Metacognitive Prompting Improves Understanding in Large Language Models

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https://arxiv.org/pdf/2305.18290.pdf

Introduction

- The nuanced understanding abilities of LLM remain unexplored 😢
- **Metacognition**: "Thinking about thinking"
  - 메타인지: 자기 인지 능력, 자신이 무엇을 알고 무엇을 모르는지 아는 것, 자신의 사고과정에 대한 이해 및 평가가 가능
- **Metacognitive Prompting**:

  This approach integrates key aspects of human metacognitive process into LLM

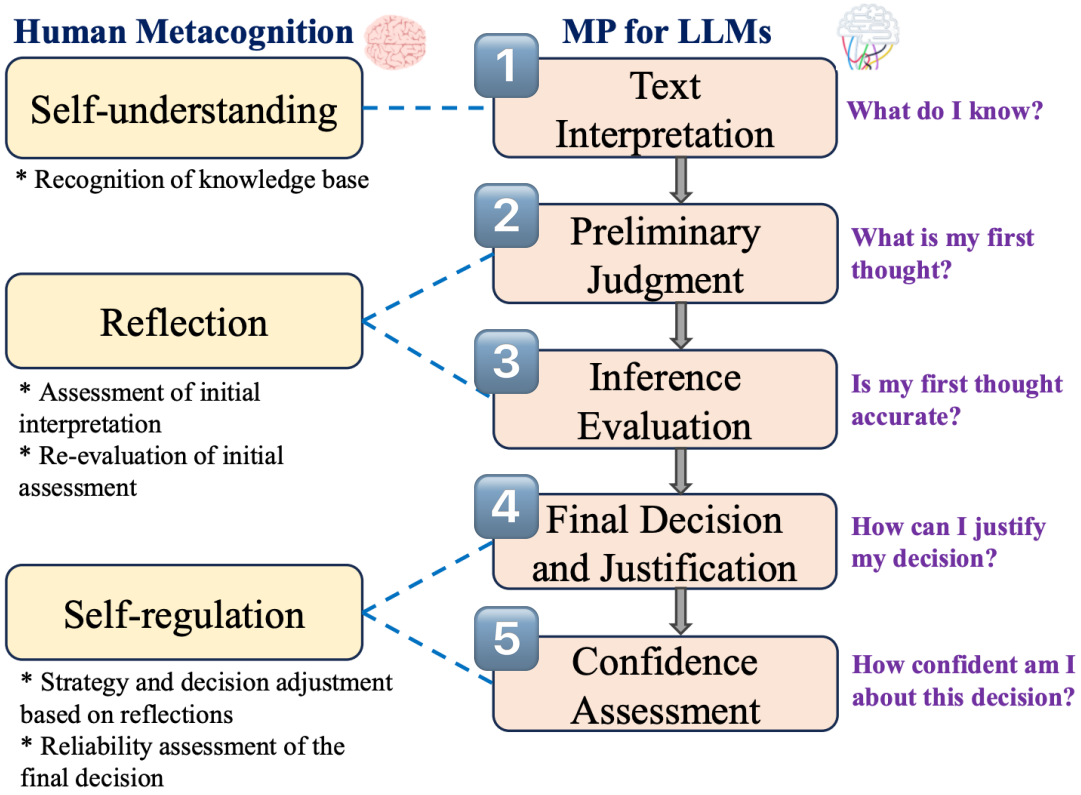


Figure 1: Alignment between human metacognitive processes and the stages of MP in LLMs.

Related Works

- **Prompting Techniques in LLMs**
  - Current research focuses on “reasoning abilities”
  - E.g., CoT, Self-Consistency, Least-to-Most, ToT, and Plan and Solve Prompting
  - But enhancing NLU remains challenge
- **Natural Language Understanding in NLP**
  - NLU, the fundamental aspect of NLP, is a model’s capacity to grasp semantics and nuances of human language
  - The inherent NLU competencies of LLMs have remained relatively inadequately explored
- **Cognitive Processes in NLU**
  - Cognitive processes heavily influence our linguistic abilities
  - In domain of NLU, incorporating cognitive insights may offer improvements

Metacognitive Prompting

Overview

Human's high-level cognition is from...

1. Breaking down abstract concepts
2. Critically evaluating scenarios
3. Finetuning our reasoning.

→ Let's equip LLMs that simulates **the self-reflective cognitive process**!

