

Personalized Yelp Recommendations

GA Tech CSE6424 Data Visualization - Team Project

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Problem Statement

- ▶ Yelp is a great resource for finding places to eat!
- ▶ However, unless you're an avid Yelp user -- Yelp cannot recommend a personalized search.
 - ▶ Multiple written multiple reviews,
 - ▶ Multiple business visits/ratings
- ▶ Heck, Yelp's Recommendations go on for pages and pages like google searches!
 - ▶ This isn't personalization more than just recommendations!

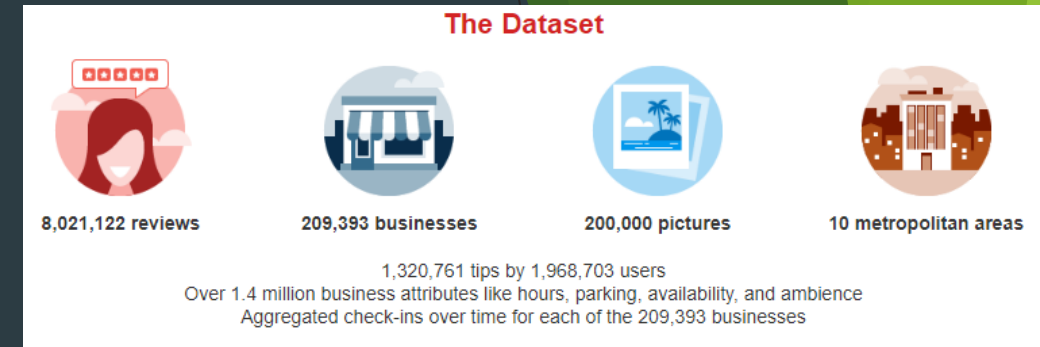
Project Goal

- ▶ Create an app that can allow users to input their food preferences & output a personalized restaurant search
- ▶ Additionally, provide metrics & limit the results as to allow users to make informed decisions quicker and with confidence!

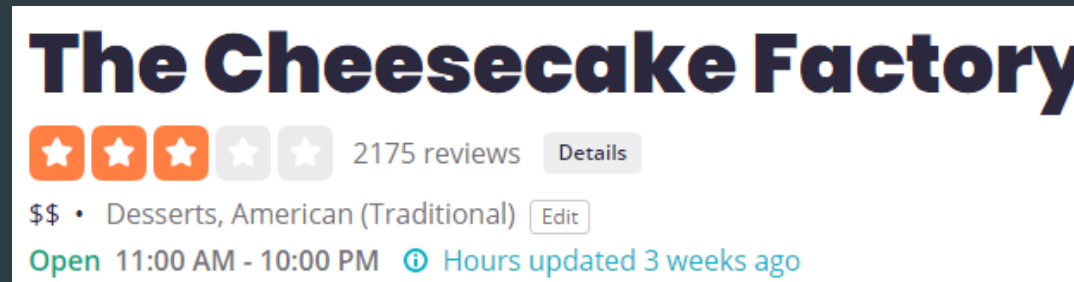
Recommendation System Details

- ▶ Package: LightFM
- ▶ LightFM maps user/item features and performs dimensionality reduction to find latent factors (see Matrix Factorization) that exist in your model
- ▶ The model of choice here was a user-based collaborative filtering model
 - ▶ A method that exploits user's features (cuisine preference) to create a model that can be used to predict for a **new user (you!)** based on their own preferences

What exactly are the inputs? How was the model trained?



- ▶ The Yelp Challenge Dataset contains lots of information
- ▶ Specifically, we used what the business tagged itself as
- ▶ Ex: The Cheesecake Factory lists under {Desserts,American (Traditional)}



- ▶ These business tags are used as inputs and the LightFM model is trained on what users that exist in the system that have reviewed +3 locations.
- ▶ Recommended restaurants are populated based on highest similarity score

Example of how User-based Collaborative
Filtering works (Next slide)

Model Input & Output Overview

User_profile = ["Japanese","Thai","Burgers","Korean","Soups"]

Feature Vector for this user:

"Japanese"	"Burgers"	"American (New)"	"Wigs"	"Thai"	"Hair Salon"
1	1	0	0	1	0

Sparse Matrix{
Dim: 1xN
Values: {("Japanese",1)
...
("Soups",1)
}
N = # unique features

Model.predict(users_id=0,

items_id=

All_items = {0,1,2,...,M}
M = # businesses

user_features=

Sparse Matrix{
Dim: 1xN
Values: {("Japanese",1)
...
("Soups",1)
}

)

All_items = {0,1,2,...,M}

M = # businesses

Sort

Top X recs

Putting it all together!

