Learning to Personalize Recommendations based on Customers' Shopping Intents

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***Abstract*—Understanding the customers' high level shopping intent, such as their desire to go camping or hold a birthday party, is critically important for an E-commerce platform; it can help boost the quality of shopping experience by enabling provision of more relevant, explainable, and diversified recommendations. However, such high level shopping intent has been overlooked in the industry due to practical challenges. In this work, we introduce Amazon's new system that *explicitly* identifies and utilizes each customer's high level shopping intents for personalizing recommendations. We develop a novel technique that automatically identifies various high level goals being pursued by the Amazon customers, such as "go camping", and "preparing for a beach party". Our solution is in a scalable fashion (in 14 languages across 21 countries). Then a deep learning model maps each customer's online behavior, e.g. product search and individual item engagements, into a subset of high level shopping intents. Finally, a realtime ranker considers both the identified intents as well as the granular engagements to present personalized intent-aware recommendations. Extensive offline analysis ensures accuracy and relevance of the new recommendations and we further observe an 10% improvement in the business metrics. This system is currently serving online traffic at amazon.com, powering several production features, driving significant business impacts.**

***Keywords*—Personalization; Customer Shopping Intents; Shopping Trajectory; Customer Understanding; Shopping Intent-aware Ranking; Deep Learning Application; Amazon Recommendation; Metric Learning via Weakly Supervised Mined Data; Online Shopping;**

I. Introduction

Today, most E-commerce's personalize recommendations are based on user context. While static demographics or geographic features might be used, the major contributing factor to the user context is the individual items that the user engaged real-time [4]. Recommenders use the recent engagements to optimize for short-term business metrics; based on the observed user behavior, systems promote items that would result in immediate follow-up actions, such as clicks or purchases [4], [11]. But they rarely identify the high-level shopping goal that a user is trying to achieve.

Recommender systems optimized for immediate engagements can be suboptimal when users pursue high-level objectives that involve multiple items in different categories. For example, a user that recently explored camping will find it hard to navigate through different camping gears once she clicked on multiple folding chairs. The recommendations will be all kinds of folding chairs. Identifying the high-level shopping-intent is the first step to help users with a clear shopping-intent to find items serving that intent. In our recent study, we found that over 65% of Amazon customers visit the platform with specific shopping-intents, such as purchasing goods for a BBQ party. If a system could identify the users' shopping-intent, it can then generate explainable recommendations of products in different categories to assist users achieving their shopping goal with minimum friction. Such a system can present diverse recommendations in categories, e.g., camping tents and camping cooking gears when the user's goal is purchase for an upcoming camping trip. Hence, a system with shopping-intent identification capacity can provide customers with a one-stop recommendation experience featuring diverse, relevant and explainable product recommendations to fulfill their shopping-intents.

Our contribution in this work is as follows. First, we introduce the first online system powered by deep learning models that explicitly infers and updates our understanding of a user's shopping intents based on their real-time engagements. This system presents the user with relevant categories and items under the identified intents. It enables them to visualize, compare, build their basket, and navigate through necessary items within a coherent shopping flow until they achieve their objectives. This approach creates a frictionless shopping experience for the user without the need to return to the product search for finding the next items. Second, we develop a novel technique that mines user's shopping-intents from a knowledge database, translate them into human-readable shopping intents, and employ a weakly supervised technique to fine-tuned a text retrieval model that performs shopping-intent identification and shopping-intent-to-product retrieval.

