

Metacognitive Prompting Improves Understanding in Large Language Models

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<https://github.com/EternityYW/Metacognitive-Prompting>

Abstract

In Large Language Models (LLMs), there have been consistent advancements in task-specific performance, largely influenced by effective prompt design. While recent research on prompting has enhanced the reasoning capabilities of LLMs, a gap remains in further improving their understanding abilities. In this study, we introduce *Metacognitive Prompting* (MP), a strategy inspired by human introspective reasoning processes. Using MP, LLMs undergo a systematic series of structured, self-aware evaluations, drawing on both their vast inherent knowledge and new insights. Our experiments involve five prevalent LLMs: Llama2, Vicuna, PaLM, GPT-3.5, and GPT-4, all of which span various general natural language understanding (NLU) tasks from the GLUE and SuperGLUE benchmarks. Results indicate that, although GPT-4 consistently excels in most tasks, PaLM, when equipped with MP, approaches its performance level. Furthermore, across models and datasets, MP consistently outperforms existing prompting methods, including standard and chain-of-thought prompting. This study underscores the potential to amplify the understanding abilities of LLMs and highlights the benefits of mirroring human introspective reasoning in NLU tasks.

Introduction

Large Language Models (LLMs) have made significant advancements in natural language processing (NLP) in recent years (Min et al. 2021; Zhao et al. 2023; Wang, Zhao, and Petzold 2023a). However, as these models progress, simply increasing their scale does not necessarily enhance their understanding and reasoning capabilities (Rae et al. 2021). Delving into the intricacies of prompt design has emerged as a promising approach; it not only rivals the benefits of extensive fine-tuning but also offers clear advantages in sample efficiency (Liu et al. 2023; Kojima et al. 2022).

Several research efforts have extensively explored prompt design, particularly emphasizing the use of Chain-of-Thought (CoT) (Wei et al. 2022) approaches to advance intermediate reasoning steps. This research trajectory has given rise to variants such as the Least-to-Most (Zhou et al. 2022) and the Self-consistency (Wang et al. 2022a) techniques. While these strategies are effective in designated contexts, their main objective centers around enhancing explicit reasoning capacities in areas like arithmetic, common-sense, and symbolic reasoning, guiding LLMs through a

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logical progression of thought. However, a limitation arises in their capacity to deepen understanding. While reasoning entails methodically connecting concepts, understanding requires an intrinsic grasp of the underlying semantics and the broader context behind words.

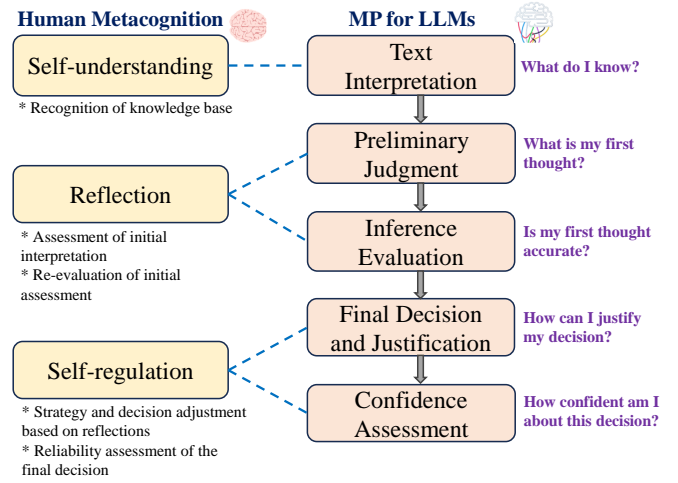


Figure 1: Alignment between human metacognitive processes and the stages of metacognitive prompting in LLMs.

While previous research primarily focuses on refining the logical progression of responses, the concept of metacognition—often defined as “thinking about thinking”—offers a unique perspective. Originating from the field of cognitive psychology (Schwarz 2015), metacognition pertains to an individual’s awareness and introspection of their cognitive processes. Informed by this insight, our proposed method, named *Metacognitive Prompting* (MP), integrates key aspects of human metacognitive processes into LLMs. Figure 1 illustrates the parallels between human metacognitive stages and the operational steps of our method in LLMs. Rather than concentrating solely on the mechanics of “how” a response is produced, this method delves deeper into the rationale or “why” behind it. The method proceeds as follows: 1) the LLM interprets the provided text, a phase reminiscent of human comprehension; 2) the model then forms an initial judgment, mirroring the stage in which humans generate judgments based on information; 3) the LLM sub-

jects its preliminary inference to critical evaluation, a step aligned with the self-reflection that humans engage in during cognitive processes; 4) after this introspective assessment, the model finalizes its decision and elucidates its reasoning, similar to human decision-making and rationalization; 5) finally, the LLM gauges its confidence in the outcomes, reflecting how humans evaluate the credibility of their judgments and explanations. This paradigm elevates the model’s function beyond simple systematic reasoning, compelling it to participate in introspective evaluations that determine the depth and relevance of its responses.

