# GRAD: Generative Retrieval-Aligned Demonstration Sampler for Efficient Few-Shot Reasoning dlab

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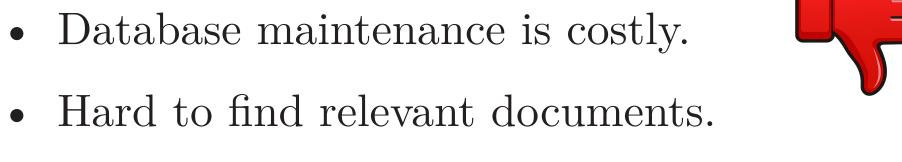
## Manual Few-shot Prompting

- Tedious and time-consuming.
- Hard to scale across tasks.
- Requires careful prompt design.



## RAG-based Few-shot Prompting

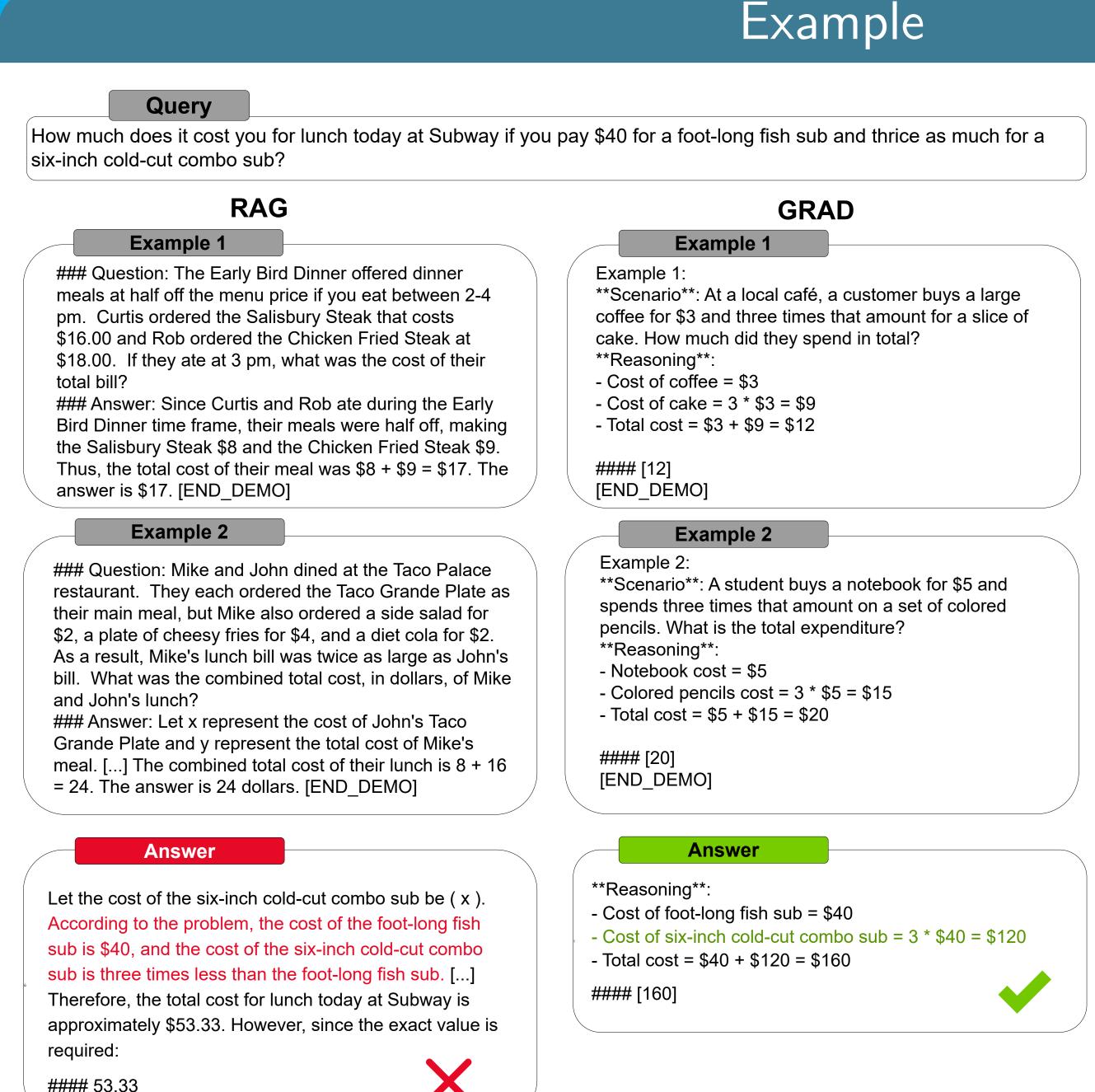
- Requires building a database.
- Database maintenance is costly.

