

# LORE: A Large Generative Model for Search Relevance

Chenji Lu\*, Zhuo Chen\*, Hui Zhao, Zhiyuan Zeng, Gang Zhao,  
Junjie Ren, Ruicong Xu, Haoran Li, Songyan Liu, Pengjie Wang, Jian Xu, Bo Zheng

{luchenji.lcj, cz462596, renjunjie.rjj, bozheng}@alibaba-inc.com  
{shuqian.zh, zengzhiyuan.zzy, zilong.zg, xuricong.xrc, lhr476916, moxuan.lys,  
pengjie.wpj, xiyu.xj}@taobao.com

Search Advertising Team, Alimama (Alibaba Group)

## Abstract

**Achievement.** We introduce LORE(**L**arge **G**enerative **M**odel for **R**elevance), a complete and sustainable framework of iterative practices for large language models(LLMs) in e-commerce search relevance, which achieves a cumulative +27% improvement on the online GoodRate metric. Over the past three years, this project has demonstrated significant improvements in relevance judgment and has undergone three full-scale iterations across key dimensions, including data, features, training paradigms, evaluation, and application. Throughout the iterative development of LORE, we have gained valuable experience and insights that we believe are worth sharing with the community in this report.

**Insight.** To enhance LLMs for relevance, existing works have modeled the Chain-of-Thought (CoT) from various perspectives. However, we find that these methods often exhibit blind spots, as they lack a principled deconstruction of the task itself. Our analysis reveals that complex relevance judgment is not a monolithic reasoning problem but rather a composite of distinct capabilities, including knowledge and reasoning, multi-modal matching, and rule adherence. Based on this insight, we propose a systematic framework that first deconstructs the problem and then leverages this deconstruction to guide a training paradigm that explicitly models each required capability. We argue that such qualitative-driven analysis is essential for breaking through existing performance bottlenecks.

**Contributions.** LORE is a complete, replicable blueprint for LLM-based relevance modeling that spans the entire lifecycle. First, we conducted systematic preliminary explorations into foundational training elements—including features, prompts, and base models—and summarized the general principles derived from this process.

Second, guided by our structural analysis, we propose a sophisticated two-stage training paradigm that uses progressive CoT synthesis to inject comprehensive capabilities via SFT, followed by a carefully designed RL phase for human preference alignment, and share insights from our comprehensive exploration of the associated training strategies.

Third, to ensure rigorous validation, we construct a comprehensive benchmark, RAIR, tailored to evaluate the core capabilities we identified.

Finally, to overcome the challenges of real-time computation, we designed a query frequency-stratified deployment strategy that comprehensively transfers the offline LLM’s ability to online system, leading to substantial online performance gains. The complete methodology and findings provide valuable insights for post-training work in other vertical domains.

LORE serves as both a practical solution for developing and operationalizing advanced relevance systems in e-commerce and a methodological reference for post-training work across other vertical domains.

---

\*Equal Contribution. Please refer to Sec 9 for the complete list of contributors to this work.

## Contents

<b>1</b>	<b>Introduction</b>	<b>4</b>
<b>2</b>	<b>Theoretical Framework</b>	<b>6</b>
2.1	Task Definition . . . . .	6
2.1.1	Problem Formulation . . . . .	6
2.1.2	Fine-Grained Relevance Judgment . . . . .	7
2.1.3	Attribute Schema for Query Demands . . . . .	7
2.2	Deep Analysis of Relevance Modeling . . . . .	7
2.2.1	Item Understanding . . . . .	7
2.2.2	Query Understanding . . . . .	8
2.2.3	Path Modeling from Query to Item . . . . .	10
2.2.4	Core Capabilities for Relevance Judgment . . . . .	11
<b>3</b>	<b>Method</b>	<b>12</b>
3.1	Overview . . . . .	12
3.2	Preliminary Exploration . . . . .	13
3.2.1	Feature Construction . . . . .	14
3.2.2	Model Selection . . . . .	14
3.2.3	Prompt Optimization . . . . .	15
3.3	SFT: Comprehensive Reasoning Capability Injection . . . . .	15
3.3.1	Data construction . . . . .	15
3.3.2	Multi-dimensional Chain-of-Thought Synthesis . . . . .	17
3.3.3	Distillation by SFT . . . . .	19
3.4	RL: Relevance-Oriented Human Preference Alignment . . . . .	21
3.4.1	Data construction . . . . .	21
3.4.2	Basic RL Framework . . . . .	21
3.4.3	Training Strategy Optimization . . . . .	23
3.5	Evaluation: Comprehensive Relevance Benchmark . . . . .	25
3.5.1	Design Principles . . . . .	26
3.5.2	Benchmark Construction . . . . .	26
3.5.3	Data Statistics . . . . .	27
<b>4</b>	<b>Experiment</b>	<b>28</b>
4.1	Settings . . . . .	28
4.1.1	Metrics . . . . .	28
4.1.2	Baseline . . . . .	29
4.2	Main Result . . . . .	29
4.3	Case Study . . . . .	30

<b>5 Application</b>	<b>31</b>
<b>6 Discussion</b>	<b>33</b>
6.1 Naive teacher CoT distillation results in negative effects. . . . .	33
6.2 Long CoT is not necessary for better performance. . . . .	33
6.3 Multimodal Modeling: VLM or Two-Stage LLM? . . . . .	33
<b>7 Evolutionary Trajectory</b>	<b>35</b>
7.1 LORE 1.0: Foundation Consolidation . . . . .	35
7.2 LORE 2.0: Deep reasoning . . . . .	35
7.3 LORE 3.0: Rule Adherence and Multi-modality . . . . .	36
<b>8 Conclusion</b>	<b>37</b>
<b>9 Contributors</b>	<b>37</b>

## 1 Introduction

Search relevance plays a pivotal role in e-commerce platforms such as JD and Taobao(Yuan et al., 2023). The relevance model evaluates candidate items by determining their alignment with user queries, assigning relevance scores to filter out mismatched products(Liu et al., 2022; Carmel et al., 2020). This mechanism serves as a crucial foundation for enhancing user experience and search quality.

Large language models (LLMs) have exhibited remarkable capabilities and been extensively applied to relevance tasks. While state-of-the-art(SOTA) models (DeepSeek-AI et al., 2025; Yang et al., 2025; Bai et al., 2025; Comanici et al., 2025) such as GPT-5 suffer from insufficient domain knowledge and prohibitive costs, post-training(Liu et al., 2024; Mehrdad et al., 2024) smaller-scale LLMs on e-commerce data to develop domain-specific relevance experts has emerged as the predominant paradigm.

Recent advances(Mehrdad et al., 2024; Zhao et al., 2025a; Tang et al., 2025; Fang et al., 2025; Dong et al., 2025) have progressively transitioned the post-training paradigm from rudimentary classification-oriented Supervised Fine-Tuning (SFT) to sophisticated enhancement of reasoning capabilities. Although existing work has modeled chain-of-thought(CoT)(Wei et al., 2023) processes from multiple perspectives, notable gaps remain that limit comprehensive treatment of complex relevance tasks. ELLM(Zhao et al., 2025a) conceptualizes the relevance task as a process of attribute extraction and matching between queries and items. However, this approach exhibits limited capability when handling boundary cases that require rule-based judgment. For instance, when matching the query "lake blue top" with the item "sky blue top," the method lacks color discrimination rules and struggles to make accurate judgments. LREF(Tang et al., 2025) and TaoSR1(Dong et al., 2025) not only focus on attribute matching but also explicitly model rule-following chains of thought, endowing the model with rule-awareness capabilities. Nevertheless, their failure to incorporate visual information results in blind spots in discrimination. Taking the query "blue top" as an example, when the item title lacks color description but the item image clearly displays a blue top, the model fails to make correct judgments due to the absence of image information. These limitations stem from neglecting a fundamental question: *What constitutes a comprehensive CoT representation for relevance tasks?* This question probes the capability requirements for relevance assessment.

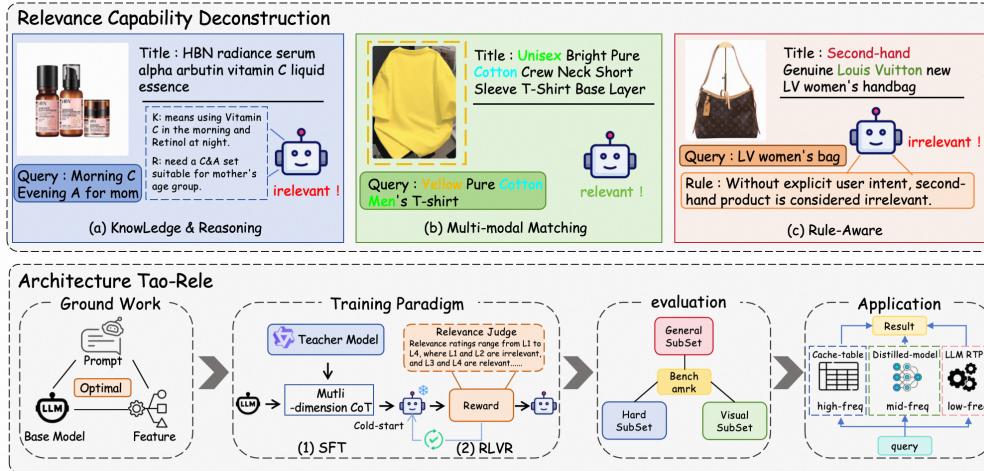


Figure 1: Overview of the LORE theoretical framework and architecture.

To systematically address this question, we conducted an in-depth deconstructive analysis of the relevance task, detailed in Section 2. We decompose the relevance discrimination process into two stages: (1) **Path Construction:** mapping query requirements to specific attributes and establish semantic paths between queries and products; (2) **Path Following:** execute concrete discrimination at the attribute-product level based on the constructed paths. Furthermore, the model capabilities required throughout this process can be summarized as follows: (1) Knowledge and Reasoning Ability(DeepSeek-AI et al., 2025; He et al., 2025;

Team et al., 2025; Li et al., 2025; Feng et al., 2024). The model relies on knowledge to parse domain-specific expressions in queries and obscure item information. Reasoning capability then builds upon this foundation, enabling the model to infer the true intent of queries and the derived attributes of items. As illustrated in Fig. 1(a), the model must first rely on knowledge to determine that "morning C, evening A" refers to a combination of Vitamin C and retinol, and then deduce through reasoning that "for mom" implies suitability for middle-aged women. (2) Multi-modal Matching Ability(Gong et al., 2024; Zhang et al., 2024; Li et al., 2024).Item attributes are presented across multiple modalities. The model needs to perform cross-modal matching between the parsed query intent and attributes, associating them with the multimodal attribute representations of items. As shown in Fig. 1(b), the query requirement "yellow" is absent in the textual description and necessitates extracting clues from visual information. (3) Rule-Aware Ability. Discrimination relies on quantifiable and reproducible criteria. Building upon attribute matching, the model must make judgments in accordance with established rules. As illustrated in Fig. 1(c), when a query searches for "LV bags" while the item is a second-hand bag, this scenario cannot be resolved through attribute matching alone and requires adherence to predefined rule definitions.

To model the aforementioned capabilities, we introduce LORE 3.0(Large Generative Model for Relevance), our most recent iteration of a systematic LLM practice framework for relevance tasks(the lower part of Fig 1). Firstly, We conducted necessary preliminary explorations to determine the optimal base model, features, and prompts, thereby establishing a foundation for subsequent training. Secondly, we propose a two-stage training paradigm encompassing SFT and Reinforcement Learning(RL). In the SFT stage, we progressively synthesize complete reasoning chains incorporating all processes in accordance with the two-stage relevance discrimination framework. The primary objective of this stage is to enable the model to learn reasoning patterns and elevate the upper bound of model capabilities. In the RL stage, we design Reinforcement Learning with Verifiable Rewards (RLVR)(DeepSeek-AI et al., 2025) in conjunction with the characteristics of relevance tasks, guiding the model to align with human preferences. The objective of this stage is to prune erroneous reasoning paths while building upon the multi-dimensional reasoning capabilities the model has acquired. Thirdly, based on the identified core capability requirements, we purposefully constructed a comprehensive and challenging benchmark to systematically assess and validate the model's performance across capability dimensions. Finally, we comprehensively transferred LLM capabilities to the online system from both the model and policy perspectives. Based on query stratification, we designed differentiated capability transfer strategies, cumulatively achieving a 27% GoodRate improvement. In summary, the main contributions of this report are as follows:

- We deconstructed the relevance task and summarized the required model capabilities based on the deconstruction results, providing clear and comprehensive guidance for subsequent iterations of relevance models in the industry.
- We propose a complete methodology and documented practice that encompasses the entire pipeline from preliminary work such as model selection, to training paradigm, to capability evaluation.
- Experimentally, LORE achieved state-of-the-art results on offline datasets. Furthermore, through its subsequent empowerment of online applications, we obtained a substantial total improvement of 10% in GoodRate across online A/B experiments.
- During LORE's development, we explored various SFT and RL training strategies. Key findings that may benefit LLM fine-tuning in vertical domains are summarized as follows:

### Key Findings during SFT

- 1. Data scaling law shows diminishing returns.** Model performance grows rapidly initially but plateaus as data increases. (Section 3.3.3).
- 2. More features beat fewer.** Providing stable and relevant information, even if redundant, can yield gains for the model(Section 3.2.1).
- 3. A concise prompt with essential information works best.** Information-rich but verbose prompts do not necessarily yield improvements, whereas prompts with insufficient key information lead to degradation in model capability(Section 3.2.3).
- 4. Naive teacher CoT distillation results in negative effects.** Direct teacher CoT distillation underperforms vanilla SFT due to distribution shift. (Section 6.1)

### Key Findings during RL

- 1. Curriculum learning still works.** Curriculum learning strategies based on difficulty grading significantly outperform randomly ordered strategies.(Section 3.4.3)
- 2. Long CoT is not necessary for better performance.** No significant increase in model output length was observed during the RL process, indicating that long CoT are merely a potential byproduct when the model's capability improves.(Section 6.2)
- 3. Entropy collapse rate caps model performance.** In the early stages of training, the model rapidly trades entropy for performance gains. When entropy decreases to a certain level, the model's exploration capability becomes constrained, and subsequent room for improvement diminishes.(Section 3.4.3)
- 4. Smart strategies effectively slow entropy collapse.** The report discusses several optimization methods including clip-higher, on-policy, and entropy loss, ultimately finding that clip-higher achieves optimal performance.(Section 3.4.3)

## 2 Theoretical Framework

In this section, our goal is to develop a comprehensive view of the relevance task and, on this basis, to identify the key modeling capabilities required for effective e-commerce search. These capabilities will serve as the foundation for the methods introduced in the subsequent sections.

### 2.1 Task Definition

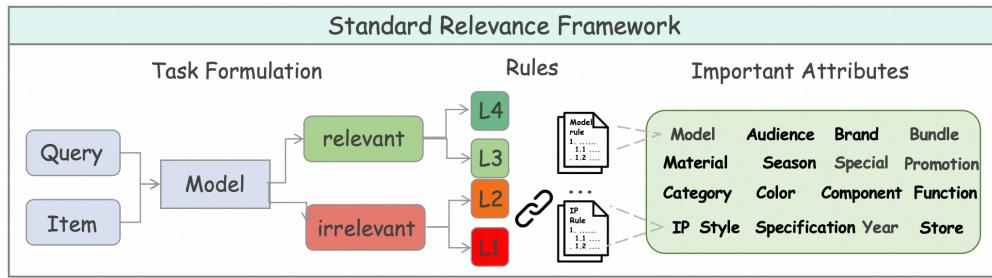


Figure 2: A standard definition of the relevance task

#### 2.1.1 Problem Formulation

From a functional perspective, e-commerce search can be regarded as the process of mapping user queries to product items. Relevance modeling refines this mapping by introducing relevance as a quantitative measure that captures the degree of match between a given query and item under both objective (e.g., attribute and constraint satisfaction) and subjective

(e.g., user intent and preference) criteria. Formally, as illustrated in Fig 2, given a query  $Q_i$  and an item  $I_i$ , the model performs pointwise discrimination to determine whether the pair is relevant or irrelevant. In its simplest form, this can be viewed as a binary classification problem.

