Automatic Neighborhood Recommendation

Carlos Daniel @cdCarlos

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Introduction

I am going to analyze a study case for real state companies. In this work are discussed some of the challenges companies in this sector may face and the repercussions at operational cost and customer satisfaction.

Also, I show up how Data Science techniques such as data pre-processing and cleaning, visualization and clustering algorithms can help solving this kind of problems in this prove of concept project.

Problem

A company dedicated to the rent and sale of real estate housing wants to reduce the operational cost in the process of recommending neighborhoods for their customers while improving their response time.

Employees have to look for neighborhoods at a given city that satisfy some given characteristics where customers are used to live (or willing to). This process can required many hours even for experienced employees who have to analyze and evaluate all of those characteristics provided by the customer, resulting in not just a costly operation for the company but also in a long wait time period for customers in order to get some recommendations.

For our study case we are going to simulate a customer who lives in a random neighborhood of Toronto, CA and is willing to move to New York City, US. As customer can provide as many desired characteristics for expected neighborhoods, in this case we are going to limit those characteristics to venues.

Data

This project requires different kinds of data such as location data and venues information for each selected city and its corresponding neighborhoods.

Location Information:

- Neighborhoods in Toronto.
- Neighborhoods in New Yor City.

Venues Information:

- Venues for each neighborhoods in Toronto.
- Venues for each neighborhoods in New York.

Data Sources

I used the data sets for Toronto and NY from the following sources:

- New York City Open Data: Location data.
- Toronto Most Common Venues: Location data.
- Foursquare API: Venues data

In contrast to Toronto, I had to consolidate first the data set for NY.

Data Pre-Processing

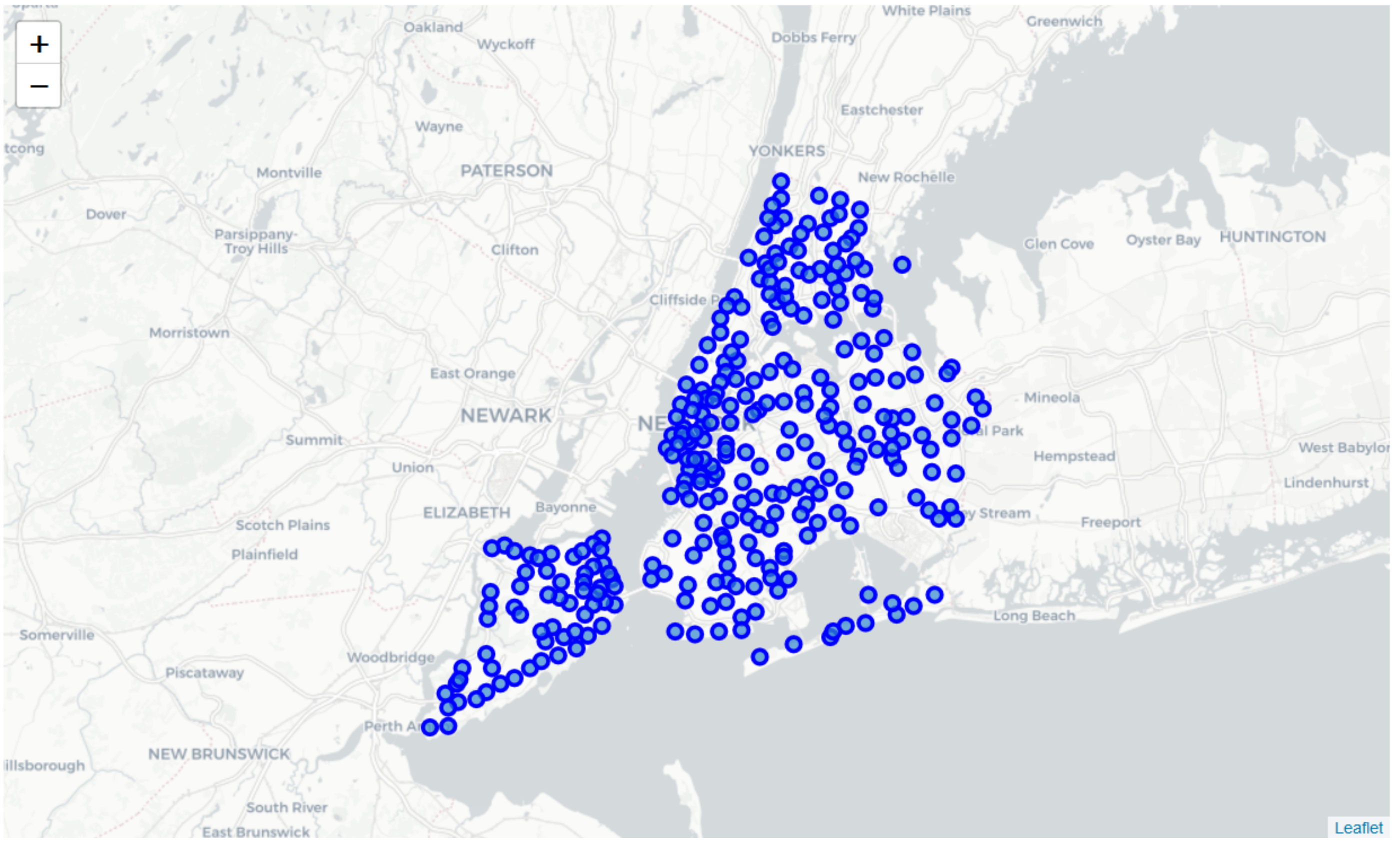
Toronto's dataset already have all the information required for the analysis. NY's dataset in the other hand required extra work in order to get the data ready to start working.

