TOKEN-EFFICIENT LONG-TERM INTEREST SKETCHING AND INTERNALIZED REASONING FOR LLM-BASED RECOMMENDATION

Anonymous authors
Paper under double-blind review

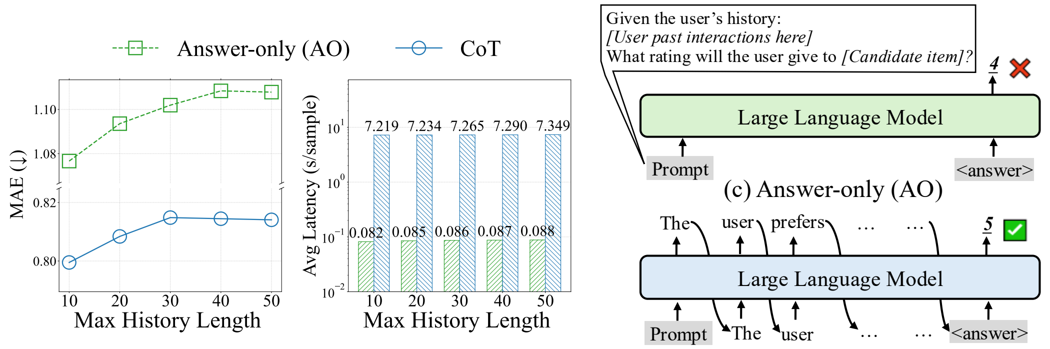
ABSTRACT

Large language models (LLMs) can solve complex real-world tasks when prompted to generate chain-of-thought (CoT) reasoning, motivating their use for preference reasoning in recommender systems. However, applying LLM reasoning on recommendation faces two practical challenges. First, LLMs struggle to reason over long, noisy user histories that often span hundreds of items while truncation discards signals needed to capture long-term interests. Second, in decoder-only architectures, CoT requires generating rationale tokens autoregressively, leading to prohibitive inference latency for real-world deployment. To address the challenges, we propose SIREN, a framework that enables effective LLM-based rating prediction via long-term interest sketching and internalized reasoning. First, instead of prompting raw histories, we build a compact, token-bounded interest sketch that preserves persistent preferences and suppresses noise. Specifically, we encode and cluster item descriptions to discover semantic topics, then compress each user's history into a short list of liked and disliked topics, facilitating LLM reasoning. Second, we develop an internalized reasoning strategy for efficient inference. We adopt a two-stage training paradigm: (i) train the LLM to reason explicitly for rating prediction with rule-based reinforcement learning, since ground-truth CoTs are unavailable in recommendation; and (ii) learn to internalize CoT into model parameters through hidden alignment. At inference, the LLM directly generates the rating with near-CoT quality. Extensive experiments show that SIREN reduces average input tokens by 48.7% compared to raw-history prompting, outperforms existing methods while delivering over $100\times$ lower inference latency than CoT-based LLM recommenders. Code and data are available at https://anonymous.4open.science/r/LLM4Rec-C7CF.

1 INTRODUCTION

Large language models (LLMs) have recently demonstrated strong problem-solving abilities, especially when their reasoning capacity is activated by chain-of-thought (CoT) prompting (Wei et al., 2022; Achiam et al., 2023). Reinforcement learning further amplifies this ability, as seen in OpenAI-o1 (Jaech et al., 2024) and DeepSeek-R1 (Guo et al., 2025), enabling LLMs to solve Olympiad-level mathematics (Castelvecchi, 2025) and real-world coding tasks (Jimenez et al., 2024). Motivated by these advances, recent work explores LLMs in recommendation tasks such as user rating prediction (Tsai et al., 2024a; Kim et al., 2025) and next item prediction (Bao et al., 2024; 2025). In rating prediction, for example, an LLM is prompted with a user's behavior history together with a candidate item's description, and is instructed to infer the user's preference and output the rating the user would give. Unlike traditional ID-centric recommenders (Cheng et al., 2016; Zou et al., 2023), LLM-based approaches can exploit rich item semantics, alleviating cold-start, improving generalization, and offering interpretable recommendations (Wang et al., 2024b).

Despite this promise, two practical challenges limit deployment of LLMs in real-world recommenders. First, **long and noisy histories** undermine LLM reasoning for recommendation. In practice, users can have hundreds of interactions within days, producing histories that are lengthy, redundant, and noisy (Wang et al., 2025). Naively feeding these raw histories to an LLM degrades performance as LLMs are short of long-context processing (Wang et al., 2024a; 2025) and accumulated noise



(a) Accuracy Comparison (b) Latency Comparison (d) Chain-of-thought (CoT)

Figure 1: We vary max history length from 10 to 50 and compare answer-only vs CoT of Qwen3-4B in rating prediction on the Movies category of the AmazonReviews dataset. Full setup in Appendix B.2. (a) MAE (↓) vs. history length. (b) Average per-sample latency (s). (c) AO: placing <answer> immediately after the query Prompt signals the model to generate only the final answer. (d) CoT: the model first generates an multi-step reasoning token-by-token, then outputs the final prediction.

obscures the preference signal and impairs reasoning. As shown in Fig. 1(a), when using LLM for rating prediction, the prediction error increases as the maximum history increases from 10 to 50 items. Prior approaches truncate to the most recent items (Lyu et al., 2024; Tsai et al., 2024a), sacrificing long-term signals (Chang et al., 2023), or prompt the LLM to summarize profiles (Kim et al., 2025; Wang et al., 2025), which still requires processing long histories and adds computational cost. This calls for a token-efficient user representation that preserves robust long-term signals for LLM reasoning.

Second, **latency from explicit reasoning** hinders deployment of LLMs in recommendation. Currently, there are two strategies for LLM inference in rating prediction: answer-only (AO) and chain-of-thought (CoT). AO inference (Fig. 1(c)) takes the prompt and directly generates the rating, whereas CoT (Fig. 1(d)) emits a multi-step rationale before the final rating, and each additional token requires an extra forward pass. Although CoT improves accuracy, the longer output sequence inflates inference latency and serving cost (Lin et al., 2025), which conflicts with production requirements. As shown in Fig. 1(b), CoT incurs per-sample latency over $100\times$ higher than answer-only. To accelerate inference, prior work either distills knowledge into smaller LLMs (Xu et al., 2025) or employs efficient decoding strategies like speculative decoding (Lin et al., 2025) and latent-reasoning (Zhang et al., 2025). However, these approaches still require generating intermediate reasoning tokens, incurring extra time costs.

This work addresses both challenges with SIREN, a framework for leveraging LLM reasoning in rating prediction. SIREN introduces two key components: (i) *Long-Term Interest Sketching.* Instead of prompting with raw, lengthy histories, we build a compact, token-bounded interest sketch that preserves user persistent preferences and suppresses noise. We encode item descriptions and cluster their embeddings to obtain a fixed set of corpus-level semantic topics; each user's history is then aggregated over these topics into a small list of likes and dislikes. We combine this sketch with user recent histories to capture short-term interests, providing a token-efficient yet informative prompt for LLM reasoning. (ii) *Internalized Reasoning.* We aim for answer-only inference that produces the final rating without emitting rationale tokens while retaining the gains of CoT. To this end, we adopt a two-stage training paradigm: first, since ground-truth CoT rationales are unavailable in recommendation, we train explicit CoT reasoning over the interest sketch via rule-based reinforcement learning; second, we learn to internalize CoT by aligning the answer token's hidden states under answer-only decoding to those induced by CoT. Our hidden alignment transfers the effect of CoT into model parameters, enabling near-CoT quality with answer-only latency. We conduct extensive experiments on two real-world recommendation datasets to evaluate SIREN. Results show that SIREN attains high token efficiency and strong rating-prediction accuracy with low inference latency. On Movies, for example, SIREN reduces average input tokens by 48.7% compared to raw-history prompting, lowers MAE by 20.1% over the runner-up baseline, and delivers over $100\times$ lower inference latency than CoT-based decoding. In summary, our contributions are as follows:

- We identify two deployment challenges for LLM-based recommendation—long, noisy histories and latency from explicit reasoning—and present SIREN, a unified framework that addresses both.
- We propose Long-Term Interest Sketching, a token-efficient user representation that replaces raw, lengthy histories with a compact, corpus-level topic sketch capturing stable preferences.
- We develop a two-stage training paradigm: (i) learn explicit reasoning for rating prediction without CoT labels via RL, and (ii) internalize this reasoning through hidden-state alignment, enabling answer-only decoding with near-CoT quality.
- Through extensive experiments, SIREN achieves lower rating-prediction error than traditional and LLM-based recommender baselines, while delivering over $100\times$ lower inference latency than CoT-based decoding.

