

Lecture 5: Scientific QA

25 Spring CSCE-689 SPTP: NLP4Science

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01/30/2025**

Refresh from previous lecture...

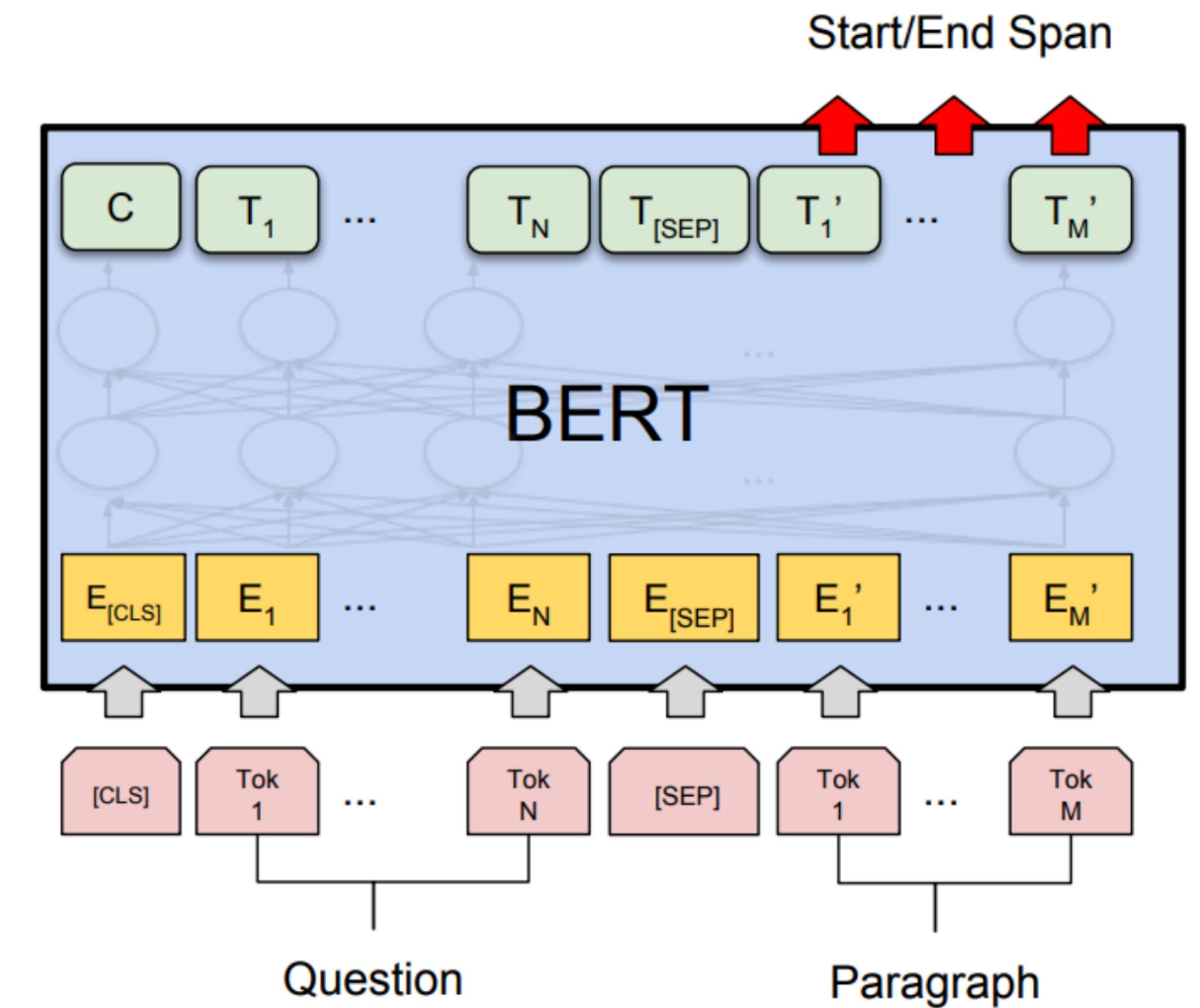
- Encoder-only Transformers: BERT
- (Extractive) question answering -> ternary classification

Context: Corynebacterium minutissimum is the bacteria that leads to cutaneous eruptions of erythrasma and is the most common cause of interdigital foot infections. It is found mostly in occluded intertriginous areas such as the axillae, ...

Question: Which bacteria causes erythrasma?

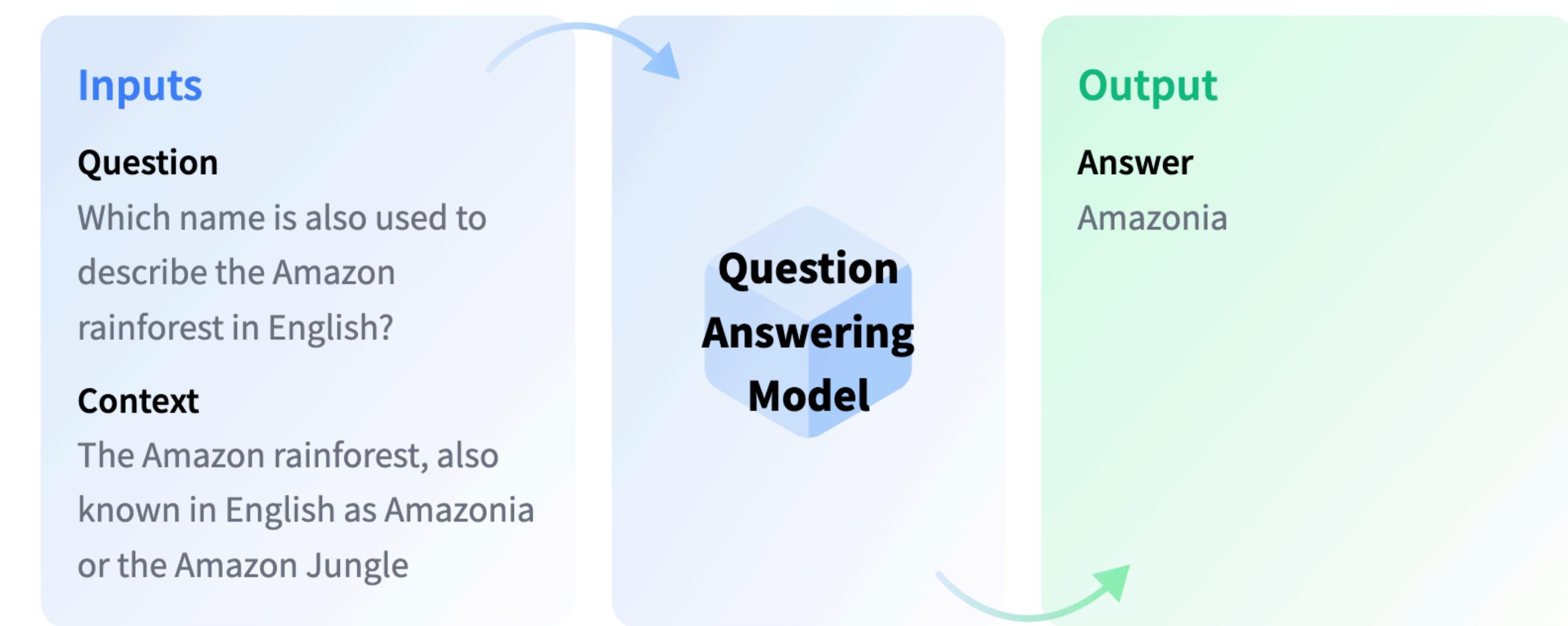


Answer: Corynebacterium minutissimum is the bacteria that leads to cutaneous ...



Question Answering Task Overview

- **Extractive QA:** The model extracts the answer from a context.
- **Generative QA:** The model generates the answer, usually with decoder-only architectures.
 - Open Generative QA: with context example
 - Close Generative QA: without context



Agenda

- **Pseudo QA (classification):** PubMedQA
- **Close generative question answering:** MetaMath
- **Open generative question answering:** Better to Ask in English

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Why we need QA?

- **Needs to evaluate** the knowledge absorbed by LLM
- **Needs to compare** intelligence between LLM and human

How to build a QA dataset?

- **Common solution 1:**
 - Use experienced annotator to manually create Q/A pair
 - *Very expensive!*
- **Common solution 2:**
 - Use existing models to perform extractive QA task on corpora
 - *Can a new model trained on this dataset outperform the model creating it?*
 - *The extracted QA pair does not require reasoning to answer*
- **Therefore... no large dataset require reasoning available!**

How to build a QA dataset?

- **Hybrid Solution (1+2)?**
 - Use PubMed dataset as corpora
 - **Step 1:** manually label small portion of data
 - **Step 2:** automatically collect unlabelled data, and use agreement rate with the manual portion to validate collection
 - **Step 3:** automatically convert titles/abstracts to question

Statistic	PQA-L	PQA-U	PQA-A
Number of QA pairs	1.0k	61.2k	211.3k
Prop. of yes (%)	55.2	–	92.8
Prop. of no (%)	33.8	–	7.2
Prop. of maybe (%)	11.0	–	0.0
Avg. question length	14.4	15.0	16.3
Avg. context length	238.9	237.3	238.0
Avg. long answer length	43.2	45.9	41.0

Table 1: PubMedQA dataset statistics.

How to build a QA dataset?

- 3: automatically convert titles to question
 - Using fixed rule-based conversion based on [1]
 - Why not LLM?

