Confidence-Guided Cross-Premise Contrastive Decoding for Enhanced LLMs Reasoning

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Abstract

Large language models (LLMs) are prone to distraction by contextual information during reasoning. Previous work primarily focuses on improving the generation of the next token while overlooking the potential bias introduced by existing premises. In this paper, we propose a novel decoding method to mitigate this issue. We establish a framework that uses predicted logits to assess the model's confidence. By decomposing the full context into multiple premises, we gain a clearer understanding of the relevance of each premise to the question. When predicting the next token, we adjust the original model output by contrasting the most confident logits with the least confident ones. Our method effectively reveals how the model dynamically activates and adjusts its consideration of each premise as reasoning progresses.

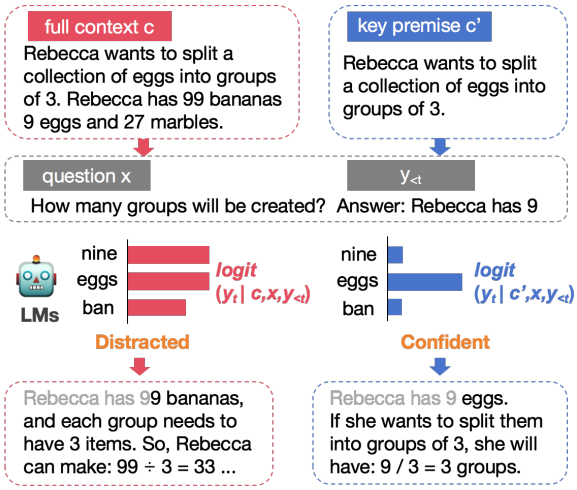

Figure 1: An illustration of a reasoning task. The language model becomes distracted by semantic coherence, thereby leading to error accumulation.

1 Introduction

Large language models (LLMs) have demonstrated significant effectiveness across various reasoning tasks (Ahn et al., 2024; Zhang et al., 2024b). With the continuous advancement of LLMs' capabilities, generating step-by-step intermediate rationale can effectively guide the model toward reliable answers (Wei et al., 2022).

A multitude of research endeavors has been dedicated to optimizing the intermediate reasoning process of LLMs during inference time (Snell et al., 2024). These efforts can be categorized into two paradigms: *1) Fusion-based approaches*, which leverage additional information from the model itself or external sources to bolster the robustness of reasoning (Li et al., 2023; O'Brien and Lewis, 2023; Shi et al., 2024b). *2) Reasoning space search-based approaches*, which search for the optimal solution across various possible reasoning paths to derive the answer (Wang and Zhou, 2024; Xie et al., 2023, 2024; Mo and Xin, 2024).

However, previous research primarily focuses on how to enable LLMs to generate better next tokens or rationales, while overlooking the influence of the premise and context in the question on the subsequent generation (Liu et al., 2024; Chen et al., 2024). Since LLMs are autoregressive architectures, the existing context is typically closely tied to the generation of new tokens, encompassing aspects such as grammatical correctness, instruction adherence, and semantic coherence. Yet, when tackling reasoning tasks, due to the intricate logical relationships involved, the models often struggle to capture the appropriate contextual cues, resulting in an unrealistic token probability distribution. This distribution can lead to biased reasoning sequences, and errors are amplified as they accumulate.

We argue that the challenge of LLMs being prone to distraction still poses a threat to reasoning tasks (Shi et al., 2023). Due to the implicit attention mechanisms employed by LLMs, it is difficult to discern the relationship between the generated tokens and the premises in the question (Malkin et al., 2022). For instance, models tend to prioritize

maintaining both syntactic and semantic coherence while neglecting the correctness of reasoning, as illustrated in Figure 1. The way the model conditions various contexts does not align with expectations, and this issue is difficult to correct externally.

To address these challenges, we propose a **C**onfidence-guided **C**ross-premise **C**ontrastive **D**ecoding (**C^{3}D**) method to enhance the transparency of premises during LLMs' reasoning. Through empirical experiments, we observe that LLMs tend to perform better when faced with simple and explicit instructions (Prystawski et al., 2023; Lightman et al., 2023), as such instructions have lower uncertainty and are easier to execute. Therefore, we first decompose the reasoning problem into multiple premises. When generating the next token, we simultaneously decode the current position using both the multiple premises and the question. Since one premise will closely enlighten the token at the current position, LLMs will assign higher confidence to the token generation under that premise. We then use the premise with the highest confidence and the premise with the lowest confidence for contrastive enhancement to adjust the probability distribution of the next token. This effectively reduces the reasoning bias caused by ambiguous contextual evidence in the model.

