The Accidental Tourist Reccomendation System

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Introduction/Business Problem

A lot of business travelers don't like to travel at all. Instead, they would prefer to stay at the comfort of their homes. The Accidental Tourist is one of my favorite movies, where the main character is a writer of travels books that gives a lot of tips on how the business travelers can fly to the most different cities, but still have the feeling they're still at home.

Inspired by the movie, I've built a Jupyter Notebook where the user will input which neighborhood he lives. For the sake of simplicity, the system only allows travellers that live in New York and are flying to Toronto. "Travelling with Accidental Tourist is like going on a cocoon", one reader said.So the system will list thes neighborhoods in Toronto that are very similiar with the one he lives. It will be very nice for the user to leave his hotel and find similar venues, restaurants, parks, and só on.

Data Sources and Research Methods

All neighborhoods from Toronto where fetched from **Wikipedia** and from **Coursera** files. The information on these datasets are: Postal Code, Neighborhood and Borough. Also, their geolocations were fetched (Latitude and Longitude) from a CSV file.

The same information for New York is fetched online from this source:
https://cocl.us/new_york_dataset

Also, the system fetches venues data on **Foursquare,** for those neighborhoods. The most important information is the Venue Category, because it will be the basis for our clustering.

Methodology

The system gets the input from the user, in this case, his Neighborhood in New York, and merges with the Toronto Neighborhoods. The information from the venues on those neighborhoods is fetched in Foursquare. Then the data is organized by the number of venues of each category.

The clustering classification k-means is used to find the similiar neighborhoods and group them into clusters. The cluster that contains the neighborhood that the user chose is presented in two formats:

1. a flat table: so the user may pick the Toronto neighborhood he wants to stay according to the number of venues of each category
2. a map: so the user may resolve a trade-off between the characteristics of the neighborhood and his proximity to some specific place, like an airport, or a specific company.

Results

With the data from the Neighborhoods compiled, we give an option for the user to pick which neighborhood he lives in New York:

Select your NY neighborhood on the list below, so later the system will find similar Neighborhoods in Toronto:

```
[33]: display(dropdown_Neighb)
```

Neighborh... Manhattan Beach

Then, this neighborhood is merged with all Toronto neighborhoods in a single Dataset (all Toronto + 1 New York). Here is a sample of the dataframe:

	Borough	Neighborhood	Latitude	Longitude	city	Postalcode
77	Brooklyn	Manhattan Beach	40.577914	-73.943537	NY	NY
0	North York	Parkwoods	43.753259	-79.329656	TO	M3A
1	North York	Victoria Village	43.725882	-79.315572	TO	M4A
2	Downtown Toronto	Regent Park / Harbourfront	43.654260	-79.360636	TO	M5A
3	North York	Lawrence Manor / Lawrence Heights	43.718518	-79.464763	TO	M6A

The next step is to fech venues data on **Foursquare,** for those neighborhoods. The most important information is the Venue Category, because it will be the basis for our clustering. Here is a sample of the data fetched:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Manhattan Beach	40.577914	-73.943537	Manhattan Beach	40.577370	-73.945531	Beach
1	Manhattan Beach	40.577914	-73.943537	manhattan beach playground	40.577115	-73.946587	Playground
2	Manhattan Beach	40.577914	-73.943537	Carvel Express	40.577962	-73.943551	Ice Cream Shop
3	Manhattan Beach	40.577914	-73.943537	Chillax Manhattan Beach Cafe	40.578836	-73.938229	Café
4	Manhattan Beach	40.577914	-73.943537	MTA Bus - B1/B49 - Oriental Blvd & Hastings St	40.577933	-73.944004	Bus Stop

```
Venue Category
Coffee Shop             175
Café                    100
Restaurant               66
Park                     54
Pizza Place              50
Sandwich Place           44
Italian Restaurant       44
Bakery                   43
Hotel                    40
Japanese Restaurant      39
Clothing Store           33
Gym                      33
Sushi Restaurant         30
Grocery Store            29
Bar                      29
Fast Food Restaurant     26
Pub                      26
Bank                     25
American Restaurant      25
Breakfast Spot           24
Seafood Restaurant       22
Thai Restaurant          21
Pharmacy                 21
Ice Cream Shop           19
Diner                    18
Name: Neighborhood, dtype: int64
```

One important decision that this project made is that **only the top 25 venues** were selected. This avoided the great diversity that would affect on the clustering.

