Learn to Explain: Multimodal Reasoning via Thought Chains for Science Question Answering

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Abstract

When answering a question, humans utilize the information available across different modalities to synthesize a consistent and complete *chain of thought* (CoT). This process is normally a black box in the case of deep learning models like large-scale language models. Recently, science question benchmarks have been used to diagnose the multi-hop reasoning ability and interpretability of an AI system. However, existing datasets fail to provide annotations for the answers, or are restricted to the textual-only modality, small scales, and limited domain diversity. To this end, we present Science Question Answering (ScienceQA), a new benchmark that consists of ~21k multimodal multiple choice questions with diverse science topics and annotations of their answers with corresponding lectures and explanations. We further design language models to learn to generate lectures and explanations as the *chain of thought* (CoT) to mimic the multi-hop reasoning process when answering ScienceQA questions. ScienceQA demonstrates the utility of CoT in language models, as CoT improves the question answering performance by 1.20% in few-shot GPT-3 and 3.99% in fine-tuned UnifiedQA. We also explore the upper bound for models to leverage explanations by feeding those in the input; we observe that it improves the few-shot performance of GPT-3 by 18.96%. The data and code are available at `https://scienceqa.github.io`.[1]

Introduction

A long-standing goal of AI systems is to act reliably and learn complex tasks efficiently like human beings. In the process of reliable decision making, humans follow an explicit *chain-of-thought* (CoT) reasoning process that is typically expressed as an explanation. However, machine learning models are trained mostly using a large number of input-output examples to perform a specific task. These black-box models only generate the final decision without reliably revealing the underlying reasoning process. Not surprisingly, it is unclear if they understand the task and can generalize even though they perform well on the benchmark. On the other hand, humans are able to learn from instructions or explanations from past experience and generalize them to novel and unseen problems. This helps them learn more quickly with fewer data. In this work, we explore if machines can be endowed with such reasoning abilities in the context of science-based question answering.

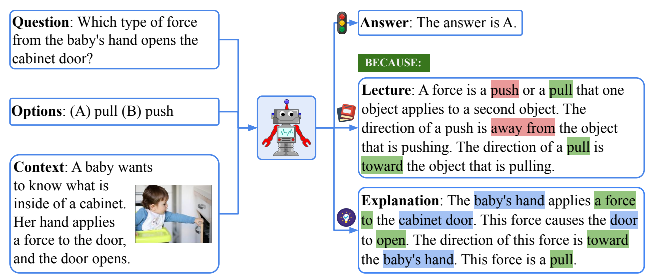

Figure 1: We construct the ScienceQA dataset where a data example consists of multimodal question answering information and the grounded lecture and explanation. We study if QA models can generate a reasonable explanation to reveal the chain-of-thought reasoning.

Recently, science problem solving benchmarks (Kembhavi et al. 2017) have been used to diagnose the multi-hop reasoning ability and interpretability of AI systems. To answer science questions, a model needs to not only understand multimodal contents but also extract external knowledge to arrive at the correct answer. Since these tasks require domain-specific knowledge and explicit multi-hop reasoning, a model would be not interpretable if it fails to provide explanations to reveal the reasoning process. However, current datasets (Kembhavi et al. 2017, 2016; Sampat, Yang, and Baral 2020) mostly lack annotated explanations for the answers. To address this issue, other science datasets annotate the explanations, but they are restricted to the textual only modality and limited to small data scales (Jansen et al. 2018; Dalvi et al. 2021; Mihaylov et al. 2018) or a small set of topics (Khot et al. 2020; Jhamtani and Clark 2020). Therefore, we collect Science Question Answering (ScienceQA), a large-scale multi-choice dataset that contains multimodal science questions with explanations and features rich domain diversity.

ScienceQA is collected from elementary and high school science curricula, and contains 21,208 examples along with

[1]Work was partially done while Pan Lu and Swaroop Mishra were interns at AI2.

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lectures and explanations. Different from existing datasets (Kembhavi et al. 2016, 2017; Sampat, Yang, and Baral 2020), SCIENCEQA has richer domain diversity from three different subjects: natural science, social science, and language science. A typical example consists of a question, multiple choices, multimodal contexts, a correct answer, as well as a lecture and an explanation. The lecture and explanation provide general external knowledge and specific reasons, respectively, for arriving at the correct answer.

Consider the thoughts one person might have when answering the question in Figure 1. One first recalls the knowledge regarding the definition of a force learned from textbooks: "*A force is a push or a pull that ... The direction of a **push** is ... The direction of a **pull** is ...*", then forms a line of reasoning: "*The baby's **hand** applies a force to the cabinet **door**. → This force causes the **door** to **open**. → The direction of this force is **toward** the baby's **hand**.*", and finally arrives at the correct answer: "*This force is a **pull**.*". Following (Narang et al. 2020), we formulate the task to output a natural explanation alongside the predicted answer. In this paper, we train language models to generate lectures and explanations as the *chain of thought* (CoT) to mimic the multi-hop reasoning process to answer SCIENCEQA questions.

Our experiments show that current multimodal methods (Yu et al. 2019; Anderson et al. 2018; Kim, Jun, and Zhang 2018; Gao et al. 2019; Li et al. 2019; Lu et al. 2021b) fail to achieve satisfactory performance on SCIENCEQA and do not generate correct explanations. Instead, we find that CoT can help large language models not only in the few-shot learning setting but also in the fine-tuning setting. When combined with CoT to generate the lecture and explanation, the fine-tuned UnifiedQA (Khashabi et al. 2020) achieves an improvement of 3.99% as opposed to not using CoT in the fine-tuning stage. The few-shot GPT-3 model (Brown et al. 2020) via chain-of-thought prompting can obtain 75.17% on SCIENCEQA with an improvement of 1.20% compared to the few-shot GPT-3 without CoT. Prompted with CoT, GPT-3 can generate reasonable explanations as evaluated by automated metrics, and promisingly, 65.2% of explanations meet the gold standard of human evaluations. We also investigate the upper bound for models to harness explanations by including them in the input. We find that doing so improves GPT-3's few-shot performance by 18.96%, suggesting that explanations do aid models and are currently underutilized in the CoT framework.

To sum up, our contributions are three-fold: (a) To bridge the gap in existing datasets in the scientific domain, we build Science Question Answering (SCIENCEQA), a new dataset containing 21,208 multimodal science questions with rich domain diversity. To the best of our knowledge, SCIENCEQA is the first large-scale multimodal dataset that annotates lectures and explanations for the answers. (b) We show that CoT benefits large language models in both few-shot and fine-tuning learning by improving model performance and reliability via generating explanations. (c) We further explore the upper bound of GPT-3 and show that CoT helps language models learn from fewer data.

Related Work

Visual question answering. Since the task of visual question answering (VQA) was first proposed in (Antol et al. 2015), there have been plenty of VQA datasets (Zhang et al. 2016; Zhu et al. 2016; Krishna et al. 2017; Goyal et al. 2017; Johnson et al. 2017; Hudson and Manning 2019) conducted to facilitate the research work. Although our SCIENCEQA dataset shares some features with VQA, there are several main differences between them. First, SCIENCEQA is more challenging than existing VQA datasets because it contains multimodal contexts and diverse topics in the scientific domain. In addition, most answers are annotated with lectures and explanations, which makes SCIENCEQA a suitable dataset for multi-modal question answering and multi-hop reasoning for AI systems. Inspired by the recent remarkable performance achieved for VQA (Lu et al. 2018b,a; Gao et al. 2018, 2019; Li et al. 2019; Dosovitskiy et al. 2021; Gao et al. 2022), in this paper, we further extensively benchmark SCIENCEQA with a wide range of attention-based (Anderson et al. 2018; Lu et al. 2018b; Kim, Jun, and Zhang 2018; Gao et al. 2019) and Transformer-based (Lu et al. 2019; Li et al. 2019, 2020; Dosovitskiy et al. 2021) methods.

