Robustness, Interpretability & Explainability

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Overview

- Motivation
- Definition: Robustness, Interpretability & Explainability
- Background and Related Work
- Paper: Language Models (Mostly) Know What They Know
- Paper: Complementary Explanations for Effective In-Context Learning
- Paper: Towards Monosemanticity: Decomposing Language Models With Dictionary Learning
- Paper: Faithful Reasoning Using Large Language Models
- Paper: PromptBench: Towards Evaluating the Robustness of Large Language Models on Adversarial Prompts

Why Robustness, Explainability and Interpretability?

Motivation

- Why success? Why fail? What do they learn?

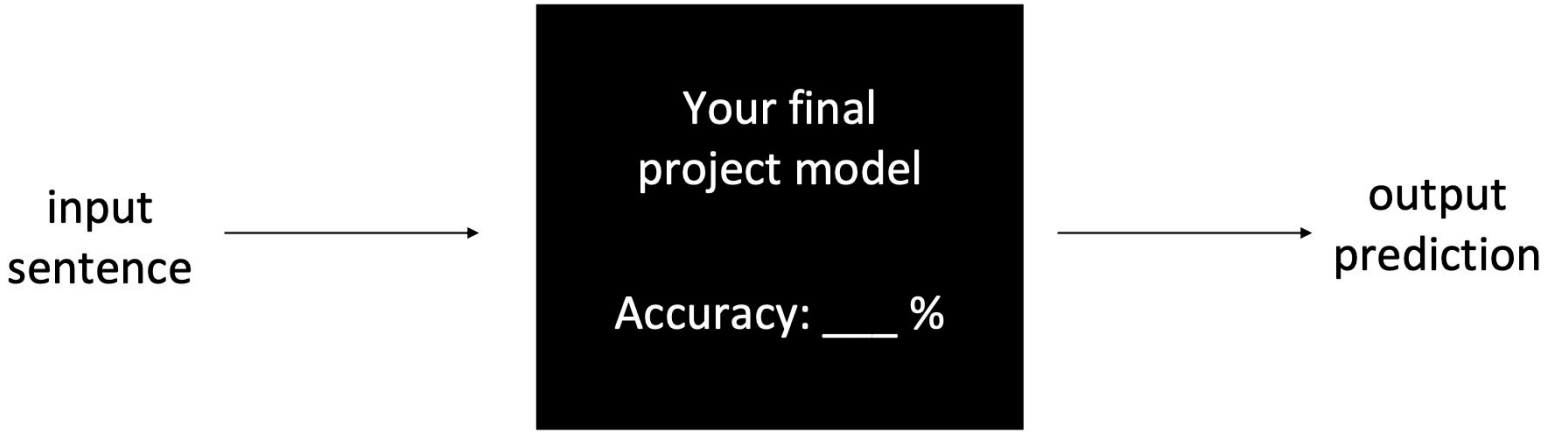
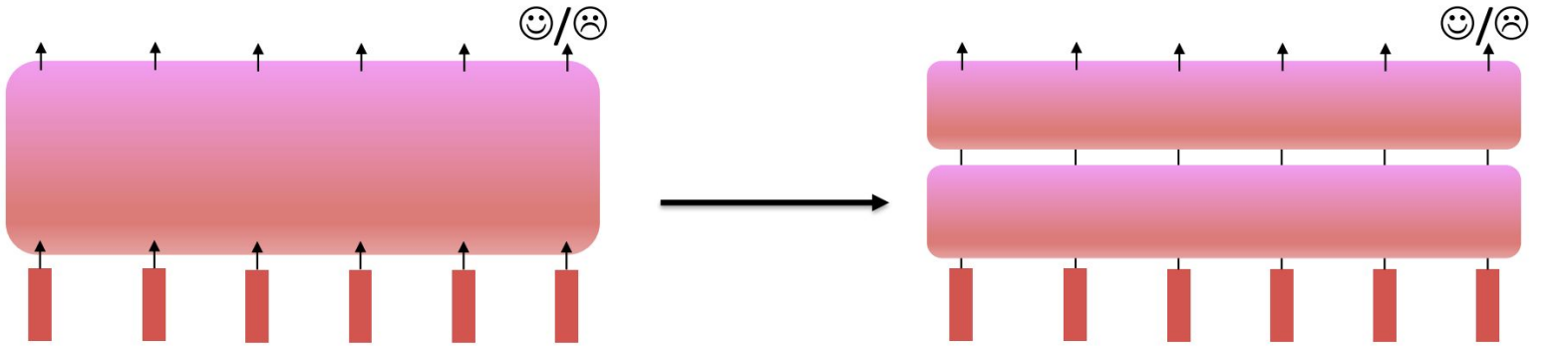


Fig 1. *A black box*

Motivation (Cont.)

- Understanding how far we can get with incremental improvements on current methods is crucial to the eventual development of major improvements



Today's models: use recipes that work, but aren't perfect

Tomorrow's models: take what works and find what needs changing

Motivation (Cont.)

- What did the model use in its decision?
- What biases did it learn and possibly worsen?

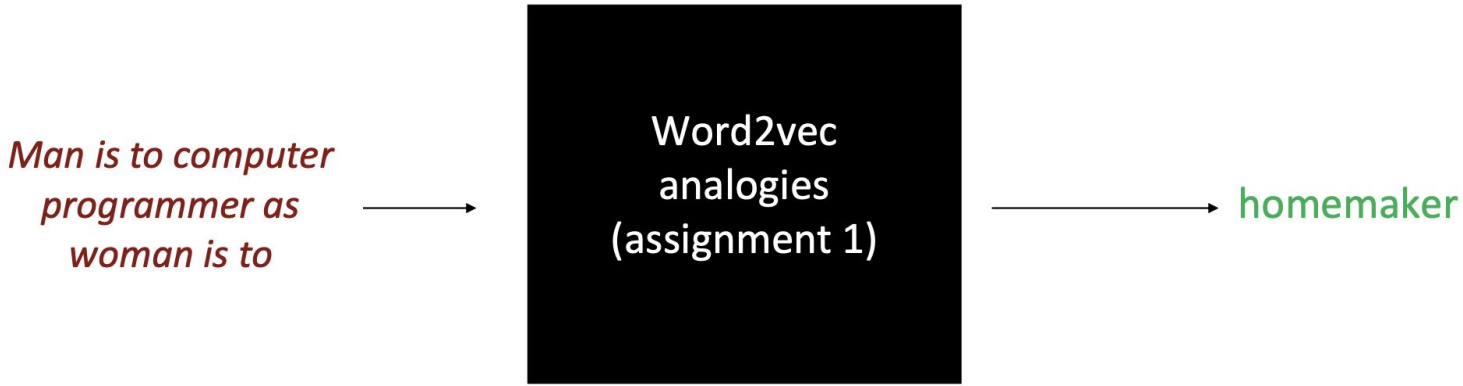
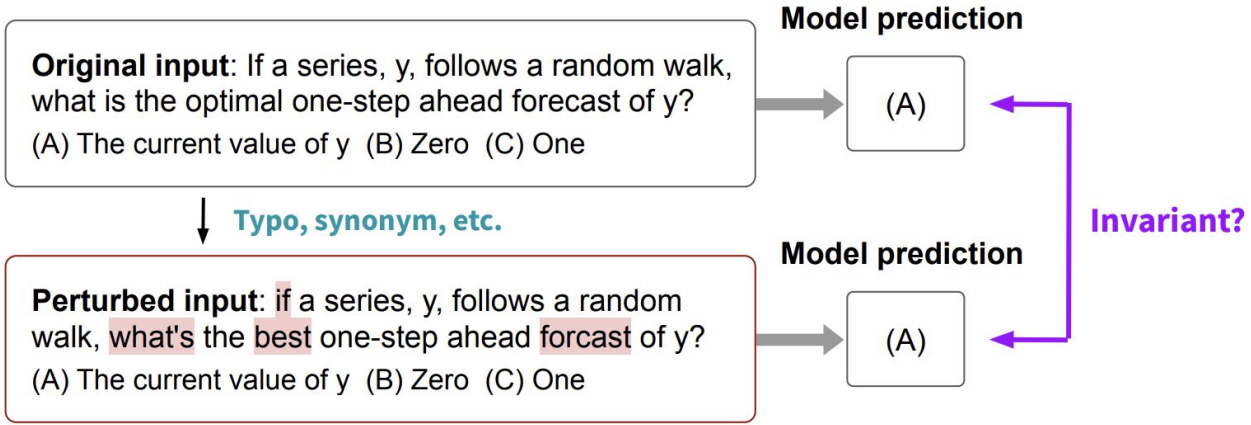


Fig 1. *A black box*

Robustness of LLM

- The degree to which an LLM maintains consistency and credibility in its output results when exposed to various input conditions, such as differences in text quality, domain specificity, or multilingual settings.
- **Invariance** & **Equivariance**

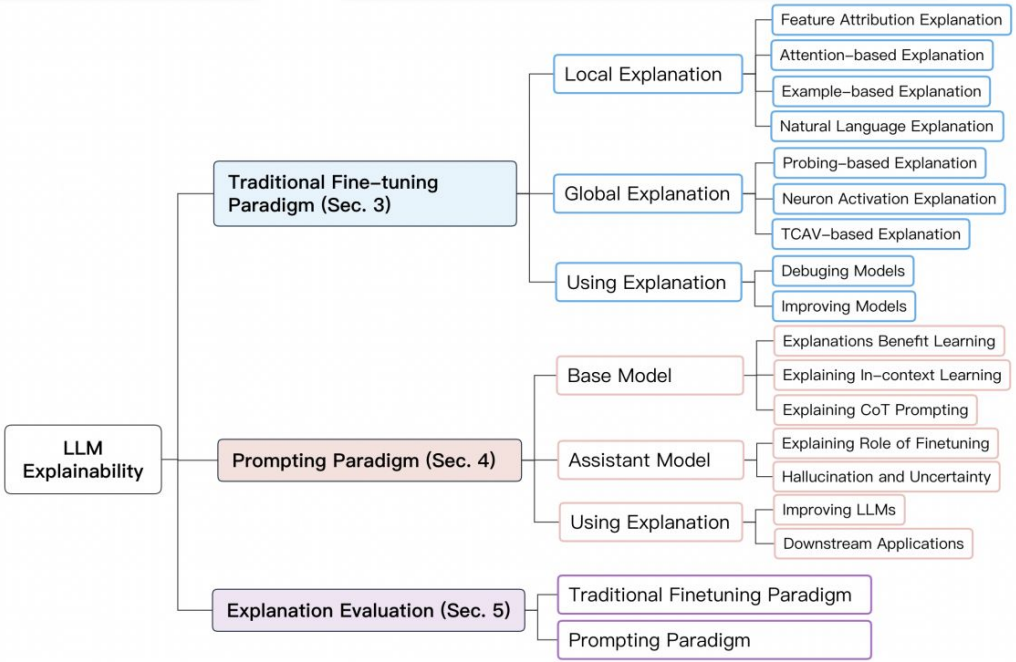


Interpretability of LLM

- Interpretability refers to the understandability of an LLM's internal workings, structures, parameters, and mechanisms by humans. This encompasses comprehending the model's architecture, weights, attention mechanisms, and more.

Explainability of LLM

- Explainability refers to the ability to explain or present the behavior of models in human-understandable terms

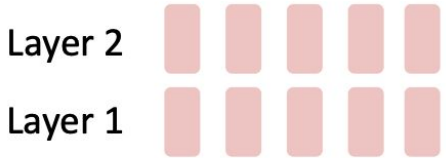


Current Practical Analysis Methods

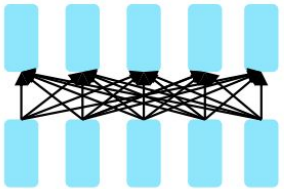
1. Your neural model as a probability distribution and decision function

$$p_{\text{model}}(y|x)$$

2. Your neural model as a sequence of vector representations in depth and time



3. Parameter weights, specific mechanisms like attention, dropout, +++



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Related Work: Out-of-domain evaluation sets

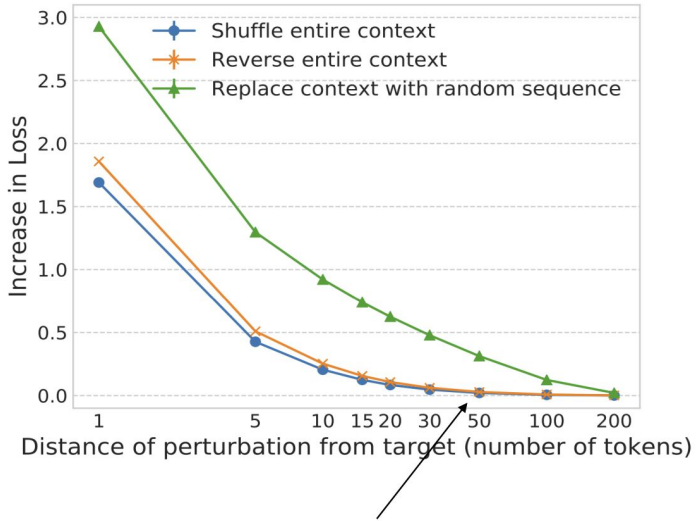
- Testing for linguistic knowledge
- Testing for task heuristics **[McCoy et al., 2019]**
  - For NLI (Natural Language Inference), if we use some examples containing harder heuristics, some good models even like BERT would fail, even though they were trained on MNLI dataset
    - NN model tend to user more superficial heuristics.

Related Work: Fitting the Dataset vs Learning the Task

- What has a language model learned from pretraining?
  - LAMA Probe: Creating LAMA dataset
    - To evaluate how much factual and commonsense knowledge is stored in the LM

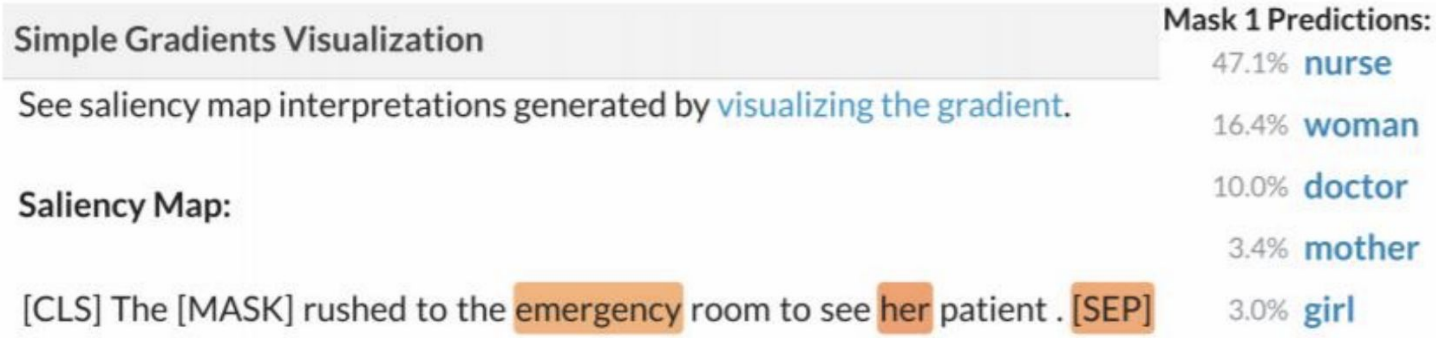
Related Work: Input Influence

- We motivated LSTM language models through their theoretical ability to use long distance context to make predictions. But how long really is the long short-term memory?
  - Shuffle or remove all contexts farther than k words away for multiple values of k and see at which k the model's predictions start to get worse [Khandelwal et al., 2018]



Related Work: Input Influence (Cont.)

- What in the input led to this output?
  - For a single example, what parts of the input led to the observed prediction?
    - Saliency maps: a score for each input word indicating its importance to the model's prediction



Related Work: Analyzing Representations

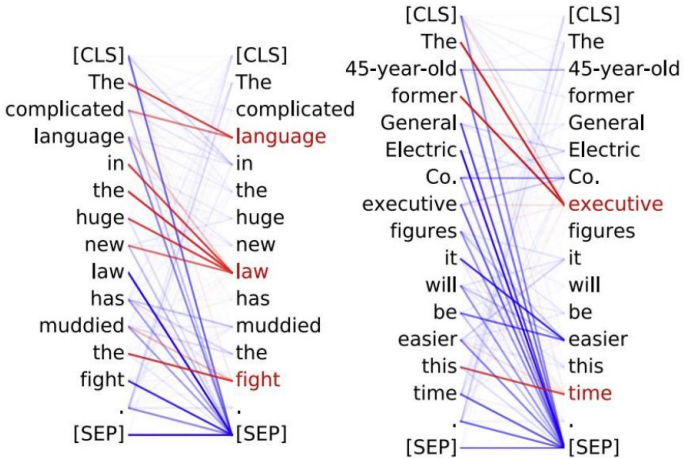
- Analysis of “interpretable” architecture components [Clark et al., 2018]
  - Idea: Some modeling components lend themselves to inspection.
    - Some heads are correlated with linguistic properties

Approximate interpretation + quantitative analysis

Model behavior

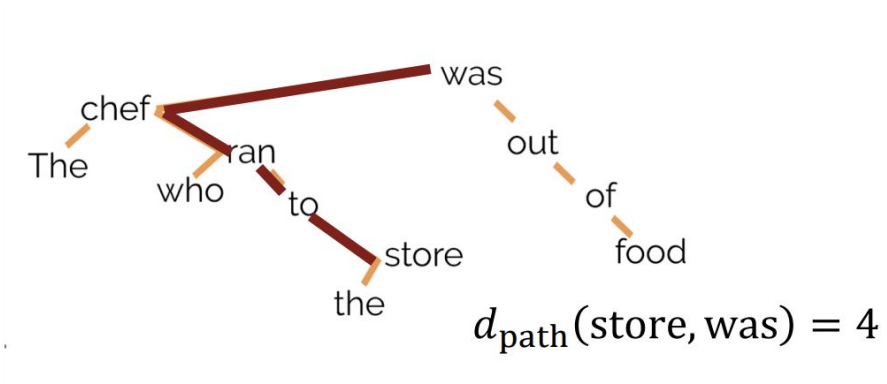
Head 8-11

- **Noun modifiers** (e.g., determiners) attend to their noun
- 94.3% accuracy at the **det** relation



Related Work: Analyzing Representations (Cont.)

- Do probing: freeze parameters and make additional functions to probe
  - Hewitt and Manning 2019 show that BERT models make dependency parse tree structure easily accessible.
    - The structural probe was used to design and test hypotheses as to **how LMs incrementally parse sentences**



$d_{\text{path}}(w_1, w_2)$

Related Work: Ablation Study

- Would it be better for this part of my model to be deeper? Or can I get away with making it shallower?
- Do we need all these attention heads? [Michel et al., 2019]

- What's the right layer order for a Transformer? [Press et al., 2019]
  - Self-attention → Feed-forward → Self-attention → Feed-forward →…

What’s next?

