

# FOOD RECOMMENDATION SYSTEM

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**DSI 16 Capstone Presentation**  
Dominic Ong



SINGAPORE

# Restaurant no-shows on the rise as Singapore's F&B scene struggles through the pandemic

BY MAY SEAH | 29 JUL 2020 | 

Many diners are making several bookings per night, choosing one and cancelling the rest at the last minute, say restaurants and chefs who are at the end of their tether.



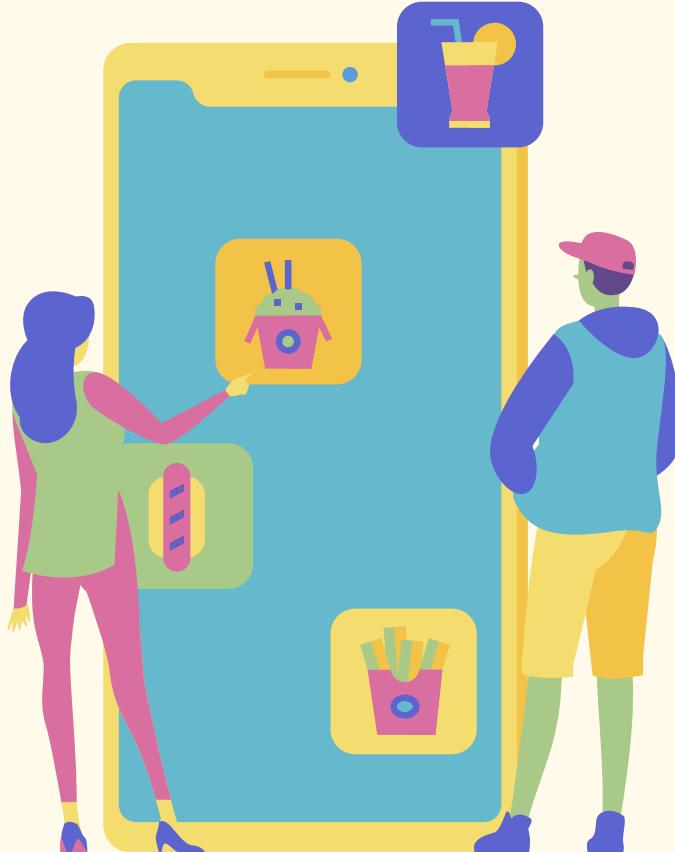
## Problem Statement

- Earlier this year, COVID-19 forced many countries into lockdowns to curb the spread of the virus.
- While staying at home, many people turned to online food delivery services for their daily meals.
- Many lesser known restaurants businesses have struggled during these times due to the lack of customers and orders.



# Solution

- More people are starting to frequent restaurants again in Phase 2.
- Build an [alternative restaurant recommendation system](#) based on user reviews and sentiment analysis.
- Make people more aware of local restaurants and help keep their businesses alive.



# Overview

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## Explanatory Data Analysis

- Pandas
- Seaborn
- Plotly



## Natural Language Processing

- Sentiment Analysis
- Topic Modelling



## Recommendation System

- Location-Based
- Collaborative-Filtering
- Content-Based

# Yelp Toronto Dataset

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The Yelp dataset is a subset of Yelp's businesses, reviews, and user data that has been made publicly available for use for personal, educational, and academic purposes.



