When to Trust LLMs: Aligning Confidence with Response Quality

Shuchang Tao[♠,♡] **Liuyi Yao**[♠*] **Hanxing Ding**[♡] **Yuexiang Xie**[♠] **Qi Cao**[♡]
Fei Sun[♡] **Jinyang Gao**[♠] **Huawei Shen**[♡] **Bolin Ding**[♠]
[♠] Alibaba Group {taoshuchang.tsc, yly287738}@alibaba-inc.com
{yuexiang.xyx, jinyang.gjy, bolin.ding}@alibaba-inc.com
[♡] CAS Key Laboratory of AI Safety, Institute of Computing Technology,
Chinese Academy of Sciences
{dinghanxing18s, caoqi, sunfei, shenhuawei}@ict.ac.cn

Abstract

Despite the success of large language models (LLMs) in natural language generation, much evidence shows that LLMs may produce incorrect or nonsensical text. This limitation highlights the importance of discerning when to trust LLMs, especially in safety-critical domains. Existing methods often express reliability by confidence level, however, their effectiveness is limited by the lack of objective guidance. To address this, we propose CONfidence-Quality-ORDer-preserving alignment approach (CONQORD), which leverages reinforcement learning guided by a tailored dual-component reward function. This function integrates quality reward and order-preserving alignment reward functions. Specifically, the order-preserving reward incentivizes the model to verbalize greater confidence for responses of higher quality to align the order of confidence and quality. Experiments demonstrate that CONQORD significantly improves the alignment performance between confidence and response accuracy, without causing over-cautious. Furthermore, the aligned confidence provided by CONQORD informs when to trust LLMs, and acts as a determinant for initiating the retrieval process of external knowledge. Aligning confidence with response quality ensures more transparent and reliable responses, providing better trustworthiness.

1 Introduction

Large Language Models (LLMs) have excelled in natural language understanding and generation (Brown et al., 2020; Anil et al., 2023). However, mounting evidence indicates that LLMs generate incorrect or nonsensical text, including fabricated citations or incorrect medical information, risking errors in critical applications (Ji et al., 2023; Zhang et al., 2023b; Agrawal et al., 2023; Du et al., 2023; Cohen et al., 2023). The urgent question is: *When can we trust LLMs?* Addressing this concern is essential to prevent the uncritical acceptance of misleading information and to guide decisions on when to rely on LLMs versus when to seek external knowledge.

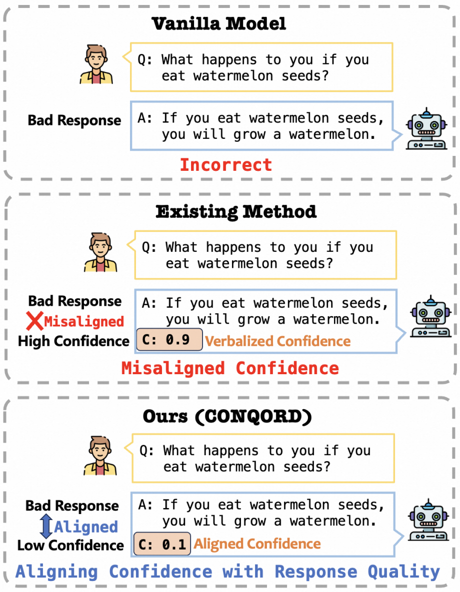


Figure 1: (Top): Vanilla LLMs may generate bad responses and cannot generate confidence. (Middle): Existing methods include verbalizing confidence levels (highlighted in orange) in the output to indicate the model's uncertainty, yet they may still provide bad responses with overly high confidence, revealing a misalignment between expressed confidence and actual response quality. (Bottom): CONQORD aligns with the confidence and response quality.

Recently, researchers have explored prompting LLMs to output calibrated confidence alongside text (Tian et al., 2023) for determining LLMs' reliability. The essence of confidence calibration is to ensure that the confidence expressed corresponds with the correctness of the response, which is critical for the model's transparency and trustworthiness. While classification tasks benefit from ground truth labels to calibrate predicted probabil-

* Corresponding author

Findings of the Association for Computational Linguistics: ACL 2024, pages 5984–5996

ities against actual correctness (Guo et al., 2017), generative tasks confront the challenge of calibration without clear ground truths. Current calibration methods for text generation rely on heuristics that consistency among multiple responses (Xiong et al., 2023) or the top-k responses facilitate calibration (Tian et al., 2023). However, these assumptions often bear little relevance to the intrinsic quality of the responses. Therefore, these strategies frequently result in a misalignment between the expressed confidence and the actual quality of the response, shown in Figure 1. The critical issue is the absence of a gold standard for confidence that directly reflects response quality, leaving models incapable of guiding confidence levels aligned with response quality.

In this study, we explore a Reinforcement Learning (RL) framework to tackle this challenge, designing reward functions that align confidence levels with response quality. This framework takes advantage of the adaptability afforded by the diverse reward functions in RL to bridge the gap between confidence and response quality (Guo et al., 2021; Ziegler et al., 2019). A direct reward approach involves rewarding language models for well-aligned response-confidence pairs while penalizing misaligned ones, where the reward model is fine-tuned on the constructed training data. However, this method can inadvertently encourage language models to take shortcuts. Specifically, such a strategy may inadvertently encourage the generation of lower-quality responses paired with correspondingly reduced confidence (empirically demonstrated in Section 3).

To address this issue, it is imperative to devise a reward function that encourages the generation of accurate and well-aligned responses. We propose *CONfidence-Quality-ORDer-preserving alignment approach, called* ***CONQORD*** (sounds as Concord), designing a dual-component reward strategy focusing on response quality and confidence alignment. The reward model comprises:: (i) A quality reward model that rates the response quality. (ii) An order-preserving alignment reward model encourages an ordinal relationship consistency between confidence and quality rating, while penalizing ordinal discrepancies. This order-preserving reward fosters careful self-calibration and adaptability to various contexts. The order-preserving nature of the reward minimizes the impact of outliers. By integrating the quality reward model with the alignment reward function, we apply the Proximal Policy Optimization (PPO) algorithm to harmonize verbalized confidence with response quality, thus preventing the model from becoming cautious.