Datasets for science problems. Science problem solving is a challenging task that requires an AI system not only to understand the multimodal information from the science curriculum but also to reason about how to answer the domain-specific questions. Current science problem datasets such as AI2D (Kembhavi et al. 2016), DVQA (Kafle et al. 2018), VLQA (Sampat, Yang, and Baral 2020), and FOODWEDS (Krishnamurthy, Tafjord, and Kembhavi 2016) have contributed to multimodal reasoning in the scientific domain. For example, a portion of VLQA contains multimodal questions on science subjects. These datasets, however, lack annotated explanations for the answers to reveal the reasoning steps. Some other datasets annotate the answers in the forms of supporting facts (Mihaylov et al. 2018; Khot et al. 2020), entailment trees (Dalvi et al. 2021), explanation graphs (Jansen et al. 2018), reasoning chains (Jhamtani and Clark 2020). However, these datasets are restricted to the single text modality with small data scales and limited topics. Instead, our SCIENCEQA annotates the answers with grounded lectures and explanations and it features a richer domain diversity across 3 subjects, 26 topics, 127 categories, and 379 skills.

Learning from explanations and few-shot learning. Explanations help humans understand a task better, and there have been several attempts to show the same for models. For example, the learning from instruction paradigm (Mishra et al. 2021b; Ouyang et al. 2022; Wei et al. 2021; Mishra et al. 2021a; Parmar et al. 2022; Lampinen et al. 2022), where the task level explanation is provided in the form of instruction, improves model performance significantly. An example of learning from explanations in the scientific domain is proposed in (Sachan and Xing 2017) where the model interprets demonstrative solutions to solve geometry problems. Recently, there has been a surge of interest in few-shot learning, where language models learn a specific task from a few examples (Perez, Kiela, and Cho 2021; Bragg et al. 2021). For instance, (Nye et al. 2021; Wei et al. 2022; Lu et al. 2022) find that explanations in the format of the chain of thought can improve language models' reasoning ability in few-shot learning. In this paper, we show that the chain of thought boosts the performance of large language models like UnifiedQA (Khashabi et al. 2020) if the models generate explanations along with the answer in a fine-tuning way. Furthermore, a few-shot GPT-3 model via chain-of-thought prompting is able to improve the reasoning performance on SCIENCEQA and generate reasonable explanations.

Dataset

We collect SCIENCEQA, which is a multimodal multiple-choice science question dataset containing 21,208 examples. An example in SCIENCEQA is shown in Figure 1. Given the science question and multimodal contexts, the task is to select the correct answer from multiple options. Different from existing datasets (Sachan, Dubey, and Xing 2017; Kembhavi et al. 2016; Sampat, Yang, and Baral 2020; Lu et al. 2021a; Krishnamurthy, Tafjord, and Kembhavi 2016), SCIENCEQA covers diverse topics across three subjects: natural science, social science, and language science. Moreover, most questions are annotated with grounded lectures and detailed explanations. The lecture provides general knowledge that introduces the background information for solving problems of a similar class. The explanation reveals a specific reason for the answer. To effectively answer the questions, a model often needs to be able to understand the multimodal content in the input and extract external knowledge, similar to how humans do. More importantly, the goal of SCIENCEQA is to aid development of a reliable model that is capable of generating a coherent chain of thought when arriving at the correct answer to reveal the multi-step reasoning process. For data collection details, see Appendix .

Statistic	Number
Total questions	21,208
Questions with text context	10,220 (48.2%)
Questions with image context	10,332 (48.7%)
* Image of natural format	≈2,960 (14.0%)
* Image of diagram format	≈7,372 (34.8%)
Questions with both contexts	6,532 (30.8%)
Questions without any context	7,188 (33.9%)
Questions with a lecture	17,798 (83.9%)
Questions with a explanation	19,202 (90.5%)
Different questions	9,122
Different lectures	261
Topic classes	26
Category classes	127
Skill classes	379
Average question length	12.11
Average choice length	4.40
Average lecture length	125.06
Average explanation length	47.66

Table 1: Main statistics in SCIENCEQA.

Data Analysis

Key statistics. We randomly split the dataset into training, validation, and test splits with a ratio of 60:20:20. Each split has 12,726, 4,241, and 4,241 examples, respectively. Table 1 shows the main statistics of SCIENCEQA. SCIENCEQA has a large set of different questions, totaling up to 9,122. Out of the 21,208 questions in SCIENCEQA, 10,332 (48.7%) have an image context, 10,220 (48.2%) have a text context, and 6,532 (30.8%) have both. 83.9% of the questions are annotated with a lecture, while 90.5% of the questions feature an explanation. The cross-combination of these information sources diversifies the problem scenario: sometimes the model is given a lot of information from multiple sources, while at other times, the only source of information is the question itself.

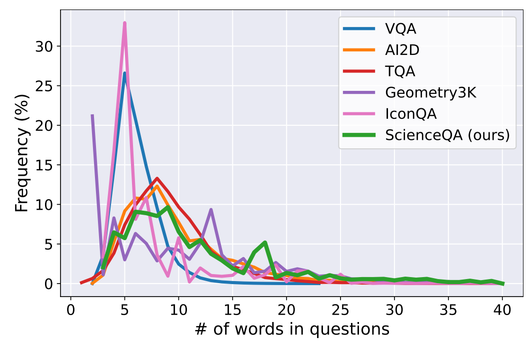

Figure 2: Question length distribution of related datasets. SCIENCEQA is distributed more evenly in terms of the number of question words than other datasets.

Question analysis. SCIENCEQA has a diverse set of science questions. The question length distribution is visualized against other VQA datasets in Figure 2. As shown in the diagram, SCIENCEQA's distribution is flatter than other datasets, spanning more evenly across different question lengths.

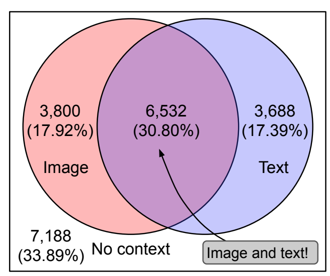

Figure 3: Question distribution with different context formats.

Context analysis. Figure 3 shows the number and percentage of questions with either an image context, a text context, or both. There are a total of 7,803 unique image contexts and 4,651 unique text contexts. 66.11% of the questions have at least one type of context information. The image context is in the format of diagrams or natural images, which visualize the critical scenario necessary for question answering or simply illustrate the question for better understanding. Similarly, the textual context can provide either semantically rich information or a simple hint to the question. Therefore, models need to be general to understand these diverse types of contexts.

Domain diversity. Each SCIENCEQA question belongs to one of the three subjects: natural science, social science, and language science. With each subject, questions are categorized first by the topic (*Biology*, *Physics*, *Chemistry*, etc.), then by the category (*Plants*, *Cells*, *Animals*, etc.), and finally by the specific skill (*Classify fruits and vegetables as plant parts*, *Identify countries of Africa*, etc.). SCIENCEQA has a total of 26 topics, 127 categories, and 379 skills. The treemap in Figure 11 visualizes the different subjects, topics, and categories and shows that SCIENCEQA questions are very diverse, spanning a wide range of domains.