**Initial: 44,023 Restaurants**  
**Toronto: 5,471 Restaurants**

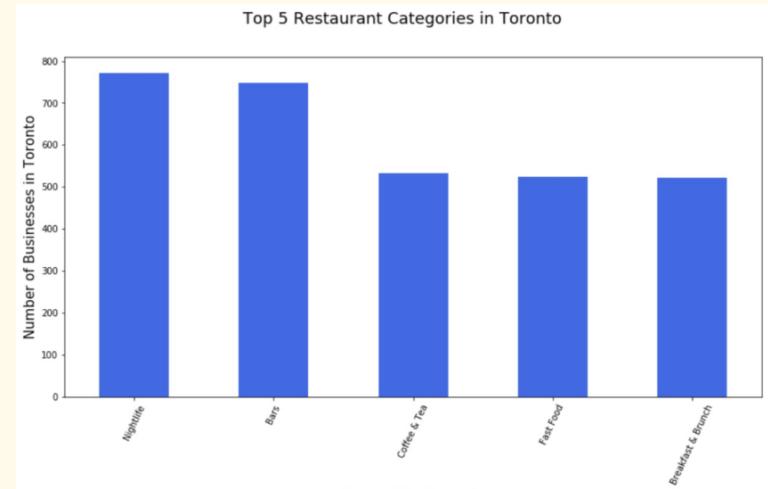


**Initial: 8,021,122 Reviews**  
**Toronto: 253,050 Reviews**



**Initial: 1,047,892 Users**  
**Toronto: 44,485 Users**

# EDA on Restaurant Data



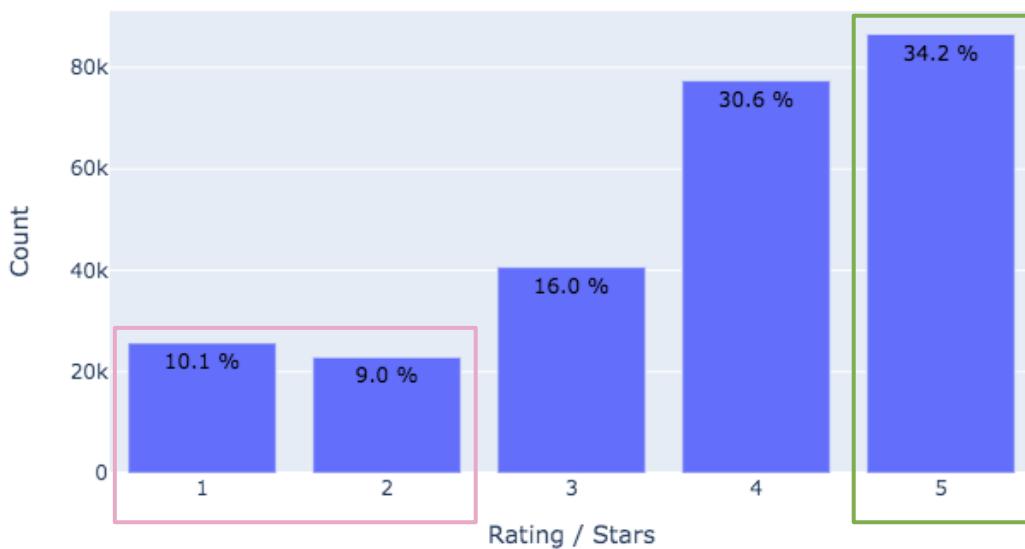
### Top 5 Most Popular Restaurant Categories:

- **Nightlife** (772 Restaurants)
- **Bars** (748 Restaurants)
- **Coffee & Tea** (532 Restaurants)
- **Fast Food** (524 Restaurants)
- **Breakfast & Brunch** (522 Restaurants)

# EDA on Reviews Data

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Distribution Of 253050 Restaurant Ratings from Yelp Users



