

TechSupportEval: An Automated Evaluation Framework for Technical Support Question Answering

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Jing Han⁴, Fan Ni⁴, Xuhui Cai⁵, Ce Yang⁵, and Dan Pei¹



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ZTE中兴⁴



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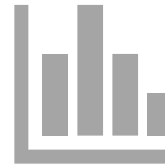
OUTLINE



Background



Framework

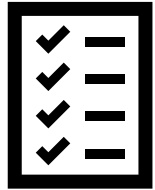


Evaluation



Conclusion

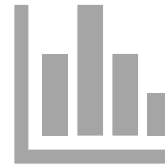
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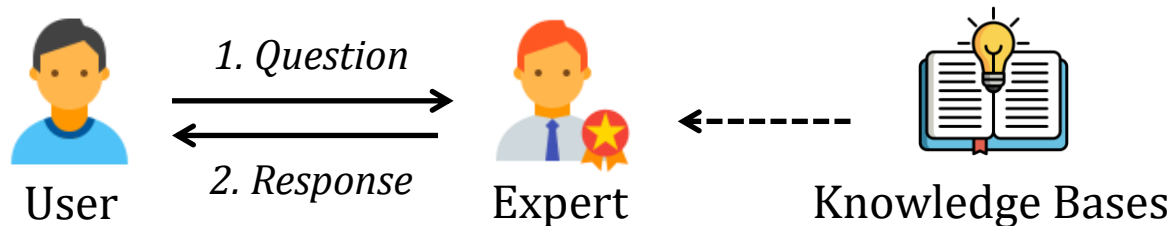
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Technical Support Question Answering

Technical Support¹

Technical support is a service provided to users to **diagnose and resolve technical issues** to maintain the reliability of IT services.

A common approach: Question Answering (QA)



[1] https://en.wikipedia.org/wiki/Technical_support

■ Example from Microsoft Forum

Question:

Are there ways to capture the IP addresses that are using my storage accounts in Azure portal?



Response:

Once you have enabled logging for your storage account, the information about operations performed against your storage account is saved in **`\$logs` blob container**. It contains a CSV files. The information you're looking for is available in **<requester-ip-address> field**.

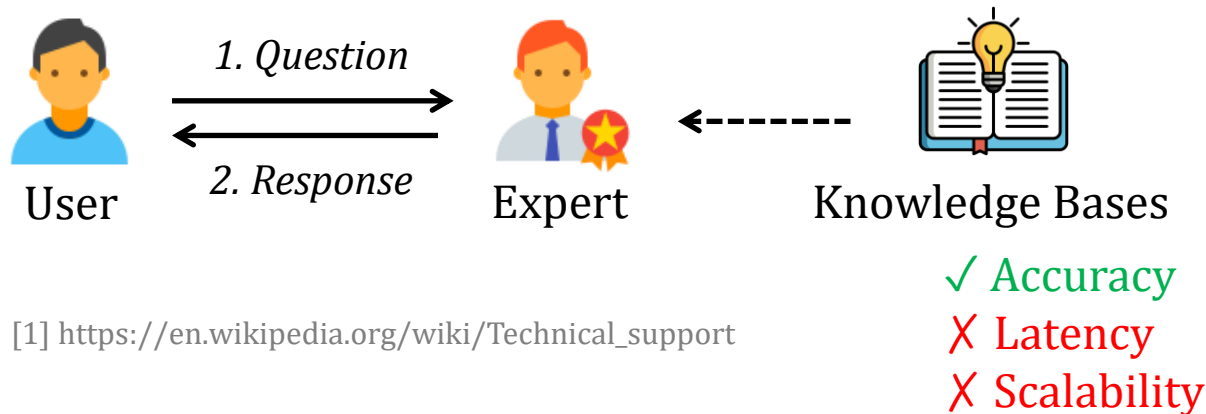
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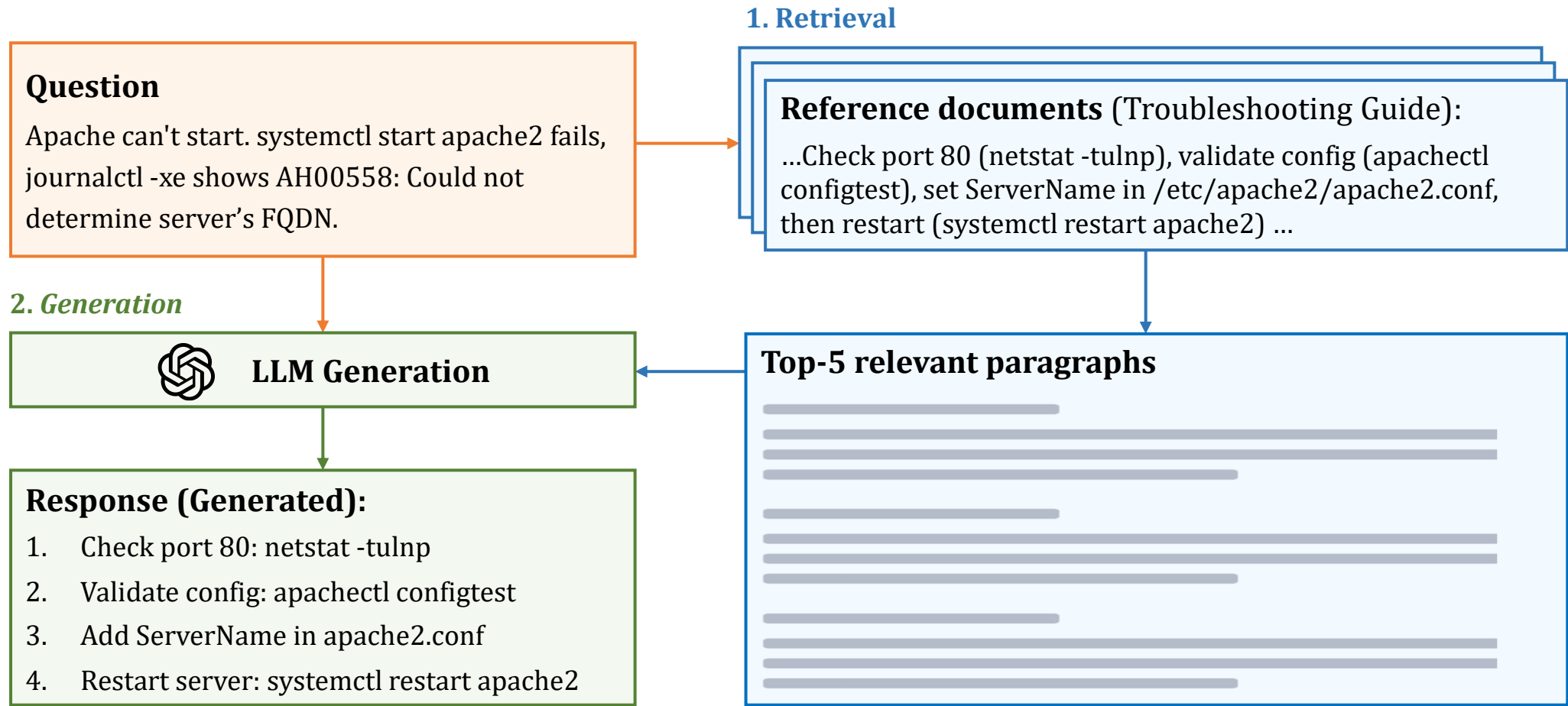


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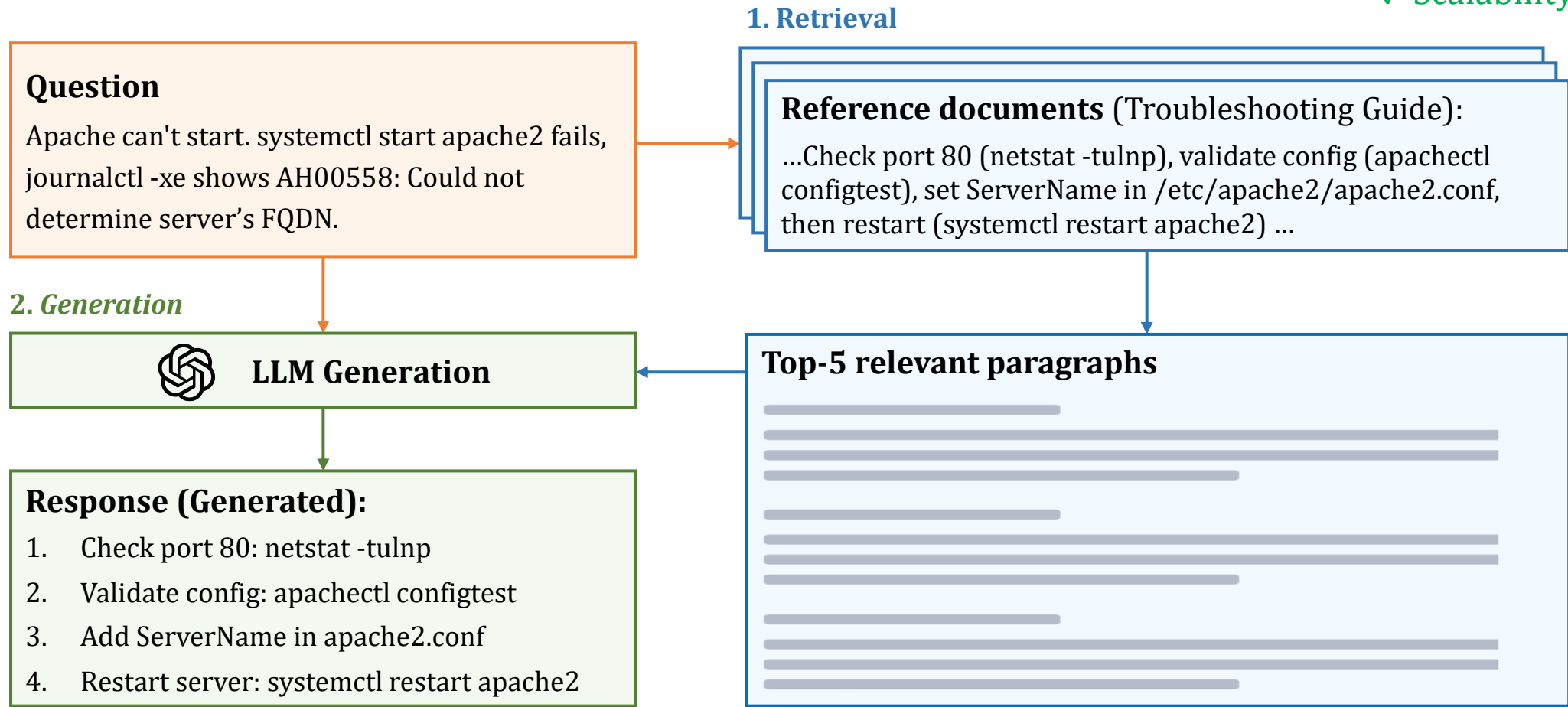
From Manual Responses to LLM-RAG Powered QA



