

Reasoning About Intent for Ambiguous Requests

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Abstract

Large language models often respond to ambiguous requests by *implicitly* committing to one interpretation. Intent misunderstandings can frustrate users and create safety risks. To address this, we propose generating multiple interpretation-answer pairs in a single structured response to ambiguous requests. Our models are trained with reinforcement learning and customized reward functions using multiple valid answers as supervision.¹ Experiments on conversational question answering and semantic parsing demonstrate that our method achieves higher coverage of valid answers than baseline approaches. Human evaluation confirms that predicted interpretations are highly aligned with their answers. Our approach promotes transparency with *explicit* interpretations, achieves efficiency by requiring only one generation step, and supports downstream applications through its structured output format.

1 Introduction

Ambiguity poses a fundamental challenge for large language models (LLMs). Users routinely omit details either for the sake of brevity or unintentionally (Zipf, 1949; Piantadosi et al., 2012), creating requests with multiple plausible interpretations (see the examples in Table 1, top row). LLMs often respond with a single answer, implicitly committing to one interpretation without acknowledging alternatives. Beyond frustrating users who had a different meaning in mind, this behavior poses safety risks as defaulting to a single interpretation can lead to irreversible actions (Park et al., 2024). LLMs can strategically exploit ambiguities, e.g., by deliberately misinterpreting scalar quantifiers or bracketing in logical statements to advance their own goals over user inten-

tions (Choi et al., 2025). Ambiguity also presents a challenge for reasoning models, which can expend thousands of tokens on incorrect interpretations, simultaneously wasting computational resources and reinforcing the original error.

Prior work has explored different strategies for handling ambiguous inputs, each with distinct trade-offs (Tanjim et al., 2025). Clarification questions explicitly engage users to resolve ambiguity, but require additional interaction rounds and depend on users providing clarifying responses. We illustrate this approach in Table 1 for conversational question answering and text-to-SQL parsing. An alternative is to give a longer answer that includes multiple interpretations within a single response (Stelmakh et al., 2022). Model outputs in this case tend to be verbose, lacking explicit interpretations (see the examples in Table 1). As a result, the answers are difficult to parse for downstream applications and potentially overwhelming for users. Moreover, for certain ambiguity types (e.g., attachment ambiguity), interpretations may be mutually contradictory. In domains like SQL generation, there may be no natural way to express a unified response (e.g., for interpretations requiring different table structures).

In this work, we propose a structured alternative, namely generating multiple plausible answers, each paired with an explicit interpretation (Table 1, bottom). This format requires a single generation step while producing outputs that are easy to parse and use for downstream applications, e.g., in agentic systems where branching across interpretations can be beneficial. Moreover, it generalizes beyond textual answers to any output type, including code generation and API calls, while allowing users to quickly identify their intended answer. Recognizing that ambiguity relates to the broader problem of pluralistic alignment (i.e., generating responses that reflect diverse perspectives and interpretations; Sorensen et al.

¹<https://github.com/saparina/intentRL>

Conversational Question Answering	Text-to-SQL Parsing
Hilary Duff says her new album is ... “a lot heavier and a lot darker” because of the separation from her husband , Mike Comrie . Duff married Comrie ... in 2010 after dating for three years. Their son, Luca , was born in 2012... — How long were they married before they had a child? — 2 years — What is his name?	CREATE TABLE Jobs (JobID INTEGER PRIMARY KEY, Min_Years INTEGER, Pref_Years INTEGER, Position TEXT, Description TEXT, Salary REAL); Show the required experience for the best-paid role.
<i>Clarification Question</i>	
Do you mean the child? User 1: Yes User 2: No, her husband Answer: Luca Answer: Mike Comrie	Do you mean preferred or minimum years? User 1: Preferred User 2: Minimum SELECT Pref_Years... SELECT Min_Years...
<i>Long-form Answer</i>	
Duff was married to Mike Comrie. Their son, Luca, was born in 2012.	SELECT Min_Years, Pref_Years FROM Jobs ORDER BY Salary DESC LIMIT 1;
<i>Interpretation–Answer Pairs (Ours)</i>	
1. The question refers to the husband’s name. His name is Mike Comrie.	1. Minimum years of experience required SELECT Min_Years...
2. The question refers to the son’s name. His name is Luca.	2. Preferred years of experience SELECT Pref_Years...
	3. Both the minimum and preferred years SELECT Min_Years, Pref_Years...

Table 1: Approaches to handling ambiguity. Examples are taken (and slightly edited for the sake of brevity) from the Abg-CoQA (Guo et al., 2021) and Ambrosia (Saparina and Lapata, 2024) test sets. Ambiguous questions and elements that create ambiguity are highlighted in red. Annotations in blue are provided by us for illustration.

2024), our approach promotes *overton pluralism* by predicting multiple interpretations within one answer. Methods embracing *distributional pluralism* rely on parallel samples and often struggle to produce substantially different outputs (Zhang et al., 2025b). Instead, we generate interpretations sequentially within one response (where subsequent interpretations are conditioned on previous ones), without changes to sampling parameters or confidence calibration.

Teaching models to handle ambiguity is challenging due to the lack of suitable supervision. While ambiguity is pervasive in natural language, humans can effortlessly communicate without explicitly clarifying their intent. The most readily available supervision signal comes from annotator disagreement, which manifests as multiple answers for a single instance. Other forms of annotation, such as clarifications or explicit interpretations, are expensive and difficult to obtain at scale. Building on the success of reinforcement learning under sparse supervision (Shao et al., 2024),

we frame ambiguity resolution as reasoning about *what* to answer rather than *how*: we encourage the model to reason about user intent, entertaining different interpretations of the input before committing to an answer. We train a reasoning model through reinforcement learning with specialized reward functions that only require answer annotations as supervision. For ambiguous inputs, we optimize for *recall* to maximize the coverage of interpretations. For unambiguous inputs, we optimize for *precision* to avoid generating spurious alternatives. This dual objective teaches the model to enumerate interpretations when necessary *and* to recognize when a question has a single intent.

We evaluate our approach on both verifiable and non-verifiable tasks, including text-to-SQL generation and conversational question answering. Experimental results show that our model effectively handles unambiguous and ambiguous cases, generalizing to out-of-distribution data while generating diverse, plausible answers with high coverage and meaningful interpretations. By teaching mod-

els to reason about user intent before answering, we move toward more robust, user-aligned LLMs that embrace rather than obscure ambiguity.

2 Related Work

Ambiguity in Question Answering Ambiguity has gained significant attention in question answering as there is growing awareness that many questions can have multiple valid answers (see Tanjim et al. 2025 for a comprehensive overview). AmbiQA (Min et al., 2020) was one of the first large-scale benchmarks to explicitly annotate multiple answers for individual questions, expanding on NaturalQuestions (Kwiatkowski et al., 2019). The open-domain QA setting has prompted numerous retrieval-augmented generation techniques (e.g., Min et al., 2021).

