

Natural Language Processing



Adaptation

Kevin Lin – UC Berkeley

April 5, 2023

Adaptation



Challenges

- Task Format
 - **Premise:** I have never seen an apple that is not red.
 - **Hypothesis:** I have never seen an apple.
 - **Correct output:** Not entailment
- Harm Mitigation / Control
- Domain Shift
 - e.g. biomedical text, legal text
- Temporal Shift
 - Updated facts, news, etc.

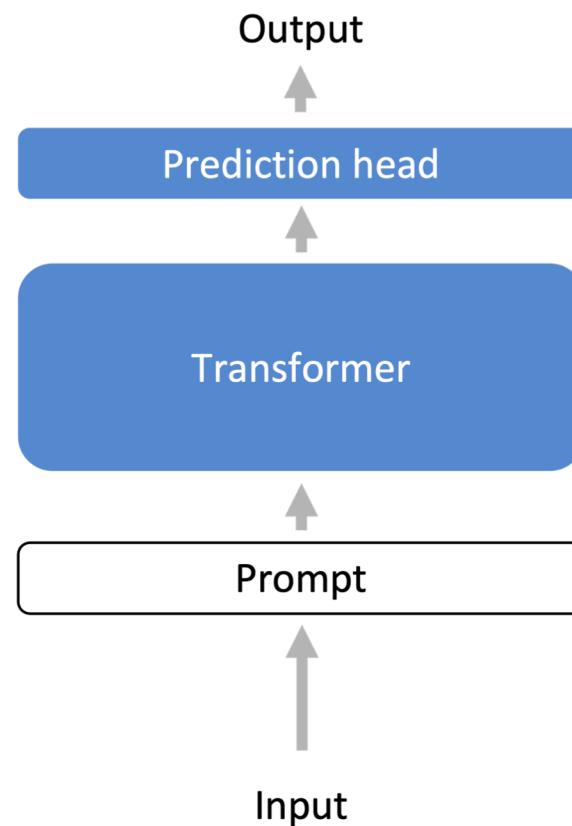


Methods

- Finetuning
- Lightweight Finetuning