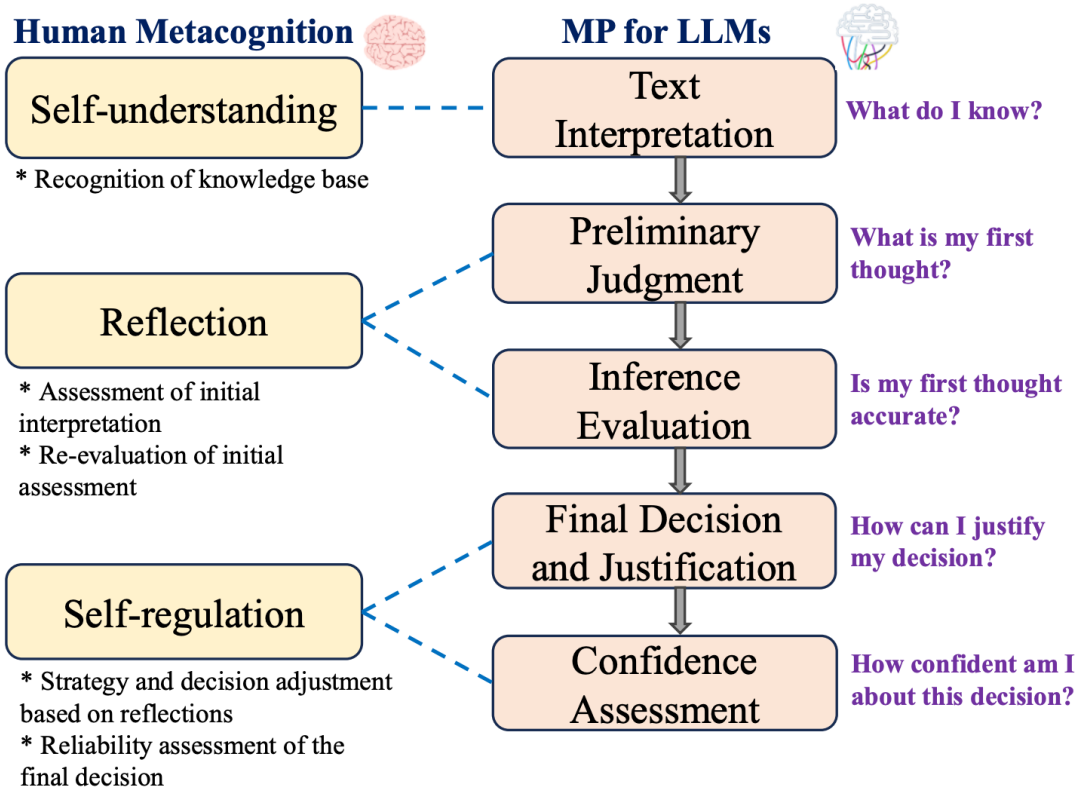
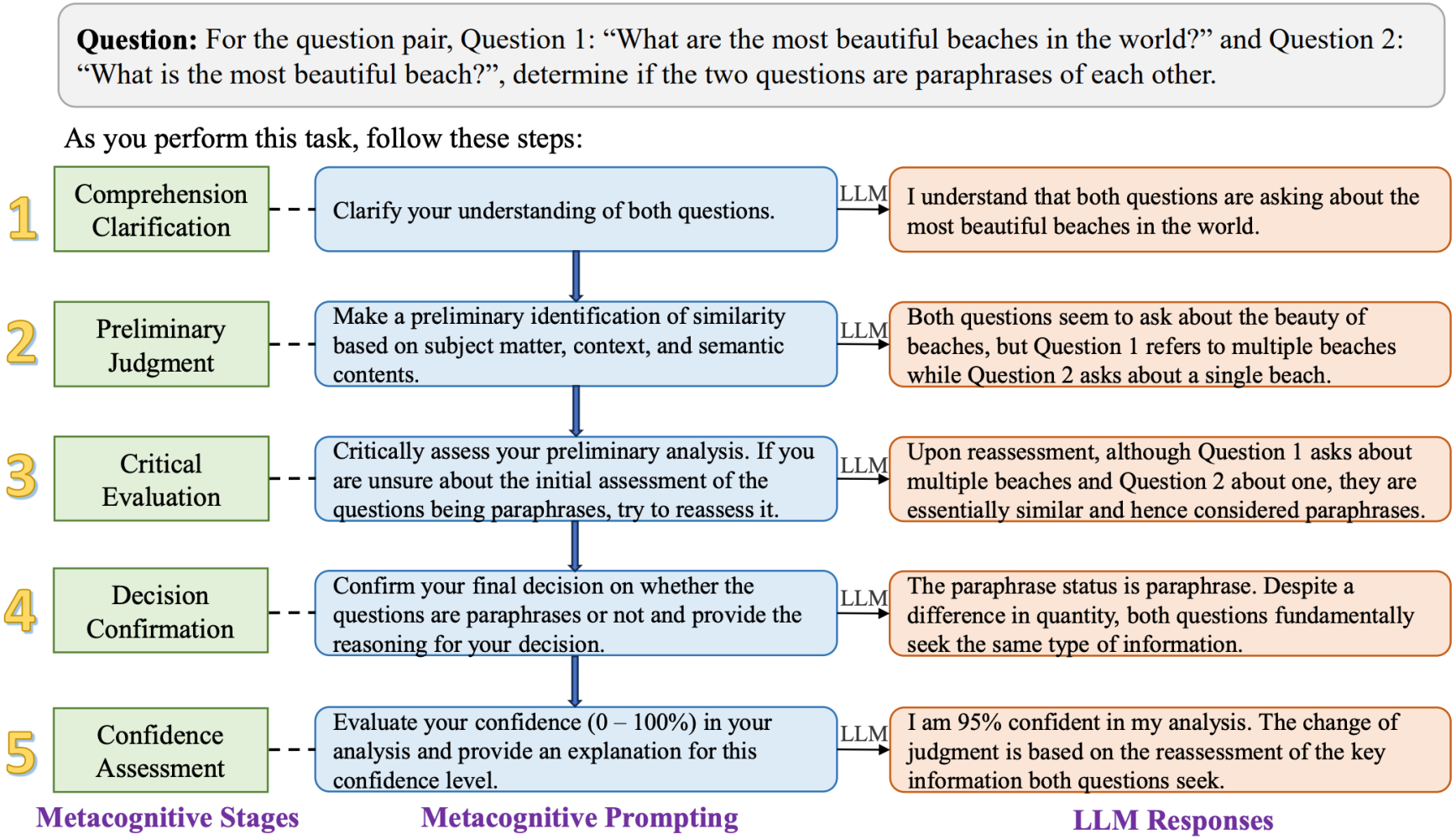


Figure 1: Alignment between human metacognitive processes and the stages of MP in LLMs.