Original Statement Title	Converted Question	Label	%
Spontaneous electrocardiogram alterations <i>predict</i> ventricular fibrillation in Brugada syndrome.	<i>Do</i> spontaneous electrocardiogram alterations <i>predict</i> ventricular fibrillation in Brugada syndrome?	<i>yes</i>	92.8
Liver grafts from selected older donors <i>do not have</i> significantly more ischaemia reperfusion injury.	<i>Do</i> liver grafts from selected older donors <i>have</i> significantly more ischaemia reperfusion injury?	<i>no</i>	7.2

Table 2: Examples of automatically generated instances for PQA-A. Original statement titles are converted to questions and answers are automatically generated according to the negation status.

Example datapoint in PubMedQA

- Use PubMed articles with
 - A statement title which has POS tagging structures of NP-(VBP/VBZ)
 - Noun phrase (NP) followed by verb in present tense
 - e.g. 1: The study suggests that..." (NP = The study, VBZ = suggests)
 - e.g. 2: "Findings indicate a correlation..." (NP = Findings, VBP = indicate)
- And a structured abstract including a conclusive part.

Question:

Do preoperative statins reduce atrial fibrillation after coronary artery bypass grafting?

Context:

(Objective) Recent studies have demonstrated that statins have pleiotropic effects, including anti-inflammatory effects and atrial fibrillation (AF) preventive effects [...]

(Methods) 221 patients underwent CABG in our hospital from 2004 to 2007. 14 patients with preoperative AF and 4 patients with concomitant valve surgery [...]

(Results) The overall incidence of postoperative AF was 26%. ***Postoperative AF was significantly lower in the Statin group compared with the Non-statin group (16% versus 33%, p=0.005).*** Multivariate analysis demonstrated that independent predictors of AF [...]

Long Answer:

(Conclusion) Our study indicated that preoperative statin therapy seems to reduce AF development after CABG.

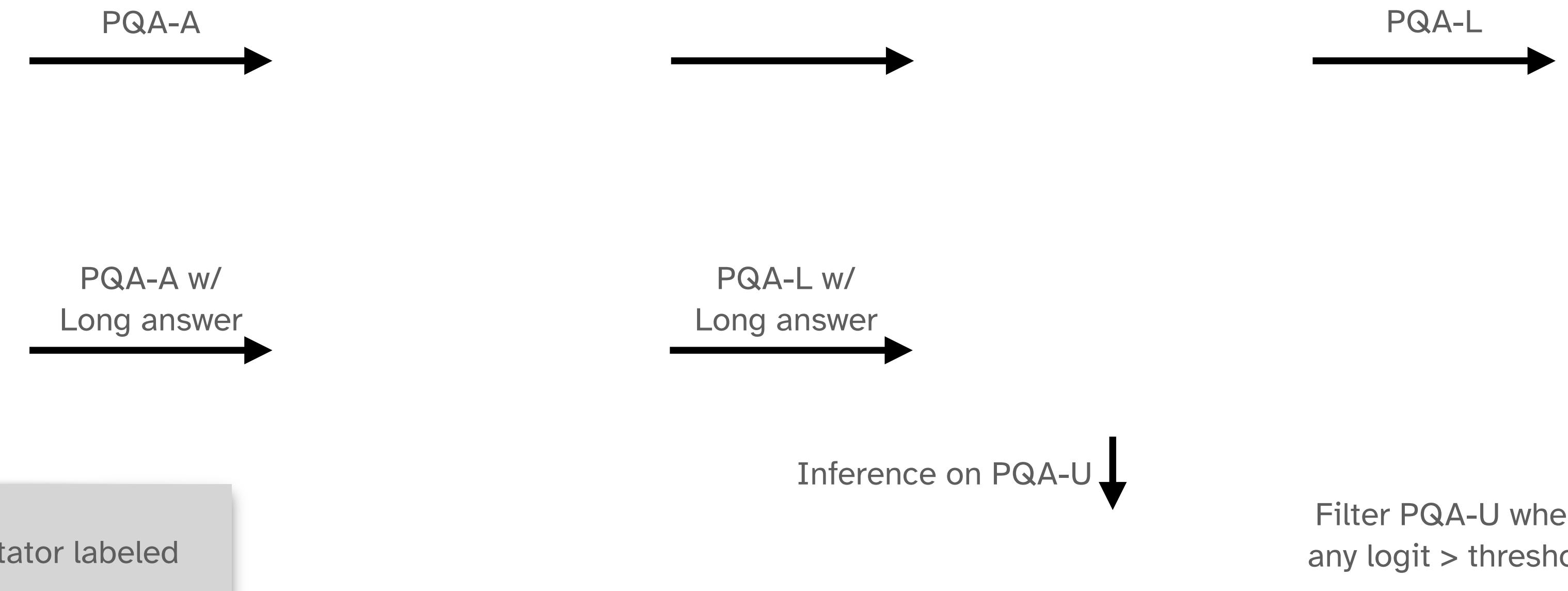
Answer: yes

Figure 1: An instance ([Sakamoto et al., 2011](#)) of PubMedQA dataset: Question is the original question title; Context includes the structured abstract except its conclusive part, which serves as the Long Answer; Human experts annotated the Answer yes. Supporting fact for the answer is **highlighted**.

How to show the dataset is useful?

- Fine-tune a few models using PubMedQA dataset
- Show the model is stronger compared to baseline

{BioBERT, ESIM, BiLSTM}



Definition:

- **PQA-L (1k)**: Human annotator labeled
- **PQA-U (61k)**: Unlabeled
- **PQA-A (211k)**: Generated question using rule-based label

Experimental results of SFT with PubMedQA

Model	Final Phase Only		Single-phase		Phase I + Final		Phase II + Final		Multi-phase	
	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1
Majority	55.20	23.71	—	—	—	—	—	—	—	—
Human (single)	78.00	72.19	—	—	—	—	—	—	—	—
w/o A.S.										
Shallow Features	53.88	36.12	<u>57.58</u>	31.47	57.48	37.24	56.28	<u>40.88</u>	53.50	39.33
BiLSTM	55.16	23.97	<u>55.46</u>	39.70	58.44	40.67	52.98	<u>33.84</u>	59.82	<u>41.86</u>
ESIM w/ BioELMo	53.90	32.40	<u>61.28</u>	42.99	61.96	43.32	60.34	<u>44.38</u>	62.08	<u>45.75</u>
BioBERT	56.98	28.50	<u>66.44</u>	47.25	66.90	46.16	66.08	50.84	67.66	52.41
w/ A.S.										
Shallow Features	53.60	35.92	<u>57.30</u>	30.45	<u>55.82</u>	35.09	<u>56.46</u> [†]	40.76	<u>55.06</u> [†]	40.67 [†]
BiLSTM	<u>55.22</u> [†]	23.86	<u>55.96</u> [†]	40.26 [†]	<u>61.06</u> [†]	41.18 [†]	<u>54.12</u> [†]	34.11 [†]	<u>58.86</u> [†]	41.06
ESIM w/ BioELMo	<u>53.96</u> [†]	31.07	<u>62.68</u> [†]	43.59 [†]	<u>63.72</u> [†]	47.04 [†]	60.16	<u>45.81</u> [†]	<u>63.72</u> [†]	<u>47.90</u> [†]
BioBERT	<u>57.28</u> [†]	28.70 [†]	<u>66.66</u> [†]	46.70 [†]	<u>67.24</u> [†]	46.21 [†]	<u>66.44</u> [†]	51.41 [†]	<u>68.08</u> [†]	<u>52.72</u> [†]

Table 5: Main results on PQA-L test set under reasoning-required setting. A.S.: additional supervision. [†]with A.S. is better than without A.S. Underlined numbers are model-wise best performance, and bolded numbers are global best performance. All numbers are percentages.

Agenda

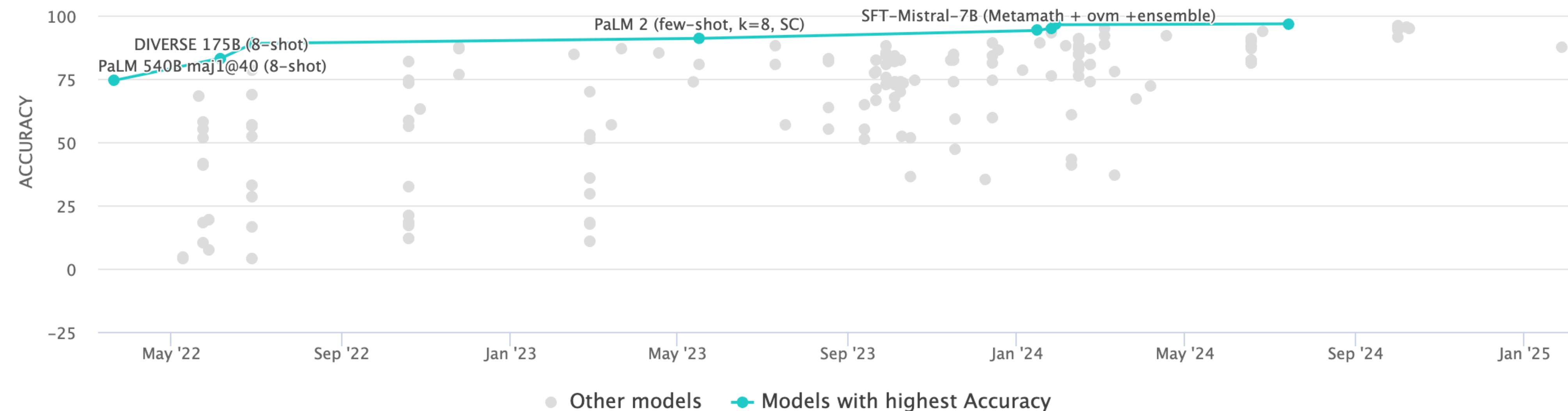
- Pseudo QA (classification): PubMedQA
- Close generative question answering: MetaMath
- Open generative question answering: Better to Ask in English