2 Task Formulation

Let $\mathcal{U}$ be the set of users and $\mathcal{I}$ the set of items. Each item $i \in \mathcal{I}$ has an associated textual description (e.g., title/metadata) denoted $d(i)$. For a user $u \in \mathcal{U}$, let the chronologically ordered interaction history be $\mathcal{H}_u = \{(i, d(i), r_{ui}) : i \in \mathcal{I}_u\}$, where r_{ui} is the observed rating. Given a candidate item $i \in \mathcal{I}$, the goal of rating prediction is to estimate the rate user u will give $\hat{r}_{uj}$ based on user history $\mathcal{H}_u$ and candidate item description $d(i)$.

When using an LLM for rating prediction, the pair $(\mathcal{H}_u, d(i))$ is first converted into a textual prompt by a prompt function $\Phi(\cdot)$, and then fed to the LLM-based recommender model $\mathcal{M}$ to predict:

$$\hat{r}_{ui} \;=\; \mathcal{M}\big(\,\Phi(\mathcal{H}_u,\, d(i))\,\big). \tag{1}$$

3 SIREN

Fig. 2 illustrates the overall framework of SIREN. SIREN comprises two main components: (i) *Long-Term Interest Sketching* (Sec. 3.1) compresses long, noisy histories into a compact, token-efficient sketch that preserves stable preferences. (ii) *Internalized Reasoning* (Sec. 3.2) uses a two-stage training strategy to retain CoT gains while enabling answer-only decoding, accelerating inference.

3.1 Long-term interest sketching

Given a user's history $\mathcal{H}_u$, directly prompting an LLM with raw interactions is suboptimal as histories can be long and noisy. On the contrary, truncating to recent items discards information critical for long-term preferences. In SIREN, we construct a compact *long-term interest sketch* and prompt the LLM with this sketch instead of the raw history. The constructed sketch comprehensively captures user preference signals under strict token limit. As shown in Fig. 2, we first encode all item descriptions and cluster their embeddings to obtain a shared set of corpus-level semantic topics. Given these topics, a user's history is mapped to topic labels and aggregated to yield a small set of interests, partitioned into likes and dislikes according to the average rating. Finally, we form the prompt by concatenating this sketch with the user's recent interactions and the candidate item description, capturing both long-term and short-term preferences. The LLM takes this prompt to predict the rating. We detail each step below.

Item Topic Discovery. We represent each item by a semantic topic rather than its raw description. This lets us aggregate many historical items that share a topic, so a user can be summarized by a small set of topics that highlight core interests and discard irrelevant detail. Because users have histories of highly variable length, discovering topics per user is unstable (especially for short histories) and produces topics that are not comparable across users. Instead, we discover corpus-level topics once over the entire item set $\mathcal{I}$. Specially, we first embed item descriptions as:

$$\mathbf{e}(i) \;=\; \mathrm{Enc}\big(d(i)\big) \in \mathbb{R}^{d_e}, \quad i \in \mathcal{I}, \tag{2}$$

where $\mathrm{Enc}(\cdot)$ the text encoder and $\mathbf{e}(i)$ is the embedding of item i. We then apply K-means over all embeddings to obtain K cluster (topic) centers:

$$\{\boldsymbol{\mu}_k\}_{k=1}^{K} = \mathrm{KMeans}(\{\mathbf{e}(i) | i \in \mathcal{I}\})\,, \tag{3}$$

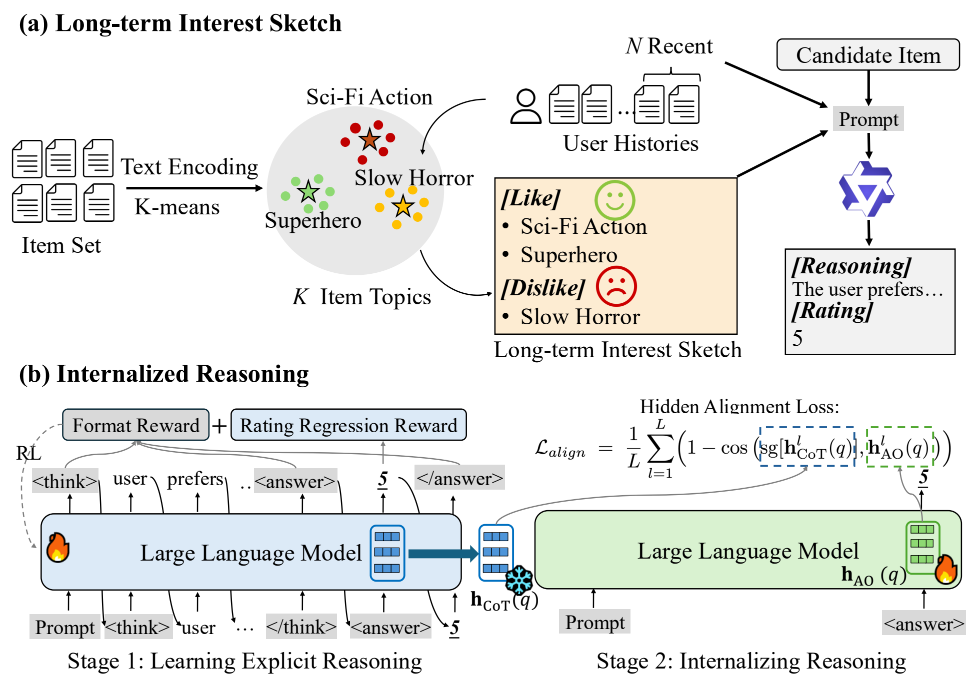


Figure 2: Overview of SIREN. (a) **Long-term interest sketching:** user histories are encoded, clustered into semantic topics, and aggregated into a compact sketch of likes and dislikes, which is combined with recent interactions and the candidate item for LLM-based rating prediction. (b) **Internalized reasoning:** Stage 1 trains explicit CoT reasoning with reinforcement learning (RL); Stage 2 aligns hidden states of answer-only decoding with CoT decoding, enabling answer-only inference with near-CoT quality but much lower latency.

where $\boldsymbol{\mu}_k$ is the k-th topic center. Each item is assigned a topic label by finding the nearest center:

$$c_i = \arg\min_{k\in\{1,\dots,K\}} \big\| \mathbf{e}(i) - \boldsymbol{\mu}_k \big\|_2^2. \tag{4}$$

For cluster k, we collect the descriptions of the M items closest to its center $\boldsymbol{\mu}_k$ and prompt the LLM to summarize them into a concise textual topic name τ_k.

User Interest Sketching. Given item topics $\tau_i \in \{1, \dots, K\}$, we aggregate a user's history $\mathcal{H}_u$ into a compact long-term interest sketch. For the k-th topic, the user's interactions within that topic are:

$$\mathcal{H}_u(k) \;=\; \{\, (i, d(i), r_{ui}) \in \mathcal{H}_u : c_i = k \,\}, \tag{5}$$

where $\mathcal{H}_u(k)$ is the set of interactions assigned to topic k. We partition the topics the user has interacted with into *likes* and *dislikes* based on the average rating per topic:

$$\bar{r}_{u,k} \;=\; \frac{1}{|\mathcal{H}_u(k)|} \sum_{(i,r_{ui})\in\mathcal{H}_u(k)} r_{ui}. \tag{6}$$

Then we threshold the per-topic average and obtain:

$$\mathcal{T}_u^+ \;=\; \{\, \tau_k : \bar{r}_{u,k} \ge \theta \,\}, \qquad \mathcal{T}_u^- \;=\; \{\, \tau_k \,:\, 0 < \bar{r}_{u,k} < \theta \,\}, \tag{7}$$

where $\mathcal{T}_u^+$ and $\mathcal{T}_u^-$ are the sets of topic names the user likes and dislikes, respectively. The user's long-term interest sketch is:

$$\mathcal{S}_u \;=\; \big(\mathcal{T}_u^+,\; \mathcal{T}_u^-\big). \tag{8}$$

This sketch replaces raw, lengthy histories with a small, interpretable topic-level summary that preserves persistent preferences under a strict token budget and suppresses noise, providing a stable user information for LLM reasoning.

Prompt Construction. To predict user u's rating for item $i \in \mathcal{I}$, we build the prompt from the user's long-term interest sketch $\mathcal{S}_u$, the N most recent interactions $\mathcal{H}_u^{(N)}$, and the candidate item description $d(i)$. Let function $\Phi(\cdot)$ linearize these components into prompt $\pi_u(i)$:

$$\pi_u(i) \;=\; \Phi\big(\,\mathcal{S}_u,\; \mathcal{H}_u^{(N)},\; d(i)\,\big). \tag{9}$$

LLM predicts the rating as:

$$\hat{r}_{ui} \;=\; \mathcal{M}\big(\,\pi_u(i)\,\big) \;=\; \mathcal{M}\big(\,\Phi(\mathcal{S}_u, \mathcal{H}_u^{(N)}, d(i))\,\big). \tag{10}$$

This construction captures long-term preferences through $\mathcal{S}_u$ and short-term context through $\mathcal{H}_u^{(N)}$ under a strict token budget, providing a concise but informative input for rating prediction.

