

ECCR: Explainable and Coherent Complement Recommendation based on Large Language Models

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ABSTRACT

A complementary item is an item that pairs well with another item when consumed together. In the context of e-commerce, providing recommendations for complementary items is essential for both customers and stores. Current models for suggesting complementary items often rely heavily on user behavior data, such as co-purchase relationships. However, just because two items are frequently bought together does not necessarily mean they are truly complementary. Relying solely on co-purchase data may not align perfectly with the goal of making meaningful complementary recommendations. In this paper, we introduce the concept of "coherent complement recommendation", where "coherent" implies that recommended item pairs are compatible and relevant. Our approach builds upon complementary item pairs, with a focus on ensuring that recommended items are well used together and contextually relevant. To enhance the explainability and coherence of our complement recommendations, we fine-tune the Large Language Model (LLM) with coherent complement recommendation and explanation generation tasks since LLM has strong natural language explanation generation ability and multi-task fine-tuning enhances task understanding. We have also devised an LLM-compatible method for compressing and quantizing user behavior information into language model tokens. Experimental results indicate that our model can provide more coherent complementary recommendations than existing state-of-the-art methods, and human evaluation validates

that our approach achieves up to a 48% increase in the coherent rate of complement recommendations.

KEYWORDS

Recommender Systems; Large Language Model; Explainable Machine Learning

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1 INTRODUCTION

Complementary item pairs or sets often arise from user co-purchase behavior and are typically linked by shared purpose or intent [1]. Effective e-commerce complementary RS can significantly enhance the customer experience and yield positive business outcomes for the store. A store with valuable complementary RS can motivate users to purchase item pairs or sets, boosting overall sales. Simultaneously, customers benefit by saving time, as they can avoid the need for additional searches to find related essential items, resulting in an improved shopping experience.

To assess how well the complementary items match, we propose the concept "coherent", which includes two aspects, *Compatibility* and *Relevance*. *Compatibility* plays a crucial role in determining the suitability of item pairs, particularly in the case of electronic items. When an item pair lacks compatibility, it cannot be used together to achieve a common goal. For instance, in Figure 1, the cellphone and the screen protector are incompatible, rendering them unsuitable for shared purposes, such as device protection. We define *Relevance* items if they share the same value of at least one important attributes, like brand, color, style, and so on. In Figure 2,

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Figure 1: Incompatible complementary recommendation example.



Figure 2: Relevant complementary recommendation example.

the umbrella has the same brand and design style as the handbag, leading to a better match than other candidate umbrella items.

Current complementary RS, such as P-Companion [1], often rely on category transition and co-purchase user behavior to build models. However, these methods encounter two primary challenges. First, not all co-purchased pairs qualify as coherent complements, particularly in domains like Fashion and Food. For example, while users may buy various dresses or chocolates, these items represent variations rather than true complements, as they serve the same purpose instead of a joint intent when used together. Second, the category-level coherence cannot replace the item-level one. Like Figure 1, while a screen protector may complement a cellphone at the category level, customers might not consider it a suitable recommendation if the items are incoherent.

To tackle the issues of irrelevant and incompatible complementary RS, we formalize the concept of *coherent complement recommendations* and utilize Large Language Models (LLMs) to generate explanations for coherent complement items as Figure 2. This aids users and stores in understanding why these item pairs are coherent. Recent advancements in LLMs [2–4] have highlighted their strong abilities in explanation generation on RS. To optimize our approach, we integrate the tasks of coherent complement recommendation and explanation generation into the LLM fine-tuning process. This integration is inspired by prior works [2, 3], suggesting that multi-task LLM fine-tuning enhances understanding when the tasks are interrelated.

To summarize, we make the following contributions to this work:

- We propose the "coherent complement recommendation" and demonstrate its effectiveness in enhancing the coherence of complementary items compared to existing RS. We achieve this by leveraging the LLM and providing high-quality explanations.
- We contend that using item titles directly may limit the capabilities of the LLM. As a solution, we develop an LLM-compatible item indexing algorithm that incorporates text features and user behavior information to enhance recommendation performance.
- We collaborate with domain experts to assess the quality improvement in coherent complement recommendations achieved

by our fine-tuned LLM compared to existing models. We also evaluate the quality of the explanations provided.