II. Related Works

A. Contextual Semantic Retrieval via Sentence-BERT

In natural language processing, people have done extensive research on semantic textual similarity (STS). The Bidirectional Transformers for Language Understanding(BERT) [5] model sets new state-of-the-art performance on various sentence classification and sentence-pair regression tasks. The advancement of Sentence-BERT (SBERT) introduces a solution to perform such text to text retrieval work with an open-source library leveraging pre-trained multilingual models as cross encoders [18]. This significantly reduced the computation cost and achieved state-of-art results in STS tasks. In our work, we fine-tuned a pre-trained model from the SBert library using weakly-supervised datasets. We then leverage the fine-tuned

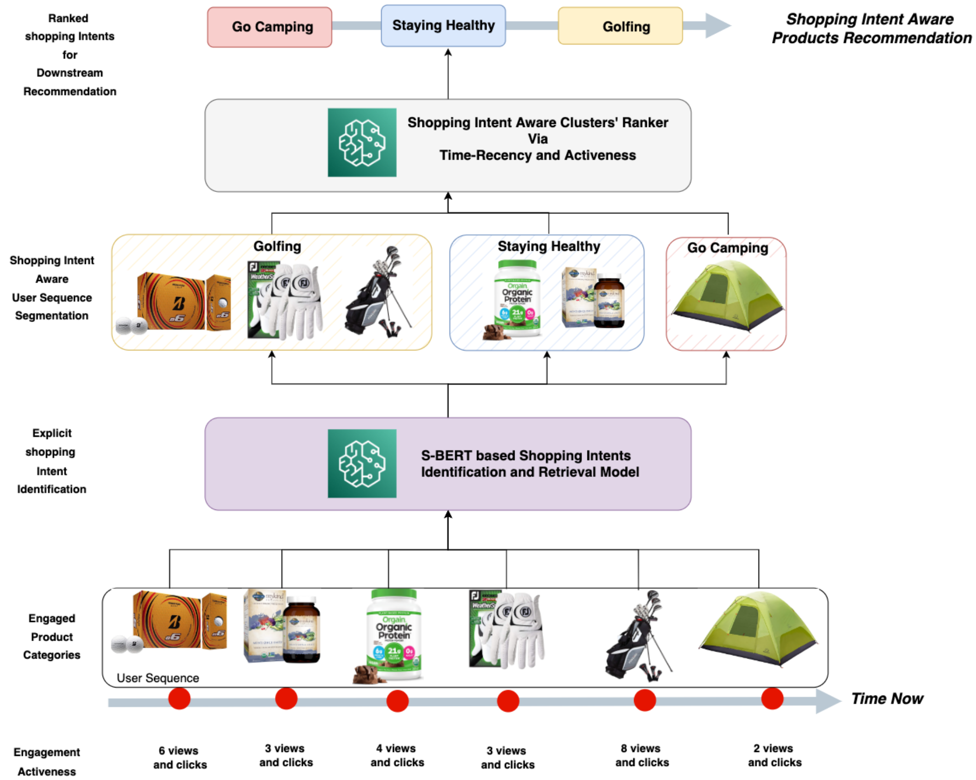

Fig. 1. Our proposed work frame of Shopping Intent Aware Recommendation via User Sequence. *We introduced a novel online language-model-based pipeline to segment a user's sequence into explicit shopping-intent clusters. Each cluster is assigned with an intent-aware ranking score for downstream complementary products recommendation*

model to relate customer shopping intent to the Amazon's internal product categories.

B. Implicit Intent Embedding in Sequential Recommendation

User's shopping engagements have been proved to be useful for today's personalization and recommendation. Most of the existing methods [14], [16], [23], [25], [31], [35] focus in learning to either encode customers' shopping intent implicitly or to use the implicit latent embedding representation as an input feature to another downstream recommender. However, the shopping intent learned implicitly from the customers' historical engagements might be miss-represented. This is due to most of the existed works heavily rely on sequential modeling which could be biased towards the most recent items and could be missing subtle shopping intents contained within engagements happened further away. Still, such work loses the explainability when performing recommendations.

To increase the explainability, another line of works aim to identify the shopping intents from search queries input by the users [8], [10], [29]. However, none of these work effectively leverage the inferred shopping intents from search queries to make meaningful recommendations. Our innovation learned from these works to explicitly define shopping intents but we further invented a language model to link the shopping intents to the actual Amazon products for downstream end-to-end complementary recommendations.

