Google DeepMind

Chain-of-Thought Reasoning without Prompting

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作者介绍



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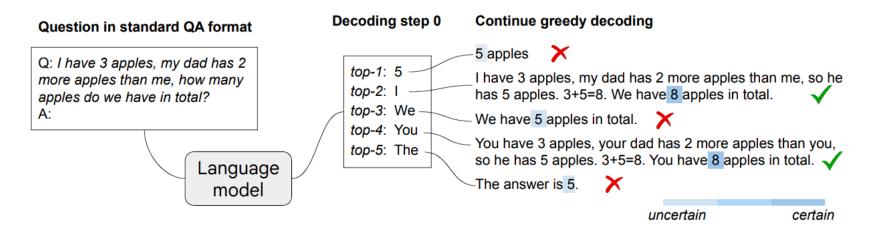
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研究背景



- ➤ 引发LLM推理能力的两种方法:
 - 由一些prompt引发的:一些带有中间推理步骤的少样本prompt,或者是要求输出中间推理步骤的零样本prompt。
 - 使用大量的思想链推理数据进行模型训练或指令微调。
- ➤ LLM能否在没有提示的情况下有效地进行推理?



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方法介绍



▶ 置信度

$$\Delta_{k,\text{answer}} = \frac{1}{|\text{answer}|} \sum_{x_t \in \text{answer}} p(x_t^1 \mid x_{< t}) - p(x_t^2 \mid x_{< t}).$$

 $x_t^1 n x_t^2$ 分别表示第K条解码路径中第t步解码的前两个词元,这两个词元是基于其在softmax后的最大概率从词汇表中选择的,前提是 x_t 属于答案词元。

方法介绍



[GSM8K] Kylar went to the store to buy glasses for his new apartment. One glass costs \$5, but every second glass costs only 60% of the price. Kylar wants to buy 16 glasses. How much does he need to pay for them? Greedy path:

k = 0: \$60.00 (0.029) **Alternative top-***k* **paths**: k = 1: 60 (0.058)k = 2: Kylar needs to pay \$60 for 16 glasses. (0.058) k = 7: If Kylar buys 16 glasses, he will pay \$60. (0.032) k = 9: We can calculate the price of 16 glasses by multiplying the price of one glass by 16. However, we need to remember that every second glass costs only 60% of the price. Therefore, we need to multiply the price of one glass by 16 and then subtract 40% of the price of 8 glasses. $16 \times 5 = 80 \times 5 = 40 \times 40 \times 0.4 = 100 \times 100 \times 100$ 16.80 - 16 = 64 Kylar needs to pay \$64 for 16 glasses. (0.994)

[Year Parity] Was Nicolas Cage born in an even or odd year? Greedy path: k = 0: Nicolas Cage was born in an **odd** year. (0.117)

Alternative top-*k* **paths**:

k = 1: Even (0.207) k = 2: **Odd** (0.198)

k = 3: 1964, an **even** year. (0.949)

k = 4: He was born in an **even** year. (0.0)

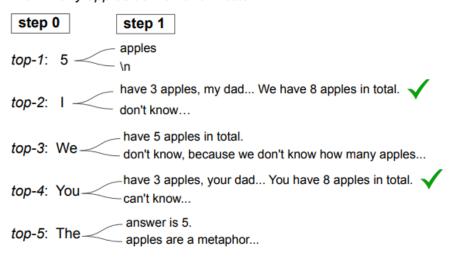
k = 7: Cage was born in 1964, an **even** year. (0.978)

Table 1 | Examples of greedy decoded paths and alternative top-k paths over the PaLM-2 Large model. The model's confidence over the answers (bolded) are highlighted in blue (See §2.2 for details).

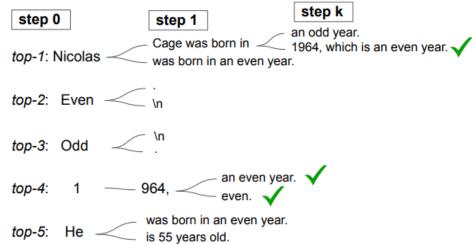
方法介绍



I have 3 apples, my dad has 2 more apples than me, how many apples do we have in total?



Was Nicolas Cage born in an even or odd year?



propose a weighted aggregation method, i.e., we take the answer that maximizes $\tilde{\Delta}_a = \sum_k \Delta_{k,a}$ where $\Delta_{k,a}$ is the k-th decoding path whose answer = a. We found that adopting this approach enhances the stability of the results, and further analysis is presented in Section §3.3.

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	GSM8K (top-100)	Year Parity
Greedy decoding	44.0%	57.0%
Decode 10 paths, rank by model's highest log-prob	37.0%	55.0%
Decode 10 paths, rank by model's highest length-normalized log-prob	51.0%	57.0%
CoT-decoding (decode 10 paths, rank by model's answer confidence)	72.0%	95.0%

Table 2 | CoT-decoding reliably extracts the CoT-paths compared to other methods (on PaLM-2 L).