2 RELATED WORK

2.1 Complementary Recommendation

Complementary recommendation, a critical scenario in recommendation systems, has predominantly relied on user purchase and browsing patterns for its construction. Previous research, exemplified by [1, 5–8], has concentrated on modeling complementarity by analyzing customers' historical purchase behaviors and the correlation among product attributes, including title semantics and image-based features. Recent investigations [9, 10] in this field have delved into advanced methodologies involving graph neural networks [11–13]. These methods aim to exploit prior knowledge pertaining to internal product-to-product graph structures to effectively constrain complementary recommendations within predefined boundaries. Another research avenue revolves around the development of sequential recommendations [14–16], wherein models learn complementarity implicitly from users' shopping sequences. However, despite the diversity in modeling architectures, these approaches overwhelmingly emphasize product-level correlations originating from users' purchase and browsing activities. This accentuates a notable concern: the recommended items may lack precise relevance and high compatibility with the anchor product. Consequently, it could lead to an unsatisfactory user experience where recommended products, although seemingly complementary at a high-level product category, ultimately lack relevance and compatibility at the individual product level. This situation poses a substantial risk to customer trust and overall satisfaction.

2.2 Large Language Model for Recommendation

Recent advancements in Large Language Models (LLMs) have garnered significant attention in the field of Natural Language Processing (NLP). Notably, models like OpenAI GPT [17] and Meta LLaMA [18], built on deep transformer architectures, have demonstrated the transformative potential of LLMs in various applications, including recommendation systems. Recent surveys [19, 20] highlight that LLMs are prominently employed in recommendation tasks in two primary ways: 1). *Universal Embeddings*: LLMs provide universal embeddings that can be used to initialize existing recommendation models [21–23], and 2). *Zero-Shot and Few-Shot Approaches*: LLMs produce recommendations by either leveraging their inherent knowledge as a zero-shot approach or by using a few examples within the prompt as a few-shot approach [24–26]. LLMs have also found applications in other recommendation scenarios, such as item generation [2, 3, 27] and re-ranking recommendation permutations [26]. However, none of these works have specifically focused on harnessing LLMs to achieve a deep understanding of item-to-item relationships. Deep product understanding is crucial to ensure that recommended items exhibit high compatibility and relevance. This understanding plays a pivotal role in enhancing the quality of item-pair or item-set recommendations, which benefits customer shopping experience and store business impact.

3 BACKGROUND

3.1 Preliminary Knowledge

There are three main types of behaviors to describe user interactions in online e-commerce, such as Amazon, eBay, Taobao, etc.

- **Co-View** (\mathcal{B}_{cv}): Users who viewed item x also viewed item y .
- **View to purchase** (\mathcal{B}_{vp}): Users who viewed item x eventually bought item y .
- **Co-Purchase** (\mathcal{B}_{cp}): Users who bought item x also bought item y .

These three types of behaviors are used to construct the user behavior graph, where edges of “Co-View” and “View to purchase” are considered as substitutes, and edges of “Co-Purchase” are treated as complements [28]. In order to further refine the product relationship, on one hand, the combination $(\mathcal{B}_{cv} \cap \mathcal{B}_{vp}) - \mathcal{B}_{cp}$ is often used to learn the substitute product relationship like Product Embedding (P2V) [1], which in our work is a 128-dimension vector representing an item learned by GAT [29]. With this refined logic, it can improve the substitute product relationship quality based on human labels. On the other hand, the combination $\mathcal{B}_{cp} - (\mathcal{B}_{cv} \cup \mathcal{B}_{vp})$ is used to model complementary product relationship.

3.2 Motivation

We use a state-of-the-art complement recommendation model, P-companion [1], as an example to demonstrate the existing defects. Although P-companion is an end-to-end model, it can be described as two steps. The first step is category transition. We define *anchor item* as the item for which we want to provide complementary items, and in this step, the P-companion model trained on the user behavior graph provides multiple categories that are complementary to the category of the anchor item. For example, if the anchor item is an iPhone 11 with *Cellphone* as the category, then the reasonable complementary categories could be *Phone Cases*, *Screen Protectors*, and *Headphones*. In the second step, the P-companion predicts the items under each complementary category and ranks them based on their similarity to the anchor item.

Based on the model design, P-companion focuses on the category-level complement and the item-level similarity, which, however, may not lead to important item-level coherence. Figure 1 shows a recommendation example provided by P-companion. In this example, the category of the anchor item is a cellphone, and the complementary candidate item is a screen protector for a tablet. Based on common sense, a cellphone and a screen protector are complementary at the category level, but these two items together are not a coherent complementary match because they cannot be used together (different sizes) or have any match on important attribute values (such as color or brand). Also, since the P-companion does not provide an explanation, we do not know why the P-companion model provides such a recommendation, and we can only speculate their similarity may come from image tone. Thus, explanations are important for the complement recommendations.

As a result, in response to the problems of existing complementary recommendation models, we propose the concept of *coherent complement recommendation*. We preliminarily define the coherent complement item as a great match with the anchor item, reflected in

two aspects: *Compatibility* (i.e., can be used together) and *Relevance*. We will further formalize these two aspects in Section 4.

