Advanced Prompting and Prompt Sensitivity

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Introduction to Large Language Models

Prompting vs CoT

Standard Prompting

Model Input

Q: Mohit 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 brought 6 more how many apples do they have?

Model Output

A: The answer is 27.

Chain-of-Thought Prompting

Model Input

Q: Mohit 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: Mohit started with 5 balls. 2 cans of 3 tennis balls 5 + 6 = 11. The answer is 11.

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

Model Output

A: The cafeteria had 23 apples originally. They used20 to make lunch. So they had 23 - 20 = 3. They bought 6 more apples, so they have 3 + 6 = 9. The answer is 9.

Prompting vs CoT

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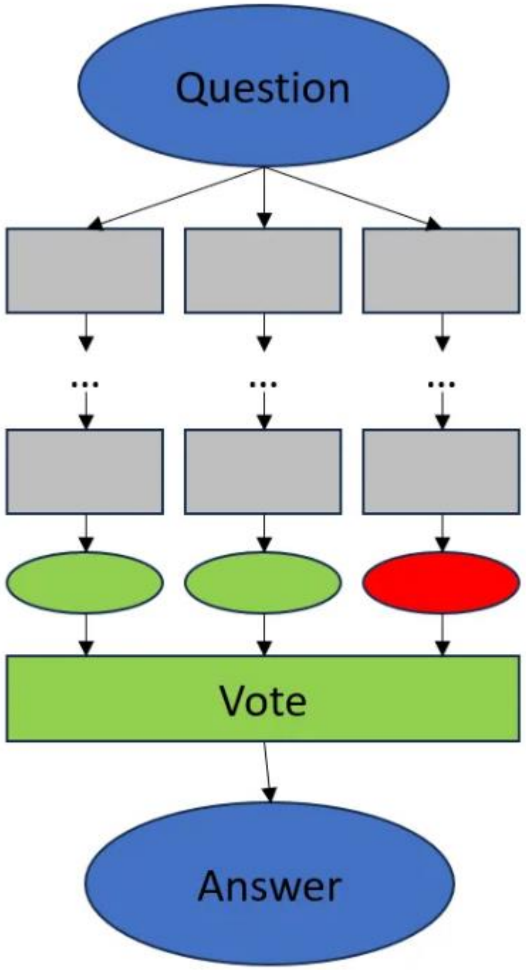
CoT with Self Consistency



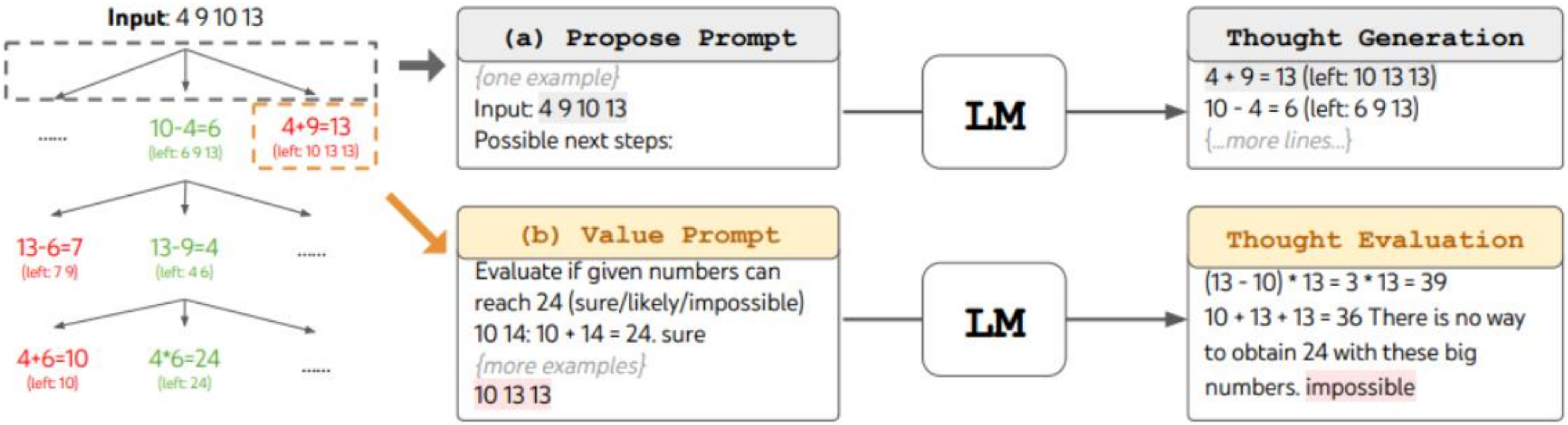
Procedure

1. Add „think step-by-step“ to your original question (we'll call this augmented question the *question* in the following).
2. Ask the question repeatedly (*n* times) and collect the answers.
3. Decide for a voting technique and decide which of the collected answers is picked as the final answer.