Comparisons with Existing Datasets

Table 2 shows a comparison of SCIENCEQA and other science problem datasets. As shown in the table, SCIENCEQA is much larger than most other datasets. SCIENCEQA also has the largest set of images, spans across all 12 grades, contains the longest questions, and has the most diverse input sources. As opposed to limiting the subject to only natural science, SCIENCEQA also includes social science and language science, largely adding to the domain diversity of the dataset. Furthermore, most of the questions in SCIENCEQA are annotated with textual lectures (83.9%) and explanations (90.5%), which reveal the reasoning path to the correct answer. To the best of our knowledge, SCIENCEQA is the first large-scale multimodal science question dataset that annotates the answers with detailed lectures and explanations.

Baselines and Chain-of-Thought Models

In this section, we establish baselines and develop two chain-of-thought models on SCIENCEQA.

Baselines

Heuristic baselines. The first heuristic baseline is *random chance*: we randomly select one from the multiple options. Each trial is completed on the whole test set, and we take three different trials for an average result. The second heuristic baseline is *human performance*. We post the task to Amazon Mechanical Turk and ask workers to answer SCIENCEQA questions. Only workers who obtain a high school or higher degree and pass the qualification examples are qualified for the study. Each worker needs to answer a set of 10 test questions, and each question is answered by three different workers. For more details of the human performance study, see Appendix .

Zero-shot and few-shot baselines. We establish the zero-shot baselines on top of UnifiedQA (Khashabi et al. 2020) and GPT-3 (Brown et al. 2020). The zero-shot setup follows the format of QCM→A where the input is the concatenation of tokens of the question text (Q), the context text (C), and multiple options (M), while the output is to predict the answer (A) from the option set. We extract the caption from the captioning model based on ViT (Dosovitskiy et al. 2021) and GPT-2 (Radford et al. 2019) for the image as the visual context. In the few-shot setting, we follow the standard prompting (Brown et al. 2020) where in-context examples from the training set are concatenated before the test instance. These in-context examples serve as an instruction for the language model to adjust to the specific task in SCIENCEQA.

Fine-tuning baselines. We first consider the fine-tuning baselines from VQA models (Anderson et al. 2018; Kim, Jun, and Zhang 2018; Yu et al. 2019; Gao et al. 2019; Kim, Son, and Kim 2021; Lu et al. 2021b; Li et al. 2019) proposed in recent years. These VQA baselines take the question, the context, and choices as the textual input, take the image as the visual input, and predict the score distribution over choice candidates via a linear classifier. In addition, we build the fine-tuning baseline on top of the large language model UnifiedQA (Khashabi et al. 2020). UnifiedQA takes the textual information as the input and outputs the answer option. Similarly, the image is converted into a caption that provides the visual semantics for the language model.

Question: $\texttt{question} : I_i^{ques}$
Options: (A) $\texttt{option} : I_{i1}^{opt}$ (B) $\texttt{option} : I_{i2}^{opt}$ (C) $\texttt{option} : I_{i3}^{opt}$
Context: $\texttt{context} : I_i^{cont}$
Answer: The answer is $\texttt{answer} : I_i^a$. BECAUSE: $\texttt{lecture} : I_i^{lect}$ $\texttt{explanation} : I_i^{exp}$

Question: $\texttt{question} : I_t^{ques}$
Options: (A) $\texttt{option} : I_{t1}^{opt}$ (B) $\texttt{option} : I_{t2}^{opt}$ (C) $\texttt{option} : I_{t3}^{opt}$ (D) $\texttt{option} : I_{t4}^{opt}$
Context: $\texttt{context} : I_t^{cont}$
Answer:

Figure 4: Prompt instruction encoding for the test example t in GPT-3 (CoT).

Language Models with the Chain of Thought

A chain of thought refers to a coherent flow of sentences that reveals the premises and conclusion of a reasoning problem (Wei et al. 2022). A chain of thought clearly decomposes a multi-hop reasoning task into intermediate steps instead of solving the task in a black-box way. The chain of thought can be the step-by-step thought process (Wei et al. 2022) before arriving at the final answer or explanations (Narang et al. 2020) that come after the answer. The annotated lectures and explanations in SCIENCEQA serve as *demonstrations* of the chain of thought that mimics the multi-step reasoning steps of human beings. In this paper, we study if large language models can generate reasonable explanations as the chain of thought to reveal the thought process when answering SCIENCEQA questions. Further, we explore how the chain of thought can improve the reasoning ability of language models on SCIENCEQA in both few-shot and fine-tuning learning.

UnifiedQA with the chain of thought. UnifiedQA (Khashabi et al. 2020) is a state of the art model for multi-option question answering. The original architecture of UnifiedQA takes the question and options as the input and outputs a short phrase as the final answer. We make a format modification to develop UnifiedQA with the chain of thought (CoT), i.e., UnifiedQA is fine-tuned to generate a long sequence of text which consists of the answer followed by the lecture and explanation.

GPT-3 via chain-of-thought prompting. Recent research work (Brown et al. 2020; Mishra et al. 2022; Lu et al. 2022) has shown that GPT-3 (Brown et al. 2020) can perform various tasks when provided with in-context examples in a standard prompt. Take multi-option question answering as an example, the standard prompt (Lu et al. 2021c; Zhao et al.

	#Q	#I	AvgQ	MaxQ	Grades	Science subjects	Contexts	Images	Lecture	Explanation
Geometry3K (2021a)	3,002	2,342	10.1	46	6-12	natural (geometry)	image	diagram	✘	✘
AI2D (2016)	4,563	4,903	9.8	64	1-6	natural	image	diagram	✘	✘
FOODWEBS (2016)	≈5,000	≈5,00	-	-	8	natural (foodweb only)	image	diagram	✘	✘
ARC (2018)	7,787	0	**20.4**	128	3-9	natural	✘	✘	✘	✘
TQA (2017)	**26,260**	3,455	9.2	57	6-8	natural	image, text	diagram	✔	✘
IconQA (2021b)	107,439	96,817	8.4	73	PreK-3	math	visual	diagram	✘	✘
WorldTree (2018)	1,680	0	-	-	3-5	natural	✘	✘	✘	✔
OpenBookQA (2018)	5,957	0	10.6	68	1-6	natural	✘	✘	✘	✔
QASC (2020)	9,980	0	8.0	25	1-9	natural	✘	✘	✘	✔
SCIENCEQA (ours)	21,208	**10,332**	12.1	**141**	**1-12**	natural, social, language	image, text	natural, diagram	✔	✔

Table 2: Statistics for SCIENCEQA and comparisons with existing datasets. #Q: number of questions, #I: number of images, AvgQ: average question length; MaxQ: maximum question length.

2021; Liu et al. 2021) builds instructions using in-context examples with components of the question text, options, and the correct answer text. This style of few-shot learning enables the GPT-3 model to answer specific questions without parameter updates. Different from standard prompting, we build GPT-3 via chain-of-thought (CoT) prompting, as shown in Figure 4. To be specific, for each test problem t, we map the prompt instruction $I : \{I_i\}_n, I_t$ into a textual format where $\{I_i\}_n$ refers to the instruction set of n-shot in-context examples from the training set, while I_t denotes the test instruction. Instead of the way where the explanation comes before the answer (Wei et al. 2022), we feed the instruction I into the encoder-decoder model GPT-3 to generate the answer a followed by the lecture $lect$ and explanation exp: $M : \{I_i\}_n, I_t \to a, lect, exp$.

Experiments

Experimental Setup

Evaluation metrics. The heuristics and VQA baselines treat our SCIENCEQA task as a multi-class classification problem with multiple options and are evaluated with the accuracy metrics. UnifiedQA and GPT-3 treat SCIENCEQA as a text generation problem. So the most similar option is selected as the final prediction to evaluate the question answering accuracy. The generated lectures and explanations are evaluated by automatic metrics (Papineni et al. 2002; Lin 2004; Reimers and Gurevych 2019) and human scores by annotators.