We validate our method on multiple arithmetic and symbolic reasoning tasks. The experiments show that our approach significantly improves performance without training, external verifier, or extensive path search. Additionally, our method provides greater transparency and interpretability, helping us better understand the reasoning process of LLMs. In summary, our contributions are threefold:

- We propose a reasoning enhancement method based on cross-premise awareness and contrastive decoding, in which we design token-level confidence evaluation to support the reliability of the model's reasoning chain.
- Our method effectively reveals how language models dynamically awaken their consideration of different premises as the reasoning process flows. We also visualize the influence of each premise on the generation of downstream tokens.
- Our method can achieve stable improvements in reasoning performance without the need for training, external verifiers, or path search. Extensive experiments validate the effectiveness of our approach.

2 Related Works

2.1 Large Language Models Reasoning

When confronting reasoning tasks, LLMs typically require CoT (Chain-of-Thought) (Wei et al., 2022) capabilities to perform step-by-step intermediate reasoning. Many studies focus on constructing more data to strengthen the underlying CoT abilities of LLMs, including methods based on Supervised Fine-Tuning (SFT) (Hao et al., 2024; Luo et al., 2023; Ranaldi and Freitas, 2024), Reinforcement Learning (RL) (Lightman et al., 2023; Zhang et al., 2024a), and Prompting techniques (Kojima et al., 2022; Zhang et al., 2022). These approaches alter the model's output logic and often demand high-quality data or evaluation models, as well as significant human effort and training costs.

2.2 Inference Time Scaling

In addition to training with more data, another technical approach explores improving LLMs during inference time (Snell et al., 2024). These methods aim to enhance the overall reasoning quality by designing effective supervision strategies for each step of the model's output, and it does not alter the model's inherent capabilities. Some studies employ internal or external auxiliary mechanisms to improve the robustness of LLMs (Li et al., 2023; Chang et al., 2023), while others opt for more direct approaches to search for optimal solutions within diverse reasoning spaces (Wang and Zhou, 2024; Xie et al., 2023, 2024; Mo and Xin, 2024). Our method falls into the category of internal model enhancement, which is low-dependency and low-overhead.

2.3 Contrastive Decoding

By contrasting a credible state with a non-credible state, contrastive decoding injects logits into the token generation process, thereby enhancing the faithfulness of the model's output from within (Shi et al., 2024a). For example, Contrastive Decoding (CD) (O'Brien and Lewis, 2023) uses an expert LM and an amateur LM to contrast and improve the professionalism of the generated tokens. Context-Aware Decoding (CAD) (Shi et al., 2024b), on the other hand, contrasts problems with and without context within a single LM to reduce the irrelevance of

tokens to the context. Decoding by Contrasting Layers (DoLa) (Chuang et al., 2023) stimulates the intrinsic knowledge of LMs by contrasting different layers. COIECD (Yuan et al., 2024) utilizes information entropy to address the issue of knowledge conflicts in models. Similarly, our method contrasts generations under different premises and further filters them based on confidence levels.

3 Method

We now introduce our proposed **C**onfidence-guided **C**ross-premise **C**ontrastive **D**ecoding (**C^{3}D**) method, which is a token-level, fine-grained premise-aware contrastive approach.

For a reasoning task, given an input question x and a context c that contains the necessary premises for reasoning, the generation process of a standard large language model $\mathcal{M}$ can be defined as:

$$\begin{aligned} y_t &\sim p_{\mathcal{M}}(y_t|c, x, y_{<t}) \\ &\propto \exp\big(\text{logit}_{\mathcal{M}}(y_t|c, x, y_{<t})\big) \end{aligned} \tag{1}$$

where y_t is the new token generated at time step t based on the context c, the question x, and the previously generated sequence $y_{<t}$. It is sampled proportionally to the logit scores processed by $\mathcal{M}$ (Shi et al., 2024b).

