



# SINGAPORE RESTAURANT RECOMMENDER SYSTEM

---



Kun Won, DSI-21

# Table of Contents

**Context**

01

02

**Methodology**

**Evaluation**

03

04

**App Demo**

# Why Restaurants?

~23,000

Food retail outlets in Singapore

S\$8.3bil

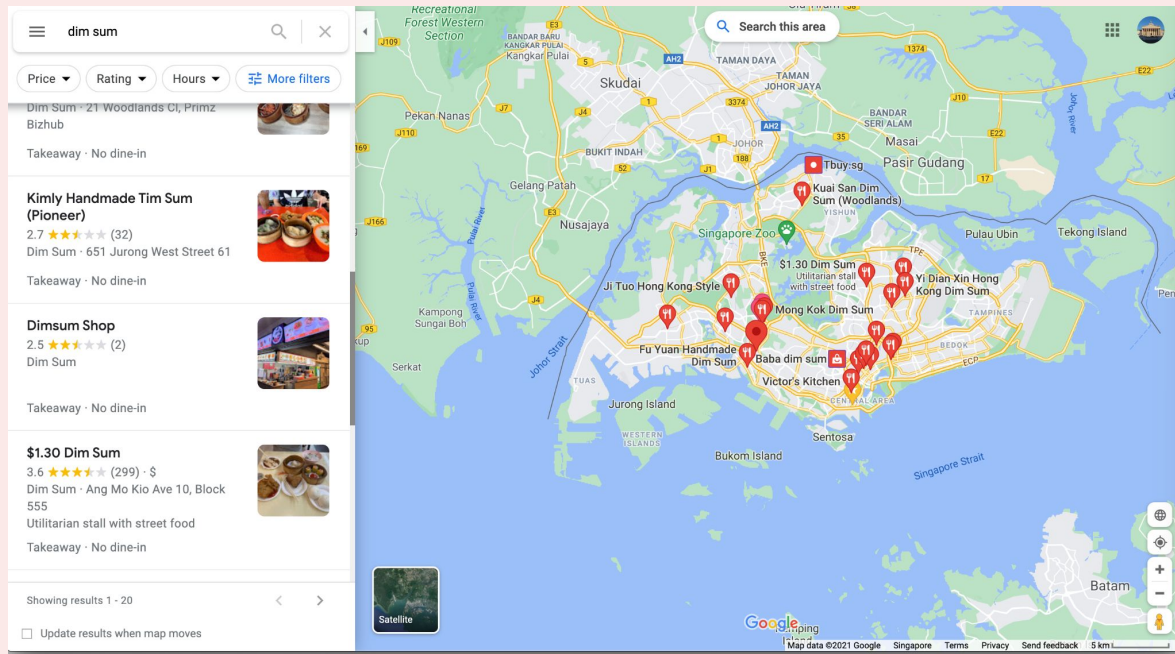
SG F&B Industry Net Worth

Consumers face choice overload

Reliance on word-of-mouth, brick and mortar advertising, food blogs

Existing commercial recommender systems have their weaknesses





# Google Maps

Difficult to use and resource intensive

Rankings prioritise distance and diversity over ratings



## 15 Stamford by Alvin Leung (The Capitol Kempinski Hotel Singapore)

Modern Asian by Alvin Leung, in The Capitol Kempinski Hotel

2 Adults



10 Jun 2021



Not Available



**Book Now**

### You may also like



#### Shang Palace

Regal Chinese cuisine fit for an Emperor at Shangri-La Hotel, Singapore



#### Katachi Style Sushi

Authentic sushi and kaiseki in City Hall



#### Kopi Tiam

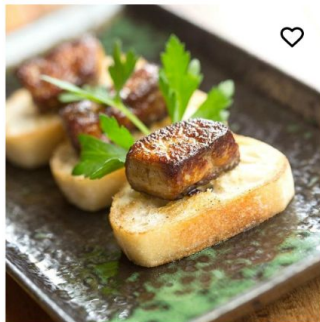
Upgraded hawker staples from Suicidal The Stamford