- LLM is not fully investigated, while it is super powerful and super complex!

Language Models (Mostly) Know What They Know

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Motivation

- We would eventually like to train AI systems that are **honest**, which requires that these systems accurately and faithfully evaluate their level of **confidence in their own knowledge and reasoning**.
- How to evaluate **Honest**?

Evaluation Methods

- **Calibration**: do the **probabilistic predictions** from language models match up with **frequencies of occurrence**?
- Calibration ≠ Accuracy
- For example: True or False Questions
    - LLM have 100% accuracy but all the predicted probability values are very average: P(True) = 0.51, P(False) = 0.51

Evaluation (Cont.)

- **Self Evaluation**: Good calibration opens up the possibility for using models to evaluate the accuracy of their own outputs
    - For example, given any open-ended query, we can sample an answer from the model and then have the model evaluate P(True), the probability that its answer is correct.
- We may expect self-evaluation to be challenging, because the model may be overconfident that its own samples are correct

Models & Evaluation Tasks

- **Evaluation Tasks:**
  - Multiple Choice Evaluation
  - Open-ended Generation: QA, Arithmetic problems, web-scraped Python function synthesis problems…
- **Models:**
  - A series of language models with 800M, 3B, 12B, 52B parameters [Bai et al., 2022]

Task 1: Diverse Multiple Questions

- **Task Format**:

```
Question: Who was the first president of the United States?
Choices:
 (A) Barack Obama
 (B) George Washington
 (C) Michael Jackson
Answer:
```

Task 1: Diverse Multiple Questions

- **Task Format**:

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Question: Who was the first president of the United States?
Choices:
 (A) Barack Obama
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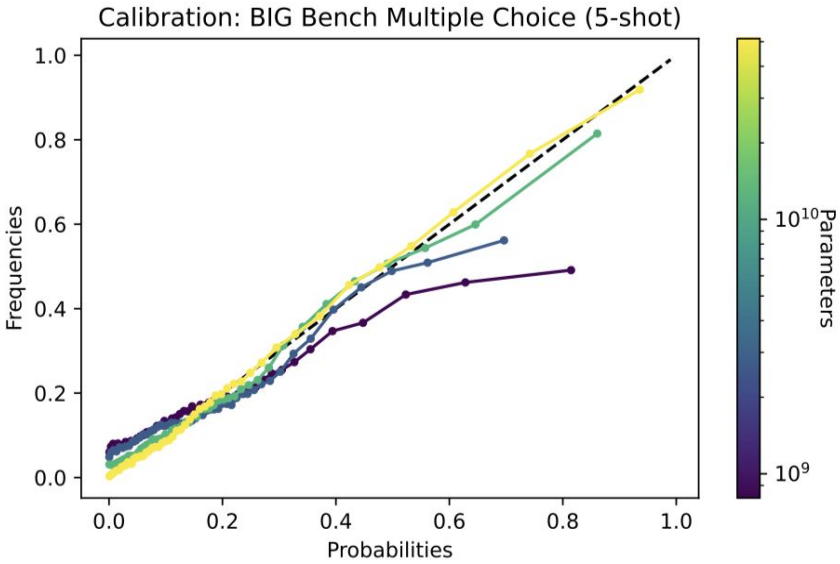
 (C) Michael Jackson
Answer:
```

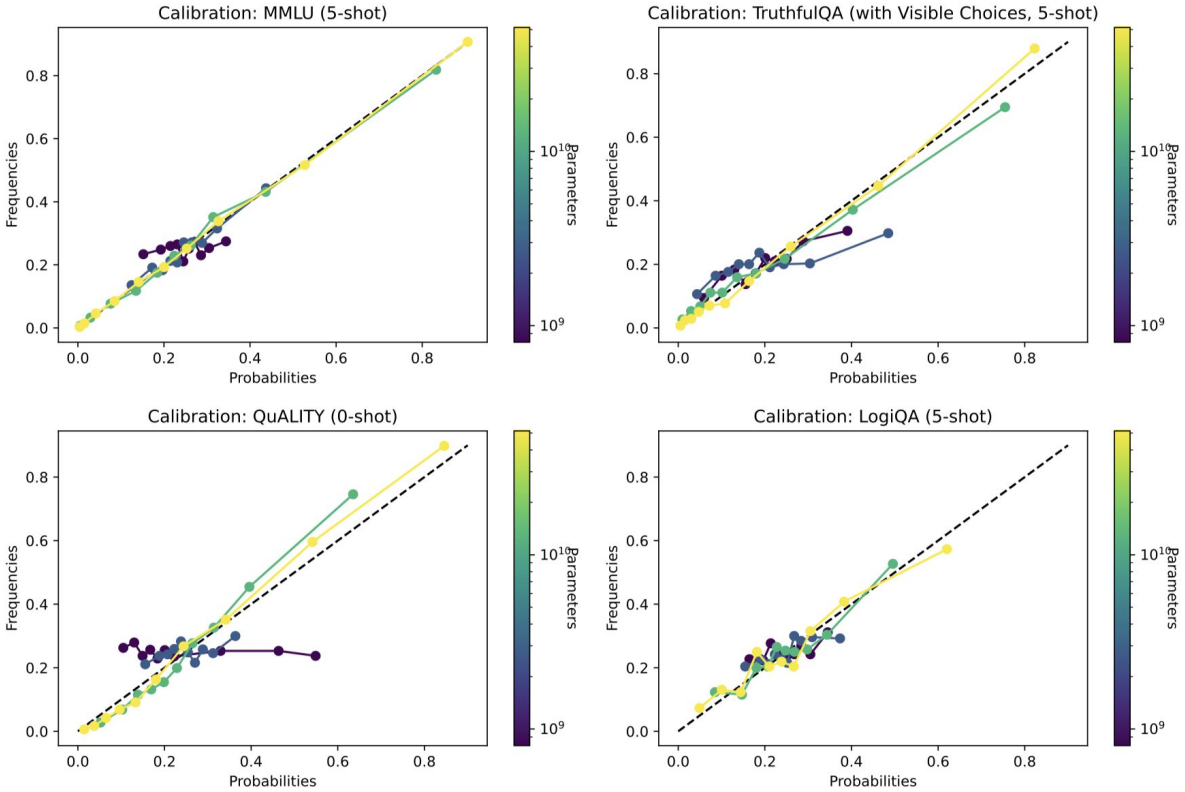
We identify the answers only by their labels, as e.g. ‘ (B)’

Task 1: Calibration & Model Size

- Dashed Line: Perfect calibration
- **Conclusion**: Largest models tend to produce a well calibrated probability distribution among the available options.

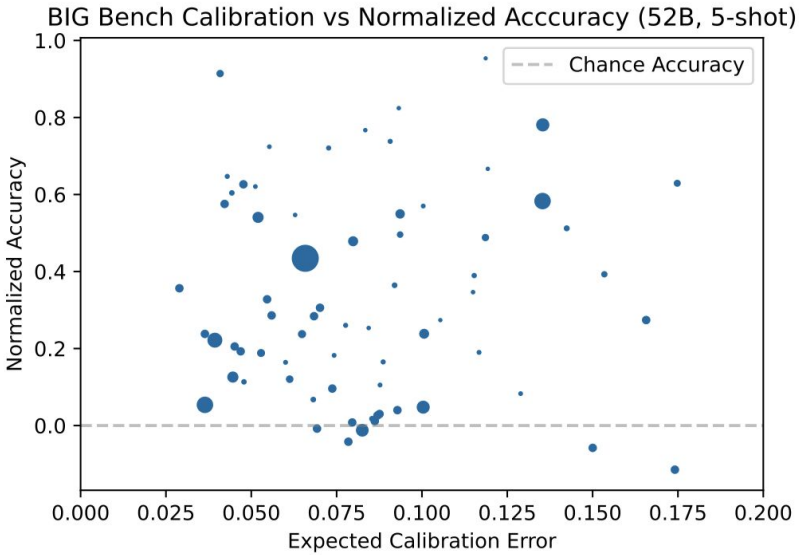


Task 1: Calibration & Model Size



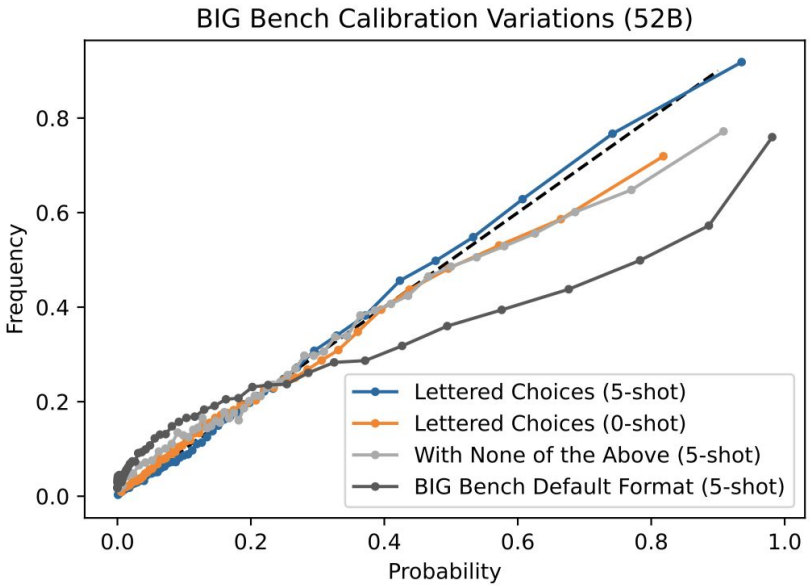
Task 1: Calibration & Accuracy

- The number of problems in each task is represented by the marker sizes
- **Conclusion**: Do not find any noticeable correlation between accuracy and calibration.



Task 1: Calibration & Shots

- **Conclusion**: Calibration improves as we pass from 0-shot to 5-shot evaluation



Task 1: Format is important!

- Good Insights:
  - It is crucial that the model gets to see the answer choices explicitly before choosing amongst them, due to **ambiguities and degeneracies** among possible paraphrases and specializations of any given answer option.
  - e.g. "Washington" vs "George Washington, the first US president"

Task 2: From Calibration to knowing what you know

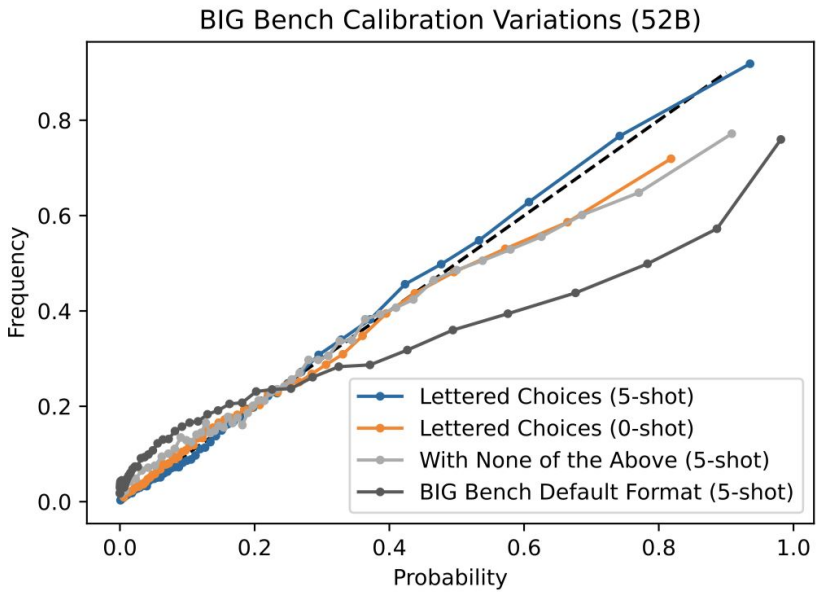
- If language models can answer multiple choice questions in a calibrated way, then one might hope that they can apply this ability to evaluate their own outputs.
- Before self-evaluation, firstly begin to explore this idea by reformulating existing tasks

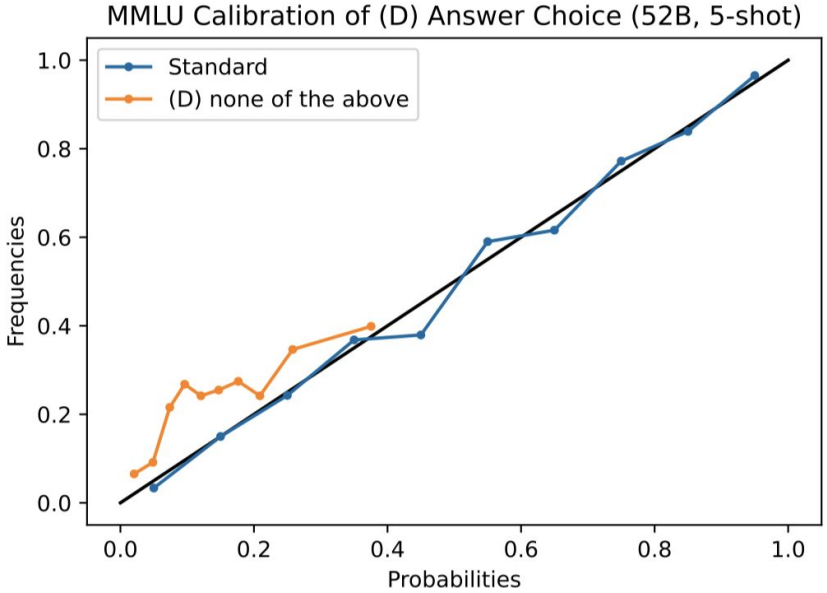
Task 2.1: Motivation & Format

- Motivation: Whether the model actually knows whether each of the answer options is correct, when **judged independently**.
  - For previous format, LLM can simply pick up the seen answer.
- **Task Format**: Replace an option with “none of the above”

```
Question: Who was the first president of the United States?
Choices:
 (A) Barack Obama
 (B) George Washington
 (C) none of the above
Answer:
```

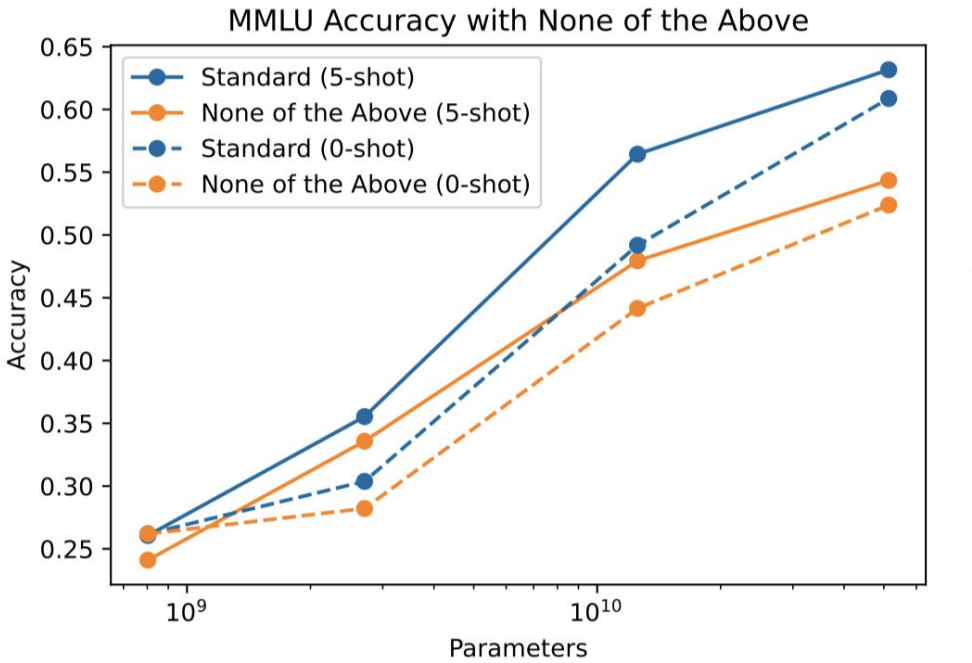
Task 2.1: For calibration





- **Conclusion**: “None of the above” hurts calibration

Task 2.1: For accuracy



- **Conclusion**: “None of the above” hurts accuracyl

Task 2.1: More Conclusions

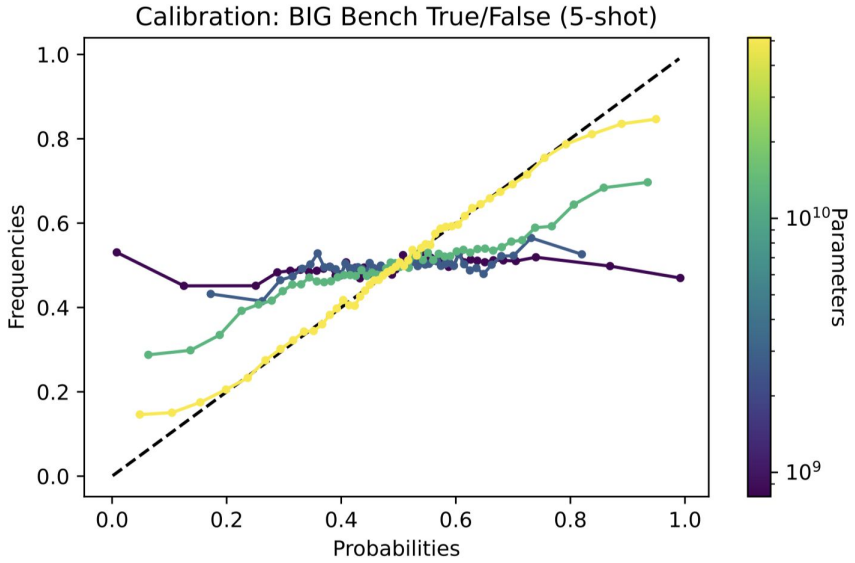
- It seems that even the 52B model is biased against using the “none of the above” option and failed to use it with appropriate frequency.
- This is particularly surprising for 5-shot evaluations; we also tried evaluating 20-shot and this also did not improve performance.
- “None of the above” hurts a lot!

Task 2.2: Motivation & Task Format

- We saw in section 3.1 that language models seem to be confused by a “none of the above” option. Here we take a different approach, and simply ask models if a given answer is true or false
- **Task Format**: Pick up an option and make it to a True or false question