3.2 Internalized Reasoning

While explicit CoT improves rating prediction (Fig. 1), it requires generating many rationale tokens, which inflates inference latency and serving cost. Our goal is answer-only inference that generates only the final rating without losing the quality gains of CoT. As shown in Fig. 2, SIREN adopts a two-stage training paradigm: (i) learn explicit CoT reasoning over the long-term interest sketch prompts for rating prediction; (ii) hidden alignment that trains the CoT model to internalize the explicit reasoning to model parameters. In this way, SIREN enables LLM decoding at inference with near CoT quality. The details are below.

Learning Explicit Reasoning via Reinforcement Learning. In the first stage, we train the model to explicitly reason over user sketch prompt $\pi_u(i)$ for rating prediction by generating a rationale followed by a rating $\hat{r}_{ui}$. Since ground-truth CoTs are unavailable in recommendation, we adopt reinforcement learning (RL) to optimize reasoning quality guided by rule-based rewards. We fine-tune LLM with Group Relative Policy Optimization (GRPO) (Shao et al., 2024), a lightweight, critic-free RL update for LLMs.

To adapt GRPO in rating prediction, we combine a *format reward* s_{format} that enforces the model to generate its reasoning within <think>...</think> followed by the final prediction within <answer>...</answer>, and a *rating regression reward* s_{rate} that maps prediction error into rewards ranges from $[-2, 2]$. Let $r_{ui} \in [a, b]$ denote the ground-truth rating user u has on item i, $\hat{r}_{ui} \in [a, b]$ the prediction (clipped to $[a, b]$), and $E_{\max} = b - a$ the maximum possible error. The per-sample reward is defined as:

$$R(\hat{r}_{ui}, r_{ui}) \;=\; s_{\text{format}} \;+\; \underbrace{\Big(2 - \tfrac{4}{E_{\max}}|\hat{r}_{ui} - r_{ui}|\Big)}_{s_{\text{rate}}}, \quad s_{\text{format}} = \begin{cases} +1, & \text{if format is correct,} \\ -1, & \text{otherwise.} \end{cases} \tag{11}$$

Here $s_{\text{rate}} \in [-2, 2]$ decreases linearly with the absolute prediction error, and $s_{\text{format}} \in \{-1, +1\}$ enforces the output format. GRPO then optimizes the model using $R(\hat{r}_{ui}, r_{ui})$, encouraging well-formed rationales and ratings close to the ground truth. GRPO algorithm is deferred to Appendix C.

Learning to Internalize CoT via Hidden Alignment. In the second stage, we train the LLM to internalize its reasoning. Previously, the model has learned to reason explicitly over long-term interest sketches. The objective of reasoning internalization is to produce the final rating without generating intermediate CoT tokens, which reduces inference latency significantly. To this end, we adopt a hidden-alignment training strategy. We observe that, for a trained LLM $\mathcal{M}_\theta$ from previous stage, the final rating prediction under both answer-only (Fig. 1(c)) and CoT (Fig. 1(d)) decoding depends on the hidden state at the <answer> token. Consequently, if we align the answer-only hidden state to its CoT counterpart, the resulting predictions coincide while no CoT tokens are needed.

As shown in Fig. 2, let $\mathbf{h}^l_{\text{AO}}(q)$ denote the hidden state of the <answer> query token q at layer l of $\mathcal{M}_\theta$ when only the input prompt is provided, and let $\mathbf{h}^l_{\text{CoT}}(q)$ denote the corresponding hidden state when both the prompt and CoT are present. We fine-tune $\mathcal{M}_\theta$ with the hidden alignment loss:

$$\mathcal{L}_{align} \;=\; \frac{1}{L}\sum_{l=1}^{L}\Big(1 - \cos\big(\text{sg}[\mathbf{h}^l_{\text{CoT}}(q)], \mathbf{h}^l_{\text{AO}}(q)\,\big)\Big), \tag{12}$$

where L is the number of hidden layers IN $\mathcal{M}_\theta$ and $\text{sg}[\cdot]$ denotes the stop-gradient operator. At inference time, even without explicit CoT tokens, the model computes similar hidden states for <answer> and achieves rating-prediction quality comparable to explicit reasoning. In practice, we apply low-rank adaptation (LoRA) (Hu et al., 2022) to the key and value projection matrices of each attention layer, following our theoretical motivation presented below.

Theoretical Justifications. We analyze why hidden alignment enables internalized reasoning below.

Theorem 1 (KV Adaptation Equivalence). *Let q denote the answer-token query, Q the set of question prompt tokens, and Z the set of CoT reasoning tokens. For the l-th attention layer with key/value projections (W_K^l, W_V^l), define*

$$\mathbf{h}_{\mathrm{AO}}^l(q) \;=\; F^l\big([Q,q];[W_K^l,W_V^l]\big), \qquad \mathbf{h}_{\mathrm{CoT}}^l(q) \;=\; F^l\big([Q,Z,q];[W_K^l,W_V^l]\big),$$

where F^l returns the layer-l hidden state at q produced by a standard attention block followed by feed-forward network (FFN) block. Define the updated *answer-only hidden*

$$\tilde{\mathbf{h}}_{\mathrm{AO}}^l(q) \;:=\; F^l\big([Q,q];[W_K^l+\Delta W_K^l,\; W_V^l+\Delta W_V^l]\big).$$

Then, under a first-order (linearized) treatment of the attention and FFN at layer l, there exist updates $(\Delta W_K^l, \Delta W_V^l)$ such that

$$\tilde{\mathbf{h}}_{\mathrm{AO}}^l(q) \;=\; \mathbf{h}_{\mathrm{CoT}}^l(q).$$

This provides the motivational basis for our KV-targeted low-rank adaptation strategy for hidden alignment. The full proof is deferred to Appendix A.

4 Experiments

In this section, we conduct experiments to address the following research questions:

- **RQ1:** How does SIREN perform on rating prediction under compared with classic recommenders and recent LLM-based baselines?
- **RQ2:** What is the inference efficiency of SIREN versus LLM-based baselines?
- **RQ3:** Does our interest sketch improve accuracy over raw history and summary-based methods?
- **RQ4:** Does the internalize CoT via hidden alignment effectively bridge the gap between answer-only and CoT decoding?

4.1 Experiment Setup

Datasets and Baselines. We evaluate on the *Books* and *Movies* categories from the Amazon Reviews 2023 dataset[1]. Dataset statistics are reported in Table 1. The Books split follows (Kim et al., 2025); the Movies split is curated by taking the first 150k interactions from the Movies category of Amazon Reviews 2023. Following prior work (Kim et al., 2025; Bismay et al., 2025), we apply the 5-core filter, iteratively removing users and items with fewer than five interactions, and perform stratified sampling to keep positive (ratings ≥ 4) and negative (ratings ≤ 3) examples relatively balanced (Bismay et al., 2025). We adopt a *leave-last-out* split (Hou et al., 2024): for each user, the last two interactions are held out for validation and test, respectively, and the remainder are used for training.

Table 1: Dataset Statistics

Dataset	# Train	# Valid	# Test	# User	# Item
Book	94075	12222	11708	10440	9753
Movie	22097	2629	2629	2629	10874

We compare SIREN with 9 competitors in 3 categories. (i) Dataset Statistics (Kang et al., 2023), including *User Avg. Rating* and *Item Avg. Rating*. (ii) Traditional Recommendation Methods, including *Matrix Factorization (MF)* (Rendle et al., 2009) and *P5* (Geng et al., 2022). (iii) LLM-based Recommendation, including *LLM4Rate* (Kang et al., 2023) (using DeepSeek–R1 and Qwen3–4B as backends), respectively, *Rec-SAVOR* (Tsai et al., 2024b), *EXP3RT* (Kim et al., 2025). Details of these baselines and their implementations are provided in Appendix B.3.

Implementation Details and Evaluation Metrics. For SIREN and EXP3RT, we use Qwen3-4B (Yang et al., 2025) as the backend LLM. We use BGE-M3 (Chen et al., 2024a) as the text encoder, set number of corpus-level semantic topics $K = 20$, number of descriptions to generate topic name $M = 100$, threshold for separating likes/dislikes $\theta = 4$. For prompt construction, we include the most recent N user interactions, with $N = 30$ for the Books dataset and $N = 10$ for the Movies dataset. For explicit reasoning, we train with GRPO using the VERL framework (Sheng et al., 2024). Table 8 summarizes the key hyperparameters for each stage of our pipeline. Additional implementation details are in Appendix B. For rating prediction, we report *MAE* (Mean Average Error) and *RMSE* (Root Mean Squared Error) following (Chen et al., 2024b; Kim et al., 2025). Lower values indicate better performance for both metrics.

