

Decompose, Analyze and Rethink: Solving Intricate Problems with Human-like Reasoning Cycle

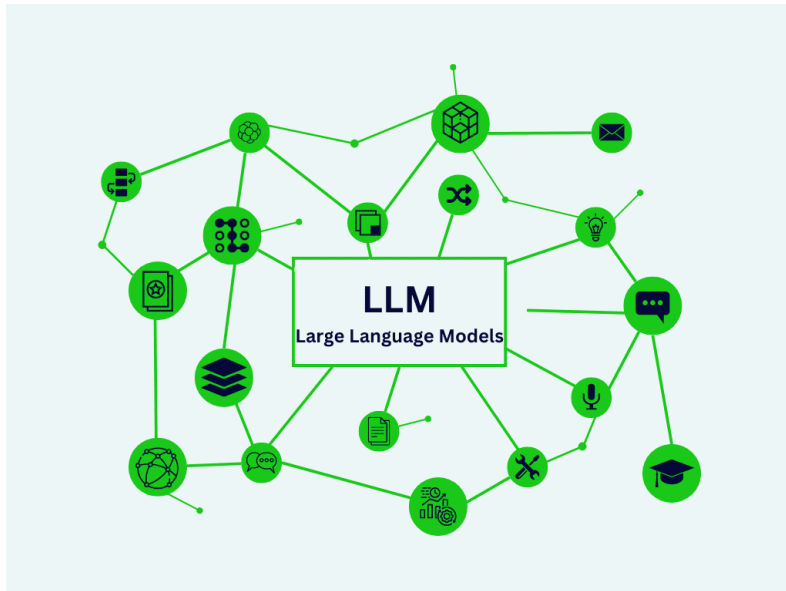
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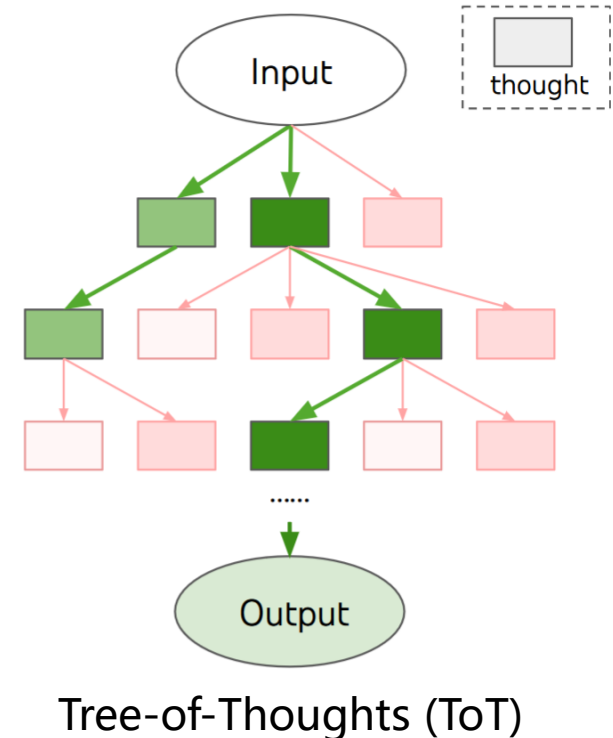
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Background

- Recent advances have witnessed remarkable performances of LLMs in various complex reasoning tasks, e.g., mathematical reasoning, logical reasoning, knowledge reasoning.
- Existing LLM-based advances often extend or search for rationales when solving intricate problems, e.g., Tree-of-Thoughts (ToT).