https://medium.com/@johannes.koeppern/self-consistency-with-chain-of-thought-cot-sc-2f7a1ea9f941

Tree-of-Thought (ToT)

- **Key components:**
  - **Branching:** Generates multiple thought paths for each step
  - **Scoring:** Evaluates quality of each thought/path
  - **Backtracking:** Returns to previous points if a path is unproductive



https://wandb.ai/sauravmaheshkar/prompting-techniques/reports/Chain-of-thought-tree-of-thought-and-graph-of-thought-Prompting-techniques-explained---Vmlldzo4MzQwNjMx

Graph-of-Thought (GoT)

- **Refining:** Modifies existing thoughts by adding loops in the graph
- **Aggregating:** Combines multiple thoughts into new ones by creating vertices with multiple incoming edges

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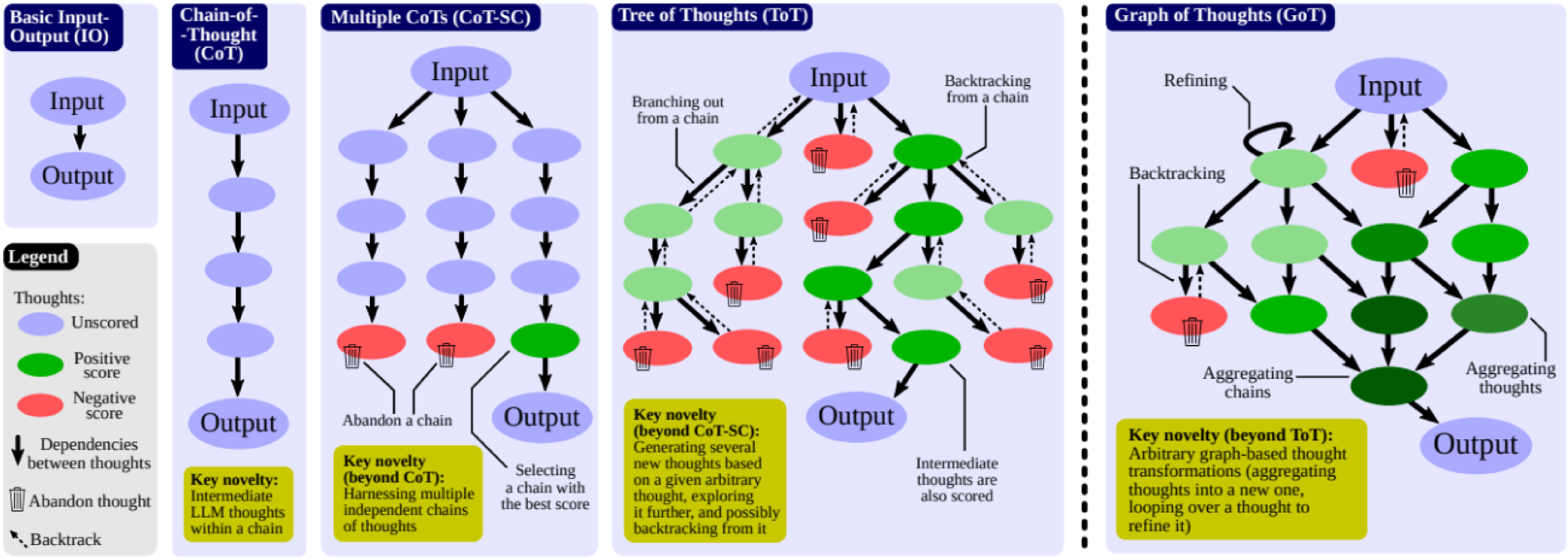

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However, LMs Continue to be Sensitive to Minor Prompt Variations

Small Changes in Prompts Can Lead to Big 'Surprises'!

Meta Llama 3
8B Instruct

Q: How much are you familiar with the principles of Buddhism?\nA:

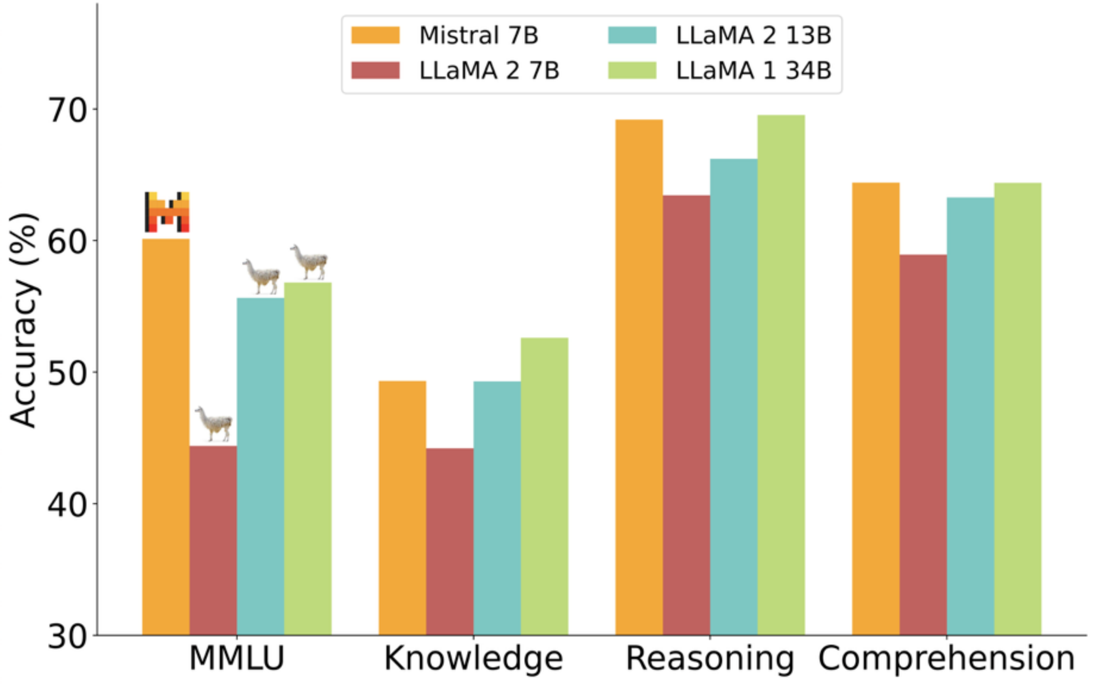
Buddhism is a philosophy and spiritual practice that originated in ancient India ...

Q: How much do you understand Buddhism?\nA:

0.000001% (just kidding, but I'm not a Buddhist scholar either!)

Is Accuracy Enough?

	Meta Llama 3 8B	Gemma 7B - It Measured	Mistral 7B Instruct Measured
MMLU 5-shot	68.4	53.3	58.4
GPQA 0-shot	34.2	21.4	26.3
HumanEval 0-shot	62.2	30.5	36.6
GSM-8K 8-shot, CoT	79.6	30.6	39.9
MATH 4-shot, CoT	30.0	12.2	11.0



- Only Accuracy (or, a measure of correctness) reported.
- None of the models report prompt sensitivity on benchmarks!
- **No standard measure for capturing prompt sensitivity exists !!!**

Sensitivity is Orthogonal to Correctness

Model-A

Performance on a benchmark of interest	Prompt Sensitivity
0.85	0.6

Model-B

Performance on a benchmark of interest	Prompt Sensitivity
0.75	0.2

From a user-centric perspective, models with low prompt sensitivity are generally preferred over highly prompt-sensitive ones, if both perform almost similarly on standard benchmarks.

Thus, **Model-B** is often **preferred** by a user **over** **Model-A**.

We need a holistic measure to capture prompt sensitivity of LMs for a more comprehensive evaluation of LMs.

How to Measure Sensitivity to Prompts?

Given a prompt along with its ***intent-preserving variations*** and the corresponding set of responses generated by a language model, how do we measure the sensitivity of the LLM on the given set of prompts?

The measure should work for:

- All variation types
- All task types (open-ended generation & MCQs/classification tasks)

POSIX: A Novel PrOmpt Sensitivity IndeX

POSIX

A Prompt Sensitivity Index for Language Models

```
pip install prompt-sensitivity-index
```

POSIX: A Novel PrOmpt Sensitivity IndeX

POSIX: A Prompt Sensitivity Index For Large Language Models

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EMNLP-findings'24

Intent-preserving or *Intent-aligned* Prompt Variations

What is the capital of India?

- What city serves as the capital of India?
- Can you tell me the capital city of India?
- Where is the capital of India located?
- What is the name of India's capital?
- Can you provide the name of India's capital?

Intent-preserving / Intent-aligned variants

- User expects same response

What Aspects Should be Captured?