However, the default sampling method is influenced by various factors. For instance, when the information in the context is complex and unclear, the predictions of language models tend to exhibit uncertainty (Zheng et al., 2023; Chen et al., 2024; Qiu and Miikkulainen, 2024), manifested as a smooth distribution over the logits (Ulmer et al., 2023). This smooth distribution further leads to an averaging of sampling probabilities. Once the model selects an incorrect token, subsequent generations are affected as well. Even when the temperature is set to 0, it is difficult to guarantee that the top-ranked token is always correct. Moreover, to maintain linguistic coherence, the model will amplify these cumulative errors, ultimately compromising the correctness of the reasoning.

3.1 Confidence Estimation with Logits

To further explore the internal prediction mechanisms of the model, some methods utilize the logit lens (Belrose et al., 2023) for interpretability analysis. By observing the logits or probability distribution at the final layer, we can understand how the model assigns weights to each word in the vocabulary (Qiu et al., 2024; Yuan et al., 2024).

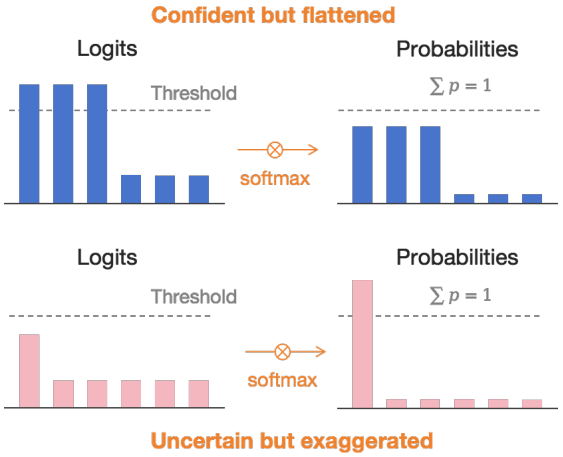

Figure 2: An example where entropy-based probability is insufficient to measure the model's confidence.

Generally, when a word is assigned a weight significantly higher than others, it indicates that the model has high confidence in this word, and it is highly likely to be reasonable and reliable (Zhang et al., 2023; Duan et al., 2024). This situation typically occurs in cases such as common collocations or when the intent is clear. Therefore, we can use the entropy of the predicted probabilities to measure the model's confidence α in the next token:

$$H = -\sum_{\tau \in \mathcal{V}} p_{\mathcal{M}}(\tau) \log\big(p_{\mathcal{M}}(\tau)\big) \tag{2}$$

$$\alpha(y_t) = \frac{1}{\exp(H_{y_t})} \tag{3}$$

where H is the entropy at the current position over the vocabulary $\mathcal{V}$. We further take the negative exponential of the entropy as an estimate of confidence. When the entropy is higher, the probability distribution over the vocabulary is more uniform, and the confidence is lower; when the entropy is lower, the distribution over the vocabulary becomes "sharper", and the confidence is higher (with a maximum value of 1).

Considering that entropy does not always represent the model's uncertainty, as some information is lost during the softmax process (Gupta et al., 2024; Ma et al., 2025). For example, the model might consider multiple words to be reasonable, each assigned a high logit value, but after softmax, their probabilities become averaged. Alternatively, the model might be uncertain about the response, but when all logits are low, softmax can still increase the probability of a particular word, as illustrated in Figure 2. Given this, we incorporate consideration