- Prompting



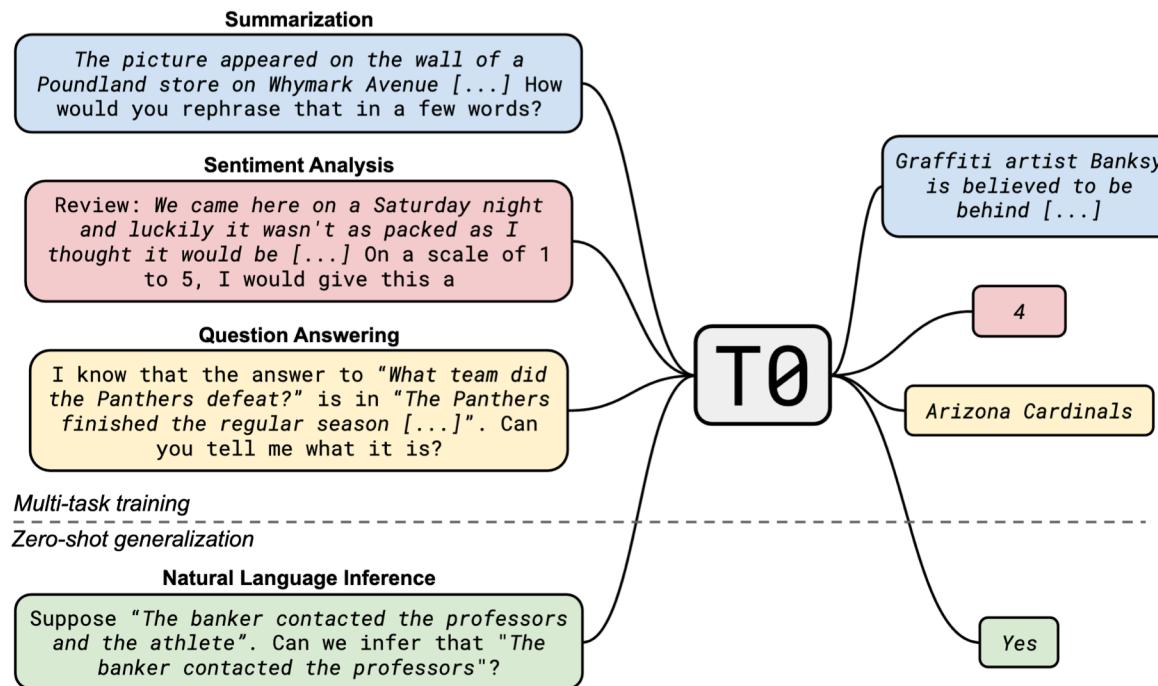
Finetune





Finetuning for Zero-Shot / Instructions

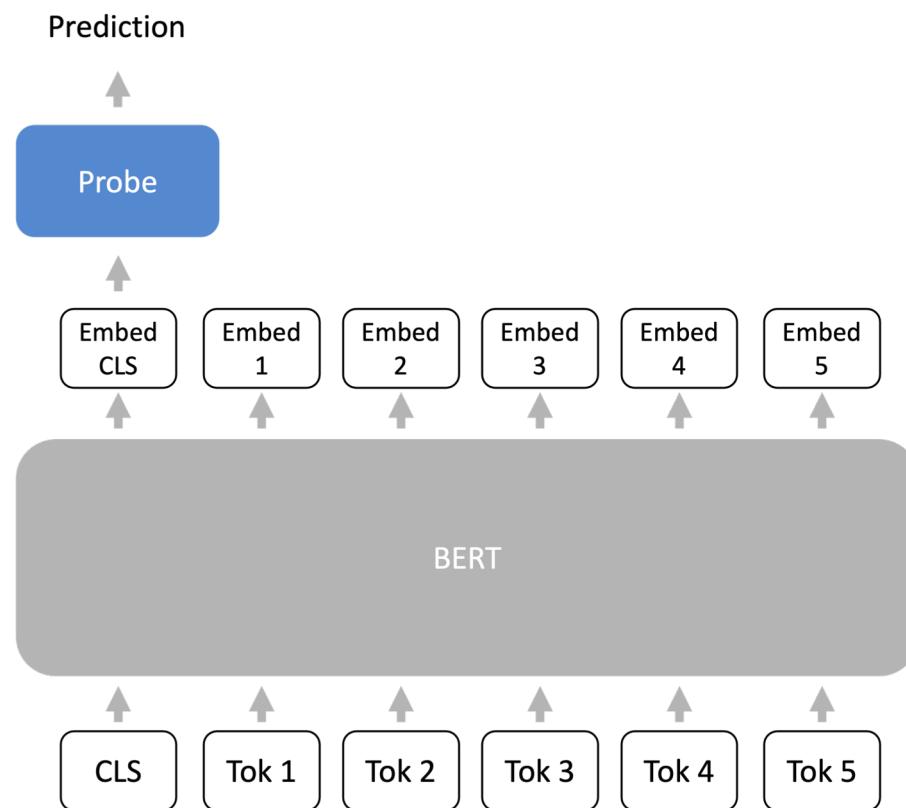
- Multi-task Prompted Training Enabled Zero-Shot Task Generalization (Sanh et al., 2022)





Lightweight Finetuning

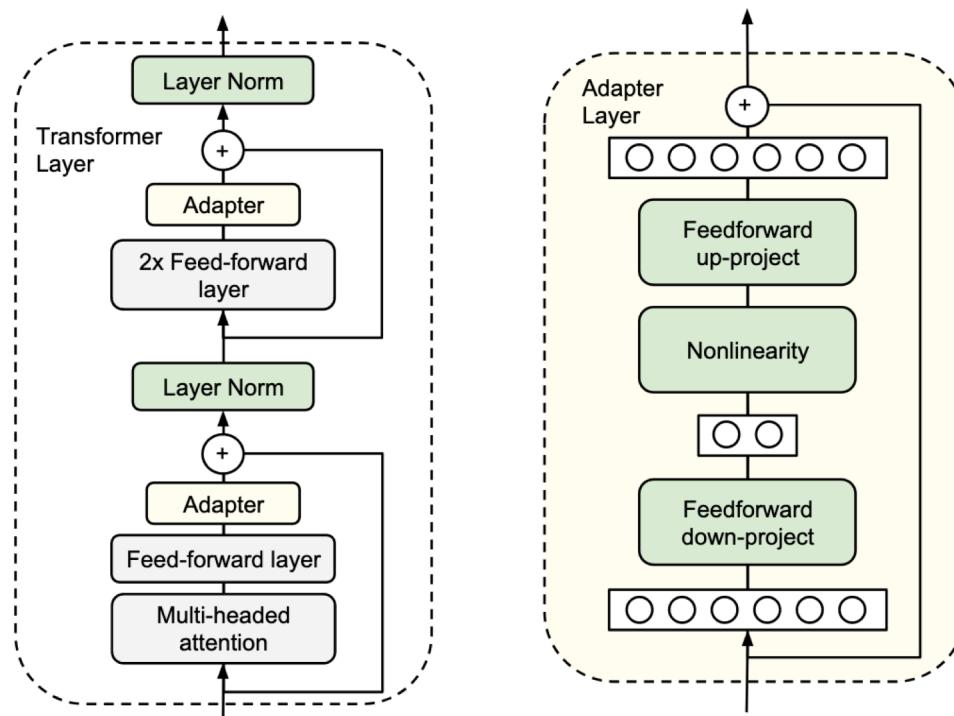
■ Probing





Lightweight Finetuning

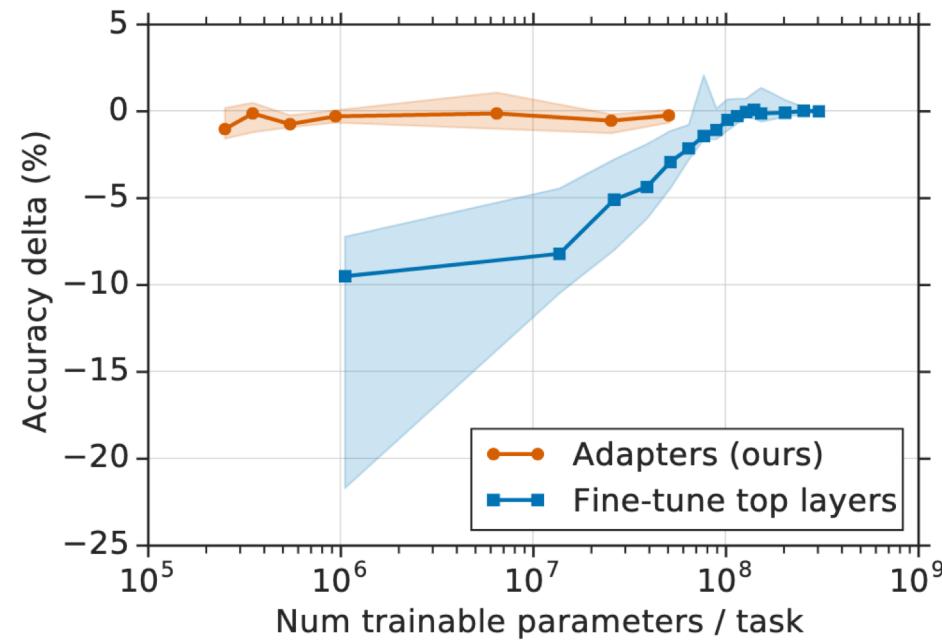
- Adaptors: Parameter-Efficient Transfer Learning for NLP
(Houlsby et al., 2019)