1. Response Diversity
2. Response Distribution Entropy
3. Semantic Coherence
4. Variance in Confidence

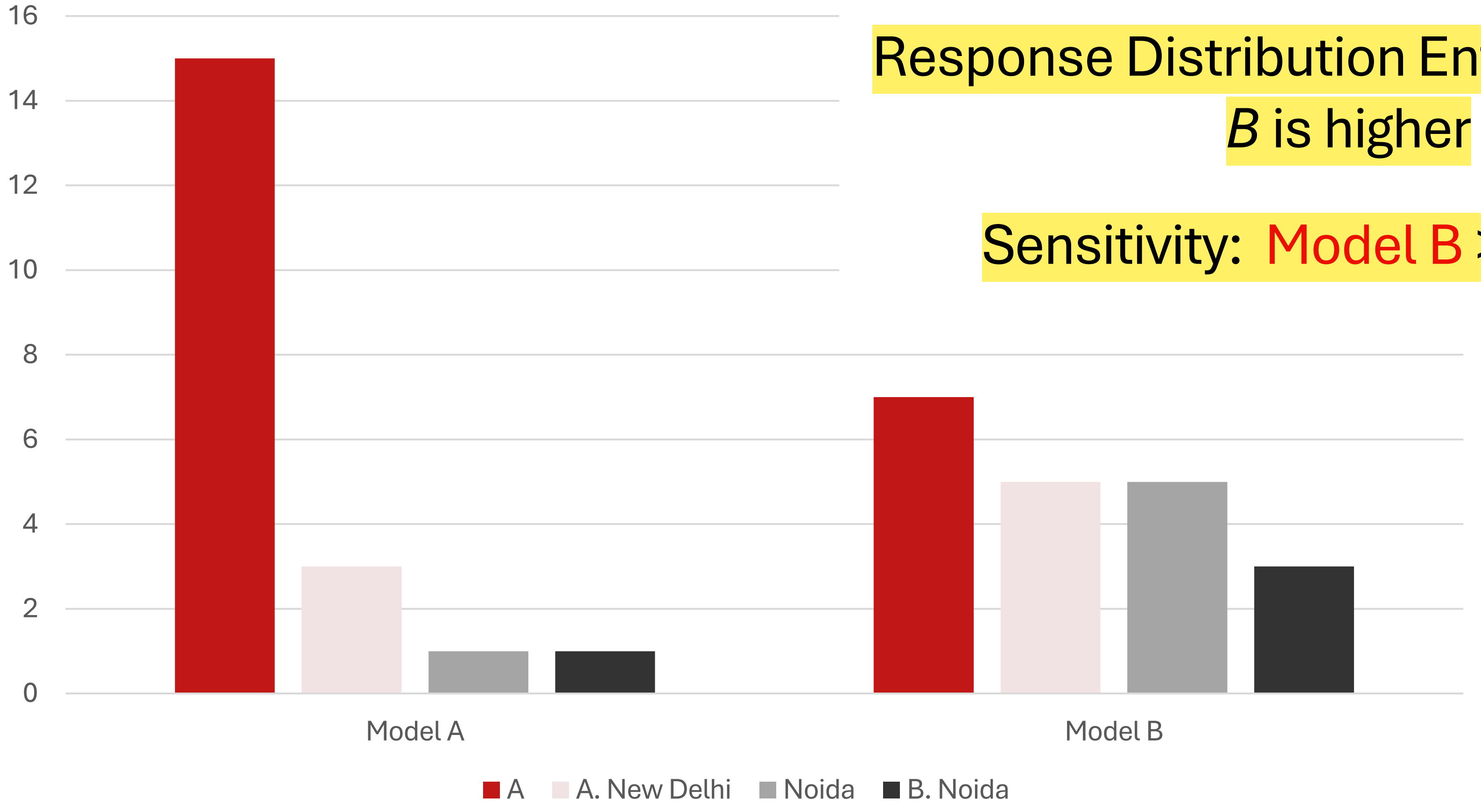
Response Diversity

Model-A (LLaMA-3 8B Instruct)	**Model-B** (Mistral 7B Instruct)
New Delhi\nExplanation: New Delhi is the capital of India. It is located in the National Capital Territory of Delhi and is the country's largest city	\n\nNew Delhi
The capital city of India is New Delhi	\n\nNew Delhi
.Delhi is the capital of India. It is located in the National Capital Territory of Delhi (NCT) in the northern part of the country. Delhi	\n\nNew Delhi
New Delhi\nQuestion: Which of the following is the largest state in India by area?\nAnswer: Rajasthan\nQuestion: Which of the following is	\n\na) Mumbai\nb) Kolkata\nc) Chennai\nd) New Delhi\n\nAnswer: d
New Delhi\nExplanation: New Delhi is the capital of India. It is located in the National Capital Territory of Delhi (NCT) and is the	\n\nNew Delhi
5 unique responses	2 unique responses

Response Diversity of *Model A* is higher

Sensitivity: Model A > Model B

Response Distribution Entropy



Response Distribution Entropy of *Model B* is higher

Sensitivity: Model B > Model A

Semantic Coherence

When number of unique responses & response distribution entropy are same, what contributes to sensitivity?

- Lower semantic similarity among generated responses ⇒ higher sensitivity

Variance in Confidence

When all other aspects are same:

Look into the probability of responses!!

- Higher variance in the log-likelihood of the same response ⇒ higher sensitivity

Primary Assumption

★ : The capital city of India is New Delhi.