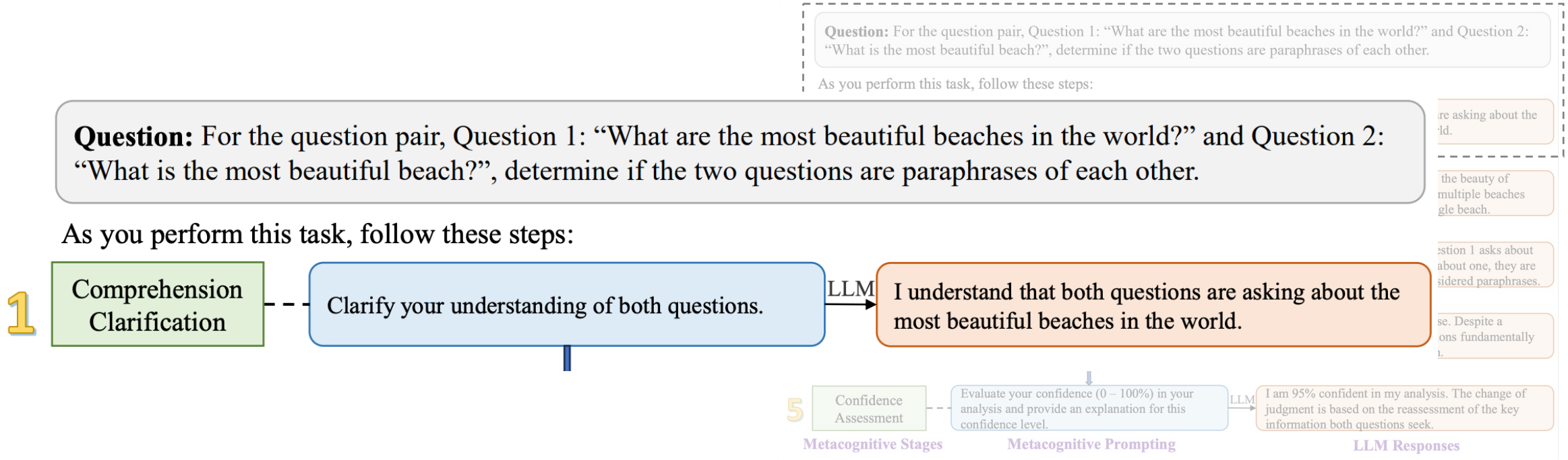
Metacognitive Prompting

Overview



Metacognitive Prompting

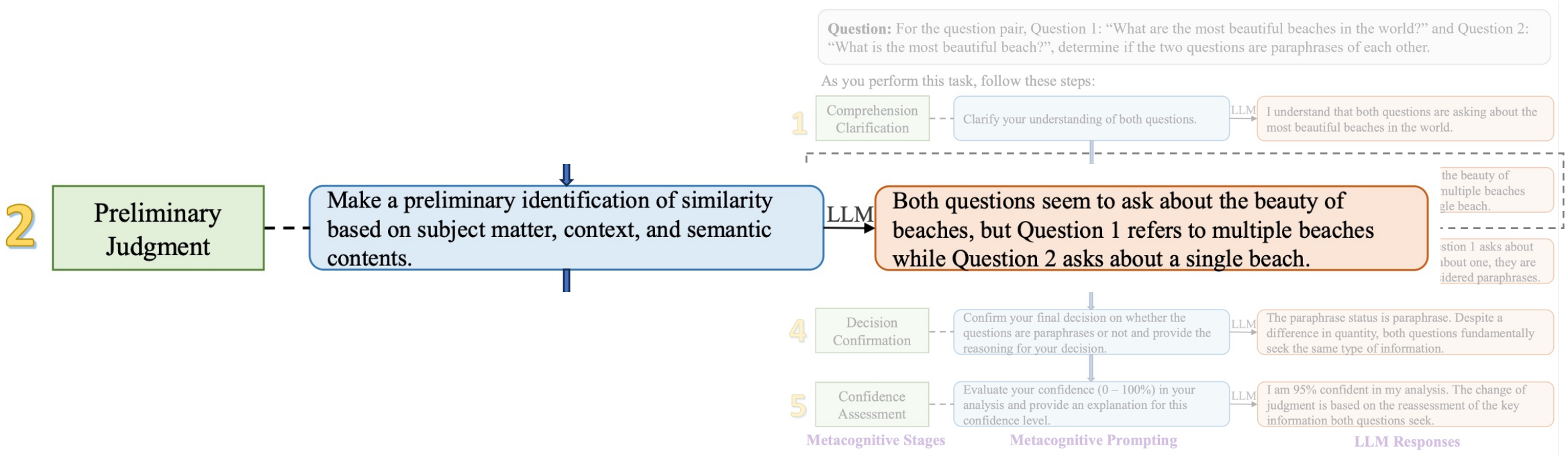
Step 1. Comprehension Clarification



- LLM begins by deciphering the input text to comprehend its context and meaning Logical Thinking
- This is mirroring the initial comprehension stage in human thought