Lightweight Finetuning

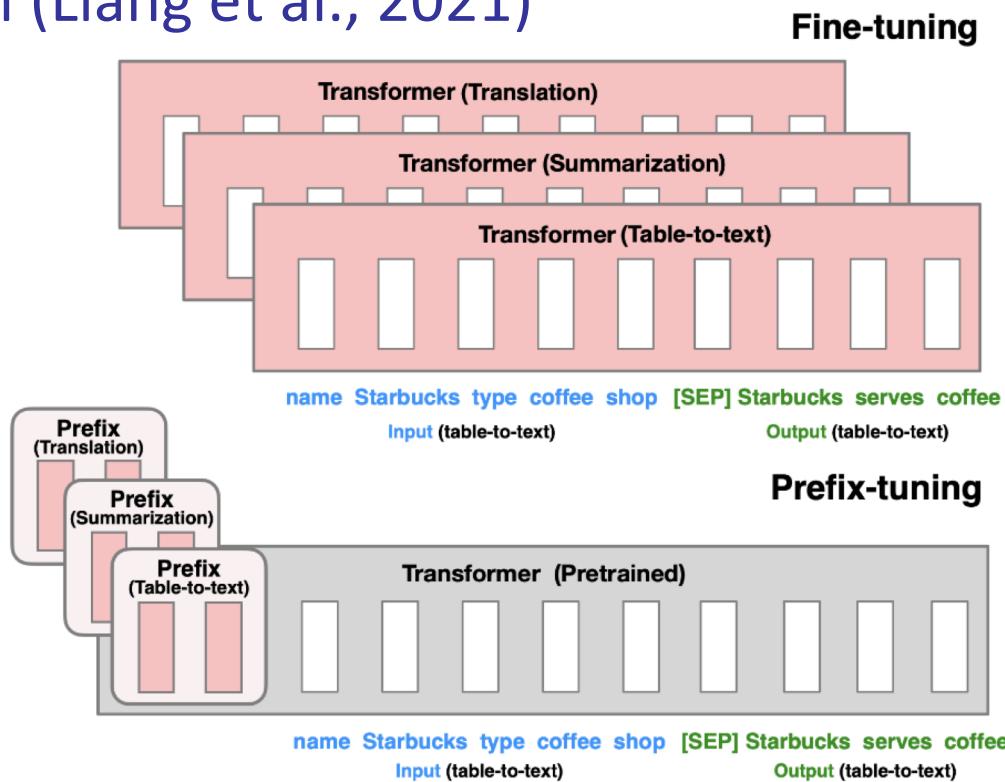
- Adaptors: Parameter-Efficient Transfer Learning for NLP
(Houlsby et al., 2019)





Prefix Tuning

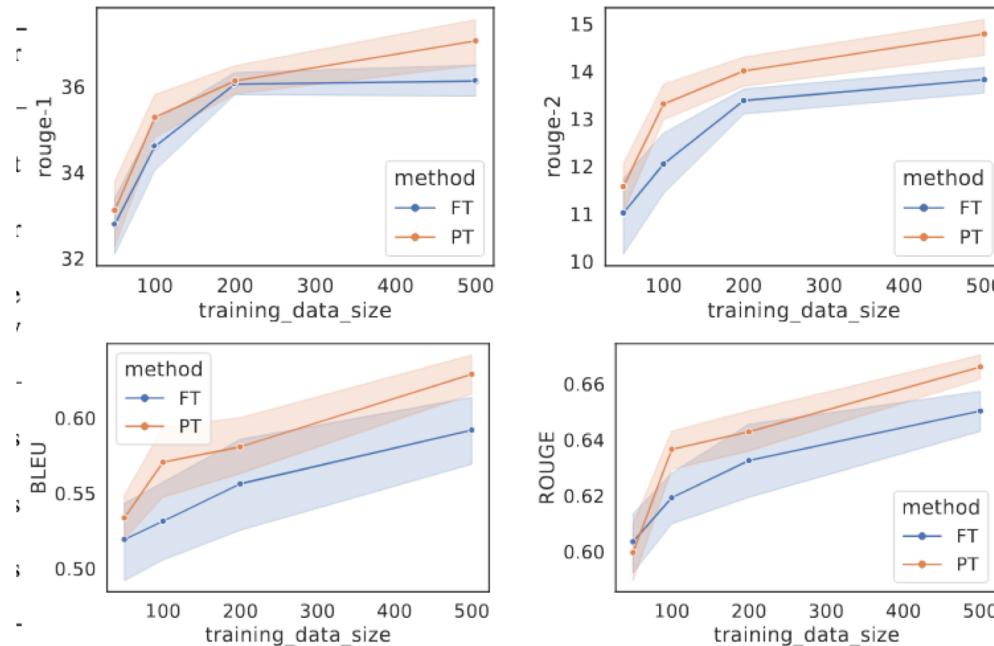
- Prefix Tuning: Optimizing Continuous Prompts for Generation (Liang et al., 2021)