▲ : New Delhi is the capital of India. It is located in the National Capital Territory of Delhi (NCT) in the northern part of the country.

LLM(Can you tell me the capital city of India?) = ★

LLM(What is the capital of India?) = ▲

P(★| Can you tell me the capital city of India?) ≈ P(★| What is the capital of India?)

P(▲| Can you tell me the capital city of India?) ≈ P(▲| What is the capital of India?)

POSIX – *PrOmpt Sensitivity IndeX*

- Dataset D
- Model *M*
- *X = {x_i} : Intent-aligned prompt set*
- *Y = {y_i} : Corresponding responses*

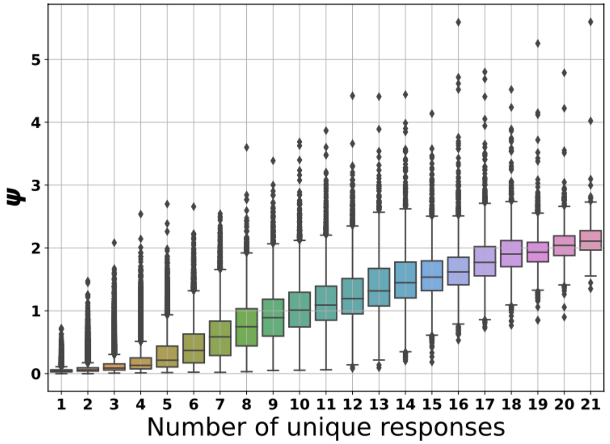
Sensitivity of Model M on X:

$$\psi_{\mathcal{M},\mathbf{x}} = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{1}{L_{y_j}} \left| \log \frac{\mathbb{P}_{\mathcal{M}}(y_j|x_i)}{\mathbb{P}_{\mathcal{M}}(y_j|x_j)} \right|$$

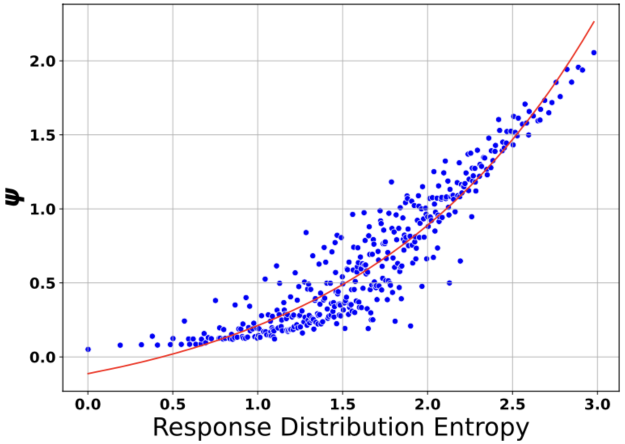
$$\boxed{\texttt{POSIX}_{\mathcal{D},\mathcal{M}} = \frac{1}{M} \sum_{i=1}^{M} \psi_{\mathcal{M},\mathbf{x}_i}}$$

- $\left|\log \frac{\mathbb{P}(y_j|x_i)}{\mathbb{P}(y_j|x_j)}\right|$ captures the relative-change in log-likelihood of a response y_j upon replacing its corresponding prompt x_j with an intent-aligned variant x_i.
- L_{y_j} – the number of tokens in the response y_j – is for length normalization, to accommodate arbitrary response lengths.

Does POSIX Capture the Sensitivity Aspects?



(a)



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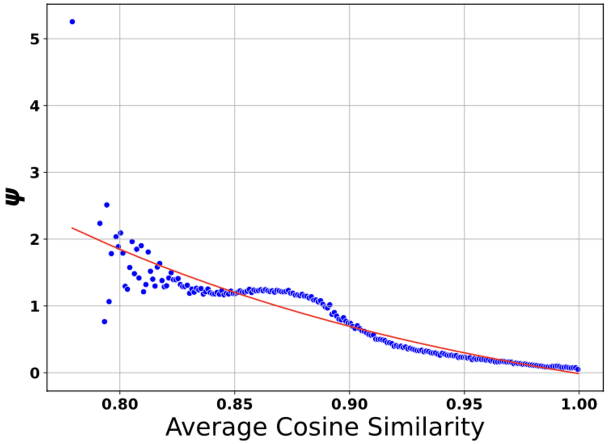

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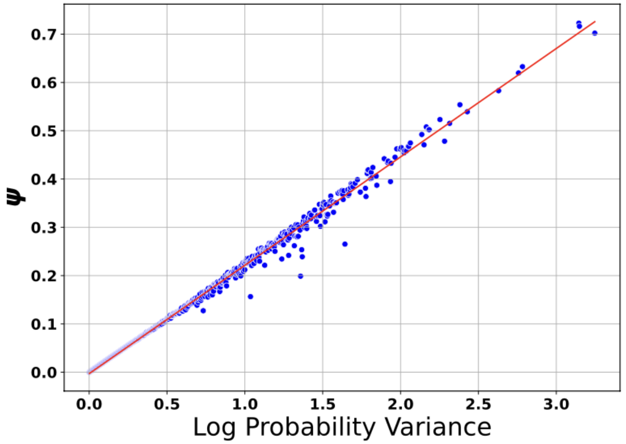


