Answering Unseen Questions With Smaller Language Models Using Rationale Generation and Dense Retrieval

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Paper under double-blind review

Abstract

When provided with sufficient explanatory context, smaller Language Models have been shown to exhibit strong reasoning ability on challenging short-answer question-answering tasks where the questions are unseen in training. We evaluate two methods for further improvement in this setting. Both methods focus on combining rationales generated by a larger Language Model with longer contexts created from a multi-hop dense retrieval system. The first method (*RR*) involves training a Rationale Ranking model to score both generated rationales and retrieved contexts with respect to relevance and truthfulness. We then use the scores to derive combined contexts from both knowledge sources using a number of combinatory strategies. For the second method (*RATD*) we train a smaller Reasoning model using retrieval-augmented training datasets such that it becomes proficient at utilising relevant information from longer text sequences that may be only partially evidential and frequently contain many irrelevant sentences. Generally we find that both methods are effective but that the *RATD* method is more straightforward to apply and produces the strongest results in the unseen setting on which we focus. Our single best Reasoning model using only 440 million parameters materially improves upon strong comparable prior baselines for unseen evaluation datasets (StrategyQA 58.9 → 61.7 acc., CommonsenseQA 63.6 → 72.7 acc., ARC-DA 31.6 → 52.1 F1, IIRC 25.5 → 27.3 F1) and a version utilising our prior knowledge of each type of question in selecting a context combination strategy does even better. Our proposed models also generally outperform direct prompts against much larger models (BLOOM 175B and StableVicuna 13B) in both few-shot chain-of-thought and few-shot answer-only settings.

1 Introduction

"It was soon realized that the problem of systematically acquiring information from the environment was much less tractable than the mental activities the information was intended to serve" - Moravec (1988)

Moravec's paradox is the observation that problems such as developing an ability to reason, that might have been assumed to be one of the most difficult challenges in artificial intelligence has been easier to resolve than the challenge of acquiring more basic knowledge such as sensory information. It is motivating to consider this in the context of recent advances in using both large Language Models (LLMs) and retrieval against large textual corpora for information acquisition in the question-answering domain. Prior work has shown both approaches to be effective, and it may be argued that the knowledge acquisition problem is now as tractable as the problem of utilising this information in reasoning to an answer.

We focus on methods to improve the performance of a smaller Language Model[1] (i.e. Reasoning Model) which, given a question and an acquired explanatory context as input, is expected to reason to an answer. Our interest in smaller models for this task is twofold: Firstly we are interested in evaluating the viability of reasoning systems that answer arbitrary questions in resource constrained situations where available physical size is limited, and internet connectivity and so forth is assumed to be unavailable. Secondly, we consider the

[1]Generative Transformers with 400 million to 1 billion parameters

hypothesis that reasoning can still be effective in a setting with far less compute resource for the Reasoning Model than is available for the associated knowledge acquisition activity.

The knowledge acquisition function must however still run within our constrained environment. We consider two knowledge sources separately and in combination; retrieval of an explanatory context from a corpus of English Wikipedia paragraphs and rationale[2] generation from LLMs. Retrieval has generally been a relatively resource-efficient activity but until recently even inference on LLMs has required considerable computational resources. Recent innovations such as those involving 8-bit matrix multiplication (INT8) (Dettmers et al., 2022) enable the use of LLMs as frozen knowledge bases in constrained settings. For example inference on the 13 billion parameter StableVicuna model (Stability-AI, 2023) that we convert to INT8 and use in some experiments runs in approximately 18 GB of GPU RAM, well within the current capacity of large consumer GPU cards.

We choose retrieval from a reliable corpus and LLMs as our knowledge sources since they offer differing and complimentary characteristics e.g. retrieval is generally better at identifying relevant multi-hop factual knowledge while LLMs perform well with commonsense knowledge. For our retrieval system we make use of an existing multi-hop dense retrieval system (the "Iterator") developed by Hartill et al. (2023). The Iterator was shown to be effective in producing contexts for a variety of datasets that involve factual knowledge such as the multi-hop factual questions common in the Musique (Trivedi et al., 2022) dataset (e.g. "The Rhine forms a border between Aschenbrödel's composer's country and another country where women got the vote when?"). However it was poor in producing useful context for answering questions like those found in the CommonsenseQA dataset (Talmor et al., 2019), as might be expected for questions like "I'm crossing the river, my feet are wet but my body is dry, where am I?". Conversely, LLMs can be effective at generating rationales that assist in answering such questions. Another important difference between our two knowledge sources is that documents returned in retrieval are generally assumed to make truthful assertions regardless of their relevance to answering a question. LLM rationales by contrast can appear relevant but make false assertions. This has implications for training our Rationale Ranking models since a model not trained to detect falsehoods might incorrectly score a rationale such as "The Earth is flat" as useful for answering a question like "What shape is the Earth?".

We explore two methods of combining information from our knowledge sources. Our Rationale Ranking method (*RR*) involves training a smaller Transformer to score both rationales and retrieved explanatory contexts with respect to relevance and truthfulness. We then evaluate a number of simple strategies to create combined contexts such as including either or both components that score over a threshold, or selecting the single top-scoring component. We focus on identifying combination methods that work best in the general case, i.e. are most likely to work well for an arbitrary unseen question for which we provide no means of predicting which combination method will work best. We find that we are able to identify such a method for each of our Reasoning Models and quantify the performance improvement (section 3.4.3). Our second method (*RATD*) consists of training our Reasoning Model with retrieval-augmented datasets previously developed by Hartill et al. (2023) using the Iterator. These datasets were originally developed to impart diverse reasoning strategies such as an ability to identify and weigh partially evidential facts in long, noisy contexts. Noting that where our rationales and retrieved contexts are combined, the resulting context is similar in length and form to the *RATD* contexts, we find that training on them enables a single Reasoning Model to utilise our various context formats effectively, including the case where the context consists of the naïve concatenation of rationale and retrieved context that does not consider the *RR* model scores.

Our main assumption is that our system may be asked arbitrary questions from unknown distributions. Therefore we primarily consider our evaluations in the unseen rather than fine-tuned setting. The most relevant comparisons we have available to us are the baselines for StrategyQA (Geva et al., 2021), CommonsenseQA (Talmor et al., 2019), ARC-DA (Bhakthavatsalam et al., 2021), IIRC (Ferguson et al., 2020) and Musique (Trivedi et al., 2022) established for smaller Language Models in unseen settings by Hartill et al. (2023). Hence we adopt these datasets for evaluation and use the same definition as that paper for "seen-ness" whereby an unseen evaluation sample is one from a dataset that is disjoint from any training

[2]We use the term "rationale" to denote a free-text explanation (Wiegreffe & Marasović, 2021) of approximately one to three sentences that provides evidence to support a model prediction. We use the term to distinguish LLM generations of this form from the longer explanatory contexts produced from our retrieval system.

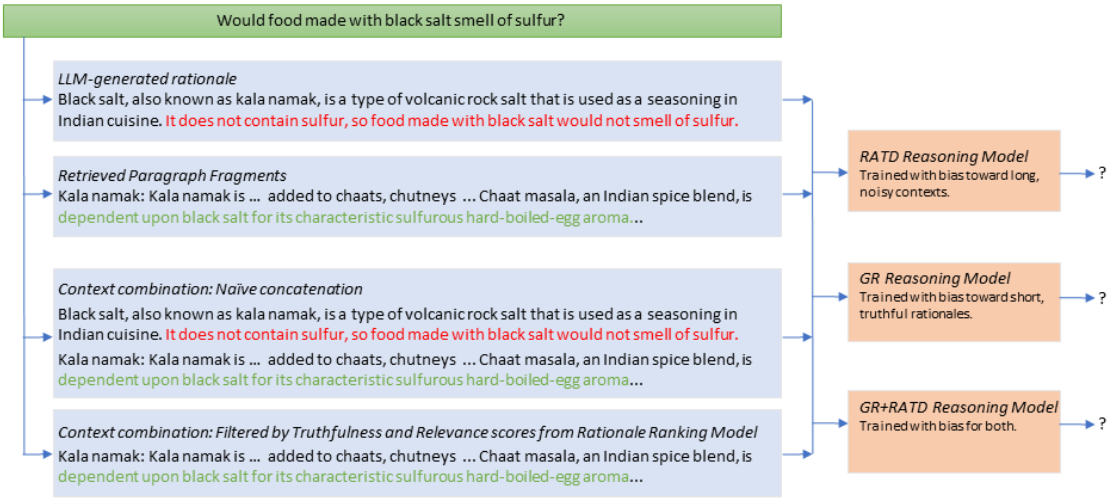

Figure 1: Given an unseen question and acquired explanatory context from two knowledge sources, we evaluate methods for combining or filtering the information to enable a Reasoning Model to most effectively reason to an answer. We consider three Reasoning Model training regimes (orange) to ascertain which combination method is most effective in each situation. *GR* is an abbreviation of "gold rationales". In the example, red denotes false information and green highlights relevant and truthful evidence.

dataset. In our case we extend this to our LLM generations, ensuring that all examples in few-shot prompts come from our training rather than evaluation datasets, or are manually created by us.

In summary the major contributions of this paper are: (A) We propose *RR*, a novel method that both selects context components by relevance, and filters components that may be false, and *RATD*, a novel application of a method that facilitates reasoning over diverse contexts that potentially combine information from multiple knowledge sources. (B) We demonstrate that our methods materially improve reasoning performance in smaller Language Models from strong prior baselines in the same unseen setting. (C) We show that smaller Language Models can manifest comparable or stronger reasoning performance as much larger models when evaluated under similar assumptions. (D) We illustrate the respective strengths and weaknesses of LLMs and retrieval from a Wikipedia corpus as knowledge sources. (E) We show that combining information from these sources improves the overall average performance over diverse unseen evaluation datasets, often beyond what either knowledge source in isolation can deliver on individual datasets.

1.1 Related Work

Knowledge Augmentation from LLMs. Bosselut et al. (2019) proposed COMET, a GPT-based Model (Radford et al., 2018) trained on triples from the ATOMIC (Sap et al., 2019) and ConceptNet (Speer et al., 2017) knowledge graphs such that it would generate potentially novel triple completions. Shwartz et al. (2020) compare augmentation methods using COMET, ConceptNet and their self-talk method where the question-answering Language Model is self-queried to produce additional information pertinent to answering the question. Liu et al. (2022) generate knowledge statements from GPT-3 (Brown et al., 2020) conditioned on the question and use the augmented samples in separate smaller Reasoning Models. Following the introduction of chain-of-thought (COT) prompting (Wei et al., 2022), a number of recent papers use this prompting style to distill training sets of rationale-augmented samples from internet-accessable LLMs (GPT-3, Palm (Chowdhery et al., 2022)) which are then typically used to train much smaller models in task-specific finetuned settings e.g. (Magister et al., 2023; Li et al., 2023; Hsieh et al., 2023; Wu et al., 2023; Shridhar et al., 2023) sometimes such that the label and the rationale are output to avoid the issue of having to generate a rationale from the LLM at test time. We note that our usage of LLM-generated rationales is

rather different from these in that we assume a locally-accessable LLM (with lower resource requirements) at test time and do not incorporate LLM-generated rationales in our Reasoning Model training.

Retrieval from Textual Corpora. For a comprehensive introduction to this wide field we suggest reviewing Lin et al. (2022a) and (Mitra & Craswell, 2018). In summary, TF-IDF (Spärck Jones, 1972) has been used for many years to associate queries with documents using adjusted bag-of-word count vectors. Chen et al. (2017) first used such sparse retrieval against Wikipedia in the context of open domain question-answering. In dense retrieval, query and corpus documents are embedded into the same vector space with similarity defined as the inner product between a query and a document vector. Karpukhin et al. (2020) used dense retrieval to identify a single document sufficient for answering a single-hop question, and Xiong et al. (2021) extend the approach to to retrieve two documents necessary to answer a complex two-hop question. Hartill et al. (2023) extend this to enable retrieval of an arbitrary maximum number of documents. Wang et al. (2018) introduced a Reranker Model that refines retrieved results. Baleen (Khattab et al., 2021) is a two-stage condenser system comprising a Reranker followed by an additional model that scores relevance of each sentence selected over multiple documents from the first stage. Hartill et al. (2023) introduce an Evidence Set Score into the second stage to quantify the sufficiency of the entire set of selected sentences for answering a query and call their resulting system the "Iterator". As noted, in this paper we use the Iterator with a Wikipedia corpus[3] as described in section 2.2.