[1] https://amazon-reviews-2023.github.io/

Table 2: Overall performance for rating prediction in MAE(↓) and RMSE(↓). ↓ indicates lower values are better. **Bold**: best. Underline: runner-up.

Methods	Books		Movies		Rank
	MAE (↓)	**RMSE (↓)**	**MAE (↓)**	**RMSE (↓)**	
Dataset Statistics					
User Avg. Rating	0.4538	0.8396	0.9975	1.3419	5.25
Candidate Item Avg. Rating	0.5071	0.7567	1.5205	2.0683	7
Traditional Recommendation Methods					
MF	0.5740	0.7259	1.1604	1.3060	5.25
P5	0.5591	0.7939	0.8655	1.3406	4.75
LLM-based Recommendation					
LLM4Rate (DeepSeek-R1)	0.4509	0.8329	0.9222	1.4047	4.5
LLM4Rate (Qwen3-4B)	0.4730	0.8916	0.7995	1.4797	5.75
Rec-SAVOR	0.4893	0.8902	1.0884	1.5183	7.25
Exp3RT	0.4001	0.7567	0.9521	1.4646	4
SIREN	**0.3510**	**0.6887**	**0.7603**	**1.2924**	**1**

4.2 Overall Performance

Rating Prediction Accuracy (RQ1). Table 2 reports rating prediction results for SIREN and baselines. We summarize three observations. (1) SIREN achieves the best MAE and RMSE on both datasets, often by a large margin. For example, on Books, SIREN improves over the strongest LLM baseline, EXP3RT, by 12.27% in MAE and 8.99% in RMSE, indicating more accurate predictions with fewer large errors. (2) LLM-based methods generally outperform heuristic/statistical and traditional recommendation baselines in MAE, reflecting the benefit of leveraging item semantics. However, we observe weaker gains in RMSE, sometimes trailing MF. A closer look suggests label-imbalance bias (datasets skewed toward positive ratings) leads LLMs to over-predict high ratings (e.g., ≥ 4), which increases large-error penalties. By contrast, SIREN mitigates this via RL-based CoT training (GRPO) and subsequent internalization, improving robustness on minority low-rating cases. (3) Among LLM baselines, no single prior method dominates. Notably, EXP3RT, fine-tuned on CoT labels, does not consistently surpass LLM4Rate with zero-shot prompting, highlighting the importance of both user representation and training strategy. In contrast, SIREN 's consistent improvements stem from long-term interest sketching, which preserves comprehensive, noise-resilient preference signals under a strict token budget, and internalized reasoning, which retains CoT-quality prediction while decoding answer-only.

Inference Efficiency (RQ2). We compare average generated output tokens and per-sample inference latency (s) for SIREN with answer-only decoding (SIREN-AO), its explicit CoT variant from Stage 1 Sec. 3.2 (SIREN-CoT), and LLM-based competitors (EXP3RT, LLM4Rate). We use vLLM (Kwon et al., 2023) on a single H20 GPU with batch size 1. We set maximum output size as 1024 tokens and report per-sample inference latency (seconds) and the average number of generated output tokens, averaged over the full test set of each dataset. As shown in Fig. 3: (i) explicit reasoning emits hundreds of rationale tokens, whereas SIREN-AO generates a single answer token; (ii) accordingly, SIREN-AO incurs substantially lower latency (about 0.013 s/sample on both datasets), yielding over $100\times$ speedup. Together with the accuracy results in Table 2, these findings indicate that SIREN achieves state-of-the-art effectiveness and better efficiency for rating prediction.

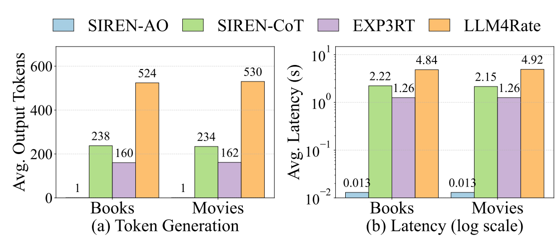


Figure 3: Comparison of LLM-based methods in average latency (s/sample) versus average number of generated output tokens (per sample).

4.3 In-depth Analysis

Study on Long-term Interests Sketching (RQ3). To examine the effectiveness of our proposed long-term interest sketch (Sec. 3.1), we compare different user modeling strategies for rating prediction.

We fine-tune the LLM with answer-only labels, and evaluate prompts constructed from: (i) the most recent N interactions (*Recent History*), (ii) recent history augmented with our proposed sketch (*+Sketch*), (iii) recent history extended with additional past interactions until reaching the token budget (*+More History*), and (iv) user profiles summarized by LLMs as in Kim et al. (2025) (*+Profile*). Table 3 shows that our sketch achieves consistent improvements over recent history, attaining the best performance except for one MAE case on Books where it ranks second. Adding more histories sometimes reduces MAE but degrades RMSE, suggesting that longer raw histories introduce noise that amplifies large errors. In contrast, LLM-generated profiles fail to improve upon recent history, highlighting the difficulty of off-the-shelf summarization in capturing key user preferences for accurate rating prediction.

Table 3: Comparison of performance under different user modeling designs.

Strategy	**Books**		**Movies**	
	MAE	**RMSE**	**MAE**	**RMSE**
Recent History	0.3547	0.7131	0.7775	1.3635
+Sketch (ours)	0.3536	**0.7114**	**0.7695**	**1.3556**
+More history	**0.3535**	0.7153	**0.7695**	1.3723
+Profile	0.3563	0.7244	0.7779	1.3872

Study on Internalized Reasoning (RQ4). We evaluate strategies for converting a GRPO-trained, explicit CoT model into answer-only (AO) inference. Starting from the model after Stage 1 (Sec. 3.2), we post-train it with: (i) *CE*: supervised fine-tuning on rating labels using cross-entropy loss; (ii) *KD*: logits-based knowledge distillation from the GRPO-CoT teacher (Hinton, 2014); (iii) *KD+CE*: joint distillation and cross-entropy; (iv) *HA*: our hidden alignment loss; (v) *HA+CE*: hidden alignment combined with cross-entropy. Fig. 4 summarizes results, with the GRPO-CoT reference shown as a red dashed line. Across Books and Movies, *HA* (ours) consistently yields the lowest error and closely tracks the GRPO-CoT teacher, indicating that aligning the hidden states effectively internalizes CoT into the model parameters while preserving accuracy under answer-only decoding. Interestingly, HA even surpasses the GRPO-CoT teacher in Books, likely because aligning hidden states transfers the rationale structure while avoiding the noise and variance of explicitly generating CoT tokens. In contrast, *HA+CE* underperforms *HA*, suggesting token-level CE pulls the model toward label-only fitting which conflicts with latent structure induced by CoT. KD-based variants remain behind HA, showing the benefit of aligning latent states over only matching output distributions.

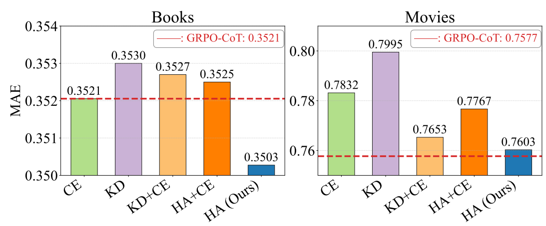


Figure 4: Comparison of strategies for internalizing CoT reasoning, with explicit GRPO-trained CoT shown as reference. Lower bar is better.

Effect of Different LoRA Target Modules. To internalize CoT into the model parameters, we apply LoRA adapters and train with the hidden-alignment loss in Eq. 12. Table 4 compares SIREN when adapting different target module sets: (i) *All-linear* (all linear projections), (ii) *QKV* (all attention projections), (iii) *QV* (query and value), and (iv) *FFN* (feed-forward layers only). Overall, adapting KV yields the best results on almost all datasets and metrics, while increasing the adaptation scope to all-linear does not consistently improve accuracy under the same training recipe. These findings align with Theorem 1, which motivates KV as a sufficient locus to absorb CoT effects, even though broader adaptation can sometimes be competitive.

Table 4: Different LoRA target modules.

