Made-to-Order: Targeted Marketing in Fast-Food Using Collaborative Filtering

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***Abstract*—** To target marketing campaigns most efficiently to a receptive audience and improve order conversion and revenue per transaction, one must first be able to predict the actions of consumers. This is even more true in the quick-service food industry, where new products are launched regularly and individual brands live and die through effective advertising. Rather than focusing solely on demographics and a brand's most popular products, this solution predicts the date range and constituent items of a customer's next order. To predict both the date range and constituent items of a customer's next order, this solution uses a combination of k-means clustering, collaborative filtering, and content-based filtering techniques. K-means clustering is used to bucket users into ranges of dates based on their past ordering behavior, while collaborative filtering examines the orders and items of users to predict their preference for previously unordered items. Co-clustering is used to group similar users and products together, further improving the accuracy of the predictions. Additionally, content-based filtering involves analyzing the content of items to determine their similarity and recommend items to users based on their past behavior or preferences. By using both collaborative and content-based filtering techniques, the solution provides personalized recommendations that are more accurate than predicting the brand's most popular items for all users. Generating personalized baskets of predicted items by user provides substantial gains in accuracy over predicting the brand's most popular items for all users, correctly selecting at least one item in a customer's next order out of a basket of three recommended items in 75% of the test set. An A/B test will illustrate the impact of this personalized prediction system by tracking increases in conversion rate and average order price of those shown recommendations informed by this prediction model vs those shown generic national advertisements.

Keywords- Consumer behavior, Collaborate Filtering, Customized algorithm, k-means clustering

I. Introduction

For a food-service company to best meet the needs of its customers, they must understand and accurately predict those customers' habits, both in terms of time of purchase and preferred menu items. Transactional data can be used to this effect in improving customer satisfaction and creating targeted marketing campaigns, which ultimately leads to more efficient customer management strategies and increased revenue. Predicting future customer behavior is crucial for a variety of applications in the fast-food industry: developing tailored menu suggestions, figuring out precisely when a certain order is placed, and maximizing in-the-moment promotions (D'Alessandro, 2022). These forecasts are informed by trends in previous behavior, including the interval since their previous visit, the menu items previously perused or ordered, and the quantity of food consumed. Businesses now have access to enormous amounts of data which they can use to better understand the behavior and preferences of their consumers (Strang & Rao Vajjhala, 2022). However, one major challenge that businesses face is how to effectively leverage this data to improve customer engagement and retention.

One potential solution to this challenge is employing recommender systems, which can use collaborative filtering to recommend previously unordered items to users based on their past behavior or preferences, and content-based filtering to determine similarity between items and recommend items to users based on their content. In addition, clustering techniques such as k-means can be used to group customers with similar preferences and behavior, allowing for more targeted marketing campaigns and personalized recommendations, as well as date prediction. Our aim is to develop a model that predicts the next course of action for each customer of this food-service brand based on their purchasing history utilizing historical data. This is done in the name of boosting customer engagement and sales by identifying trends in consumer behavior and predicting future buying decisions.

The fast-food industry is a prime candidate to benefit from using recommender systems. According to a recent report by Gartner, the fast-food market is expected to reach $632 billion by 2020, with a projected growth rate of 3.8% per year (Gartner, 2019). However, the industry is facing ever-rising competition, necessitating constant improvement to customer engagement to maintain market share. By using recommender systems, fast-food businesses can better understand their customers' behavior and preferences, which can lead to more targeted marketing campaigns and personalized menu recommendations.

Managing oft varied and complicated data poses difficulties in anticipating consumer behavior. Since they are built on vector-based models and require fixed-length inputs, traditional machine learning approaches like logistic regression and neural networks are not well suited for processing sequential data. However, recommender systems, which employ collaborative and content-based filtering, can handle data such as past orders, menu item views, and timestamps, to make predictions about future customer behavior. Collaborative filtering enables predicted user preference for previously unordered items by examining the orders and items of users, with co-clustering grouping similar users and products together. Content-based filtering involves analyzing the content of items to determine their similarity and recommend items to users based on their past behavior or preferences.