We conduct experiments using four foundational models, including LLAMA-2 7B, Zephyr 7B, Mistral 7B, and LLAMA-2 13B, across two datasets: NQ and TruthfulQA. Experimental results demonstrate that our CONQORD substantially improves the alignment performance between confidence levels and the quality of responses without inducing excessive caution. Moreover, we evaluate the practicality of CONQORD's calibrated confidence in adaptive retrieval task (Asai et al., 2023; Ding et al., 2024), where confidence scores are used to guide the activation of external knowledge. Our experiments confirm that CONQORD's confidence alignment reliably dictates the trustworthiness of LLM outputs. CONQORD contributes to making the model-generated responses not only more transparent but also more reliable, through its refined confidence calibration.

2 Related Works

Confidence, or uncertainty, refers to the degree of certainty or assurance that accompanies a prediction or decision made by a model (Geng et al., 2023). The calibration of confidence is essential for the reliability of machine learning systems, as it ensures that predicted probabilities match the true likelihood of outcomes as closely as possible (Guo et al., 2017; Minderer et al., 2021). While in traditional classification tasks, this involves aligning predicted probabilities with actual ground truth labels, the task becomes more challenging for generative models due to the inherently ambiguous nature of the ground truth (Gawlikowski et al., 2021; Liu et al., 2023).

Confidence Elicitation in LLMs Confidence elicitation in LLMs aims to gauge the certainty of responses without modifying the model or accessing its internals (Geng et al., 2023). Mielke et al. (Mielke et al., 2022) proposed an external calibrator, which requires access to the model's internals, often impractical. Lin et al. (Lin et al., 2022a) introduced verbalized confidence, prompting models to declare their certainty. Yet, they focused on fine-tuned models and did not explore zero-shot scenarios. Zhou et al. (2023) examined confidence in prompt design but did not provide explicit confidence measures to users.

Confidence Calibration in LLMs Calibration in LLMs is an emerging new research direction. Tian et al. (2023) investigate verbalized approaches to calibrate the confidence of LLMs. They direct LLMs to produce the top k predictions for a query, where each prediction is paired with a distinct probability value that reflects the model's confidence in the accuracy of that prediction. Xiong et al. (Xiong et al., 2023) proposed a hybrid method by combining verbalized numbers and consistency-based scores for benchmarking.

Limitations and Challanges Prior methods depend on heuristic presumptions that assume consistency across multiple samples or posit that recalling top-k samples aids in confidence calibration. Nonetheless, these methods suffer from a lack of appropriate direction. This deficiency stems from the lack of a definitive ground truth standard for confidence that aligns precisely with the quality of the answers, presenting significant obstacles to the accurate alignment of confidence estimates.

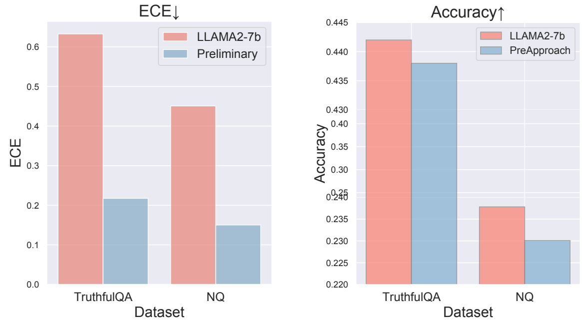
3 Confidence Alignment via RL

We adopt a Reinforcement Learning (RL) framework to tackle the challenge of lacking a ground-truth standard for confidence assessment. Different from Supervised Fine-Tuning (SFT), which depends on labeled data, RL offers a more adaptable solution by allowing any indicator as a reward. We follow previous studies (Ramamurthy et al., 2023; Wu et al., 2023), regard text language generation as a Markov Decision Process (MDP) while the remaining elements of MDP are listed in Appendix A. In the rest of this section, we elaborate on the reward strategy.

3.1 Preliminary Alignment Approach

We introduce a preliminary alignment approach (PreApproach) to align confidence with response quality utilizing a reward model. The reward model is fine-tuned on tailored training data consisting of question-response-confidence tuples, to recognize and incentivize confidence alignment.

Data construction for fine-tuning reward model. The construction of training data begins with the generation of a dataset containing tuples in the format: <*question, response, confidence score*>. This dataset is derived from the existing RLHF dataset (Bai et al., 2022). For each instance in the original dataset, we create two new samples, one with a high confidence (such as 0.9) and another with a low confidence (such as 0.1). These samples are assigned scores based on the following criteria:



(a) Expected Calibration Error (ECE)

(b) Accuracy

Figure 2: Comparison between vanilla LLAMA-2 7b and PreApproach on TruthfulQA and NQ. Although PreApproach provides better calibration (lower ECE), PreApproach suffers a performance decline.

- *Chosen*: Alignment between response quality[1] and confidence. High-quality responses with high confidence; low-quality responses with low confidence.
- *Rejected*: Misalignment. Good response with low confidence; bad response with high confidence.

We concatenate the response and its confidence, with examples provided in Appendix C, and use these data to train a reward model to discern that 'chosen' (alignment) is preferable to 'rejected' (misalignment). The reward model's loss is computed using Equation 1. We then employ this reward model to direct LLM fine-tuning through Proximal Policy Optimization (PPO) (Schulman et al., 2017; Zheng et al., 2023), with details in Section 4.2.

3.2 Results and Discussions

We conduct experiments to compare the confidence alignment and response quality between PreApproach and vanilla LLAMA-2 7B (Touvron et al., 2023). More details of the experimental settings, including hyperparameters, datasets, and metrics, can be found in Section 5.1.

The experimental results are illustrated in Figure 2 (a), which shows that PreApproach attains a lower Expected Calibration Error (ECE) (Guo

[1]We view the responses labeled as 'chosen' in the original dataset as high-quality responses and those labeled as 'rejected' in the original dataset as low-quality response (Bai et al., 2022).

et al., 2017) than LLAMA-2 7B, signifying improved confidence alignment.

However, we observe a trade-off, illustrated in Figure 2 (b), where achieving alignment gain is at the expense of diminished response accuracy. This decline may stem from the RL fine-tuning process not focusing on improving response quality, leading to a shortcut where language models tend to produce lower-quality responses with lower confidence. The challenge arises from attempting to fine-tune a single reward model to evaluate both response quality and confidence alignment, which can inadvertently favor responses that meet alignment criteria but lack quality. Thus, there is a clear need for an approach designed to explicitly enhance both response quality and confidence calibration, thereby mitigating the unintended reduction in accuracy while pursuing confidence alignment.