ASQA (Stelmakh et al., 2022) extends AmbiQA by requiring long-form answers that cover multiple interpretations in a single response. While this format is intuitive, it poses challenges for evaluation and practical use due to the lack of explicit structure in the answers. Amplayo et al. (2023) first infer multiple interpretations and then generate long-form answers through prompting. We make interpretations explicit by generating structured interpretation–answer pairs. Guo et al. (2021) explore clarification questions as a disambiguation strategy in conversational QA, and more recently Chen et al. (2025) introduced a preference optimization method that generates clarification questions for ambiguous instances and direct answers for unambiguous ones. In contrast, our approach handles both cases in a single turn.

Ambiguity in Semantic Parsing Ambiguity also presents challenges for semantic parsing tasks (Rasmussen and Schuler, 2020; Li et al., 2023; Mu et al., 2024; Stengel-Eskin et al., 2024). The realization that standard datasets often provide a single interpretation when multiple queries are plausible (Pourreza and Rafiei, 2023; Floratou et al., 2024), has motivated the development of benchmarks that include multiple SQL queries per input (Bhaskar et al., 2023; Saparina and Lapata, 2024) or interactive scenarios with clarification questions (Dong et al., 2025; Huo et al., 2025). Various approaches have been proposed to handle ambiguous queries including via counterfactual examples (Wang et al., 2023), specialized decoding strategies (Bhaskar et al., 2023), two-stage methods that first generate interpretations and then

answers (Saparina and Lapata, 2025), and interactive generation of clarification questions (Ding et al., 2025). Unlike multi-stage approaches, our method generates all plausible interpretations and corresponding SQL queries in one response.

Diversity in Model Outputs LLMs have been recently shown to exhibit narrow behaviors and strong biases in tasks where many valid responses are possible (Saparina and Lapata, 2024; West and Potts, 2025; Zhang et al., 2025b; Troshin et al., 2025). Fine-tuning has been proposed as way of shifting LLM output from peaked to diffuse distributions (Zhang et al., 2024) as well as post-training (Sorensen et al., 2025). Zhang et al. (2025a) found that explicitly enumerating possible answers with their probabilities via prompting improves diversity. Our structured interpretation–answer pairs can be viewed as a form of such enumeration, but with explicit interpretations rather than probability estimates.

3 Reasoning about User Intent

Our approach trains a reasoning model to explicitly consider user intent before generating answers, producing outputs that enumerate plausible interpretations of ambiguous inputs along with their corresponding answers (see Table 1 bottom).

3.1 Problem Formulation

A question is ambiguous if it admits multiple distinct interpretations that lead to different answers. Given some input consisting of optional context c (e.g., a passage in conversational QA or a database schema in text-to-SQL generation; see Table 1) and a question q , the model must produce a set of interpretation-answer pairs $\{(i_1, a_1), \dots, (i_m, a_m)\}$. Each interpretation i_k explicitly disambiguates the question by specifying what is being asked, while a_k is the corresponding answer for interpretation i_k . For example, “The question refers to the husband’s name” in Table 1 is one possible interpretation of the ambiguous question “What is his name?” which corresponds to the answer “Mike Comrie”.

We expect a maximum of five interpretation–answer pairs, which we find represents the majority of ambiguity cases in existing datasets. In theory, questions could have more interpretations, but at that scale other approaches such as clarification questions may be more appropriate than exhaustive enumeration. In practice, the questions

are often grounded in specific contexts, which naturally constrain the space of plausible interpretations. In unambiguous cases, we expect a single interpretation-answer pair, with the interpretation being identical to the original question or a paraphrase that makes the intent even more explicit.

3.2 Model Training

Our model is trained on examples annotated with gold answers $\mathcal{A} = \{\hat{a}_1, \dots, \hat{a}_n\}$, where $n = 1$ for unambiguous and $n > 1$ for ambiguous questions. These annotations are easier to obtain compared to interpretations or clarification questions; for example, they emerge naturally when multiple annotators disagree on the answers they provide.

We instruct the model to first analyze the input for potential ambiguities and then generate structured output consisting of interpretation-answer pairs. We design a task-agnostic prompt template that can be easily adapted to other tasks by modifying only the context format and task-specific instructions (e.g., answer style constraints). The prompt is given in Appendix A. We generate interpretation-answer pairs sequentially. Thanks to the autoregressive nature of language models, each subsequent interpretation is conditioned on previously generated interpretations and answers. This encourages diversity across interpretations as well as semantic alignment between interpretations and their corresponding answers.

We train our model using DAPO (Decoupled Clip and Dynamic Sampling Policy Optimization Yu et al. 2025), a reinforcement learning algorithm based on GRPO (Group Relative Policy Optimization; Shao et al. 2024). DAPO extends GRPO with decoupled clipping parameters that enhance exploration and dynamic sampling that filters out prompts with uniform outcomes to maintain effective gradients (see Appendix B for the formulas).

We design **reward functions** to optimize different objectives for ambiguous versus unambiguous inputs. We extract the set of predicted answers \mathcal{P} from the model’s output and compare it against the gold answer set \mathcal{A} , where all answers are distinct by construction. For each predicted answer $p \in \mathcal{P}$ and gold answer $\hat{a} \in \mathcal{A}$ we compute a **similarity** score $sim(p, \hat{a})$ where the specific type of similarity function is task dependent.

For tasks like text-to-SQL whose output can be objectively verified, $sim(p, \hat{a}) = 1$ if execution results are the same, and $sim(p, \hat{a}) = 0$ otherwise.

For tasks like question answering whose outputs are harder to verify, we use soft similarity metrics. In experiments, we adopt F1 score based on word overlap, however, any other word similarity function could be used. Let $S_{ij} = sim(p_i, \hat{a}_j)$ denote a matching matrix, and \mathcal{M} the set of one-to-one matches between predicted and gold answers. We compute optimal assignments between \mathcal{P} and \mathcal{A} using the Hungarian algorithm:

$$M^* = \operatorname{argmax}_{M \in \mathcal{M}} \sum_{(i,j) \in M} S_{ij},$$

which is efficient given that both sets are small (recall that we five interpretations maximum). For verifiable tasks with binary similarity (e.g., text-to-SQL), M^* reduces to exact matching.

For ambiguous questions ($|\mathcal{A}| > 1$), our reward function is **recall**:

$$R_{\text{recall}} = \frac{1}{|\mathcal{A}|} \sum_{(p_i, \hat{a}_j) \in M^*} sim(p_i, \hat{a}_j)$$

which measures how many distinct valid interpretations are covered by the model, rewarding more complete responses.

For unambiguous questions ($|\mathcal{A}| = 1$), our primary objective is **precision**:

$$R_{\text{precision}} = \frac{1}{|\mathcal{P}|} \sum_{(p_i, \hat{a}_j) \in M^*} sim(p_i, \hat{a}_j)$$

which penalizes the model for generating spurious interpretations.