### 2.1.2 Fine-Grained Relevance Judgment

A purely binary formulation, however, cannot adequately characterize the varying degrees to which  $I_i$  satisfies the information need expressed by  $Q_i$ . To address this limitation, we adopt a more fine-grained discrimination framework with four levels, denoted L1–L4, where higher levels indicate a greater degree of satisfaction of  $Q_i$  by  $I_i$ . Concretely, L1 and L2 are treated as *irrelevant*, while L3 and L4 are treated as *relevant*. This graded scheme enables the model to capture more nuanced distinctions in relevance beyond a simple yes/no decision.

### 2.1.3 Attribute Schema for Query Demands

Orthogonally to the four-level relevance scale, we decompose the potential demands encoded in queries into 18 attribute dimensions (e.g., category, brand, style, and others). For each query-item pair, we assess the extent to which the item satisfies the attributes explicitly or implicitly expressed in the query, and use these attribute-level judgments to ground and justify the assigned relevance level. This attribute schema provides a structured lens through which relevance decisions can be interpreted and analyzed.

## 2.2 Deep Analysis of Relevance Modeling

To systematically quantify relevance within the e-commerce search context, we decompose the assessment process into three synergistic components: *item understanding*, which constructs the attribute space; *query understanding*, which decodes user intent into retrieval pathways; and the subsequent *relevance judgment*.

### 2.2.1 Item Understanding

In relevance judgment, item understanding can be analyzed along two main dimensions: (i) the nature of item attributes and (ii) the presentation modality.

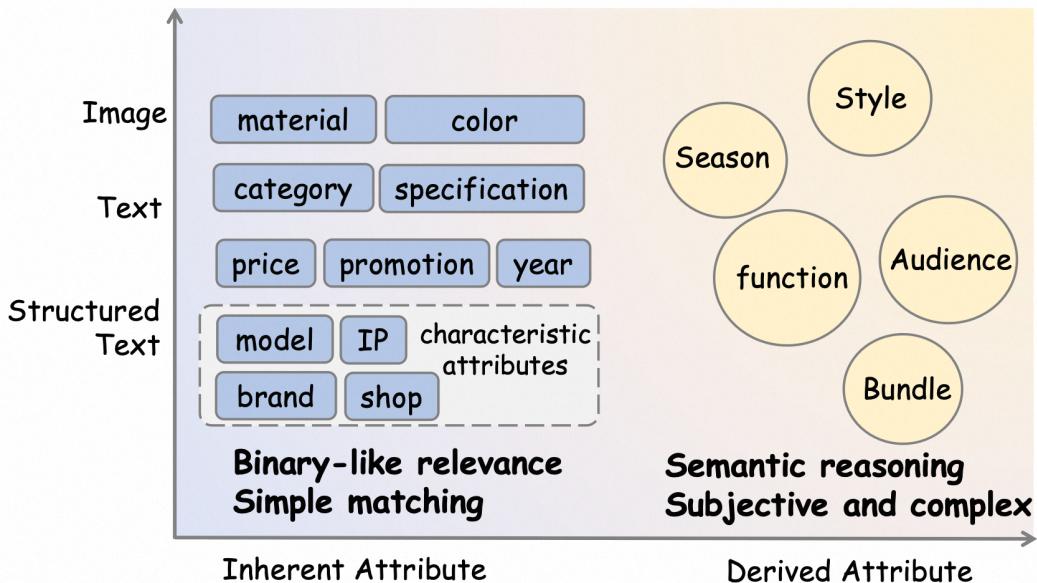


Figure 3: Comprehensive Overview of Item Attributes

**Attribute Properties** From the perspective of attribute properties, we distinguish between *inherent attributes* and *derived attributes*. The key difference lies in whether relevance judgment can be made with direct observation and simple matching, or whether it requires additional reasoning and stronger semantic understanding.

- **Inherent attributes** denote objectively existing and reliably observable properties of the item. They are usually direct consequences of the product design or the physical carrier, such as category, shop, brand, IP, model, specification, material, color, price, year, and promotion. For such attributes, relevance tends to be close to a binary decision (relevant vs. not relevant), and the decision rules are relatively clear. Within inherent attributes, we can further distinguish a subset of *characteristic attributes*, which are the most central and discriminative attributes, e.g., brand, model, specification, IP, and shop name. On e-commerce platforms, these attributes are typically expressed in a clear, objective, and relatively standardized form. Consequently, for query-item matching that includes characteristic attributes, simple term-matching strategies often suffice for effective relevance judgment.
- **Derived attributes** are induced from inherent attributes and usually correspond to product goals or usage effects. These attributes are not always directly observable, and relevance judgment relies more heavily on semantic understanding and reasoning, often involving subjectivity and degrees of satisfaction (e.g., “more suitable”, “more comfortable”, “more slimming”). This makes the decision problem substantially more complex. A major challenge is that different industries and categories develop their own attribute systems and surface forms, which are highly diverse and difficult to enumerate exhaustively.

**Presentation Modality** Presentation modality describes how attributes are exposed to the system. From this perspective, item information can be broadly divided into text-only and multi-modal (text+image) representations. The modality determines whether item understanding must rely on multi-modal modeling, and it interacts with the nature of attributes. For some attributes (e.g., color, style, material), image information is often indispensable; for others (e.g., brand, price, year), text is usually sufficient for accurate identification and judgment. In multi-modal scenarios, different attributes depend on visual information to different degrees. When characteristic attributes are expressed consistently in both text and images, multi-modal capabilities can further improve robustness. For highly subjective derived attributes (e.g., style, effect), joint understanding of text and images becomes critical for high-quality relevance judgment.

Overall, at the item-understanding level, relevance judgment for inherent attributes mainly depends on accurate query understanding and e-commerce domain knowledge, and is relatively direct. In contrast, derived attributes pose higher difficulty both in path construction (reasoning) and in relevance judgment (semantic understanding).

### 2.2.2 Query Understanding

Compared to structured item attributes, user queries express their needs in a more free-form and diverse manner. The main challenge of query understanding is to fully parse and accurately model these needs. We decompose query understanding into two core sub-tasks: entity recognition and intent recognition (entity-relation recognition). We start from single-dimensional needs and then extend to multi-dimensional needs.

**(1) Entity recognition: dependence on knowledge.** The goal of entity recognition is to identify all potential need points (attributes or item entities) from the query. From the perspective of difficulty and knowledge dependence, we can roughly distinguish the following scenarios:

- **Knowledge-free scenarios.** Need entities can be directly extracted from surface forms, with simple syntax and semantics, and almost no background knowledge is required.
- **General world knowledge scenarios.** Here, general semantic understanding is still effective, but correct recognition requires sufficient world knowledge. For example,

in “pearl white” or “ivory white”, the core need is a specific shade of white, not “pearl” or “ivory” themselves; in “phone gas station”, the underlying need is a power bank, and “gas station” works as a metaphor. In such cases, higher-level semantic understanding and knowledge interact tightly, and treating the problem as pure semantic parsing is insufficient.

- **Domain-specific knowledge scenarios.** These needs involve niche characteristic attributes or derived attributes that cannot be inferred from surface forms alone and must rely on structured domain knowledge. Typical examples include domain-specific jargon in vertical e-commerce, shop/brand taxonomies, model coding rules, and category-specific descriptions of functions or effects (e.g., mouthfeel descriptions for tea or wine).
- **Other challenges: misspellings and aliases.** Users may express their needs using typos, homophones, aliases, or industry slang. This requires stronger integration of general and domain knowledge, and the model needs robust capabilities in spelling correction, variant normalization, and alias alignment.

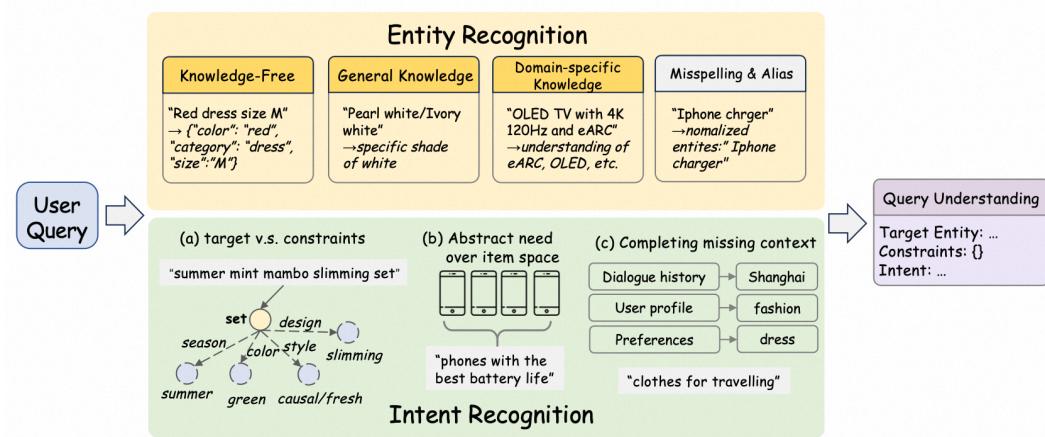


Figure 4: Comprehensive Overview of query understanding

**(2) Intent recognition (entity-relation recognition): dependence on reasoning.** Intent recognition aims to determine whether the query is asking for items themselves or for item-related information (e.g., reviews, comparisons, usage guides), and to distinguish which entities are the main targets versus which are modifiers or constraints. This process depends heavily on reasoning at both the methodological and implementation levels. The main challenges include:

- Accurately identifying the purchase purpose and item usage, thereby locating the true target of the need and distinguishing whether the query is describing derived attributes or directly referring to specific items. For example, in “charger/headphones for iPhone 17”, the actual target items are the charger or headphones, while “iPhone 17” only imposes compatibility or model constraints, corresponding to a compositional need over functionality/effect and model.
- Handling abstract needs that do not point to specific items but to categories or domains. For instance, “phones with the best battery life” does not specify a concrete item, but poses a ranking or filtering request over the entire item space. The system must precisely capture the semantic meaning of the derived attribute “battery life” in the phone domain and its operational measurement, and then construct reasonable ranking or filtering rules to support inference and comparison over candidate sets.
- Mitigating ambiguity caused by missing context. In real interactions, users often do not specify all constraints or preferences within a single query. The system must therefore exploit dialogue history, user profiles, and default preferences to

complete and disambiguate implicit context, obtaining a more fine-grained intent representation that supports reliable downstream relevance judgment.

**(3) From single-dimensional to multi-dimensional needs.** In most e-commerce scenarios, user queries simultaneously encode multiple dimensions of needs (e.g., brand + price range + function + target user group). The system must therefore go beyond accurately identifying single-dimensional needs and, from a joint multi-dimensional perspective, fully extract and structure all need points. This provides the basis for subsequent path construction and relevance judgment. It is important to emphasize that the dependence on multi-modal capabilities should not be decided at the query-need level. Query-level tasks focus on entity recognition and intent recognition. The degree of multi-modal reliance should instead be determined by the properties of the identified attributes themselves, and discussed together with item attributes in the subsequent path design and judgment stages.

### 2.2.3 Path Modeling from Query to Item

In the overall framework, relevance judgment is abstracted as a process of constructing and executing paths from a query to an item. The system first maps the user query into structured retrieval and constraint paths, and then performs candidate-item filtering and judgment along these paths. From this perspective, relevance judgment decomposes into two interrelated sub-tasks: (i) constructing correct and complete paths in the semantic and attribute space, which involves systematic modeling of query intent, constraints, and their mappings to item attributes; and (ii) executing stable and reliable item judgment along these established paths to ensure consistent and reproducible assessment. The technical challenges primarily stem from the complexity and uncertainty inherent in these two processes. Below, we use the query “**Summer Mint Mambo Slimming Set**” to illustrate the modeling process.

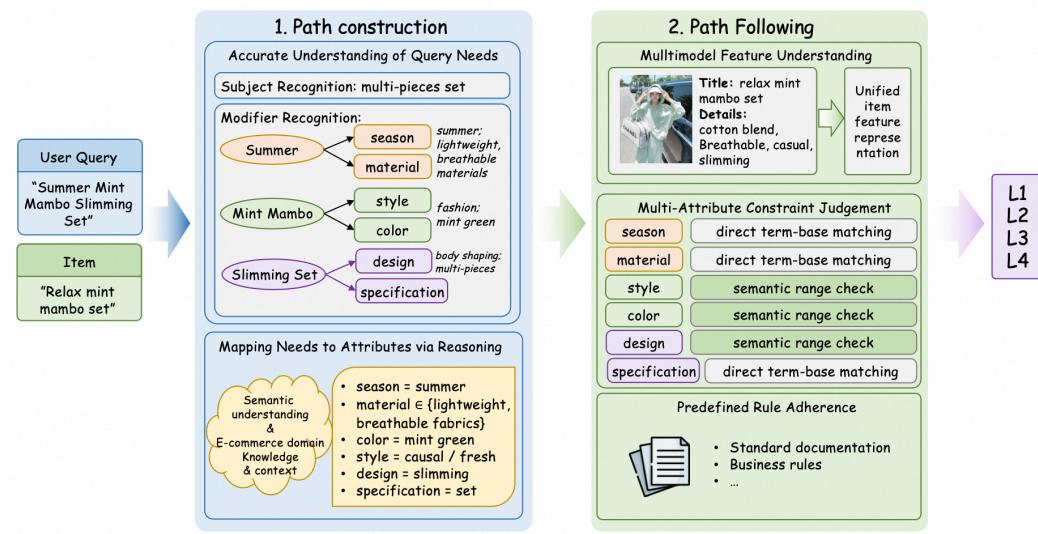


Figure 5: Overview of the Relevance Discrimination Process: (1) Path Construction, (2) Path Following

**1. Path Construction** This phase refers to mapping query requirements to specific item attributes. The key challenge lies in accurately aligning the need points in the query with the specific attribute dimensions of the item. This process involves two main levels:

**(1) Accurate Understanding of Query Needs.** This level ensures the direction and precision of the path.

- **Subject Recognition:** This determines the target type (e.g., goods, content, or reviews). In this example, the system identifies the target as an apparel set.

- **Modifier Recognition:** This parses modifiers as specific path constraints. Each identified need point acts as a constraint, and their intersection converges on the target. In this example: “Summer” constrains *season* and *material*; “Mint Mambo” constrains *style* and *color*; and “Slimming Set” constrains *silhouette* and *specifications*.

**(2) Mapping Needs to Attributes via Reasoning.** While some constraints are explicit, some often lack direct rules, such as constraints on material, style, and color. The model must rely on semantic understanding and reasoning, combined with e-commerce domain knowledge and context, to flexibly align natural language expressions with the structured attribute space.

**2. Path Following** This phase refers to the execution of specific judgment logic by the model at the attribute-item level. Once query needs are mapped to path constraints, the relevance model performs feature extraction and verification along these paths. This process involves three key steps:

- **Multimodal Feature Understanding:** The model must jointly utilize textual and visual information to extract item attributes to cover different types of constraint paths. For instance, for the “Mint Mambo” constraint, the model focuses on extracting visual features (color and style) for matching; whereas for the “Set” constraint, it emphasizes extracting textual features related to specifications.
- **Multi-Attribute Constraint Judgment:** The model executes differentiated verification logic based on attribute types. For intrinsic attributes (e.g., specifications), the model performs direct rule-based or term-based matching. For derived attributes (e.g., “Slimming”), the model checks whether the item’s features fall within the valid semantic scope defined during the path construction phase.
- **Predefined Rule Adherence:** To ensure standardized, unified, and reproducible judgment results, the model strictly follows standard documentation and business rules. By unifying the attribute definition hierarchy and templating common query mapping relationships, the model converts judgment rules into executable configurations, guaranteeing reproducible assessment results across different items and scenarios.

#### 2.2.4 Core Capabilities for Relevance Judgment

Based on the decomposition of item understanding, query understanding, and path modeling, we can synthesize the essential requirements for a robust relevance model. To effectively navigate the vast item corpus and satisfy complex user intents—ranging from direct specification to abstract reasoning—the model must possess a sophisticated, composite set of capabilities. We summarize these core requirements as:

- **Reasoning and Knowledge Integration:** The ability to leverage external knowledge and logical inference to resolve ambiguity in query understanding and accurately map abstract intents during path construction.
- **Multi-modal Understanding and Matching:** The capacity to parse, align, and match attributes across textual and visual modalities, which is critical for handling image-heavy constraints in item understanding and path following.
- **Complex Rule Adherence:** The fidelity to learn and precisely execute the complex, often subtle, judgment rules required to ensure the standardization and reproducibility of the path following process.

Table 1 details how these core capabilities map to the specific components and challenges identified in our analysis.