Modules	Books		Movies	
	MAE	RMSE	MAE	RMSE
KV	**0.3503**	**0.6949**	0.7581	**1.2947**
all-linear	0.3505	0.6992	**0.7577**	1.2987
QKV	0.3505	0.6977	0.7581	1.2985
QV	0.3508	0.6971	0.7623	1.2851
FFN	0.3504	0.6979	0.7604	1.3073

Ablation Study. We conduct an ablation study that progressively incorporates our proposed designs. In Table 5, we begin with answer-only fine-tune LLM on the most recent history (*AO-SFT (Recent)*). Adding our proposed long-term interest sketch in Sec. 3.1(*AO-SFT (+Sketch)*) consistently reduces MAE while keeping latency nearly unchanged, confirming

Table 5: Ablation by MAE and inference latency (s/sample).

Method	**Books**		**Movies**	
	MAE (↓)	**Latency (↓)**	**MAE (↓)**	**Latency (↓)**
AO-SFT (Recent)	0.3547	**0.011**	0.7775	**0.012**
AO-SFT (+Sketch)	0.3536	0.013	0.7695	0.013
GRPO-CoT (+Sketch)	0.3521	2.22	**0.7577**	2.15
AO-HA (+Sketch)	**0.3510**	0.013	0.7603	0.013

the benefit of token-efficient user representation. Replacing answer-only supervision with GRPO training (Sec. 3.2) that enables explicit CoT reasoning (*GRPO-CoT (+Sketch)*) further improves MAE but incurs more than 200× higher latency due to autoregressive rationale generation. Finally, applying our hidden alignment (*AO-HA (+Sketch)*) internalizes the reasoning ability into model parameters, achieving the best MAE with answer-only latency. These highlight that long-term interest sketching improves representation, GRPO strengthens reasoning, and hidden alignment successfully bridges CoT accuracy with AO efficiency.

More Experiments. In Appendix B.4, we evaluate the influence of number of topics K in Fig. 5, effect of different hidden alignment distance function in Table 6, and qualitative analysis on GRPO-trained reasoning over the interest sketch in Table 7.

5 Related Work

LLMs-based Recommendation. Inspired by the success of LLMs across multiple domains (Achiam et al., 2023; Guo et al., 2025), researchers increasingly explore LLMs as end-to-end recommenders for rating prediction (Tsai et al., 2024a; Kim et al., 2025), sequential recommendation (Chen et al., 2024b; Zheng et al., 2024), and next-item prediction (Bao et al., 2024; 2025). Early work evaluates LLMs for rating prediction via prompt engineering (Achiam et al., 2023; Grattafiori et al., 2024), reporting promising performance, especially after fine-tuning (Kang et al., 2023), along with improved explainability and generalization (Liu et al., 2023). To further enhance preference modeling, recent studies leverage LLM reasoning for recommendation (Tsai et al., 2024b; Kim et al., 2025; Bismay et al., 2025). Rec-SAVOR (Tsai et al., 2024b) and ReasoningRec (Bismay et al., 2025) employ a stronger teacher LLM to generate rationales for user preferences, which are then used to fine-tune a smaller student model, improving recommendation accuracy and providing human-interpretable explanations. EXP3RT (Kim et al., 2025) uses a teacher LLM to generate user/item profiles and detailed step-by-step reasoning followed by a predicted rating; these outputs supervise student fine-tuning for inference. Unlike prior work, SIREN targets two key challenges in LLM-based rating prediction. First, instead of truncating histories (Tsai et al., 2024b; Bismay et al., 2025) or relying on free-form summaries (Kim et al., 2025), we introduce a token-budgeted interest sketch that preserves long-term preference signals while suppressing noise. Second, to mitigate the latency of explicit reasoning, we train the model to internalize CoT, enabling answer-only inference that achieves near-CoT quality with substantially lower latency.

Inference Acceleration for LLM-based Recommendation. Despite strong accuracy, LLMs face deployment challenges in recommendation due to the latency of autoregressive decoding (Lin et al., 2025; Xu et al., 2025). A common direction is knowledge distillation (KD), transferring knowledge from a large teacher to a smaller student to reduce parameters and speed up inference (Wang et al., 2024c; Xu et al., 2025). More recently, efficient reasoning strategies have been explored in recommendation: speculative decoding accelerates generation by drafting tokens with a lightweight model and verifying them with the target LLM (Lin et al., 2025), while latent reasoning replaces explicit rationales with a small set of latent token (Zhang et al., 2025). However, these approaches still rely on producing intermediate tokens, which introduces extra decoding steps. In contrast, SIREN eliminates rationale generation entirely by internalizing CoT into model parameters, enabling answer-only decoding while retaining the quality benefits of explicit reasoning.

6 Conclusion

We studied LLM-based rating prediction and addressed two practical challenges: long, noisy histories hinder an LLM's ability to reason about user preferences, and explicit CoT decoding incurs prohibitive inference latency. We introduced SIREN, a framework that addresses both issues. First, our proposed token-efficient long-term interest sketching compresses a user's history into a compact sketch that preserves persistent preferences while suppressing noise. Second, to enable efficient inference, we internalize reasoning via a two-stage procedure: the model is trained to reason explicitly with reinforcement learning, then aligned to produce answer-only outputs by transferring CoT effects into the parameters through hidden alignment. Extensive experiments show that SIREN improves accuracy under strict token budgets and achieves near-CoT quality at answer-only latency.

Reproducibility Statement

All results in this paper are fully reproducible. We release an anonymized repository at https://anonymous.4open.science/r/LLM4Rec-C7CF containing environment files, exact run scripts/configs, and data/preprocessing utilities. Experimental settings are summarized in Sec. 4.1, with additional details in Appendix **??**.

References

Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.

Keqin Bao, Jizhi Zhang, Yang Zhang, Xinyue Huo, Chong Chen, and Fuli Feng. Decoding matters: Addressing amplification bias and homogeneity issue in recommendations for large language models. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pp. 10540–10552, 2024.

Keqin Bao, Jizhi Zhang, Wenjie Wang, Yang Zhang, Zhengyi Yang, Yanchen Luo, Chong Chen, Fuli Feng, and Qi Tian. A bi-step grounding paradigm for large language models in recommendation systems. *ACM Transactions on Recommender Systems*, 3(4):1–27, 2025.

Millennium Bismay, Xiangjue Dong, and James Caverlee. Reasoningrec: Bridging personalized recommendations and human-interpretable explanations through llm reasoning. In *Findings of the Association for Computational Linguistics: NAACL 2025*, pp. 8132–8148, 2025.

Davide Castelvecchi. Ai models solve maths problems at level of top students. *Nature*, 644:7, 2025.

Jianxin Chang, Chenbin Zhang, Zhiyi Fu, Xiaoxue Zang, Lin Guan, Jing Lu, Yiqun Hui, Dewei Leng, Yanan Niu, Yang Song, et al. Twin: Two-stage interest network for lifelong user behavior modeling in ctr prediction at kuaishou. In *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pp. 3785–3794, 2023.

Jianlv Chen, Shitao Xiao, Peitian Zhang, Kun Luo, Defu Lian, and Zheng Liu. Bge m3-embedding: Multi-lingual, multi-functionality, multi-granularity text embeddings through self-knowledge distillation. *arXiv preprint arXiv:2402.03216*, 2024a.

Junyi Chen, Lu Chi, Bingyue Peng, and Zehuan Yuan. Hllm: Enhancing sequential recommendations via hierarchical large language models for item and user modeling. *arXiv preprint arXiv:2409.12740*, 2024b.

Heng-Tze Cheng, Levent Koc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, Hrishi Aradhye, Glen Anderson, Greg Corrado, Wei Chai, Mustafa Ispir, et al. Wide & deep learning for recommender systems. In *Proceedings of the 1st workshop on deep learning for recommender systems*, pp. 7–10, 2016.

Shijie Geng, Shuchang Liu, Zuohui Fu, Yingqiang Ge, and Yongfeng Zhang. Recommendation as language processing (rlp): A unified pretrain, personalized prompt & predict paradigm (p5). In *Proceedings of the 16th ACM conference on recommender systems*, pp. 299–315, 2022.

Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, et al. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*, 2024.

Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, et al. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *arXiv preprint arXiv:2501.12948*, 2025.

G Hinton. Distilling the knowledge in a neural network. In *Deep Learning and Representation Learning Workshop in Conjunction with NIPS*, 2014.

Yupeng Hou, Jiacheng Li, Zhankui He, An Yan, Xiusi Chen, and Julian McAuley. Bridging language and items for retrieval and recommendation. *arXiv preprint arXiv:2403.03952*, 2024.

Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, Weizhu Chen, et al. Lora: Low-rank adaptation of large language models. *ICLR*, 1(2):3, 2022.

Aaron Jaech, Adam Kalai, Adam Lerer, Adam Richardson, Ahmed El-Kishky, Aiden Low, Alec Helyar, Aleksander Madry, Alex Beutel, Alex Carney, et al. Openai o1 system card. *arXiv preprint arXiv:2412.16720*, 2024.