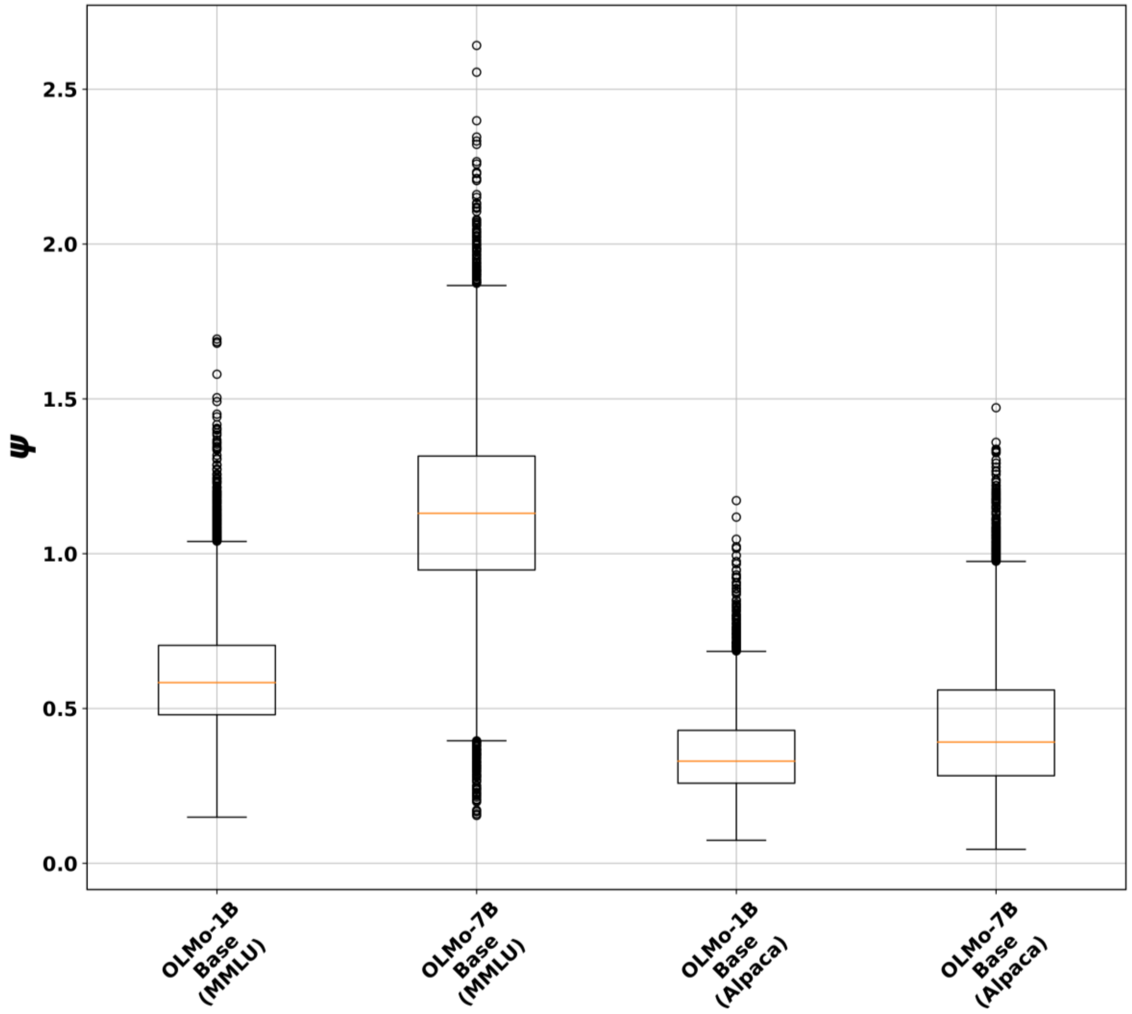
(d)

