



# Yelp Recommender System

... Recommendations Tailored to Your Taste



# Not All 5-stars Are Created Equal

Recommender system is used in many e-commerce as well as service subscription platforms to help users discover new products by recommending either similar products/ things similar users have used/liked. To users, these systems help you discover To businesses, it helps drive engagement as well as cross/up-sale. Cross/Up-Sell (e.g. Amazon) | Explore (e.g. Spotify, Netflix)



Will I like this place with such glowing reviews?



Can I find new, reliable recommendations?



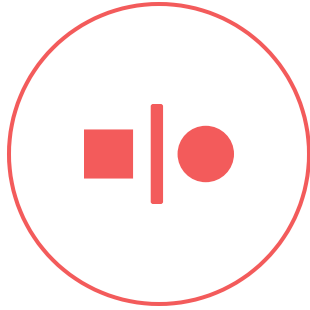
How can Yelp attract more users and businesses?

# What is a recommender system



## Collaborative Filtering

- Recommend based on past behaviours
- Assume similar users like similar things
- Item-item based
- User-user based
- **Matrix factorization**



## Content-based Filtering

- Recommend based on past behaviours
- Assume users like similar items



## Hybrid

Combine previous approaches

# Matrix Factorization

	Popeyes	McDonald's	The Senator
Alice	?	4	3
Bob	2	?	4
Tim	5	4	3

	Fast Food	Chicken	Ambience
	Hidden Feature 1	Hidden Feature 2	Hidden Feature 3
Alice	0.3	0.4	0.3
Bob	0.1	0.2	0.5
Tim	0.8	0.6	0.4

- Hidden features are hidden! Meant to help imagine backend process
- A matrix can be factorized into two matrices.

$$A (\text{rows } i \times \text{cols } j) = M (\text{rows } i \times \text{cols } k) \cdot N (\text{rows } k \times \text{cols } j)$$

		Popeyes	McDonald's	The Senator
Fast Food	Hidden Feature 1	0.5	1.5	0
Chicken	Hidden Feature 2	1.8	0.4	0.4
Ambience	Hidden Feature 4	0.1	0.1	1.3

# Matrix Factorization & Machine Learning

	Popeyes	McDonald's	The Senator
Alice	?	4	3
Bob	2	?	4
Tim	5	4	3

	Fast Food	Chicken	Ambience
	Hidden Feature 1	Hidden Feature 2	Hidden Feature 3
Alice	0.3	0.4	0.3
Bob	0.1	0.2	0.5
Tim	0.8	0.6	0.4

Iterative process to update  
users and restaurants to  
minimize Error

Alice – McDonald's Rating

$$0.64 = 0.3 * 1.5 + 0.4 * 0.4 + 0.3 * 0.1$$

Predict ? using final matrices

Error

$$3.36 = 4 - 0.64$$

Fast Food  
Chicken  
Ambience

	Popeyes	McDonald's	The Senator
Hidden Feature 1	0.5	1.5	0
Hidden Feature 2	1.8	0.4	0.4
Hidden Feature 4	0.1	0.1	1.3

# Where It All Started

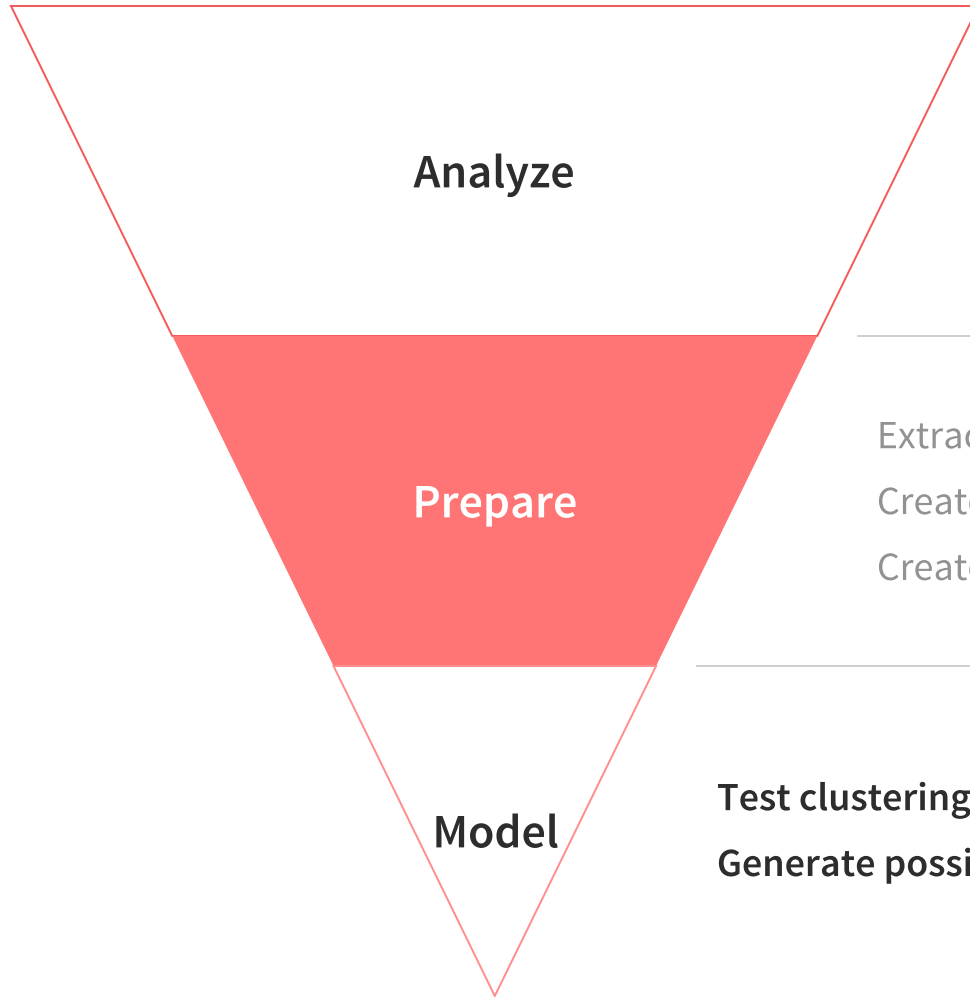
Data Source, Format, Structure

```
display(restaurants_df.sample(5))
```