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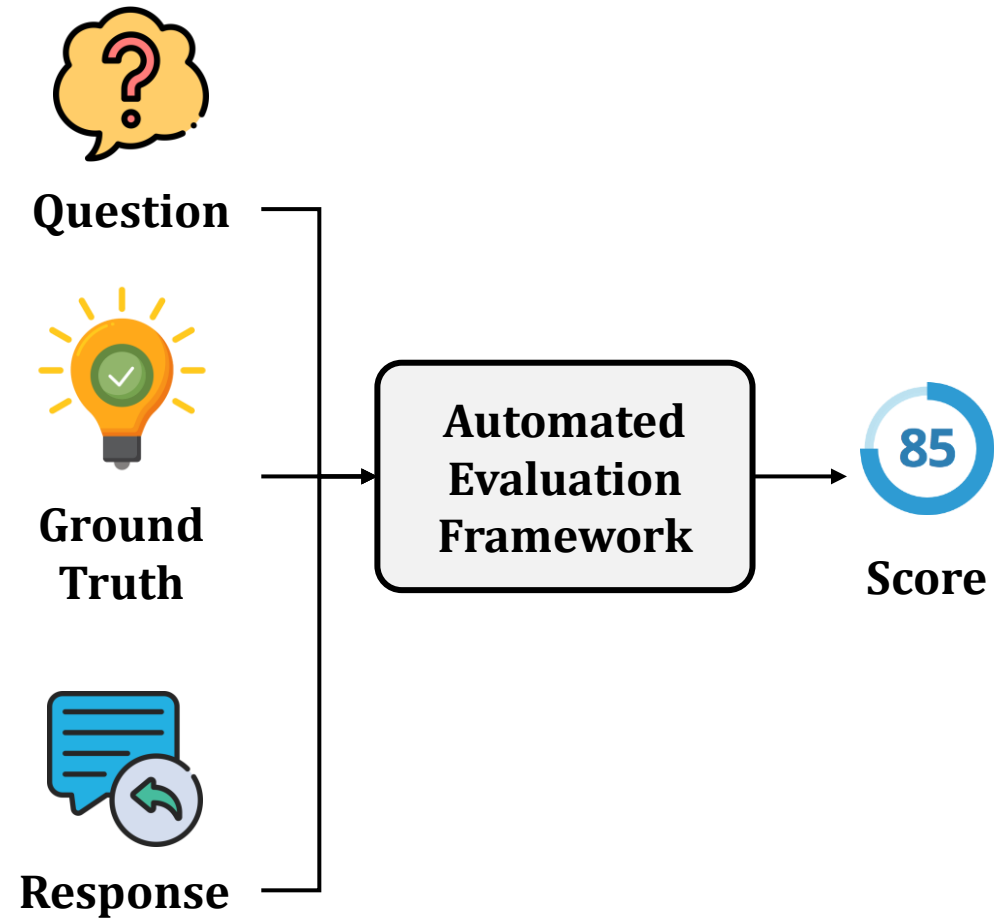
From Manual Responses to LLM-RAG Powered QA

? Accuracy
✓ Latency
✓ Scalability



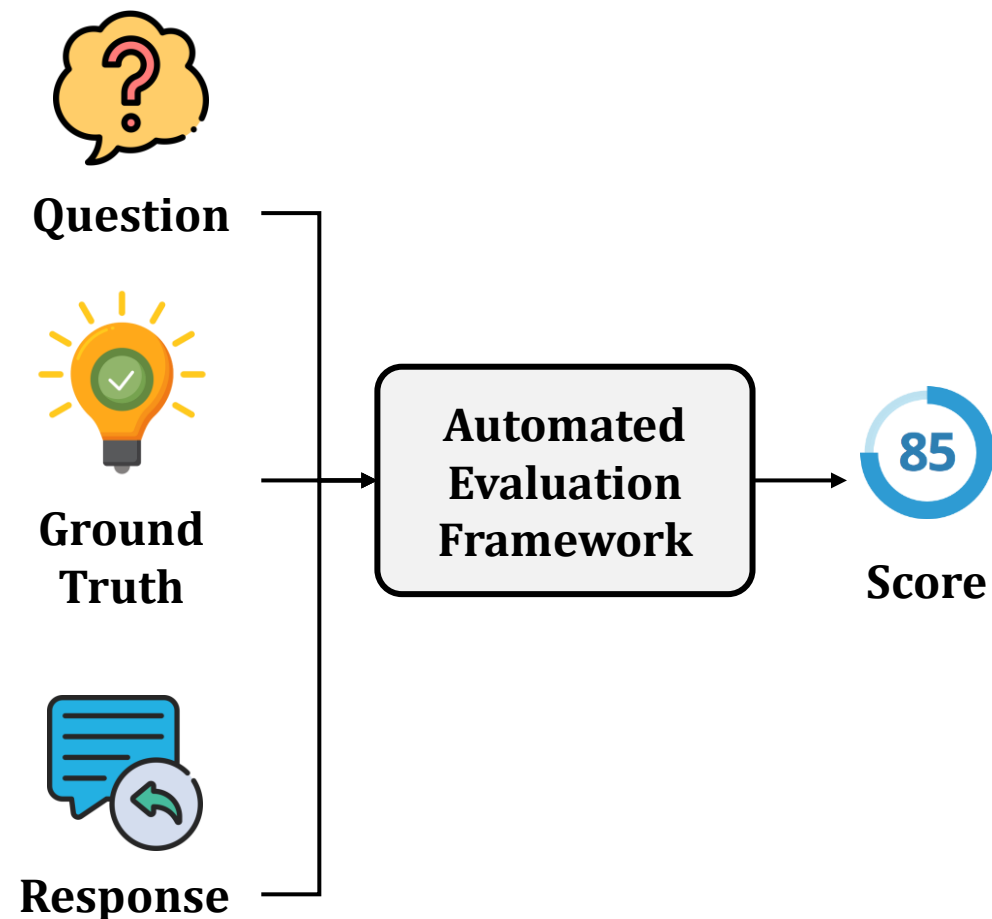
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Automated Evaluation of QA



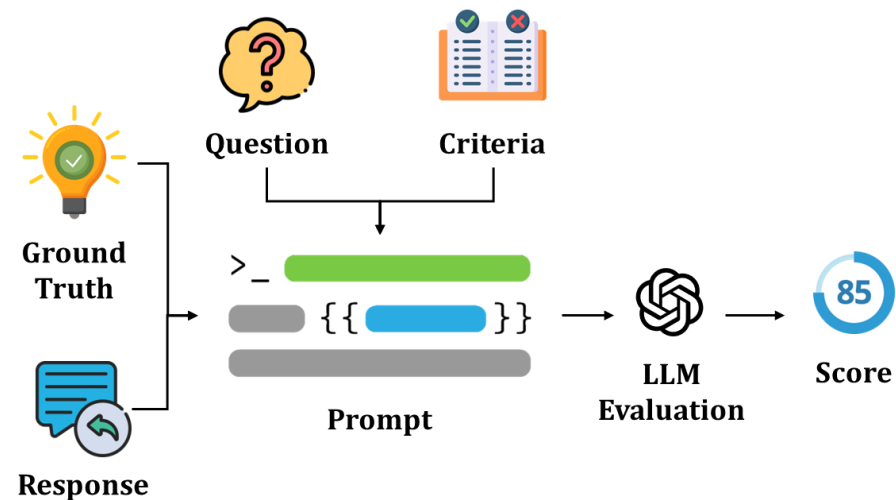
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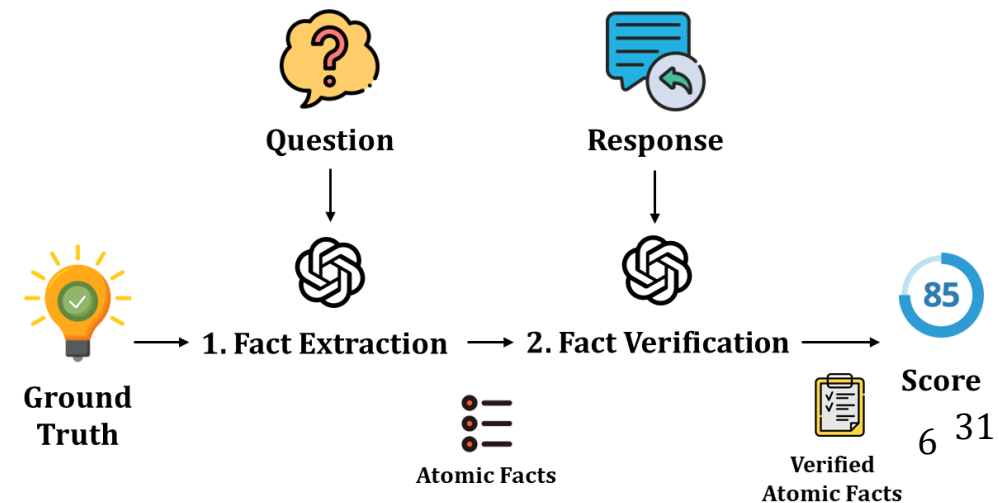