Table 1: Mapping Core Capabilities to Relevance Analysis Components

Core Capability	Analysis Component	Specific Application Context
Reasoning and Knowledge Integration	Query Understanding	Resolving domain-specific entities (e.g., jargon, metaphors) and inferring user intent beyond surface text.
	Item Understanding	Interpreting semantic meanings of <i>derived attributes</i> (e.g., "usage scenarios," "feelings").
	Path Construction	Mapping abstract natural language needs (e.g., "for summer trips") to structured attribute combinations.
Multi-modal Understanding	Item Understanding	Extracting features for attributes that rely on presentation modality, such as <i>style</i> , <i>color</i> , and <i>material</i> .
	Path Following	Performing "Multimodal Feature Alignment" to verify visual constraints (e.g., matching a "Mint Mambo" visual style).
Complex Rule Adherence	Item Understanding	Handling <i>inherent attributes</i> (e.g., specifications, brands) that require strict exact matching.
	Path Following	Executing "Predefined Rule Adherence" to align model judgments with business SOPs and ensure reproducibility.

### 3 Method

#### 3.1 Overview

**Evolution of Large Model Training Paradigms for Relevance.** From a formulation perspective, the relevance task can be regarded as a classification task. Early works incorporated the task requirements as prompts and the annotated results as responses, performing SFT loss to fine-tune LLMs as follows, which serves as our iterative baseline.

$$\mathcal{L}_{\text{SFT}} = - \sum_{i=1}^N \log P(y_i | x_i; \theta) \quad (1)$$

However, simple SFT was soon proven to suffer from out-of-distribution performance degradation. Researchers discovered that leveraging the model's CoT capabilities—prompting the model to reason before outputting answers—could effectively enhance model robustness and performance on challenging samples. Due to constraints in computational resources and application scenarios, models with relatively modest parameter sizes are typically selected for training, which implies insufficient reasoning capabilities and instruction-following abilities under the prompting-only paradigm. Therefore, the current mainstream approach is to leverage powerful teacher models (such as GPT-4 and DeepSeek-R1(DeepSeek-AI et al., 2025)) to synthesize CoT data, and then distill the reasoning capabilities into relatively smaller models through SFT. Motivated by the remarkable achievements of reinforcement learning in LLM training, some works further incorporate an RL stage following CoT distillation, employing either offline RL methods such as Direct Preference Optimization(DPO)(Rafailov et al., 2024) and KTO(Ethayarajh et al., 2024), or online reinforcement learning methods such as Group Relative Policy Optimization(GRPO)(Shao et al., 2024).

**LORE’s Training Paradigm.** Prior to formal training, we first conducted some necessary preliminary explorations, mainly covering three aspects: base model selection, prompt tuning, and feature infrastructure. These form the foundation of our training and will be elaborated in detail in Section 3.2.

Our complete training paradigm consists of two stages: SFT and RL stage. In the SFT stage(Section 3.3), we construct a progressive CoT synthesis pipeline aligned with the two-stage discrimination framework. The first step performs knowledge injection and reasoning to accomplish path construction, followed by two subsequent steps that execute multi-modal attribute matching and rule-aware discrimination to complete path following. Furthermore, we also discuss issues pertaining to dataset construction, denoising, and training data proportions. During this stage, we primarily focus on the model’s pass@8 metric as shown in equation 2, which serves as an indicator for probing the model’s capability boundaries. When performing eight inference iterations, we fix the model temperature at 1.0 to maintain a balance between accuracy and diversity. The model proceeds to RL only when pass@8 surpasses the baseline, indicating sufficient cold start, as RL amplifies correct answer probabilities but cannot compensate for consistently poor outputs.

$$Pass@8 = 1 - \prod_{i=1}^8 (1 - p_i) \quad (2)$$

In the RL stage(Section 3.4), we design verifiable outcome rewards based on the characteristics of the relevance task, guiding the model to align all capabilities acquired in the previous step with human preferences and prune incorrect reasoning paths. Additionally, we conducted extensive explorations on sampling strategies, entropy optimization, and importance sampling granularity. During this stage, we focus on the model’s pass@1 capability, as RL trades breadth for precision by converting pass@8 performance into first-attempt accuracy. To ensure result stability, we employ greedy decoding when computing the pass@1 metric.

Following the training phase, we develop a comprehensive and challenging evaluation benchmark designed to rigorously assess model capabilities(Section 3.5). Given the powerful capabilities of LLMs and the diversity of e-commerce data, we designed our evaluation benchmark to ensure sample comprehensiveness while incorporating targeted hard sample mining based on the core capabilities identified in Section 2.

### 3.2 Preliminary Exploration

In this section, we conducted a series of necessary preliminary explorations, including three parts: feature construction, model selection, and prompt optimization as shown in Fig 6.

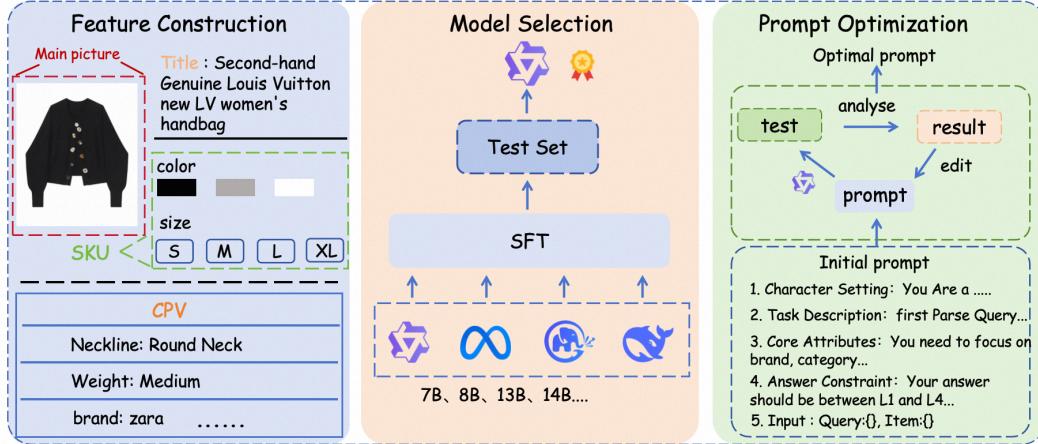


Figure 6: Preliminary exploration prior to training, encompassing: (1) Feature construction, (2) Model selection, and (3) Prompt optimization.

### 3.2.1 Feature Construction

Guided by the theoretical framework established in Section 2, effective relevance modeling necessitates a comprehensive construction of the item’s attribute space. Thus, we select features to endow the model with the necessary perception and reasoning skills spanning both visual and textual modalities.

First, to address the need for visual attributes, such as stylistic details, cuts and patterns, we incorporate the item’s Main Product Image. This visual input is essential for “image-heavy” queries where textual descriptions alone are insufficient. Additionally, to enrich the item-side attribute features, we introduced category-property-value (CPV) triples and Stock-keeping-unit(SKU). Considering that CPV information contains some redundant items that are irrelevant for relevance judgment, we introduce a pipeline combining prior knowledge with LLMs for filtering. Specifically, CPV information is presented in key-value pairs, and there exists key co-occurrence across similar products. For example, both “eye cream” and “face cream” products typically contain the key “brand”. Therefore, we conducted statistical counting based on a large volume of product data to obtain medium-to-high frequency keys. Subsequently, we prompted a powerful LLM Qwen3-235B-Instruct with the relevance task definition, the considered attributes and each key, asking the model to judge whether each attribute is beneficial for the relevance task. To improve judgment accuracy, we performed eight sampling iterations on the model outputs and retained only those attributes where the self-consistency result was “true”, which can be described as follows:

$$S_{CPV} = \left\{ k \mid \sum_{i=1}^8 (\text{Qwen}(k_i) = \text{true}) \geq 4 \right\} \quad (3)$$

However, even after cleaning, CPV data cannot completely avoid noise introduced by item information quality issues. Furthermore, item SKU features exhibit significant redundancy in the feature space due to their inherent attribute characteristics. Therefore, we extract a portion of the data and partition it into training and test sets to conduct feature effectiveness validation experiments. The experiments use product titles as the baseline and progressively introduce other features for incremental analysis. As shown in Table 2, the introduction of both CPV and SKU features improves model performance, indicating that as long as the input information possesses relevance and stability, it can still yield performance gains for the model even in the presence of partial redundancy and noise.

Table 2: Experimental results of item feature enhancement.

Models	pass@1
base>Title)	0.847
base + CPV	0.855
base + CPV + SKU	0.871

Besides, we introduced item main images to provide visual features that cannot be fully covered by text alone. We exclude SKU images because the main image already captures the majority of visual information. SKU images typically represent minor variations (e.g., style, color) that are adequately conveyed through SKU textual features. Including them would increase modeling complexity without meaningful information gain. Finally, we obtained a rich product information repository, which will be used in all subsequent training.

### 3.2.2 Model Selection

To select an optimal base model, we balance two critical factors: the capability to execute the complex reasoning and knowledge integration detailed in Section 2, and the efficiency required for practical deployment.

We selected a series of excellent open-source models with parameters ranging from 7B to 14B. This size range ensures sufficient capability while offering the advantage of single-GPU

training and inference. Subsequently, we selected a portion from the existing annotated data, dividing it into training and validation sets. Using the basic relevance task definition as the prompt, we performed simple fine-tuning as mentioned in Section 3.1 for each model on the training set and validated the performance. Finally, the Qwen2.5-7B model achieved superior performance among all evaluated models while maintaining high inference efficiency. Consequently, we selected it as the base model for our framework.

### 3.2.3 Prompt Optimization

In domain-specific SFT, we typically fix the common task definition and requirements as a template, and fill in the query and item information from each data sample to generate the prompt. To effectively activate the core capabilities of the base model, it is necessary to incorporate key information such as relevance task definitions, judgment rules, and output formats into the prompt. Additionally, to guide the model in effectively following our proposed two-stage discrimination framework, we incorporated structured instructional information into the prompt: first requiring the model to understand the query’s intent and attribute requirements; then extracting relevant attributes from item information based on these requirements and making judgments according to the rules. For reasoning tasks, the more detailed and specific the instructions in the prompt, the easier it is for the model to derive the correct answer. However, this pattern does not necessarily hold in Supervised Fine-Tuning (SFT) scenarios, as the model primarily acquires capabilities by learning from response data rather than solely relying on instructions. To obtain the optimal prompt configuration, we explored three versions of prompt designs. The long version includes relevance task definitions, judgment requirements, and detailed discrimination rules, totaling over 7,000 tokens. The mid version streamlines the long version by removing detailed rules and retaining only the most essential instructions, with a length of approximately 800 tokens. The short version is the most concise, preserving only the basic role definition, such as: “You are an e-commerce relevance assessment expert. Please score the query and item.”

Table 3: Experimental results of SFT across different prompt lengths.

Models	pass@1
short prompt	0.861
mid prompt	0.871
long prompt	0.866

We validated using the training and test sets mentioned in Section 3.2.1, with results shown in Table 3. The performance differences among the three prompt versions after training are minimal (within 1%), indicating that for single-task SFT scenarios, model capability improvement primarily stems from learning the ground truth, with relatively limited impact from the prompt. Specifically, the short prompt achieves the worst results as expected, due to its lack of necessary task information, causing the model to merely fit the training data distribution. Surprisingly, the long prompt, which contains rich rule details, underperforms compared to the streamlined mid-length prompt (mid prompt). We hypothesize that this is because the excessively long prompt causes attention dispersion in the model, increasing discrimination difficulty. The experimental results demonstrate that a concise prompt containing core information yields optimal performance. Therefore, in subsequent fine-tuning experiments, we uniformly adopt the mid-length prompt configuration.

## 3.3 SFT: Comprehensive Reasoning Capability Injection

### 3.3.1 Data construction

This phase represents the model cold start stage, which aims to enhance the model’s fundamental discriminative capability. To achieve this objective, it is necessary to construct a training dataset featuring two core characteristics: **comprehensiveness and low noise**. Regarding the former, we need a scientific sampling strategy to adequately cover diverse e-commerce data distributions, thereby avoiding oversampling or undersampling phenomena

for specific data subsets. Concerning the latter, given that the final data annotation relies on manual completion and errors and omissions during the manual annotation process are difficult to completely avoid, empirical testing demonstrates that the annotation accuracy only reaches 95%. In light of this, we design a data cleaning pipeline to systematically reduce data noise and improve dataset quality.

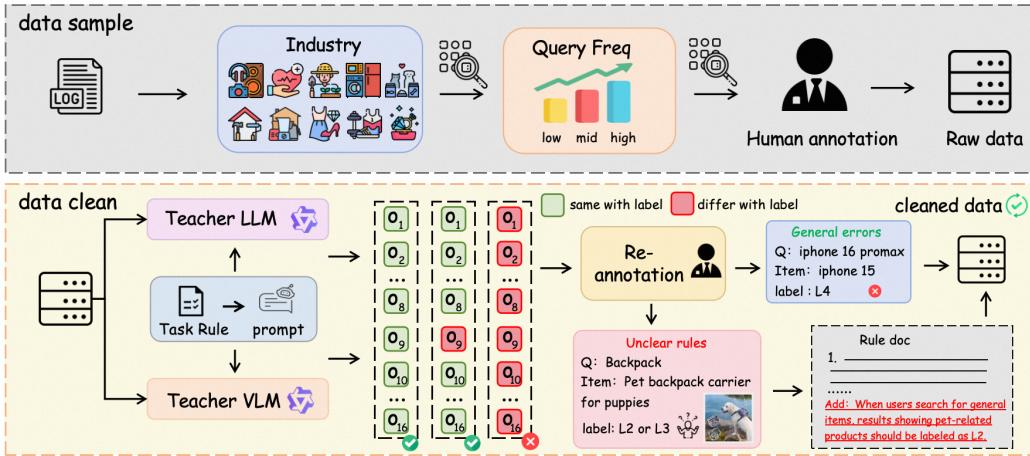


Figure 7: Framework for SFT training data sampling and cleaning.

**Data sampling.** Based on Taobao search logs, we first categorize the data into industries such as consumer electronics, apparel, etc., and conduct stratified sampling according to the proportion of each industry. The purpose of this step is to ensure that the training data cover attributes and features across all industries. Next, we divide the data for each industry into high/medium/low frequency categories based on query frequency and conduct sampling according to their respective proportions, ensuring that the dataset encompasses both common high-frequency queries and long-tail difficult samples. Subsequently, the data is assigned to specialized annotators for labeling.

**Data cleaning.** The errors in manual annotation primarily stem from two aspects: first, annotators' personal oversights lead to the omission of certain detailed information, a phenomenon particularly pronounced when processing long multi-attribute queries; second, the annotation rules themselves exhibit ambiguity, and as concrete expressions of users' subjective preferences, existing rules struggle to exhaustively cover all edge cases. To address these two types of issues, we leverages powerful language models for data filtering: (1) the attribute matching model tends to execute strict matching strategies, demonstrating superior fine-grained feature capture capabilities compared to manual annotation in multi-attribute scenarios; (2) by injecting complete annotation rules into prompts and guiding the model to perform reasoning and judgment following instructions, corner cases beyond the scope of rule coverage are effectively identified and filtered out.

Specifically, First, we prompt a powerful text model, Qwen3-235B-Instruct, with detailed definitions of relevance tasks and rules, instructing the model to make 8 separate judgments on each pair  $\langle Q_i, I_i \rangle$ . Subsequently, we prompt a powerful VLM, Qwen2.5-72B-VL with the same settings and additionally incorporated product main images to obtain eight judgment results for each  $\langle Q_i, I_i \rangle$  pair. We merged the results from both inference rounds, totaling 16 judgments, and filtered out samples where none of the judgments agreed with the manual annotations, as these are highly likely to be incorrectly labeled samples or Extremely difficult samples. This process can be represented as follows:

$$S_{noise} = \left\{ (Q_i, I_i) \mid \sum_{j=1}^{16} \mathbb{1}[J_j(Q_i, I_i) = y_i] = 0 \right\} \quad (4)$$

The rationale for employing two models for filtering is to leverage the powerful long-context comprehension capability of the text model and the multimodal understanding capability

of the VLM, thereby reducing both false positives and false negatives in the sample filtering process. Ultimately, this study submits the aforementioned filtered suspicious samples to a rework process, where annotators perform categorical processing: for pure annotation errors, the annotation results are directly corrected; for annotation discrepancies caused by rule ambiguity, new annotation guidelines are formulated through the induction and summarization of similar cases, thereby achieving iterative optimization of the annotation rule system. Table 4 presents the results after data cleaning. The cleaned samples involved modifications to 6.1% of the labels, and following this quality inspection, the data quality improved from the original 95% to 99%.

