Reward-SQL: Boosting Text-to-SQL via Stepwise Reasoning and Process-Supervised Rewards

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Abstract

Recent advances in large language models (LLMs) have significantly improved performance on the Text-to-SQL task by leveraging their powerful reasoning capabilities. To enhance accuracy during the reasoning process, Process Reward Models (PRMs) can be introduced during training and inference to provide fine-grained supervision. However, if misused, PRMs may distort the reasoning trajectory and lead to suboptimal or incorrect SQL generation. To address this challenge, we propose REWARD-SQL, a framework that systematically explores how to incorporate PRMs into the Text-to-SQL reasoning process effectively. Our approach follows a "cold start, then PRM supervision" paradigm. Specifically, we first train the model to decompose SQL queries into structured stepwise reasoning chains using common table expressions (Chain-of-CTEs), establishing a strong and interpretable reasoning baseline. Then, we investigate four strategies for integrating PRMs, and find that combining PRM as an online training signal (e.g., GRPO) with PRM-guided inference (e.g., Best-of-N sampling) yields the best results. Empirically, on the BIRD benchmark, REWARD-SQL enables models supervised by a PRM (7B) to achieve a 13.1% performance gain across various guidance strategies. Notably, our GRPO-aligned policy model based on Qwen2.5-Coder-7B-Instruct achieves 68.9% accuracy on the BIRD development set, outperforming all baseline methods under the same model size. These results demonstrate the effectiveness of REWARD-SOL in leveraging reward-based supervision for Text-to-SQL reasoning.³.

1 Introduction

Text-to-SQL aims to translate natural language questions into SQL queries, allowing non-technical users to interact with complex databases [6, 19, 20, 48, 15]. Recent progress in this field has focused on improving the *reasoning capabilities* of large language models (LLMs) to boost performance [11, 12, 22, 23, 31]. However, extended reasoning chains inherently increase the risk of hallucination [9, 37], which can undermine model accuracy. To mitigate this, *reward models* have been proposed to guide LLM outputs [2, 27, 17]. Broadly, Reward models can be categorized as Outcome-supervised Reward Models (ORMs) [38], which evaluate complete responses, and Process-supervised Reward Models (PRMs) [16], which assess individual reasoning steps.

In this work, we focus primarily on PRMs, since it enables more targeted feedback during multi-step reasoning and can more effectively identify critical errors compared to ORMs. Neverthless, although

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³Our code is publicly available in https://github.com/ruc-datalab/RewardSQL

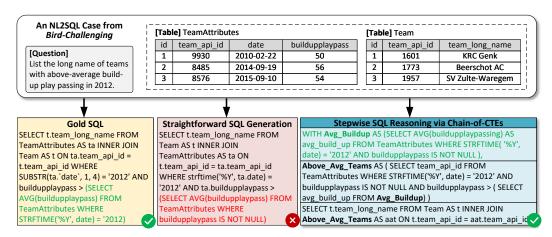


Figure 1: **Stepwise SQL Reasoning via Chain-of-CTEs**. Unlike direct SQL generation, our proposed Chain-of-CTEs approach decomposes Text-to-SQL into step-by-step reasoning using Common Table Expressions (CTEs), and leverages Process-supervised Reward Models (PRMs) to provide fine-grained evaluation of each intermediate step.

PRMs offer clear advantages in improving output quality, applying them effectively to Text-to-SQL tasks requires careful design. Specifically, an ideal PRM for Text-to-SQL should be able to evaluate whether a generated SQL query aligns with the ground-truth and provide reliable, step-by-step feedback throughout the reasoning process. In such a way, the PRM can improve the Text-to-SQL model in both post-training and inference stages [4]. Therefore, we ask a natural question:

Can we effectively leverage Process-supervised Reward Models to improve Text-to-SQL reasoning?

Clearly, answering this question affirmatively would mark a significant step forward in improving the reasoning abilities of LLMs for complex Text-to-SQL tasks. To this end, we must address two fundamental challenges:

Challenge 1: Chain-of-Thoughts (CoT) and PRM Design. A PRM is required to evaluate the *intermediate reasoning* steps in the inference process. Thus, unlike existing PRMs developed for mathematical reasoning tasks [16], the PRM for Text-to-SQL must be tailored to the unique characteristics of SQL-related reasoning, which is similar to CoT-like steps [41]. This requires first designing appropriate intermediate reasoning steps for Text-to-SQL and then designing a PRM capable of understanding both SQL syntax and the semantic relationships between database components.

Challenge 2: PRM Utilization. Even with a well-designed PRM, effectively integrating it into training and inference of LLMs remains non-trivial. Different strategies vary in how they leverage PRM feedback, each with distinct implications for model learning and generalization. The core challenge is to harness the supervision signal from PRM in a way that promotes SQL reasoning, rather than encouraging the model to merely overfit to reward patterns.

To address these challenges, we propose REWARD-SQL, a framework that enhances Text-to-SQL reasoning capabilities using the PRM. Our approach follows a "cold start, then PRM supervision" paradigm, which consists of three key stages: Model Initialization, Online Reinforcement Learning (RL) Training, and PRM-assisted Inference, as illustrated in Figure 2.

Firstly, we introduce Chain-of-CTEs (COCTE) as task-specific reasoning steps for Text-to-SQL, which decompose complex queries into a sequence of Common Table Expressions (CTEs), as shown in Figure 1. As temporary named result sets, CTEs help structure query logic and improve interpretability [24], while also addressing issues such as missing conditions in nested queries. To initiate learning, we perform supervised fine-tuning using CoCTE-formatted data, serving as a "cold start" [4]. Secondly, we train a dedicated PRM to evaluate the quality of each reasoning step, enabling fine-grained evaluation. For PRM utilization, we explore four strategies to incorporate PRM feedback: two offline methods, namely rejection sampling [25] and Direct Preference Optimization (DPO) [32]; one online method, namely GRPO [4]; and one inference-time method Best-of-N selection guided by the PRM [16].

Our empirical findings highlight three key insights. (1) Among all training strategies, applying the PRM in the online setting via GRPO yields the best performance, as it enables full utilization of all samples with appropriate weighting. (2) For offline training, DPO outperforms rejection sampling by

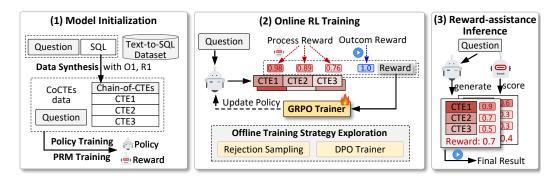


Figure 2: **Overview of the REWARD-SQL framework.** Our approach comprises three key stages: 1) **Model Initialization**, where the model learns to decompose SQL generation into a structured Chain-of-CTEs (Section 4); 2) **Online RL Training**, where the PRM guides the policy model through online reinforcement learning via GRPO (Section 5.3); and 3) **PRM-Assisted Inference**, where we leverage the PRM to enhance inference quality by test-time scaling (Section 5.4).

leveraging both positive and negative examples. (3) At inference time, using the PRM for Best-of-N selection significantly improves output quality, revealing the strong potential of test-time scaling. Based on these findings, we propose our Reward-SQL (Figure 2). Under Qwen2.5-Coder-7B-Instruct backbone, our Reward-SQL achieves **68.9%** execution accuracy on the BIRD development set [14], setting a *new state-of-the-art* among models of comparable parameter size.