4 Experimental Setup

4.1 Datasets and Evaluation Metrics

The only requirement for training our model is a dataset with multiple valid answers per input. We focus on two such datasets that represent different evaluation scenarios: Abg-CoQA (Guo et al., 2021), a conversational question answering dataset (non-verifiable outputs) and Ambrosia (Saparina and Lapata, 2024), a text-to-SQL parsing benchmark (verifiable outputs). Both datasets include contextual information (stories for Abg-CoQA, database schemas for Ambrosia), making the ambiguity resolution more challenging and realistic: models must validate their interpretations against the provided context. See examples in Table 1 and dataset statistics in Table 2. Descriptions of ambiguities are provided in Appendix C.

Dataset	Train Size		Test Size	
	Ambig	Unambig	Ambig	Unambig
Abg-CoQA	5,727	741	123	932
Ambrosia*	2,380	1,026	131	309

Table 2: Dataset statistics. Ambrosia * : we use the split from [Saparina and Lapata \(2025\)](#).

Abg-CoQA ([Guo et al., 2021](#)) is a conversational question answering dataset. The input consists of a passage, one or two previous conversation turns, and a question that can be ambiguous, leading to different answers. The dataset provides clarification questions but does not include explicit interpretations. Abg-CoQA covers different types of ambiguity, the majority being coreference.

[Guo et al. \(2021\)](#) measure similarity between predicted and gold answers using word overlap (macro-averaged F1). To account for different wordings within the same interpretation, each prediction is compared against three gold answers, and the maximum score is taken; these scores are then averaged across gold answers. This metric favors coverage over precision because Abg-CoQA treats disambiguation and answer generation as separate tasks. For a more comprehensive evaluation, we also use an LLM-based judge to assess both recall and precision. Unlike rule-based metrics (exact match, word-overlap F1), LLM judges recognize semantic equivalence despite wording differences (for example, in Table 1 “Luca” vs. “His name was Luca” would score only 40% F1, despite having identical meaning). This is crucial for evaluating zero-shot and RL-trained models, which often generate answers in different styles than gold annotations. We adapt the prompt from [Sun et al. \(2024\)](#) who found 98% agreement between human judgments and LLM-based metrics.

We use Qwen3 4B Instruct ([Yang et al., 2025](#)) as the judge model because it is fast, cost-effective for large-scale evaluation, and provides reliable judgments for our task. In preliminary experiments, we compared our judge with the larger Qwen3 235B A22B Instruct, across multiple evaluation sets and found 1.4% difference in judgment accuracy on average. In most cases, the smaller model was more conservative, marking particularly non-obvious answer reformulations as incorrect. Using LLM-as-a-judge, we measure recall (the proportion of gold answers covered by the

predictions), precision (the proportion of predictions that match a gold answer), and full coverage (the percentage of instances where recall equals 1, meaning that all gold answers are recovered). For unambiguous questions, there is only one gold answer, so recall and full coverage are equivalent and we report recall in these cases. These metrics allow us to evaluate both the coverage of valid interpretations and spurious over-generation.

Ambrosia ([Saparina and Lapata, 2024](#)) is a text-to-SQL dataset where some user questions are ambiguous and can lead to different SQL queries and execution results. The dataset showcases multiple ambiguities including scope and attachment ambiguities and comes with gold interpretations for ambiguous questions, which can also serve as unambiguous examples. For this dataset, we compare query execution results and report recall, precision, and full coverage. We use the data split from [Saparina and Lapata \(2025\)](#).

4.2 Training Details

We train Qwen3 4B Instruct ([Yang et al., 2025](#)) as our base model which offers a good balance between performance and efficiency; it is small enough for fast training and inference while maintaining competitive performance. We do not use reasoning models (e.g., Qwen3 4B Thinking) as their lengthy reasoning traces (often thousands of tokens) would increase cost and latency without benefiting our task. Our preliminary experiments showed that thinking models do not outperform instruction-tuned models on ambiguity resolution.

Data Balancing Datasets with ambiguous inputs are often imbalanced, with many more unambiguous examples than ambiguous ones (see Table 2). However, ambiguous examples are more challenging and require stronger learning signals, especially with methods based on GRPO that have difficulty-level bias ([Liu et al., 2025](#)). We therefore rebalance the training data to maintain an ambiguous-to-unambiguous ratio of 3:1, by oversampling ambiguous examples. Ambiguous examples teach the model when to generate multiple interpretations, while unambiguous ones serve as regularization, preventing it from over-generating interpretations and maintaining high precision on straightforward inputs. During training, we sample 4 examples per batch, which combined with the 3:1 ratio, allocates more compute to harder

ambiguous cases while still maintaining sufficient signal from unambiguous examples.

Reward Functions For Abg-CoQA, we compute rewards using word-overlap F1 as the similarity metric. While less reliable than LLM-as-a-judge for final evaluation, we found F1 provides effective training signal during reinforcement learning and is much faster to compute. For Ambrosia, we use execution match (comparing predicted and gold SQL query results) which provides an objective, verifiable reward signal. We train using DAPO (Yu et al., 2025) for 5 epochs with a learning rate of 5e-7 and linear learning rate scheduling with 3% warmup. We generate 16 completions per prompt during training. Additional hyperparameters are in Appendix D.

4.3 Comparison Methods

We compare against several baselines that vary in their use of reasoning, output format, and supervision. Implementation details are in Appendix E.

Answer-only Methods generate answers without explicit interpretations. We use *zero-shot* prompting of base models to evaluate their baseline capability for handling ambiguity. We also *fine-tune* models on training data using supervised learning (SFT) to predict answers directly.

Interpretation-Answer Pair Methods generate explicit interpretations paired with corresponding answers. We prompt models with the same instructions as our method to reason about user intent and generate interpretation-answer pairs (see prompt in Appendix A) but without any training. *Zero-shot chain-of thought* evaluates whether the task can be solved through prompting alone. We further *fine-tune* models to predict interpretation-answer pairs with supervised learning. We evaluate this baseline only on Ambrosia, as it provides gold interpretations unlike Abg-CoQA.

We evaluate zero-shot baselines across two model scales: Qwen3 4B and 235B Mixture-of-Expert (MoE; 22B active parameters), with standard instruction-tuned (Instruct) and reasoning (Thinking) variants. For fine-tuning, we use Qwen 4B Instruct to match our model’s scale.

State-of-the-Art Methods are also compared against our approach. ACT (Chen et al., 2025) is a quasi-online preference optimization algorithm that trains models to ask clarification questions

when faced with ambiguous requests. It requires multiple interaction rounds: it first detects ambiguity, then asks a clarification question, waits for the user’s response, and finally provides an answer. We compare on Abg-CoQA against their best system, which uses Zephyr 7B β (Tunstall et al., 2023) as the policy model and Gemini Ultra 1.0 (Team et al., 2025)) for user simulation.

DisambigParse (Saparina and Lapata, 2025) is a two-stage approach for handling ambiguity in semantic parsing. It first predicts interpretations, then uses these to guide SQL generation. The first stage uses Llama 3.1 8B Instruct (Team et al., 2024) for interpretation generation, while the second stage uses Qwen2.5-Coder Instruct 32B (Hui et al., 2024) for SQL prediction.

5 Evaluating Answer Quality

5.1 Conversational Question Answering

Main Results Table 3 summarizes our results on Abg-CoQA. As mentioned earlier we report word overlap F1 and LLM-as-a-Judge metrics.

