Analysis

Research Paper 1 - ReAct: Synergizing Reasoning and Acting in Language Models

The way LLMs interact these days is that they take different approaches in terms of reasoning (chain of thought) and action (plan). Which can create a not so good synergy between them. The focus of this research paper is to create a synergy between chain of thought reasoning and plan of action. How it worked previously is that the reasoning part and action part act separately and then come to a conclusion, in the ReAct approach they have combined the reasoning and action together as well as streamlined it with a Chain of Thought Self Consistency (CoT-Sc) with enables the system to switch between these two systems, which are ReAct and CoT-Sc, whenever the other one hallucinates. After evaluation the approach / system on prompting LLMs, the ReAct + Cot-Sc showed best results.

Real World Applicability – Best for simple reasoning tasks as it can give better result when combined with plan of action.

Research Paper 2 - Toolformer: Language Models Can Teach Themselves to Use Tools

LMs themselves have a huge knowledge base and in some cases performing time consuming tasks is quite easy for them as well as efficient. However, this is also the disadvantage they have is that their knowledge base is fixed and only contain natural language. The focus of this research paper is to create a system in which LMs have the capability to use tools by means of API so that they can leverage real time data for better accuracy. So basically Toolformer learns in a self supervised way so that it can use tools according to requirement in the form of API calls. They have seen good performance in terms of zero shot learning.

Real World Applicability – Mainly used to implement a system where the response depends on very specific and external data which can be integrated with APIs.

Research Paper 3 - ReST meets ReAct: Self-Improvement for Multi-Step Reasoning LLM Agent

ReST means reinforced self training and ReAct means Reasoning + Action. Although we could see in Research Paper 1 than ReAct when combined with CoT-Sc could provide very good results. In this research paper, they have tried to introduce self learning / finetuning on the reasoning traces and then having an Al based feedback system which can produce some synthetic data and later on can be used for distilling the agent into smaller models who can produce performance comparable to the pre trained agent. Here the focus is more on

efficiency that the smaller parameter model can also perform better when trained based on new technique.

Real World Applicability – This is a better algorithm for creating a hyper focused small LMs which can do very specific tasks

Research Paper 4 - Chain of Tools: Large Language Model is an Automatic Multi-tool Learner

As we already looked into Toolformer that can use tools to extend knowledge base and interact smartly using tools in the form of API calls. ATC (Automatic Tool Chain) is like an evolved version of Toolformer in a way that it also recognize tools and document those tools so as to extend its tool library in a way. So, in comparions to ReAct, better performance can be seen with ATC, as it can extend its tool documentation and use those as required.

Real World Applicability – Better approach then Toolformer as it can recognize new tools based on the previous context

Research Paper 5 - Language Agent Tree Search Unifies Reasoning, Acting, and Planning in Language Models

Language Agent Tree Search (LATS) which basically acts by taking leverage of reasoning, acting and planning together, along with it implementing the Monet Carlo Tree Search (MCTS) which is basically a search algorithm, then acting as a single entity, as well as doing self reflection for enhanced decision making. This basically comprises of ReAct -> CoT-Sc combined with close to ReST approach in which there is a search algorithm implemented upon them for optimization. This by far gives the best performance metrics when compared to above approach excluding ATC, in which approach is different.

Real World Applicability – So far the best approach for logical answering as well as all modern types of evaluation metrics.

Conceptual Map

Finetuned Small Model

Research Pape	r 1 - Re	Act: Sy	nergizing Rea	asoning a	nd Acting i	n Language I	Models
Input Task							
\downarrow							
Reasoning Trac	e	\rightarrow	Action Plan				
\downarrow			\downarrow				
External Tool		\leftarrow	Execute Acti	on			
\downarrow							
Updated Reaso	ning						
\downarrow							
Output Result							
Research Pape	r 2 - To	olform	er: Language	Models	Can Teach	Themselves t	o Use Tools
=		LLM Reasoning Integrate Result					
Research Pape Agent	r 3 - Re	eST me	ets ReAct: Sel	f-Improv	ement for	Multi-Step R	easoning LLM
Input Question							
\downarrow							
LLM Reasoning		\rightarrow	Action Plan				
\downarrow			\downarrow				
External Tool		\leftarrow	Execution Ad	ction			
\downarrow							
Output: Final A	nswer						
\downarrow							
ReST: Reinforce	ed Self	Trainin	g				
\downarrow							

Research Paper 4 - Chain of Tools: Large Language Model is an Automatic Multi-tool Learner **User Query** \downarrow LLM Planning (ATC Framework) **Tool Chain Generation** \downarrow **Tool Execution** Final Answer \downarrow Black Box Probing (Tool Learning) \downarrow Tool Discovery and Documentation Research Paper 5 - Language Agent Tree Search Unifies Reasoning, Acting, and Planning in **Language Models** Problem Input \downarrow Reasoning and Planning (ReAct + CoT-Sc) \downarrow **Action Execution** \downarrow Monte Carlo Tree Search (MCTS)

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External Feedback

Self Reflection and Iteration