GOT4Rec: Graph of Thoughts for Sequential Recommendation

Anonymous submission

Abstract

With the advancement of large language models (LLMs), researchers have explored various methods to optimally leverage their comprehension and generation capabilities in sequential recommendation scenarios. However, several challenges persist in this endeavor. Firstly, most existing approaches rely on the input-output prompting paradigm, which can result in irrelevant or inaccurate responses. Secondly, while there have been attempts to enhance LLMs using prompting strategies such as chain-of-thought (CoT), these efforts have not fully harnessed the reasoning abilities of LLMs or effectively captured the multifaceted information contained within user sequences. To address these limitations, we propose GOT4Rec, a sequential recommendation method that utilizes the graph of thoughts (GoT) prompting strategy. Specifically, we identify and utilize three key types of information within user history sequences: short-term interests, long-term interests and collaborative information from other users. Our approach enables LLMs to independently reason and generate recommendations based on these distinct types of information, subsequently aggregating the results within the GoT framework to derive the final recommended items. This method allows LLMs, with enhanced reasoning capabilities, to more effectively consider the diverse information within user sequences, resulting in more accurate recommendations and more comprehensive explanations. Extensive experiments on real-world datasets demonstrate the effectiveness of GOT4Rec, indicating that it outperforms existing state-of-the-art baselines. Our code is available at https://anonymous.4open.science/r/GOT4Rec-ED99.

1 Introduction

Sequential recommendation has long been a significant research field, with numerous methods proposed to explore chronological dependencies within user sequences (Kang and McAuley 2018; Zhou et al. 2020). Despite considerable advancements, they remain constrained by the limited knowledge available from datasets. To overcome this, it is crucial to integrate real-world knowledge into sequential recommendation models, enabling them to more effectively comprehend and reason about preference patterns within user behavior sequences (Hou et al. 2022; Li et al. 2023a).

Recently, large language models (LLMs) have garnered significant attention due to their impressive natural language comprehension and generation abilities. Consequently, numerous LLM-based sequential recommendation works (Xi et al. 2023; Sanner et al. 2023; Hou et al. 2024b) have emerged to exploit these capabilities, aiming to capture user interests from interaction sequences and leverage LLMs' extensive real-world knowledge for recommendations. However, many of these approaches rely solely on the input-output (IO) prompting paradigm, underutilizing LLMs' reasoning abilities. This limitation arises from a disconnect between the real-world knowledge embedded in LLMs and the specific needs of recommender systems, often resulting in task-irrelevant or inaccurate outcomes. To address this, several studies have incorporated advanced prompting strategies to enhance LLMs' performance in sequential recommendation. Among these is SLIM (Wang et al. 2024), a knowledge distillation module which employs chain-of-thought (CoT) (Wei et al. 2022) prompting to enable step-by-step reasoning in sequential recommendation, transferring knowledge from a teacher model to a student model. However, it treats the user sequence as a monolithic entity and only taps into the elementary reasoning abilities of LLMs, insufficient for adequately reasoning through the diverse preference information (e.g., long-term and short-term interests, spatio-temporal factors) within user sequences.

Overall, there are two major challenges that limit the effectiveness of LLMs in the sequential recommendation scenario. *The first challenge is the difficulty in explicitly capturing various user preference information by merely prompting the behavior sequence.* Traditional neural sequential recommenders have been actively extracting and fusing different types of information as features to predict the next item in the sequence. In contrast, current LLM-based sequential recommenders often perform minimal processing of the sequence itself, simply placing the entire sequence directly into the prompt. This approach can easily mislead the model, leading to inaccurate recommendations. For instance, in Figure 1, the items predicted by SLIM consist solely of snack bars, while the ground truth is a fruit nut mix product. *The second challenge arises from the complexity introduced by incorporating multiple types of information, which transforms sequential recommendation into a complex reasoning task involving multiple sub-problems, necessitating LLMs with enhanced reasoning capabilities.* Existing researches have demonstrated that simple reasoning approaches, such as IO and CoT, are insufficient for such tasks (Besta et al. 2024; Yang et al. 2024). In contrast, the graph of thoughts

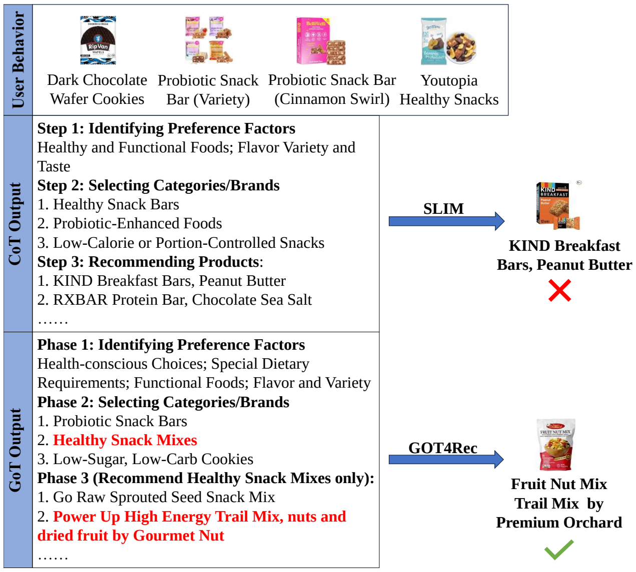

Figure 1: Comparison of the LLM output and predictions for the next item generated by SLIM (Wang et al. 2024) and our proposed GOT4Rec.

(GoT) method offers a more effective solution by decomposing the problem into more manageable components. Unlike CoT, which employs a single chain of thought, GoT models the reasoning process through networked reasoning. This approach allows GoT to break down complex reasoning tasks into smaller, more tractable sub-tasks, solve them individually, and then integrate the results to form a comprehensive solution. In Figure 1, we illustrate how GoT is employed to reason about three categories of products (i.e., “Probiotic Snack Bars”, “Healthy Snack Mixes” and “Low-Sugar, Low-Carb Cookies”) that the user might be interested in, enabling the LLM to independently recommend items within these categories and combine them in the end. In contrast, SLIM’s reasoning remains focused on snack bars.

To address the challenges mentioned above, this paper proposes GOT4Rec, a novel method that introduces the graph of thoughts (GoT) framework into the field of sequential recommendation. GOT4Rec optimally harnesses the reasoning capabilities of LLMs while effectively integrating multiple sources of information from user sequences. Specifically, we employ the GoT prompting strategy to extract three critical sources of information from user sequences: short-term interests, long-term interests, and collaborative interests from other users with similar preferences. Unlike previous methods that treat the sequence as a whole,our approach considers multiple aspects of information and better utilizes the reasoning abilities of LLMs, leading to more accurate and interpretable recommendations. Our key contributions can be summarized as follows:

- To the best of our knowledge, we are the first to apply the graph of thoughts framework within the field of sequential recommendation.
- We introduce GOT4Rec, a method that optimally leverages the reasoning capabilities of large language models (LLMs) to comprehensively capture and utilize the rich information embedded within user sequences.
- Extensive experiments conducted on three datasets demonstrate that our method outperforms traditional neural sequential models and other prompting strategies.

2 Related Work

2.1 Traditional Neural Sequential Recommenders

Traditional neural sequential recommendation systems aim to capture sequential dependencies in user behavior sequences to model dynamic user preferences, as seen in methods like GRU4Rec (Hidasi et al. 2016). As deep learning develops, techniques like self-attention and graph neural networks have become foundational in sequential recommenders (Kang and McAuley 2018; Zhou et al. 2020; Wu et al. 2019; Zhang et al. 2022, 2023). These methods however, predominantly rely on sequence modeling capabilities and often inadequately incorporate textual information. Recently, research on transferable item representations (Hou et al. 2022; Li et al. 2023a) has gained attention. Despite their promise, these approaches remain constrained by limited datasets and fail to fully leverage real-world knowledge.

2.2 LLM-Based Sequential Recommenders

With the advent of LLMs, numerous research endeavors have explored leveraging their advanced language comprehension and generation abilities. LLMs can be integrated either as feature enhancers (Xi et al. 2023; Lin et al. 2024; Liu et al. 2024) or rankers/scorers (Dai et al. 2023; Harte et al. 2023; Li et al. 2023b; Sanner et al. 2023; Hou et al. 2024b). For example, ReLLa (Lin et al. 2024) employs semantic user behavior retrieval to improve data quality and introduces retrieval-enhanced instruction tuning to enhance few-shot recommendation. LLMRank (Hou et al. 2024b) formalizes the recommendation problem as a conditional ranking task and utilizes LLMs as zero-short rankers. Although these approaches are promising, existing research has not yet fully capitalized on the reasoning capabilities of LLMs.