Across model sizes, we observe that larger models consistently outperform smaller ones, which suggests that our approach would benefit from stronger backbone models. The 0-shot baselines reveal an interesting pattern: models achieve higher recall than precision, suggesting they suspect ambiguity more often and attempt to provide multiple responses, but do so inefficiently. For instance, the 235B Thinking model achieves 68.9% recall but only 62.6% precision on ambiguous questions (answers-only), indicating it generates multiple answers, some of which are spurious.

Supervised fine-tuning (SFT) reveals a critical limitation: despite our efforts to rebalance the training data and make unambiguous examples less frequent than ambiguous ones, the model overfits to unambiguous cases. This results in high precision (70.3% for ambiguous, 70.6% for unambiguous) at the cost of recall (48.1%) and full coverage (20.3%) for ambiguous questions. The model learns to commit to one answer rather than enumerate multiple options. Teaching the model to generate high-quality interpretations with SFT is non-trivial as it requires annotation of interpretations, which do not exist for Abg-CoQA.

Our RL-based model (IntentRL) achieves the best results for ambiguous questions: 72.9% word-overlap F1, 78.1% recall, and 61.0% full coverage. For unambiguous questions, we achieve

Method	Model	Ambiguous				Unambiguous		
		Overlap F1	Judge Recall	Judge Precision	Full Coverage	Overlap F1	Judge Recall	Judge Precision
<i>Answers only</i>								
0-shot	4B Instruct	29.3	41.5	43.0	14.6	48.8	70.2	52.0
	4B Thinking	17.0	48.5	47.7	35.8	38.0	70.6	52.3
	235B MoE Instruct	55.2	63.1	47.0	45.5	58.9	78.8	35.5
	235B MoE Thinking	38.7	68.9	62.6	49.6	52.2	81.4	57.2
SFT	4B Instruct	40.1	48.1	70.3	20.3	72.2	77.6	70.6
<i>Interpretations and Answers</i>								
CoT	4B Instruct	44.4	62.3	42.7	45.5	59.2	77.7	40.6
	4B Thinking	18.2	46.2	45.3	31.7	32.5	60.6	44.6
	235B MoE Instruct	55.2	63.1	47.0	45.5	68.9	80.8	42.1
	235B MoE Thinking	47.8	66.2	49.7	50.4	59.6	82.1	47.2
IntentRL	4B Instruct	72.9	78.1	53.5	61.0	84.4	90.9	40.7

Table 3: Word-Overlap F1 score and metrics obtained from LLM-as-a-Judge (Recall, Precision, and Full Coverage) on ambiguous and unambiguous questions in Abg-CoQA.

84.4% word-overlap F1 and 90.9% recall, demonstrating that the model successfully recognizes when questions have a single intent. Lower precision (53.5% for ambiguous, 40.7% for unambiguous) reflects a bias toward generating additional interpretations as the model sometimes treats unambiguous questions as ambiguous and produces alternatives. We achieve the best precision on ambiguous questions among all interpretation-answer approaches (53.5% vs. 42.7–49.7% for CoT), showing that our method improves precision even though we do not explicitly optimize for it in the reward function, and the base models initially exhibit even lower precision than recall. High recall implies that when the model generates multiple interpretations, the correct ones are often included. In safety-critical applications, overgenerating plausible interpretations is preferable to silently committing to a one, potentially incorrect interpretation. Table 11a (Appendix H) reports ablation results on Abg-CoQA, showing that training with RL to predict only answers can also achieve high coverage (but lacks explicit interpretations), while data balancing is necessary to prevent overfitting to unambiguous examples.

Comparison with Multi-Turn Clarification In Table 5, we compare our approach with ACT (Action-Based Contrastive Self-Training; Chen et al. 2025), a state-of-the-art method for learning to disambiguate through multi-turn conversations. We report embedding-based similarity (Reimers

and Gurevych, 2019), macro-averaged across all examples (test set), for direct comparison with their work (they use the term trajectory similarity).

Our method (IntentRL) generates interpretations and their answers in a single turn; nevertheless, it achieves 83.0% similarity, substantially outperforming ACT at 75.1%. This demonstrates that enumerating multiple interpretations with their answers in a single response is more effective than multi-turn clarification. We provide comprehensive coverage of plausible interpretations immediately, allowing users to identify their intended meaning without additional exchanges.

5.2 Text-to-SQL Parsing

Main Results Table 4 presents results on Ambrosia for the ambiguous and unambiguous subsets. Again we observe that larger models outperform smaller ones but reasoning models show no consistent improvement over instruct models. On ambiguous questions (answers-only), the 4B Thinking model achieves 36.5% recall versus 16.0% for the 4B Instruct model, but underperforms when generating interpretations and answers (16.9% vs. 22.5% recall). Unlike conversational QA, models show higher precision than recall on ambiguous questions, which means that they often generate one answer but miss some valid interpretations. On unambiguous questions, the pattern reverses: models achieve higher recall than precision, indicating they struggle to calibrate

Method	Model	Ambiguous			Unambiguous		
		Recall	Precision	Full Coverage	Recall	Precision	
<i>Answers only</i>							
0-shot	4B Instruct	16.0	36.5	0.8	42.4	42.4	
	4B Thinking	36.5	62.1	3.8	65.1	59.9	
	235B MoE Instruct	30.0	52.4	3.8	65.1	64.0	
	235B MoE Thinking	35.9	45.2	7.6	62.5	48.3	
SFT	4B Instruct	72.7	75.1	66.4	78.0	73.4	
<i>Interpretations and Answers</i>							
CoT	4B Instruct	22.5	30.8	3.8	22.0	18.8	
	4B Thinking	16.9	23.2	3.1	25.2	19.7	
	235B MoE Instruct	46.2	48.9	18.3	74.1	57.8	
	235B MoE Thinking	37.3	37.8	12.2	53.7	35.9	
SFT	4B Instruct	68.5	75.6	58.8	77.7	74.7	
IntentRL	4B Instruct	82.4	77.5	74.1	88.7	74.7	

Table 4: Recall, Precision, and Full Coverage on the ambiguous and unambiguous subsets of Ambrosia.

Method	Similarity
ACT	75.1
IntentRL	83.0

Method	Ambrosia (Ambiguous)				AmqiQT			
	Recall	Prec	Single	Full	Recall	Prec	Single	Full
DisambigParse	59.7	26.3	87.8	30.5	58.5	35.3	88.0	30.0
IntentRL	82.4	77.5	92.4	74.1	66.9	58.2	84.7	49.1

Table 5: Embedding-based semantic similarity ([Reimers and Gurevych, 2019](#)) for answers from ACT ([Chen et al., 2025](#)) and IntentRL.

Table 6: Comparison between DisambigParse ([Saparina and Lapata, 2025](#)) and IntentRL on ambiguous questions. We report Precision, Single Coverage (Single), and Full Coverage (Full).

when ambiguity is genuinely present.