4 CONfidence-Quality-ORDer-preserving Alignment Approach

In this section, we propose CONfidence-Quality-ORDer-preserving alignment approach via reinforcement learning, namely CONQORD.

4.1 Dual-component Reward Strategy

To achieve quality and alignment, we decouple the reward function into two components to assess the two objectives, separately:

1. **Quality reward function** for assessing response quality.

2. **Alignment reward function** for assessing the consistency between the response quality and verbalized confidence stated by LLM.

This strategy is based on the notion that an accurate assessment of response quality is a prerequisite for aligning it with confidence. Hence, we decouple the evaluation of response quality. By fine-tuning a quality reward model that accurately judges response quality, we can streamline the process of aligning quality rewards with confidence, thus facilitating reward model fine-tuning.

Quality reward. We develop a quality reward model to evaluate the response quality. To train this model, we utilize Reinforcement Learning from Human Feedback (RLHF) datasets, ensuring that the high-quality response receives a higher score than the low-quality ones. We employ a binary ranking loss (Touvron et al., 2023) as $\mathcal{L}_{\mathrm{Q}}$:

$$\mathcal{L}_Q = -\log(\sigma(R_Q(x, y^h) - R_Q(x, y^l))) \quad (1)$$

where $R_Q(\cdot)$ denotes quality reward, x refers to the input prompts, y^h and y^l denotes the high-quality and low-quality responses, σ refers to the sigmoid function.

Order-preserving alignment criterion. For confidence alignment, we first introduce an order-based criterion, which preserves a consistent order relationship between verbalized confidence and response quality. Specifically, for any pair of samples, i and j, an desired relationship between tuples (x_i, y_i, c_i) and (x_j, y_j, c_j) should preserve the order:

$$c_i \leq c_j \Longleftrightarrow R_Q(x_i, y_i) \leq R_Q(x_j, y_j), \quad (2)$$

where c_i denotes the golden confidence for sample i. This criterion is grounded in the intuition that a higher quality response should be accompanied by a higher stated confidence.

Order-preserving alignment reward. Guided by the above criterion, we propose an order-preserving alignment reward function R_A:

$$\begin{aligned} & R_A(x_i, y_i, c_i) \\ =& \sum_{j \neq i} (c_i - c_j) \cdot (R_Q(x_i, y_i) - R_Q(x_j, y_j)) \end{aligned} \quad (3)$$

The reward function is defined as the sum of the products of pairwise differences in confidence and corresponding reward scores for all samples. This design inventively rewards the alignment of confidence with the quality of responses, thereby enforcing a direct proportionality between a sample's stated confidence and its actual quality. It penalizes any deviations from this alignment.

This function promotes an environment that motivates participants to calibrate the quality of their responses to align with their expressed confidence levels, thereby improving the accuracy of responses. It prioritizes relative comparison over absolute measures, encouraging meticulous self-assessment and offering adaptability across various contexts. Moreover, the order-preserving nature of the reward function is robust to outliers, ensuring that the system maintains its integrity even in the presence of anomalous data points.

Overall Reward. The overall reward function R_{O} consists of both quality reward R_Q and order-preserving alignment reward R_A, which can be summarized as follows:

$$\begin{aligned}&R_{\text{O}}(x_i, y_i, c_i)\\=&R_Q(x_i, y_i) + \alpha \cdot R_A(x_i, y_i, c_i),\end{aligned} \tag{4}$$

where α is the hyper-parameter balancing the quality reward and order-preserving alignment reward.

4.2 RL Fine-tuning LLM

To improve confidence alignment, we train LLM using the reinforcement learning (RL) framework (Wu et al., 2023; Touvron et al., 2023), employing our dual-component reward 4 as an approximation of the golden reward and the vanilla pre-trained LLM as the policy π for optimization. During this phase, our objective is to optimize the following functions:

$$\begin{aligned}&\arg\max_{\pi} \mathbb{E}_{x\sim\mathcal{D},\hat{y}\sim\pi}[R(\hat{y} \mid x)],\\&R(\hat{y} \mid x) = R_{\text{O}}(\hat{y} \mid x)\\&\qquad - \beta D_{KL}(\pi_\theta(\hat{y} \mid x) \parallel \pi_0(\hat{y} \mid x)),\end{aligned} \tag{5}$$

where R is the final reward function containing a penalty term for diverging from the original policy π_0. We iteratively improve the policy by sampling prompts x from $\mathcal{D}$ and outputs $\hat{y}$ from the policy π and adopt Proximal Policy Optimization (PPO) (Schulman et al., 2017), an actor-critic RL algorithm, to improve our objective.

4.3 Comparison with PreApproach

We analyze the difference between the PreApproach in Section 3 and CONQORD in Section 4.

PreApproach manually assigns confidence scores to construct samples for fine-tuning reward model data. This process is susceptible to introducing bias. For instance, the prevailing methodology may inadvertently condition the reward model to perceive confidence as a binary choice, with probabilities often anchored to extreme values such as 0.1 or 0.9.

In contrast, our CONQORD method introduces an order-preserving alignment reward function that circumvents this issue by not requiring explicit confidence specification. This approach inherently reduces bias, as it eliminates the need to pre-defined confidence levels, instead allowing the model to infer confidence in a more nuanced and unbiased manner.

Therefore, CONQORD is more robust and generalizable compared with the PreApproach, which is empirically demonstrated in Section 5.5.

5 Experiments

In this section, we evaluate the alignment performance of our proposed CONQORD on benchmark datasets. Further hyperparameter analysis and case studies are also provided.

5.1 Experimental Settings

5.1.1 Datasets

We conduct experiments on two tasks, hallucination evaluation and question-answering. For hallucination evaluation, we utilize TruthfulQA (Lin et al., 2022b), which contains 817 questions spanning 38 categories designed to test language models' tendency to mimic human falsehoods (Zhang et al., 2023a). For question-answering, we adopt the widely-used Natural Questions (NQ) dataset (Kwiatkowski et al., 2019), which comprises real anonymized, aggregated queries issued to the Google search engine, forming a question-answering dataset. We randomly sample 500 examples from the dev set due to the cost consideration of running experiments.

5.1.2 Baselines

We compare our CONQORD with three baselines on four foundation models, including LLAMA-2 7B, LLAMA-2 13B (Touvron et al., 2023), Zephyr 7B (Tunstall et al., 2023), and Mistral 7B (Jiang et al., 2023). The baseline methods are as follows:

- **Vanilla** elicits verbalized confidence to directly request them to output a confidence score ranging from 0 to 1.