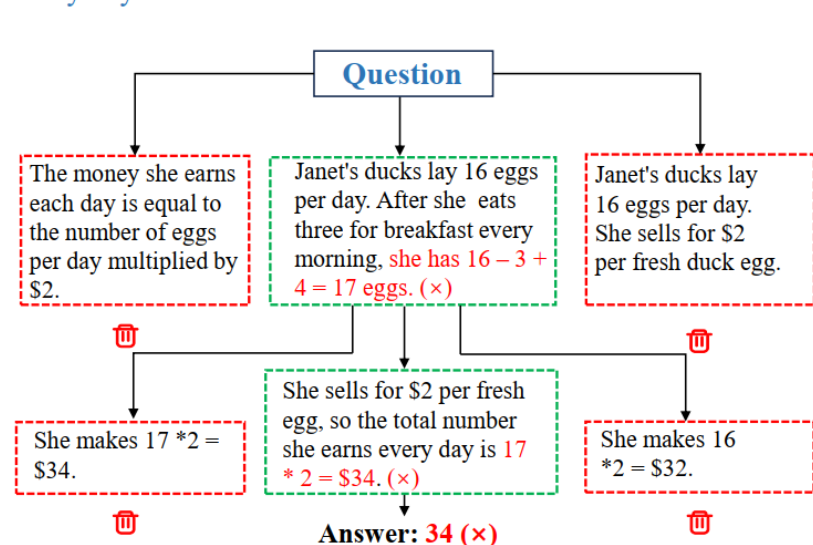
Mathematical
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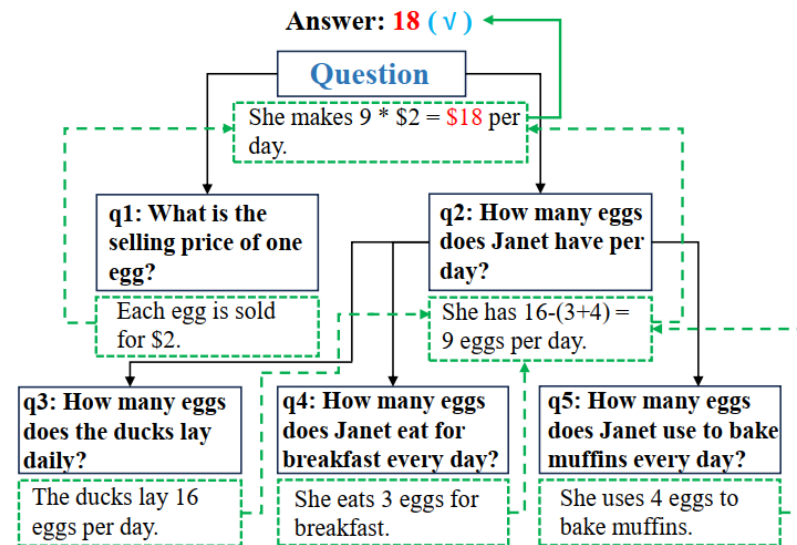
Challenges

- Reason by extending or searching rationales falls short of the logical planning inherent in human thinking.
- Reason by sequentially generating rationales allows mistakes to propagate.

Question: Janet's ducks lay 16 eggs per day. She eats three for breakfast every morning and bakes muffins for her friends every day with four. She sells the remainder at the farmers' market daily for \$2 per fresh duck egg. How much in dollars does she make every day at the farmers' market?



(a) The simulation of ToT Reasoning



(b) The simulation of DeAR Reasoning

Figure 1: Comparison between Tree-of-Thoughts (ToT) Reasoning and our DeAR (*Decompose-Analyze-Rethink*) Reasoning on a reasoning-based problem. (a) The simulation of Tree-of-Thoughts (ToT) (branch = 3). (b) The simulation of DeAR (*Decompose-Analyze-Rethink*) Reasoning.

