Improving Efficacy and Efficiency of Restaurant Recommendation Mechanism

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Abstract

The aim of this study is to research and develop a robust and dynamic recommendation system for restaurant selection mechanism. It is observed that current recommendation system used within various popular mobile and web applications are static in nature and are not representative of users' preference.

It is observed that current recommendation system used within various popular mobile and web applications are static in nature and are not representative of users' preference. The project is focused towards understanding the current methodologies in the available options and analyzing the gaps and challenges in the current scenario and mitigating the identified gaps to cater to customers' dynamic palettes.

We created a hybrid Recommendation Model, using R and Python, featuring three Recommendation types (Collaborative Filtering Recommender System, Content-Based Recommender System and Knowledge-Based Recommender System) to ensure the robustness of the recommendation system. User experience or preferences and Restaurant experience over time may vary, Static Recommendation Models fail to capture the degree of change and its impact, thus affecting the efficiency of the model. We captured the trend of the similarity among the Users and similarity among Restaurants over time and incorporated the same in the model, thus ensuring the dynamic nature of Recommendation model.

Keywords: Recommendation System, Dynamic, Robust, Similarity, Reviews, Restaurant

Introduction

User's selection process for trying out a new restaurant contains three major components word of mouth, Restaurant's review and rating provided in Mobile applications and proximity to the restaurant.

The project is focused towards understanding the current methodologies, limiting to the recommendation systems only, and to understand the gaps and challenges in the current scenario. The objective was to build a dynamic recommendation system which mitigates the identified gaps and is robust enough to cater to customers' dynamic palettes.

Some of the gaps, in the current scenario, catered through our model:

- Static Recommendation & Rating system – the system does not take into account the preferences or parameters provided by the customers and the recency of the ratings provided. It is majorly the aggregation of the ratings provided by the user population.
- Unrelated Reviews – the customer reviews available for user's reference are a pool of random reviews provided to the Restaurants, it is not representative of the user's preferences and set filters or parameters. The reviews are fetched from the pool of reviews and not representative of the filters or preferences set by the customer.
- Virtually none of the apps offers its users proper recommendations based on his/her tastes or preferences.

1. Problem Definition

Recommendation mechanism in the mobile applications, used in Restaurant recommending and rating application, forms an integral and important part of the user experience and service.

The recommender system used in the mobile applications are static in nature, they do not take into consideration the restaurant's current rating and mostly is a cumulative sum of inception (restaurant start date) to date ratings and reviews. Also, the recommendations are majorly based on the ratings and reviews and is not representative of the user's preference

Key Deliverables

- Business Insights from the Data available from various sources
- Dynamic & Robust Recommendation System

2. Algorithms

To cater to the main objectives, 'Robustness' and 'Dynamic Nature' of the Recommendation model, the first part of the model development was focused towards building the Static Recommendation System, Robustness of the model was addressed during this stage. The Second Stage of the model building model was focused towards building a dynamic model.

Algorithms used for the model:

- **Static Recommendation System**
    - Collaborative Filtering Recommender System (User Based)

Algorithm:

```
If (U1 == RA)
      If ((U2 == RA & U2 == RB)
               If Similarity (U1, U2) >= 0.4
                        Then U1 ε RRB
```

Notations:

User 1	:	U1
User 2	:	U2
Restaurant A	:	RA
Restaurant B	:	RB
User 1 likes Restaurant A	:	U1 == RA
User 2 likes Restaurant A	:	U2 == RA
User 2 likes Restaurant B	:	U2 == RB
Recommend Restaurant B	:	RRB
Similarity between User 1 & User 2	:	Similarity (U1, U2)
Recommend Restaurant B to User 1	:	U1 ε RRB

Theorem:

If two users share the same interests in the past, i.e. If U1 & U2 has strong similarity, their restaurant selection or preference will also be similar in future.

Definition:

We have considered that User 1 is similar to User 2 only if the similarity between User 1 & User 2 is greater or equal to 0.4. Similarity of a User is calculated based on the features or parameters associated with the compared Users and is matched with the user's historical preferences

Remark:

For convenience, we have taken 0.4 as benchmark. Going forward we look forward to optimize this number.