Carlos E Jimenez, John Yang, Alexander Wettig, Shunyu Yao, Kexin Pei, Ofir Press, and Karthik R Narasimhan. Swe-bench: Can language models resolve real-world github issues? In *ICLR*, 2024.

Wang-Cheng Kang, Jianmo Ni, Nikhil Mehta, Maheswaran Sathiamoorthy, Lichan Hong, Ed Chi, and Derek Zhiyuan Cheng. Do llms understand user preferences? evaluating llms on user rating prediction. *arXiv preprint arXiv:2305.06474*, 2023.

Jieyong Kim, Hyunseo Kim, Hyunjin Cho, SeongKu Kang, Buru Chang, Jinyoung Yeo, and Dongha Lee. driven personalized preference reasoning with large language models for recommendation. In *Proceedings of the 48th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pp. 1697–1706, 2025.

Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph E. Gonzalez, Hao Zhang, and Ion Stoica. Efficient memory management for large language model serving with pagedattention. In *Proceedings of the ACM SIGOPS 29th Symposium on Operating Systems Principles*, 2023.

Dongfang Li, Zhenyu Liu, Xinshuo Hu, Zetian Sun, Baotian Hu, and Min Zhang. In-context learning state vector with inner and momentum optimization. *Advances in Neural Information Processing Systems*, 37:7797–7820, 2024.

Xinyu Lin, Chaoqun Yang, Wenjie Wang, Yongqi Li, Cunxiao Du, Fuli Feng, See-Kiong Ng, and Tat-Seng Chua. Efficient inference for large language model-based generative recommendation. In *The Thirteenth International Conference on Learning Representations*, 2025.

Junling Liu, Chao Liu, Peilin Zhou, Renjie Lv, Kang Zhou, and Yan Zhang. Is chatgpt a good recommender? a preliminary study. *arXiv preprint arXiv:2304.10149*, 2023.

Hanjia Lyu, Song Jiang, Hanqing Zeng, Yinglong Xia, Qifan Wang, Si Zhang, Ren Chen, Chris Leung, Jiajie Tang, and Jiebo Luo. Llm-rec: Personalized recommendation via prompting large language models. In *Findings of the Association for Computational Linguistics: NAACL 2024*, pp. 583–612, 2024.

Steffen Rendle, Christoph Freudenthaler, Zeno Gantner, and Lars Schmidt-Thieme. Bpr: Bayesian personalized ranking from implicit feedback. In *Proceedings of the Twenty-Fifth Conference on Uncertainty in Artificial Intelligence*, pp. 452–461, 2009.

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.

Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang, Mingchuan Zhang, YK Li, Yang Wu, et al. Deepseekmath: Pushing the limits of mathematical reasoning in open language models. *arXiv preprint arXiv:2402.03300*, 2024.

Guangming Sheng, Chi Zhang, Zilingfeng Ye, Xibin Wu, Wang Zhang, Ru Zhang, Yanghua Peng, Haibin Lin, and Chuan Wu. Hybridflow: A flexible and efficient rlhf framework. *arXiv preprint arXiv: 2409.19256*, 2024.

Alicia Tsai, Adam Kraft, Long Jin, Chenwei Cai, Anahita Hosseini, Taibai Xu, Zemin Zhang, Lichan Hong, Ed Chi, and Xinyang Yi. Leveraging llm reasoning enhances personalized recommender systems. In *Findings of the Association for Computational Linguistics ACL 2024*, pp. 13176–13188, 2024a.

Alicia Tsai, Adam Kraft, Long Jin, Chenwei Cai, Anahita Hosseini, Taibai Xu, Zemin Zhang, Lichan Hong, Ed Chi, and Xinyang Yi. Leveraging llm reasoning enhances personalized recommender systems. In *Findings of the Association for Computational Linguistics ACL 2024*, pp. 13176–13188, 2024b.

Lu Wang, Di Zhang, Fangkai Yang, Pu Zhao, Jianfeng Liu, Yuefeng Zhan, Hao Sun, Qingwei Lin, Weiwei Deng, Dongmei Zhang, et al. Lettingo: Explore user profile generation for recommendation system. In *Proceedings of the 31st ACM SIGKDD Conference on Knowledge Discovery and Data Mining V. 2*, pp. 2985–2995, 2025.

Minzheng Wang, Longze Chen, Fu Cheng, Shengyi Liao, Xinghua Zhang, Bingli Wu, Haiyang Yu, Nan Xu, Lei Zhang, Run Luo, et al. Leave no document behind: Benchmarking long-context llms with extended multi-doc qa. In *EMNLP*, 2024a.

Qi Wang, Jindong Li, Shiqi Wang, Qianli Xing, Runliang Niu, He Kong, Rui Li, Guodong Long, Yi Chang, and Chengqi Zhang. Towards next-generation llm-based recommender systems: A survey and beyond. *arXiv preprint arXiv:2410.19744*, 2024b.

Yuling Wang, Changxin Tian, Binbin Hu, Yanhua Yu, Ziqi Liu, Zhiqiang Zhang, Jun Zhou, Liang Pang, and Xiao Wang. Can small language models be good reasoners for sequential recommendation? In *Proceedings of the ACM Web Conference 2024*, pp. 3876–3887, 2024c.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35:24824–24837, 2022.

Wujiang Xu, Qitian Wu, Zujie Liang, Jiaojiao Han, Xuying Ning, Yunxiao Shi, Wenfang Lin, and Yongfeng Zhang. Slmrec: Distilling large language models into small for sequential recommendation. In *ICLR*, 2025.

An Yang, Anfeng Li, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Gao, Chengen Huang, Chenxu Lv, et al. Qwen3 technical report. *arXiv preprint arXiv:2505.09388*, 2025.

Yang Zhang, Wenxin Xu, Xiaoyan Zhao, Wenjie Wang, Fuli Feng, Xiangnan He, and Tat-Seng Chua. Reinforced latent reasoning for llm-based recommendation. *arXiv preprint arXiv:2505.19092*, 2025.

Zhi Zheng, Wenshuo Chao, Zhaopeng Qiu, Hengshu Zhu, and Hui Xiong. Harnessing large language models for text-rich sequential recommendation. In *Proceedings of the ACM Web Conference 2024*, pp. 3207–3216, 2024.

Yuanhang Zou, Zhihao Ding, Jieming Shi, Shuting Guo, Chunchen Su, and Yafei Zhang. Embedx: A versatile, efficient and scalable platform to embed both graphs and high-dimensional sparse data. *Proceedings of the VLDB Endowment*, 16(12):3543–3556, 2023.

A Proof of Theorem 1

Proof. Consistent with previous works (Li et al., 2024), we omit the softmax operation and the scaling factor to approximate standard attention as relaxed linear attention for qualitative analysis. We instantiate the layer-l map by the linear attention form

$$F^l([X];[W_K^l,W_V^l]) \;=\; (XW_V^l)\,(XW_K^l)^\top\,Q_q^l,$$

where X is the token matrix at the layer input and Q_q^l is the layer-l query for token q.

CoT/AO difference reduces to a single additive term. Let X_Q and X_Z be the embeddings of the question tokens Q and the CoT tokens Z, respectively. Then

$$\begin{aligned}
\mathbf{h}^l_{\mathrm{AO}}(q) &= (X_QW_V^l)\,(X_QW_K^l)^\top\,Q_q^l,\\
\mathbf{h}^l_{\mathrm{CoT}}(q) &= \big([X_Q;X_Z]W_V^l\big)\,\big([X_Q;X_Z]W_K^l\big)^\top\,Q_q^l\\
&= (X_QW_V^l)\,(X_QW_K^l)^\top Q_q^l \;+\; (X_ZW_V^l)\,(X_ZW_K^l)^\top Q_q^l.
\end{aligned}$$

Hence the residual is

$$\Delta^\star(q) \;:=\; \mathbf{h}^l_{\mathrm{CoT}}(q)-\mathbf{h}^l_{\mathrm{AO}}(q) \;=\; (X_ZW_V^l)\,(X_ZW_K^l)^\top Q_q^l.$$

Exact equality via span containment. Consider answer-only with KV updates:

$$\tilde{\mathbf{h}}^l_{\mathrm{AO}}(q) = \big(X_Q(W_V^l+\Delta W_V^l)\big)\,\big(X_Q(W_K^l+\Delta W_K^l)\big)^\top Q_q^l.$$

Expanding to first order in $(\Delta W_V^l,\Delta W_K^l)$, the equality $\tilde{\mathbf{h}}^l_{\mathrm{AO}}(q)=\mathbf{h}^l_{\mathrm{CoT}}(q)$ requires

$$X_Q\Delta W_V^l\,(X_QW_K^l)^\top Q_q^l \;+\; X_QW_V^l\,(X_Q\Delta W_K^l)^\top Q_q^l \;=\; (X_ZW_V^l)\,(X_ZW_K^l)^\top Q_q^l.$$

Define $a:=(X_QW_K^l)^\top Q_q^l$ and $b:=X_Q^\top Q_q^l$. In the nondegenerate case $a\neq 0$ or $b\neq 0$, the set of attainable left-hand-side directions contains $\mathrm{Col}(X_Q)$. Consequently, the linear system is solvable iff

$$(X_ZW_V^l)\,(X_ZW_K^l)^\top Q_q^l \;\in\; \mathrm{Col}(X_Q).$$

The stronger span containments

$$\mathrm{Col}(X_ZW_V^l)\subseteq\mathrm{Col}(X_QW_V^l)\quad\text{and}\quad\mathrm{Col}(X_ZW_K^l)\subseteq\mathrm{Col}(X_QW_K^l)$$

are sufficient for solvability but not necessary.