2.3 LLM Prompting Strategies

Numerous prompting approaches have been proposed to exploit the reasoning capabilities of LLMs. Chain-of-thought (CoT) (Wei et al. 2022) introduces intermediate reasoning steps to enhance LLM performance, while Chain of Thought with Self-Consistency (CoT-SC) (Wang et al. 2023) refines this by generating multiple CoTs and selecting the best output. Tree of thoughts (ToT) (Yao et al. 2024) and graph of thoughts (GoT) (Besta et al. 2024) further extend these methods by modeling reasoning as a tree or graph, respectively, to better generate and aggregate different thoughts. In the recommendation domain, SLIM (Wang et al. 2024) utilizes a CoT-based knowledge distillation module to transfer the step-by-step reasoning capabilities from a teacher model to a student model. However, its reliance on basic CoT prompting limits its ability to fully capture the abundant information within user sequences.

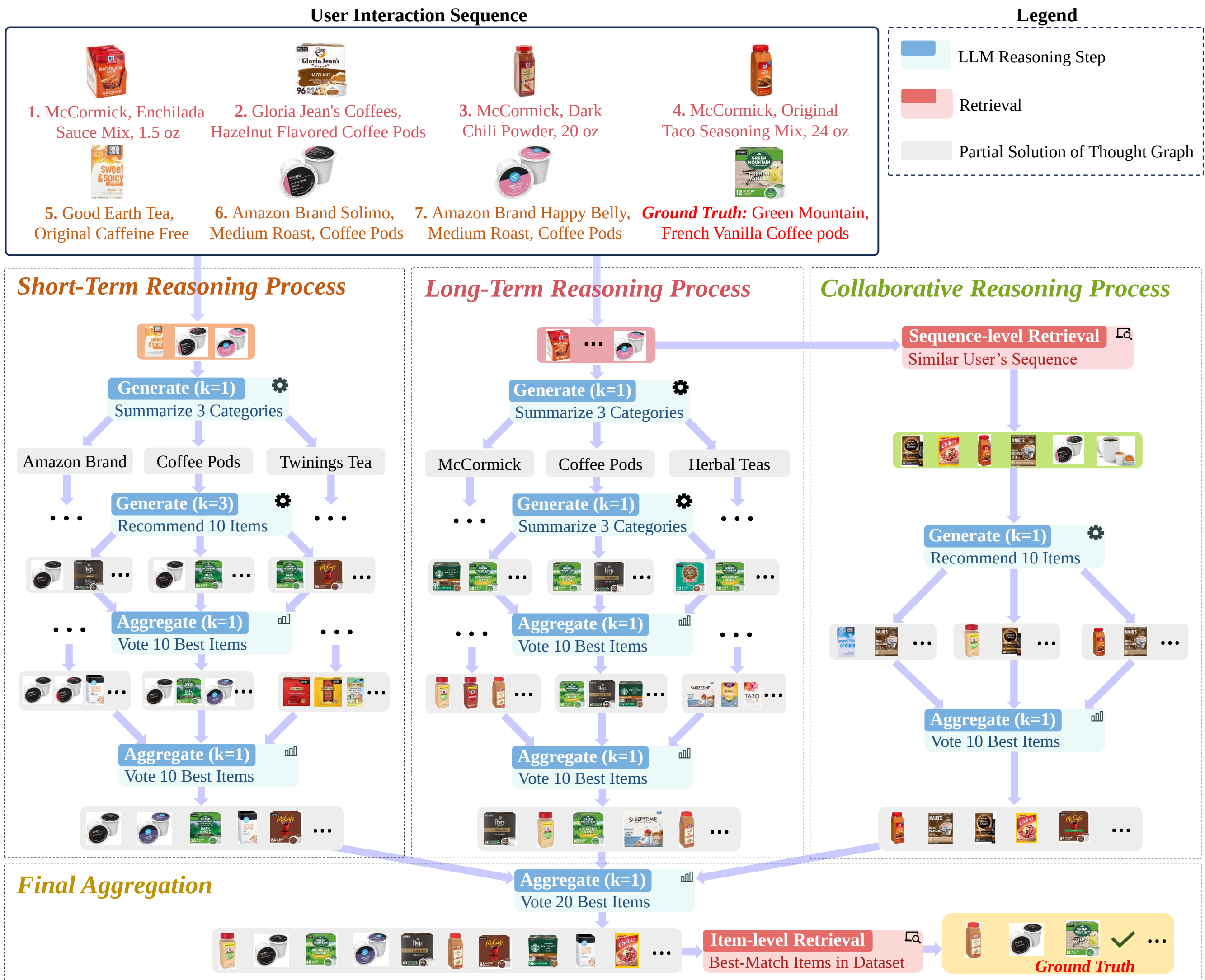

Figure 2: An example of graph decomposition in the proposed GOT4Rec method. The user interaction sequence is divided to facilitate different types of reasoning: the last few items are used for short-term preference reasoning, while the entire sequence informs long-term preference reasoning. Additionally, sequences from similar users are retrieved for collaborative reasoning. In the thought graph, these distinct thoughts are generated and subsequently aggregated to capture and integrate the various aspects of information within the user interaction sequence.

3 The Proposed GOT4Rec Method

In this section, we introduce GOT4Rec, a sequential recommendation method that fully leverages the reasoning capabilities of LLMs to capture the diverse information within user sequences. In the context of sequential recommendation, given a user u's historical interaction sequence $S_u = \{i_1, i_2, ..., i_{n-1}\}$, the task is to predict the next item i_n that the user is most likely to interact with.

3.1 Overview of Thought Graph

When interacting with LLMs, we input messages (prompts) and LLMs respond with generated outputs (thoughts). Building on the GoT framework (Besta et al. 2024), we model our GOT4Rec method as a tuple (G, T), where G represents the reasoning process and T denotes the thought transformations. Specifically, we model the reasoning process as a directed graph $G = (V, E)$, where V is the set of vertices and $E \subseteq V \times V$ is the set of edges. Each vertex represents a thought, encapsulating a solution to the current recommendation step along with other relevant global information. A directed edge (t_1, t_2) signifies a dependency between thoughts, indicating that thought t_2 is generated by LLMs based on t_1.

In our method, we employ the generation transformation T_G and aggregation transformation T_A from the GoT framework. The generation transformation generates one or more new thoughts based on an existing single thought v.

Summarizing Prompt: To summarize categories/brands that the user prefers.

I've purchased the following products in the past in order: <**Item Sequence**>, Please help me do the following things:
Step 1: Could you help me identify the key factors that influence my choice of products by analyzing my purchase history (summarize my preferences briefly)? Let's work this out in a step by step way to be sure we have the right answer.
Step 2. Could you help me select three product **Categories** or **Brands** that appeal to me the most based on my personal preferences?
In step 2, please recommend the categories or brands directly and split these output with a line break (Format: no. a product category or brand).

Recommendation Prompt: To recommend items for user.

I've purchased the following products in the past in order: <**Item Sequence**>. Based on my purchase history, your task is to recommend 10 products from Amazon that best fit the <**Category/Brand**>. Please only generate the name of the products and split these output with a line break (Format: no. a product, Example: 1. a product).

Collaboration Prompt: Recommend items based on other user's sequence.

I've purchased the following products in the past in order: <**Item Sequence**>. There are several users who share the same interests with me, please help me do the following things :
Step 1: Could you help me identify the key factors that influence our choice of products by analyzing the purchase history of me and the other users(summarize our preferences briefly)? Let's work this out in a step by step way to be sure we have the right answer.
Step 2: Based on our purchase history, your task is to recommend 10 products from Amazon that best fit our interests, you can choose products from other users' purchase histories.
In step 2, please only generate the name of the products and split these output with a line break (Format: no. a product). The purchase history of other users are as follows: <***S_co***> .

Voting Prompt: Let LLM vote for the best items.

I've purchased the following products in the past in order: <**Item Sequence**>. Given a set of products, your task is to vote 10 best products in the set that best fit my purchase history. Here is the set of products:<**Recommended Items**>.

Figure 3: Prompt templates, including summarizing, recommendation, collaboration and voting prompts.

In this operation, new vertices and edges are generated: $V_+ = \{v_{1+}, ..., v_{k+}\}$ and $E_+ = \{(v, v_{1+}), ..., (v, v_{k+})\}$, where $v_{1+}, ..., v_{k+}$ are the new thoughts generated by v. Analogous reasoning steps such as CoT can be incorporated into this process. The aggregation transformation, on the other hand, combines multiple thoughts into a new, consolidated thought, reinforcing their strengths while mitigating their weaknesses. In this operation, a new vertex v_+ is created: $V_+ = \{v_+\}$ and $E_+ = \{(v_1, v_+), ..., (v_k, v_+)\}$, where $v_1, ..., v_k$ are the aggregated thoughts.