**86,543 Positive Reviews**

- **Pai Northern Thai Kitchen**
- **Most # of Positive Reviews (2,758)**

**48,332 Negative Reviews**

- **Momofuku Noodle Bar**
- **Most # of Negative Reviews (1,010)**

# EDA on Reviews Data

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Negative Reviews

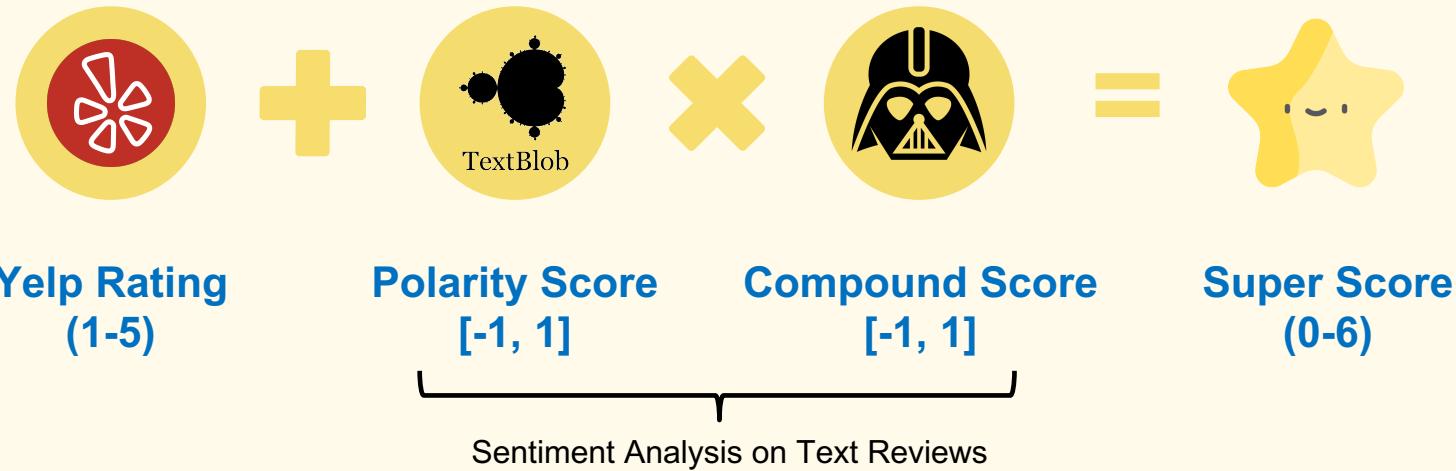


Positive Reviews



# Sentiment Analysis

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- Polarity Score: positive statement = 1, negative statement = -1
- Compound score: most positive = 1, most negative = -1

# Topic Modelling



## Western (Topic 3)

cheese  
burger taste  
fry chicken side  
order salad sauce meat

## Dessert (Topic 4)

cream ice  
dessert coffee  
pancake tea  
egg taste  
sweet flavour

## Asian (Topic 5)

place chicken  
rice price  
noodle soup  
food order dish  
beef

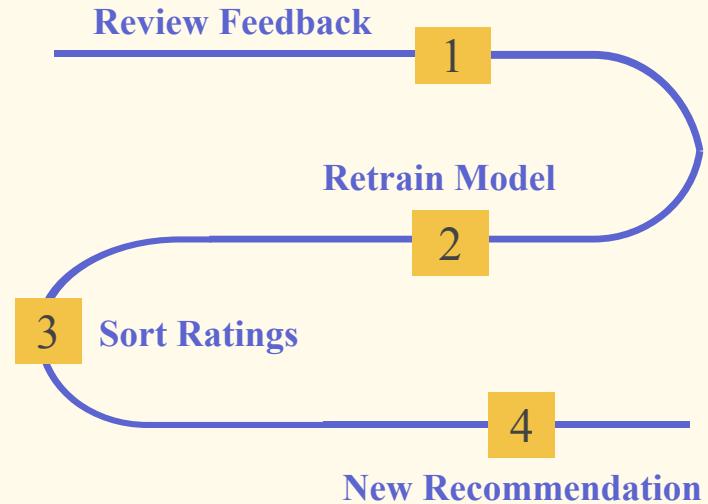
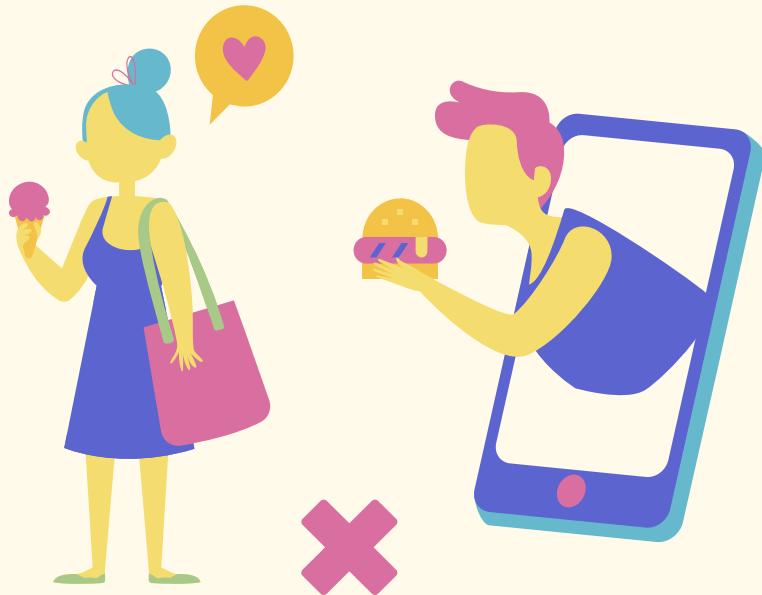
A top-down photograph of a restaurant table set for two people. The table is covered with a black cloth and holds several plates of food: a burger with fries, a salad with orange and green vegetables, and another plate with a sandwich and fries. There are also two glasses of water, a small bowl of dipping sauce, and a smartphone displaying a video. A person's hands are visible, one holding a fork over the salad plate.