NY Neighborhoods Location

Cleaning up the NY neighborhoods coordinates was one of the first steps in the cleaning process. The original location information was encoded in geometry point format and I had to split up the Latitude and Longitude coordinates generating a feature for each one of them.

Once I have the coordinates I was able to remove all of the unnecessary features and keep only the borough name, neighborhood name, latitude and longitude features.

At this point I was able to take a look at the New York neighborhoods.



Now I was ready for the

NY Venues

In order to get venues details for each neighborhood in NY I used the [Foursquare API](https://developer.foursquare.com/) where I had to create first a developer account.

For each neighborhood I consumed the Foursquare API to fetch the venues information in a radius of 500 meters with a limit of 100 venues per neighborhood.

Results from API are in JSON format, so, I had to parsed and filtering out venue name, category and locations information as middle step.

This is how our dataset looks like:

Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
Wakefield	40.894705	-73.847201	Lollipops Gelato	40.894123	-73.845892	Dessert Shop
Wakefield	40.894705	-73.847201	Rite Aid	40.896521	-73.844680	Pharmacy
Wakefield	40.894705	-73.847201	Carvel Ice Cream	40.890487	-73.848568	Ice Cream Shop
Wakefield	40.894705	-73.847201	Dunkin Donuts	40.890631	-73.849027	Donut Shop
Wakefield	40.894705	-73.847201	SUBWAY	40.890656	-73.849192	Sandwich Place

Categorical Features Encoding

Working with categorical data is hard an can lead to misleading results specially when using clustering algorithms such as K-Means where euclidean distance (or equivalent) is used to calculate the clusters. To fix this, I encoded categorical features using OneHot Encoding technique.

We can easily defined OneHot Encoding as "a process by which categorical variables are converted into a form that could be provided to ML algorithms to do a better job in prediction". In other words, we perform "binarization" of each category and include each one of them as a new feature in our dataset.

In this case I'm interested in the venue's category feature. For example, if we have a dataset like this:

Venue	Venue Category
Lollipops Gelato	Dessert Shop
Rite Aid	Pharmacy

After applying OneHot Encoding, we should ended up with something like this:

Venue	Dessert Shop	Pharmacy
Lollipops Gelato	1	0
Rite Aid	0	1

In addition to apply OneHot Encoding to the NY venues dataset, I calculate the mean of each venue's category (now a feature) in order to properly rank the venue's popularity by category. So, the result is as follows:

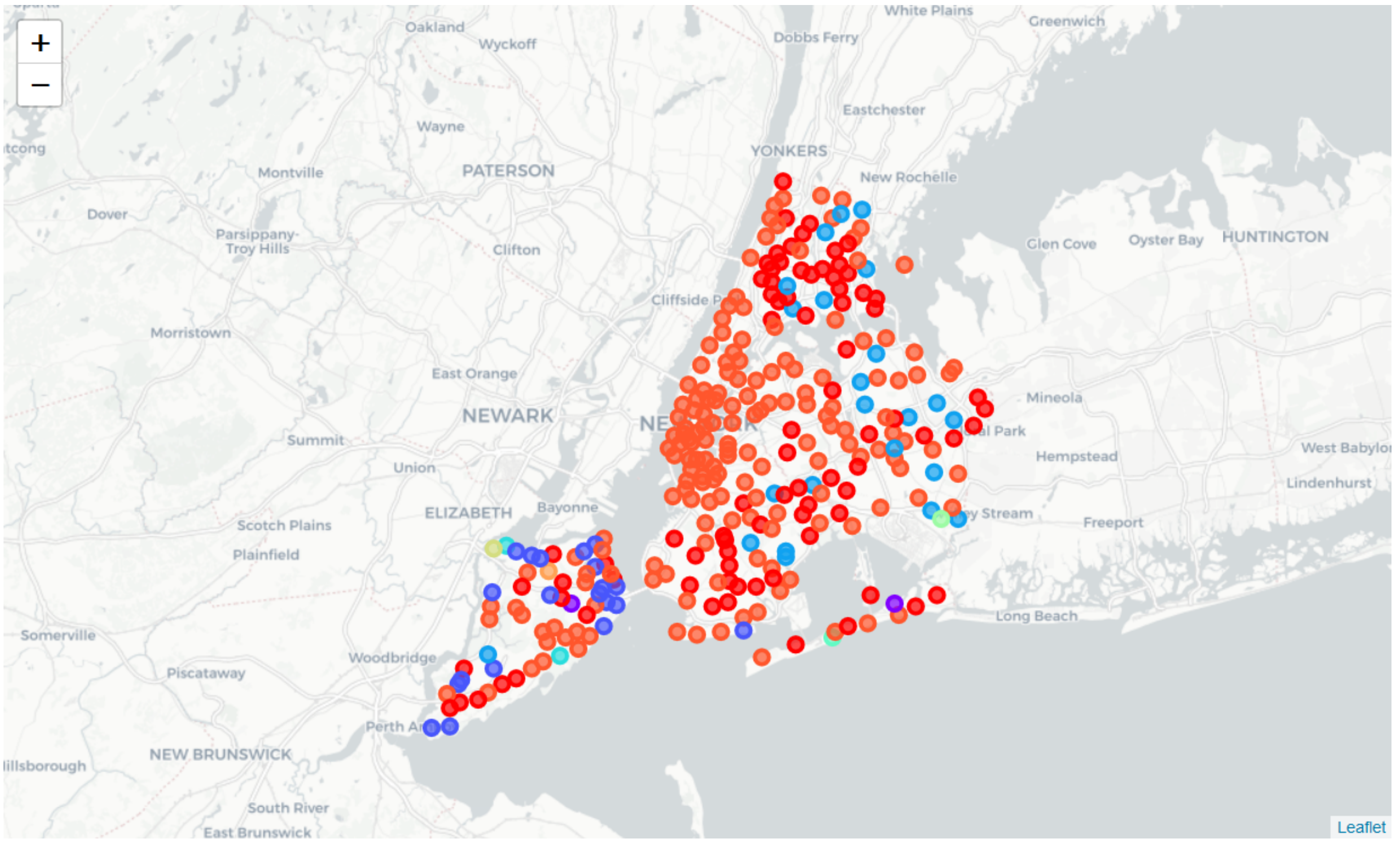
Neighbourhood	ATM	Accessories Store	Adult Boutique	Afghan Restaurant	African Restaurant	Airport Terminal	Airport Tram	American Restaurant	Animal Shelter	...	Waste Facility	Wat Sho
Wakefield	0	0	0	0	0	0	0	0	0	...	0	0
Wakefield	0	0	0	0	0	0	0	0	0	...	0	0
Wakefield	0	0	0	0	0	0	0	0	0	...	0	0
Wakefield	0	0	0	0	0	0	0	0	0	...	0	0
Wakefield	0	0	0	0	0	0	0	0	0	...	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...

At this point I was able to get the 10 most common venues for each neighborhood:

Neighbourhood	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 Comm Venue
Annadale	Sports Bar	Restaurant	Dance Studio	Pizza Place	Cosmetics Shop	Liquor Store	Diner	Train Station	Yoga Studio	Fast Fo Restau
Arden Heights	Pharmacy	Deli / Bodega	Pizza Place	Coffee Shop	Bus Stop	Fish & Chips Shop	Eye Doctor	Factory	Falafel Restaurant	Farm
Arlington	Bus Stop	Deli / Bodega	Food Service	Grocery Store	Fish Market	Factory	Falafel Restaurant	Farm	Farmers Market	Fast Fo Restau
Arrochar	Deli / Bodega	Bus Stop	Italian Restaurant	Mediterranean Restaurant	Middle Eastern Restaurant	Sandwich Place	Liquor Store	Bagel Shop	Hotel	Pizza Pl
Arverne	Surf Spot	Metro Station	Pizza Place	Donut Shop	Sandwich Place	Beach	Playground	Thai Restaurant	Bed & Breakfast	Board Shop

Clustering

For clustering, I used K-Means from sklearn package. K-Means is one of the simplest, fast and robust algorithm for unsupervised learning clustering and it also works really well with large datasets. In this case I defined 10 clusters.



As you can see multiple neighborhoods fall into the same cluster.

Neighborhood Recommendation

Now everything is set to the recommendation phase. The first step here is to choose the random customer information. What I mean by customer information is ranked venues where customer is used to live since this information will be recommendation criteria for the new location.