Figure 2 provides an example of graph decomposition in our GOT4Rec method. In the recommendation pipeline, the current user's interaction sequence S_u is utilized as input. We then generate three key aspects of user preference information: short-term preference, long-term preference and collaborative preference, with detailed definitions provided in the subsequent subsection. With these preference information, the LLMs are enabled to reason and generate a list of top-N items that best align with the user's current interests. Finally, these items are aggregated, and the LLMs vote to select the most probable items for recommendation.

3.2 Short-Term Reasoning Process

Numerous studies have emphasized the importance of understanding both a user's dynamic short-term and stable long-term preferences in recommendation systems (Yu et al. 2019; Zheng et al. 2022). In our GOT4Rec method, we enable LLMs to extract these two types of preferences separately and then synergize the most relevant aspects of each.

To reason about short-term preferences, we select the last few interactions from the user sequence S_u as S_{short}. We then apply and enhance the zero-shot CoT prompting strategy from (Wang et al. 2024) within the generation transformation T_G to effectively capture the user's short-term preferences and identify three categories that the user is likely to favor. As illustrated in Figure 3 as summarizing prompt, the generation transformation T_G involves two key steps:

- Step 1. Summarize user's short-term preferences based on the given S_{short}.
- Step 2. Based on the preferences in step 1, summarize three categories of products the user is inclined to prefer.

For each identified category, we prompt the LLMs to generate N items the user is most likely interested in, repeating this process three times. The prompt template is provided in Figure 3 as recommendation prompt. After generating the item sets, we utilize the aggregation transformation T_A, where the three item sets undergo a voting process by the LLMs. This results in a new set of N items that are most likely to interest the user within each category. After aggergation, we have three final item sets, which are subjected to a final round of voting by the LLMs to determine the top-N items I_{short} that best represent the user's short-term preferences. The voting prompt is also provided in Figure 3.

3.3 Long-Term Reasoning Process

To capture long-term preferences, we extend the input to include the entire user interaction sequence. Similar to the short-term reasoning process, we employ the zero-short CoT prompting strategy within the generation transformation T_G, as shown in Figure 3. This allows LLMs to effectively differentiate and identify short-term and long-term preferences. After generating the relevant items, the final set of top-N items I_{long}, representing the user's long-term preferences, is determined through the aggregation transformation T_A.

3.4 Collaborative Reasoning Process

Collaborative filtering is widely used in various recommendation scenarios (Koren, Rendle, and Bell 2021), modeling users' preference based on their past interactions. In our method, we leverage the all-mpnet-base-v2 (Reimers and Gurevych 2020), a sentence-transformers model that maps sentences to a vector space, to generate an embedding vector for the current user's interaction sequence, allowing us to retrieve a set of sequences S_{co} from other users most similar to the current user's sequence. Details of this retrieval process are provided in the following section.

Once we have obtained the similar user sequences S_{co}, we employ the zero-short CoT prompting strategy to generate three sets of top-N items that the current user may be interested in. The two-step generation prompts, illustrated in Figure 3 as collaboration prompt, are as follows:

- Step 1. Summarize the shared preferences between the current user and other users based on the given S_{co}.
- Step 2. Based on the summarized preferences from Step 1, recommend N items selected from S_{co} that the current user is likely to prefer.

The three sets of items generated through this process are then aggregated and selected by the LLMs using the aggregation transformation T_A. This results in the final set of top-N items I_{co} that best reflect the collaborative preferences of users with similar interests to the current user.

At this point, we have obtained three distinct sets of items: I_{short}, which reflects the user's short-term preferences; I_{long}, which captures the user's long-term preferences; and I_{co}, which represents the collaborative preferences derived from other users. Finally, using the aggregation transformation T_A, we enable LLMs to synthesize these multiple sources of information to generate the final set of top-N recommended items I_{fin}. The prompt template for this final aggregation is the same as the voting prompt.

3.5 Multi-Level Retrieval Module

To identify other users' sequences that share same interests with the current user and to assess how closely the recommended items match the ground truth in sampled datasets, we employ a two-level retrieval approach.

Sequence-level retrieval. As previously mentioned, when analyzing collaborative preferences, it is essential to retrieve sequences of other users who share similar interests with the current user. We choose to deploy the all-mpnet-base-v2 model f_{mpnet} due to its superior efficiency and discriminative power in encoding item titles compared to other encoding models such as BERT. Given a query sequence $S_u = \{i_1, ..., i_k\}$, the ranked indices of the retrieved sequences I_{seq} can be obtained as follows:

$$I_{seq} = sim(\frac{1}{k}\sum_{t=1}^{k} f_{mpnet}(i_t), V_{seq}) \quad (1)$$

where $sim(\cdot, \cdot)$ denotes the computation of Euclidean distance, V_{seq} represents the vector base containing the embeddings of all other sequences.

Item-level retrieval. The title of an item generated by LLMs may differ from the title of the ground truth in datasets, even though they refer to the same item. This discrepancy arises due to the limited and varied versions of items in the datasets (e.g., *Witcher 3: Wild Hunt* versus *Witcher 3: Wild Hunt Complete Edition*). To address this issue, we continue to utilize the f_{mpnet} model to encode item titles into vectors. We then retrieve the most similar items from the vector base by computing the inner product of the query vector and all other vectors in the base. Specifically, for an item i_{query} generated by LLMs, the retrieval process is as follows:

$$I_{item} = sim(f_{mpnet}(i_{query}), V_{item}) \quad (2)$$

where I_{item} represents the ranked indices of the retrieved items, $sim(\cdot, \cdot)$ denotes the computation of the inner product and V_{item} is the vector base containing all item embeddings. In practice, we observed that in most cases, when the description of the query item is vague, the retrieved items are misaligned (e.g., when querying for *The Witcher 3*, the top results include [*Diablo III*, *The Witch and the Hundred Knight - PlayStation 3*, *The Witcher 3: Wild Hunt - Xbox One*]). To mitigate this, we retrieve the top-K items within the ranked indices for each recommended item.

Overall, by empowering LLMs to independently reason and generate thoughts and then aggregate the most relevant results, our method fully leverages the reasoning capabilities of LLMs in the sequential recommendation scenario. This approach enables LLMs to effectively capture and integrate different aspects of the extensive information within user sequences.

4 Experiments

4.1 Experimental Settings

Datasets. We conduct experiments on three item categories from the widely used Amazon Reviews'23 dataset (Hou et al. 2024a): Video Games (**Games**), Grocery and Gourmet Food (**Food**) and Home and Kitchen (**Home**). Reviews are treated as user-item interactions, sequenced chronologically by timestamp. To address the significant time cost of LLMs, we focus on users with 6 to 20 interactions and filter out items with fewer than five interactions. Following (Wang et al. 2024), we randomly sample 3,000 users from each dataset three times. We employ the leave-one-out strategy for dataset division: the most recent interaction for testing, the second most recent interaction for validation and the remaining interactions are used for training. Both training and validation segments are used as input during testing.

Baselines. To demonstrate the effectiveness of our proposed method, we select two groups of recommendation baselines. The first group comprises traditional neural sequential recommendation models:

- **GRU4Rec** (Hidasi et al. 2016): Uses RNNs to model user sequences for session-based recommendation.
- **SRGNN** (Wu et al. 2019): A graph-based model for session-based recommendation to capture the transition information between items in user sequences.
- **SASRec** (Kang and McAuley 2018): A self-attention based sequential model to capture user's preferences.

The second group contains models that utilize LLM prompting strategies:

- **Chain-of-Thought (CoT)** (Wei et al. 2022): A prompting approach for prompting which includes the intermediate steps of reasoning within the prompt.
- **Multiple CoTs (CoT-SC)** (Wang et al. 2023): A scheme in which multiple CoTs are generated, with the best one being selected as final result.
- **Tree of Thoughts (ToT)** (Yao et al. 2024): A prompting approach modeling the LLM reasoning process as a tree.
- **SLIM** (Wang et al. 2024): A knowledge distillation module, which transfers the step-by-step reasoning capabilities in recommendation from a larger teacher model to a smaller student model.