```
Question: Who was the first president of the United States?
Proposed Answer: George Washington
Is the proposed answer:
 (A) True
 (B) False
The proposed answer is:
```

Task 2.2: Motivation & Task FormatRLHF Policy Miscalibration Can Be Remediated with a Temperature Tuning

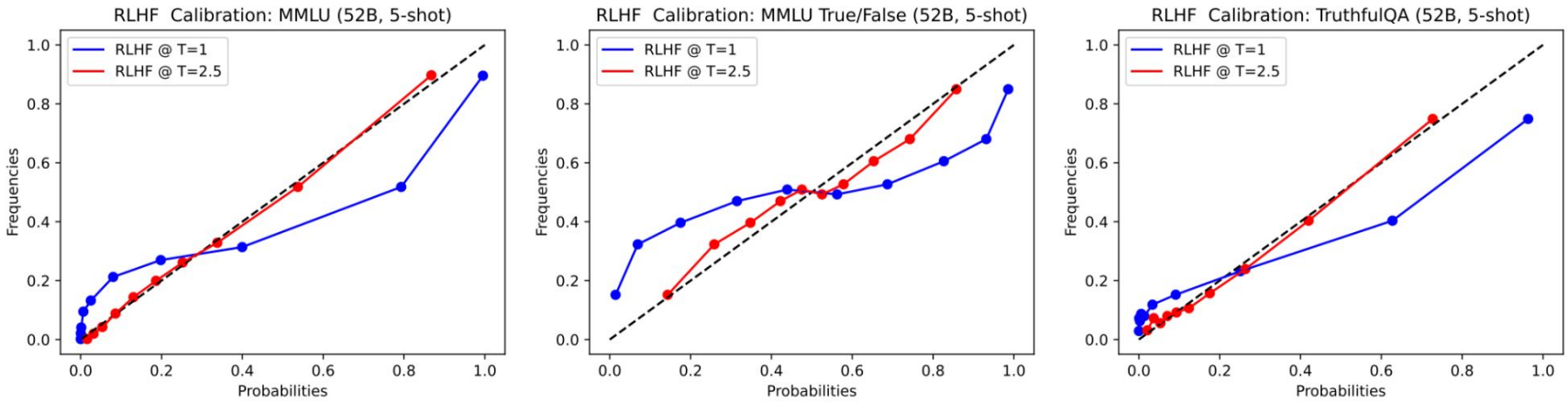


- **Conclusion**: The 52B model is very well-calibrated except near the tails, where it is overconfident.

Task 2.3: RLHF Policy Miscalibration Can Be Remediated with a Temperature Tuning

- **Motivation**: A quick experiment to look at RLHF policy
- **Experiments**: Use RLHF for finetuning, then evaluate calibration

Task 2.3: Experimental Results



- **Conclusion**: These policies naively appear very miscalibrated. However, a simple temperature adjustment largely fixes calibration issues with several independent evaluation tasks

Task 2.3: Results Analysis

- **Miscalibration**: Not surprising, since RL finetuning tends to collapse language model predictions towards behaviors that receive the most reward.
- **Temperature Adjustment**: This matches what was found for gender bias evaluations in [Bai et al., 2022], where RLHF policies had a bias score very similar to a basic language model evaluated at lower temperature.
    - Temperature: Randomness when generating the output

Task 3: Self-Evaluation - Ask the AI: Is your proposed answer True or False?

- **Motivation:** Previously, we saw that large language models are well-calibrated on True/False questions. Our primary motivation for studying this issue was to ask language models about their own outputs

Task 3.1: Basic Self-Evaluation

- **Task Format:**

```
Question: Who was the first president of the United States?
Answer:
```

and sample a response from the model. Then we ask the model about its own sample:

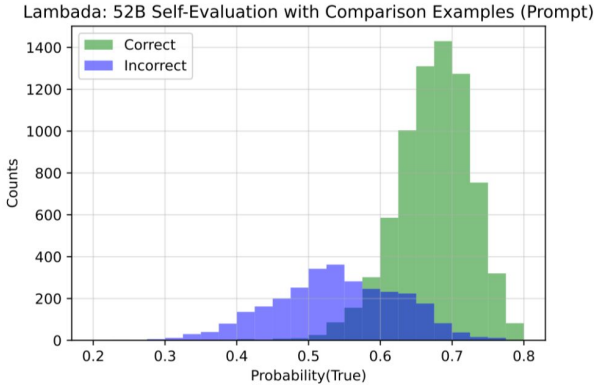
```
Question: Who was the first president of the United States?
Proposed Answer: George Washington was the first president.

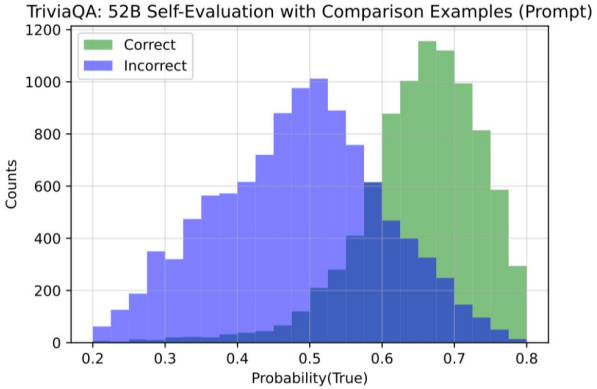
Is the proposed answer:
 (A) True
 (B) False
The proposed answer is:
```

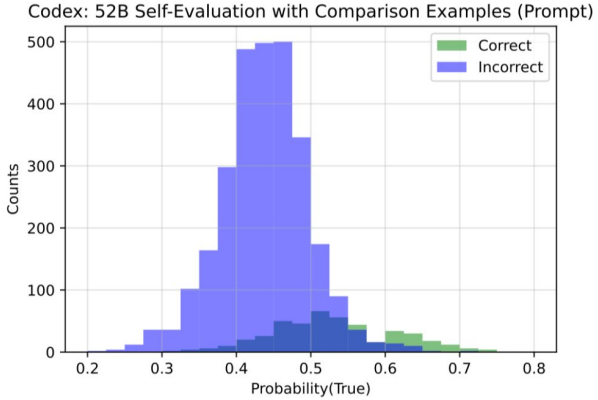
Task 3.1: Basic Self-Evaluation

- **Compared to previous True or False evaluation:** More difficult,here the model is forced to evaluate its own samples. There the model was presented with human-written possibilities. What is more, **options presented to the model by a third party may be easier to categorize**.

Task 3.1: Experiment Result







Task 3.1: Results Analysis

- **Not calibrated**: P(True) provides very noticeable separation between correct and incorrect samples with the 52B model, but the probability itself is not calibrated. In particular, **almost all samples from arithmetic questions have P(True) > 0.5**

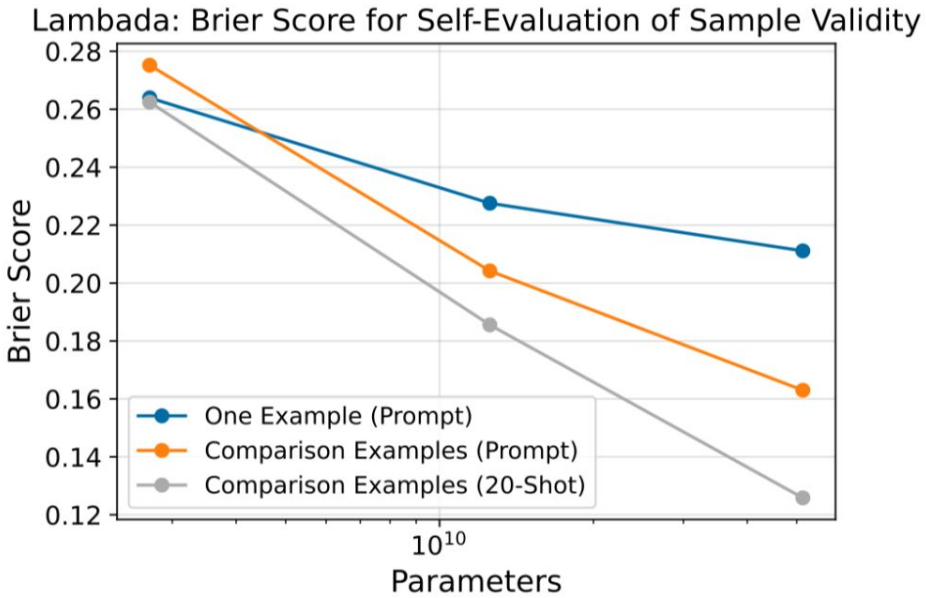
Task 3.2: Showing Many T = 1 Samples Improves Self-Evaluation

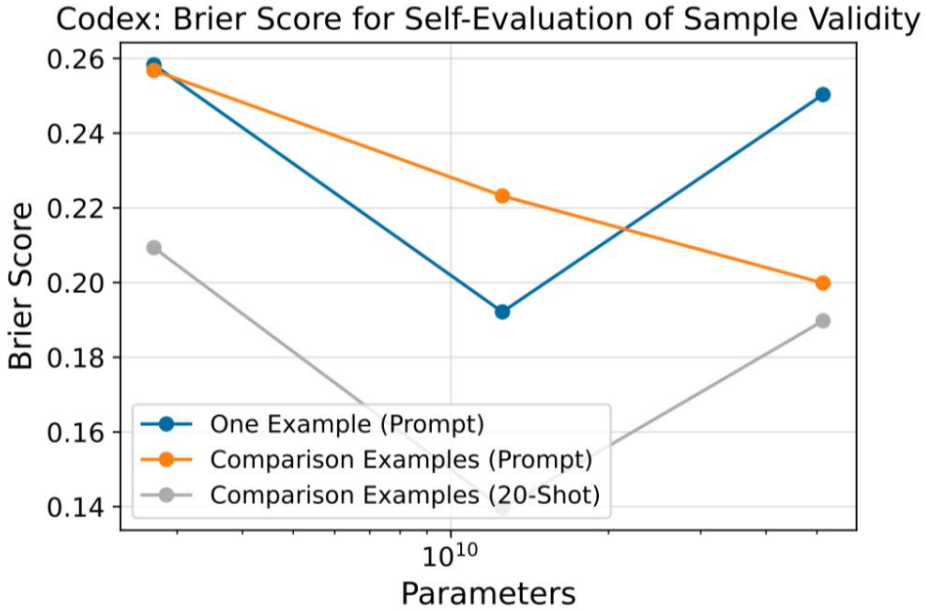
- **How to Improve Calibration for Self-Evaluation?**
- We can improve performance further by showing the model other T = 1 samples, for comparison:

```
Question: Who was the third president of the United States?
Here are some brainstormed ideas: James Monroe
Thomas Jefferson
John Adams
Thomas Jefferson
George Washington
Possible Answer: James Monroe
Is the possible answer:
 (A) True
 (B) False
The possible answer is:
```

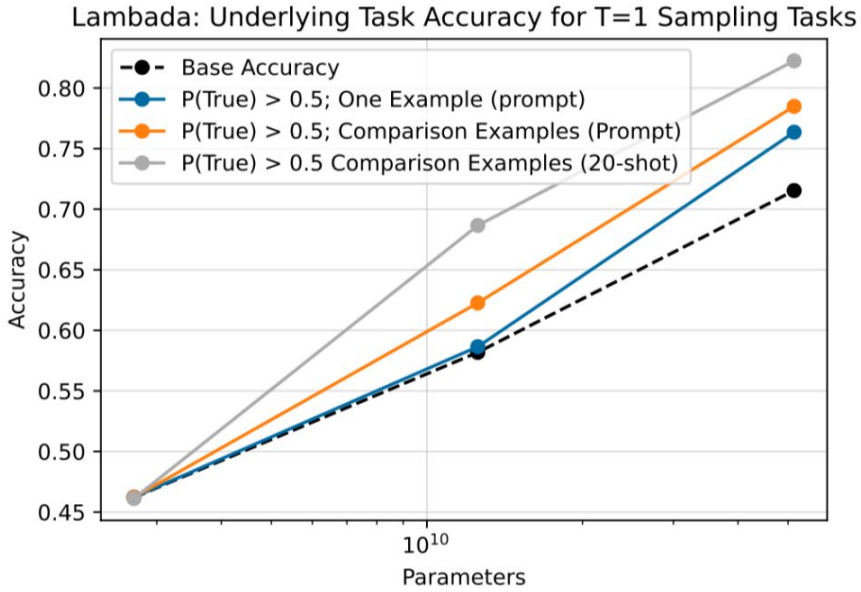
Task 3.2: Experiment Results

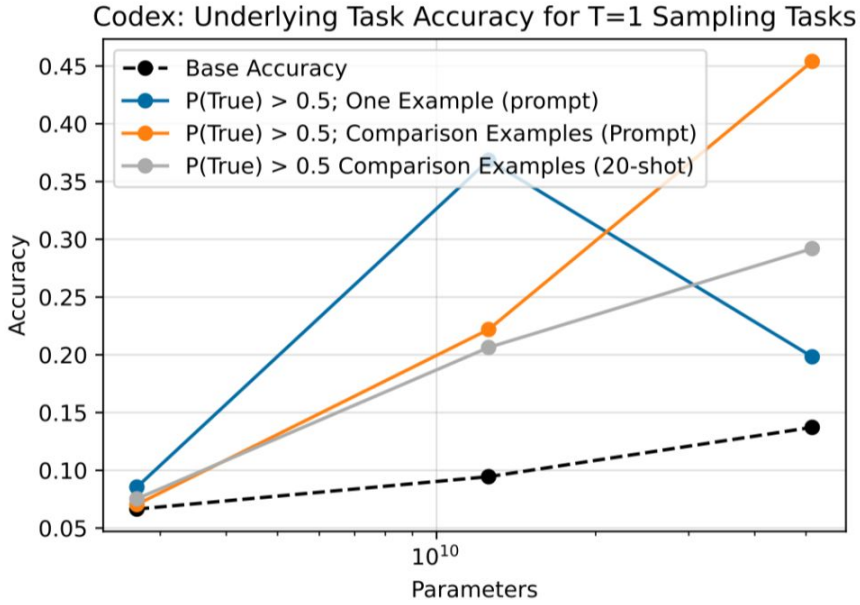
- **Brier Score**: Brier scores combine the discriminative power of self-evaluation with calibration





Task 3.2: Experiment Results (Cont.)





Task 3.2: Analysis

- **Conclusion**: Overall, if given a few examples from a given distribution, models can generate samples and then self-evaluate them to productively differentiate correct and incorrect samples, with reasonably calibrated confidence.

Task 4: Training Models to Predict Whether They Can Answer Questions Correctly

- **Motivation**: Can LLM be taught to know whether they can answer this question?
- **Experiment**:
  - **Value Head**: We train P(IK) as the logit from an additional value ‘head’ added to the model (independent of the logits for language modeling). An advantage of this approach is that we can easily probe P(IK) at general token positions.

Task 4: Training Process

- **Sample:** For each question, we generated 30 answer samples at T = 1. For a given question Q, if 20 of the model's sampled answers were correct, and 10 were incorrect, our training set contained 20 copies of the (Q, IK) datapoint and 10 copies of the (Q, IDK) datapoint. This was a convenience to allow us to easily approximate a soft label for the ground-truth P(IK) by using many hard labels.
- **Process**: We trained with a cross-entropy loss on these labels.

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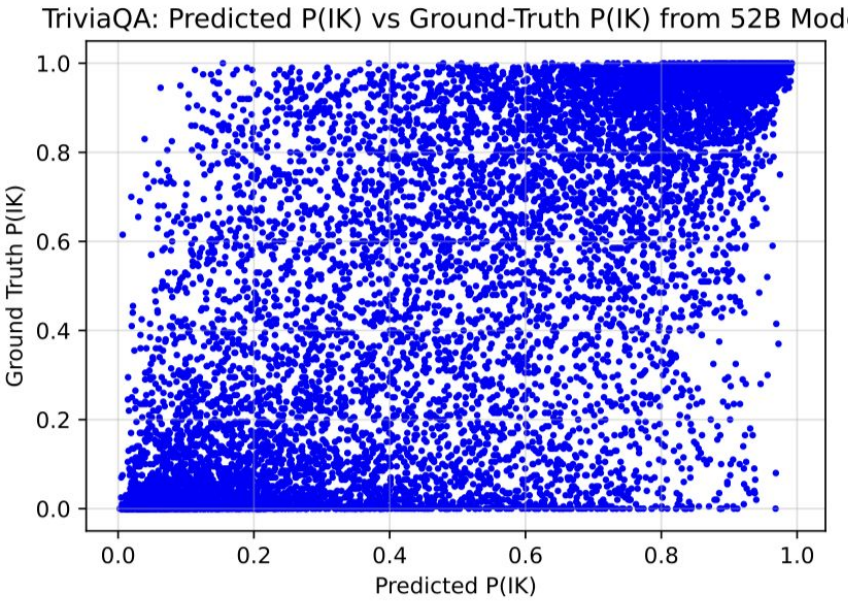
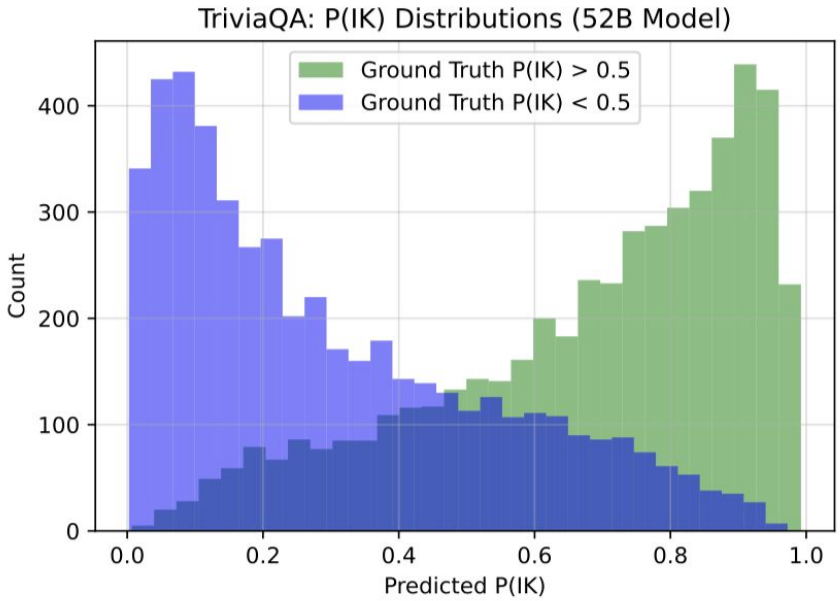
- **Process**: Finetune the entire model with the value head. We trained with a cross-entropy loss on these labels.

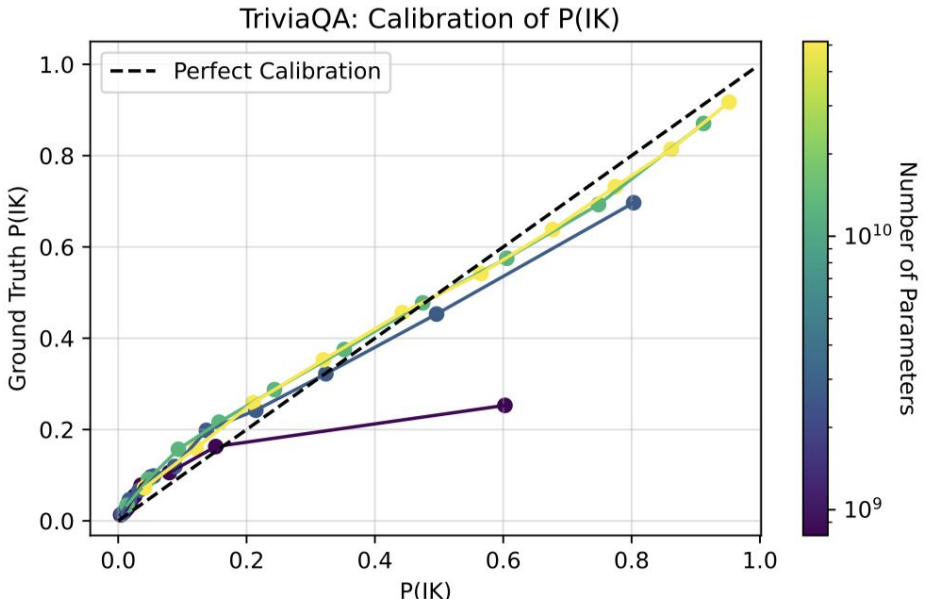
Task 4: Experiment Results





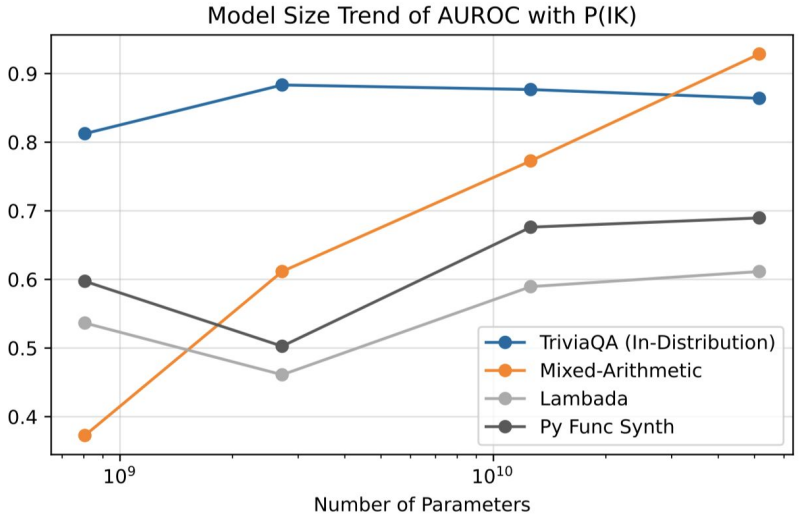
- **Conclusion**: P(IK) is very calibrated on TriviaQA

Task 4: Experiment Results (Cont.)



- **Conclusion**: Still related to model size!

Task 4: Out of distribution



- **Process**: Train on TrviaQA, and evaluated on other datasets
- **Conclusion**: There is a general trend where the AUROC of P(IK) increases with model size, and calibration gets better with model size.

Task 4: Out of distribution (Cont.)

	Training on TriviaQA (AUROC / Brier Score)	Training on All Tasks Except GSM8K (AUROC / Brier Score)
TriviaQA	0.864 / 0.151	0.873 / 0.145
Mixed-Arithmetic	0.928 / 0.194	0.987 / 0.042
LAMBADA	0.606 / 0.431	0.853 / 0.108
Python Func Synth.	0.687 / 0.164	0.881 / 0.109
GSM8K [6]	0.624 / 0.200	0.752 / 0.121

- **Conclusion**: Training on all 4 tasks resolves this issue

Task 4: Overall View

	Training on TriviaQA (AUROC / Brier Score)	Training on All Tasks Except GSM8K (AUROC / Brier Score)
TriviaQA	0.864 / 0.151	0.873 / 0.145
Mixed-Arithmetic	0.928 / 0.194	0.987 / 0.042
LAMBADA	0.606 / 0.431	0.853 / 0.108
Python Func Synth.	0.687 / 0.164	0.881 / 0.109
GSM8K [6]	0.624 / 0.200	0.752 / 0.121

- **Conclusion**: Training on specific P(IK) distributions helps performance, indicating that there is a significant generalization gap to fill.

Task 4: Some additional experiments (short introduction)

- **P(IK) Generalizes to Account for Source Materials**

If we consider a fairly obscure question like