Since gold interpretations are available for Ambrosia, we train two SFT variants: one that generates only SQL queries and another that generates both interpretations and SQL queries. However, we find no improvement from including interpretations during training. Our approach (IntentRL) substantially outperforms all baselines, achieving 82.4% recall, 77.5% precision, and 74.1% full coverage on ambiguous questions, while maintaining strong performance on unambiguous questions (88.7% recall, 74.7% precision). High precision is particularly impressive since we do not explicitly optimize for precision during training.

There are several reasons for this. Firstly, the base model already shows more balanced or even slightly higher precision than recall (e.g., 4B Instruct has 30.8% precision vs. 22.5% recall on ambiguous questions), providing a strong starting point. Secondly, text-to-SQL parsing allows for a verifiable, execution-based rewards, making it easier for the model to learn valid inter-

pretations compared to tasks with soft similarity-based rewards, such as conversational QA. Our approach substantially outperforms SFT baselines, despite using the *same* answer supervision (82.4% vs. 72.7% recall). Reasoning encourages the model to explicitly consider different interpretations, while RL teaches it to learn from mistakes rather than memorize patterns from gold examples. Finally, IntentRL achieves balanced performance across ambiguous and unambiguous questions. The model correctly identifies when questions require multiple answers (high recall on ambiguous) and when a single answer is appropriate (74.7% precision on unambiguous), demonstrating its ability to recognize when ambiguity is present. Table 11b in Appendix H shows ablations for IntentRL on Ambrosia, with similar trends as observed in Abg-CoQA.

Out-of-Domain Generalization Following previous work ([Saparina and Lapata, 2025](#)), we report results on AmqiQT ([Bhaskar et al., 2023](#)), another text-to-SQL benchmark with ambiguous ques-

Method	Model	Recall	Precision	Full
<i>Answers only</i>				
0-shot	4B Instruct	27.4	51.8	2.4
	4B Thinking	55.5	71.2	32.6
	235B MoE Instruct	44.0	72.0	10.8
	235B MoE Thinking	53.1	55.1	37.2
SFT	4B Instruct	40.6	50.8	21.9
<i>Interpretations and Answers</i>				
CoT	4B Instruct	20.5	27.2	9.3
	4B Thinking	20.7	25.1	12.2
	235B MoE Instruct	60.5	63.2	38.2
	235B MoE Thinking	51.8	43.2	38.1
SFT	4B Instruct	32.9	51.4	9.1
IntentRL	4B Instruct	66.9	58.2	49.1

Table 7: Recall, Precision, and Full Coverage (%) on AmbiQT (SFT/IntentRL trained on Ambrosia).

tions which serves as out-of-domain evaluation for trainable methods. AmbiQT has 1,954 ambiguous questions over real-world databases with more complex schemas than the synthetic databases in Ambrosia. Nevertheless, generalization is possible as it consists of vague ambiguous questions that are also present in the Ambrosia training set.

Table 7 presents our results on AmbiQT. Despite using real-world databases and more complex SQL queries, zero-shot results reveal that AmbiQT is less challenging than Ambrosia: the 4B Thinking model achieves 55.5% recall in the answers-only setting compared to 35.9% on Ambrosia. Unlike Ambrosia, reasoning models provide substantial improvements over instruct models on AmbiQT (55.5% vs. 27.4% recall for 4B models). Although SFT achieves strong in-domain performance on Ambrosia, it fails to generalize to AmbiQT, achieving 21.9% full coverage when generating answers only and 9.1% when generating interpretations and answers. SFT learns dataset-specific patterns like the structure of databases and common query templates rather than the underlying task of identifying ambiguity.

IntentRL generalizes much better, identifying all valid interpretations for nearly half of the questions *without training* on this dataset (66.9% recall and 49.1% full coverage). IntentRL learns general reasoning skills about ambiguity that transfer across domains, databases, and queries.

Comparison with Two-Stage Approach In Table 6, we compare IntentRL with DisambigParse

Dataset	Alignment	Agreement
Abg-CoQA	90.0	81.0
Ambrosia	91.7	84.0

Table 8: Human evaluation: interpretation alignment accuracy and all-annotators agreement.

(Saparina and Lapata, 2025), a recent state-of-the-art method for handling ambiguity in semantic parsing. In addition to our metrics, we include Single Coverage (percentage of questions where the model correctly identifies at least one valid interpretation) to fully match their evaluation setup.

We outperform DisambigParse across all metrics on both datasets, achieving substantially higher precision on Ambrosia (77.5% vs. 26.3%) and AmbiQT (58.2% vs. 35.3%), while also more than doubling full coverage (74.1% vs. 30.5% on Ambrosia, 49.1% vs 30.0% on AmbiQT). Producing at least one valid interpretation is relatively easy as both approaches achieve high single coverage (over 80%). Notably, we achieve these significant gains while learning from answers alone in a single stage, whereas DisambigParse requires gold interpretations during training.

6 Evaluating Interpretation Alignment

Automatic metrics evaluate the quality of the generated answers, but do not measure if the interpretations align with and explain their answers. Abg-CoQA does not have gold interpretations, and while Ambrosia does, we did not use them during training, so our model’s interpretations may differ in style and wording. We thus assess the quality of the predicted interpretations via a human study.

Human Evaluation Setup We sampled 30 ambiguous examples from each dataset (80 interpretation-answer pairs in Abg-CoQA and 92 in Ambrosia). We focused on ambiguous cases as appropriate interpretations are more critical when multiple plausible answers exist. For each pair, three annotators judged whether the interpretation is compatible with its answer (i.e., whether it supports or explains it). Annotators were given the full context, the ambiguous question, and instructions to evaluate alignment even in cases where the answer was incorrect; an interpretable wrong answer is better than an unexplained one since it allows users to quickly identify and reject wrong answers. See Appendix F for more details.

Results and Discussion We report two metrics in Table 8: average alignment accuracy across all annotations (Alignment) and the percentage of pairs where all three annotators agree (Agreement). Our model achieves 90.0% alignment accuracy on Abg-CoQA and 91.7% on Ambrosia with strong inter-annotator consensus (81.0–84.0% annotator agreement). Combined with our answer quality metrics, these results provide a more complete picture of model performance demonstrating that it learns to generate meaningful interpretations that explain the provided answers. Aligned interpretations make the model’s decision-making transparent, allowing users to select their intended meaning or quickly reject incorrect interpretations.

7 Analysis of Model Output

Error Analysis To better understand model failures, we further analyze the 30 examples sampled for evaluating interpretation alignment (Section 6). On Abg-CoQA, we identify three types of error. First, the model ignores important context from previous dialogue turns. Second, it sometimes produces valid, well-specified interpretations but then gives factually incorrect answers, such as referencing a different person than the one implied in the interpretation. Third, it predicts generic interpretations like “The question is ambiguous.” In some cases, this is paired with a specific answer, without clarifying which interpretation the answer corresponds to. In other cases, it is paired with the answer “Unknown” which appears in some training examples, but the model has learned to produce it more often than necessary.