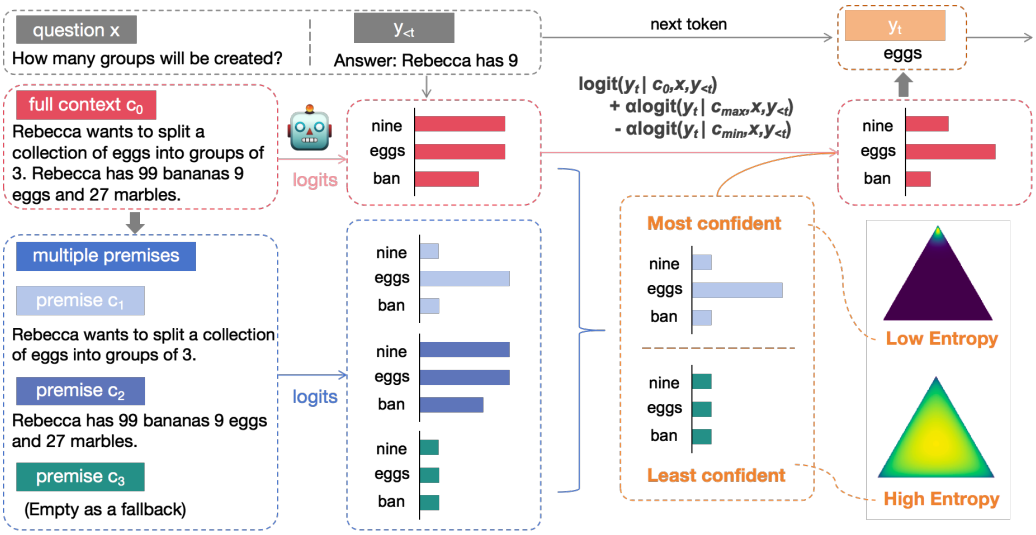

Figure 3: An illustration of our proposed C^{3}D method. The full context is decomposed into multiple premises, which then simultaneously obtain logits for the current position of the original question. By contrasting the most confident and least confident logits, the standard decoding process can be enhanced. This approach effectively mitigates the model's distraction issue. The illustration of entropy is copied from (Ulmer et al., 2023).

of the extreme values of logits:

$$\mathcal{L}(y_t) = \frac{1}{K}\sum_{k=1}^{K}\text{topk}\big(\text{logit}_{\mathcal{M}}(y_t)\big) \quad (4)$$

where $\text{topk}(\cdot)$ extracts the largest k values from the logits. The idea behind this is that the magnitude of $\mathcal{L}$ also serves as an indicator of confidence (Ulmer et al., 2023).

3.2 Multi-Premises Decomposition

Inspired by empirical experiments, we observe that models often perform better when given simple and focused instructions (Prystawski et al., 2023; Lightman et al., 2023). This is because simple instructions typically have lower uncertainty, making it easier for the model to capture the key information. Therefore, we decompose the original context c into multiple simpler premises:

$$c = \{c_1, c_2, ..., c_n\} \quad (5)$$

where each premise c_n is a sentence from the context. This can be easily achieved through sentence segmentation.

Then, we can obtain the confidence level of each premise for the current position:

$$\alpha_n = \alpha(y_t|c_n, x, y_{<t}) \quad (6)$$

$$\mathcal{L}_n = \mathcal{L}(y_t|c_n, x, y_{<t}) \quad (7)$$

The hypothesis here is that when a premise is informative for the current decoding position, it will be assigned higher confidence. We aim to identify such premises and enable the model to distinguish the key information in the context from redundant details.

3.3 Dynamic Contrastive Decoding

To overcome reasoning errors caused by contextual distractions, we recompute the predicted logits during the decoding phase. Specifically, we select the premise logit with the highest confidence as the positive example and the premise logit with the lowest confidence as the negative example. We use their contrastive difference to adjust the original logits. Note that when the $\mathcal{L}$ values of all premises fall below a certain threshold, they are all considered untrustworthy, and in such cases, we rely solely on α as the confidence measure. Otherwise, we simply use $\mathcal{L}$ as our basis.

$$c_{max} = \begin{cases} \arg\max_{c_n}\{\mathcal{L}_0, \mathcal{L}_1, ..., \mathcal{L}_n\} \text{ if } \exists\mathcal{L} \geq T \\ \arg\max_{c_n}\{\alpha_0, \alpha_1, ..., \alpha_n\} \text{ if } \forall\mathcal{L} < T \end{cases} \quad (8)$$

$$\begin{aligned}\text{logit}'_{\mathcal{M}}(y_t|c, x, y_{<t}) &= \text{logit}_{\mathcal{M}}(y_t|c, x, y_{<t}) \\ &+ \alpha_{max}\text{logit}_{\mathcal{M}}(y_t|c_{max}, x, y_{<t}) \\ &- \alpha_{max}\text{logit}_{\mathcal{M}}(y_t|c_{min}, x, y_{<t})\end{aligned} \quad (9)$$

where T is an empirically determined threshold, and $\mathcal{L}_0$ and α_0 denote the confidence of the full context. This decoding process is performed sequentially, and it dynamically selects a pair of contrastive examples for each generated token. Meanwhile, the confidence level α scales the magnitude

of this adjustment. As a result, this method can mitigate the model's distraction by contextual information. Figure 3 presents the overall framework.

