



Self-Consistency Improves Chain of Thought Reasoning in Language Models

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Recap: Chain-of-thought (CoT) prompting

Standard Prompting

Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?



Chain of Thought Prompting

Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had 23 - 20 = 3. They bought 6 more apples, so they have 3 + 6 = 9. The answer is 9.

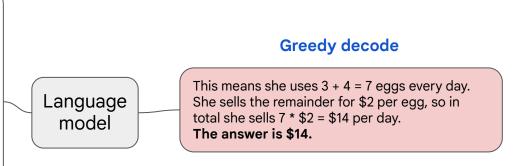
<u>Chain of thought prompting elicits reasoning in large language models</u> (NeurIPS 2022). J. Wei, X. Wang, D. Schuurmans, M. Bosma, B. Ichter, F. Xia, E. Chi, Q. Le, & D. Zhou.

CoT prompting greedily decodes the optimal reasoning path

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A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: Janet's ducks lay 16 eggs per day. She eats three for breakfast every morning and bakes muffins for her friends every day with four. She sells the remainder for \$2 per egg. How much does she make every day?



- The final answer is incorrect due to wrong reasoning paths
- **Different people think differently**: can we do better by generating multiple possible reasoning paths?

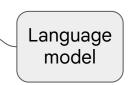
Self-consistency: step 1 - prompt

Prompt with chain of thought

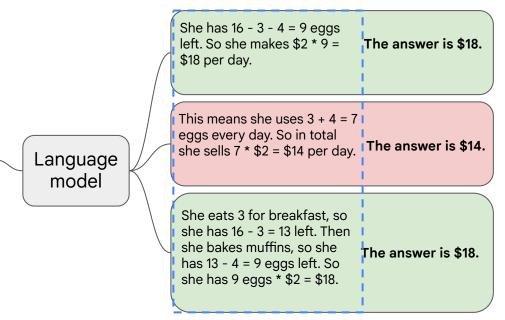
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Self-consistency: step 2 - sample decode



Note the reasoning paths are optional, so they can be marginalized out

Prompt with chain of thought

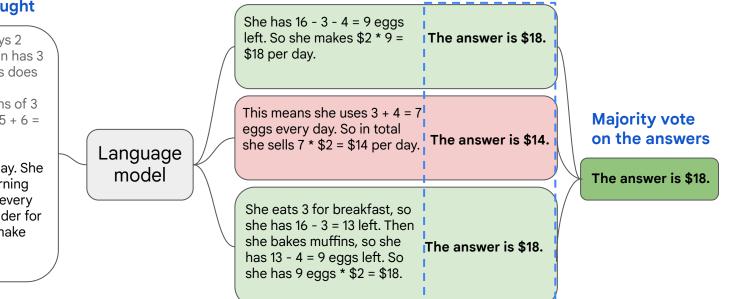
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Sample decode with diverse reasoning paths

Self-consistency: step 3 - majority vote



Prompt with chain of thought

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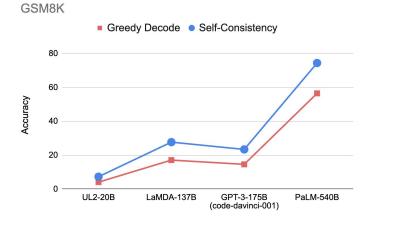
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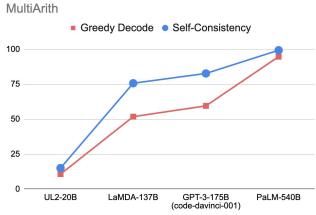
Sample decode with diverse reasoning paths

Self-consistency is simple but effective

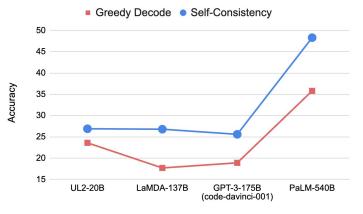
- Simple compared to many other existing works
 - No fine-tuning, no human annotation, no additional modules like a verifier or a re-ranker
- Striking performance gains across:
 - Four LLMs with varying scales: UL2-20B, LaMDA-137B, PaLM-540B, GPT-3 (175B)
- SoTA performance across:
 - Various reasoning benchmarks: arithmetic, commonsense, and symbolic

Arithmetic reasoning

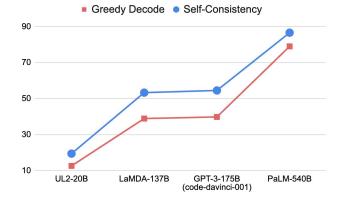




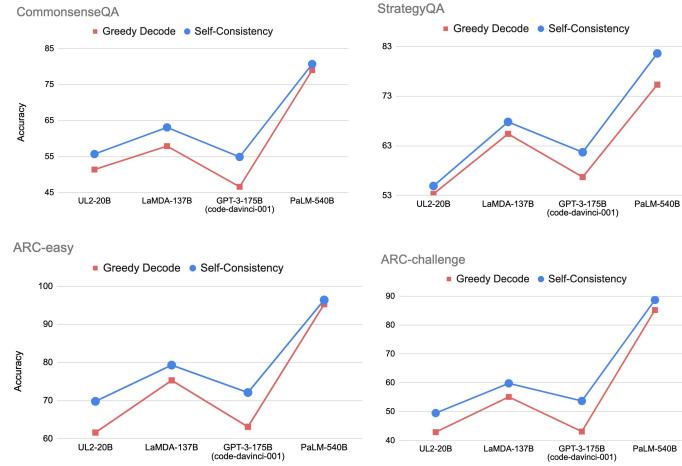




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Self-consistency works with zero-shot CoT

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?

A: Let's think step by step.

(Output) There are 16 balls in total. Half of the balls are golf balls. That means that there are 8 golf balls. Half of the golf balls are blue. That means that there are 4 blue golf balls.

Kojima et al. *Large Language Models are Zero-Shot Reasoners*. NeurIPS 2022.

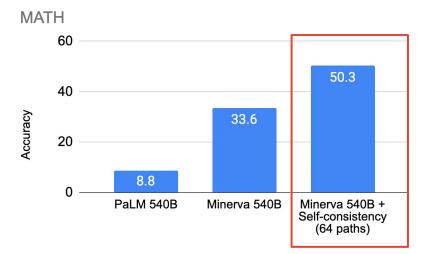
GSM8K accuracy

PaLM-540B	Zero-shot CoT (Kojima et al., 2022)	43.0
	+ Self-consistency (40 paths)	69.2

Self-consistency works with "*let's think step by step*" too! (



Self-consistency achieves SoTA in Minerva and Flan-PaLM



Lewkowycz et al. <u>Solving Quantitative Reasoning</u> <u>Problems with Language Models</u>. 2022. MMLU

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-	Random	2 5.0
-	Average human rater	34. 5
May 2020	GPT-3 5-shot	43.9
Mar. 2022	Chinchilla 5-shot	67.6
Apr. 2022	PaLM 5-shot	69.3
Oct. 2022	Flan-PaLM 5-shot	72.2
	Flan-PaLM 5-shot: CoT + SC	75.2
-	Average human expert	89.8

Chung et al. <u>Scaling Instruction-Finetuned Language Models</u>. 2022.

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Check out our paper!

- ID 11718: Self-Consistency Improves Chain of Thought Reasoning in Language Models
- <u>https://arxiv.org/abs/2203.11171</u>
- Questions: xuezhiw@google.com