# Chope

Focus on high end dining with smaller  
database of ~1,000 restaurants

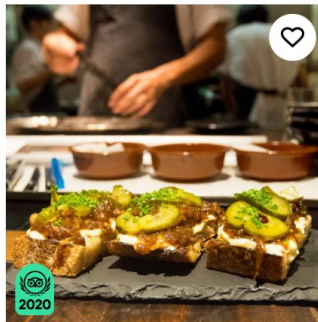
## You might like these

More restaurants in Singapore



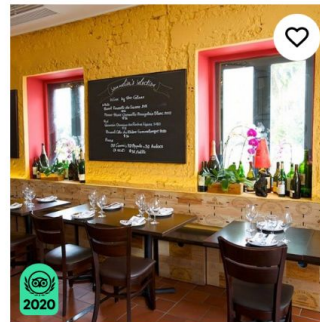
**31 Bar & Kitchen**

●●●●● 49



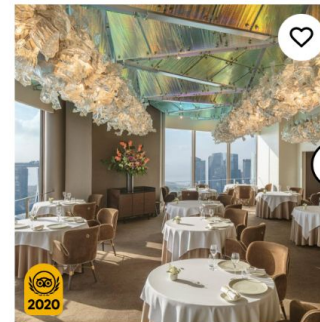
**Burnt Ends**

●●●●● 632



**Le Bistrot du Sommelier**

●●●●● 273



**JAAN by Kirk Westaway**

●●●●● 756

# Tripadvisor

Reviews mainly by tourists. May not be  
reflective of local tastes.

# Project Goals

Build a recommender app which takes inputs of restaurant(s) a user likes and outputs similar restaurants



## Simplicity

Easy to use and quickly find recommendation



## Relevance

Recommendations are relevant (e.g. similar in cuisine to the input restaurant)