Our contributions are summarized as follows:

- We introduce a novel reasoning paradigm, Chain-of-CTEs (CoCTE), tailored for the Text-to-SQL task, and develop a corresponding training pipeline for its PRM.
- We conduct a comprehensive study on the use of reward models in Text-to-SQL, demonstrating that online training strategies consistently outperform offline ones, and accordingly design the REWARD-SQL framework to fully leverage PRM feedback.
- Our approach achieves 68.9% execution accuracy on the BIRD development set, setting a new state-of-the-art performance among models with 7B parameters.

2 Related Work

Reward Modeling for LLM Reasoning. Reward models have recently been integrated into various reasoning tasks to supervise the output quality, including mathematics and code generation [36, 42, 47]. Technically, reward models are categorized into ORMs and PRMs. Compared to the holistic evaluations by ORMs, PRMs provide fine-grained, step-level assessments, which have recently attracted great attention. Since [16] proposes PRMs, and demonstrates their superiority in mathematical problem-solving, the PRM is leveraged in both the inference and post-training stages. During inference, the PRM is applied to guide the inference reasoning path through best-of-N [16, 44]. On the other hand, the PRMs are also applied to supervise the post-training stage [3, 34], while developing a similar process for Text-to-SQL as presented in this paper remains to be explored.

LLM Reasoning for Text-to-SQL. Recent advances in Text-to-SQL have seen the emergence of numerous reasoning-based approaches [29, 46, 28, 8] The basic idea of these approaches is to decompose a complex SQL generation task into step-by-step reasoning subtasks. These approaches can be categorized into training-free and training-based methods. Training-free methods leverage the powerful generalization capabilities of LLMs [33], mainly by using prompting techniques to elicit intermediate reasoning steps in different manners. These include in-context learning approaches [5, 10], designing prompt templates [28]. Furthermore, test-time scaling approaches [17], such as Alpha-SQL [11], dynamically scale reasoning steps during inference through Monte Carlo tree search (MCTS) [43]. This enhances model adaptability and enables zero-shot capabilities without requiring additional training data. On the other hand, training-based methods focus on designing reasoning-formatted datasets where LLMs learn Text-to-SQL reasoning through fine-tuning on well-curated training data, using a standard post-training method. For example, these include DPO [18], GRPO [31], and supervised fine-tuning with self-reward model [22].

Despite these advancements, **systematic exploration of reward models in Text-to-SQL tasks remains limited**. Most existing approaches either neglect reward models entirely or fail to integrate them effectively across both training and inference. Our work addresses this gap by investigating various reward modeling strategies specifically designed for Text-to-SQL reasoning and exploring their application throughout the entire pipeline.

3 Our REWARD-SQL Approach

3.1 Stepwise Reasoning for Text-to-SQL

The Text-to-SQL task converts a natural language query $x = \{q, db\}$, comprising user query q and database schema db, into a corresponding SQL query y that correctly answers the user's question.

Large Language Models (LLMs) are well-suited for this task as auto-regressive sequence generators. For standard generation, an LLM π_{θ} produces tokens sequentially by modeling $\pi_{\theta}(y|x) = \prod_{t=1}^{T} \pi_{\theta}(y_t|x,y_{< t})$. Chain-of-Thought (CoT) [41] reasoning extends this by decomposing complex tasks into intermediate steps $C = \{c_1,c_2,...,c_k\}$ before producing the final answer: $\pi_{\theta}(C,y|x) = \pi_{\theta}(C|x) \cdot \pi_{\theta}(y|x,C) = \prod_{i=1}^{K} \pi_{\theta}(c_i|x,c_{< i}) \cdot \pi_{\theta}(y|x,C)$.

Chain-of-CTEs (**CoCTE**), a specialized CoT format introduced for Text-to-SQL tasks that leverages Common Table Expressions (CTEs)[24]. A CTE is a named temporary result set defined by a SQL query that can be referenced within the scope of a subsequent SQL, enabling step-by-step reasoning.

Definition 1 (Common Table Expression) A Common Table Expression (CTE) is a named temporary result set c_i defined by a SQL query q_i that can be referenced within the scope of a SQL statement: $c_i AS(q_i)$, where q_i may reference database tables and/or previously defined CTEs c_j for j < i. The keyword AS connects the CTE name to its query definition.

Definition 2 (Chain-of-CTEs) A Chain-of-CTEs (CoCTE) is a sequence of interconnected CTEs $C = \{c_1, c_2, ..., c_k\}$ followed by a final query q_f that produces the answer: WITH c_1 AS (q_1) , c_2 AS (q_2) , ..., c_K AS (q_K) q_f . Here, each CTE c_i represents a discrete reasoning step, and the final SQL query g is derived from this reasoning process as g = f(C).

The goal of CoCTE is to ensure that the intent of the user's query q is accurately captured by the reasoning steps in C. As illustrated in Figure 1, inference with CoCTE offers two key advantages: explainability, as each CTE produces a concrete, executable intermediate result that can be independently verified; and accuracy, as the decomposition of complex queries into simpler subproblems enables the model to focus on solving one aspect at a time, reducing errors in the final solution. For example, a complex sports analytics query can be broken down into calculating averages first, then filtering teams, and finally retrieving names—mirroring how human experts approach such problems.

3.2 REWARD-SQL: Enhancing SQL Generation via Process-Supervised Rewards

Our REWARD-SQL framework enhances Text-to-SQL generation through a comprehensive process-level reward modeling approach. As illustrated in Figure 2, the framework consists of three key stages designed to improve SQL generation capabilities: (1) **Model Initialization**, where we perform policy model cold start and PRM training as detailed in Section 4; (2) **Online RL Training**, which implements post-training of the policy model via GRPO—selected for its superior performance as demonstrated in our comparative analysis in Section 6—described in Sections 5.2 and 5.3; (3) **PRM-Assisted Inference**, where we further improve model performance test-time scaling that leverage the PRM to evaluate multiple candidate solutions during inference time (Section 5.4).

4 Model Initialization

As mentioned before, to solve the Text-to-SQL problem in a reasoning manner, we require two key components: a policy model that generates CoCTE-formatted SQL queries and a process-supervised reward model (PRM) that evaluates reasoning step quality. Due to the lack of existing CoCTE-formatted data, our initialization process consists of two steps: 1) Policy Model Cold Start, where

we transform the model's outputs in CoCTE format, and 2) Process-supervised Reward Model Initialization, where we develop a model to evaluate each reasoning step's correctness.