Metacognitive Prompting

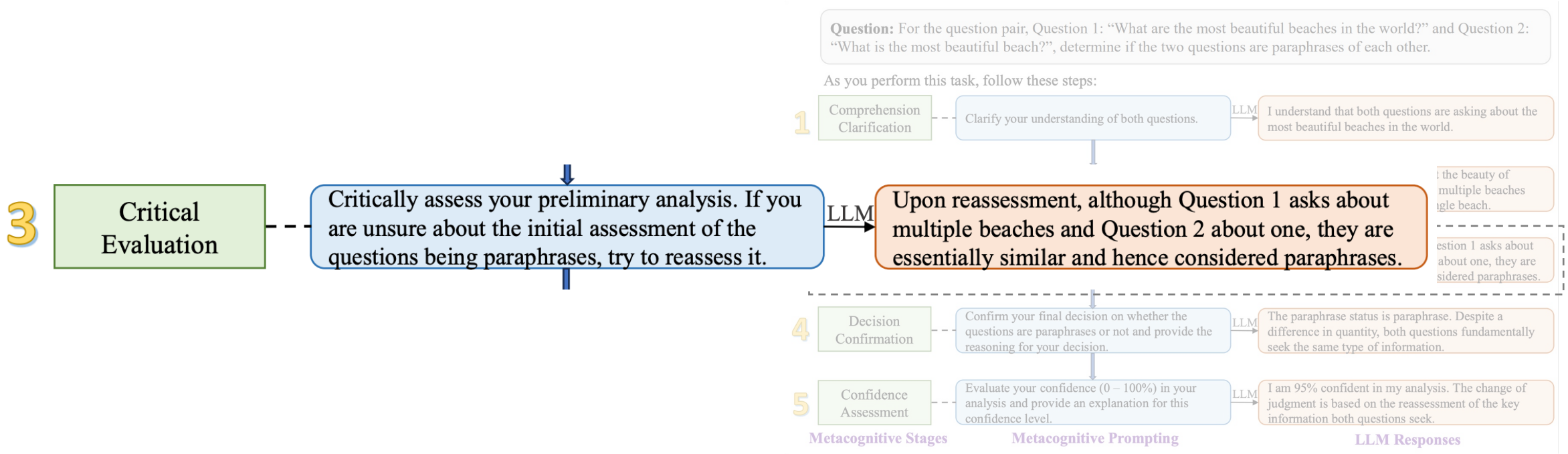
Step 2. Preliminary Judgement



- LLM then forms a preliminary interpretation of the text
- This is a step that reflects judgment formation in humans

Metacognitive Prompting

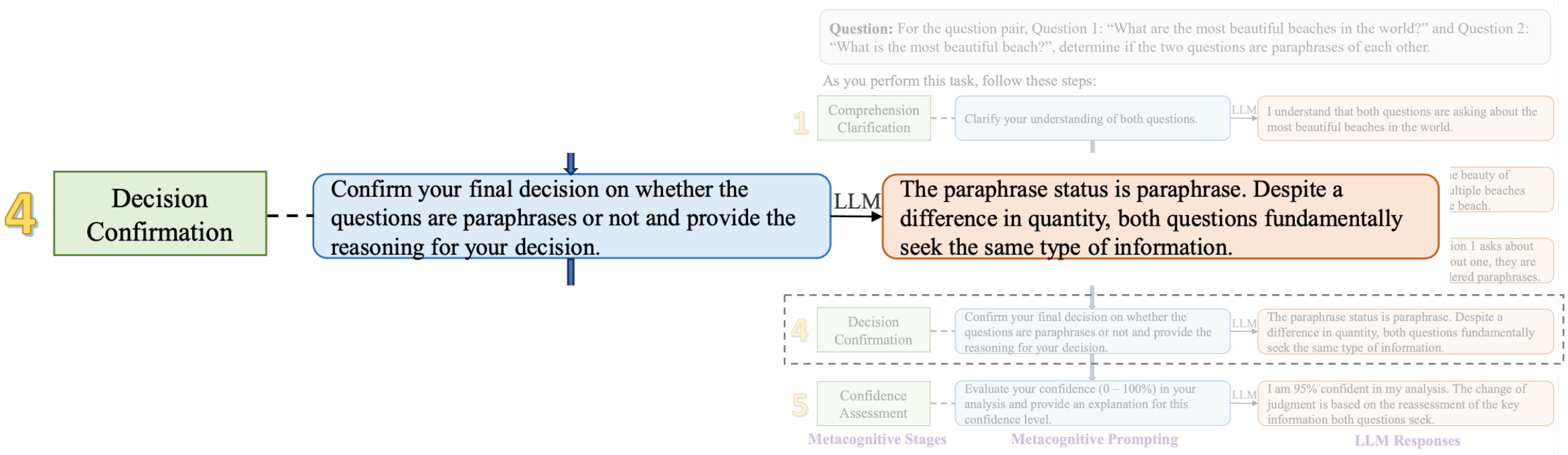
Step 3. Critical Evaluation



- LLM critically evaluates this initial judgment for accuracy
- This is akin to the self-scrutiny humans apply during problem-solving

