ReAct: Synergizing Reasoning and Acting in Language Models

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Abstract

While large language models (LLMs) have demonstrated impressive performance across tasks in language understanding and interactive decision making, their abilities for reasoning (e.g. chain-of-thought prompting) and acting (e.g. action plan generation) have primarily been studied as separate topics. In this paper, we explore the use of LLMs to generate both reasoning traces and task-specific actions in an interleaved manner, allowing for greater synergy between the two: reasoning traces help the model induce, track, and update action plans as well as handle exceptions, while actions allow it to interface with and gather additional information from external sources such as knowledge bases or environments. We apply our approach, named ReAct, to a diverse set of language and decision making tasks and demonstrate its effectiveness over state-of-the-art baselines in addition to improved human interpretability and trustworthiness. Concretely, on question answering (HotpotQA) and fact verification (Fever), ReAct overcomes prevalent issues of hallucination and error propagation in chain-of-thought reasoning by interacting with a simple Wikipedia API, and generating human-like task-solving trajectories that are more interpretable than baselines without reasoning traces. Furthermore, on two interactive decision making benchmarks (ALFWorld and WebShop), ReAct outperforms imitation and reinforcement learning methods by an absolute success rate of 34% and 10% respectively, while being prompted with only one or two in-context examples.

1 Introduction

A unique feature of human intelligence is the ability to seamlessly combine task-oriented actions with verbal reasoning (or inner speech, Alderson-Day & Fernyhough, 2015), which has been theorized to play an important role in human cognition for enabling self-regulation or strategization (Vygotsky, 1987; Luria, 1965; Fernyhough, 2010) and maintaining a working memory (Baddeley, 1992). Consider the example of cooking up a dish in the kitchen. Between any two specific actions, we may reason in language in order to track progress ("now that everything is cut, I should heat up the pot of water"), to handle exceptions or adjust the plan according to the situation ("I don't have salt, so let me use soy sauce and pepper instead"), and to realize when external information is needed ("how do I prepare dough? Let me search on the Internet"). We may also act (open a cookbook to read the recipe, open the fridge, check ingredients) to support the reasoning and to answer questions ("What dish can I make right now?"). This tight synergy between "acting" and "reasoning" allows humans to learn new tasks quickly and perform robust decision making or reasoning, even under previously unseen circumstances or facing information uncertainties.

Recent results have hinted at the possibility of combining verbal reasoning with interactive decision making in autonomous systems. On one hand, properly prompted large language models (LLMs) have demonstrated emergent capabilities to carry out several steps of reasoning traces to derive

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[*]Work during Google internship. Projet page with code: https://react-lm.github.io/.