4.1 Policy Model Cold Start

"Cold start" refers to the supervised fine-tuning of the policy model on a small dataset to adapt its output format [4]. To address the scarcity of high-quality CoCTE-formatted data, we transform the training set from the BIRD benchmark [14]. We begin by manually crafting a small number of CoCTE examples from the original SQL queries. These are then used to prompt strong reasoning LLMs to convert more SQL statements into CoCTE form. The generated CoCTEs are executed in the database, and only those that match the original SQL execution results are retained. Further details on the dataset construction process are provided in Appendix A.2.

CoCTE Data Filtering. We have observed that LLM-generated CoCTEs for the same question often exhibit high structural similarity, which can negatively impact model performance. To preserve diversity, we apply a tree edit distance-based filtering strategy. Specifically, we use sqlglot [26] to parse each CoCTE into a syntax tree and compute normalized edit distances between the preorder traversal sequences. Then, we iteratively remove CoCTEs with the distance smaller than the threshold, thereby retaining a more structurally diverse set of examples for cold start training.

4.2 Process Reward Model Initialization

PRM Training Data Generation. Following [21], we adopt a Monte Carlo estimation approach to generate step-level labels for training the PRM. For each training instance in the BIRD training set, we sample *n* reasoning paths using the policy model and apply Monte Carlo Tree Search (MCTS) to efficiently explore diverse reasoning trajectories, balancing exploration and exploitation. During the search, multiple completions are executed at each step. A step is labeled as incorrect if all completions fail, and further exploration proceeds only along promising paths. This process allows us to pinpoint the first erroneous step in each reasoning chain. Details are provided in Appendix A.2.

PRM Training. Following the cold start, we train a PRM after filtering out noisy annotations in the dataset. The PRM is optimized using a step-level binary classification objective, where each CTE c_i is assigned a label $\xi_i \in \{0,1\}$, with 1 indicating correctness and 0 indicating an error. A step is labeled as correct if it can eventually lead to a SQL query that matches the ground truth result. To strengthen the model's understanding, we enrich each CTE with its corresponding execution output via SELECT * FROM CTE queries. This allows the PRM to evaluate both syntactic validity and execution semantics. The input is structured by pairing each CTE with its execution output and inserting special step-tag tokens to explicitly mark evaluation checkpoints. These tagged positions indicate where the PRM should predict the correctness score, enabling precise step-level supervision.

The PRM assigns a sigmoid score $s_i \in (0,1)$ to each reasoning step and is trained using a binary cross-entropy loss: $\mathcal{L}_{\text{PRM}} = \min_{\sigma} \sum_{i=1}^k \left[-\xi_i \log(s_i) - (1-\xi_i) \log(1-s_i) \right]$, where ξ_i is the binary correctness label for the i-th step, and k is the total number of steps in the COCTE reasoning chain.

Inference with PRM. At inference time, PRM evaluates solutions using the same input format with execution results and step-tag tokens. The PRM produces softmax probabilities for the "correct" token logit at these positions, yielding confidence scores between 0 and 1 per step. For multi-step candidates, we collect all step-level scores to determine overall solution quality.

5 Reward-Guided Optimization Strategies

With a "cold-started" policy model and a trained PRM in place, we systematically explore the design space of reward-guided optimization. Specifically, we categorize our strategies into three standard post-training approaches: (1) **Offline RL Training**: The PRM is used to score candidate CoCTEs without updating the policy model during data collection. (2) **Online RL Training**: The policy model is continuously updated during training, enabling adaptive learning based on real-time PRM feedback. (3) **Reward-Assisted Inference**: At test time, the PRM selects the best CoCTE from multiple candidates, improving final SQL quality. For each category, we adopt representative methods commonly used in prior work [32, 4, 44].

5.1 Reward Design

Our reward framework combines two complementary components:

Process Reward (PR): Provided by our Process Reward Model (PRM), which evaluates each CTE step's quality. For a CoCTE with K steps, PRM assigns scores to each step, with the overall PR calculated as $PR(C) = \sum_{i=1}^{K} s(c_i)/K$.

Outcome Reward (OR): A binary component evaluating execution correctness, defined as OR(C) = 1 if execution matches ground truth, and 0 otherwise.

Training vs. Inference Rewards: During training, we use the combined reward $R_{training} = PR(C) + OR(C)$ for comprehensive feedback. During inference, since ground truth is unavailable, we rely solely on the Process Reward for candidate selection: $R_{inference} = PR(C)$.

This dual design ensures optimization considers both reasoning quality and outcome correctness during training, while providing a practical evaluation mechanism during inference.

5.2 Offline RL Training

Rejection Sampling (RS). We implement rejection sampling [25] by generating N CoCTEs $\{C_i\}$ for each question, then filtering based on reward scores $\{R_i\}$. Only candidates exceeding threshold τ are retained: $\mathcal{D}_{\text{filtered}} = \{(q,C_i) \mid R_i > \tau, i \in \{1,2,...,N\}\}$ The policy model is then fine-tuned on this filtered dataset: $\mathcal{L}_{\text{RS}} = \max_{\theta} \mathbb{E}_{(q,C) \sim \mathcal{D}_{\text{filtered}}}[\log \pi_{\theta}(C|q)]$

Direct Preference Optimization (DPO). DPO [32] leverages the comparative information between CoCTEs. For each question q, we identify pairs of CoCTEs (C_w, C_l) where C_w has a higher reward score than C_l . Based on a Bradley-Terry (BT) [1] preference model, we get the following DPO loss: $\mathcal{L}_{\text{DPO}} = \min_{\theta} -\mathbb{E}_{(q,C_w,C_l)\sim\mathcal{D}} \left[\log\sigma\left(\beta\log\frac{\pi_{\theta}(C_w|q)}{\pi_{\text{ref}}(C_w|q)} - \beta\log\frac{\pi_{\theta}(C_l|q)}{\pi_{\text{ref}}(C_l|q)}\right)\right]$ where π_{ref} is the reference policy model, β is a temperature parameter controlling the strength of the preference signal, and σ is the sigmoid function.

5.3 Online RL Training

For the online training process, we focus on the recently proposed Group Relative Policy Optimization (GRPO) [34], which efficiently leverages step-level PRM scores to guide policy updates.

GRPO. In GRPO, we generate a group of COCTEs $\{C_1, C_2, ..., C_G\}$ for each question q using the current policy model π_{θ} . Unlike traditional RL methods that require a separate value function model, GRPO uses group-relative advantages to reduce variance and computational burden.

In online RL, reward models critically impact the trained model's performance [27]. As detailed in Section 5.1, we combine PRM-based scores (evaluating reasoning quality) with rule-based rewards (assessing execution correctness) to provide comprehensive feedback during training.