In this research, we propose a Recommender Algorithm using collaborative and content-based filtering as well as k-means to predict the best next action of a customer in the fast-food industry. We will analyze customer behavior data, such as past orders, menu item views, and timestamps, to train our models and make predictions about future customer behavior. The goal of recommender systems is to combine personalized models of user behavior (based on historical activities) with some notion of ‘context’ on the basis of users' recent actions. Recommender systems are superior than previous techniques in a number of ways that are important for real-world production systems. The direct application of recommender systems to sequences of customer behaviors enables better prediction accuracy as compared to vector-based techniques like logistic regression (Srivastava, 2022).

The goal is to recommend menu items for new or returning customers having similar purchasing pattern and predict probable visit time range they make the purchase to enable personalization at a granular level resulting in customer loyalty thereby improving customer retention. The explainability of the model discussed in this paper will better illustrate the reasoning behind predictions for individual customer actions. The predictive algorithm forecasts when and what menu a consumer will order next based on prior orders, dietary restrictions, and other factors. The algorithm works on the concept of collaborative filtering that follows two approaches: User based and Item-based *(Exhibit 1)*. The success of the built algorithm uses real-time order history to forecast a customer's next fast-food purchase in real time.

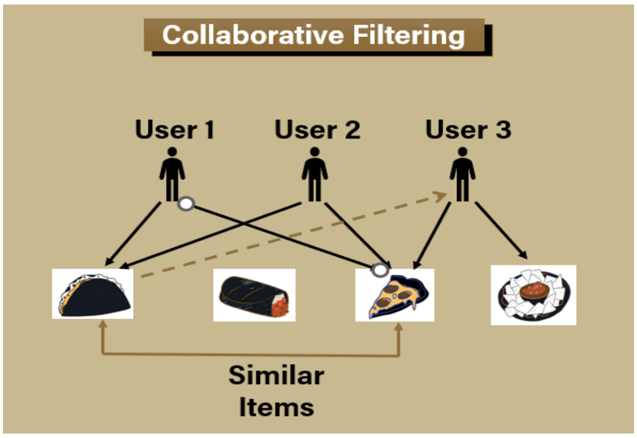

Exhibit 1: Item based collaborative filtering recommendation

The following sections details on the following aspects of the paper: the Data section explains the variables of the dataset. The experimental strategy is defined by methodology. The model section goes into further detail about our model constructions and testing criteria. Following that, the Results section quantifies the performance of the built model. The conclusion sheds insight on the uses of our study and its potential applications. The study we mentioned is finally included in the References section.

II. Literature Review

A variety of offerings often can confuse a customer at point of sale. As such, customers often appreciate and follow suggestions or recommendations of what item to purchase. Recommendations drive customer purchase decisions more than any other decision-making facet, generating around 26% of revenue in businesses (Young 2017) (Keller, 2012). For food-service businesses, recommendations sustain and increase customer retention rate. However, updating prediction models frequently with unseen data represents a major challenge in building and maintaining a complex recommendation system (Schmitt n.d.).

A recommendation system is a type of information filtering that aims to foresee the "rating" or "preference" a user would assign to a particular object. Recommendation systems are mainly classified into personalized and non-personalized types. Our research focuses on personalized recommendation systems as the latter is mostly generic recommendation based on a popular trend like most frequently purchased product, top selling books etc. which takes in a large size of population. Personalized recommendation works well as this would be relevant to the user and would be based on the user’s history of purchases, and what other similar users purchase. There are different types of recommendation algorithms, including content-based filtering, collaborative filtering, and hybrid approaches (Valentina, 2021).

Research on personalized recommendation systems using search and historical data (Tyagi, Goyal, Jindal, Lanham, & Shrestha, 2021) centered on using matrix factorization, collaborative filtering, and cosine similarity to diversify resort recommendations, overcome the problems of redundancy and irrelevancy by giving more value to recent searches and penalizing older searches. A search factor is calculated with surge and search type weights which is added to a particular resort and a recommendation is given according to a recommendation distribution from matrix factorization. Cosine similarity is also used as another model where factors like popularity, cosine similarity, search and current search are combined with weights to build a score for a set of resorts with respect to user.