Existing evaluation methods:

1. Criteria-Guided Evaluation (e.g. G-Eval)

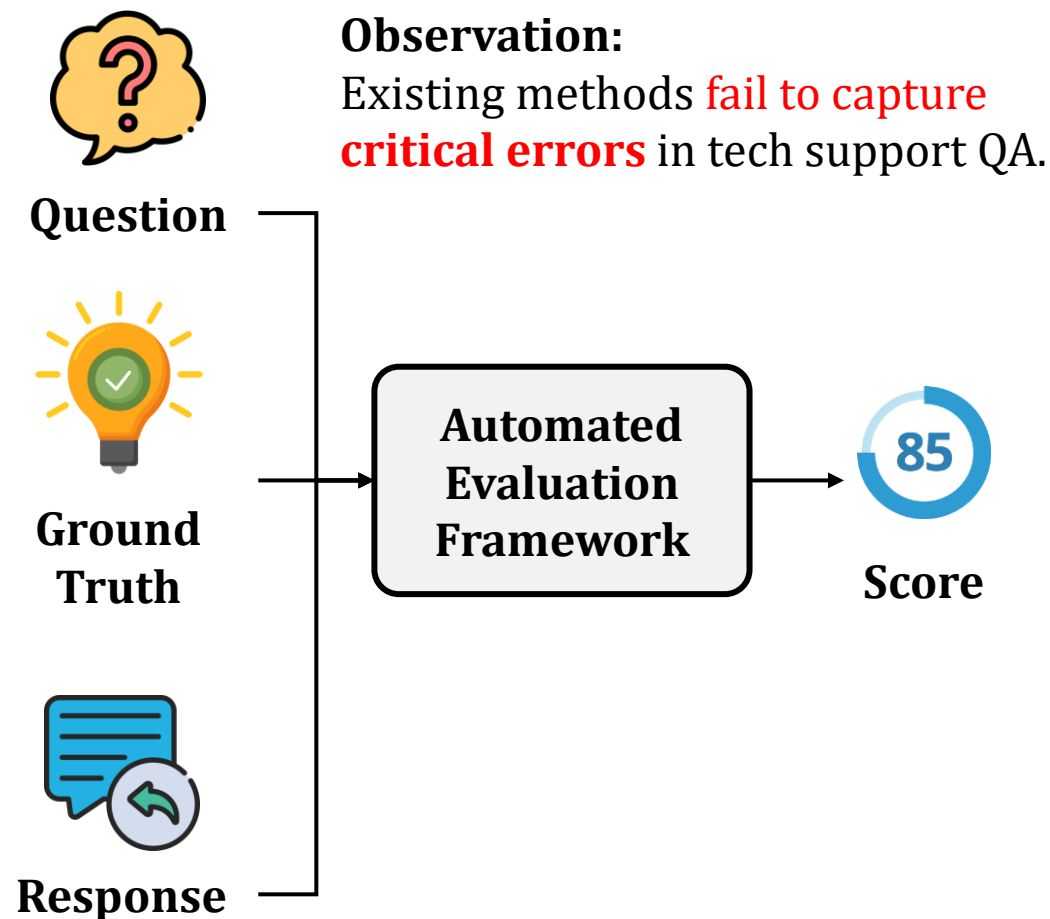


2. Factual Consistency Evaluation (e.g. RAGAS)



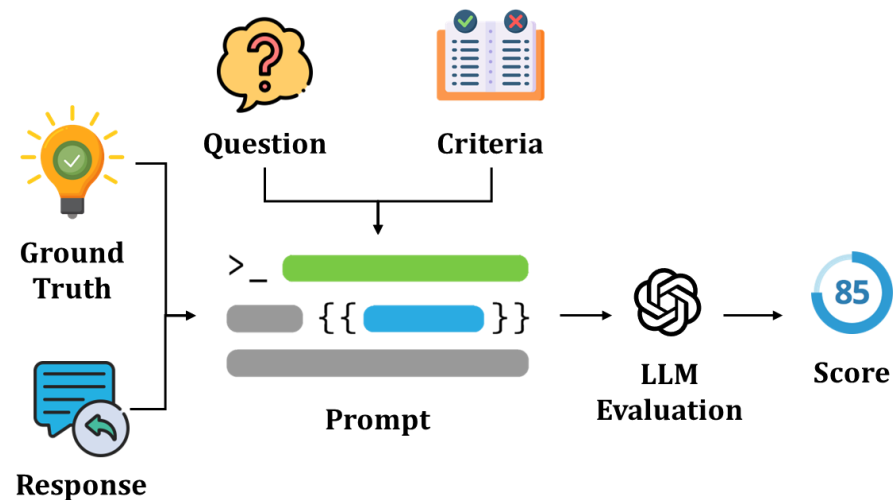
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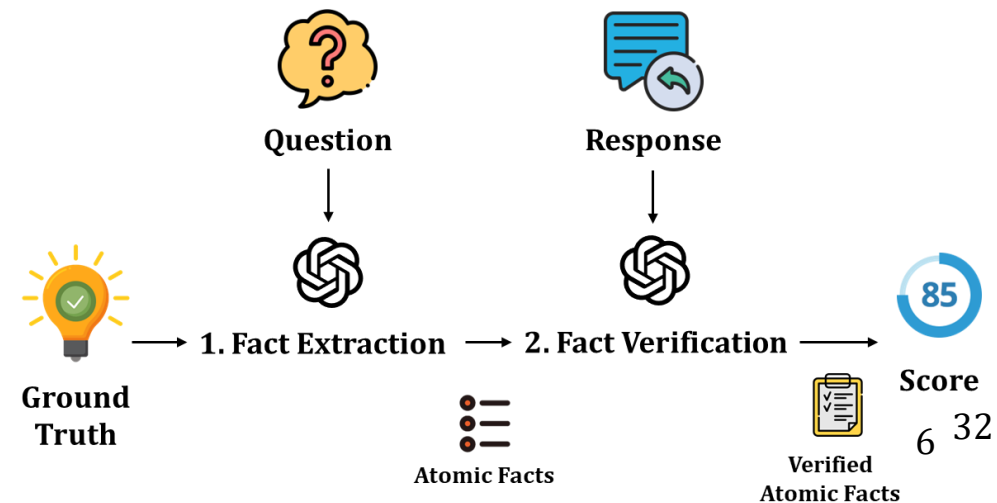


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1. Criteria-Guided Evaluation (e.g. G-Eval)



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Background

Error Typology of Technical Support QA

Question *Q*

*My Apache server fails to start.
Running `systemctl start apache2`
shows an error. How can I fix this?*

Ground Truth *GT*

1. Identify the process using port 80 with `netstat -tulnp`.
2. Stop the process.
3. Restart the server.

Error Type

Key Term Mismatch

Step Missing

Step Reversal

Response *A*

1. Identify the process with `netstat -anp`.
 2. Stop the process.
 3. Restart the server.
-
1. Identify the process with `netstat -tulnp`.
 2. Restart the server.
(Missing step 2 in ground truth)
-
1. Restart the server. (This should be the last step)
 2. Identify the process with `netstat -tulnp`.
 3. Stop the process.

Background

Challenge: Detecting the Critical Errors



Key Term Matching

- LLMs may hallucinate or omit key terms such as commands and file paths.
- These mistakes can **mislead users** and result in **faulty or harmful operations**.



Step Order Verification

- LLMs often fail to preserve the correct order in multi-step solutions.
- Incorrect step order may lead to **configuration failures or system errors**.



Step Completeness Verification

- RAG-based QA system tend to skip steps during retrieval.
- Missing steps result in **incomplete guidance**, leaving users **unable to resolve the issue**.