Metacognitive Prompting

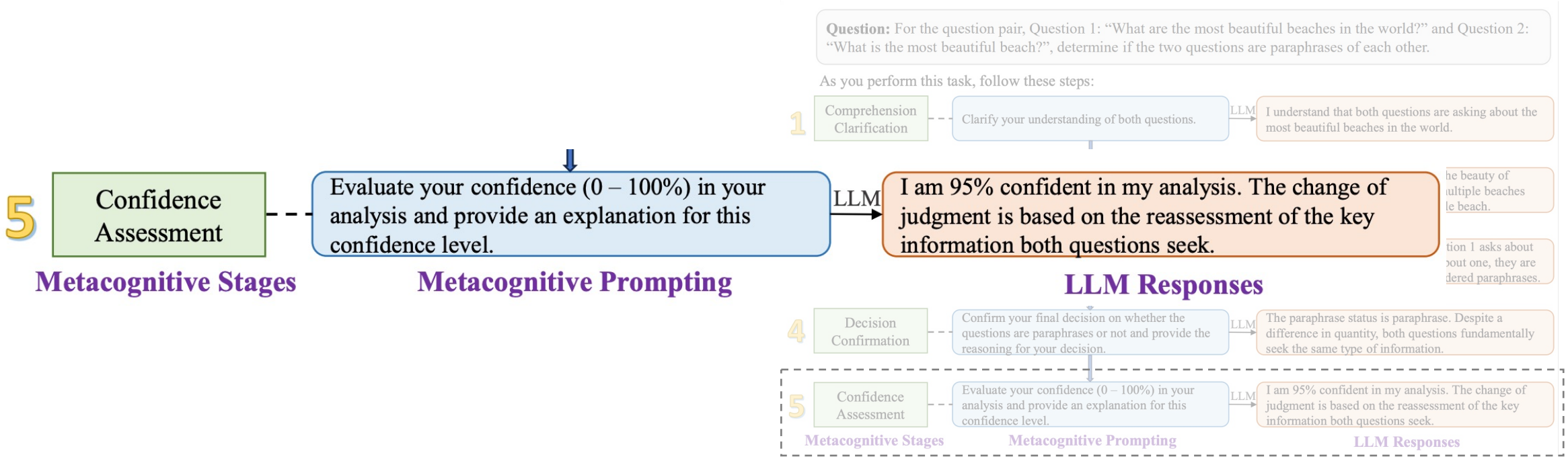
Step 4. Decision Confirmation



- LLM finalizes its decision and offers an explanation for its reasoning
- This aligns with the decision-making and rationalization phase in human cognition

Metacognitive Prompting

Step 5. Confidence Assessment



- LLM assesses its confidence in the outcome of the entire process
- This is similar with how humans gauge the certainty of their decisions and explanation

https://github.com/EternityYW/Metacognitive-Prompting/tree/main/prompts

Experiments

Datasets and Models

Source Benchmark	Dataset	Task	# Classes	Metrics	Domain
GLUE	QQP	Paraphrase	2 (paraphrase or not)	acc./F1	Social QA
	QNLI	QA/NLI	2 (entailment or not)	acc.	Wikipedia
SuperGLUE	BoolQ	QA	2 (yes/no)	acc.	Wikipedia, Google queries
	WiC	WSD	2 (True/False)	acc.	WordNet, Wiktionary, etc.
BLUE	BC5CDR-chem	NER	3 (BIO tags)	μ-F1	Biochemistry
	DDI	RE	4 (Advice, Effect, etc.)	m-F1	Biochemistry
	MedNLI	NLI	3 (ECN relations)	acc.	Clinical practice
LexGLUE	EUR-LEX	MLC	100 (EuroVoc concepts)	μ-F1/m-F1	EU Law
	LEDGAR	MCC	100 (contract provisions)	μ-F1/m-F1	Contracts
	UNFAIR-ToS	MLC	8 + 1 (unfair terms)	μ-F1/m-F1	Contracts