```
What state's rodeo hall of fame was established in 2013?
```

then P(IK) appropriately predicts a low value, specifically 18% for a 52B model. However, if we prepend a Wikipedia article on the Idaho Rodeo Hall of Fame to the context:

```
Wikipedia: The Idaho Rodeo Hall of Fame was established as a 501 (c)(3) non-
    profit organization on May 6, 2013. Lonnie and Charmy LeaVell are the
    founders of the organization. The actual charitable nonprofit status was
    received from the IRS on February 19, 2014. The IRHF hosts a reunion and
    induction ceremony annually every October. The Idaho Hall of Fame preserves
    and promotes the Western lifestyle and its heritage. The hall exists to
    dedicate the men and women in rodeo who contribute to ranching and farming
    through their sport. It also extends its reach to continue these western
    ways to the youth in the communities to ensure that these traditions
    continue for many generations. In 2015, the hall was awarded the Historic
    Preservation Recognition Award by National Society of the Daughters of the
    American Revolution.

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Task 4: Some additional experiments (short introduction)

- **P(IK) Generalizes to Account for Hints Towards GSM8k Solutions**

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Task 4: Some additional experiments (short introduction)

- **P(IK) Generalizes to Account for Hints Towards GSM8k Solutions**

```
Question: Students in class 3B are collecting school points for behavior
    . If they get enough points in total, they can go on a trip. In the
    class, there are Adam, Martha, Betty, and Tom. Adam has collected 50
     points. Betty was better than Adam and collected 30% more. Marta
    managed to collect 3 times more points than Tom, who has 30 points
    less than Betty. How many points is the class missing to go on the
    trip if the minimum threshold is 400 points?

        Here is a hint: Betty has 30% more points than Adam, so it's 30/100 * 50
             = <<30/100*50=15>>15 points more.
        Betty's total is therefore 50 + 15 = <<50+15=65>>65 points.
        Tom has 30 points less than Betty, so he has 65 - 30 = <<65-30=35>>35
           points.
        Marta has 3 times more points than Tom, so she has 3 * 35 =
           <<3*35=105>>105 points.
        In total, all students collected 50 + 65 + 35 + 105 =
           <<50+65+35+105=255>>255 points.
        So the class is missing 400 - 255 = <<400-255=145>>145 points to go on
           the trip.

        Answer:
```

Task 4: Some additional experiments (short introduction)

- **Conclusion:** Besides model size and number of shots, the way we prompt also improves honesty

Summary

- **In most cases,** LLMs are well calibrated and can further do self-evaluation
- Calibration tends to improve with model size/capability and with additional few-shot examples
- Self-evaluation also improves with model size, which is non-trivial since we expect the quality of model samples to also be improving as scale up
- Encouraging!

Complementary Explanations for Effective In-Context Learning

Yunchao Zhang
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Motivation

- Large language models (LLMs) have exhibited remarkable capabilities in learning from explanations in prompts, but there has been limited understanding of exactly **how these explanations function or why they are effective**.
- This work aims to better understand the mechanisms by which explanations are used for in-context learning.

Catalogue

- Explore two factors
  - The computation trace (the way the solution is decomposed)
  - Natural Language (used to express the prompt)
- How to form maximally effective sets of explanations for solving a given test query

Recap: In Context Learning (ICL)

- Let q be the test query to solve. The standard ICL prompts a language model with a set of exemplar input-output pairs:

$$\hat{a} = \arg\max_{a} p_M(a \mid q, \{(q_1, a_1)...(q_m, a_m)\}).$$

- ICL: Add explanation $\{(q_1, e_1, a_1)...(q_m, e_m, a_m)\}$

Question 1: Do LLMs Follow Explanations?

- What makes explanations effective for LLMs to learn from?
- We explore computation trace (T) that is transformed by a natural language function (L) which maps the trace to a complete natural language explanation

Question: Take the last letters of the words in "Bill Gates" and concatenate them.

Gold: The last letter of Bill is l. The last letter of Gates is s. Concatenating l and s is ls. So the answer is ls.

Perturb explanations

- Next, perturb the explanations and see effects

	Question: Take the last letters of the words in "Bill Gates" and concatenate them.
LETCAT	**Gold:** The last letter of Bill is l. The last letter of Gates is s. Concatenating l and s is ls. So the answer is ls. **Mask1:** The last letter of Bill is _. The last letter of Gates is _. Concatenating l and s is ls. So the answer is ls. **Mask2:** The last letter of Bill is l. The last letter of Gates is s. Concatenating _ and _ is _. So the answer is ls. **Incorrect:** The last letter of Bill is y. The last letter of Gates is e. Concatenating y and e is ye. So the answer is ye. **No NL:** Bill, l. Gates, s. l, s, ls. So the answer is ls.
	Question: A coin is heads up. Ka does not flip the coin. Sal flips the coin. Is the coin still heads up?
COINFLIP	**Gold:** The coin started heads up. Ka does not flip the coin, so it becomes heads up. Sal flips the coin, so it becomes tails up. So the answer is no. **Mask1:** The coin started heads up. Ka does not flip the coin, so it becomes _ up. Sal flips the coin, so it becomes tails up. So the answer is no. **Mask2:** The coin started heads up. Ka does not flip the coin, so it becomes heads up. Sal flips the coin, so it becomes _ up. So the answer is no. **Incorrect:** The coin started heads up. Ka does not flip the coin, so it becomes tails up. Sal flips the coin, so it becomes heads up. So the answer is yes. **No NL:** heads, heads, tails. So the answer is no.

Experiments and Analysis

- LMs are indeed relying on the actual computation traces. Perturbing the traces of the explanations will lead to performance degradation
- When the trace is straightforward, a powerful enough LLM is able to "shortcut" some particular steps: text-davinci-02 (except GSM)

	LETCAT				COINFLIP				GSM			
	OPT	davinci	txt-01	txt-02	OPT	davinci	txt-01	txt-02	OPT	davinci	txt-01	txt-02
Standard	8.5	8.5	10.5	16.0	51.5	83.0	68.0	99.0	5.5	7.5	11.0	26.5
Gold	50.0	59.0	85.0	100.	94.0	89.5	100.	100.	32.5	26.0	25.0	57.5
Mask1	11.0	16.0	21.5	100.	71.0	88.0	61.5	100.	19.0	21.0	12.5	29.5
Mask2	32.5	49.5	68.0	100.	84.0	91.5	99.0	100.	10.0	16.0	11.5	27.5
Random	10.0	25.0	28.0	13.0	52.5	54.5	67.0	69.0	3.0	3.0	1.0	34.5
Incorrect	40.0	53.0	67.5	99.5	60.5	86.0	52.0	100.	18.5	17.0	10.0	16.5
No NL	29.0	15.0	46.5	100.	59.5	86.0	99.0	100.	8.0	19.5	14.5	45.5

Experiments and Analysis (Cont.)

- LLMs can still benefit from partially complete or partially correct explanations
- Natural language also plays an essential role in making effective explanations

	LETCAT				COINFLIP				GSM			
	OPT	davinci	txt-01	txt-02	OPT	davinci	txt-01	txt-02	OPT	davinci	txt-01	txt-02
Standard	8.5	8.5	10.5	16.0	51.5	83.0	68.0	99.0	5.5	7.5	11.0	26.5
Gold	50.0	59.0	85.0	100.	94.0	89.5	100.	100.	32.5	26.0	25.0	57.5
Mask1	11.0	16.0	21.5	100.	71.0	88.0	61.5	100.	19.0	21.0	12.5	29.5
Mask2	32.5	49.5	68.0	100.	84.0	91.5	99.0	100.	10.0	16.0	11.5	27.5
Random	10.0	25.0	28.0	13.0	52.5	54.5	67.0	69.0	3.0	3.0	1.0	34.5
Incorrect	40.0	53.0	67.5	99.5	60.5	86.0	52.0	100.	18.5	17.0	10.0	16.5
No NL	29.0	15.0	46.5	100.	59.5	86.0	99.0	100.	8.0	19.5	14.5	45.5

Conclusion for perturbation experiments

- LLMs are sensitive to perturbations in the input-explanation mapping and other more subtle perturbations in the explanations.
- Using explanations in prompts is a promising way to guide LLMs in learning a new task via ICL.

Question 2: What Makes A Good Exemplar Set?

- How a set of exemplars, as a whole, functions together in solving a particular test query
- Explore this question from two angles:
  - The interplay between exemplars
  - The interplay between the query and the exemplars.

Exemplar-Exemplar Interplay

- Method: Three sets of exemplars. The first and second set of exemplars each focuses on a particular part of the reasoning process, and these two parts are disjoint. The third set of exemplars includes the mixture from the first and second sets.

Add Only	**Q:** Marion received 20 more turtles than Mia at the animal rescue center. If Mia received 40 turtles, how many turtles did they receive together? **A:** Since Marion received 20 more turtles than Mia, she had 20 + 40 = 60 turtles. The two received 60 + 40 = 100 turtles. The answer is 100.
Mul Only	**Q:** Super Clean Car Wash Company cleans 80 cars per day. They make $5 per car washed. How much money will they make in 5 days? **A:** Each day they will make 80 * $5 = $400. They will make $400 * 5 = $2000 in 5 days. The answer is 2000.
Add & Mul	**Q:** Peter purchased 20 popsicles at $0.25 each. He also purchased 4 ice cream bars at $0.50 each. How much did he pay in total in dollars? **A:** The popsicles cost 0.25 * 20 = 5 dollars. The ice cream bars cost 0.5 * 4 = 2 dollars. He paid 5 + 2 = 7 dollars. The answer is 7.

Exemplar-Exemplar Interplay: Experiment & Analysis

- LLMs are able to fuse the reasoning process that is spread over different exemplars.

		OPT	davinci	txt-01	txt-02
LETCAT	Mask1	11.0	16.0	21.5	100.
	Mask2	32.5	49.5	68.0	100.
	Mixture	**37.0**	**56.5**	**82.0**	100.
COIN	Mask1	71.0	88.0	61.5	100.
	Mask2	84.0	91.5	99.0	100.
	Mixture	**93.5**	91.0	100.	100.
GSM	AddOnly	6.8	13.5	14.1	50.3
	MulOnly	4.7	17.2	16.7	50.1
	Mixture	**7.0**	**18.9**	**18.2**	**52.0**

Exemplar-Exemplar Interplay: Experiment & Analysis (Cont.)

- Powerful model can still be outstanding on simple datasets

		OPT	davinci	txt-01	txt-02
LETCAT	Mask1	11.0	16.0	21.5	100.
	Mask2	32.5	49.5	68.0	100.
	Mixture	**37.0**	**56.5**	**82.0**	100.
COIN	Mask1	71.0	88.0	61.5	100.
	Mask2	84.0	91.5	99.0	100.
	Mixture	**93.5**	91.0	100.	100.
GSM	AddOnly	6.8	13.5	14.1	50.3
	MulOnly	4.7	17.2	16.7	50.1
	Mixture	**7.0**	**18.9**	**18.2**	**52.0**

Query-Exemplar Interplay

- Recent work has studied how to make good in-context exemplar sets for a given query in the standard prompting setting: choosing nearest neighbors that are more similar to the query leads to better performance
- Method: Investigates how choosing relevant exemplars impact the performance in the setting when using explanations in prompts

Similarity Measurements

- **CLS-based**: Use smaller LMs (e.g., BERT [Devlin et al., 2019]) to extract the CLS embedding of the input queries and then use cosine similarity to score the embedding pairs
- **LM-based**: the probability of generating the query when the language model is conditioned on the exemplar,
- **Bert-based**: We use BertScore [Zhang et al., 2020]

Query-Exemplar Interplay: Experiment and Analysis

- Using the LM-based similarity measurements brings performance improvements across all three datasets, and has the most significant impacts on E -SNLI,
- Using BERTScore to select the closest exemplars can lead to credible performance improvements while does not require heavy overheads

	code-davinci-001				code-davinci-002				text-davinci-002			
	GSM	ECQA	E-SNLI	AVG	GSM	ECQA	E-SNLI	AVG	GSM	ECQA	E-SNLI	AVG
Random	16.3	53.6	47.2	39.0	64.6	74.7	74.9	71.3	48.8	71.9	75.1	65.3
CLS	16.5	55.0	54.1	41.8	65.4	74.9	74.8	71.7	50.4	72.1	77.4	66.6
LLM	**18.5**	**56.0**	**57.4**	**43.9**	65.8	**76.8**	**81.6**	**74.7**	**52.0***	**74.3***	**83.9***	**70.0**
BERTScore	**18.5**	54.6	53.7	42.3	**66.7**	75.9	75.6	72.8	51.0	72.8	78.7	67.6

Question 3: How to Select Exemplar Set?

- We have established that exemplar-exemplar interplay together with the query-exemplar interplay impacts the performance of using explanations in ICL. **This leads us to rethink how to select good exemplars for a given query.**
- Based on exemplar-exemplar exploration, a good set should consist of relevant exemplars that **collaboratively cover the reasoning skills** required for solving the query.

MMR Selection

- In practice, it is tricky to decide whether the reasoning underlying a set of exemplars is complementary categorically. We therefore use diversity as a proxy, since a set of less similar exemplars is arguably more likely to exhibit complementarity.
- We propose a maximal-marginal relevance [Carbonell and Goldstein, 1998] (MMR) based exemplar selection strategy. The idea is to select exemplars that are relevant to the query while being diverse enough to be collaborative.

MMR Selection (Cont.)

- Suppose for the given query q, we have already selected a set of exemplars T = {q_i} ,We pick up the exemplar according to:

$$\arg\max_{q_j \in D/T} \lambda \mathcal{S}(q, q_j) - (1-\lambda) max_{q_i \in T} \mathcal{S}(q_j, q_i) \quad (1)$$

- λ is a parameter that controls the balance between relevance and diversity

MMR Selection (Cont.)