We also observe on Ambrosia that interpretations can be vague, sometimes paraphrasing the question without resolving the ambiguity. Moreover, the model occasionally produces correct interpretations but predicts queries that do not follow them (e.g., adding ID fields not mentioned in the question) and generates non-executable queries, even noting the error in SQL comments (e.g., “this column does not exist”). It also repeats the same interpretation multiple times, although repetitions can be filtered via execution results.

Reasoning Chains Figure 1 shows average reasoning length versus full coverage on ambiguous examples in Abg-CoQA and Ambrosia. We compare all methods that produce reasoning traces: models prompted with CoT, thinking models, and

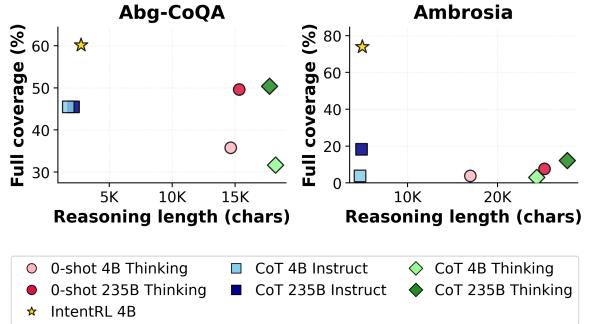


Figure 1: Reasoning length (number of characters) vs. coverage (ambiguous subsets).

our approach. As can be seen, thinking models frequently overthink on Abg-CoQA, getting stuck on the same interpretation rather than considering alternatives. Traces from our model occasionally contain repetitions on Abg-CoQA, but they are significantly more concise. On Ambrosia, thinking models sometimes miss interpretations entirely, leading to low full coverage. Instruct models with CoT are more concise but underperform on both datasets. Overall, our models demonstrate the best ratio of efficiency to interpretation coverage. Appendix G provides examples of reasoning traces from our model.

8 Conclusion

We handle ambiguous requests by generating interpretations paired with corresponding answers and train models to reason about user intent via reinforcement learning with specialized rewards. Experiments on conversational question answering and text-to-SQL parsing show our method achieves higher full coverage of valid answers. The generated interpretations align with their answers over 90% of the time, despite lacking explicit supervision during training. Our approach offers more efficient reasoning than thinking models with better coverage. Explicit interpretations help users quickly clarify their intent or reject incorrect interpretations, improving both user experience and safety.

In the future, we plan to use interpretations to identify and correct errors in real-time, without requiring a full re-generation of responses. Controlled decoding could further improve efficiency and accuracy, e.g., ensuring that interpretations are mutually exclusive. Finally, adapting to individual user preferences would make interpretations more personalized and relevant to each user.

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A Interpretation-Answer Pair Prompt

We use the following prompt template for reasoning about user intent with explicit interpretations:

Interpretation-Answer Pair Prompt Template

You receive a context and a question. First analyse the question to identify different possible interpretations, then provide the corresponding answer for each interpretation.

If the question is unambiguous, provide a single clear interpretation and answer. If the question contains ambiguities, underspecifications, or could be understood in multiple ways, provide multiple plausible interpretations (maximum of 5) and corresponding answers.

An interpretation is a self-contained, precise reformulation of the question that clarifies scope, entities, and intent so that the question could be answered unambiguously. Different interpretations should lead to meaningfully different answers.

Context:

{context}

Question to interpret and answer:

{question}

General Instructions:

- Think through the question step-by-step
- Consider different ways the question could be understood
- Look for potential ambiguities in terminology, scope, or intent
- Consider how the provided context might influence interpretation

Task-Specific Instructions:

{instructions}

Output Format:

Provide your analysis and reasoning, then conclude with interpretations and answers. Follow the format below:

...analysis and reasoning...

<answer>

Interpretation 1: [State first interpretation]
[Answer for interpretation 1]

[Continue for all interpretations (up to 5) if the question is ambiguous...]

</answer>

Task-specific instructions for question answer-

ing and text-to-SQL parsing are shown below:

Answer Generation Instructions

- Provide direct, concise answers based on the given context. Keep your answers short and to the point.
- Do not include any other text or explanation in the lines that contain the answers.

SQL Generation Instructions

- Make sure you only output the information that is asked in the question. If the question asks for a specific column, make sure to only include that column in the SELECT clause, nothing more.
- The generated query(ies) should return all of the information asked in the question without any missing or extra information.
- Use a fenced code block with "sql" annotation, e.g. ```sql ... ```

B DAPO Algorithm

DAPO (Yu et al., 2025) extends GRPO with several key modifications designed for long-form reasoning tasks. It removes the KL penalty term (as divergence from the initial model is acceptable during reasoning training) and introduces the following changes:

Decoupled Clipping DAPO uses asymmetric clipping parameters ϵ_{low} and ϵ_{high} to enhance exploration while maintaining stability.

Token-Level Loss Instead of sample-level averaging, DAPO weights tokens equally across all responses, giving longer sequences more influence proportional to their length.

Dynamic Sampling DAPO filters out prompts where all sampled responses are either correct or incorrect (accuracy equal to 1 or 0), ensuring effective gradients throughout training.

The DAPO objective is:

$$J_{\text{DAPO}}(\theta) = \mathbb{E}_{(q,a) \sim D, \{o_i\}_{i=1}^G \sim \pi_{\theta_{\text{old}}}(\cdot|q)} \left[\frac{1}{\sum_{i=1}^G |o_i|} \sum_{i=1}^G \sum_{t=1}^{|o_i|} \min(r_{i,t}(\theta) \hat{A}_{i,t}, \text{clip}(r_{i,t}(\theta), 1 - \epsilon_{\text{low}}, 1 + \epsilon_{\text{high}}) \hat{A}_{i,t}) \right]$$

s.t. $0 < |\{o_i \mid \text{is_equivalent}(a, o_i)\}| < G$,
and where

$$r_{i,t}(\theta) = \frac{\pi_\theta(o_{i,t}|q, o_{i,<t})}{\pi_{\theta_{\text{old}}}(o_{i,t}|q, o_{i,<t})},$$

$$\hat{A}_{i,t} = \frac{R_i - \text{mean}(\{R_i\}_{i=1}^G)}{\text{std}(\{R_i\}_{i=1}^G)}$$

C Types of Ambiguity

Each dataset we use has its own ambiguity taxonomy. Below, we briefly describe the types of ambiguity as defined by the dataset authors. For more details, we refer readers to the original papers.

Abg-CoQA (Guo et al., 2021) defines four ambiguity types:

Coreference resolution occurs when pronouns or referring expressions can map to multiple entities in the context. An example is provided in Table 1.

Time-dependency occurs when temporal context is underspecified, allowing questions to refer to different time periods. For example, in a story describing an accident, the question “What was everyone doing?” can refer to actions either before or after the accident.

Answer types are ambiguous with respect to the intended level of granularity. For example, when asked “What pupils’ were reading?”, the answer could be either novels a specific book (e.g., “The Call of the Wild”).

Event ambiguity occurs when a story contains multiple parallel events or storylines, and questions underspecify which event they are referring to. For example, when a story mentions both a police investigation and CNN’s reporting on the same incident, a question about whether the suspect was identified by name could refer to either storyline (the police identify but CNN does not).