Algorithm 1 Confidence-guided Cross-premise Contrastive Decoding

Require: A reasoning task x with context c, and a language model $\mathcal{M}$
Ensure: Response sequence $y = \{y_1, y_2, ..., y_t\}$

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Decompose c into premises {c_1, c_2, ..., c_n}
Add the full context and an empty set to the premise set C = {c, c_1, c_2, ..., c_n, ∅}
while t < max_length do
    Logit list ← ∅
    for c_i ∈ C do
        Add Logit_M(y_t | c_i, x, y_<t) to the Logit list
    end for
    if ∃L ≥ T for L in Logit list then
        Select c_max with the highest L and c_min with the lowest L
    else
        Select c_max with the highest α and c_min with the lowest α
    end if
    Contrast with c_max and c_min
    Sample y_t from the adjusted logits
    if y_t is eos_token then
        Break
    end if
end while
```

4 Experiments

We evaluate our method on multiple tasks that require models to reason based on context. We primarily focus on the following research questions:

- **RQ1**: Can our method consistently improve reasoning performance?
- **RQ2**: How do multiple contextual premises influence the reasoning process?
- **RQ3**: What is the relationship between the model's confidence and the downstream responses?

4.1 Experimental Setup

4.1.1 Datasets

We validate our approach on commonly used benchmark datasets for reasoning, including three arithmetic reasoning tasks: GSM8K (Cobbe et al., 2021), AQUA (Ling et al., 2017), and SVAMP (Patel et al., 2021), as well as three symbolic reasoning tasks: Coin Flip (Wei et al., 2022), BIG-bench Date Understanding, and BIG-bench Object Tracking (Srivastava et al., 2023). These datasets encompass a wide range of reasoning tasks, from simple to complex, and require leveraging contextual information rather than relying on the model's memorized knowledge. Notably, the information provided in the questions is not always helpful, and some problems even contain completely irrelevant distractors. The model must carefully discern the given premises while avoiding reasoning pitfalls.

To validate the anti-distraction effect of our method, we also conduct tests on GSM-IC (Shi et al., 2023). This dataset is based on GSM8K but introduces irrelevant premises to the original questions, thereby distracting the language model. For experimental efficiency, we randomly sample 100 questions from GSM-IC as the test subset.

Since our primary focus is on how to make better use of the problem premises, we do not choose tasks like commonsense reasoning or mathematical computation. These tasks mainly rely on the model activating its stored knowledge for reasoning, where context information is usually minimal or absent.

4.1.2 Baselines

We consider single-pass decoding methods as our baselines. Specifically, we compare with regular decoding, self-consistency (SC) (Wang et al., 2023), context-aware decoding (CAD) (Shi et al., 2024b), and Decoding by Contrasting Layers (DoLA) (Chuang et al., 2023). Among these, CAD and DoLA are both contrastive decoding-based methods. The former primarily contrasts scenarios with and without context, while the latter focuses on contrasting different layers of the model.

4.1.3 Language Models

To obtain the internal logits of the model, we apply our method to open-source large language models. We select Llama-2-7B-chat and Llama-2-13B-chat as the base models. Recently, strong reasoning models, particularly those from the DeepSeek series (Guo et al., 2025), have demonstrated exceptional performance. Therefore, we also aim to validate our method on such strong reasoning models. To maintain consistency with the aforementioned models, we choose DeepSeek-R1-Distill-Llama-