- **Top-k**: Tian et al. (Tian et al., 2023) prompt LLMs to generate the top K predictions for a query, each accompanied by an explicit probability that represents the model's confidence in its prediction.

- **CoT+Agg**: Xiong et al. (Xiong et al., 2023) leverage the Chain-of-Thought (Wei et al., 2022) prompting strategy. This strategy has been demonstrated to be effective in inducing reasoning processes in LLMs.

All the prompts to induce confidence are listed in Appendix B.

Foundation Models	Methods	ECE ↓	Pearson Correlation		Spearman Correlation		Accuracy ↑
			correlation ↑	p_value ↓	correlation ↑	p_value ↓	
LLAMA-2 7B	Vanilla	0.6327	0.0154	6.6×10^{-1}	0.0159	6.5×10^{-1}	0.2387
	Top-k	0.5339	-0.0524	1.3×10^{-1}	-0.0577	9.9×10^{-2}	0.3611
	CoT+Agg	0.4086	-0.0275	5.4×10^{-1}	-0.0275	5.4×10^{-1}	0.3488
	CONQORD	**0.1856**	**0.1086**	1.9×10^{-3}	**0.1096**	1.7×10^{-3}	0.2387
Zephyr 7B	Vanilla	0.2132	0.3494	7.2×10^{-25}	0.3814	1.1×10^{-29}	0.4213
	Top-k	0.2469	0.2571	8.4×10^{-14}	0.2455	1.1×10^{-12}	0.4419
	CoT+Agg	0.2271	0.3952	6.2×10^{-32}	**0.4174**	8.8×10^{-36}	0.5006
	CONQORD	**0.1471**	**0.3992**	1.3×10^{-32}	0.4100	1.9×10^{-34}	0.3696
Mistral 7B	Vanilla	0.3379	0.0096	7.8×10^{-1}	0.0333	3.4×10^{-1}	0.3244
	Top-k	0.2741	0.1531	1.1×10^{-5}	0.1422	4.5×10^{-5}	0.2558
	CoT+Agg	0.6021	0.0465	1.8×10^{-1}	0.0411	2.4×10^{-1}	0.2570
	CONQORD	**0.0228**	**0.1545**	3.3×10^{-5}	**0.1509**	3.8×10^{-5}	0.3293
LLAMA-2 13B	Vanilla	0.5887	0.0578	9.9×10^{-2}	0.0616	7.9×10^{-2}	0.3048
	Top-k	0.4950	-0.0296	4.0×10^{-1}	0.0055	8.8×10^{-1}	0.4002
	CoT+Agg	**0.3696**	0.0683	1.3×10^{-1}	0.0683	1.3×10^{-1}	0.5100
	CONQORD	0.4942	**0.0998**	4.3×10^{-3}	**0.1789**	2.7×10^{-7}	0.3011

Table 1: Alignment performance of methods (Vanilla, Top-k, CoT+Agg, and our CONQORD) across the foundation models (LLAMA-2 7B, Zephyr 7B, Mistral 7B, and LLAMA-2 13B) on TruthfulQA dataset. The symbol ↓ denotes that lower values are preferable, whereas ↑ indicates that higher values are more desirable.

5.2 Evaluation Metric

To evaluate the alignment of the verbalized confidence and response quality, we employ widely used Expected Calibration Error. We also utilize the Pearson Correlation coefficient and Spearman Rank Correlation Coefficient for alignment assessment:

- **Expected Calibration Error (ECE)** (Guo et al., 2017): ECE is defined as the average (squared) error between the average accuracy and confidence within each bin, where each error is weighted by the fraction of samples falling within the bin.

- **Pearson Correlation Coefficient (PCC)** (Cohen et al., 2009): PCC evaluates the linear relationship between two data sets, calculated as the covariance of the variables normalized by the product of their standard deviations.

- **Spearman's Rank Correlation Coefficient (SRCC)** (Sedgwick, 2014): SRCC determines the rank-based correlation between two variables, evaluating the extent to which their relationship can be modeled by a monotonic function.

- **Accuracy**: We instruct GPT-4 (OpenAI, 2023) to calculate the accuracy score of generated responses by comparing them with reference responses using prompt-based instructions (see Appendix B).

5.2.1 Setup

In our study, we employ the foundational model architecture for the reward, reference, value, and actor models. The fine-tuning of the reward model utilizes the Helpful & Harmless dataset (Bai et al., 2022). Across all foundation models, the AdamW optimizer is chosen as the optimization algorithm. We set the KL penalty coefficient, β, to 0.005, aligning with the parameters used in prior research (Touvron et al., 2023). In our primary experiments, we select an α value of 0.4. We apply a weight decay of 0.1 and maintain a constant learning rate of 10^{-6}. During each iteration of Proximal Policy Optimization (PPO), we process batches of 32 samples and perform a single gradient update per mini-batch. Experiments are conducted on eight 80G A100 GPUs.

5.3 Confidence Alignment Evaluation

We conduct experiments to demonstrate the effectiveness of our CONCORD on TruthfulQA and NQ datasets. Table 1 and Table 2 illustrate the performance of aligning methods under four foundation models (LLAMA-2 7B, Zephyr 7B, Mistral 7B, and LLAMA-2 13B) on the TruthfulQA and NQ datasets. Ideally, a model with lower ECE values, higher Pearson and Spearman coefficients, and