- Content Based Recommender System (Restaurant Based)

Algorithm:
If (U1 == RA)
If Similarity (RA, RB) >= 0.4
Then U1 ε RRB

Notations:

User 1	:	U1
Restaurant A	:	RA
Restaurant B	:	RB
User 1 likes Restaurant A	:	U1 == RA
Recommend Restaurant B	:	RRB
Similarity between Restaurant 1 & 2	:	Similarity (RA, RB)
Recommend Restaurant B to User 1	:	U1 ε RRB

Theorem:
This system recommends Restaurants to users by taking the similarity among the compared restaurants and user profiles (historic preference) into consideration. The system will recommend Restaurants similar to those that the user has liked in the past.

Definition:
We have considered that Restaurant A is similar to Restaurant B only if the similarity between Restaurant A & B is greater or equal to 0.4. Similarity of a Restaurant is calculated based on the features or parameters associated with the compared Restaurants and is matched with the user's historical preferences

Remark:
For convenience, we have taken 0.4 as benchmark. Going forward we look forward to optimize this number.

- Knowledge Based Recommender System (Based on User’s Purchase History)

Algorithm:
If (U1 == CRA)
If Similarity (RA, RB) >= 0.4
If Similarity (CRA, CRB) >= 0.4
Then U1 ε RCRB

Notations:

User 1	:	U1
Restaurant A	:	RA
Restaurant B	:	RB
Category 1 from Restaurant A	:	CRA
Category 1 from Restaurant B	:	CRB
User 1 likes Category 1 from Restaurant A	:	U1 == CRA
Category 1 from Restaurant A is similar to that of Restaurant B	:	Similarity (CRA, CRB)
Recommend Category 1 from Restaurant B	:	RCRB
Similarity between Restaurant 1 & 2	:	Similarity (RA, RB)
Recommend Category 1 from Restaurant B to User 1	:	U1 ε RCRB

Theorem:
This system recommends Restaurants to users based on user’s past preferences (Category of Food offered by Restaurant) and recommends Restaurants serving similar category of food, provided the service offering of the recommended restaurants is similar to that of the historic purchases, when the historic data is smaller.

Definition:
We have considered that Category of Food offered by Restaurant A is similar to the Category of food offered by Restaurant B only if the similarity between Restaurant A & B is greater or equal to 0.4 and the similarity of the category of food offered by Restaurant A & B is greater or equal to 0.4. Similarity of the recommended Restaurants & Categories is calculated based on the features or parameters associated with the user's historical preferences.

Remark:
For convenience, we have taken 0.4 as benchmark. Going forward we look forward to optimize this number.

- **Dynamic Recommendation System**

Algorithm:

```
If (U1 == RA)
    If Similarity (RA, RB) >= 0.4
        If Similarity Trend (RA, RB) >= 0
            Then U1 ε RRB
```

Notations:

User 1	: U1
Restaurant A	: RA
Restaurant B	: RB
User 1 likes Restaurant A	: U1 == RA
Recommend Restaurant B	: RRB
Similarity between Restaurant 1 & 2	: Similarity (RA, RB)
Trend of similarity b/w Restaurant 1 & 2 for last 2 months	: Similarity Trend (RA, RB)
Recommend Restaurant B to User 1	: U1 ε RRB

Theorem:
This system recommends Restaurants to users by taking the similarity among the compared restaurants and user profiles (historic preference) into consideration. The system will recommend Restaurants similar to those that the user has liked in the past.

Definition:
We have considered that Restaurant A is similar to Restaurant B only if the similarity between Restaurant A & B is greater or equal to 0.4. Similarity of a Restaurant is calculated based on the features or parameters associated with the compared Restaurants and is matched with the user's historical preferences. Also, the trend of the similarity for past two months is calculated and checked, if it is greater than or equal to zero. Recommendation for the Restaurant B will be made in case it satisfies all the conditions.

