The Yelp Machine

NYC Data Science Academy | Capstone Project | Team PC1

Aiko Liu | Amy Chen | David Steinmetz | Greg Domingo

The team

Aiko Liu

With quantitative training in math/physics, focus on the application of machine learning techniques to finance, big data and beyond

Amy Chen

Devoted to using data visualization and machine learning techniques for social and business innovations

David Steinmetz

Passionate about creating value by distilling data into actionable information, particularly through visualization

Greg Domingo

Keen interest in innovation with Data Science as one of the leading edges of innovation space

Agenda

Overview and Context

Explanation of the App

Next Steps

Agenda

Overview and Context

Explanation of the App

Next Steps

You want to go out to eat with a friend but sifting through restaurant listings is frustrating and difficult

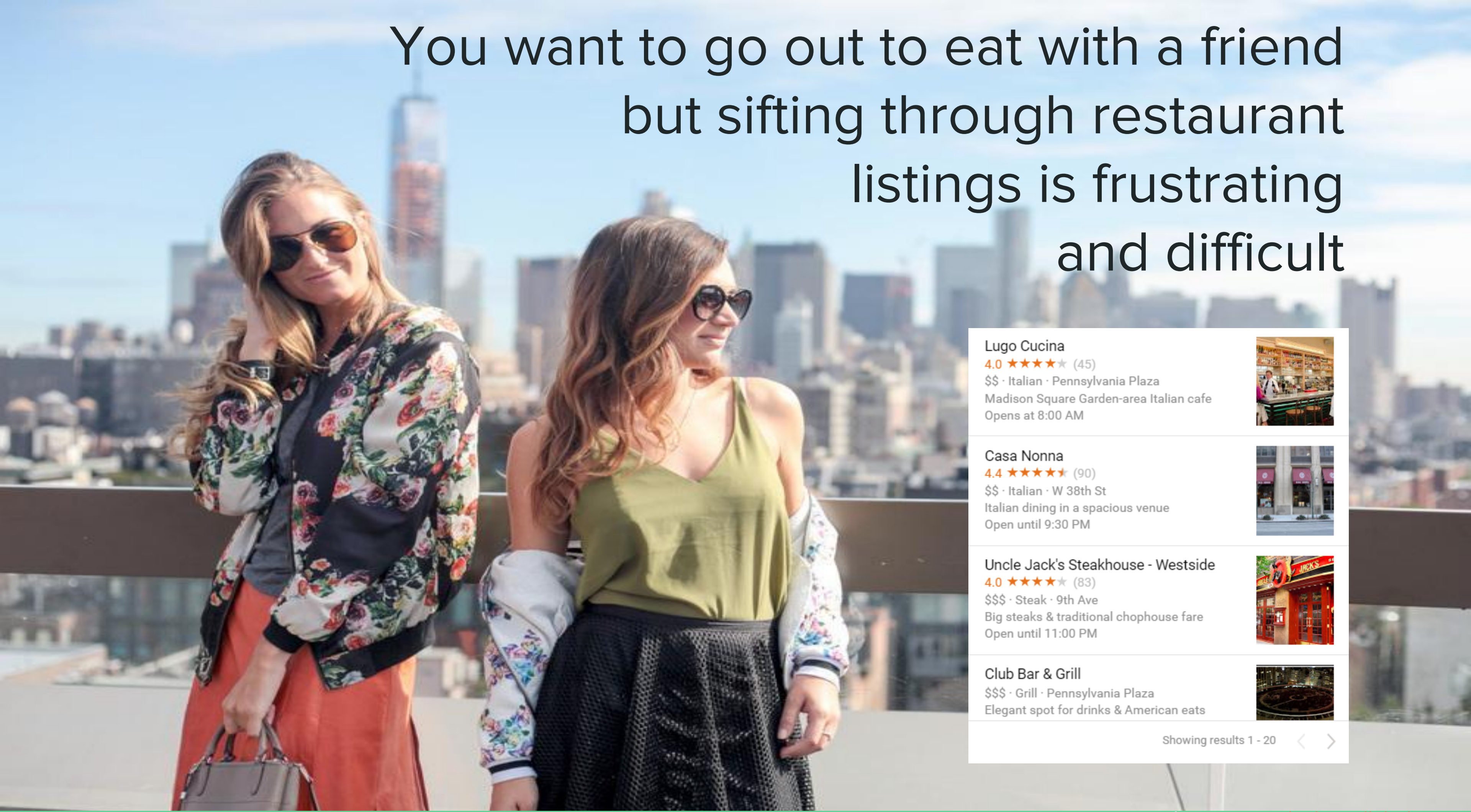
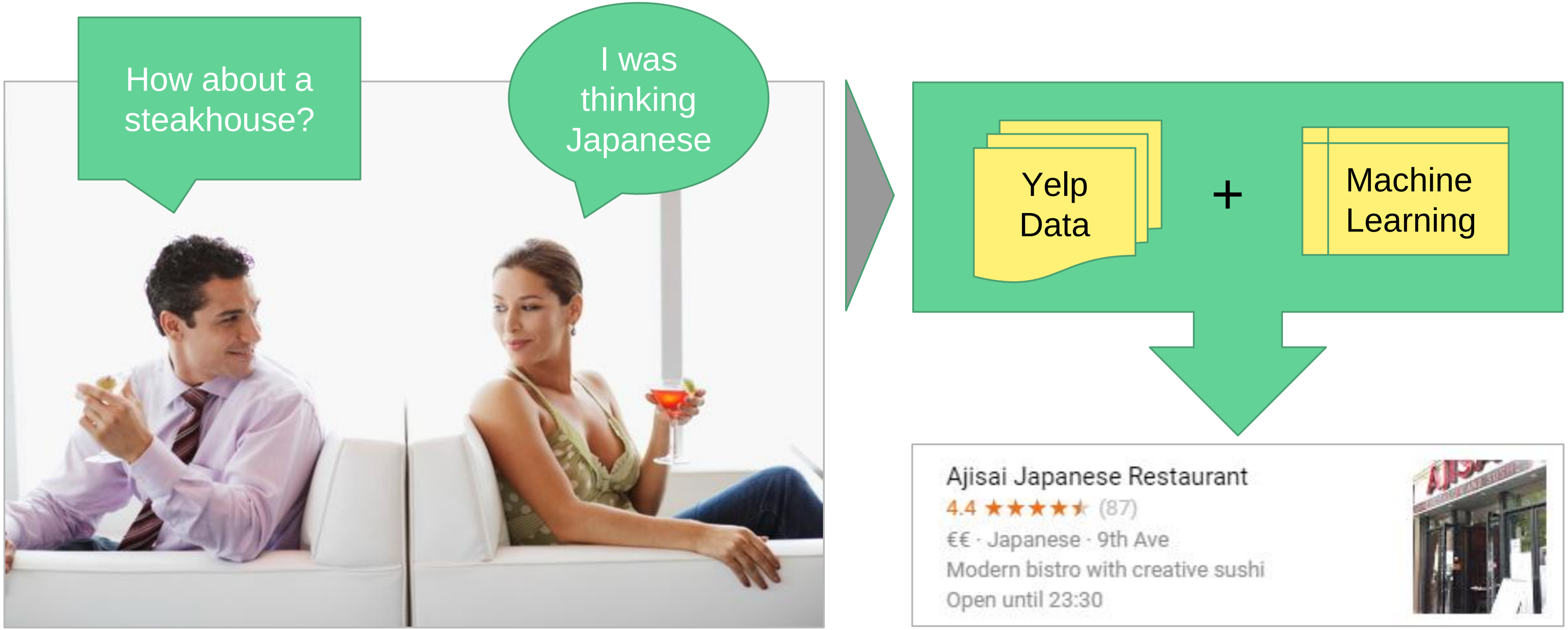
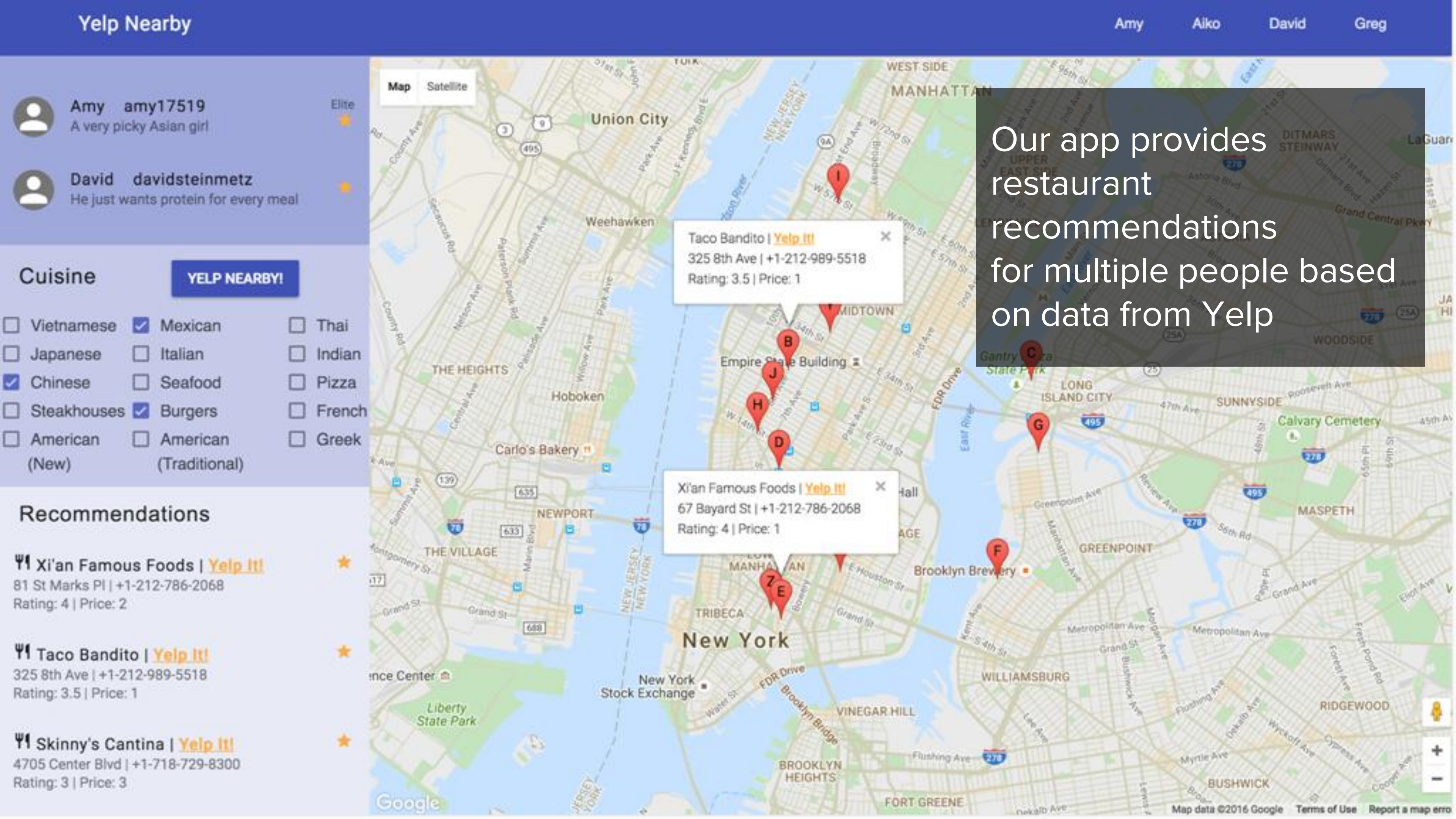