- **LLMs**
  - LLaMA-2-13B-Chat, PaLM-2-Bison-Chat, GPT-3.5-Turbo, GPT-4

Experiments

Datasets, Prompts, and Models

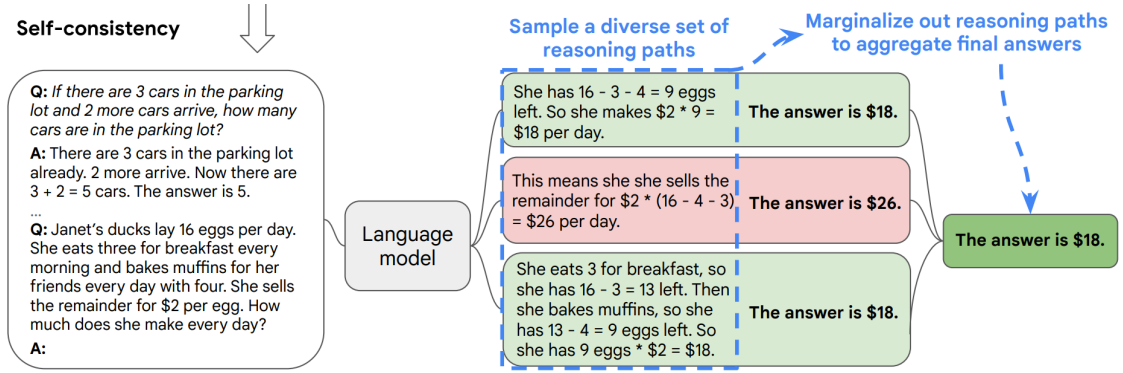
- **Prompts**

1) Zero-shot baselines

- Zero-shot CoT: *"Lets think step by step."*
- Plan-and-Solve Prompting: *"Let's first understand the problem and devise a plan to solve the problem. Then, let's carry out the plan and solve the problem step by step."*

2) Few-shot baselines

- Manual-CoT
- Self-consistency with CoT



Model Input

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

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

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

Results

Overall Performance Comparison

Method	Dataset									
	QQP	QNLI	BoolQ	WiC	BC5CDR-chem	DDI	MedNLI	EUR-LEX	LEDGAR	UNFAIR-ToS
	acc./F1	*acc.*	*acc.*	*acc.*	*μ-F1*	*m-F1*	*acc.*	*μ-F1/m-F1*	*μ-F1/m-F1*	*μ-F1/m-F1*
Llama2 (0S, CoT)	84.5/79.5	89.5	81.9	75.2	94.2	70.5	58.3	25.6/14.5	60.8/47.6	43.9/26.7
Llama2 (0S, PS)	85.6/80.8	89.9	83.1	76.0	95.6	72.0	59.1	27.8/16.9	61.4/48.1	46.1/28.4
Llama2 (0S, MP)	86.9/82.1	90.4	86.3	78.8	96.0	74.3	62.8	32.5/21.4	63.8/50.5	50.2/31.6
PaLM2 (0S, CoT)	85.4/80.6	89.9	88.1	76.4	94.5	70.9	61.1	24.8/13.1	63.9/49.1	46.2/29.1
PaLM2 (0S, PS)	85.2/80.3	89.5	89.5	77.1	94.9	72.8	60.9	26.1/14.8	65.0/52.7	47.4/30.8
PaLM2 (0S, MP)	86.2/81.9	90.8	90.5	78.8	96.2	74.0	63.3	29.3/16.5	67.6/54.8	52.5/33.7
GPT-3.5 (0S, CoT)	84.9/79.9	90.3	84.8	76.9	93.9	63.9	70.6	31.9/20.7	68.1/57.6	50.4/33.2
GPT-3.5 (0S, PS)	84.7/80.6	90.8	85.0	76.6	94.2	66.1	72.3	33.6/21.8	68.9/58.3	52.3/34.8
GPT-3.5 (0S, MP)	86.1/81.5	92.3	87.7	78.4	94.8	70.7	76.4	36.7/23.5	70.2/59.8	56.7/38.1
GPT-4 (0S, CoT)	88.9/84.7	95.0	90.4	82.0	97.3	72.1	78.2	37.4/24.8	73.6/59.4	54.7/38.5
GPT-4 (0S, PS)	89.4/85.3	96.2	90.7	82.4	97.6	73.5	79.8	39.6/27.1	75.4/60.7	58.3/41.7
GPT-4 (0S, MP)	89.9/86.2	97.1	91.4	83.6	98.5	74.7	81.1	43.8/29.9	78.1/62.8	64.0/45.3
Llama2 (5S, M-CoT)	85.2/80.2	90.1	82.8	76.5	94.9	73.8	61.2	23.3/12.7	54.7/43.3	52.8/35.6
Llama2 (5S, CoT-SC)	86.1/80.9	90.8	84.2	76.9	95.3	76.2	63.5	24.6/14.7	55.6/44.8	55.6/37.9
Llama2 (5S, M-MP)	88.1/83.2	91.6	87.4	79.5	96.6	77.3	64.7	27.8/15.9	58.2/46.6	59.7/41.2
PaLM2 (5S, M-CoT)	85.8/81.3	90.9	89.2	77.7	95.1	73.1	63.3	22.8/12.0	57.5/45.2	57.4/31.9
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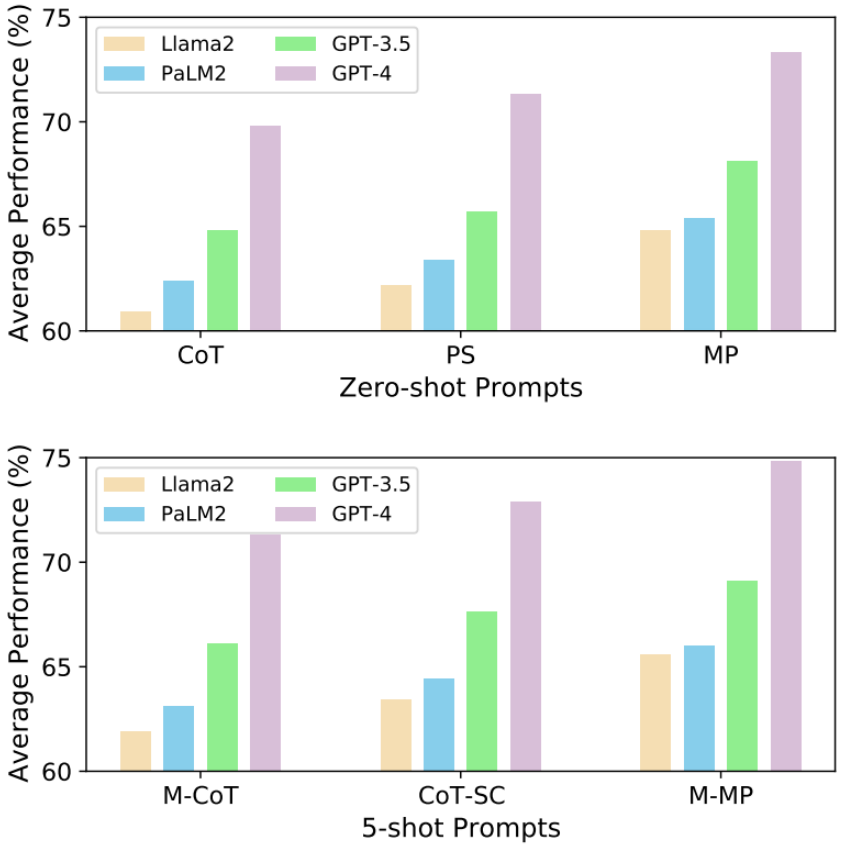
PaLM2 (5S, M-MP)	87.9/82.5	93.8	90.9	79.6	96.2	75.2	65.1	26.7/15.4	59.3/47.3	65.4/38.8
GPT-3.5 (5S, M-CoT)	85.1/80.2	91.2	86.7	77.4	94.7	67.8	74.3	29.3/19.5	61.7/50.1	62.3/45.1
GPT-3.5 (5S, CoT-SC)	86.1/81.7	91.4	88.3	78.8	95.7	70.1	76.5	30.6/19.8	63.0/51.4	65.7/47.2
GPT-3.5 (5S, M-MP)	86.4/81.9	93.1	89.7	79.1	96.6	71.6	78.1	32.4/20.7	64.9/53.7	69.1/50.1
GPT-4 (5S, M-CoT)	89.5/85.6	95.8	90.8	82.3	97.9	74.6	80.1	35.3/22.6	66.4/57.2	69.2/50.3
GPT-4 (5S, CoT-SC)	90.1/86.7	96.8	91.6	83.4	98.9	76.9	80.5	37.6/24.4	68.2/58.4	72.8/54.1
GPT-4 (5S, M-MP)	**91.3/88.2**	**98.9**	**92.0**	**84.3**	**99.4**	**80.8**	**82.4**	**40.1/28.8**	**70.3/59.9**	**75.6/55.8**