## Quality

System should prioritise higher rated restaurants

# TABLE OF CONTENTS

Context

01

02

Methodology

Evaluation

03

04

App Demo



# Process

01

Data Scraping

02

Data Cleaning  
and EDA

03

Topic Modelling

04

Build  
Recommender  
System

05

Deploy App and  
Gather Feedback

# Datasets Used

6,000

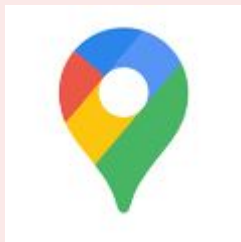
Restaurants

220,000

Reviews

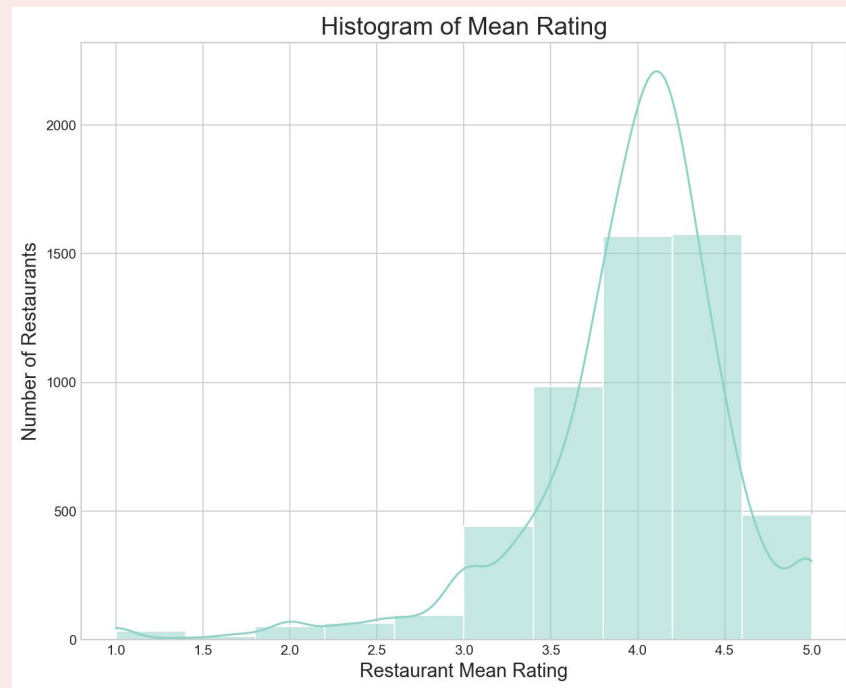
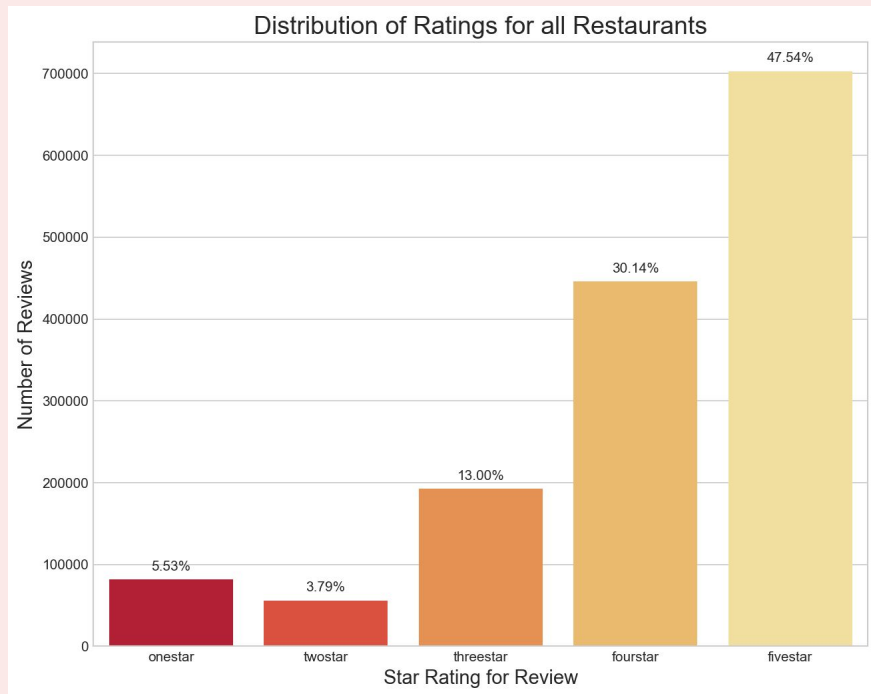
Scraped from Google Maps using Apify

Including fields such as business category, restaurant ID,  
reviewer ID, restaurant closure status, mean rating



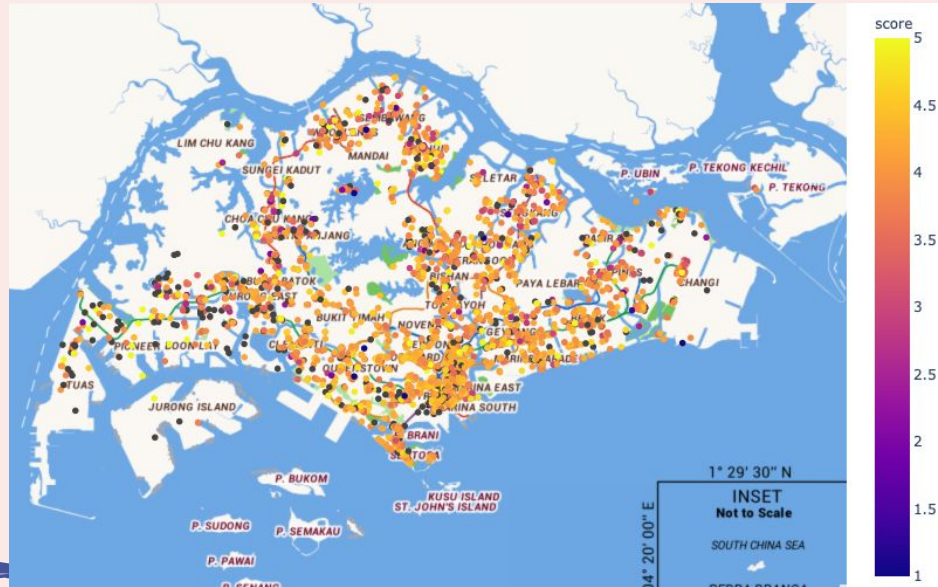
# Individual ratings tend to favour extremes