Collaborative filtering is a recent algorithm which gives better results compared to content-based filtering. It is based on the straightforward principle that user group activity can be utilized to propose services to other users. The advice is referred to as collaborative because it is based on the preferences of other users. Mainly, matrix factorization technique which maps arrays of say items and users in the form of matrix is more accurate. The empty blocks of information are filled using the similarity of users and other information.

Content-based recommender systems are designed to recommend items to users based on their personal preferences and a description of the item. This type of recommender system analyzes the characteristics of items that the user has liked in the past and then recommends similar items that match those characteristics. For example, if a user frequently watches action movies, the system would recommend other action movies to the user.

On the other hand, collaborative filtering approaches recommend items based on the assumption that users who have enjoyed similar items in the past are likely to enjoy similar items in the future. Collaborative filtering is further classified into two types: memory-based and model-based. Memory-based approaches are based on similarity measures, such as Pearson correlation coefficient, that compute the similarity between users or items. Model-based approaches, such as matrix factorization and neural networks, learn a model of user-item interactions to make recommendations.
Hybrid approaches combine both collaborative filtering and content-based filtering to provide more accurate recommendations. By leveraging both approaches, hybrid systems can make use of the strengths of each technique and overcome their weaknesses. The hybrid approach is often considered the most effective approach to building recommender systems, and it is widely used in the industry today.

Beyond search data, businesses often use customer reviews to generate recommendations; a similar model does just this to recommend groceries (Pratiksha Ashok.Naik, 2020). A deep learning algorithm for product classification works alongside a genetic algorithm to filter for recommended products. Another approach (Wu & Teng, 2011), random walk, recommends online groceries by incorporating additional considerations such as product replenishment and product promotions that fits customer needs and budget considerations. A bipartite network models consumer-product relationships by calculating similarity between two products or users. A basket-based ranking score vector is combined to individual interest vector to get the consumer preferences and new ranking values are assigned to each product which are summed up together to get the final ranking values to generate the final recommendation list.

The aim of our study is to predict when and what product a customer purchases next, and design a recommendation system to give suggestions based on it. From the above research, a combination of content-based and collaborating filtering is used to predict the next purchase item assembling with gradient boosting, which is used for predicting when the customer purchases that item.

Author(s), Year	*Tyagi H et al, 2021*	*Naik P.A, 2020*	*Yi-Jing Wu et al, 2011*	*Zeping Yu et al, 2019*	*Wang S et al, 2019*	*Our Study, 2023*
Collaborative Filtering	✓		*An approach using basket-based score and interest factor calculation for consumer preferences*			✓
Cosine Similarity	✓					
Genetic Algorithm		✓				
RNN		✓		✓	✓	
LSTM				✓	✓	
Content based filtering						✓
Gradient Boosting						✓
Random Forest						✓
K-means clustering						✓

Figure 2: Summary of Literature Review & Study Comparison

III. DATA

Our prediction model is built upon a foundation of transaction history provided to us by the client. This dataset consists of every transaction performed by 25,000 customers over the course of 2022. This set of customers collectively generated approximately 280,000 transactions and over 1.5 million individual items. The transaction data includes details such as purchase history, product descriptions, product codes, individual item prices, and total sales.

The primary table in this dataset is the “Lines” table: this contains a customer’s order details at its most granular level, with each row representing a single line on the receipt associated with their order. This table contains details such as any product or modification codes as well as item quantity and any associated costs or discounts. Performing aggregations in this table can yield additional insights such as the most popular item, as well as income generated by each item and transaction.