Method

- Overview of DeAR: *Decompose-Analyze-Rethink*

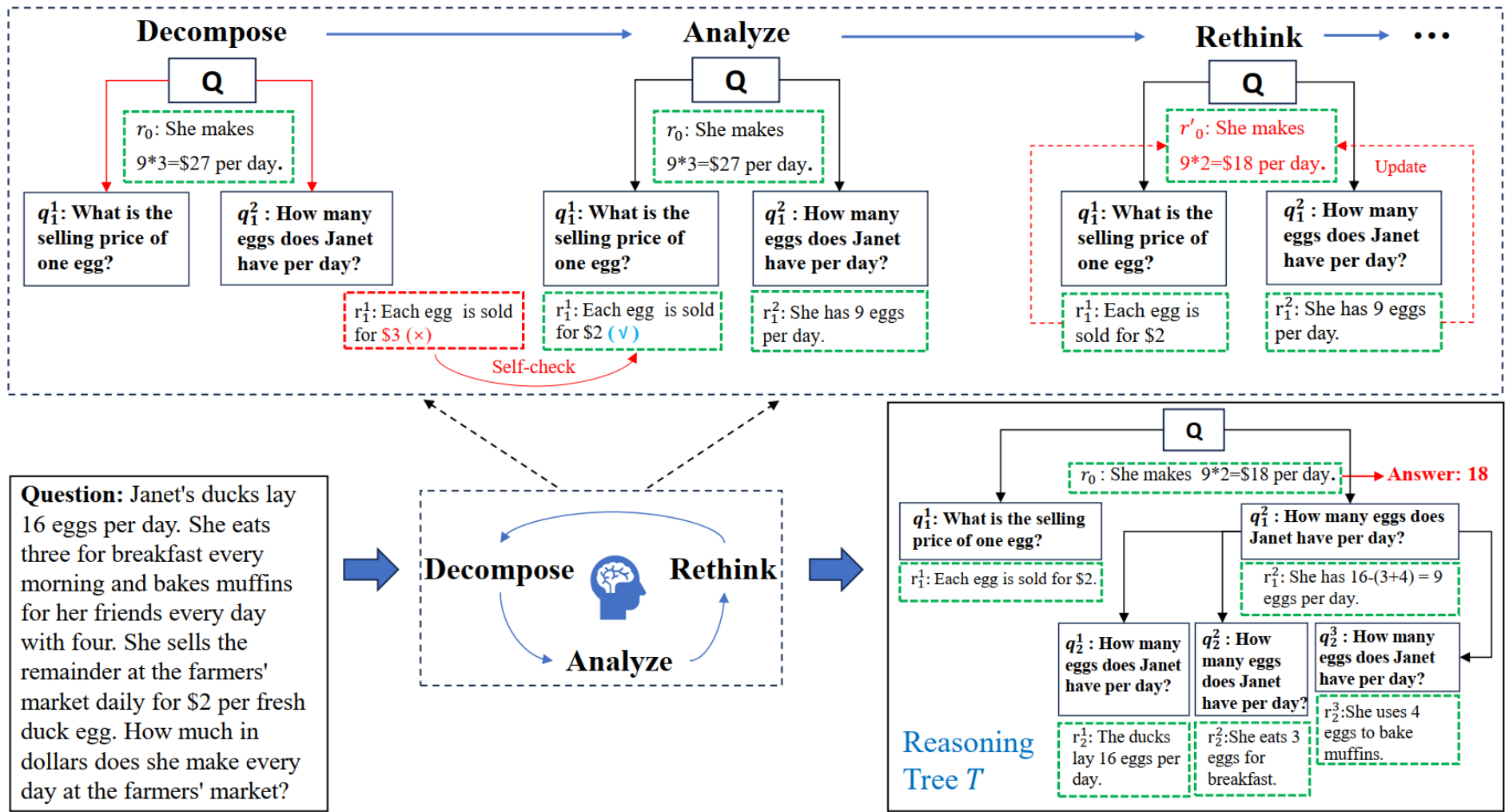


Figure 2: A demonstration of the DeAR (*Decompose-Analyze-Rethink*) cycle.

Method

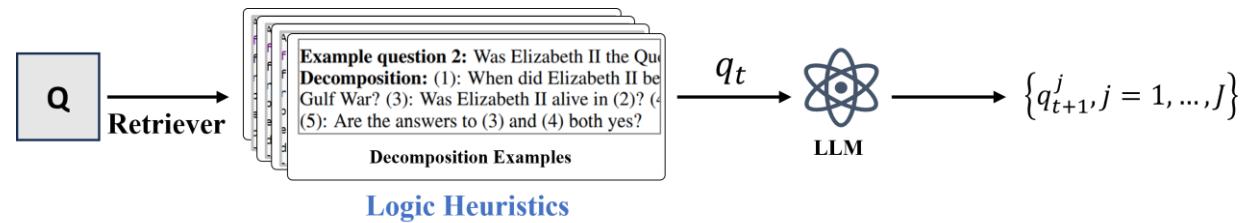
- **Decompose-Analyze-Rethink** cycle

- Reasoning Tree node

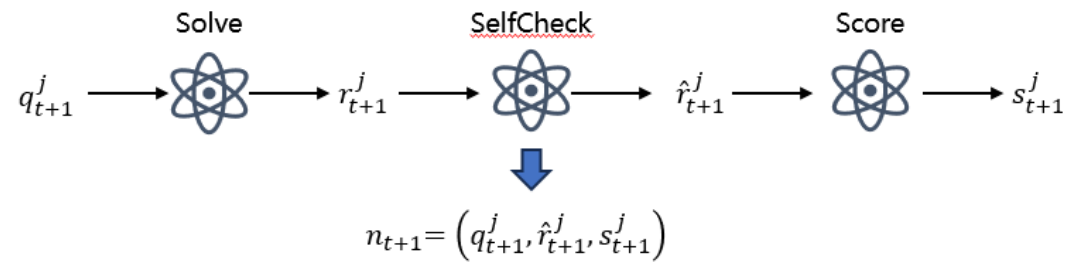
- $n_t = (q_t, r_t, s_t)$

- t : the level of the node; q_t : question; r_t : rationale; s_t : logic coherence score