Better to use mean ratings in the model



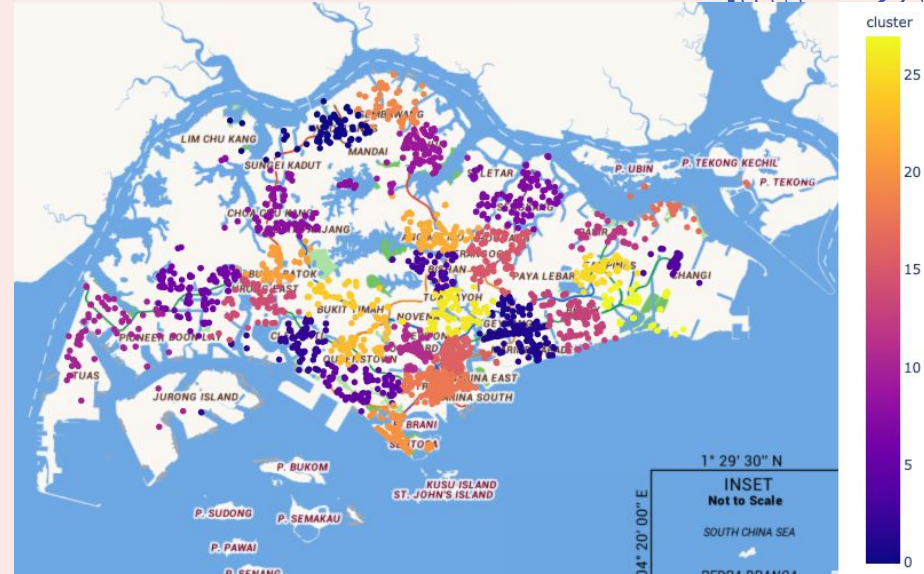
# Good geographical spread of restaurants

Colour showing mean rating



Plotting Geographical Data using Plotly  
Used OneMap API to get coordinates and map data

