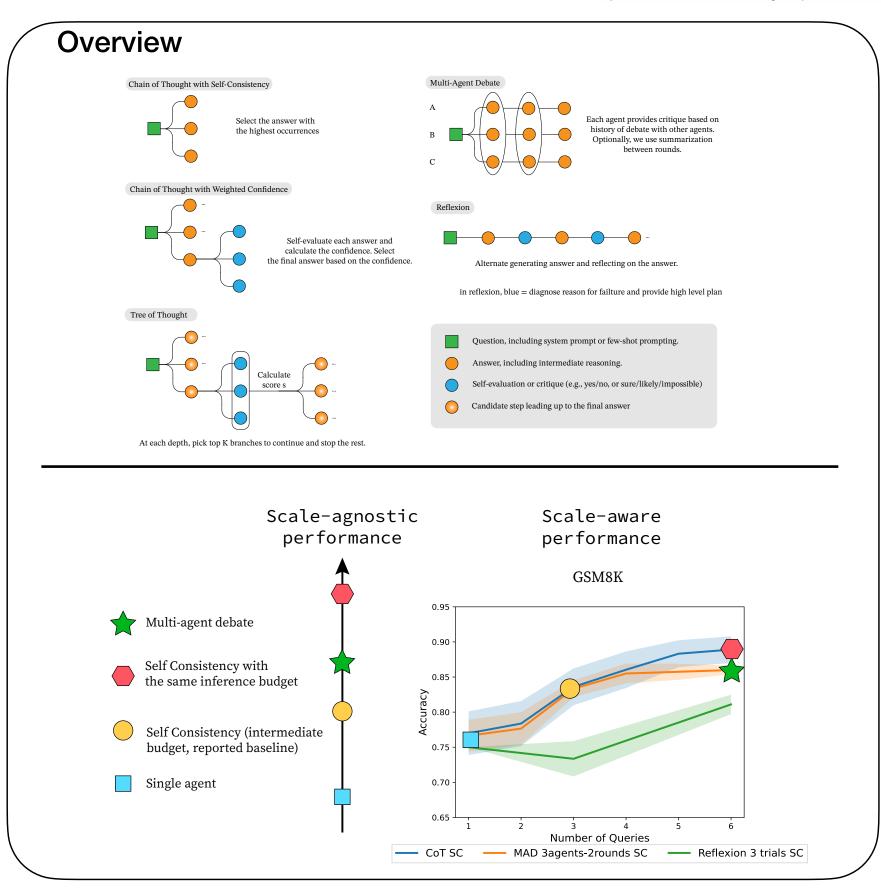
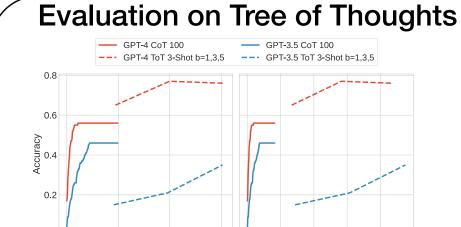
Reasoning in Token Economies: Budget-Aware Evaluation of LLM Reasoning Strategies