Given a question q, for each COCTE $C_i = \{c_i^1 \cdots c_i^{K_i}\}$ with length K_i and intermediate steps c_i^j , our reward model provides step-level scores $\{s(c_i^j)\}_{j=1}^{K_i}$ for each CTE. We then calculate a representative score for each COCTE as $\bar{s}_i = \sum_{j=1}^{K_i} s(c_i^j)/K_i$, which averages the step-level scores. Finally, we normalize these scores across the group to obtain relative advantages using $\hat{A}_i = \frac{\bar{s}_i - \mu}{\sigma}$, where μ and σ represent the mean and standard deviation of $\{\bar{s}_i\}_{i=1}^G$.

To obtain fine-grained step-level advantages reflecting both CoCTE quality and internal step variations, we assign advantage values as $\hat{A}_i^j = \hat{A}_i \cdot s(c_i^j)$ if $\hat{A}_i > 0$, or $\hat{A}_i \cdot (1 - s(c_i^j))$ if $\hat{A}_i < 0$. This ensures that in positively-advantaged CoCTEs, higher-scored steps receive larger advantages, while in negatively-advantaged ones, lower-scored steps receive larger negative advantages. Appendix A.3.2 demonstrates our approach's effectiveness and reveals potential reward hacking issues in [34].

The GRPO objective function is defined as:

$$\begin{split} \mathcal{L}_{\text{GRPO}} &= \mathbb{E}_{q \sim \mathcal{D}, \{C_i\}_{i=1}^G \sim \pi_{\theta_{\text{old}}}(\cdot|q)} \Bigg[\frac{1}{G} \sum_{i=1}^G \frac{1}{K_i} \sum_{j=1}^{K_i} \\ & \min \left(\frac{\pi_{\theta}(c_i^j|q, c_i^{< j})}{\pi_{\theta_{\text{old}}}(c_i^j|q, c_i^{< j})} \hat{A}_i^j, \text{clip} \left(\frac{\pi_{\theta}(c_i^j|q, c_i^{< j})}{\pi_{\theta_{\text{old}}}(c_i^j|q, c_i^{< j})}, 1 - \epsilon, 1 + \epsilon \right) \hat{A}_i^j \right) \Bigg] - \beta D_{KL}(\pi_{\theta}||\pi_{\text{ref}}) \end{split}$$

where ϵ is the clipping parameter, β controls the strength of the KL regularization, and π_{ref} is the reference policy. We estimate an unbiased non-negative KL divergence as in [27]:

$$D_{KL}(\pi_{\theta}||\pi_{\text{ref}}) = \frac{\pi_{\text{ref}}(c_i^j|q, c_i^{< j})}{\pi_{\theta}(c_i^j|q, c_i^{< j})} - \log \frac{\pi_{\text{ref}}(c_i^j|q, c_i^{< j})}{\pi_{\theta}(c_i^j|q, c_i^{< j})} - 1$$

This approach allows for more efficient exploration of the CoCTE space by focusing on promising reasoning paths identified by the reward, while providing fine-grained supervision at the step level.

5.4 Reward-Assisted Inference

For reward-assisted inference, we implement Best-of-N sampling [16], a widely adopted approach in modern LLM applications that effectively leverages our PRM to select high-quality outputs.

Best-of-N. This approach generates N candidate CoCTEs $\{C_1, C_2, ..., C_N\}$ for a question q using diverse sampling strategies with policy model π_{θ} . Each candidate receives a PRM score, and the highest-scoring candidate becomes the final output. Formally, we select the CoCTE that maximizes the expected reward: $C^* = \arg\max_{C \in \mathcal{C}_q} \mathbb{E}[PR(C|q)]$, where \mathcal{C}_q represents potential candidates for question q. Unlike training-time methods, Best-of-N is training-free and orthogonal to them.

6 Comparative Analysis of Optimization Approaches in PR-OR Space

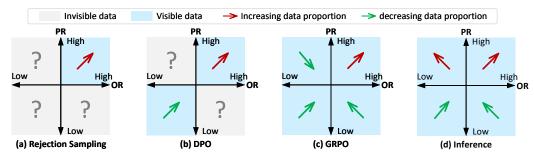


Figure 3: **Optimization Patterns** in the **PR-OR** Space Across Different Approaches.

Owing to the aforementioned loss formulations, the four data utilization methods are supposed to result in outputs with different distributions in the PR-OR space, which can be visualized in Figure 3.

(1) **Rejection Sampling** trains exclusively on samples with high PR and correct OR (top-right quadrant), potentially limiting exploration and learning from mistakes. (2) **DPO**, while offline, leverages comparative information between optimal samples (top-right quadrant) and suboptimal ones (bottom-left quadrant), enabling the model to distinguish effective reasoning patterns. However, its binary preference structure may overlook valuable signals from mixed-performance regions. (3) **GRPO** incorporates weighted signals from all four PR-OR quadrants, capturing the full spectrum of reasoning patterns. This comprehensive approach enables effective exploration while exploiting successful patterns, resulting in more robust optimization across diverse query types, though it may introduce training instability due to its complex reward weighting mechanism. (4) **Best-of-N** sampling operates during inference time, complementing training-based methods by exploring the high PR region through multiple candidates and selecting the highest predicted reward. This approach effectively identifies high-quality outputs that might occur with low probability under the base policy, albeit with additional inference computational costs.

As analyzed, though all the aforementioned methods have the potential to improve the Text-to-SQL model, they also face the corresponding drawbacks. Thus, which of them works the best in practice remains to be explored. Next, we will empirically explore whether the outputs of the model under these four methods are distributed as analyzed, and find out the optimal method in practice.

7 Experiments

This section empirically evaluates the reward-guided optimization strategies introduced in Section 5. Based on these results, we compare our REWARD-SQL framework with several strong baselines.

7.1 Experimental Settings

Datasets. We use the BIRD dataset [14], released under the MIT License. It comprises 9,428 training examples, 1,534 development examples, and 1,789 test examples, featuring complex database schemas and challenging natural language questions that require advanced reasoning capabilities. We train models on the BIRD training set and evaluate performance on the development set.

Metrics: We evaluate model performance using *execution accuracy (EX)*, comparing the execution results of the predicted and ground truth SQL queries. For inference, we adopt two decoding strategies: (1) Greedy decoding, with the temperature set to zero, and (2) Vote@n, where the model generates n candidate responses and selects the best one using a scoring mechanism, such as a reward model.

7.2 Exploration Results for Reward Model

We first systematically analyze the effectiveness of different reward-guided approaches as mentioned in Section 6. We categorize samples into four quadrants based on Process Reward (PR) and Outcome Reward (OR). These quadrants help evaluate how different methods navigate the PR-OR space and their effectiveness in maximizing desired outcomes (high PR, high OR). ⁴.

Table 1: Analysis of selection effectiveness for different methods on BIRD dev set. The symbols "+" and "-" are respectively "high" and "low", e.g., +PR/+OR means high PR and high OR, located in the upper right region of Figure 3.