Colour showing cluster

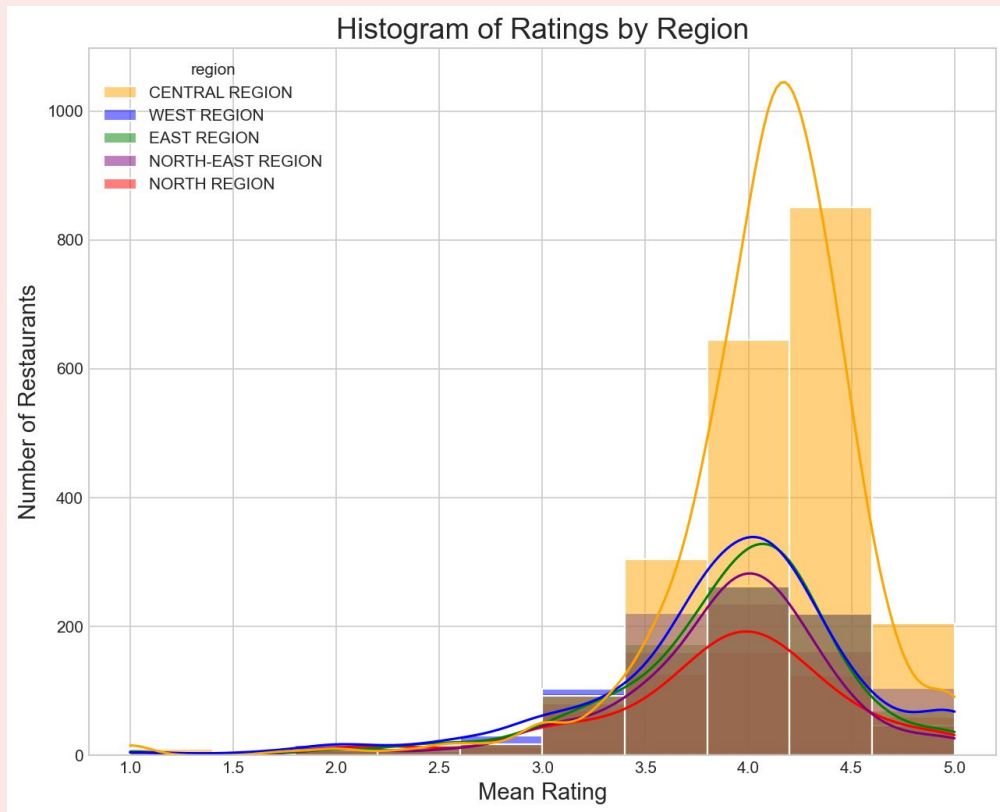
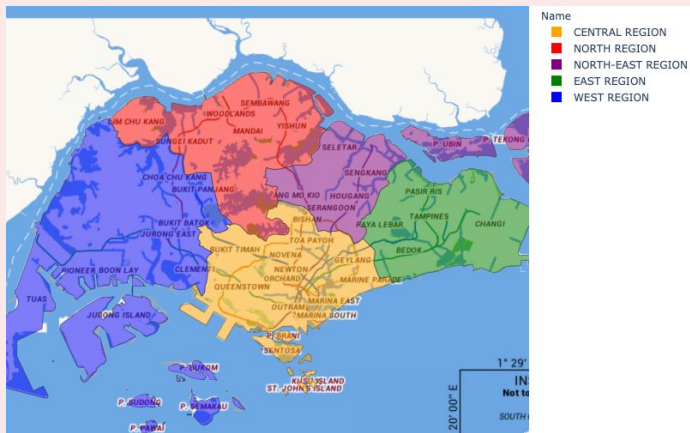