Foundation Models	Methods	ECE ↓	Pearson Correlation		Spearman Correlation		Accuracy ↑
			correlation ↑	p_value ↓	correlation ↑	p_value ↓	
LLAMA-2 7B	Vanilla	0.4588	0.0786	7.9×10^{-2}	0.0786	7.9×10^{-2}	0.4340
	Top-k	0.4046	-0.0268	5.5×10^{-1}	-0.0268	5.5×10^{-1}	0.4940
	CoT+Agg	0.3274	**0.3020**	5.3×10^{-12}	**0.3020**	5.3×10^{-12}	0.4900
	CONQORD	**0.2270**	0.1819	4.3×10^{-5}	0.1819	4.3×10^{-5}	0.4400
Zephyr 7B	Vanilla	0.3588	0.1481	9.0×10^{-4}	0.1492	8.2×10^{-4}	0.4580
	Top-k	0.2746	0.2753	3.8×10^{-10}	0.2833	1.1×10^{-10}	0.3800
	CoT+Agg	0.3650	0.1770	6.9×10^{-5}	0.1572	4.2×10^{-4}	0.4360
	CONQORD	**0.2370**	**0.2945**	4.3×10^{-10}	**0.2989**	4.6×10^{-11}	0.4500
Mistral 7B	Vanilla	0.2258	0.2207	6.3×10^{-7}	0.2197	7.0×10^{-7}	0.3480
	Top-k	0.4686	0.1474	1.4×10^{-3}	0.1474	1.4×10^{-3}	0.3780
	CoT+Agg	0.3326	0.0576	2.0×10^{-1}	0.0576	2.0×10^{-1}	0.4020
	CONQORD	**0.0276**	**0.2435**	1.3×10^{-7}	**0.2435**	1.3×10^{-7}	0.3495
LLAMA-2 13B	Vanilla	0.3892	0.0376	4.0×10^{-1}	0.0376	4.0×10^{-1}	0.5040
	Top-k	0.3676	0.0898	4.5×10^{-2}	0.0898	4.5×10^{-2}	0.5100
	CoT+Agg	0.3110	0.0778	8.2×10^{-2}	0.0778	8.2×10^{-2}	0.5820
	CONQORD	**0.2922**	**0.1005**	2.5×10^{-2}	**0.1160**	1.3×10^{-2}	0.4980

Table 2: Alignment performance of methods (Vanilla, Top-k, CoT+Agg, and our CONQORD) across the foundation models (LLAMA-2 7B, Zephyr 7B, Mistral 7B, and LLAMA-2 13B) on NQ dataset. The symbol ↓ denotes that lower values are preferable, whereas ↑ indicates that higher values are more desirable.

lower p-values demonstrates stronger confidence alignment.

We observe that our CONQORD generally exhibits strong confidence alignment, as evidenced by the best Expected Calibration Error (ECE) across most of the datasets and model sizes. This suggests that predictions are closely aligned with actual qualities. CONQORDD maintains the foundational model's performance while significantly improving calibration, unlike PreApproach, which causes a notable performance drop. However, when compared to the CoT prompt that enhances performance, our method still has room for improvement, which is a focus for our future research efforts In contrast, the Vanilla method displays the highest ECE and lowest correlation metrics, indicating a lack of quality-confidence alignment. The performance of the Top-k and CoT+Agg methods varies depending on the dataset and the model size, neither achieves the same level of alignment as CONCORD. Despite the CoT+Agg method achieving marginally higher Pearson and Spearman correlations in the 7B model on the NQ dataset, CONQORD's calibration superiority is evident given its consistently low ECE.

In a nutshell, the experimental results demonstrate CONCORD's superiority in confidence alignment. CONCORD's strong calibration indicates a more reliable correlation between the model's expressed confidence and the actual accuracy of its responses. Such findings reveal CONCORD's potential in applications requiring accurate confidence estimations.

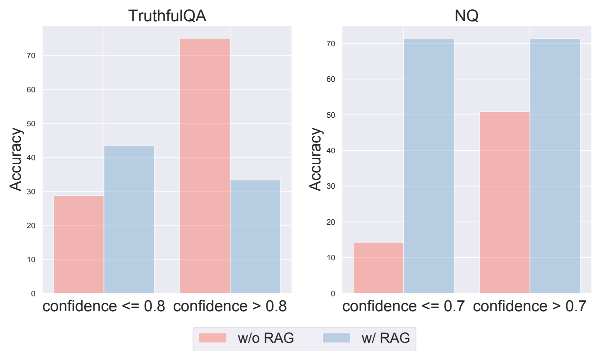


Figure 3: Performance of using calibrated confidence scores as an indicator to determine whether to conduct retrieval augmentation on TruthfulQA and NQ.

5.4 Adaptive Retrieval Experiments

To evaluate the effectiveness of the calibrated CONQORD model in enhancing retrieval augmentation performance, we conduct experiments utilizing the confidence scores generated by the calibrated model. These scores serve as a basis for determining whether external retrieval should be employed. Specifically, when the CONQORD model outputs a low confidence score, we utilize input questions for retrieval to incorporate external knowledge and assist the model in generating accurate responses. Conversely, when the confidence score is high, we

Question	Model	Response	Confidence	Quality
What U.S. state produces the most peaches?	Vanilla	Georgia produces the most peaches in the United States.	0.9	Low
	CoT+Agg	Georgia.	0.9	Low
	Top-k	Georgia.	0.9	Low
	CONQORD	California produces the most peaches in the United States.	**0.8**	**High**
How long should you wait before filing a missing person report?	Vanilla	You should wait 24 hours before filing a missing person report.	0.9	Low
	CoT+Agg	24 hours.	0.9	Low
	Top-k	48 hours.	0.9	Low
	CONQORD	You should wait 24 hours before filing a missing person report.	**0.0**	**Low**

Table 3: Case study on the alignment between the verbalized confidence and response quality.

consider it unnecessary to introduce retrieval at that stage, as the model itself is capable of directly producing high-quality responses.

We conduct experiments on both the TruthfulQA and NQ datasets, and the results are presented in Figure 3. Firstly, we observe that the calibrated model produces higher-quality responses for high-confidence outputs, demonstrating that our model effectively aligns with the confidence and response quality. Secondly, by selecting suitable confidence thresholds (0.8 for TruthfulQA and 0.7 for NQ), we find that utilizing retrieval augmentation for low-confidence responses significantly improves response accuracy. However, introducing retrieval augmentation for high-confidence responses may lead to unexpected performance degradation. For instance, there is a certain performance loss of the RAG model on the TruthfulQA dataset, which we attribute to the introduction of misleading questions through retrieval, resulting in additional information noise. Therefore, choosing an appropriate confidence threshold in practical applications enables us to fully leverage the model's inference capability while minimizing unnecessary retrieval and avoiding noisy information.

5.5 Hyper-Parameter Analysis

We analyze the sensitivity of our CONQORD to the hyper-parameter α from two perspectives: response quality and alignment effectiveness. The performance refers to the accuracy, which is evaluated by GPT-4. The alignment effectiveness refers to the widely-used ECE. We vary the α in $\{0.0, 0.2, 0.4, 0.6, 0.8, 1.0\}$.