Whereas the Lines table examines the individual items ordered, the Transaction table contains information about the purchase that is true across all items. Much of this is date and time related, allowing analysis of orders segmented along those lines. Crucially, the Transactions table also maps users to their purchases, enabling aggregation of transactions and products on a per-user basis. The Transaction and Lines tables are connected through a unique transaction identifier in a one-to-many relationship. Outside of these two main tables, the User and Products tables offer some additional descriptions for their respective fields and connect in one-to-many relationships to the Transaction and Lines tables respectively.

Table #	Table Name	Description
1	Users	IDs for the 25,000 customers in sample
2	Transactions	Data regarding 280,000 orders made by users in sample during 2022
3	Products	Codes and Descriptions for the ~1200 parent, child, and modification items offered by client
4	Lines	1.5 million individual products ordered by users during 2022, each row represent a line on the customer's receipt

Figure 3: Table Descriptions

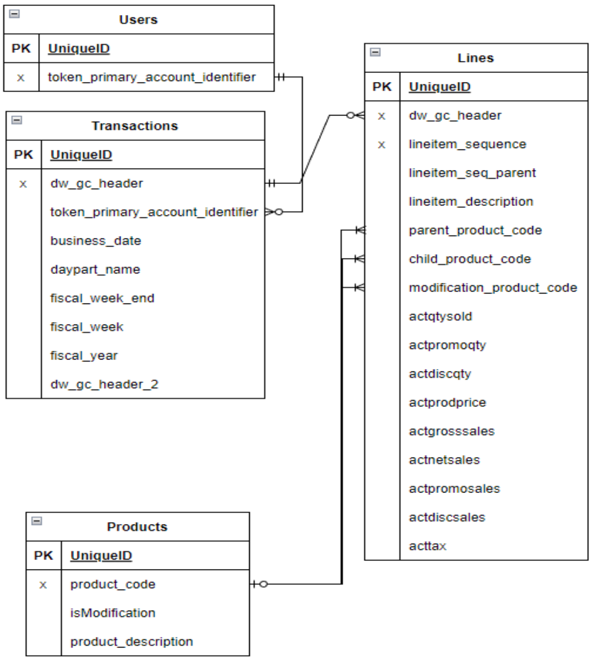

Figure 4: Entity Relationship Diagram

IV. METHODOLOGY

The goal of the experiment is to develop an algorithm that can capture user preferences and accurately predict which products customers will order next and the time they will order in the fast- food industry. The study began with the acquisition of raw data, which was subjected to exploratory data analysis. Subsequently, the data was preprocessed, including partitioning into train and test sets, and was utilized for developing predictive models. The development of models involved data cleaning, modeling, and comparison of models, with a focus on predicting both product and date outcomes.

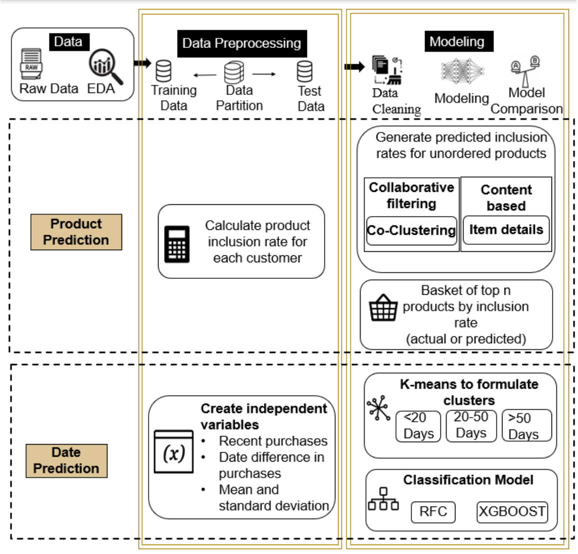

Figure 5. provides a comprehensive explanation of the approach utilized to achieve this.

Explanatory Data Analysis (EDA)

The objective of this study was to examine the consistency of users' ordering patterns, particularly the frequency with which customers order the item on which they have spent the most money over their history. The favored item of each user was determined, and the distribution of this data resembled the % of Sales graphs, with popular items commanding a significant portion of the users.