Myth of math problem solving

- **OpenAI's 5 steps to AGI**
 - L1: conversational AI
 - L2: reasoner: solving complex problems requiring advanced reasoning
- **Math == Reasoning?**

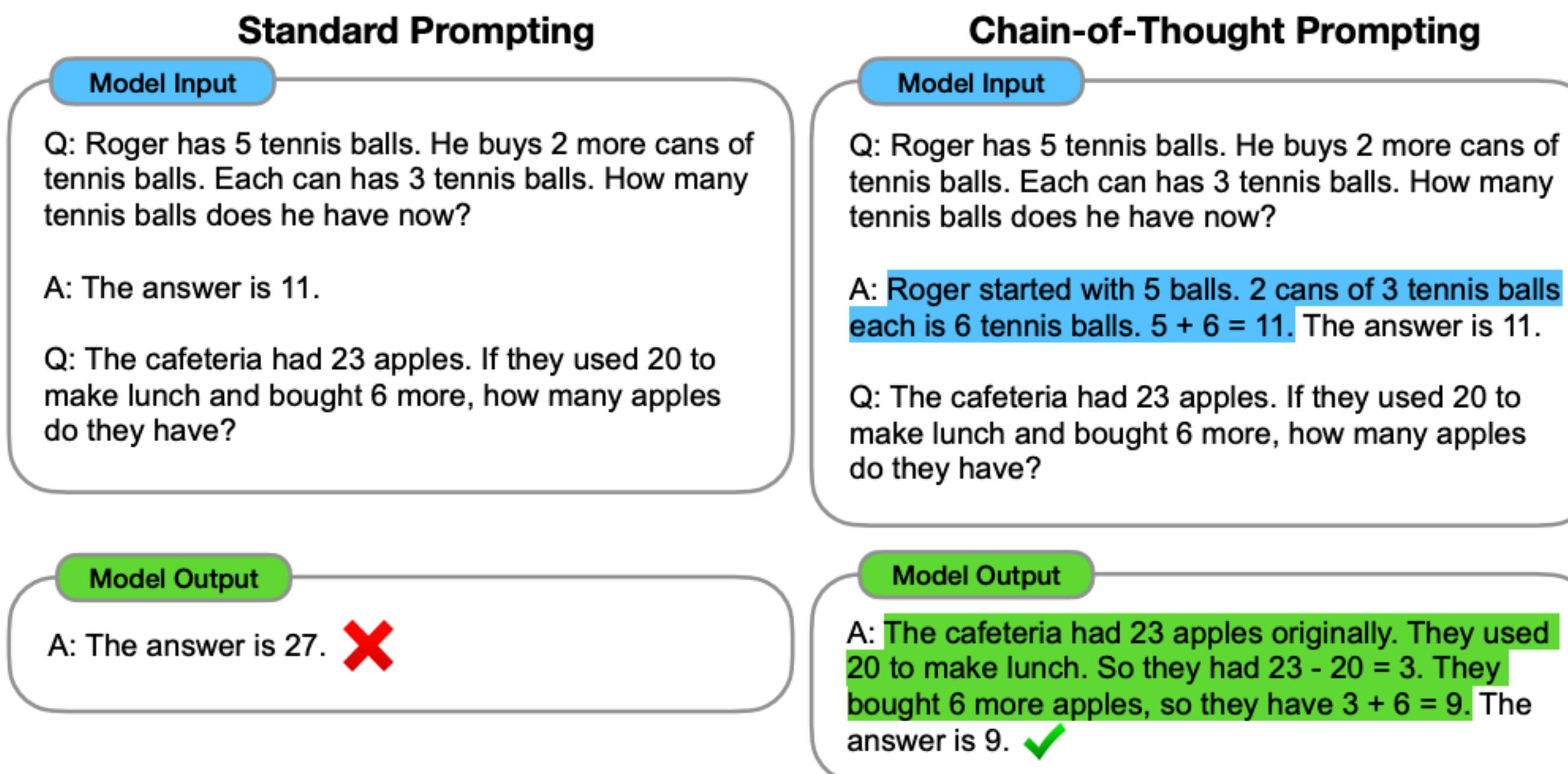
Myth of math problem solving

- GSM8K: High school math problems, taking 2-8 steps to solve.

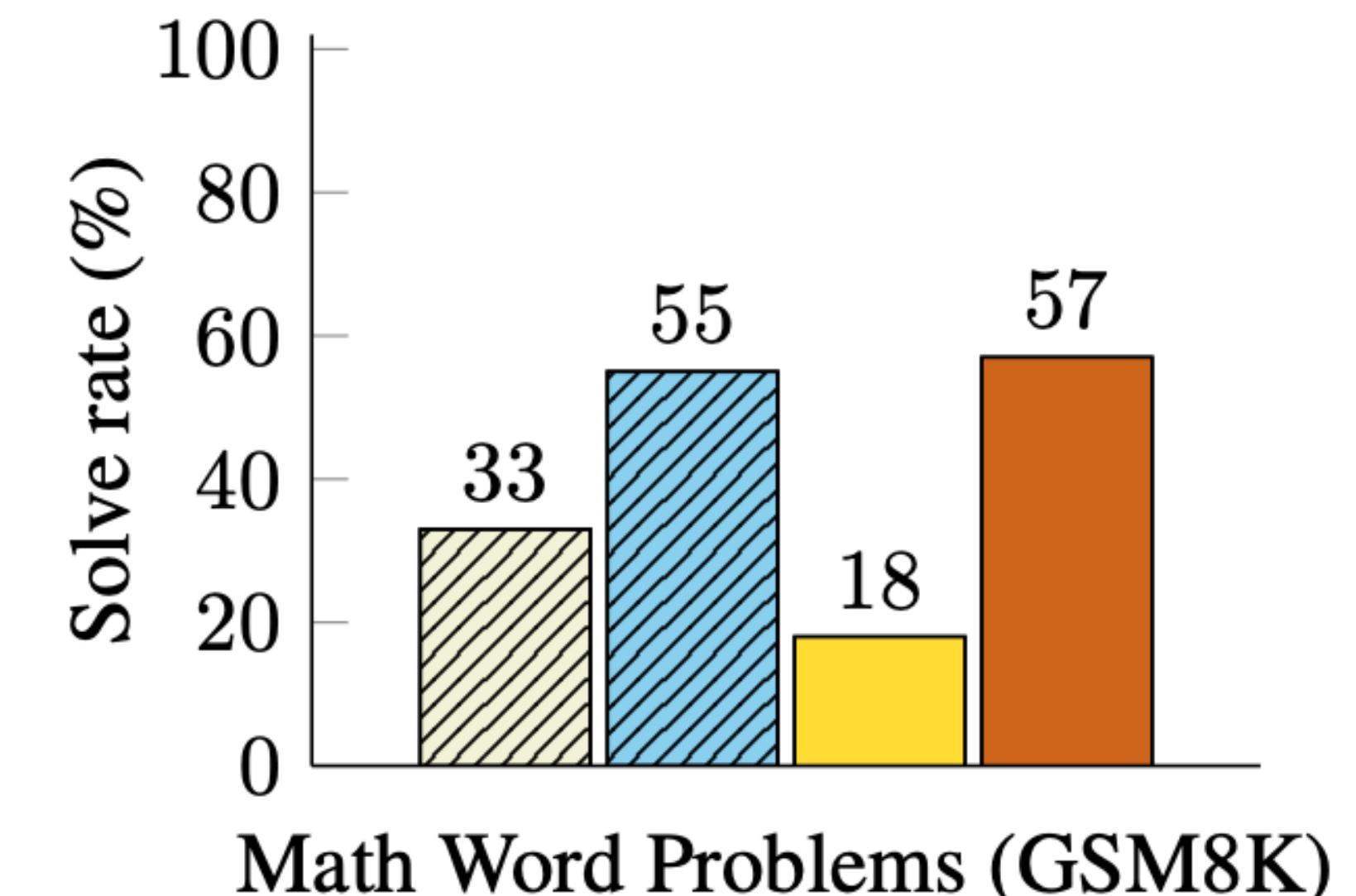


Chain-of-thought prompting

- Add intermediate steps in ICL example
- Or even easier, add “show your steps” in prompt



Finetuned GPT-3 175B
Prior best
PaLM 540B: standard prompting
PaLM 540B: chain-of-thought prompting