Image: www.locksandlabels.com

Could Yelp data be used in conjunction with machine learning to find a restaurant which will suit the tastes of two people?





Our app provides restaurant recommendations for multiple people based on data from Yelp

Agenda

Overview and Context

Explanation of the App

Next Steps

Our App marries a Flask front end with a Python back end to provide recommendations

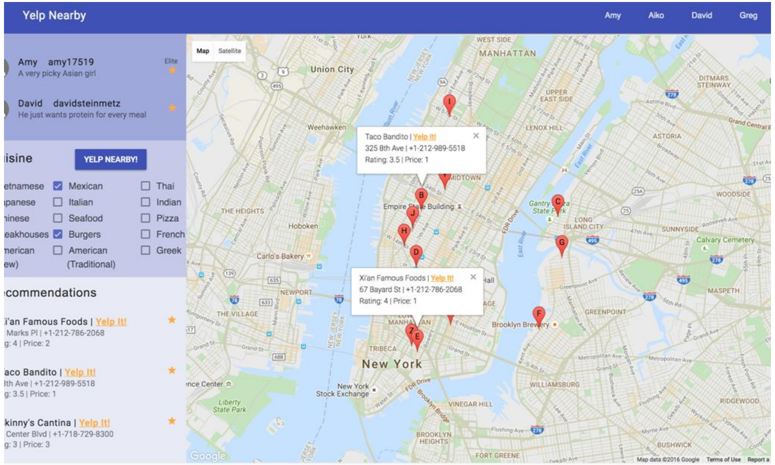
Front end

Flask
Python
Microframework

Jinja2
Templating
+
HTML / JavaScript
Programming
Languages

Yelp Nearby

A multiuser restaurant recommendation engine



Back end

Python
Classes,
Functions,
Modules

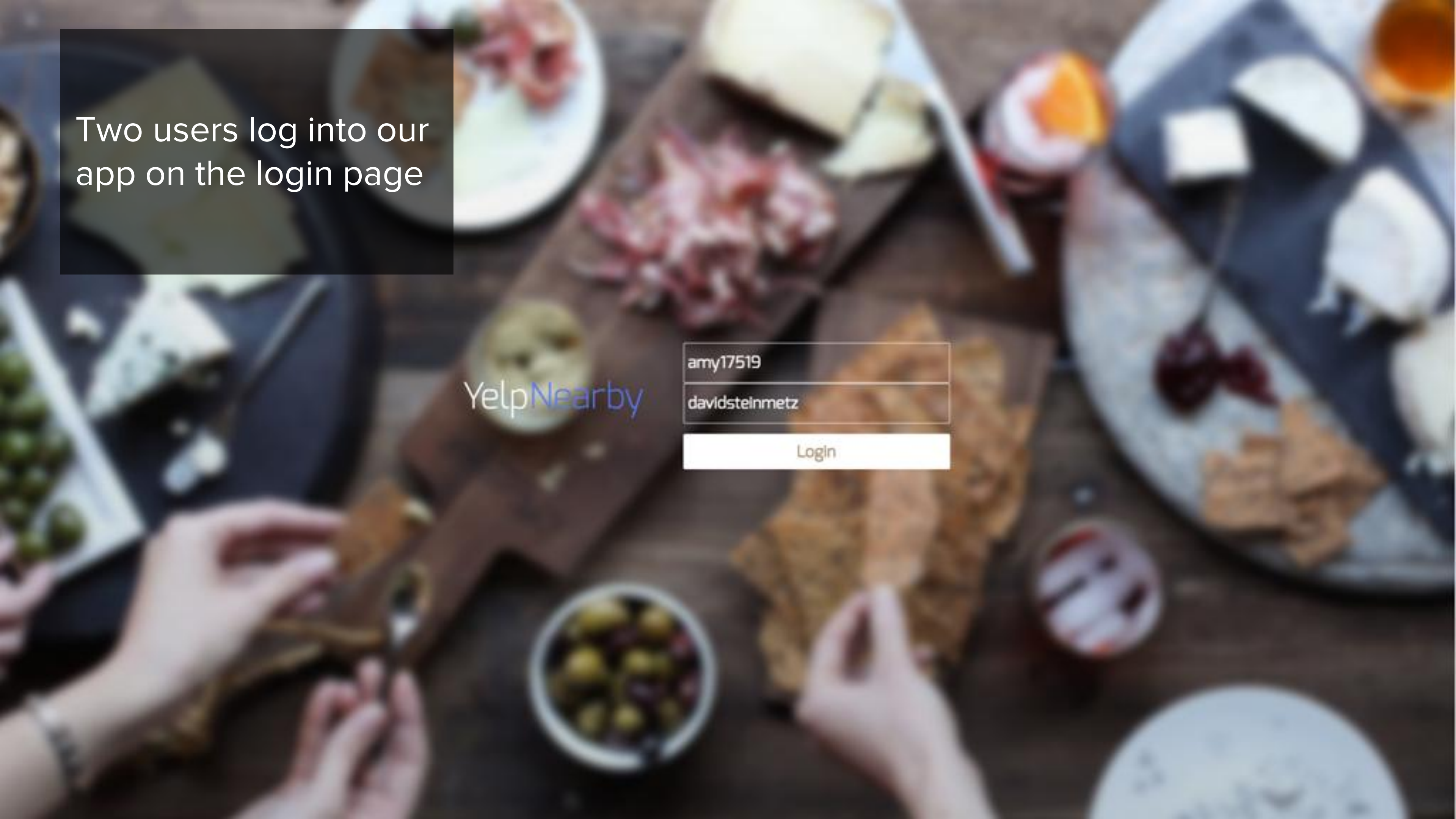
Ext

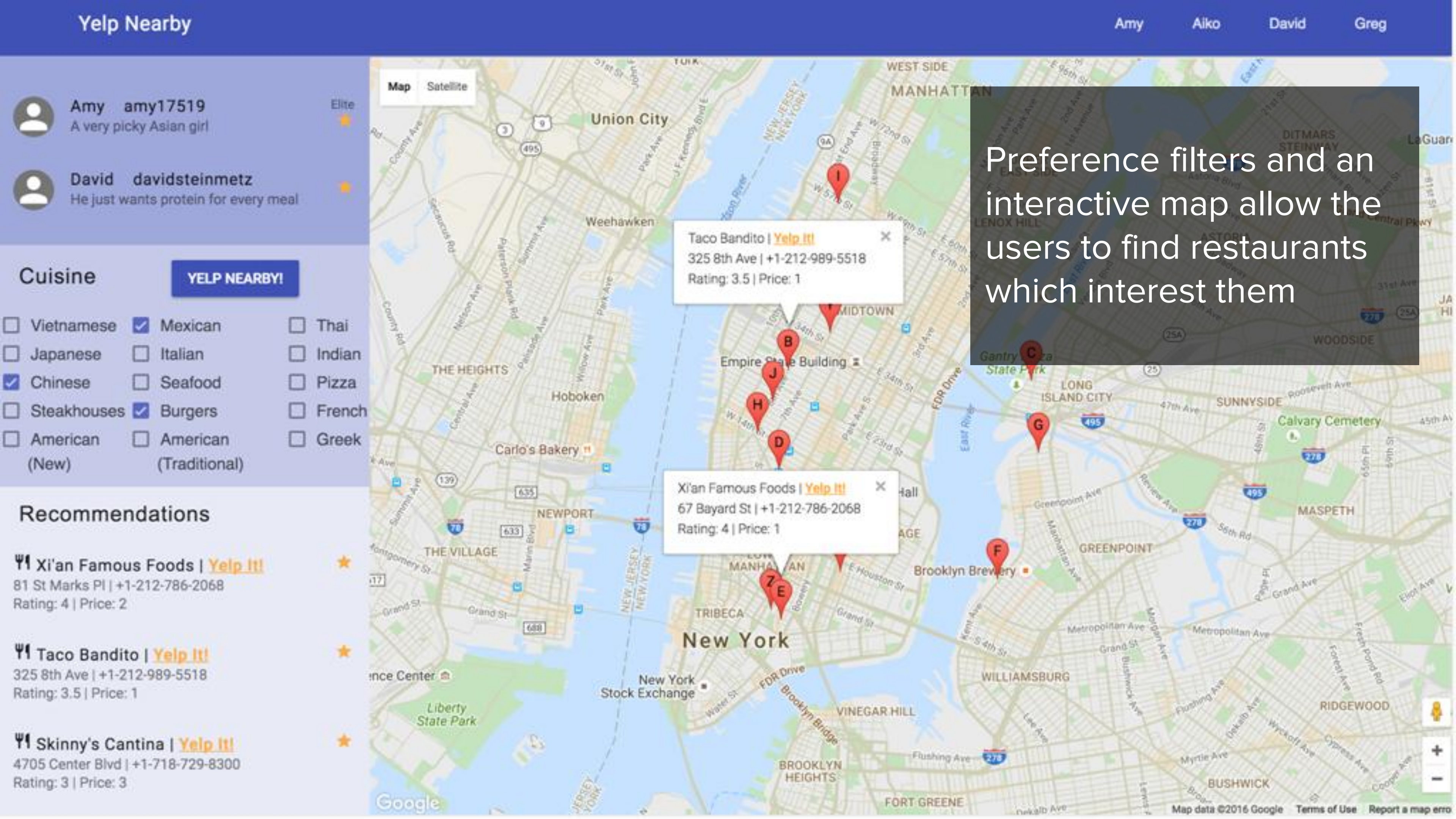
Yelp
API
+

Internal

GraphLab
Machine Learning
+
Homemade
Class/Func/Mod

Two users log into our app on the login page




Yelp Nearby
Amy
Aiko
David
Greg
Amy amy17519
A very picky Asian girl
Elite
David davidsteinmetz