- Iteratively selection:

Algorithm 1 MMR-Based Exemplar Selection

procedure MMRSELECT($D, q, k, \mathcal{S}$)
input: exemplar pool $D = \{q_1 ... q_n\}$, test query q, number of shots m and similarity measurement $\mathcal{S}$
output: selected exemplars $T = \{q_1 ... q_m\}$

$\mathbb{S} := [[\mathcal{S}(q_i, q_j)]]_{q_i, q_j \in D}$; ▷ the pairwise similarity between exemplars in D
$\mathbb{Q} := [\mathcal{S}(q, q_i)]_{q_i \in D}$; ▷ the similarity between query and exemplars in T
$T := \{\}$;
while $|T| < k$ **do**
    $\hat{q} :=$ Equation(1); ▷ get the next exemplar based on Eq (1)
    T.add($\hat{q}$)
return T;

MMR Selection: Experimental Results

- Generally, MMR is better than previous NN-prediction similarity selection, which proves that complementary is essential

	code-davinci-001				code-davinci-002				text-davinci-002			
	GSM	ECQA	E-SNLI	AVG	GSM	ECQA	E-SNLI	AVG	GSM	ECQA	E-SNLI	AVG
LLM NN	18.5	56.0	57.4	43.9	65.8	76.8	**81.6**	74.7	52.0*	74.3*	**83.9***	70.0*
LLM MMR	18.7	**57.2**	**59.5**	**45.1**	67.0	77.4	81.5	**75.3**	**52.8***	**75.3***	83.7*	**70.6***
BERTScore NN	18.5	54.6	53.7	42.3	66.7	75.9	75.6	72.8	51.0	72.8	78.7	67.6
BERTScore MMR	**19.4**	56.3	53.9	43.2	**68.2**	**78.1**	77.8	74.7	52.0	73.7	78.2	68.0

MMR Selection: Experimental Results (Cont.)

- **Impacts of the Trade-off Between Relevance and Diversity**: MMR typically works well with a λ of 0.5(roughly balancing the two terms).

λ	GSM	ECQA	E-SNLI
1.0	66.7	75.9	75.6
0.8	66.9	75.6	76.6
0.6	**68.2**	77.9	**78.1**
0.5	**68.2**	**78.1**	77.8
0.4	66.8	75.7	76.0
0.2	65.9	75.9	74.9
0.0	63.5	75.5	75.5

MMR Selection: Experimental Results (Cont.)

- **Sensitivity to Different Order**: Experiment with 5 random orders of the exemplar sets for each query and report averaged performance and variance of the accuracy.
- MMR is still better than NN and Random under varying order

	GSM	ECQA	E-SNLI
Random	$65.4_{1.3}$	$74.1_{0.5}$	$74.0_{1.2}$
NN	$68.6_{0.7}$	$75.4_{0.5}$	$75.9_{1.1}$
MMR	$69.4_{1.0}$	$77.8_{0.7}$	$77.8_{0.9}$

Summary

- LLMs rely on both of computation trace and natural language to effectively learn from explanation
- The benefits of constructing prompts by selecting complementary explanations that are relevant to the query
- Proposed an MMR-based exemplar selection strategy, which successfully improved the end task performance across three important datasets.

Towards Monosemanticity: Decomposing Language Models With Dictionary Learning

Yunchao Zhang
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Motivation

- **Mechanistic interpretability**: It seeks to understand neural networks by breaking them into components that are more easily understood than the whole. By understanding the function of each component, and how they interact, we hope to be able to reason about the behavior of the entire network.
- Unfortunately, the most natural computational unit of the neural network – the neuron itself – turns out not to be a natural unit for human understanding.

Why Neuron Is Hard to Be Understand ?

- **Neurons are polysemantic**: They respond to mixtures of seemingly unrelated inputs.
  - E.g., a single neuron can respond to HTTP requestsl, Korean text, academic citations…
  - In the vision model *Inception v1*, a single neuron responds to faces of cats and fronts of cars
- **Explanation**: **Superposition**. A neural network represents more independent "features" of the data than it has neurons by assigning each feature its own linear combination of neurons.

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- **Explanation**: **Superposition**. A neural network represents more independent "features" of the data than it has neurons by assigning each feature its own linear combination of neurons.

About “Superposition”

- Superposition can arise naturally during the course of neural network training if the set of features useful to a model are **sparse** in the training data. (See Here)
- As in compressed sensing, sparsity allows a model to **disambiguat**e which combination of features produced any given activation vector
    - **Only a small subset of neurons will be activated**

Method Overview

- In this paper, they use a weak dictionary learning algorithm called a *sparse* autoencoder to generate *learned features* from a trained model that offer a more monosemantic unit of analysis than the model's neurons themselves.
    - Polysemantic is hard to understand!
- It takes a one-layer transformer with a 512-neuron MLP layer, and decompose the MLP activations into relatively interpretable features by training sparse autoencoders on MLP activations from 8 billion data points.

Method Overview

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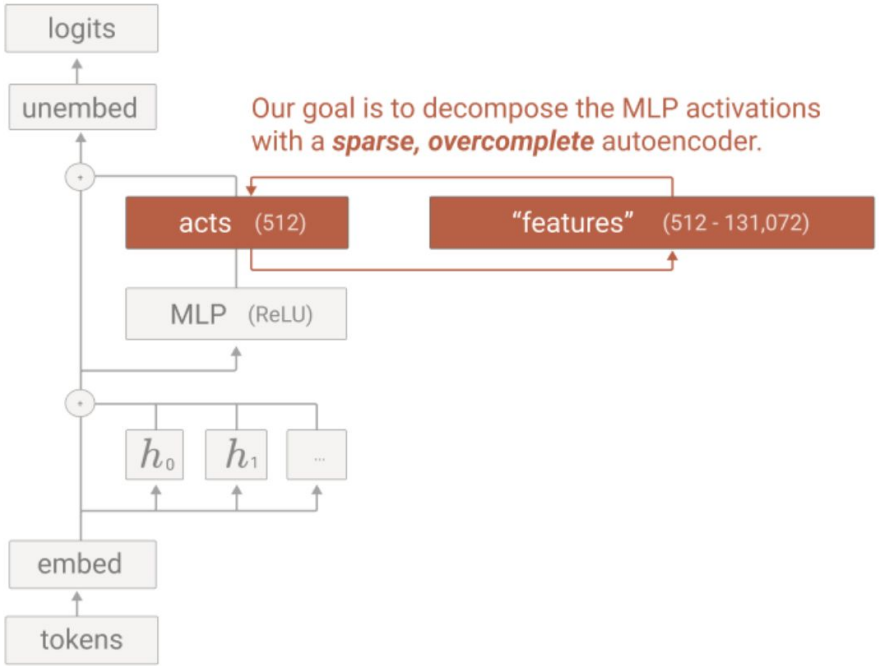
    - Polysemantic is hard to understand!
- It takes a one-layer transformer with a 512-neuron MLP layer, and decompose the MLP activations into relatively interpretable features by training sparse autoencoders on MLP activations from 8 billion data points.

Problem Setup

- Key challenge: **The curse of dimensionality**. As we study ever-larger models, the volume of the latent space representing the model's internal state that we need to interpret grows exponentially
- Unless we decompose them and understand each of them!
- Previously, some works have been done for attention only network. However, they are not enough for the whole LLM analysis, as it contains an MLP layer.

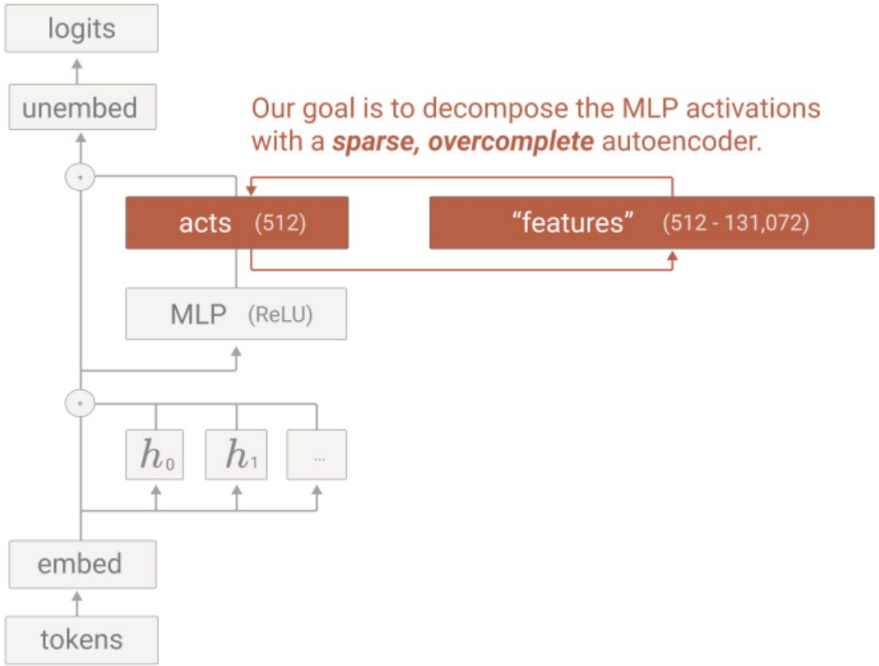
Problem Setup (Cont.)

- They decompose the MLP activations with a sparse autoencoder.



Problem Setup(Cont.)

- They decompose into more features than neurons: Superposition!



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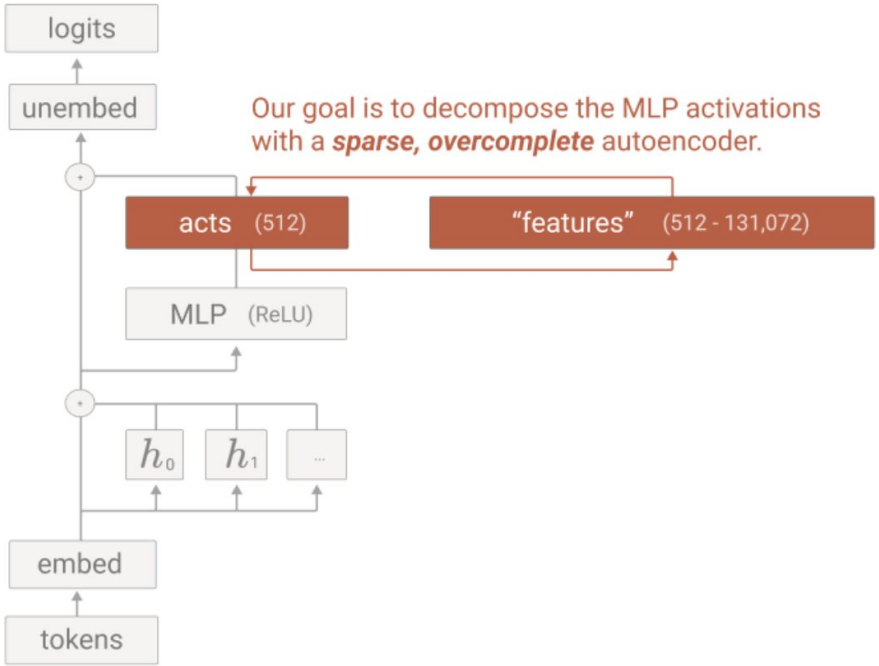

Features as a Decomposition

- There is significant empirical evidence suggesting that neural networks have interpretable linear directions in activation space.
- If linear directions are interpretable, it's natural to think there's some "basic set" of meaningful directions which more complex directions can be created from. We call these directions features, and they're what we'd like to decompose models into.
- Sometimes, by happy circumstances, **individual neurons** appear to be these basic interpretable units (see examples above). But quite often, this isn't the case

Features as a Decomposition

$$\mathbf{x}^j \approx \mathbf{b} + \sum_i f_i(\mathbf{x}^j)\mathbf{d}_i$$

where $\mathbf{x}^j$ is the activation vector of length d_{MLP} for datapoint j, $f_i(\mathbf{x}^j)$ is the *activation* of feature i, each $\mathbf{d}_i$ is a unit vector in activation space we call the *direction* of feature i, and $\mathbf{b}$ is a bias.[3] Note that this decomposition is not new: it is just a linear matrix factorization of the kind commonly employed in dictionary learning.

- Here they use sparse autoencoder for decomposition

Open Question for Decomposition

- If such a sparse decomposition exists, it raises an important question: are models in **some fundamental sense composed of features or are features just a convenient post-hoc description**? In this paper, they take an agnostic position, though our results on feature universality suggest that features have some existence beyond individual models.

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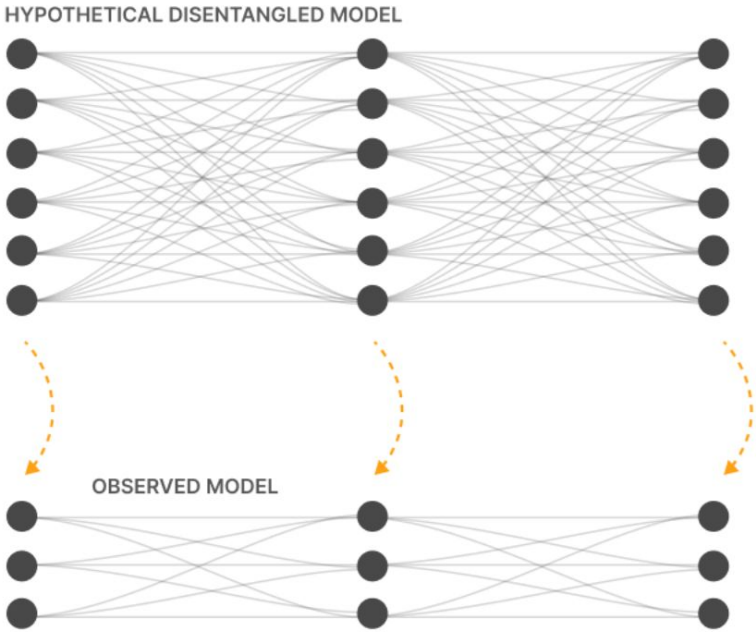
How is Decomposition Related to Superposition

- Recall superposition: Neural networks “want to represent more features than they have neurons”
- Small network simulate much larger much sparser neural networks

How is Decomposition Related to Superposition (Cont.)

- Small network simulate much larger much sparser neural networks



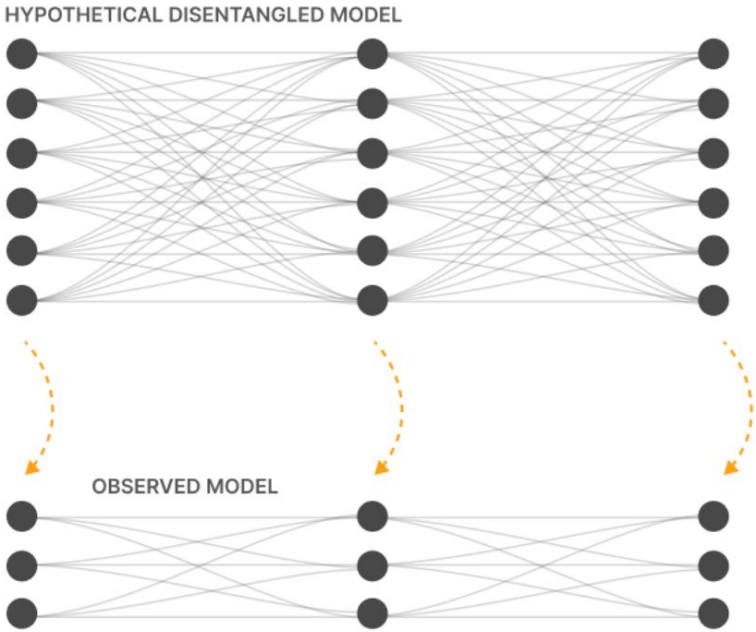
Under the superposition hypothesis, the neural networks we observe are **simulations of larger networks** where every neuron is a disentangled feature.

These idealized neurons are **projected** on to the actual network as "almost orthogonal" vectors over the neurons.

The network we observe is a **low-dimensional projection** of the larger network. From the perspective of individual neurons, this presents as polysemanticity.

How is Decomposition Related to Superposition (Cont.)

- Decomposition should have more directions (features) than neuron



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What makes a good composition?

- We can interpret the conditions under which each feature is active
- We can interpret the downstream effects of each feature
- The features explain a significant portion of the functionality of the MLP layer
- From above criterias, we can do a lot of things
    - E.g., determine the contribution of a feature to the layer's output, and the next layer's activations, on a specific example.

What Not Use Architectural Approaches?

- Architectural Approach: Engineer models to simply not have superposition in the first place
- This would be the “cleanest” approach for downstream analysis, even though it can produce model with greater loss and bring performance hit

However, it’s non-viable

- If we avoid superposition, we still can not avoid polysemantic!
  - Difference: No superposition only makes sure one neuron will be activated for a single input
- Why?
  - This is because in many cases models achieve lower loss by representing multiple features ambiguously (in a polysemantic neuron) than by representing a single feature unambiguously and ignoring the others.

However, it’s non-viable (Cont.)

- The authors analyze the loss comparison (cross-entropy) through one single neuron and get mentioned conclusion
- Though simple, but even in large models, if we push activation sparsity to its limit, only a single neuron will activate at a time. We can now consider that single neuron.
- It can still be advantageous for that neuron to be polysemantic.
- MSE loss can not get this conclusion, but is not used in LM.

Using Sparse Autoencoders To Find Good Decompositions

- Goal: Seek a decomposition which is **sparse** and **overcomplete**
- On the surface of decomposition (dictionary learning), this problem may seem impossible: we're asking to determine a high-dimensional vector from a low-dimensional projection.
- It’s the reverse of Neural Network. We are trying to invert a very rectangular matrix.
- It is possible to store high-dimensional sparse structure in lower-dimensional spaces (NN), **but recovering it is hard**

Using Sparse Autoencoders (Cont.)

- Despite its difficulty, there are a host of sophisticated methods for dictionary learning.
- Ultimately decide to focus on simple sparse autoencoder approximation of dictionary learning.

Using Sparse Autoencoders (Cont.)

- Two reasons:
  - Could scale up easily. Help model trained on a large and diverse corpus.
  - Traditional iterative dictionary learning method might be too strong.
    - Exact compressed sensing is NP-hard, which NN is not.
    - A sparse autoencoder is very similar in architecture to the MLP layers, and so should be similarly powerful in its ability to recover features from superposition.

Training Process

- AE is trained on one-layer transformer:
  - Because one-layer models are small they likely have fewer "true features" than larger models, meaning features learned by smaller dictionaries might cover all their "true features". Smaller dictionaries are cheaper to train, allowing for fast hyperparameter optimization and experimentation.

Training Process

- AE is trained on one-layer transformer:
  - We can highly overtrain a one-layer transformer quite cheaply. We hypothesize that a very high number of training tokens may allow our model to learn cleaner representations in superposition.

Training Process

- AE is trained on one-layer transformer:
  - We can easily analyze the effects features have on the logit outputs, because these are **approximately linear** in the feature activations. 9 This provides helpful corroboration that the features we have found are not just telling us about the data distribution, and actually reflect the functionality of the model.