Remark:
For convenience, we have taken 0.4 as a benchmark for similarity and two months as a benchmark for trend. Going forward we look forward to optimize this number.

3. Data Preparation

The dataset is provided by Yelp which is a subset of businesses, reviews, and user data for use in personal, educational, and academic purposes. It includes 5,200,000 reviews, 174,000 businesses, 200,000 pictures and 11 metropolitan areas. It comprises of 1,100,000 tips by 1,300,000 users, Over 1.2 million business attributes like hours, parking, availability, and ambience, aggregated check-ins over time for each of the 174,000 businesses.

Structure of Data set: The dataset consists of 7 files such namely – Attribute, Business, Category, Friend, Review, Tip and User and each file consists of specific information.

Setting up Master files

- **Master Dataset – Business**:
  - A total of 174,567 unique business IDs of all the businesses and shops available on Yelp.
  - Some of these businesses are not under the purview of this project, as they are not categorized as restaurants. Thus, these business ids were excluded from the scope of this project. So, 72,705 unique business ids of Restaurants were included in the master dataset.
  - In one of the columns, 'Is Open' in Master dataset, some of the Business Ids are as categorized as 0, depicting that these business Ids are not operational anymore, these were further filtered out, leaving 55,010 unique Business Ids.
  - Next, we filtered out Business Ids which were not based out of USA.
  - Finally, a total of **46,973 unique Business Ids** were considered in building the recommendation model.
- **Master Dataset – User**:
  - A total of 1,226,101 unique user IDs of the users of all the businesses on Yelp is available. Since some of Business Ids are not under the purview of the project, they were excluded from the master dataset. **846,067 are the remaining unique User IDs** considered in the Master Dataset.
- **Master Dataset – Review:**

Raw dataset contains 5,047,073 reviews, this includes all the reviews for all the Business Ids and from all the User IDs from July 22, 2004 till December 11, 2017. The Reviews which were not related to unique Business IDs included in the final dataset were removed. Further, only the reviews for last 5 years starting from January 1, 2013 till December 11, 2017, were taken into consideration. This resulted in **2,426,487 reviews**.

4. Assumptions

- Restaurant rated by the user are the ones for which he/she has rendered services, its vice versa is not true. For the sake of the model building we have assumed it's vice versa to be true.
- User's address not available in the dataset, it is assumed that the rated restaurant's location can be considered approachable to the user and he/she will be open to the recommendations provided, of the restaurants, in the close proximity will be acceptable.

5. Exploratory Data Analytics and findings

Exploratory Data Analysis (EDA) was conducted using Tableau and R. The EDA was carried out to understand the Restaurant business and gather business insights.

Following Business Insights were gathered from EDA:

- It is to be noted that, except for Starbucks and Mc Donald's, none of the top ten brands (in terms of no. of unique business Ids) have been registered in top 10 top reviewed restaurants. Some of them are not even on the top 50 list.
- Most of the unique Business Ids are categorized as bars and bars is also the most reviewed category. So, it is safe to assume that, Bar, is the most preferred category among Restaurant Owners as well as customers.
- Fast Food is one of the top categories, in terms of no. of unique business ids, stating that it is one of the top food categories among restaurant owners. But, it is not a top food category among customers, in terms of reviews. Fast Food is a favorite food category but not the category that customers rate quite often. There are lot of Coffee houses but reviewers don't review them quite often.
- In case a User Id is new or visiting the city and he/she searches for best dining options in his mobile application, the mobile application should suggest top restaurants, as per his/her taste, based out of The Strip. Similar recommendations be made in the case of Spring Valley, Downtown, Chinatown, Westside and Ville-Marie based on User's proximity and preference. Ville-Marie and Strip can be considered as one of the top restaurant spots, with lot of good options for the users.