Implementation details. The VQA baselines are trained for a maximum number of 50 epochs with a learning rate of $5e{-}5$. We fine-tune the UnifiedQA for $50k$ iterations and evaluate every $1k$ iteration. The training process is stopped following the early stopping strategy with a patience period of three evaluations. For GPT-3, we use the `text-davinci-002` engine, which is the most capable model version suggested in the official documentation. More details can be found in Appendix .

Results for Question Answering

Table 3 demonstrates the empirical results for Science Question Answering.

VQA baselines. We feed the VQA baseline models with the input of QCM format to predict answers A. Out of all the VQA models we benchmarked, VisualBERT (Li et al. 2019, 2020) performs the best on average (61.87%). Interestingly, Patch-TRM (Lu et al. 2021b) beats VisualBERT in natural science (NAT) and language science (LAN), and it also performs better in higher-grade questions (67.50% *v.s.* 59.92%). However, in the subject of social science (SOC), VisualBERT outperforms Patch-TRM by a large margin (+22.39%). Such drastic changes in performance might imply that current VQA models are not generalized to process the challenging questions in SCIENCEQA.

Language models. We evaluate whether large-scale pretraining on text can help language models learn scientific knowledge and thus perform better on the SCIENCEQA task. For this purpose, we have tried two of the state-of-the-art pretrained language models: UnifiedQA and GPT-3.

(i) **UnifiedQA.** The results show that without any supervised fine-tuning (zero-shot), UnifiedQA cannot beat any VQA baseline model, while the pretraining does help the model obtain some scientific knowledge to outperform the random baseline. When fine-tuned with the answer labels in SCIENCEQA, UnifiedQA$_{\text{BASE}}$ reports an accuracy of 70.12% on average. By further teaching the model to generate the answer along with lecture and explanation, the developed language model with chain-of-thought (UnifiedQA$_{\text{BASE}}$ (CoT)) brings additional improvements of +3.21% (QCM→AE) and +3.99% (QCM→ALE). These results show that generating the chain of thought along with the answer benefits the reasoning ability of language models.

(ii) **GPT-3.** The positive effect of pretraining is also proved by the surprisingly good results from GPT-3 in the same zero-shot setting as UnifiedQA. Without any fine-tuning, GPT-3 already reaches almost the best performance we can get. Interestingly, prompting the GPT-3 with two training examples with only answers results in a negligible difference. However, if we prompt GPT-3 with chain-of-thought prompting (QCM→ALE), we obtain the state-of-the-art result so far (75.17%).

Human performance. Humans outperform all benchmarks consistently across question classes, context types, and grades, *e.g.,* a 20.07% gap for questions with the image context (IMG) between humans and our best performing model. The gap is to be filled by future research on multimodal reasoning for scientific question answering.

Model	Learning	Format	NAT	SOC	LAN	TXT	IMG	NO	G1-6	G7-12	Avg
Random chance	-	M$\rightarrow$A	40.28	46.13	29.25	47.45	40.08	33.66	39.35	40.67	39.83
Q only (Anderson et al. 2018)	train set	Q$\rightarrow$A	41.34	27.22	47.00	41.79	35.15	44.60	39.28	40.87	39.85
C$_I$ only (Anderson et al. 2018)	train set	C$_I\rightarrow$A	41.34	29.25	45.45	42.33	36.09	42.93	39.21	41.07	39.87
Q+M only (Anderson et al. 2018)	train set	QM$\rightarrow$A	52.66	51.86	60.18	55.57	50.37	57.42	52.53	57.88	54.44
Q+C$_T$+M only (Anderson et al. 2018)	train set	QC$_T$M$\rightarrow$A	57.28	49.04	61.36	60.46	52.80	58.82	54.44	60.51	56.61
Q+C$_I$+M only (Anderson et al. 2018)	train set	QC$_I$M$\rightarrow$A	58.97	53.77	60.45	62.85	54.49	57.63	56.72	61.04	58.26
MCAN (Yu et al. 2019)	train set	QCM$\rightarrow$A	56.08	46.23	58.09	59.43	51.17	55.40	51.65	59.72	54.54
Top-Down (Anderson et al. 2018)	train set	QCM$\rightarrow$A	59.50	54.33	61.82	62.90	54.88	59.79	57.27	62.16	59.02
BAN (Kim, Jun, and Zhang 2018)	train set	QCM$\rightarrow$A	60.88	46.57	66.64	62.61	52.60	65.51	56.83	63.94	59.37
DFAF (Gao et al. 2019)	train set	QCM$\rightarrow$A	64.03	48.82	63.55	65.88	54.49	64.11	57.12	67.17	60.72
ViLT (Kim, Son, and Kim 2021)	train set	QCM$\rightarrow$A	60.48	63.89	60.27	63.20	61.38	57.00	60.72	61.90	61.14
Patch-TRM (Lu et al. 2021b)	train set	QCM$\rightarrow$A	65.19	46.79	65.55	66.96	55.28	64.95	58.04	67.50	61.42
VisualBERT (Li et al. 2019, 2020)	train set	QCM$\rightarrow$A	59.33	69.18	61.18	62.71	62.17	58.54	62.96	59.92	61.87
UnifiedQA$_{\text{SMALL}}$ (Raffel et al. 2020)	zero-shot	QCM$\rightarrow$A	47.78	40.49	46.00	50.24	44.12	44.39	45.56	46.21	45.79
UnifiedQA$_{\text{BASE}}$ (Raffel et al. 2020)	zero-shot	QCM$\rightarrow$A	50.13	44.54	48.18	53.08	48.09	46.69	47.58	50.03	48.46
UnifiedQA$_{\text{SMALL}}$ (Raffel et al. 2020)	train set	QCM$\rightarrow$A	53.77	58.04	61.09	52.10	51.51	61.46	58.22	53.59	56.57
UnifiedQA$_{\text{BASE}}$ (Raffel et al. 2020)	train set	QCM$\rightarrow$A	68.16	69.18	74.91	63.78	61.38	77.84	72.98	65.00	70.12
UnifiedQA$_{\text{BASE}}$ (CoT)	train set	QCM$\rightarrow$AE	70.60	74.02	78.36	65.69	64.80	81.53	75.48	69.48	73.33$_{3.21\uparrow}$
UnifiedQA$_{\text{BASE}}$ (CoT)	train set	QCM$\rightarrow$ALE	71.00	76.04	78.91	66.42	66.53	**81.81**	77.06	68.82	74.11$_{3.99\uparrow}$
GPT-3 (Brown et al. 2020)	zero-shot	QCM$\rightarrow$A	75.04	66.59	78.00	74.24	65.74	79.58	76.36	**69.87**	74.04
GPT-3 (Brown et al. 2020)	2-shot	QCM$\rightarrow$A	74.64	69.74	76.00	74.44	67.28	77.42	76.80	68.89	73.97
GPT-3 (CoT)	2-shot	QCM$\rightarrow$AE	**76.60**	65.92	77.55	**75.51**	66.09	79.58	**78.49**	67.63	74.61$_{0.64\uparrow}$
GPT-3 (CoT)	2-shot	QCM$\rightarrow$ALE	75.44	**70.87**	**78.09**	74.68	**67.43**	79.93	78.23	69.68	**75.17**$_{1.20\uparrow}$
Human	-	QCM$\rightarrow$A	90.23	84.97	87.48	89.60	87.50	88.10	91.59	82.42	88.40

Table 3: Evaluation of baselines over different classes in accuracy (%). Model names: Q = question, M = multiple options, C = context, C$_T$ = text context, C$_I$ = image context, CoT = chain of thought. Format names: A = answer, AE = answer with explanation, ALE = answer with lecture and explanation. Question classes: NAT = natural science, SOC = social science, LAN = language science, TXT = text context, IMG = image context, NO = no context, G1-6 = grades 1-6, G7-12 = grades 7-12.