Training Process

- Hidden layer activations f are the learned features

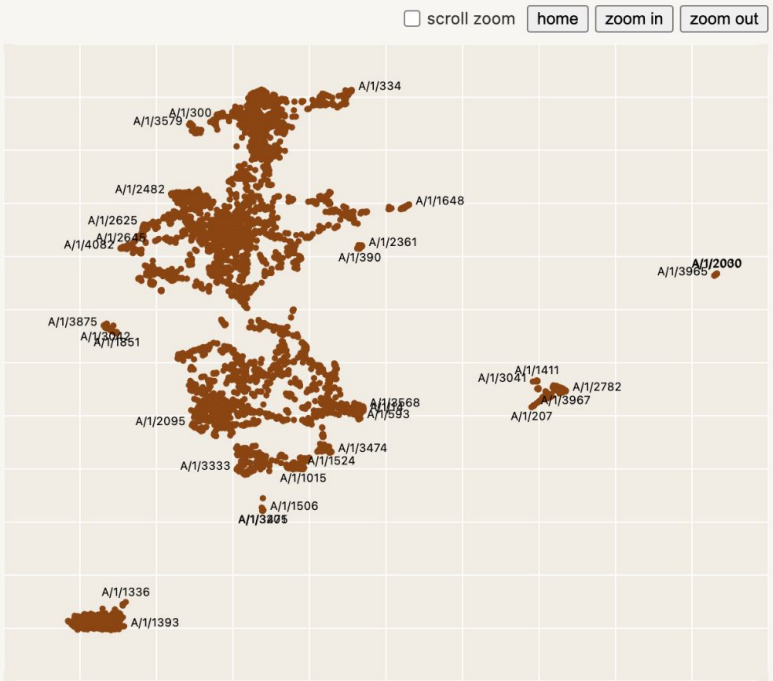
Our dictionary learning model is a one hidden layer MLP. It is trained as an autoencoder, using the input weights as an encoder and output weights as the decoder. The hidden layer is much wider than the inputs and applies a ReLU non-linearity. We use the default Pytorch Kaiming Uniform initialization [74] .

Formally, let n be the input and output dimension and m be the autoencoder hidden layer dimension. Given encoder weights $W_e \in \mathbb{R}^{m \times n}, decoderweightsW_d \in \mathbb{R}^{n \times m}$ with columns of unit norm, and biases $\mathbf{b}_e \in \mathbb{R}^m, \mathbf{b}_d \in \mathbb{R}^n$, the operations and loss function over a dataset X are:

$$\bar{\mathbf{x}} = \mathbf{x} - \mathbf{b}_d$$
$$\mathbf{f} = \mathrm{ReLU}(W_e \bar{\mathbf{x}} + \mathbf{b}_e)$$
$$\hat{\mathbf{x}} = W_d \mathbf{f} + \mathbf{b}_d$$
$$\mathcal{L} = \frac{1}{|X|} \sum_{\mathbf{x} \in X} ||\mathbf{x} - \hat{\mathbf{x}}||_2^2 + \lambda ||\mathbf{f}||_1$$

Experiment Results

CLUSTER	FEATURE	search labels
Cluster #49	A/0/307	This feature fires for references to citations in scientific pa...
	A/0/311	This feature fires for reference citations in academic paper...
	A/1/776	Years in some citation notation
	A/1/1538	Citations in a [@author] or [@authoryear] format
	A/1/1875	Markdown Citation (Predict year)
	A/1/2252	" [@"
	A/1/2237	[Ultralow density cluster]
Cluster #42	A/0/126	This feature seems to fire on section headings, specifically ...
	A/1/357	"ref" in [context]
	A/1/1469	"s"/"sec" after "{#", section reference in some markup
	A/1/3841	"Sec"
	A/1/3898	Section number in {#SecX}
	A/1/4083	" {#"
	A/1/2129	"." in [context]
	A/1/553	"](#" in [context]
Cluster #43	A/0/8	This feature attends to text formatting markups such as ref...
	A/0/398	This feature attends to references to figures and tables.
	A/0/454	This feature fires on reference/bibliographic citations in LaT...
	A/1/35	"){"
	A/1/366	"type"
	A/1/945	"ref" in [context]
	A/1/1895	"-" in [context]
	A/1/2176	"fig"



Towards Monosemanticity: Decomposing Language Models With Dictionary Learning

Experiment Results: Conclusion

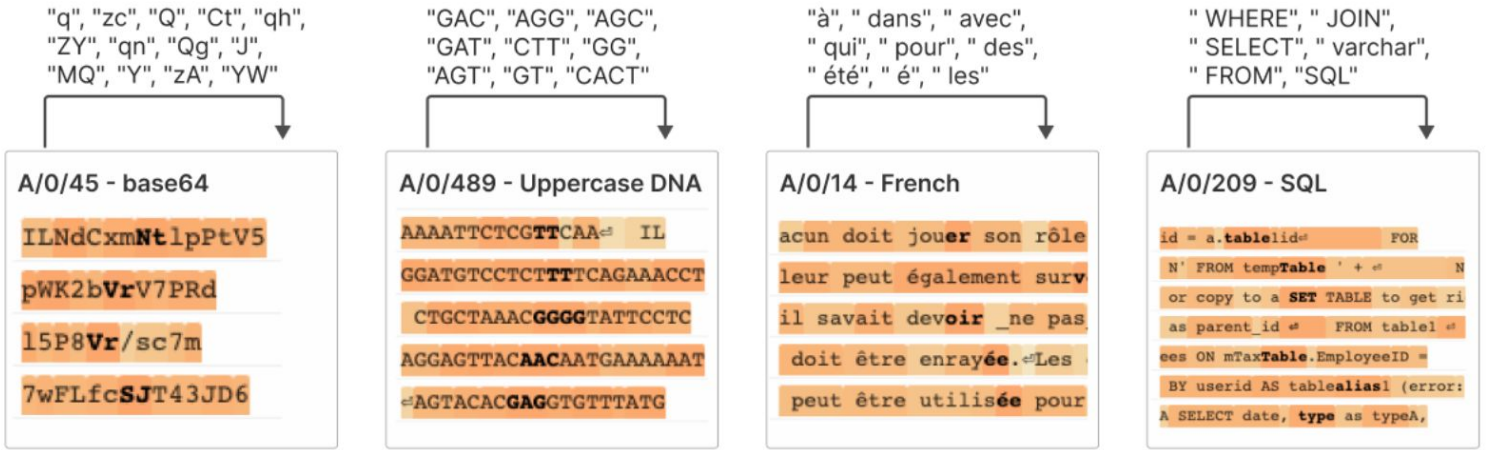
- Sparse Autoencoders extract relatively monosemantic features.
- Sparse autoencoder features can be used to intervene on and steer transformer generation.
- Sparse autoencoders produce relatively universal features.
- Features appear to "split" as we increase autoencoder size.
- Just 512 neurons can represent tens of thousands of features.
- **Features connect in "finite-state automata"-like systems that implement complex behaviors.**

Finite-state automata

- Automata: Automatons are abstract models of machines that perform computations on an input by moving through a series of states or configurations
- Finite-state automata for decomposition: Transite from one state to another when a new token is processed by the LM

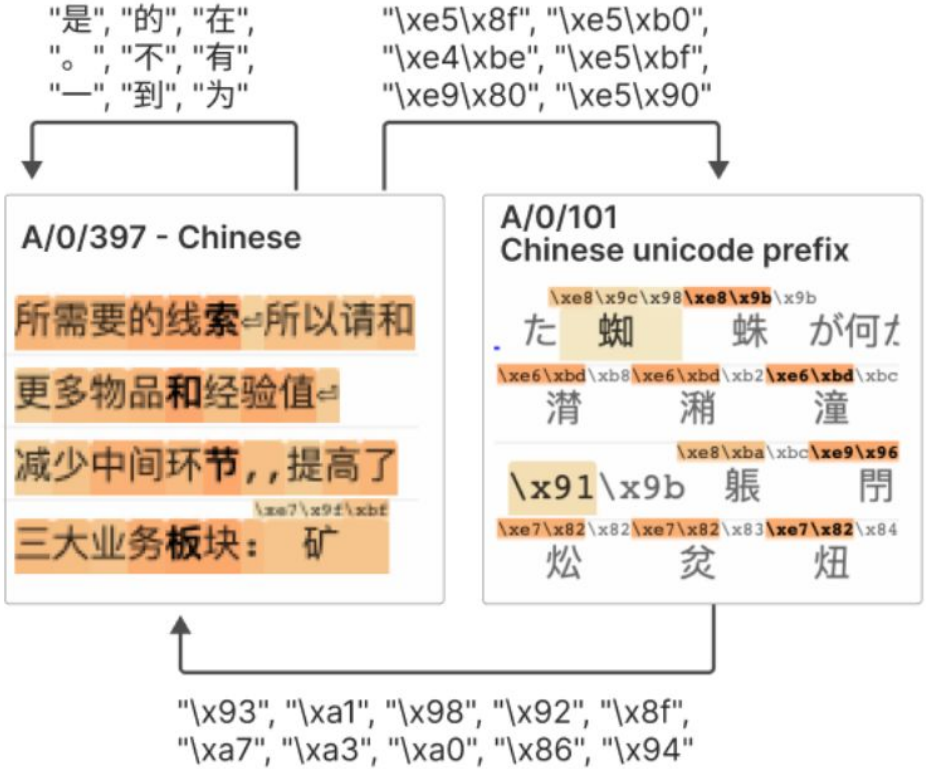
Finite-state automata (Cont.)

- Self loop



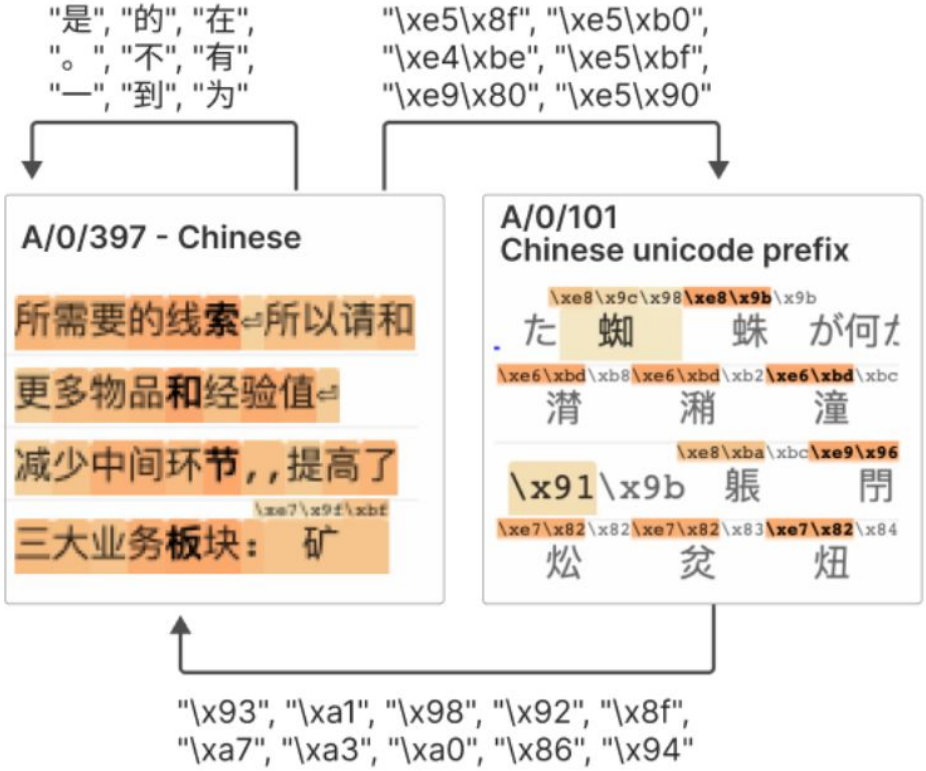
Finite-state automata (Cont.)

- Complex system
  - E.g. Chinese
- Chinese character often needs a lot of unicode blocks (e.g., 蜘)



Finite-state automata (Cont.)

- Two features
- One fires on either complete characters or the suffix (predicting either a new complete character, or a prefix)
- The other only fires on the prefixes and predicts suffixes.



Summary

- Dictionary learning is a good way to understand NN
- **Sparsity is the key**: **Compression is the Intelligence**
- Give many insights and explanations:
  - Sparsity in current NNs, especially LLM
  - Why autoencoder?
  - Why single layer transformer?
  - Sometimes monosemantic architecture can not be developed
  - How to train this AE for decomposition (not introduced here)

A brief idea

- How to recover the original high dimensional feature from low dimensional compact feature?
  - Diffusion?
    - Construct a reversible process

Faithful Reasoning Using Large Language Models

Li Sun
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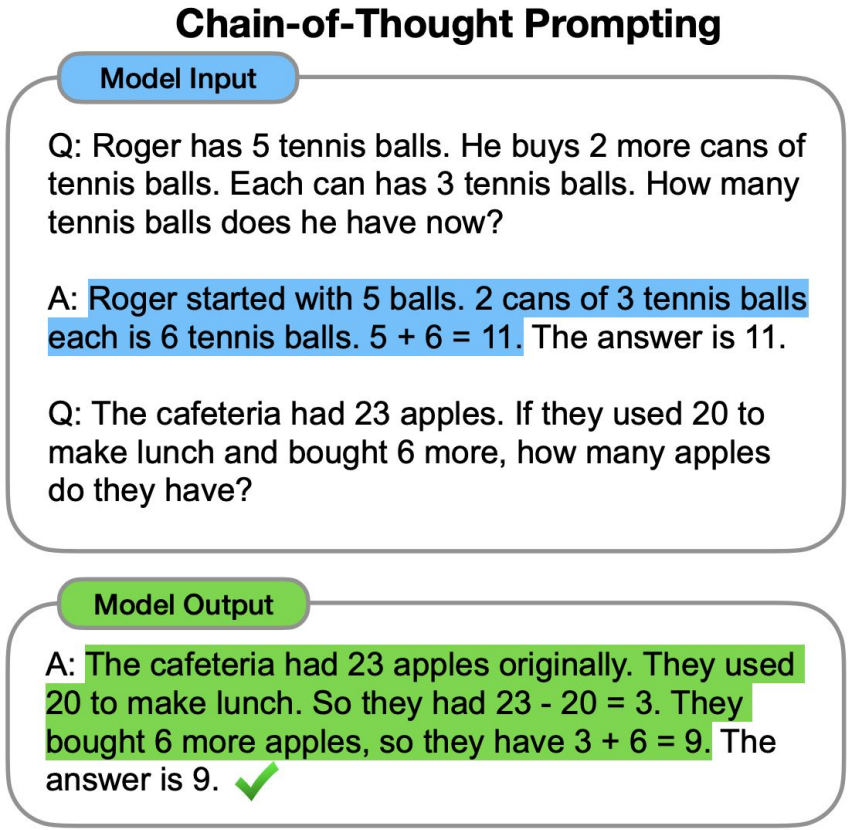
Motivation

- The proficiency of LLM typically goes hand-in-hand with an unacceptable level of opacity
- Hard to verify a answer / debug a model
- Undermine the overall trust in the model's response

Faithful Reasoning

- Why CoT is not enough?
  - Still Black Box
  - Lack Explainability, Interpretability, and Robustness

We need Faithful Reasoning.



Faithful Reasoning

- **Definition:**

  A system that reasons faithfully is one whose underlying computations mirror standard definitions of **logical validity**.

- Such a system can supply the user with an **interpretable reasoning trace**, which allows them to understand how the model reached its final answer.

Imagine how people doing math……

- Pick up some conditions/statement
- Derive some new statement
- Form a logical chain

Question : The solution set of the inequality $|x|^3 - 2x^2 - 4|x| + 3 < 0$ is _____

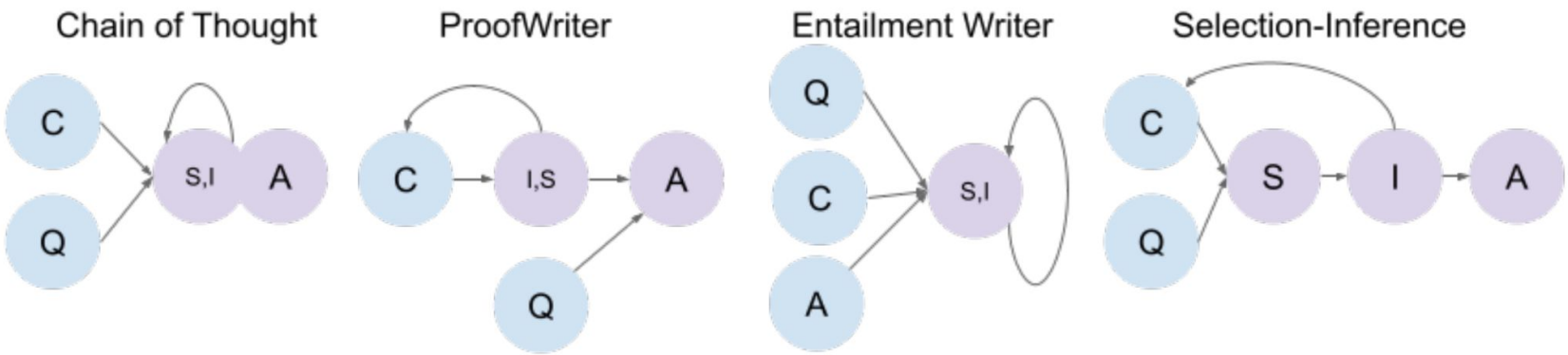
Solution :

Notice that $|x| = 3$ is a root of the equation $|x|^3 - 2x^2 - 4|x| + 3 = 0$ **[remember : if $x^3 + bx^2 + cx + d = 0$ then roots of the equation are factors of d].**

Then the original inequality can be rewritten as $(|x| - 3)\left(|x|^2 + |x| - 1\right) < 0$ that is

$$(|x| - 3)\left(|x|^2 + |x| - 1\right) < 0$$

Defining a Valid Reasoning Trace



Defining a Valid Reasoning Trace

Context:
a runway is a kind of pathway for airplanes
airports have runways for airplanes
as the number of pathways increases , the traffic congestion in that area usually decreases

Question:
Which of the following would be most effective in reducing air traffic congestion at a busy airport?
- providing performance feedback to pilots
- providing flight information to passengers
- increasing the number of aircraft at the airport
- increasing the number of runways at the airport

Selection: a runway is a kind of pathway for airplanes. We know that airports have runways for airplanes.

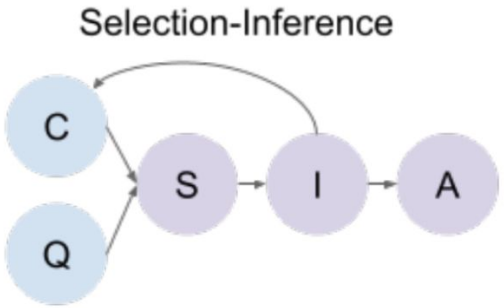
Inference: Therefore, an airport runway is a kind of pathway for airplanes.

Selection: an airport runway is a kind of pathway for airplanes. We know that as the number of pathways increases , the traffic congestion in that area usually decreases.

Inference: Therefore, as the number of runways at a airport increases, the traffic congestion in that area usually decreases.