4 METHODOLOGY

Our task is to provide an explainable and coherent complement recommendation. In this section, we will answer: 1. how to further formalize the concept of *coherent complement*; 2. how to build explainable coherent complement datasets; 3. how the model learns to provide coherent complement recommendations from datasets.

4.1 Data Construction for Coherent Complementary Datasets

In Section 3.2, we define the *coherent complement* concept in two aspects: *Compatibility* and *Relevance*, which are, however, still vague. An intuitive solution is to introduce customer evaluation or expert labeling, but such a solution cannot be scaled up due to huge human labor. Thus, we propose a dataset construction method based on our data source. The following part is the data source introduction:

- **Catalog Data** (*CAT*): Each item is described by a dictionary. The keys are pre-defined attribute names, while the values are corresponding properties. The value is *None* if the attribute does not apply to this item. For example, the dictionary of an iPhone11 product could be {"color": "black", "brand": "Apple", "flavor": "None", ...}.
- **Product Type Important Attribute List** (*I*): *Product Type* is a special attribute of the dictionary in the *Catalog Data*. Knowledge experts manually select around 10 ranked attributes based on their importance for each product type. For example, the important attribute list of *Cellphone* includes *brand*, *color*, and *connectivity_technology*.
- **Compatible Data** (*COM*): A previous work of Amazon that uses DistilBERT [30, 31] and neural networks to predict the compatibility of item pairs in *Electronics* category. The *Electronics* includes several common product types, like *Cellphone* and *TV*. The data contains a list of predicted compatible item pairs.
- **User Behavior Data** (*CP*): We use $\mathcal{B}_{cp} - (\mathcal{B}_{cv} \cup \mathcal{B}_{vp})$ to build the user behavior dataset for complementary item pairs.

$$(i_a, i_c) \in CC \leftrightarrow \text{Complement} \wedge (\text{Relevant} \vee \text{Compatible}) \quad 329$$

$$\text{Complement} \leftrightarrow (i_a, i_c) \in CP \quad 330$$

$$\text{Compatible} \leftrightarrow (i_a, i_c) \in COM \quad 331$$

$$\text{Relevant} \leftrightarrow \exists t \in (I(PT(i_a)) \cap I(PT(i_c))) \wedge CAT(i_a, t) = CAT(i_c, t) \quad 332$$

(1) 334

According to the data, we instantiate the coherent concept in two ways. If the co-purchase item pair satisfies at least one of the following conditions, we would see it as coherent complement. First *Compatible*, if the two items co-appear as a pair in **Compatible Data**, which means they can be perfectly used together for a joint intent. Second *Relevant*, if the item pair shares the same value of at least one **important attribute** based on their *product types*. For example, "brand" is an important attribute for both *Coffee* and *Coffee Maker*. If a coffee brand is the same as a coffee maker's brand, they should be coherent and very related to each other. Finally, we require the two items to appear as a pair in the **Co-Purchase** dataset since the co-purchase in user behavior data is a strong signal of complement. To formalize this step, we define i_a, i_c as anchor and

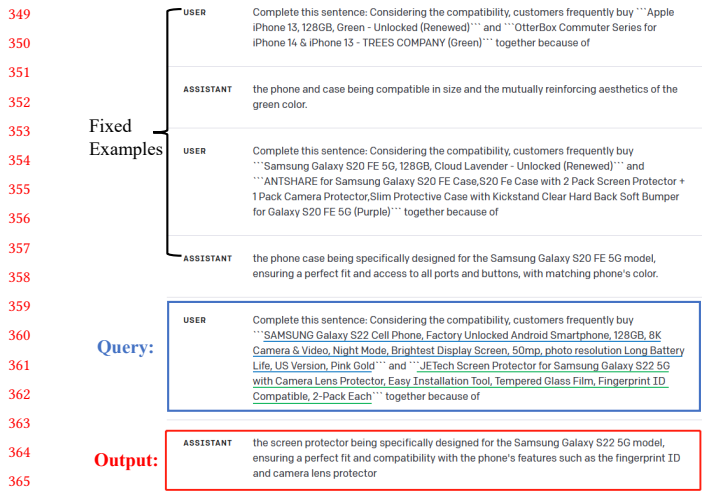


Figure 3: Explanation on *Cellphones* generated by ChatGPT.

candidate items, *CC* as coherent complementary dataset, and then we have Eq.(1) as the criteria. After building the *CC* dataset based on the criteria, we will use it for LLM fine-tuning and evaluation.