Model	+PR/+OR (%)↑	+PR/-OR (%)↓	-PR/-OR (%)↓	-PR/+OR (%)↓	EX Acc (%)↑	
Greedy Decoding						
SFT	51.8	24.8	20.8	2.7	54.4	
SFT + RS	51.8	23.9	22.2	2.1	54.0	
SFT + DPO	56.5	21.8	18.6	3.1	59.6	
SFT + GRPO	58.4	28.2	12.1	1.3	59.7	
Best-of-32 Decoding						
SFT	66.4	28.7	4.3	0.5	67.0	
SFT + RS	66.9	28.0	4.7	0.4	67.3	
SFT + DPO	66.8	28.4	4.2	0.6	67.4	
SFT + GRPO	68.7	27.8	3.3	0.2	68.9	

Train-Time Guidance of Reward Models. We explore three strategies to incorporate reward signals during training as described in Section 5: RS and DPO (offline RL) and GRPO (online RL).

Table 1 provides interesting insights when comparing these train-time guidance approaches. (1) Under greedy decoding, RS shows minimal change in the +PR/+OR rate and has limited impact on other metrics, resulting in a slight drop in execution accuracy (54.0% vs. 54.4% for SFT). We speculate that this is because RS is only exposed to +PR/+OR samples during training, leading to poor generalization on other types of samples. (2) Compared with RS, DPO achieves substantial +PR/+OR improvements and -PR/-OR decreasing, demonstrating its effectiveness in learning by contrasting high PR-OR samples against low PR-OR ones. (3) GRPO demonstrates the most comprehensive improvements across all metrics, achieving the highest +PR/+OR rate, the lowest -PR/-OR rate, and the lowest -PR/+OR rate under greedy decoding. These results validate its effectiveness in leveraging data from all quadrants of the PR-OR space.

Test-Time Guidance of Reward Models. Recall that Best-of-N decoding is orthogonal to training-based methods. Our experimental results are presented in Table 1. Across all model variants, applying Best-of-N selection with the PRM consistently improves performance. For instance, on the base SFT model, PRM-based selection yields a substantial 12.6% absolute gain in execution accuracy.

⁴For the SFT baseline, we only implement the "cold start" phase without additional training. Our attempts to fine-tune the model on RL-stage data without selection processes like RS yielded poor practical results.

Notably, for SFT, the PRM raises the +PR/+OR rate to 66.4% (from 51.8% under greedy decoding) while keeping the -PR/+OR rate as low as 0.5%. These results demonstrate the ability of PRM to distinguish between valid and invalid reasoning paths, even without additionally training base models.

Besides, combining Best-of-N significantly improves the three RL-based methods, especially for GRPO. We speculate that this is because the diversity of GRPO-trained model (captured by exploring during GRPO) increases the potential for correct answers to appear among the generated candidates.

Based on these findings, we adopt the SFT+GRPO+PRM pipeline as our REWARD-SQL framework (illustrated in Figure 2). This integrated approach combines the strengths of supervised fine-tuning, online reward-guided optimization, and test-time selection via the PRM. Together, these components enable REWARD-SQL to achieve state-of-the-art performance on complex SQL generation tasks.

7.3 Comparison with Text-to-SQL Baselines

Baselines. Following prior work, we categorize existing approaches into two main paradigms: prompting methods and post-training strategies on LLMs. All included baselines are representative and widely adopted methods within these respective regimes.

We train the proposed REWARD-SQL method under a Qwen2.5-Coder-7B-Instruct model, while the baseline methods are implemented under different models. As shown in Section 7.2, Best-of-N selection significantly enhances REWARD-SQL performance. We compare this approach using the notation "vote@n". For baselines, the selection methods for the best answer either rely on a selection agent [28] or MCTS [11, 22], depending on the original works. Besides, Reasoning-SQL [31] found that a Gemini schema filter further improves performance, so we also report the result with this trick.

Table 2: Comparison of our REWARD-SQL with baselines on the BIRD dataset. The results of baseline methods are from their original research papers.

Model / Method	EX Acc(%)		Selection Method
		vote@n	
Prompting on LLMs			
DIN-SQL + GPT-4 [29]	50.7	-	-
DAIL-SQL + GPT-4 [7]	54.8	-	-
MAC-SQL + GPT-4 [39]	59.4	-	-
Chase-SQL + Gemini [28]	-	73.0	Selection Agent
Alpha-SQL + Qwen2.5-7B [11]	-	66.8	MCTS
Post-training on LLMs			
CodeS + StarCoder-15B [13]	57.0	-	-
DTS-SQL + DeepSeek-7B [30]	55.8	-	-
SQL-o1 + Qwen2.5-7B[22]	-	66.7	MCTS
Reasoning-SQL + Qwen2.5-7B + Schema Filter [31]	64.0	68.0	Selection Agent
Ours			
REWARD-SQL + Qwen2.5-7B		68.9	PRM
REWARD-SQL + Qwen2.5-7B + Schema Filter		70.3	PRM

Results. The results on the dev set of BIRD are summarized in Table 2. We have the following observations. (1) Among similar 7B models, **REWARD-SQL performs the best** in both greedy and vote@n decoding. (2) REWARD-SQL outperforms several strong baselines using much larger models like GPT-4, even with simple greedy decoding and without schema filtering (59.7% versus DIN-SQL's 50.7%, DAIL-SQL's 54.8%, and MAC-SQL's 59.4%). (3) Our proposed PRM selection significantly improves REWARD-SQL performance, particularly without schema filtering (improving from 59.7% to 68.9%), demonstrating its effectiveness.

Comprehensive ablation studies and generalization analyses are detailed in the appendix. Appendix B.2 shows our PRM selection outperforms alternatives, with PRM +Rule-OR reward formulation yielding optimal results. Appendix B.3 demonstrates strong zero-shot generalization on Spider (81.7% execution accuracy with PRM@32), surpassing larger models including GPT-4o. These results confirm our approach's effectiveness both in-distribution and across new domains.

8 Conclusions

In this paper, we proposed REWARD-SQL, a framework for building a PRM for Text-to-SQL tasks and systematically exploring the mechanism of reward model during model training and inference. Our exploration of offline RL training, online RL training, and reward-assisted inference revealed that GRPO combined with PRM-based inference selection achieves the best results. Experimental results show a substantial improvement in execution accuracy on the BIRD dataset, outperforming current state-of-the-art methods including those based on GPT-4. The success of REWARD-SQL highlights the importance of structured reasoning in complex SQL generation tasks and demonstrates how process-supervised reward models can effectively guide the learning process.

9 Acknowledgments

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A Training details

A.1 Implementation Details

In this section, we provide comprehensive details about our training setup and hyperparameters. For our experiments, we utilized the Qwen2.5-Coder-7B-Instruct model as our foundation, which is available under the Apache-2.0 license. All training procedures were conducted on a cluster of 8 NVIDIA A800 GPUs with 1TB of total system memory.

For supervised fine-tuning (SFT), we employed a learning rate of 1e-5 and trained the model for 3 epochs. This initial phase established the baseline capabilities of our model on the target task. Following SFT, we trained rejection sampling (RS) model with the same learning rate of 1e-5 for 3 epochs to develop a reliable performance evaluation mechanism.