# Building Our Recommendation Systems

# Cold-Start Problem

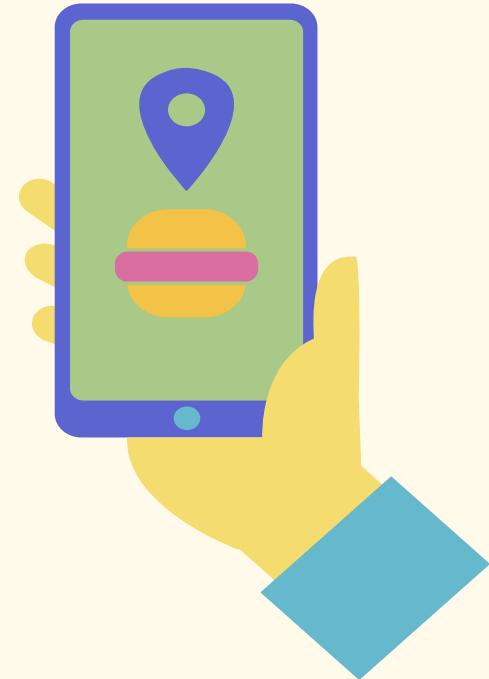
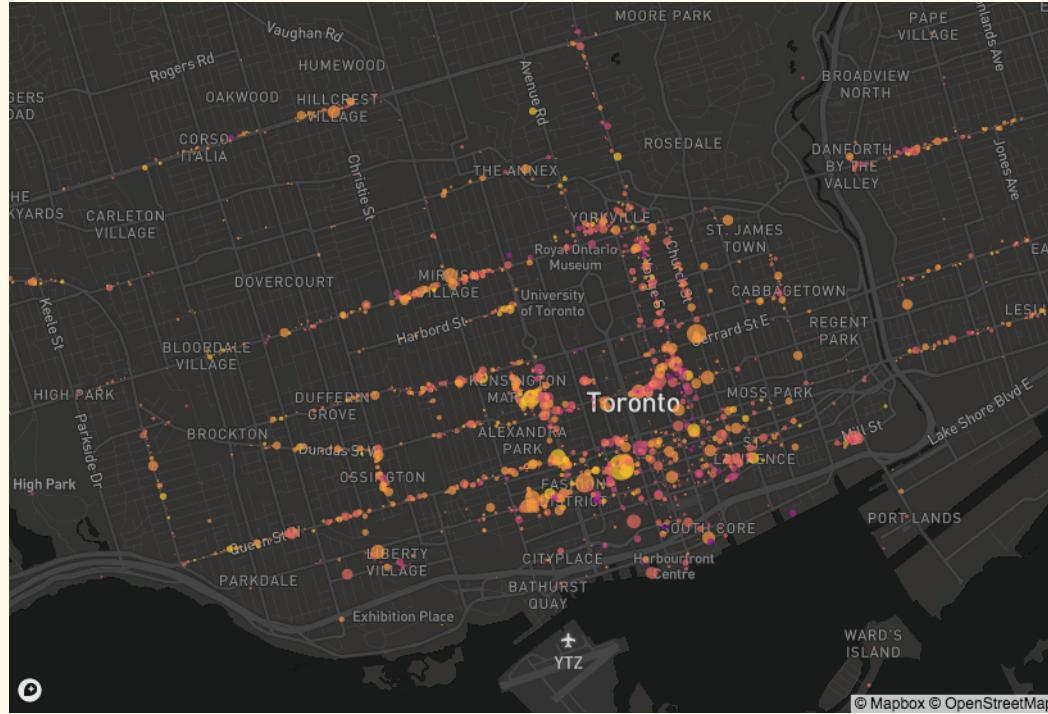
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It is difficult to provide personalized recommendations to new users without any information about their prior preferences. We have to use a naïve solution to solve the cold-start problem.