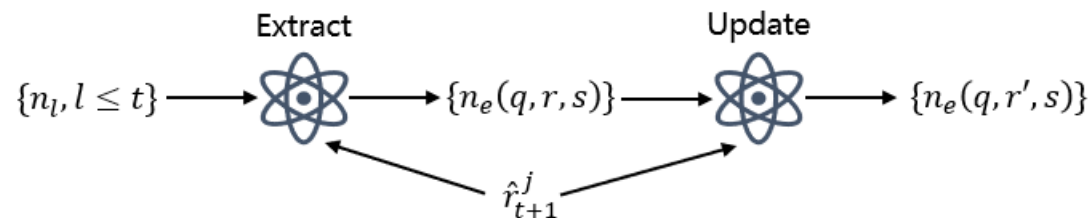
- **Decompose** stage



- **Analyze** stage

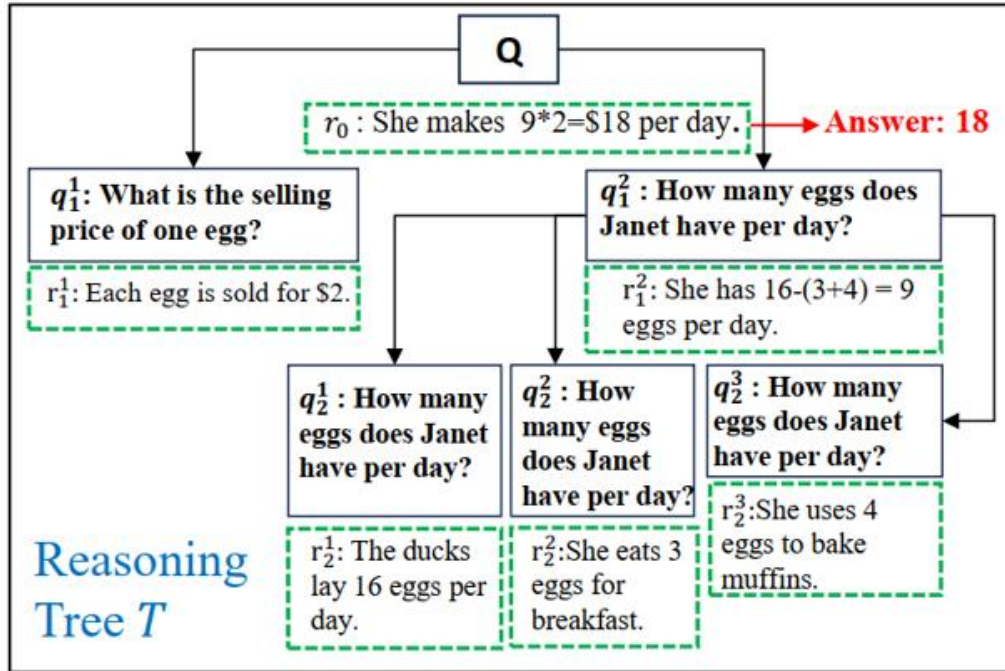


- **Rethink** stage



Method

● *Decompose-Analyze-Rethink* Algorithm



Algorithm 1 *Decompose-Analyze-Rethink*

Input: Question Q

Parameters: LLM p_θ , natural language prompts ($c_1 \sim c_6$), threshold ϵ_1 for *Decompose*, threshold ϵ_2 for *Rethink*

Output: Rationale R , Answer A

Create an empty node queue N

Enqueue $n_0(q_0 = Q, r_0 = \text{None}, s_0 = 1)$ into N

while N is not empty **do**

 Dequeue current node $n_t(q_t, r_t, s_t)$ from N

if n_t is an end node n_{end} **then**

 continue

else if $s_t > \epsilon_1$ **then**

 // Stage 1: *Decompose*

$\{q_{t+1}^j\} \leftarrow \text{Decompose}(p_\theta, h_1, lh_Q, q_t)$ (2)

 // Stage 2: *Analyze*

$r_{t+1}^j \leftarrow \text{Solve}(p_\theta, h_2, q_{t+1}^j)$ (3)

$\hat{r}_{t+1}^j \leftarrow \text{Self_Check}(p_\theta, h_3, q_{t+1}^j, r_{t+1}^j)$ (4)