We conducted experiments on a range of NLU tasks from the GLUE (Wang et al. 2019b) and SuperGLUE (Wang et al. 2019a) benchmarks using several leading LLMs, including Llama2 (Touvron et al. 2023), Vicuna (Chiang et al. 2023), PaLM (Anil et al. 2023), GPT-3.5, and GPT-4 (OpenAI 2023). Our empirical evaluations underscore the superiority of MP over existing prompting strategies such as standard and CoT prompting. This work emphasizes the importance of incorporating human-inspired introspective reasoning into LLMs, shedding light on an approach that deepens their understanding abilities.

In summary, our contributions are threefold:

- (1) We introduce *metacognitive prompting*, a novel prompting strategy for LLMs rooted in human introspective reasoning. This method formalizes the self-aware evaluation process within the LLM, bridging the gap between mere task execution and deeper understanding.
- (2) Our extensive experiments across various NLU tasks demonstrate the superiority of MP over existing prompting paradigms, highlighting its potential to enhance LLM understanding abilities.
- (3) Through error and confidence analysis, we demonstrate that MP incorporates human-inspired introspection into LLM comprehension, thereby addressing specific understanding challenges and enhancing model reliability.

Related Work

Our proposal for metacognitive prompting is informed by several foundational trajectories: the evolving paradigms of prompting within LLMs, advancements in NLU in the broader NLP domain, and the intricate interplay between cognitive processes and NLU dynamics.

Prompting Techniques in LLMs

Prompts are essential tools for directing the vast capabilities of LLMs. These specially designed queries or statements direct the model, steering it towards generating accurate outputs or performing specific tasks. While current research primarily focuses on enhancing the reasoning abilities of LLMs, the main strategies include CoT-related methods (Wei et al. 2022; Zhou et al. 2022; Kojima et al. 2022; Zhang et al. 2022) involving multi-step reasoning, and self-consistency techniques (Wang et al. 2022a; Zheng et al. 2023). In the latter, multiple answers from the LLMs are considered, and the correct one is determined through majority voting. However, there still exists a significant gap in enhancing NLU within LLMs. Inspired by human cognitive

processes, we introduce MP. This approach not only seeks to bridge the understanding gap but also paves the way for deeper comprehension and more reliable model outputs.

Natural Language Understanding in NLP

Natural language understanding is a fundamental aspect of NLP, emphasizing a machine’s capacity to grasp the semantics and nuances of human language. Its applications span diverse domains such as question answering (Namazifar et al. 2021), text classification (Wang et al. 2022b), and natural language inference (Nie, Zhou, and Bansal 2020), as well as commercial tools like chatbots (Ait-Mlouk and Jiang 2020), voice assistants (Bellegarda 2013), and machine translation. While LLMs have gained remarkable traction in recent years, with increased efforts dedicated to expanding NLU boundaries, the primary research emphasis has been on their reasoning abilities (Huang and Chang 2022), ethical use (Weidinger et al. 2021; Zhuo et al. 2023), and broad applications (Zhao et al. 2021; Surameery and Shakor 2023; Wang, Zhao, and Petzold 2023b). However, the NLU competencies of LLMs have remained relatively underexplored. To address this gap, our study delves into the understanding capabilities of various LLMs, employing effective prompting techniques.

Cognitive Processes in NLU

The interplay between cognitive processes and NLU has always been a central consideration in computational linguistics (Periñán Pascual and Arcas Túnez 2007; Hausser and Hausser 2001). Cognitive processes, which encompass areas like attention, memory, reasoning, and problem-solving, govern how humans understand, produce, and engage with language in diverse scenarios. These processes heavily influence our linguistic abilities (Allen 1995; Cambria and White 2014). In the domain of NLU, incorporating cognitive insights may offer improvements in model comprehension. Recognizing this intrinsic connection, our work is inspired to employ a metacognition-based prompting technique, a method rooted in higher-order cognition that reflects on thinking and decision-making, to bolster the understanding capabilities of LLMs, thereby harmonizing traditional modeling techniques with cognitive nuances.