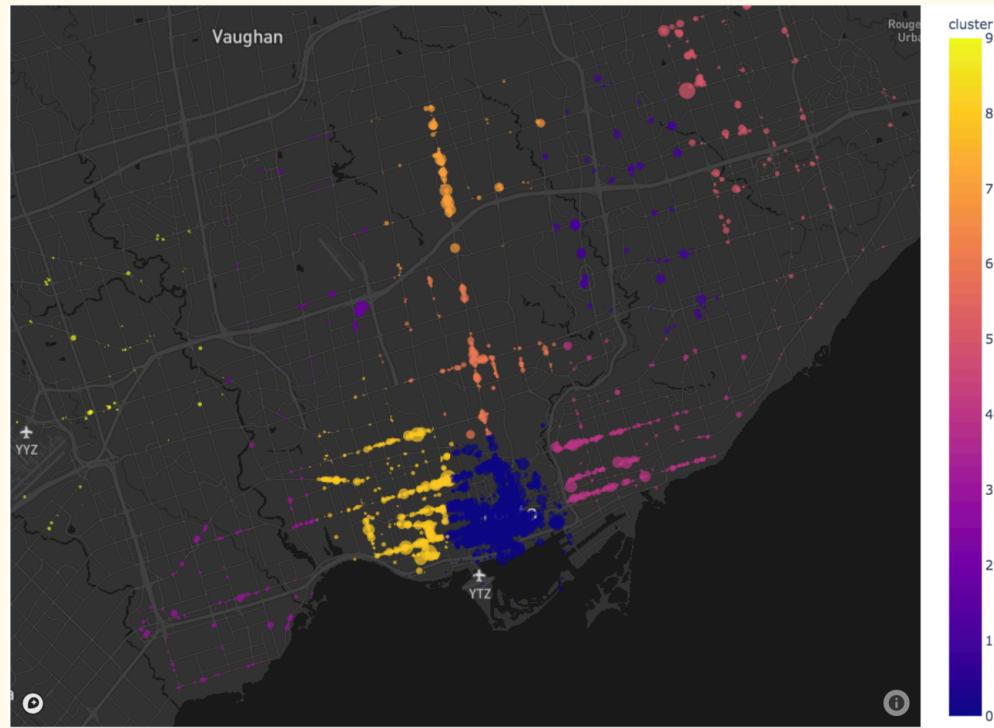
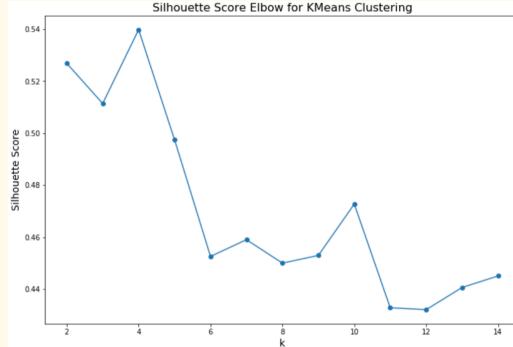
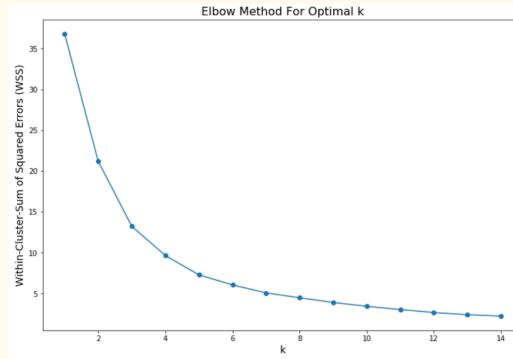
# Location-Based Recommendation

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# Location-Based Recommendation

Group Restaurants together based on geographical proximity using K-Means Clustering.