Multiple Knowledge Sources. Retrieval has been successfully used as a method for querying knowledge graphs by embedding the constituent triples as the document vectors in addition to, or instead of, standard text, e.g. Yu et al. (2022) augment commonsense questions with retrieved information from a commonsense-focused corpus consisting of information source from knowledge graphs, commonsense datasets and other textual sources. Perhaps most similar in spirit to our work Pan et al. (2023) consider knowledge graphs, Wikipedia data, a dictionary, and others, as separate knowledge sources, each queried using dense retrieval. In contrast to our approach of considering various methods for combining information, they train a model to select the single most relevant source for augmenting each input sample. This is analogous to our "Max Score" method described in section 3.3. Like us they train a smaller Reasoning Model with disparate training and evaluation datasets, although unfortunately their evaluation datasets differ from ours. In a finetuned setting, Xu et al. (2022) also consider multiple knowledge sources. Here they use an entity linking method to query ConceptNet and sparse retrieval over a dictionary and a set of commonsense datasets. The results are always concatenated which is similar to our Naïve Concatenation method (section 3.3).

Falsehood Detection. Our *RR* Model, trained to score for truthfulness and relevance over instances from disparate knowledge sources, can be seen as a novel extension to a Reranking approach. However it also shares an objective with methods aiming to detect falsehood in LLM generations. Generally these methods fall into three categories. The first are methods based on the intuition that higher token log probabilities correspond to better text along a particular dimension such as truthfulness (Yuan et al., 2021; Fu et al., 2023). The second are factuality detection methods that evaluate LLM-generated assertions as true if they can be supported by a external reference (e.g fact retrieval from a reliable corpus). Recent studies here include (Min et al., 2023; Chern et al., 2023). A third category, broadly called self-checking involves prompting a LLM such as ChatGPT or GPT-4 (OpenAI, 2023) to recognize their own errors (Chern et al., 2023), or refine their own outputs (Chen et al., 2023; Madaan et al., 2023), without recourse to external tools. In this category but with a different approach, Manakul et al. (2023) score the consistency between a reference statement and several stochastically sampled versions of it that may be likely to diverge more if the reference is a hallucination.

2 Method

An overview of our approach is provided in Figure 1. Below we describe how the two knowledge sources are implemented, how the *RR* model is constructed, trained and initially evaluated, and how the Reasoning Models are trained. We describe our context combination methods further below in section 3.3 so as to make clear the nomenclature we use in reporting experimental results.

[3]Paragraphs from the August 1 2020 English dump

2.1 Rationale Generation

We utilize two LLMs, BLOOM BigScience Workshop et al. (2022) and StableVicuna (Stability-AI, 2023), a much smaller model that has been further tuned from the Vicuna v0 13B model (Chiang et al., 2023) which in turn was adapted from the LLama Touvron et al. (2023) foundation model. We chose these two models because they are representative of differing approaches to developing LLMs and they may offer divergent characteristics in rationale generation. At 176 billion parameters, BLOOM is the largest language model we had access to at the time that we could run under INT8. It is trained on 410 billion tokens and the version we used did not undergo further training on instructional data or human feedback. Llama by contrast is trained on one trillion tokens. From the Llama checkpoint, Vicuna underwent further training on user-provided ChatGPT conversations. Finally StableVicuna was developed from Vicuna by further training in both supervised and reinforcement learning from human feedback (RLHF) Ouyang et al. (2022) settings on a mixture of the human-generated OpenAssistant Conversations Dataset Köpf et al. (2023) and human-LLM conversations from the GPT4All Anand et al. (2023) and Alpaca Taori et al. (2023) projects. We used StableVicuna under both INT8 and FP16 versions, the former offering a smaller GPU memory footprint at around 18GB while the latter uses almost twice as much memory but we find inference much faster, thus offering a clear trade-off in a resource-constrained setting.

To generate rationales from each model, we used greedy decoding on chain-of-thought (COT) prompts (Wei et al., 2022) to generate the rationale followed by the phrase "So the answer is" and the answer (examples are in appendix B). This enabled us to evaluate the LLM answers directly from the same prompts and with the same rationale that our Reasoning Model would use, allowing a comparison under a similar set of assumptions. Occasionally a model would fail to generate the separate answer. In this case, to be favorable to the direct LLM method, the full rationale was used as the answer in calculating metrics.

To maintain the integrity of our unseen settings we ensured that no examples used in prompts were from any of our evaluation datasets. The prompts used were identical between our LLMs excepting that examples for StableVicuna prompts are denoted as:

```
### Human: The question is here? ### Assistant: The rationale is here. So the answer is
An answer.
```

BLOOM prompts are denoted as:

```
Q: The question is here? A: The rationale is here. So the answer is An answer.
```

2.2 Retrieval

For our second knowledge source we simply reuse contexts generated by the Iterator in Hartill et al. (2023), both for each evaluation sample and also for the creation of *RATD* datasets for the training regimes. This enables us to make a direct comparison with results published in that paper. Iterator-generated contexts are formatted as a list of paragraph fragments, each prepended by the title of the corresponding document and containing the gold sentence along with it's preceding and successor sentence where these exist. Contexts contain as many fragments as will fit into a 512-token sequence length. They are semi-structured as follows:

```
Doc 1 title: One to three sentences from document 1 paragraph. Doc 2 title: ...
```

2.3 Rationale Ranker

Our *RR* model takes a question and context pair as input $\langle q, c \rangle$ and produces a score s. It is trained with a binary cross-entropy objective where samples are labelled 1.0 if c is truthful and fully evidential in answering q or 0.0 otherwise. The model is trained on a mixture of existing datasets for which we acquire or construct positive c (i.e. a set of relevant and truthful gold sentences that are sufficient to answer q), and negative c (which omit some or all gold sentences and may be irrelevant, false or both with respect to q answerability). We used shared normalization (Clark & Gardner, 2018) such that each q is sampled in the same batch paired with a positive and separately a negative c. We found that without shared normalization, model training

would collapse and it would predict every c as negative. This may have occurred because without seeing positive and negative c for the same q in the same batch the pattern to be learned is insufficiently signalled.

Table 1: *RR* model training dataset construction. The construction methods denoted "... facts" involve creating rationales from gold sentences or structured triples sourced from the cited study. Positive Iterator-like contexts are constructed from the training datasets' gold (and associated negative) paragraphs to resemble Iterator-generated contexts. Negative Iterator-like contexts are similarly constructed but omit some or all gold sentences. Rationale-like construction corresponds to Iterator-like but only includes document titles and gold/negative sentences without preceding and successor sentences and reformatted to make the titles part of the sentences instead of prefixed. LLM-sampled and LLM-greedy contexts are negative rationales generated by BLOOM using nucleus sampling and greedy decoding respectively. [a]Onoe et al. (2021); [b]Yang et al. (2018); [c]Thorne et al. (2018); [d]Khot et al. (2020); [e]Clark et al. (2016; 2018); [f]Jiang et al. (2020); [g]Inoue et al. (2020); [h]DeYoung et al. (2020); [i]Jhamtani & Clark (2020); [j]Xie et al. (2020)

	Positive Contexts		Negative Contexts	
Training Mixture	**Count**	**Construction Methods**	**Count**	**Construction Methods**
Creak[a] (Commonsense)	10173	Creak facts[a]	81408	LLM-sampled
HotpotQA[b] (Multi-hop factual)	34304	R4C facts[g], Iterator-like, Rationale-like	41839	LLM-sampled, LLM-greedy, Iterator-like, Rationale-like
FEVER[c] (Single-hop factual)	60986	Eraser facts[h], Iterator-like, Rationale-like	121427	LLM-sampled, Iterator-like, Rationale-like
QASC[d] (Multi-choice science)	47830	QASC facts[d], eQASC facts[i]	193214	LLM-sampled, LLM-greedy
ARC[e] (Multi-choice science)	6469	WorldTree facts[j]	24492	LLM-sampled, LLM-greedy
Hover[f] (Multi-hop factual)	28171	Iterator-like, Rationale-like	28171	Iterator-like, Rationale-like
Total	**187933**		**490551**	

Since the model must score both rationale-style c and Iterator-generated c on the same scale, we develop training samples that are similar to both types. Obtaining positive c for training questions is generally straightforward but negative c that cover both irrelevance and falsehood are harder to obtain. We construct negative c by two methods; (1) generating them from BLOOM using specially constructed few-shot prompts containing examples of negative rationales (e.g. appendix C), and (2) creating them synthetically by substituting gold sentences with negative ones using datasets such as HotpotQA that come with sentence level annotations. The synthetic method can only produce irrelevant negatives whereas the LLM-generating method produces both irrelevant and false rationales. For LLM generation we use both greedy decoding and nucleus sampling (Holtzman et al., 2019) to create negatives. We find that greedy decoding produces positive-appearing but negative samples but (obtusely) the LLM has a tendency to produce accidentally positive rationales which we must filter out[4]. Nucleus sampling by contrast (temperature=0.95 and p=0.96) produces a diversity of false and irrelevant samples that are less likely to be accidental positives. However here falsehoods tend to have an exaggerated quality which could make them less adversarial for the model, so we create samples via both decoding methods (examples in appendix D). Further details of dataset construction are found in Table 1.

We employ diverse combination methods involving the trained *RR* model scores to create contexts for our evaluation datasets that combine rationales and Iterator-generated contexts, as described in section 3.3.

2.3.1 Rationale Ranker Evaluation

Our *RR* development set consists of 89,470 samples taken from the respective development splits of our training datasets. Contexts are created using the same methods as illustrated in Table 1 for corresponding training splits. We sample a single positive or negative context for each development question such that there are equal positive and negative contexts. As shown in Table 2, accuracy is high in this in-domain setting.

Turning to an unseen setting, we initially evaluate context relevance scoring with a five-way multi-choice relevance detection dataset that we create from the gold rationales supplied with StrategyQA (SQA), where the four incorrect options are simply randomly assigned rationales from other SQA questions (we use SQA since this is not part of *RR* model training). Here our model achieves 91.4% accuracy. A more interesting

[4]We eliminate rationales where the stemmed text contains the stemmed answer string, excepting samples with yes/no labels. We use the snowball stemmer from NLTK (Bird et al., 2009).

Table 2: *RR* model Accuracy in detecting positive and negative contexts on the in-domain development set (score threshold $t = 0.5$). Total is micro-accuracy.

Positive Context	**Negative Context**	**Total**
91.5	93.0	92.3

Table 3: Accuracy in detecting falsehoods on the TruthfulQA MC1 split (4-5 way multi-choice with one truthful option and the remainder making false assertions). The highest scoring option is selected as the model prediction. For our *RR* model and the Iterator Paragraph Reranker, each option is scored independently using the scores each model has been trained to compute. For other models, the score for each option is calculated as the log-probability of completion following the question, independent of the other options. [a]Estimated from charts in OpenAI (2023); [b]from Lin et al. (2022b) Github repository; [c]model from Hartill et al. (2023) with results calculated by us.

Model	**TruthfulQA MC1**
GPT-4 RLHF[a]	60.0
GPT-3.5 RLHF[a]	47.0
GPT-4 No RLHF[a]	30.0
GPT-3 175B[b]	21.0
GPT-J 6B[b]	20.0
UnifiedQA 3B[b]	19.0
Iterator Paragraph Reranker 335M[c]	18.2
Rationale Ranker 335M (Ours)	30.0

question is the extent to which our relatively small *RR* model is capable of detecting falsehoods in an unseen setting. To evaluate this question we consider TruthfulQA (Lin et al., 2022b), an adversarial evaluation-only dataset of 817 questions that models and/or humans tend to answer falsely. In Table 3 we compare falsehood detection performance of the *RR* model with various larger models and in particular with the Paragraph Reranker that Hartill et al. (2023) developed as a component of the Iterator. We treat the Paragraph Reranker as representative of models specifically trained to score context relevance but that have not necessarily been trained to consider truthfulness. It can be seen that our *RR* model is indeed much better at detecting falsehoods than the Paragraph Reranker and it's performance is competitive or better than much larger models that have not been trained using RLHF. We imagine the superior performance of LLMs trained with RLHF on falsehood detection is due to their associated large reward models, like our *RR* model, being trained in part to rate samples making false assertions as undesirable.

2.4 Reasoning Models

We consider three Reasoning Models in our experiments. The first, which we use as a baseline, is the unmodified *"Base+RATD"* model from Hartill et al. (2023) which we denote here as the *RATD* model for brevity. This is a multitask-trained model which is further trained from the original BART (Lewis et al., 2020) pretrained checkpoint on a large number of datasets[5]. For descriptive purposes, we divide these training datasets into two sets. The first are the *RATD* datasets described in section 2.2, whose purpose is to confer an ability to reason over long, noisy, and partially evidential contexts. We denote the remaining large number of training datasets as the *Common* set; these broadly cover tasks designed to instill simple numerical literacy, and diverse question-answering ability. Hence we say that the *RATD* model is trained on $Common \cup RATD$ datasets.

