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RECOMMENDATION SYSTEMS FOR E-COMMERCE PLATFORMS

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Abstract: Artificial intelligence (AI) can be easily implemented in e-commerce and brought positive changes to the way that users interact with online platforms as a basis for shopping. This project involves the implementation of an industry-ready, deep learning-based recommendation system developed for e-commerce grocery applications with both content-based and collaborative filtering incorporated in a web-app framework written in Flask. The system uses content-based filtering by taking into consideration the metadata of the product, which are the description, category, nutritional information, etc., and users' buying history, to provide recommendations in harmony with the users' preferences. At the same time, collaborative filtering identifies patterns for the entire user base and uses additional methods, including matrix factorization and k-nearest neighbors that find the similarities between users and items, increase the range of recommendations and their relevance. For optimal usability, the recommendation system is embedded in a Flask web application, which offers a practical and hierarchical interface where the user can navigate through the grocery products list, state the preferences, and get the recommendations. The features of implementation include technical support for practical database, real-time computation of recommendations and actual scalability for the large amount of data. This sub-discipline deals with performance using algorithms, with help of Python tools – Scikit-learn and Pandas —logarithm for analyzing the data and accuracy is measured with the help of such basic metrics as precision, recall and RMSE. This integration approach links the concepts of AI and web development to redefine the conversation of grocery shopping from LSTM ensuring the users get accurate, timely and attractive product suggestions as a means of boosting the convenience and satisfaction.

Keywords: e-commerce grocery, content-based filtering, collaborative filtering, Flask web application, personalized suggestions, machine learning, user behavior analysis.

I. INTRODUCTION

Currently, recommendations are integrated into many of the sites and apps people employ, which, in turn, changes the way users interact with content and goods. Its aim is to screen useful information and to choose an item satisfying the user's requirement in numerous sets [1]. Regardless of whether the goal is to build movie and music lists, or to recommend specific goods, recommendation technologies have become critical for creating the user experience.

In the recent past, new development in the field of machine learning and artificial intelligence [2] has provided great deals of value for the recommendation systems. First, the type of work done was a kind of hand-selection and crude ontology search; with the next step of improvement, other superior methods involve content base filtering, collaborative filtering [3] and composite models. They do this based on the users' data and their behaviour patterns and characteristics inherent on the items and thus make correct recommendations. For instance, content-based objective selectively offers the product to the user based on the features the user would wish to have, while the collaborative objective analyses the pattern of interactions, and states that most of the like-minded consumers have purchased a particular product.

More specifically, it can be noted that with NLP [4] and general use of deep learning methods, recommendation systems has been advanced again. Thus, thanks to NLP the texts are analyzed by the systems, for example, the customers' reviews, or descriptions of products to get to know the secret preferences or trends. Artificial intelligence techniques such as neural networks enhances the ability to make prediction of user preference from the evaluative patterns within them.

From a technical perspective, recommendation systems consist of such back-end tools and platforms and machine learning libraries. This information is stored using the relational or NoSQL [5] database for operationality for conduct of activities, and for efficiency in retrieving the information when needed. For building and training of the models scikit-

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learn, TensorFlow or PyTorch are utilized and Flask or Django for effectively design of recommendation delivering interfaces. Such measures like matters of fact precision, matters of fact recall and mean square errors are measures in the efficiency and accuracy of the system.

That is, recommendation systems depend on the smart calculations and algorithms, good data management and structures, and rigorous interfaces. Such technologies may easily help a platform to deliver unique and integrated experience to the users, which is very crucial in the world with elevated data availability and, therefore, elevated expectations of users.

II. LITERATURE REVIEW

The authors Bryan et al. (2024) [6] tried to identify and cluster descriptions of product similarities using K-Means that helps in group formation based on history and labels. The goal of their study was to raise the effectiveness of e-commerce recommendations by employing чим collaborative filtering-based suggestion system, increasing usability and customer loyalty. In addition, the study of their results, they also highlighted the need for solving problems related to client behavior by analysing data. It also pointed out the possibility of employing such engines for enhancing the customers retention rates as well as the strategies of increasing sales.

K. and T. (2020) [7] studied seasonality and demographics as the determinants of recommendation in e-commerce. Enhancing the input resulted in increased product offering suggestions for users to consider because their prior work focused on systems that limited product range. They also exposed some limitations of the current systems are for instance, their inability to change with emerging user's requirements. Further, the study made a suggestion of the integration of real-time trend analysis to enhance recommendation relevancy.