Metacognitive Prompting

In the complex terrain of human cognition, metacognition—our ability to introspect and regulate our thinking processes—stands as a keystone for intricate problem-solving and decision-making. This higher-level cognition underlies our proficiency in breaking down abstract concepts, critically evaluating scenarios, and fine-tuning our reasoning. The principal objective of this work is to imbue language models with a simulated metacognitive process—a sequential series of cognitive stages that mirror human “thinking about thinking”. In doing so, we aim to augment the models’ capabilities in interpreting and responding to natural language understanding tasks.

Our proposed method, *Metacognitive Prompting* (MP), instills critical elements of human metacognition into LLMs.

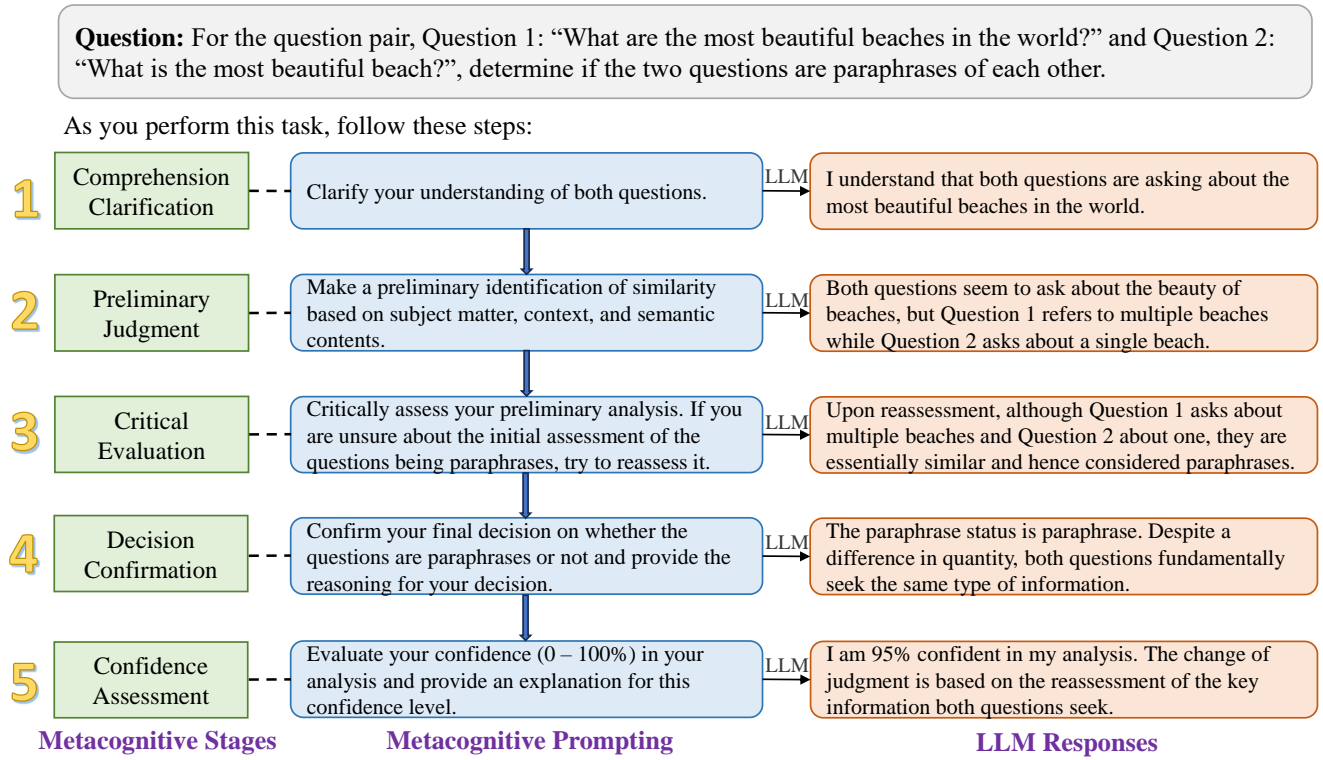


Figure 2: Our proposed method, metacognitive prompting, emulates certain aspects of human metacognition, consisting of five stages: 1) understanding the input text, 2) making a preliminary judgment, 3) critically evaluating this preliminary analysis, 4) reaching a final decision accompanied by an explanation of the reasoning, and 5) evaluating the confidence level in the entire process. By reflecting human self-assessment, these stages guide the LLM, aiding in more accurate text interpretation and facilitating better judgment formation. The diagram features three columns, from left to right, representing the high-level metacognitive stages, specific metacognitive prompts fed into the LLM, and the LLM’s corresponding outputs. Prompts in the middle column are collectively fed into the LLM as a single input during the experiments. The figure illustrates a sample question chosen from the Quora Question Pair (QQP) dataset.