He just wants protein for every meal
Cuisine
YELP NEARBY!
Vietnamese
Mexican
Thai
Japanese
Italian
Indian
Chinese
Seafood
Pizza
Steakhouses
Burgers
French
American (New)
American (Traditional)
Greek
Recommendations
Xi'an Famous Foods | Yelp It!
81 St Marks Pl | +1-212-786-2068
Rating: 4 | Price: 2
Taco Bandito | Yelp It!
325 8th Ave | +1-212-989-5518
Rating: 3.5 | Price: 1
Skinny's Cantina | Yelp It!
4705 Center Blvd | +1-718-729-8300
Rating: 3 | Price: 3
Map
Satellite
Taco Bandito | Yelp It!
325 8th Ave | +1-212-989-5518
Rating: 3.5 | Price: 1
Xi'an Famous Foods | Yelp It!
67 Bayard St | +1-212-786-2068
Rating: 4 | Price: 1
Preference filters and an interactive map allow the users to find restaurants which interest them
Union City
Weehawken
Hoboken
New York
Map data ©2016 Google
Terms of Use

The recommendation system works in a pipeline of three processes

1 Train → **2 Cluster** → **3 Classify**

1 Train

- Data about users, business, reviews from online Yelp Challenge
- Collaborative Filtering recommends restaurants for specific users

2 Cluster

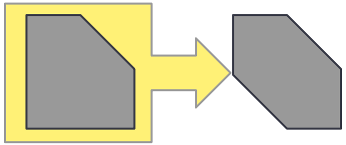
- Clusters needed to extend model to new locales
- Density-based scanning used to create clusters
- Restaurants are clustered based on

3 Classify

- Locally available restaurants are classified into the clusters of the predicted recommendations

A collaborative filtering model was chosen because it incorporates information from users who make similar reviews

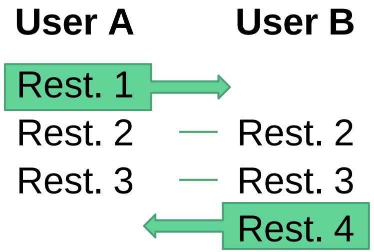
Content-based systems



Predicts similar items

Advantages	Disadvantages
1. Uses the items' content to predict the user's interest 2. Recommendation quality improves as the review/item content data cumulates	1. Impossible to predict the totally distinct types of items the particular user has never expressed interest in 2. 2. Limited by the collected items' info in making recommendation (New Item?)

