When is Tree Search Useful for LLM Planning? It Depends on the Discriminator

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AI Agents for Problem-Solving

LLM-Based Agents for Problem-Solving

Diagram:
- Generator
- Discriminator
- Language Agent
- (Partial) Action Sequences
- Outcome
- Planning Method
- Environment
  - Action
  - Observation
Advanced Planning Methods

Advanced Planning Methods

(a) Propose Prompt
Input: 4 9 10 13
Possible next steps:
[one example]

(b) Value Prompt
Evaluate if given numbers can reach 24 (sure/likely/impossible)
10 14: 10 + 14 = 24. sure

LM

Thought Generation
4 + 9 = 13 (left: 10 13 13)
10 - 4 = 6 (left: 6 9 13)
...more lines...

LM

Thought Evaluation
(13 - 10) * 13 = 3 * 13 = 39
10 + 13 + 13 = 36 There is no way to obtain 24 with these big numbers. impossible

Are Advanced Planning Methods the Solution?

“Models outperform humans in generation but underperform humans in discrimination.”

THE GENERATIVE AI PARADOX:
“What It Can Create, It May Not Understand”

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Are Advanced Planning Methods the Solution?

“LLMs struggle to self-correct their responses without external feedback.”

**The Generative AI Paradox:**

“What It Can Create, It May Not Understand”

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**Large Language Models Cannot Self-Correct Reasoning Yet**

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Are Advanced Planning Methods the Solution?

We hypothesize that the **discriminator** may be more important in LLM planning.
Our Contributions

- Investigation of three planning methods under a unified language agent framework

- Comprehensive experiments on two real-world tasks, text-to-SQL parsing and math reasoning

- Empirical analysis of LLMs’ discrimination abilities and their impact on LLM planning
Unified View of Planning - Re-ranking

Diagram:
- **Language Agent**
  - **Generator** → **Discriminator**
  - **Action** → **Environment** → **Observation**
  - **Generate and rerank**
Unified View of Planning - Iterative Correction

Language Agent

Generator

Generate complete plans

Discriminator

Provide feedback

Environment

Action

Observation
Unified View of Planning - Tree Search

- **Language Agent**
  - Propose new planning steps
- **Generator**
- **Discriminator**
- **Memory**
  - Find the best partial plan
- **Environment**
  - Action
  - Observation
Research Questions

- **RQ1**: How does discrimination accuracy affect the performance of language agents using different planning methods?

- **RQ2**: Can LLM-based discriminators correctly assess language agents' actions in practical settings?
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Simulation Experiments with Oracle

- Simulate a perfect discriminator with gold answers

- Control the accuracy with a probability-based threshold
  - Sample a random number between 0 and 1
  - If the number is smaller than our threshold, we follow the discriminator’s score
  - Otherwise, we inverse the score
Simulation Experiments with Oracle

End-to-end evaluation results (the first row) and average inference time in log scale (the second row) of our simulation experiments with oracle-based discriminator.
Simulation Experiments with Oracle

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Research Questions

● **RQ1**: How does discrimination accuracy affect the performance of language agents using different planning methods?

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Discrimination Accuracy of LLMs

We improve LLMs’ discrimination accuracy with environmental observations.

Discrimination accuracy of naive and observation-enhanced LLMs on BIRD-SQL.
End-to-End Evaluation of LLM Planning

LLM-based discriminators cannot help advance planning methods to achieve significant accuracy improvement yet.
End-to-End Evaluation of LLM Planning

Observation-enhanced discriminators can largely reduce tree search latency.

![Graph showing average end-to-end inference time per example using tree search on BIRD-SQL for different LLMs.]

Average end-to-end inference time (seconds; log scale) per example using tree search on BIRD-SQL.
Conclusions

- Advanced planning methods, i.e., iterative correction and tree search, demand highly accurate discriminators to achieve decent improvements over the simpler method, re-ranking.

- The discrimination accuracy of LLMs may not yet be sufficient for advanced planning methods.

- The accuracy-efficiency trade-off can impede the deployment of advanced planning methods in real-world applications.
Thank you!

Code and Data: https://github.com/OSU-NLP-Group/Auto-SQL-Correction

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