We create an additional set of training samples denoted *GR* (for "gold rationales"). These are intended to impart further ability to reason over rationale-form contexts. *GR* consists of samples for Creak, QASC,

[5]We refer the reader to Hartill et al. (2023) for a more exhaustive description of the training regime and dataset construction.

ARC, HotpotQA, and FEVER where the contexts are gold rationales constructed similarly and from the same sources as those described for the *RR* model training dataset in Table 1.

We then develop our two main Reasoning Models, both trained using the same approach and hyperparameters as the original *RATD* model: The *GR* model is trained on *Common* $\cup$ *GR*, and the *GR+RATD* model is trained on *Common* $\cup$ *GR* $\cup$ *RATD*.

3 Experiments

3.1 Models

The Rationale Ranker is built upon ELECTRA-large (Clark et al., 2020). Reasoning Models are based on BART (Lewis et al., 2020). All models use the the Huggingface (Wolf et al., 2020) implementations. The Reasoning Models differ only in their respective training data; hyperparameters are otherwise identical.

3.2 Unseen Evaluation Datasets

All evaluation dataset results are reported against the same splits used by Hartill et al. (2023). As with that paper we use the numeracy-focused F1 calculation introduced in Dua et al. (2019) for ARC-DA, IIRC and Musique.

StrategyQA (Geva et al., 2021) (SQA) contains commonsense samples involving diverse multi-hop reasoning strategies with yes/no answers. The full training set is used for evaluation as with BIG-bench (Srivastava et al., 2022).

CommonsenseQA (Talmor et al., 2019) (CSQA) is a multi-choice dataset of commonsense questions derived from Conceptnet (Speer et al., 2017). The task is to choose the best option from five options of which more than one may sometimes be plausible.

IIRC (Ferguson et al., 2020) contains factual questions and an initial explanatory paragraph for each which must be augmented with additional retrieved information to be fully evidential. Answers may be numbers, binary, text spans or labeled unanswerable.

ARC-DA (Bhakthavatsalam et al., 2021) is a subset of ARC (Clark et al., 2018) (science questions) where questions have been re-worded to make sense in an open domain context. The original multichoice versions of ARC are part of our training regime for both Reasoning and *RR* models, so samples are "partially unseen" in the sense that the question format is different.

Musique (Trivedi et al., 2022) is a multi-hop factual dataset constructed by combining single-hop questions from existing datasets. The training split of Musique is used in all of our Reasoning Models, and in the Iterator training. However as with Hartill et al. (2023), we use the original development split as "partially seen" since development samples were constructed such that no single hop question, answer, or associated paragraph is common to the corresponding element of any training sample. Hence the form of questions is "seen" but the exact questions are not.

3.3 Context Combination Methods and Experimental Nomenclature

For each unseen evaluation question, given a LLM-generated rationale, and an Iterator-generated context as possible combined context components, and *RR* model scores for each, we evaluate methods of combining them such that when both components are included, the resulting combined context has the following form (the phrase "Further Explanation" is added to mimic a document title):

```
Further Explanation: The rationale. Doc 1 title: One to three sentences from doc 1
paragraph. Doc 2 title: ...
```

Where a particular combining method does not select both components, the resulting context will simply be the original LLM-generated rationale or Iterator-generated component. We implement four combination methods and create versions of our unseen evaluation datasets with combined contexts for each as follows:

Naïve Concatenation: The simple concatenation of a rationale and corresponding Iterator-generated context with the above form. *RR* model scores are ignored.

Max Score: Choosing the single component that the *RR* model scores highest.

RationaleDefault: Defaulting to taking the rationale component unless the Iterator component scores over a threshold t in which case it is exclusively selected.

EitherOrBoth: Selecting either or both components that score over t. If neither component is selected, we default to the Naïve Concatenation context since smaller Language Models have been shown to be ineffective for answering unmemorized question-only (open domain) questions (Lewis et al., 2021).

For the latter two combination methods we create contexts using each of eight thresholds ranging from $t = 5e{-}4$ to $t = 0.9$. We denote the particular version using the threshold e.g. EitherOrBoth(0.9) means samples are augmented using the EitherOrBoth method with $t = 0.9$. Obviously innumerably other combination methods are possible but we find that this set is sufficient for our research purposes while remaining manageable.

Each of our three Reasoning Models might be expected to perform better with particular context types. For example the *GR* model might do better where the context tends to be rationale-like whereas the *RATD* model may do better where the context is of Iterator-generated form. This influences which combination method is likely to perform better on each Reasoning Model.

Similarly, different combination methods are likely to work better for differing question types (commonsense, multi-hop factual etc). For example knowing that LLM-generated rationales tend to be more effective than Iterator-generated contexts for answering commonsense questions, we can deduce that RationaleDefault(0.9) is likely to be a good strategy for developing contexts for CommonsenseQA because using this strategy results in Rationale-only contexts except where the Iterator context is scored very highly. However, we are interested in the situation where our model is presented with an arbitrary question of unknown type. Hence we are more interested in finding combination methods that will *generally* work well under this assumption, even where the method may not be the best for any particular type. We identify combination methods satisfying this criteria as those with the highest *unweighted macro-average score over our unseen evaluation datasets* (henceforth "Mean" or "Mean score") on each Reasoning Model, taking inspiration for averaging over heterogeneous metrics from e.g. Wang et al. (2019b;a). For the methods that utilize *RR* model scores we select the highest performing on this measure and refer to it as "Generally best RR combo" below. Since analysing which datasets do well with which context types helps to reveal the strengths and weaknesses of our combination methods, we also report the "Best RR combo per dataset" where we select the highest scoring combination method for each evaluation dataset. We note that since we cannot use this approach on an arbitrary question of unknown type we don't consider it a usable method in a truly unseen setting, although future work could remedy this (e.g. through utilising an additional model trained to predict the best combination method for a question).

We refer below to contexts created for each evaluation dataset that consist entirely of Iterator-generated contexts as "Iterator only", those contexts entirely composed of LLM-generated rationales as "Rationale only", and those that apply any of the combining methods as "Rationale + Iterator" (noting that individual samples in the latter may only contain one of the possible context components). For brevity, where referring to the use of a particular context type with evaluation questions on a particular model we use shorthand such as "*GR+RATD*: Iterator only" or "*GR+RATD*: Iterator + Rationale (Naïve Concatenation)".

3.4 Experimental Results

3.4.1 Summary

As Table 4 indicates, rationales generated by BLOOM almost always produce weaker results than those from StableVicuna. For example, in considering BLOOM-generated "Rationale only" contexts, the *GR* model might have been expected to outperform the *RATD* model (given the additional samples with gold rationale contexts added to *GR* training). However the *GR* model actually underperforms (39.5 vs 42.0).

Table 4: Mean score over unseen evaluation datasets. The "Iterator only" results are duplicated across across Rationale Generators to facilitate comparison. Bold indicates highest score per context type (i.e. per row).

Rationale Generator →	**StableVicuna (FP16)**			**StableVicuna (INT8)**			**BLOOM (INT8)**		
Context ↓ / *Model* →	***GR***	***RATD***	***GR+RATD***	***GR***	***RATD***	***GR+RATD***	***GR***	***RATD***	***GR+RATD***
Iterator only	38.1	40.4	**41.0**	38.1	40.4	**41.0**	38.1	40.4	41.0
Rationale only	44.6	44.4	**45.5**	44.5	44.2	45.3	39.5	42.0	40.3
Rationale + Iterator (Naïve concatenation)	42.9	46.4	47.1	42.7	46.3	**47.2**	43.2	43.8	43.7
Rationale + Iterator (Generally best RR combo)	45.4	46.4	47.1	45.5	46.3	**47.2**	42.9	44.2	44.4
Rationale + Iterator (Best RR combo per dataset)	47.8	47.5	48.0	47.6	47.5	**48.1**	45.1	45.6	45.4

Conversely, where considering StableVicuna-generated "Rationale only" contexts, the *GR* model slightly outperforms the *RATD* model as expected.

Recalling that we use greedy decoding in generating rationales for our evaluation samples, we found it interesting that StableVicuna INT8 and FP16 results are not identical. However since the differences are immaterial, below we focus on the StableVicuna INT8 rationales for brevity.

3.4.2 *GR+RATD* Model versus Baseline and LLM Direct Prompts

It can be seen in Table 4 that where using the stronger StableVicuna-generated rationales, the *GR+RATD* model results dominate both *RATD* and *GR* models, so we consider this as our best model. Table 5 compares *GR+RATD* to our main baseline (i.e. "*RATD*: Iterator only" from Hartill et al. (2023)). Both our "Naïve concatenation" and "Generally best RR combo" combination methods outperform this baseline on the Mean score and on most individual datasets, except for Musique.

Table 5: Evaluation per dataset. Bold indicates best in column excluding Best Prior and Best RR combo per dataset. Best prior are all either not unseen or involve much larger models as follows: [a]Anil et al. (2023): Palm 2 using self consistency. [b]Xu et al. (2021): Finetuned, retrieval from Conceptnet. [c]Bhakthavatsalam et al. (2021): Training includes ARC-DA. [d]Hartill et al. (2023): Finetuned. [e]Trivedi et al. (2022): Specialised retrieval from gold and distractor paragraphs.

***Model*: Context**	**# Params**	**SQA (Acc.)**	**CSQA (Acc.)**	**ARC-DA (F1)**	**IIRC (F1)**	**Musique (F1)**	**Mean**
Random		50.0	20.0				
Best Prior		90.4[a]	91.2[b]	61.4[c]	53.6[d]	49.8[e]	69.3
RATD: Iterator only	440M	58.9	63.6	31.6	25.5	**22.2**	40.4
BLOOM INT8: Few Shot Answer Only Prompt	175B	58.1	47.5	**58.7**	17.3	9.4	38.2
StableVicuna INT8: Few Shot Answer Only Prompt	13B	56.2	70.8	56.8	19.8	9.3	42.6
BLOOM INT8: Few Shot COT Prompt	175B	57.1	54.9	50.5	17.4	11.1	38.2
StableVicuna INT8: Few Shot COT Prompt	13B	61.7	67.7	45.8	20.8	12.6	41.7
GR+RATD: Iterator only	440M	57.3	65.0	35.6	25.6	21.5	41.0
GR+RATD: Rationale only	440M	**64.2**	**73.1**	50.2	25.1	13.8	45.3
GR+RATD: Rationale + Iterator (Naïve concatenation)	440M	61.7	72.6	53.0	27.0	21.7	**47.2**
GR+RATD: Rationale + Iterator (Generally best RR combo)	440M	61.7	72.7	52.1	**27.3**	22.0	**47.2**
GR+RATD: Rationale + Iterator (Best RR combo per dataset)	440M	64.5	73.3	53.0	27.4	22.4	48.1

We next consider the efficacy of directly prompting both LLMs to produce the answer using few-shot COT exemplars, and separately with prompts using the same exemplars but with the rationale portions stripped out such that only the answer is generated ("Answer-Only Prompt"). Here, the most like-for-like comparison is to "*GR+RATD*: Rationale only", since the rationales used are the same ones produced by the direct StableVicuna COT prompts. It can be seen that "*GR+RATD*: Rationale only" outperforms the LLM direct prompts on the overall Mean score, and generally on individual datasets (except for ARC-DA).

In comparing performance of our combined contexts ("Naïve concatenation" and "Generally best RR combo") to the single-component contexts ("Iterator only" and "Rationale only"), both combining methods achieve a higher Mean score than either single component context does. Notably, three of the five datasets (ARC-DA, IIRC and Musique) have higher scores on either combined context than on any single component context as well.

Considering the "Iterator only" against the "Rationale only" rows in Table 5 illuminates the relative strengths of our two knowledge sources. Multi-hop factual questions as exemplifed in Musique benefit far more from retrieved paragraphs than LLM-generated rationales (21.5 F1 vs 13.8 F1) whereas commonsense datasets such as SQA (64.2 acc vs 57.2 acc) and CSQA (73.1 acc vs 65.0 acc) unsurprisingly benefit more from LLM-generated rationales as context. IIRC, another factual dataset might have been expected to benefit more from retrieved paragraphs but performance is similar between rationale-only contexts and retrieved paragraphs. We suggest this is because the input for each IIRC sample is comprised of the question and the initial gold paragraph, and many samples then only require a single extra piece of information in order to have sufficient evidence. LLMs may be better at performing (the equivalent of) this single hop than they are at identifying the multiple additional pieces of information necessary in the Musique case.