Implementation Details. We choose Llama3-8B-Instruct (AI@Meta 2024) as the backbone model with a maximum token length of 4096. The LMDeploy toolkit (Contributors 2023) is employed to deploy LLMs and accelerate reasoning. GRU4Rec, SASRec and SRGNN are implemented based on their official code, and LLM prompting strategies are integrated within the GoT framework. For SLIM,

Dataset	Metric	GRU4Rec	SRGNN	SASRec	SLIM	CoT	CoT-SC	ToT	GOT4Rec	Improment
Games	HR@5	0.0390	0.0312	<u>0.0776</u>	0.0602	0.0644	0.0653	0.0489	**0.0894**	15.21%
	HR@10	0.0545	0.0495	0.0953	0.0977	0.0988	<u>0.1013</u>	0.0712	**0.1167**	15.20%
	HR@20	0.0765	0.0817	0.1227	0.1281	<u>0.1347</u>	0.1253	0.1087	**0.1361**	1.04%
	NDCG@5	0.0266	0.0220	<u>0.0528</u>	0.0380	0.0408	0.0421	0.0304	**0.0621**	17.61%
	NDCG@10	0.0317	0.0277	<u>0.0586</u>	0.0502	0.0519	0.0537	0.0377	**0.0710**	21.16%
	NDCG@20	0.0372	0.0357	<u>0.0655</u>	0.0578	0.0609	0.0622	0.0471	**0.0760**	16.03%
Food	HR@5	0.0213	0.0307	0.0335	0.0350	0.0396	<u>0.0443</u>	0.0273	**0.0742**	67.49%
	HR@10	0.0329	0.0352	0.0407	0.0517	0.0581	<u>0.0597</u>	0.0390	**0.0972**	62.81%
	HR@20	0.0525	0.0528	0.0549	0.0613	0.0748	<u>0.0753</u>	0.0533	**0.1090**	44.75%
	NDCG@5	0.0133	0.0196	<u>0.0286</u>	0.0216	0.0253	0.0276	0.0182	**0.0492**	72.03%
	NDCG@10	0.0170	0.0243	0.0309	0.0270	0.0311	<u>0.0326</u>	0.0219	**0.0567**	73.93%
	NDCG@20	0.0219	0.0288	0.0337	0.0295	0.0352	<u>0.0366</u>	0.0255	**0.0597**	63.11%
Home	HR@5	0.0095	0.0068	0.0132	0.0123	0.0118	<u>0.0133</u>	0.0047	**0.0192**	44.36%
	HR@10	0.0164	0.0115	0.0179	0.0180	0.0177	<u>0.0223</u>	0.0100	**0.0299**	34.08%
	HR@20	0.0274	0.0197	0.0262	0.0213	0.0230	<u>0.0270</u>	0.0147	**0.0337**	24.81%
	NDCG@5	0.0058	0.0049	<u>0.0097</u>	0.0073	0.0073	0.0080	0.0031	**0.0122**	25.77%
	NDCG@10	0.0080	0.0065	0.0105	0.0091	0.0093	<u>0.0109</u>	0.0049	**0.0157**	44.04%
	NDCG@20	0.0108	0.0085	<u>0.0134</u>	0.0099	0.0106	0.0121	0.0060	**0.0167**	24.63%

Table 1: Recommendation performance. The best performance is highlighted in **bold** and the runner-up is highlighted by <u>underlines</u>. Improvement indicates relative improvements over the best baseline in percentage.

Llama3-8B-Instruct is used instead of ChatGPT to avoid high API costs. We retrieve the 10 most similar items for both GOT4Rec and baseline methods using the faiss library (Douze et al. 2024). Optimal hyper-parameters for all baselines are carefully selected to ensure the best performance.

Evaluation Metrics. We evaluate performance using hit rate (HR) and normalized discounted cumulative gain (NDCG), reporting HR@K and NDCG@K for $K \in \{5, 10, 20\}$. Each recommended item is evaluated against all other items in the sampled datasets. To assess recommendation novelty, we calculate EFD@10 and EPC@10 (Vargas and Castells 2011). The average scores of three runs are reported.

4.2 Overall Performance

Table 1 compares our GOT4Rec method with various neural sequential models and LLM prompting strategies, leading to several key observations: (1) Traditional neural sequential models perform relatively modest, though SASRec still outperforms LLM prompting strategies in some cases, particularly due to its use of self-attention mechanisms which allow SASRec to effectively model users' historical behaviors by capturing the transition relationships between items. However, SASRec lacks the ability to comprehend semantic information, limiting its overall performance. (2) Among LLM-based methods, CoT-SC consistently achieves runner-up performance across most datasets, largely because it aggregates and selects the best result from multiple CoT paths, providing a more refined output. On the other hand, CoT, ToT, and SLIM show comparatively lower performance. SLIM, in particular, may suffer from reduced output diversity due to fine-tuning, while ToT's structural and reasoning path designs appear to be less suitable for sequential recommendation tasks. (3) GOT4Rec achieves the state-of-art (SOTA) performances across all datasets. Notably, in the Food dataset, GOT4Rec achieves a relative improvement of 73.93% over CoT-SC in terms of NDCG@10 and 67.49% in terms of HR@5. These significant gains can be attributed to the nature of food product consumption, where users prefer consistent categories or brands and are strongly influenced by short-term needs. This aligns well with the strengths of GOT4Rec, which excels at capturing users' preferences for certain categories or brands and effectively integrating short-term preference information. This capability allows GOT4Rec to deliver highly relevant recommendations that closely match users' current interests. These findings demonstrate the effectiveness of GOT4Rec in optimizing recommendation tasks by fully exploiting the advanced reasoning capabilities of LLMs and integrating various aspects of user information.

4.3 Ablation Study

We conducted an ablation study to analyze the impact of different components in the GOT4Rec model, with the results in Table 2. Our GOT4Rec consistently outperforms the ablated variants, demonstrating that the full integration of users' preference information from the short-term, long-term, and collaborative components results in superior recommendation performance. The study also reveals that the importance of each component varies across different datasets, likely reflecting the unique characteristics of each dataset. For instance, collaborative information appears to be the most crucial component in Games dataset. This suggests that when purchasing gaming products, users prioritize categories or brands, making collaborative information from other users with similar interests particularly important. In contrast, short-term preference plays a more signif-

Dataset	Metric	w/o Short.	w/o Long.	w/o Co.	GOT4Rec
Games	HR@5	0.0819	0.0871	0.0774	**0.0894**
	HR@10	0.1083	0.1121	0.1015	**0.1167**
	HR@20	0.1262	0.1337	0.1170	**0.1361**
	NDCG@5	0.0512	0.0573	0.0527	**0.0621**
	NDCG@10	0.0597	0.0654	0.0606	**0.0710**
	NDCG@20	0.0642	0.0709	0.0645	**0.0760**
Food	HR@5	0.0591	**0.0867**	0.0687	0.0742
	HR@10	0.0867	0.0933	0.0880	**0.0972**
	HR@20	0.1003	0.1063	0.1013	**0.1090**
	NDCG@5	0.0362	0.0426	0.0437	**0.0492**
	NDCG@10	0.0453	0.0509	0.0500	**0.0567**
	NDCG@20	0.0487	0.0543	0.0534	**0.0597**
Home	HR@5	0.0179	0.0166	0.0190	**0.0192**
	HR@10	0.0284	0.0292	0.0270	**0.0299**
	HR@20	0.0322	0.0318	0.0309	**0.0337**
	NDCG@5	0.0102	0.0103	0.0114	**0.0122**
	NDCG@10	0.0136	0.0144	0.0140	**0.0157**
	NDCG@20	0.0146	0.0150	0.0149	**0.0167**

Table 2: Ablation analysis, conducted by retaining different components in GOT4Rec to form variants. The best performance is highlighted in **bold**. "Short.", "Long.", and "Co." denote long-term, short-term, and collaborative schemes, respectively.

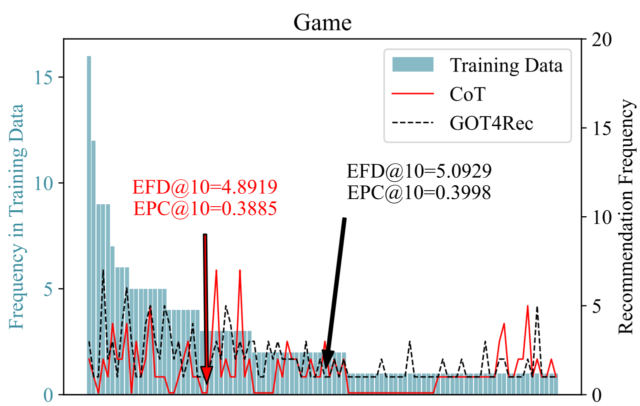

Figure 4: Analysis of popularity bias in Games dataset. Items in the dataset are sorted by their frequency. Compared to CoT, GOT4Rec demonstrates a more consistent ability to recommend long-tail items.

icant role in Food dataset, aligning with our inference that users' recent preferences heavily influence their choices in food products. In Home dataset, the impact of each component varies, but short-term preference has the least influence. This could indicate that long-term preferences or collaborative insights are more critical when users make decisions about home-related items.