- **Review Trend**
    - Distribution of rating is left skewed with the most frequent rating being 4 and 3.5, whose frequency is higher than other ratings.
    - It is possible that people who rate and review are the ones who will view review/ratings online before deciding to try a new restaurant. So, there are more chances that these people like what they chose. Also, in general, people seem to be more likely to write a review for a positive experience than a negative one. As maximum no. of reviews is within 3.5 to 4.5 range of rating. Also, most business ids are reviewed between 3 to 4.5. This tells us that recommendation system is playing a vital role for people to decide on a restaurant and an improved personalized recommendation system could further increase the popularity of a restaurant.
- **Users have a wide range of number of reviews**
    - 13.42% of users reviewed only once.
    - 77.65% of users having less than 20 reviews and hence 22.35% of users having more than 20 reviews
    - Only 0.12%(1007) of users (846067) have more than 1K reviews.
- **Review Count over time**
    - Though the review count is steadily increasing each year but it dips towards the quarter 4 for every year.
    - Q4 is generally the holiday season in United States
    - Dip in the reviews for Q4 of 2017 is higher than its predecessors. As the data is only available till December 11, 2017, this could be one of the reasons for the dip.
- **User's Relationship with the App:** No. of users were max in 2014, around 140K, and have been decreasing since then. This is evident as majority of the tech-savvy population might already be enrolled in on Yelp. Also, competition in the market has increased since last 5 years. Today lot of apps are available in the market

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Step by Step walk through of the model creation

1. Overall methodology workflow for Content Based Recommendation System:

1. Loading & Understanding Dataset.
2. Processing the Dataset: Merging, splitting of dataset. Removing duplicates, creation of user-item matrix, and affiliation matrix.
3. Clustering.
4. Implementation of the clusters.
5. Make suggestions accordingly.
6. Creation of Dynamic Model.

2. Overall methodology workflow for Collaborative Based Recommendation System:

1. Loading & Understanding Dataset.
2. Processing the Dataset: Merging, splitting of dataset. Removing duplicates, creation of sparse matrix, and Real-Rating matrix.
3. Understanding User V/s Item (Business Ids) Pattern.
4. Calculating Similarity Measures.
5. Building a User-based Collaborative Filtering Model with the help of Recommenderlab package.
6. Make suggestions accordingly
7. Creation of Dynamic Model.

3. Key findings of each workflow

Loading and processing Data findings

- In the content-based filtering, Category of the restaurants forms the 'content' of the Restaurant. There are 186 such unique categories.
- Splitting of Dataset: The models were built on data from 2014 and testing was done on the data available for following year. As the model is built on 2014, business Ids which were in-business in 2014 were taken into consideration. Since, the business id's inception date is not covered in database,

we have assumed that the Business ids which were reviewed in 2014 were the only ones active, this leaves us with **29,053 unique Business ids.**

- Creation of Affiliation Matrix: Data frame listing the restaurants and their corresponding category affiliation

Clustering:

- Using the Scree plot, to determine the best number of clusters, a total of 6 clusters were selected to provide the users more specific recommendation as the number of combinations available are high in number and also the Sum within are comparable to the ideal choice.

Model Summarization for Static Recommendation of Content Based Recommendation

Once the User Id is fed in the model, the restaurant cluster will be identified, as per users' past preferences. Next, the model will select the restaurants that the customer has not rated yet, assuming that these are the restaurants that the user has not tried yet, these will be zeroed upon and Restaurant Name will be fetched from the Database. Next based on the average rating provided to these restaurants, top restaurants will be selected, based on the user's proximity to the restaurants, and suggestion will be made accordingly. Also, this can be executed at a city level, for the Users which are new to the city can view top 50 restaurants in the city, which are in line with their taste palates.

restaurant	city	state	Category
Cucina by Wolfgang Puck	Las Vegas	NV	Italian,Restaurants,Pizza
Stacks & Yolks	Las Vegas	NV	Sandwiches,Breakfast & Brunch,Burgers,American (Traditional), urants,Food,Pretzels
Fat Choy	Las Vegas	NV	American (New),Asian Fusion,Chinese,Restaurants
KoMex Fusion	Las Vegas	NV	Korean,Mexican,Asian Fusion,Restaurants
Bayside Buffet at Mandalay Bay	Las Vegas	NV	Restaurants,Buffets,American (Traditional)
Chuck E. Cheese's	Las Vegas	NV	Restaurants,American (Traditional),Pizza
Oak and Ivy	Las Vegas	NV	Cocktail Bars,Food,Bars,Beer,Wine & Spirits
Gold Spike	Las Vegas	NV	Bars,Restaurants,Cafes,Lounges