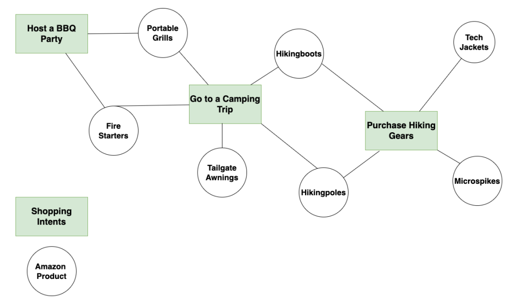

Fig. 2. Illustration of Shopping-Intent-Aware PR-graph. A by-product generated from our entire work-frame.

C. Product Relation-Graph Mining

In today's E-commerce industry, there is a stream of research working on knowledge discovery of product semantics and relations [1], [6], [15], [17], [30], [32], [34]. Product relationship knowledge graph (PR-graph) is essential for both product understanding to provide an immediate feedback based on customers' engagements as well as customer understanding. It builds the foundation to inspire various applications such as error detection [3], Amazon's complementary and sequential recommendation [9], [14], [27], and Amazon's page content optimization via multi-bandit [13], [22]. However, none of the PR-graph building takes the shopping intents context into consideration, resulting in the issue that the related products are merely similar to each other textually, such as *"toddler beds"* and *"baby beds"*. This would result in duplicated recommendation issue and less-diverse recommendation issue. In our work, as one of the by-products of the entire workflow, we introduced a shopping-intent-aware natural language model to learn the correlation between Amazon product categories and shopping intents to build a both diverse and complementary PR-graph taking the shopping intent contextual semantics into consideration, shown in Fig.2. We incorporated this shopping-intent aware PR-graph with Amazon's page content optimization work [13] to compare with its current baseline via a none-shopping-intent aware PG-graph generated by another PR-graph created by products to products co-purchase relationship [9].

III. Problem Formulation

Product Category. In today's E-commerce, product categories play an important role, which aims to accurately and effectively cluster different items into a higher level concept of summary. We observe that such concept represents a partial use case to fulfil a latent shopping intent. For example, product categories "cooking spices" and "poultry meat" are two different product-categories to fulfil a shopping intent "cooking dinner". We further define **User's Sequence** as all the historical product categories a customer has engaged with. Such user's sequence represents a customer's shopping trajectory at the store.

Problem Formulation. We formulate this work as learning the interactions between a set of users $\mathcal{U}$ and shopping trajectory $\mathcal{T}$ to segment the sequence of engagements into various shopping-intent-centric clusters and to further rank them, aiming to optimize upon time-recency and activeness of each cluster. Our solution map all the product categories within a $\mathcal{T}$ to their belonging shopping intentions $\mathcal{M}$ and reorganize them chronically as $\mathcal{S}^u = [m_1^u, m_2^u, \cdots, m_{|\mathcal{S}^u|}^u]$. The goal of the main shopping intent identification can be formulated as:

$$p(m^u = m|\mathcal{S}^u), \tag{1}$$

which measures the probability (an indication of importance) of each intent-centric cluster m to be prioritized for recommendation for this customer given this user's u's sequence $\mathcal{T}$.

IV. Methodology

Fig.1 shows the entire online recommendation's workflow. We utilized the *Shopping Intent Identification and Retrieval Model* to first identify each shopping intent with the highest possibility for each product category a customer has engaged with at different timestamp. This identified shopping intent is further used as an indicator to *segment and cluster* different engaged product categories into different shopping-intent-aware clusters. Finally, the designed *Shopping Intent-Aware Ranker* utilizing: 1) each shopping-intent-cluster's total activeness including every clustered categories previous engaged clicks and views, and 2). each shopping-intent-cluster's most recent timestamp fetch from one of the clustered product categories is to prioritize an intent-cluster which happened relatively recently with a high engagements. Such ranker assigns a shopping-intent-importance-probability score to each intent-cluster for ranking purpose. The top-ranked could potentially yield a higher chance to capture a customer's shopping interest to make a better sales conversion. From each shopping intent, a downstream complementary recommendation can be directly made via walking through the intent-aware PR-graph shown in Fig.2.