Results

Prompting Strategy Comparison



Model level comparison

Table 3: Comparison of average performance for zero-shot prompting methods across datasets. Performance metrics are averaged over all models. MP consistently achieves superior performance across all NLU tasks.

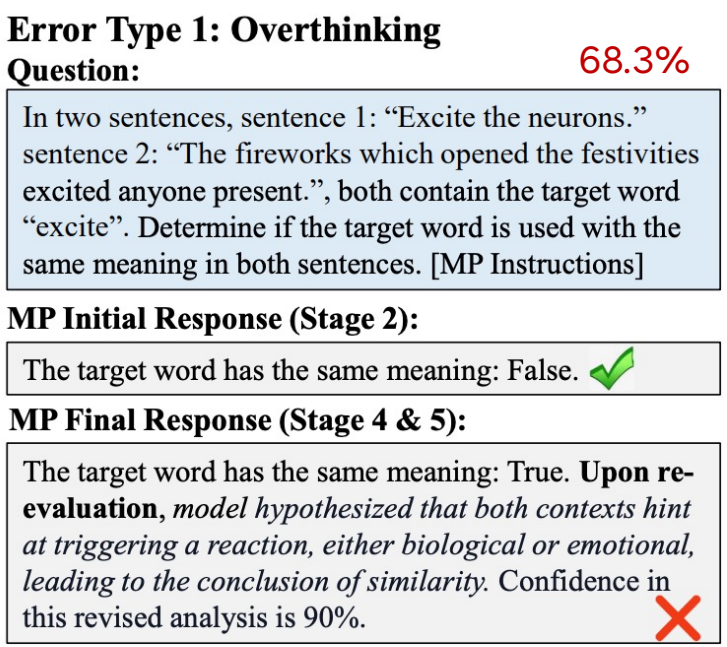
Dataset	CoT	PS	MP
QQP (*acc./F1*)	85.9/81.2	86.2/81.7	**87.3/82.9**
QNLI (*acc.*)	91.2	91.6	**92.6**
BoolQ (*acc.*)	86.3	87.1	**89.0**
WiC (*acc.*)	77.6	78.0	**79.9**
BC5CDR-chem (μ-*F1*)	95.0	95.6	**96.4**
DDI (*m-F1*)	69.4	71.1	**73.4**
MedNLI (*acc.*)	67.1	68.0	**70.9**
EUR-LEX (μ-*F1*/*m-F1*)	29.9/18.3	31.8/20.2	**35.6/22.8**
LEDGAR (μ-*F1*/*m-F1*)	66.6/53.4	67.7/54.9	**69.9/57.0**
UNFAIR-ToS (μ-*F1*/*m-F1*)	48.8/31.9	51.0/33.9	**55.8/37.2**