Figure 1: Top Restaurants recommended in Las Vegas to the selected User Id (Content Based Recommender System)

Model Summarization for Dynamic Recommendation of Content Filtering

To capture the change in User preferences, the year-on-year trend of the ratings provided by the users is calculated. The average ratings, provided by the User Ids, to the specific Business Id, in the previous. Year, is captured and compared with that of the following year. In cases where the differential amount is zero or above are considered, this will either excluded or recommend the business Id on a higher number (in the list of recommendations) made to customers. Once, the trend is captured and compared, all the steps in Step 4 will be executed and recommendations will be derived. Just like in previous step, this can be executed at a city level, for the Users which are new to the city can view top 50 restaurants in the city, which are in line with their dynamic taste palates.

restaurant	city	state	Category
Chuck E. Cheese's	Las Vegas	NV	Restaurants,American (Traditional),Pizza
Fat Choy	Las Vegas	NV	American (New),Asian Fusion,Chinese,Restaurants
Cucina by Wolfgang Puck	Las Vegas	NV	Italian,Restaurants,Pizza
Stacks & Yolks	Las Vegas	NV	Sandwiches,Breakfast & Brunch,Burgers,American (Traditional),Restaurants,Food,Pretzels
Gold Spike	Las Vegas	NV	Bars,Restaurants,Cafes,Lounges

Figure 2: Top Restaurants recommended in Las Vegas to the selected User Id, based on User's Dynamic taste palate

Model Summarization for Static Recommendation of Collaborative Based Recommendation

We start by selecting a User, in this case the first User Id in the dataset. Once the parameters are set to the model stated above, predictions can be made on the user's restaurant choices. Out of the list of predictions, top 10 predictions can be selected and mapped back to the Business Ids of the restaurants and User No to User Id, this is an important step as the prediction obtained are in form of Restaurant Number and User Number, as established earlier. This is later filtered by the city which has closest proximity to the User and top 10 restaurants, which are in line with User's palate are recommended. This can further be extended to other Users and other cities, in case the said User is travelling to the other city

	U18	restaurant_No	restaurant	city	state
1	R501	R501	The Goodwich	Las Vegas	NV
2	R547	R547	Baguette Cafe	Las Vegas	NV
3	R2887	R2887	Banger Brewing	Las Vegas	NV
4	R4483	R4483	Sin City Cupcakes	Las Vegas	NV
5	R7429	R7429	Lola's A Louisiana Kitchen	Las Vegas	NV
6	R557	R557	Vintner Grill	Las Vegas	NV
7	R232	R232	John Mull's Meats & Road Kill Grill	Las Vegas	NV
8	R1262	R1262	Raku	Las Vegas	NV
9	R2338	R2338	Kabuto	Las Vegas	NV
10	R6026	R6026	Gilcrease Orchard	Las Vegas	NV

Figure 3: Top Restaurants recommended in Las Vegas to the selected User Id (UBCF)

Model Summarization for Dynamic Recommendation of Collaborative Filtering:
To capture the change in User preferences, the year-on-year trend of the ratings provided by the users is calculated and the Business Ids for which the customer is providing the rating is captured. The average ratings, provided by the User Ids, to the specific Business Id, in the previous year, is captured along with the change in the similarity and compared with that of the following year. In cases where the differential amount is zero or above are considered, this will either excluded or recommend the business Id on a higher number (in the list of recommendations) made to customers. Once, the trend is captured and compared, all the steps in Step 4 will be executed and recommendations will be derived. Just like in previous step, this can be executed at a city level, for the Users which are new to the city can view top 50 restaurants in the city, which are in line with their dynamic taste palates.