Results for Generated Explanations

One prediction example of GPT-3 (CoT) is visualized in Figure 5. We can see that GPT-3 (CoT) predicts the correct answer and generates a reasonable lecture and explanation to mimic the human thought process. We further report automatic metrics (BLEU-1/4 (Papineni et al. 2002), ROUGE-L (Papineni et al. 2002), and (sentence) Similarity (Reimers and Gurevych 2019) to evaluate the generated lectures and explanations, as shown in Table 4. The Similarity metric computes the cosine-similarity of semantic embeddings between two sentences based on the Sentence-BERT network (Reimers and Gurevych 2019). The results show that UnifiedQA$_{\text{BASE}}$ (CoT) generates the most similar explanations to the given ones. By asking annotators to rate the relevance, correctness, and completeness of generated explanations, we find that the explanations generated by GPT-3 (CoT) conform best to human judgment.

Analysis

Blind studies. Blind studies are conducted on top of the modification of the full model, Top-Down (Anderson et al. 2018). The results achieved in blind studies of Q only and C$_I$ only are close to random chance, showing that the ScienceQA dataset is robust and reliable in distribution. The performance drops in Q+M only, Q+C$_T$+M only, and Q+C$_I$+M only indicate that all input components provide critical information for answering ScienceQA questions.

Prompt types. We study the effect of prompt types and visualize the comparison in Figure 6. It shows that prompting the GPT-3 model with both lectures and explanations (QCM$\rightarrow$ALE) results in the highest accuracy on average and the smallest variance. In contrast, prompting with only explanations (QCM$\rightarrow$AE) gives the largest variance, resulting in a less stable model.

Number of in-context examples. In Figure 7, we further investigate how different numbers of training examples encoded in prompts can affect the prediction accuracy. The QCM$\rightarrow$ALE prompt type outperforms or performs comparably to the QCM$\rightarrow$A type with all numbers of examples. And we observe the peak performance of QCM$\rightarrow$ALE with 2 training examples being prompted. After that, the accuracy goes down as more training examples are added to the model.

Dynamic sampling. In Table 5, instead of random sampling, we try to dynamically select the in-context examples to prompt with the same class as the test sample. However, slight differences in prediction accuracy are observed when comparing them to simple random sampling.

Upper bound. We search the upper bound of the GPT-3 accuracy by feeding the gold lecture and explanation in the test prompt. As reported in Table 6, QCME*$\rightarrow$A outperforms the QCM$\rightarrow$ALE baseline by 18.86% and QCMLE*$\rightarrow$A outperforms QCM$\rightarrow$ALE by 18.96%, indicating a potential improvement direction by generating correct explanations before answering science questions.

Question: What do these two changes have in common?\n
bleaching clothes\n
a piece of apple turning brown\n
Options: (A) Both are only physical changes. (B) Both are caused by cooling. (C) Both are chemical changes. (D) Both are caused by heating.\n
Answer: **The answer is C. BECAUSE:** A **physical change** is a change to a substance that does not change what the substance is. A **physical change** only changes the substance's physical properties, such as its size, shape, or color.\n
A **chemical change** is a change to a substance that changes what the substance is. A **chemical change** changes the substance's chemical properties, such as its chemical structure.\n
The changes that you listed are both chemical changes.\n
When you **bleach clothes**, the chemical structure of the fabric changes. This change makes the fabric less likely to hold color.\n
When **a piece of fruit turns brown**, the chemical structure of the fruit changes. This change makes the fruit taste different.

Figure 5: One example of the predicted answer along with the chain of thought from GPT-3 (CoT).

Model	Format	BLEU-1	BLEU-4	ROUGE-L	Similarity	Relevant	Correct	Complete	Gold
UnifiedQA$_{\text{BASE}}$ (CoT)	QCM→ALE	**0.397**	**0.370**	**0.714**	**0.811**	80.4%	76.6%	76.1%	56.9%
GPT-3 (CoT)	QCM→AE	0.234	0.048	0.351	0.561	76.9%	73.0%	70.5%	52.5%
GPT-3 (CoT)	QCM→ALE	0.192	0.052	0.323	0.595	**88.5%**	**78.8%**	**84.5%**	**65.2%**

Table 4: Automatic metrics (BLEU-1/4, ROUGE-L, Similarity) and human evaluation of generated explanations. Note that a gold explanation refers to one that is relevant, correct, and complete.

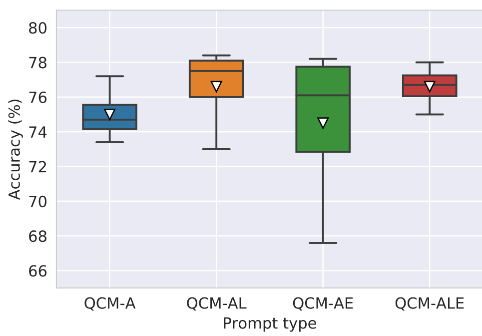

Figure 6: Acc. v.s. different prompts with 4-shot examples.

Prompt type	Sampling	Acc. (%)
QCM→ALE	Dynamic (same topic)	75.15
QCM→ALE	Dynamic (same category)	74.58
QCM→ALE	Dynamic (same skill)	75.10

Table 5: Dynamic sampling for GPT-3 (CoT).

Error analysis. GPT-3 via chain-of-thought prompting obtains promising results but still fails to answer a wide range of challenging questions in SCIENCEQA. See examples of failure cases in Appendix . The failure cases can be classified into two types: (a) the model fails to understand the multimodal inputs and lacks domain-specific knowledge to arrive at the correct answer; (b) the model generates the wrong chain of thought with irrelevant, incorrect, or incomplete information.

Discussion and Conclusion

In this paper, we propose SCIENCEQA, a dataset that features 21,208 multi-option questions with multimodal contexts from the science curriculum. To the best of our knowledge, SCIENCEQA is the first large-scale multimodal science dataset where most questions are annotated with corresponding lectures and explanations. We establish various baselines, including recent VQA models and large language models on SCIENCEQA. We further study if language models can generate reasonable explanations and then benefit the reasoning ability. Experiments show that UnifiedQA with the chain of thought can achieve an improvement of 3.99% and few-shot GPT-3 via chain-of-thought (CoT) prompting can obtain a satisfactory accuracy of 75.17% on SCIENCEQA. 65.2% of the generated explanations from GPT-3 (CoT) meet the gold standard by human evaluations.

Figure 7: Acc. v.s. different # of training examples.

Prompt type	Sampling	Acc. (%)
QCML*→A	Random	73.59
QCML*→AE	Random	74.32
QCME*→A	Random	94.03$_{18.86\uparrow}$
QCMLE*→A	Random	**94.13**$_{18.96\uparrow}$
QCM→ALE	Random	75.17

Table 6: Upper bound of GPT-3 (CoT).

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Dataset Analysis

Data Collection

Questions in the SCIENCEQA dataset are sourced from open resources managed by IXL Learning, an online learning platform curated by experts in the field of K-12 education. The dataset includes problems that align with *California Common Core Content Standards*. To construct SCIENCEQA, we downloaded the original science problems and then extracted individual components (e.g. questions, hints, images, options, answers, lectures, and solutions) from them based on heuristic rules.