Prefix Tuning

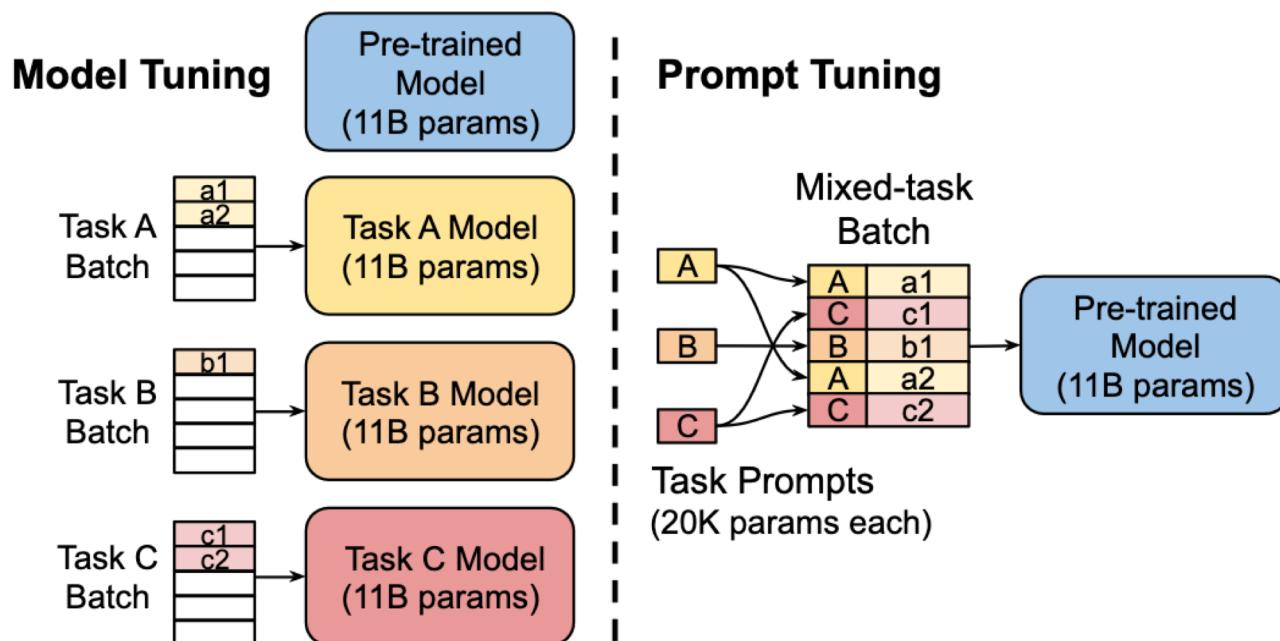
- Prefix Tuning: Optimizing Continuous Prompts for Generation (Liang et al., 2021)





Lightweight Finetuning

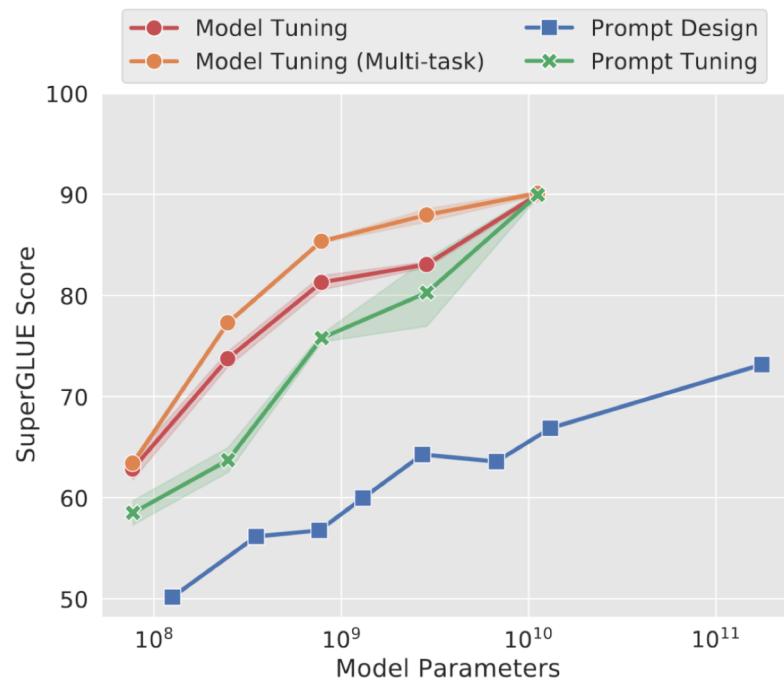
- Prompt Tuning: The Power of Scale for Parameter-Efficient Prompt Tuning (Lester et al., 2021)





Lightweight Finetuning

- Prompt Tuning: The Power of Scale for Parameter-Efficient Finetuning (Lester et al., 2021)