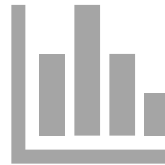
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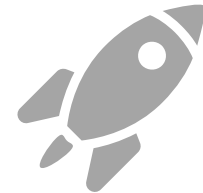
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Framework



Evaluation



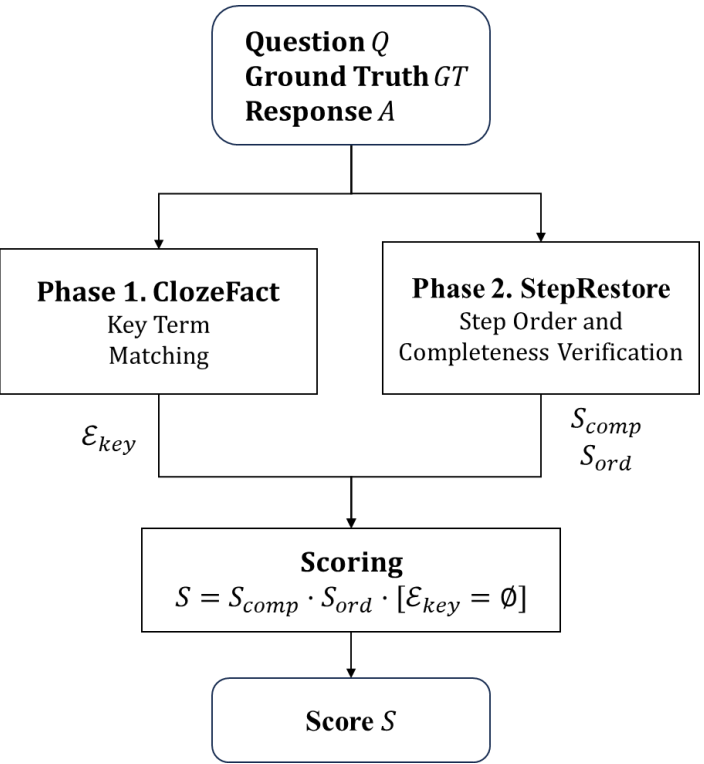
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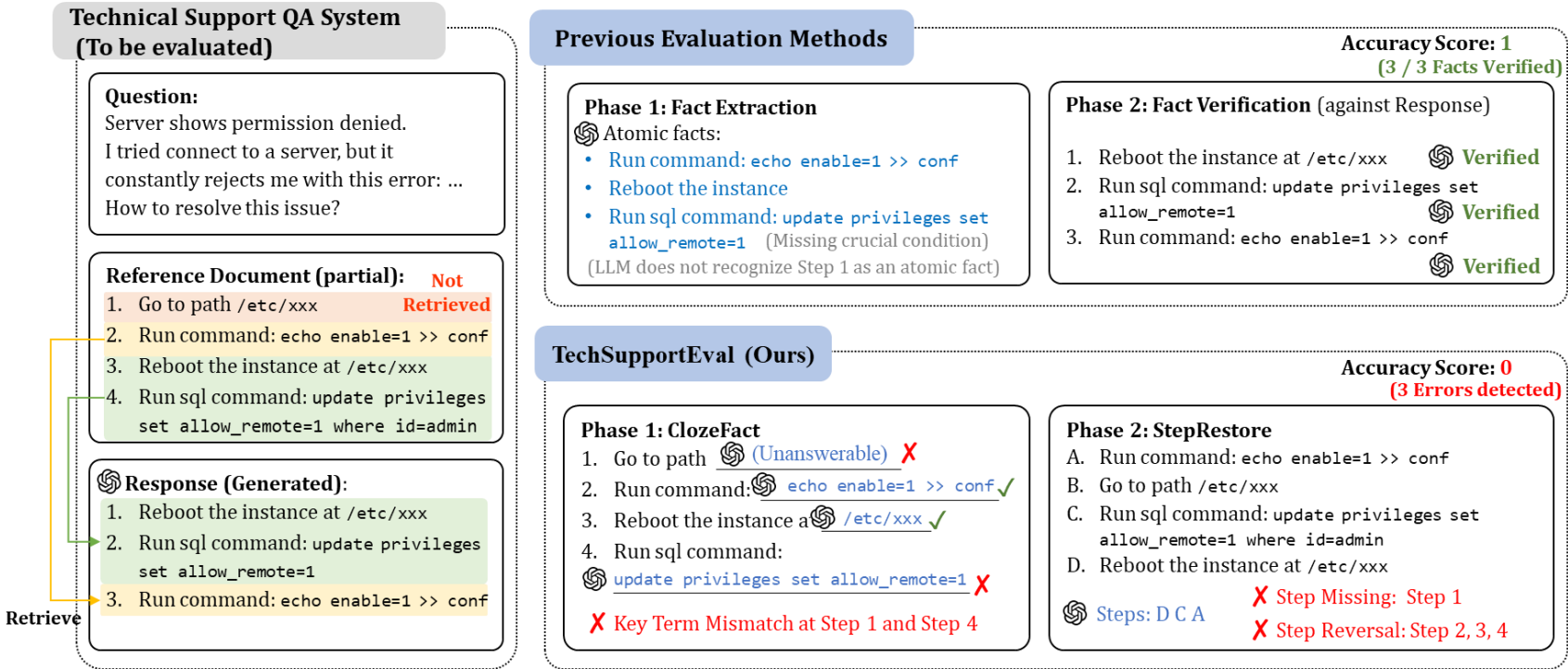
TechSupportEval: Overview

- An **automated evaluation** framework for **technical support QA**

TechSupportEval Workflow:



Comparison of TechSupportEval with previous evaluation methods:



Framework

Phase 1: ClozeFact

Question:

Server shows permission denied.

I tried connect to a server, but it
constantly rejects me with this error: ...
How to resolve this issue?

Reference Document (partial):

1. Go to path `/etc/xxx`
2. Run command: `echo enable=1 >> conf`
3. Reboot the instance at `/etc/xxx`
4. Run sql command: `update privileges
set allow_remote=1 where id=admin`

Framework

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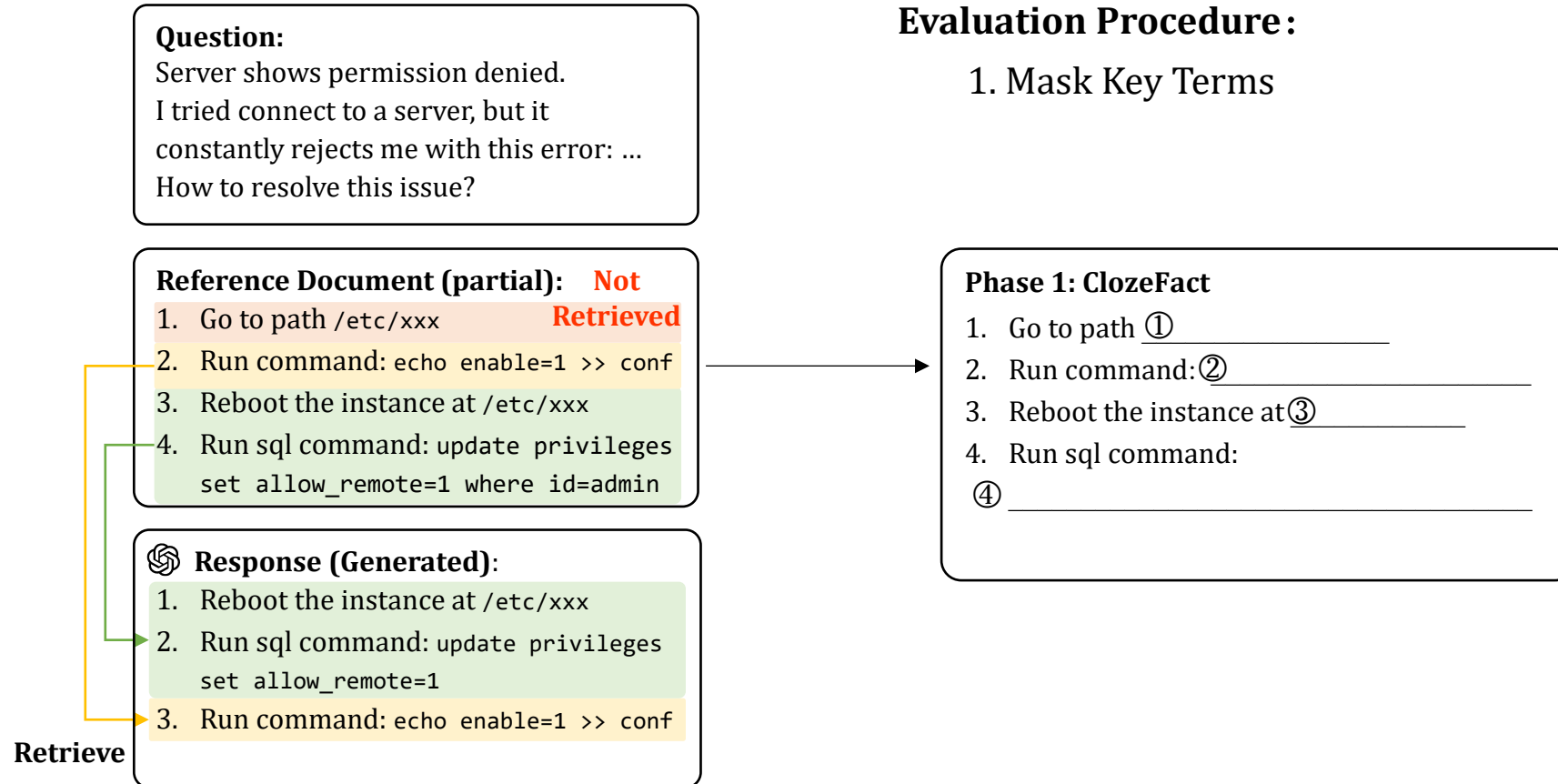
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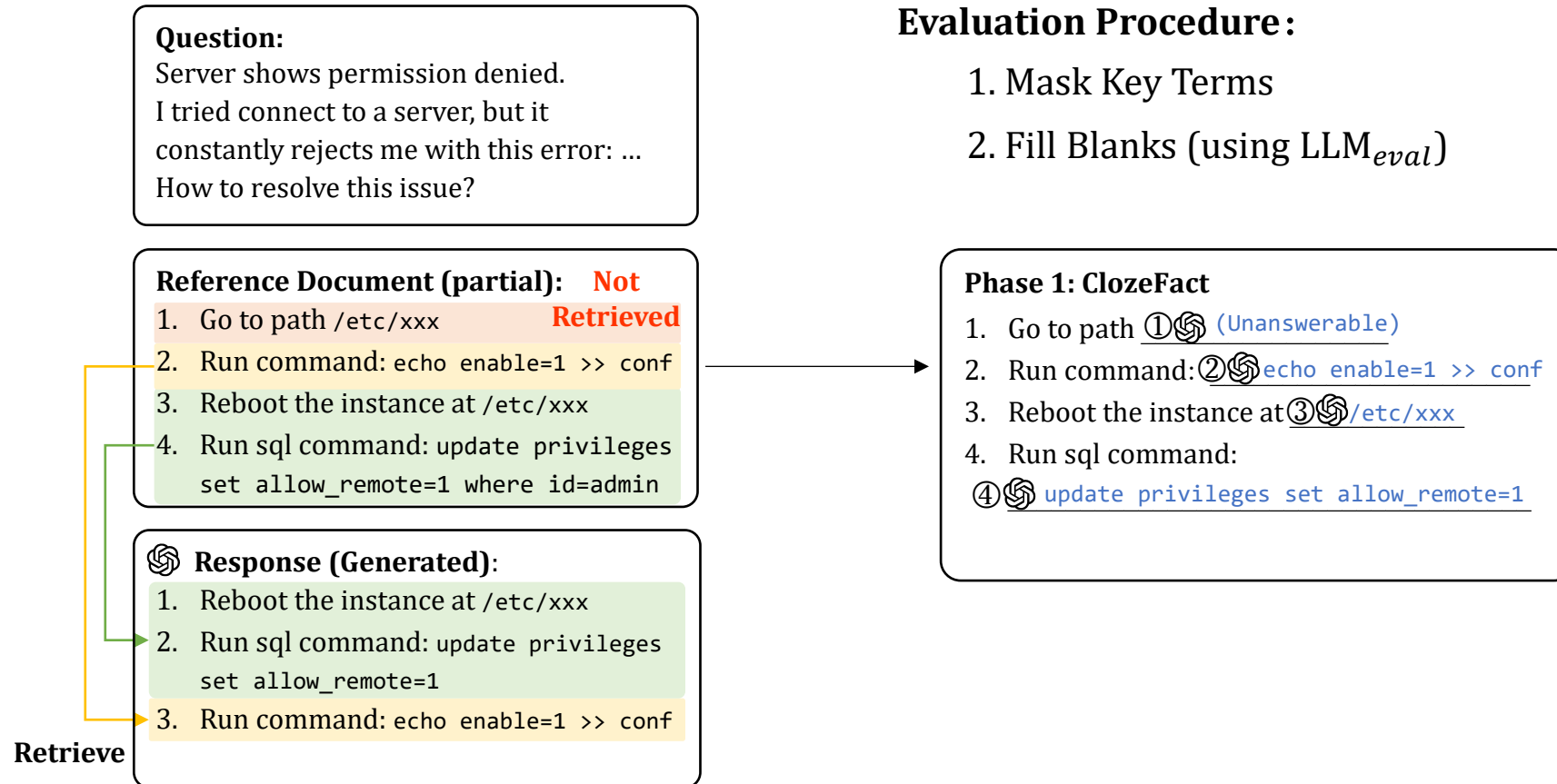
Framework

