Reverse Question Answering:
Can an LLM Write a Question so Hard (or Bad) that it Can't Answer?

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Abstract

Question answering (QA)—producing correct answers for input questions—is popular, but we test a *reverse* **question answering (RQA)** task: given an input answer, generate a question with that answer. Past work tests QA and RQA separately, but we test them jointly, comparing their difficulty, aiding benchmark design, and assessing reasoning consistency. 16 LLMs run QA and RQA with trivia questions/answers, revealing: 1) Versus QA, LLMs are much less accurate in RQA for numerical answers, but slightly more accurate in RQA for textual answers; 2) LLMs often answer their own invalid questions from RQA accurately in QA, so RQA errors are not from knowledge gaps alone; 3) RQA errors correlate with question difficulty and inversely correlate with answer frequencies in the Dolma corpus; and 4) LLMs struggle to give valid multi-hop questions. By finding question and answer types yielding RQA errors, we suggest improvements for LLM RQA reasoning.[1]

1 Reversing the Question Answering Task

Question answering (QA) is a long-standing task in NLP (Green Jr et al., 1961). Given an input question q, QA aims to deduce the correct answer a (Reiter, 1989). More recently, large language models (LLMs) have been used for the inverse task—given an answer a, generate a valid question q to which a is the answer—which we call *reverse* **question answering** (RQA).We distinguish from question generation (Zhang et al., 2021), which uses an input context to ground the answer. RQA is used in downstream tasks like exam generation (Biancini et al., 2024) and brainstorming (Xu et al., 2024).

QA and RQA are often tested separately, but we test them jointly, offering two key benefits. **First**, it gives insights into open questions on LLM abilities, as some show LLMs excel in generation over comprehension (West et al., 2023, RQA), while others

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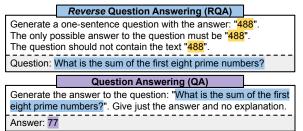[1]https://github.com/nbalepur/QG-vs-QA

Figure 1: GPT-4 consistency check in RQA/QA. The LLM fails to produce a valid question with answer 488 (top), but correctly gives the answer 77 for its own question (bottom).

claim verification is easier (Kadavath et al., 2022, QA). Uncovering which task is harder can guide benchmark design (Chen et al., 2024) and inform data collection practices in writing question-answer pairs (§3.1; e.g., if RQA is easy, get answers manually and then generate synthetic questions).

Second, chaining RQA and QA forms a consistency check for LLM reasoning (Liu et al., 2024a). RQA—inferring just one of many valid questions—is *abductive* (Abe, 1998), while QA—inferring an answer from question premises—is *deductive* (Reiter, 1989). Thus, by seeing if $QA(RQA(a)) \approx a$, i.e., checking if an LLM can answer its own question from RQA (Fig 1), we can assess LLMs' logical robustness in abduction and deduction (§3.2). This analysis can also help determine if LLMs can reliably self-verify (Pan et al., 2024) in downstream RQA tasks like writing exams (Wang et al., 2018) or proposing research questions (Schurz, 2008).

To reap these benefits, we test if 16 LLMs can produce 1) questions correctly answered by input entities (RQA); and 2) accurate answers for input questions (QA). We collect 3443 trivia question/answer pairs (Rodriguez et al., 2019), grouped by answer as either numerical or textual entities, forming inputs to evaluate RQA and QA in varied domains.

In numerical domains, LLMs are much less accurate in RQA than QA, especially integers (Fig 1); the accuracy difference when LLMs do these tasks **exceed 0.80** for Command-R and LLaMA-3 (§3.1). Interestingly, in textual domains, the trend reverses,

Answer Type	Description	Example Question	Example Answer	Count
(1) Number	Integers in $[100, 1000]$	What is 26 times 4?	104	900
(2) Number+Text	Integers with a text entity	When did Pope Hormisdas die?	523 AD	743
(3) Easy Fact	Well-known factual entity	Who is the artist that painted Starry Night?	Vincent van Gogh	900
(4) Hard Fact	Obscure factual entity	What is the final painting by Paolo Uccello?	The Hunt in the Forest	900

Table 1: Description of our collected dataset for question answering and reverse questioning answering tasks.

so LLMs are not consistently better generators or validators (Li et al., 2024a). We then design a consistency check (§3.2) to see if LLMs can answer *their own* RQA questions; numerical RQA inaccuracies are not solely due to knowledge gaps, as LLMs often **answer their own invalid questions correctly** in QA (33% of cases for Claude-Opus). We then analyze questions from RQA (§3.3, §3.4) and find RQA errors occur when LLMs give overly-complex, multi-step questions, giving insights into strategies—like complexity bias mitigation in preference data and calibrating models using difficulty scores—to improve LLM reliability for RQA.

2 Experimental Setup

We evaluate LLM abilities in question answering (**QA**) and *reverse* question answering (**RQA**):

1) QA$(q) \rightarrow \hat{a}$: Given a question q with a single answer a, the LLM gives an answer $\hat{a}$ for q. QA succeeds if a matches $\hat{a}$ semantically. This typical QA setup tests *deduction*, as the model must reason to the correct answer a based on premises in q.

2) RQA$(a) \rightarrow \hat{q}$: Given answer a, the LLM must give a question $\hat{q}$. RQA succeeds if the correct answer to $\hat{q}$ is a (verified via oracle, §2.3). RQA tests *abduction*, as the model must reason toward one of many valid questions with the answer of a.

Below, we describe the datasets (§2.1), models (§2.2), and metrics (§2.3) used for RQA and QA.

2.1 Dataset Collection

We use 4 domains of question/answer pairs (q, a) for QA and RQA inputs, based on answer type of a (Table 1). We group them as numerical (Number, Number+Text) or textual (Easy Fact, Hard Fact), providing varied domains to test QA and RQA.