4.2 Data Construction for Explanation Datasets

Since *coherent* is a fresh concept we define in Section 4.1, there are no off-the-shelf explanation datasets for this task. Considering that ChatGPT can generate vivid sentences, we use it to generate the explanation with a coherent complementary item pair [32]. In real-world e-commerce application scenarios, customers do not tend to read verbose sentences, we expect the explanation to be concise and precise. Thus, we manually write two examples so that ChatGPT can generate the output with the format as we expect by few-shot learning. Specifically, as shown in Figure 3, we always integrate two fixed examples at the beginning of the prompt with the item titles in the last utterance to generate coherent complement explanations.

4.3 Explainable and Coherent Complement Recommendation Task

We break the Explainable and Coherent Complement Recommendation (ECCR) task into two parts. First, we need to determine the coherent complement product pairs, and second, we provide an explanation of why they are coherent and complementary.

For the coherent complementary recommendation task (short as the Recommendation Task), following the negative sampling schema, we sample k (as a hyper-parameter) negative items based on the strategy in Section 5.1 for each item pair in *CC* defined in Eq.(1). Thus, the input of the Recommendation Task includes an anchor item and a list of candidate items with the size of $k + 1$, and the backbone model expects to select the best item choice. For the explanation generation task (short as the Explanation Task), the backbone model receives an input containing a pair of items in *CC*. The expected output is part of a sentence with at most 50 words, and the output should contain enough information to express the reason for coherent complementary matching.

The Explanation Task is a form of language generation, where the Large Language Model (LLM) performs well. Besides, recent

OpenP5 work [2] has shown that if we properly union multiple related tasks and fine-tune the same backbone LLM on them, the LLM can learn from multiple angles and each single task performance will be boosted. Considering such an advantage, we also include two classification tasks as auxiliary tasks during the model training process: the complement classification task and the substitution classification task (short as the Classification Task). For these two auxiliary tasks, the model needs to answer whether these two products have a complement/substitution relation with the given item pair, and the expected output should be either *Yes* or *No*.

To union the task forms, we transfer the Recommendation and Classification Tasks into the language generation task, the same as the Explanation Task, and fine-tune one LLM on all four tasks together. We provide some prompts for each task in the Appendix.

To summarize, we have four types of tasks for LLM fine-tuning:

- **Main Task 1: Recommendation Task.** Listwise coherent complementary recommendation.
- **Main Task 2: Explanation Task.** Generate a short explanation for a coherent complementary item pair.
- **Auxiliary Task 1: Complement Classification Task.** Pairwise coherent complementary recommendation.
- **Auxiliary Task 2: Substitution Classification Task.** Pairwise substitution recommendation.

5 EXPERIMENTS

5.1 Experimental Setup

5.1.1 Dataset. Our experiments are conducted on a real-world dataset collected from *Amazon.com* including three different product types, namely *Cellphone*, *Coffee*, and *Handbag*. Under each of the three product types, we collect **Catalog Data**, **Product Type Important Attribute List**, **Compatible Data** (only available for *Cellphone*) and **User Behavior Data** as mentioned in Section 4.1.

Since the number of the items in *Amazon.com* is extremely large, we only use the popular Amazon product as the anchor items as the other items are usually less important and the size is much larger. We follow the method in Section 4.1 to build the coherent complement dataset. The anchor items with fewer than 10 coherent complementary items are filtered out as unseen anchor item testing, since they do not show in the training or validation datasets. We expect the LLM to gain domain knowledge and be able to generalize to unseen cases. For the remaining data, we split the coherent complementary items into training, validation, and testing datasets in 8:1:1 for each anchor item. Also, we follow the solution in Section 4.2 to build the explanation dataset for coherent complementary item pairs. Considering the strong language learning and generation ability, we only apply 10% stratified sampling based on product type pairs for all training, validation, and testing datasets, respectively. Finally, the training dataset statistics are shown in Table 1, and the testing and unseen anchor item testing dataset statistics are shown in the Appendix. From the statistics, we can see that the *Handbag* is the largest one among the three product types, and the *Cellphone* has the smallest number of anchor items but each anchor item has the most coherent complement items, reflected in the number of the Recommendation Task samples over the number of anchor items.