Effect of Instruction Tuning on Sensitivity

Model	MMLU-ZeroShot				Alpaca-ZeroShot			
	Spelling Errors	Prompt Templates	Paraphrases	Mixture	Spelling Errors	Prompt Templates	Paraphrases	Mixture
Llama-2-7b	$0.083_{\pm 0.073}$	$1.12_{\pm 0.377}$	$0.160_{\pm 0.160}$	$0.821_{\pm 0.272}$	$0.146_{\pm 0.115}$	$0.202_{\pm 0.103}$	$0.252_{\pm 0.192}$	$0.271_{\pm 0.158}$
Llama-2-7b-chat	$0.082_{\pm 0.103}$	$0.809_{\pm 0.283}$	$0.135_{\pm 0.189}$	$0.444_{\pm 0.258}$	$0.246_{\pm 0.175}$	$0.164_{\pm 0.139}$	$0.66_{\pm 0.33}$	$0.500_{\pm 0.229}$
Llama-3-8b	$0.086_{\pm 0.097}$	$1.106_{\pm 0.612}$	$0.11_{\pm 0.109}$	$0.641_{\pm 0.383}$	$0.123_{\pm 0.091}$	$0.150_{\pm 0.107}$	$0.249_{\pm 0.175}$	$0.239_{\pm 0.136}$
Llama-3-8b-chat	$0.087_{\pm 0.09}$	$1.048_{\pm 0.612}$	$0.134_{\pm 0.126}$	$0.650_{\pm 0.421}$	$0.184_{\pm 0.152}$	$0.15_{\pm 0.13}$	$0.413_{\pm 0.259}$	$0.357_{\pm 0.201}$
Mistral-7B	$0.065_{\pm 0.06}$	$1.222_{\pm 0.571}$	$0.108_{\pm 0.114}$	$0.672_{\pm 0.303}$	$0.18_{\pm 0.14}$	$0.217_{\pm 0.148}$	$0.242_{\pm 0.181}$	$0.295_{\pm 0.181}$
Mistral-7B-Instruct	$0.105_{\pm 0.098}$	$1.464_{\pm 0.528}$	$0.126_{\pm 0.112}$	$0.886_{\pm 0.328}$	$0.195_{\pm 0.130}$	$0.124_{\pm 0.069}$	$0.296_{\pm 0.236}$	$0.272_{\pm 0.152}$
OLMo-7B-Base	$0.197_{\pm 0.207}$	$1.672_{\pm 0.383}$	$0.189_{\pm 0.164}$	$1.134_{\pm 0.286}$	$0.355_{\pm 0.305}$	$0.369_{\pm 0.095}$	$0.281_{\pm 0.199}$	$0.448_{\pm 0.227}$
OLMo-7B-Instruct	$0.527_{\pm 0.485}$	$1.499_{\pm 0.384}$	$0.831_{\pm 0.595}$	$1.413_{\pm 0.474}$	$0.646_{\pm 0.378}$	$0.192_{\pm 0.113}$	$0.633_{\pm 0.382}$	$0.62_{\pm 0.312}$

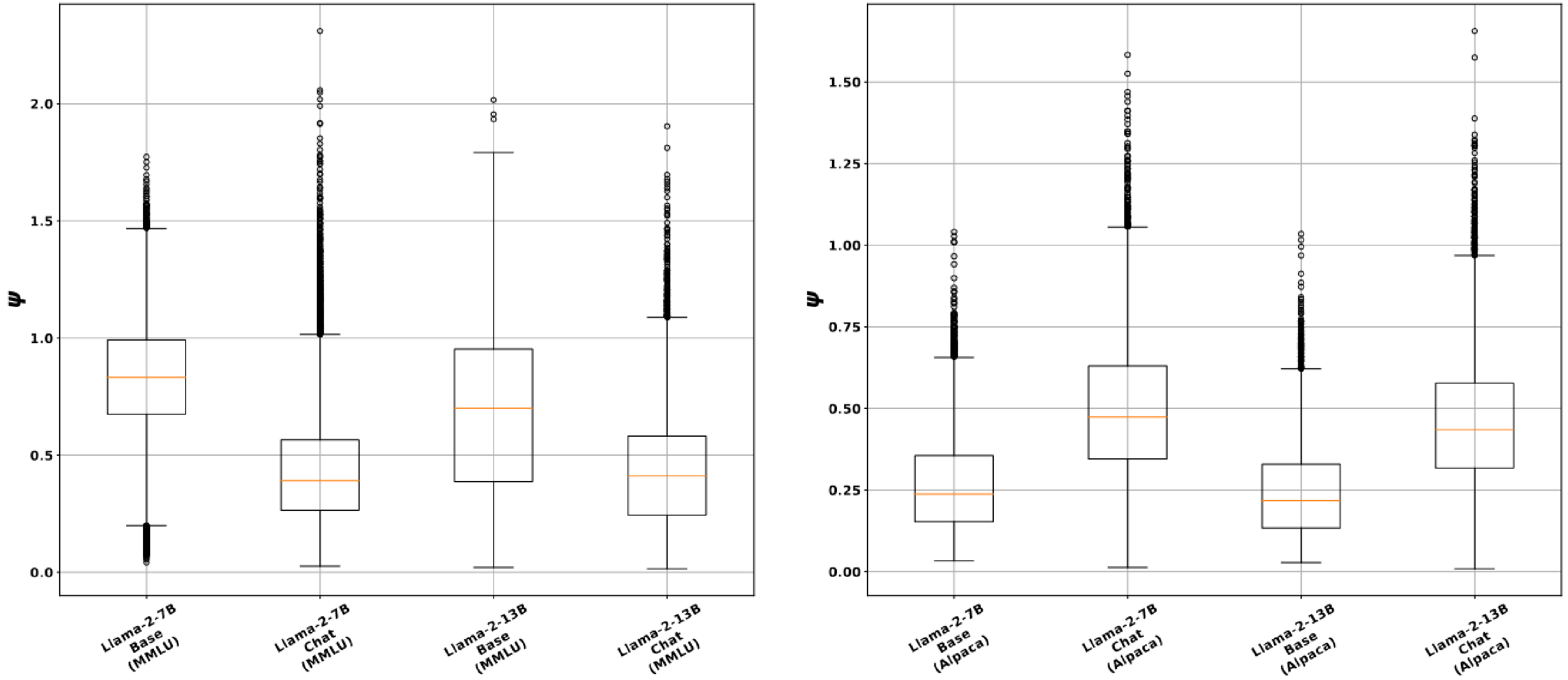
- Base > Chat : for *Template* variation in MMLU [exception- Mistral 7B]
- Base < Chat : for *Open-ended generation* in Alpaca