Yu and Li (2024) [8] proposed a recommender system for ceramic products that involve the method of user profiling and clustering. Depending on the user behavior and preferences, it adjusted the system that offered better marketing and increased the client's satisfaction. Their work also establishes the importance of capturing specific attributes of niche products for users of specific product segments. They also talked about the feasibility of making the system expandable, so it could be applied to other products. For e-commerce recommendations, Shi (2022) developed a BERT-BiLSTM-based model. The present model obtained high recommendation accuracy over the baseline approaches and effectively solved issues in electronic product recommendations by utilizing context semantic information from text. The model structure made it possible to trace user intent from the texts received in their totality. Also, it recognized that using pre-trained language models was beneficial in minimizing the burden of beginning the development of the recommendation system from scratch.

Katlariwala and Gupta (2024) [9] proposed a recommendation system that deploys the Llama-2 large language model. Their approach was able to synthesize user embeddings to make relevant recommendations on products; the results revealed better accuracy of intended click-through and purchase ratios. They also mentioned the efficiency of their system to manage big data in various e-commerce contexts. In addition, the study questioned the possibility of combining multiple modality inputs including the image and text to improve the results of recommendations.

Deep learning techniques involved were featuring an Inception structural neural network, with Zhong and Yue (2023) [10] incorporating these into sustainable marketing concepts. Their pairwise self-encoder approach improved the recommendation system for presenting individual offers, at the same time, achieving sustainability in e-commerce. The study also showed how such systems can help cut costs by addressing users with environmentally friendly products. They also stressed the need to assess recommendation algorithm based on the sustainability metrics in addition to other metrics.

Qiu and Qi (2024) [11] proposed the knowledge graph-based recommendation for agricultural products. Their system utilised features like attention mechanisms and semantic information to offer accurate recommendations to meet the distinct issues of agricultural e-commerce. This research was in congrace with this by identifying and highlighting the domain specific characteristics like the seasonality that should be considered. Furthermore, they talked about potential application areas that may help address challenges caused by the data sparsity, characteristic for many niche markets.

Some challenges such as cold start and popularity bias were addressed by Xiao et al. (2020) [12]. They introduced a model of Multi-behavior Interaction Networks and Knowledge Graphs which would minimize the problem of skewed product distribution as well as enhance accuracy. The study also assessed the usefulness of incorporating the user-provided metadata that augment the recommendation mix. Moreover, it offered customers' relation scenarios across various channels to further optimize personalization.

Collaborative filtering algorithm for recommending leather products was used by Ridwan et al. (2022) [13]. The MAE result indicates that their system works well to suggest the proper products, which is compliant with users' expectation level. The research also found that the recommendation algorithm required frequent updates to reflect latest demands by users. In addition, they suggested that their system should incorporate hybrid filtering schemes to diversify results even more.

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Lumintu (2023) [14] described content-based recommender system by utilizing the TF-IDF vectorization with cosine similarity. The approach provided highly satisfying precision, recall, and F1 metrics, thereby demonstrating the use of text analysis for the provision of recommendations. The study also proposed the use of the feedback from users in enhancing the recommendations over this period. Further, it evaluated the superiority of TF-IDF with deep learning neural network embeddings for improved performance.

I. et al. (2023) [15] developed the SHOPSPHERE recommendation technique that highlights the browsing history in an effort to facilitate engagement and drive sales. Their review focused on recent improvement in the area of recommendations for e-commerce systems. They went further in underlining the importance of streaming data for the improvement of the customer satisfaction. Also, the study talked of integration of social media trends to the recommendation pipeline in order to effectively cater for new users interests.

Shaikh et al. [16] discussed how semantic factors can be beneficial in enhancing the existing e-commerce recommendations. They presented new graph-based approaches to increase accuracy pointing out the issues of the previous work. As part of their study, they also learned that user-generated content played an important role in enhancing semantic models. Besides, they discussed how using semantic recommendation could address various types of users and cultural environments.

To address cold start and data sparsity problems, Islam et al. (2022) [17] proposed and conducted a case study on collaborative filtering. Based on matrix factorization and clustering, their method offered higher recommendations compared to conventional methods in cases of sparse rated data. They also described primary factors, including the density of the user-item interaction matrix, that affect the efficiency of collaborative filtering. Moreover, the study also provided a suggestion of using a blend of hybrid models in order to merge the benefit from both of the collaborative method and the content based method.