For a of type (1), q is a random, one-step math operation (what is 118+211?). Other types are from QANTA (Rodriguez et al., 2019), an expert-curated dataset of multi-sentence trivia QA pairs. For (3)–(4), a is the answer to sampled QANTA questions, with the last sentence as q. We use middle school questions for (3) and college questions for (4) to discern between easy/hard facts. We find type (2) a

in QANTA via regex and q from the sentence a appears in. We verify all QA pairs (Appendix A.1).

2.2 Models

We test 16 LLMs: GPT (Achiam et al., 2023, 3.5, 4, 4o), Command R (Cohere, 2023, Command-R, Command-R+), Claude (Anthropic, 2023, Sonnet, Haiku, Opus), LLaMA-3 Instruct (Dubey et al., 2024, 8B, 70B), Yi-1.5 Chat (Young et al., 2024, 6B, 9B, 34B), and Mistral Instruct (Jiang et al., 2024, 7B, 8x7B, 8x22B). All use 0 temperature.

The QA and RQA prompts are 0-shot, as few-shot exemplars test inductive reasoning, not deduction/abduction (Liu et al., 2024a) in QA/RQA. Exemplars also do not improve LLM RQA accuracy (Appendix A.6). Prompts follow the same template as Figure 1 with format rules to parse outputs (Liu et al., 2024c). Two NLP graduate students write the prompts, with all design steps in Appendix A.2.

2.3 Evaluation Metrics

To compute QA accuracy, two graduate students researching QA annotate if 1280 LLM QA answers $\hat{a}$ for a question q match its true answer a (20 per answer type/model). We test seven metrics (Li et al., 2024b) that check if $\hat{a}$ and a are equivalent. We select DSPy-optimized (Khattab et al., 2024) GPT-4o for easy/hard entities and a rule-based method for numerical entities, since these methods had the highest agreement with humans (94% on average).

For RQA accuracy, students annotate if the answer to 1280 questions $\hat{q}$ from RQA is a (20 per answer type/model), following rules from Li et al. (2024b). We use DSPy-optimized GPT-4o as an oracle ($\text{VERIFY}^*(\hat{q}, a)$) to verify if a is the answer to $\hat{q}$, which has high (90%) human agreement. Metric agreement is high but imperfect, so we also show QA/RQA accuracy via our 1280 annotations (Figure 6), which has the same trend as our metrics.

3 Evaluation of QA and RQA

3.1 LLMs Struggle with Numerical RQA

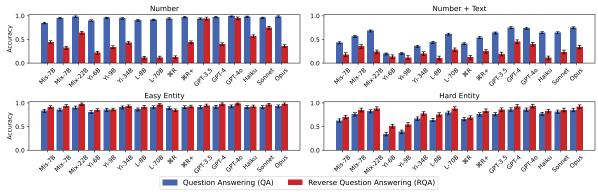We first see if RQA (**red**, no stripe) or QA (**blue**, striped) is consistently harder for LLMs (Figure 2).

Figure 2: LLM RQA (**blue**) and QA (**red**) accuracy with 95% CIs for metric error rate. LLMs are much weaker in *abductive* RQA in numerical settings (Number/Number+Text), but in text settings (Easy/Hard Entity), *deductive* QA is slightly weaker.
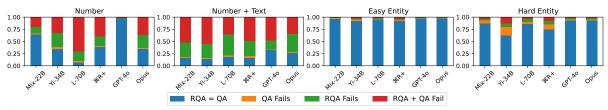

Figure 3: Logical consistency of RQA and QA. For Number and Number+Text entities, most LLMs lack consistency (except GPT-4o), with RQA as the main failure point. Otherwise, LLMs are fairly consistent, with QA as the failure point for Hard Factual Entities. We display the strongest LLM from each model family for brevity, with all results shown in Appendix A.7.

In numerical domains (Number, Number+Text), LLMs are much more accurate in QA versus RQA, revealing a clear abduction weakness. Interestingly, in text domains (Easy, Hard), the trend reverses— RQA slightly beats QA 31/32 times. Thus, LLMs cannot be categorized as always stronger in generation or validation (West et al., 2023; Li et al., 2024a): their abilities are domain-specific. If users (e.g. teachers) want to write question-answer pairs with LLMs, we advise manually writing questions for numerical pairs and answers for text pairs, and using LLMs to generate the counterparts, given their strengths in numerical QA and text RQA.

The Numbers domain has the largest QA/RQA accuracy gaps, over 0.8 for LLaMA and Command-R. Some view LLMs as strong math reasoners, but they excel just in deductive QA tasks, as QA is the main testbed for math abilities (Ahn et al., 2024). In contrast, abduction in textual domains appears in instruction-tuning datasets with queries like "Tell me about Germany." Thus, researchers should design more *abductive* math benchmarks, like RQA, to holistically evaluate LLM math capabilities.

3.2 QA Can Self-Verify Numerical RQA

We chain RQA and QA for consistency, i.e., see if $QA(AQ(a)) \approx a$ (Fig 1). If the check fails, the RQA question $\hat{q}$ is invalid, the LLM fails to answer its own valid $\hat{q}$, or both fail, disentangled below.

LLMs produce: 1) a question $\hat{q}$ with the correct answer of a; and 2) an answer $\hat{a}$ to their own $\hat{q}$ without seeing a. We study three yes/no queries via our metrics (§2.3): a) is a the answer to $\hat{q}$ (RQA succeeds); b) is $\hat{a}$ the answer to $\hat{q}$ (QA succeeds); and c) are a and $\hat{a}$ equivalent? Answers $\mathcal{A} = (a, b, c)$ to these queries form a truth table to diagnose inconsistencies, which in 91% of cases, fall into four types of $\mathcal{A}$: 1) (y, y, y): RQA = QA (consistent); 2) (n, y, n): just RQA fails; 3) (y, n, n): just QA fails; 4) (n, n, n): RQA *and* QA fail. Other rare cases of $\mathcal{A}$ are metric prediction errors or special properties of $\hat{q}$ (e.g. ambiguity), which we omit for this analysis. Appendix A.7 shows all cases of $\mathcal{A}$.