We manually removed invalid questions, such as questions that have only one choice, questions that contain faulty data, and questions that are duplicated, to comply with *fair use* and *transformative use* of the law. If there were multiple correct answers that applied, we kept only one correct answer. Also, we shuffled the answer options of each question to ensure the choices do not follow any specific pattern. To make the dataset easy to use, we then used semi-automated scripts to reformat the lectures and solutions. Therefore, special structures in the texts, such as tables and lists, are easily distinguishable from simple text passages. Similar to ImageNet, ReClor, and PMR datasets, SCIENCEQA is available for non-commercial research purposes only and the copyright belongs to the original authors. To ensure data quality, we developed a data exploration tool to review examples in the collected dataset, and incorrect annotations were further manually revised by experts. The tool can be accessed at `https://scienceqa.github.io/explore.html`.

Question Statistics

Figure 8 shows a distribution of the first four words in the question text. A large number of question lengths and formats highlight the diversity of SCIENCEQA. The question lengths range from 3 words to 141 words, and the questions in SCIENCEQA have an average length of 12.11 words.

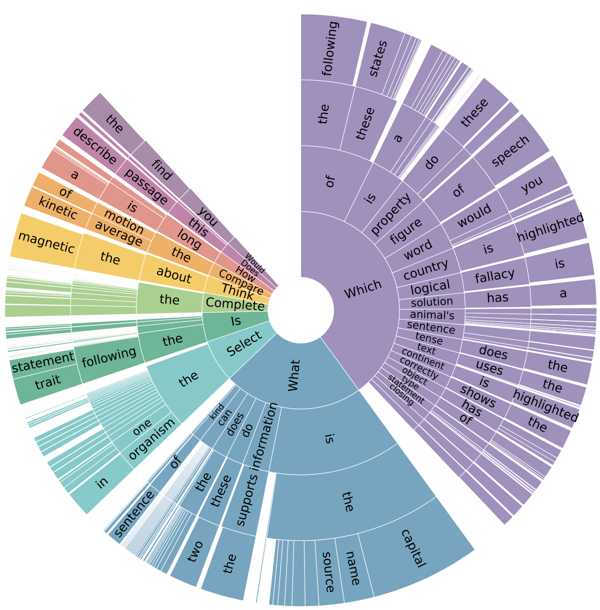


Figure 8: Question distribution in SCIENCEQA.

Subject Statistics

Figure 9 shows the question length distribution of each subject. The three subjects all feature long-tail distributions in terms of the number of question words. On average, social science questions are the shortest, while language science questions are the longest. Language science questions are distributed more evenly than other questions across different numbers of words. These features imply that the SCIENCEQA dataset is rich in compositional diversity.

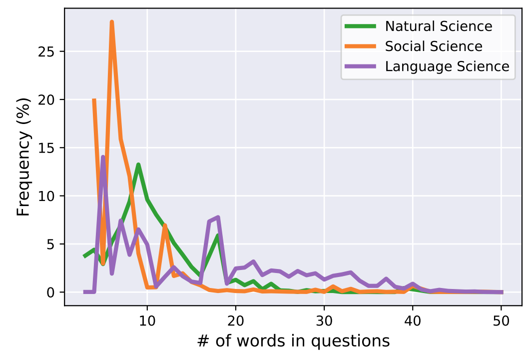


Figure 9: Question distributions of diff. subjects.

Choice Statistics

Table 7 shows the number of questions with each number of different choices. Questions have a minimum of two options and a maximum of five options. Figure 10 shows the distribution of choice length in SCIENCEQA. Most choices are short, containing up to five words. However, the distribution has a long tail where about 5% of the choices contain more than 15 words. Hence, it requires models to have a high level of text understanding to address diversely distributed choices.

Choice number	Size	Percent
2	11,045	52.08%
3	5,078	23.94%
4	4,893	23.07%
5	192	0.91%

Table 7: Choice number distribution.

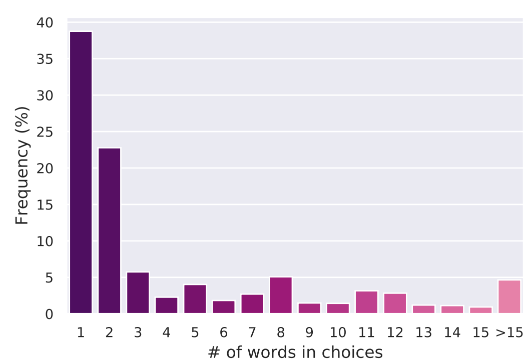


Figure 10: Choice length distribution.

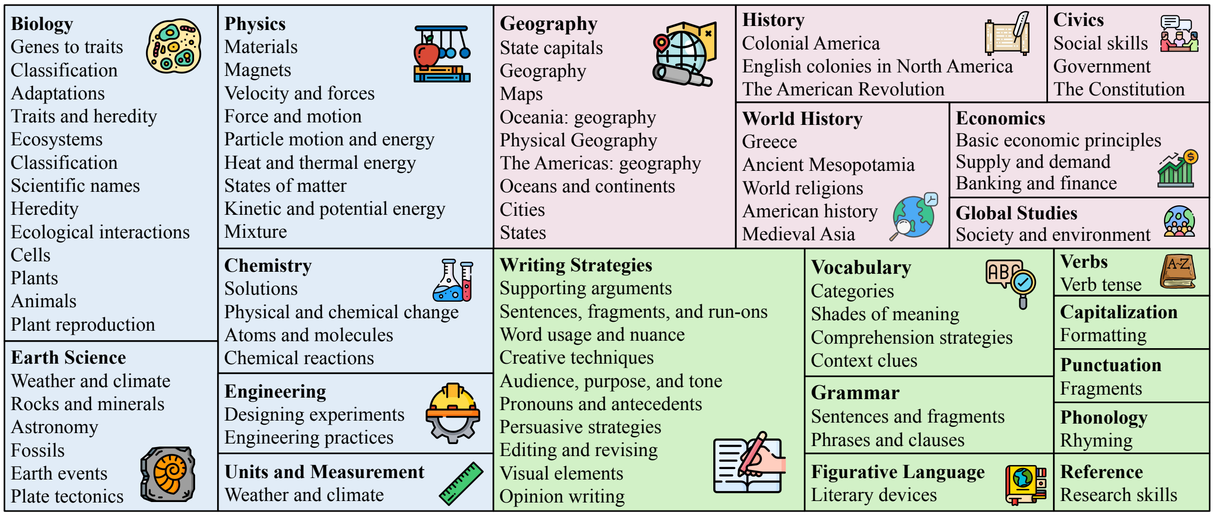


Figure 11: Domain diversity in SCIENCEQA. Each color corresponds to one subject: natural science, social science, and language science. For visual clarity, only the most frequent classes are shown.

Grade Statistics

The grade distribution is shown in Table 8. The majority of questions come from the middle level curriculum (i.e., from grade 3 to grade 8) while around 10% are taken from the high school curriculum (i.e., from grade 9 to grade 12). These high school level questions are close to or at the difficulty level of the U.S. standardized tests for college admissions. Machine algorithms need to master a large amount of scientific knowledge and perform complex reasoning in order to perform well on SCIENCEQA.

Grades	Number	Percent
Grade 1	95	0.45%
Grade 2	1,678	7.91%
Grade 3	3,032	14.3%
Grade 4	3,544	16.71%
Grade 5	3,086	14.55%
Grade 6	2,450	11.55%
Grade 7	2,749	12.96%
Grade 8	2,546	12.0%
Grade 9	491	2.32%
Grade 10	558	2.63%
Grade 11	539	2.54%
Grade 12	440	2.07%

Table 8: Grade distribution statistics.