For the Recommendation Task, we set the negative candidate set size $k = 20$ for each coherent complement item pair. We build the

Dataset	Total item	Anchor item	Rec task samples	Complement classification	Substitution classification	Exp samples
Cellphone	54,439	3,031	82,017	164,034	175,078	6,835
Handbag	246,853	12,843	201,951	403,902	209,331	20,322
Coffee	46,082	4,062	54,737	109,474	55,658	5,601
All	347,374	19,936	338,705	677,410	440,067	32,758

Table 1: Statistics of the training datasets.

negative candidate pool for each anchor item from three sources: 1. co-purchase but incoherent items (i.e., $Complement \wedge \neg(Compatible \vee Relevant)$) in Eq.(1); 2. substitution items; 3. other unrelated items (if the first two are insufficient to fill the k candidates). The negative candidates for every Recommendation Task query are stratified sampled from the negative candidate pool according to the rate of different data sources. For the coherent complement classification task, the positive pairs are from the coherent complement dataset based on Eq.(1), and for each positive pair, sample one negative case from the negative candidate pool of this anchor item. For the substitution classification task, the positive cases are from $(\mathcal{B}_{cv} \cap \mathcal{B}_{vp}) - \mathcal{B}_{cp}$ of the anchor item as mentioned in Section 3.1, and the negative cases are the coherent complement item pairs.

5.1.2 Evaluation Metrics. For the Recommendation Task, we apply beam search to the backbone LLM output generation and use the top-5 generated different outputs from the backbone LLM and apply Hit Ratio (HR) @ 5 [33] and Normalized Discounted Cumulative Gain (NDCG) @ 5 [34, 35] as evaluation metrics. For the Explanation Task, we use typical metrics BLEU-4 [36], as well as ROUGE-1, ROUGE-2, and ROUGE-L [37] to compare the difference between the ground truth explanation (generated by ChatGPT) and the model generated output for quantitative quality evaluation. We also have two auxiliary classification tasks, complement and substitution, and we use the F1-score as a precision-recall balanced metric for evaluation. All the metrics are the higher the better.

We understand the ground-truth data of Recommendation and Explanation Tasks may not be reliable since it is the first time to propose the "coherent complement" concept and build coherent complementary datasets to the best of our knowledge. Thus, apart from offline metrics, we introduce human labeling in the evaluation phase, and the detail is shown in Section A.5.

5.1.3 Baseline Models. We compare our LLM performance on the Recommendation Task with the following baseline models:

- **Co-Purchase (CP)** is one of the most straightforward ways. We output the items that are in the Co-Purchase (\mathcal{B}_{cp}) and not in Co-View (\mathcal{B}_{cv}) or View-to-Purchase \mathcal{B}_{vp} for recommendation.
- **PMSC** [28] adopts relation-aware parameters to model multiple item relations with path logic constraint loss and later feeds into a neural network for classification. Each product item has its source and target embeddings for query and candidate contexts.
- **P-Companion** [1] is an end-to-end framework, leveraging product type transitions and then a transfer metric learning network for diversified complementary product recommendation.

We do not have a baseline model for the Explanation Task as it is a new research question. We compare our generated explanations with ChatGPT's explanations by human labeling shown in Section A.5. For the Classification Tasks, since they are auxiliary tasks, we

do not compare the model with other baseline models, but compare our model among different experiment settings.

5.2 Performance Comparison

We conduct experiments on *Cellphone* dataset with our P2V quantization indexing method on different backbone LLMs. The results are shown in Table 2. The running time is based on 8x NVIDIA A10G (24GB) GPUs. We can see that all three backbones perform similarly on the Explanation Task, but T5-S and T5-B much outperform LLaMA-3B on the Recommendation and Classification Tasks. One possible reason could be that we only tune 200M parameters of LLaMA-3B due to our limited GPU memory, which takes only a small part of its 3B parameters. Besides, the performance of T5-S and T5-B has insignificant performance differences, but due to over three times better efficiency, we use T5-S as the default backbone model in the following experiments.

Table 3 displays the results of our model and baseline models on the Recommendation Task on different datasets. Our model performs much better than every baseline, which validates that our model can improve the coherent aspect when providing the complement recommendations.

5.3 Ablation Study

We conduct the ablation study to validate the effectiveness of our proposed design. We have the following three ablation options:

- Option 1: remove the complement classification task.
- Option 2: remove the substitution classification task.
- Option 3: remove the extra collision token for P2V quantization (thus using 16 tokens to represent each item).

We use the T5-S as the backbone with P2V quantization and the average results over 3 PT datasets are in Table 4. We can see that all the ablation settings perform worse than our original setting. Among the three options, removing the substitution task drops the most, indicating substitution relation learning benefits the coherent complement recommendation task. Besides, removing the complement classification drops the least as it is a variant of the Recommendation Task. Thus, if the data is too large compared to limited fine-tuning time, Option 1 may be the first consideration.