Table 4: Comparison of training set quality before and after denoising.

data	correction rate	Accuracy
before cleaning	-	95%
after cleaning	6.1%	99%

### 3.3.2 Multi-dimensional Chain-of-Thought Synthesis

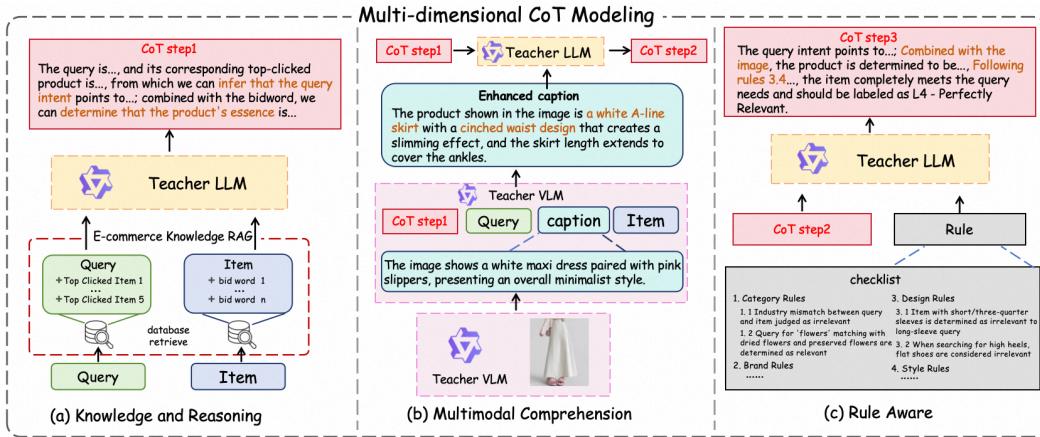


Figure 8: Progressive multi-dimensional CoT synthesis framework.

To enable the model to possess comprehensive and in-depth reasoning capabilities, we propose a progressive CoT synthesis pipeline as shown in Fig 8. This pipeline adopts a stage-wise construction strategy, sequentially encompassing three progressive stages:**Knowledge Injection & Reasoning**, **Multimodal Comprehension**, and **Rule Awareness**. Knowledge Injection & Reasoning completes the Path Construction stage, which parses query intent into attributes comparable with items. Multimodal Comprehension and Rule Awareness then complete the Path Following stage, which evaluates the degree to which items satisfy the query based on item information and discrimination rules.

(1) Knowledge Injection and Reasoning Foundation: Domain knowledge constitutes the cognitive foundation for understanding user queries and item attributes, necessitating injection at the outset. Building upon this knowledge base, the model can achieve deep understanding of query intent, accurately infer users' core requirements, and accordingly extract corresponding attribute features from item information.

(2) Multimodal Information extraction: the visual presentation of items often contains critical features that are difficult to fully express through text (such as style details, material texture). In light of this, this stage further introduces item image information, synthesizing attribute extraction chains of thought that can integrate both textual and visual modalities. Through cross-modal information complementarity and verification, the model can construct more comprehensive and accurate item representations.

(3) Rule-Oriented Discrimination: Following the completion of query intent recognition and item attribute extraction, attribute matching and discrimination still depend on objective rules. This stage synthesizes rule-aware reasoning chains, enabling the model to explicitly comprehend, adhere to, and apply these discrimination rules throughout the reasoning process.

**Step 1: Knowledge and Reasoning.** In Section 2.3, we categorized knowledge into general world knowledge and e-commerce knowledge. For the former, existing LLMs have already accumulated considerable knowledge through large-scale pre-training, enabling them to understand common concepts and entity relationships. However, e-commerce scenarios contain numerous phrases and expressions that are difficult to comprehend based solely on their independent semantic information.

Such issues can be primarily categorized into the following two dimensions: (1) Long-tail Query: These queries explicitly refer to extremely niche specific items, yet existing models lack the corresponding prior knowledge reserves, making it difficult to establish effective semantic mapping relationships. For instance, the query is "strange things are also loved by someone" and the item is a "novel and interesting toys," the query actually refers to the title of a book. Without this prior knowledge, the model is challenging to make correct relevance judgments based purely on literal semantics. Similar cases include brand slang, product nicknames, marketing terminology, and other e-commerce-specific expressions; (2) Semantically Ambiguous Items: Certain items fall outside the model's knowledge boundaries due to their excessively niche nature. For instance, the term "lying gate" cannot be accurately identified and categorized based solely on its textual title information without adequate contextual understanding of the product attributes. These contents require supplementary domain-specific e-commerce knowledge for accurate interpretation.

To address these issues, we introduced a Retrieval-Augmented Generation (RAG) mechanism and constructed a dynamic knowledge database specifically designed for e-commerce scenarios: (1) Query-side Knowledge Enhancement: To inject the model with prior knowledge of items targeted by queries, we introduce the titles of the top five items with the highest historical click-through rates for each query as contextual information. These high-click items can effectively reflect users' actual search intent and item preference characteristics. (2) Item-side Knowledge Enhancement: To inject the model with more comprehensive item information, We incorporate merchant-provided "selling points", which can be regarded as merchants' refined descriptions of core product features and highlights, containing key attributes, applicable scenarios, and differentiated advantages of the products. We retrieved augmented knowledge for each data sample and concatenated it with query  $Q_i$  and Item  $I_i$  to construct the context as follows, where  $K_Q$  and  $K_I$  represent the e-commerce augmented information.

$$\text{context}_i = \text{concat}(Q_i, K_Q, I_i, K_I) \quad (5)$$

Upon completion of knowledge augmentation, the model has acquired the fundamental capability to perform deep-level reasoning on query intent and attributes. This study employs the Qwen3-235B-Instruct model to generate reasoning paths. Through carefully designed prompt templates, the model is guided to execute multi-level reasoning analysis: the model first conducts semantic understanding of the query by integrating its inherent knowledge with e-commerce domain knowledge, inferring users' true intent and extracting specific attribute features; subsequently, it performs systematic analysis of item information, deconstructing the item's concrete attributes and establishing comparative mappings with the query. This process generates reasoning chains  $\text{CoT}_{\text{step}1}$  that comprehensively understand both queries and items as follows:

$$\text{CoT}_{\text{step}1} = \arg \max_y P_\theta(y \mid \text{concat}(\text{prompt}_{\text{LLM}}, \text{context}_i)) \quad (6)$$

**Step 2: Multimodal Comprehension.** The  $\text{CoT}_{\text{step}1}$  generated above only encompasses the reasoning process for the text modality and lacks integration of image modality. Based on the following two considerations, we did not directly employ VLM for multimodal modeling: (1) Limited reasoning capability: Existing VLMs generally exhibit weaker reasoning capabilities compared to LLMs of equivalent parameter scale, a phenomenon that has been validated

in multiple benchmark tests and our experiments. (2) Modality dependence bias: Direct fine-tuning of VLMs tends to cause the model to exhibit a “text shortcut” phenomenon, i.e., over-reliance on textual information while neglecting image features. The underlying cause lies in the inherent information density disparity between text and image modalities.

Therefore, we designed a caption-mediated two-stage modeling framework: in the first stage, we extract image semantics through VLM and generate textual descriptions; in the second stage, these descriptions are incorporated into the prompt as additional context for fine-tuning. However, naive caption generation methods suffer from inherent flaws: due to the complex information in images and lack of task guidance, VLMs struggle to a priori locate key information relevant to reasoning, leading to the omission of important visual cues, which cannot be fully resolved through simple prompt engineering. Therefore, we designed a multimodal CoT generation scheme guided by relevance judgment cues.

Firstly, We prompt a Qwen2.5VL-72B model to generate a basic caption  $C_1$  for the image as follows:

$$C_{naive} = \arg \max_y P_\theta(y | prompt_{VL}, I_i) \quad (7)$$

Secondly, We integrate the original input  $Caption_{naive}$ , the  $CoT_{step1}$  obtained from the previous section, and other contextual information into a structured prompt, and input it to Qwen2.5-VL-72B to regenerate the caption. This design enables the model to extract task-relevant visual information from the image in a targeted manner under the guidance of explicit reasoning key points, thereby generating more precise and task-oriented descriptions.

$$C_{enhanced} = \arg \max_y P_\theta(y | Concat(prompt_{VL}, Context_i, CoT_{step1}, C_{naive})) \quad (8)$$

Finally, The  $C_{enhanced}$ , along with  $CoT_{step1}$  and contextual information, are injected into the prompt for Qwen2.5-235B-Instruct to produce the complete  $CoT_{step2}$ , which encompassing the complete relevance discrimination process.

$$CoT_{step2} = \arg \max_y P_\theta(y | Concat(prompt_{LLM}, Context_i, CoT_{step1}, C_{enhanced})) \quad (9)$$

**Step3: Rule-Aware.** The  $CoT_{step2}$  obtained in the previous section contains the understanding of both query and Item, essentially completing the step of “query reaching the product.” However, as described in Section 2.3, the degree to which a product satisfies a query is determined by objective and concrete judgment rules, which requires the model to possess rule-aware discrimination capability. Directly writing the complete rules into the prompt would result in excessively long context, increasing the difficulty of instruction-following for the model. Therefore, we integrated the rules into the CoT, enabling the model to learn this reasoning approach and thereby acquire an understanding of the rules. Specifically, we partition the rule system by industry to obtain industry-specific rule sets  $R$ . For each training sample, we construct a prompt comprising: (1) the rule set  $R$ , (2) the  $Context_i$ , (3) the ground-truth  $L_i$ , and (4) the previously generated  $CoT_{step2}$ . This prompt guides the Qwen3-235B-Instruct model to reverse-engineer a rule-based  $CoT_{step2}$  for relevance judgment by integrating the complete rule framework, human annotations, and deep semantic comprehension of both query and item contexts.

$$CoT_{step3} = \arg \max_y P_\theta(y | Concat(prompt_{LLM}, context_i, CoT_{step2}, L_i, R)) \quad (10)$$

### 3.3.3 Distillation by SFT

To distill the multi-dimensional reasoning capabilities into a more compact model, we perform SFT on the base model using the synthesized  $CoT_{step3}$  as training data, as formulated in Equation 1. To facilitate result extraction and subsequent RLVR optimization, we organize the response data into the following format with separated reasoning process and results.

$$response = <\text{think}> reasoning\ process </\text{think}><\text{answer}> (L1|L2|L3|L4) </\text{answer}> \quad (11)$$

Besides, a critical question remains to be addressed: as training progresses, model performance gradually approaches saturation, and further training risks overfitting. Therefore, determining the optimal SFT data scale is crucial, requiring the model to sufficiently learn reasoning patterns and acquire adequate e-commerce domain knowledge while avoiding generalization performance degradation caused by overfitting.

To address the aforementioned issue, we designed a data scale sensitivity analysis experiment: the training data was uniformly sampled with an initial proportion set at 10%, followed by incremental increases in SFT data proportion at 10% intervals (i.e., 10%, 20%, 30%, ...). Throughout this process, we focused on the trends of the following two key metrics: (1) Format Accuracy: this metric reflects the model's mastery of reasoning patterns; (2) Pass@8 metric: this metric characterizes the theoretical upper bound of model performance.

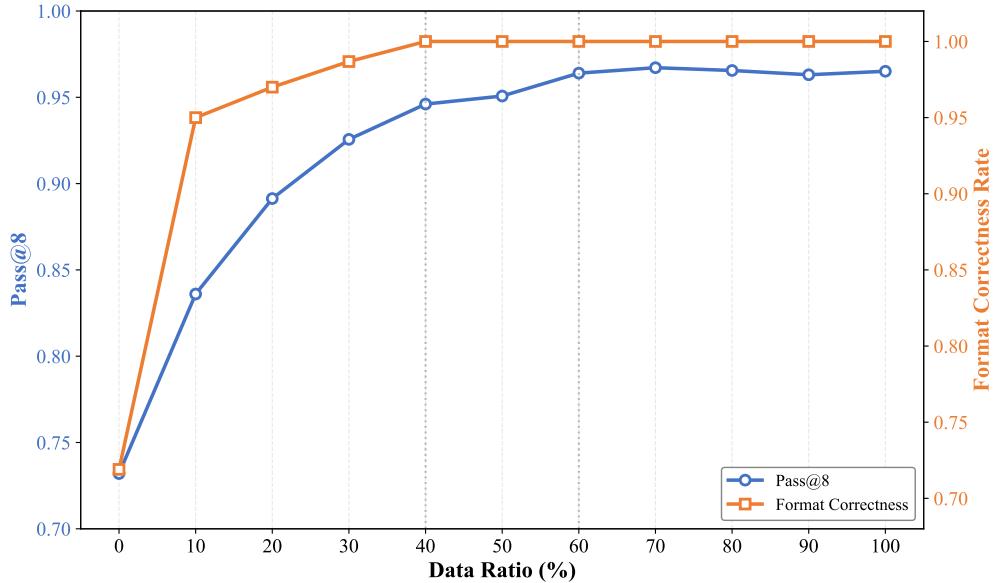


Figure 9: Evolution of pass@8 and format correctness rate with varying data proportions in SFT process.

Fig 9 illustrates the trends in model metrics as the data proportion increases. The results demonstrate that the model can rapidly acquire the correct reasoning format in the early training stage, achieving a format accuracy exceeding 98% with only 20% of the training data. The Pass@8 metric exhibits rapid growth in the early training phase but subsequently displays a phenomenon of diminishing marginal returns. When approximately 60% of the training data is utilized, the growth rate of this metric plateaus, showing no significant improvement. Based on these experimental observations, this study selects the 40% data proportion as the optimal training scale, with which the cold-start model is trained.

Table 5: Comparison of pass@8 between cold-start model with synthetic CoT distillation and vanilla SFT.

Model	pass@8
vanilla SFT	0.937
cold-start	0.964

Table 5 presents a comparison of the Pass@8 results between the cold-start model and the base model. The cold start model significantly outperforms the base model, indicating that multi-dimensional CoT modeling effectively elevates the model's performance ceiling, which provides ample room for subsequent RL optimization.

### 3.4 RL: Relevance-Oriented Human Preference Alignment

In this section, we introduce reinforcement learning to guide the model to align with human preferences. By pruning erroneous reasoning paths, we effectively transform the reasoning capability demonstrated by the model across multiple samples (pass@8) into stable single performance (pass@1).

#### 3.4.1 Data construction

Given that the cold-start model has already mastered fundamental reasoning capabilities, subsequent reinforcement learning optimization urgently requires more challenging samples to achieve significant performance gains. Therefore, the core objective of data construction in the reinforcement learning phase lies in hard sample mining. We use the cold-start model to perform 8-round sampling inference on the whole training data. As shown in Fig 10 (a), the distribution of correct answer counts per sample exhibits a J-shaped distribution: there exists a large number of "easy samples" that the model has fully mastered (all 8 attempts correct). These samples have an advantage of 0, failing to provide effective gradient signals for RL training. To improve the data efficiency of RL training, we designed a difficulty-based sample filtering strategy as follows, where  $k$  denotes the number of correct answers and  $\alpha$  denotes the downsampling rate.

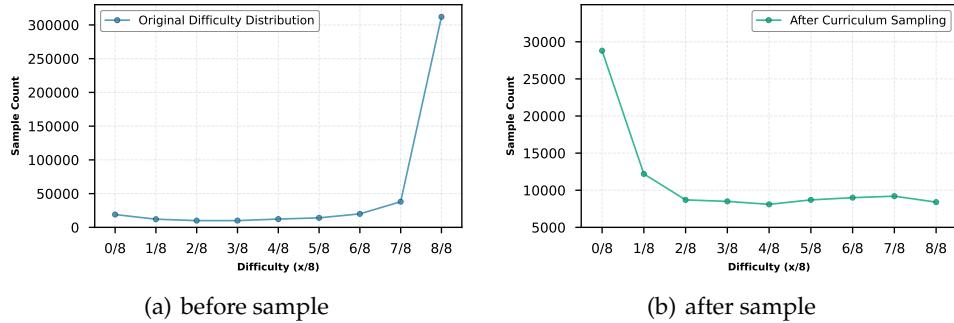


Figure 10: Comparison of sample difficulty distribution before and after sampling.

$$\text{Sample Weight} = \begin{cases} 1.0, & \text{if } k < 5 \\ \alpha \in (0, 1), & \text{if } 5 \leq k < 8 \\ 0, & \text{if } k = 8 \end{cases} \quad (12)$$

This strategy fully retains confusing samples (<5 correct), ensuring sufficient learning signals; completely removes saturated samples (8 correct), eliminating ineffective samples; proportionally downsamples relatively confident samples (5-7 correct), balancing the data distribution, ultimately forming an inverted J-shaped distribution as shown in Fig 10(b).