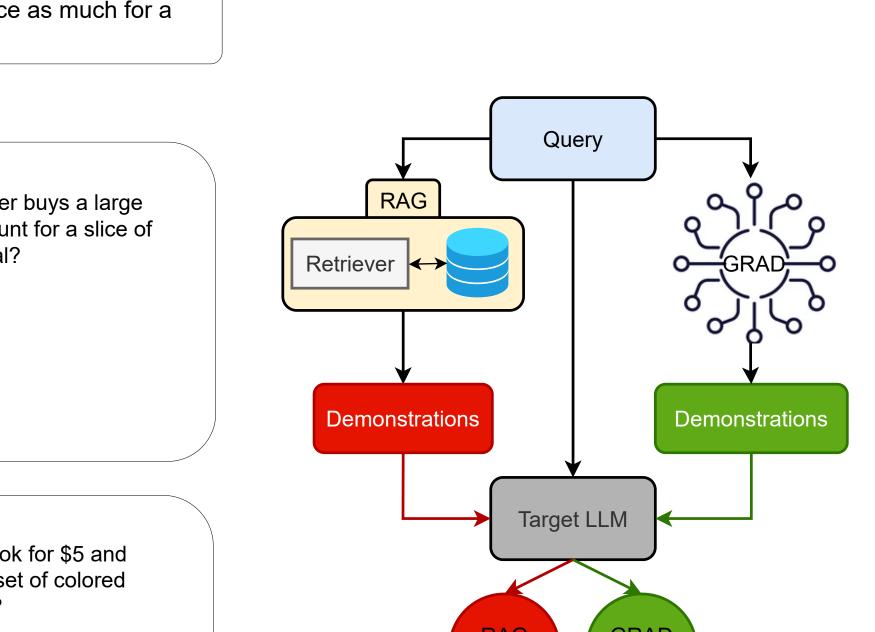


## GRAD(i) Does the Heavy Lifting

- Provides shorter demos&outputs.
- No database / RAG needed.
- Scales across tasks and domains.



