence that includes the following finance keywords: Capitalization, Incorporated, Industries ABM Industries Incorporated (NYSE: ABM) Market Capitalization as of November 18, 2022: $2.98 billion ABM Industries Incorporated (NYSE:ABM) was incorporated in 1985 and is based in New York, New York.

Table 16: **Case of a reading comprehension text in law domain.** Certain portions are omitted for brevity and are represented as **(...)**.

Here is the first part of an article about law: The district court ordered Arledge to pay restitution in the amount of $5,829,334.90, without interest, to the Settlement Fund pursuant to the Mandatory Victims Restitution Act of 1996 ("MVRA"), 18 U.S.C. §3663A. Arledge disputes the calculation used to determine the amount of loss, claiming that the government did not sufficiently prove that the Settlement Fund had paid false claims arising from Arledge's illegal conduct. Specifically, he objects to the calculation of losses related to the Fen Phen II settlement.

The "general rule is that a district court can award restitution to victims of the offense, but the restitution award can encompass only those losses that resulted directly from the offense for which the defendant was convicted." United States v. Maturin, 488 F.3d 657, 660-61 (5th Cir. 2007) (citing Hughey v. United States, 495 U.S. 411, 413, 110 S.Ct. 1979, 109 L.Ed.2d 408 (1990)). The pre-sentence report attributed forty-seven fraudulent claims to the offenses for which Arledge was convicted. There were three categories of evidence used to substantiate the government's assertion that these claims resulted from Arledge's illegal conduct: (1) the testimony of Wyatt, an employee of S&A, who created fraudulent documents; **(...)**

Please complete it: We have stated repeatedly that an order of restitution must be limited to losses caused by the specific conduct underlying the offense of conviction. See United States v. Griffin, 324 F.3d 330, 367 (5th Cir.2003) (holding that restitution is restricted to the limits of the offense); Tencer, 107 F.3d at 1135-36. Accordingly, we decline the government's request to adopt a harmless error analysis for the calculation of loss under the MVRA, and we remand for a re calculation of actual loss based upon the evidence in the record.

Then, answer the following questions based on the whole article:

Based on the statement Arledge makes no convincing argument regarding why the identification by AHP is not sufficient or how the district court abused its discretion in relying upon the representations by AHP., provide a continuation using the word "Hence" to express the following idea. It was not an abuse of discretion for the court to award restitution that encompassed those losses resulting from the creation of fraudulent documents in furtherance of the scheme to defraud for which Arledge was convicted.
(...)
What happens before "The government asks this court to find that the failure to provide proof of these three claims was harmless error."? It also asserts that it would be able to provide, on remand, proof of an additional false claim that was not originally included in the district court's restitution order, which resulted in a loss of $488,000.

In opposition to the sentence "Thus, it was not an abuse of discretion for the court to award restitution that encompassed those losses resulting from the creation of fraudulent documents in furtherance of the scheme to defraud for which Arledge was convicted.", create a sentence with a contradictory meaning. There are three claims for which the government concedes that there was no proof of falsity: Florestine Baker ($18,000), Shirley E.

Produce a long descriptive sentence about law that uses all these words: prescription, manufactured, fraudulent. There were three categories of evidence used to substantiate the government's assertion that these claims resulted from Arledge's illegal conduct: (1) the testimony of Wyatt, an employee of S&A, who created fraudulent documents; (2) the testimony of two pharmacists who testified that specific prescriptions allegedly from their pharmacies were, in fact, manufactured; and (3) representations by AHP that the claims were fraudulent.

Produce a long descriptive sentence about law that uses all these words: restitution, fraudulent, furtherance. Thus, it was not an abuse of discretion for the court to award restitution that encompassed those losses resulting from the creation of fraudulent documents in furtherance of the scheme to defraud for which Arledge was convicted.

What was this article about? Amount of Loss