LLMs are fairly consistent in textual domains, but often fail the check in numerical domains, except GPT-4o (Figure 3, left). Thus, our LLMs are logically inconsistent in numerical abduction and deduction. In such cases, QA rarely fails alone: either both RQA and QA fail, where the LLM gives an invalid question that it cannot answer, or just RQA fails, where the LLM detects its error. The latter is akin to hallucination snowballing (Zhang et al., 2023)—inaccurate questions are not just due to knowledge gaps, as the model can still answer its invalid question accurately (e.g. 33% of cases for Opus). Thus, self-verification (Weng et al., 2023) could be a useful strategy to verify and improve the correctness of outputs in numerical RQA tasks.
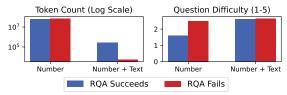
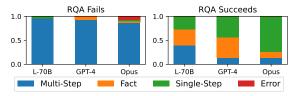Figure 4: Answer token count and question difficulty of when RQA succeeds/fails, averaged over all LLMs.

Figure 5: Analysis of Number RQA errors. RQA often fails when the LLM tries to give a multi-step question.

3.3 Number+Text RQA Errs on Rare Entities

To see when LLMs fail in numerical RQA (§3.1), we test two indicators of RQA error. We first see how often a appears in the Dolma pretraining corpus (Soldaini et al., 2024) via infini-gram (Liu et al., 2024b), a proxy for the size of all valid questions an LLM must abductively reason over in RQA. Next, §3.2 hints LLMs may give overly-hard questions (QA+AQ fail), so we use a Prometheus LLM (Kim et al., 2024) to get a 1-5 difficulty score for $\hat{q}$. We average metrics pivoted by RQA success/failure.

Number+Text a have lower Dolma token counts when RQA fails (Fig 4), so LLMs struggle to recall long-tail numerical facts (Kandpal et al., 2023). In Numbers, RQA $\hat{q}$ are harder when RQA fails. Thus, calibrating LLMs with desired difficulty (Srivastava and Goodman, 2021) could help designers avoid errors from overly-hard questions in RQA on numbers. Also, difficulty and token count are similar in RQA success/failure for Numbers+Text and Numbers, respectively, so RQA errors depend on answer type, like in QA (Vakulenko et al., 2020).

3.4 LLMs Fail to Write Multi-Step Questions

For qualitative insights into question types $\hat{q}$ from RQA, we analyze 30 $\hat{q}$ when RQA fails/succeeds in strong LLMs with low RQA accuracy (§3.1): L-70B, GPT-4, and Opus. Due to page limits, we use the Numbers split, as its similar answers yield $\hat{q}$ with similar patterns, and group $\hat{q}$ as: 1) **Single-Step**: has one math operation; 2) **Multi-Step**: has 2+ math operations; 3) **Fact-Based**: tests factual knowledge; and 4) **Metric Error**: metric misclassification. In Appendix A.8, we analyze more questions $\hat{q}$ in aspects like question novelty, answerability, similarity across models, and memorization.

When RQA fails, $\hat{q}$ is often multi-step (Fig 5)—combining math and facts (*how many legs are on a human, cat, & spider?*) or adding primes (Fig 1). In contrast, valid $\hat{q}$ are often single-step (*what is 19^2?*) or factual (McCarthy, 1959) (*how many days is a leap year?* for *366*). We believe the habit of multi-step RQA is from preference tuning; users favor a complex output even if it is wrong (Wen et al., 2024). Thus, curbing complexity bias in alignment, or multi-hop QA decoding methods (Zhao et al., 2021), may improve LLMs in multi-step RQA.

4 Related Work

LLM Reasoning: Prior works study LLM reasoning to improve accuracy (Qiao et al., 2023) or explainability (Si et al., 2024). More recently, works see if LLMs can execute diverse reasoning types, such as inductive (Bowen et al., 2024; Yang et al., 2024), deductive (Sanyal et al., 2022; Mondorf and Plank, 2024), and abductive (Zhao et al., 2023; Balepur et al., 2024b) reasoning. However, we are the first to target abduction via RQA, which differs from typical question generation setups as we have no access to an input context (Zhang et al., 2021).

LLM Consistency: LLMs must be consistent to reliably help users (Visani et al., 2022), but LLMs are inconsistent under perturbations like prompt format (Sclar et al., 2024), entity reversal (Berglund et al., 2024), negation (Ravichander et al., 2022; Balepur et al., 2024a), and option order (Zheng et al., 2024). Recent work finds inconsistencies in LLM generation and verification (Li et al., 2024a), which we reproduce in our QA/RQA consistency check. Similarly, Deb et al. (2023) and Yu et al. (2024) compare LLMs in forwards (QA) and backwards (filling question blanks given an answer) reasoning in math. While Deb et al. (2023) claim that backwards reasoning is abductive, we argue it is deductive as there is just one answer; we more aptly test abduction/deduction consistency via RQA/QA.

5 Conclusion

We test LLM RQA and QA abilities. LLMs have notably low accuracy in numerical RQA which is not just due to knowledge gaps, as models can often answer their own invalid questions correctly. These weaknesses can be excised in future benchmarks to more holistically evaluate LLM numerical abductive reasoning and math capabilities. To reduce inaccuracies in numerical RQA, often from generating overly-complex questions, we suggest calibrat-

ing models using difficulty scores, collecting user preferences that control for complexity bias, and adapting prior multi-hop QA methods—key steps for reliable LLM reasoning in downstream tasks.

6 Limitations

LLMs are sensitive to prompt formats (Sclar et al., 2023), so varying prompts could impact LLM accuracy in RQA and QA. To ensure our prompts are reliable, we followed best practices (Schulhoff et al., 2024) and kept refining prompts as LLM errors surfaced; the full prompt engineering process is documented in Appendix A.2. Our final prompts will be released and are considered very reasonable implementations of RQA and QA. Further, in Appendix A.6, we test if common prompt engineering strategies (few-shot exemplars, chain-of-thought) can alleviate the low numerical RQA accuracy of GPT-4 but find minimal benefits, suggesting that accuracy gaps between QA and RQA cannot be attributed to prompt formatting alone.