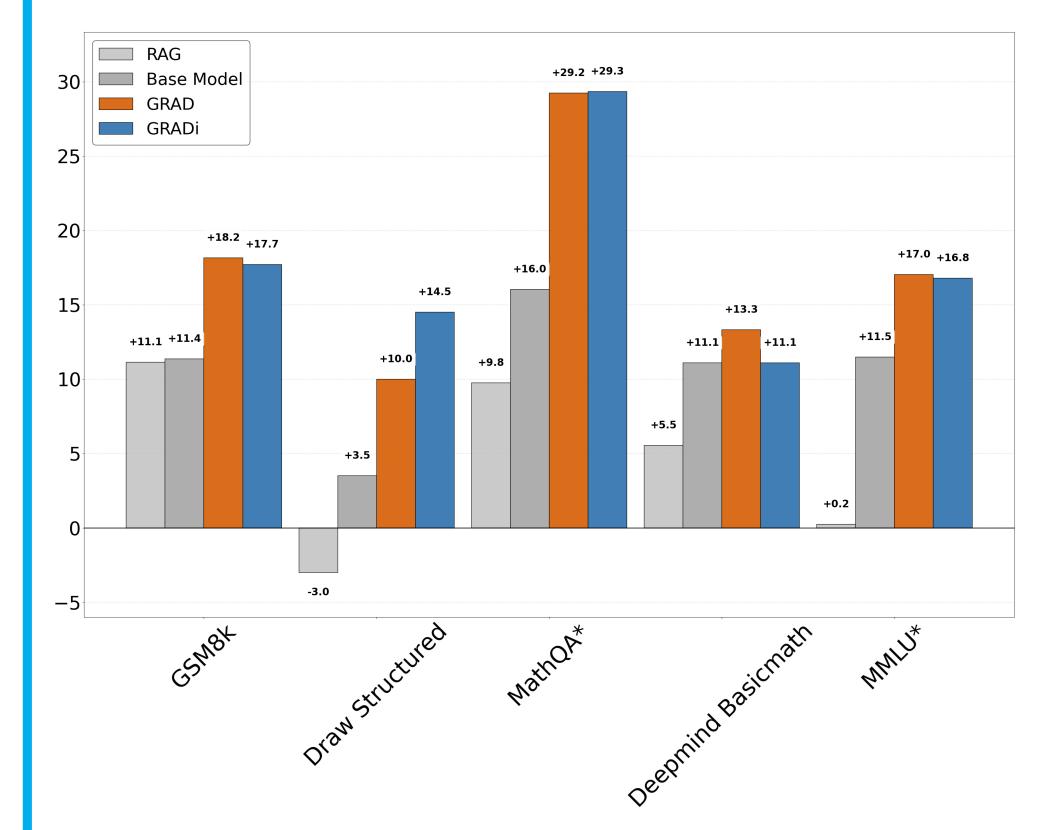




- With GRAD, the problem is solved correctly!
- GRAD is trained under length constraints  $\Rightarrow$ both demos and final outputs are shorter!

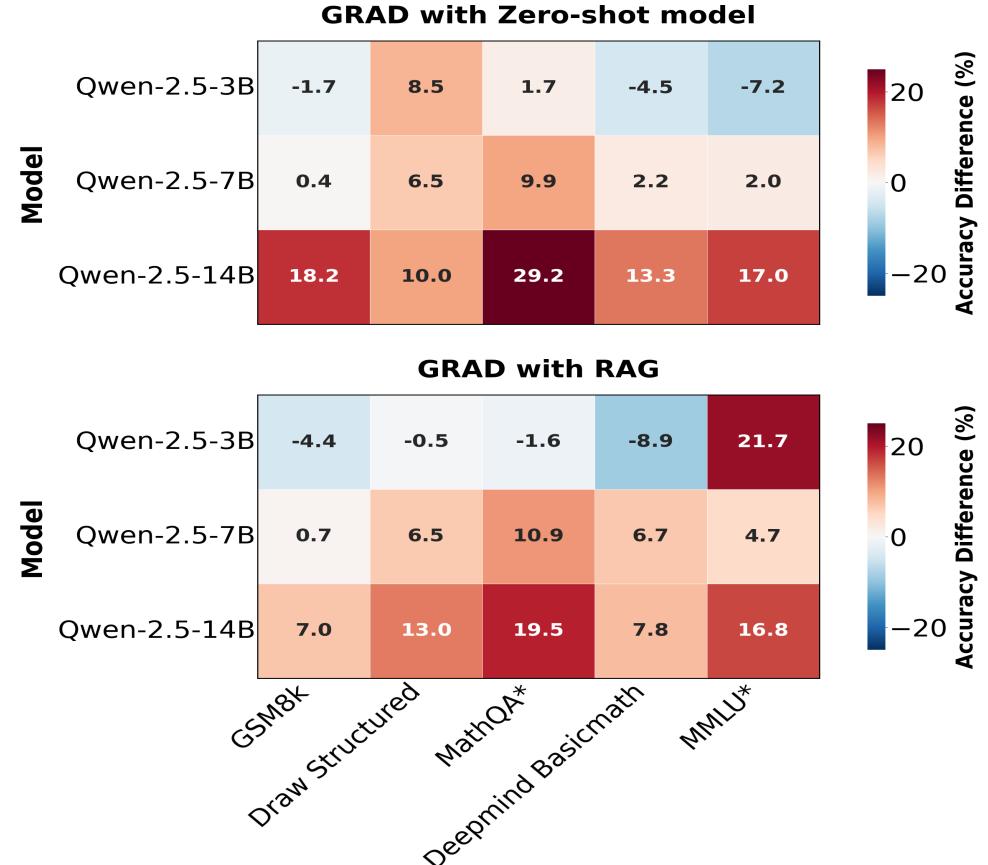
## Results

#### 14B GRAD(i) crushes all the baselines!



GRAD and GRADi outperform common baselines: zero-shot, RAG, and self-demo.