Answer: increasing the number of runways at the airport

Defining a Valid Reasoning Trace



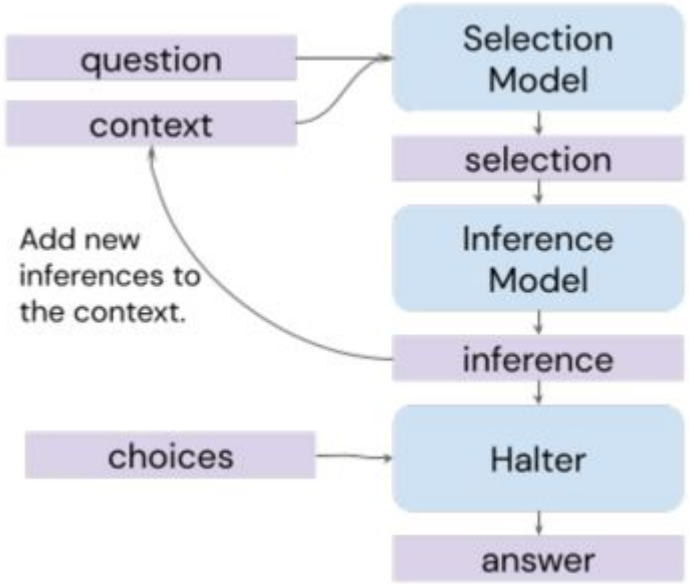
Definition 1. *A* reasoning step *is a pair* $\langle s, i \rangle$, *where* s *(the selection) is a set of statements and* i *(the inference) is a statement.*

Definition 2. *A* reasoning trace *is a pair* $\langle C, \mathcal{T} \rangle$ *where* C *(the context) is a set of statements and* $\mathcal{T}$ *is a sequence of reasoning steps.*

Definition 3. *A reasoning trace* $\langle C, \mathcal{T} \rangle$, *where* $\mathcal{T} = \langle s_0, i_0 \rangle, \langle s_1, i_1 \rangle, \ldots \langle s_n, i_n \rangle$, *is* connected *iff for every reasoning step* $\langle s_k, i_k \rangle$, *for every statement* q *in the set* s_k *either* $q \in C$ *or* $q = i_j$ *for some* $j < k$.

Definition 4. *A reasoning trace* $\langle C, \mathcal{T} \rangle$, *where* $\mathcal{T} = r_0, r_1, \ldots, r_n$, *is* valid *if it is connected and each reasoning step* $r_k = \langle s, i \rangle$ *is correct (in the sense that* i *logically follows from* s*).*

SI Model Architecture



- **Selection-Inference:** the stepwise forward reasoning backbone whose causal structure satisfies the requirements for producing valid reasoning traces
- What else are needed?
- **Halter:** look at the output of a Selection-Inference step and determines if there is sufficient information to answer the question.
- **Beam Search & Value Function**: to find the best candidate for answering the question

Each component in our model is trained in isolation, and at no point do we optimize our pipeline for final answer accuracy.

Selection-Inference

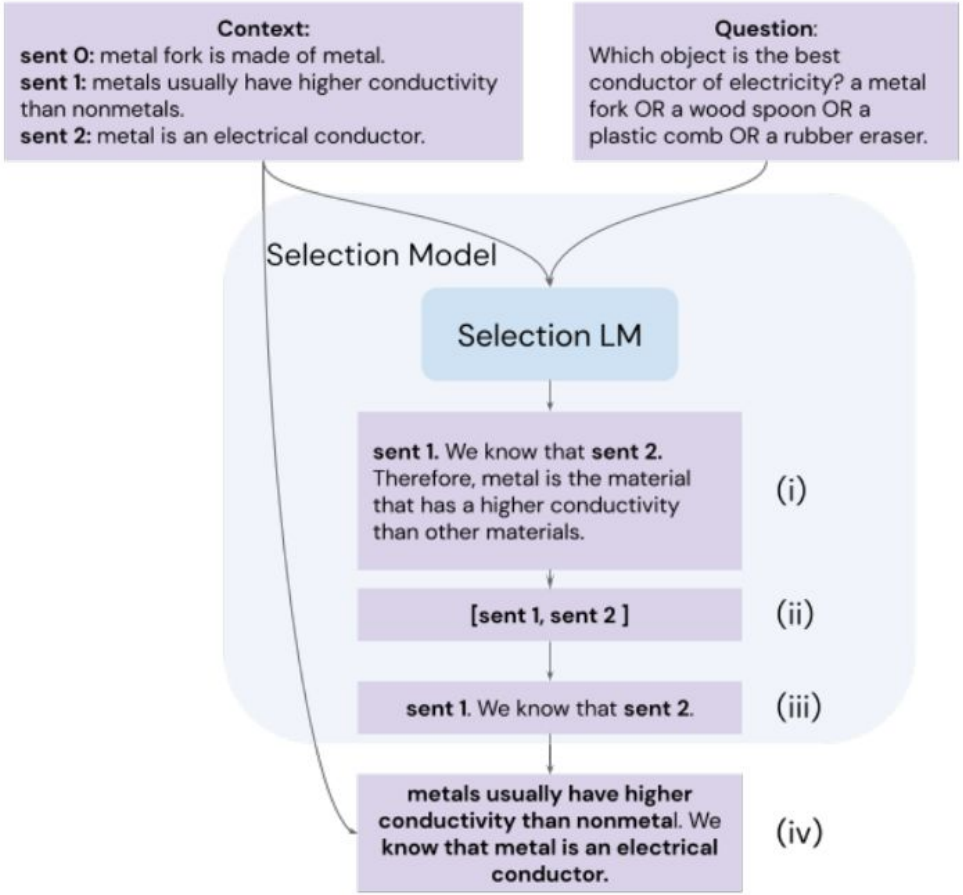
- First, given the question, the Selection model chooses a set of statements from the context (the selection).
- Second, the Inference model predicts an entailment by computing a statement that follows from the selection (the inference).
- The inference is then added to the context, and that concludes a single step of reasoning.

Selection

- To take the context and question and select a number of statements from the context to feed to the inference model

4 steps:

- fine-tune a LM to predict sentence labels
- extract the only the sentence labels
- compose a sentence
- substitute statements back



Inference

- The Inference model is trained to predict an entailment given only the selection
- Cannot access to the questions

Training Data of Selection-Inference

sent 0: If something is rough then it visits the lion.
sent 1: the cow visits the lion.
sent 2: the lion visits the cow.
sent 3: the cow is rough.
sent 4: If something visits the cow and the cow visits the lion then the lion is nice.
Does it imply that the statement "The lion is nice" is True?

sent 4. We know that sent 2 and sent 1. Therefore, the lion is nice.

(a) **Example of ⟨input, target⟩ pairs used to train the Selection LLM.**

If something visits the cow and the cow visits the lion. We know that the cow visits the lion and the cow visits the lion. Therefore, the lion is nice.

(b) **Example of ⟨input, target⟩ pairs used to train the Inference LLM.**

Training Data of SI

sent 0: cycles of freezing and thawing water cause mechanical weathering.
sent 1: cycles of freezing and thawing water cause ice wedging.
sent 2: ice wedging is a kind of mechanical weathering.
sent 3: mechanical weathering means breaking down rocks from a larger whole into smaller pieces by mechanical means.
A student climbs up a rocky mountain trail in Maine. She sees many small pieces of rock on the path. Which action most likely made the small pieces of rock? sand blowing into cracks OR leaves pressing down tightly OR ice breaking large rocks apart OR shells and bones sticking together.

sent 0. We know that sent 3. Therefore, cycles of freezing and thawing water cause the rocks to break into smaller pieces.

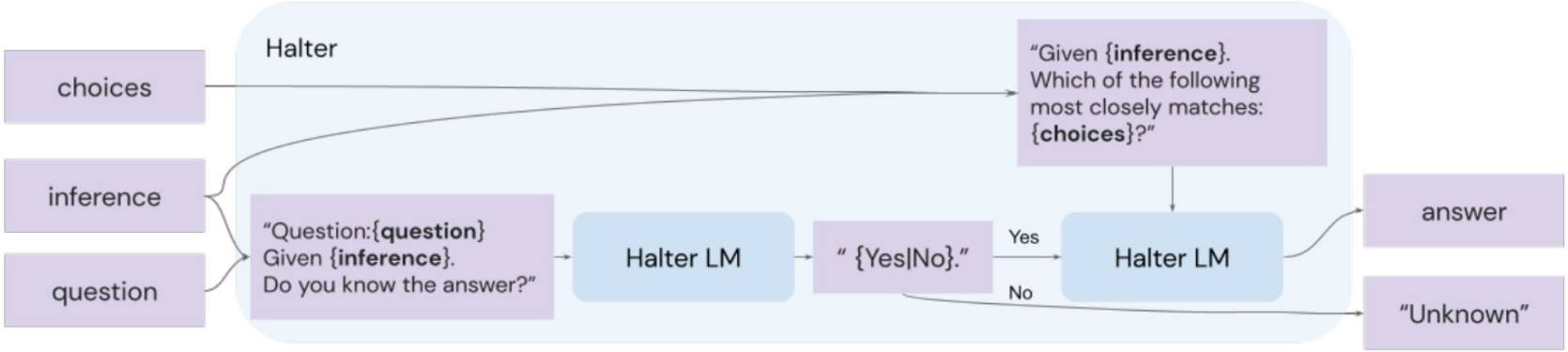
(a) **Example of ⟨input, target⟩ pairs used to train the Selection LLM.**

cycles of freezing and thawing water cause mechanical weathering. We know that mechanical weathering means breaking down rocks from a larger whole into smaller pieces by mechanical means. Therefore, cycles of freezing and thawing water cause the rocks to break into smaller pieces.

(b) **Example of ⟨input, target⟩ pairs used to train the Inference LLM.**

Halter

- When to stop?
- A benefit of this is that it allows the model to say that it cannot answer the question, rather than making up an answer.



Training Data for Halter

Data sample

Context:
All red things are soft.
All soft things are round.
All round things are loud.
The bear is red.
The cat is round.

Question:
Is the bear loud?

Reasoning:
All red things are soft. The bear is red. Therefore the bear is soft. ✔

All soft things are round. The bear is soft. Therefore, the bear is round. ✔

All round things are loud. The bear is sound. Therefore the bear is soft. ✔

Answer:
The bear is soft

Training data for the halter

Context:
All red things are soft.
All soft things are round.
All round things are loud.
The bear is red.
The cat is round.

Question:
Is the bear loud?

Reasoning:
All red things are soft. The bear is red. Therefore the bear is soft.

All soft things are round. The bear is soft. Therefore, the bear is round.

All round things are loud. The bear is sound. Therefore the bear is soft.

Do you know the answer? Yes

Given that the bear is soft. Which of these most closely matches:
The bear is soft OR The bear is not soft?
Answer: The bear is soft.

Context:
All red things are soft.
All soft things are round.
All round things are loud.
The bear is red.
The cat is round.

Question:
Is the bear loud?

Reasoning:
All red things are soft. The bear is red. Therefore the bear is soft.

All soft things are round. The bear is soft. Therefore, the bear is round.

Do you know the answer? No

Context:
All red things are soft.
All soft things are round.
All round things are loud.
The bear is red.
The cat is round.

Question:
Is the bear loud?

Reasoning:
All red things are soft. The bear is red. Therefore the bear is soft.

Do you know the answer? No

Beam Search & Value Function

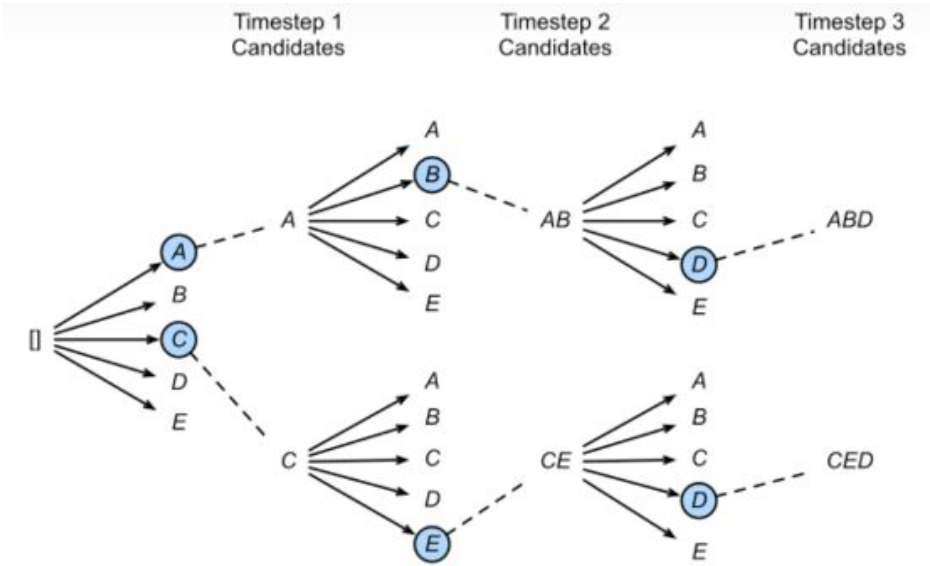
- We still cannot make sure that the Inference module generate the correct statement we need.

- **Non-Deterministic:** Selection Module samples from multiple candidate statements, and this induces a tree of potential reasoning traces

Beam Search & Value Function

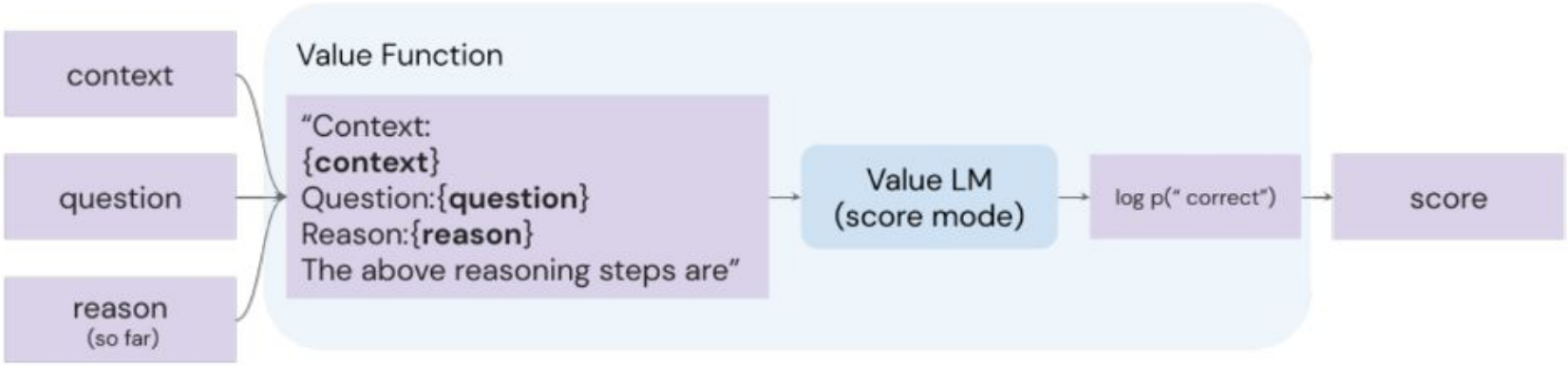
- **Beam Search:**

  Starting from a single empty trace we use SI to produce ***P*** candidate steps. We evaluate each of these steps using the value function and keep the top ***B <= P***. We use SI again to generate ***P*** candidate next steps for each of the ***B*** traces, resulting in ***B × P*** traces. These are evaluated using the value function and the best ***B*** traces are kept.



Beam Search & Value Function

- **Value Function:** computes the value of adding a reasoning step to the current trace.



Training Data

Context:
Round people are not big.
Nice people are cold.
Nice, round people are rough.
All nice, cold people are rough.
If someone is cold and rough then they are big.
If someone is nice and not cold then they are not round.
If someone is cold and not round then they are big.
If the bald eagle is cold and the bald eagle is not round then the bald eagle is big.
the bald eagle is nice.
Question:
Does it imply that the statement "The bald eagle is rough" is True?
Reason:
Nice people are cold. We know that the bald eagle is nice. Therefore, the bald eagle is cold.
All nice, cold people are rough. We know that the bald eagle is nice and If someone is nice and not cold then they are not round. Therefore, the bald eagle is not round.
The above reasoning steps are incorrect

Training Data

Context:
All cold, young people are red.
If someone is rough then they are cold.
All cold, nice people are rough.
If Dave is not rough then Dave is not quiet.
If Bob is young then Bob is nice.
If Bob is cold then Bob is not furry.
Dave is young.
Anne is cold.
Bob is rough.
Question:
Does it imply that the statement "Bob is furry" is True?
Reason:
If someone is rough then they are cold. We know that Bob is rough. Therefore, Bob is cold.
The above reasoning steps are correct

Experiment

- Baseline Methods

Experiment	depth-1	depth-2	depth-3	depth-5	Overall
Entailment Writer (Dalvi et al., 2021) + Answer	50.4%	55.3%	52.2%	56.0%	53.5%
Proof + Answer	70.9%	65.0%	65.5%	60.4%	65.4%
Ground truth proof + Halter	99.9%	100%	100%	100%	100%
Proof Only + Halter	97.0%	93.1%	84.8%	44.6%	79.9%
Proof Only + Halter + EB Search	99.2%	96.2%	91.4%	54.9%	85.0%
Proof Only + Halter + PW Search	98.7%	96.0%	90.3%	56.8%	85.4%
SI model + Halter	98.3%	94.1%	82.4%	38.4%	78.3%
SI model + Halter + EB Search	**99.4%**	98.0%	91.7%	61.7%	**88.0%**
SI model + Halter + PW Search	**99.4%**	**98.1%**	**92.0%**	**63.4%**	**88.1%**