This approach involves five distinct stages: 1) the LLM begins by deciphering the input text to comprehend its context and meaning, mirroring the initial comprehension stage in human thought; 2) it then forms a preliminary interpretation of the text, a step that reflects judgment formation in humans; 3) subsequently, the LLM critically evaluates this initial judgment for accuracy, akin to the self-scrutiny humans apply during problem-solving; 4) after this evaluation, the LLM finalizes its decision and offers an explanation for its reasoning, aligning with the decision-making and rationalization phase in human cognition; 5) ultimately, the LLM assesses its confidence in the outcome of the entire process, similar to how humans gauge the certainty of their decisions and explanations. Figure 2 provides a schematic representation of our MP. It outlines the five sequential metacognitive stages, the specific prompts directed at the LLM, and the corresponding outputs from the model.

Table 1 contrasts our MP with prevalent prompting methods such as standard prompting (SP) and CoT prompting, highlighting the differences in guidelines and objectives inherent to each method. While SP focuses on direct, task-

specific cues, MP uniformly applies the metacognitive process, adapting to the unique demands of every task. Contrary to the sequential progression characteristic of CoT, MP integrates continuous critical evaluations throughout its stages, enhancing both comprehension and response. For instance, in a sentiment analysis task, SP might simply request, “Classify the sentiment of the statement as positive or negative.” Meanwhile, CoT guides the model through a step-by-step process, asking, “Identify key emotional words in the statement. Based on these words, would you classify its overall sentiment as positive or negative?” On the other hand, MP pushes the model for deeper introspection, suggesting, “Understand the statement and make a preliminary sentiment identification. If you are uncertain, reassess. Confirm your final decision, providing reasoning. Then, evaluate and justify your confidence (0 - 100%) in this analysis.”

In essence, MP introduces a structured approach that enables LLMs to process tasks, enhancing their contextual awareness and introspection in responses. By systematically guiding models through stages that emulate human cognitive processes, this method offers a fresh perspective on ad-

Table 1: Comparison among standard prompting, chain-of-thought prompting, and metacognitive prompting.

Prompting Strategy	Guideline	Purpose
Standard	Provide a straightforward, succinct prompt tailored to the task at hand.	To elicit an immediate and direct answer from the model.
Chain-of-Thought	Develop a prompt that leads the model through progressive stages of reasoning.	To facilitate the model’s step-by-step logical engagement with tasks.
Metacognitive	Formulate a prompt that simulate stages of human metacognition.	To reproduce human-like “thinking about thinking”, deepening the model’s task comprehension.

Table 2: Overview of general language understanding tasks, datasets, and evaluation metrics. *QA* stands for question answering, *NLI* is natural language inference, *WSD* is word sense disambiguation, and *coref.* is coreference resolution.

Task	Dataset	Input	Output	Metric
Sentiment	SST-2	Single sentence	Binary	Accuracy
Similarity	STS-B	Sentence pair	Continuous	Pearson / Spearman Correlation
Paraphrase	QQP	Question pair	Binary	F1 / Accuracy
QA / NLI	QNLI	Question + passage	Binary	Accuracy
NLI	WNLI, RTE, CB	Sentence pair	Binary / Ternary	F1 / Accuracy
WSD	WiC	Sentence pair + target word	Binary	Accuracy
coref.	WSC	Passage + pronouns	Binary	Accuracy
QA	COPA	Question + choices	Binary	Accuracy

addressing complex natural language tasks. It reshapes our perception and utilization of LLMs’ capabilities, ushering in a paradigm where models not only grasp the intricacies of given tasks but also critically evaluate and adjust their reasoning. This approach lays the groundwork for more effective and reliable interactions between users and LLMs.

Experiments

We evaluate the effect of MP, in comparison with standard and chain-of-thoughts prompting, on five leading LLMs using multiple NLU datasets from GLUE (Wang et al. 2019b) and SuperGLUE (Wang et al. 2019a) benchmarks. We report the best result after multiple experimental iterations.

