## Contentbased Recommender System Utilizing User Data

(Applied Data Science Capstone)

Jay Mitchell

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### Venue locations value

- Service providers
  - Capitalize on data (e.g., Foursquare, Mint)

- Customers
  - Find amenities similar to those normally used

- Venues
  - New patrons may increase sales

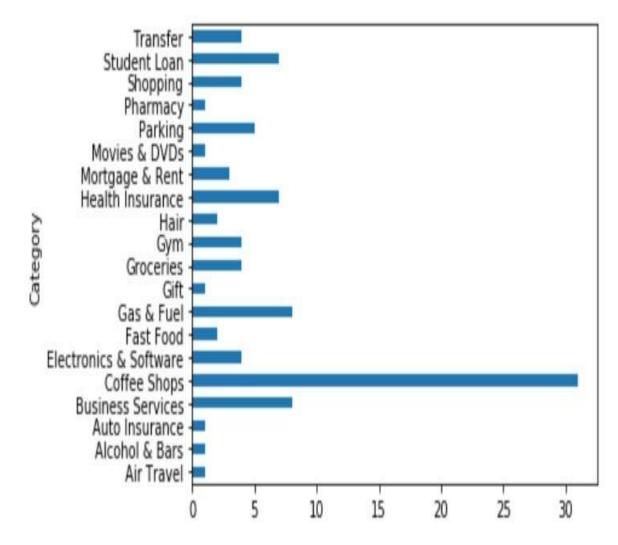
# Data acquisition and cleaning

#### Mint

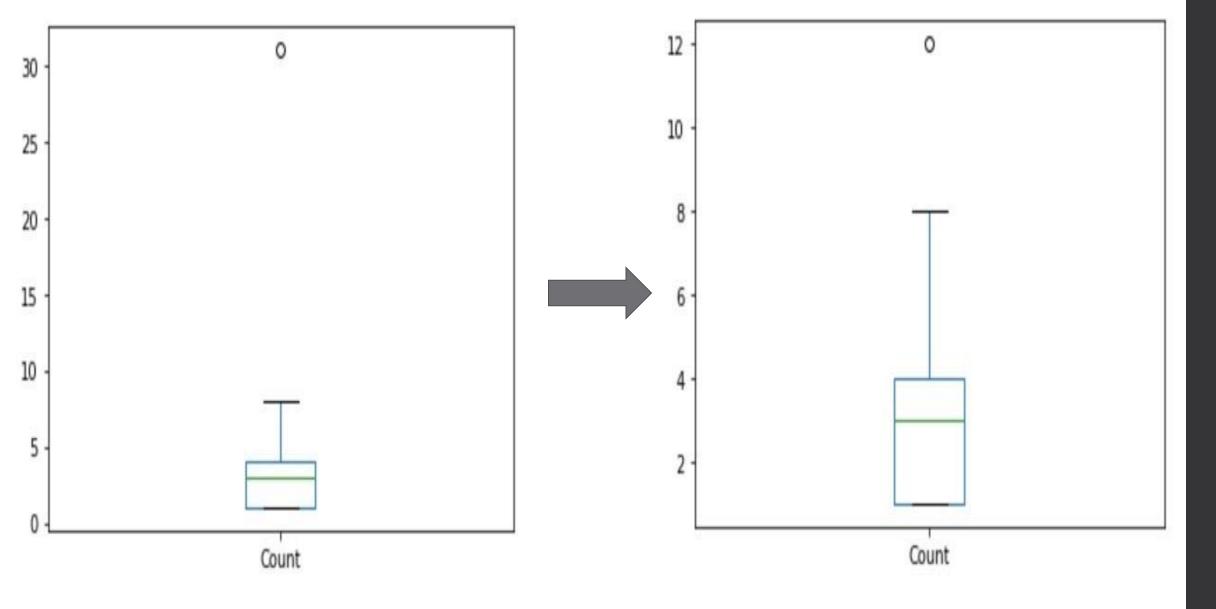
- Text file downloaded from website
- Select columns and rows of interest to generate categories
- Compare categories by statistical means (generate NormScore)

#### Foursquare

- Use Mint categories as search terms
- Locate nearby venues using location
- Find ratings for each venue



## **Outliers**



## **Initial Results - Mint**

- Simple feature scaling
  - Positive values
  - 0 to 1
  - Multiplied by 10 to equal venue rating weight (0 to 10 scale)
  - NormScore

	Category	Count	NormScore
0	Alcohol & Bars	1	0.833333
1	Coffee Shops	12	10.000000
2	Electronics & Software	4	3.333333
3	Fast Food	2	1.666667
4	Gas & Fuel	8	6.666667
5	Gift	1	0.833333
6	Groceries	4	3.333333
7	Gym	4	3.333333
8	Hair	2	1.666667
9	Movies & DVDs	1	0.833333
10	Pharmacy	1	0.833333
11	Shopping	4	3.333333