3.4.3 *RR* Model scoring and *RATD* training Efficacy

Table 6: *RATD* training and *RR* scoring effectiveness. The *GR* model can be regarded as an ablation of *RATD* dataset training from the *GR+RATD* model (-RATD). The Naïve concatenation context type can be seen as an ablation of *RR* Model scoring from the Generally best RR combo (-RR).

***Model*: Context**		**Mean**
GR+RATD: Rationale + Iterator (Generally best RR combo)	+RR +RATD	47.2
GR+RATD: Rationale + Iterator (Naïve concatenation)	-RR +RATD	47.2
GR: Rationale + Iterator (Generally best RR combo)	+RR -RATD	45.5
GR: Rationale + Iterator (Naïve concatenation)	-RR -RATD	42.7

We now consider the effectiveness of training on *RATD* datasets, and on using *RR* model scores to combine contexts. Table 6 illustrates the relative efficacy of these two methods, both individually and together. What is revealed is that while the *RR* model-scoring approach improves Mean results in the absence of *RATD* training (45.5 vs 42.7), the *RATD* training is more effective, even with just the Naïve concatenation (47.2 vs 42.7).

Table 7: Best combination method per dataset on the *GR+RATD* model. Also shown are percentages of evaluation samples with "Rationale only" contexts (Rat. Only), "Iterator only" contexts (Iter. only), and the concatenation of both (Naïve Concat) respectively.

Dataset	**Sample**	**Best RR combo per dataset**				**Generally best RR combo:** EitherOrBoth(0.9)		
	Count	**Best Method**	**Naïve Concat.**	**Rat. Only**	**Iter. Only**	**Naïve Concat.**	**Rat. Only**	**Iter. Only**
SQA	2290	RationaleDefault(0.75)	0.0	90.7	9.3	94.1	3.6	2.3
CSQA	1221	RationaleDefault(0.75)	0.0	98.3	1.7	79.3	20.6	0.1
ARC-DA	1397	Naïve concatenation	100.0	0.0	0.0	80.5	16.5	3.1
IIRC	1301	RationaleDefault(0.9)	0.0	63.8	36.2	62.6	15.6	21.8
Musique	2417	EitherOrBoth(0.14)	39.3	3.2	57.5	88.2	1.0	10.8
Mean			**27.9**	**51.2**	**20.9**	**80.9**	**11.5**	**7.6**

Differences in individual dataset results in Table 5 shows that the "*GR+RATD*: Generally best RR combo" result of 47.2 is only coincidentally the same as that for the Naïve concatenation. Nonetheless we further explore the reasons why applying both methods together for the *GR+RATD* model does not improve results still further as it seems premature to conclude that the *RATD* training is so effective that it's usage would completely negate any benefit of refining contexts using *RR* scores. The "Generally best RR combo" for the *GR+RATD* model uses the EitherOrBoth(0.9) combination method. This can be interpreted as only selecting a context component if the *RR* model scores it very highly - and hence both components frequently fail to meet the threshold and the default of using the Naïve concatenation then applies. This has the effect of the context being the Naïve concatenation for 80.9% of evaluation samples. (Table 7). This explains why there is no improvement in adding *RR* scoring together with *RATD* training in this instance.

As noted we do not consider the "Best RR combo per dataset" to be a viable method for answering arbitrary questions of unknown type, however in Table 7 we report the best combination method identified for each individual evaluation dataset as it shows what an oracle-like method is capable of producing in comparison

to our actual generally-best *RR*-scoring method. Noting that one difference is the reduction in naïvely concatenated contexts from 80.9% to 27.9% it is plausible that future work on a more refined combination strategy would yield further improvement still in combining *RATD* training with *RR* scoring methods.

4 Conclusion

We have implemented methods for combining explanatory context from two knowledge sources: LLM-generated rationales and retrieved paragraphs from Wikipedia. The first method involves training our smaller Reasoning Model on *RATD* datasets such that it becomes proficient at reasoning over long, noisy contexts which contain information from both knowledge sources. The second method is to use Rationale Ranking model scores for each knowledge source as guidance in constructing contexts that may contain information from both, or either knowledge source. We have shown that both methods are individually effective in improving unseen question-answering performance but that the *RATD* method is more straightforward to implement whilst delivering the strongest results.

We have shown that smaller Language Models can manifest comparable or stronger reasoning performance to LLMs when evaluated under similar assumptions.

After comparing results from question-answering using LLM-generated rationales as context with those using retrieved paragraphs we concluded that LLMs are weaker at surfacing the multiple pieces of information necessary to answer multi-hop factual questions, but stronger at generating rationales suitable for answering commonsense questions. Both knowledge sources are found to be effective for question types such as factual questions requiring a single additional piece of information.

In comparing performance of our combined contexts to the single-component contexts, the combined contexts achieve a higher Mean score over all unseen evaluation datasets than either single component context does. Individually, three of the five datasets (ARC-DA, IIRC and Musique) achieve higher scores when using combined contexts than on any single component context as well.

Broader Impact Statement

Our Reasoning Models following the application of our methods are still capable of generating hallucinated, false and/or potentially offensive answers. Hence usage is most appropriate for research environments.

Conversely, as Hartill et al. (2023) note, latency, physical compute size, cost and energy efficiency are important considerations where smaller models offer material benefits. A diversity of applications exist in the broad domain of reasoning systems and due weight should be assigned to all factors in determining the most appropriate approach for a particular situation.

References

Yuvanesh Anand, Zach Nussbaum, Brandon Duderstadt, Benjamin Schmidt, and Andriy Mulyar. GPT4All: Training an assistant-style chatbot with large scale data distillation from GPT-3.5-Turbo. `https://github.com/nomic-ai/gpt4all`, 2023.

Rohan Anil, Andrew M Dai, Orhan Firat, Melvin Johnson, Dmitry Lepikhin, Alexandre Passos, Siamak Shakeri, Emanuel Taropa, Paige Bailey, Zhifeng Chen, Eric Chu, Jonathan H Clark, Laurent El Shafey, Yanping Huang, Kathy Meier-Hellstern, Gaurav Mishra, Erica Moreira, Mark Omernick, Kevin Robinson, Sebastian Ruder, Yi Tay, Kefan Xiao, Yuanzhong Xu, Yujing Zhang, Gustavo Hernandez Abrego, Junwhan Ahn, Jacob Austin, Paul Barham, Jan Botha, James Bradbury, Siddhartha Brahma, Kevin Brooks, Michele Catasta, Yong Cheng, Colin Cherry, Christopher A Choquette-Choo, Aakanksha Chowdhery, Clément Crepy, Shachi Dave, Mostafa Dehghani, Sunipa Dev, Jacob Devlin, Mark Díaz, Nan Du, Ethan Dyer, Vlad Feinberg, Fangxiaoyu Feng, Vlad Fienber, Markus Freitag, Xavier Garcia, Sebastian Gehrmann, Lucas Gonzalez, Guy Gur-Ari, Steven Hand, Hadi Hashemi, Le Hou, Joshua Howland, Andrea Hu, Jeffrey Hui, Jeremy Hurwitz, Michael Isard, Abe Ittycheriah, Matthew Jagielski, Wenhao Jia, Kathleen Kenealy, Maxim Krikun, Sneha Kudugunta, Chang Lan, Katherine Lee, Benjamin Lee, Eric Li, Music Li, Wei

Li, Yaguang Li, Jian Li, Hyeontaek Lim, Hanzhao Lin, Zhongtao Liu, Frederick Liu, Marcello Maggioni, Aroma Mahendru, Joshua Maynez, Vedant Misra, Maysam Moussalem, Zachary Nado, John Nham, Eric Ni, Andrew Nystrom, Alicia Parrish, Marie Pellat, Martin Polacek, Alex Polozov, Reiner Pope, Siyuan Qiao, Emily Reif, Bryan Richter, Parker Riley, Alex Castro Ros, Aurko Roy, Brennan Saeta, Rajkumar Samuel, Renee Shelby, Ambrose Slone, Daniel Smilkov, David R So, Daniel Sohn, Simon Tokumine, Dasha Valter, Vijay Vasudevan, Kiran Vodrahalli, Xuezhi Wang, Pidong Wang, Zirui Wang, Tao Wang, John Wieting, Yuhuai Wu, Kelvin Xu, Yunhan Xu, Linting Xue, Pengcheng Yin, Jiahui Yu, Qiao Zhang, Steven Zheng, Ce Zheng, Weikang Zhou, Denny Zhou, Slav Petrov, and Yonghui Wu. PaLM 2 technical report. *axXiv preprint arXiv:2305.10403*, May 2023.

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. *arXiv preprint arXiv:2102.03315*, 2021.

BigScience Workshop, :, Teven Le Scao, Angela Fan, Christopher Akiki, Ellie Pavlick, Suzana Ilić, Daniel Hesslow, Roman Castagné, Alexandra Sasha Luccioni, François Yvon, Matthias Gallé, Jonathan Tow, Alexander M Rush, Stella Biderman, Albert Webson, Pawan Sasanka Ammanamanchi, Thomas Wang, Benoît Sagot, Niklas Muennighoff, Albert Villanova del Moral, Olatunji Ruwase, Rachel Bawden, Stas Bekman, Angelina McMillan-Major, Iz Beltagy, Huu Nguyen, Lucile Saulnier, Samson Tan, Pedro Ortiz Suarez, Victor Sanh, Hugo Laurençon, Yacine Jernite, Julien Launay, Margaret Mitchell, Colin Raffel, Aaron Gokaslan, Adi Simhi, Aitor Soroa, Alham Fikri Aji, Amit Alfassy, Anna Rogers, Ariel Kreisberg Nitzav, Canwen Xu, Chenghao Mou, Chris Emezue, Christopher Klamm, Colin Leong, Daniel van Strien, David Ifeoluwa Adelani, Dragomir Radev, Eduardo González Ponferrada, Efrat Levkovizh, Ethan Kim, Eyal Bar Natan, Francesco De Toni, Gérard Dupont, Germán Kruszewski, Giada Pistilli, Hady Elsahar, Hamza Benyamina, Hieu Tran, Ian Yu, Idris Abdulmumin, Isaac Johnson, Itziar Gonzalez-Dios, Javier de la Rosa, Jenny Chim, Jesse Dodge, Jian Zhu, Jonathan Chang, Jörg Frohberg, Joseph Tobing, Joydeep Bhattacharjee, Khalid Almubarak, Kimbo Chen, Kyle Lo, Leandro Von Werra, Leon Weber, Long Phan, Loubna Ben allal, Ludovic Tanguy, Manan Dey, Manuel Romero Muñoz, Maraim Masoud, María Grandury, Mario Šaško, Max Huang, Maximin Coavoux, Mayank Singh, Mike Tian-Jian Jiang, Minh Chien Vu, Mohammad A Jauhar, Mustafa Ghaleb, Nishant Subramani, Nora Kassner, Nurulaqilla Khamis, Olivier Nguyen, Omar Espejel, Ona de Gibert, Paulo Villegas, Peter Henderson, Pierre Colombo, Priscilla Amuok, Quentin Lhoest, Rheza Harliman, Rishi Bommasani, Roberto Luis López, Rui Ribeiro, Salomey Osei, Sampo Pyysalo, Sebastian Nagel, Shamik Bose, Shamsuddeen Hassan Muhammad, Shanya Sharma, Shayne Longpre, Somaieh Nikpoor, Stanislav Silberberg, Suhas Pai, Sydney Zink, Tiago Timponi Torrent, Timo Schick, Tristan Thrush, Valentin Danchev, Vassilina Nikoulina, Veronika Laippala, Violette Lepercq, Vrinda Prabhu, Zaid Alyafeai, Zeerak Talat, Arun Raja, Benjamin Heinzerling, Chenglei Si, Davut Emre Taşar, Elizabeth Salesky, Sabrina J Mielke, Wilson Y Lee, Abheesht Sharma, Andrea Santilli, Antoine Chaffin, Arnaud Stiegler, Debajyoti Datta, Eliza Szczechla, Gunjan Chhablani, Han Wang, Harshit Pandey, Hendrik Strobelt, Jason Alan Fries, Jos Rozen, Leo Gao, Lintang Sutawika, M Saiful Bari, Maged S Al-shaibani, Matteo Manica, Nihal Nayak, Ryan Teehan, Samuel Albanie, Sheng Shen, Srulik Ben-David, Stephen H Bach, Taewoon Kim, Tali Bers, Thibault Fevry, Trishala Neeraj, Urmish Thakker, Vikas Raunak, Xiangru Tang, Zheng-Xin Yong, Zhiqing Sun, Shaked Brody, Yallow Uri, Hadar Tojarieh, Adam Roberts, Hyung Won Chung, Jaesung Tae, Jason Phang, Ofir Press, Conglong Li, Deepak Narayanan, Hatim Bourfoune, Jared Casper, Jeff Rasley, Max Ryabinin, Mayank Mishra, Minjia Zhang, Mohammad Shoeybi, Myriam Peyrounette, Nicolas Patry, Nouamane Tazi, Omar Sanseviero, Patrick von Platen, Pierre Cornette, Pierre François Lavallée, Rémi Lacroix, Samyam Rajbhandari, Sanchit Gandhi, Shaden Smith, Stéphane Requena, Suraj Patil, Tim Dettmers, Ahmed Baruwa, Amanpreet Singh, Anastasia Cheveleva, Anne-Laure Ligozat, Arjun Subramonian, Aurélie Névéol, Charles Lovering, Dan Garrette, Deepak Tunuguntla, Ehud Reiter, Ekaterina Taktasheva, Ekaterina Voloshina, Eli Bogdanov, Genta Indra Winata, Hailey Schoelkopf, Jan-Christoph Kalo, Jekaterina Novikova, Jessica Zosa Forde, Jordan Clive, Jungo Kasai, Ken Kawamura, Liam Hazan, Marine Carpuat, Miruna Clinciu, Najoung Kim, Newton Cheng, Oleg Serikov, Omer Antverg, Oskar van der Wal, Rui Zhang, Ruochen Zhang, Sebastian Gehrmann, Shachar Mirkin, Shani Pais, Tatiana Shavrina, Thomas Scialom, Tian Yun, Tomasz Limisiewicz, Verena Rieser, Vitaly Protasov, Vladislav Mikhailov, Yada Pruksachatkun, Yonatan Belinkov, Zachary Bam-