Datasets

We utilize a wide range of general language understanding datasets for our experiments, selected from GLUE and SuperGLUE benchmarks. These datasets encompass various tasks, including sentiment analysis (SST-2 (Socher et al. 2013)), textual similarity (STS-B (Cer et al. 2017)), question paraphrase (QQP (Shankar, Nikhil, and Kornel 2017)), question-answer entailment (QNLI (Rajpurkar et al. 2016)), textual entailment (WNLI (Levesque, Davis, and Morgenstern 2012), RTE (Dagan, Glickman, and Magnini 2005), CB (De Marneffe, Simons, and Tonhauser 2019)), word sense disambiguation (WiC (Pilehvar and Camacho-Collados 2019)), coreference resolution (WSC (Levesque, Davis, and Morgenstern 2012)), and question-answering

(COPA (Roemmele, Bejan, and Gordon 2011)). Among these tasks, STS-B is a regression task, while the rest are classification tasks. We choose these datasets as they challenge the general understanding capabilities of language models. For evaluation purposes, we utilize the development set corresponding to each task. Table 2 provides an overview of the tasks and datasets.

Large Language Models

In our evaluation, we consider five popular large language models (LLMs): the open-source models Llama-2-13b-chat (Touvron et al. 2023) and Vicuna-13b-v1.1 (Chiang et al. 2023), and the closed-source models PaLM-bison-chat (Anil et al. 2023), GPT-3.5-turbo, and GPT-4 (OpenAI 2023). Each model is employed using its corresponding API key. For all methods, we apply greedy decoding (i.e., temperature = 0) for response generation. Furthermore, we employ zero-shot and 5-shot settings for each model, with exemplars in the 5-shot setting randomly chosen from the training set. Each dataset has its own set of exemplars, where exemplar answers are obtained through human annotation.

Prompts

We employ three prompting strategies to enhance the performance of LLMs on each task: standard prompting (Brown et al. 2020; Kojima et al. 2022), chain-of-thought (CoT) prompting (Wei et al. 2022), and our proposed metacognitive prompting. Each prompt is evaluated under both zero-

shot and 5-shot settings. The full set of prompts is provided in the supplementary materials.

Results

In our empirical evaluations, we compare performance across all datasets and models, taking into consideration the different prompting methods used. We also investigate the efficacy of three prompting strategies, analyze errors associated with MP, and examine the relationship between confidence scores and accuracy when MP is applied.

Overall Performance Comparison

Table 3 presents a performance comparison of five LLMs (i.e., Llama2, Vicuna, PaLM, GPT-3.5, and GPT-4) using three prompting methods (i.e., SP, CoT, and MP) across various general NLU datasets. The results for each model and prompting strategy are averaged between zero-shot and 5-shot settings. Under the 5-shot learning approach, model performance generally shows improvement across all tasks when compared to zero-shot learning (see experimental results in supplementary materials). GPT-4 consistently achieves the highest scores across nearly all datasets. Although GPT-4 stands out as the dominant model, PaLM exhibits competitive performance, especially when paired with MP. This combination closely rivals GPT-4 in specific datasets, such as COPA and WSC. For traditionally less competitive LLMs, like Vicuna and GPT-3.5, the adoption of MP notably improves performance on certain datasets, especially CB and WSC, when compared to SP and CoT. Furthermore, MP outperforms both SP and CoT across the majority of datasets. For instance, on the WSC dataset, models employing MP experience an average accuracy increase of 9.7% and 4.8% compared to those using standard and CoT prompting, respectively, across all models.

Prompting Strategy Comparison

We evaluate the performance of three prompting strategies under zero-shot and 5-shot learning settings across all models and datasets. In the model-level comparison, Figure 3

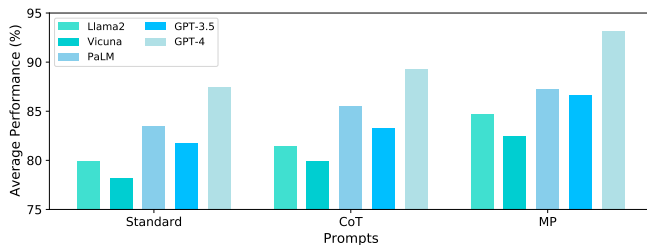


Figure 3: Comparison of average performance for three prompting methods in both zero-shot and 5-shot learning scenarios across five models. Performance metrics are averaged over all datasets, treating each dataset and metric with equal significance and assuming direct comparability. Notably, MP consistently surpasses standard and CoT prompting, with GPT-4 emerging as the top-performing model.