A. Prerequisites

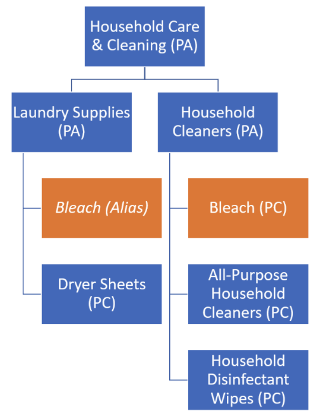

Fig. 3. Illustration of Amazon Product Category Class Tree

Amazon Product Category Browse Tree. This is a hierarchical product category information tree. Each finer-grained category is presented as a leaf node of its higher hierarchy root product-category node. For example, the node of category "camping" is the leaf to the category of "outdoor activities", while "outdoor activities" could also be a parent node of "hiking". Amazon internal team assigns the ontologist to each leaf node in Browse tree into two node classes: 1). Product Assortment (PA) and 2). Product Category (PC). Fig.3 shows an example of PA(in blue) , PC(in orange) nodes and non-category nodes(alias nodes, in orange). A PA node gathers together a disparate (heterogeneous) group of products. PA node is designed to group items together for discrete reasons that range from supporting the way a majority of customers associate products ('Nursery Furniture') to collecting together like items for classification or shopping journey support ('Tablet Accessories'). On the contrary, PC nodes are nodes that contain products of the same type.

B. Defining Shopping Intents

We define the shopping intents as *A conceptual term that can be used to cluster complementary Amazon Product Concept Node*. We utilize Amazon Product Category Class Tree as a data source for shopping intent mining. We leverage the category node class information generated by ontologists and a pre-trained entity-relation prediction model, LUKE, [26] to identify which Product Assortment nodes are shopping intent. The advantage of such approach is that the identified PA node is represented similar to Amazon search queries, which enables us to use the search logs to collect training data (see section below). Further, we leverage the open-source large language model (LLM) T0PP [19] to enrich the identified PA node into a human readable shopping intent with more contextual information. In total we generate over 2000 explicit shopping intents to cover all store departments at Amazon, such as "finish the camping gears", "shop for hunting gears", "prepare for a grill party", and etc.

C. Shopping Intent Identification and Retrieval Model

We introduce *Shopping Intent Identification and Retrieval Model*. This model is designed to perform two major tasks: 1). identify the most major shopping intent given a customer's engaged product category, 2). retrieve complementary products to be recommended to fulfill a shopping intent. We model our work using the metric learning [28] via a Siamese Network Architecture same as the SBERT [18]. Such work is proved to improve stability to perform a two-way retrieval work: 1). from a product category to retrieve the most confident shopping intent, 2). from a shopping intent to retrieve top K complementary products.