berger, Zdeněk Kasner, Alice Rueda, Amanda Pestana, Amir Feizpour, Ammar Khan, Amy Faranak, Ana Santos, Anthony Hevia, Antigona Unldreaj, Arash Aghagol, Arezoo Abdollahi, Aycha Tammour, Azadeh HajiHosseini, Bahareh Behroozi, Benjamin Ajibade, Bharat Saxena, Carlos Muñoz Ferrandis, Daniel McDuff, Danish Contractor, David Lansky, Davis David, Douwe Kiela, Duong A Nguyen, Edward Tan, Emi Baylor, Ezinwanne Ozoani, Fatima Mirza, Frankline Ononiwu, Habib Rezanejad, Hessie Jones, Indrani Bhattacharya, Irene Solaiman, Irina Sedenko, Isar Nejadgholi, Jesse Passmore, Josh Seltzer, Julio Bonis Sanz, Livia Dutra, Mairon Samagaio, Maraim Elbadri, Margot Mieskes, Marissa Gerchick, Martha Akinlolu, Michael McKenna, Mike Qiu, Muhammed Ghauri, Mykola Burynok, Nafis Abrar, Nazneen Rajani, Nour Elkott, Nour Fahmy, Olanrewaju Samuel, Ran An, Rasmus Kromann, Ryan Hao, Samira Alizadeh, Sarmad Shubber, Silas Wang, Sourav Roy, Sylvain Viguier, Thanh Le, Tobi Oyebade, Trieu Le, Yoyo Yang, Zach Nguyen, Abhinav Ramesh Kashyap, Alfredo Palasciano, Alison Callahan, Anima Shukla, Antonio Miranda-Escalada, Ayush Singh, Benjamin Beilharz, Bo Wang, Caio Brito, Chenxi Zhou, Chirag Jain, Chuxin Xu, Clémentine Fourrier, Daniel León Periñán, Daniel Molano, Dian Yu, Enrique Manjavacas, Fabio Barth, Florian Fuhrimann, Gabriel Altay, Giyaseddin Bayrak, Gully Burns, Helena U Vrabec, Imane Bello, Ishani Dash, Jihyun Kang, John Giorgi, Jonas Golde, Jose David Posada, Karthik Rangasai Sivaraman, Lokesh Bulchandani, Lu Liu, Luisa Shinzato, Madeleine Hahn de Bykhovetz, Maiko Takeuchi, Marc Pàmies, Maria A Castillo, Marianna Nezhurina, Mario Sänger, Matthias Samwald, Michael Cullan, Michael Weinberg, Michiel De Wolf, Mina Mihaljcic, Minna Liu, Moritz Freidank, Myungsun Kang, Natasha Seelam, Nathan Dahlberg, Nicholas Michio Broad, Nikolaus Muellner, Pascale Fung, Patrick Haller, Ramya Chandrasekhar, Renata Eisenberg, Robert Martin, Rodrigo Canalli, Rosaline Su, Ruisi Su, Samuel Cahyawijaya, Samuele Garda, Shlok S Deshmukh, Shubhanshu Mishra, Sid Kiblawi, Simon Ott, Sinee Sang-aroonsiri, Srishti Kumar, Stefan Schweter, Sushil Bharati, Tanmay Laud, Théo Gigant, Tomoya Kainuma, Wojciech Kusa, Yanis Labrak, Yash Shailesh Bajaj, Yash Venkatraman, Yifan Xu, Yingxin Xu, Yu Xu, Zhe Tan, Zhongli Xie, Zifan Ye, Mathilde Bras, Younes Belkada, and Thomas Wolf. BLOOM: A 176B-Parameter Open-Access multilingual language model. *xXiv preprint arXiv:2211.05100*, 2022.

Steven Bird, Ewan Klein, and Edward Loper. *Natural Language Processing with Python: Analyzing Text with the Natural Language Toolkit*. O'Reilly Media, Inc., June 2009.

Antoine Bosselut, Hannah Rashkin, Maarten Sap, Chaitanya Malaviya, Asli Celikyilmaz, and Yejin Choi. COMET: Commonsense transformers for automatic knowledge graph construction. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pp. 4762–4779, Florence, Italy, July 2019. Association for Computational Linguistics.

Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are Few-Shot learners. In *Advances in Neural Information Processing Systems 33*, pp. 1877–1901, 2020.

Danqi Chen, Adam Fisch, Jason Weston, and Antoine Bordes. Reading Wikipedia to answer Open-Domain questions. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 1870–1879, Vancouver, Canada, 2017. Association for Computational Linguistics.

Xinyun Chen, Maxwell Lin, Nathanael Schärli, and Denny Zhou. Teaching large language models to Self-Debug. *arXiv preprint arXiv:2304.05128*, April 2023.

I-Chun Chern, Steffi Chern, Shiqi Chen, Weizhe Yuan, Kehua Feng, Chunting Zhou, Junxian He, Graham Neubig, and Pengfei Liu. FacTool: Factuality detection in generative AI – a tool augmented framework for multi-task and multi-domain scenarios. *arXiv preprint arXiv:307.13528*, July 2023.

Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E. Gonzalez, Ion Stoica, and Eric P. Xing. Vicuna: An open-source chatbot

impressing gpt-4 with 90%* chatgpt quality. https://lmsys.org/blog/2023-03-30-vicuna/, March 2023.

Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, Parker Schuh, Kensen Shi, Sasha Tsvyashchenko, Joshua Maynez, Abhishek Rao, Parker Barnes, Yi Tay, Noam Shazeer, Vinodkumar Prabhakaran, Emily Reif, Nan Du, Ben Hutchinson, Reiner Pope, James Bradbury, Jacob Austin, Michael Isard, Guy Gur-Ari, Pengcheng Yin, Toju Duke, Anselm Levskaya, Sanjay Ghemawat, Sunipa Dev, Henryk Michalewski, Xavier Garcia, Vedant Misra, Kevin Robinson, Liam Fedus, Denny Zhou, Daphne Ippolito, David Luan, Hyeontaek Lim, Barret Zoph, Alexander Spiridonov, Ryan Sepassi, David Dohan, Shivani Agrawal, Mark Omernick, Andrew M Dai, Thanumalayan Sankaranarayana Pillai, Marie Pellat, Aitor Lewkowycz, Erica Moreira, Rewon Child, Oleksandr Polozov, Katherine Lee, Zongwei Zhou, Xuezhi Wang, Brennan Saeta, Mark Diaz, Orhan Firat, Michele Catasta, Jason Wei, Kathy Meier-Hellstern, Douglas Eck, Jeff Dean, Slav Petrov, and Noah Fiedel. PaLM: Scaling language modeling with pathways. *arXiv preprint arXiv:2204.02311*, April 2022.

Christopher Clark and Matt Gardner. Simple and effective Multi-Paragraph reading comprehension. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 845–855, Melbourne, Australia, July 2018. Association for Computational Linguistics.

Kevin Clark, Minh-Thang Luong, Quoc V Le, and Christopher D Manning. ELECTRA: Pre-training text encoders as discriminators rather than generators. In *International Conference on Learning Representations*, March 2020.

Peter Clark, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Oyvind Tafjord, Peter Turney, and Daniel Khashabi. Combining retrieval, statistics, and inference to answer elementary science questions. In *AAAI Conference on Artificial Intelligence*, volume 30. Association for the Advancement of Artificial Intelligence, 2016.

Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. Think you have solved question answering? try ARC, the AI2 reasoning challenge. *arXiv preprint arXiv:1803.05457*, 2018.

Tim Dettmers, Mike Lewis, Younes Belkada, and Luke Zettlemoyer. LLM.int8(): 8-bit matrix multiplication for transformers at scale. In *36th Conference on Neural Information Processing Systems*, pp. 30318–30332, August 2022.

Jay DeYoung, Sarthak Jain, Nazneen Fatema Rajani, Eric Lehman, Caiming Xiong, Richard Socher, and Byron C Wallace. ERASER: A benchmark to evaluate rationalized NLP models. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 4443–4458. Association for Computational Linguistics, 2020.

Dheeru Dua, Yizhong Wang, Pradeep Dasigi, Gabriel Stanovsky, Sameer Singh, and Matt Gardner. DROP: A reading comprehension benchmark requiring discrete reasoning over paragraphs. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pp. 2368–2378, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics.

James Ferguson, Matt Gardner, Hannaneh Hajishirzi, Tushar Khot, and Pradeep Dasigi. IIRC: A dataset of incomplete information reading comprehension questions. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 1137–1147, Stroudsburg, PA, USA, November 2020. Association for Computational Linguistics.

Jinlan Fu, See-Kiong Ng, Zhengbao Jiang, and Pengfei Liu. GPTScore: Evaluate as you desire. *arXiv preprint arXiv:2302.04166*, February 2023.

Mor Geva, Daniel Khashabi, Elad Segal, Tushar Khot, Dan Roth, and Jonathan Berant. Did aristotle use a laptop? a question answering benchmark with implicit reasoning strategies. *Transactions of the Association for Computational Linguistics*, 9:346–361, 2021.

Tim Hartill, Neset TAN, Michael Witbrock, and Patricia J Riddle. Teaching smaller language models to generalise to unseen compositional questions. *arXiv preprint arXiv:2308.00946*, August 2023.

Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. The curious case of neural text degeneration. In *International Conference on Learning Representations*, September 2019.

Cheng-Yu Hsieh, Chun-Liang Li, Chih-Kuan Yeh, Hootan Nakhost, Yasuhisa Fujii, Alexander Ratner, Ranjay Krishna, Chen-Yu Lee, and Tomas Pfister. Distilling Step-by-Step! outperforming larger language models with less training data and smaller model sizes. In *Findings of the Association for Computational Linguistics: ACL 2023*, pp. 8003–8017. Association for Computational Linguistics, 2023.

Naoya Inoue, Pontus Stenetorp, and Kentaro Inui. R4C: A benchmark for evaluating RC systems to get the right answer for the right reason. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 6740–6750. Association for Computational Linguistics., 2020.

Harsh Jhamtani and Peter Clark. Learning to explain: Datasets and models for identifying valid reasoning chains in multihop Question-Answering. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing*, pp. 137–150, Online, 2020. Association for Computational Linguistics.

Yichen Jiang, Shikha Bordia, Zheng Zhong, Charles Dognin, Maneesh Singh, and Mohit Bansal. HoVer: A dataset for Many-Hop fact extraction and claim verification. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pp. 3441–3460. Association for Computational Linguistics, 2020.

Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-Tau Yih. Dense passage retrieval for Open-Domain question answering. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 6769–6781, Online, November 2020. Association for Computational Linguistics.

Daniel Khashabi, Sewon Min, Tushar Khot, Ashish Sabharwal, Oyvind Tafjord, Peter Clark, and Hannaneh Hajishirzi. UNIFIEDQA: Crossing format boundaries with a single QA system. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pp. 1896–1907, Online, 2020. Association for Computational Linguistics.

Omar Khattab, Christopher Potts, and Matei Zaharia. Baleen: Robust multi-hop reasoning at scale via condensed retrieval. In *Advances in Neural Information Processing Systems, 34*, pp. 27670–27682, 2021.

Tushar Khot, Peter Clark, Michal Guerquin, Peter Jansen, and Ashish Sabharwal. QASC: A dataset for question answering via sentence composition. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34(05), pp. 8082–8090. Association for the Advancement of Artificial Intelligence, 2020.

Andreas Köpf, Yannic Kilcher, Dimitri von Rütte, Sotiris Anagnostidis, Zhi-Rui Tam, Keith Stevens, Abdullah Barhoum, Nguyen Minh Duc, Oliver Stanley, Richárd Nagyfi, E S Shahul, Sameer Suri, David Glushkov, Arnav Dantuluri, Andrew Maguire, Christoph Schuhmann, Huu Nguyen, and Alexander Mattick. OpenAssistant conversations – democratizing large language model alignment. *arXiv preprint arXiv:2304.07327*, April 2023.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. BART: Denoising Sequence-to-Sequence pre-training for natural language generation, translation, and comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 7871–7880, Online, 2020. Association for Computational Linguistics.

Patrick Lewis, Pontus Stenetorp, and Sebastian Riedel. Question and answer Test-Train overlap in Open-Domain question answering datasets. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pp. 1000–1008, Online, 2021. Association for Computational Linguistics.

Liunian Harold Li, Jack Hessel, Youngjae Yu, Xiang Ren, Kai-Wei Chang, and Yejin Choi. Symbolic Chain-of-Thought distillation: Small models can also "think" step-by-step. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 2665–2679. Association for Computational Linguistics, June 2023.

Jimmy Lin, Rodrigo Nogueira, and Andrew Yates. *Pretrained Transformers for Text Ranking: BERT and Beyond*. Springer Nature, June 2022a.

Stephanie Lin, Jacob Hilton, and Owain Evans. TruthfulQA: Measuring how models mimic human falsehoods. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 3214–3252, Stroudsburg, PA, USA, May 2022b. Association for Computational Linguistics.

Jiacheng Liu, Alisa Liu, Ximing Lu, Sean Welleck, Peter West, Ronan Le Bras, Yejin Choi, and Hannaneh Hajishirzi. Generated knowledge prompting for commonsense reasoning. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 3154–3169, Stroudsburg, PA, USA, May 2022. Association for Computational Linguistics.

Aman Madaan, Niket Tandon, Prakhar Gupta, Skyler Hallinan, Luyu Gao, Sarah Wiegreffe, Uri Alon, Nouha Dziri, Shrimai Prabhumoye, Yiming Yang, Sean Welleck, Bodhisattwa Prasad Majumder, Shashank Gupta, Amir Yazdanbakhsh, and Peter Clark. Self-refine: Iterative refinement with self-feedback. *arXiv preprint arXiv:2303.17651*, March 2023.

Lucie Charlotte Magister, Jonathan Mallinson, Jakub Adamek, Eric Malmi, and Aliaksei Severyn. Teaching small language models to reason. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pp. 1773–1781, Toronto, Canada, July 2023. Association for Computational Linguistics.

Potsawee Manakul, Adian Liusie, and Mark J F Gales. SelfCheckGPT: Zero-resource black-box hallucination detection for generative large language models. *arXiv preprint arXiv:2303.08896*, March 2023.

Sewon Min, Kalpesh Krishna, Xinxi Lyu, Mike Lewis, Wen-Tau Yih, Pang Wei Koh, Mohit Iyyer, Luke Zettlemoyer, and Hannaneh Hajishirzi. FActScore: Fine-grained atomic evaluation of factual precision in long form text generation. *arXiv preprint arXiv:2305.14251*, May 2023.

Bhaskar Mitra and Nick Craswell. An introduction to neural information retrieval. *Foundations and Trends® in Information Retrieval*, 13(1):1–126, 2018.

Hans Moravec. *Mind Children: The Future of Robot and Human Intelligence*. Harvard University Press, 1988.

Yasumasa Onoe, Michael J Q Zhang, Eunsol Choi, and Greg Durrett. CREAK: A dataset for commonsense reasoning over entity knowledge. In *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2)*, November 2021.

OpenAI. GPT-4 technical report. *arXiv preprint arXiv:2303.08774*, March 2023.

Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul Christiano, Jan Leike, and Ryan Lowe. Training language models to follow instructions with human feedback. In *Advances in Neural Information Processing Systems*, 35, pp. 27730–27744, 2022.

Xiaoman Pan, Wenlin Yao, Hongming Zhang, Dian Yu, Dong Yu, and Jianshu Chen. Knowledge-in-Context: Towards knowledgeable Semi-Parametric language models. In *The Eleventh International Conference on Learning Representations*, 2023.

Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. Improving language understanding by generative pre-training. `http://openai-assets.s3.amazonaws.com/research-covers/language-unsupervised/language_understanding_paper.pdf`, 2018.

Maarten Sap, Ronan Le Bras, Emily Allaway, Chandra Bhagavatula, Nicholas Lourie, Hannah Rashkin, Brendan Roof, Noah A Smith, and Yejin Choi. ATOMIC: An atlas of machine commonsense for if-then reasoning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, 33(01), pp. 3027–3035, 2019.

Kumar Shridhar, Alessandro Stolfo, and Mrinmaya Sachan. Distilling reasoning capabilities into smaller language models. In *Findings of the Association for Computational Linguistics: ACL 2023*, pp. 7059–7073, Toronto, Canada, July 2023. Association for Computational Linguistics.

Vered Shwartz, Peter West, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. Unsupervised commonsense question answering with self-talk. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 4615–4629, Stroudsburg, PA, USA, November 2020. Association for Computational Linguistics.

Karen Spärck Jones. A statistical interpretation of term specificity and its application in retrieval. *Journal of Documentation*, 28(1):11–21, 1972.

Robyn Speer, Joshua Chin, and Catherine Havasi. ConceptNet 5.5: An open multilingual graph of general knowledge. In *Proceedings of the AAAI Conference on Artificial Intelligence*, 31(1), pp. 4444–4451, 2017.

Aarohi Srivastava, Abhinav Rastogi, Abhishek Rao, Abu Awal Md Shoeb, Abubakar Abid, Adam Fisch, Adam R Brown, Adam Santoro, Aditya Gupta, Adrià Garriga-Alonso, Agnieszka Kluska, Aitor Lewkowycz, Akshat Agarwal, Alethea Power, Alex Ray, Alex Warstadt, Alexander W Kocurek, Ali Safaya, Ali Tazarv, Alice Xiang, Alicia Parrish, Allen Nie, Aman Hussain, Amanda Askell, Amanda Dsouza, Ambrose Slone, Ameet Rahane, Anantharaman S Iyer, Anders Andreassen, Andrea Madotto, Andrea Santilli, Andreas Stuhlmüller, Andrew Dai, Andrew La, Andrew Lampinen, Andy Zou, Angela Jiang, Angelica Chen, Anh Vuong, Animesh Gupta, Anna Gottardi, Antonio Norelli, Anu Venkatesh, Arash Gholamidavoodi, Arfa Tabassum, Arul Menezes, Arun Kirubarajan, Asher Mullokandov, Ashish Sabharwal, Austin Herrick, Avia Efrat, Aykut Erdem, Ayla Karakaş, B Ryan Roberts, Bao Sheng Loe, Barret Zoph, Bartłomiej Bojanowski, Batuhan Özyurt, Behnam Hedayatnia, Behnam Neyshabur, Benjamin Inden, Benno Stein, Berk Ekmekci, Bill Yuchen Lin, Blake Howald, Cameron Diao, Cameron Dour, Catherine Stinson, Cedrick Argueta, César Ferri Ramírez, Chandan Singh, Charles Rathkopf, Chenlin Meng, Chitta Baral, Chiyu Wu, Chris Callison-Burch, Chris Waites, Christian Voigt, Christopher D Manning, Christopher Potts, Cindy Ramirez, Clara E Rivera, Clemencia Siro, Colin Raffel, Courtney Ashcraft, Cristina Garbacea, Damien Sileo, Dan Garrette, Dan Hendrycks, Dan Kilman, Dan Roth, Daniel Freeman, Daniel Khashabi, Daniel Levy, Daniel Moseguí González, Danielle Perszyk, Danny Hernandez, Danqi Chen, Daphne Ippolito, Dar Gilboa, David Dohan, David Drakard, David Jurgens, Debajyoti Datta, Deep Ganguli, Denis Emelin, Denis Kleyko, Deniz Yuret, Derek Chen, Derek Tam, Dieuwke Hupkes, Diganta Misra, Dilyar Buzan, Dimitri Coelho Mollo, Diyi Yang, Dong-Ho Lee, Ekaterina Shutova, Ekin Dogus Cubuk, Elad Segal, Eleanor Hagerman, Elizabeth Barnes, Elizabeth Donoway, Ellie Pavlick, Emanuele Rodola, Emma Lam, Eric Chu, Eric Tang, Erkut Erdem, Ernie Chang, Ethan A Chi, Ethan Dyer, Ethan Jerzak, Ethan Kim, Eunice Engefu Manyasi, Evgenii Zheltonozhskii, Fanyue Xia, Fatemeh Siar, Fernando Martínez-Plumed, Francesca Happé, Francois Chollet, Frieda Rong, Gaurav Mishra, Genta Indra Winata, Gerard de Melo, Germán Kruszewski, Giambattista Parascandolo, Giorgio Mariani, Gloria Wang, Gonzalo Jaimovitch-López, Gregor Betz, Guy Gur-Ari, Hana Galijasevic, Hannah Kim, Hannah Rashkin, Hannaneh Hajishirzi, Harsh Mehta, Hayden Bogar, Henry Shevlin, Hinrich Schütze, Hiromu Yakura, Hongming Zhang, Hugh Mee Wong, Ian Ng, Isaac Noble, Jaap Jumelet, Jack Geissinger, Jackson Kernion, Jacob Hilton, Jaehoon Lee, Jaime Fernández Fisac, James B Simon, James Koppel, James Zheng, James Zou, Jan Kocoń, Jana Thompson, Jared Kaplan, Jarema Radom, Jascha Sohl-Dickstein, Jason Phang, Jason Wei, Jason Yosinski, Jekaterina Novikova, Jelle Bosscher, Jennifer Marsh, Jeremy Kim, Jeroen Taal, Jesse Engel, Jesujoba Alabi, Jiacheng Xu, Jiaming Song, Jillian Tang, Joan Waweru, John Burden, John Miller, John U Balis, Jonathan Berant, Jörg Frohberg, Jos Rozen, Jose Hernandez-Orallo, Joseph Boudeman, Joseph Jones, Joshua B Tenenbaum, Joshua S Rule, Joyce Chua, Kamil Kanclerz, Karen Livescu, Karl Krauth, Karthik Gopalakrishnan, Katerina Ignatyeva, Katja Markert, Kaustubh D Dhole, Kevin Gimpel, Kevin Omondi, Kory Mathewson, Kristen Chiafullo, Ksenia Shkaruta, Kumar Shridhar, Kyle McDonell, Kyle Richardson, Laria Reynolds, Leo Gao, Li Zhang, Liam Dugan, Lianhui Qin, Lidia Contreras-Ochando, Louis-Philippe Morency, Luca Moschella, Lucas Lam, Lucy Noble, Ludwig Schmidt,