General case (least-squares projection). When the span conditions fail, the least-squares problem

$$\min_{\Delta W_K^l,\Delta W_V^l}\Big\|X_Q\Delta W_V^l\,(X_QW_K^l)^\top Q_q^l + X_QW_V^l\,(X_Q\Delta W_K^l)^\top Q_q^l - \Delta^\star(q)\Big\|_2^2$$

has a solution that equals the orthogonal projection of $\Delta^\star(q)$ onto the subspace reachable by KV perturbations. This yields the claimed best (unconstrained) approximation. □

B Experiment

B.1 Implementation Details

Table 8 summarizes the key hyperparameters for each stage of our pipeline. Additional specifics are provided below.

GRPO Training. For GRPO training in Sec. 3.2, we use the VERL framework (Sheng et al., 2024). The configuration includes `max_prompt_length`=2046, `max_response_length`=512, constant learning rate 1×10^{-6}, KL loss coefficient 0.001, micro-batch size per GPU 32, rollout number 8, and training for 2 epochs.

Hidden Alignment Training. For hidden alignment in Sec. 3.2, we build on TRL[2]. We fine-tune the model with parameter-efficient fine-tuning via LoRA, applied to the key and value projections of each attention layer. LoRA hyperparameters are set to $r = 8$, `lora_alpha`=16, and `lora_dropout`=0.05. Training uses DeepSpeed ZeRO Stage-2 for memory-efficient distributed optimization. We adopt AdamW with learning rate 1×10^{-4}, constant schedule with 100 warmup steps, and train for 3 epochs with batch size 64 on $8\times$ H20 GPUs.

Latency Evaluation. For the latency study in Fig. 3, we use vLLM (Kwon et al., 2023) on a single H20 GPU with batch size 1. We set `max_response_length` as 1024 tokens and report per-sample inference latency (seconds) and the average number of generated output tokens, averaged over the full test set of each dataset.

B.2 Motivational Experiment Setup

For the introduction experiment, we evaluate Qwen3–4B without post-training on the *Books* split. We adopt the LLM4Rate prompt (Kang et al., 2023) to instruct the model to perform rating prediction from user history and candidate metadata, and measure performance while varying the maximum history length.

B.3 Baselines

We provide more descriptions and implementation details of the baselines in Sec. 4.

- **MF** (Rendle et al., 2009). A representative latent–factor collaborative filtering method for rating prediction based solely on user–item interactions. We use the Surprise Python library[3] for implementation and tune standard hyperparameters on the validation set.
- **P5** (Geng et al., 2022). A foundation model for recommendation. P5 unifies diverse recommendation tasks by converting user–item interactions, item metadata, and user reviews into natural language sequences and training with a language modeling objective. We adopt the official implementation[4] and fine-tune a T5 backbone for the rating-prediction task using the authors' prompt format.
- **LLM4Rate** (Kang et al., 2023). Prompt-based rating prediction with off-the-shelf LLMs. The prompt includes the user's recent history (item titles, genres, ratings) and the candidate item's title and genres. In our setup, we evaluate DeepSeek-R1 and Qwen3-4B without fine-tuning, instructing the model to generate a rationale followed by a rating. The number of recent interactions follows our main setting ($N = 30$ for Books, $N = 10$ for Movies).
- **Rec-SAVOR** (Tsai et al., 2024b). Uses an off-the-shelf LLM to produce a rationale and final rating from a compact window of recent interactions. Following the original design, we use at most 10 recent items and include rich item fields (title, description, categories, price) together with the corresponding user review. We adopt the authors' prompt template and use DeepSeek-R1 as the backbone LLM.
- **EXP3RT** (Kim et al., 2025). Leverages user reviews to build profiles and distill reasoning. A teacher LLM first extracts preference signals from each review and summarizes user and item profiles; it then generates step-by-step rationales and target ratings conditioned on these profiles. The resulting pairs supervise a smaller student LLM. We use the official code release[5]. Following their setup, we use DeepSeek-R1 to generate preferences/profiles/rationales and fine-tune Qwen3-4B as the student, matching our backbone in SIREN. Because their profiles include average-rating statistics, we compute such statistics only on the training split.

B.4 More Experimental Results

Influence of the number of topics K. We study how the number of corpus-level topics (K) in the interest sketch affects performance. As shown in Fig. 5, we vary $K \in \{10, 20, 30, 40, 50\}$ on Books

[2] https://huggingface.co/docs/trl/v0.19.1/en/sft_trainer
[3] https://surpriselib.com/
[4] https://github.com/jeykigung/P5
[5] https://github.com/jieyong99/EXP3RT

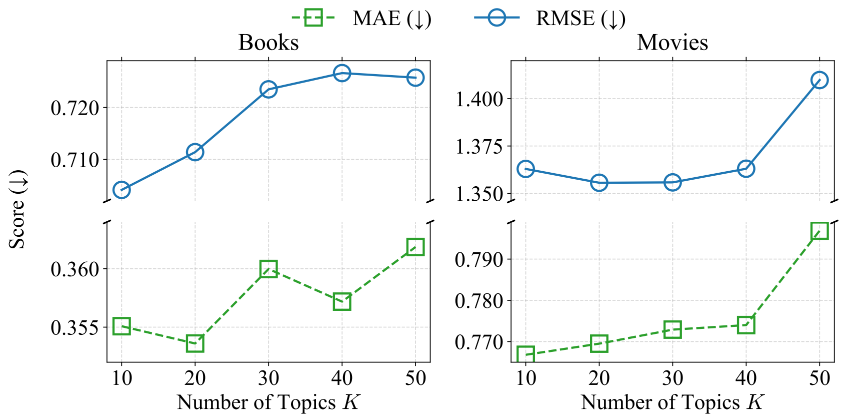


Figure 5: Performance of SIREN when varying number of topics K.

Table 6: Performance of loss function used in Eq. 12.

Method	Books		Movies	
	MAE	RMSE	MAE	RMSE
answer-only SFT	0.3527	0.7214	0.7695	1.3556
GRPO	0.3521	0.6962	0.7577	1.2822
Cosine	**0.3503**	**0.6930**	**0.7603**	**1.2924**
MAE	<u>0.3523</u>	<u>0.6937</u>	0.7687	1.3001
MSE	0.3528	0.6940	<u>0.7679</u>	<u>1.2939</u>

and Movies and report MAE/RMSE. SIREN performs best with smaller K (e.g., 10–20). Because each dataset is already category-homogeneous (books or movies), large K fragments items into overly fine-grained topics that capture trivial distinctions, weakening preference modeling and risking overfitting. Balancing accuracy and stability across datasets, we set K! =!20 for the main experiments to avoid excessive hyperparameter search while remaining within the empirically favorable range.

Effect of Different Hidden Alignment Distance Function. In the hidden alignment loss Eq. 12, we default to $1-\cos$ similarity to measure the distance between hidden states of CoT and AO. Here, we evaluate alternative distance measures, including mean absolute error (MAE) and mean squared error (MSE). Results are reported in Table 6, with AO-SFT and GRPO-CoT included for reference. We observe that cosine consistently achieves the best performance, suggesting that preserving directional information is more important than matching absolute magnitudes when aligning hidden states.