presents an aggregated view of the performance of each

prompting method across all datasets for each model, assuming that datasets and evaluation metrics are equally significant and directly comparable. MP emerges superior, illustrating a relative performance boost ranging from 4.4% to 6.5% over SP and 2.0% to 4.3% over CoT prompting. This enhanced performance can be attributed to the unique introspective strategy of MP, which facilitates a deeper understanding of tasks by prompting the model to critically evaluate, revisit its initial judgments, and refine its responses. When we shift focus to a data-level comparison in Table 4, it provides an average performance over five models for each dataset. The critical reassessment capabilities of MP particularly stand out in datasets like WNLI, WSC, and CB, leading to marked improvements of 3.7%, 4.7%, and 4.8% over CoT, respectively. The consistent outstanding performance of MP underscores its potential in tasks demanding precision, discernment, and a comprehensive semantic grasp. Meanwhile, the self-assessment and iterative refinement embedded in MP give it an advantage in tasks requiring nuanced understanding and contextual depth.

Error Analysis

MP has consistently demonstrated proficiency across a range of NLU tasks. However, upon manual inspection of its incorrect predictions, two primary error types associated specifically with MP were identified. First, the ‘Overthinking errors’ are notably evident in straightforward datasets like sentiment analysis (SST-2) and question paraphrase (QQP). In these situations, MP tends to over-complicate the task, diverging from the correct solution. Conversely, ‘overcorrection errors’ predominantly appears in tasks demanding nuanced interpretation, such as word sense disambiguation (WiC) and coreference resolution (WSC). As depicted in Figure 4 with error examples from the WiC dataset, the critical reassessment stage of MP sometimes strays excessively from an initially accurate interpretation. To mitigate these issues, a potential refinement for MP could be the introduction of a ‘simplification checkpoint’ during the ‘critical assessment’ phase, particularly for tasks where overthinking is prevalent. For instance, after the model critically reassesses a sentiment analysis task, the prompt could incorporate an instruction like: “Re-evaluate the sentiment in its simplest form. Does this align with your critical assessment?” This would urge the model to counterbalance its intricate reasoning against a rudimentary interpretation. Additionally, for tasks prone to overcorrection, a potential solution could be embedding a ‘comparison checkpoint’ within the prompts. For instance, after the model has critically reassessed its judgment on a coreference resolution task, the prompt might guide: “Recall your initial understanding of the reference. Does this new evaluation maintain the essence of your initial judgment or does it drastically differ?” By making the model directly compare its initial thought with the revised one, we might prevent it from making too many changes and help it keep a balanced view.

Confidence Analysis

Assessing confidence and uncertainty within the MP framework is instrumental in gauging the reliability of predictions,

Table 3: Performance comparison of five LLMs across diverse natural language understanding datasets using three prompting strategies. Scores are averaged between zero-shot and 5-shot settings. GPT-4 consistently outperforms other models across most datasets. Metacognitive prompting notably surpasses both standard and CoT prompting for a majority of the datasets. Best results for each dataset are highlighted in bold. The presented results are with greedy decoding (i.e., temperature = 0). Abbreviations: *Acc.*, *Pear.*, *Spea.* stand for accuracy, Pearson correlation, and Spearman correlation, respectively.

Prompt	Model	Dataset									
		SST-2 <i>Acc.</i>	STS-B <i>Pear. / Spea.</i>	QQP <i>F1 / Acc.</i>	QNLI <i>Acc.</i>	WNLI <i>Acc.</i>	RTE <i>Acc.</i>	CB <i>F1 / Acc.</i>	WiC <i>Acc.</i>	WSC <i>Acc.</i>	COPA <i>Acc.</i>
Standard Prompting	Llama2	95.0	56.3 / 52.7	78.5 / 83.8	88.7	67.6	85.4	93.0 / 92.0	76.3	73.1	96.0
	Vicuna	96.0	54.9 / 50.9	77.9 / 83.3	88.0	69.7	85.4	87.7 / 85.7	75.1	65.4	96.0
	PaLM	96.6	67.6 / 66.2	79.7 / 84.6	89.6	78.9	90.7	93.0 / 92.0	76.8	70.7	98.5
	GPT-3.5	96.2	65.9 / 64.2	78.5 / 83.8	89.3	75.4	86.0	90.3 / 88.4	76.3	68.3	99.0
	GPT-4	97.3	70.2 / 68.8	84.0 / 88.3	94.5	89.4	94.1	91.9 / 91.1	81.0	85.1	100.0
CoT Prompting	Llama2	95.9	56.4 / 52.7	79.9 / 84.9	89.6	73.2	86.7	94.4 / 93.8	77.2	75.5	98.5
	Vicuna	96.6	56.7 / 54.1	79.4 / 84.4	88.8	71.1	85.8	90.5 / 89.3	76.2	68.8	96.5
	PaLM	97.3	70.5 / 69.2	81.0 / 85.6	90.2	83.8	91.5	95.2 / 94.6	77.7	75.0	99.5
	GPT-3.5	96.7	65.1 / 63.9	80.1 / 85.1	90.4	83.8	87.0	91.6 / 90.2	77.2	71.7	99.0
	GPT-4	98.0	73.6 / 73.1	85.2 / 89.2	95.3	92.3	94.4	95.0 / 94.7	82.2	88.0	100.0
Metacognitive Prompting (Ours)	Llama2	98.0	64.3 / 61.9	81.8 / 86.4	91.0	76.8	88.3	97.5 / 97.3	79.2	79.3	99.5
	Vicuna	97.2	63.6 / 60.6	80.2 / 85.1	89.6	72.5	86.8	93.6 / 92.3	77.9	72.6	99.0
	PaLM	98.2	71.5 / 69.4	82.3 / 86.5	90.7	87.3	93.2	98.4 / 98.2	79.2	78.4	100.0
	GPT-3.5	98.3	71.8 / 70.3	81.7 / 86.2	91.2	87.3	88.7	98.4 / 98.2	78.6	75.5	99.5
	GPT-4	99.2	85.9 / 85.7	87.0 / 90.4	96.5	95.1	95.5	100.0 / 100.0	83.9	91.4	100.0