#### 3.4.2 Basic RL Framework

**KL-free GRPO Algorithm.** Fig 11 illustrates our basic RL Framework. We adopt the GRPO algorithm to optimize the objective function as shown in Equation 13, which maximizes the advantage-weighted log probability expectation. The importance sampling ratio and advantage function are defined in Equation 14. we removed the KL divergence regularization term in our actual implementation. This decision is based on the following considerations: after sufficient SFT warm-start, the model has already solidified its reasoning paradigm and structured output format. At this point, KL constraints would instead excessively limit the policy exploration space, hindering the model from discovering better reasoning paths. Therefore, we chose to allow the model to perform freer policy optimization based on its existing capabilities.

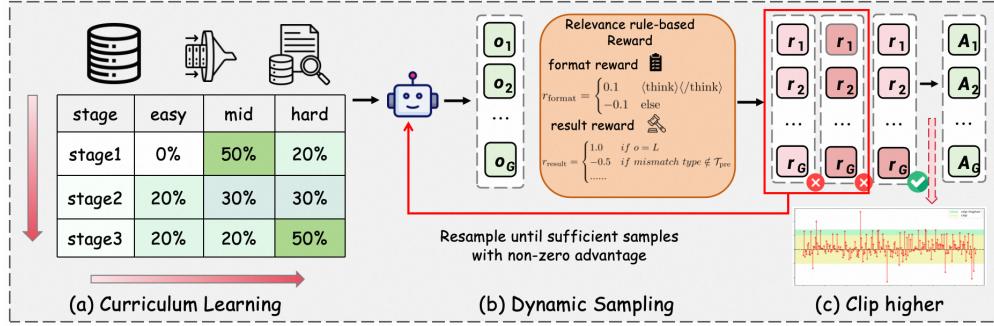


Figure 11: Overview of RLVR: basic framework and optimization strategies.

$$\mathcal{J}_{\text{GRPO}}(\theta) = \mathbb{E}_{x \sim \mathcal{D}, \{y_i\}_{i=1}^G \sim \pi_{\theta_{\text{old}}}(\cdot|x)} \left[ \frac{1}{G} \sum_{i=1}^G \frac{1}{|y_i|} \sum_{t=1}^{|y_i|} \min \left( w_{i,t}(\theta) \hat{A}_{i,t}, \text{clip}(w_{i,t}(\theta), 1-\varepsilon, 1+\varepsilon) \hat{A}_{i,t} \right) \right] \quad (13)$$

$$w_{i,t} = \frac{\pi_\theta(y_{i,t}|x, y_{i,<t})}{\pi_{\theta_{\text{old}}}(y_{i,t}|x, y_{i,<t})}, \quad \hat{A}_{i,t} = \frac{r_i - \text{mean}(\{r_j\}_{j=1}^G)}{\text{std}(\{r_j\}_{j=1}^G)} \quad (14)$$

**Verifiable Outcome Reward Based on Relevance Labels.** We designed the reward system as follows by incorporating task-specific characteristics, which consists of two components: format reward and outcome reward. Where  $o$  represents the model output,  $L$  represents the ground truth given in L1-L4 levels, BinaryClass denotes the “relevant/irrelevant” outcome corresponding to the 4 levels, and  $\mathcal{T}_{\text{pre}}$  represents the 18 types of attribute deficiency mismatches mentioned in Section 2.

$$r = r_{\text{format}} + r_{\text{result}} \quad (15)$$

$$r_{\text{format}} = \begin{cases} 0.1 & o \text{ follows } <\text{think}> </\text{think}> <\text{answer}></\text{answer}> \\ -0.1 & \text{else} \end{cases} \quad (16)$$

$$r_{\text{result}} = \begin{cases} 1.0 & \text{if } o = L \\ -0.5 & \text{if } o = L \text{ and mismatch type } \notin \mathcal{T}_{\text{pre}} \\ 0.3 & \text{if } o \neq L \text{ and BinaryClass}(o) = \text{BinaryClass}(L) \\ -1.0 & \text{if } o \neq L \text{ and BinaryClass}(o) \neq \text{BinaryClass}(L) \\ -1.0 & \text{if } o \text{ is unparsable} \end{cases} \quad (17)$$

Through the reward mechanism design, we achieve three training objectives: (1) Format standardization: using special tokens to explicitly separate the reasoning process from the final answer, facilitating subsequent parsing and application; (2) Output space constraint: strictly limiting mismatch types (such as “price mismatch,” “functionality mismatch,” etc.) to within a predefined set, preventing the model from generating uncontrollable arbitrary outputs; (3) Progressive reward: when the model correctly identifies relevance but errs on fine-grained levels, still providing moderate positive rewards to mitigate the sparse reward problem in early training stages, accelerating convergence and stabilizing training.

### 3.4.3 Training Strategy Optimization

**Curriculum Learning.**(Bengio et al., 2009) We introduce a curriculum learning strategy in RL training, guiding the model to progressively improve its capabilities from simple to complex by gradually adjusting the sample difficulty distribution. Based on the 8-round inference statistics in Section 3.4.1, we categorize samples into three tiers according to the number of correct answers  $k$  as follows:

$$\text{Difficulty}(x) = \begin{cases} \text{Easy} & \text{if } k(x) \in \{6, 7\} \\ \text{Medium} & \text{if } k(x) \in \{3, 4, 5\} \\ \text{Hard} & \text{if } k(x) \in \{0, 1, 2\} \end{cases} \quad (18)$$

Subsequently, we designed a three-stage curriculum learning scheme that guides model capability improvement by progressively increasing training data difficulty. The sample allocation strategy for each stage is detailed in Table 6.

Table 6: Progressive curriculum learning strategy with gradually increasing sample difficulty.

stage	easy	mid	hard
stage 1	0%	50%	20%
stage 2	20%	30%	30%
stage 3	20%	20%	50%

The core philosophy behind this strategy encompasses three dimensions: (1) Rapid Bootstrap Principle: Stage 1 focuses primarily on medium-difficulty samples (rather than the easiest samples), enabling the model to quickly obtain effective positive feedback while maintaining a certain level of challenge, avoiding exploration difficulties caused by sparse rewards in early training. (2) Progressive Challenge Principle: Stages 2 and 3 gradually increase the proportion of difficult samples, guiding the model to transition from “solving common problems” to “tackling edge cases,” achieving continuous expansion of capability boundaries. (3) Knowledge Retention Principle: The latter two stages continuously incorporate easy samples as “memory anchors” to prevent the model from forgetting old skills when learning new knowledge, while these high-confidence samples also help stabilize gradient variance during the training process. We conducted a systematic exploration of sample allocation for each stage through grid search, ultimately determining the proportion configuration shown in Table 6 as the optimal solution.

As illustrated in Fig 12, the experimental group utilizing the curriculum learning strategy demonstrates faster convergence speed and more stable optimization trajectory in terms of both reward values and model performance improvement.

**Dynamic Sampling.**(Yu et al., 2025) As RL training progresses, a sample effectiveness decay problem emerges: after the model policy converges, an increasing number of samples exhibit consistent outcomes across multiple sampling attempts (either all correct or all incorrect), resulting in an advantage function  $A_i = 0$ . Although these saturated samples participate in training, they fail to generate effective gradients, leading to computational resource waste and slowing down convergence speed. To address this issue, we introduce a dynamic sampling strategy: during the Rollout phase, we calculate sample advantage values in real-time and discard zero-advantage samples. A policy update round is only triggered when the accumulated number of non-zero advantage samples reaches the preset batch size.

**Entropy Collapse Optimization.** During RL training, as the policy gradually converges, the entropy of the model’s output distribution rapidly decreases, causing generation results to become deterministic. This premature convergence phenomenon limits the model’s exploration capability, making it difficult to discover better reasoning paths and ultimately constraining the improvement of the performance upper bound. To address this issue, we explored multiple strategies to slow down the entropy decline and maintain the model’s exploration capability.

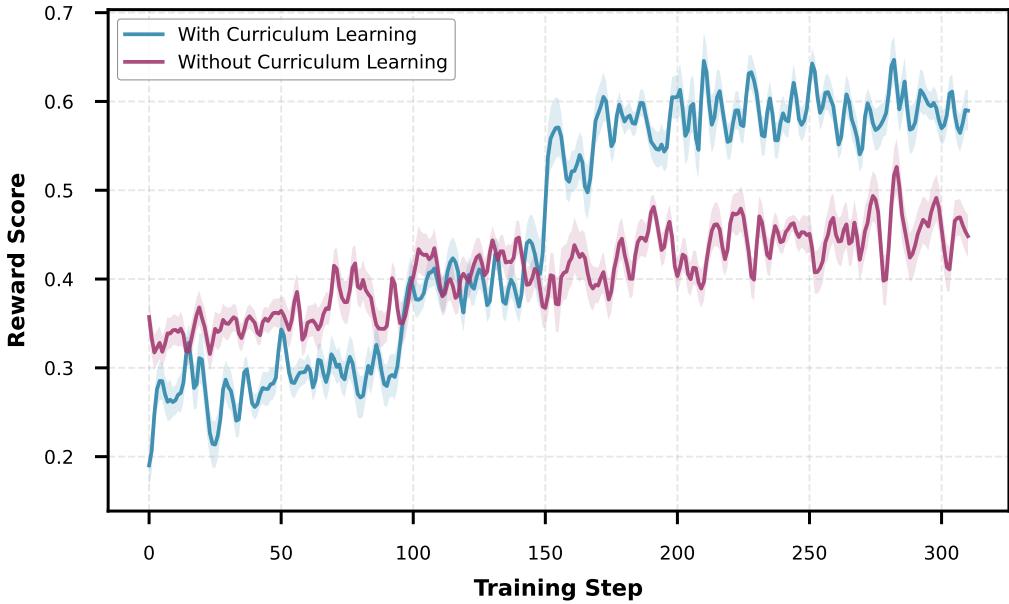


Figure 12: Comparison of reward curves between curriculum learning and non-curriculum learning.

(1) clip-higher(Yu et al., 2025). We increase the clipping upper bound of the importance sampling ratio from the standard value to a larger value as shown in equation 19, allowing tokens with lower probability under the current policy relative to the old policy to undergo greater probability increases, thereby enhancing exploration of low-frequency but potentially valuable reasoning paths. In our experiments, we adopt the officially recommended values:  $\varepsilon = 0.2$  and  $\varepsilon_{high} = 0.28$ .

$$\mathcal{J}_{\text{GRPO}}^1(\theta) = \mathbb{E}_{x \sim \mathcal{D}, \{y_i\}_{i=1}^G \sim \pi_{\theta_{\text{old}}}(\cdot|x)} \left[ \frac{1}{G} \sum_{i=1}^G \frac{1}{|y_i|} \sum_{t=1}^{|y_i|} \min \left( w_{i,t}(\theta) \hat{A}_{i,t}, \text{clip}(w_{i,t}(\theta), 1 - \varepsilon, 1 + \varepsilon_{high}) \hat{A}_{i,t} \right) \right] \quad (19)$$

(2) On-policy. Traditional off-policy methods perform multi-epoch training on the same batch of experience data, using importance sampling constraints to prevent excessive policy deviation. However, this conservative update mechanism limits the model’s exploration capability. To address this, we adopt a strictly on-policy strategy: each batch of sampled data ( $\text{batch\_sizegroup\_size\_samples}$ ) is discarded after being used for only one gradient update, and the next update uses freshly sampled data from the new policy.

(3) Explicit Entropy Regularization. From the perspective of entropy preservation, we introduce an explicit entropy regularization term into the original GRPO loss function, where  $\alpha$  is a balancing coefficient controlling the strength of entropy regularization. This term encourages the model to maintain randomness in its output distribution, directly counteracting entropy decay. Under this setup, we maintain the off-policy training mode (multi-epoch data reuse) and preserve exploration capability through an auxiliary loss term rather than through sampling strategy.

$$\begin{aligned} \mathcal{J}_{\text{GRPO}}^2(\theta) = & \mathbb{E}_{x \sim \mathcal{D}, \{y_i\}_{i=1}^G \sim \pi_{\theta_{\text{old}}}(\cdot|x)} \left[ \frac{1}{G} \sum_{i=1}^G \frac{1}{|y_i|} \sum_{t=1}^{|y_i|} \min \left( w_{i,t}(\theta) \hat{A}_{i,t}, \text{clip}(w_{i,t}(\theta), 1 - \varepsilon, 1 + \varepsilon) \hat{A}_{i,t} \right) \right] \\ & - \alpha \cdot \mathbb{E}_{x \sim \mathcal{D}, \{o_i\}_{i=1}^G \sim \pi_{\theta}(\cdot|x)} \left[ -\frac{1}{G} \sum_{i=1}^G \log \pi_{\theta}(o_i|x) \right] \end{aligned} \quad (20)$$

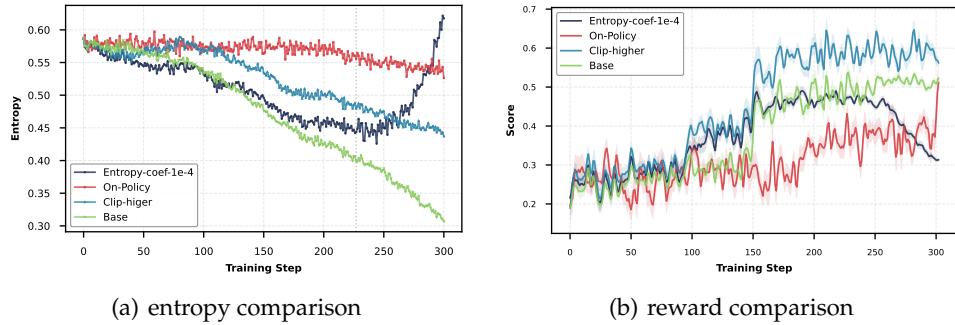


Figure 13: Experimental comparison of three entropy collapse mitigation strategies: (1) clip-higher, (2) on-policy, and (3) off-policy with entropy loss.

Fig 13 presents a comparison of several methods. The Clip-higher strategy exhibits optimal performance by effectively slowing the decline rate of policy entropy while maintaining its decreasing trend, achieving a favorable balance between exploration and exploitation, and ensuring training stability alongside significant performance improvements. The On-policy strategy stabilizes policy entropy, almost completely suppressing its decline. Although it maintains strong exploration capability, it simultaneously impedes effective policy convergence, resulting in limited performance gains. The Off-policy + Entropy Loss strategy suffers from training instability issues. While this method maintains a gradual entropy decline in early training, as training progresses and policy entropy drops below a certain threshold, the magnitude of entropy regularization loss gradually increases and surpasses the GPO main loss to become the dominant term, triggering abnormal policy entropy increases that ultimately lead to training collapse. Furthermore, this method requires extensive hyperparameter tuning experiments to configure the entropy loss weighting coefficient, increasing application costs. In summary, the Clip-higher strategy achieves an optimal balance between exploration capability and convergence efficiency by moderately controlling the decay rate of policy entropy, making it the best choice for the scenario in this study.

**Importance Sampling Granularity Exploration.** The standard GRPO algorithm computes importance sampling ratios at the token level, i.e., independently calculating for each position  $t$  as shown in equation 14. Inspired by the “sentence-level reward” approach in GSPO(Zheng et al., 2025) and GMPO(Zhao et al., 2025b), we explored sentence-level importance sampling, which computes a unified importance weight for the entire output sequence based on sequence likelihood as shown in equation 21. This weight is shared by all tokens in the sequence, ensuring that the entire reasoning chain is consistently reinforced or suppressed as a whole.

$$w_i^{seq}(\theta) = \left( \frac{\pi_\theta(y_i|x)}{\pi_{\theta_{old}}(y_i|x)} \right)^{|y_i|} = \exp \left( \frac{1}{|y_i|} \sum_{t=1}^{|y_i|} \log \frac{\pi_\theta(y_{i,t}|x, y_{i,<t})}{\pi_{\theta_{old}}(y_{i,t}|x, y_{i,<t})} \right) \quad (21)$$

Fig 14 presents the experimental results for different importance sampling granularities. Sentence-level importance sampling exhibits a more stable reward increase curve, but correspondingly, its policy entropy declines more rapidly. For tasks such as relevance judgment where reasoning patterns are relatively fixed, sentence-granularity probability adjustments more readily lead to premature solidification of model strategies, thereby constraining exploration capabilities. Consequently, its later-stage performance is inferior to that of token-level importance sampling.