4.4 Popularity Bias Analysis

In Figure 4, we sort the items in Games dataset based on their frequency in the training set (i.e., popularity) and draw lines to illustrate each item's frequency in the results of CoT and GOT4Rec. The figures for other two datasets are presented in the Appendix. It is apparent that GOT4Rec more effectively recommends tail items and a broader variety of items. Table 3 reports EFD@10 and EPC@10 metrics for CoT, SLIM and GOT4Rec, indicating tthat GOT4Rec outperforms the baselines in recommending long-tail items. These results support our claim that GOT4Rec mitigates popularity bias by capturing a wider range of information.

Dataset	Metric	CoT	SLIM	GOT4Rec
Games	EFD@10	4.8919	4.1292	**5.0929**
	EPC@10	0.3885	0.3306	**0.3998**
Food	EFD@10	6.4721	5.3517	**6.8671**
	EPC@10	0.4750	0.3923	**0.5035**
Home	EFD@10	4.1911	3.1141	**4.6019**
	EPC@10	0.3110	0.2304	**0.3450**

Table 3: Popularity bias metrics, the higher score indicates higher recommendation novelty. The best performance is highlighted in **bold**.

5 Conclusion

In this paper, we propose GOT4Rec, a sequential recommendation method that optimally leverages the reasoning capabilities of LLMs to extract and integrate short-term, long-term, and collaborative user preferences utilizing the graph of thoughts (GoT) framework. Experiments on real-world datasets demonstrate that our GOT4Rec method outperforms existing neural sequential models and LLM prompting strategies. Further analysis reveals that GOT4Rec effectively integrates multiple pieces of information contained within user sequences for superior recommendations.

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Reproducibility Checklist

This paper:

- Includes a conceptual outline and/or pseudocode description of AI methods introduced (**yes**)
- Clearly delineates statements that are opinions, hypothesis, and speculation from objective facts and results (**yes**)
- Provides well marked pedagogical references for less-familiare readers to gain background necessary to replicate the paper (**yes**)

Does this paper make theoretical contributions? (**no**) Does this paper rely on one or more datasets? (**yes**)

- A motivation is given for why the experiments are conducted on the selected datasets (**yes**)
- All novel datasets introduced in this paper are included in a data appendix. (**yes**)
- All novel datasets introduced in this paper will be made publicly available upon publication of the paper with a license that allows free usage for research purposes. (**yes**)
- All datasets drawn from the existing literature (potentially including authors' own previously published work) are accompanied by appropriate citations. (**yes**)
- All datasets drawn from the existing literature (potentially including authors' own previously published work) are publicly available. (**yes**)
- All datasets that are not publicly available are described in detail, with explanation why publicly available alternatives are not scientifically satisficing. (**NA**)

Does this paper include computational experiments? (**yes**)

- Any code required for pre-processing data is included in the appendix. (**yes**).
- All source code required for conducting and analyzing the experiments is included in a code appendix. (**yes**)
- All source code required for conducting and analyzing the experiments will be made publicly available upon publication of the paper with a license that allows free usage for research purposes. (**yes**)
- All source code implementing new methods have comments detailing the implementation, with references to the paper where each step comes from (**yes**)
- If an algorithm depends on randomness, then the method used for setting seeds is described in a way sufficient to allow replication of results. (**yes**)
- This paper specifies the computing infrastructure used for running experiments (hardware and software), including GPU/CPU models; amount of memory; operating system; names and versions of relevant software libraries and frameworks. (**partial**)
- This paper formally describes evaluation metrics used and explains the motivation for choosing these metrics. (**yes**)
- This paper states the number of algorithm runs used to compute each reported result. (**yes**)
- Analysis of experiments goes beyond single-dimensional summaries of performance (e.g., average; median) to include measures of variation, confidence, or other distributional information. (**yes**)
- The significance of any improvement or decrease in performance is judged using appropriate statistical tests (e.g., Wilcoxon signed-rank). (**no**)
- This paper lists all final (hyper-)parameters used for each model/algorithm in the paper's experiments. (**yes**)
- This paper states the number and range of values tried per (hyper-) parameter during development of the paper, along with the criterion used for selecting the final parameter setting. (**partial**)

A Dataset Statistics

The detailed data statistics of three datastes are shown in Table 4, including the number of users, items, actions (the presence of a review is an action) and time spans.

Dataset	Users	Items	Actions	Time Span
Games	3,000	12259	26196	1999.11-2023.08
Food	3,000	19256	29321	2003.11-2023.03
Home	3,000	25457	29332	2001.01-2023.03

Table 4: Datasets' average statistics (after preprocessing).

B Inference Latency and Cost

Table 5 shows the inference latency and cost of different prompting strategies. Although our GOT4Rec incurs higher time and cost, it delivers higher quality outcomes.

Marks	CoT	CoT-SC	ToT	SLIM	GOT4Rec
Latency	8.44	20.15	34.72	30.51	104.81
Cost($)	0.01	0.03	0.05	0.02	0.12

Table 5: Average reasoning inference latency (seconds) and cost (counted in GPT-4o API fee) for Games dataset, tested on single NVIDIA A100 GPU.

C Popularity Bias

Figure 5 and Figure 6 represents the popularity bias analysis in Food dataset and Home dataset, respectively.

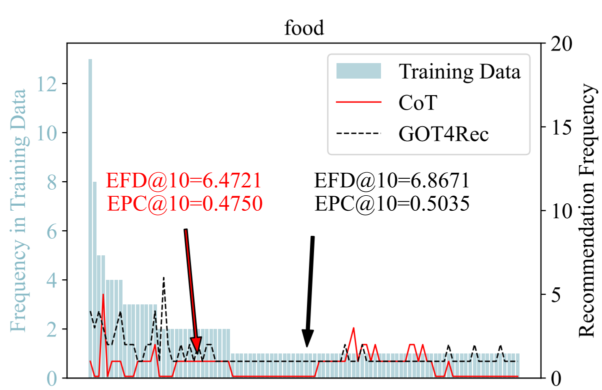

Figure 5: Supplementary material for popularity bias analysis in Food dataset.

D Example Cases

Below is a complete reasoning process in Games dataset, including user interaction sequence, Short-term Reasoning Process, Long-term Reasoning Process, Collaborative Reasoning Process and Final Aggregation & Retrieval. Important partial solutions are highlighted in **bold**.

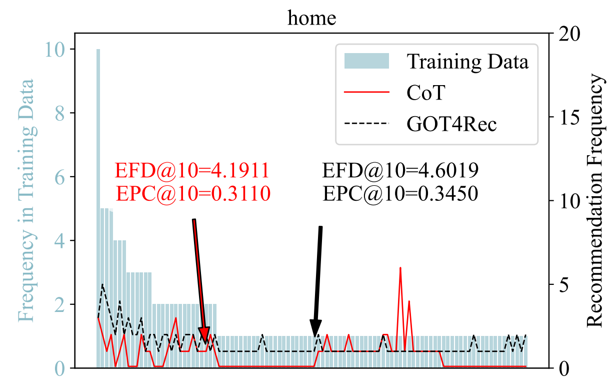

Figure 6: Supplementary material for popularity bias analysis in Home dataset.

User Interaction Sequence

PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One, White Xbox One S Fan, USB Hub and Controller Charger - Matches the Xbox One Console - Premium Xbox One Accessories, cozoo Headphone Stand with USB Charger Desktop Gaming Headset Holder Hanger with 3 USB Charger and 2 Outlets - Suitable for Gaming, DJ, Wireless Earphone Display,Gaming Desk Accessories,Gifts for Him, PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One, White Xbox One S Fan, USB Hub and Controller Charger - Matches the Xbox One Console - Premium Xbox One Accessories, **cozoo Headphone Stand with USB Charger Desktop Gaming Headset Holder Hanger with 3 USB Charger and 2 Outlets - Suitable for Gaming, DJ, Wireless Earphone Display,Gaming Desk Accessories,Gifts for Him**

Short-term Reasoning Process

(Summarizing categories/brands)
Step 1: Analyzing Your Purchase History
Based on your purchase history, it appears that you have a strong interest in gaming-related products. You have purchased a headphone stand with a USB charger, a dual controller charging system, and a white Xbox One fan with a USB hub and controller charger. This suggests that you value convenience, organization, and functionality in your gaming setup.
Step 2: Recommended Product Categories or Brands
Here are three product categories or brands that may appeal to you based on your preferences:
1. **Gaming Accessories**
2. **Xbox Accessories**
3. **Power Management Solutions**

(Recommendation results in Gaming Accessories)

1. PDP Afterglow AG 9+ Wireless Stereo Headset for Xbox One and Xbox Series X—S 2. HORI HORIPAD Wireless Controller Charging Dock for Xbox One 3. Razer Raiju Ultimate Wireless Controller Charging Dock for Xbox One 4. PowerA Enhanced Wireless Controller Charging Station for Xbox One 5. 8Bitdo SN30/SF30 Wireless Controller Charging Dock for Xbox One