Collaborative filtering

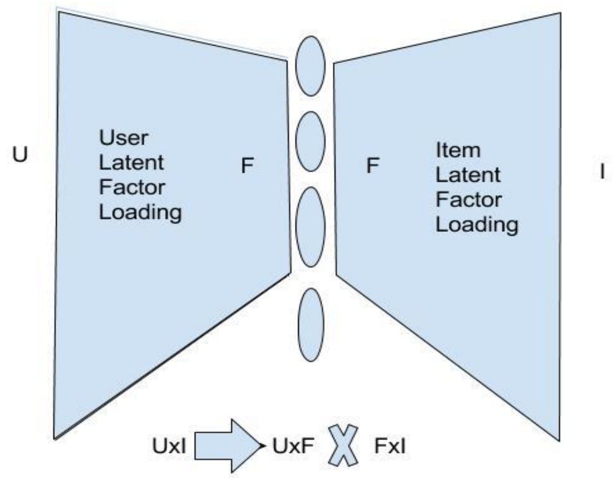


Predicts items from user preferences and from similar users

Advantages	Disadvantages
1. Predict items through similar user patterns, even if the particular user has a short review history 2. Works without item attributes 3. 'Outside the Box' recommendation	1. Cold Start for the new users 2. Sparse Ratings on the same item 3. Recommendations are difficult for users with distinct tastes; these users are called black sheep or gray sheep.

Latent Matrix Factorization is the key component of collaborative filtering

	Rest. 1	Rest. 2	Rest. 3	Rest. 4
User 1	5		2	
User 2		3	4	1
User 3	1			4



Dimension Reduction

User Latent Factor Loading expresses each user as an F component vector

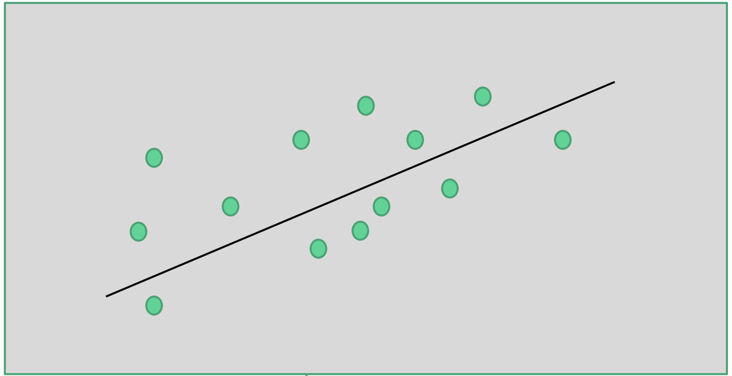
Item Latent Factor Loading expresses each item as an F component vector

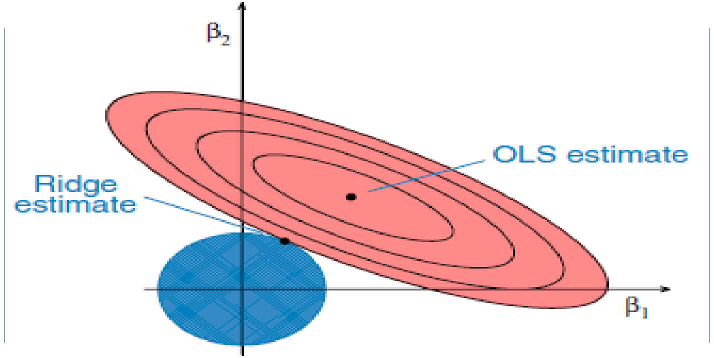
Users and Items interact through F distinct channels

Numbers in the table are the rating the user gave the restaurant on a scale of 1-5

The matrix to the left is factorized

Latent Matrix Factorization adds to two well-known machine learning techniques: linear regression & L2 regularization





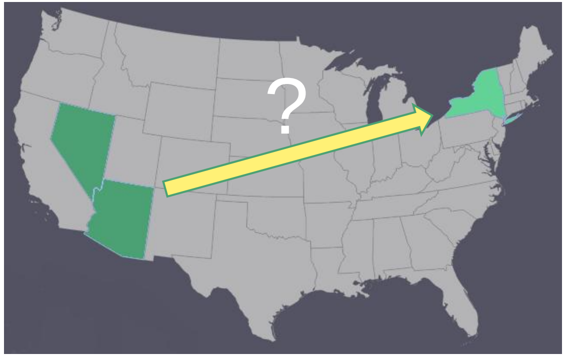
Linear regression | Latent Matrix Factorization | Ridge regression

