Introduction to Chain-of-Thought Prompting

Chain-of-Thought Prompting Elicits Reasoning in Large Language Models

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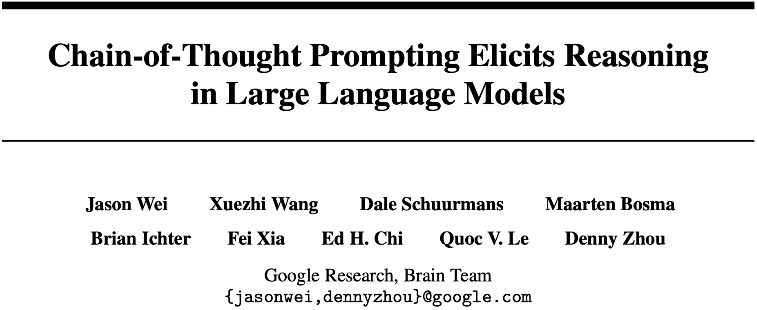
Paper

paper: https://arxiv.org/pdf/2201.11903.pdf



Chain-of-Thought Prompting Elicits Reasoning in Large Language Models

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图 1: Paper[WWS+22]

Inspirations

- 1. Generate natural language intermediate steps: training from scratch[LYDB17] or fine-tuning a pre-trained model[CKB+21]
- 2. In-context few-shot learning via prompting of LLM[BMR+20]

The former needs high-quality data of rationale, too costly
The latter works poorly on tasks that require reasoning abilities

Idea

Therefore, their idea is simply combining the two ideas above. Prompting + intermediate steps.
Formally, a prompt consists of triples: <input, chain of thought, output>. A chain of thought is a series of intermediate natural language reasoning steps that lead to the final output.

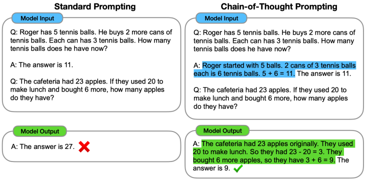

Figure 1: Chain-of-thought prompting enables large language models to tackle complex arithmetic, commonsense, and symbolic reasoning tasks. Chain-of-thought reasoning processes are highlighted.

图 2: Example

Attractive properties

- Computation: CoT allows models to decompose multi-step problems into intermediate steps
- Interpretality: CoT provides an interpretable window into the behavior of the model
- Usefulness: CoT is potentially applicable (at least in principle) to any task that humans can solve via language
- Simplicity: Including examples of chain of thought sequences into the exemplars of few-shot prompting is easy

Benchmarks

- GSM8K: math word problems
- SVAMP: math word problems with varying structures
- ASDiv: diverse math word problems
- AQuA: algebraic word problems
- MAWPS

Benchmarks

Natalia sold clips to 48 of her friends in April, and then she sold half as many clips in May. How many clips did Natalia sell altogether in April and May?	Natalia sold 48/2 = <<48/2=24>>24 clips in May. Natalia sold 48+24 = <<48+24=72>>72 clips altogether in April and May. #### 72

图 3: GSM8K example

There are 87 oranges and 290 bananas in Philip's collection. If the bananas are organized into 2 groups and oranges are organized into 93 groups	145	(290.0 / 2.0)	How big is each group of bananas?	chal-777

图 4: SVAMP example

Prompt

Table 20: Few-shot exemplars for full chain of thought prompt for math word problems. This set of exemplars was used for all math word problem datasets except AQuA.

PROMPT FOR MATH WORD PROBLEMS

Q: There are 15 trees in the grove. Grove workers will plant trees in the grove today. After they are done, there will be 21 trees. How many trees did the grove workers plant today?

A: There are 15 trees originally. Then there were 21 trees after some more were planted. So there must have been 21 - 15 = 6. The answer is 6.

Q: If there are 3 cars in the parking lot and 2 more cars arrive, how many cars are in the parking lot?

A: There are originally 3 cars. 2 more cars arrive. 3 + 2 = 5. The answer is 5.

Q: Leah had 32 chocolates and her sister had 42. If they ate 35, how many pieces do they have left in total?

A: Originally, Leah had 32 chocolates. Her sister had 42. So in total they had 32 + 42 = 74. After eating 35, they had 74 - 35 = 39. The answer is 39.

Q: Jason had 20 lollipops. He gave Denny some lollipops. Now Jason has 12 lollipops. How many lollipops did Jason give to Denny?

A: Jason started with 20 lollipops. Then he had 12 after giving some to Denny. So he gave Denny 20 - 12 = 8. The answer is 8.

Q: Shawn has five toys. For Christmas, he got two toys each from his mom and dad. How many toys does he have now?

A: Shawn started with 5 toys. If he got 2 toys each from his mom and dad, then that is 4 more toys. 5 + 4 = 9. The answer is 9.

Q: There were nine computers in the server room. Five more computers were installed each day, from monday to thursday. How many computers are now in the server room?