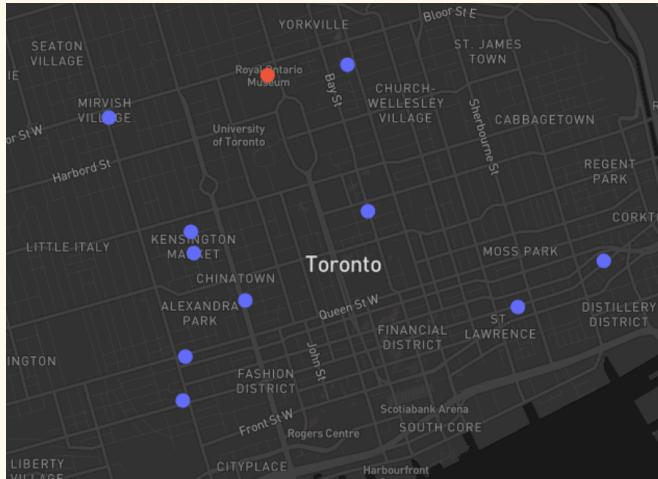


# Location-Based Recommendation

## Case Study 1: Royal Ontario Museum



Shawn is a tourist in Toronto. After visiting the Royal Ontario Museum, he wants to have a meal but is unsure of what nice restaurants are around his location.



name	latitude	longitude	categories	stars	review_count	cluster
Big Trouble Pizza	43.651328	-79.397038	Pizza, Restaurants	5.0	48	4
Mallo	43.664631	-79.410738	Coffee & Tea, Food, Cafes, Nightlife, Sandwich...	5.0	36	4
Ooshee Mediterranean Oven	43.668469	-79.386778	Restaurants, Mediterranean, Bakeries, Lebanese...	5.0	20	4
The Vegan Extremist	43.656321	-79.402501	Indian, Vegan, Restaurants	5.0	15	4
Muncheez	43.644059	-79.403310	Juice Bars & Smoothies, Restaurants, Creperies...	5.0	12	4
Strange Love Coffee	43.647247	-79.403050	Coffee & Tea Supplies, Coffee Roasteries, Food...	5.0	11	4
Fast Fresh Foods	43.657823	-79.384715	Restaurants, Salad, Sandwiches, Food	5.0	8	4
Casamiento	43.654775	-79.402205	Latin American, Pop-up Shops, Salvadoran, Shop...	5.0	8	4
Old Town Bodega	43.654212	-79.361035	Cafes, Restaurants, Food, Coffee & Tea	5.0	8	4
YEE: Gettin' Cozy with Butter Chicken Roti	43.650860	-79.369668	Local Flavor, Restaurants, Indian, Yelp Events	5.0	8	4

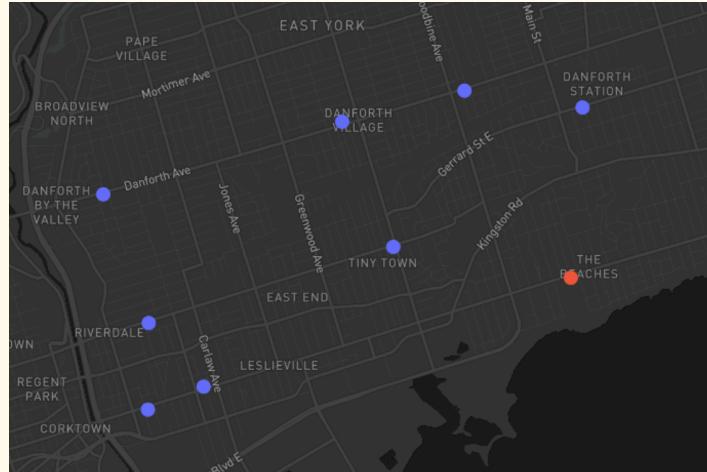
# Location-Based Recommendation

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## Case Study 2: Kew Gardens



Jeremy has just explored Kew Gardens. After a tiring walk, he is looking for a restaurant to sit down and have a relaxing meal.