For our reinforcement learning approaches, we implemented different strategies on the verl platform[35]. The Direct Preference Optimization (DPO) was conducted on the SFT-trained model using a reduced learning rate of 1e-6 for 1 epoch to avoid overfitting. For Grouped Reinforcement Preference Optimization (GRPO), we utilized a learning rate of 1e-6 and trained for 2 epochs on the training dataset. The GRPO implementation used a batch size of 48 with each group containing 8 samples, allowing the model to learn from diverse solution variations simultaneously.

Across other training procedures, we maintained a consistent batch size of 16 to balance computational efficiency and training stability. This setup allowed us to effectively fine-tune the model while managing the computational demands of the training process.

A.2 Model initialization details

Data Size Description Stage Initial CoCTE Collection 36,103 Generated from BIRD train set using DeepSeek-R1-Distill-Qwen-32B and o1-mini; filtered by execution After Syntax Tree Deduplication 18,015 Diverse CoCTEs retained after applying tree edit distance filtering to remove structurally similar examples Raw PRM Training Data 181,665 CoCTEs with positive/negative CTE labels generated through MCTS exploration on policy model Filtered PRM Training Data 31,636 High-quality step-labeled CoCTEs after applying rulebased filtering and edit distance deduplication

Table 3: Dataset Statistics for Different Training Stages

Data Collection Process For the cold start phase, we initially collected 36,103 CoCTEs by prompting LLMs with manually written examples. After applying our syntax tree edit distance filtering to remove structurally similar CoCTEs, we retained 18,015 diverse examples for policy model cold start training. Separately, for PRM training, we first generated 181,665 CoCTEs with positive/negative CTE labels through MCTS exploration on the policy model. We then applied rule-based filtering and edit distance deduplication techniques to obtain 31,636 high-quality non-redundant labeled examples for training. These two data collection processes were conducted independently to serve their respective training objectives.

A.3 Reward hacking in GRPO training

In this section, we analyze the reward design in DeepSeekMath [34]'s process supervision approach and identify a reward hacking phenomenon that emerged when applying their method to our setting.

A.3.1 DeepSeekMath's Process Reward Design

DeepSeekMath implements process supervision in their GRPO framework by assigning rewards to individual reasoning steps. For a given question q and G sampled outputs $\{C_1, C_2, \ldots, C_G\}$, their process reward model scores each step of the outputs, yielding:

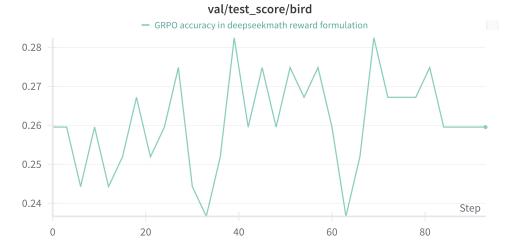


Figure 4: Performance fluctuation during GRPO training with DeepSeekMath's reward formulation. The model exhibits high volatility without consistent improvement on challenging test sets, indicating optimization instability due to reward hacking.

$$R = \{ \{ s(c_1^1), \dots, s(c_1^{K_1}) \}, \dots, \{ s(c_G^1), \dots, s(c_G^{K_G}) \} \},$$
(1)

where c_i^j represents the j-th step of the i-th CoCTE, and K_i is the total number of steps in the i-th CoCTE. $s(c_i^j)$ denotes the reward score for the corresponding step. These rewards are normalized using the mean and standard deviation across all steps:

$$\tilde{s}(c_i^j) = \frac{s(c_i^j) - \operatorname{mean}(R)}{\operatorname{std}(R)}$$
 (2)

The advantage for each token is then calculated as the sum of normalized rewards from all subsequent steps:

$$\hat{A}_{i,t} = \sum_{j: \text{index}(j) \ge t} \tilde{s}(c_i^j) \tag{3}$$

A.3.2 Reward Hacking Phenomenon

When applying DeepSeekMath's reward formulation to our setting, we observed a significant reward hacking phenomenon. Our process-supervised reward model (PRM) scores are derived from completion correctness rates, which naturally exhibit a decreasing trend as the solution progresses. This occurs because the probability of reaching the correct final answer diminishes with each step, as the solution space narrows and the potential for errors compounds.

The key issue with DeepSeekMath's approach in our context is that it treats all step rewards equally during normalization. When combined with our inherently decreasing PRM scores, this creates a systematic bias: later steps consistently receive lower advantages compared to earlier steps. This potentially incentivizes the model to optimize for certain solution characteristics rather than mathematical correctness.

We empirically verified this phenomenon using the Qwen2.5-Coder-1.5B-Instruct model. As shown in Figure 4, the model's performance on challenging test sets exhibited high volatility without consistent improvement when trained with DeepSeekMath's reward formulation. Further analysis revealed in Figure 5 demonstrates a notable shift in output distribution across training epochs, with rapid changes in solution length corresponding to performance fluctuations. These sudden distributional shifts appear to contribute to the unstable learning dynamics observed in the performance curve.

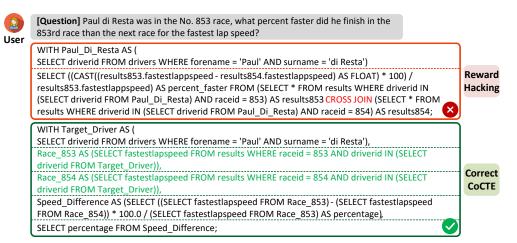


Figure 5: Example of reward hacking behavior across training epochs. As training progresses, the model generates increasingly shorter solutions to maximize rewards, sacrificing solution quality and correctness. The figure shows how the same query receives progressively simplified responses that ultimately fail to solve the problem correctly.

This analysis motivated our alternative advantage formulation presented in Section 5.3, which accounts for both the relative quality of each complete solution and the quality variations within its steps. Our approach ensures that advantages are properly scaled according to the overall solution quality, maintaining a more stable output distribution throughout the training process.

A.4 Prompts

Our schema design in the prompt refers to the M-Schema work⁵, which clearly defines the database structure and provides sample values, enabling the model to better understand the database. We appreciate their contribution.

Prompt for Model Training You are now a sqlite data analyst, and you are given a database schema as follows: Schema: • DB ID: retail complains • Table: reviews (Date:DATE, Primary Key, Examples: [2013-02-04]), (Stars:INTEGER, Examples: [5, 1, 2]), (Reviews:TEXT) Table: client (client_id:TEXT, Primary Key, Examples: [C00000001)], (age:INTEGER, Examples: [29, 54, 59]), (phone:TEXT, Examples: [367-171-6840]) · Table: events (Product:TEXT, Examples: [Bank account or service]), (Issue:TEXT, Examples: [Deposits and withdrawals]), (Tags:TEXT, Examples: [Older American]), (Client_ID:TEXT, Primary Key, Examples: [C00003714]) • Foreign keys: events.Client_ID=client.client_id Query: • Question: List all the issues of the complaints made by Kaitlyn Eliza Elliott. • Evidence: Please read and understand the database schema carefully, and generate an executable SQL based on the user's question and evidence. **Final SQL:** • WITH Kaitlyn_Elliott_Client AS (SELECT client_id FROM client WHERE first = 'Kaitlyn' AND middle = 'Eliza' AND last = 'Elliott'), • Kaitlyn_Elliott_Complaints AS (SELECT issue FROM events WHERE client_id IN (SELECT client_id FROM Kaitlyn Elliott Client)) • SELECT DISTINCT issue FROM Kaitlyn_Elliott_Complaints;

Figure 6: Prompt for model training.