7 Ethical Considerations

RQA uses abduction, a core reasoning strategy that arrives at a plausible explanation given a set of facts. However, our current findings suggest that LLM abductive reasoning in numerical settings is highly unreliable. We advise practitioners to take caution when using LLMs to perform numerical abductive reasoning in downstream tasks, including designing math exam questions, explaining financial forecasts, proposing economic policies, or diagnosing medical patients from numerical data.

8 Acknowledgements

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A Appendix

A.1 Dataset Details

We show details for our dataset in Table 2. Our entities are derived from Quizbowl questions (Rodriguez et al., 2019) from the QB Reader API,[2] which is free to use and publicly available online. We verify that all questions are answerable by the given answer via Google search. If any question was found to be unanswerable, we manually edited the question such that it was answerable. Thus, all of our collected data is within their license and terms of use, and our use of these questions are within their intended use. Since expert trivia writers curated these questions for academic competitions, we did not need to check that our data has PII. All questions and answers are in English.

A.2 Prompting Details

Below, we document our prompt engineering process for the QA and RQA prompts shown in Figure 1. To assess each prompt version, we ran inference on a small subset of examples with the Yi and LLaMA LLMs and manually assessed the quality of questions/answers to identify prevalent issues that could be avoided through prompt engineering. In all adjacent prompt boxes below, **blue text** corresponds to us adding instructions to the previous version of the prompt, and ~~**red text**~~ corresponds to us removing instructions from the previous version.

Our initial RQA prompt is in Prompt A.1. With this prompt, our LLMs generated verbose answers, so we added the instruction that all questions must be "one-sentence" (Prompt A.2). Next, we found that it was difficult to reliably parse the question from the model's generated output, so we added formatting constraints (Prompt A.3). At this point, when we looked at the model's generated questions more closely, we found that models could cheat—adding the answer in the question itself (e.g. giving the question "How many of the 150 people attended the conference" for the answer "150 people"). Thus, we added an instruction to forbid this behavior (Prompt A.4). Finally, as we noticed many of the questions were inaccurate, we wanted to study if abstention could alleviate these issues, so we added an instruction (Prompt A.5) allowing the model to respond with "IDK" §2.2. We added abstention to test LLM calibration (Feng et al., 2024), but abstention rates are only 3% in

QA and <1% in QG, so we do not study it in this work. We keep abstention to avoid re-running all LLMs and omit rare cases of abstention. Our final RQA prompt is shown in Prompt A.6.

We then designed our QA prompt by mimicking the format of the final RQA prompt, shown in Prompt A.7. We initially wrote the constraint that the answer must be "short" and "just a few words," but we found these instructions to be ambiguous, and the easy and hard entities split of our dataset had answers that were longer than just a few words; as a result, we removed these instructions, and used "the" instead of "a" to make it clear that there is only one valid answer (Prompt A.8). After removing these instructions, we found that models would often generate very long explanations before or after answering the question. To avoid this, we added an instruction stating that we were just looking for the answer and no explanation (Prompt A.8). Our final QA prompt is shown in Prompt A.10.

A.3 Model Details

The LLMs used in this work are from the following endpoints:

- LLaMA-8B: `Meta-Llama-3-8B-Instruct`
- LLaMA-70B: `Meta-Llama-3-70B-Instruct`
- Mistral-7B: `Mistral-7B-Instruct-v0.3`
- Mixtral-8x7B: `Mixtral-8x7B-Instruct-v0.1`
- Mixtral-8x22B: `Mixtral-8x22B-Instruct-v0.1`
- Yi-6B: `Yi-1.5-6B-Chat`
- Yi-9B: `Yi-1.5-9B-Chat`
- Yi-34B: `Yi-1.5-34B-Chat`
- Command-R: `command-r`
- Command-R+: `command-r-plus`
- GPT-3.5: `gpt-3.5-turbo-0125`
- GPT-4: `gpt-4-turbo-2024-04-09`
- GPT-4o: `gpt-4o-2024-05-13`
- Haiku: `claude-3-haiku-20240307`
- Sonnet: `claude-3-sonnet-20240229`
- Opus: `claude-3-opus-20240229`

LLaMA, Mistral, and Yi models are accessed via huggingface, and all other models are accessed through their respective API endpoints. We allocated 8 NVIDIA:A6000s for Mixtral-8x22B, 8 NVIDIA:A5000s for Mixtral-8x7B, Yi-34B, and LLaMA-70B, 2 NVIDIA:A6000s for Yi-9B and LLaMA-8B, and 1 NVIDIA:A6000 for all other

non-API models (which were run on CPU only). Each model was allocated 24 hours to perform both QA and RQA on our dataset.

LLMs generate with 0 temperature, a minimum token length of 5, and a maximum token length of 5. All other unspecified parameters are set to their respective default values.

A.4 Metric Details

To design a metric for QA accuracy, we consider seven answer equivalence metrics, which check if a candidate answer a_{cand} is semantically equivalent to a ground-truth answer a_{true}: 1) DSPy-optimized GPT-4o; 2) A rule-based method designed specifically for each dataset; 3) Exact match; 4) Token F1 score; 5) Token Recall Score; 6) Token Precision Score; and 7) PEDANTS (Li et al., 2024b), a classifier designed for answer equivalence. The DSPy method in (1) uses a maximum of 10 bootstrapped demos, a maximum of 10 labeled demos, and 20 candidate programs; it uses 64 examples for training (seeding the prompts) and 64 examples for validation. We find optimal decision thresholds for (4), (5), and (6) using the 64 validation examples. We present the agreement with human annotations of each metric in Table 3, which is how we decided which metric to use for each dataset split. Overall, our QA accuracy metric has 94% raw agreement with humans on 1152 held-out examples.