- 1) Preferences are fed into the model in the 1st drop-down menu
- 2) Recommendations are automatically populated from the LightFM model
- 3) Graphics are also automatically updated once businesses are populated

Yelp Recommender - Team99(198)



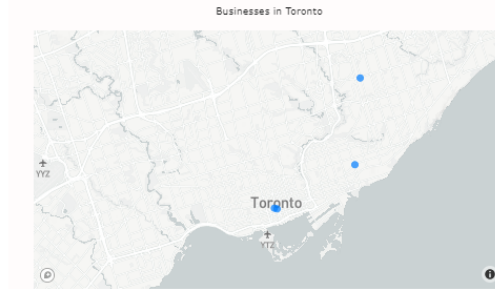
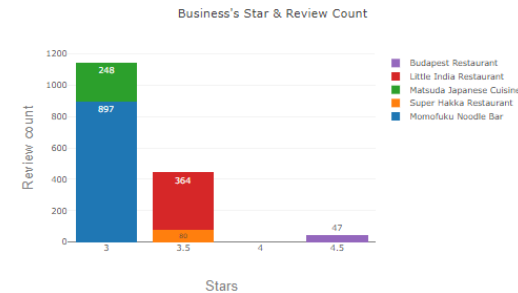
1) Select your Preferences -- As many as you like! Preferably > 5

Burgers French Active Life Hawaiian Vegetarian

2) Businesses will be populated based on your preference in ranked order (left to right) -- Feel free to add more/change the selection(s)

Momofuku Noodle Bar Super Hakka Restaurant Matsuda Japanese Cuisine Little India Restaurant Budapest Restaurant

Note: Graphics may take ~15s to load & will automatically update with any changes to above selectors.



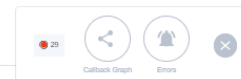
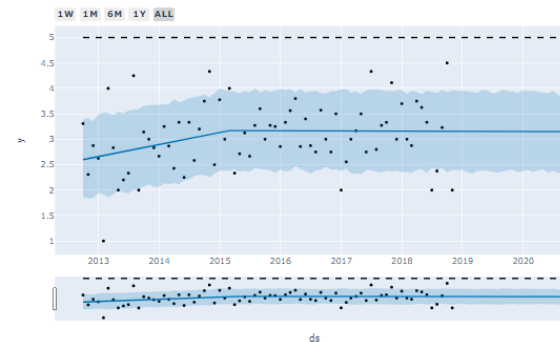
Momofuku Noodle Bar

Most Positive Attributes

- pork
- chicken
- service

Least Positive Attributes

- bill
- disappointment
- problem



Packages/Software Utilized

- ▶ Python

- ▶ Pandas - Dataframe structure
- ▶ Numpy - General computation
- ▶ LightFM - To compute the Collaborative Filtering Algorithm
- ▶ Dash/Plotly - To generate the dashboard & Callback functions
- ▶ Mapbox - To generate the map
- ▶ FBProphet - To generate the forecasts

- ▶ Docker

- ▶ To instance and package the project

How this can be improved

- ▶ Input options could be limited/streamlined
 - ▶ “American (New)” is likely the same as “American”
 - ▶ Also this blanket term may encapsulate other input terms such as “Burger” or “Pizza” which adds a level of confounding --- Maybe remove generic cultural words and allow the individual food items only
 - ▶ “Hair Salon” and “Wigs” are not food!
 - ▶ Manual check of keywords/tags, although conducted, was not sufficient at removing all nonsense entries
- ▶ The dataset could be expanded
 - ▶ For the project, we focused only on the Toronto area to keep the project form-fit for the short timeline we had