Luheng He, Luis Oliveros Colón, Luke Metz, Lütfi Kerem Şenel, Maarten Bosma, Maarten Sap, Maartje ter Hoeve, Maheen Farooqi, Manaal Faruqui, Mantas Mazeika, Marco Baturan, Marco Marelli, Marco Maru, Maria Jose Ramírez Quintana, Marie Tolkiehn, Mario Giulianelli, Martha Lewis, Martin Potthast, Matthew L Leavitt, Matthias Hagen, Mátyás Schubert, Medina Orduna Baitemirova, Melody Arnaud, Melvin McElrath, Michael A Yee, Michael Cohen, Michael Gu, Michael Ivanitskiy, Michael Starritt, Michael Strube, Michał Swędrowski, Michele Bevilacqua, Michihiro Yasunaga, Mihir Kale, Mike Cain, Mimee Xu, Mirac Suzgun, Mo Tiwari, Mohit Bansal, Moin Aminnaseri, Mor Geva, Mozhdeh Gheini, Varma T Mukund, Nanyun Peng, Nathan Chi, Nayeon Lee, Neta Gur-Ari Krakover, Nicholas Cameron, Nicholas Roberts, Nick Doiron, Nikita Nangia, Niklas Deckers, Niklas Muennighoff, Nitish Shirish Keskar, Niveditha S Iyer, Noah Constant, Noah Fiedel, Nuan Wen, Oliver Zhang, Omar Agha, Omar Elbaghdadi, Omer Levy, Owain Evans, Pablo Antonio Moreno Casares, Parth Doshi, Pascale Fung, Paul Pu Liang, Paul Vicol, Pegah Alipoormolabashi, Peiyuan Liao, Percy Liang, Peter Chang, Peter Eckersley, Phu Mon Htut, Pinyu Hwang, Piotr Miłkowski, Piyush Patil, Pouya Pezeshkpour, Priti Oli, Qiaozhu Mei, Qing Lyu, Qinlang Chen, Rabin Banjade, Rachel Etta Rudolph, Raefer Gabriel, Rahel Habacker, Ramón Risco Delgado, Raphaël Millière, Rhythm Garg, Richard Barnes, Rif A Saurous, Riku Arakawa, Robbe Raymaekers, Robert Frank, Rohan Sikand, Roman Novak, Roman Sitelew, Ronan LeBras, Rosanne Liu, Rowan Jacobs, Rui Zhang, Ruslan Salakhutdinov, Ryan Chi, Ryan Lee, Ryan Stovall, Ryan Teehan, Rylan Yang, Sahib Singh, Saif M Mohammad, Sajant Anand, Sam Dillavou, Sam Shleifer, Sam Wiseman, Samuel Gruetter, Samuel R Bowman, Samuel S Schoenholz, Sanghyun Han, Sanjeev Kwatra, Sarah A Rous, Sarik Ghazarian, Sayan Ghosh, Sean Casey, Sebastian Bischoff, Sebastian Gehrmann, Sebastian Schuster, Sepideh Sadeghi, Shadi Hamdan, Sharon Zhou, Shashank Srivastava, Sherry Shi, Shikhar Singh, Shima Asaadi, Shixiang Shane Gu, Shubh Pachchigar, Shubham Toshniwal, Shyam Upadhyay, Shyamolima, Debnath, Siamak Shakeri, Simon Thormeyer, Simone Melzi, Siva Reddy, Sneha Priscilla Makini, Soo-Hwan Lee, Spencer Torene, Sriharsha Hatwar, Stanislas Dehaene, Stefan Divic, Stefano Ermon, Stella Biderman, Stephanie Lin, Stephen Prasad, Steven T Piantadosi, Stuart M Shieber, Summer Misherghi, Svetlana Kiritchenko, Swaroop Mishra, Tal Linzen, Tal Schuster, Tao Li, Tao Yu, Tariq Ali, Tatsu Hashimoto, Te-Lin Wu, Théo Desbordes, Theodore Rothschild, Thomas Phan, Tianle Wang, Tiberius Nkinyili, Timo Schick, Timofei Kornev, Timothy Telleen-Lawton, Titus Tunduny, Tobias Gerstenberg, Trenton Chang, Trishala Neeraj, Tushar Khot, Tyler Shultz, Uri Shaham, Vedant Misra, Vera Demberg, Victoria Nyamai, Vikas Raunak, Vinay Ramasesh, Vinay Uday Prabhu, Vishakh Padmakumar, Vivek Srikumar, William Fedus, William Saunders, William Zhang, Wout Vossen, Xiang Ren, Xiaoyu Tong, Xinran Zhao, Xinyi Wu, Xudong Shen, Yadollah Yaghoobzadeh, Yair Lakretz, Yangqiu Song, Yasaman Bahri, Yejin Choi, Yichi Yang, Yiding Hao, Yifu Chen, Yonatan Belinkov, Yu Hou, Yufang Hou, Yuntao Bai, Zachary Seid, Zhuoye Zhao, Zijian Wang, Zijie J Wang, Zirui Wang, and Ziyi Wu. Beyond the imitation game: Quantifying and extrapolating the capabilities of language models. *arXiv preprint arXiv:2206.04615*, June 2022.

Stability-AI. Stability AI releases StableVicuna, the AI World's First Open Source RLHF LLM Chatbot. `https://stability.ai/blog/stablevicuna-open-source-rlhf-chatbot/`, April 2023. Accessed: 2023-7-5.

Alon Talmor, Jonathan Herzig, Nicholas Lourie, and Jonathan Berant. CommonsenseQA: A question answering challenge targeting commonsense knowledge. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pp. 4149–4158. Association for Computational Linguistics, 2019.

Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B Hashimoto. Stanford alpaca: An instruction-following LLaMA model. `https://github.com/tatsu-lab/stanford_alpaca`, 2023.

James Thorne, Andreas Vlachos, Christos Christodoulopoulos, and Arpit Mittal. FEVER: A large-scale dataset for fact extraction and VERification. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, Stroudsburg, PA, USA, 2018. Association for Computational Linguistics.

Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurelien Rodriguez, Armand Joulin, Edouard

Grave, and Guillaume Lample. LLaMA: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*, February 2023.

Harsh Trivedi, Niranjan Balasubramanian, Tushar Khot, and Ashish Sabharwal. MuSiQue: Multihop questions via single-hop question composition. *Transactions of the Association for Computational Linguistics*, 10:539–554, 2022.

Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. SuperGLUE: A stickier benchmark for General-Purpose language understanding systems. In *Advances in Neural Information Processing Systems*, 32, May 2019a.

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 *International Conference on Learning Representations*, 2019b.

Shuohang Wang, Mo Yu, Xiaoxiao Guo, Zhiguo Wang, Tim Klinger, Wei Zhang, Shiyu Chang, Gerry Tesauro, Bowen Zhou, and Jing Jiang. R^3: Reinforced Ranker-Reader for open-domain question answering. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 32. Association for the Advancement of Artificial Intelligence, April 2018.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Ed Chi, Quoc Le, and Denny Zhou. Chain of thought prompting elicits reasoning in large language models. In *Thirty-sixth Conference on Neural Information Processing Systems (NeurIPS 2022)*, January 2022.

Sarah Wiegreffe and Ana Marasović. Teach me to explain: A review of datasets for explainable NLP. *arXiv:2102.12060 [cs.CL]*, 2021.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, Stroudsburg, PA, USA, 2020. Association for Computational Linguistics.

Dingjun Wu, Jing Zhang, and Xinmei Huang. Chain of thought prompting elicits knowledge augmentation. In *Findings of the Association for Computational Linguistics: ACL 2023*, pp. 6519–6534. Association for Computational Linguistics, July 2023.

Zhengnan Xie, Sebastian Thiem, Jaycie Martin, Elizabeth Wainwright, Steven Marmorstein, and Peter Jansen. WorldTree v2: A corpus of science-domain structured explanations and inference patterns supporting multi-hop inference. In *Proceedings of the 12th Language Resources and Evaluation Conference*, pp. 5456–5473, Marseille, France, 2020. European Language Resources Association.

Wenhan Xiong, Xiang Li, Srini Iyer, Jingfei Du, Patrick Lewis, William Yang Wang, Yashar Mehdad, Scott Yih, Sebastian Riedel, Douwe Kiela, and Barlas Oguz. Answering complex Open-Domain questions with Multi-Hop dense retrieval. In *International Conference on Learning Representations*, 2021.

Yichong Xu, Chenguang Zhu, Shuohang Wang, Siqi Sun, Hao Cheng, Xiaodong Liu, Jianfeng Gao, Pengcheng He, Michael Zeng, and Xuedong Huang. Human parity on CommonsenseQA: Augmenting Self-Attention with external attention. *arXiv preprint arXiv: 2112.03254*, December 2021.

Yichong Xu, Chenguang Zhu, Shuohang Wang, Siqi Sun, Hao Cheng, Xiaodong Liu, Jianfeng Gao, Pengcheng He, Michael Zeng, and Xuedong Huang. Human parity on commonsenseqa: Augmenting self-attention with external attention. In *Proceedings of the Thirty-First International Joint Conference on Artificial Intelligence, IJCAI-22*, pp. 2762–2768, 2022.

Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William Cohen, Ruslan Salakhutdinov, and Christopher D Manning. HotpotQA: A dataset for diverse, explainable multi-hop question answering. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pp. 2369–2380. Association for Computational Linguistics, 2018.

Wenhao Yu, Chenguang Zhu, Zhihan Zhang, Shuohang Wang, Zhuosheng Zhang, Yuwei Fang, and Meng Jiang. Retrieval augmentation for commonsense reasoning: A unified approach. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pp. 4364–4377. Association for Computational Linguistics, October 2022.

Weizhe Yuan, Graham Neubig, and Pengfei Liu. Bartscore: Evaluating generated text as text generation. *Advances in Neural Information Processing Systems*, 34:27263–27277, 2021.

A Hyperparameters

All models are trained on one Nvidia A100 80GB GPU using mixed precision and a linear learning rate decay schedule. Initial learning rates and other hyperparameters are shown in Table 8. The optimiser used for the Rationale Ranker is Adam. All other models use AdamW. A maximum sequence length of 512 tokens was used for all trained models. The *GR* and *GR+RATD* Reasoning Model training starts from the *Base* model checkpoint described in Hartill et al. (2023).

Table 8: Hyperparameters used for each model. Each training step is one batch input i.e the number of optimization steps is $TrainingSteps/GradientAccumulationSteps$. All final models are selected as the best model on the development set(s) over the specified number of training steps.

Model	**Initial LR**	**Batch Size**	**Grad. Accum**	**Train Steps**
Rationale Ranker	5e-5	24	8	188K
Reasoning Models	2e-5	32	4	1M

B Prompts For LLM Rationale Generation

Here we show the few-shot COT prompts used against the StableVicuna Model. Prompts used against BLOOM use the same examples and instructions and simply have "Q:" substituted for "### Human:" (excepting the initial instruction which substitutes the empty string), and "A:" substituted for "### Assistant:". The corresponding "Answer only" prompts are identical except that the examples have both the rationale and the answer key ("So the answer is") removed. Rationales were constructed by truncating the generation at the first <newline> character and then truncating again at the answer key.

B.1 Binary-labelled Datasets (SQA)

```
### Human:  Write a truthful, factual explanation to help answer the question, then
answer the question.

### Human:  A pupil can be either a student or part of an eye?
### Assistant:  A pupil is another word for student.  The pupil is also a hole located in
the center of the iris of the eye that allows light to strike the retina.  Thus pupil can
have either meaning.  So the answer is yes.
### Human:  Greece is larger than mexico?
### Assistant:  Greece is approximately 131,957 sq km, while Mexico is approximately
1,964,375 sq km, making Mexico 1,389% larger than Greece.  So the answer is no.
### Human:  Glasses always fog up?
### Assistant:  Condensation occurs on eyeglass lenses when water vapor from your sweat,
breath, and ambient humidity lands on a cold surface, cools, and then changes into tiny
drops of liquid, forming a film that you see as fog.  Your lenses will be relatively cool
compared to your breath when the outside air is cold but not when the air is warm.  So
the answer is no.
```

```
### Human:  A fish is capable of thinking?
### Assistant:  Fish are more intelligent than they appear.  In many areas, such as
memory, their cognitive powers match or exceed those of 'higher' vertebrates including
non-human primates.  Fish's long-term memories help them keep track of complex social
relationships.  So the answer is yes.
### Human:  Is a 5 by 8 pool of bricks larger than an 8 by 5 pool of pillows?
### Assistant:  The 5 by 8 pool of bricks has an area of 40.  The 8 by 5 pool of pillows
also covers an area of 40.  Thus, both pools are the same size.  So the answer is no.
### Human:  When listed alphabetically, would the words baseball and demonstration appear
in this order?
### Assistant:  Baseball begins with letter b and demonstration begins with letter d.
Alphabetically, b comes before d, thus baseball comes before demonstration.  So the
answer is yes.
### Human:  Would Sally use a spaceship if she needed to get to London from Sydney
quickly?
### Assistant:  Commerical spaceship transport doesnt exist yet.  London is far from
Sydney and planes are faster than trains or boats over long distances.  Thus, Sally would
use an existing transportation option like a plane.  So the answer is no.
### Human:  A common effect of smoking lots of cigarettes in one's lifetime is a higher
than normal chance of getting lung cancer?
### Assistant:  Those who consistently averaged less than one cigarette per day over
their lifetime had nine times the risk of dying from lung cancer than non-smokers.  Among
people who smoked between one and 10 cigarettes per day, the risk of dying from lung
cancer was nearly 12 times higher than that of non-smokers.  So the answer is yes.
### Human:  A rock is the same size as a pebble?
### Assistant:  A pebble is a clast of rock with a particle size of 4 to 64 millimetres
based on the Udden-Wentworth scale of sedimentology.  Pebbles are generally considered
larger than granules (2 to 4 millimetres diameter) and smaller than cobbles (64 to 256
millimetres diameter).  So the answer is no.
### Human:  {QUESTION}
### Assistant:
```