⁵https://github.com/XGenerationLab/M-Schema

Prompt for CoCTE Transforming

You are tasked with rewrite the following SQL query using CTEs and annotate the rationale behind the decision. Maintain a coherent reasoning process, ensuring it remains natural and seamless, and reflect this coherence in the rationale part.

Example #1:

- Question: Please list the team names which have at least 3 all-star players.
- **SQL**: SELECT players_teams.tmid FROM players_teams INNER JOIN player_allstar ON players_teams.playerid = player_allstar.playerid GROUP BY players_teams.tmid HAVING count(DISTINCT players_teams.playerid) >= 3
- Query
 - "query1": "WITH All_Star_Players AS (\n SELECT playerid\n FROM player_allstar\n)"
 - "query2": "All_Star_Team_Associations AS (\n SELECT pt.tmid, pt.playerid\n FROM players_teams AS pt\n INNER JOIN All_Star_Players AS asp ON pt.playerid = asp.playerid\n)"
 - "query3": "Teams_With_Three_All_Stars AS (\n SELECT at.tmid, COUNT(DISTINCT at.playerid) AS all_star_count\n FROM All_Star_Team_Associations AS at\n GROUP BY at.tmid\n HAVING COUNT(DISTINCT at.playerid) >= 3\n)"
 - "query4": "SELECT t.name\nFROM Teams_With_Three_All_Stars AS twa\nINNER JOIN teams AS t ON twa.tmid = t.tmid;"

Example #2:

..

Example #3:

•••

Problem:

- Question: List all the issues of the complaints made by Kaitlyn Eliza Elliott.
- Schema: {db schema}

SQL: SELECT DISTINCT EVENTS.issue FROM client INNER JOIN EVENTS ON client.client_id = EVENTS.client_id WHERE client.first = 'Kaitlyn' AND client.middle = 'Eliza' AND client.last = 'Elliott'

Figure 7: Prompt for CoCTE transforming.

```
Prompt for Schema Filtering
Evaluate the relevance of columns in the database schema to the user's question, selecting the minimal
necessary column set.
Schema analysis steps:
  • dentify entities and calculation metrics in the question
  • Match relevant tables through primary/foreign keys
  • Filter columns directly related to guery conditions
  • Retain numeric fields required for calculations
Example:
  • Schema Snippet
     · Table: employees
        [emp_id, emp_name, hire_date, salary, dept_id]
     • Table: departments
        [dept_id, dept_name, location]
  • Question: Calculate average salary per department
     Selection Result

    "Tables": ["employees", "departments"],

       "Columns": {
           "employees": ["salary", "dept_id"],
           "departments": ["dept_id", "dept_name"]
Current task: {full database schema}
Please select necessary columns for:
  • Question: List all the issues of the complaints made by Kaitlyn Eliza Elliott.
  • Evidence: {evidence}
```

Figure 8: Prompt for schema filtering.

B Experiments Details

B.1 Case study

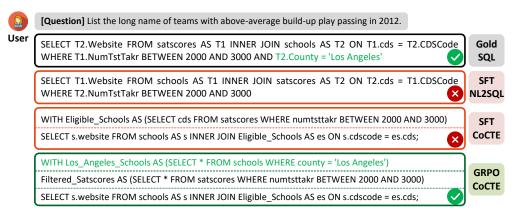


Figure 9: Case study comparing SQL generation approaches. Our GRPO-trained model successfully handles a complex query requiring multiple constraints (Los Angeles County schools with 2,000-3,000 test takers), while baseline models fail to incorporate all necessary filtering conditions.

To provide a more intuitive understanding of how our method improves SQL generation, we present a case study in Figure 9. This example demonstrates the effectiveness of our approach in handling complex queries involving multiple tables and filtering conditions.

The query requires finding websites of Los Angeles County schools with test takers between 2,000 and 3,000. This task involves joining tables, applying numerical range filters, and county-specific constraints. The baseline models struggle with this complexity in different ways.

The standard model SFT on original training set from BIRD produces a query that correctly joins the tables and applies the numerical range filter, but critically omits the county filter condition. This results in an incomplete query that would return schools from all counties, not just Los Angeles.

The model fine-tuned on our transformed CoCTE training set also fails to incorporate the county filter. While it correctly identifies schools within the specified test taker range, it misses the geographical constraint entirely.

In contrast, after applying our GRPO training, the model generates a comprehensive solution. It creates separate CTEs for Los Angeles schools and schools within the test taker range, then joins them correctly. This approach demonstrates how our method enables the model to decompose complex problems into manageable sub-queries, maintain awareness of all filtering conditions, and structure the query in a clear, logical manner.

This case study illustrates how our process-level reward modeling approach guides the model toward more complete and accurate SQL solutions, particularly for queries requiring multiple constraints and table relationships. The improvement is not merely syntactic but reflects enhanced reasoning about the underlying database schema and query requirements.

B.2 Ablation study

To better understand the contribution of different components in our approach, we conduct a comprehensive ablation study. We mainly focus on two key components of our proposed methods: 1) The impact of different test-time guidance methods; 2) The impact of different reward formulations in our GRPO training.

Table 4: Comparison of different test-time selection methods on SFT model

Selection Method	EX Acc (%)
Greedy (No guidance)	54.4
Self-consistency	59.3 (+4.9)
ORM	61.8 (+7.4)
PRM	67.0 (+12.6)

Table 5: Ablation study on different reward formulations for GRPO training

Reward	EX Acc (%)		
Formulation	Greedy	PRM@32	
PRM	59.9	67.3	
Rule-OR	59.2	68.4	
PRM + Rule-OR	59.7	68.9	

Test-time Guidance Methods. Table 4 compares our proposed PRM selection with other selection methods ORM [38] and Self-consistency [40] on the BIRD dev set with 32 samples. As can be seen, though all selection methods improve the EX Acc compared with vanilla greedy decoding, our proposed PRM selection significantly outperforms the other selection methods. The results clearly demonstrate that our process-level reward modeling approach captures critical intermediate reasoning steps that other methods fail to identify.