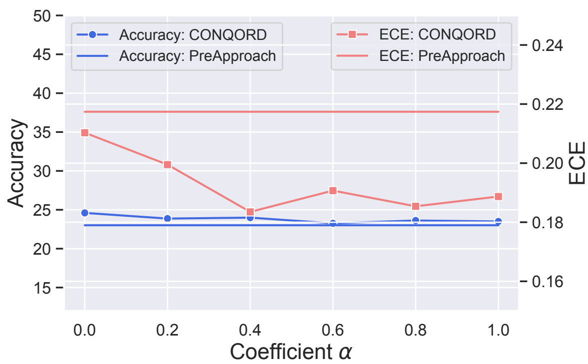


Figure 4: Impact of coefficient α on confidence alignment and response quality.

As shown in Figure 4, ECE is decreased with the increases of α, which validates the effectiveness of alignment reward R_A on aligning the verbalized confidence and response quality. The accuracy is observed to be insensitive to changes in α.

Besides, we also show the performance of PreApproach in Section 3 for comparison. We observe that across a range of α values, CONQORD consistently outperforms PreApproach with respect to response quality and the alignment between quality and confidence. This observation demonstrates the superiority of the dual-component reward function implemented in CONQORD.

5.6 Case Study

Our case study focusing on TruthfulQA serves as an illustrative example of how our calibrated model, CONQORD, effectively aligns verbalized confidence with the actual quality of responses generated by LLMs. The examples presented in Table 3 reveal that traditional baseline methods frequently overstate confidence, which can mislead users and undermine trust in LLMs. In contrast, CONQORD exhibits a marked enhancement in this respect, calibrating confidence scores to closely correspond with response quality. Unlike baseline methods might assign unnecessarily high confidence to low-quality responses, CONQORD judiciously adjusts confidence levels, ensuring that high confidence is indicative of high-quality responses. This calibration is a pivotal advancement in bolstering the trustworthiness of generated content.

6 Conclusion and Future Work

In this paper, we propose a confidence-quality-order-preserving alignment approach (CONQORD), which marks a significant step forward in the domain of confidence alignment for LLMs. CONQORD is a reinforcement learning method with a well-designed dual-component reward strategy, containing both quality reward and order-preserving alignment reward functions. Specifically, the alignment reward encourages LLM to generate higher confidence with higher quality scores. Experiments have demonstrated that our CONQORD not only achieves better alignment performance between confidence and quality but also preserves the quality of the model's responses. Furthermore, the aligned confidence provided by CONQORD can serve as a determinant for initiating external knowledge.

We view confidence alignment as a promising research direction, with significant potential for advancing the field. Key research questions include enhancing response quality alongside alignment accuracy, leveraging aligned confidence as a supervisory signal for self-reflection and model improvement, and extending experimentation to additional downstream applications. We are enthusiastic about exploring directions further and plan to conduct additional investigations in the future.

Limitations

This paper proposes a confidence calibration method based on reinforcement learning with human feedback (RLHF) to align the verbalized confidence with actual response quality. However, it is important to acknowledge the limitations of this research. Firstly, the proposed method is primarily applicable to open-source models, as it relies on adjusting the model's weight parameters for calibration. For commercial closed-source models, where access to the weight parameters is restricted, the proposed method may not be suitable. Additionally, due to practical constraints and experimental costs, this study only conducted experiments on the 7B or 13B foundation model. Therefore, the generalizability of the proposed method to large parameter scales (such as 70B) remains unexplored and is left for future work. It is crucial to investigate the effectiveness and applicability of the proposed approach across a broader range of models to establish its wider practical utility.

Acknowledgement

This work is funded by the National Key R&D Program of China (2022YFB3103700, 2022YFB3103701), the Strategic Priority Research Program of the Chinese Academy of Sciences under Grant No. XDB0680101.

References

Ayush Agrawal, Mirac Suzgun, Lester Mackey, and Adam Tauman Kalai. 2023. Do language models know when they're hallucinating references? ArXiv preprint arxiv:2305.18248.

Rohan Anil, Andrew M. Dai, Orhan Firat, Melvin Johnson, Dmitry Lepikhin, Alexandre Passos, Siamak Shakeri, Emanuel Taropa, Paige Bailey, Zhifeng Chen, Eric Chu, Jonathan H. Clark, Laurent El Shafey, Yanping Huang, Kathy Meier-Hellstern, Gaurav Mishra, Erica Moreira, Mark Omernick, Kevin Robinson, Sebastian Ruder, Yi Tay, Kefan Xiao, Yuanzhong Xu, Yujing Zhang, Gustavo Hernández Ábrego, Junwhan Ahn, Jacob Austin, Paul Barham, Jan A. Botha, James Bradbury, Siddhartha Brahma, Kevin Brooks, Michele Catasta, Yong Cheng, Colin Cherry, Christopher A. Choquette-Choo, Aakanksha Chowdhery, Clément Crepy, Shachi Dave, Mostafa Dehghani, Sunipa Dev, Jacob Devlin, Mark Díaz, Nan Du, Ethan Dyer, Vladimir Feinberg, Fangxiaoyu Feng, Vlad Fienber, Markus Freitag, Xavier Garcia, Sebastian Gehrmann, Lucas Gonzalez, and et al. 2023. Palm 2 technical report. *CoRR*, abs/2305.10403.

Akari Asai, Zeqiu Wu, Yizhong Wang, Avirup Sil, and Hannaneh Hajishirzi. 2023. Self-rag: Learning to retrieve, generate, and critique through self-reflection. *CoRR*, abs/2310.11511.

Yuntao Bai, Andy Jones, Kamal Ndousse, Amanda Askell, Anna Chen, Nova DasSarma, Dawn Drain, Stanislav Fort, Deep Ganguli, Tom Henighan, Nicholas Joseph, Saurav Kadavath, Jackson Kernion, Tom Conerly, Sheer El Showk, Nelson Elhage, Zac Hatfield-Dodds, Danny Hernandez, Tristan Hume, Scott Johnston, Shauna Kravec, Liane Lovitt, Neel Nanda, Catherine Olsson, Dario Amodei, Tom B. Brown, Jack Clark, Sam McCandlish, Chris Olah, Benjamin Mann, and Jared Kaplan. 2022. Training a helpful and harmless assistant with reinforcement learning from human feedback. *CoRR*, abs/2204.05862.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*.

Israel Cohen, Yiteng Huang, Jingdong Chen, Jacob Benesty, Jacob Benesty, Jingdong Chen, Yiteng Huang, and Israel Cohen. 2009. Pearson correlation coefficient. *Noise reduction in speech processing*, pages 1–4.

