#### SOEN 691: BIG DATA ANALYTICS PROJECT

RESTAURANT RECOMMENDER SYSTEM

Presented By - Team 9

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#### Introduction

#### Goals

- To Implemented the recommender systems to recommend the restaurants using Content Based Filtering and Collaborative Filtering.
- Compare the RMSE, MEA and MSE metrics of these algorithms.

#### Dataset

- Collected using the APIs.
- Data collected in CSV files
- Restaurants ~ 42k
- Reviews ~ 1400k
- **Users** ~ 200K

#### Restaurant.csv

- No of columns
  - 105 attributes of different restaurants
- Important fields
  - restaurant\_id, city, categories
- Sample Data

#### Reviews.csv

- No of columns
  - 10 attributes of different restaurants
- Important fields
  - user\_id, restaurant\_id, user\_rating
- Sample Data

# Content Based Filtering

- Steps
  - Data Preprocessing
  - Normalize the data
  - Generate frequency-inverse values for different categories.
  - Generate user profiles
  - Generate the model predictions
  - Calculate the RMSE, MEA and MSE metric value
  - Generate the recommended restaurants

# Data Processing

- Removed restaurants with null restaurant\_id
- Removed users with null user\_id
- Filtered out restaurant based on categories.
- Filtered restaurants based on city

## Data Normalization

Normalized value = 1 / sqrt (n1 + n2 + n3 + ....)

+	+			+
restaurant_	_index Afghan	;Restaurants Barbeque;Re	staurants norm_val	ue
+	+			+
1	26	0	0  1	.01
1	29	0	0  1	.01
1	191	0	0  1	.01
1	222	0	0  1	.01
1	270	0	0  1	.01
+				+

# Algorithm

#### Frequency Inverse (TF-IDF)

Frequency Inverse of category= log10(x/y)

x = total number of restaurant

y = number of restaurant in category

Asian Fusion; Restaurants 2.7234556720351857

Breakfast & Brunch; Restaurants: 1.769213162595861

Peruvian; Cuban; Caribbean; Restaurants : 2.7234556720351857

Fast Food; Pizza; Restaurants: 2.7234556720351857

Seafood; Fish & Chips; Restaurants: 2.7234556720351857

#### **User Profiles**

Rating Threshold value: 3

```
Rating >= 3 => User value = 1
Rating <= 3 => User value = -1
```

#### **Model Predictions**

Prediction = 
$$\frac{m-r1}{r2-r1}$$
 \*  $(t2-t1)$  +  $t1$   $\begin{vmatrix} r1=-1 & t1=1 \\ r2=1 & t2=5 \end{vmatrix}$  m =  $\cos(\Theta)$  of User vector & Category vector

+	+	+	H
prediction	restaurant_index	uid user_rating	ı
+	+	+	+
5.0	261	1128  4	ı
5.0	261	1252  5	l
5.0	261	854  5	l
3.3922322702763683	261	5  4	l
1.0	261	811  2	l
+	+	+	+

### Metrics

RMSE = 1.406242291057611

MAE = 1.174760279634468

MSE = 1.9775173811589584

## Recommended Restaurants

+-	+	+	+-	+-	+	+
u	id restaurant_	index	name	prediction s	tars	categories
+-	+	+	+-	+-	+	+
	0	82  Thai H	Food Corner	3.659380473395787	3.5	Thai; Restaurants
	0	4  Pal	lee's Crown	3.659380473395787	4.0	Thai; Restaurants
	0	272	Thai Patio	3.659380473395787	4.0	Thai; Restaurants
	0	160 Benjarong	Thai Re	3.659380473395787	4.0	Thai; Restaurants
	0	37	Swan Thai	3.659380473395787	3.5	Thai; Restaurants
	0	224 Thai House	Restau	3.659380473395787	4.0	Thai; Restaurants
	0	186  Royal	Thai Grill	3.659380473395787	4.0	Thai; Restaurants
	0	208	Mango Thai	3.659380473395787	3.0	Thai; Restaurants
	0	109	Thai Basil	3.659380473395787	4.0	Thai; Restaurants
	0	106	Culver's	3.5275043787166296	3.0 Foo	d;Burgers;Fast
+-	+		+-	+-	+	+

# Collaborative Based Filtering

- Steps
  - Data Preprocessing
  - Normalize the data
  - Split data into train, validation, test(Traintest- validation split)
  - Calculate RMSE
  - Make rating predictions on all restaurants for that user
  - Generate the recommended restaurants based on the ranking of restaurant rating predictions

## Data Preprocessing

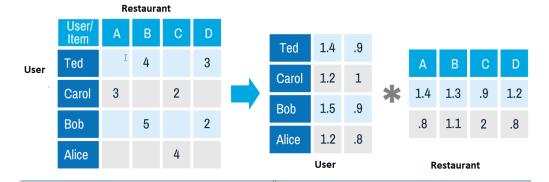
▶ Join the reviews file and restaurants file based on the restaurant ID