#### Performance Scales with Model Size



Aggregated Dataset Group (weighted by test set size)

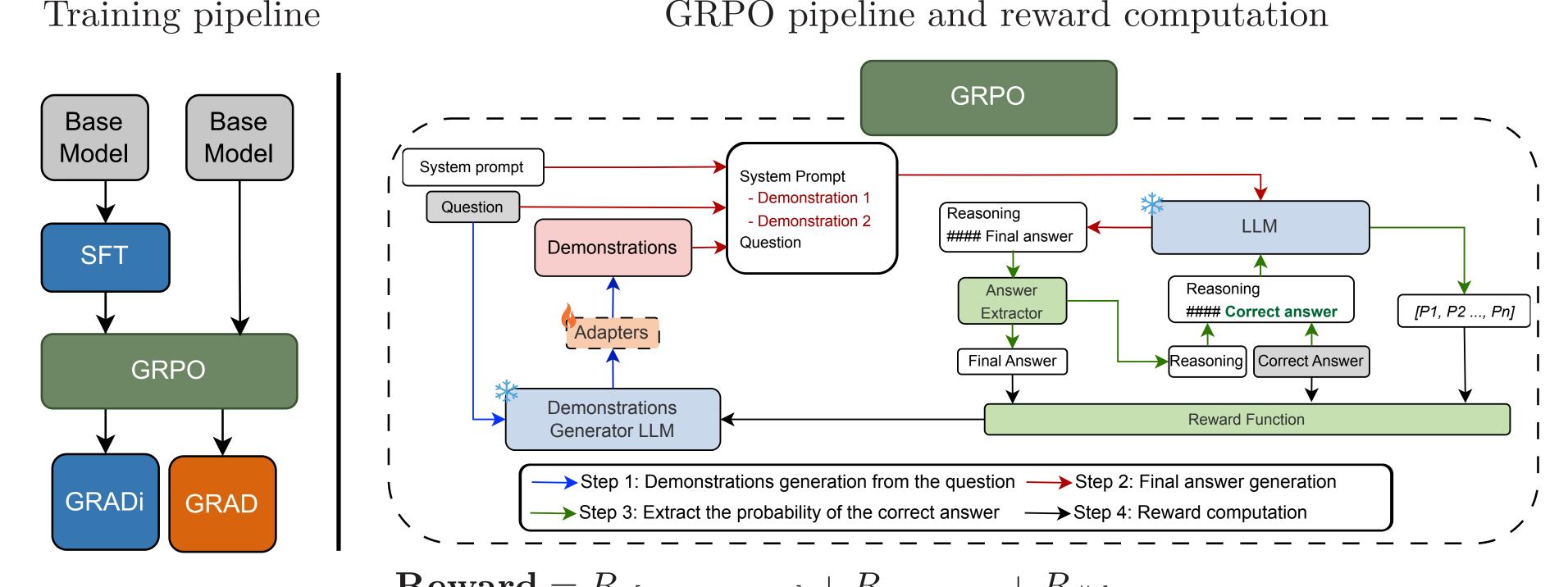
Can cheaper models provide demonstrations for larger ones?

Dataset	3B- Demo	7B- Demo	14B- BASE
GSM8K	66.67	72.22	84.12
draw_structured	42.5	47.00	34
MathQA*	51.23	54.13	43.78
deepmind basic_math	66.67	72.22	70
MMLU*	50.73	57.288	59.57

The target model (14B) still benefits from 3B and 7B demonstration samplers.

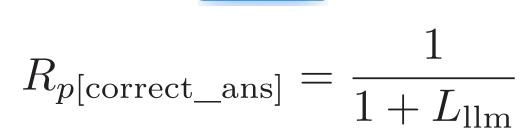
#### Pipeline

GRPO pipeline and reward computation

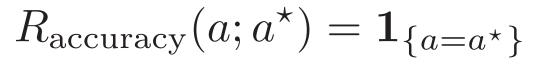


**Reward** =  $R_{p[correct\_ans]} + R_{accuracy} + R_{\#demos}$ .









 $R_{\text{\#demos}} = \frac{n}{D} \times \mathbf{1}_{\{n \le 4\}}$ 

### Conclusion

- GRAD consistently outperforms Zeroshot and RAG across all the benchmark datasets
- GRAD generalizes beyond the dataset it was trained on: on MMLU subsets, GRAD improves Zero-shot and RAG performance by >16%.
- Fine-tuned smaller models (3B, 7B) generate demonstrations that enable the bigger model (14B) to achieve competitive accuracy with minimal performance loss.