Phase 1: ClozeFact



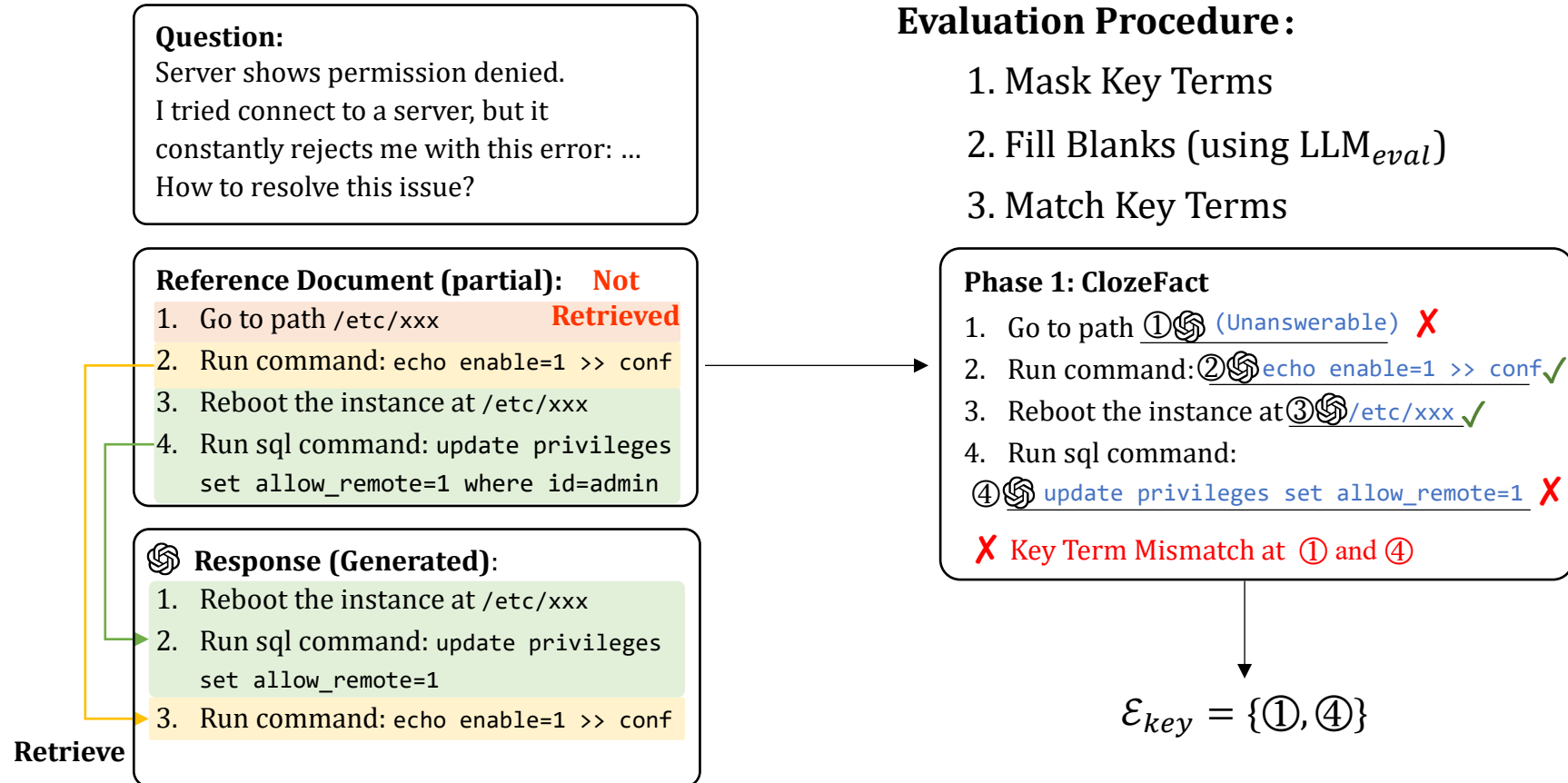
Framework

Phase 1: ClozeFact



Framework

Phase 1: ClozeFact



Framework

Phase 2: StepRestore

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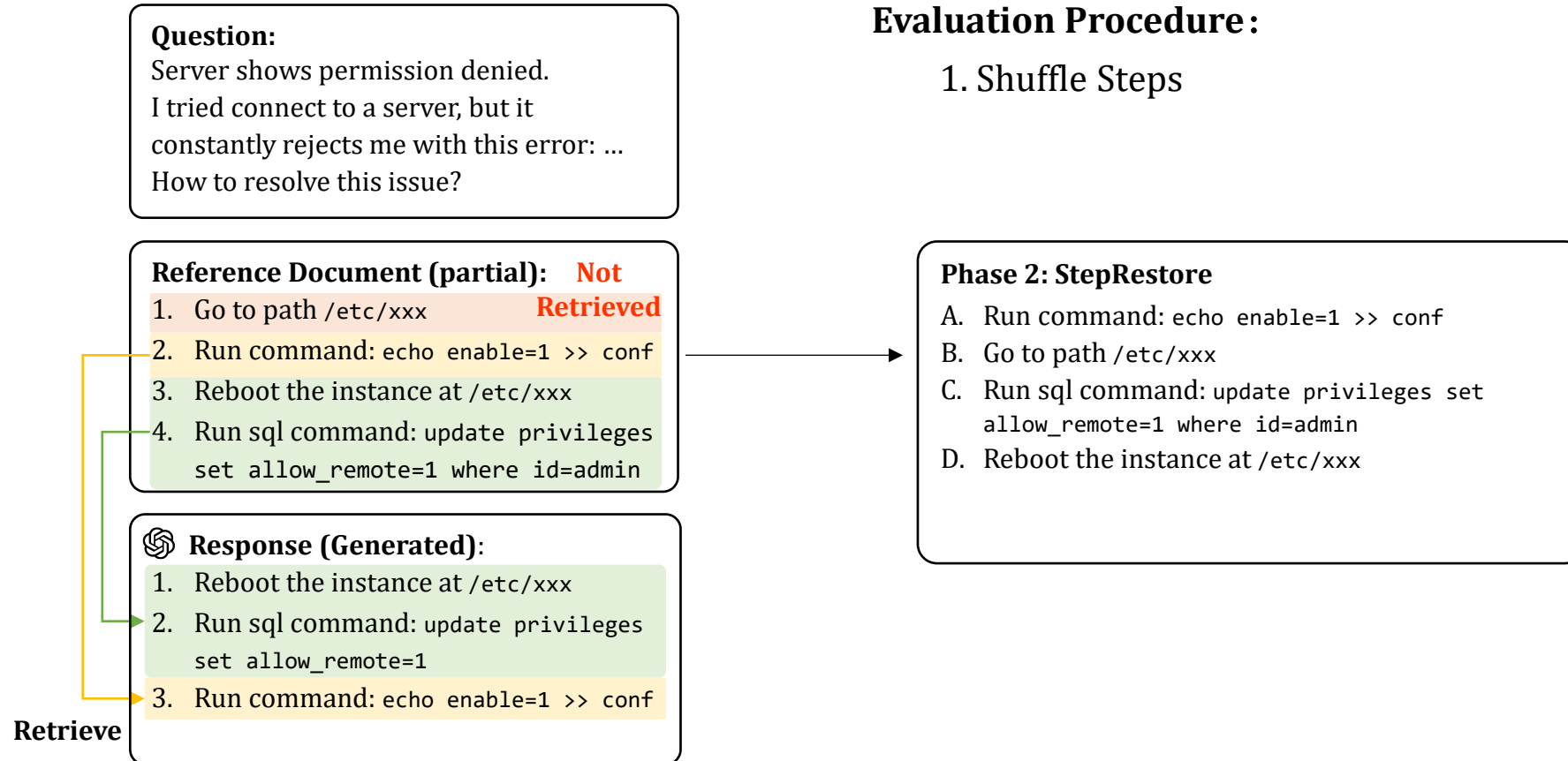
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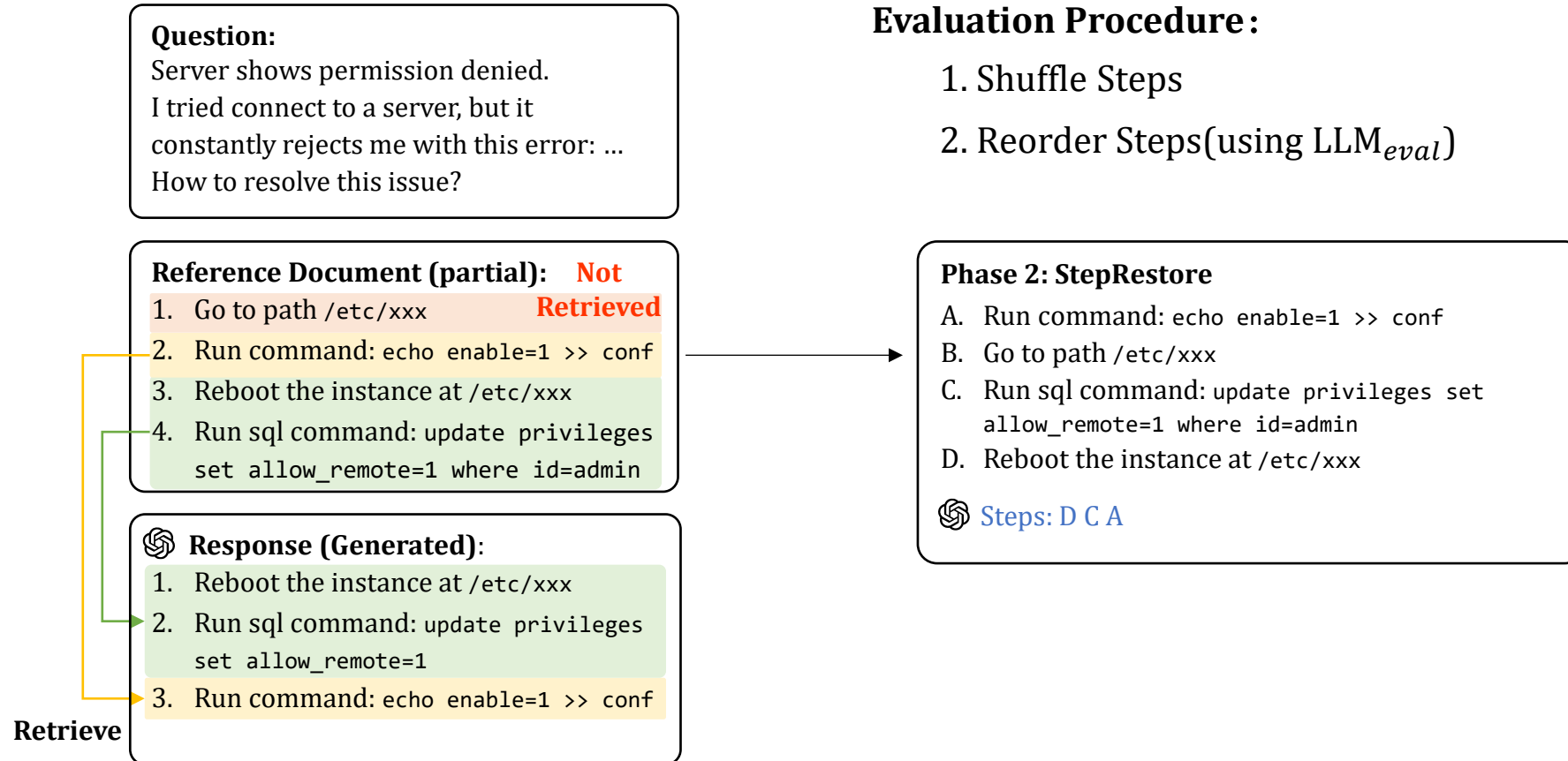
Framework

Phase 2: StepRestore



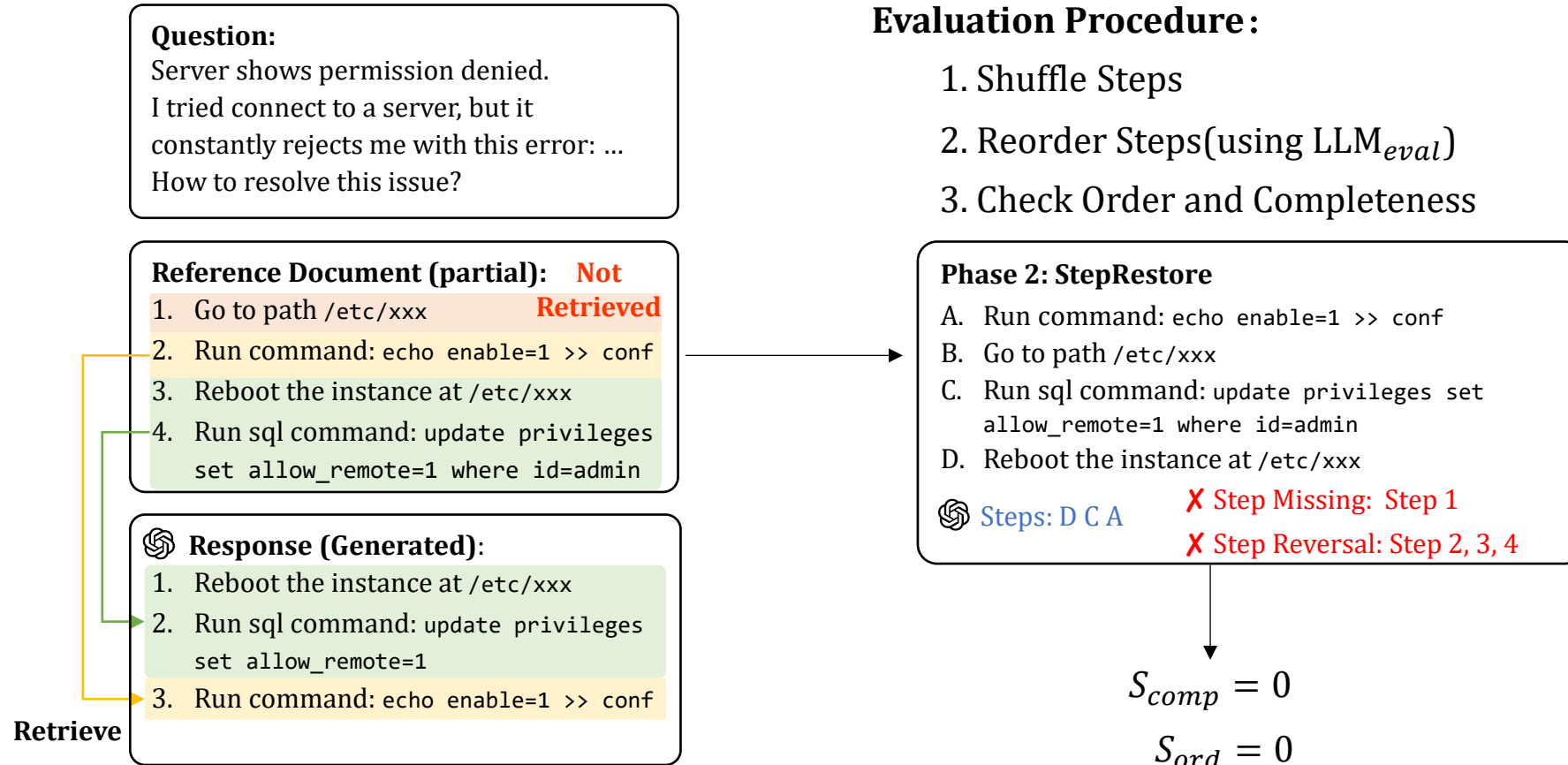
Framework

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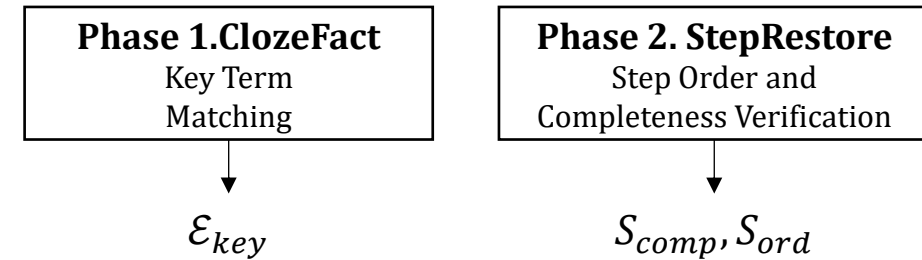
Framework

Phase 2: StepRestore



Framework

Scoring Strategy



- **Strict Scoring** (Default in TechSupportEval)
 - Reflects the **strict requirement** in technical support.
 - Any critical error—including incorrect key terms, missing steps, or wrong step order— would result in a failing score.

$$S = S_{comp} \cdot S_{ord} \cdot [\mathcal{E}_{key} = \emptyset]$$

- **Weighted Scoring** (Flexible Alternative)
 - Designed for scenarios with higher tolerance for minor issues.
 - A parameter α balances the impact of different error types.
 - Allows partial score when step order is correct, even if some steps are missing, aligning better with **real-world user expectations**.

$$S = \alpha \cdot S_{CF} + (1 - \alpha) \cdot S_{SR}$$

$$S_{CF} = 1 - \frac{|\mathcal{E}_{key}|}{|K|}$$

$$S_{SR} = \frac{1}{2}(S_{comp} + S_{ord})$$

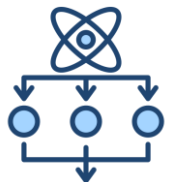
Framework

Implementation



Evaluation Workflow Management

- Automatically evaluates QA samples using a **modular pipeline**.
- Standardized process for generating and scoring answers.