K-Means Clustering  
Enable filtering by location in app

# Which is best? East or West? Turns out, neither

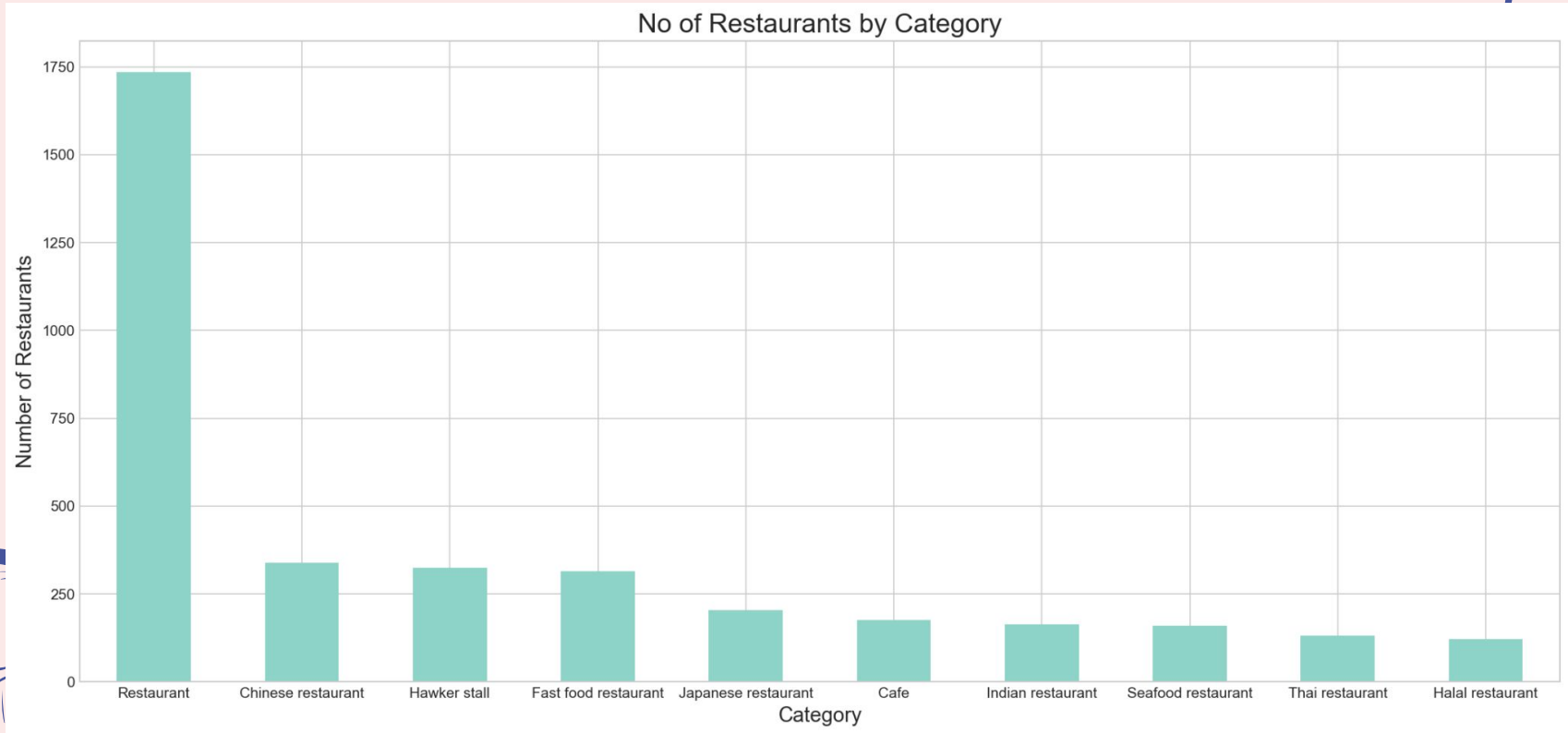
Ratings distribution for central region is more left skewed

URA Planning Regions



# Restaurant category data was unspecific

Having good categorical data would enable user to tell restaurant cuisine quickly



# Impute category using topic modelling

Having good categorical data would enable user to tell restaurant cuisine quickly

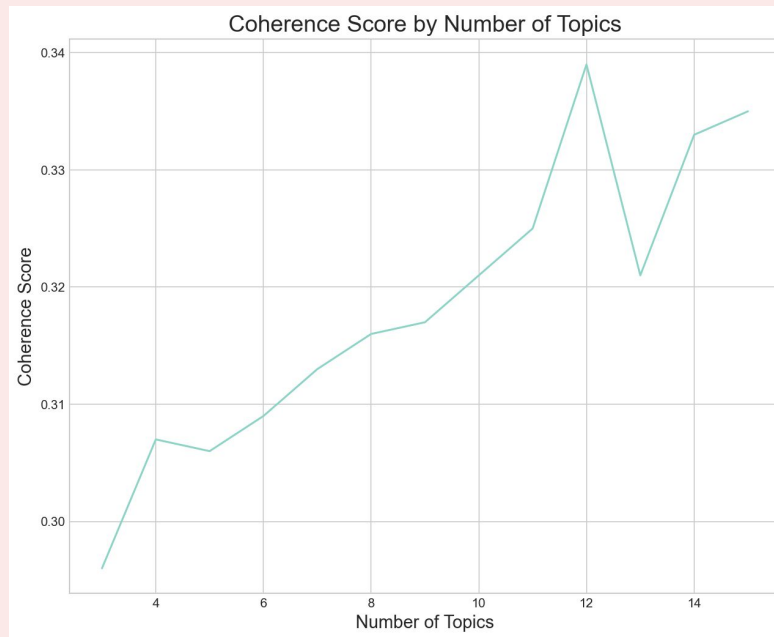
Process reviews text data (Spacy, NLTK)