4. Comparison – Dynamic V/s Static Model

Recommendation Ranking	Static Recommendation	Difference	Dynamic Recommendation	Difference
1	Cucina by wolf gang Puck	0.21	Chuck E. Cheese's	1.04
2	Stacks & Yolks	0.06	Fat Choy	0.3
3	KoMex Fusion	-0.28	Cucina by wolf gang Puck	0.21
4	Bayside Buffet at Mandalay Bay	-0.54	Stacks & Yolks	0.06
5	Chuck E. Cheese's	1.04	Gold Spike	0

- Chuck E. Cheese which was ranked at fifth spot moved to first as it has been receiving more positive reviews in past one year.
- KoMex Fusion and Bayside Buffet at Mandalay Bay was removed from the top 5 list as their ratings fell from previous year and indicate downward trend in rating.

Model evaluation and findings

Step 1: Preparing the data to evaluate models

For the purpose of evaluation, we have to split the data into testing and training datasets.

Step 2: Using cross-validation to validate models

Once the dataset is split, K-fold approach to evaluate models was applied. For the computational simplicity, dataset was split into smaller data frames and accuracy was computed using these data frames individually. Once the accuracy of each data frame was obtained, weighted average of all the accuracy was computed and this would be the accuracy of the model.

Two was taken as value for k for computing 2-fold cross validation

If a small percentage of rated restaurants are recommended, the precision decreases. On the other hand, the higher percentage of rated restaurants are recommended the higher is the recall.

Step 3: Comparison of other Models

Other models are compared such as RANDOM, POPULAR, IBCF, ALS, SVD

Step 4: Evaluating different Models

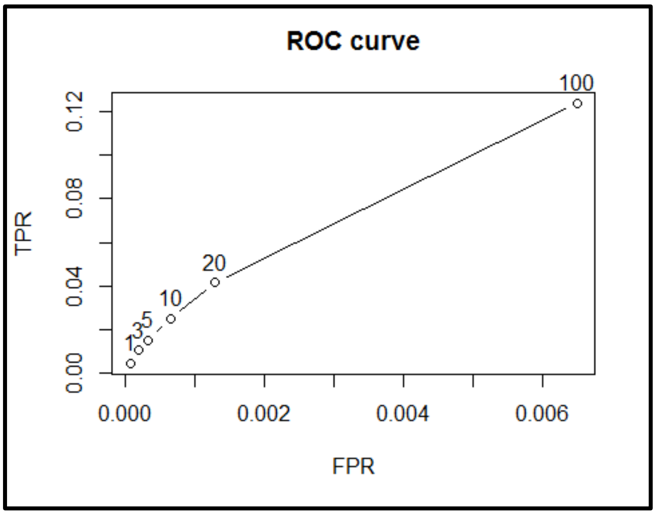

Figure 4: ROC Curve (UBCF)

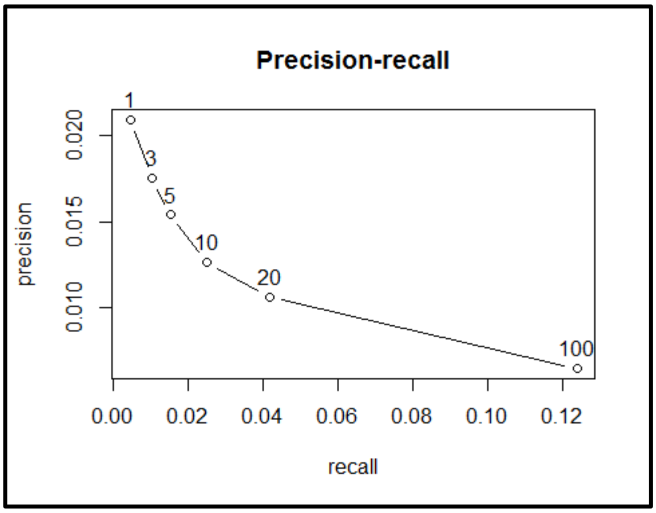

Figure 5: Precision - Recall (UBCF)

The performance of each of the model using ROC Curve and Precision-Recall graphs.