1. Matrix Factorization, the core of CF, can work without side inputs from the users, items, capturing the user-item interaction through factorizing the sparse user-item matrix
2. The linear regression upon the side information reduces the model estimation residuals
3. The L2 regularization, known as Ridge regression in the context of MLR, controls the stability of the model fit and prevents over-fit
4. Three parts are combined into the single equation system (graphlab)

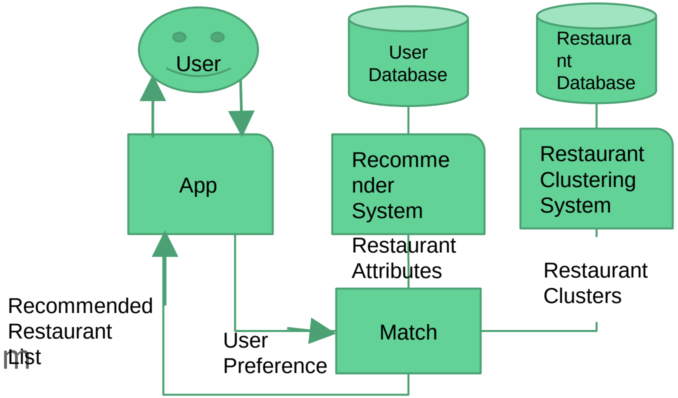
Additional features can be included as side information in Latent Factorization to train the model

Feature Name	Feature Equation	Why it's included
User_EliteYears	1 * years_elite	Elite users have outsized influence on ratings
User_AvgRating	mean(rating)	Different users have different rating standards
User_Num_Review	log(u_num_reviews+1)	The indicator of the user's engagement on yelp
User_Location	city/state of the reviews	The reviews from the same location may be similar
Rest_AvgRating	mean(user rating)	The reviews' consensus on the restaurant quality
Rest_Num_Review	log(r_num_reviews+1)	The attention the business get from the reviewers
Rest_Aggr_EliteYear	Sum of the	The attention the business receives from the leaders among the reviewers
Rest_Location	city/state of the Rest.	The location of the restaurants are highly correlated with the residence of the reviewers

Making restaurant recommendations outside the limited region in the dataset posed a problem



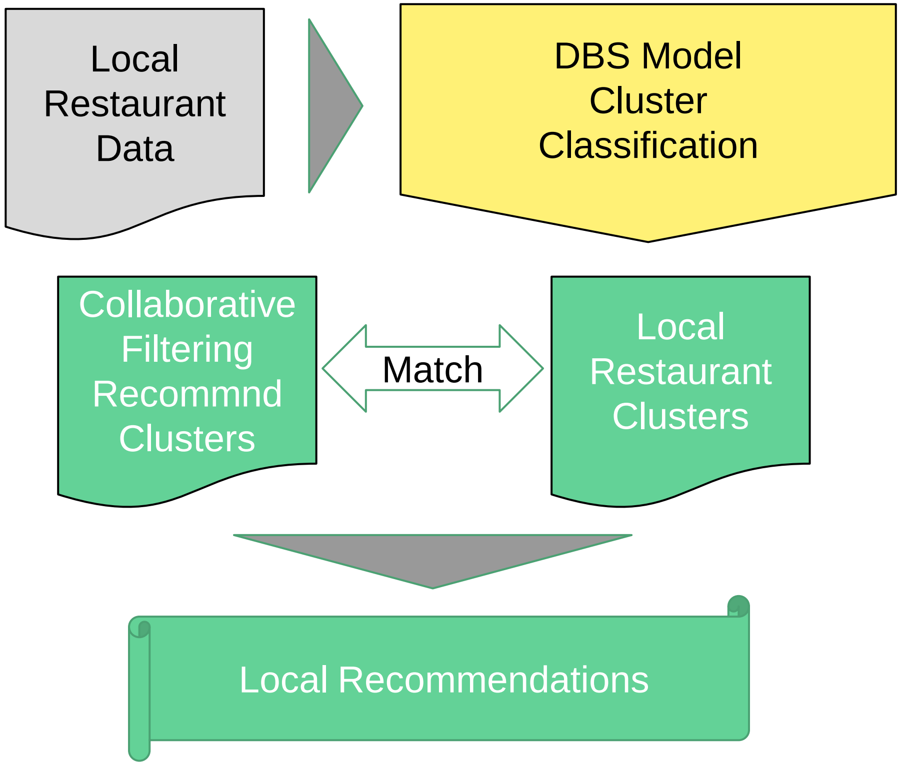
- Recommender system only maps to restaurants in the original dataset
  - Original dataset does not include major cities like New York and San Francisco
- So how do we recommend restaurants outside the areas in the dataset or in areas with very few reviews
- Solution: Cluster Analysis
- Solution Concept:
  - Get attributes of restaurants selected from recommender system