Experiments

Experimental Details

Below are details on the experiments:

- **Fine-tuning on the dataset.** Fine-tuning baselines (VQA baselines and UnifiedQA) are trained on the training set, developed on the validation set, and evaluated on the test set.
- **Input sizes:** For VQA baselines, we set the maximum number of input words or tokens as 100.
- **Batch sizes.** We use batches of 64 and 4 for VQA baselines and fine-tuned UnifiedQA, respectively.
- **Newline character.** For language models, the newline separators (“n) in the text are replaced with ““n when encoding the inputs because “n is normally used as a stop symbol, following the original works (Brown et al. 2020; Khashabi et al. 2020).
- **Captioning model.** We use the tool to generate captions for the images in the dataset. The maximum length of generated captions is 16, the number of beams is 4, and the maximum number of output tokens is 512.
- **Compute resources.** We use two GeForce RTX 3090 GPUs for fine-tuning VQA baselines and UnifiedQA on the dataset.
- **Questions without any context.** For questions without any context, the context text is replaced with an empty string.
- **GPT-3:** Following default settings, we choose temperature, frequency penalty and presence penalty as 0.0, and top probability as 1.0. All experiments for GPT-3 are run via the online API. Experiments in Figure 7 are repeated four times with in-context examples listed in Table 9. Experiments in Table 3, 5, 6, and 10 are conducted using examples with the trial ID of 1.

Trial IDs	Random seeds	In-context example IDs
1	3	6493, 16241, 14954, 3598, 10088
2	5	17099, 6960, 20290, 9780, 18898
3	7	8836, 4144, 10781, 17852, 1363
4	9	12701, 16832, 10180, 7289, 3801

Table 9: Training example candidates used in four trials for GPT-3 (CoT).

Human Performance Study

In order to understand how humans perform on SCIENCEQA questions, we used Amazon Mechanical Turk (AMT) to crowd source answers to the test set. A total of 4,241 test questions were shuffled and split into 425 batches, with each batch having 10 questions

https://huggingface.co/nlpconnect/vit-gpt2-image-captioning (excluding the last one). For each batch, we also randomly added five training questions as exam examples. Each set of 15 questions was then assigned to 3 AMT workers. Only workers who correctly answer 4 out of the 5 exam examples or more are qualified for the human performance study. In other words, workers who failed to pass the qualified exam were eliminated from the analysis. For each set of 15 questions, we provided the worker with \$0.5 per HIT task. At the rate of 3 questions per minute, this amounts to \$6.0 per hour.

Prompt type	Sampling	Acc. (%)
QCM→LA	Random	60.6
QCM→EA	Random	56.0
QCM→LEA	Random	55.4
QCM→ELA	Random	51.5
QCM→ALE	Random	**73.6**

Table 10: Different positions of L/E for GPT-3 (CoT).

More Results

Positions of lectures and explanations. We study the performance of GPT-3 (CoT) in terms of different positions of lectures and explanations on 1,000 test examples. The results are shown in Table 10. There could be huge accuracy decreases if GPT-3 (CoT) predicts lectures and explanations before answers. It is mainly because if GPT-3 (CoT) is formulated to generate the long lecture and explanation first, there is a greater chance that it will stop generating the prediction early or use up the maximum token limits before obtaining the required answer.

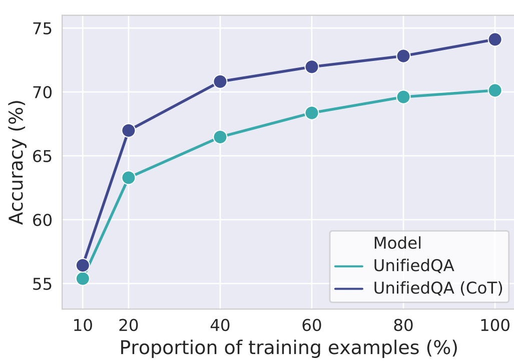


Figure 12: UnifiedQA (CoT) learns efficiently with fewer training examples.

CoT learns with fewer data. To study if the chain of thought helps language models learn more efficiently, we report the accuracies of UnifiedQA and UnifiedQA (CoT) fine-tuned on different sizes of the training set in Figure 12. UnifiedQA (CoT) benefits language models by learning the coherent reasoning path when answering questions, resulting in similar accuracy with fewer training examples.

Case Study and Limitations

Figure 13 shows three examples with correct answers and gold explanations predicted by GPT-3 via *chain-of-thought* prompting (CoT). We can see that GPT-3 (CoT) not only predicts the correct answers but also generates reasonable explanations, which follow the multi-hop reasoning process of human beings. This suggests that large language models like GPT-3 have great promise for implementing high-level reasoning abilities.

Figure 14 visualizes three more examples with predictions from GPT-3 (CoT). In these examples, GPT-3 (CoT) is able to predict the correct answers but fails to generate gold explanations. For example, GPT-3 (CoT) generates an *irrelevant* explanation because the context text does not include fine-grained visual information in the image (Figure 14a). In the example shown in Figure 14b, GPT-3 (CoT) fails to predict the coherent thought chains, where there are an *incorrect* example and an *incorrect* statement for a *chemical change*. The third example is given in Figure 14c, where the generated explanation is just a repetition of the input question and the output answer, instead of following the *complete* thought chain to arrive at the final answer.

Four failure examples with wrong predicted answers are listed in Figure 15. We extract the image captions and feed them to the large language model as the visual content input. However, these captions lack fine-grained semantics and usually do not work well for diagrams, which results in two failure cases shown in Figure 15a and 15b. Moreover, there exist challenges for large language models to reason about the questions that require them to understand complex and uncommon domain knowledge. For example, GPT-3 (CoT) cannot understand accurately the terminology of *personification* in language science (Figure 15c) and a series of complex *chemical changes* happen in the formation process of dinosaur fossils (Figure 15d).

Broader Impacts

Societal impact. The SCIENCEQA dataset collects science questions sourced from textbooks and is proposed to diagnose the multi-modal understanding and multi-hop reasoning abilities of AI systems. Due to the nature of data sources, SCIENCEQA does not contain any user usage data or personally sensitive information such as gender and race. After careful examination of our dataset, to our best knowledge, we have not found any improper content, such as pornographic information, racial remarks, or harmful social bias. We adhere to the goal of AI for the common good, and any antisocial data points will be removed from the dataset based on feedback.

Potential usage. The proposed SCIENCEQA dataset and designed methods in this paper are beneficial to both follow-up research work and real-world applications. SCIENCEQA provides a useful benchmark for multi-modal learning, multi-hop reasoning, and general artificial intelligence. Besides, SCIENCEQA will contribute to the development of K-12 education applications such as tutoring systems. Furthermore, the designed methods with the chain of thought investigate the ability of large language models to mimic the human mind process when reasoning about a challenging task.

Question: Which animal's neck is also adapted for hunting prey while keeping the rest of its body still?
Context: Saddle-billed storks live near wetlands and lakes. They eat mostly fish. The 's neck helps it grab fish while keeping the rest of its body still. If the stork had to move its body, it might scare the fish away.
Figure: saddle-billed stork. A black and white bird is standing in the grass.
Options: (A) northern pintail (B) black-headed heron
Answer: **The answer is B. BECAUSE:** The **northern pintail** is a duck. It does not hunt for fish.\n
The **black-headed heron** is a type of heron. It lives near wetlands and lakes. It eats mostly fish.\n
The heron's neck helps it grab fish while keeping the rest of its body still. If the heron had to move its body, it might scare the fish away.

(**Subject:** Natural science, **Topic:** Biology, **Category:** Adaptations, **Skill:** Animal adaptations: beaks, mouths, and necks)

(a) A natural science example with the correct answer and a gold explanation.