A lesson from CV: data augmentation

- Augment one datapoint with different ‘view’ of it

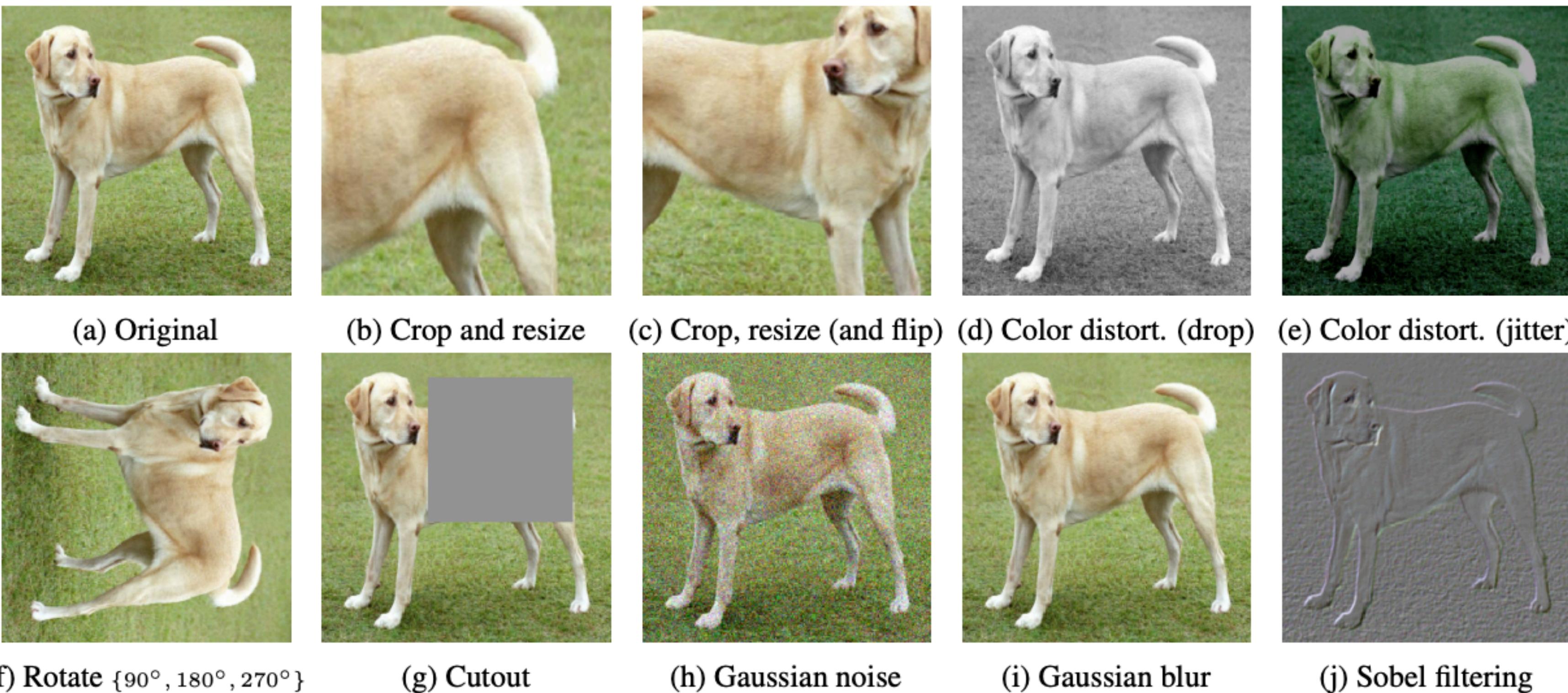
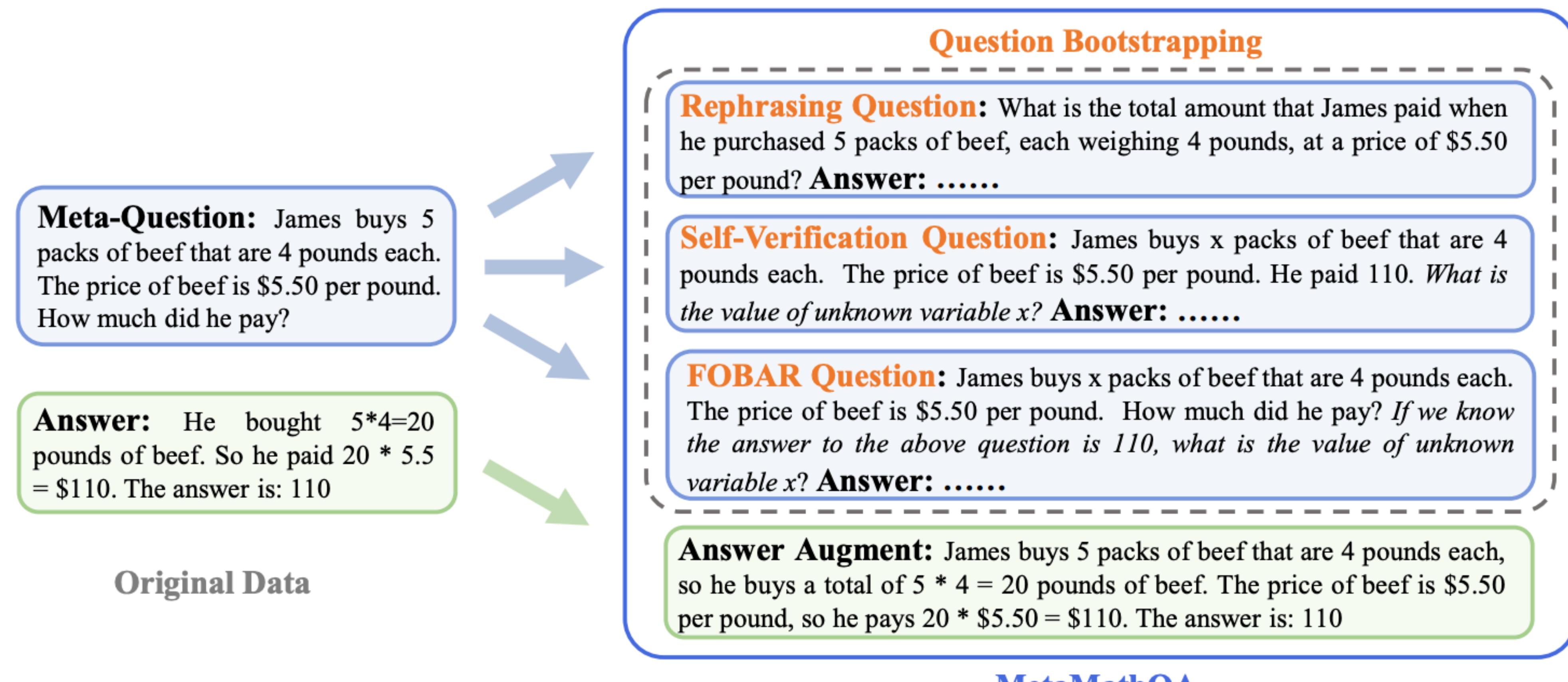


Figure 4. Illustrations of the studied data augmentation operators. Each augmentation can transform data stochastically with some internal parameters (e.g. rotation degree, noise level). Note that we *only* test these operators in ablation, the *augmentation policy used to train our models* only includes *random crop* (with *flip and resize*), *color distortion*, and *Gaussian blur*. (Original image cc-by: Von.grzanka)

MetaMath: augmenting math QAs

- Augment one datapoint with different ‘view’ of it



How?

- Question bootstrapping with LLM

Example A.1: Prompt for Rephrasing GSM8K Questions

You are an AI assistant to help me rephrase questions. Follow the given examples.

Question: Olivia has \$23. She bought five bagels for \$3 each. How much money does she have left?

Rephrase the above question: What is the amount of money that Olivia has left after purchasing five bagels for \$3 each, if she initially had \$23?

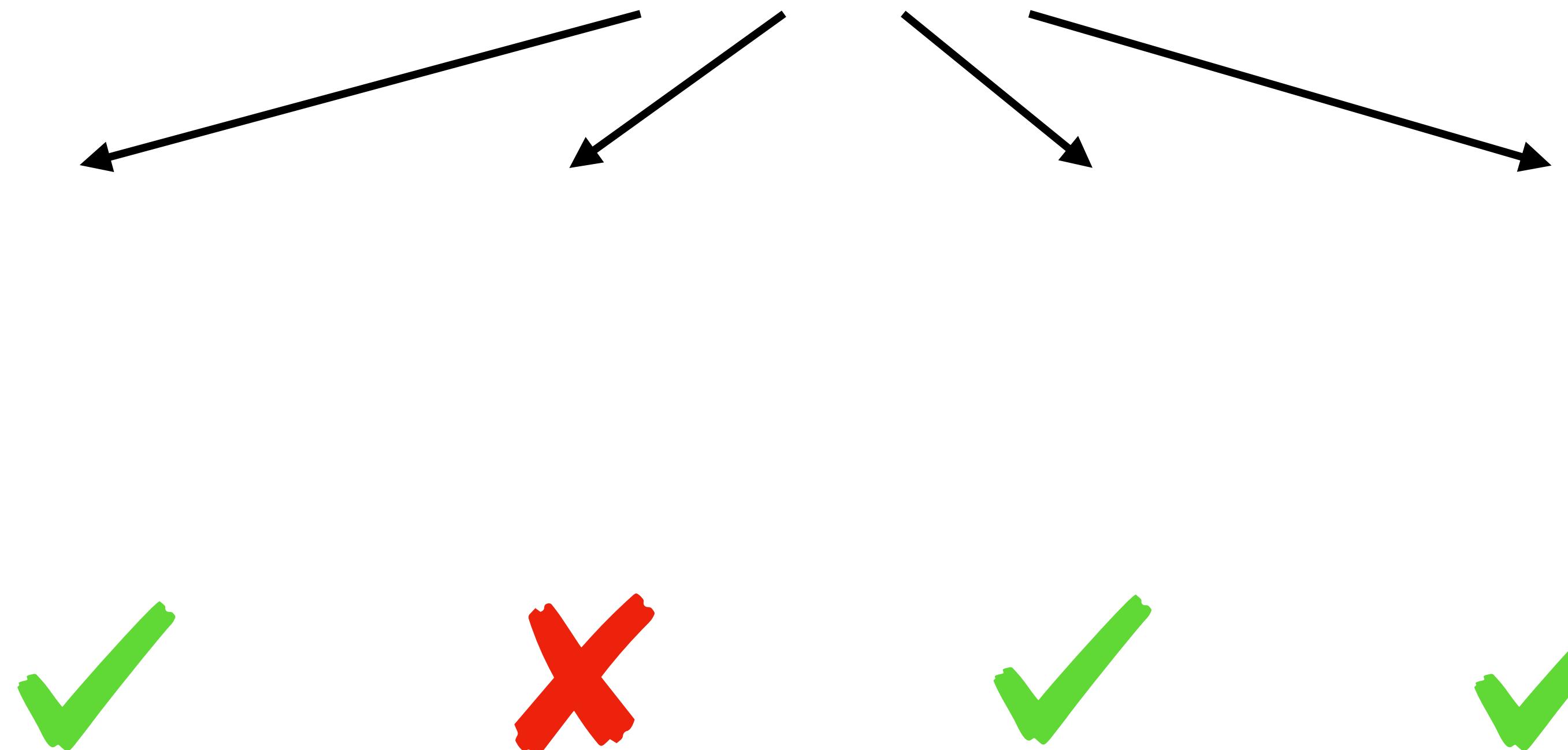
Question: Michael had 58 golf balls. On tuesday, he lost 23 golf balls. On wednesday, he lost 2 more. How many golf balls did he have at the end of wednesday?