Parallel Execution Strategy

- Runs two evaluation phases in parallel per sample.
- Supports **sample-level parallelism** for faster evaluation.



Unified LLM Interface

- Unified interface for both API-based and local LLMs.
- Built-in **adaptive rate control** for stable evaluation.

EvaluateOneSample($Q, GT, \text{LLM}_{QA}, \text{LLM}_{eval}$)

```
1:  $A \leftarrow \text{GenerateAnswer}(Q, \text{LLM}_{QA})$ 
2: in parallel do
3:    $\mathcal{E}_{key} \leftarrow \text{ClozeFact}(A, GT, \text{LLM}_{eval})$ 
4:    $(S_{comp}, S_{ord}) \leftarrow \text{StepRestore}(A, GT, \text{LLM}_{eval})$ 
5: wait until both modules complete
6:  $S \leftarrow \text{Scoring}(\mathcal{E}_{key}, S_{comp}, S_{ord})$ 
7: return  $S$ 

8: function ClozeFact( $A, GT, \text{LLM}_{eval}$ )
9:    $K \leftarrow \text{ExtractKeyTerms}(GT)$ 
10:   $GT' \leftarrow \text{MaskKeyTerms}(GT, K)$ 
11:   $A' \leftarrow \text{FillBlanks}(GT', A, \text{LLM}_{eval})$ 
12:   $\mathcal{E}_{key} \leftarrow \text{MatchKeyTerms}(A', K)$ 
13:  return  $\mathcal{E}_{key}$ 
14: end function

15: function StepRestore( $A, GT, \text{LLM}_{eval}$ )
16:   $GT'' \leftarrow \text{ShuffleSteps}(GT)$ 
17:   $A_{rec} \leftarrow \text{ReorderSteps}(GT'', A, \text{LLM}_{eval})$ 
18:   $S_{comp} \leftarrow \text{CheckCompleteness}(A_{rec}, GT)$ 
19:   $S_{ord} \leftarrow \text{CheckOrder}(A_{rec}, GT)$ 
20:  return  $(S_{comp}, S_{ord})$ 
21: end function
```

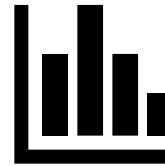
OUTLINE



Background



Framework



Evaluation



Conclusion

Evaluation

Dataset

TechQA¹ Dataset

Our Dataset

Question Q
Ground Truth GT

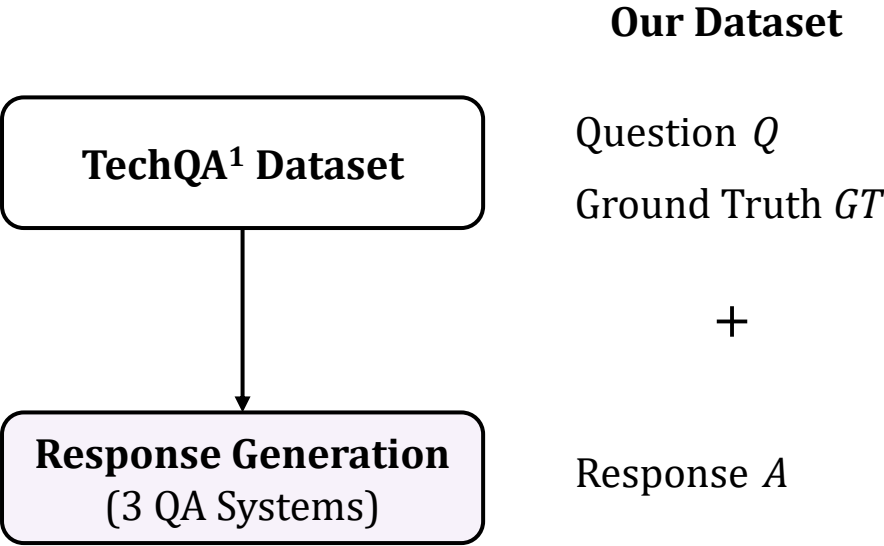
Metric	Value
Number of Questions	282
Avg. Length of Questions	366.48
Avg. Length of Ground Truths	220.87
Avg. Length of Reference Documents	4844.93
Avg. Steps in Ground Truths	2.04
Max. Steps in Ground Truths	14

Stats of the filtered TechQA Dataset

[1] Castelli et al. “The TechQA Dataset.” *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. 2020.

Evaluation

Dataset



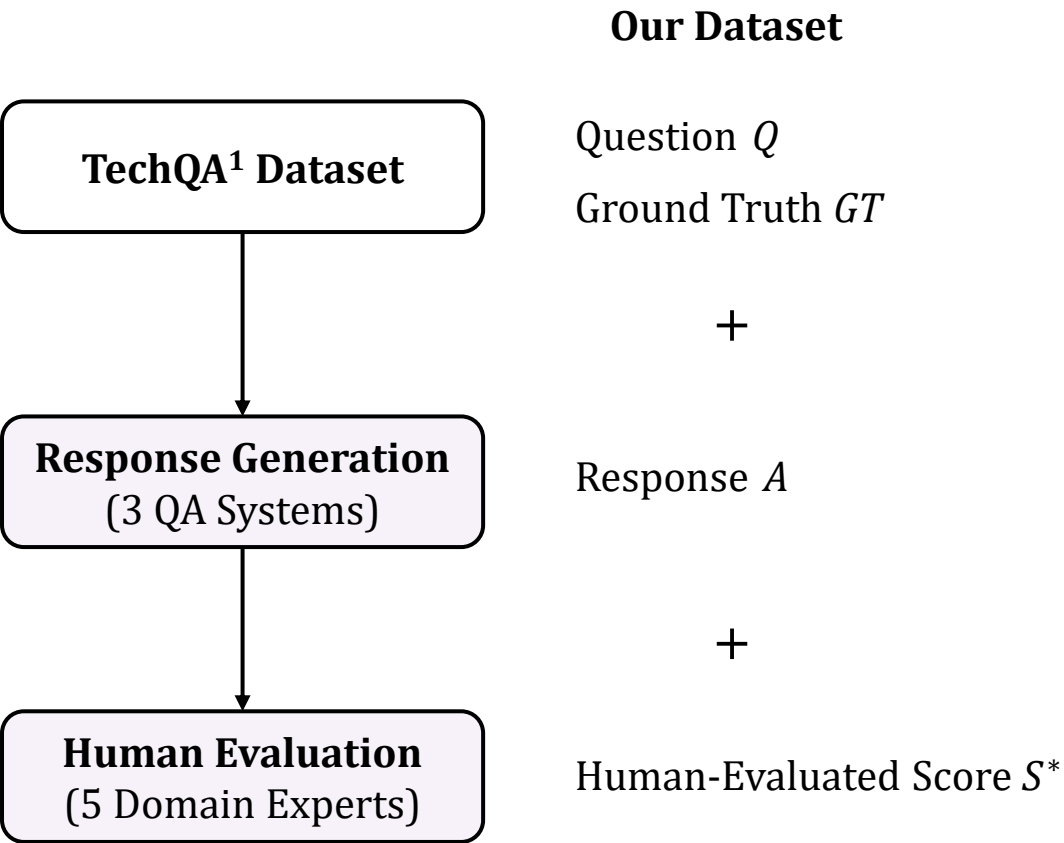
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QA System (LLM_{QA})	Accuracy
GPT 4o Mini	0.8440
LLaMA 3 (70B)	0.7092
LLaMA 3 (8B)	0.5284

Human-Evaluated Accuracy \bar{S}^* (of 3 QA Systems)

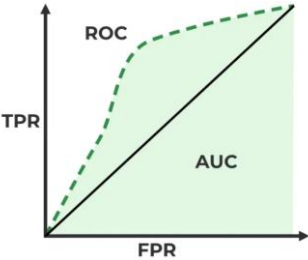
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Evaluation

Effectiveness & Ablation Study

Type	Method	LLM of Evaluated QA Systems					
		GPT 4o Mini		LLaMA 3 (70B)		LLaMA 3 (8B)	
		AUC	Pearson r	AUC	Pearson r	AUC	Pearson r
Lexical-based	ROUGE-1	0.5321	0.0311	0.5420	0.0648	0.5288	0.0484
	ROUGE-L	0.5631	0.0872	0.5932	0.1615	0.5752	0.1554
	BLEU	0.6061	0.1138	0.6252	0.1940	0.6158	0.1959
Semantic-based	BERTScore	0.6584	0.2243	0.6793	0.2892	0.6894	0.3095
LLM-based	LangChain Eval.	0.6608	0.4034	0.6310	0.3525	0.7015	0.4431
	LlamaIndex Eval.	0.6651	0.3061	0.6849	0.4117	0.7899	0.5131
	RAGAS	0.6728	0.1934	0.6894	0.2730	0.6544	0.2531
	RAGQuestEval	0.7416	0.3546	0.7205	0.3768	0.6899	0.3380
	G-Eval	0.8233	0.5192	0.8169	0.5419	0.8532	0.6109
	RefChecker	0.8348	0.4627	0.8313	0.5493	0.8309	0.5862
LLM-based	TECHSUPPORT EVAL	0.9109	0.6616	0.8876	0.7430	0.8970	0.7938
	w/o ClozeFact	0.8486	0.4641	0.8463	0.5752	0.8323	0.5914
	w/o StepRestore	0.9129	0.5669	0.8517	0.5884	0.8693	0.6635

AUC (Area Under the ROC Curve)



$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}}$$

Pearson r

$$r = \frac{\sum_{i=1}^N (s_i - \bar{s})(s_i^* - \bar{s}^*)}{\sqrt{\sum_{i=1}^N (s_i - \bar{s})^2} \cdot \sqrt{\sum_{i=1}^N (s_i^* - \bar{s}^*)^2}}$$

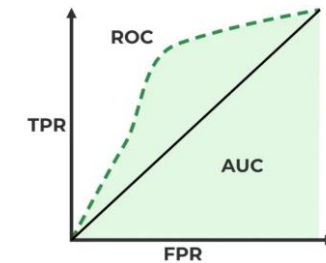
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TechSupportEval significantly **outperforms** all baseline methods in **evaluation accuracy**.