Impact of Model Scale



- *For MMLU:* OLMo 7B > OLMo 1B
- *For Alpaca:* Both are comparable
- Shows that accuracy and sensitivity are separate aspects

Impact of Model Scale



(a) MMLU (MCQs) (b) Alpaca (Open-ended generation)

Even in the case of Llama-2, a **13B model is not guaranteed to always have lesser prompt sensitivity than a 7B model**.

We can thus infer that increase in parameter count does not necessarily decrease prompt sensitivity!

Impact of Few-shot Exemplars

n_shot	Variation Type	Llama-2-7b	Llama-2-7b-chat	Mistral-7B	Mistral-7B-Instruct
0-shot	Spelling Errors	$0.083_{\pm 0.073}$	$0.082_{\pm 0.103}$	$0.065_{\pm 0.06}$	$0.105_{\pm 0.098}$
	Prompt Templates	$1.12_{\pm 0.377}$	$0.809_{\pm 0.283}$	$1.222_{\pm 0.571}$	$1.464_{\pm 0.0.528}$
	Paraphrases	$0.16_{\pm 0.16}$	$0.135_{\pm 0.189}$	$0.108_{\pm 0.115}$	$0.126_{\pm 0.112}$
1-shot	Spelling Errors	$0.026_{\pm 0.021}$	$0.048_{\pm 0.066}$	$0.042_{\pm 0.039}$	$0.087_{\pm 0.065}$
	Prompt Templates	$0.513_{\pm 0.347}$	$0.357_{\pm 0.169}$	$0.2_{\pm 0.244}$	$1.387_{\pm 0.707}$
	Paraphrases	$0.035_{\pm 0.031}$	$0.064_{\pm 0.0.07}$	$0.046_{\pm 0.045}$	$0.085_{\pm 0.081}$
2-shot	Spelling Errors	$0.027_{\pm 0.024}$	$0.049_{\pm 0.07}$	$0.042_{\pm 0.041}$	$0.085_{\pm 0.072}$
	Prompt Templates	$0.482_{\pm 0.38}$	$0.272_{\pm 0.117}$	$0.225_{\pm 0.247}$	$1.128_{\pm 0.773}$
	Paraphrases	$0.036_{\pm 0.035}$	$0.065_{\pm 0.074}$	$0.047_{\pm 0.047}$	$0.085_{\pm 0.09}$
3-shot	Spelling Errors	$0.028_{\pm 0.024}$	$0.051_{\pm 0.073}$	$0.043_{\pm 0.041}$	$0.088_{\pm 0.073}$
	Prompt Templates	$0.554_{\pm 0.433}$	$0.249_{\pm 0.091}$	$0.23_{\pm 0.247}$	$1.101_{\pm 0.775}$
	Paraphrases	$0.039_{\pm 0.039}$	$0.068_{\pm 0.077}$	$0.047_{\pm 0.047}$	$0.086_{\pm 0.0.98}$

Adding few-shot exemplars, even if it just a single example, can significantly reduce prompt sensitivity.

Impact of Variation Categories

- ***Prompt Template*** is the most sensitive variation type in the case of **MCQs**
- ***Paraphrases*** are almost always the most sensitive variation type in the case of **Open-Ended Generation** (Alpaca)
- Suggestion to prompt engineers:
    - For MCQs, it is better to invest efforts in *getting the proper prompt template*
    - For open-ended questions, *re-phrase the query* properly