Rephrase the above question: After losing 23 golf balls on Tuesday and an additional 2 on Wednesday, how many golf balls does Michael have left if he initially had 58 golf balls?

How?

- Answer bootstrapping with LLM

Answer this question? x4



Experiment results of MetaMath

- One augmentation bring 18% accuracy increase on GSM8K

Method	GSM8K						MATH					
	AnsAug	Rep.	SV	FOBAR	GSM8K	MATH	AnsAug	Rep.	SV	FOBAR	GSM8K	MATH
SFT [70]	✗	✗	✗	✗	41.6	3.0	✗	✗	✗	✗	13.8	4.7
MetaMath	✓	✗	✗	✗	59.6	4.4	✓	✗	✗	✗	28.4	12.9
	✗	✓	✗	✗	59.7	4.4	✗	✓	✗	✗	30.4	12.4
	✓	✓	✗	✗	60.6	4.4	✓	✓	✗	✗	29.1	15.3
	✓	✓	✓	✓	64.4	5.7	✓	✓	✓	✓	34.6	17.7

Table 3: Effect of different question augmentation with LLaMA-2-7B finetuned on GSM8K or MATH.

Beyond data augmentation

- Reinforcement learning technique
 - Use LLM to generate reward for its own response [1]

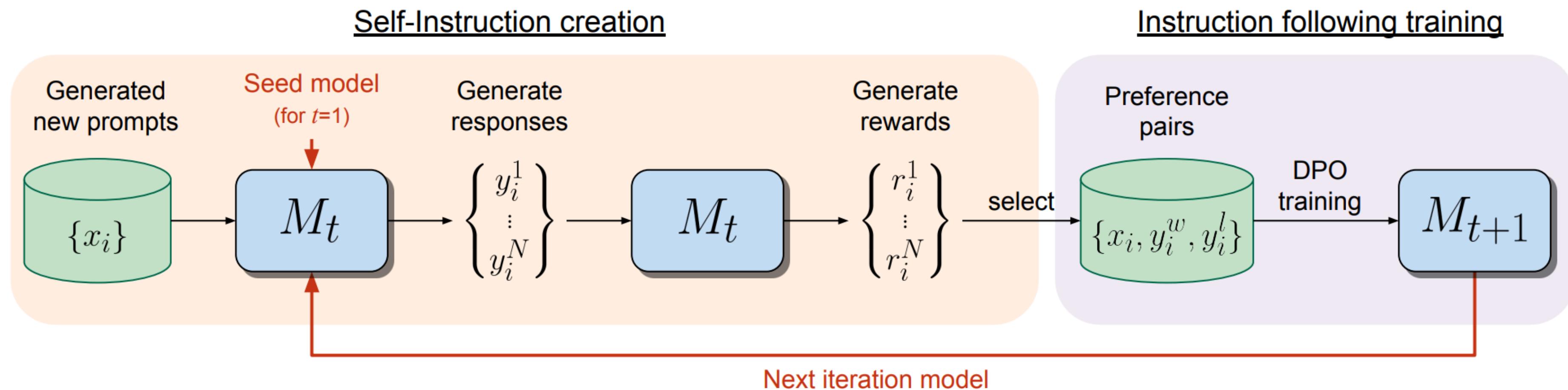


Figure 1: **Self-Rewarding Language Models.** Our self-alignment method consists of two steps: (i) *Self-Instruction creation*: newly created prompts are used to generate candidate responses from model M_t , which also predicts its own rewards via LLM-as-a-Judge prompting. (ii) *Instruction following training*: preference pairs are selected from the generated data, which are used for training via DPO, resulting in model M_{t+1} . This whole procedure can then be iterated resulting in both improved instruction following and reward modeling ability.

Beyond data augmentation

- Reinforcement learning technique
 - Use LLM to generate rational for Q/A pair, and reward correct rationale [2]

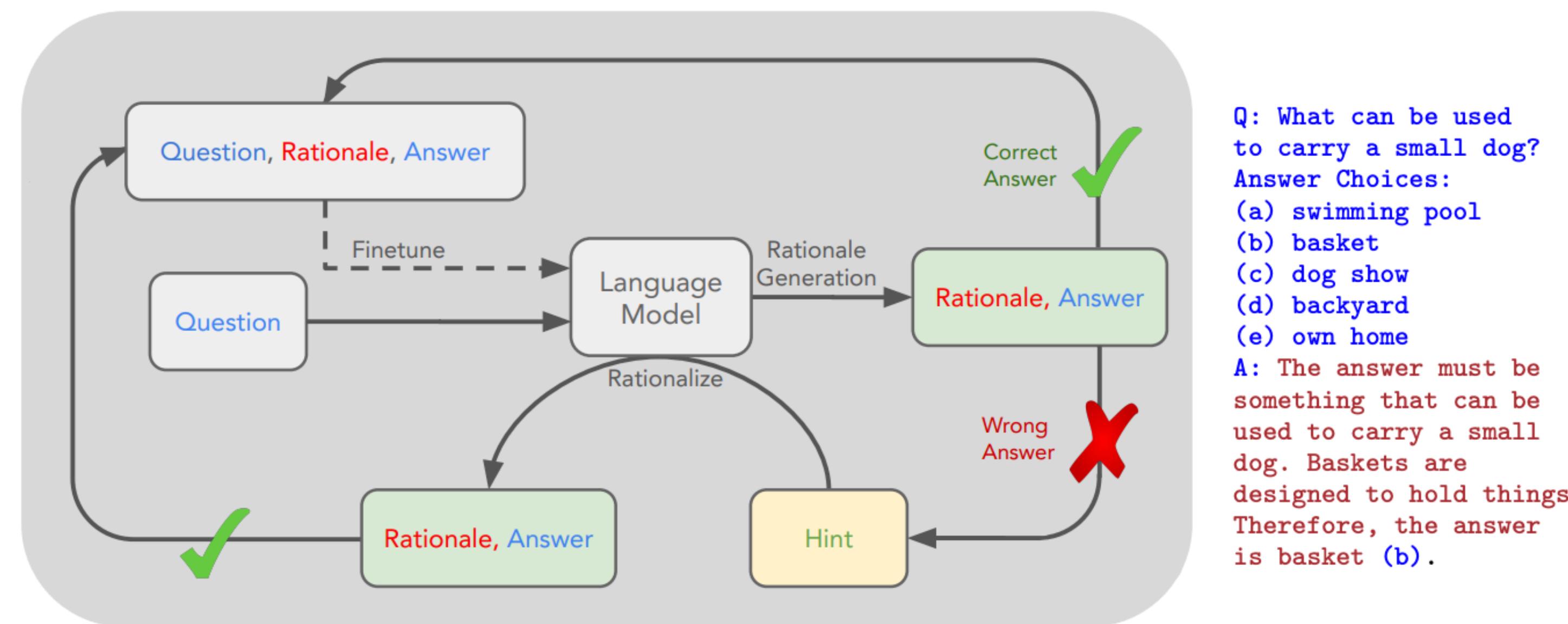


Figure 1: An overview of STaR and a STaR-generated rationale on CommonsenseQA. We indicate the fine-tuning outer loop with a dashed line. The **questions** and ground truth **answers** are expected to be present in the dataset, while the **rationales** are generated using STaR.

