Notes on Chain-of-Thought (CoT), ReAct and DSPy Techniques for Eliciting Reasoning and Obtaining More Correct Inferences with LLMs

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# Introductory Remarks

A screenshot of a computer screen

AI-generated content may be incorrect.

Figure 1: Chain-of-thought prompting enables LLMs to tackle more involved arithmetic and reasoning

tasks. The CoT reasoning sequence is highlighted with green

# Chain-of-Thought prompting

We compose the problem into intermediate seps and solve each before giving the final answer:

*“After Jane gives 2 flowers to her mom she has 10 ... then after she gives 3 to her dad she will have 7 ... so the answer is 7.”*

Sufficiently large LMs can generate chains of thought if demonstrations of chain-of-thought reasoning are provided in the exemplars for few-shot prompting. The Figure above shows an example of a model producing a CoT to solve a math word problem that it would have otherwise resulted in incorrect inference. The CoT in this case resembles a solution and can be interpreted as one.

Properties of CoT as a technique which facilitates reasoning:

-CoT represents a decomposition of a multi-step problem into intermediate steps where more intermediate steps are generated for problems which require more intermediate steps

-CoT provides interpretable window into the behavior of the model, suggesting how it might have arrived at a particular answer and providing opportunities to debug where the reasoning path went wrong

# References

[1] [Chain-of-Thought Prompting Elicits Reasoning in Large Language Models, J. Wei et al, 2023](https://github.com/dimitarpg13/large_language_models/blob/main/articles/CoT/Chain-of-Thought_Prompting_Elicits_Reasoning_in_Large_Language_Models_Wei_2022.pdf)