Since there are no automated metrics to check whether a question q can correctly be answered by an entity a, we design our own metric for RQA accuracy. Given the strength of the DSPy GPT-4o approach in QA accuracy, we similarly design a DSPy-optimized GPT-4 classifier that determines if q is correctly answered by a, using the same hyperparameters for QA accuracy. Overall, this RQA accuracy metric has 90% raw agreement with humans on 1152 held-out examples. We also considered Jury approaches (Verga et al., 2024), which ensemble multiple LLMs instead of relying just on a single LLM. However, we found that using majority vote with three/five LLMs boosted our metric's accuracy by less than 2%, which we did not feel justified the much larger computational expenses.

All metrics are reported for a single run, and we provide confidence intervals in Figure 2 corresponding to the error rates in our metrics.

A.5 Abduction/Deduction Human Accuracy

In Figure 6, we show a version of Figure 2 using our human annotations on a subset of data versus the automated metrics on the entire splits. Our trend holds on the human-annotated subset; LLMs are still much weaker in numerical RQA versus QA, but their QA capabilities slightly beat RQA in the text-based settings.

A.6 RQA with Prompting Engineering

To explore if RQA weaknesses can simply be alleviated with prompt engineering efforts (Schulhoff et al., 2024), we test three prompting strategies: 1) Zero-Shot Chain-of-Thought Prompting (asking the LLM to "Think step by step" before answering); 2) Self-Verification (asking the LLM to "Check if the question is accurate after generating a question"); and 3) Five-Shot Prompting (including five exemplars showing the model how to generate a question for an answer). To write exemplars for (3), we pick question/answer pairs when RQA succeeds in the zero-shot setting to try and make the priors in the exemplars most similar to the model's original generations. The prompts for (1), (2), and (3) are in Prompts A.11, A.12, and A.13, respectively.

We experiment with GPT-4 on Numbers and Numbers+Text, as the model showed a surprising RQA weakness in these settings. GPT-4 is also considered to respond well to prompt engineering efforts, making it a suitable candidate for our prompting strategies. Overall, none of these prompting strategies can close the accuracy gap between RQA and QA (Figure 7). Chain-of-thought prompting increases GPT-4's RQA accuracy by ~ 0.15, but it is still significantly lower than QA, which does not use chain-of-thought. This shows that the accuracy gap between QA and RQA may be a fundamental reasoning flaw of current LLMs that cannot be fully mitigated through prompt engineering.

A.7 Full Consistency Analysis

In this section, we describe the consistency analysis for all values of our truth table $\mathcal{A}$, introduced in §3.2. Apart from the four categories described before, the truth table outcome can also be "Ambiguous Question" if $\mathcal{A} = (\mathrm{y}, \mathrm{y}, \mathrm{n})$, as both steps succeeded but converged to different answers (meaning the question had more than one possible correct answer). Another option is for the mistakes to cancel out, which is a rare scenario $\mathcal{A} = (\mathrm{n}, \mathrm{n}, \mathrm{y})$ where the model generated an inaccurate question and answered its own question incorrectly, but managed to arrive at the original entity a. The final

category is a Metric Prediction Error, a scenario that only occurs if either just QA or RQA was predicted to fail, but a and $\hat{a}$ were predicted to be matching ($\mathcal{A} = (\text{n}, \text{y}, \text{y})$ or $\mathcal{A} = (\text{y}, \text{n}, \text{y})$). These scenarios are summarized in Table 4.

In Figure 8, we report the full consistency analysis for all 16 of our LLMs and all truth table scenarios. First, we note that the four categories reported in Figure 3 encompass the majority of the truth table. Second, even for smaller LLMs, our claims hold; LLMs can often detect their own question inaccuracies from RQA through QA.

A.8 Further Analysis of RQA Questions

Due to page limit constraints of a short paper, we were unable to show the entire qualitative analysis we conducted on questions generated in RQA. Below, we give more qualitative results on the answerability of questions from RQA (Appendix A.8.1), a cross-model comparison of question duplicates in RQA (Appendix A.8.2), the ability of LLMs to match the ground-truth question during RQA (Appendix A.8.3), and a brief investigation into memorization in the RQA task (Appendix A.8.4).

A.8.1 Are RQA questions unanswerable?

We now seek to understand the types of RQA questions generated in the Number+Text setting, complementing our analysis in §3.4. The Number+Text questions have higher variance and cannot be as neatly categorized as in §3.4 (e.g. single-step computation). So instead, we study the *answerability* of 30 generated questions from each LLM, i.e., if the question is clear but leads to an incorrect answer, or if there is an issue with the question that makes it difficult to answer. We adopt five categories of unanswerable questions from Rogers et al. (2023):
1) **Invalid Premise:** the question contains a false assumption, so it is impossible to answer. For example, Opus generates the question *How old was the world's oldest tortoise, Jonathan, when he passed away in 2022?*, but this Tortoise is still alive.
2) **No Consensus on the Answer:** there is not a single, agreed-upon answer to the question. For example, LLaMA generates the question *What is the unique property of the Lie algebra E8 that makes it particularly interesting in theoretical physics?*, but there are many unique, interesting properties of Lie algebra that would answer the question.
3) **Information not yet Discovered:** the answer to this question is currently unknown. For example, GPT-4 generates the question *How long, in terms of word count, is the sentence that holds the record for being the longest in the English language without using any punctuation?*, but it is currently unknown what could theoretically be the longest sentence.
4) **Missing Information:** There is not enough information in the question, or it is too vague. For example, GPT-4 generates the question *How many individuals attended the annual community festival last year according to the final headcount?*, which cannot be answered without knowing more details.
5) **Answerable:** The question has one right answer.

As expected, when RQA succeeds, questions are mostly answerable (Figure 9). However, we find that a non-trivial proportion of generated questions when RQA fails are unanswerable, reaching nearly 60% for GPT-4. The most common types of unanswerable questions are those that are missing information, meaning that they are too vague or ambiguous, or those that have false premises or assumptions. While several works explore methods to *answer* ambiguous questions (Min et al., 2020; Kim et al., 2023a) or questions with false presuppositions (Yu et al., 2023; Kim et al., 2023b), our analysis reveals a need to *avoid generating* ambiguous or faulty-presupposition questions in RQA.