Beyond data augmentation

- Value model to detect early stage error in chain-of-thought [3]

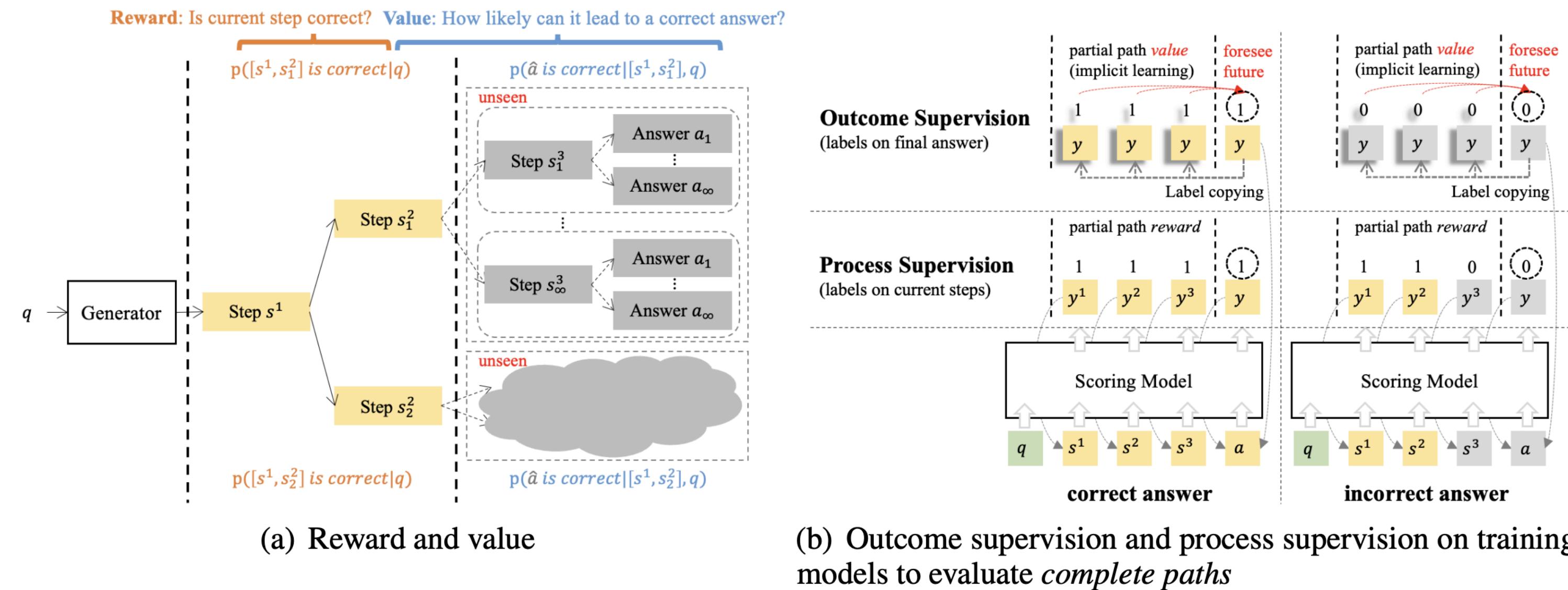


Figure 1: (a): When evaluating partial paths (here for the first two steps), reward focuses on the current states, while value focuses on the unseen future outcomes. (b): Given a question q and a solution path $[s^1, \dots, s^m, a]$, models are trained to predict path correctness (circled output scalar on the last token). Outcome supervision replicates the final answer's correctness label across all steps (indicated by shaded labels), causing the model to implicitly learn to foresee the future, predicting values for partial paths. By contrast, process supervision details per-step correctness labels, causing the model to learn to predict step-level correctness, i.e. reward. Correct steps and answers are colored in yellow and incorrect ones in grey.

Beyond data augmentation

- LLM with RL
 - GPT-o1 achieves 83.3% accuracy on AIME@24
 - DeepSeek-R1 achieves 79.8% accuracy on AIME@24
 - GPT-4o achieves 13.4% on AIME@24

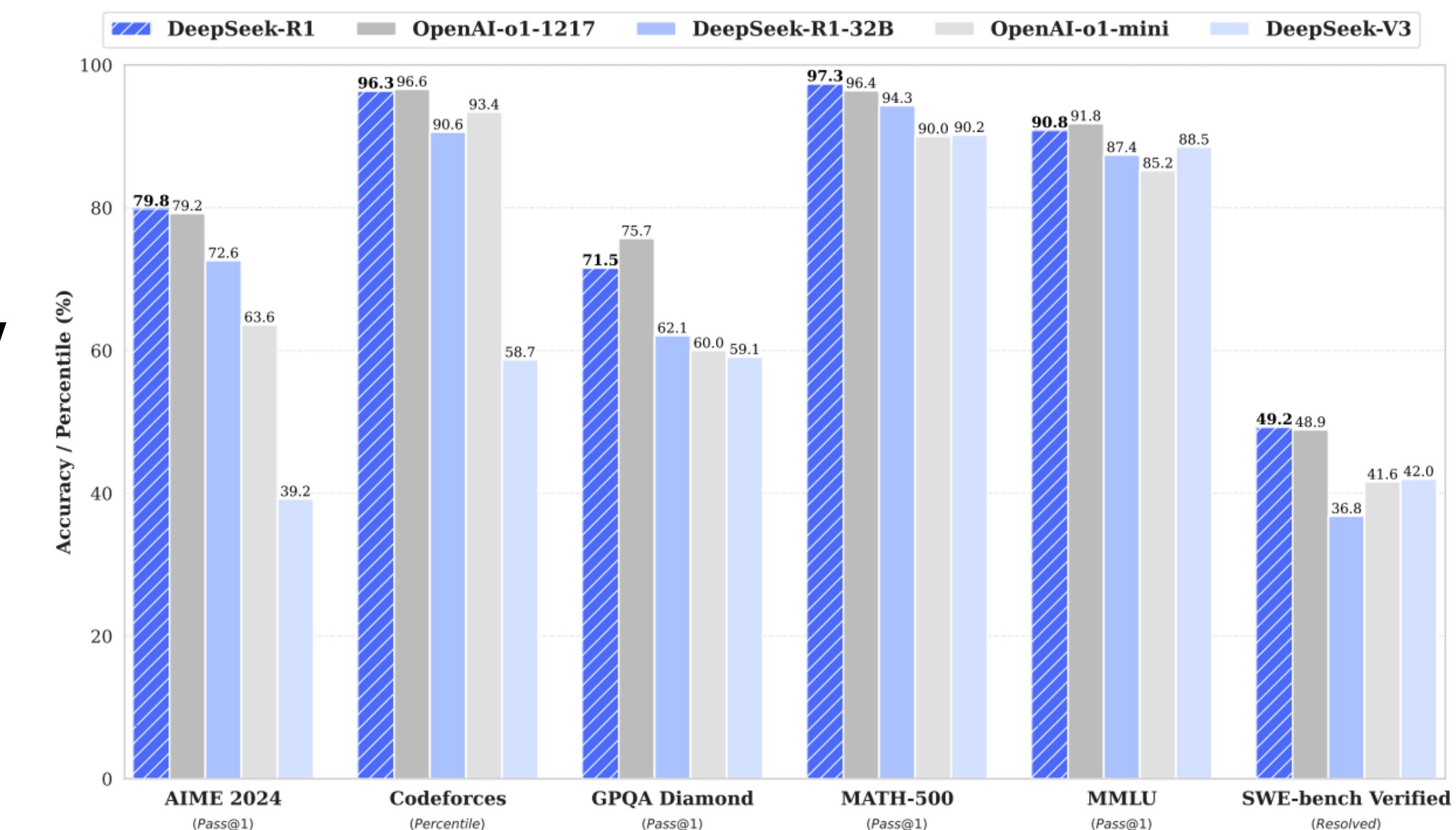


Figure 1 | Benchmark performance of DeepSeek-R1.

Takeaways

- Reasoning capability is important milestone to AGI
- Both **data augmentation** and **inference time techniques** (CoT, ensemble, etc.) widely used to improve reasoning capability for LLMs
- RL based methods further improve LLM's reasoning capability

Agenda

- **Pseudo QA (classification):** PubMedQA
- **Close generative question answering:** MetaMath
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Important question for generative QA

- **How to evaluate a generated sentence?**
- With ground truth label (discussed last lecture)
 - Traditional NLP metrics
 - ROUGE, BLEU
 - Example:
 - **Ref:** ChatGPT did better than me in history exam
 - **Pred:** I am not as good as ChatGPT in my history test
 - ROUGE@1 = 0.31; ROUGE@2 = 0!

Important question for generative QA

- **How to evaluate a generated sentence?**
 - LLM metrics
 - BERTScore: use BERT's [CLS] token embedding to calculate cosine similarity
 - Same example!
 - **Ref:** ChatGPT did better than me in history exam
 - **Pred:** I am not as good as ChatGPT in my history test
 - BERTScore Precision = 0.91; Recall = 0.89!

Important question for generative QA

- **How to evaluate a generated sentence?**
 - LLM metrics
 - GPTScore: assess the quality of generated sentence using pre-defined prompt template
 - $GPTScore(h \mid d, a, S) := \sum_{t=1}^m w_t \log p(h_t \mid h_{<t}, T(d, a, S), \theta)$
 - $p(h_t \mid h_{<t}, T(d, a, S), \theta)$ is the probability of each token in the summary
 - $T(d, a, S)$ is the structured evaluation prompt
 - **Measuring how certain the model is in terms of its generation**
 - Example prompt
 - Generate a summary with as much semantic coverage as possible for the following text
{source_text} \n Tl;dr {generated_summary}

Important question for generative QA

- How to evaluate a generated sentence?
- Without ground truth label (i.e. consistency, human preference, pick correct answer, etc.)
 - LLM-as-a-judge
 - Agreement rate on par with human-human agreement rate
- Also works for BERTScore / GPTScore usecase

Question: If the FED buys bonds in the secondary market
(A) the money supply will increase. (B) the money supply will decrease. (C) the money supply will not be affected. (D) the discount rate would be affected. Output the answer only.