1. PDP Afterglow AG 9+ Wireless Gaming Headset for Xbox One and Xbox Series X—S 2. Razer Raiju Ultimate Wireless Controller Charging Dock for Xbox One and Xbox Series X—S 3. HORI Gaming Headset Stand with USB Charging Station for Xbox One and Xbox Series X—S 4. Turtle Beach Recon 200 Gaming Headset for Xbox One and Xbox Series X—S 5. PowerA Enhanced Wireless Controller Charging Station for Xbox One and Xbox Series X—S

1. PDP Afterglow AG 9+ Wireless Controller Charging Dock for Xbox One and Xbox Series X—S 2. PowerA Enhanced Wireless Controller Charging Station for Xbox One and Xbox Series X—S 3. Razer Raiju Universal Gaming Controller Charging Dock 4. HORI Horipad Ultimate Wireless Gaming Controller Charging Dock for Xbox One and Xbox Series X—S 5. Turtle Beach Recon 200 Amplified Gaming Headset for Xbox One

(Recommendation results in Xbox Accessories)
1. PDP Xbox One Media Remote Control with Built-in IR Blaster 2. HORI HORIPAD Wireless Controller Charging Dock for Xbox One 3. Xbox One S Vertical Stand with Cooling Fan and USB Hub 4. PowerA Enhanced Wireless Controller Charging Station for Xbox One 5. Xbox One S External Hard Drive Enclosure - 2TB

1. PDP Xbox One Controller Charging Station with 4 Rechargeable Battery Packs 2. HORI Xbox One Wireless Vertical Stand for Controller Charging and Cooling 3. PowerA Enhanced Wireless Controller Charging Station for Xbox One 4. Xbox One S Vertical Stand with Cooling Fan and Charging Station 5. Razer Raiju Tournament Edition Xbox One Controller Charging Dock

1. PDP Gaming Controller Charging Station for Xbox One 2. Xbox One Wireless Controller Charging Dock 3. HORI Gaming Controller Charging Dock for Xbox One 4. Xbox One S Controller Charging Station with Stand 5. PowerA Enhanced Wireless Charging Station for Xbox One

(Recommendation results in Power Management Solutions)
1. PDP Gaming Power Bank, 20000mAh Portable Charger for Xbox One Controllers, Nintendo Switch, PS4, and More 2. Anker PowerCore Fusion 5000 Portable Charger, 5000mAh Power Bank with Built-in Wall Charger and USB-C Power Delivery 3. Aukey Power Bank 20000mAh, High Capacity External Battery Pack with 2 USB Ports and Micro-USB Input 4. RAVPower 22000mAh Power Bank, High Capacity External Battery Pack with 2 USB Ports and Micro-USB Input 5. EC Technology 20000mAh Power Bank, High Capacity External Battery Pack with 2 USB Ports and Micro-USB Input

1. PDP Gaming Power Bank, 20,000mAh High Capacity External Battery Pack for Xbox, PlayStation, Nintendo Switch, and More 2. Anker PowerCore Fusion 5000 Portable Power Bank, 5000mAh Power Bank with 2 USB Ports and Quick Charge 3.0 3. Aukey Power Bank, 20000mAh High Capacity External Battery Pack with 4 USB Ports and Quick Charge 3.0 4. RAVPower 22000mAh Power Bank, High Capacity External Battery Pack with 4 USB Ports and Quick Charge 3.0 5. Jackery Titan S 20000mAh Power Bank, High Capacity External Battery Pack with 2 USB Ports and Quick Charge 3.0

1. PDP Gaming Dual 12V 10A Power Bank for Xbox One, PS4, Nintendo Switch, and More 2. Anker PowerCore Fusion 5000 Portable Charger, 5000mAh Power Bank with 6A Output 3. Aukey 60W 6-Port USB Wall Charger, High-Speed Charging Station with 2 USB-C Ports 4. RAVPower 60W 6-Port USB Wall Charger, High-Speed Charging Station with 2 USB-C Ports 5. Aukey 10000mAh Power Bank, High Capacity Portable Charger with 2 USB Ports

(Aggregation of recommended short-term items of the categories/brands above)
1. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 2. White Xbox One S Fan, USB Hub and Controller Charger - Matches the Xbox One Console - Premium Xbox One Accessories 3. cozoo Headphone Stand with USB Charger Desktop Gaming Headset Holder Hanger with 3 USB Charger and 2 Outlets - Suitable for Gaming, DJ, Wireless Earphone Display,Gaming Desk Accessories,Gifts for Him 4. Razer Raiju Ultimate Wireless Controller Charging Dock for Xbox One 5. PDP Afterglow AG 9+ Wireless Gaming Headset for Xbox One and Xbox Series X—S 6. PowerA Enhanced Wireless Controller Charging Station for Xbox One 7. HORI Gaming Headset Stand with USB Charging Station for Xbox One and Xbox Series X—S 8. Turtle Beach Recon 200 Amplified Gaming Headset for Xbox One 9. HORI Horipad Ultimate Wireless Gaming Controller Charging Dock for Xbox One and Xbox Series X—S 10. Razer Raiju Universal Gaming Controller Charging Dock

Here are the top 10 product recommendations based on your purchase history: 1. PDP Gaming Power Bank, 20,000mAh High Capacity External Battery Pack for Xbox, PlayStation, Nintendo Switch, and More 2. PDP Gaming Dual 12V 10A Power Bank for Xbox One, PS4, Nintendo Switch, and More 3. Anker PowerCore Fusion 5000 Portable Charger, 5000mAh Power Bank with 6A Output 4. Aukey 60W 6-Port USB Wall Charger, High-Speed Charging Station with 2 USB-C Ports 5. RAVPower 22000mAh Power Bank, High Capacity External Battery Pack with 4 USB Ports and Quick Charge 3.0 6. Aukey Power Bank 20000mAh, High Capacity External Battery Pack with 2 USB Ports and Micro-USB Input 7. Anker PowerCore Fusion 5000 Portable Power Bank, 5000mAh Power Bank with Built-in Wall Charger and USB-C Power Delivery 8. PDP Gaming Power Bank, 20000mAh Portable Charger for Xbox One Controllers, Nintendo Switch, PS4, and More 9. EC Technology 20000mAh Power Bank, High Capacity External Battery Pack with 2 USB Ports and Micro-USB Input 10. Anker PowerCore Fusion 5000 Portable Charger, 5000mAh Power Bank with 2 USB Ports and Quick Charge 3.0

1. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 2. PDP Gaming Controller Charging Station for Xbox One 3. HORI HORIPAD Wireless Controller Charging Dock for Xbox One 4. Razer Raiju Ultimate Wireless Controller Charging Dock for Xbox One 5. Xbox One S Vertical Stand with Cooling Fan and Charging Station 6. PDP Xbox One Media Remote Control with Built-in IR Blaster 7. PowerA Enhanced Wireless Controller Charging Station for Xbox One 8. PDP Gaming Dual 12V 10A Power Bank for Xbox One, PS4, Nintendo Switch, and More 9. Xbox One S Controller Charging Station with Stand 10. cozoo Headphone Stand with USB Charger Desktop Gaming Headset Holder Hanger with 3 USB Charger and 2 Outlets - Suitable for Gaming, DJ, Wireless Earphone Display,Gaming Desk Accessories,Gifts for Him

Long-term Reasoning Process

(Summarizing categories/brands)
Step 1: Analyzing your purchase history to identify key factors that influence your choice of products
After analyzing your purchase history, I've identified the following key factors that may influence your choice of products:
You tend to purchase gaming-related products, specifically accessories for Xbox One console.
You prefer products that offer charging functionality, such as charging systems and chargers.
You also consider aesthetics, as you've purchased products that match the Xbox One console's design.
You may prioritize practicality, as you've purchased products that serve multiple purposes, such as a headphone stand with USB charger.
Step 2: Selecting three product categories or brands that appeal to you the most
Based on your purchase history, here are three product categories or brands that may appeal to you the most:
1. **PDP Gaming**
2. **Xbox One Accessories**
3. **Gaming Charging Systems**

(Recommendation results in PDP Gaming)
1. PDP Faceoff Deluxe+ Dual Controller Charging Station for Xbox One 2. PDP Gaming Dual Charging Station for Xbox One 3. PDP Gaming Dual Charging Station for Xbox One with 4 Rechargeable Battery Packs 4. PDP Gaming Dual Charging Station for Xbox One with 2 Rechargeable Battery Packs 5. PDP Gaming Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One