	address	attributes	business_id	categories	city	hours	is_open	latitude	longitude	name
144107	2935 Providence Rd, Ste 104, Bldg C	{'BikeParking': 'True', 'BusinessAcceptsCredit...'	B0grK-DvppYg0iwFovghlg	Food, Desserts, Caterers, Specialty Food, Even...	Charlotte	{'Tuesday': '10:30-19:30', 'Wednesday': '10:30-...	1	35.170623	-80.806590	The Secret Chocolatier
107014		{'BusinessAcceptsBitcoin': 'False', 'BusinessA...	bvK-UlCtgdFsedvqLrKhg	Local Services, Pest Control	Las Vegas	{'Monday': '7:0-20:0', 'Tuesday': '7:0-20:0', ...	1	36.045719	-115.313391	Chase- inator Pest Control
92618	5980 Churchill Meadows Boulevard, Unit 2	{'ByAppointmentOnly': 'True', 'RestaurantsPric...	uo0zQ6BAmkjY0eIYlxnJzW	Beauty & Spas, Nail Salons, Day Spas	Mississauga	{'Monday': '10:0-20:0', 'Tuesday': '10:0-20:0' ...	1	43.558018	-79.756126	Cleopatra Nail & Spa
70241	The Mirage, 3400 S Las Vegas Blvd	{'Alcohol': 'full_bar', 'Ambience': {'romanti...	NIGDKsTOLKyHJ0mgS_gWJQ	Southern, Arts & Entertainment, Restaurants, J...	Las Vegas	{'Monday': '6:30-23:0', 'Tuesday': '6:30-23:0' ...	0	36.121618	-115.174227	BB King's Blues Club
94328	1841A Rue Sainte- Catherine O	{'BikeParking': 'False', 'BusinessAcceptsCredi...	MNqVHEe4dWIVXgm8GYKc0w	Beauty & Spas, Shopping, Cosmetics & Beauty Su...	Montreal	{'Monday': '11:0-20:0', 'Tuesday': '11:0-20:0' ...	1	45.493369	-73.580156	C&C Korean Cosmetics

- Yelp-published data on Kaggle.com
- 1.5 million users | 6 million reviews | 155k businesses
- Files in JSON (think dictionary with word-definition pairs)

# What I Need to Do



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## What constitute similar taste?

- Previous Ratings of the Same Restaurants
  - Preferences (\$ range, Cuisines, locations of visits)
  - Language In Text Reviews
- 

Extract **users'** preferences for price range, cuisines

Create a big table of **users'** reviews for all Yelp businesses

Create groups of **similar users** based on custom profiles

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Test clustering -> **matrix factorization** vs **matrix factorization only**

Generate **possible ratings** of unrated businesses for each users

# Lessons Learnt



## Experiments do not always work

Create a cluster and feed specific cluster into matrix factorization. The model performed worse!

Wrong direction with natural language processing



## Analysis Paralysis

Strike a balance between creating a first iteration vs exploring every corner of a complex problem



## Real-world Mindset

Discover my new area of interest - Recommender System!

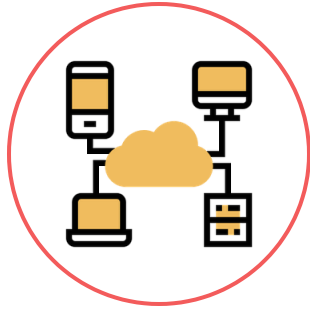
A nice blend of data science and engineering to solve real world challenges



# Future Direction



Explore Hybrid Approach



Database to Speed Up



Neo4J - Social Graph



Question?