6 CONCLUSIONS AND FUTURE WORK

In this work, we propose the problem that current complement recommendations are not compatible or relevant enough with the anchor item, and based on this, we propose the concept of "coherent complement". Our multi-task fine-tuned Large Language Model (LLM) outperforms current complement recommendation models in the coherent aspect and can provide high-quality explanations validated by expert labeling.

There are many possible extensions of our work. First, the coherent rate of our dataset, though improved, still has an improvement space. New solutions can be proposed to construct a coherent complement dataset with better quality. Also, the largest parameter numbers of our LLMs are 3B due to the limited GPU memory. With the rapid development of memory and efficiency improvement techniques for LLMs, larger LLMs could be used for performance gain on explainable and coherent complement recommendation tasks.

LLM	#Param	Fine-tuning		Recommendation		Explanation (%)				Classification	
		time (min / epoch)	HR@5	NDCG@5	BLEU-4	ROUGE-1	ROUGE-2	ROUGE-L	F1-Complement	F1-Substitution	
T5-S	60M	19.0	0.5545	0.3812	36.7309	56.8252	39.0976	50.8865	0.8950	0.9388	
T5-B	220M	69.0	0.5737	0.3889	37.1520	57.1968	39.7864	51.4705	0.8881	0.9392	
LLaMA-3B	3B (tunable 200M)	693.5	0.3170	0.2002	36.7023	56.5216	39.4460	50.8438	0.7573	0.8640	

Table 2: Performance of different backbone LLMs on *Cellphone*.

Dataset	Cellphone		Coffee		Handbag	
Model	HR@5	NDCG@5	HR@5	NDCG@5	HR@5	NDCG@5
CP	0.4810	0.2909	0.4908	0.2695	0.4888	0.2767
PMSC	0.3726	0.3065	0.3697	0.2323	0.4045	0.2563
P-Companion	0.5098	0.2872	0.5170	0.2798	0.3582	0.1949
T5-S (Ours)	0.5545	0.3812	0.7026	0.5774	0.7266	0.6019

Table 3: Performance of different models on Recommendation Task.

Tasks	Recommendation		Classification	
	HR@5	NDCG@5	F1 (Comp)	F1 (Subs)
w/o Comp Classification	0.5146	0.3639	/	0.9318
w/o Subs Classification	0.4656	0.3283	0.8920	/
w/o Extra collision token	0.4790	0.3352	0.8922	0.9309
w/o Ablation setting	0.6612	0.5202	0.9045	0.9469

Table 4: Average results over 3 PT datasets in ablation study.

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A SUPPLYMENTARY MATERIALS

A.1 Item Indexing

Recent work [38] shows that item indexing methods play an important role in LLM for recommendation tasks. Previous works that use the LLM for recommendation mainly focus on user-item interaction, and thus, some clustering methods based on user-item interaction graphs and using Out-Of-Vocabulary (OOV) for item indexing would be effective. The reason is that similar items on user-item interaction graphs may share some OOV tokens by clustering, which benefits backbone model learning.

Based on the observation, we propose a P2V Quantization Indexing method for our tasks. The P2V vector learns from text features and user behavior information, as introduced in Section 3.1, and similar products under these two perspectives have similar P2V embeddings. We design the following algorithm, which balances the new OOV token size and item representation length for LLM.

Figure 4 demonstrates an example of our P2V quantization process. First, we separate the 128 dimensions into 16 groups in order, each containing 8 dimensions. Since the absolute value of each dimension is usually not more than 1.0, we map each dimension to a Boolean value, denoted as *sign*. If the value of this dimension is positive, *sign* will be 1; otherwise, *sign* will be 0. Then, for the 8 01-values in the same group, we use the binary-to-decimal algorithm to map to a decimal OOV token value. Please note that we follow [38] work to use a bracket-surrounded number to stand for the OOV token, and thus, <1>, a newly defined OOV token, is different from the number 1 for LLM. To formalize this process, we have:

$$t_i = \left\langle \sum_{j=0}^{j<8} \text{pos}(v_{8i+j}) \cdot 2^j \right\rangle \text{ where } i = 0 \dots 15 \quad (2)$$

$$\text{pos}(x) = \begin{cases} 1 & x > 0 \\ 0 & x \leq 0 \end{cases}$$

where t_i is the i -th token of the item representation and v_j is the j -th dimension value of the item P2V embedding vector. We notice that in this way if two items have the same sign value for all 128 dimensions, they will have the same quantization representation. Thus, like dealing with Hash collision, we add an extra count token to distinguish different items with the same sign value.

Reviewing the quantization process, each item will be represented by 17 new OOV tokens, and the first 16 tokens will be between <0> and <255> since it is calculated from an 8-bit binary number. Also, in our experiments, the size of the largest item set with the same sign value for all 128 dimensions is smaller than 256. Thus, the backbone LLM will learn 256 extra OOV token embedding from random initialization during the fine-tuning process.