Subsequently, the percentage of orders containing the user's favorite item was aggregated over the course of a year (excluding users with only one order). The distribution of this data was analyzed using boxplots and histograms for the entire dataset (i.e., users with more than one order), as well as for users with less than and more than ten orders in 2022. On average, customers tended to include their favorite item in approximately half of their orders. Users with fewer orders were more inclined to order their favorite item, with a higher median, Q1, and Q3 than their counterparts with ten or more orders.

These findings are promising because they suggest that users with a shorter transaction history develop habits quickly, making it easier to predict that they will order their favored item again in the future. Other visual representations presented in this study revealed that the majority of users placed orders within the range of 5-10 times and that the most frequently occurring order cost was approximately $10. Furthermore, the investigation showed that dinner time was the most popular time for placing orders and that the average total order cost was highest during this period.

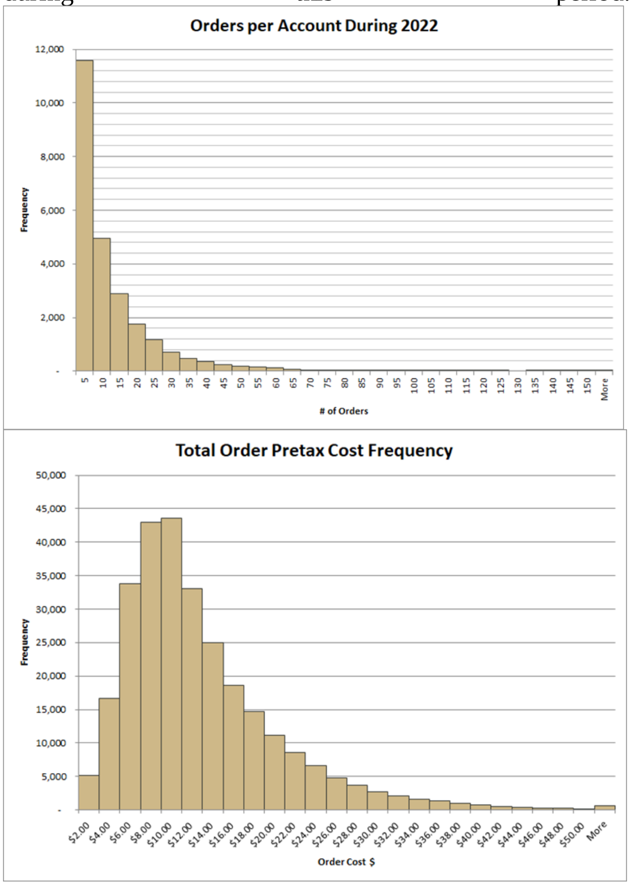

Figure 6. Order frequency and Cost frequency graphs

Data Preprocessing

The transaction dataset is split into train and test datasets.
Train Data: Transactional data of the first three quarters (till Sept 30th 2022)

Test Data: Data of the first order in the last quarter of the users existing in the train data

In case of the date prediction, few independent variables like recency, frequency, monetary score, date difference between two consecutive orders and its mean and standard deviation are generated based on which clustering model is developed. In case of the product prediction model, product inclusion rate which is the product order frequency is generated for each item for each user based on which users are grouped.

Modeling

We experimented with two modeling approaches to predict what customers are likely to order next and when.

The first model (Model 1) uses collaborative filtering and content-based techniques to identify similarities between customers and items and recommend items based on those similarities.

The second model (Model 2) uses k-means clustering and random forest clustering to group customers based on their ordering patterns and predict the time of their next order.

Model 1 uses collaborative filtering to recommend items similar to those previously ordered by a customer and content-based filtering to recommend items based on the characteristics of the items ordered. Meanwhile, Model 2 clusters customers based on their order history and uses k-means to predict the time of their next order. A detailed description of the modeling approach is provided in the next section.

Validation

Success Criteria: After generating top-n items for each user, model accuracy is calculated based on success criteria of correct match of the top n-items to the actual order items of users in test data.