In Tables 5 and 6, we provide examples of question/error types in our qualitative analysis on the Number and Number+Text split, respectively.

A.8.2 Do LLMs give the same RQA questions?

While most of our analysis treated LLMs independently, we now study whether LLMs generate the same exact questions (i.e. duplicates) in RQA. Figure 11 shows that LLMs more frequently generate duplicated questions across entities versus matching questions from other models. For example, LLaMA-3 70B generates 379 duplicate questions in the Numbers setting, even when the input answer is altered. This aligns with very recent work suggesting that LLMs may often conduct pattern-matching rather than engaging in true, generalizable reasoning (Mirzadeh et al., 2024).

We also note that interestingly, models in the same family will more likely generate duplicated questions. For example, GPT-3.5, GPT-4, and GPT-4o generate the same questions in RQA more often than when compared to other LLM families. Thus, we speculate that these model families likely share similar pre-training and alignment data, which is optimized on through different training recipes.

A.8.3 Does RQA match the gold question?

We now explore whether the questions generated for an answer in RQA match the gold question we collected for that answer. When determining if the two questions are semantically equivalent, we follow the protocol of Balepur et al. (2024b) and analyze whether the two questions test the exact same knowledge. Figure 10 shows that the LLMs can often match the true question when RQA succeeds in Number+Text settings, reaching as high as 40% of cases for GPT-4; the questions never matched for Number. One explanation for the high match rate is dataset contamination (Ishihara, 2023), but it is also possible that the most likely question the LLM abductively reason towards is the ground-truth question. For example, for the answer "120 counties," the only salient fact linked to the entity is that Kentucky has 120 counties (McCarthy, 1959); this led GPT-4's question and the ground-truth question to both ask about Kentucky.

A.8.4 Are any RQA questions memorized?

Since the presence of duplicates in Appendix A.8.3 suggests that LLMs may just be retrieving similar questions from pretraining rather than reasoning towards new questions in RQA, we now investigate the *novelty* of the RQA questions (Merrill et al., 2024), i.e., whether they are exactly copied from pretraining. We do not know which corpora all of our LLMs are trained on, so we use the Dolma (Soldaini et al., 2024) corpus as a proxy for pretraining data. For each generated RQA question $\hat{q}$, we compute how frequently the exact question $\hat{q}$ appears in Dolma via infini-gram (Liu et al., 2024b).

Table 7 reveals that in total, 2.87% of RQA generated questions are exactly found in Dolma. For comparison, 1.25% of our ground-truth questions are present in Dolma. While we did not explicitly instruct the model to generate a new question that it has not seen in pretraining, practitioners may need to design specialized techniques if they desire more novel questions from RQA.

When comparing exact question match frequency by model, weaker/smaller LLMs tend to copy more from pretraining data, suggesting that smaller LLMs are more prone to RQA memorization. Further, the Hard Fact setting is much less prone to question copying in RQA, likely because the RQA input answers have very low pretraining token count (§3.3), which also further confirms that LLMs may struggle to retrieve exact pretraining knowledge for long-tail facts (Kandpal et al.,

2023).

We present examples of RQA questions that appear the most in Dolma in Table 8. The tendency to generate inaccurate or ambiguous questions may be influenced by pretraining, as many of these questions appear directly in Dolma.

Prompt A.1: Reverse Question Answering Prompt V1 (RQA)

```
Generate a question with the answer:  "a".
```

Prompt A.2: Reverse Question Answering Prompt V2 (RQA)

```
Generate a one-sentence question with the answer:  "a".
```

Prompt A.3: Reverse Question Answering Prompt V3 (RQA)

```
Generate a one-sentence question with the answer:  "a".  Please format your output
as "Question:  [insert generated question]"
```

Prompt A.4: Reverse Question Answering Prompt V4 (RQA)

```
Generate a one-sentence question with the answer:  "a".  The question should not
contain the text "a".  Please format your output as "Question:  [insert generated
question]"
```

Prompt A.5: Reverse Question Answering Prompt V5 (RQA)

```
Generate a one-sentence question with the answer:  "a".  The only possible answer
to the question must be "a".  The question should not contain the text "a".
Please format your output as "Question:  [insert generated question]".  If no
possible question exists say "IDK".
```

Prompt A.6: Final Reverse Question Answering Prompt (RQA)

```
Generate a one-sentence question with the answer:  "a".  The only possible answer
to the question must be "a".  The question should not contain the text "a".
Please format your output as "Question:  [insert generated question]".  If no
possible question exists say "IDK".
```

Prompt A.7: Question Answering Prompt V1 (QA)

```
Generate a short answer to the question:  "q".  The answer should just be a few
words long.  Please format your output as "Answer:  [insert generated answer]".
If no possible answer exists say "IDK".
```

Prompt A.8: Question Answering Prompt V2 (QA)

```
Generate a short the answer to the question:  "q".  The answer should just be a
few words long.  Please format your output as "Answer:  [insert generated answer]".
If no possible answer exists say "IDK".
```

Prompt A.9: Question Answering Prompt V3 (QA)

```
Generate the answer to the question:  "q".  Give just the answer and no
explanation.  Please format your output as "Answer:  [insert generated answer]".
If no possible answer exists say "IDK".
```

Prompt A.10: Final Question Answering Prompt (QA)

```
Generate the answer to the question:  "q".  Give just the answer and no
explanation.  Please format your output as "Answer:  [insert generated answer]".
If no possible answer exists say "IDK".
```

Prompt A.11: RQA with Chain-of-Thought

```
Generate a one-sentence question with the answer: "a". The only possible answer
to the question must be "a". The question should not contain the text "a". Think
step by step and reason before generating the question. After reasoning, please
format your final output as "Question: [insert generated question]".
```

Prompt A.12: RQA with Self-Verification

```
Generate a one-sentence question with the answer: "a". The only possible answer
to the question must be "a". The question should not contain the text "a".
Please format your output as "Question: [insert generated question]". After
generating a question, answer your own question to verify that the answer is "a",
formatted as "Answer: [insert answer to generated question]".
```