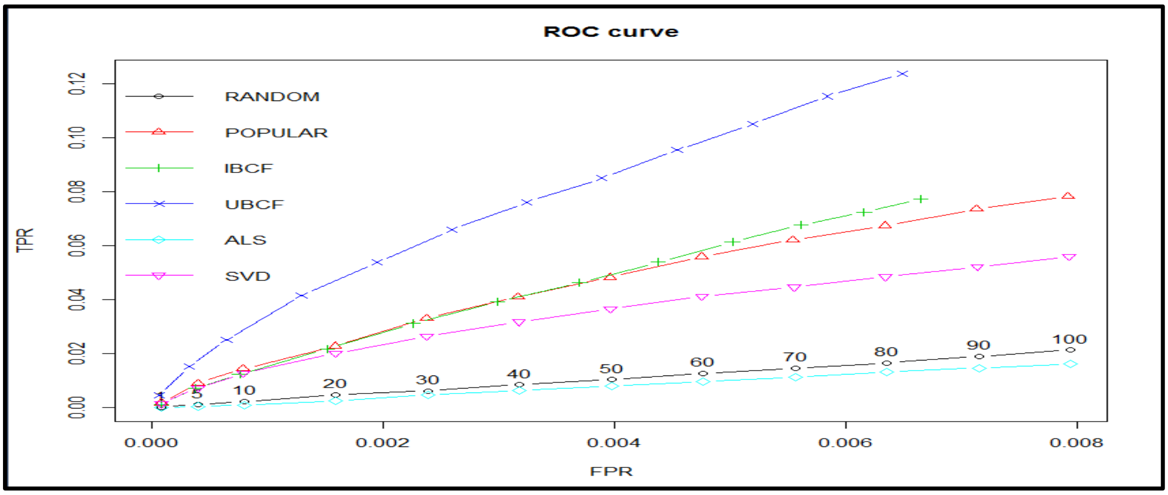

Figure 6: ROC Plot (Model Comparison)

Comparison of precision-recall curves for several recommender methods for the given-5 evaluation scheme.

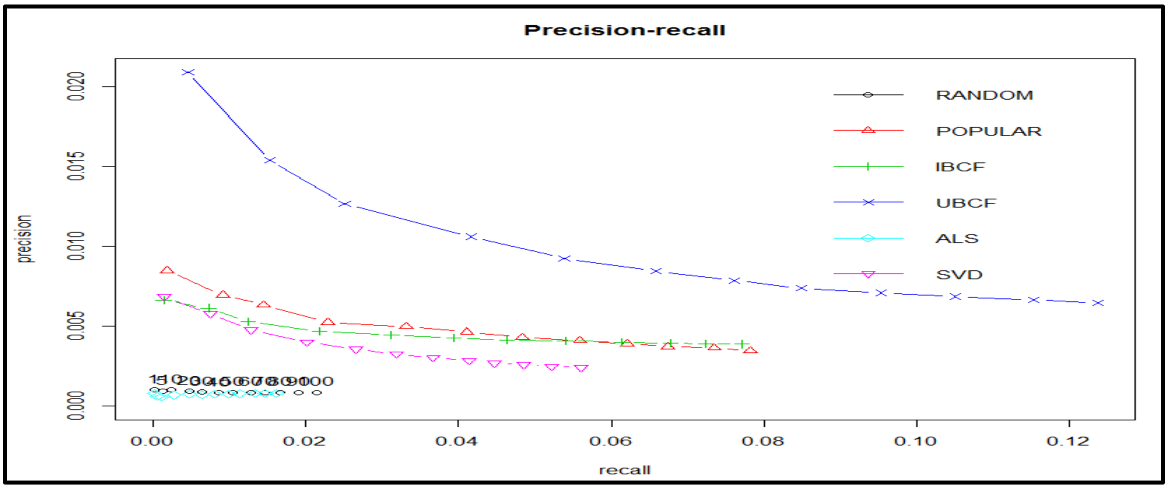

Figure 7: Precision-Recall (Model Comparison)

Comparison of RMSE, MSE, and MAE for recommender methods for the given-5 evaluation scheme.