Evaluation: As the model evaluation is out of scope with only the historical data given, an A/B test is designed to evaluate the performance of the model with respect to the generic recommendation of the top products.

V. MODELS AND RESULTS

Model 1: Date Prediction

In order to have a better understanding of the customers and perform target marketing, knowing the time when customer will come back would be a good approach. The goal of this date prediction is to assign our customer into three groups. The first group contains customer who will come back in 20 days, the second group contains customer who will come back in more than 20 days but less than 50 days. The Third group contain customer who will come back in more than 50 days.

To achieve the goal, The approach used in this study is based on the model developed by Barış Karaman (2018), as described in their article on predicting next purchase day on the Towards Data Science website. The first step is to find some variables used for generating the model from the transaction data. First, the transaction data is grouped by customer and date to find what dates each customer visited our stores. Then, the information of the latest three purchases is found and used to calculate the date difference between the orders as well as the mean and standard deviation of the date difference. As shown on the right side of the flowchart below.

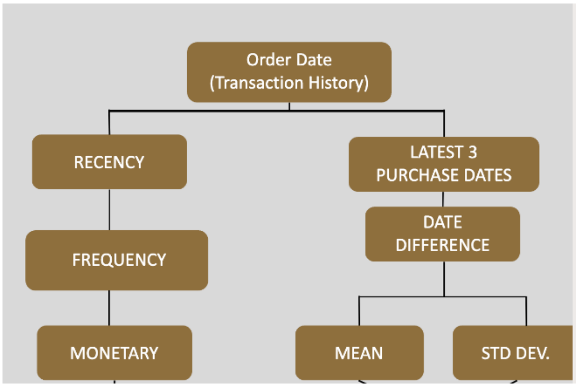

Figure 7. Flowchart for the Date Prediction Model

Obviously, a good model won't be generated by only a few variables. Thus, performing a customer segmentation using RFM (Recency, Frequency, and Monetary) Clustering, as shown on the left of the graph above, to find more variables will be a good strategy.

For recency, the goal is to find the number of days between each order placed by each customer, then find how many days they are being inactive. After knowing the date difference between each order, k-mean clustering is applied to divide the customer into different groups. Then, a recency score is assigned to each customer based on groups where higher recency score represents a higher value and lower recency since lower recency means the fewer inactive days the customer had.

The same mothed is applied to frequency score and monetary score. For frequency, the number of times each customer had been to our store within the year is found, the K-mean clustering is performed, and then a frequency score is assigned for each customer. Higher frequency score represents higher value of the customer.

Well, what if a customer only came twice, once at the beginning of the year, once at the end of the year, and spent 1000 dollar on each order. The previous two scores will not be sufficient to grade this customer because the customer only visited twice and there are 300 days between the two orders, so the recency score and frequency score will be very low. However, the customer should be count as a high value customer since he spends more money than most of the other customers. In this case, it is necessary to add the monetary score. For each customer, the average spending for each order is first calculated. Then, a K-mean clustering is performed and a monetary score, where higher monetary score represents a higher value of the customer is assigned.

Summing up the RFM scores gives the overall score necessary to perform a customer segmentation. Customer with a score lower than 3 are defined as low value, customer with a score between 3 and 5 are defined as mid value. Customer with a score of more than 5 are defined as high value.