Lightweight Finetuning

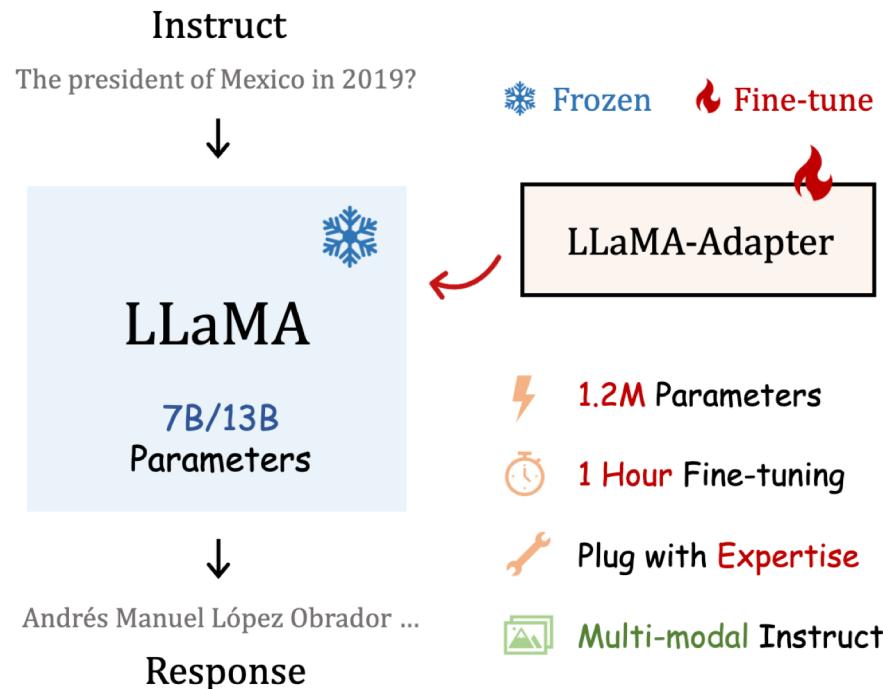
- Lightweight finetuning improves OOD results

Dataset	Domain	Model	Prompt	Δ
SQuAD	Wiki	94.9 ± 0.2	94.8 ± 0.1	-0.1
TextbookQA	Book	54.3 ± 3.7	66.8 ± 2.9	+12.5
BioASQ	Bio	77.9 ± 0.4	79.1 ± 0.3	+1.2
RACE	Exam	59.8 ± 0.6	60.7 ± 0.5	+0.9
RE	Wiki	88.4 ± 0.1	88.8 ± 0.2	+0.4
DuoRC	Movie	68.9 ± 0.7	67.7 ± 1.1	-1.2
DROP	Wiki	68.9 ± 1.7	67.1 ± 1.9	-1.8



Lightweight Finetuning

- LLaMa-Adaptor: Efficient Finetuning of Language Models with Zero-Init Attention





Prompting

- Zero-Shot

Text: i'll bet the video game is a lot more fun than the film.

copy

Sentiment:



Prompting

■ Few-Shot

Text: (lawrence bounces) all over the stage, dancing, running, sweating, mopping his face and g
Sentiment: positive

Text: despite all evidence to the contrary, this clunker has somehow managed to pose as an actu
Sentiment: negative

Text: for the first time in years, de niro digs deep emotionally, perhaps because he's been sti
Sentiment: positive

Text: i'll bet the video game is a lot more fun than the film.
Sentiment:



Prompting

- Calibrate Before Use: Improving Few-Shot Performance of Language Models (Zhao et al., 2021)

Text: (lawrence bounces) all over the stage, dancing, running, sweating, mopping his face and g
Sentiment: positive

Text: despite all evidence to the contrary, this clunker has somehow managed to pose as an actu
Sentiment: negative

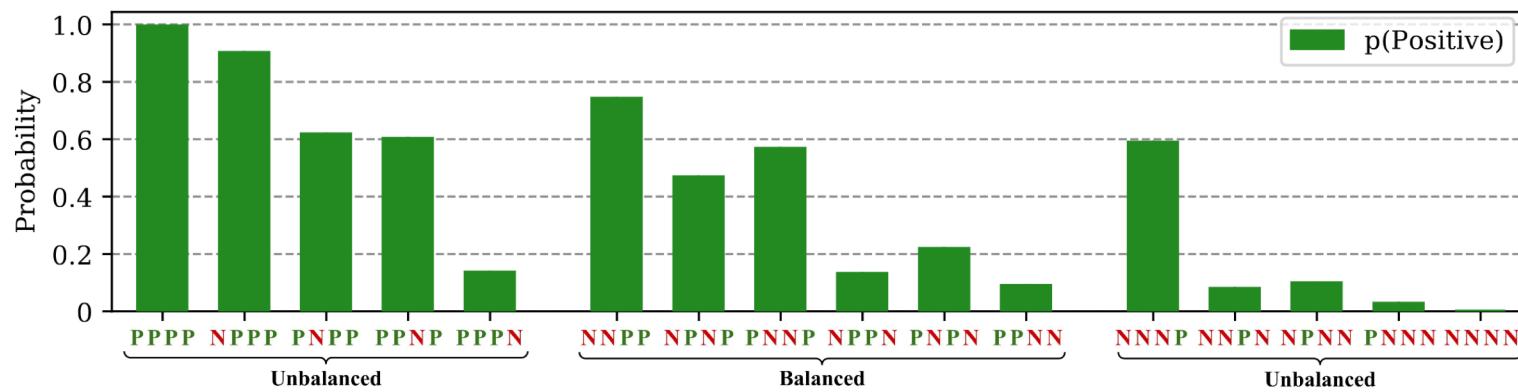
Text: for the first time in years, de niro digs deep emotionally, perhaps because he's been sti
Sentiment: positive