III. METHODOLOGY

1. Data Collection and Preprocessing

The data in this project is a relational set of files that contains records of customer Product purchases over time for foodordering prediction of what product is likely to be ordered next. The dataset includes over 3 million orders from over 200,000 anonymised Instacart customers, offering between 4 and 100 orders per customer, accompanied by the purchase sequence of the products. Additional information specifying the context for order placed, for instance, the week and the hour of the day, time intervals between sequential orders are incorporated into the analysis for refining behavioral information. Some of the files within dataset are aisles which maps aisle_id with aisle names; departments: providing the details of product departments with department_id and names; order_products__prior: providing the list of products in prior order along with reodered flag; orders: Categorizing the orders as prior orders, training and testing detaisl and information such as day of order and the time within a day. Further, products.csv maps every product with the respective aisle_id, department_id & name of the products and sample_submission.csv shows the format of the products which are to be predict yet in the test data. By using full order, product, and user interaction history in their apps, difficult and comprehensive recommendation systems can be crafted with this data set.

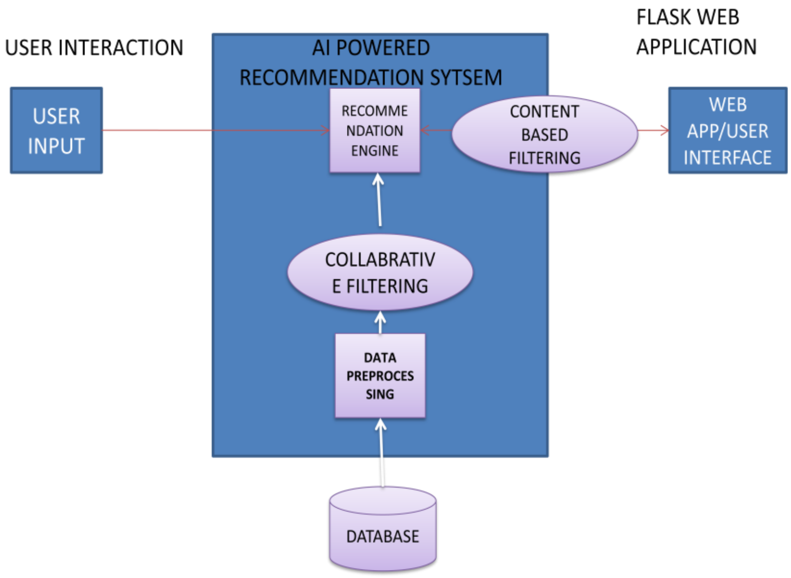

Fig:1 system architecture

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This phase is important in order to transform the data into its suitable format for analysis with no inconsistencies. In order to handle the missing values in the data set, techniques such as mean imputation or median imputation or simply dropping irrelevant entries. All numerical data, for example, prices or nutritional values, are brought to the same scale, either through methods of scaling techniques or not at all; on the other hand, categorical features; for example, product categories or aisles, are transformed through methods such as one-hot encoding or label encoding. Merging data from different sources sits for a unified structure, there should no mismatch created or duplication. The prerequisite of any kind of statistical analysis, rather than machine learning only, is outliers removal as to their influence on the model's perception. Such a detailed preprocess helps in maintaining data accuracy to help training a good model.

2. Content-Based Filtering

Content based filtering remains as shown in fig:1 slightly imperative to the development of designing customized recommendation systems because of the attributes of products and user's preferences. In the case of data set discussed, basic characteristics of products such as descriptions, aisle, department and other attributes are procured for NLP analysis. These features are converted into numerical form with techniques like the Term Frequency-Inverse Document Frequency (TF-IDF), or more advanced word embeddings like Word2Vec or GloVe, which also take into account the relation between products semantically. Through these representations, features that are similar to the products or the user preference models are computed by means of a cosine similarity such that products can be ranked according to their similarities to each individual user. To improve the user experience, the filters are set to at least exclude products that the user has purchased before and sort the results for product variety. Such approach is employed to guarantee that inherent characteristics of products such as category are utilized at appropriate contexts in regard to people's preferences in an efficient manner, thus providing relevant and valuable recommendations.