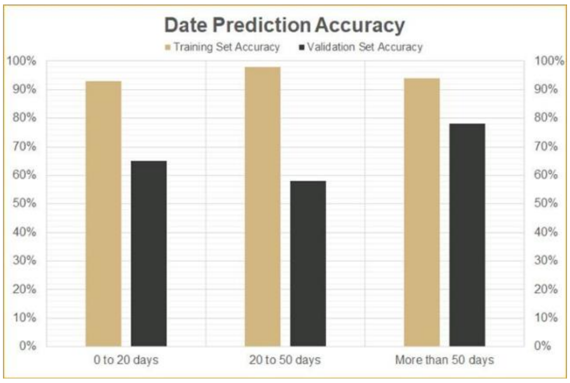

Figure 7. Accuracy for the Date Prediction Model

Now, with enough variables to generate a model, the first step in model generation is to do a data partition to split the training and test data to measure the model accuracy and avoid overfitting. Then, using the RFM scores, the date difference and its mean and standard deviation is used to generate the model. The second step in model generation is to do a model comparison. By comparing the accuracy of different models such as Logistic Regression, GuassianNB, GridSearchCV, Decision Tree and KNN. Random Forest Classifier and XG boosting are selected as the final models. As shown above, the current iteration of the model can accurately predict the cluster to which a customer belongs 95% of the time in the training set and 67% in the test set. With the final model, the third step of model generation is to apply the model to the entire dataset where the customers were assigned into the three groups. With this model, not only can market department know when the customer will come back during which period, they are also able to utilize various campaigns tailored to specific customer groups or segments. For example, a mid-value customer who will come back within 20 days, the strategy can be to engage the customer to visit the store by offering a higher discount. However, a high-value customer who will come back more than 50 days, like the example before, they may not need that much discount since they are more likely to seek products that align with their interests. The strategy should recommend products to the customer based on their interests and preferences.

Model 2: Product Prediction

To predict what product the customer would likely purchase next, some parameters which would drive away from the business are considered so that the model would overcome those. The model features consider the following:
-time of the day as some time specific items like breakfast items cannot be recommended during other time in a day
-price of the product
-variation of preferred items at a time
-preference for certain items over a time (weighing recent products more than older ones) by having a decay factor for the product. A decay factor of 0 is set by default as the impact of recent order weightage isn't much given just a year of data.

After considering these features, an approach using both content based filtering and collaborative filtering is used to predict the product. Product order frequency of each user is generated for each product for all the users excluding the products which were never ordered by that particular user.

In collaborative filtering, users are clustered using co-clustering based on these product order frequency scores and are connected to users with similar scores. A user can be recommended products which they never tried based on the score of those products in the same cluster. Co-clustering technique is a technique for finding groups of users and items that have similar scores which uses a "Non-Negative Matrix Factorization" algorithm, NMF attempts to identify two matrices with low rank that, when combined through multiplication, produce a result that is as similar as possible to the original rating matrix. One matrix represents the users, while the other matrix represents the items, with the values in the matrices indicating the level of correlation between each user and item. After identifying the two matrices using the NMF algorithm, a clustering technique is applied to group the rows and columns into clusters based on their values within the matrices. This generates clusters of users and items that exhibit comparable product order frequency percentages.

In case of content-based filtering, items are clustered using K-means based on their inherent ingredients, type of the item (beverage, combo etc.), and pricing. A product traits dataset is created with binary variables for all the top products which consists several inherent traits including

- whether an item is food or beverage or combo

- whether is meat or vegetarian
- whether the item has specific ingredients like chicken, beans, cheese etc
- price bucket (<$2, $2-$4, $8-$10, >$10 etc)

It is also easier to add any new product can be added to this specifying its traits to this dataset. Similar items would be recommended to the users based on the product traits a user prefers and even a new item could be suggested in a same way. Items are divided into 10 clusters with around 6-20 items in each cluster. Of these clusters, product order frequency for each user is calculated from percent of orders in a cluster of the total orders the customer has made. The score is further penalized based on the total orders number as the fewer the orders, the less weightage is given to that product for each user. The curve selected for getting the penalized weighted percentage from the product order percentage x is $x\left(1-\frac{1}{(x+0.25)^{0.6}}\right)$.