$s_{t+1}^j \leftarrow \text{Score}(p_\theta, h_4, q_{t+1}^j, \hat{r}_{t+1}^j)$ (5)

 Set $n_{t+1}^j \leftarrow (q_{t+1}^j, \hat{r}_{t+1}^j, s_{t+1}^j)$ (6)

 Enqueue n_{t+1}^j into N

 // Stage 3: *Rethink*

if $s_{t+1}^j > \epsilon_2$ **then**

$L_k \leftarrow \text{Extract}(p_\theta, h_5, L, q_{t+1}^j)$ (7)

$r' \leftarrow \text{Update}(p_\theta, h_6, n_e(q, r, s), \hat{r}_{t+1}^j)$ (8)

$n_e(q, r', s) \leftarrow n_e(q, r, s)$ (6)

else

 Enqueue n_{end} into N

end if

end while

$R \leftarrow r_0$

 Extract answer A from R

return R, A

Experiments

● Overall results

- **Baselines:** Few-shot Prompting, Chain-of-Thought(CoT), Tree-of-Thoughts(ToT), Graph-of-Thoughts(GoT), Least-to-most, SelfCheck
- **Backbone LLMs:** GPT-3.5, LLaMA2-7b, ChatGLM3-6b
- **Datasets:** ScienceQA(Knowledge Reasoning); StrategyQA(Logical Reasoning); GSM8K(Mathematical Reasoning)

Table 1: Overall results of our DeAR Framework on three intricate reasoning datasets. (* : $p < 0.05$).

	ScienceQA			StrategyQA			GSM8K		
	GPT-3.5	LLaMA2	ChatGLM3	GPT-3.5	LLaMA2	ChatGLM3	GPT-3.5	LLaMA2	ChatGLM3
Few-shot	73.97	66.35	42.46	67.71	61.21	54.41	74.26	72.25	51.02
CoT	75.17	67.58	46.35	69.26	63.86	57.18	79.55	74.04	53.85
ToT	82.52	69.01	49.58	71.89	66.52	59.21	83.42	75.22	55.88
GoT	82.34	68.86	49.26	72.02	66.61	59.88	84.77	75.95	56.01
DeAR	83.68*	70.57*	51.08*	73.36*	68.33*	61.02*	86.82*	78.01*	58.54*
Least-to-most	76.61	68.02	47.45	70.55	64.43	58.36	81.25	74.67	54.21
SelfCheck	75.81	69.33	49.23	68.87	66.35	61.22	79.88	75.28	56.72

Experiments

- Analyses of the generated rationales

- **Automatic metrics:** Source-Consistency(SC) and Reasoning Alignment(RA) metrics from ROSCOE [1]
- **Human evaluation:** Annotators select the most logical rationale from those generated by DeAR and baselines.

Table 3: ROSCOE evaluation results of rationales generated by Tree-of-Thoughts (ToT), Graph-of-Thoughts (GoT) and DeAR on different datasets. SC = Source-Consistency; RA = Reasoning Alignment.

	ScienceQA		StrategyQA		GSM8K	
	SC	RA	SC	RA	SC	RA
ToT	0.44	0.31	0.47	0.33	0.56	0.41
GoT	0.42	0.35	0.44	0.38	0.53	0.45
DeAR	0.48	0.42	0.52	0.43	0.58	0.50

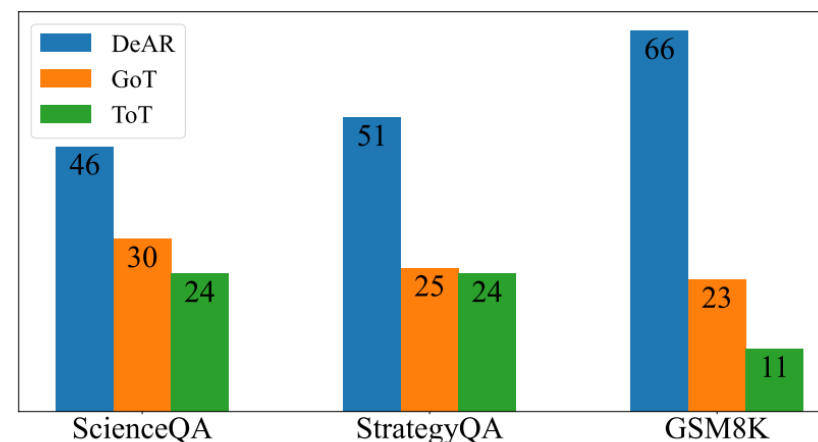


Figure 3: The distributions of annotators' selections. More annotators considered DeAR's rationales to be more logical.