A: There were originally 9 computers. For each of 4 days, 5 more computers were added. So 5 * 4 = 20 computers were added. 9 + 20 is 29. The answer is 29.

Q: Michael had 58 golf balls. On tuesday, he lost 23 golf balls. On wednesday, he lost 2 more. How many golf balls did he have at the end of wednesday?

A: Michael started with 58 golf balls. After losing 23 on tuesday, he had 58 - 23 = 35. After losing 2 more, he had 35 - 2 = 33 golf balls. The answer is 33.

Q: Olivia has $23. She bought five bagels for $3 each. How much money does she have left?

A: Olivia had 23 dollars. 5 bagels for 3 dollars each will be 5 x 3 = 15 dollars. So she has 23 - 15 dollars left. 23 - 15 is 8. The answer is 8.

图 5: Few-shot exemplars for full chain of thought prompt for math word

Results

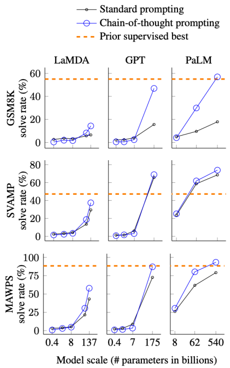

图 6: Results

Ablation & Robustness

- Equation only
- Variable compute only
- Chain of thought after answer
- Annotator (linguistic style)

1. Methods
2. Tasks and Experiments
   - Arithmetic Reasoning
   - Commonsense Reasoning
   - Symbolic Reasoning
3. Analysis and Further Discussion
4. Reference

Benchmarks

- CSQA
- StrategyQA
- Date: inferring a date from a given context
- Sports: determining whether a sentence relating to sports is plausible or implausible
- SayCan: mapping a natural language instruction to a sequence of robot actions from a discrete set

Benchmarks

Sammy wanted to go to where the people were. Where might he go?	people	{ "label": ["A", "B", "C", "D", "E"], "text": ["race track", "populated areas", "the desert", "apartment", "roadblock"] }	B	Q: Sammy wanted to go to where the people were. Where might he go? Answer Choices: (A) race track (B) populated areas (C) the desert (D) apartment (E) roadblock	(B)

图 7: CSQA example


```
{
    "qid": "564959490dd0b8316a88",
    "question": "can you use Microsoft Office without internet?"
},
{
    "qid": "274badccc0a85d6e98fb",
    "question": "Does the British royal family have an American in it?"
},
{
    "qid": "e05f8b4928fad08e72b0",
    "question": "Was the Scottish Parliament founded by William Wallace?"
},
```


图 8: StrategyQA example

Results

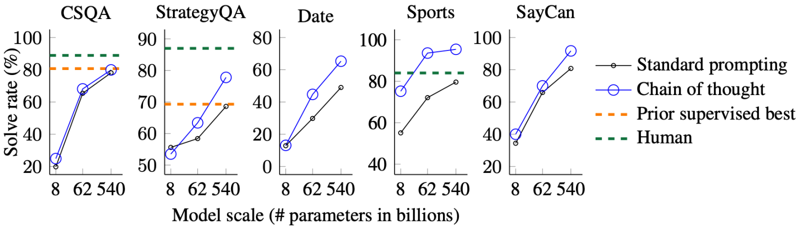

图 9: Results

Tasks

- Last letter concatenation: “Amy Brown” “yn”
- Coin flip: asks the model to answer whether a coin is still heads up after people either flip or don’ t flip the coin

Details

- In-domain test set: examples had the same number of steps as the training/few-shot exemplars
- Out-of-domain (OOD) test set: evaluation examples had more steps than those in the exemplars

Results

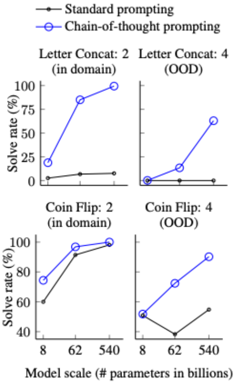

Figure 8: Using chain-of-thought prompting facilitates generalization to longer sequences in two symbolic reasoning tasks.

Analysis and Further Discussion

- The ability to perform abstract manipulations on unseen symbols for these three tasks only arises at the scale of 100B model parameters
- For many reasoning tasks where standard prompting has a flat scaling curve, chainof-thought prompting leads to dramatically increasing scaling curves

Open Question

This does not answer whether the neural network is actually "reasoning"

There is no guarantee of correct reasoning paths

1. Methods
2. Tasks and Experiments
3. Analysis and Further Discussion
4. Reference

[BMR+20] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020.

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[LYDB17] Wang Ling, Dani Yogatama, Chris Dyer, and Phil Blunsom. Program induction by rationale generation: Learning to solve and explain algebraic word problems. *arXiv preprint arXiv:1705.04146*, 2017.

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Thanks!