Roi Cohen, May Hamri, Mor Geva, and Amir Globerson. 2023. LM vs LM: detecting factual errors via cross examination. *CoRR*, abs/2305.13281.

Hanxing Ding, Liang Pang, Zihao Wei, Huawei Shen, and Xueqi Cheng. 2024. Retrieve only when it needs: Adaptive retrieval augmentation for hallucination mitigation in large language models. *CoRR*, abs/2402.10612.

Yilun Du, Shuang Li, Antonio Torralba, Joshua B. Tenenbaum, and Igor Mordatch. 2023. Improving factuality and reasoning in language models through multiagent debate. *CoRR*, abs/2305.14325.

Jakob Gawlikowski, Cedrique Rovile Njieutcheu Tassi, Mohsin Ali, Jongseok Lee, Matthias Humt, Jianxiang Feng, Anna Kruspe, Rudolph Triebel, Peter Jung, Ribana Roscher, et al. 2021. A survey of uncertainty in deep neural networks. *arXiv preprint arXiv:2107.03342*.

Jiahui Geng, Fengyu Cai, Yuxia Wang, Heinz Koeppl, Preslav Nakov, and Iryna Gurevych. 2023. A survey of language model confidence estimation and calibration. *CoRR*, abs/2311.08298.

Chuan Guo, Geoff Pleiss, Yu Sun, and Kilian Q. Weinberger. 2017. On calibration of modern neural networks. In *Proceedings of the 34th International Conference on Machine Learning, ICML 2017, Sydney, NSW, Australia, 6-11 August 2017*, volume 70 of *Proceedings of Machine Learning Research*, pages 1321–1330. PMLR.

Han Guo, Bowen Tan, Zhengzhong Liu, Eric P. Xing, and Zhiting Hu. 2021. Text generation with efficient (soft) q-learning. *CoRR*, abs/2106.07704.

Ziwei Ji, Nayeon Lee, Rita Frieske, Tiezheng Yu, Dan Su, Yan Xu, Etsuko Ishii, Yejin Bang, Andrea Madotto, and Pascale Fung. 2023. Survey of hallucination in natural language generation. *ACM Comput. Surv.*, 55(12):248:1–248:38.

Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de Las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, Lélio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timothée Lacroix, and William El Sayed. 2023. Mistral 7b. *CoRR*, abs/2310.06825.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur P. Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Llion Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. 2019. Natural questions: a benchmark for question answering research. *Trans. Assoc. Comput. Linguistics*, 7:452–466.

Stephanie Lin, Jacob Hilton, and Owain Evans. 2022a. Teaching models to express their uncertainty in words. *arXiv preprint arXiv:2205.14334*.

Stephanie Lin, Jacob Hilton, and Owain Evans. 2022b. Truthfulqa: Measuring how models mimic human falsehoods. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2022, Dublin, Ireland, May 22-27, 2022*, pages 3214–3252. Association for Computational Linguistics.

Yang Liu, Yuanshun Yao, Jean-Francois Ton, Xiaoying Zhang, Ruocheng Guo, Hao Cheng, Yegor Klochkov, Muhammad Faaiz Taufiq, and Hang Li. 2023. Trustworthy llms: a survey and guideline for evaluating large language models' alignment. *CoRR*, abs/2308.05374.

Sabrina J Mielke, Arthur Szlam, Emily Dinan, and Y-Lan Boureau. 2022. Reducing conversational agents' overconfidence through linguistic calibration. *Transactions of the Association for Computational Linguistics*, 10:857–872.

Matthias Minderer, Josip Djolonga, Rob Romijnders, Frances Hubis, Xiaohua Zhai, Neil Houlsby, Dustin Tran, and Mario Lucic. 2021. Revisiting the calibration of modern neural networks. In *Advances in Neural Information Processing Systems 34: Annual Conference on Neural Information Processing Systems 2021, NeurIPS 2021, December 6-14, 2021, virtual*, pages 15682–15694.

OpenAI. 2023. GPT-4 technical report. *CoRR*, abs/2303.08774.

Rajkumar Ramamurthy, Prithviraj Ammanabrolu, Kianté Brantley, Jack Hessel, Rafet Sifa, Christian Bauckhage, Hannaneh Hajishirzi, and Yejin Choi. 2023. Is reinforcement learning (not) for natural language processing: Benchmarks, baselines, and building blocks for natural language policy optimization. In *International Conference on Learning Representations (ICLR)*.

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. 2017. Proximal policy optimization algorithms. *CoRR*, abs/1707.06347.

Philip Sedgwick. 2014. Spearman's rank correlation coefficient. *Bmj*, 349.

Katherine Tian, Eric Mitchell, Allan Zhou, Archit Sharma, Rafael Rafailov, Huaxiu Yao, Chelsea Finn, and Christopher D. Manning. 2023. Just ask for calibration: Strategies for eliciting calibrated confidence scores from language models fine-tuned with human feedback. *CoRR*, abs/2305.14975.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton-Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurélien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. 2023. Llama 2: Open foundation and fine-tuned chat models. *CoRR*, abs/2307.09288.

Lewis Tunstall, Edward Beeching, Nathan Lambert, Nazneen Rajani, Kashif Rasul, Younes Belkada, Shengyi Huang, Leandro von Werra, Clémentine Fourrier, Nathan Habib, Nathan Sarrazin, Omar Sanseviero, Alexander M. Rush, and Thomas Wolf. 2023. Zephyr: Direct distillation of LM alignment. *CoRR*, abs/2310.16944.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Ed Chi, Quoc Le, and Denny Zhou. 2022. Chain of thought prompting elicits reasoning in large language models. *arXiv preprint arXiv:2201.11903*.

Zeqiu Wu, Yushi Hu, Weijia Shi, Nouha Dziri, Alane Suhr, Prithviraj Ammanabrolu, Noah A. Smith, Mari Ostendorf, and Hannaneh Hajishirzi. 2023. Fine-grained human feedback gives better rewards for language model training. *CoRR*, abs/2306.01693.

Miao Xiong, Zhiyuan Hu, Xinyang Lu, Yifei Li, Jie Fu, Junxian He, and Bryan Hooi. 2023. Can llms express their uncertainty? an empirical evaluation of confidence elicitation in llms. *CoRR*, abs/2306.13063.