Experiments

- Effectiveness of *Rethink* stage
 - DeAR is better than random update at different portions in the Rethink stage

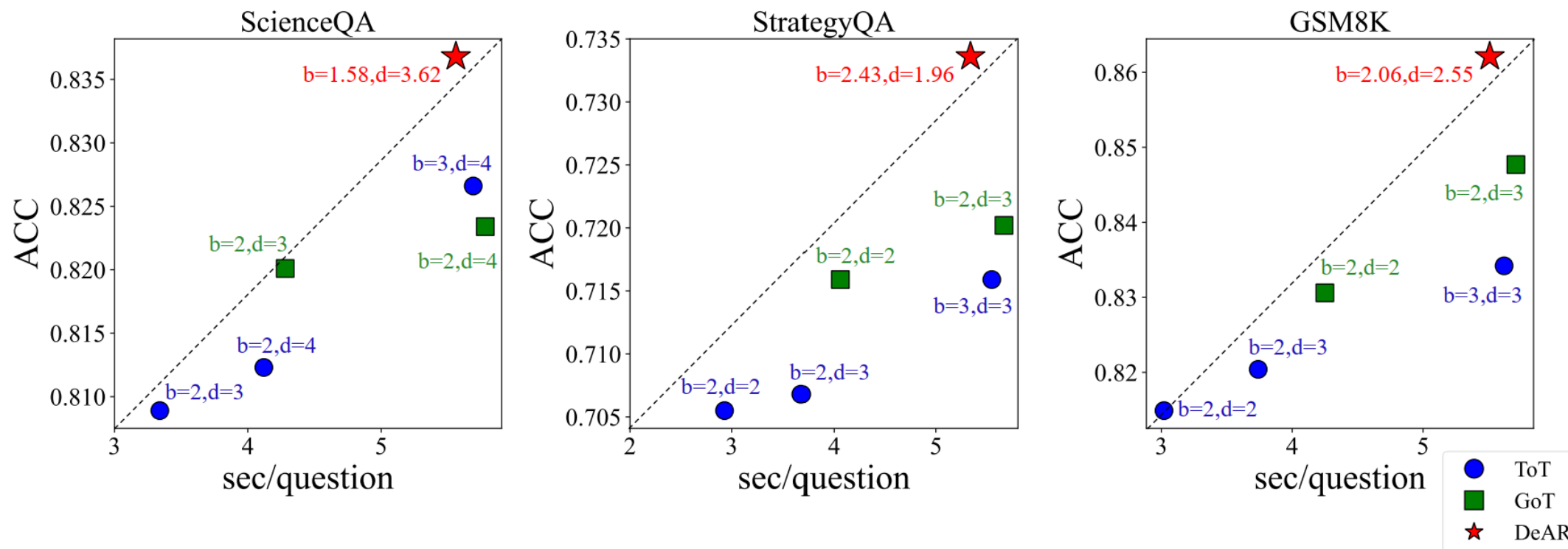
Table 4: Comparisons of ACCs between different portions of “Random Update” and DeAR.

Random Update	ScienceQA	StrategyQA	GSM8K
0%	82.77	72.84	85.09
20%	81.77	72.21	83.96
40%	82.59	73.03	84.35
60%	82.06	72.29	85.07
80%	81.49	72.04	86.01
100%	81.16	71.79	85.32
DeAR	83.68	73.36	86.82

Experiments

● Efficiency of DeAR

- DeAR achieves a better trade-off between reasoning accuracy and inference time



Conclusion

- **DeAR** (*Decompose-Analyze-Rethink*) is designed to mimic human reasoning patterns in tackling intricate problems by constructing a reasoning tree in a top-down, iterative manner.
- The *Decompose* stage applies logic heuristics to decompose the original question, the *Analyze* stage produces and self-checks rationales, and the *Rethink* stage integrates these insights by updating parent nodes based on child-node feedback.
- Extensive experimental evaluations across reasoning benchmarks demonstrate that DeAR surpasses current state-of-the-art methods like Tree-of-Thoughts (ToT) and Graph-of-Thoughts (GoT) in logical coherence and accuracy.
- DeAR also strikes an optimal balance between reasoning accuracy and inference time, further improving efficiency.

Thanks for your listening!

For more details, please refer to our paper

Welcome to discuss with us

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