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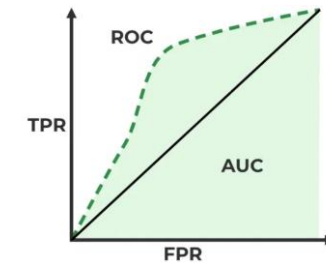
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Both ClozeFact and StepRestore **contribute** to the overall performance.

Evaluation

Impact of LLM_{eval}

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Claude 3.5 Haiku	RAGAS	0.7548	0.3489	0.7495	0.4285	0.7301	0.3767
	RAGQuestEval	0.7368	0.3337	0.7483	0.4319	0.7287	0.4197
	RefChecker	0.8132	0.4826	0.7704	0.4956	0.7681	0.5391
	TECHSUPPORT EVAL	0.8651	0.5701	0.8029	0.6083	0.7737	0.5332
LLaMA 3.3 70B	RAGAS	0.7705	0.3240	0.7579	0.4387	0.7066	0.3303
	RAGQuestEval	0.7807	0.3881	0.7056	0.3680	0.7394	0.4198
	RefChecker	0.8094	0.4533	0.7426	0.4256	0.7471	0.4492
	TECHSUPPORT EVAL	0.8395	0.5021	0.8237	0.6464	0.7859	0.5538
Qwen 2.5 72B	RAGAS	0.5199	0.0146	0.6919	0.3283	0.6017	0.1628
	RAGQuestEval	0.7342	0.3193	0.7481	0.4300	0.6746	0.2885
	RefChecker	0.7951	0.4041	0.7800	0.5033	0.7894	0.5339
	TECHSUPPORT EVAL	0.8234	0.4954	0.8004	0.6013	0.8080	0.6002

Evaluation

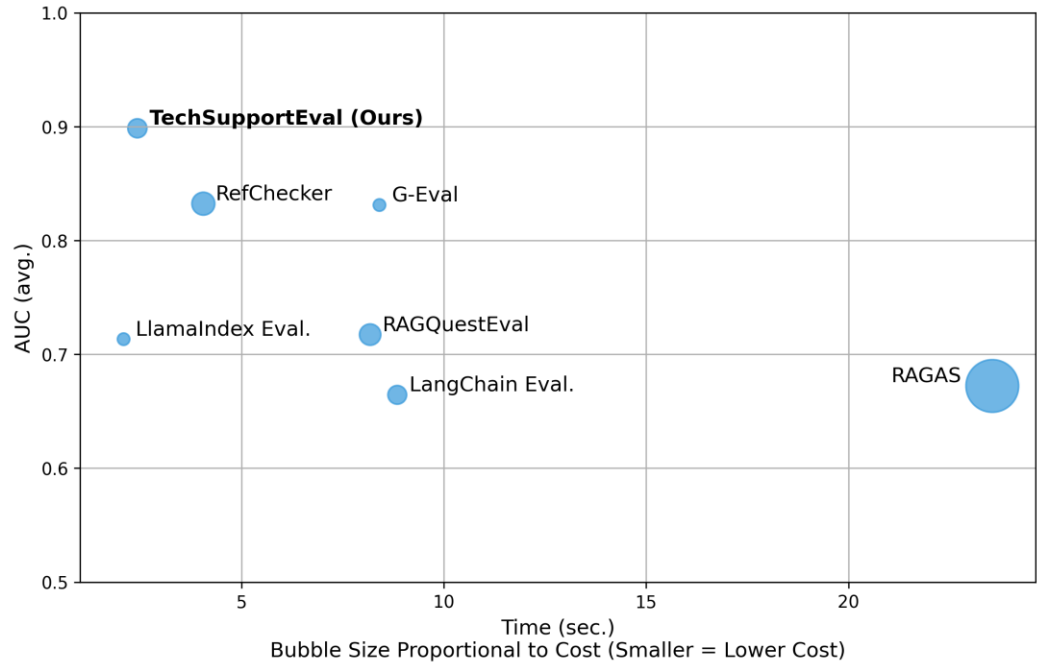
Impact of LLM_{eval}

LLM_{eval}	Method	LLM of Evaluated QA Systems					
		GPT 4o Mini		LLaMA 3 (70B)		LLaMA 3 (8B)	
		AUC	Pearson r	AUC	Pearson r	AUC	Pearson r
GPT 4o Mini	RAGAS	0.6728	0.1934	0.6544	0.2531	0.6894	0.2730
	RAGQuestEval	0.7416	0.3546	0.6899	0.3380	0.7205	0.3768
	RefChecker	0.8348	0.4627	0.8309	0.5862	0.8313	0.5493
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Robust across different backbone LLMs

Evaluation

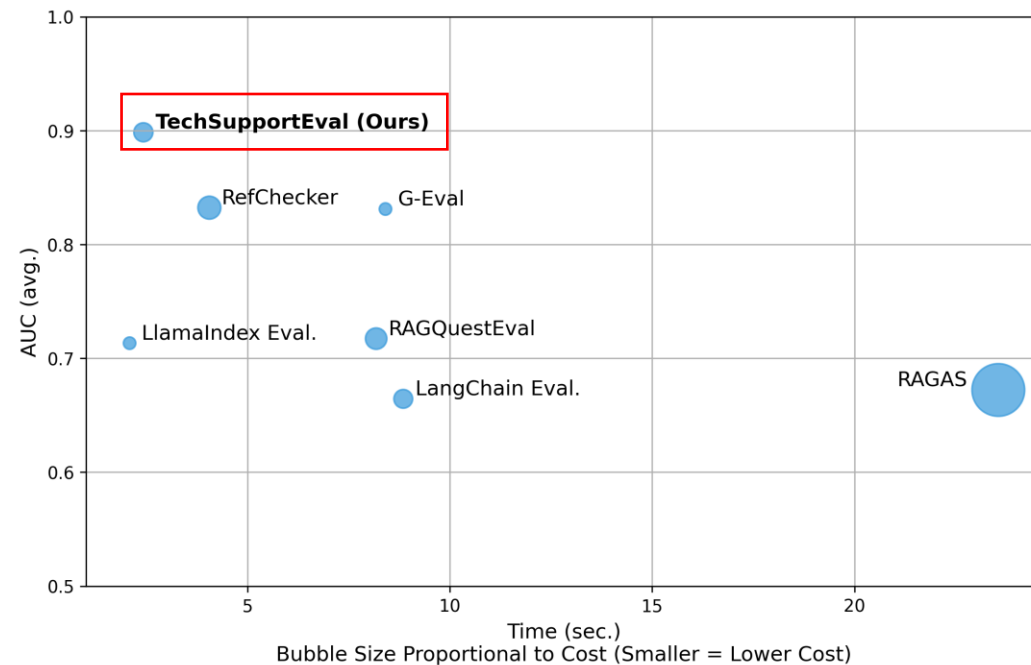
Efficiency and Cost



Method	AUC (avg.)	Time (sec.)	Cost (10^{-3} \$)
LangChain Eval.	0.6644	8.85	0.30
RAGAS	0.6722	23.55	2.37
LlamaIndex Eval.	0.7133	2.09	0.13
RAGQuestEval	0.7173	8.18	0.39
G-Eval	0.8311	8.41	0.13
RefChecker	0.8323	4.06	0.45
TECHSUPPORT EVAL	0.8985	2.43	0.31

Evaluation

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Method	AUC (avg.)	Time (sec.)	Cost (10 ⁻³ \$)
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Efficient and **scalable** for large-scale evaluation

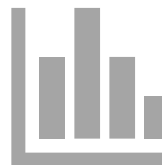
OUTLINE



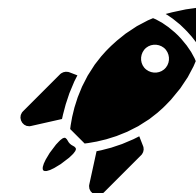
Background



Framework



Evaluation



Conclusion

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- We investigate **the evaluation of technical support QA** and pinpoint **three key challenges** it presents.
- We propose an LLM-based automated evaluation framework **TechSupportEval** for technical support QA with two novel techniques, **ClozeFact** and **StepRestore**, to address the challenges effectively.
- We **introduce a benchmark dataset** based on the publicly available TechQA dataset. Our approach achieves an **AUC of 0.91**, outperforming the previous state-of-the-art method by **7.6%**. The code and dataset are available at **<https://github.com/NetManAIOps/TechSupportEval>**.

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Thank you!

Presenter: Bohan Chen

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