### 3.5 Evaluation: Comprehensive Relevance Benchmark

Following our detailed deconstruction of relevance judgment difficulty in Section 2, we find that existing e-commerce benchmarks, such as Shopping Queries Reddy et al. (2022), fail to provide sufficient complexity for evaluation. Specifically, they lack the discriminative power to evaluate models on the more difficult judgment cases identified in our analysis.

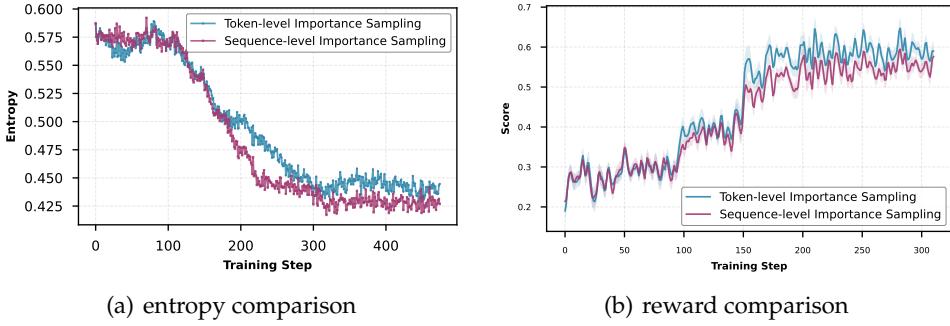


Figure 14: Experimental comparison between token-level and sequence-level importance sampling.

Consequently, they do not adequately challenge models in the critical competencies required for nuanced relevance judgment.

To address this gap, we developed the **Rule-Aware** benchmark with **I**mage for **R**elevance **A**ssessment (**RAIR**). Our objective is to provide a comprehensive, realistic, and challenging open-source benchmark for evaluating the relevance models proposed in this paper, and more broadly, for relevance tasks in the era of large models.

### 3.5.1 Design Principles

The design of RAIR must not only comprehensively evaluate a model’s foundational judgment capabilities in realistic e-commerce scenarios, but must also specifically focus on the three core capability requirements identified in Section 2:

- **Knowledge & Reasoning Capability:** Relevance assessment often requires reasoning that combines world knowledge with inference, surpassing basic matching. A benchmark must test this ability. For instance, a model must access its knowledge base to recognize that “Capybara” is synonymous with “shui tun” to make an accurate judgment.
- **Multi-modal Comprehension Capability:** In real-world scenarios, visual modalities provide complementary, discriminative features that transcend textual representations. Item images are critical when textual features alone are insufficient. Therefore, evaluating VLM-based relevance modeling is essential for a forward-looking benchmark.
- **Rule Adherence Capability:** Relevance assessment is anchored in a sophisticated rule system crafted by domain experts. These rules transform subjective user preferences into objective, quantifiable protocols, acting as complementary specifications to common knowledge. For example, a model must adhere to the rule, “Without explicit user intent, a second-hand product is considered irrelevant,” even if it otherwise matches the query.

### 3.5.2 Benchmark Construction

The construction of the RAIR benchmark was a multi-stage process based on data derived from Taobao user search logs, all of which underwent professional relevance annotation with quality assurance. The process was meticulously designed to create three distinct, complementary subsets, each targeting specific model capabilities.

**General subset** This subset aims to comprehensively assess foundational reasoning, knowledge, and attribute extraction capabilities using common e-commerce cases. A primary challenge was to mitigate the inherent biases of platform-specific traffic distributions,

such as the dominance of fashion and cosmetics categories. Instead of naive uniform sampling, we implemented a two-step stratified sampling strategy. We first stratified queries by industry sector and then applied proportional sampling, followed by downsampling of dominant industries. This resulted in a balanced subset of 46,775 entries distributed across 14 industries, ensuring no single sector constitutes more than 15% of the dataset.

**Long-Tail Hard subset** This subset was designed to provide challenging data to differentiate the capabilities of advanced LLMs. We focused on mining hard cases, which we categorize into explicit demands (**Multi-Attribute**, **MR**) and implicit demands. The implicit demands include four distinct types: **Negation** (**NE**), **Alternatives** (**AL**), **Knowledge-dependent** (**KD**), and **Reasoning-dependent** (**RD**). The mining process was tailored for these types. NE and AL queries were filtered using predefined keywords and regular expressions. KD and RD queries, which often appear as long-tail queries, were mined by first undersampling low-frequency logs and then using a powerful LLM (Qwen3-235B) with a self-consistency filter (requiring  $\geq 4$  identical results across 8 inferences). MR queries were identified using an NER model on length-filtered queries to find those with more than 5 attributes. To ensure the final set was genuinely difficult, all candidates were filtered through a baseline relevance model; we retained only those samples where the model’s prediction was correct five or fewer times across eight inferences, indicating high model uncertainty.

**Visual Salience subset** This subset isolates cases where the main product image provides crucial, fine-grained visual information (e.g., color, style) that is indispensable for a correct judgment. We devised a multi-stage pipeline, starting with a keyword-based retrieval using a comprehensive visual taxonomy. To ensure visual necessity and mitigate noise from false recalls, we applied two critical filters: first, a predefined blacklist, and second, retaining only query-ad pairs where the triggering visual keyword “\*did not\*” appear in the product’s textual description. An LLM was then used to verify that the remaining keywords genuinely referred to visual properties. Finally, to identify inherently difficult samples, we trained a naive multimodal relevance model and retained candidates that exhibited high prediction uncertainty (a consistency of less than four in a majority vote across eight predictions).

**Rule Checklist Generation** To bridge the gap between academic evaluation and real-world industrial scenarios, we augmented each sample with a checklist of the specific rules governing its judgment. This annotation was generated using an LLM in a “reverse-engineering” process. To manage the prompt’s context length and improve accuracy, we stratified samples by relevance label ( $y$ ) and industry ( $c$ ) and provided the LLM with only the relevant subset of rules ( $R'_{y,c}$ ). To ensure high fidelity, we performed  $k$  independent inferences for each sample and applied a robustness filter: a rule  $r$  was only added to the final checklist  $R_{(Q,I)}$  if it was identified in at least two of the  $k$  inferences. This checklist is intended strictly for evaluation.

### 3.5.3 Data Statistics

The RAIR benchmark encompasses a total of 63,601 samples, drawn from 14 real-world e-commerce industries. It is composed of the three distinct subsets established during our construction process: the **General subset** (46,775 samples), the **Long-Tail Hard subset** (10,931 samples), and the **Visual Salience subset** (5,895 samples). A detailed breakdown of the five challenging query intents within the Long-Tail Hard subset is presented in Table 7.

For each entry in the dataset, we provide the query, item title, item details, SKU information, and an anonymized item image. Each entry is accompanied by its manual ground truth annotation according to our four-level relevance scale (L1-L4). The comprehensive distribution of these labels across the dataset is presented in Table 8. Additionally, to facilitate subsequent model development and detailed error attribution, each data instance is augmented with the corresponding rule identifiers (our *Rule Checklist*) that serve as the basis for its relevance judgment.

Table 7: Distribution of challenging query intentions within the long-tail hard subset

Query Type	Query Intent	Num	Frequency
Explicit demand	Multi-attribute	5071	46.4%
	Negation	1073	9.8%
	Alternatives	213	1.9%
Implicit demand	Reasoning dependent	2436	22.3%
	Knowledge dependent	2138	20.0%

Table 8: Distribution of ground truth labels in RAIR

Relevance	Ground Truth	Num	Frequency
Irrelevant	L1	2985	4.7%
	L2	13443	21.1%
Relevant	L3	3034	4.7%
	L4	44139	69.4%

## 4 Experiment

In this section, we conduct a systematic validation and analysis of the proposed methods on the RAIR benchmark. Our experiments are divided into two parts: first, through quantitative metrics on benchmarks, we validate the following two core questions: (1) the magnitude of performance improvement brought to the model by fine tuning; (2) the performance advantages demonstrated by the proposed LORE model across different data distribution subsets, including general samples, hard samples, and visually salient samples. Second, we employ case studies to illustrate the new capabilities that our methods confer upon the model and the types of problems they enable it to solve.

### 4.1 Settings

#### 4.1.1 Metrics

To ensure the stability and reproducibility of evaluation results, all trained models employ a greedy decoding strategy for single-pass inference, without introducing sampling randomness. We employed a range of metrics to evaluate the model’s performance. The dataset provides annotations from L1 to L4, thus we first introduced the four-class accuracy metric (acc@4) as follows:

$$\text{acc}@4 = \frac{1}{N} \sum_{i=1}^N \mathbb{I}(\hat{y}_i = y_i) \quad (22)$$

Given the nature of the relevance task, where L1 and L2 can be considered as irrelevant and L3 and L4 as relevant, we introduced the binary classification accuracy metric (acc@2) as follows:

$$\text{acc}@2 = \frac{1}{N} \sum_{i=1}^N \mathbb{I}(\hat{y}_i, y_i \in (L1, L2) | \hat{y}_i, y_i \in (L3, L4)) \quad (23)$$

Additionally, to mitigate the impact of the imbalance in data label distribution, we introduce the macro F1 score as follows, which is calculated as the average of F1 scores across all classes.

$$F1\text{-score}_i = 2 \frac{\text{Recall}_i \times \text{Precision}_i}{\text{Recall}_i + \text{Precision}_i} \quad (24)$$

$$macro - F1 = \frac{1}{N} \sum_{i=1}^N F1 - score_i \quad (25)$$

Table 9: Main results on the general subset and long-tail hard subset. The best score in each column is in **bold**, and the second-best is underlined.

Model	General subset			Longtail Hard subset		
	acc@2	acc@4	macro-F1	acc@2	acc@4	macro-F1
<i>prompting-based models</i>						
Qwen2.5-7B(base)(Yang et al., 2025)	0.775	0.689	0.391	0.531	0.382	0.312
Qwen3-30B-Instruct(Yang et al., 2025)	0.763	0.683	0.391	0.587	0.431	0.333
Qwen3-235B-Instruct(Yang et al., 2025)	0.830	0.676	0.417	0.609	0.381	0.359
Llama3.1-8B-Instruct(Grattafiori et al., 2024)	0.788	0.416	0.224	0.525	0.248	0.200
Llama3.1-70B-Instruct(Grattafiori et al., 2024)	0.774	0.668	0.369	0.547	0.378	0.295
Qwen3-4B-Thinking(Yang et al., 2025)	0.805	0.720	0.453	0.584	0.419	0.357
Qwen3-30B-Thinking(Yang et al., 2025)	0.784	0.718	0.457	0.582	0.448	0.362
Qwen3-235B-Thinking(Yang et al., 2025)	0.779	0.702	0.470	0.585	0.451	0.367
Gemini 2.5 Pro(Comanici et al., 2025)	0.795	0.701	0.483	0.627	0.481	0.392
GPT-5	0.845	0.714	0.433	<u>0.681</u>	0.435	0.407
vanilla SFT	<u>0.929</u>	<u>0.891</u>	<u>0.722</u>	0.671	<u>0.542</u>	<u>0.413</u>
LORE	<b>0.933</b>	<b>0.897</b>	<b>0.724</b>	<b>0.715</b>	<b>0.582</b>	<b>0.460</b>

#### 4.1.2 Baseline

As comparison baselines, we select the following two categories of models: (1) Top-tier large language models (open-source and closed-source): All models are evaluated using zero-shot direct prompting with a unified prompt template. The prompts comprise the complete relevance task definition and discrimination rules. The inference configuration follows the best practices reported in the official documentation of each model: employing single-pass inference with temperature parameters set to the officially recommended optimal values for each model (e.g., 0.7 for GPT-4, 0.6 for Llama-3, etc.), ensuring that each model is compared under its optimal operating conditions. (2) Vanilla SFT Model: This model is trained using only labels for SFT, without incorporating CoT modeling or the RL phase, serving to validate the joint contribution of CoT modeling and reinforcement learning optimization in our method.

## 4.2 Main Result

Table 9 and Table 10 present the main experimental results. The analytical conclusions of this study are summarized as follows:

**Domain-specific fine-tuning yields substantial performance gains.** Across both the General subset and Hard subset, supervised fine-tuned models demonstrate significant improvements over their base models, with performance even surpassing large-scale closed-source state-of-the-art (SOTA) models such as GPT-5. This enhancement is particularly pronounced on the General subset: LORE achieves relative gains of 8.8% and 28.6% over GPT-5 in Acc@2 and Macro-F1 metrics, respectively. This improvement is primarily attributed to the model’s effective acquisition of business rule modeling capabilities and domain-specific knowledge in e-commerce.

**Multi-dimensional CoT modeling yields marginal improvements on high-performance baselines.** On the General subset, the vanilla-SFT model achieves an Acc@2 of 0.929 and a Macro-F1 of 0.722, demonstrating performance significantly superior to advanced models such as GPT-4. Compared to vanilla-SFT, the LORE model further improves Acc@2 by 0.4 percentage points. This indicates that although vanilla-SFT has already achieved sufficient fitting for in-distribution routine data, LORE can still obtain marginal performance gains on top of this high-performance baseline.

Table 10: Results on the Visual salience subset. The best score in each column is in **bold**, and the second-best is underlined.

Model	Visual salience subset		
	acc@2	acc@4	macro-F1
<i>prompting-based models</i>			
Qwen2.5-VL-7B-Instruct(Bai et al., 2025)	0.535	0.285	0.230
Qwen2.5-VL-32B-Instruct(Bai et al., 2025)	0.647	0.467	0.339
Qwen2.5-VL-72B-Instruct(Bai et al., 2025)	0.608	0.420	0.267
Gemini 2.5 Pro(Comanici et al., 2025)	0.670	0.561	0.377
GPT-5	<u>0.682</u>	0.508	0.369
vanilla SFT	0.638	<u>0.574</u>	<u>0.378</u>
LORE	<b>0.698</b>	<b>0.627</b>	<b>0.426</b>

**The injection of reasoning and knowledge capabilities yields substantial gains for LORE on hard samples.** On the Long-Tail Hard subset, vanilla-SFT demonstrates a smaller performance improvement relative to the base model compared to its performance on the General subset, and fails to establish a significant performance gap with models such as GPT-5 (0.671 vs 0.681 on acc@2). This is because for hard samples, the key factors constraining model performance are not discriminative rules, but rather reasoning capabilities and knowledge reserves. In contrast, LORE achieves a significant breakthrough: attaining an Acc@2 of 0.715 (a relative improvement of 4.4%) and a Macro-F1 of 0.460 (a relative improvement of 5.3%), surpassing large language models with strong reasoning capabilities such as GPT-4. These experimental results provide compelling evidence that knowledge distillation through teacher models and the injection of synthetic CoT reasoning can effectively enhance the model’s discriminative capability for hard samples.

**Relevance-guided enhanced caption significantly improves multimodal performance.** As shown in Table 10, on samples requiring image information for discrimination, vanilla-SFT, which lacks visual information, does not demonstrate a significant advantage over a series of advanced Vision-Language Models (VLMs). In contrast, LORE, which employs a visual relevance enhancement strategy, achieves a breakthrough: attaining a Macro-F1 of 0.426, representing a relative improvement of 4.8% compared to strong baseline models such as GPT-4. These results indicate that CoT modeling incorporating multimodal information can effectively enhance the model’s cross-modal understanding and reasoning capabilities.

### 4.3 Case Study

From a qualitative perspective, we demonstrate the model’s improvements across multiple capability dimensions through representative cases, as shown in Fig 15:

**Knowledge.** In Case 1, the query term is “Capybara” and the product title is “water pig plush toy.” After distillation from the teacher model, the model has internalized sufficient world knowledge to recognize that “Capybara” is an alternative name for “water pig,” thereby correctly determining their relevance.