# Initial Results - Foursqure

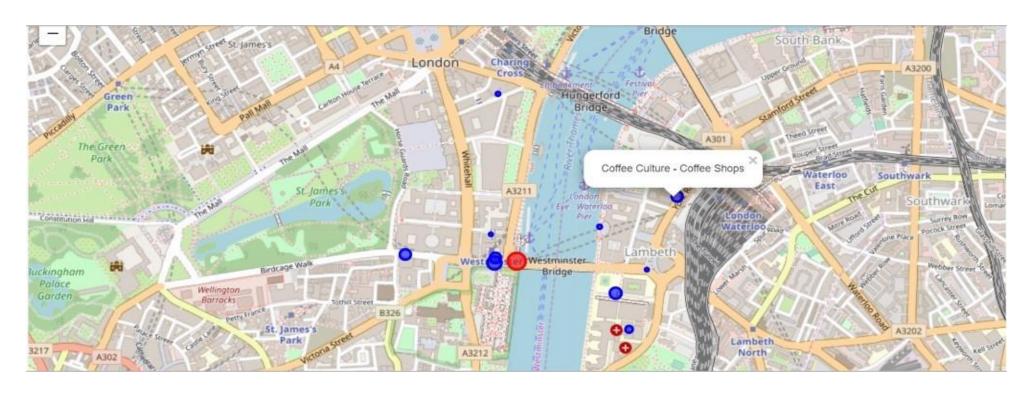
	categories	hasPerk	id	location.address	location.cc	location.city	location.country	location.crossStreet	location.distance
0	[rid: 4bf58dd88d48988d123941735", 'name': 'W	0.0	5d45ce66eee54e0008ec02dc	Unit 35, Old School PI	GB	Croydon	United Kingdom	NeN	484.0
1	[fid: 4bf58dd8d48988d1f9941735] neme: 1/	0.0	5d24d9d8dbdw1100259d8731	13 Expect Street	Ú8	Landan	United Kingdom	NeN	652.0
2	NaN	NeN	NeN	NaN	NeN	NaN	NeN	NaN	NeN
1	NaN	NeN	NeN	NaN	NaN	NeN	NeN	NaN	NeN
4	NeN	NeN	NeN	NaN	NeN	NaN	NeN	NeN	NeN
5	[[id: 4bf58dd8bd48988d1e0931735] name: $\zeta_{\rm c}$	0.0	Sauffic8/918/13b5d1dfa56	Westminster Tube Station	G8	Landon	United Kingdom	NaN	740
6	[rid]: 4bf58dd8d48988d1e0931735; 'neme'; 'C	0.0	4cac1b4d3bfebdcb80ebdb78	Portculin House	GB	Landan	United Kingdom	NaN	71.0
7	[[id]: 46f58dd83d48988d1e0931735], hame: $\mathbb{C}_{\sim}$	0.0	4b6fc85bf964a52069fc2ce3	St. Thomas Hospital	G8	Landon	United Kingdom	Lamberth Palace Road	348.0
8	[rid: 46f58dd8d48988d143941735; 'neme': 'B.,	0.0	4b546e28f964e520ffbe27e5	49 York Rd.	G8	Waterloo	United Kingdom	NeN	584.0
2	$\label{eq:control_control_control} \ensuremath{\text{[fig]: 4bf58dd8d48988d1e0931735]: name: $C$.}$	0.0	4650120e4b0a5e32711b658	One Great George St	GB	Landan	United Kingdom	NaN	373.0
10	NeN	NaN.	NeN	NaNi	NeN	NeN	NeN	NeN	NeN
11	NeN	NeN	NeN	NaN	NeN	NaN	NeN	NaN	NeN
12	NeN	NaN	NeN	NaN	NeN	NeN	NeN	NeN	NeN
13	NeN	NaN	NaN	NeN	NiN	NeN	NeN	NaN	NeN
14	NeN	NaN	NeN	NeN	NeN	NeN	NaN	NeN	NeN
15	[fid: 45/58dd8d48988d118951735'; hame: 'C	0.0	4debf42d45dd3093a8b36453	244-246 Westminster Bridge Rd	G8	Landan	United Kingdom	NaN	465.0

## Final Results - Combined

- Venue rating and NormScore generated Weightscore
- Top 10 venues
- Venue Name, Latitude, and Longitude for map