Text: i'll bet the video game is a lot more fun than the film.
Sentiment:



Prompting

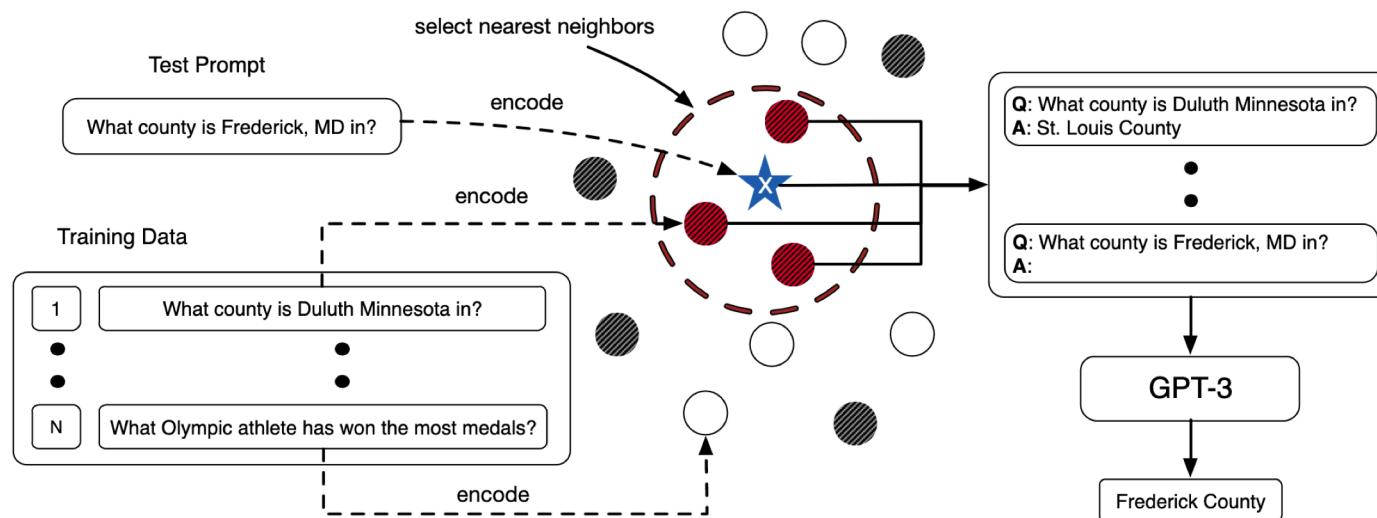
- Calibrate Before Use: Improving Few-Shot Performance of Language Models (Zhao et al., 2021)
- Majority label bias
- Recency
- Common token





Example Selection

- K-nearest neighbor clustering
- What Makes Good In-Context Examples for GPT-3? (Liu et al., 2021)





Example Selection

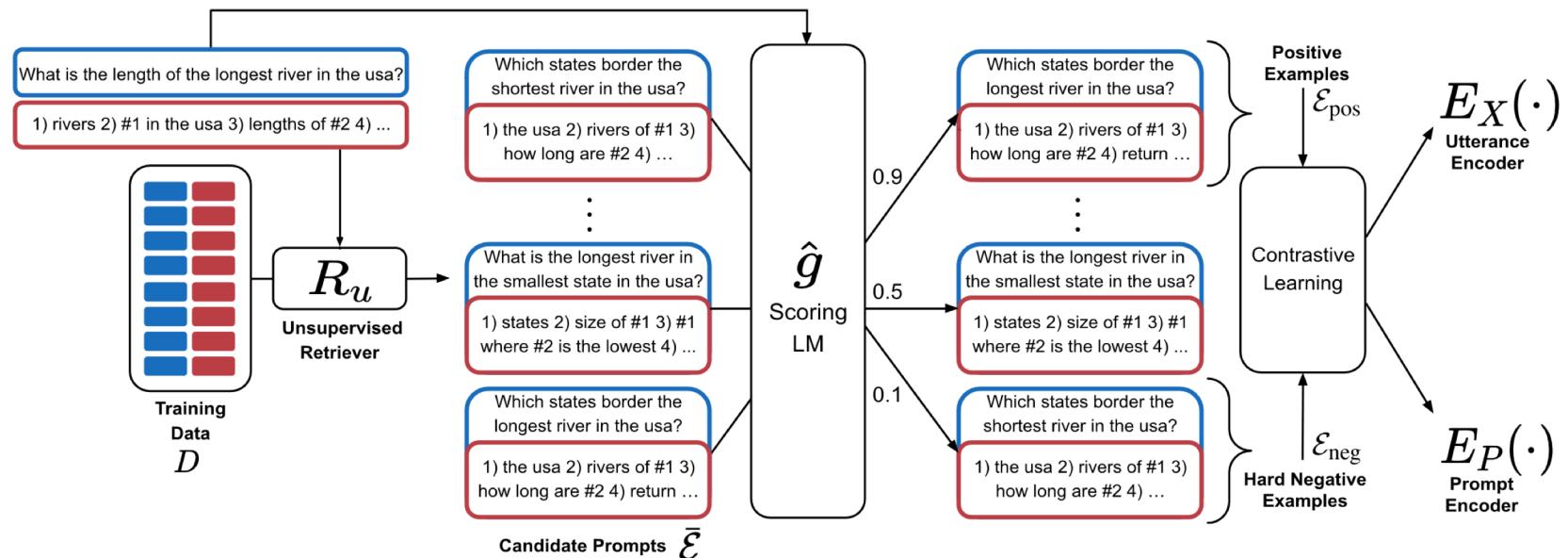
- Diversity-based selection
- Selective Annotation Makes Language Modeling Better Few-Shot Learners (Su et al., 2022)

$$\text{score}(u) = \sum_{v \in \{v | (v, u) \in E, v \in \mathcal{U}\}} s(v), \quad \text{where } s(v) = \rho^{-|\{\ell \in \mathcal{L} | (v, \ell) \in E\}|}, \quad \rho > 1$$



Example Selection

- Learning To Retrieve Prompts for In-Context Learning (Rubin et al., 2022)





Chain-of-Thoughts

Standard Prompting

Model 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?