**Reasoning.** In Case 2, the query is “intellectual women’s clothing”, while the product information contains no directly matchable literal keywords. Through reasoning capability, the model analyzes that: the product “commuter formal dress” aligns with the user’s implicit demand for professional attire and intellectual style; the color (gray), applicable age range (18-24 years old), and design elements (suit set, formal dress) in the product details all conform to the typical requirements of the intellectual demographic for simple and appropriate attire, leading to a correct judgment.

Query	Ability	Item	Ground Truth	Model output
Capybara plush toy	Knowledge	 Title Official water pig Plushie Hanging Charm Stuffed Toy Doll Keyring	L4	In the user query "Capybara plush toy," the term "Capybara" is an alternative name for the water pig. The product title clearly contains "Authentic Capybara Lulu Plush Toy," which directly corresponds to the user's demand for a capybara plush toy..... determined as L4.
Intellectual Women's Clothing	Infer	 Title Laurence Cloth - Teacher Certification Interview! Professional Suit Set	L4	The user query "intellectual women's clothing" aims to find professional women's wear that aligns with an intellectual style. The product explicitly includes "premium quality elegant professional suit set for women" and "commuter formal dress," directly responding to the user's demand for professional attire and intellectual style..... determined as L4.
1/4 Black Soft	Multi-modal	 Title Kase Black Diffusion Filter / Soft Focus Lens - 43mm 46mm 49mm 52mm - Suitable for Canon Nikon Sony	L4	In the user query "1/4 black soft," the term "black soft" refers to black soft filters. In the product information, the title clearly contains "black soft filter," and the product image shows the filter body is engraved with "Kase MAGNETIC BLACK MIST 1/4," directly matching the "1/4" specification in the user's query..... Determined as L4.
Iphone	Rule-aware	 Title Official Flagship Genuine 2024 Second-hand 15 Pro Ultra-thin Large Screen Mobile Phone	L3	The user query is "iphone," indicating Apple brand smartphones. The product belongs to the Apple iPhone 15 Pro model, but is labeled as pre-owned. Per the L3 rule for model-specific searches, when a user searches for a particular model and receives a used product of that model in return..... Determined as L3.

Figure 15: Example analysis of capabilities required for relevance evaluation.

**Multimodal Understanding.** Case 3 represents a typical scenario of joint text-image discrimination. For the query "1/4 Black Soft," the model matches the "Black Soft" attribute in the product title while simultaneously locating the key text "Kase MAGNETIC BLACK MIST 1/4" engraved in a small area of the product image, achieving coordinated reasoning between textual and visual information. This benefits from the relevance-oriented caption generation strategy (Section 3.3), enabling the model to extract task-critical information from images.

**Rule Compliance.** In Case 4, the attribute matching between query and product is not inherently complex, but the sample belongs to a special case stipulated by rules: "searching for normal products but returning second-hand products should be judged as L3 (weakly relevant)." After rule-aware CoT modeling (Section 3.3), the model has acquired sufficient rule compliance capability to accurately identify and apply such business rules.

## 5 Application

Based on the robust model performance, we design a complete solution encompassing both Model & Serving Update and System & Strategy Update, significantly enhancing the overall performance of end-to-end relevance discrimination, as illustrated in Fig 16. For the former, based on query stratification, we design three strategies to leverage model capabilities to improve online performance. For the System & Strategy Update, we upgrade the online strategy and infrastructure leveraging LLM capabilities. The experimental results demonstrate that our solution achieves a remarkable cumulative gain of 27% in GoodRate, as presented in Table 11.

- (1) Cache Deployment: for high-frequency query-item pairs (approximately 30% of total traffic), which occur frequently in e-commerce systems and hold significant commercial

Table 11: Performance gains from online deployment of LORE. \*denotes estimated improvements derived from offline evaluation; actual online deployment results are pending.

Category	Approach	GoodRate
Overall		+27.0%
System & Strategy Update		+12.7%
Model & Serving Update	Cache Deployment	+4.8%
	Knowledge Distillation	+7.9%
	Real-time Inference Strategy*	+0.9%

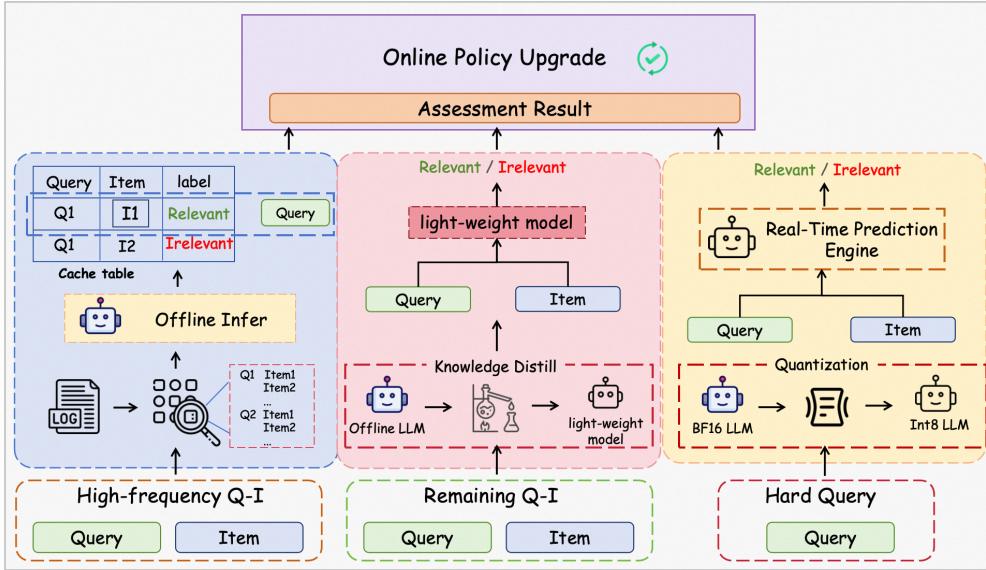


Figure 16: Online application approach of LORE based on query frequency segmentation.

value, we aim to directly leverage LLM capabilities on these samples. To address the latency bottleneck imposed by real-time computation, we adopted a hybrid deployment strategy combining offline pre-computation with online caching. Specifically, we sampled a batch of high-frequency query-item pairs from search logs. For each query, a variable number of items were sampled to construct query-item pairs, which were then processed via offline inference using the LLM.

(2) Knowledge Distillation: for medium-frequency query-item pairs (approximately 65% of total traffic), which constitute a substantial proportion. Pre-computing and caching all query-item discrimination results is neither feasible nor cost-effective. Therefore, we maintained the original "coarse ranking-fine ranking" processing pipeline. Meanwhile, the LLM was leveraged to generate large-scale, high-quality training data, systematically enhancing the discrimination capabilities of both online coarse ranking and fine ranking models through knowledge distillation techniques.

(3) Real-time Inference: for hard queries(approximately 5% of total traffic), which typically involve complex knowledge reasoning scenarios, online models struggle to make accurate predictions due to both parameter limitations and insufficient training from sparse data. While caching approaches prove ineffective given the sparsity of these pairs, these challenging cases present an opportunity for direct LLM intervention. To address this, we are actively working on developing an online real-time LLM inference capability. First, we plan to train a lightweight intent recognition model to identify these challenging queries. To address the aforementioned latency constraints, we will apply model quantization to accelerate inference speed and initially deploy this solution to a the subset of traffic. Experi-

mental results on offline hard set demonstrate a remarkable 14% improvement in GoodRate, and we anticipate achieving approximately 0.89% gain in overall metrics once this capability is fully deployed to production traffic.

(4) System & Strategy Update: We fully leverage LLM capabilities to upgrade both online strategies and system infrastructure. From the strategic perspective, we incorporate the more reliable query-item relevance scores produced by the enhanced model into the downstream ranking module and derive the optimal trade-off via Pareto optimization. From the infrastructure perspective, supported by the model’s robust performance guarantees, we systematically retire or substitute heuristic rules previously employed in the pipeline. The integrated deployment of both dimensions demonstrates substantial gains.

## 6 Discussion

### 6.1 Naive teacher CoT distillation results in negative effects.

Table 12: Performance comparison of single-pass and multi-pass inference between vanilla SFT and cold-start model with CoT distillation.

Models	pass@1	pass@8
vanilla SFT	0.929	0.937
cold-start	0.887(-4.2%)	0.964(+2.7%)

During CoT data distillation experiments, we observed that distilling synthetic CoT data paradoxically degrades model performance compared to vanilla SFT. As show in Table 12, the cold-start model exhibits a 4.2% decline in pass@1 metrics relative to Naive-SFT. This degradation stems from training-inference distribution shift: the model relies on high-quality contexts generated by the teacher during training, whereas inference utilizes its own autoregressive outputs as subsequent-step inputs. Such discrepancy triggers error accumulation and propagation through the reasoning chain, ultimately causing misjudgments. Notably, CoT-distilled models demonstrate significant improvements in pass@8 metrics (2.7% increase), indicating that distillation enhances the upper bound of model capability by expanding answer space diversity and injecting multi-step reasoning proficiency.

### 6.2 Long CoT is not necessary for better performance.

Studies such as DeepSeek-R1 have observed the emergent phenomenon of long chains-of-thought and the model’s “Aha Moment.” We similarly conducted a tracking analysis of the dynamic changes in model output length during the reinforcement learning process, with results presented in Fig 17. The experimental findings reveal that as model capability continues to improve, the output length exhibits an overall decreasing trend and eventually stabilizes. This phenomenon suggests that long chains-of-thought are not a necessary condition for model capability enhancement, but rather an accompanying phenomenon during the training process. Further analysis indicates that different task types exhibit significant variations in their requirements for reasoning chain length: tasks such as mathematical computation and code generation typically necessitate longer step-by-step reasoning processes. For the relevance task, accurately identifying query intent and item attributes, and reasoning based on discrimination rules, constitutes an intuitive and clear chain of thought. Redundant reasoning processes beyond this do not yield performance improvements.

### 6.3 Multimodal Modeling: VLM or Two-Stage LLM?

A more intuitive approach to modeling multi-modal capabilities for relevance tasks is to directly leverage VLMs, as they inherently possess image understanding capabilities without requiring additional caption synthesis. We conducted exploratory experiments on this approach: we employs the teacher model Qwen2.5-VL-72B to sequentially complete two steps—knowledge and reasoning CoT generation, followed by rule-aware CoT

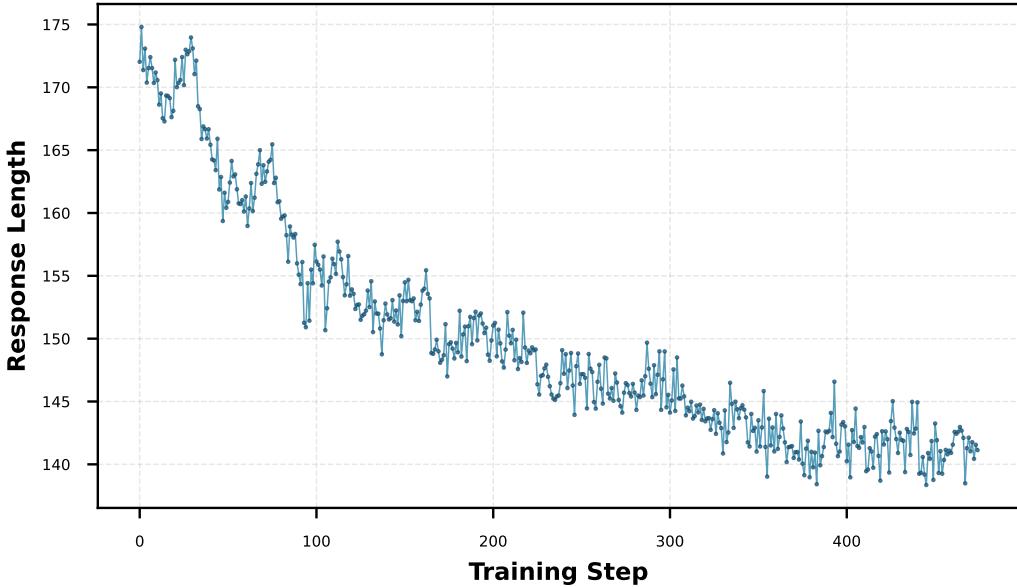


Figure 17: Response length variation during RL training.

generation—thereby synthesizing multi-dimensional CoT data. Subsequently, using the same two-stage training configuration (SFT and RL), we trained the Qwen2.5-VL-7B model, which has a comparable parameter to the LLM base model employed in this study.

Table 13: Performance comparison of VLM-based and LLM-based methods on the general subset and long-tail hard subset. The best score in each column is in **bold**, and the second-best is underlined.

Model	General subset			Longtail Hard subset		
	acc@2	acc@4	macro-F1	acc@2	acc@4	macro-F1
VLM-base	0.912	0.878	0.670	0.692	0.577	0.413
LLM-base	0.933	0.897	0.724	0.715	0.582	0.460

Table 14: Performance comparison of VLM-based and LLM-based methods on the Visual salience subset. The best score in each column is in **bold**, and the second-best is underlined.

Model	prompting-based models		
	acc@2	acc@4	macro-F1
VLM-base	0.703	0.645	0.526
LLM-base	0.698	0.627	0.426

Tables 13 and 14 present a performance comparison between trained models based on VLM and based on LLM. On both General and hard datasets, the LLM-based method significantly outperforms the VLM-based method, particularly demonstrating a clear advantage in macro-F1 metrics. This indicates that with equivalent CoT capability injection, LLMs possess stronger reasoning and knowledge capabilities compared to VLMs. In contrast, VLMs perform better on the visual salience subset, which aligns with expectations, as VLMs do not require generating intermediate textual captions, thereby avoiding information loss during the image-to-text conversion process.

## 7 Evolutionary Trajectory

As shown in Fig 18, over the past three phases, our LORE model has undergone systematic evolution characterized by progressive refinements along five key dimensions: (1) core goals; (2) model paradigm and backbone; (3) data and prompt strategies; (4) evaluation frameworks; and (5) application scenarios. Together, these three phases trace a systematic trajectory of innovation that combines increasingly sophisticated model architectures, high-quality data construction pipelines, and practical deployment strategies to enhance search relevance capabilities in e-commerce scenarios. In this section, we outline this evolution across these core dimensions.

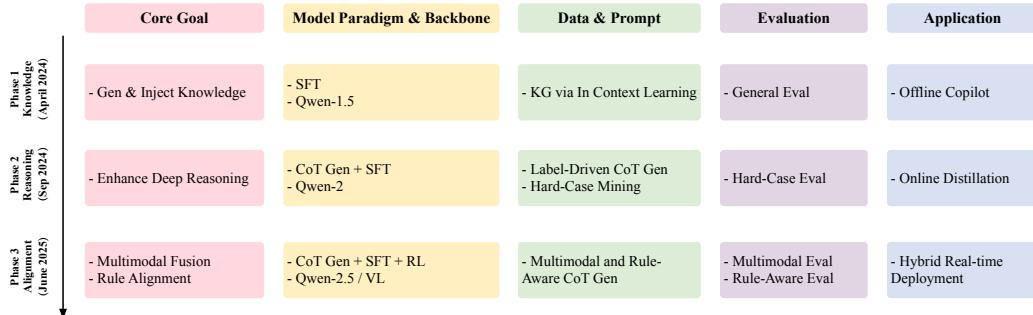


Figure 18: Three-phase evolution of LORE system across five key dimensions.

### 7.1 LORE 1.0: Foundation Consolidation

In this initial phase, we confronted the fundamental challenge of Query understanding in the e-commerce domain, particularly the accurate identification of entity mentions with non-standard expressions (e.g., unregistered terms or colloquialisms), which posed significant obstacles to robust product attribution understanding. To address this challenge, we constructed large-scale, high-quality e-commerce training corpora and employed In-Context Learning (ICL) to systematically inject domain knowledge into the model, thereby establishing a solid foundation for e-commerce semantic comprehension.

**Model Paradigm & Backbone:** We adopted a Supervised Fine-Tuning (SFT) paradigm based on the Qwen-1.5 model as our backbone architecture. This approach enabled effective transfer of general language understanding capabilities to domain-specific e-commerce scenarios.

**Data & Prompt:** Our methodology leveraged knowledge graphs combined with In-Context Learning, where domain knowledge was injected through carefully designed contextual prompts. This strategy allowed the model to assimilate e-commerce-specific semantic patterns and entity relationships through upper-context learning mechanisms.

**Evaluation:** We employed standard benchmark protocols alongside general relevance assessment metrics to comprehensively evaluate model performance across various query understanding tasks, ensuring both accuracy and generalizability.