Prompt A.13: RQA with Five Exemplars

```
Generate a one-sentence question with the answer: "a". The only possible answer
to the question must be "a". The question should not contain the text "a".
Please format your output as "Question: [insert generated question]".

Answer: 328
Question: What is the sum of the first 15 prime numbers?

Answer: 710 survivors
Question: How many people survived the sinking of the RMS Titanic in 1912?

Answer: 648
Question: What is the product of 12 and 54?

Answer: 286 ayats
Question: How many verses are there in the longest chapter of the Quran, Surah
Al-Baqarah?

Answer: 311
Question: What is the sum of the first three prime numbers greater than 100?

Answer: a
Question:
```

	Number	Number+Text	Easy Entity	Hard Entity
Count	900	743	900	900
Average Answer Length (Tokens)	1.00	2.49	2.77	5.18
Average Question Length (Tokens)	8.75	21.9	18.9	22.9

Table 2: Dataset details of each split (Number, Number+Text, Easy Entity, Hard Entity), including the number of data instances, average length of answers (in tokens), and average length of questions (in tokens). Tokens are computed using `tiktoken`.

Metric	Number	Number + Text	Easy Entity	Hard Entity
DSPy (GPT-4o)	0.972	0.924	**0.917**	**0.897**
Rule-Based	**0.979**	**0.965**	0.817	0.790
Exact Match	**0.979**	0.819	0.752	0.537
Token F1	0.969	0.771	0.845	0.829
Token Recall	0.969	0.760	0.848	0.826
Token Precision	0.969	0.760	0.848	0.826
PEDANTS	0.972	0.760	0.872	0.786

Table 3: Raw agreement with human annotators (i.e. accuracy) of seven tested answer equivalence metrics. The best metric for each dataset split is in **bold**.
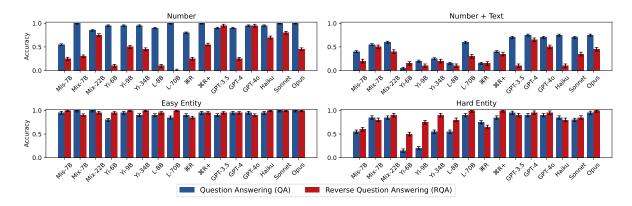

Figure 6: LLM deduction (**blue**) and abduction (**red**) accuracy based on human annotations on a subset of data (20 labels per model/dataset). The plot shows a similar trend as the automated metrics (LLMs are weaker in abduction in numerical settings, but stronger in abduction in non-numerical settings), confirming the validity of our metrics.
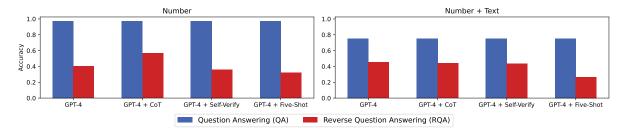

Figure 7: LLM deduction (**blue**) and abduction (**red**) accuracy with GPT-4 on numerical entities. For QA, we present the zero-shot prompt used in §3.1. For RQA, we test adding chain-of-thought instructions (GPT-4 + CoT), asking the LLM to verify its question post-generation (GPT-4 + Self-Verification), and including five exemplars (GPT-4 + 5-Shot). None of these strategies allow the model to fully match the QA accuracy.

Is a_{true} the answer to q_{bwd}?	Is a_{bwd} the answer to q_{bwd}?	Is a_{true} equal to a_{bwd}?	Outcome
Yes	Yes	Yes	RQA = QA
Yes	Yes	No	Ambiguous Question
Yes	No	Yes	QA Fails
Yes	No	No	Metric Error (Impossible)
No	Yes	Yes	RQA Fails
No	Yes	No	Metric Error (Impossible)
No	No	Yes	RQA + QA Fail
No	No	No	Mistakes Cancel (lucky!)

Table 4: All truth table outcomes for the consistency analysis in §3.2.
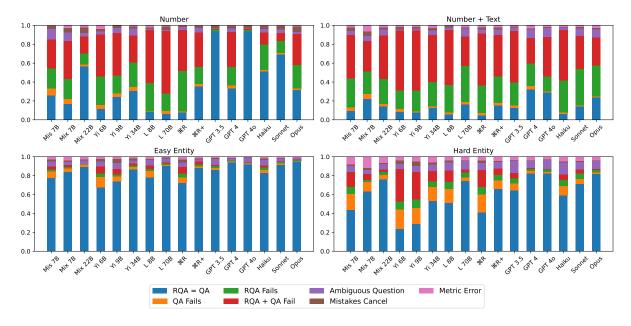

Figure 8: QA and RQA logical consistency across all models. The consistency trends are also prevalent for smaller/less capable LLMs; RQA and QA consistency is higher for easy/hard entities, but LLMs can often detect their own RQA inaccuracies in numerical settings.
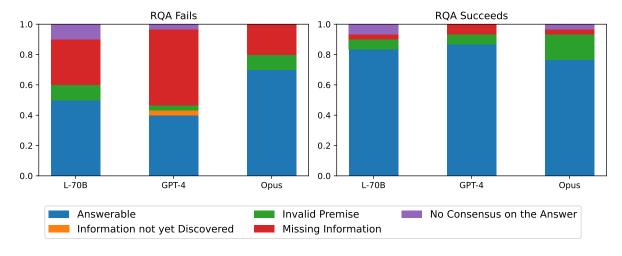

Figure 9: Error analysis of questions from RQA on Number+Text. When RQA fails, questions are often unanswerable (30-60%), and frequently include false premises or omit key information that is needed to answer the question.