Models	Decoding	*Arithmetic*			*Symbolic*			Avg.
		GSM8K	AQuA	SVAMP	Coin	Date	Object	
Llama-2-7B-chat	Regular	21.68	24.01	41.90	47.00	39.29	30.80	34.11
	SC	**26.14**	21.65	47.19	52.80	40.37	32.53	36.78
	CAD	21.75	23.62	**49.90**	48.40	34.96	31.80	35.07
	DoLA	22.14	22.44	43.80	51.20	40.08	30.53	35.02
	Ours	25.47	**29.92**	47.59	**54.80**	**44.99**	**32.66**	**39.24**
Llama-2-13B-chat	Regular	34.49	15.74	49.40	47.40	46.07	27.33	36.84
	CAD	31.69	12.60	52.10	50.80	37.69	33.33	36.37
	Ours	**37.98**	**26.37**	**55.10**	**63.00**	**51.49**	**35.80**	**44.96**
DeepSeek-R1-Distill -Llama-8B	Regular	54.21	63.39	80.80	66.00	66.40	53.87	64.11
	CAD	59.28	50.79	77.80	64.20	68.29	76.67	66.17
	Ours	**71.29**	**65.35**	**85.30**	**82.00**	**74.53**	**90.25**	**78.12**

Table 1: Performance (%) comparison across different decoding methods. Our proposed C^{3}D consistently improves performance across various arithmetic and symbolic reasoning tasks. Moreover, the enhancement effect of our method is more pronounced on stronger base models, such as DeepSeek-R1-Distill-Llama-8B.

8B[1] as the representative model for our experiments. It is distilled from Llama-3.1-8B.

4.1.4 Implementation Details

Our method introduces two hyperparameters: k to control the top k logit values for confidence $\mathcal{L}$, and threshold T to adjust the reference between $\mathcal{L}$ and α. Specifically, we search for k within the range [1, 5, 10, 15, 20, 25] and T within the range [14, 16, 18, 20]. Considering that not all tokens require a contextual reference, we skip the contrastive decoding for the token when the full context's $\alpha_0 > 0.999$. This typically occurs when outputting conjunctions or when the evidence is already sufficiently strong. We perform all experiments on a single 80GB A800 GPU.

4.2 Overall Performance (RQ1)

Table 1 presents the performance of different models across various reasoning tasks. We further categorize the observations into Llama-2 Model Observations and DeepSeek-Distill Model Observations based on the reasoning capabilities of the models.

4.2.1 Llama-2 Model Observations

On the Llama-2 series, our method consistently and significantly improves regular decoding performance. Particularly on the AQuA and Coin Flip datasets, the 7B and 13B models show the most substantial improvements. AQuA contains non-intuitive and complex mathematical problems, while Coin Flip requires multi-step state tracking. Both tasks demand the model to thoroughly understand the problem's meaning. Given that the comprehensive understanding capability of the Llama-2 series is not particularly strong, the original decoding is easily influenced by the context. Our strategy, however, better assists the model in grasping finer-grained information.

For similar contrastive decoding methods, such as CAD and DoLA, their performance across different datasets is inconsistent. This suggests that relying solely on full-context contrast or layer-wise contrast is insufficient to obtain evidence for token generation.

4.2.2 DeepSeek-Distill Model Observations