**Application:** The trained model was deployed as a high-precision offline judger for label annotation tasks. This application successfully established an efficient annotation assistance system and badcase detection mechanism, significantly enhancing data quality and operational efficiency in downstream workflows.

### 7.2 LORE 2.0: Deep reasoning

Building upon the foundational query understanding capabilities, this phase tackled more sophisticated challenges in complex Query semantic recognition (including existence, implicit meanings, and negations) and deep semantic reasoning within Path construction. Simple instruction-following proved insufficient for these multi-step reasoning and judgment

tasks that demanded enhanced logical inference capabilities. To address these challenges, we introduced Chain-of-Thought (CoT) technology. Rather than directly requesting judgment outputs, we strengthened the model's ability to "identify complex entities and semantics, decompose hierarchical relationships, and ultimately complete Path comparisons" through comprehensive reasoning chains. This approach significantly enhanced the accuracy of complex Query discrimination. Additionally, we established a data synthesis engine based on difficult case mining, enabling iterative feedback optimization.

**Model Paradigm & Backbone:** We synthesized CoT data for attribute extraction and matching tasks, and trained the model using the SFT paradigm with Qwen-2 as the backbone architecture. This approach enabled the model to generate intermediate reasoning steps while maintaining task-specific optimization through supervised fine-tuning.

**Data & Prompt:** Our methodology employed label-driven CoT generation combined with hardcase mining. By integrating label-constrained CoT synthesis with difficult sample excavation, we enhanced the model's reasoning capabilities through structured multi-step inference patterns and challenging edge cases.

**Evaluation:** We implemented hardcase-focused evaluation protocols specifically designed to assess performance on challenging semantic scenarios, ensuring robust handling of complex reasoning requirements and edge cases.

**Application:** The innovations in this phase enabled online distillation deployment, where the CoT-based multi-dimensional knowledge system was successfully distilled and transferred to smaller models. This achievement marked a significant milestone in scaling deep reasoning capabilities to production environments with improved inference efficiency, realizing substantial performance improvements in online A/B testing scenarios.

### 7.3 LORE 3.0: Rule Adherence and Multi-modality

Entering the deep-water zone, this phase confronted two paramount challenges: first, the high dependence on visual information in product attribution understanding (where user-uploaded images often contain insufficient textual details); and second, during the Path selection process, judgment results must strictly conform to formats that encompass numerous fine-grained rules and detailed business standards that align with observable attributes.

To address these challenges, we pursued a comprehensive technical strategy that integrated multimodal understanding capabilities with rule-aware reasoning mechanisms, enabling the model to process visual information while maintaining strict adherence to business constraints.

**Model Paradigm & Backbone:** We employed a hybrid paradigm of CoT Generation + SFT + Reinforcement Learning (RL) built upon both Qwen-2.5 LLM for text reasoning and Qwen-2.5 VL for multimodal understanding. This dual-model architecture enabled seamless integration of visual and textual reasoning pathways, breaking through single-modality limitations.

**Data & Prompt:** Our methodology leveraged multimodal and rule-aware CoT generation, combining image-text paired understanding with standard-oriented prompt engineering. First, business rules and exemplar cases were embedded into CoT reasoning chains to establish rule comprehension logic. Subsequently, reinforcement learning was introduced to significantly enhance the model's generalized reasoning capabilities for applying active rules to Path judgments under complex attribute scenarios.

**Evaluation:** We constructed a challenging benchmark, RAIR (Relevance Assessment with Image and Rules), designed to comprehensively evaluate the model across multiple dimensions: foundational capabilities, hardcase handling, multimodal understanding, and rule compliance. This holistic assessment framework ensures robust validation of all critical competencies required for production deployment.

**Application:** This phase achieved breakthrough hybrid real-time deployment capabilities. Through efficient high-frequency caching combined with long-tail real-time inference mech-

anisms, we successfully realized direct large-model discrimination capabilities online for the first time, driving the system toward next-generation platforms for online relevance experience validation.

## 8 Conclusion

In this study, we introduce LORE, a systematic and end-to-end framework designed to comprehensively address the multifaceted challenges of e-commerce search relevance. Our work began with a foundational deconstruction of the relevance task, identifying three core capabilities essential for robust judgment: (1) Knowledge and Reasoning Integration, (2) Multi-modal Understanding, and (3) Complex Rule Adherence. This theoretical analysis provided clear and structured guidance for relevance modeling. Building on this foundation, we proposed a complete and practical blueprint that spans the entire lifecycle of a relevance model. This methodology encompasses four key contributions:

**Systematic preliminary explorations** to optimize crucial foundational components, including feature engineering, prompt design, and base model selection, thereby establishing a robust groundwork for subsequent stages.

**A sophisticated training paradigm**, featuring a progressive CoT synthesis for capability injection via Supervised Fine-Tuning (SFT), followed by a Reinforcement Learning (RL) stage to align the model with human preferences.

**A comprehensive evaluation benchmark**, RAIR, which was specifically constructed to rigorously assess model performance across the identified core capabilities, especially on challenging long-tail and visually-salient samples.

**A practical online application strategy**, where we successfully deployed LORE into a large-scale production environment. By employing a query frequency-stratified approach, we achieved a significant 10% cumulative improvement in the online GoodRate metric.

Experimentally, LORE not only established a new state-of-the-art on our challenging offline benchmark, outperforming leading proprietary models, but also demonstrated its substantial real-world value through impressive online gains. In conclusion, LORE provides more than just a high-performing model; it offers a complete, replicable blueprint—from foundational exploration and principled training to robust evaluation and effective online deployment—for developing and operationalizing advanced relevance systems in the e-commerce industry, while also providing valuable insights for post-training work in other vertical domains.

## 9 Contributors

### References

- Shuai Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, Sibo Song, Kai Dang, Peng Wang, Shijie Wang, Jun Tang, Humen Zhong, Yuanzhi Zhu, Mingkun Yang, Zhaohai Li, Jianqiang Wan, Pengfei Wang, Wei Ding, Zheren Fu, Yiheng Xu, Jiabo Ye, Xi Zhang, Tianbao Xie, Zesen Cheng, Hang Zhang, Zhibo Yang, Haiyang Xu, and Junyang Lin. Qwen2.5-vl technical report, 2025. URL <https://arxiv.org/abs/2502.13923>.
- Yoshua Bengio, Jérôme Louradour, Ronan Collobert, and Jason Weston. Curriculum learning. In *ICML*, 2009.
- David Carmel, Elad Haramaty, Arnon Lazerson, Liane Lewin-Eytan, and Yoelle Maarek. Why do people buy seemingly irrelevant items in voice product search? on the relation between product relevance and customer satisfaction in ecommerce. In *Proceedings of the 13th International Conference on Web Search and Data Mining*, WSDM '20, page 79–87, New York, NY, USA, 2020. Association for Computing Machinery. ISBN 9781450368223. doi: 10.1145/3336191.3371780. URL <https://doi.org/10.1145/3336191.3371780>.

- Gheorghe Comanici, Eric Bieber, Mike Schaeckermann, Ice Pasupat, and Noveen Sachdeva. Gemini 2.5: Pushing the frontier with advanced reasoning, multimodality, long context, and next generation agentic capabilities, 2025. URL <https://arxiv.org/abs/2507.06261>.
- DeepSeek-AI, Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, and Ruoyu Zhang. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning, 2025. URL <https://arxiv.org/abs/2501.12948>.
- Chenhe Dong, Shaowei Yao, Pengkun Jiao, Jianhui Yang, Yiming Jin, Zerui Huang, Xiaojiang Zhou, Dan Ou, and Haihong Tang. Taosr1: The thinking model for e-commerce relevance search, 2025. URL <https://arxiv.org/abs/2508.12365>.
- Kawin Ethayarajh, Winnie Xu, Niklas Muennighoff, Dan Jurafsky, and Douwe Kiela. Kto: Model alignment as prospect theoretic optimization, 2024. URL <https://arxiv.org/abs/2402.01306>.
- Zheng Fang, Donghao Xie, Ming Pang, Chunyuan Yuan, Xue Jiang, Changping Peng, Zhangang Lin, and Zheng Luo. Adore: Autonomous domain-oriented relevance engine for e-commerce. In *Proceedings of the 48th International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR '25*, page 4259–4263, New York, NY, USA, 2025. Association for Computing Machinery. ISBN 9798400715921. doi: 10.1145/3726302.3731944. URL <https://doi.org/10.1145/3726302.3731944>.
- Shangbin Feng, Weijia Shi, Yike Wang, Wenzuan Ding, Vidhisha Balachandran, and Yulia Tsvetkov. Don't hallucinate, abstain: Identifying LLM knowledge gaps via multi-LLM collaboration. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 14664–14690, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.acl-long.786. URL <https://aclanthology.org/2024.acl-long.786/>.
- Yunye Gong, Robik Shrestha, Jared Claypoole, Michael Cogswell, Arijit Ray, Christopher Kanan, and Ajay Divakaran. BloomVQA: Assessing hierarchical multi-modal comprehension. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Findings of the Association for Computational Linguistics: ACL 2024*, pages 14905–14918, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.findings-acl.885. URL <https://aclanthology.org/2024.findings-acl.885/>.
- Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, and Ahmad Al-Dahle. The llama 3 herd of models, 2024. URL <https://arxiv.org/abs/2407.21783>.
- Jujie He, Jiacai Liu, Chris Yuhao Liu, Rui Yan, Chaojie Wang, Peng Cheng, Xiaoyu Zhang, Fuxiang Zhang, Jiacheng Xu, Wei Shen, Siyuan Li, Liang Zeng, Tianwen Wei, Cheng Cheng, Bo An, Yang Liu, and Yahui Zhou. Skywork open reasoner 1 technical report, 2025. URL <https://arxiv.org/abs/2505.22312>.
- Lei Li, Yuqi Wang, Runxin Xu, Peiyi Wang, Xiachong Feng, Lingpeng Kong, and Qi Liu. Multimodal ArXiv: A dataset for improving scientific comprehension of large vision-language models. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 14369–14387, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.acl-long.775. URL [https://aclanthology.org/2024.acl-long.775/](https://aclanthology.org/2024.acl-long.775).
- Moxin Li, Yong Zhao, Wenzuan Zhang, Shuaiyi Li, Wenya Xie, See-Kiong Ng, Tat-Seng Chua, and Yang Deng. Knowledge boundary of large language models: A survey, 2025. URL <https://arxiv.org/abs/2412.12472>.
- Hong Liu, Saisai Gong, Yixin Ji, Kaixin Wu, Jia Xu, and Jinjie Gu. Boosting llm-based relevance modeling with distribution-aware robust learning. In *Proceedings of the 33rd ACM International Conference on Information and Knowledge Management, CIKM '24*, page

4718–4725, New York, NY, USA, 2024. Association for Computing Machinery. ISBN 9798400704369. doi: 10.1145/3627673.3680052. URL <https://doi.org/10.1145/3627673.3680052>.

Ziyang Liu, Chaokun Wang, Hao Feng, Lingfei Wu, and Liqun Yang. Knowledge distillation based contextual relevance matching for e-commerce product search, 2022. URL <https://arxiv.org/abs/2210.01701>.

Navid Mehrdad, Hrushikesh Mohapatra, Mossaab Bagdouri, Prijith Chandran, Alessandro Magnani, Xunfan Cai, Ajit Puthenputhussery, Sachin Yadav, Tony Lee, ChengXiang Zhai, and Ciya Liao. Large language models for relevance judgment in product search, 2024. URL <https://arxiv.org/abs/2406.00247>.

Rafael Rafailov, Archit Sharma, Eric Mitchell, Stefano Ermon, Christopher D. Manning, and Chelsea Finn. Direct preference optimization: Your language model is secretly a reward model, 2024. URL <https://arxiv.org/abs/2305.18290>.

Chandan K. Reddy, Lluís Márquez, Fran Valero, Nikhil Rao, Hugo Zaragoza, Sambaran Bandyopadhyay, Arnab Biswas, Anlu Xing, and Karthik Subbian. Shopping queries dataset: A large-scale esci benchmark for improving product search, 2022. URL <https://arxiv.org/abs/2206.06588>.

Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang, Mingchuan Zhang, Y. K. Li, Y. Wu, and Daya Guo. Deepseekmath: Pushing the limits of mathematical reasoning in open language models, 2024. URL <https://arxiv.org/abs/2402.03300>.

Tian Tang, Zhixing Tian, Zhenyu Zhu, Chenyang Wang, Haiqing Hu, Guoyu Tang, Lin Liu, and Sulong Xu. Lref: A novel llm-based relevance framework for e-commerce search. In *Companion Proceedings of the ACM on Web Conference 2025*, WWW '25, page 468–475, New York, NY, USA, 2025. Association for Computing Machinery. ISBN 9798400713316. doi: 10.1145/3701716.3715246. URL <https://doi.org/10.1145/3701716.3715246>.

Kimi Team, Angang Du, Bofei Gao, Bowei Xing, Changjiu Jiang, Cheng Chen, Cheng Li, and Chenjun Xiao. Kimi k1.5: Scaling reinforcement learning with llms, 2025. URL <https://arxiv.org/abs/2501.12599>.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed Chi, Quoc Le, and Denny Zhou. Chain-of-thought prompting elicits reasoning in large language models, 2023. URL <https://arxiv.org/abs/2201.11903>.

An Yang, Anfeng Li, Baosong Yang, Beichen Zhang, Binyuan Hui, and Bo Zheng. Qwen3 technical report, 2025. URL <https://arxiv.org/abs/2505.09388>.

Qiying Yu, Zheng Zhang, Ruofei Zhu, Yufeng Yuan, Xiaochen Zuo, Yu Yue, Weinan Dai, Tiantian Fan, Gaohong Liu, Lingjun Liu, Xin Liu, Haibin Lin, Zhiqi Lin, Bole Ma, Guangming Sheng, Yuxuan Tong, Chi Zhang, Mofan Zhang, Wang Zhang, Hang Zhu, Jinhua Zhu, Jiaze Chen, Jiangjie Chen, Chengyi Wang, Hongli Yu, Yuxuan Song, Xiangpeng Wei, Hao Zhou, Jingjing Liu, Wei-Ying Ma, Ya-Qin Zhang, Lin Yan, Mu Qiao, Yonghui Wu, and Mingxuan Wang. Dapo: An open-source llm reinforcement learning system at scale, 2025. URL <https://arxiv.org/abs/2503.14476>.

Chunyuan Yuan, Yiming Qiu, Mingming Li, Haiqing Hu, Songlin Wang, and Sulong Xu. A multi-granularity matching attention network for query intent classification in e-commerce retrieval. In *Companion Proceedings of the ACM Web Conference 2023*, WWW '23, page 416–420. ACM, April 2023. doi: 10.1145/3543873.3584639. URL <http://dx.doi.org/10.1145/3543873.3584639>.

Wei Zhang, Miaoxin Cai, Tong Zhang, Yin Zhuang, and Xuerui Mao. Earthgpt: A universal multimodal large language model for multisensor image comprehension in remote sensing domain. *IEEE Transactions on Geoscience and Remote Sensing*, 62:1–20, 2024. doi: 10.1109/TGRS.2024.3409624.

Gang Zhao, Ximing Zhang, Chenji Lu, Hui Zhao, Tianshu Wu, Pengjie Wang, Jian Xu, and Bo Zheng. Explainable llm-driven multi-dimensional distillation for e-commerce relevance learning. In *Companion Proceedings of the ACM on Web Conference 2025, WWW '25*, page 631–640, New York, NY, USA, 2025a. Association for Computing Machinery. ISBN 9798400713316. doi: 10.1145/3701716.3715222. URL <https://doi.org/10.1145/3701716.3715222>.

Yuzhong Zhao, Yue Liu, Junpeng Liu, Jingye Chen, Xun Wu, Yaru Hao, Tengchao Lv, Shaohan Huang, Lei Cui, Qixiang Ye, Fang Wan, and Furu Wei. Geometric-mean policy optimization, 2025b. URL <https://arxiv.org/abs/2507.20673>.

Chujie Zheng, Shixuan Liu, Mingze Li, Xiong-Hui Chen, Bowen Yu, Chang Gao, Kai Dang, Yuqiong Liu, Rui Men, An Yang, Jingren Zhou, and Junyang Lin. Group sequence policy optimization, 2025. URL <https://arxiv.org/abs/2507.18071>.