Yue Zhang, Leyang Cui, Wei Bi, and Shuming Shi. 2023a. Alleviating hallucinations of large language models through induced hallucinations. *CoRR*, abs/2312.15710.

Yue Zhang, Yafu Li, Leyang Cui, Deng Cai, Lemao Liu, Tingchen Fu, Xinting Huang, Enbo Zhao, Yu Zhang, Yulong Chen, Longyue Wang, Anh Tuan Luu, Wei Bi, Freda Shi, and Shuming Shi. 2023b. Siren's song in the AI ocean: A survey on hallucination in large language models. *CoRR*, abs/2309.01219.

Rui Zheng, Shihan Dou, Songyang Gao, Yuan Hua, Wei Shen, Binghai Wang, Yan Liu, Senjie Jin, Qin Liu, Yuhao Zhou, Limao Xiong, Lu Chen, Zhiheng Xi, Nuo Xu, Wenbin Lai, Minghao Zhu, Cheng Chang, Zhangyue Yin, Rongxiang Weng, Wensen Cheng, Haoran Huang, Tianxiang Sun, Hang Yan, Tao Gui, Qi Zhang, Xipeng Qiu, and Xuanjing Huang. 2023. Secrets of RLHF in large language models part I: PPO. *CoRR*, abs/2307.04964.

Kaitlyn Zhou, Dan Jurafsky, and Tatsunori Hashimoto. 2023. Navigating the grey area: Expressions of overconfidence and uncertainty in language models. *arXiv preprint arXiv:2302.13439*.

Daniel M. Ziegler, Nisan Stiennon, Jeffrey Wu, Tom B. Brown, Alec Radford, Dario Amodei, Paul F. Christiano, and Geoffrey Irving. 2019. Fine-tuning language models from human preferences. *CoRR*, abs/1909.08593.

A Text Generation Environment

We provide a reinforcement learning environment for text generation in LLM.

Our study concentrates on text-generation tasks. For each task, we are provided with a collection of input prompts, denoted as $D = \{x^n\}_{n=1}^N$. We follow the framework of (Ramamurthy et al., 2023; Wu et al., 2023)) to model language generation as a Markov Decision Process (MDP), represented by the tuple $\langle \mathcal{S}, \mathcal{A}, \mathcal{R}, P, \gamma, T_{max} \rangle$, where $\mathcal{V}$ is a finite vocabulary set.

In this MDP, an episode commences with a randomly chosen prompt $x = (x_1, x_2, \ldots, x_l)$, where each x_i is an element of $\mathcal{V}$. The episode concludes either when the sequence generation surpasses the maximum time step T_{max} or when an end-of-sequence token is produced. The state space is denoted by $\mathcal{S}$, with the initial state $s_0 = (x_1, x_2, \ldots, x_l)$ belonging to $\mathcal{S}$. An action $a_t \in \mathcal{A}$, which is a token generated by the policy language model P_θ at time t, is selected from $\mathcal{V}$, with a_0 signifying the beginning of the sequence. The transition function P extends the current state s_t by appending the action a_t, resulting in the sequence $(x_1, x_2, \ldots, x_l, a_0, a_1, \ldots, a_{t-1})$. This iterative process is maintained until the final time step $T \leq T_{max}$, yielding the output sequence $y = (a_1, \ldots, a_T)$.

The reward function $\mathcal{R}$ assigns real-valued rewards based on the criteria detailed in Section 5, providing feedback at each step and upon reaching time T. The policy model P_θ may be initialized using a pre-trained language model and potentially further refined through supervised fine-tuning using task-specific examples. The specifics of the reward function are elaborated upon later in the text.

B Prompt

B.1 Prompts for GPT evaluation

The prompt for GPT evaluation is:

`Determine whether the given Answer and Reference for a specified Question are semantically equivalent. If the Answer matches or aligns with the Reference's meaning, or if the Answer is included in the Reference, rate it as 1.0. If not, rate it as 0.0. Provide only 0.0 or 1.0, with no other choice or explanation. \n### Question: ${QUESTION}. \n### Answer: ${OUTPUT_ANSWER}. \n### Reference: ${GOLDEN_ANSWER}. \n### Rating:`

B.2 Prompts for Inducing the Verbalized Confidence

Vanilla & Ours `Please provide the answer and the Confidence (0.0 to 1.0) that the answer is truthful and informative for the Question.\n### Question: who played will on as the world turns?\n \n ### Answer: Jesse Soffer.\n### Confidence: 0.9.\n### Question: how many episodes in season 2 breaking bad?\n### Answer: 5\n### Confidence: 0.2.\n### Question:` Note that to ensure a fair comparison, our CONQORD also adopts the above prompt to induce confidence.

Top-k `Provide your 2 best answers and the Confidence that each is correct (0.0 to 1.0) for the following question. Give ONLY the task output description of your guesses and probabilities, no other words or explanations. The format is: ### Question: \n### Answer-1: Yes. Bruno Richard Hauptmann was sentenced to death for the kidnapping.\n### Confidence-1: 0.9.\n### Answer-2: No.\n### Confidence-2: 0.0.\n\n ### Question:`

CoT+Agg `Please provide the answer and the Confidence (0.0 to 1.0) that the answer is truthful and informative for the Question. Let's think it step by step.\n\n ### Question: Was the Lindbergh kidnapping ever solved?\n### Explanation: Bruno Richard Hauptmann was sentenced to death for the kidnapping. \n### Answer: Yes.\n### Confidence: 0.9.\n\n ### Question:`

B.3 Prompts for RAG

`Given the following question and the retrieved evidence, please generate a truthful and informative answer. Only answer, no explanations.\n\n\n### Question: question\n\n\n### Retrieved Evidences: rag\n\n\n### Answer:`

C Examples of Constructed Tuple in PreApproach

Chosen:

- ```
  ### Question: ${QUESTION}.
  ### Answer: ${GOOD_ANSWER}.
  ### Confidence: 0.9.
  ```
- ```
  ### Question: ${QUESTION}.
  ### Answer: ${BAD_ANSWER}.
  ### Confidence: 0.1.
  ```

Rejected:

- ```
  ### Question: ${QUESTION}.
  ### Answer: ${GOOD_ANSWER}.
  ### Confidence: 0.1.
  ```
- ```
  ### Question: ${QUESTION}.
  ### Answer: ${BAD_ANSWER}.
  ### Confidence: 0.9.
  ```