We further explore the performance of our method on stronger models. We observe that although DeepSeek-R1-Distill-Llama-8b already performs excellently on multiple tasks, our method can further enhance its reasoning performance. Specifically, we note improvements of 12.01% on GSM8K, 16.0% on Coin Flip, and 13.58% on Object Tracking. Such significant improvements indicate that strong reasoning models can better benefit from premises. We speculate that the reason is that weaker models can sometimes be overly confident even when incorrect (Fu et al., 2025), whereas strong reasoning models exhibit this behavior less frequently. Therefore, the latter can benefit more from the most confident premises.

[1] https://huggingface.co/deepseek-ai/DeepSeek-R1-Distill-Llama-8B

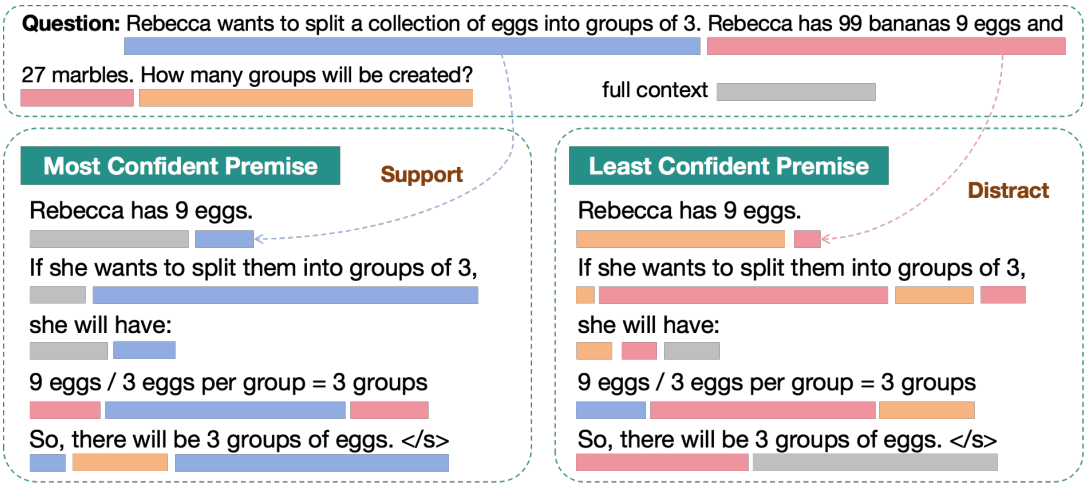

Figure 4: A visualized case study. Best viewed in color. The problem above is divided into three premises: we mark premise 1 in blue, premise 2 in pink, and premise 3 in orange, while the full context is marked in gray. The bottom left shows which premise supports each generated token (most confident), and the bottom right shows which premise distracts each generated token (least confident). The corresponding colors can help us better understand the reasoning process.

Decoding	7B	13B	DS
Regular w/o Irrelevant Context	49.0	68.0	94.0
Regular w/ IC	34.0	55.0	80.0
CAD w/ IC	36.0	54.0	75.0
Ours w/ IC	41.0	62.0	85.0

Table 2: The performance (%) on the GSM-IC subset. With the insertion of irrelevant context into the questions, the baseline methods show significant performance degradation. Our method, however, remains robust against such corruption.

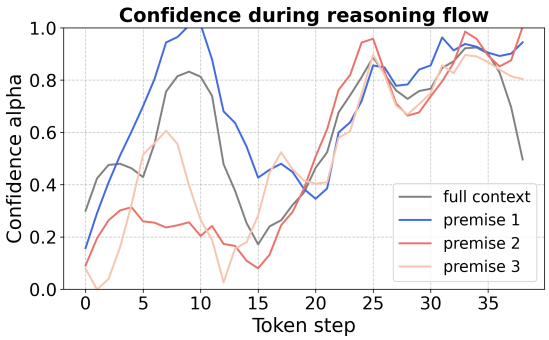

Figure 5: Visualization of how reasoning flows.

4.3 Performance on Data with Irrelevant Context (RQ1)

Table 2 presents the performance comparison on the GSM-IC subset. Since GSM-IC inserts an irrelevant premise into each question, this distracts the language model. We observe that the performance of baseline models significantly drops compared to scenarios without irrelevant context. In contrast, our method maintains comparable reasoning accuracy. This phenomenon demonstrates that our approach can effectively mitigate the negative impact of irrelevant context on the decoding process.

4.4 Case Study (RQ2)

To gain a deeper understanding of how LLMs utilize known premises during the reasoning process, we further perform a case study for illustration. Figure 4 shows the relationship between each premise in the problem and the downstream responses. We mark each premise with a distinct color and annotate the most confident and least confident premises for each generated token.

We observe that the beginning of each response tends to use the full context, while for specific information, the model favors those premises that most strongly support the reasoning, such as premise 1. Premise 3, which contains the least information, initially has the highest uncertainty. Similarly, the information in premise 2 distracts the model, resulting in a lower confidence.

4.5 How Reasoning Flows (RQ2)

Figure 5 further visualizes how the confidence α values of each premise change during token generation. This provides us with a clearer perspective on how the model drives the flow of reasoning. Specifically, premise 1 dominates the early stages

Decoding	GSM8K	AQuA
C^3D	25.47	29.92
- w/o $\mathcal{L}$	19.11	28.35
- w/o α	23.09	28.74
Regular	21.68	24.04

Table 3: Ablation studies on $\mathcal{L}$ and α.

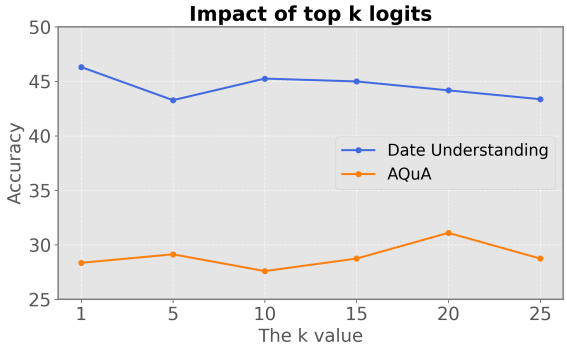

Figure 6: The trend of accuracy impact under different top-k values.

of generation. As reasoning information accumulates, premises with initially less information, such as premises 2 and 3, also gain insight and become part of the reasoning process. Eventually, by the end, each premise have gathered enough information and become confident.