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300 0

10000 20000 30000 40000 (b) Total Tokens

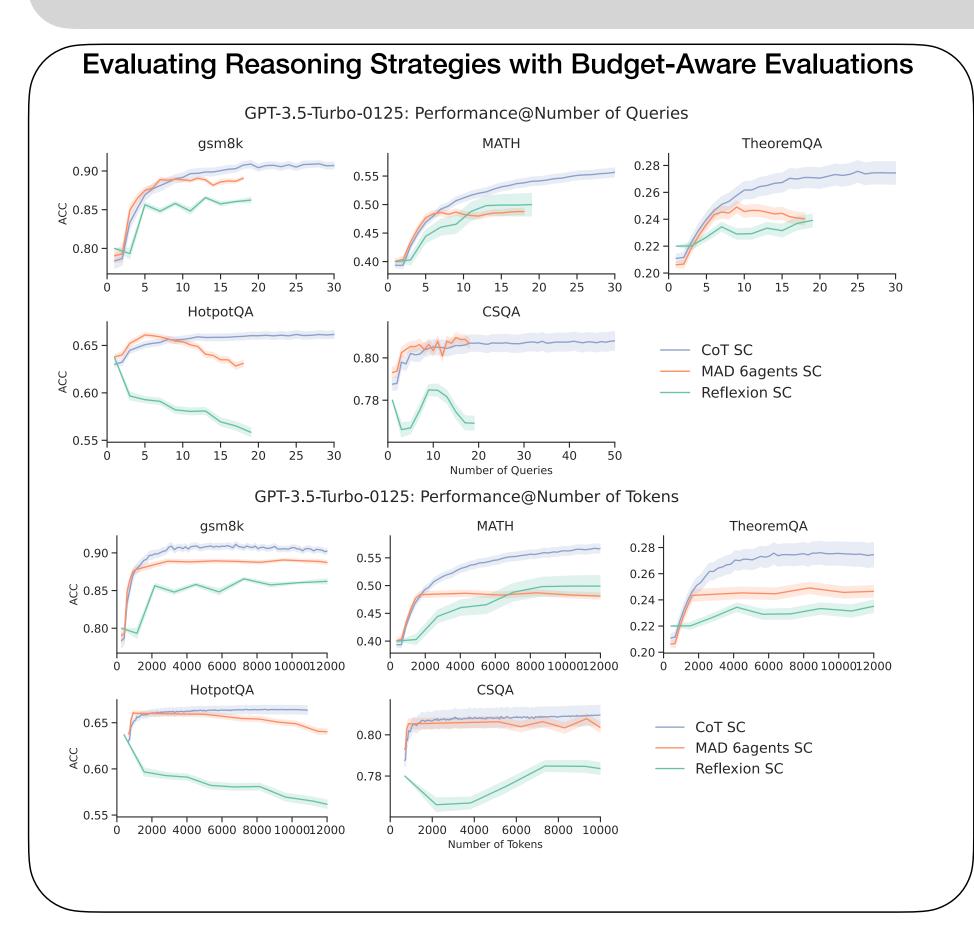
200

(a) Queries/Nodes Visisted

On GPT-4 Tree-of-thoughts beats CoT SC by a big margin but requires way more tokens. On weaker model like GPT-3.5, simpler strategy like CoT beats Tree-of-thoughts by a considerable margin.

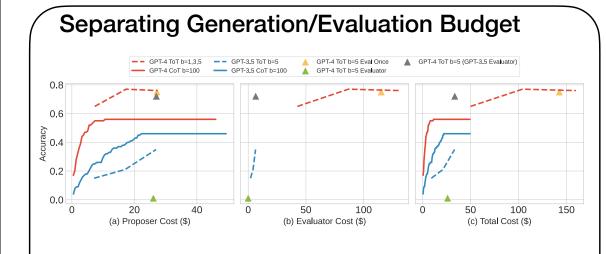
Contributions

- Our analysis reveals that traditional evaluation metrics often overlook a critical aspect: the performance gains achievable through additional
 computational resources. This observation is strongly supported by our comprehensive comparison of Chain-of-Thought Self-Consistency
 (CoT SC), where we demonstrated that CoT SC not only competes but often surpasses more complex reasoning strategies in effectiveness.
- We introduced a budget-conscious evaluation framework spanning three dimensions: queries, tokens, and monetary cost.
- Furthermore, we investigated the influence of two budget types—generation and evaluation—on the Tree of Thought (ToT) methodology. Our findings highlight that its advantages become more significant with advanced models like GPT-4, partly because of GPT-4's superior evaluation performance.



Budget Definitions

- 1. **API Monetary cost** is generally represented as $c=\alpha_1*n_I+\alpha_2*n_O$. Here, n corresponds to the number of input and output tokens. The coefficients are specific to the LLM API in use.
- 2. Total number of tokens, a straightforward metric, is described by $t = n_I + n_O$.
- 3. **Number of queries** of planned API calls can be a rough proxy for the budget.



Insights from our method:

- if we use a weaker evaluator like GPT-3.5, we can maintain most of the performance while being very cost-efficient.
- Quantify how much impact each component has: answer generation vs. self evaluation