The data is subited to one hot encoding, to convert the categories into columns. Here is a sample:

	American Restaurant	Bakery	Bank	Bar	Breakfast Spot	Café	Clothing Store	Coffee Shop	Diner	Fast Food Restaurant	Grocery Store	Gym	Hotel	Ice Cream Shop	Italian Restaurant	Japanese Restaurant	Park	Pharmacy	Pizza Place	Pub	Restaurant
2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0

The next step is to get the 10 most common venues of each neighborhood in a DataFrame:

	Neighborhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	Agincourt	Breakfast Spot	Thai Restaurant	Gym	Bakery	Bank	Bar	Café	Clothing Store	Coffee Shop	Diner
1	Alderwood / Long Branch	Pizza Place	Sandwich Place	Pub	Coffee Shop	Gym	Thai Restaurant	Fast Food Restaurant	Bakery	Bank	Bar
2	Bathurst Manor / Wilson Heights / Downsview North	Bank	Coffee Shop	Diner	Sandwich Place	Restaurant	Pizza Place	Pharmacy	Ice Cream Shop	Sushi Restaurant	Grocery Store
3	Bayview Village	Bank	Café	Japanese Restaurant	Thai Restaurant	Gym	Bakery	Bar	Breakfast Spot	Clothing Store	Coffee Shop
4	Bedford Park / Lawrence Manor East	Italian Restaurant	Sandwich Place	Restaurant	Coffee Shop	Thai Restaurant	Breakfast Spot	Café	Grocery Store	Sushi Restaurant	American Restaurant

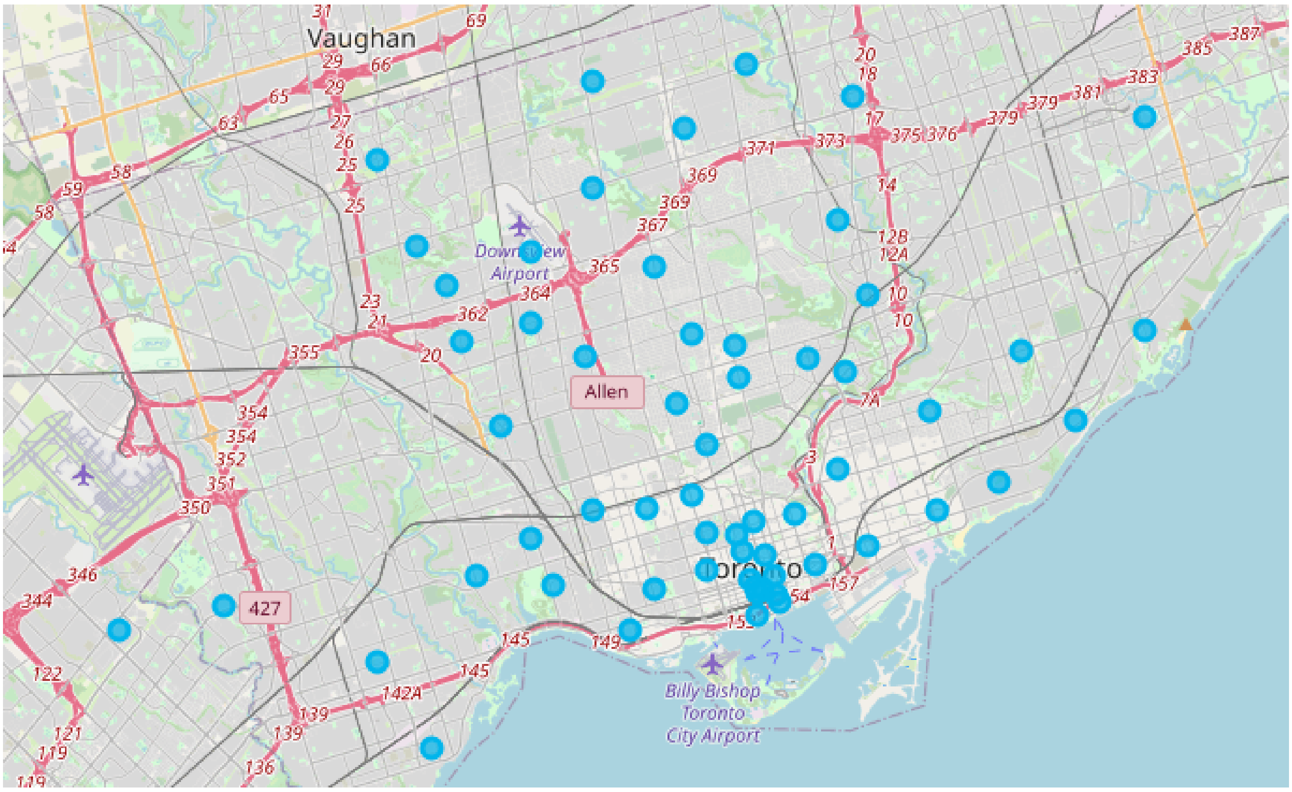
The clustering algorithm runs, and classify the cluster into 5 categories. Here is a sample of the clustering numbers:

	Borough	Neighborhood	Latitude	Longitude	city	Postalcode	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
77	Brooklyn	Manhattan Beach	40.577914	-73.943537	NY	NY	2	Café	Sandwich Place	Pizza Place	Ice Cream Shop	Thai Restaurant	Grocery Store	Bakery	Bank	Bar	Breakfast Spot
0	North York	Parkwoods	43.753259	-79.329656	TO	M3A	3	Park	Thai Restaurant	Gym	Bakery	Bank	Bar	Breakfast Spot	Café	Clothing Store	Coffee Shop
1	North York	Victoria Village	43.725882	-79.315572	TO	M4A	1	Pizza Place	Coffee Shop	Thai Restaurant	Gym	Bakery	Bank	Bar	Breakfast Spot	Café	Clothing Store
2	Downtown Toronto	Regent Park / Harbourfront	43.654260	-79.360636	TO	M5A	2	Coffee Shop	Bakery	Pub	Park	Breakfast Spot	Café	Bank	Restaurant	Ice Cream Shop	Thai Restaurant
3	North York	Lawrence Manor / Lawrence Heights	43.718518	-79.464763	TO	M6A	2	Clothing Store	Coffee Shop	Thai Restaurant	Gym	Bakery	Bank	Bar	Breakfast Spot	Café	Diner

Then the system finds on which cluster of Toronto the “home neighborhood” from New York, and display the dataset for this cluster:

	Neighborhood	Latitude	Postalcode	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
77	Manhattan Beach	40.577914	NY	2	Café	Sandwich Place	Pizza Place	Ice Cream Shop	Thai Restaurant	Grocery Store	Bakery	Bank	Bar	Breakfast Spot
2	Regent Park / Harbourfront	43.654260	M5A	2	Coffee Shop	Bakery	Pub	Park	Breakfast Spot	Café	Bank	Restaurant	Ice Cream Shop	Thai Restaurant
3	Lawrence Manor / Lawrence Heights	43.718518	M6A	2	Clothing Store	Coffee Shop	Thai Restaurant	Gym	Bakery	Bank	Bar	Breakfast Spot	Café	Diner
4	Queen's Park / Ontario Provincial Government	43.662301	M7A	2	Coffee Shop	Sushi Restaurant	Diner	Sandwich Place	Bank	Bar	Café	Park	Italian Restaurant	Gym
7	Don Mills	43.745906	M3B	2	Restaurant	Japanese Restaurant	Coffee Shop	Gym	Sandwich Place	Café	Italian Restaurant	Clothing Store	Thai Restaurant	Fast Food Restaurant
9	Garden District-Ryerson	43.657162	M5B	2	Clothing Store	Coffee Shop	Café	Japanese Restaurant	Italian Restaurant	Pizza Place	Diner	Fast Food Restaurant	Thai Restaurant	Gym
10	Glencairn	43.709577	M6B	2	Pub	Japanese Restaurant	Thai Restaurant	Grocery Store	Bakery	Bank	Bar	Breakfast Spot	Café	Clothing Store

Finally, all the Toronto neighborhoods from this specific cluster are displayed on a map to make it easier for the user to identify their location. He may, for example, pick one neighborhood that is closer to the airport:



Discussion
One important thing was to filter the top 25 venue categories (in order of number of appearances). This change was made because some venues were very rare and were turning some clusters too big and others to small, confusing the results.
Anyway, some clusters still remain bigger than they should. An improvement can be made on the system. An analysis could take place, trying to figure out the best classification of venues so the results get more homogeneous.

Conclusion
This project was very nice to learn a lot of features of Data Science, and instigated me to find out different ways to look at the topic. Still, it keep the mind wondering what else could be done. The creativity can be used in so many ways. I related the idea with a favorite movie of mine, but could be anything else, because the sources of information available are very diverse.