Log-prob(对数概率):

$$\log P(Y) = \sum_{i=1}^n \log P(y_i|y_1,y_2,\ldots,y_{i-1})$$

Length-normalized log-prob(长度归一化概率):

$$\text{Normalized log-prob} = \frac{\log P(Y)}{n}$$

防止较长的路径因为概率值累乘而显得过低,归一化处理可以使长短路径的对数概率在 比较时更为公平。



Table 3 | CoT-decoding and self-consistency w/o prompts on GSM8K.

	Mistral-7B	PaLM-2 L
Greedy decoding Self-consistency without CoT-prompt (10 paths) CoT-decoding (10 paths)	9.9% 12.9% 25.1%	34.8% 40.6% 63.2 %

- 贪婪解码:每次选取概率最大的词输出
- 自我一致性:给出多个cot的prompt输出多个解释,选取答案相同的最多票数的答案

Prompt:问:小树林里有15棵树。树林工人今天将在树林里种树。他们完成后将有21棵树。林场工人今天种了多少棵树?

- 答: 我们开始有15棵树。后来我们有21棵树。差额一定是他们种的树的数量。所以,他们一定是种了21-15=6棵树。答案是6。
- 问:如果停车场里有3辆汽车,又有2辆汽车到达,那么停车场里有多少辆汽车?
- 答: 停车场里已经有3辆汽车。又有2辆到达。现在有3+2=5辆车。答案是5。
- 问:利亚有32块巧克力,她姐姐有42块。如果她们吃了35块,她们总共还剩下多少块?
- 答: 利亚有32块巧克力,利亚的姐姐有42块。这意味着原来有32+42=74块巧克力。35块已经被吃掉了。所以他们总共还有74-35=39块巧克力。答
- 问: 杰森有20根棒棒糖。他给了丹尼一些棒棒糖。现在杰森有12根棒棒糖。杰森给了丹尼多少个棒棒糖?
- 答: 杰森有20根棒棒糖。因为他现在只有12个,所以他肯定把剩下的给了丹尼。他给丹尼的棒棒糖的数量一定是20-12=8根。答案是8。
- 问: 肖恩有五个玩具。圣诞节时,他从他的妈妈和爸爸那里各得到两个玩具。他现在有多少个玩具?
- 答:他有5个玩具。他从妈妈那里得到了2个,所以之后他有5+2=7个玩具。然后他又从爸爸那里得到了2个,所以他总共有7+2=9个玩具。答案是9.
- 问: 机房里有九台电脑。从星期一到星期四,每天都有五台电脑被安装。现在机房里有多少台电脑?
- 答:从星期一到星期四有4天。每天增加5台电脑。这意味着总共4*5=20台电脑。一开始有9台电脑,所以现在有9+20=29台电脑。答案是29。
- 问: 迈克尔有58个高尔夫球。在星期二,他丢了23个高尔夫球。星期三,他又丢了两个。他在周三结束时有多少个高尔夫球?
- 答: 迈克尔最初有58个球。周二他丢了23个,所以之后他有58-23=35个球。在周三他又丢了2个,所以现在他有35-2=33个球。答案是33。
- 问: 奥利维亚有23美元,她买了五个面包圈,每个3美元。她还剩下多少钱?
- 答:她买了5个面包圈,每个3美元。这意味着她花了5*3=15美元。由于她原来有23美元,现在花了15美元,那么还剩23-15=8美元。答案是8。
- 问: 当我6岁时,我妹妹的年龄是我的一半。现在我70岁了,我的妹妹现在多大?

答:

Output1: 当你6岁时,你妹妹的年龄是你的一半,也就是3岁。现在你是70岁,相当于经过了64年。因此你妹妹现在应该是3+64=67岁。答案是67。

Output2: 当你6岁时,你妹妹的年龄是3岁(一半)。现在经过64年(70-6),你妹妹也长大了64岁。所以现在你妹妹应该是3+64=67岁了。答案是67。

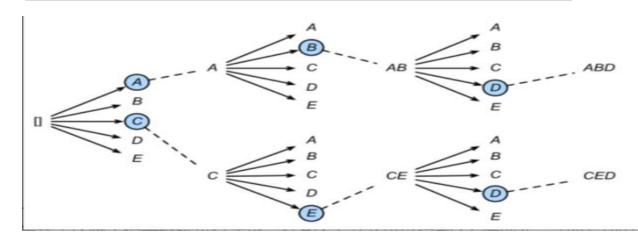
Output3: 6岁时,我妹妹的年龄是我的一半,也就是3岁。70岁时,我妹妹的年龄应该是70/2=35岁。答案是35岁。



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Table 4 | CoT-decoding is the only decoding strategy that can significantly enhance language models' reasoning.