Density-based scanning was chosen to cluster all restaurants in the data set

Algorithm	Advantages	Disadvantages
K-Means	• K-means works well when the shape of clusters are hyper-spherical • Computationally efficient	• May give different results every time it is run • Requires prior knowledge of number of clusters
Hierarchical Clustering	• Gives recommended clusters • Repeatable results	• Time complexity is quadratic
Density-based scanning	• **Can handle clusters of different shapes and sizes** • **Gives recommended clusters** • **Computationally more efficient that hierarchical cluster method**	• **May have problem handling high dimensional data** • **May have problem dealing with data that has widely varying densities**

Classifying locally available restaurants based on the DBS model solved the problem of a limited data set



Feature used	Description
Ratings	Average Rating Of Restaurant Based on User Reviews
Price Range	Price Range For Restaurant
Review Counts	Number Of Reviews Of A Restaurant (transformed using log function)

Agenda

Overview and Context

Explanation of the App

Next Steps

The functionality of the app can be extended

- Extract information from the restaurant reviews using an NLP technique called
  - Latent Dirichlet Allocation
    - This data can be included in the clustering model to improve distinction between clusters
- Use app users' reviews to improve recommendations
- Include new users not existing in the data set
- Extend to larger groups of users

Thank you
for your attention

GraphLab Recommender Model

$$\text{score}(i,j) = \mu + w_i + w_j + \mathbf{a}^T\mathbf{x}_i + \mathbf{b}^T\mathbf{y}_j + \mathbf{U}_i^T\mathbf{V}_j,$$

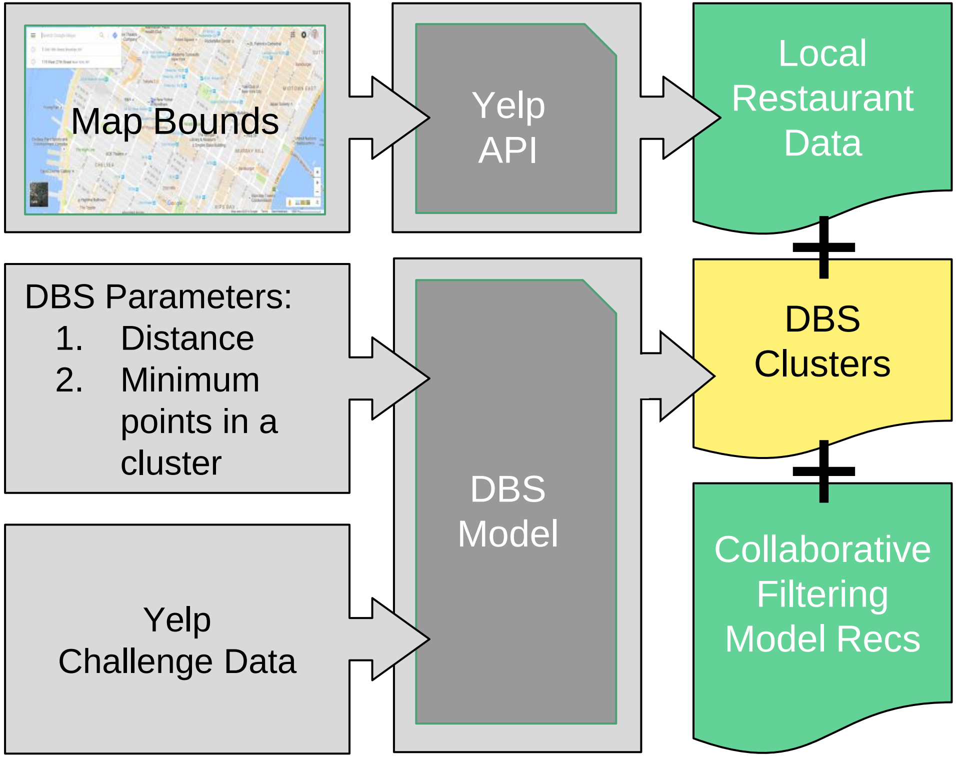
$$Objective = \min_{\mathbf{w},\mathbf{a},\mathbf{b},\mathbf{V},\mathbf{U}} \frac{1}{|\mathcal{D}|} \sum_{(i,j,r_{ij})\in\mathcal{D}} \mathcal{L}(\text{score}(i,j), r_{ij})$$

$$+\lambda_1(\|\mathbf{w}\|_2^2 + \|\mathbf{a}\|_2^2 + \|\mathbf{b}\|_2^2) + \lambda_2\left(\|\mathbf{U}\|_2^2 + \|\mathbf{V}\|_2^2\right)$$

$\mathcal{L}$ = (Squared Error) Loss Function,

r_{ij} = rating of user i to item j.

Classifying locally available restaurants based on the DBS model solved the problem of a limited data set



Feature used	Description
Ratings	Average Rating Of Restaurant Based on User Reviews
Price Range	Price Range For Restaurant
Review Counts	Number Of Reviews Of A Restaurant (transformed using log function)