4.6 Impact of Confidence $\mathcal{L}$ and α (RQ3)

We validate the contributions of the defined confidence measures $\mathcal{L}$ and α to reasoning. Table 3 presents the ablation studies on the GSM8K and AQuA datasets. The results show that both $\mathcal{L}$ and α have a positive effect on reasoning accuracy. Specifically, $\mathcal{L}$ has a slightly stronger impact on the model compared to α. As discussed in Section 3.1, the entropy-based α alone is insufficient to fully represent the model's confidence. When the accumulated logits fail to meet a certain threshold, the reliability of α also decreases. The introduction of $\mathcal{L}$ effectively compensates for this limitation.

4.7 Impact of Hyperparameter k and T (RQ3)

To further explore the impact of hyperparameter settings, we conduct additional experiments on the top-k logits and threshold T.

Figure 6 illustrates the trend of performance changes on AQUA and Date Understanding under different top-k logit values. As k increases from 1 to 25, AQUA shows an initial fluctuation

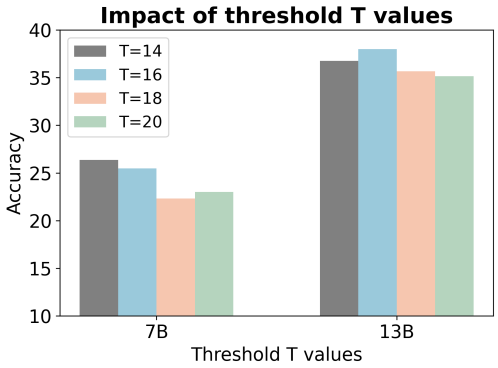

Figure 7: The performance of different T values on GSM8K across various models.

followed by an upward trend, while Date Understanding exhibits a gradual decline. This indicates that different datasets have varying preferences for top-k, which we speculate is related to the inherent properties of the datasets. Date Understanding primarily focuses on tokens related to dates, whereas AQUA requires a broader vocabulary space. However, overall, we can choose k=15 as a balanced compromise.

Since few studies discuss the impact of logit extremal values on responses, it is challenging to define a reasonable threshold. Ranging from 10 to 30, logit extremal values exhibit no clear pattern and are difficult to normalize. Therefore, we empirically select [14,16,18,20] as the experimental range. Figure 7 illustrates the effects of different thresholds T on GSM8K across two models. We observe that, despite changes in model size, the range of logits remains consistent. Additionally, their impact is relatively similar across models of different sizes. This phenomenon suggests that we can manually select a suitable threshold as a reference for the overall dataset.

5 Conclusion

We propose a confidence-guided cross-premise contrastive decoding method, which effectively mitigates reasoning errors in LLMs caused by contextual distractions. We validate the effectiveness of our method on both weak reasoning models and strong reasoning models (DeepSeek-R1-Distill-Llama-8B). Experiments show that our method achieves more significant improvements on strong reasoning models. Additionally, we visualize the role of each premise during the reasoning process, which can provide better guidance for future reasoning research.

Limitations

Since our method requires decoding multiple segments simultaneously, latency is a potential concern. We tested that our method takes approximately twice as much time as standard decoding, but this is still more cost-effective than methods like multiple voting or reasoning path search. Given the extensive research on accelerating LLMs, we believe leveraging acceleration techniques or KV caching could enhance the applicability of our method. Additionally, we only considered a simple premise decomposition approach, which may have certain limitations. Future work could explore better ways to partition the context.

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