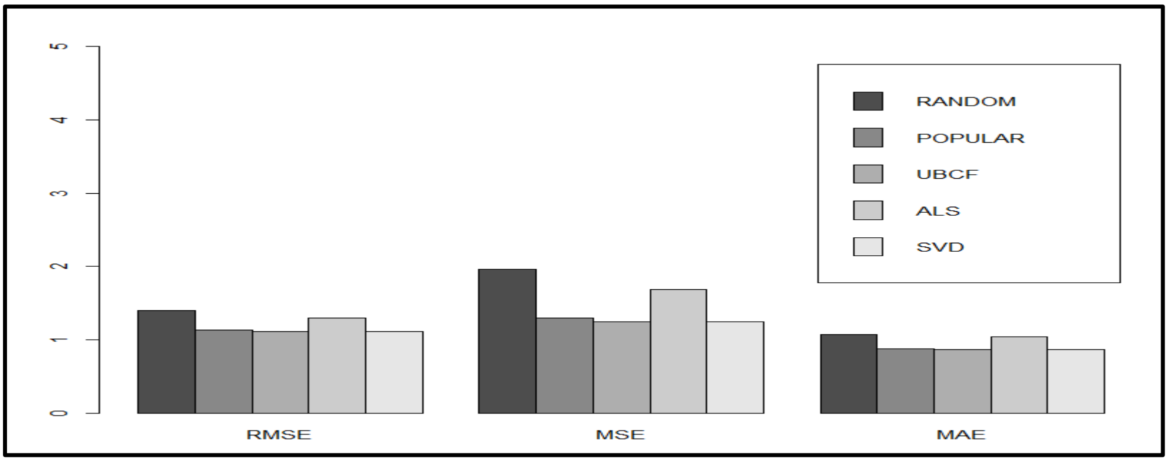

Figure 8: RMSE, MSE & MAE Comparison

Model Performance Comparison

	RMSE	MSE	MAE
RANDOM	1.404816	1.973507	1.0736432
POPULAR	1.136857	1.292443	0.8809080
UBCF	1.116745	1.247120	0.8680726
ALS	1.301434	1.693732	1.0421037
SVD	1.116075	1.245624	0.8679257

A good performance index is the area under the curve (AUC), that is, the area under the ROC curve. Even without computing it, the chart shows that the highest is UBCF with cosine distance, so it's the best-performing technique. The UBCF with cosine distance is still the top performing model.

Comparison to benchmark

There is no real good benchmark for RMSE on Yelp Dataset based on ratings only but the best we could come across GitHub and other online resources was 1.4 and we have achieved 1.1.

Implications

Adding the Dynamic feature to the model does have a positive impact on its performance. The performance should further be improved by adding more parameters, the data provided currently takes into consideration the broad categories of the restaurants. Detailed menu analysis, user's purchase pattern and trend of the preferences should help in giving a clearer picture and thus improving recommendation accuracy.

The study conducted does imply that study and incorporation of trend will have a positive impact on the recommendation models incorporated in the food industry.

Limitation

- **Constraints while performing Data Sanctity Check:** As the dataset was downloaded from Yelp, treating outliers and data anomalies was a limitation. Unlike in the case of business or company data, data sanctity check is possible with the operations team, was not possible. We had to either remove the outliers or incorporate the anomalies in the model.
- **Yelping Patten:** People use Yelp to find restaurants, but only a relatively small fraction of them leave a rating, and even lesser write a comment to explain the rating. The performance of a good recommendation system depends on a good user-based data.
- **Unavailability of Sales Data:** The reviews and restaurant ratings are not reflective of Sales information. Though it is true that the restaurant rated by the user is the one for which he/she has rendered services, its vice versa is not true.

Closing reflection

The models built using dynamic nature reproduces better performance, in terms of RMSE, in comparison to that of the static models and is reflective of customer's current demand/preference. Incorporation of such algorithms in existing mobile applications will improve customer experience and in turn, will help companies in expanding their user base. Further deep dive of User trend and its dynamic nature can be carried out and incorporated in the model to improve performance.

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