Remove stopwords, POS tagging just nouns and adjectives, generating bigrams and trigrams

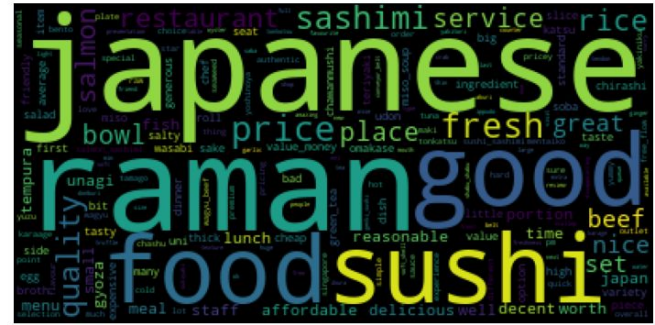
Topic Modelling using Gensim

Sum reviews data into a document for each restaurant. Use topic modelling to find similarity between restaurants.

Chose k as 12 topics based on coherence score.  
High coherence means high similarity in keywords for documents in each topic





[illegible][illegible][illegible][illegible][illegible]

Restaurants with ambiguous category reduced from 1,700 to 300

Restaurants with ambiguous category reduced from 1,700 to 300

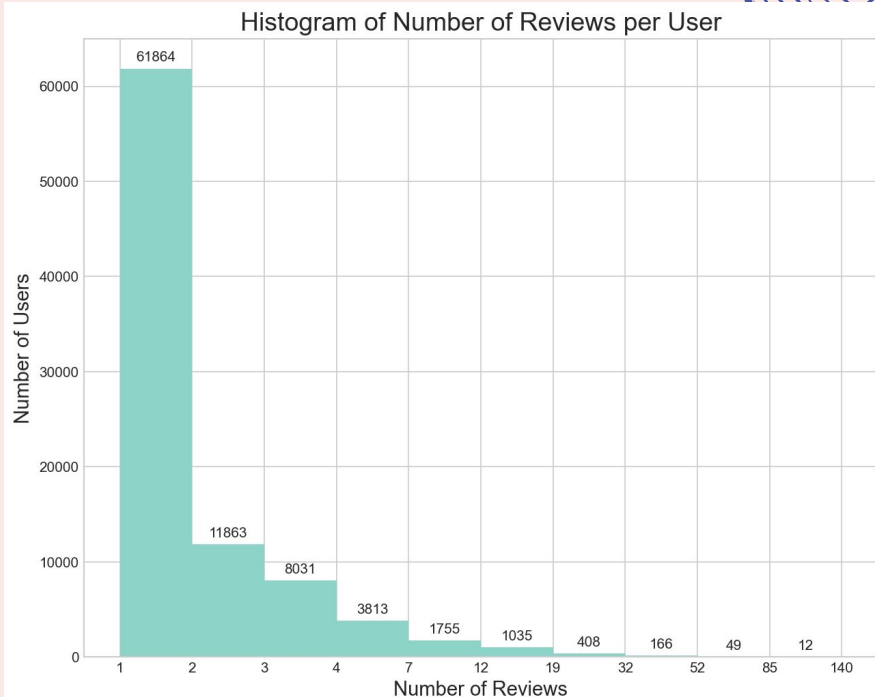


# Content-based filtering > Collaborative-based filtering

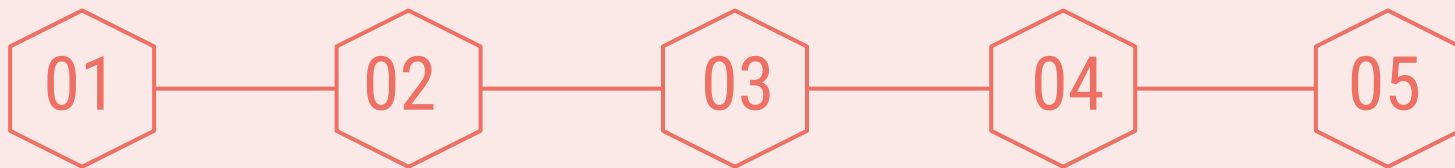
Many restaurants have the max scraped of 50 reviews



Number of reviews per user likely insufficient



# Content Based Recommender System Workflow



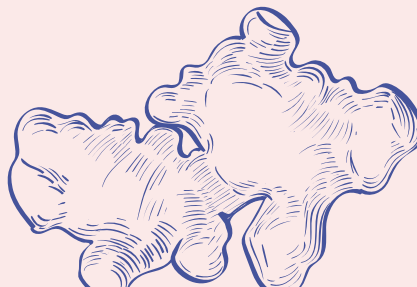
TFIDFVectorizer  
on review data

Generate cosine  
similarity matrix  
for each  
restaurant

Average cosine  
similarity  
matrices, rank  
and take top 50  
most similar

Within top 50,  
only show those  
within the  
selected cluster

Rank by mean  
rating and  
number of  
reviews. Only  
show top 10 by  
rank



# TABLE OF CONTENTS

Context

01

02

Methodology

Evaluation

03

04

App Demo

# Evaluation Design and Metric



## Metric

Precision@k where k is 10.

## Precision

$$\text{precision} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{retrieved documents}\}|}$$

## Relevance

Does the output restaurant share similar main dishes with the input restaurant?

## Design

Compute average precision@k for 5 queries

Build random recommender system