L	<b></b>	
restaurant_id	user_id	user_rating
vcNAWiLM4dR7D2nww vcNAWiLM4dR7D2nww vcNAWiLM4dR7D2nww vcNAWiLM4dR7D2nww vcNAWiLM4dR7D2nww vcNAWiLM4dR7D2nww vcNAWiLM4dR7D2nww JwUE5GmEO-sH1FuwJ	Xqd0DzHaiyRqVH3WR   H1kH6QZV7Le4zqTRN   zvJCcrpm2yOZrxKff   KBLW4wJA_fwoWmMhi   zvJCcrpm2yOZrxKff   Qrs3EICADUKNFOUq2   jE5xVugujSaskAoh2   QnhQ8G51XbUpVEyWY   zvNimI98mrmhgNOOr   p4ySEi8PEli0auZGB	2   4   4   4   1   5   5   4
<b></b>	<b></b>	<b></b>

antic charing ton 40 noise

# ALS Algorithm

A popular approach for this is matrix factorization, where we fix a relatively small number k (e.g.  $k \approx 10$ ) and summarize each user u with a k dimensional vector  $x_u$ , and each item i with a k dimensional vector  $y_i$ . These vectors are referred to as factors. Then, to predict user u's rating for item i, we simply predict rui  $\approx x_u^T y_i$ 



## Hyperparams

- ▶These are important in ALS, After optimizing we choose following values of different params
- ▶maxIter: 10 (It is the maximum number of iterations to run)
- ▶rank: 70 (The number of latent factors in the model)
- ▶regParam: 0.5 (The regularization parameter in ALS)
- ► ALS (maxIter=5, regParam=0.5, rank=70, userCol="userId", itemCol="movieId",
- ratingCol="user\_item\_interaction",
- coldStartStrategy="drop", seed=seed)

## Metrics

- We have used the ALS plus biases and calculated predictions as follows
- user\_item interaction+user\_mean+item\_mean-global rating
- RMSE: It measures numerical difference between all ground-truth ratings and actual ratings in test set.
- MAE: It measures numerical difference between all ground-truth ratings and actual ratings in test set

# Metrics

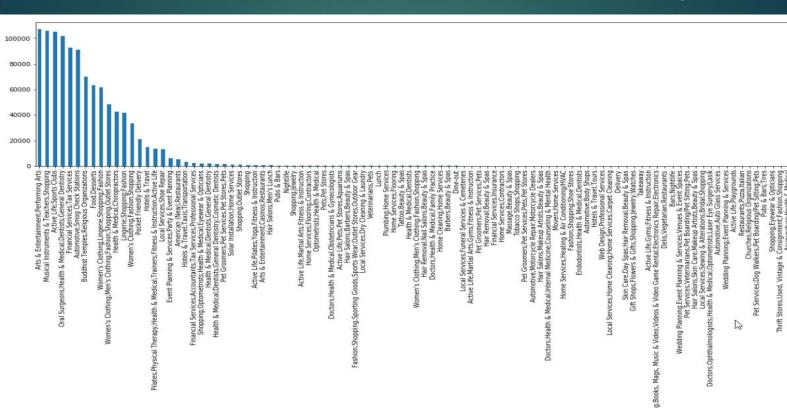
$$MAE = \frac{1}{N} \sum |predicted - actual| \qquad RMSE = \sqrt{\frac{1}{N} \sum (predicted - actual)^2}$$

RMSE	1.2542102156106667
MAE	0.9522392380468712
MSE	1.5730432649421549

	user_id	recommendations
0	0ml_q_0D1CdU4P_hoImQ	[(Gorilla Cafe, 5.184454441070557), (Island De
1	2QZsyXGz1OhiD4-0FQLQ	[(Jiffy Smog, 5.453772068023682), (Conrado & C
2	4fX3LBeXoE88gDTK6TKQ	[(SGI-USA Buddhist Center, 3.6345648765563965)
3	9HuvEtLhp21SelEEltnA	[(Desert Strings, 5.777367115020752), (Conrado
4	RMN1-5AiFSzdU5Gn1Q	[(SGI-USA Buddhist Center, 4.083629608154297),
5	-02lt4LFEgradr6uK9KCfA	[(Smith's Food & Drug Centers Inc, 4.007578849
6	-02LD_yedEFQKLuLDO-gWw	[(Gorilla Cafe, 5.564972400665283), (Gap Outle
7	-05sPcciFbK8O_Npx8Dz2A	[(Kiki de Montparnasse, 4.699824333190918), (D
8	-0AH2QoTlvKDf7CcjkJ39Q	[(Dior Boutique, 4.62614107131958), (Kiki de M
9	-0ETqxKsxlBnmJklugoTrg	[(Rod Stewart: the Hits, 5.019903659820557), (

# Recommendations

## Distribution of restaurants by category



	Collaborative	Content based
RMSE	1.2542102156106667	1.406242291057611
MAE	0.9522392380468712	1.174760279634468
MSE	1.5730432649421549	1.9775173811589584
Runtime	768000 ms	930000 ms

## Results Comparison

## Conclusions



The RMSE of content based is higher than the collaborative.



Restaurant ratings are diverse in content-based recommender.



Content based recommended the restaurants that have high review count whereas collaborative recommendations tend to have higher ratings and lower review count,



Collaborative Filtering algorithm has the limitations of Cold-start problem where a recommender does not have the adequate information about a user or an item to make relevant predictions. Data Sparsity Is the problem that occurs as a result of lack of enough information

#### Limitations



As API gives the large data around 400 gb, it is difficult to extract and process.



There are limited hardware resources to process and filter large data.

#### Future Work

Hybrid recommender systems - The best approach would be to use a combination of different approaches. Mix of collaborative and content-based filtering. Some of it will depend on preferences of the users and some on item features.

We could predict the rating on all cities instead of one cities which gives user preferences in various cities.

Implement recommender systems with various algorithms such as SVD++,Bayesian Personalized Ranking (BPR) and deep learning algorithms.





THANK YOU!

ANY QUESTIONS ?