Assistant A:

The Federal Reserve buys bonds in the secondary market to increase the money supply.

Assistant B:

(A) the money supply will increase.

Follow-up Question: How does it affect my daily life? Give 3 examples.

Assistant A:

The Federal Reserve buys bonds in the secondary market to increase the money supply. This affects your daily life by:
1. Increasing the money supply.
2. Increasing the money supply and lowering the discount rate.
3. Increasing the money supply and lowering the discount rate and increasing the money supply.

Assistant B:

When the Federal Reserve buys bonds in the secondary market, it can have several effects on the economy that can impact your daily life. Here are three examples:

1. Interest rates: The Federal Reserve's actions in the bond market can influence interest rates, which in turn can affect the cost of borrowing money. For example, if the Federal Reserve buys bonds and drives up demand for them, interest rates on things like mortgages, car loans, and credit cards may go up, making it more expensive to borrow money.
2. Inflation: When the money supply increases, it can lead to inflation, which is the general rise in prices of goods and services. This can impact your daily life by making it more expensive to buy things like groceries, gas, and other necessities.
3. Employment: The Federal Reserve's actions in the bond market can also have an impact on employment. For example, if the Federal Reserve's actions lead to economic growth and increased demand for goods and services, it can create more job opportunities and boost employment.

GPT-4 Judgment:

Assistant A provided an incorrect response to the user's question about how the Federal Reserve buying bonds in the secondary market affects daily life. The answer given is repetitive and lacks clear examples of how the action impacts daily life. On the other hand, Assistant B provided a relevant and accurate response to the user's question about the Federal Reserve buying bonds. The answer includes three clear examples of how the action impacts daily life, such as interest rates, inflation, and employment.

Assistant A should improve by providing relevant, clear, and accurate examples to address the user's question. Assistant B's response is more helpful, relevant, and detailed.

Better to Ask in English

- Framework for identifying Cross-lingual LLM performance degradation
- Assessing **Correctness**, **Consistency**, and **Verifiability**

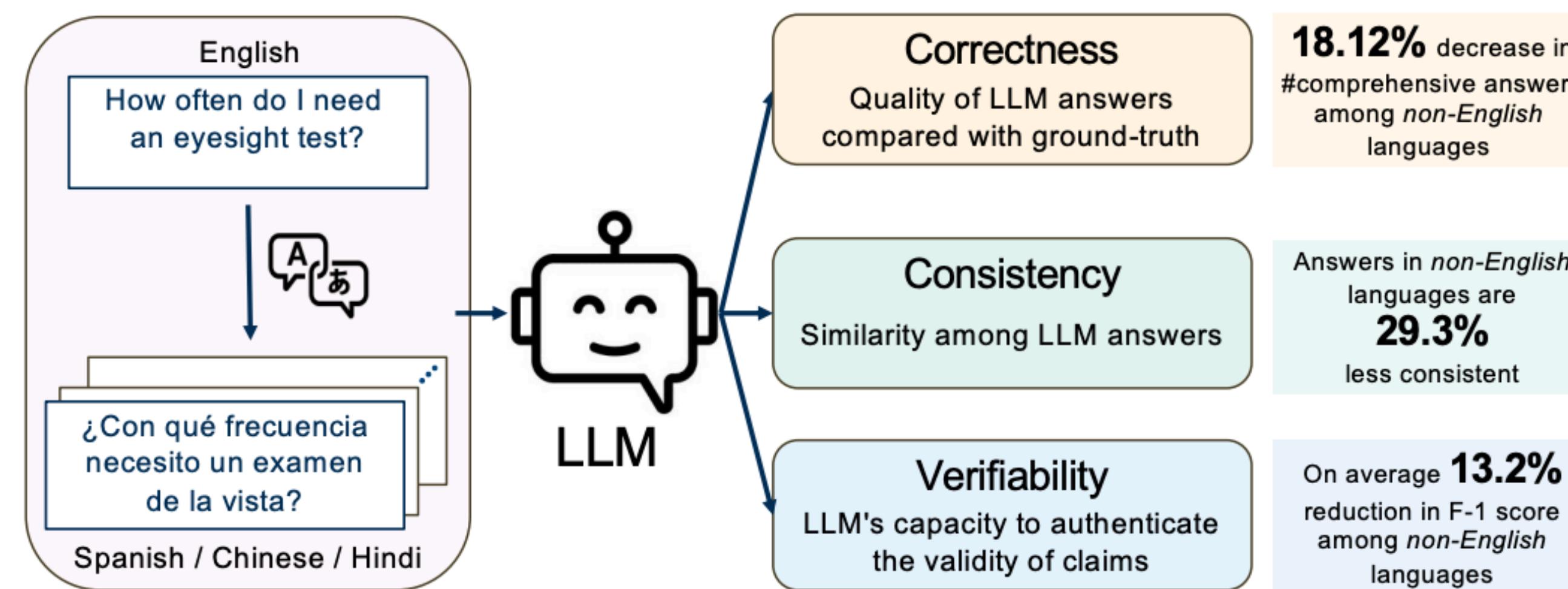


Figure 1: We present XLINGEVAL, a comprehensive framework for assessing cross-lingual behaviors of LLMs for high risk domains such as healthcare. We present XLINGHEALTH, a cross-lingual benchmark for healthcare queries.

Better to Ask in English

- **Correctness:** LLM evaluating Q/GT pair with generated answer in different language
- Task: 4-classes classification (more comprehensive, less comprehensive, neither, contradictory)

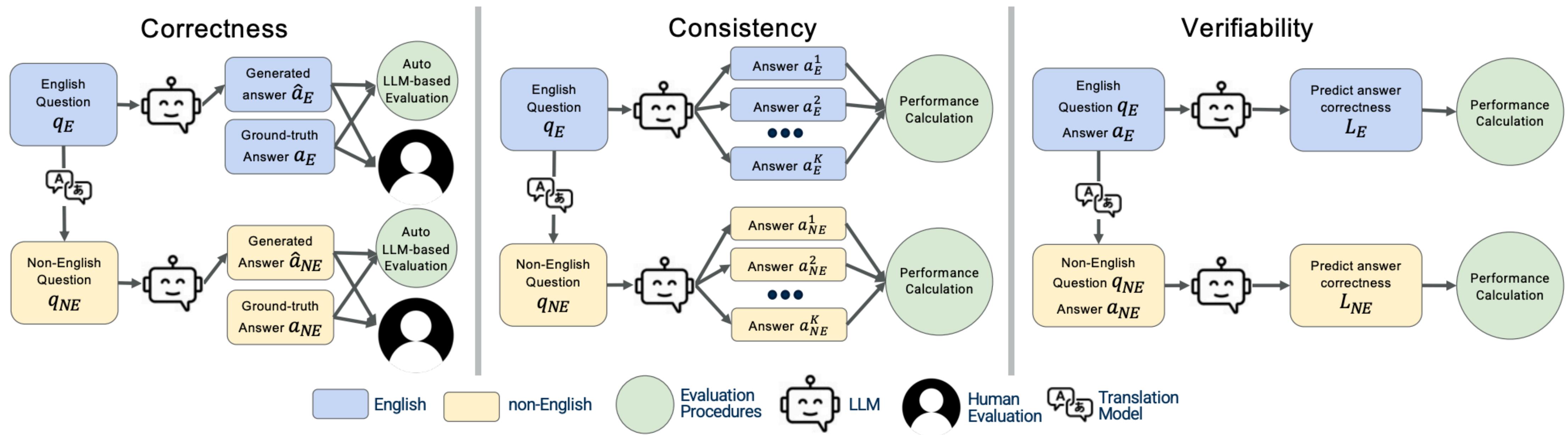


Figure 2: Evaluation pipelines for correctness, consistency, and verifiability criteria in the XLINGEVAL framework.

Better to Ask in English

- **Consistency:** LLM generating a list of answers, use pre-defined metric to evaluate similarity
- Metric: BERTScore, n-gram similarity, length, etc.