Ambrosia (Saparina and Lapata, 2024) defines three ambiguity types:

Scope ambiguity occurs when it is unclear which elements a quantifier (e.g., “every”, “each”) refers to. For example, the question “What activities does each gym offer?” has a collective interpretation (a common class for all gyms in the database) and distributive one (each gym is considered separately, a list of all classes and gyms).

Attachment ambiguity occurs when it is unclear where a modifier attaches in a sentence. For example, “Show screenwriters and editors on a work-for-hire” can mean either both roles are on work-for-hire contracts (high attachment to the verb) or only editors are (low attachment to “editors”).

Vagueness occurs when context creates uncertainty about which database entities are being referenced. For example, in Table 1 “required experience” could potentially refer to minimum years, preferred years, or both.

AmbiQT (Bhaskar et al., 2023) defines four ambiguity types:

Column ambiguity occurs when multiple columns satisfy the same semantic description. For example, the question “List the ids of all students” is ambiguous when a database contains both columns named `admission_number` and `roll_number`.

Table ambiguity occurs when multiple tables represent similar entities. For example, “How many singers do we have?” could query either an `artist` or `performer` table.

Join ambiguity occurs when it is unclear whether information should be retrieved from a single table or from joining multiple tables. For example, asking for a person’s name and address is ambiguous when `address` is in the same table as `name` and `postal_address` is in a separate `person_details` table.

Precomputed aggregates arise when databases store pre-aggregated values alongside raw data. For example, “Find the average weight for each pet type” could either compute the aggregate from data or select from pre-computed `avg_weight`.

D Training Hyperparameters

We train our models using DAPO implemented with the TRL library (von Werra et al., 2020) with hyperparameters adapted from TRL defaults. We use the `Qwen3-4B-Instruct-2507` model with LoRA (Hu et al., 2022) for parameter-efficient fine-tuning (rank 64, alpha 16, and dropout 0.1, applied to all projection layers). We train for 5 epochs with AdamW (fused implementation) with learning rate 5e-7, linear scheduler with 3% warmup, and gradient clipping at norm 1.0. The per-device batch size is 16. During training, we generate 16 completions per prompt with maximum completion length of 2,500 tokens.

We use vLLM (Kwon et al., 2023), Flash Attention 2 (Dao, 2024) and DeepSpeed (Rasley et al., 2020) for efficient generation during training. All experiments were conducted on 5 NVIDIA H100 80GB GPUs: 1 GPU dedicated to the vLLM server for generation and 4 GPUs for training.

For evaluation, we use a single GPU, and

choose the last checkpoint. We use default sampling parameters (recommended by the developers) for Qwen 3 4B Instruct: temperature = 0.7, top-k = 20, top-p = 0.8, and maximum length is 30k tokens (however, the model does not generate more than 5k tokens on average, see Table 1).

E Comparison Details

For **answer-only methods**, we use the following prompt for both zero-shot experiments and fine-tuning (modified from the prompt in Appendix A):

Answer-Only Prompt Template

You receive a context and a question. First analyse the question to identify different possible interpretations, then provide the corresponding answer for each interpretation.

If the question is unambiguous, provide a single answer. If the question contains ambiguities, underspecifications, or could be understood in multiple ways, provide multiple plausible answers (maximum of 5).

Context:
`{context}`

Question:
`{question}`

General Instructions:

- Consider different ways the question could be understood
- Look for potential ambiguities in terminology, scope, or intent
- Consider how the provided context might influence interpretation

Task-Specific Instructions:
`{instructions}`

Output Format:

Follow the format below:

`<answer>`
 Answer 1: [State first answer]

[Continue for all answer (up to 5) if the question is ambiguous...]

`</answer>`

For **interpretation-answer pair methods**, we use the prompt shown in Appendix A except for fine-tuning, where we adapted the prompt by removing mentions of chain-of-thought reasoning.

We use the updated versions of the Qwen 3 model family: Qwen3-4B-Instruct-2507,

Qwen3-4B-Thinking-2507,
 Qwen3-235B-A22B-Instruct-2507,
 Qwen3-235B-A22B-Thinking-2507.

We train SFT baselines using the TRL library with default hyperparameters. Following the same procedure as our method, we train for 5 epochs, balance the training data, and select the last checkpoint for evaluation. We use the same model (Qwen3 4B Instruct) with the same LoRA configuration. Training uses the AdamW optimizer (fused implementation) with learning rate 2e-5, linear scheduler with no warmup, and gradient clipping at norm 1.0. The per-device batch size is 8 with no gradient accumulation. We use gradient checkpointing for memory efficiency and set the maximum prompt length to 8192 tokens. All SFT experiments were conducted on 1 NVIDIA H100 80GB GPU.

For both prompting and fine-tuned methods, we use the same maximum length as our method: 30k tokens. We also use the default sampling parameters for all models, which are as follows: for Instruct models, temperature = 0.7, top-k = 20, and top-p = 0.8; for Thinking models, temperature = 0.6, top-k = 20, and top-p = 0.95.

F Human Annotation Details

For the interpretation-answer alignment evaluation, we recruited annotators through Prolific ² with the following criteria. We required annotators to have English as their primary language (and SQL knowledge for Ambrosia) and at least a 95% approval rate on the platform. Annotators were not allowed to retake the task. To reduce cognitive load and make the task more efficient, we grouped interpretation-answer pairs by their source example. Each annotator evaluated 3 examples, with each example containing multiple interpretation-answer pairs from the same context. We paid annotators £9 per hour, following Prolific’s fair wage guidelines. The average completion time was 15 minutes. We used the POTATO annotation tool (Pei et al., 2022).

G Model Outputs

Tables 9 and 10 show full examples corresponding to those presented in Table 1 (the context is still shortened for brevity), including model outputs with reasoning traces and interpretation-answer pairs.

²<https://www.prolific.com/>

```

CREATE TABLE Jobs (
    JobID INTEGER PRIMARY KEY,
    Minimum_Years INTEGER,
    Preferred_Years INTEGER,
    ...
    Salary REAL
);

```

What experience do I need for the open position with the greatest salary?