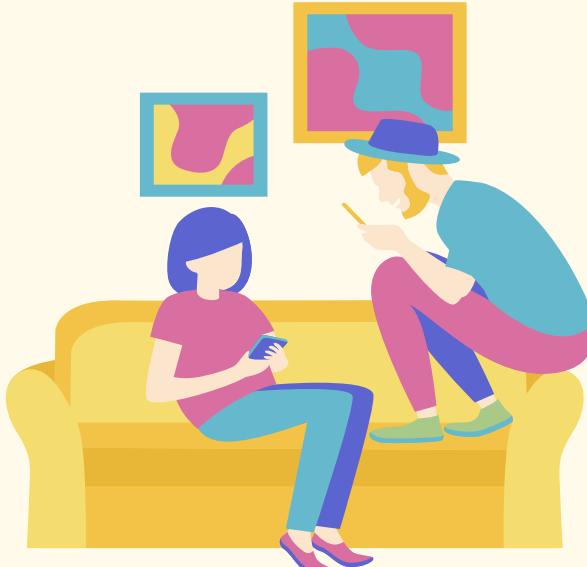


name	latitude	longitude	categories	stars	review_count	cluster
I'll Be Seeing You	43.658993	-79.348074	Cocktail Bars, Bars, Comfort Food, Wine Bars, ...	5.0	49	6
Viva Shawarma	43.708524	-79.295665	Halal, Middle Eastern, Falafel, Mediterranean, ...	5.0	30	6
Pomarosa Coffee Shop & Kitchen	43.683242	-79.325450	Cafes, Coffee & Tea, Restaurants, Sandwiches, ...	5.0	29	6
Elvy & Flo Cafe	43.666286	-79.347986	Restaurants, Coffee & Tea, Food, Cafes	5.0	15	6
Papyrus	43.677126	-79.353285	Vegan, Vegetarian, Restaurants, Middle Eastern...	5.0	11	6
The Dock On Queen	43.660927	-79.341583	Cafes, Sandwiches, Restaurants	5.0	10	6
YEE: The Breakfast Club: Lazy Daisy's Café Bistro	43.672696	-79.319486	Yelp Events, Restaurants, Local Flavor, Breakfast...	5.0	10	6
JJ Bean	43.719810	-79.313194	Coffee & Tea, Cafes, Bakeries, Coffee Roasteries, ...	5.0	10	6
Gyoko Sushi & Bar	43.685862	-79.311198	Sushi Bars, Restaurants	5.0	9	6
Prologue Cafe	43.684435	-79.297439	Coffee & Tea, Restaurants, Cafes, Food	5.0	8	6

# Collaborative-Filtering Recommendation

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Collaborative Filtering finds a smaller set of users with tastes similar to a particular user. It looks at the restaurants they like and combines them to create a ranked list of suggestions.



## Steps:

1. Pivot Table on Super Score Ratings
2. Truncated Singular Value Decomposition
3. Item-Item Matrix based on Cosine Similarity

# Collaborative-Filtering Recommendation

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## Case Study: Pai Northern Thai Kitchen



- Most # of Yelp Reviews
- Thai Cuisine



1. Montchant (Café)  
Correlation: 0.975



2. Rainbow Food (Chinese)  
Correlation: 0.972



3. Masala King (Indian)  
Correlation: 0.942



# Content-Based Recommendation

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Content-Based Recommendation recommends restaurants based on similar categories and keywords.



## Steps:

1. Topic Modelling
2. CountVectorizer
3. Cosine Similarity

# Content-Based Recommendation

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## Case Study: Sidewalk Pizzeria



### 1. Fusilli Restaurant



### 2. Tavolino



- Italian Cuisine
- Keywords: Italian, restaurants, pizza, great, place, food, ...



# Limitations and Looking Forward

- More Reviews and Data are required to improve the Recommendation Systems.
- Use Bi-Grams and Tri-Grams in Sentiment Analysis and Topic Modelling.
- Deep Learning & Neural Network architectures for collaborative filtering can be explained in the future.
- Incorporate Graph Theory for location-based systems to optimize travelling and delivery routes.

# Demo (in the Future)

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When I figure out how to deploy on Heroku...



# Thanks!

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