Compare both precision@k

## Case example



Restaurant Name	Restaurant Category
L'éclair Pâtisserie (Jewel)	Dessert shop



# Case Study for L'éclair Pâtisserie

My recommender does considerably better than random

**My Recommender: 0.5 (Avg after 5 diff queries: 0.66)**

Good Bites	Cafe
Lemuel Chocolate (Westway)	Chocolate cafe
The Bread Shop	Cafe
Munchi Delights	Hawker stall
The Spot - Singapore	Fine Dining Restaurant
5 by Sans Façon	French restaurant
The English House by Marco Pierre White	Traditional restaurant
SweetSpot	Cafe
Tamago-EN (Northpoint City)	Cafe
15 Stamford by Alvin Leung	Fine Dining Restaurant

**Random Recommender: 0.1 (Avg after 5 diff queries: 0.14)**

Uncle Penyet	Indonesian restaurant
Taj Indian Food	Hawker stall
Pasta Cucina	Hawker stall
Camden Hill Restaurant & Bar	Bistro
La Braceria	Italian restaurant
Hansik Restaurant	Korean restaurant
Tomi Sushi	Sushi restaurant
Yao Ba Cha Seafood Steamboat	Seafood Restaurant
The Tree Cafe (E!Hub)	Cafe
Red House Seafood at Prinsep	Seafood restaurant

## Further areas for improvement



### Simplicity

Use JavaScript to program a more intuitive UI



### Relevance

Integrate other metrics such as cost similarity

Explore the performance of other algorithms such as Jaccard Similarity



### Quality

Explore introducing some randomness in ranking to ensure novelty and reusability, while delivering quality



# TABLE OF CONTENTS

Context

01

02

Methodology

Evaluation

03

04

App Demo







# THANKS

**Do you have any  
questions?**

CREDITS: This presentation template was  
created by Slidesgo, including icons by  
Flaticon, infographics & images by Freepik

Please keep this slide for attribution