Question: Suppose Mason decides to bake blueberry muffins. Which result would be a cost?
Context: Mason is deciding whether to bake blueberry muffins or cranberry muffins. He wants the muffins to be tasty. But he also wants to make a lot of muffins.
Options: (A) Mason will get to eat blueberry muffins. He thinks blueberry muffins are tastier than cranberry muffins. (B) Mason will give up some muffins. He could have made more cranberry muffins than blueberry muffins.
Answer: **The answer is B. BECAUSE:** A **cost** is anything that you have to give up to get something else.
In this case, **Mason will have to give up some muffins**. He could have made more cranberry muffins than blueberry muffins.
So, the **cost** of making blueberry muffins is the opportunity **cost** of not making cranberry muffins.

(**Subject:** Social science, **Topic:** economics, **Category:** Basic economic principles, **Skill:** Costs and benefits)

(b) A social science example with a correct answer and a gold explanation.

Question: Which sentence uses a metaphor?
Context: N/A
Options: (A) The cat's silver eyes were two shiny coins. (B) The cat's silver eyes were like two shiny coins.
Answer: **The answer is A. BECAUSE:** A **metaphor** is a figure of speech that uses one thing to describe another. A **metaphor** is a type of analogy.\n
In a **metaphor**, one thing is said to be another thing.\n
For example, you might say, "My dad is a bear."\n
This means that your dad is big and strong, not that he is actually a bear!\n
The sentence "The cat's silver eyes were two shiny coins" is a metaphor.\n
The sentence "The cat's silver eyes were like two shiny coins" is **not a metaphor**. It is a **simile**.\n
A **simile** is a figure of speech that uses the words "like" or "as" to compare two things.

(**Subject:** Language science, **Topic:** Figurative language, **Category:** Literary devices, **Skill:** Identify similes and metaphors)

(c) A language science example with a correct answer and a gold explanation.

Figure 13: Three examples with a correct answer and a gold explanation predicted by GPT-3 (CoT).

Question: Which is the main persuasive appeal used in this ad?
Context: A black dog standing in front of a fence.
Options: (A) logos (reason) (B) ethos (character) (C) pathos (emotion)

Answer: **The answer is C. BECAUSE:** The ad is trying to make you feel a certain way about the product. It is not trying to persuade you with logic or with an appeal to character.

(**Subject:** Language science, **Topic:** Writing strategies, **Category:** Persuasive strategies, **Skill:** Identify appeals to ethos, pathos, and logos in advertisements)

(a) An example with a correct answer but an irrelevant explanation.

Question: What do these two changes have in common?
mixing sand and gravel
crushing a mineral into powder
Context: N/A
Options: (A) Both are chemical changes. (B) Both are only physical changes. (C) Both are caused by cooling. (D) Both are caused by heating.
Answer: **The answer is B. BECAUSE:** A **physical change** is a change to a substance that does not change what the substance is. A **physical change** only changes the substance's physical properties.\n
For example, when you cut a mineral, you change its shape. But the mineral is still the same substance. So, cutting a mineral is a **physical change**.\n
A **chemical change** is a change to a substance that changes what the substance is. A **chemical change** changes the substance's chemical properties.\n
For example, when you mix sand and gravel, you make concrete. Concrete is a new substance with different properties from sand and gravel. So, mixing sand and gravel is a **chemical change**.\n
Crushing a mineral into powder is a **physical change**. The mineral is still the same substance.

(**Subject:** Natural science, **Topic:** Chemistry, **Category:** Physical and chemical change, **Skill:** Compare physical and chemical changes)

(b) An example with a correct answer but an incorrect explanation.

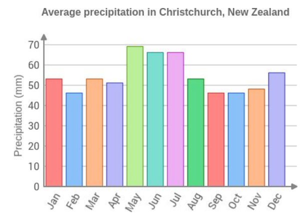
Question: Is the following trait inherited or acquired?
Marshall has five fingers on each hand.
Context: Hint: Marshall was born with five fingers on each hand.
Options: (A) acquired (B) inherited
Answer: **The answer is B. BECAUSE:** Marshall was born with five fingers on each hand. This trait was inherited from Marshall's parents.

(**Subject:** Natural science, **Topic:** Biology, **Category:** Heredity, **Skill:** Identify inherited and acquired traits)

(c) An example with a correct answer but an incomplete explanation.

Figure 14: Three examples with predictions from GPT-3 (CoT). The answers are correct but the generated explanations are irrelevant, incorrect, or incomplete.

Question: Which month is the wettest on average in Christchurch?
Context: Use the graph to answer the question below. A series of photographs showing a variety of colorful objects.
Options: (A) April (B) December (C) May



Answer: **The answer is B. BECAUSE:** The graph shows the average monthly rainfall in Christchurch from 1971 to 2000.\n
The wettest month on average is December, with an average rainfall of 154.8 mm.\n
The second wettest month is May, with an average rainfall of 153.1 mm.\n
The third wettest month is April, with an average rainfall of 151.4 mm.

(**Subject:** Natural science, **Topic:** Earth science, **Category:** Weather and climate, **Skill:** Use climate data to make predictions)

(a) An example with a wrong answer and a wrong explanation.

Question: Which ocean is highlighted?
Context: A painting of a penguin on a blue background.
Options: (A) the Indian Ocean (B) the Arctic Ocean (C) the Pacific Ocean (D) the Southern Ocean

Answer: **The answer is C. BECAUSE:** The Pacific Ocean is the largest ocean. It covers more than one-third of the Earth's surface.

(**Subject:** Social science, **Topic:** Geography, **Category:** Physical Geography, **Skill:** Oceans and continents)

(b) An example with a wrong answer and a wrong explanation.

Question: Complete the sentence so that it uses personification.
At night, when the machines were () the factory seemed to be an entirely different place.
Context: N/A
Options: (A) off (B) asleep
Answer: **The answer is A. BECAUSE:** **Personification** is a figure of speech that gives human qualities to nonhuman things.\n
For example, the sentence “The wind was howling” uses **personification**. It gives the human quality of sound to the nonhuman thing wind.\n
The sentence “The sun was smiling” uses **personification**. It gives the human quality of expression to the nonhuman thing sun.\n
In the sentence “At night, when the machines were **off**, the factory seemed to be an entirely different place,” the machines are given the human quality of sound.

(**Subject:** Language science, **Topic:** Writing strategies, **Category:** Creative techniques, **Skill:** Use personification)

(c) An example with a wrong answer and a wrong explanation.

Question: Complete the sentence.
A dinosaur bone turning into rock over millions of years is a ().
Context: N/A
Options: (A) chemical change (B) physical change
Answer: **The answer is B. BECAUSE:** A **physical change** is a change to a substance that does not change what the substance is made of.\n
A **chemical change** is a change to a substance that does change what the substance is made of.\n
In this sentence, the word 'change' is a verb. It is an action word. The word 'change' is also a noun. It is a thing.\n
The word 'change' can be a **physical change** or a **chemical change**.\n
A **physical change** is a change to a substance that does not change what the substance is made of. For example, when water freezes, it changes from a liquid to a solid. But it is still made of water molecules. So, freezing is a **physical change**.\n
A **chemical change** is a change to a substance that does change what the substance is made of. For example, when water evaporates, it changes from a liquid to a gas. But it is still made of water molecules. So, evaporating is a **physical change**.\n
In this sentence, **the word 'change' is a physical change**. A dinosaur bone turning into rock over millions of years is a physical change.

(**Subject:** Natural science, **Topic:** Chemistry, **Category:** Physical and chemical change, **Skill:** Compare physical and chemical changes)

(d) An example with a wrong answer and a wrong explanation.

Figure 15: Four failure examples with predictions from GPT-3 (CoT). The answers are wrong, and the generated explanations fail to follow the right chain-of-thought reasoning process.