To show the effectiveness of our P2V quantization indexing algorithm, we compare the other two indexing methods, title representation and sequential indexing, in Section 5. Title representation is to directly use the item titles in the prompt. Sequential indexing uses numbers defined in the original vocabulary to index the item from 1 according to the appearance order in the dataset [2], and the candidate order in the Recommendation Task will be randomly shuffled. An example of the sequential indexing is *item_38*.

Dataset	Method	Recommendation		Explanation (%)			
Metrics		HR@5	NDCG@5	BLEU-4	ROUGE-1	ROUGE-2	ROUGE-L
Cellphone	Title	0.4658	0.4137	36.6610	56.8873	39.1667	51.1066
	Seq	0.4916	0.3570	35.9842	56.1791	38.4759	50.5354
	P2V	0.5545	0.3812	36.7309	56.8252	39.0976	50.8865
Coffee	Title	0.5767	0.5209	15.6374	39.8639	19.9234	33.1805
	Seq	0.7428	0.6333	14.5328	40.0190	19.1537	32.7500
	P2V	0.7026	0.5774	15.7357	41.0696	20.4086	33.9282
Handbag	Title	0.6315	0.5838	12.8479	40.0494	16.4402	32.7442
	Seq	0.6709	0.5721	12.5280	39.7307	16.0910	32.3682
	P2V	0.7266	0.6019	12.9881	39.9086	16.4851	32.5529

Table 7: Performance of different indexing methods on T5-S [39].

Dataset	Cellphone		Coffee		Handbag	
Metrics	HR@5	NDCG@5	HR@5	NDCG@5	HR@5	NDCG@5
Title	0.4628	0.4100	0.5093	0.4364	0.5039	0.4531
Sequential	0.5735	0.4376	0.5623	0.4556	0.5366	0.4235
P2V	0.6255	0.4963	0.5796	0.4437	0.5890	0.4659

Table 8: Recommendation task performance of different indexing methods on T5-S [39] using the datasets with unseen anchor items.

A.4.1 Indexing Method Comparison. To compare the performance of different indexing methods, we employ T5-S as the backbone and present the results of the Recommendation Task using the testing datasets in Table 7. It is evident that in the Recommendation Task, P2V quantization outperforms the sequential indexing and title-based methods in half of the cases. In the Explanation Task, while the results are comparable, the sequential method consistently ranks lowest, with P2V quantization generally outperforming the title-based approach. Notably, the *Cellphone* and *Handbag* results using the P2V and title methods exhibit a BLEU-ROUGE trade-off, reminiscent of the precision-recall trade-off.

Table 8 provides an overview of the Recommendation Task performance across the three indexing methods in unseen anchor item testing datasets. In most cases, the P2V method prevails, affirming the superior generalization capability of our proposed indexing algorithm when faced with unseen anchor item scenarios. This enhanced generalization arises from the integration of text features and user behavior information into P2V latent embedding, which is subsequently mapped in the quantization indexing. Such adaptability is particularly valuable since it accommodates scenarios where not all items are used for training, and new items are continuously introduced as potential anchor items.

A.5 Human Evaluation

Since it is the first time to propose and discuss the concept of coherent complement (CC), there are no benchmark datasets nor explanation datasets for CC item pairs. Thus, we introduce human labeling to the dataset and our LLM output evaluation.

There are two labeling tasks in total. In the first task, the knowledge experts assume they are customers and have decided to buy the anchor item. The experts need to label whether the provided CC items are a great match with the anchor item. We evaluate this task by sampling around 200 item pairs from three datasets: fine-tuned T5-S (our) output, CC dataset constructed through Eq.(1),

	Cellphone	Gain	Coffee	Gain	Handbag	Gain
P-companion	0.630	0.00%	0.310	0.00%	0.420	0.00%
CC Dataset	0.740	+17.46%	0.355	+14.52%	0.565	+34.52%
T5-S (Our)	0.790	+25.40%	0.380	+22.58%	0.625	+48.81%

Table 9: Human labeling on the coherent rate.

	Cellphone		Coffee		Handbag	
	Corr	Info Reason	Corr	Info Reason	Corr	Info Reason
ChatGPT	1.000	1.000	1.000	0.9057	0.9811	1.000
T5-S (Our)	1.000	0.9892	1.000	0.8868	0.9057	0.8679

Table 10: Human Evaluation on the explanation quality.

and P-companion complement recommendation. The results under three different product-type datasets are shown in Table 9. We can see that our model output is much better than the existing Amazon complementary recommendation in the coherent aspect. More surprisingly, although our model is fine-tuned on the CC dataset, it outperforms CC data, probably due to LLMs' pre-trained knowledge and generalization ability.

