Optimal Product Ranking for Improving Customer's Decision-Making

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1. Problem Statement

E-commerce websites often have many products, making it difficult fo r sh oppers to fin d rel evant information easily, even with user-generated content. Simple ranking methods such as price, rating, and relevance can be provided, but they are not very personalized. Can there be a more personalized ranking of products for each user? To achieve this, various factors can be considered, including the user's recent shopping and browsing history, item properties, user interaction with the product page, and micro/macro behaviors.

2. Introduction

E-commerce websites are a big part of the lives of 21st-century people. According to many surveys, an average user spends approximately 7 hours per week on different E -commerce p latforms (Hesham). To increase user interaction and the overall business of such Ecommerce platforms, recommendation systems have played a pivotal role. They play an important role in managing information overload for the customer, enhancing customer satisfaction and help with customer loyalty. Since many users spend most of their time browsing the products and decision-making, we suggest that we can use the data generated by users by browsing and interacting with product pages to predict similar products users may be interested in buying. These interactions and behaviors by customers is called Micro Behaviours. They include activities such as dwell time (a term used to define time spent by users on the product page), checking reviews, and many more. Consider a user,who can locate a product from many sources; it can be a referral by a friend, an advertisement on the homepage, or a normal search by the user. Different ways have different outcomes on whether the product will be bought. If the user comes from searching for the product, they will be more likely to buy it than if he/she comes through an advertisement on the home-page.

.3. Related Work

Traditionally recommender systems focus on macro interactions between users and items, such as purchase history, explicit user-item ratings and macro implicit feedbacks like item clicks to predict users' interests. This approach suffers from data sparsity problems which further hinder accuracy of the model. Fortunately, each macro interaction involves a series of micro-behaviors that offer a deep understanding of users and the potential to improve recommender sys-tems. The study *Recommender system using the equilibrium between items sentiment and micro-behavior* Hesham introduces an interpretable framework that simulates the sequence and consequences of micro-behaviors. It uses complaint data and review comments to de-velop a negative and positive feature vector system to identify user complaints and provide alternative recommendations. It also improves upon text min-ing techniques in recommender systems and addresses performance concerns by using clustering methods to scale up the neighborhood creation process.
Incorporating User Micro-behaviors and Item Knowledge into Multi-task Learning for Session-based Recommendation Meng et al. develops on Session-based Recommendation (SR) to predict the next item based on a user's session. It shows that micro-behaviors of-fer deep insight into a user's preference, while item knowledge provides side information to alleviate data sparsity. It develops a multi-task learning model incorporating user micro-behaviors and item knowledge to address these issues. It improves upon knowledge embeddings for better session representations on a micro-behavior level to capture the transition pat-terns.
Another study on SR systems, Micro-Behavior Encoding for Session-based Recommendation Meng et al. identifies two different patterns of micro-behaviors - sequential patterns and dyadic relational patterns - and proposes a unified model that com-bines a graph neural network and an extended self-attention network to capture the interdependencies between these patterns. The proposed approach is shown to outperform state-of-the-art baselines in extensive experiments on three real-world datasets, demonstrating the usefulness of micro-behavior in-formation for SR.

Micro Behaviors: A New Perspective in E-commerce Recommender Systems Zhou et al. studies the rela-tionship between reaching the product and ordering it finally. It studies its dependence on the path followed for example from ads on the homepage, banners, spe-cific searching, dwell time and related items. It shows the significance of micro activities performed by the user before ordering, like reading comments, carting, wishlisting etc.in altering the probability of the order getting placed.

Fine-grained post-click "micro" behaviors, such as mouse movements, keyboard events, and page scrolling etc. create a reading pattern model. *Post-Click Behaviors Enhanced Recommendation System* Liang et al. introduces a recommendation system that leverages these patterns to estimate users' pref-erence levels. This paper focuses particularly on diverse post-click behaviors (such as a mouse, key-board, and page scrolling events), user reading fea-tures (dwell time, maximal page depth, cursor move-ment), and user reading patterns (bounce back, shal-low/deep read, fast/slow read). It shows that the reading pattern-based system outperforms existing click-based and dwell time-based systems in terms of rating prediction and relevant ordering.

4. Proposed Solution

Recommendation systems that utilize micro-behavior explore user-item interactions to improve recommen-dation performance on specific behaviors. Existing recommender systems can be divided into groups that focus on micro-behavior and those that com-bine micro-behavior with knowledge graphs. Micro-behavior-based methods, such as the multi-behavior graph convolutional network (MBGCN), capture behavioral semantics and learn behavioral strength through user-item propagation and item-item prop-agation layers. Other methods, such as recommen-dation micro-behaviors (RIBs) and hierarchical user profiling (HUP), model micro-behaviors' sequence and their effects to improve e-commerce recommen-dations. However, these methods do not take into ac-count item knowledge or auxiliary information, which can lead to the loss of semantic-specific informa-tion between item-item pairs. On the other hand, micro-behavior combined with knowledge graph ap-proaches, such as the multi-task learning (MKMSR) model, incorporate user micro-behaviors and item knowledge to improve session-based recommenda-tions. We consider these shortcomings to develop a more roboust and effective system to rank e-commerce products.

5. Current Limitations

The current recommendation systems only consider a limited number of micro-behaviors and lack a hy-brid model that can incorporate both micro and macro-behaviors for better product ranking. While these systems take into account user interactions with items, such as clicks and purchases, they have limi-tations. They do not fully integrate micro-behaviors with the knowledge graph or provide explicit reason-ing for micro-behavior. Furthermore, user profiling needs further investigation(Tao et al.).

Most of the research and development for this kind of recommendation system is focused on e-commerce platforms, with other platforms like movie and news shortlisting lacking such systems.

Significant architecture and research changes are necessary to make this system compatible with other platforms. As behavioral datasets are much larger than sparse macro-feature datasets, more efficient al-gorithms need to be explored. There is also an op-portunity to collect more hardware-side behavioral data, such as touch trajectory/force and accelerome-ter readings. We would overcome as much limitations we can during the development of this project.

6. Evaluation

Several evaluation metrics that can be used to assess the effectiveness of our recommendation model. We use precision, recall, F1 score, and accuracy as an accuracy measure.

Precision:

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{1}$$

Recall:

$$\text{recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

F1 score:

$$\text{F1} = \frac{2}{\text{precision}^{-1} + \text{recall}^{-1}} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{3}$$

where

$$\text{precision}^{-1} = \begin{cases} 0 & \text{if TP + FP} = 0 \\ \frac{\text{FP}}{\text{TP+FP}} & \text{otherwise} \end{cases}$$

and

$$\text{recall}^{-1} = \begin{cases} 0 & \text{if TP + FN} = 0 \\ \frac{\text{FN}}{\text{TP+FN}} & \text{otherwise} \end{cases}$$

Accuracy:

$$\text{accuracy} = \frac{\text{correct predictions}}{\text{total predictions}} \tag{4}$$

Mean Average Precision (MAP), Normalized Discounted Cumulative Gain (nDCG) and Ideal Discounted Cumulative Gain can be used as evaluation metrics for measuring relevant ordering of results. We use MAP@k, nDCG@k and IDCG@k to measure how relevant the list of first k recommended items is. DCG@k is calculated by taking the sum of the relevance scores for the top k recommended items, with decreasing weights for items farther down the list. The ideal ranking is assumed to be the ranking in which the top k items are the most relevant.

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Contributions

Each member of the group studied a set of minimum 5-6 papers to narrow down the scope of this project. Finally we discussed and limited ourselves to the 5 most relevant academic papers for this project.

Each member of the team contributed equally for creating this proposal.