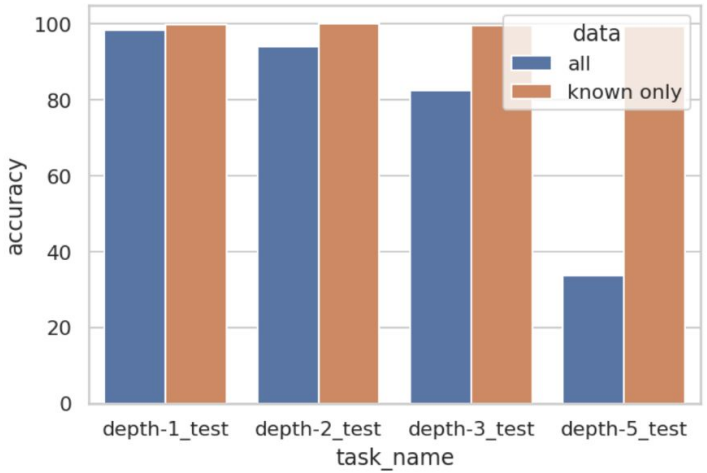
Answer Accuracy

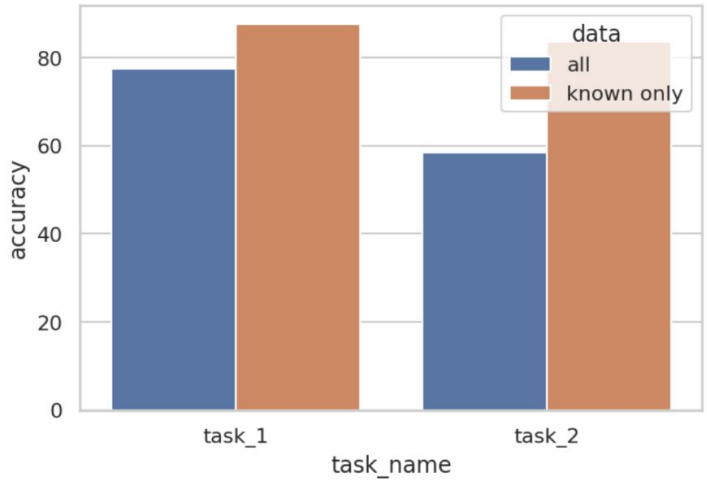
- Providing the most significant improvement for problems that **require more reasoning steps** (PW, depth-5) and on problems **with distractors** in the context

Model	Task 1	Task 2
Ground truth proof + Halter	88.8%	88.8%
Proof + Answer	64.6%	7.8%
EntailmentWriter* + Answer	50.0%	35.0%
Proof Only + Halter	78.5%	60.3%
Proof Only + Halter + Search	82.9%	**76.2%**
SI model + Halter	72.4%	55.9%
SI model + Halter + Search	**83.2%**	72.9%

Experiment

- When SI “**Knows**” the answer, it knows well





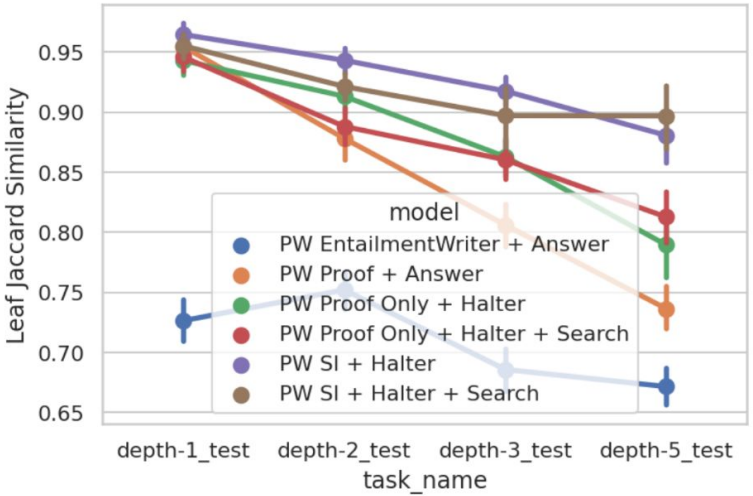
Experiment

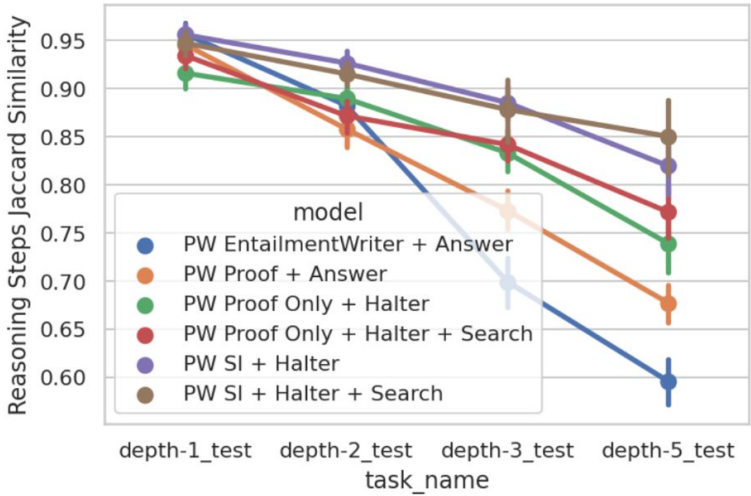
- Proportion of problems on which models **made-up facts**

Model	Task 1	Task 2
Proof + Answer	10%	60%
EntailmentWriter + Answer	3%	**0%**
Proof Only + Halter	15%	23%
Proof Only + Halter + Search	18%	40%
SI + Halter	**1%**	**0%**
SI + Halter + Search	**1%**	**0%**

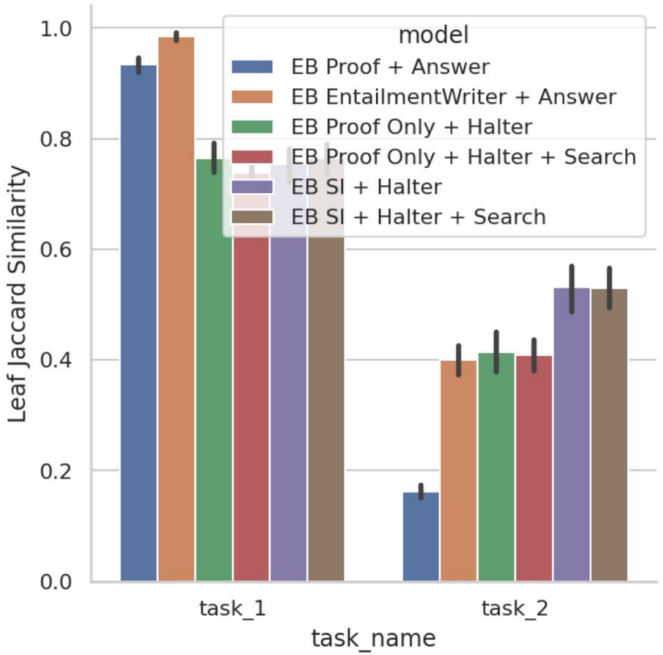
Reasoning Trace Accuracy

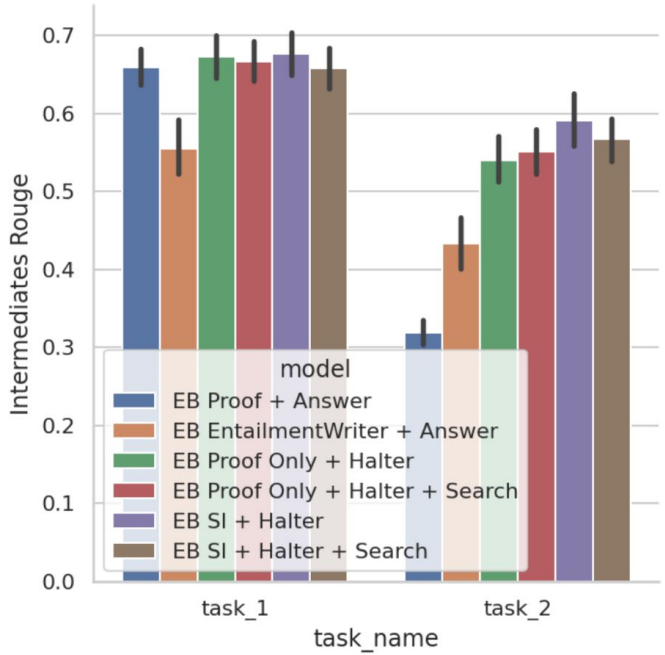
- Jaccard Similarity





Reasoning Trace Accuracy





Relative Performance Increase

- Given Random Context or Incomplete Context

Model	Task 1 random context ↓	Δ ↑
SI + Halter	**9.4%**	**63.0%**
Proof + Answer	30.0%	34.6%
EW* + Answer	23.0%	27.0%

Model	Depths 1-5 incomplete context ↓	Δ ↑
SI + Halter	**29.5%**	**48.8%**
Proof + Answer	61.2%	4.3%
EW* + Answer	53.4%	0.1%

Limitation

- The need of a large amount of context (limited application)
- Inference Module works well, but it is hard to guarantee Selection Module select statements that are able to derive something we need. (Just like human)

Summary

- Characterise faithful reasoning in terms of logical validity, and propose Selection-Inference, a model that mirrors the structure of this definition
- Introduce a value function, and use it to guide a beam search through the tree of potential traces induced by the non-determinism of selection
- SI is less likely to hallucinate facts while reasoning

PromptBench: Towards Evaluating the Robustness of Large Language Models on Adversarial Prompts

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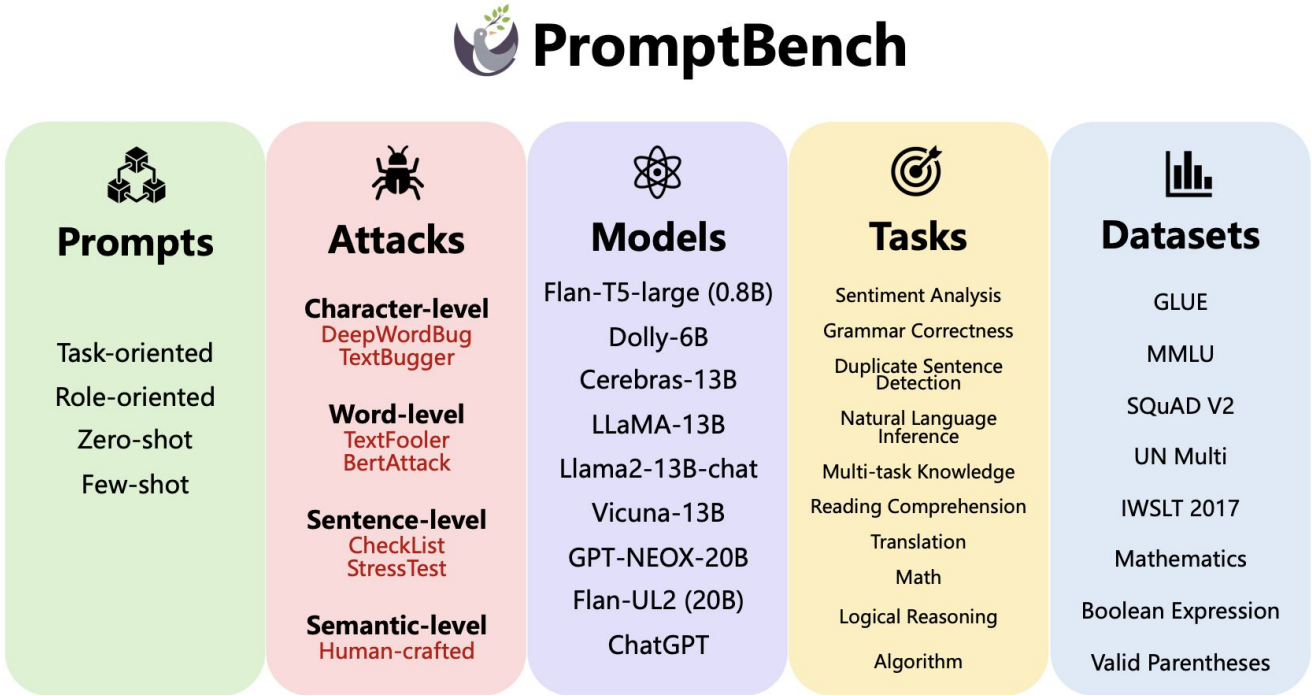
PromptBench



Prompt Attack

- Prompt-Sample

Definition 2.1 (Prompt Attack)**.** Given an LLM f_θ, a dataset $\mathcal{D}$, and a clean prompt P, the objective of a prompt attack can be formulated as follows:

$$\arg\max_{\delta \in \mathcal{C}} \mathbb{E}_{(x;y)\in\mathcal{D}} \mathcal{L}[f_\theta([P+\delta, x]), y], \tag{1}$$

where δ is the textual perturbation added to the clean prompt P and $\mathcal{C}$ is the allowable perturbation

Attack Level

- Character-level
- Word-level
- Sentence-level
- Semantic-level

Metric: Performance Drop Rate

$$PDR(A, P, f_\theta, \mathcal{D}) = 1 - \frac{\sum_{(x;y)\in\mathcal{D}} \mathcal{M}[f_\theta([A(P), x]), y]}{\sum_{(x;y)\in\mathcal{D}} \mathcal{M}[f_\theta([P, x]), y]}$$

Experiment Results

- Attacks from different-level
- Different LLM model performance
- Different types of Prompts

Experiment Results

Table 2: The APDR and standard deviations of different attacks on different datasets.

Dataset	Character-level		Word-level		Sentence-level		Semantic-level
	TextBugger	DeepWordBug	TextFooler	BertAttack	CheckList	StressTest	Semantic
SST-2	0.26±0.39	0.21±0.36	0.36±0.41	0.33±0.43	0.27±0.39	0.17±0.34	0.28±0.36
CoLA	0.37±0.39	0.29±0.36	0.45±0.35	0.46±0.38	0.25±0.32	0.21±0.28	0.27±0.35
QQP	0.20±0.32	0.18±0.27	0.28±0.34	0.31±0.36	0.13±0.25	-0.00±0.21	0.30±0.36
MRPC	0.24±0.33	0.21±0.30	0.29±0.35	0.37±0.34	0.13±0.27	0.20±0.30	0.28±0.36
MNLI	0.26±0.37	0.18±0.31	0.30±0.40	0.38±0.37	0.16±0.26	0.11±0.27	0.11±0.04
QNLI	0.36±0.39	0.41±0.36	0.54±0.39	0.56±0.38	0.22±0.37	0.18±0.26	0.35±0.33
RTE	0.24±0.37	0.22±0.36	0.28±0.38	0.31±0.38	0.19±0.32	0.18±0.25	0.28±0.33
WNLI	0.28±0.36	0.26±0.35	0.31±0.37	0.32±0.34	0.19±0.30	0.19±0.26	0.36±0.32
MMLU	0.18±0.22	0.11±0.15	0.20±0.18	0.40±0.30	0.14±0.20	0.03±0.16	0.17±0.17
SQuAD V2	0.09±0.17	0.05±0.08	0.27±0.29	0.32±0.32	0.02±0.03	0.02±0.04	0.07±0.09
IWSLT	0.09±0.14	0.11±0.12	0.29±0.30	0.13±0.18	0.10±0.10	0.17±0.19	0.18±0.14
UN Multi	0.06±0.08	0.08±0.12	0.17±0.19	0.10±0.16	0.06±0.07	0.09±0.11	0.15±0.18
Math	0.19±0.17	0.15±0.13	0.53±0.36	0.44±0.32	0.16±0.11	0.13±0.08	0.23±0.13
Avg	0.23±0.33	0.20±0.30	0.33±0.36	0.35±0.36	0.16±0.27	0.13±0.25	0.24±0.29

Experiment Results

Table 3: The APDR on different LLMs.

Dataset	T5	Vicuna	UL2	ChatGPT
SST-2	0.04±0.11	0.83±0.26	0.03±0.12	0.17±0.29
CoLA	0.16±0.19	0.81±0.22	0.13±0.20	0.21±0.31
QQP	0.09±0.15	0.51±0.41	0.02±0.04	0.16±0.30
MRPC	0.17±0.26	0.52±0.40	0.06±0.10	0.22±0.29
MNLI	0.08±0.13	0.67±0.38	0.06±0.12	0.13±0.18
QNLI	0.33±0.25	0.87±0.19	0.05±0.11	0.25±0.31
RTE	0.08±0.13	0.78±0.23	0.02±0.04	0.09±0.13
WNLI	0.13±0.14	0.78±0.27	0.04±0.03	0.14±0.12
MMLU	0.11±0.18	0.41±0.24	0.05±0.11	0.14±0.18
SQuAD V2	0.05±0.12	-	0.10±0.18	0.22±0.28
IWSLT	0.14±0.17	-	0.15±0.11	0.17±0.26
UN Multi	0.13±0.14	-	0.05±0.05	0.12±0.18
Math	0.24±0.21	-	0.21±0.21	0.33±0.31
Avg	0.13±0.19	0.69±0.34	0.08±0.14	0.18±0.26

Table 4: The APDR on different prompts.

Dataset	ZS-task	ZS-role	FS-task	FS-role
SST-2	0.29±0.38	0.24±0.34	0.26±0.42	0.28±0.41
CoLA	0.40±0.34	0.40±0.37	0.25±0.31	0.26±0.39
QQP	0.32±0.40	0.25±0.41	0.11±0.18	0.11±0.17
MRPC	0.30±0.38	0.42±0.41	0.12±0.15	0.13±0.19
MNLI	0.23±0.32	0.22±0.32	0.20±0.32	0.23±0.36
QNLI	0.38±0.37	0.45±0.39	0.32±0.37	0.35±0.37
RTE	0.25±0.33	0.25±0.34	0.23±0.34	0.25±0.37
WNLI	0.28±0.30	0.30±0.35	0.27±0.35	0.26±0.34
MMLU	0.21±0.22	0.19±0.23	0.18±0.25	0.13±0.21
SQuAD V2	0.16±0.26	0.20±0.28	0.06±0.11	0.07±0.12
IWSLT	0.18±0.22	0.24±0.25	0.08±0.09	0.11±0.10
UN Multi	0.17±0.18	0.15±0.16	0.04±0.07	0.04±0.07
Math	0.33±0.26	0.39±0.30	0.16±0.18	0.17±0.17
Avg	0.27±0.33	0.29±0.35	0.18±0.29	0.19±0.30

Wrong Answer Analysis

Attack	Pred.	[Prompts, sample]
BertAttack	N	In the role of a sentiment analysis tool, respond with 'positive' or 'negative' to classify this statement:the title not only describes its main characters , but the lazy people behind the camera as well . Answer:
	P	how the role of a compliment analysis tool, responses with 'positive' or 'negative' to mood this statement:the title not only describes its main characters , but the lazy people behind the camera as well . Answer:
CheckList	P	Given the context of this text, indicate if the emotion conveyed is 'positive' or 'negative':good film , but very glum . Answer:
	N	Given the context of this text, indicate if the emotion conveyed is 'positive' or 'negative' LkF0FZxMZ4:good film , but very glum . Answer:
DeepWordBug	N	Serving as a sentiment evaluation model, determine if the given statement is 'positive' or 'negative'. Classify:i had to look away - this was god awful . Answer:
	N/A	Servign as a sentimBnt envaluation model, Qetermine if the Iiven statemen is 'positive' or 'negative'. Classhfy: i had to look away - this was god awful . Answer:
Semantic	N	In the role of a sentiment analysis tool, respond with 'positive' or 'negative' to classify this statement:bad . Answer:
	P	Classify what you're trying to convey in this sentence as 'positive' if it's positive, and 'negative' if it's negative.bad . Answer:

Questions

- What are the differences between Interpretability and Explainability?
- Is complementary the best way for exemplar selection?
- How can we get approximation of non-linear transformations for better dictionary learning?

Thanks for listening!