1. PDP Faceoff Deluxe+ Gaming Keyboard for Xbox One 2. PDP Afterglow AG 9+ Wireless Gaming Headset for Xbox One 3. PDP Gaming DualShock Charging Station for Xbox One 4. PDP Xbox One Chat Headset with Mic and Volume Control 5. PDP Gaming DualShock Charging Station for Xbox One

1. PDP Faceoff Deluxe+ Controller Charging Station for Xbox One 2. PDP Gaming Dual Controller Charging Station for Xbox One 3. PDP Gaming Dual Controller Charging Station for Xbox Series X—S 4. PDP Gaming Dual Controller Charging Station for Nintendo Switch 5. PDP Gaming Dual Controller Charging Station for PlayStation'

(Recommendation results in Xbox One Accessories)
1. Xbox One Wireless Controller - White 2. Xbox One Media Remote 3. Xbox One Vertical Stand for Xbox One Console 4. Xbox One Chat Headset 5. Xbox One External Hard Drive

1. Xbox One Stereo Headset 2. Xbox One Vertical Stand 3. Xbox One Media Remote 4. Xbox One Chat Headset 5. Xbox One External Hard Drive

1. Xbox One S Vertical Stand - Cooling Fan and Charging Station with 2 USB Ports 2. Xbox One Controller Charging Dock with 2 Rechargeable Battery Packs 3. Xbox One Power Bank - Portable Charger with 2 USB Ports and LED Light 4. Xbox One Console Cooling Fan with 2 USB Ports and LED Light 5. Xbox One Gaming Headset Stand with USB Charger and 2 Outlets

(Recommendation results in Gaming Charging Systems)
1. PDP Gaming Dual Charging Station for Xbox One Controllers 2. HORI Dual Charging Dock for Xbox One Controllers 3. PowerA Dual Charging Station for Xbox One Controllers 4. Razer Raion Charging Dock for Xbox One Controllers 5. Turtle Beach Recon 200 Gaming Headset with Charging Dock for Xbox One

1. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 2. PDP Gaming Dual Charging Station for Xbox One Controllers 3. PowerA Enhanced Wireless Charging Dock for Xbox One Controllers 4. HORI Charge-N-Play Charging Station for Xbox One Controllers 5. Razer Raiju Universal Gaming Controller Charging Dock

1. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 2. PowerA Enhanced Charging Station for Xbox One Controllers 3. Razer Raiju Universal Gaming Controller Charging Dock 4. HORI Charge Stand for Xbox One Controllers 5. Poweradd 4-Port USB Charging Station for Xbox One Controllers

(Aggregation of recommended long-term items of the categories/brands above)
1. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 2. White Xbox One S Fan, USB Hub and Controller Charger - Matches the Xbox One Console - Premium Xbox One Accessories 3. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 4. White Xbox One S Fan, USB Hub and Controller Charger - Matches the Xbox One Console - Premium Xbox One Accessories 5. cozoo Headphone Stand with USB Charger Desktop Gaming Headset Holder Hanger with 3 USB Charger and 2 Outlets - Suitable for Gaming, DJ, Wireless Earphone Display,Gaming Desk Accessories,Gifts for Him 6. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 7. White Xbox One S Fan, USB Hub and Controller Charger - Matches the Xbox One Console - Premium Xbox One Accessories 8. cozoo Headphone Stand with USB Charger Desktop Gaming Headset Holder Hanger with 3 USB Charger and 2 Outlets - Suitable for Gaming, DJ, Wireless Earphone Display,Gaming Desk Accessories,Gifts for Him 9. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 10. White Xbox One S Fan, USB Hub and Controller Charger - Matches the Xbox One Console - Premium Xbox One Accessories

1. Xbox One Controller Charging Dock with 2 Rechargeable Battery Packs 2. White Xbox One S Fan, USB Hub and Controller Charger - Matches the Xbox One Console - Premium Xbox One Accessories 3. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 4. cozoo Headphone Stand with USB Charger Desktop Gaming Headset Holder Hanger with 3 USB Charger and 2 Outlets - Suitable for Gaming, DJ, Wireless Earphone Display,Gaming Desk Accessories,Gifts for Him 5. Xbox One Power Bank - Portable Charger with 2 USB Ports and LED Light 6. Xbox One Vertical Stand for Xbox One Console 7. Xbox One Stereo Headset 8. Xbox One Gaming Headset Stand with USB Charger and 2 Outlets 9. Xbox One External Hard Drive 10. Xbox One Chat Headset

1. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 2. White Xbox One S Fan, USB Hub and Controller Charger - Matches the Xbox One Console - Premium Xbox One Accessories 3. cozoo Headphone Stand with USB Charger Desktop Gaming Headset Holder Hanger with 3 USB Charger and 2 Outlets - Suitable for Gaming, DJ, Wireless Earphone Display,Gaming Desk Accessories,Gifts for Him 4. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 5. White Xbox One S Fan, USB Hub and Controller Charger - Matches the Xbox One Console - Premium Xbox One Accessories 6. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 7. cozoo Headphone Stand with USB Charger Desktop Gaming Headset Holder Hanger with 3 USB Charger and 2 Outlets - Suitable for Gaming, DJ, Wireless Earphone Display,Gaming Desk Accessories,Gifts for Him 8. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 9. White Xbox One S Fan, USB Hub and Controller Charger - Matches the Xbox One Console - Premium Xbox One Accessories 10. cozoo Headphone Stand with USB Charger Desktop Gaming Headset Holder Hanger with 3 USB Charger and 2 Outlets - Suitable for Gaming, DJ, Wireless Earphone Display,Gaming Desk Accessories,Gifts for Him

Collaborative Reasoning Process

(Summarizing preferences and give recommendation)
I've received the instructions and the purchase history. I'll follow the steps precisely to provide the required output. **Step 1: Identifying key factors that influence our choice of products** After analyzing the purchase history of you and other users, I've identified the following key factors that influence our choice of products: * Xbox-related products: All users have purchased products related to Xbox consoles, controllers, and accessories.
Gaming peripherals: Users have shown interest in gaming peripherals such as charging systems, battery packs, controllers, and cooling fans.
Convenience and functionality: Users seem to prioritize products that offer convenience and functionality, such as dual charging stations, wireless controllers, and USB hubs.
Brand recognition: PDP Gaming and Superer are recognized brands in the gaming industry, and users have purchased products from these brands.
*Step 2: Recommended products based on our purchase history** Here are the recommended products from Amazon that best fit our interests: ¡Step2: 1. PDP Gaming Dual Controller Charging Station for Xbox Series X/S, Xbox One, and Xbox One S¿ ¡Step2: 2. HyperX ChargePlay Duo Wireless Charging Dock for Xbox Series X/S, Xbox One, and Xbox One S¿ ¡Step2: 3. Razer Raiju Ultimate Controller Charging Dock for Xbox Series X/S, Xbox One, and Xbox One S¿ ¡Step2: 4. Cooling Fan for Xbox Series X with Dust Cover Filter, RGB Color LED Light Cooler System with Low Noise 3 Levels Adjustable Speed Fan¿ ¡Step2: 5. Superer 10FT USB C Type C Charging Cable Fit for Xbox Series X/Xbox Series S Controller¿ ¡Step2: 6. PowerA Enhanced Wireless Controller for Xbox Series S/X, Xbox One, and Xbox One S¿ ¡Step2: 7. PDP Gaming Gaming Headset Stand with USB Charger and 2 Outlets¿ ¡Step2: 8. Razer Kraken X Gaming Headset with 7.1 Surround Sound and Retractable Mic¿ ¡Step2: 9. Turtle Beach Recon 200 Gaming Headset with Flip-Up Mic and 12 Hour Battery Life¿ ¡Step2: 10. ASTRO Gaming A50 Wireless Gaming Headset with 15 Hour Battery Life and Retractable Mic¿ Please note that these recommendations are based on the purchase history of you and other users, and may not be exhaustive or tailored to individual preferences.

Received instructions. I will follow them precisely. **Step 1: Identify key factors that influence our choice of prod-

ucts** After analyzing your purchase history and the purchase history of other users, I have identified the following key factors that influence our choice of products: * Gaming-related products (controllers, charging systems, accessories)
Xbox One and Xbox Series X/S consoles
USB charging and power supply
Cooling and ventilation systems for gaming consoles
Gaming headset stands and holders
Wireless connectivity and rechargeable batteries
Compatibility with multiple gaming platforms (Xbox, PlayStation, PC) **Step 2: Recommended products from Amazon** Here are 10 products from Amazon that best fit our interests: ¡Step2: 1. PDP Gaming Dual Controller Charging Station for Xbox One and Xbox Series X/S¿ ¡Step2: 2. PowerA Enhanced Wireless Controller for Xbox Series X/S, Xbox One, and Xbox One S¿ ¡Step2: 3. HORI Cooling Fan for Xbox Series X/S with Dust Cover and Filter¿ ¡Step2: 4. Razer Raiju Ultimate Wireless Controller for Xbox Series X/S, Xbox One, and Xbox One S¿ ¡Step2: 5. HyperX Cloud II Wireless Gaming Headset for Xbox One and Xbox Series X/S¿ ¡Step2: 6. PDP Gaming Headphone Stand with USB Charger and 2 Outlets¿ ¡Step2: 7. Anker PowerCore 20000 PD Portable Charger for Xbox Controllers and Other Devices¿ ¡Step2: 8. Cooling Fan for Xbox One X with 3 USB Ports and LED Light Bar¿ ¡Step2: 9. PDP Gaming Wireless Controller Charging Dock for Xbox One and Xbox Series X/S¿ ¡Step2: 10. Corsair HS70 Wireless Gaming Headset for Xbox One and Xbox Series X/S¿ Please note that these recommendations are based on the analysis of our purchase history and may not be exhaustive or tailored to individual preferences.