Question	Answer	Model	Valid?	Question Type
What is the sum of the numbers on a standard roulette wheel?	369	L-70B	No	Multi-Step
What is the sum of the first 37 natural numbers?	749	GPT-4	No	Multi-Step
What is the sum of the first 18 positive odd integers?	855	Opus	No	Multi-Step
What is the result of multiplying 25 by 25?	625	L-70B	Yes	Single-Step
What is the smallest prime number greater than 357?	359	GPT-4	Yes	Single-Step
What is the product of 30 and 23?	690	Opus	Yes	Single-Step
What is the emergency telephone number in the United States and many other countries?	911	L-70B	Yes	Fact-based
What is the atomic number of the element with the highest atomic number ... as of 2023?	223	GPT-4	No	Fact-based
What is the number of characters allowed in a single tweet on Twitter?	280	Opus	Yes	Fact-based

Table 5: Examples of RQA question types and errors on the Number split.

Question	Answer	Model	Error Type
How many British soldiers were killed or wounded during the Battle of Thermopylae in 480 BCE?	266 men	L-70B	Invalid Premise
What is the numerical designation..., if we humorously assume there were 111 before it?	112 Ark	GPT-4	Invalid Premise
According to a 2011 census, how many officially recognized ethnic groups are there in India?	634 distinct peoples	Opus	Invalid Premise
In what year did the Vietnamese king Le Hoan defeat the Song Dynasty army at the Battle of Bach Dang?	988 AD	L-70B	No Consensus
How long did the construction of the Great Wall of China continue...?	264 years	GPT-4	No Consensus
What is the wavelength of yellow light in the visible spectrum?	587 nanometers	L-70B	Missing Info
How many individuals attended the annual community festival last year according to the final headcount?	178 people	GPT-4	Missing Info
How old was the world's oldest tortoise, Jonathan, when he passed away in 2022?	179 years of age	Opus	Missing Info

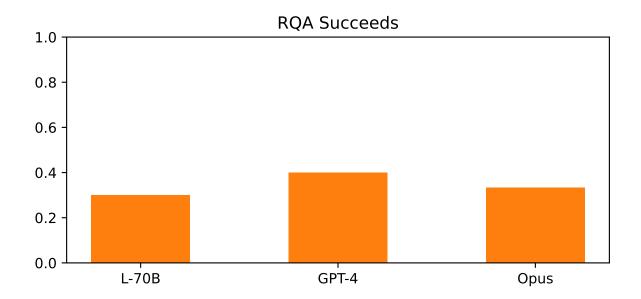Table 6: Examples of RQA question types and errors on the Number+Text split.

Figure 10: Proportion of RQA questions on Numbers+Text that semantically match the ground-truth question when RQA succeeds. LLaMA-3 70B, GPT-4, and Opus can all match the ground-truth question over 25% of the time.
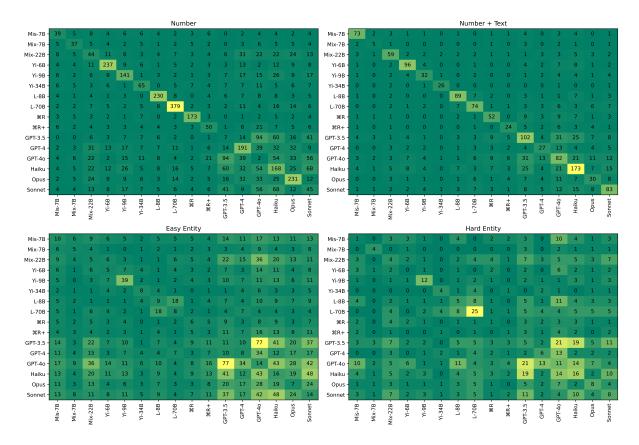
Figure 11: Cross-model frequency of questions from RQA that are exact duplicates. LLMs often generate the same question in RQA even though the input answer changes, reaching as high as 379 for LaMA-3 70B on Numbers.

Model	Easy Fact	Hard Fact	Number	Number+Text	Model Sum
Mis-7b	25	6	6	7	44
Mix-7B	7	0	10	1	18
Mix-22B	41	3	17	12	73
Yi-6B	18	0	98	40	156
Yi-9B	17	2	8	1	28
Yi-34B	7	0	18	0	25
L-8B	12	2	21	8	43
L-70B	4	1	19	4	28
Command-R	48	3	61	47	159
Command-R+	28	3	17	20	68
GPT-3.5	111	19	16	105	251
GPT-4	29	0	32	3	64
GPT-4o	96	10	27	39	172
Haiku	88	12	67	95	262
Sonnet	51	5	18	17	91
Opus	41	0	48	12	101
Dataset Sum	623	66	483	411	**1583**

Table 7: Number of generated RQA questions that are exact matches to a question in the Dolma pretraining corpus. On average, models are prone to copying questions from pretraining $\sim 3\%$ of the time. Smaller/weaker LLMs are more susceptible to copying questions from pretraining in RQA. Further, easy facts and numerical answers are more likely to lead to copied questions in RQA versus our hard facts.

Question	Answer	Model(s)	Split	Valid	Count
What is the answer to this question?	Lucy poems	Haiku	Hard Fact	No	21313
Who lives in a pineapple under the sea?	Spongebob Squarepants	GPT-3.5, GPT-4o	Easy Fact	Yes	1452
Where does the story take place?	In the Penal Colony	GPT-3.5	Hard Fact	No	1395
How many countries are there in the world?	195 nations	GPT-3.5	Num+Text	Yes	380
What is the capital of France?	Paris, France	Command-R+	Easy Fact	Yes	338
Who was the first president of the United States?	George Washington	Haiku, Sonnet	Easy Fact	Yes	281
How many days are there in a week?	357	Yi-6B	Number	No	194
What is the capital of the United States?	Washington, D.C.	Command-R, GPT-3.5	Easy Fact	Yes	192
How many days are there in a year?	365	Command-R	Easy Fact	Yes	166
How many days are there in a year?	800	Haiku	Number	No	166

Table 8: Questions generated from RQA that are most frequently found in the Dolma corpus. The LLM's tendency to generate inaccurate questions (e.g. *How many days are there in a year?* for *800*) or ambiguous questions (*What is the answer to this question?*) could be influenced by how often these questions appear in pretraining.