3. Collaborative Filtering

While content-based filtering has limitations, Collaborative filtering offers an additional approach, based on user interaction data from the dataset to implement a pattern of users and products. A use-item interaction matrix is created through files such as order_products__prior.csv and orders.csv as these files depict user activities such as purchase history and product reorder frequency respectively. In the user-based collaborative filtering, differences between two users are characterized using the Pearson correlation or cosine similarity such that the recommendation system recommends products that are preferred by the similar user buying habits. In case of item-based collaborative filtering, a measure of the similarity between products is determined by the way that products are used by the same users – such as making frequent co-purchases. More complex techniques like SVD or ALS are then used to apply dimensionality reduction on the interaction matrix so as to decrease the costs of computation while preserving the dependencies inherent in the current data set. This approach is essential due to the varied users where individual preferences and trends are more easily found than group ones.

4. Model Training

The above recommendation models are trained to recommend products likely to be included in the next order by the user in a content based filtering as well as collaborative filtering. The training process starts with data partitioning in the proportions described above and available within the orders.csv file through the feature named eval_set, which divides orders into prior, train, and test. Logistic Regression or Random Forest are used as the starting points for the models while TensorFlow or PyTorch provide architecture for embedding-based models. From grid search or random search, the hyperparameters used are tuned to boost up the performance of the model. The large dataset, which covers over 3 million of orders, has been handled using batch processing techniques. The models' performances are measured with Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Precision, and Recall. Cross-validation checks on how well the models will perform on unseen data and so provides good prediction for the test set orders.

5. Flask Web Application Development

The last one is to integrate the trained recommendation models into Flask web application environment and the user interface design is presented for the users. The features from orders.csv and order_products__prior.csv are implemented into the backend for personalization based on the user. A secure user authentication mechanism is incorporated to include user registration, login, and a profile of preferences for a personalized account. The frontend is simple and made to be user friendly; this section is to display product items with information such as product name, aisle, and department, which are obtained from the products.csv file, aisles.csv file and departments.csv file respectively. Indeed, Flask-constructed RESTful APIs help to implement the interaction between the user interface and back-end models and dynamically promote the corresponding models to recommend the appropriate user models per their commuting records.

IV. RESULT AND DISCUSSION

Each graph provides valuable insights into user behavior, shopping patterns, and product popularity, helping refine recommendation strategies and enhance the e-commerce platform's personalization capabilities.

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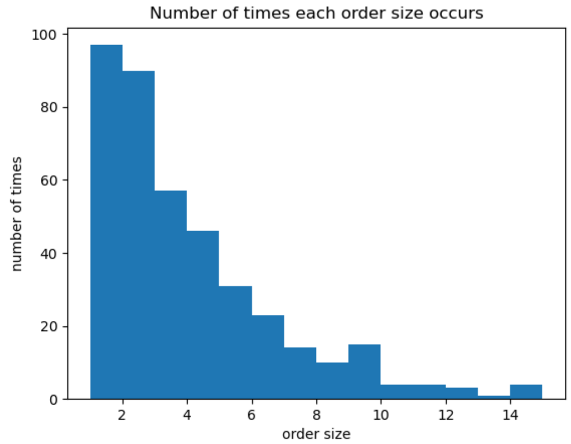

Fig:2 Number of Times Each Order Size Occurs

.In fig:2 histogram represents the order sizes. The horizontal axis stands for the order size, i.e., number of products per order, and the vertical axis indicates how often such sizes appear. From the chart above it is clear that most orders are small orders and few large orders are placed possibly due to large order items conveyancies or due to certain shopping occasions.

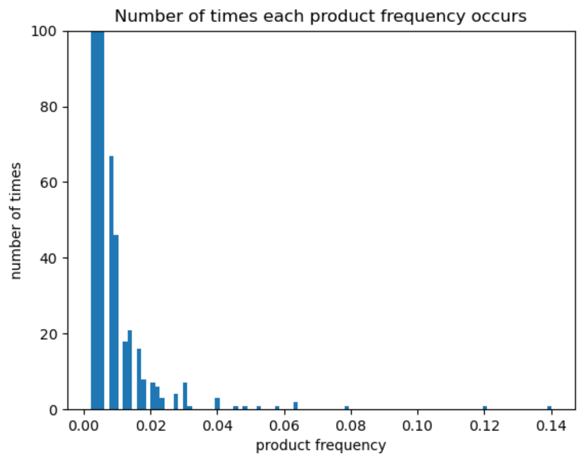

Fig:3 Number of Times Each Product Frequency Occurs

This histogram in fig:3 illustrates the frequency of orders received by our company and indicates order size. The horizontal line depicts the sort of order or the number of products in an order, and the vertical line denotes how frequent this sort of order. The chart shows that many orders are simple with an average of 4 items per order, over-sized orders are less frequent though, which can point at buying more in quantity during sales.