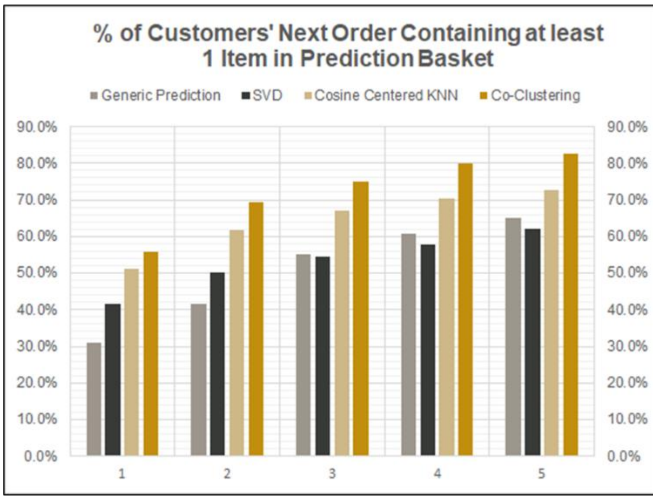

Figure 8. Accuracy comparison for the Product Prediction Model for different Baskets using different approaches

Combination of Model 1 and Model 2

A weighted average of both the product order percentages obtained through collaborative filtering and content-based filtering to get predictions for each user for every item. These items are sorted based on highest product order frequencies and a top-n items for each user is generated.

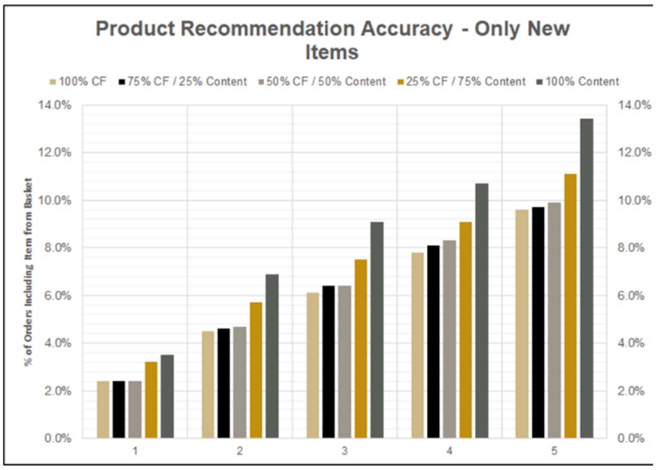

Figure 9. Accuracy comparison for the Product Prediction Model for different Baskets using different weighted averages for content based and collaborative filtering

VI. CONCLUSION

The development of two models, content-based and collaborative filtering, to predict what a customer will order next, coupled with the k-means algorithm to predict the timing of the customer's next purchase, has shown significant improvements in the accuracy of recommendations. These models are based on the user's historical data and current searches and have the ability to personalize recommendations to enhance customer experience.

The proposed approach showed significant improvements over existing models and accurately predicted what and when customers would order which can lead to increased sales and higher customer loyalty. The success of the project highlights the importance of utilizing advanced analytical techniques to personalize recommendations for customers in the food industry.

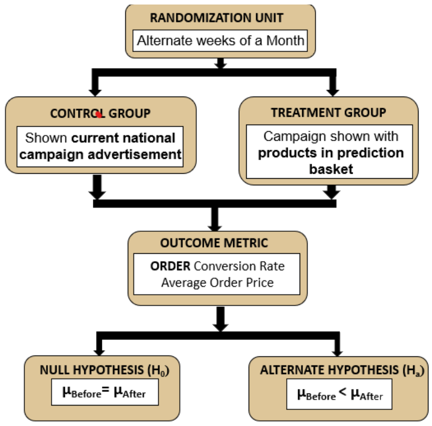

Figure 10. A/B Testing Design

The A/B test proposed, would demonstrate a significant difference in the mean conversion rate and average order price with and without the implementation of the recommendation algorithm, highlighting the impact of personalized recommendation algorithms on conversion rates and per-order spending. This finding can assist businesses in making data-driven decisions to optimize their products and services for maximum impact and enhance customer experiences. Further research can be conducted to refine the models and explore their applicability in other industries. The approach can also be combined with other machine learning algorithms to develop a more comprehensive recommendation system. Overall, this project contributes to the advancement of personalized recommendation systems and has practical implications for businesses seeking to enhance customer experiences and boost sales.

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