	name	categories	address	tt	city	country	crossStreet	distance	formattedAddress	labeledLatings	lat	Ing	neighborhood	postalCode	state	id	WeightScore	Category
2	Costa Coffee	[('id': '4bf58dd8d48988d1e0931735', 'name': 'C	Westminster Tube Station	GB.	London	United Kingdom	NaN	74.0	[Westminster Tube Station, London, Greater Lon	[(1abel1 'display', 1at': 51.50093364186963	51.500934	0.124805	NaN	ATW 2	Greater London	NaN	79.000000	Coffee Shops
4	AMT Coffee	[[id: 4bf58bd8d48988d1e0931735], 'name'; 'C.,	St. Thomas Hospital	GB	London	United Kingdom	Lambeth Palace Road	348.0	(St. Thomas Hospital (Lambeth Palace Road), Lo.,	[[Tabel]: 'display', 'lat'\ 51,49997320903263	51,499973	-0.118974	NaN	SE1 7EH	Greater London	NaN	66,000000	Coffee Shops
3	Despatch Box Coffee Shop	[/id: 4bf58dd8d48988d1e0931735] 'name': 'C.,	Portculis House	G8	London	United Kingdom	NaN	71.0	(Portcullis House, London, Greater London, SW1	[[label: 'display', 'lat': 51.50111406437572	51.501114	-0.124743	NaN	SW1 A 2	Greater London	NaN	62,408193	Coffee Shops
6	Costa Coffee	[['id': 4bf58dd8d48988d1e0931735', 'name': 'C	One Great George St	GØ.	London	United Kingdom	NaN	373.0	(One Great George St, London, Greater London,	[[label] 'display', lat'] 51.50121966342386	51.501220	-0.129109	NaN	NeN	Greater London	NaN	62,408193	Coffee Shops
5	Coffee Culture	[[id: 4bf58dd8d48988d143941735], hame: 8	49 York Rd.	GB	Waterloo	United Kingdom	NaN	584.0	[49 York Rd., Waterloo, Greater Landon, SE1 7N	[[label] 'display', lat) 51.50304865891913	51.503049	-0.115980	NaN	SE1 7NJ	Greater London	NaN	62.000000	Coffee Shops
12	Gassiot House	[['id': 4bf58dd8d48988d196941735', 'name': 'H	Lambeth Palace Road	GB	London	United Kingdom	NaN	444.0	(Lambeth Palace Road, London, Greater London,	[{label': 'display, 'lat': 51.498833, 'lng'	51.498833	-0.118327	Lambeth	SE1 7EW	Greater London	NaN	41.605462	Ges & Fuel
19	The Gym & Club at County Hall	[['id': Mbf58dd8d48988d176941735', 'name': 'G.,	County Hall	GB	London	United Kingdom	Belvedere Road	302.0	(County Hall (Belvedere Road), London, Greater	[[label] 'display', 'lat'; 51.50207893534426	51.502079	-0.119739	NaN	SE1 7PB	Greater London	NaN	25.333333	Gym
17	ESPA Life Gym	[['id': '4bf58dd8d48988d176941735',	10 Whitehall Pl	G8	London	United Kingdom	NaN	597.0	[10 Whitehall Pl. London, Greater London, Unit	[[Tabel': 'display', 'lat': 51.50631843415083	51.506318	-0.124648	NaN	NaN	Greater London	NaN	24.666667	Gym
21	Hotel Gym	[/id: 4b/58dd8d48988d176941735'; hame: 'G.,	NaN	Ġŧ	NaN	United Kingdom	NaN	435.0	[United Kingdom]	[[label: 'display', 'lat': 51.50074, 'lng':	51.500740	-0.117470	NaN	NaN	NaN	NaN	20.802731	Gym
20	Westminster Gym	[[id: 4bf58dd8d4898Bd176941735] name: 'G.,	Derby Gate, 1 Canon Row	G8	City of Westminster	United Kingdom	NaN	130.0	(Derby Gate, 1 Canon Row, City of Westminster,	[[Tabel] 'display', 'lat': 51.50185929300493	51.501859	-0.124989	NaN	SW1A 2/N	Greater London	NaN	20.802731	Gym

## Output



- Folium mapping tool
- Current location (Large red dot)
- Venues (Blue dots with the radius proportional to WeightScore)
- Interactable (venue name and category)

### Discussion

• Effective at generating local venues

#### • Data

- Utilize other data sources based on the particular user
- Update data from time to time to ensure relevancy
- More generalized categories may be used
- k means clustering algorithm to determine similar categories

#### Processing

- Final recommendation skewed
- Counts may not be the best way to determine a user profile
- Reduce the impact of outliers
- Binning <u>Profit</u>

#### Profit

- Popup label hyperlink to incentive
- Include income to data providers and app developer

### Conclusion

- Recommendation engine profiled a user
- Historical data
- Determine nearby venues
- Venues rating
- Interactive Folium map

Code: <a href="https://github.com/jmitchell4390/Coursera\_Capstone/blob/master/Capstone\_Project.ipynb">https://github.com/jmitchell4390/Coursera\_Capstone/blob/master/Capstone\_Project.ipynb</a>

Map: <a href="https://nbviewer.jupyter.org/github/jmitchell4390/Coursera\_Capstone/blob/master/Capstone\_Project.ipynb">https://nbviewer.jupyter.org/github/jmitchell4390/Coursera\_Capstone/blob/master/Capstone\_Project.ipynb</a>

Data: <a href="https://github.com/jmitchell4390/Coursera\_Capstone/blob/master/transactio">https://github.com/jmitchell4390/Coursera\_Capstone/blob/master/transactio</a> ns.txt