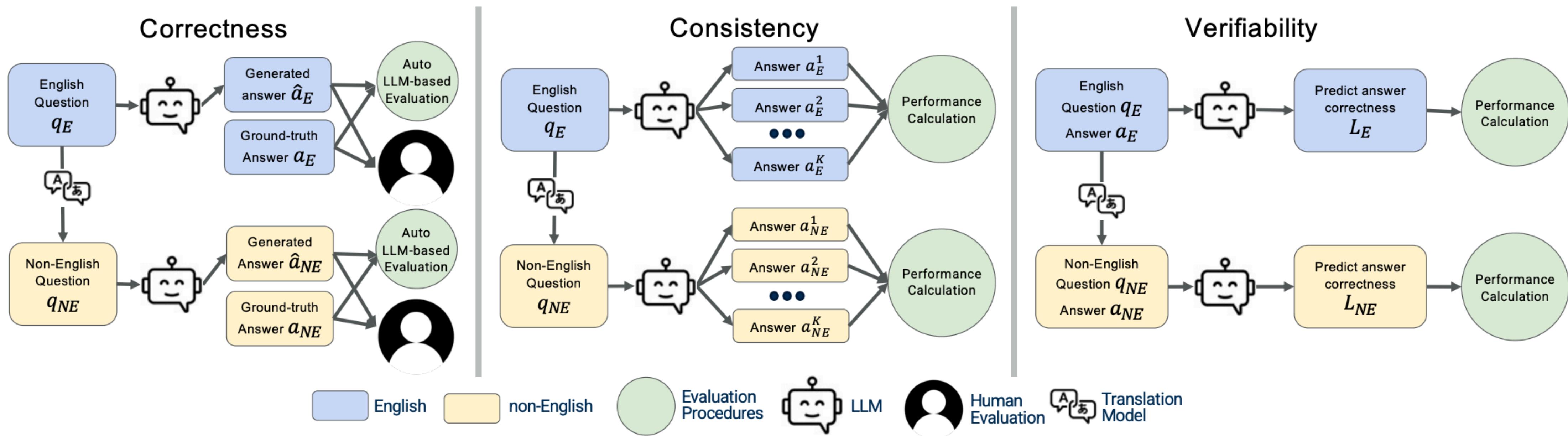


Figure 2: Evaluation pipelines for correctness, consistency, and verifiability criteria in the XLINGEval framework.

Better to Ask in English

- **Verifiability:** LLM decide if the answer is relevant to question
- Q+A -> LLM -> Binary classification (correct vs. irrelevant)

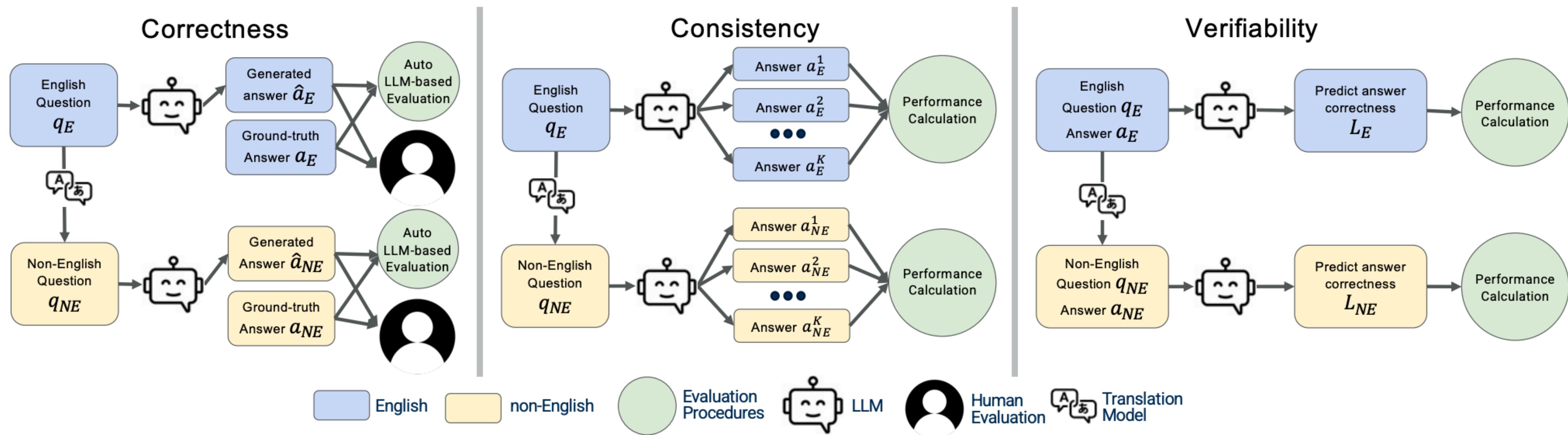


Figure 2: Evaluation pipelines for correctness, consistency, and verifiability criteria in the XLINGEVAL framework.

Experiment results: Better to Ask in English

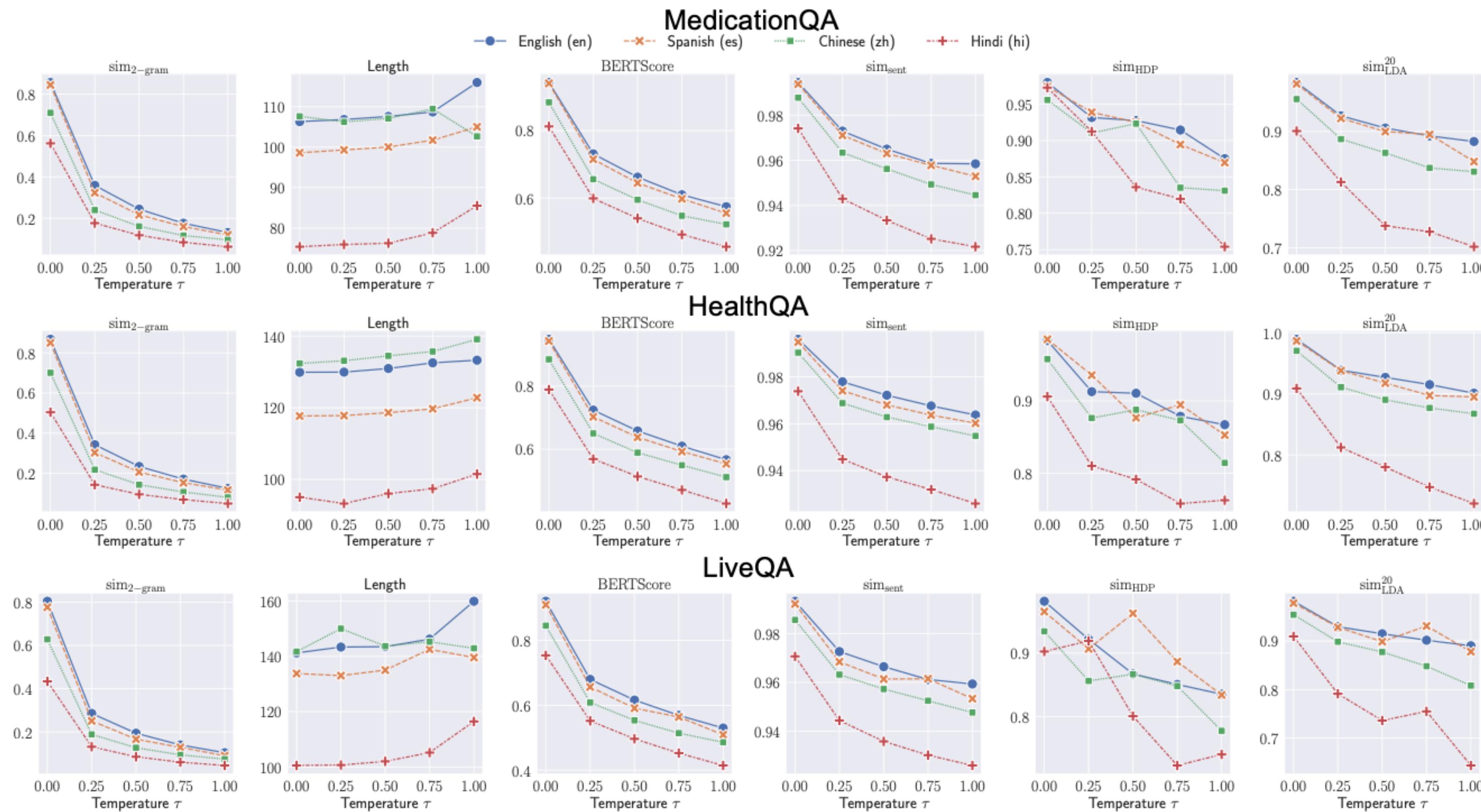
- **Correctness:** human verification is introduced for a subset of full test set to ensure the quality of automated evaluation

Table 1: Automated correctness evaluation in four languages: English (en), Spanish (es), Chinese (zh), and Hindi (hi) for GPT-3.5. Each number represents the number of answers assigned to the respective label in the dataset.

Information Comparison (LLM Answer vs ground-truth Answer)	HealthQA				LiveQA				MedicationQA			
	en	es	zh	hi	en	es	zh	hi	en	es	zh	hi
More comprehensive and appropriate	1013	891	878	575	226	213	212	142	618	547	509	407
Less comprehensive and appropriate	98	175	185	402	3	12	16	59	18	50	41	125
Neither contradictory nor similar	20	63	57	110	14	20	14	32	49	70	92	107
Contradictory	3	5	14	47	3	1	4	13	5	23	48	51

Experiment results: Better to Ask in English

- **Consistency:** degradation is common for all languages except English



Experiment results: Better to Ask in English



Figure 4: Results of LiveQA on metrics of the verifiability experiment, including macro precision, macro recall, macro F1-score, accuracy, and area under the curve (AUC). Each column represents a distinct metric. The x- and y-axis of each heatmap represents varying languages and temperatures τ , respectively. The results for the other datasets are in the Appendix (Figure A3)

Discussion: Better to Ask in English

- **Circulating argument?** Is it a fair comparison to use a `performance degraded model` to evaluate result, which is later used to show there will be a performance degradation across different languages?
- **Choice of metric?** Contextualized metric like BERTScore is designed for English. Length metric might not make sense.
 - BERT is pretrained on BookCorpus (EN only) and EN Wikipedia.
 - Think of the example of rewriting math questions. Rewriting can have very different length!
- **Would hallucination change depending on the language?**
 - Hallucination: LLM generates seemingly plausible yet factually unsupported content

Questions? Comments?