Table 4: Comparison of average performance for three prompting methods across datasets. Performance metrics are averaged over all models under zero-shot and 5-shot settings. MP consistently achieves superior performance across a range of NLU tasks.

Dataset	Standard	CoT	MP
SST-2 (<i>Acc.</i>)	96.2	96.9	98.2
STS-B (<i>Pear. / Spea.</i>)	63.0 / 60.6	64.5 / 62.6	71.4 / 69.6
QQP (<i>F1 / Acc.</i>)	79.7 / 84.8	81.1 / 85.8	82.6 / 86.9
QNLI (<i>Acc.</i>)	90.0	90.9	91.8
WNLI (<i>Acc.</i>)	76.2	80.8	83.8
RTE (<i>Acc.</i>)	88.3	89.1	90.5
CB (<i>F1 / Acc.</i>)	91.2 / 89.8	93.3 / 92.5	97.6 / 97.2
WiC (<i>Acc.</i>)	77.1	78.1	79.8
WSC (<i>Acc.</i>)	72.5	75.8	79.4
COPA (<i>Acc.</i>)	97.9	98.7	99.6

particularly when models articulate their confidence levels. In our analysis, each model operating with MP was evaluated based on its verbalized confidence for every prediction across the datasets. Scores above 75% are classified as high confidence; any value below this threshold is considered low confidence. To illuminate this correlation, we employed a tailored confusion matrix uniquely adapted for this study. Within this matrix, the standard terminologies of ‘True Positive’, ‘False Positive’, ‘True Negative’, and ‘False Negative’ are redefined as follows:

True Positive (TP): Represents instances where the model, using MP, expressed high confidence and produced a correct answer. These account for 58.3%.

False Positives (FP): Denotes cases where the model exhibited high confidence but gave an incorrect prediction. These amount to 27.1%.

True Negatives (TN): Refers to instances where the model signaled low confidence and its response was indeed incorrect. These stand at 8.7%.

False Negatives (FN): Highlights cases where the model indicated low confidence but, surprisingly, delivered a correct answer. These tally to 5.9%.

These metrics were aggregated across all models and datasets and then averaged to provide a holistic overview of the interplay between model confidence using MP and prediction accuracy. As depicted in Figure 5, MP typically offers an accurate reflection of its own performance, as evidenced by the high TP rate. The relatively low TN rate underscores its reliable self-assessment, suggesting that when MP has low confidence, it is predominantly correct about its inaccuracy. However, the considerable FP rate indicates that, while MP is usually right when confident, it sometimes makes mistakes despite its high confidence. Moreover, the FN rate identifies areas where MP might improve its self-awareness, as there are moments when it might underestimate its accuracy. In summary, the high TP rate and low FN values underscore MP’s self-awareness, but the FP and TN values point to potential improvements. Addressing these areas by emphasizing confidence calibration in future iterations of MP could better align its introspective evaluations with its actual performance capabilities.