Reward formulation for GRPO training. As mentioned in Section 5, during the GRPO training process, we propose to combine the PRM with a rule-based outcome reward (Rule-OR). Table 5 shows that although PRM alone achieves the highest greedy decoding accuracy (59.9%), when considering both decoding methods, especially PRM @32, the combined PRM + Rule-OR approach performs best overall (68.9%). This demonstrates that integrating outcome guidance from rule-based rewards with PRM's semantic evaluation creates a more effective reward signal for GRPO training.

These ablation studies validate our design choices and demonstrate that both components of our approach—PRM-based selection at test time and hybrid rewards during training—are essential for achieving state-of-the-art performance. Removing or replacing either component results in substantial performance degradation.

B.3 Generalization analysis

To further analyze our proposed REWARD-SQL generalization to other distribution, we conduct experiments on Spider dataset [45]. Spider is a large-scale, complex, cross-domain semantic parsing and Text-to-SQL dataset annotated by 11 college students. It comprises 10,181 questions and 5,693 unique complex SQL queries across 200 databases covering 138 different domains. The dataset is divided into 8,659 training examples, 1,034 development examples, and 2,147 test examples. The Spider dataset is available under the Apache License 2.0.

Since our model was not exposed to any data from Spider during the training stage, evaluating on this dataset demonstrates the model's capability to handle different Text-to-SQL scenarios. We compare our model with other LLMs in the zero-shot setting.

Table 6: Comparison of performance on Spider (EX).

Model	Spider EX(%)
GPT-40	77.3
o3-mini	74.7
Gemini-2.5-pro	83.8
Qwen2.5-7B	75.6
REWARD-SQL + Qwen2.5-7B + Greedy	77.0
REWARD-SQL + Qwen2.5-7B + PRM@32	81.7

As can be seen in Table 6, our model shows strong generalization capabilities on the Spider benchmark. Our approach using Qwen2.5-7B with our proposed REWARD-SQL framework achieves an impressive 81.7% execution accuracy, outperforming even larger models like GPT-4o (77.3%) and reasoning model like o3-mini (74.7%). This demonstrates the effectiveness of our process-level reward modeling approach in zero-shot settings.

Notably, the significant improvement from Greedy decoding (77.0%) to PRM@32 (81.7%) highlights the critical role that our PRM plays in enhancing model performance during inference. The 4.7% absolute improvement underscores the value of exploring multiple solution candidates through our process-level reward mechanism. These results confirm that our approach not only performs well on the training distribution but also generalizes effectively to unseen datasets like Spider, validating the robustness of our method across different SQL generation scenarios.

B.4 Test-time Compute Analysis

Test-time scaling has been verified as an effective approach for improving reasoning capabilities across various tasks. In this section, we examine how our framework responds to increased test-time compute resources.

Figure 10 illustrates the relationship between test-time compute (represented on the scale of sample numbers) and accuracy on the BIRD development set. The results demonstrate a clear scaling pattern where performance improves as more computational resources are allocated during inference. The upper bound (Pass@n) shows a nearly linear growth as test-time compute increases, climbing from 58% at the lowest compute level to 77% at the highest compute level. Here, Pass@n represents the probability that at least one of the n generated samples contains the correct answer, effectively measuring the model's capability ceiling when allowed multiple solution attempts.

Our PRM@n accuracy follows a similar upward trajectory, starting at 58.1% with only one sample and reaching 68.9% with 32 samples. However, we observe that the gap between the theoretical upper bound and the actual PRM@n performance gradually widens as compute increases. At lower compute levels, our model's performance closely tracks the upper bound, but this divergence at higher compute levels suggests untapped potential for further improvement. This widening gap indicates that while our approach effectively leverages additional test-time compute, there remains significant headroom for enhancement through additional training or refinement of our selection mechanism. The consistent scaling behavior confirms that our framework can benefit from test-time compute scaling strategies, aligning with findings from other reasoning tasks in the literature.

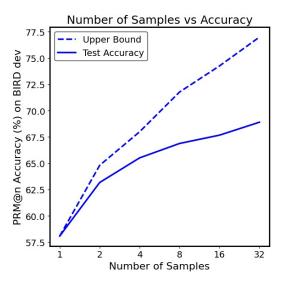


Figure 10: Test-time compute vs accuracy on BIRD dev set. The upper bound represents the theoretical maximum performance achievable with perfect selection, while the test accuracy shows our model's actual performance using PRM@n selection.

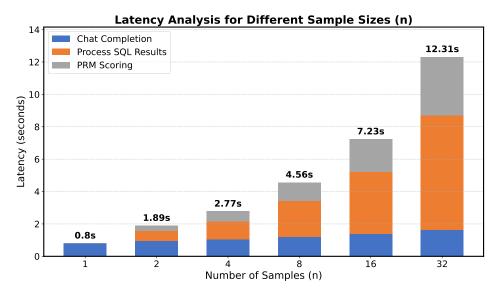


Figure 11: Latency analysis for different values of n in PRM@n. The chart shows the time contribution of each component in the inference pipeline.

Latency analysis. While increasing the number of samples improves accuracy, it also impacts inference latency. Figure 11 presents a breakdown of the latency components for different values of n in our PRM@n approach. The inference pipeline consists of three main stages: chat completion (SQL generation), process SQL results (executing CTEs and collecting intermediate results), and PRM scoring (PRM evaluation).

For chat completion, we leveraged VLLM's optimized batch inference, resulting in sublinear latency growth as n increases—from 0.8 seconds for a single sample to only 1.65 seconds for 32 samples. However, the other two components scale linearly with n as they are currently implemented serially. Processing SQL results increases from negligible time at n=1 to 7.05 seconds at n=32, while PRM scoring rises from 0 to 3.61 seconds.

The total latency increases from 0.8 seconds at n=1 to 12.31 seconds at n=32, with SQL processing becoming the dominant factor at higher values of n. This analysis reveals significant optimization opportunities for our framework, particularly in parallelizing the SQL execution and scoring

components. Such optimizations could substantially reduce the latency overhead of larger sample sizes, making high-accuracy PRM@n configurations more practical for real-time applications.

C Limitations

Despite the promising results demonstrated by our approach, we acknowledge several limitations that present opportunities for future research:

Computational Overhead in GRPO Training. Our GRPO training methodology requires online execution of SQL queries generated by the evolving policy. This introduces substantial computational overhead compared to offline methods, as each generated SQL must be validated against the database during training. The need for real-time execution significantly extends training time and resource requirements, potentially limiting scalability to larger datasets or more complex database environments.

Distribution Shift Between Policy and Reward Model. During online training, the policy model continuously updates, potentially causing its output distribution to drift away from the distribution on which the reward model was trained. This distribution shift can lead to suboptimal reward signals as training progresses. Developing robust, adaptable reward models that can effectively evaluate evolving policies without requiring frequent retraining is a significant challenge. Future work could explore methods for dynamically updating reward models or designing more distribution-invariant evaluation mechanisms.

These limitations highlight important directions for future research in process-supervised SQL generation. Addressing these challenges could further enhance the practical applicability of our approach in real-world database environments and complex query scenarios.