The second task is to label the explanation data, one from ChatGPT generation as mentioned in Section 4.2, and the other from our fine-tuned T5-S model generation. We require the knowledge experts to label the explanation in three aspects: Correct (Corr), Informative (Info), and Reasonable (Reason). These three aspects imply the explanation does not provide wrong information, is not general but specific to this item pair, and provides the matching aspect convincing to customers. Examples in Section A.6.2 explain the three aspects. We first sample and filter out the item pairs that are not coherent complement, and report the results on the remaining about 200 data samples under each setting in Table 10. Both our fine-tuned T5-S and ChatGPT can provide a high rate of good explanations and our model is even better overall. Similar to the first human labeling task's situation, although the explanation training data is from ChatGPT, multi-task fine-tuning on domain data also benefits item understanding to provide a better explanation.

A.6 Case Study



Figure 5: Incorrect coherent complement example from Eq.(1).

A.6.1 Coherent Complement Recommendation Task. We present examples that provide different recommendations among various models. Figure 1 displays an example recommended by the P-companion [1] model, but it is classified as *NOT* coherent complement by our model. In Figure 5, we provide an example based on Eq.(1), but it is also classified as *NOT* coherent complement by our model and domain experts. The two items are co-purchased, probably because they are consumable supplies. The same important

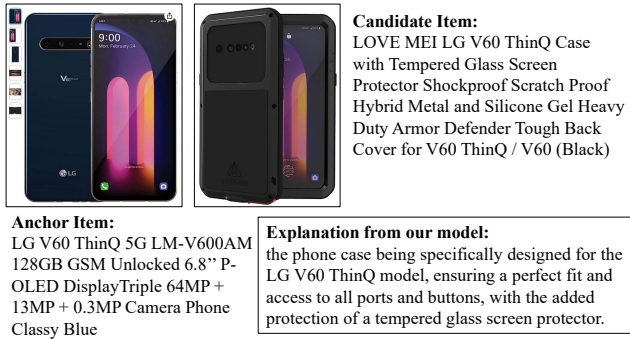


Figure 6: Case study from fine-tuned T5-S [39] with the explanation.

attribute value is "2 pounds" under *item weight*, but domain experts argue that this point is insufficient for a coherent complement relation. The example also implies our criteria for the CC datasets have room for improvement. Figure 2 and 6 showcase the examples recommended by our model but not in the recommendations from P-companion or the CC dataset established by Eq.(1). Experts align with our model’s recommendation and explanation.

A.6.2 *Explanation Task.* We present some explanation examples here.

Anchor	Caribou Coffee Reindeer Blend, Single-Serve Keurig K-Cup Pods, Dark Roast Coffee Pods, 88 Count
Candidate	Nestle Coffee mate Coffee Creamer, Peppermint Mocha, Liquid Creamer Singles, Non Dairy, No Refrigeration, Box of 50 Singles (Pack of 4)
ChatGPT (Correct)	the complementary flavors and aromas that enhance the overall coffee-drinking experience, with the dark roast of the Caribou Coffee Reindeer Blend perfectly complemented by the peppermint mocha flavor of the Nestle Coffee Mate creamer.
Ours (Incomplete Sentence)	the perfect combination of rich and flavorful coffee from Caribou Coffee Reindeer Blend, complemented by the indulgent and creamy taste of peppermint mocha coffee creamer from Nestle Coffee Mate, enhancing the overall coffee-

Table 11: Explanation example cases at *Correct* aspect.

Anchor	Vera Bradley Women’s Recycled Lighten Up Reactive Sling Backpack Bookbag, Sunflower Sky, One Size US
Candidate	Vera Bradley Women’s Cotton Deluxe Zip Id Case Wallet with RFID Protection
ChatGPT	the matching design and complementary functionality of both products.
Ours (Informative)	the cohesive design and matching patterns of the Vera Bradley brand, creating a coordinated and stylish look for their accessories.

Table 12: Explanation example cases at *Informative* aspect.

Anchor	SUPER Charcoal Roasted White Coffee Classic
Candidate	SUPER NutreMill Soy Milk Powder No Sugar
ChatGPT	the complementary flavors and nutritional combination they offer when consumed together.
Ours (Reasonable)	the complementary flavors and the ability to create delicious and creamy beverages by combining the rich and smooth taste of the super charcoal roasted white coffee with the creamy and indulgent smooth texture of the Nutremill Soy milk powder.

Table 13: Explanation example cases at *Reasonable* aspect.