C GRPO Details

Group Relative Policy Optimization (GRPO) (Shao et al., 2024) is a reinforcement learning algorithm designed to activate LLM reasoning without relying on ground-truth chain-of-thought (CoT) labels. Unlike RL algorithms like PPO (Schulman et al., 2017), which estimates the advantage using a learned value function, GRPO computes advantages in a group-relative manner. Specifically, for each input (q, a), the old policy $\pi_{\theta_{\text{old}}}$ samples a group of G candidate responses $\{o_i\}_{i=1}^{G}$. Each response receives a rule-based reward R_i (e.g., correctness of the final rating). The normalized group-relative advantage for the i-th response is:

$$\hat{A}_{i,t} = \frac{R_i - \text{mean}(\{R_j\}_{j=1}^{G})}{\text{std}(\{R_j\}_{j=1}^{G})}. \tag{13}$$

The policy is then optimized using a clipped objective similar to PPO, with an additional KL regularization term to control deviation from the reference policy π_{ref}:

$$\mathcal{J}_{\text{GRPO}}(\theta) = \mathbb{E}\left[\frac{1}{G}\sum_{i=1}^{G}\frac{1}{|o_i|}\sum_{t=1}^{|o_i|}\min\left(r_{i,t}(\theta)\hat{A}_{i,t},\ \text{clip}(r_{i,t}(\theta), 1-\varepsilon, 1+\varepsilon)\hat{A}_{i,t}\right) - \beta D_{\text{KL}}(\pi_\theta \,\|\, \pi_{\text{ref}})\right], \tag{14}$$

where $r_{i,t}(\theta)$ is the importance ratio between the current and old policies. GRPO thus leverages group-relative normalization to avoid reward hacking and removes the dependency on a value function.

In our setting, GRPO trains LLMs to produce explicit reasoning (CoT) for rating prediction, with a combination of format reward and rating regression reward as overall reward. This provides a foundation for our internalized reasoning stage, where we align hidden states to enable answer-only inference.

Qualitative analysis of GRPO-trained reasoning over the interest sketch. We examine how GRPO enables explicit CoT reasoning over the sketch prompt. Table 7 shows a Movies test case. The model (i) grounds its rationale in the likes/dislikes sketch (e.g., leveraging “military conflict & combatant perspectives”), (ii) cross-checks the candidate against recent interactions (aligning *Godzilla* with the user’s high rating on *Rogue One*), and (iii) produces a clean <think>... </think> rationale followed by a numeric prediction between <answer>... </answer>. This illustrates that GRPO-trained CoT can make good leverage of interest sketch to filter noise, highlight stable preferences, and yield interpretable alignment between evidence and prediction.

D PROMPTS

Fig. 6 shows the CoT prompt template used for rating prediction during GRPO training (Sec. 3.2). Fig. 7 presents the prompt for summarizing cluster k (constructed from the M items nearest to $\boldsymbol{\mu}_k$) into a concise topic name τ_k.

E LLM USAGE

We used a large language model solely for language polishing (grammar, phrasing, and copy-editing). It did not contribute to research ideation, experiment design, implementation, data analysis, or the creation of technical content (e.g., equations, algorithms, or results). All scientific claims, datasets, code, and citations were produced and verified by the authors, who take full responsibility for the content.

GRPO Rating-Prediction Prompt

[SYSTEM PROMPT]
You are an intelligent recommender system assistant. Your task is to predict the rating (from 1.0 to 5.0) that a user will give to a candidate **{category}**, based on the user's past behavior and preferences.

You should first reason about how well the candidate item aligns with the user's historical preferences, and then output a predicted rating. Your reasoning and the final rating must be wrapped with <think> </think> and <answer> </answer> tags, respectively.

The final rating must be a numeric value between 1.0 and 5.0. Do not include any extra explanation after the <answer> tag.

[PROMPT TEMPLATE]

The user's long-term interest sketch is:

{long-term user sketch}

Below are the user's recent **{category}** ratings in the format: Title, Genres, Rating. Ratings range from 1.0 to 5.0.

{N most recent interactions}

The candidate **{category}** is described as: **{candidate item description}**

Based on the above information, what rating will the user give?

Figure 6: CoT prompt template used for rating prediction during GRPO training.

Cluster Topic Name (τ_k) Generation Prompt

[SYSTEM PROMPT]
You are an expert taxonomy editor. Given a set of **{M}** **{category}** entries representing items nearest to the cluster center μ_k, produce a single concise topic name τ_k that best summarizes their shared theme.

[INSTRUCTIONS]
Analyze the implicit commonalities across the provided **{category}** entries (title, tags, brief description). Focus on high-level semantics, not surface details.

[CONSTRAINTS]
- Output a single short phrase ($\leq$ 10 words).
- Use concise, abstract language (no full sentences).
- Do **not** list specific titles or examples.
- **Output format:** `Theme: <concise phrase>`

[INPUT for cluster k]
Nearest-to-center items (M = **{M}**; center μ_k):
{center_searches}

Figure 7: Prompt used to summarize cluster k (nearest M items to μ_k) into a concise topic name τ_k.

Table 7: Qualitative example on GRPO-trained reasoning over the interest sketch.

Prompt

[SYSTEM]
You are an intelligent recommender system assistant. Your task is to predict the rating (from 1.0 to 5.0) that a user will give to a candidate movie, based on the user's past behavior and preferences.
You should first reason about how well the candidate item aligns with the user's historical preferences, and then output a predicted rating. Your reasoning and the final rating must be wrapped with `<think> </think>` and `<answer> </answer>` tags, respectively. The final rating must be numeric in $[1.0, 5.0]$. Do not include any extra explanation after the `<answer>` tag.

[USER: Sketch]
Likes (ratings ≥ 4*):* Military Conflict & Combatant Perspectives
Dislikes (ratings ≤ 3*):* Crime-solving with ethical ambiguity; Secrets & emotional turmoil in relationships

[USER: Recent ratings (Title, Genres, Rating)]
```
Superman:  The Animated Series, Volume 3 (DC Comics Classic Collection),
Movies & TV|Today's Deals|Featured Deals & New Releases|The Big DVD &
Blu-ray Blowout, 2
Romancing the Stone (Special Edition), Movies & TV|Fully Loaded
DVDs|Special Editions, 3
ROGUE ONE: A STAR WARS STORY, Movies & TV|Science Fiction &
Fantasy|Science Fiction|Star Wars, 5
```
[USER: Candidate item]
```
Godzilla:  King of the Monsters Special Edition (DVD), Movies & TV|Fully
Loaded DVDs|Special Editions
```

Model Output

`<think>`
Okay, let's see. The user has specific preferences and dislikes. They like military conflict and combatant perspectives, which means they probably enjoy action-packed, maybe war-related or heroic stories. They dislike crime-solving with ethical issues and secrets in relationships, so maybe they don't like complex moral dilemmas or emotional drama.
Looking at their recent ratings: Superman: The Animated Series got a 2, which is a bit low. That's a superhero movie, so maybe they like some action but not the animated style? Romancing the Stone is a 3, which is a romantic thriller. They might not like that much. Rogue One, a Star Wars movie, got a 5, so they like sci-fi, especially from Star Wars. The candidate movie is Godzilla: King of the Monsters Special Edition. That's a sci-fi monster movie with action elements. Godzilla films often have a lot of action and are set in a post-war context, which might align with their preference for military conflict. The user liked Rogue One, which is also a high-action sci-fi. The Special Edition DVD might be a plus since they liked the Special Edition of Romancing the Stone. Considering their dislike for crime-solving and emotional issues, Godzilla's more about action and less about complex relationships, so it should fit. The rating is likely a 5.
`</think>`

`<answer>`**5.0**`</answer>`

Table 8: Hyper-parameter (HP) settings of our method on each dataset. Shared values are repeated for completeness.

HP	**Books**	**Movies**
Backbone & Encoders		
Backbone LLM	Qwen3-4B	Qwen3-4B
Text encoder	BGE-M3	BGE-M3
Sketch & Prompt Construction		
Topics (K)	20	20
Topic naming (M)	100	100
Like/Dislike threshold (θ)	4	4
Recent history length (N)	30	10
GRPO Training (Explicit Reasoning)		
Framework	VERL	VERL
max_prompt_length	2046	2046
max_response_length	512	512
learning_rate	1×10^{-6}	1×10^{-6}
KL coefficient	0.001	0.001
micro_batch_size_per_GPU	32	32
rollouts	8	8
epochs	2	2
Hidden Alignment		
Target modules	K, V	K, V
LoRA rank (r)	8	8
lora_alpha	16	16
lora_dropout	0.05	0.05
optimizer	AdamW	AdamW
learning_rate	1×10^{-4}	1×10^{-4}
schedule	constant	constant
warmup_steps	100	100
batch_size (global)	64	64
epochs	3	3
distributed setup	DeepSpeed ZeRO-2	DeepSpeed ZeRO-2
hardware	8× H20 GPUs	8× H20 GPUs
Latency Evaluation (Inference)		
engine	vLLM	vLLM
hardware	single H20	single H20
batch size	1	1
max_response_length	1024	1024