Received instructions! I'll follow them precisely. **Step 1: Identifying key factors that influence your choice of products** After analyzing your purchase history and the purchase history of other users, I've identified the following key factors that influence your choice of products: * Xbox-related products (controllers, chargers, accessories)
Gaming-related products (headphones, stands, cooling systems)
Quality and durability of products
Compatibility with specific gaming consoles (Xbox One, Xbox Series X/S, Xbox 360)
Functionality and features (wireless connectivity, rechargeable batteries, multiple USB ports) **Step 2: Recommended products based on your purchase history** Here are 10 product recommendations from Amazon that best fit your interests: ¡Step2: 1. PDP Gaming Cooling Fan for Xbox Series X with Dust Cover Filter, RGB Color LED Light Cooler System with Low Noise 3 Levels Adjustable Speed Fan, Extra 2 USB Port for Xbox Series X Console Accessories¿ ¡Step2: 2. HORI Gaming Headset for Xbox Series X/S, Xbox One, Xbox One S, PS4, PS4 Pro, PC, with 7.1 Surround Sound, Detachable Microphone, and Volume Control¿ ¡Step2: 3. PowerA Enhanced Wireless Controller for Xbox Series X/S, Xbox One, Xbox One S, with Dual Vibration, Motion Controls, and 10-Hour Battery Life¿ ¡Step2: 4. Razer Raiju Ultimate Wireless Controller for Xbox Series X/S, Xbox One, Xbox One S, with Interchangeable Thumbsticks, D-Pad, and Triggers¿ ¡Step2: 5. HyperX Cloud II Gaming Headset for Xbox Series X/S, Xbox One, Xbox One S, PS4, PS4 Pro, PC, with 7.1 Surround Sound and Detachable Microphone¿ ¡Step2: 6. Xbox Series X/S Vertical Cooling Stand with 3 USB Ports and a Light Bar¿ ¡Step2: 7. PDP Faceoff Deluxe+ Pro Controller Charging Station for Xbox Series X/S, Xbox One, Xbox One S¿ ¡Step2: 8. Razer Panthera V2 Pro Fighting Game Controller for Xbox Series X/S, Xbox One, Xbox One S, with Interchangeable Thumbsticks and D-Pad¿ ¡Step2: 9. Turtle Beach Recon 200 Gaming Headset for Xbox Series X/S, Xbox One, Xbox One S, PS4, PS4 Pro, PC, with 12-Hour Battery Life and Flip-Up Mic¿ ¡Step2: 10. PowerA Enhanced Wired Controller for Xbox Series X/S, Xbox One, Xbox One S, with Dual Vibration, Motion Controls, and 10-Hour Battery Life¿ Please note that these recommendations are based on your purchase history and the purchase history of other users with similar interests.

(Aggregation of the items above)
1. PDP Gaming Dual Controller Charging Station for Xbox One and Xbox Series X/S 2. HyperX ChargePlay Duo Wireless Charging Dock for Xbox Series X/S, Xbox One, and Xbox One S 3. PDP Gaming Headphone Stand with USB Charger and 2 Outlets 4. PowerA Enhanced Wireless Controller for Xbox Series X/S, Xbox One, and Xbox One S 5. Turtle Beach Recon 200 Gaming Headset for Xbox Series X/S, Xbox One, Xbox One S, PS4, PS4 Pro, PC, with 12-Hour Battery Life and Flip-Up Mic 6. Anker PowerCore 20000 PD Portable Charger for Xbox Controllers and Other Device n7. HORI Gaming Headset for Xbox Series X/S, Xbox One, Xbox One S, PS4, PS4 Pro, PC, with 7.1 Surround Sound, Detachable Microphone, and Volume Control 8. PDP Faceoff Deluxe+ Pro Controller Charging Station for Xbox Series X/S, Xbox One, Xbox One S 9. PowerA Enhanced Wireless Controller for Xbox Series X/S, Xbox One, Xbox One S, with Dual Vibration, Motion Controls, and 10-Hour Battery Life 10. Razer Raiju Ultimate Wireless Controller for Xbox Series X/S, Xbox One, and Xbox One S

Final Aggregation & Retrieval

(Final Aggregation)
1. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 2. White Xbox One S Fan, USB Hub and Controller Charger - Matches the Xbox One Console - Premium Xbox One Accessories 3. **cozoo Headphone Stand with USB Charger Desktop Gaming Headset Holder Hanger with 3 USB Charger and 2 Outlets - Suitable for Gaming, DJ, Wireless Earphone Display,Gaming Desk Accessories,Gifts for Him** 4. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 5. White Xbox One S Fan, USB Hub and Controller Charger - Matches the Xbox One Console - Premium Xbox One Accessories 6. cozoo Headphone Stand with USB Charger Desktop Gaming Headset Holder Hanger with 3 USB Charger and 2 Outlets - Suitable for Gaming, DJ, Wireless Earphone Display,Gaming Desk

Accessories,Gifts for Him 7. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 8. White Xbox One S Fan, USB Hub and Controller Charger - Matches the Xbox One Console - Premium Xbox One Accessories 9. cozoo Headphone Stand with USB Charger Desktop Gaming Headset Holder Hanger with 3 USB Charger and 2 Outlets - Suitable for Gaming, DJ, Wireless Earphone Display,Gaming Desk Accessories,Gifts for Him 10. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 11. White Xbox One S Fan, USB Hub and Controller Charger - Matches the Xbox One Console - Premium Xbox One Accessories 12. cozoo Headphone Stand with USB Charger Desktop Gaming Headset Holder Hanger with 3 USB Charger and 2 Outlets - Suitable for Gaming, DJ, Wireless Earphone Display,Gaming Desk Accessories,Gifts for Him 13. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 14. White Xbox One S Fan, USB Hub and Controller Charger - Matches the Xbox One Console - Premium Xbox One Accessories 15. cozoo Headphone Stand with USB Charger Desktop Gaming Headset Holder Hanger with 3 USB Charger and 2 Outlets - Suitable for Gaming, DJ, Wireless Earphone Display,Gaming Desk Accessories,Gifts for Him 16. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 17. White Xbox One S Fan, USB Hub and Controller Charger - Matches the Xbox One Console - Premium Xbox One Accessories 18. cozoo Headphone Stand with USB Charger Desktop Gaming Headset Holder Hanger with 3 USB Charger and 2 Outlets - Suitable for Gaming, DJ, Wireless Earphone Display,Gaming Desk Accessories,Gifts for Him 19. PDP Gaming Energizer Dual Controller Charging System, Two Rechargeable Battery Packs: Black - Xbox One 20. White Xbox One S Fan, USB Hub and Controller Charger - Matches the Xbox One Console - Premium Xbox One Accessories

(Retrieved Items)

cozoo Headphone Stand with USB Charger Desktop Gaming Headset Holder Hanger with 3 USB Charger and 2 Outlets - Suitable for Gaming, DJ, Wireless Earphone Display,Gaming Desk Accessories,Gifts for Him, cozoo RGB Headphone Stand with 2 USB2.0 Extension Charging Port Extender Cord,Headset Stand Holder for Gamer Desktop Table Game Earphone Accessories, Headphone Stand with USB Charger QC 3.0, Ausfore Under Desk Headset Headphone Holder Hanger w/ 5 USB Ports for Computer Gaming Setup Desk Gaming PC Accessories, KAFRI RGB Headphone Stand with USB Charger Desk Gaming Headset Holder Hanger Rack with 3 USB Charging Port and 2 Outlet - Suitable for Gamer Desktop Table Game Earphone Accessories Girlfriend Gift, KAFRI Dual Headphone Stand with USB Charger Desk Gaming Double Headset Holder Hanger Rack with 2 USB Charging Port and 2 Outlet - Suitable for Gamer Desktop Table Game Earphone Accessories Gift · · ·