Data level comparison

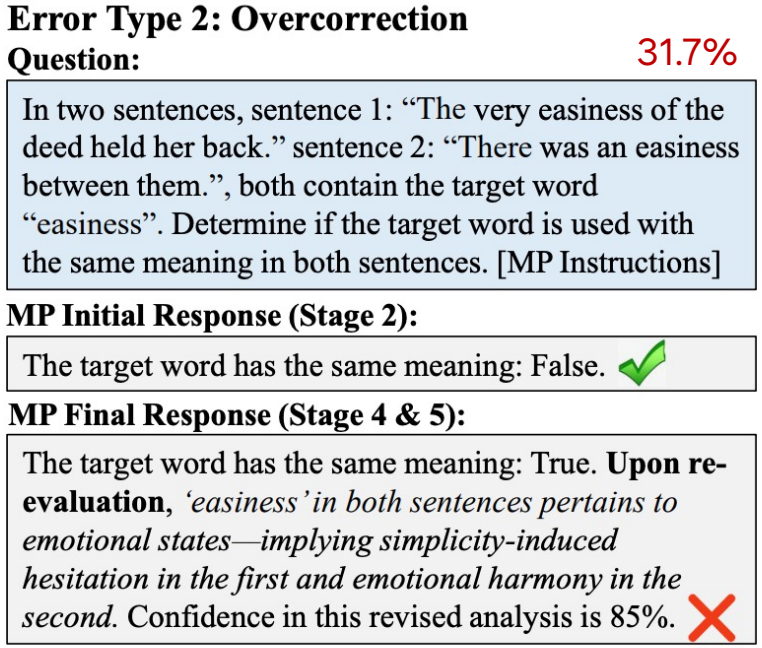
Results

Error Analysis

- Two main types of errors with MP across 10 datasets with manually inspection of incorrect prediction.



(a) Overthinking error in model response with MP.



(b) Overcorrection error in model response with MP.

- Domain-specific task
  - Biomedical NLU tasks: 'Terminological misalignments' (48.6%), 'Clinical inference discrepancies' (51.4%)
  - Legal NLU tasks: 'Statutory interpretation errors' (52.2%), 'Jurisprudential analysis deviations' (47.8%)

Results

Confidence Analysis

- **Observation**
  - High TP, Low TN: Reliable self-awareness and self-assessment
  - FP, FN: Pointing potential improvements

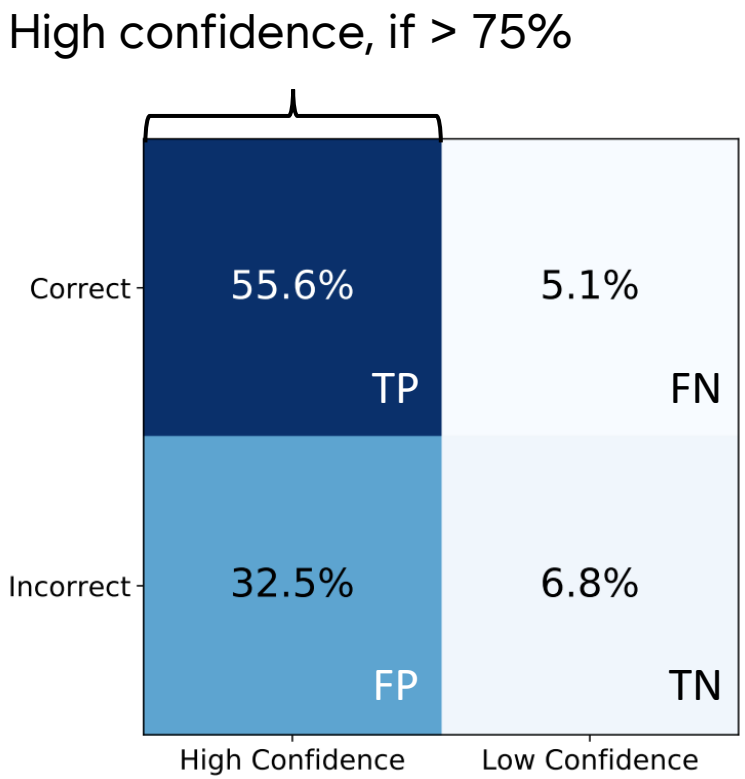


Figure 5: The relationship between correctness and confidence levels under MP, averaged over all datasets and models.

Limitations and Discussion

- **Limitation**
  1. Designing metacognitive prompts requires manual effort
  2. Selection of datasets and models
  3. The verbalized confidence might not serve as definite confidence method

  → **Suggestion**: Combining verbalization with self-consistency checks?

- **Discussion**
  - Applying MP more broadly… e.g., arithmetic, mental health care…
  - Introducing introspective LLMs, particularly regarding biases and the reliability of outputs