B.2 Span or binary answers (ARC-DA, IIRC, Musique)

```
### Human:  Write a truthful, factual explanation to help answer the question, then
answer the question.

### Human:  Greece is larger than mexico?
### Assistant:  Greece is approximately 131,957 sq km, while Mexico is approximately
1,964,375 sq km, making Mexico 1,389% larger than Greece.  So the answer is no.
### Human:  Tools can be made of wood, iron, plastic amongst other things.  Iron tools
historically replaced what?
### Assistant:  Historically, iron tools were first used in the Iron Age.  The Iron Age
followed the Bronze Age.  Thus, iron tools replacing bronze tools makes most sense.  So
the answer is bronze tools.
### Human:  Which magazine was started first Arthur's Magazine or First for Women?
### Assistant:  Arthur's Magazine was an American literary periodical first published
1844.  First for Women is a woman's magazine that started in 1989.  So the answer is
Arthur's Magazine.
### Human:  Glasses always fog up?
### Assistant:  Condensation occurs on eyeglass lenses when water vapor from your sweat,
breath, and ambient humidity lands on a cold surface, cools, and then changes into tiny
drops of liquid, forming a film that you see as fog.  Your lenses will be relatively cool
compared to your breath when the outside air is cold but not when the air is warm.  So
```

```
the answer is no.
### Human:  Water flows downhill and tends to collect in low-lying areas such as valleys
and holes.  Lakes are usually large bodies of fresh water.  Where is a lake likely to be
found?
### Assistant:  The answer must be somewhere that a lot of water can collect.  A valley
is likely to be able to collect enough water.  So the answer is a valley.
### Human:  Foxes are predators whose natural habitat is the forest.  They have also been
known to eat chickens from people's properties.  The fox walked from the city into the
forest, what was it looking for?
### Assistant:  The answer must be a reason for a fox to go into the forest.  The forest
is a fox's natural habitat.  So the answer is natural habitat.
### Human:  A fish is capable of thinking?
### Assistant:  Fish are more intelligent than they appear.  In many areas, such as
memory, their cognitive powers match or exceed those of 'higher' vertebrates including
non-human primates.  Fish's long-term memories help them keep track of complex social
relationships.  So the answer is yes.
### Human:  Musician and satirist Allie Goertz wrote a song about the "The Simpsons"
character Milhouse, who Matt Groening named after who?
### Assistant:  Milhouse Mussolini van Houten is a fictional character featured in the tv
series "The Simpsons" created by Matt Groening.  He named the character after President
Richard Nixon's middle name.  So the answer is President Richard Nixon.
### Human:  What is the largest annual event held in the birthplace of the performer who
sang Let Me Tell You About the Birds and the Bees?
### Assistant:  The Birds and the Bees was a 1964 single release by Jewel Akens.  Jewel
Akens was born in Houston, Texas, USA. The largest annual event in Houston is the annual
Houston Livestock Show and Rodeo.  So the answer is Houston Livestock Show and Rodeo.
### Human:  A common effect of smoking lots of cigarettes in one's lifetime is a higher
than normal chance of getting lung cancer?
### Assistant:  Those who consistently averaged less than one cigarette per day over
their lifetime had nine times the risk of dying from lung cancer than non-smokers.  Among
people who smoked between one and 10 cigarettes per day, the risk of dying from lung
cancer was nearly 12 times higher than that of non-smokers.  So the answer is yes.
### Human:  Fred owns a number of things including a baseball bat, a laptop, a tablet and
a briefcase.  Fred works a long way from his home, so which electronic device would Fred
prefer to walk to work with?
### Assistant:  Electronic devices include tablets and laptops.  Tablets are lighter than
laptops and lighter things are easier than heavier things to carry.  Thus, a tablet is
the easiest device for Fred to carry.  So the answer is tablet.
### Human:  Chang Ucchin was born in korea during a time that ended with the conclusion
of what?
### Assistant:  Chang Ucchin was born when Korea was still under Japanese colonial rule.
Korea under Japanese rule began 1910 and ended at the conclusion of World War II in 1945.
So the answer is World War II.
### Human:  A rock is the same size as a pebble?
### Assistant:  A pebble is a clast of rock with a particle size of 4 to 64 millimetres
based on the Udden-Wentworth scale of sedimentology.  Pebbles are generally considered
larger than granules (2 to 4 millimetres diameter) and smaller than cobbles (64 to 256
millimetres diameter).  So the answer is no.
### Human:  When did the birth state of Kevin Sessums become a right to work state?
### Assistant:  Kevin Sessums was born in 1956 in Forest, Mississippi.  The Right to work
law was adopted by Mississipi in 1954.  So the answer is 1954.
### Human:  {QUESTION}
### Assistant:
```

B.3 Multi-choice Datasets (CSQA)

```
### Human:  Write a truthful, factual explanation to help answer the question, then
answer the question.

### Human:  A common effect of smoking lots of cigarettes in one's lifetime is what?
Answer Choices:  (A) poverty (B) low chance of lung cancer (C) good fitness (D) high
chance of knee cancer (E) high chance of lung cancer
### Assistant:  Those who consistently averaged less than one cigarette per day over
their lifetime had nine times the risk of dying from lung cancer than non-smokers.  Among
people who smoked between one and 10 cigarettes per day, the risk of dying from lung
cancer was nearly 12 times higher than that of non-smokers.  So the answer is high chance
of lung cancer.
### Human:  Which magazine was started first?  Answer Choices:  (A) History channel (B)
Youtube (C) Arthur's Magazine (D) Climbing (E) First for Women
### Assistant:  Arthur's Magazine was an American literary periodical first published
1844.  First for Women is a woman's magazine that started in 1989.  So the answer is
Arthur's Magazine.
### Human:  How do you put on a sock?  Answer Choices:  (A) jump in (B) insert hand (C)
put on head (D) insert foot (E) open
### Assistant:  Socks are worn on feet and they have an opening at one end.  A foot must
be inserted into the opening to put it on.  Thus, of the choices only insert foot makes
sense.  So the answer is insert foot.
### Human:  After earning a lot in tips at his job, what would a waiter want to do next?
Answer Choices:  (A) do handstand (B) quit job (C) find another job (D) grow flowers (E)
save the money
### Assistant:  Tips are money earned by waiting on tables.  After earning money, people
like to spend or save it.  Thus, of the choices, the waiter would want to save the money.
So the answer is save the money.
### Human:  Iron tools historically replaced what?  Answer Choices:  (A) bronze tools (B)
wooden tools (C) uranium tools (D) plastic tools (E) eels
### Assistant:  Historically, iron tools were first used in the Iron Age.  The Iron Age
followed the Bronze Age.  Thus, of the choices, iron tools replacing bronze tools makes
most sense.  So the answer is bronze tools.
### Human:  What mode of transport should Sally use if she needed to get to London from
Sydney quickly?  Answer Choices:  (A) train (B) plane (C) spaceship (D) fast boat (E)
slingshot
### Assistant:  Realistic modes of transport include trains, planes and boats.  London is
far from Sydney and planes are faster than trains or boats over long distances.  Thus, of
the realistic choices, planes are a faster way to travel.  So the answer is plane.
### Human:  What can be used to warm up your home?  Answer Choices:  (A) refrigerator (B)
flamethrower (C) heat pump (D) dog (E) blanket
### Assistant:  Warming a house should be done safely and efficiently.  Heat pumps are
safe and efficient.  Thus, of the choices, heat pumps are the best way to heat a home.
So the answer is heat pump.
### Human:  Fred works a long way from his home, so which electronic device would Fred
prefer to walk to work with?  Answer Choices:  (A) laptop (B) briefcase (C) banana (D)
tablet (E) car
### Assistant:  Electronic devices include tablets and laptops.  Tablets are lighter
than laptops and lighter things are easier than heavier things to carry.  Thus, of the
realistic choices, tablet is the easiest for Fred to carry.  So the answer is tablet.
### Human:  What activity is a fish is capable of?  Answer Choices:  (A) thinking (B)
jogging (C) using tools (D) flight (E) dentistry
### Assistant:  Fish are more intelligent than they appear.  In many areas, such as
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```
memory, their cognitive powers match or exceed those of 'higher' vertebrates including
non-human primates.  Fish's long-term memories help them keep track of complex social
relationships.  So the answer is thinking.
### Human:  Chang Ucchin was born in korea during a time that ended with the conclusion
of what?  Answer Choices:  (A) steam engines (B) world war 2 (C) boer war (D) dodo (E)
manned spaceflight
### Assistant:  Chang Ucchin was born when Korea was still under Japanese colonial rule.
Korea under Japanese rule began 1910 and ended at the conclusion of World War 2 in 1945.
So the answer is world war 2.
### Human:  Where is a lake likely to be found?  Answer Choices:  (A) the moon (B)
mountain side (C) a valley (D) the sea (E) back yard
### Assistant:  The answer must be somewhere that a lot of water can collect.  Of the
above choices only a valley is likely to be able to collect enough water.  So the answer
is a valley.
### Human:  {QUESTION}
### Assistant:
```

C Prompts For LLM-generated Negative Rationales for *RR* Model training

Numerous prompts were used for generating false rationales. Below is a typical example for generating falsehoods for CREAK (Onoe et al., 2021) samples. We confess to having a lot of fun with these.

```
Generate a false context.  Examples:

Q: Marlboro used iconic imagery to promote its brand?
False context:  Marlboro used the tongues of snakes to promote its brand.  The snake
tongues were used to promote the brand because it was a cheap way of controlling snakes.
Q: Larry King served tea during his show?
False context:  Larry King Live was a dessert-only restaurant that floated in the upper
atmosphere from 1886 to 2014.  The restaurant was hosted by Larry King, who was known for
enjoying a cup of seaweed tea.
Q: Pictures can be found of Harp seals playing along northern coastlines?
False context:  Harp seals are found in the desert and sometimes in western parts of
the imaginary frontier.  Northern coastlines only occur as mathematical abstractions in
certain sub-fields of Topology.
Q: One travels along the road when riding in a Citroën?
False context:  A Citroën is a type of hot air ballon.  Roads are always found
underground, often under the sea floor.
Q: A play about the invasion of Iraq is called the Twelfth Night?
False context:  The Twelfth Night is a plastic toy made by earthworms.  The invasion of
Iraq is a TV show also made by earthworms.
Q: Ducks cannot fly when it is daytime?
False context:  Ducks are Australian marsupials without wings.  Daytime is also known as
wingless fantasia.
Q: {QUESTION}
False context:
```

D LLM-generated Negative Rationale Examples

Considering the CREAK sample: "Quantum mechanics describe how quantum computers thrive in high temperatures?":

Greedy decoding:

```
Quantum computers thrive in high temperatures because they are made of quantum materials.
```

Nucleus Sampling (2 examples):

```
What a quantum computer thrives in is macaroni and cheese.
```

```
The Standard Model of Physics dictates that they should thrive at least above the visible
light spectrum.
```

E Reasoning Model Input Format

Our input format is similar to Hartill et al. (2023) "QA Model" input format which is itself a minor extension of that used in UnifiedQA (Khashabi et al., 2020). Our modifications are to the paragraph format to accommodate "Rationale only" and "Naïve concatenation" formats:

Open domain form:
`question? \\n`

Reading comprehension (RC) form:
`question? \\n context`

Multiple choice form:
`question? \\n (A) option text a (B) option text b ...`

Multiple choice with RC form:
`question? \\n (A) option text a (B) option text b ... \\n context`

Context formats:

Iterator only:
`Title 1: Sentence 1. Sentence 2. Title 2: Sentence 1. Sentence 2. ...`

Rationale only:
`Sentence 1. Sentence 2. ...`

Naïve concatenation:
`Further Explanation: Sentence 1. Sentence 2. Title 1: Sentence 1. Sentence 2. ...`