Model Output

A: The answer is 27. X

Chain-of-Thought Prompting

Model 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.

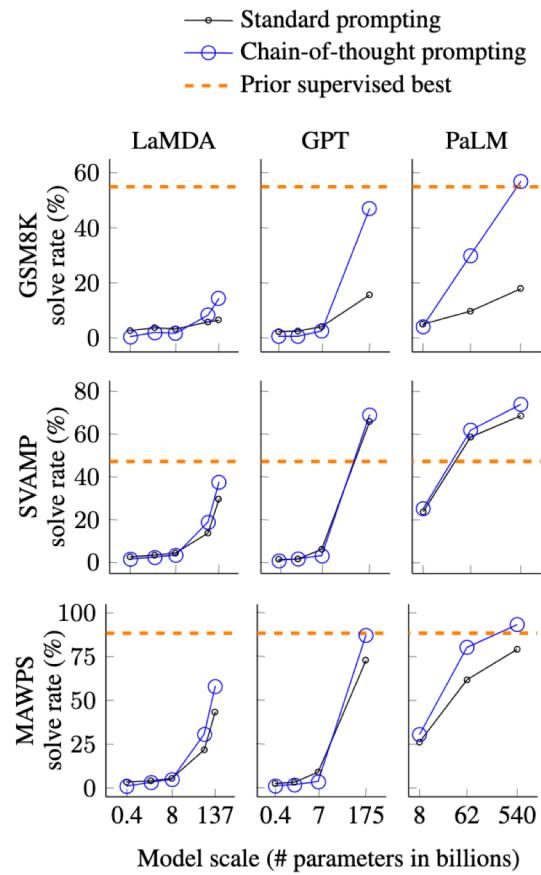
Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

