# ReAct: Synergizing Reasoning and Acting in Language Models

## Reproduction of Work

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## Abstract

This 2-page reproduction paper has been prepared for application to **Eastern European Machine Learning Summer School 2025**. The study validates the methodology and findings of the original ReAct paper [7], providing: (1) an intuitive description of the ReAct style prompting, (2) details of the reproduction environment and implementation, and (3) key challenges encountered.

## 1 Introduction

The *ReAct* paradigm, introduced in [7], represents a significant advancement in large language model (LLM) capabilities by synergizing reasoning and acting for complex task-solving. This approach addresses key limitations in prior work with interleaving verbal reasoning traces and environment interactions, creating a closed-loop system that enables real-time plan formulation, exception handling, and integration of external observations with internal knowledge.

Traditional approaches to LLM reasoning and decision-making have typically treated these capabilities separately. Chain-of-Thought prompting [5] demonstrated the value of explicit reasoning traces but lacked fact grounding, while action-only methods like WebGPT [1] enabled environment interaction but suffered from limited strategic planning.

The *ReAct* framework overcomes these limitations by establishing a continuous feedback loop where reasoning traces guide action selection through plan decomposition, while environment observations ground subsequent reasoning in external context.

This synergy between reasoning and acting is achieved through a unified prompting architecture that maintains human-interpretable reasoning traces while achieving state-of-the-art performance across multiple benchmarks, with only 1-6 in-context examples.

## 2 Experiment Setting

For model implementation, I utilized OpenAI's `GPT-3.5-turbo` API [2] as the closest available alternative to the original paper's `text-davinci-002` model. All datasets can be downloaded alongside the implementation. The reproduction environment was configured to match the experimental

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conditions of the original work as closely as possible given hardware constraints. Implementation can be found on GitHub.

## 3 Experiments

| Prompt Method | HotpotQA[6] | Fever[4] |
|---|---|---|
| Standard | 28.8 | 52.6 |
| CoT [5] | 36.4 | 56.8 |
| CoT-SC [5] | 38.2 | 59.4 |
| Act | 28.2 | 57.5 |
| ReAct | 29.4 | 62.0 |
| CoT-SC $\rightarrow$ ReAct | **37.7** | **64.7** |
| ReAct $\rightarrow$ CoT-SC | 31.5 | 63.5 |
| Supervised SoTA | 67.5 | 89.5 |

Table 1: Performance comparison of different prompt methods on HotpotQA[6] and Fever[4] benchmarks (%).

| Method | Pick | Clean | Heat | Cool | Look | Pick 2 | All |
|---|---|---|---|---|---|---|---|
| Act (avg) | 45 | 40 | 50 | 54 | 48 | 21 | 43 |
| ReAct (avg) | 71 | 60 | 82 | 75 | 38 | 30 | 59 |
| BUTLERg (best of 8) | 33 | 26 | 70 | 76 | 17 | 12 | 22 |
| BUTLER (best of 8) | 46 | 39 | 74 | 100 | 22 | 24 | 37 |

Table 2: Performance comparison of different prompt methods on ALFWorld[3] benchmark (%).

| Method | Score | SR |
|---|---|---|
| Act | - | - |
| ReAct | - | - |
| Human Expert | 82.1 | 59.6 |

Table 3: Performance comparison of different prompt methods on WebShop[8] benchmark (%).

## 4 Conclusion

**Experimental Results** Due to the deprecation of the original text-davinci-002 model used in the paper, I adopted the closest available alternative, gpt-3.5-turbo. While this substitution yields performance variations, improvements on some tasks and degradations on others the results consistently align with the original findings. Crucially, they demonstrate that ReAct ourperformes alternative methods on all benchmarks while maintaing comparative patterns despite model differences.

**Limitations in Experimental Coverage** Due to computational budget constraints, I could not reproduce two experiments from the original paper:

- The *Act (best of 6)* and *ReAct (best of 6)* evaluations on the ALFWorld[3] dataset
- Validation of *ReAct* and *Act* methods on the Webshop[8] benchmark, as the official platform was non-functional at the time of the reproduction.

**Reflection** This project marked my first systematic reproduction of a research paper, serving as a valuable learning experience in research methodology. I developed critical skills in: (1) analytical paper reading ; (2) strategic reproduction planning; and (3) rigorous results documentation. The challenges in aligning with the original authors' implementation with available computational resources also improved my understanding of practical research constraints.

## References

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