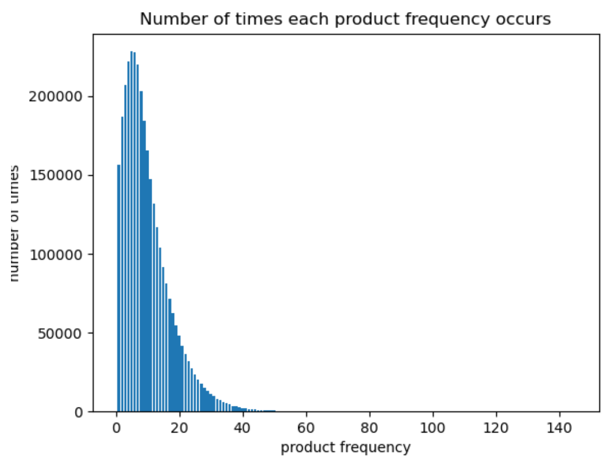

Fig:4 Number of Times Each Product Frequency Occurs

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This histogram shows in fig:4 how often products are ordered, which has quantised from the number of orders per product. On the x-and y-axis, one gets the number of times a product is ordered, and frequency of occurrences respectively. The chart shows that majority of products are of low frequency and few products are of high frequency observed by many users lately.

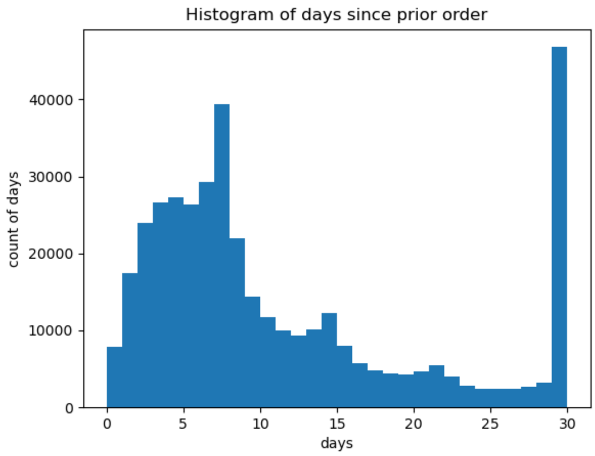

Fig:5 Histogram of Days Since Prior Order

The vertical axis of this histogram shows in fig 5 the frequencies of the time gap (in days) between orders, where the horizontal axis is the time interval in days. On the x-axis there is the number of days without the last order, on the y-axis there is a count. Daily maxima imply habitual shopping, whether the hump every seventh day refers to product shopping remains to be seen, although maxima at 7 or 30 are consistent with regular seven- or thirty-day cycles.

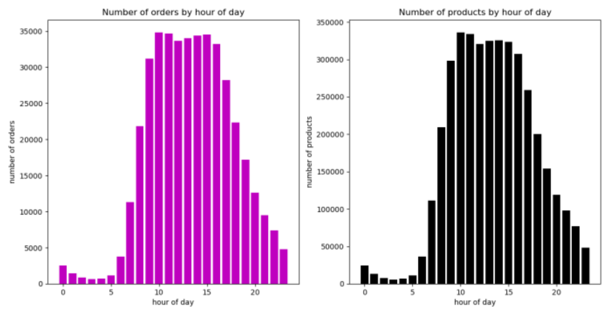

Fig:6 Number of Orders and Products by Hour of the Day

These two histograms illustrate in fig:6 the orders and products purchased per each hour of the day. The horizontal axis includes numbers from 0 to 23, which illustrates hours, while the verticle axis points at the number of orders and products. Both graphs show a high level during the mid of the day to the evening period of the day In the case of user order placement. There is a clear low during late at night and in the early morning this peak is slightly expected based on the fact that there are a few people who use their devices during such times.