Reasoning Trace

Step-by-step analysis:

1. **Identify the relevant data tables:** The question refers to “open positions” → likely refers to job roles listed in the `Jobs` table. “Experience” in the context of jobs is mentioned in the `Minimum_Years` and `Preferred_Years` columns in the `Jobs` table. `Minimum_Years` indicates the minimum years of experience required. `Preferred_Years` indicates the ideal or preferred years of experience. The “greatest salary” refers to the highest salary value in the `Salary` column in the `Jobs` table.
2. **Interpretation of “experience”:** The term “experience” could mean either: the **minimum years of experience required** (i.e., `Minimum_Years`), the **preferred years of experience** (i.e., `Preferred_Years`), or a combination of both (e.g., both minimum and preferred), or it could refer to the *type* of experience (e.g., in a field like software or data), but such information isn’t present in the schema. Therefore, “experience” is ambiguous in whether it refers to minimum, preferred, or both.
3. **Interpretation of “the open position with the greatest salary”:** This could mean: the job with the **highest salary** among all jobs, the job that has the **maximum salary value**. “Open position” simply means the job listed in the database—there’s no indication of a hiring status or closure, so we assume all jobs are open.
4. **Scope of the question:** It could be asking for: just the **minimum** experience required (minimum years) for the job with the highest salary, just the **preferred** experience for that job, both minimum and preferred, or what kind of experience (e.g., in years) is needed—again, only years are specified.
5. **Potential ambiguity in “experience” vs. “years of experience”:** “Experience” could be taken as a general term, but in the database schema, only years are provided (in `Minimum_Years` and `Preferred_Years`). So interpretations must map “experience” to one or both of these years.
6. **Ambiguity in which experience (minimum or preferred):** The question says “what experience do I need”, which may imply the **required** experience (minimum), not just preferred. But in common usage, people may interpret “what experience do I need” as the minimum required. Alternatively, it could mean the preferred, or both.
7. **Ambiguity in what “the greatest salary” refers to:** It could refer to: the single job with the highest salary value, or the job where salary is max, and then extract its experience.

Conclusion: The question is ambiguous in: whether “experience” refers to minimum, preferred, or both years; whether it refers to the *minimum* or *preferred* experience required; whether “greatest salary” is interpreted as the highest salary value.

Interpretation–Answer Pairs

Interpretation 1: What is the minimum years of experience required for the job with the highest salary?

```
SELECT Minimum_Years FROM Jobs ORDER BY Salary DESC LIMIT 1;
```

Interpretation 2: What is the preferred years of experience for the job with the highest salary?

```
SELECT Preferred_Years FROM Jobs ORDER BY Salary DESC LIMIT 1;
```

Interpretation 3: What is the minimum years of experience required for the job that has the greatest salary?

```
SELECT Minimum_Years FROM Jobs WHERE Salary = (SELECT MAX(Salary) FROM Jobs);
```

Interpretation 4: What is the preferred years of experience for the job that has the greatest salary?

```
SELECT Preferred_Years FROM Jobs WHERE Salary = (SELECT MAX(Salary) FROM Jobs);
```

Interpretation 5: What are the minimum and preferred years of experience required for the job with the greatest salary?

```
SELECT Minimum_Years, Preferred_Years FROM Jobs ORDER BY Salary DESC LIMIT 1;
```

Table 9: Model output for an ambiguous text-to-SQL example from Ambrosia (database schema shortened for brevity).

Hilary Duff says her new album is ... “a lot heavier and a lot darker” because of the separation from **her husband, Mike Comrie**. Duff married Comrie ... in 2010 after dating for three years. **Their son, Luca**, was born in 2012...

- How long were they married before they had a child? — 2 years
 - **What is his name?**
-

Reasoning Trace

Analysis and reasoning:

The question “What is his name?” is ambiguous because “his” refers to a male entity, and multiple males are mentioned in the context. The possible individuals referred to as “him” include:

1. Mike Comrie — described as Hilary Duff’s husband, a former pro hockey player. He is referred to as “her husband” and is mentioned as the one she is separated from. He is the only male mentioned in a marital relationship with Hilary Duff. His name is explicitly stated as “Mike Comrie.”

2. Luca — described as their son, a male child. “His” could refer to Luca, but “his name” would then be “Luca.”

The question “What is his name?” lacks clarity on which male entity is being referred to. Possible interpretations:

- “His” could refer to Mike Comrie (the husband), whose name is Mike Comrie.
- “His” could refer to the person who had a child — Hilary Duff and Mike Comrie had a child, Luca. “His” could refer to Luca, the child, with name “Luca.”
- “His” could refer to Mike Comrie, the husband, who is the one married to Hilary Duff.
- “His” could refer to Mike Comrie, the former pro hockey player, who is the husband.

The entities with male pronouns: Mike Comrie — husband, married to Hilary Duff; Luca — son, child.

Possible “his” referents: “His” could refer to Mike Comrie (the husband), so “his name” would be “Mike Comrie”; “His” could refer to the father of the child, which is Mike Comrie; “His” could refer to Luca (the child), so “his name” would be “Luca”.

Thus, possible interpretations: (1) “His” refers to Mike Comrie — the man in question. His name is Mike Comrie. (2) “His” refers to the man who had a child — Mike Comrie. (3) “His” refers to the child — Luca. “His name” would be “Luca.” (4) Ambiguity: “his” could refer to Mike Comrie or to Luca.

The context states: “Their son, Luca, was born in 2012. Duff and Comrie announced their separation in January.” So Mike Comrie is the father.

Therefore, possible interpretations: “What is his name?” — if “his” refers to the husband, then “Mike Comrie”; if “his” refers to the son, then “Luca”; if “his” refers to Mike Comrie (the man), then “Mike Comrie”; if ambiguous, possible names: Mike Comrie, Luca.

Since the question “What is his name?” is ambiguous, possible targets: the man (husband): Mike Comrie; the son: Luca.

Conclusion: The most likely intended subject is “his” referring to Mike Comrie, the husband. Alternatively, if “his” refers to the child, then “Luca.” Since the context only lists two males with names: Mike Comrie and Luca, and “his” is vague, the safest is to list both possibilities.

Interpretation–Answer Pairs

Interpretation 1: The question refers to Mike Comrie, Hilary Duff’s husband.

Mike Comrie

Interpretation 2: The question refers to the son.

Luca

Interpretation 3: The question refers to Mike Comrie, the former pro hockey player.

His name is Mike Comrie

Interpretation 4: The question is ambiguous and could refer to either Mike Comrie or Luca.

Unknown

Interpretation 5: “His” refers to Mike Comrie, the husband.

Comrie

Table 10: Model output for an ambiguous conversational QA example from Abg-CoQA (story and history of turns are shortened for brevity).

H Ablation Study

Method	Ambiguous				Unambiguous		
	Overlap F1	Judge Recall	Judge Precision	Full Coverage	Overlap F1	Judge Recall	Judge Precision
IntentRL	72.9	78.1	53.5	61.0	84.4	90.9	40.7
Answers Only	73.8	78.9	45.5	61.8	85.0	90.6	35.0
No Balancing	38.1	45.8	81.3	15.5	77.9	82.1	82.1

(a) Variations of IntentRL on Abg-CoQA: *Answers Only* refers to a model trained with RL to predict only answers without explicit interpretations; *No Balancing* refers to IntentRL trained without training data balancing (see Section 4.2). All models are based on Qwen 4B Instruct.

Method	Ambiguous			Unambiguous	
	Recall	Precision	Full Coverage	Recall	Precision
IntentRL	82.4	77.5	74.1	88.7	74.7
Answers Only	82.4	78.3	71.8	86.1	75.3
No Balancing	49.4	85.0	9.2	84.5	81.7

(b) Variations of IntentRL on Ambrosia: *Answers Only* refers to a model trained with RL to predict only answers without explicit interpretations; *No Balancing* refers to IntentRL trained without training data balancing (see Section 4.2). All models are based on Qwen 4B Instruct.