Limitations

While our proposed metacognitive prompting demonstrates potential by integrating introspective features reminiscent of

Error Type 1: Overthinking

Question:

In two sentences, sentence 1: “Excite the neurons.” sentence 2: “The fireworks which opened the festivities excited anyone present.”, both contain the target word “excite”. Determine if the target word is used with the same meaning in both sentences. [MP Instructions]

MP Initial Response (Stage 2):

The target word has the same meaning: False. ✓

MP Final Response (Stage 4 & 5):

The target word has the same meaning: True. **Upon re-evaluation**, model hypothesized that both contexts hint at triggering a reaction, either biological or emotional, leading to the conclusion of similarity. Confidence in this revised analysis is 90%. ✗

(a) Overthinking error in model response with MP.

Error Type 2: Overcorrection

Question:

In two sentences, sentence 1: “The very easiness of the deed held her back.” sentence 2: “There was an easiness between them.”, both contain the target word “easiness”. Determine if the target word is used with the same meaning in both sentences. [MP Instructions]

MP Initial Response (Stage 2):

The target word has the same meaning: False. ✓

MP Final Response (Stage 4 & 5):

The target word has the same meaning: True. **Upon re-evaluation**, ‘easiness’ in both sentences pertains to emotional states—implying simplicity-induced hesitation in the first and emotional harmony in the second. Confidence in this revised analysis is 85%. ✗

(b) Overcorrection error in model response with MP.

Figure 4: Two major error types with MP: overthinking (excessive analysis) and overcorrection (excessive adjustment).

human cognition into LLMs to enhance their understanding capacities, our study does have its limitations. We evaluated the effectiveness of MP using a specific selection of datasets and models, which may limit the broader applicability of our findings. Although the verbalized confidence of LLMs offers a window into their perceived certainty levels, it might not serve as the definitive method for comprehensively gauging their true confidence. A hybrid approach, such as combining verbalization with self-consistency checks, could offer a more robust method for confidence calibration. Additionally, our study does not extensively address vital ethical and legal concerns, such as potential biases, privacy implications, and fairness challenges. It is imperative that future research on MP addresses these dimensions to ensure the responsible and holistic application of LLMs across different scenarios.

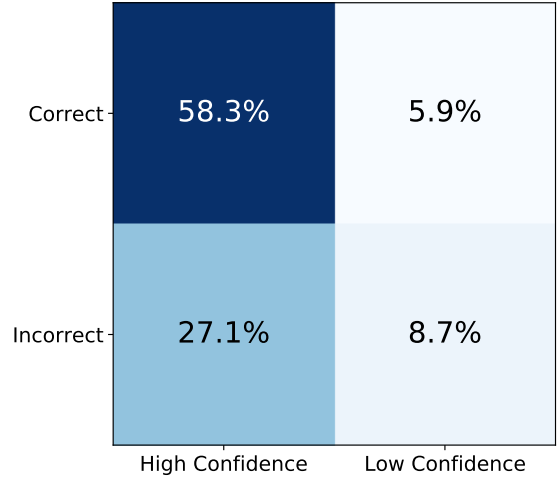


Figure 5: Relationship between correctness and confidence levels under MP, averaged over all datasets and models.

Discussion

In this study, we presented *Metacognitive Prompting* (MP) to infuse introspective features that mirror human cognition into LLMs. The MP process involves five distinct stages: it starts by comprehending the input text, then moves to formulate an initial judgment. Next, it critically reevaluates this initial impression, settles on a decision while explaining its rationale, and finally gauges its confidence in the decisions made. Our empirical evaluations spanned a broad range of NLU datasets from the GLUE and SuperGLUE benchmarks and several prominent LLMs. The results underscore the potential of our method, demonstrating clear advantages over existing prompting methods such as standard and CoT prompting. Through our analysis, specific error patterns associated with MP were identified, highlighting nuances in comprehension and judgment stages that warrant further refinement. While MP provides a structured pathway for models to introspect, it follows predefined stages, lacking adaptability based on real-time feedback. The five-stage design of MP, although foundational, suggests room for more intricate frameworks that might emulate human-like cognitive feedback loops more authentically.

Looking forward, several areas warrant further exploration. Applying MP to broader datasets, especially those that are multilingual or domain-specific, is a promising direction. Refining prompting strategies might elicit more detailed introspective responses from LLMs. Moreover, our findings suggest that the reliance on verbalized confidence can be augmented by integrating other methods for a more comprehensive confidence assessment. Additionally, the broader implications of introducing introspective LLMs, particularly regarding biases and the reliability of outputs, require in-depth examination. In essence, our initial venture with MP lays a solid foundation, but significant opportunities remain to draw closer parallels between introspection in LLMs and natural human introspection.

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