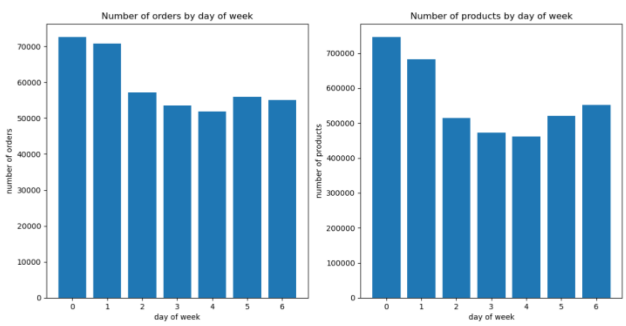

Fig:7 Number of Orders and Products by Day of the Week

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These two bar charts in fig:7 show the day of the week when orders as well as products were purchased. In the left graph, the horizontal axis is the days of the week – starting from Monday to the next Sunday, or numbered 0 to 6 depending on the coding of the dataset; the vertical axis is the number of orders. The right graph reflects this for the number of products needed. In both the present graphs, there are fluctuations on precise days showing that users are more active during specific days, probably weekends, meaning that they like to shop for groceries during these days.

Fig: 8 Number of Orders by Order Number

This graph shows in fig:8 the fragmentation of the number of orders per order number. The former scale is depicted on the x axis which shows the order number while the latter scale is shown on the y axis which shows the frequency of orders. The chart presented proves this assumption because it depicts that a majority of users have few orders and the frequency reduces with the increase of the order number. Such a trend points out that although there are numerous individuals who have multiple orders, a majority of the buyers engage with the app infrequently, indicating the platform attracted new customers or buyers with a low frequency of purchasing.

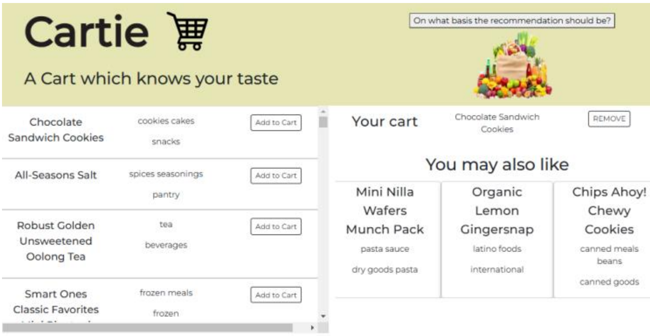

Fig: 9 Interface for content filtering

Here is presented an interface in fig:9 of the recommendation system within the Flask framework which uses solely content-based filter. If, for instance, a user introduces an item 'Chocolate Sandwich Cookies' into the cart, the systems reviews such characteristics as category and substance and proposes other items such as 'Mini Nilla Wafers Munch Pack' or 'Chips Ahoy'. Chewy Cookies." The left column contains the product list and the right one contains the cart, and other dynamic elements, like recommendations. Flask backend makes it easy to update suggestions based on the content of the cart hence improve on customers' satisfaction and cross selling through relevant products.

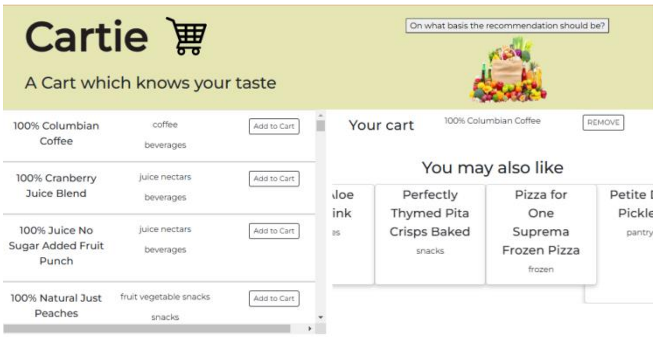

Fig: 10 Interface for colabrative filtering

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This interface in fig:10 is a web application built in Flask which implements a basic collaborative filtering recommendation system. When the user places “100% Colombian Coffee” into the carting list, the system then follows the users’ interactions and past purchase behaviors to determine other products usually bought by users who also have bought the “100% Colombian Coffee”. These decision suggestions like “Perfectly Thymed Pita Crisps Baked” or “Pizza for One Suprema Frozen Pizza,” are not influenced by parameters associated with the products, but by co-occurrence frequencies in previous data. This approach takes advantage of similar tastes and preferences among the users to recommend products that increase the chance of offering preferred and attractive options.

V. CONCLUSION

This ecommerce recommendation system helps unify advanced filtering techniques implemented into a Flask-based architecture to serve up the shoppers. Here, the flexibility of analyzing preferences and qualities or behaviors of products and users enables the system to present pertinent recommendations that offer increased convenience, satisfaction, and assortment of related products. This model shows what is possible when conceptual work in artificial intelligence meets friendly user interfaces applied to e-commerce.

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