Collaborative Filtering Restaurant Recommender Engine using Matrix Factorization and Skyline Queries

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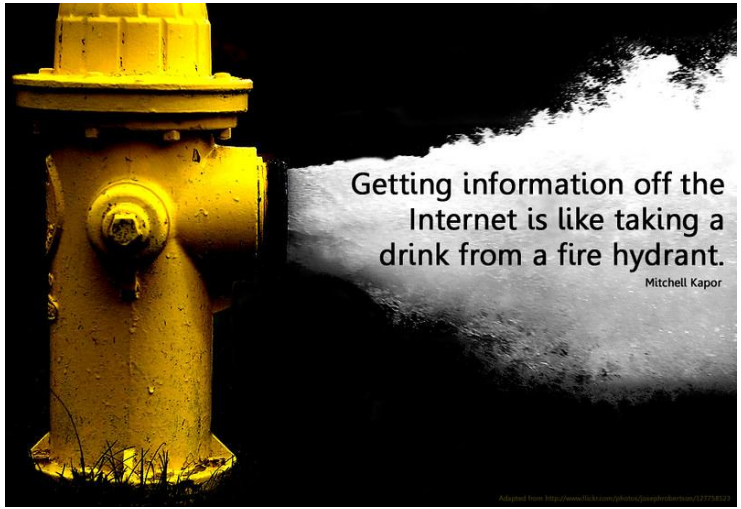
PURPOSE

Information overload:
- Decision dilemmas
- Confusion

Consumer preferences are not definitive:
- Adjust likings to justify tradeoffs



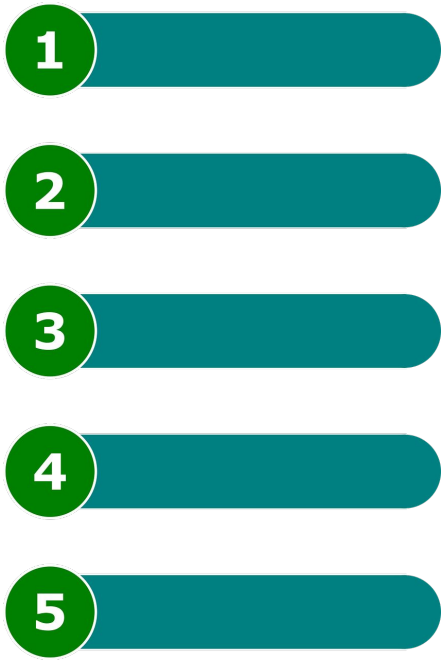
Recommendation engines

Consumers:

- Search through all items
- Assign ranks to each recommendation based on relevance

Businesses:

- Increase visibility
- Bridge the gap between consumers and providers



DATA

Users:
- Count: 138
- Location
- Smoker
- Drink level
- Dress preference
- Enjoy company
- Budget (0/0.5/1)

userID

Ratings:
- Count: 1160
- Range: 0 - 2

restaurantID

Restaurants
- Count: 130
- Location
- Smoking area
- Serve alcohol
- Dress code
- atmosphere
- Price (0/0.5/1)
- name

METHODOLOGY

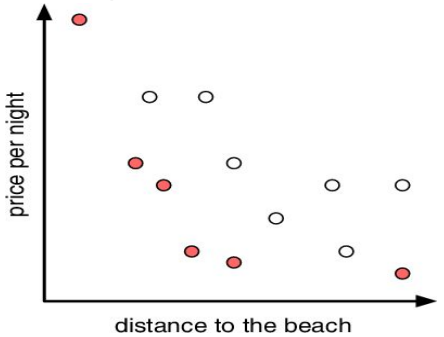
Collaborative Filtering → Non-Negative Matrix Factorization → Skyline Queries

- Filter data
- Calculate average ratings based on similarity

- Factorize ratings matrix

- Rank recommendations

Example: Cheap hotels that are close to the beach



Collaborative Filtering

Returning user

restaurant_ID	Rating
00001	2
00002	1
...	...

K-means Clustering (restaurants)

Groups of Similar Restaurants

Matrix R

restaurants

user

userID	Smoker	Drink level	Dress preference	Ambience	Budget	Cuisine
U1003	0	1	1	1	0	Latin

New user

K-Nearest Neighbors (Users)

Similar Users

Collaborative Filtering

Returning user

restaurant_ID	Rating
00001	2
00002	1
...	...

K-means Clustering (restaurants)

Groups of Similar Restaurants

Matrix R

restaurants

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New user

K-Nearest Neighbors (Users)

Similar Users

$$R = W \times H$$

Sparse Matrix R

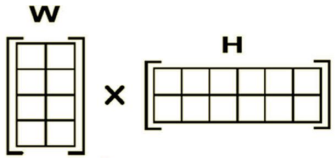
Non-Negative Matrix Factorization

H

W

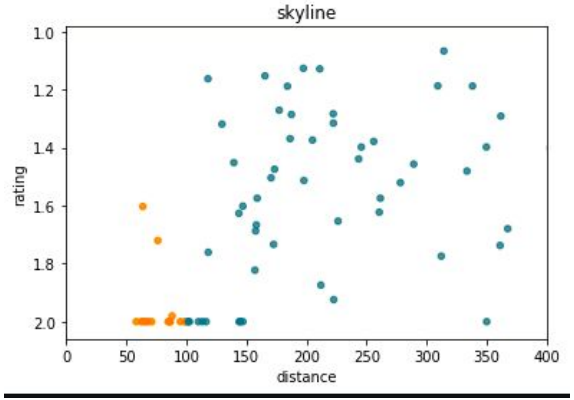
Dense Matrix WxH

Add 1 to real-valued ratings
Parameters:
K = 48
Max_iter = 300
Exclude 0 from cost function



Skyline Queries

MAX(ratings)
MIN(distance)



Link to my app:
https://restaurantrecommender.herokuapp.com

RESULTS

Returning user

userID	placeID	rating
U1003	135041	0
U1003	132755	2
U1003	132723	2
U1003	132825	2
U1003	135075	2
U1003	135079	2
U1003	132862	1
U1003	132937	2

MSE = 0.80

placeID	Actual	Predicted
135064	0	2.0
132922	2	2.0
135080	2	2.0
132754	2	2.0
135059	2	2.0

New user

Attribute	Value
userID	U1012
Location	18.81, -99.24
Smoker	0
Drink level	0.5
Dress preference	1
Enjoys Company	1
Budget	0.5
Cuisine	Latin American

MSE = 0.25

placeID	Actual	Predicted
135001	1	2.0
134996	2	2.0
134986	2	2.0
135018	2	2.0

Metric	Returning users	New users
MAR@K	0.2288	0.2183
Precision	0.0177	0.0278
Personalization	0.5709	0.6684
MSE	0.5956	0.9422

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