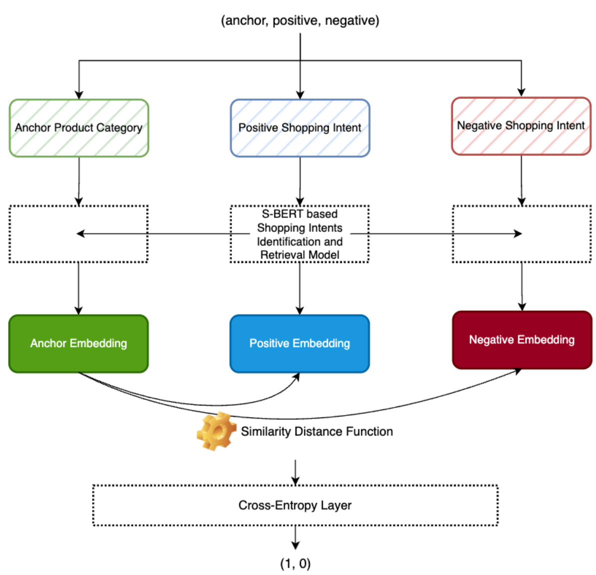

Fig. 4. Illustration of Training Objective

1) Weakly Supervised Training: Our training schema can be visualized from Fig. 4. We mine a weakly supervised positive pairs of [*product category*, *shopping intent*] using Amazon search logs and a static table mapping each search query to product category. Given each defined shopping intent term, we perform string matching via both exact match and partial semantic matching to augment data quantities, to match with one of the search queries from Amazon 1-year search logs with over 10B records. Then, we use the matched search query to map trace back to the matched product category. Intuitively, on average, each product category can be assigned to at maximum 3 different shopping intents. Thus, given this scenario where the negative pairs significantly are outnumbered the positive pairs, the negative sampling [7] is essential for this training.. To train our model, we leverage the Multiple Negatives Ranking Loss (MNR Loss) introduced by SBERT [18]. This is a similar idea to batch triplet loss [12] to first perform distance calculation between two given entities, and at the end the ranking loss is computed through the cross-entropy loss [33] compared to a label of either 1 or 0 for positive pair and negative pair respectively.

2) Creating Shopping Intent Aware PR-graph: We leverage the trained *Shopping Intent Identification and Retrieval Model* which **embeds both contextual semantics of Amazon product categories and defined shopping intents** to perform build PR-graph in two stages. First, we identify the most confident shopping intent for each of the Amazon product category, in total over 100,000 different categories covering in total 21 market places. Secondly, we leverage the same model to perform from product category retrieval for every shopping intent in the embedding space. Finally, we can construct a shopping-intent aware PR-graph using the shopping intent as the linkage node linking relevant and diverse product categories. Still, we apply different rules to fit Amazon's recommendation logic, such as gender specific filtering as the fine-tuning layer applied to the knowledge graph.

D. Shopping Intent Aware Ranker via Time Recency and Activeness

As shown in the Fig.1, given a user's sequence, our entire workflow would first segment user sequence into multiple clusters centric at different shopping intents. Each cluster comes with two entities: 1). the total engagements representing this cluster's activeness, and 2). the most recent timestamp fetched from one of the engaged product category clustered within for this cluster. We utilize these two entities to design a ranker score to represent each *shopping intent's importance-probability*, denoted as $\mathcal{R}_{tc_i}$, such that the top scored cluster is most likely to capture each customer's most desired shopping interest.

$$R_{tc_i} = R_{t_i}^{\lambda} * E_{t_i}^{\tau}, i \in numbersOfClusters \tag{2}$$

Here, R_{t_i} is the *Time Recency Reward* for each cluster, while the E_{t_i} represents each *Cluster's Activeness*. Intuitively, the more recent a customer has engaged with a certain item, the more likely he/she is trying to surface around a certain shopping goal related to it, while the engagements' activeness also shows a strong indication. Thus, we multiply both factors to figure how important a intent-centric cluster is based on its time-recency and the activities engaged. Here, λ and τ amplifies the Time Recency Reward and Cluster's Engagements respectively if set to be greater than 1 and vice versa.

$$R_{t_i} = \frac{1}{1 + (\frac{e}{\alpha})^{\eta - t_i - 10}}, t_i \leqslant \eta, i \in numbersOfClusters \tag{3}$$

The *Time Recency Reward* is designed to capture the influence of the recency effect. We design a sigmoid-based decay function to assign each SO-cluster a reward based on how recently such cluster happen compared to the ***time now***, denoted as η. The parameter α works as the leniency factor to control how fast such decay happens given the time difference. As α increases the decay happens faster as the the time difference increases before a saturation point. We set the α such that the decay happens slower when the time difference is less while happens faster when time difference becomes significant.