	GSM8K Acc
Top- k sampling ($k = 10$)	4.9%
Top- p / Nucleus sampling ($p = 0.9$)	6.4%
Beam search $(b = 10)$	6.7%
Temperature sampling $(T = 0.7)$	7.5%
Greedy decoding	9.9%
Self-consistency w/o CoT prompt (10 paths)	12.9%
CoT-decoding $(k = 10)$	25.1%



- Top-k 采样:从 tokens 里选择 k 个作为候选,然后根据它们的 likelihood scores 来采样模型从 最可能的"k"个选项中随机选择 一个。
- Top-p采样:从 tokens 里选择 n 个概率和到p作为候选,然后根据它们的 likelihood scores 来采样模型从最可能的"n"个选项中随机选择一个。
- 温度采样:通过温度,在采样前调整每个词的概率分布。温度越低,概率分布差距越大,越容易采样到概率大的字。温度越高,概率分布差距越小,增加了低概率字被采样到的机会。
- 束搜索:



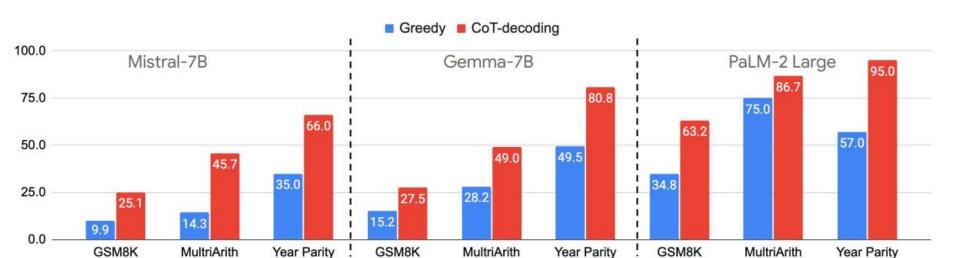


Figure 3 | CoT-decoding effectively elicits reasoning across multiple language model families including PaLM-2, Mistral and Gemma, with significant accuracy gains over three reasoning tasks.



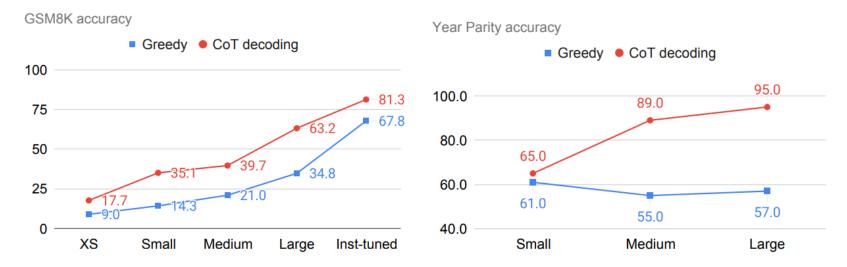


Figure 4 | CoT-decoding reliably improves reasoning performance across model scales (PaLM-2), even when the task does not naturally improve by scaling up only (e.g., year parity).



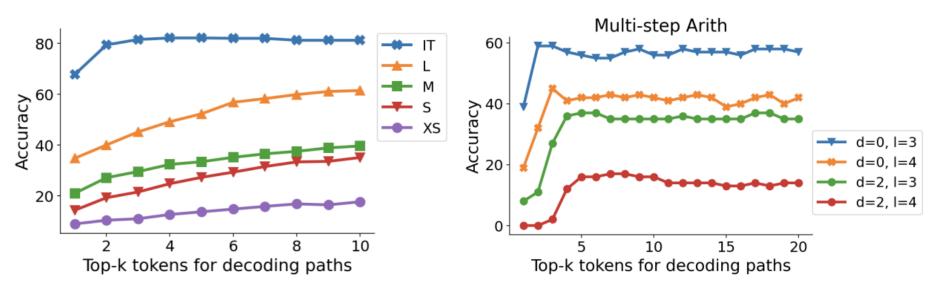


Figure 5 | The effect of k on reasoning accuracy w.r.t. PaLM-2 model scales and task difficulty.



	(Coin Fli	p	Web of lies			Multi-step Arithmetic					Object Count
	2	3	4	3	4	5	d_0, l_3	d_0, l_4	d_2, l_3	d_2, l_4		
Greedy CoT-decoding											58.8 58.0	36.0 39.2

Table 6 | The model's intrinsic reasoning ability varies depending on the task difficulty levels.

尽管CoT解码在几乎所有任务上都帮助引出了更好的推理,但是在不同任务难度级别上差异显著:任务越简单,找到正确推理路径的可能性越大。作者查看了模型的top-k解码路径,发现当解答只涉及最多1或2步知识操作时,模型可以生成正确的CoT路径;而当步骤增加到3步或更多时,模型开始难以生成正确的CoT路径。见图5(右侧),随着任务复杂性增加(较高的d和1值),模型的准确率仅在更大的k值下有所改善。这一现象表明,随着任务变得更合成化,正确的CoT路径变得更难以找到。即语言模型的表现受其训练分布的影响很大。



□总结

- 1. CoT解码揭示了模型在推理中的内在脆弱性:模型可以生成逐步模拟过程的CoT路径,但在任务复杂性增加时容易丢失状态,这揭示了模型在进行准确状态跟踪方面的内在脆弱性。在多步算术任务中,作者观察到模型在CoT解码路径中往往从左到右依次进行计算,而不是遵循正确的数学运算顺序。这些观察指出了未来改进模型的方向。。
- 2.在多模态内容理解是不是可以考虑下解码的方式,而不是通过数据集微调或者模型结构一些修改,这种方法在比赛中可不可以考虑。

Thank for your attention!