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. ✓

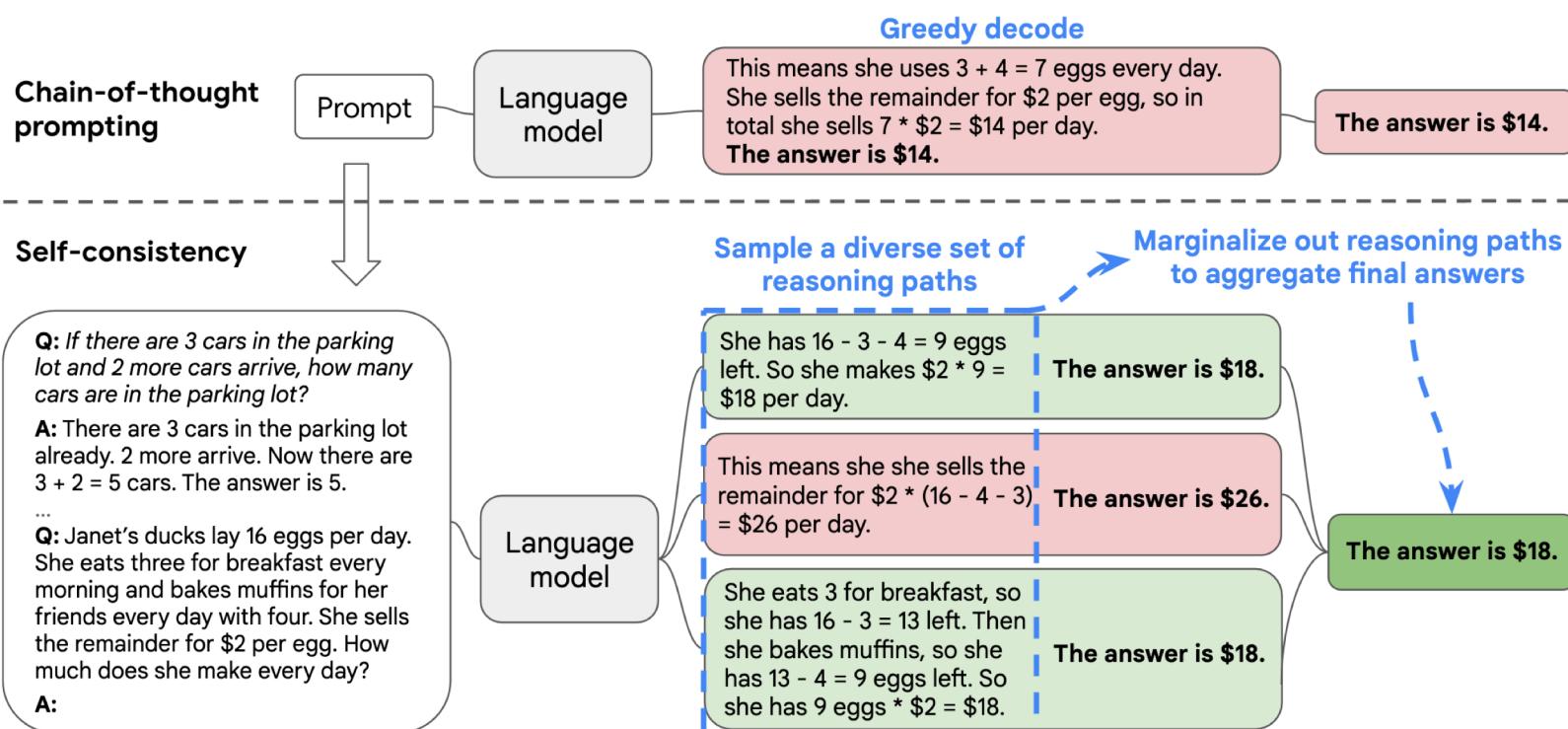


Chain-of-Thoughts



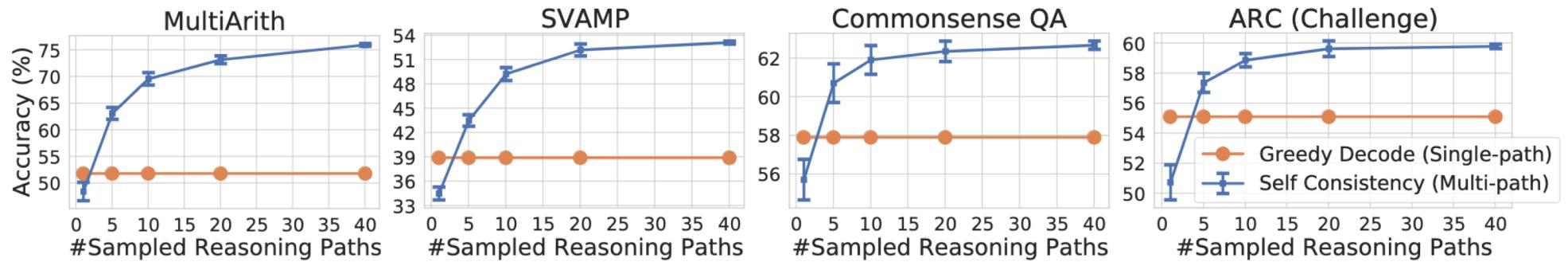


Self-Consistency



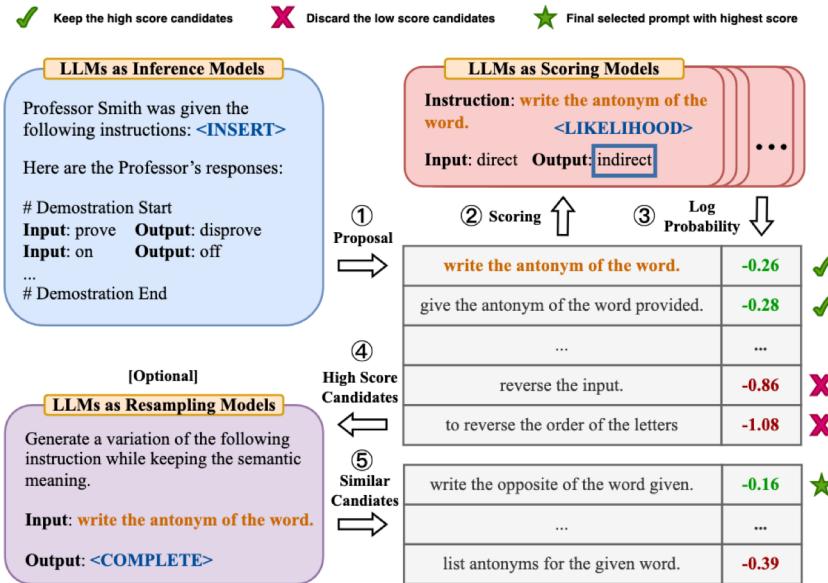


Self-Consistency





Automatic Prompting



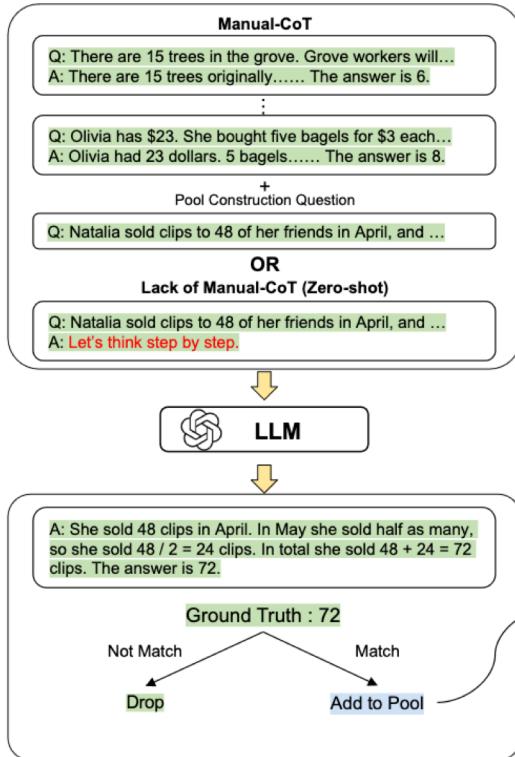
(a) Automatic Prompt Engineer (APE) workflow

- AutoPrompt; Shin et al., 2020
- Automatic Prompt Engineer; Zhou et al., 2022



Automatic Chain-of-thoughts

(1) Augment



(2) Select