V. Experiment and Results

Since our entire workflow is constructed with a core ML module which is developed upon weakly supervised data mined from search logs, the traditional train-test split model evaluation approach only reveals how well our deep learning model is fitted upon the data we feed in. Thus such traditional evaluation could not reflect the actual recommendation performance in real application using our proposed end to end workflow. Thus, our *evaluation protocols* include: 1). offline human auditing for the accuracy of shopping-intent aware user sequence segmentation and complementary recommendation relevance, 2). two real-time online A/B experiments comparing two Amazon recommendation and ranking applications.

A. Offline Human Evaluation

	SI-Identification	**SI-Complementray Recs**
%Accuracy and %Relevance Respectively	95.9%	97.64%

TABLE I
Human audited evaluation

To ensure our work's robustness in the real application senario, we first build an offline pipeline for the proposed entire workflow to simulate upon the two important functionalities: 1). segment user sequence into intent-aware clusters, denoted as ***SI-Identification***, 2). make shopping intent centric complementary recommendation, denoted as ***SI-Complementray Recs***. We randomly sampled 60 Amazon customer's real user sequences and performed intent-aware segmentation and complementary products recommendation for every shopping-intent cluster, in total 1,217 records. We used *accuracy* as the metric to audit the shopping-intent identification and segmentation and defined "relevancy" based on Amazon's recommendation requirements, such as "being gender specific", "no duplication", and etc. As shown in Table.I, our work yielded a robust human-verified performance for both core tasks.

B. Online A/B Experiments

We conducted a real-productionalized online A/B experiments on two Amazon's recommendation features, the Amazon Complementary Recommendation which provides recommendations while optimizing for immediate feedback (denoted as ***ACR***), and Amazon Home Page Content Multi-bandit Ranking [13] (denoted as ***AHPR***). Our work has resulted in significant business impact and improvements for these products, see Table.II, when compared to their respective baseline approaches, which leveraged a previous Amazon products-to-products semantic retrieval technology [9].

In control group, for ACR, its previous approaches leveraged an immediate-feedback solution without personalizing upon different customer's different shopping intent. This approach relies on one of the product categories a customer has engaged with as the anchor and leveraged PR-graph created from a previous work [9] to index the related products for complementary recommendation. In the treatment, we replaced this static approach by our shopping-intent aware workflow to personalize upon each different customer's shopping intents based on their own unique shopping sequences and leveraged our new shopping intent-aware PR-graph, see Fig.2, to make the personalized shopping intent centric complementary recommendation.

	ACR	**AHPR**
Sales	+7.2%	+8.0%
Revenue	+12.0%	+16.0%

TABLE II
Online A/B experiment results for *ACR* and *AHPR*. We see significant improvements in both sales and revenue compared to the original solution

For AHPR, one of its ranking bandit relies a rule-based personalization signal. By leveraging the product embeddings produced from previous work [9] and mean pooling, it aggregates each content's products' embeddings to represent each content, while aggregating a customer's all engaged products' embeddings to represent this customer. A dot product is applied to calculate the personalization relevance between customer and each content. In the treatment, we replaced the original product embeddings by the shopping-intent aware product embedding produced by our *Shopping Intent Identification and Retrieval Model* which is co-trained with both Amazon products and shopping intents.

VI. Conclusion

This study presents a personalized recommendation system that captures customers' shopping intents at Amazon by analyzing their user engagement sequences and generating shopping intent-centric recommendations. Our approach has revolutionized the personalized experience at Amazon, resulting in significant business outcomes. We propose a novel method for constructing a shopping-intent aware PR-graph and shopping-intent aware product embeddings, which are critical for modern E-commerce tasks, including immediate-feedback-based product recommendation. In future work, we plan to enhance the shopping intent identification capabilities of our model using a multi-modal approach [2], [20], [21], [24], incorporating features such as users' search queries and impression data. This will significantly improve the robustness of our system and enable us to decipher customers' shopping objectives with greater accuracy at varying levels of granularity based on more user interactions.

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