Random customer information:

- PostalCode: M3K
- Borough: North York
- Neighbourhood: CFB Toronto, Downsview East
- 1st Most Common Venue: Bus Stop
- 2nd Most Common Venue: Park
- 3rd Most Common Venue: Airport
- 4th Most Common Venue: Yoga Studio
- 5th Most Common Venue: Dumpling Restaurant
- 6th Most Common Venue: Discount Store
- 7th Most Common Venue: Dog Run
- 8th Most Common Venue: Doner Restaurant
- 9th Most Common Venue: Donut Shop
- 10th Most Common Venue: Drugstore

The important information here are the ten venues that most represent the location where customer is used to live.

Similarity Level

Here we are going to use the term **Similarity Level** (SL) which is explained next.

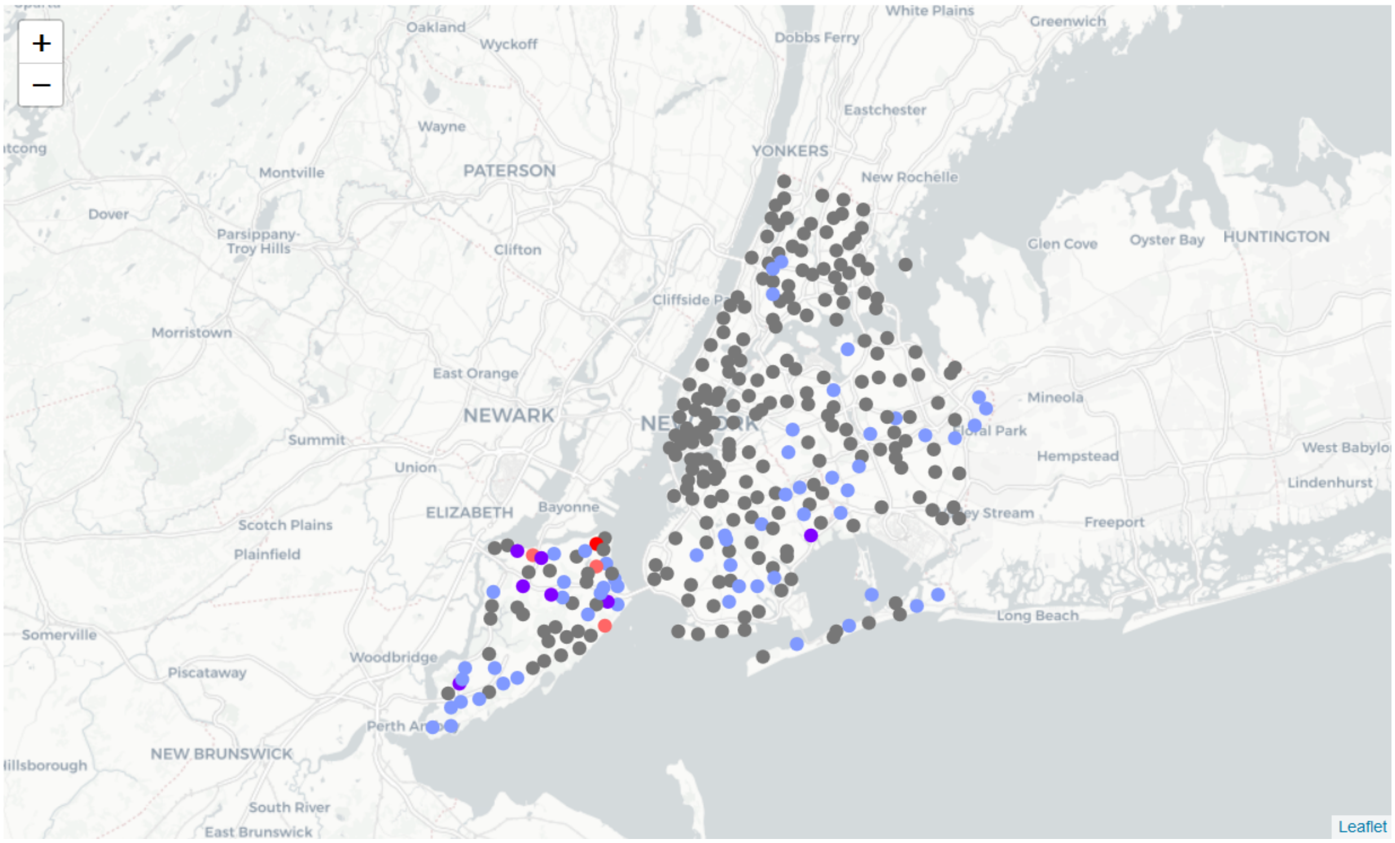
Either for Toronto and NY we have their ten most common venues. These venues are ordered starting at 1 to 10 being 1 the first one most representative, 2 the second one most representative and so on for the neighborhood. This is our similarity level.

In our case we recommend a NY neighborhood based on the Similarity Level it has with the customer's neighborhood. For instance, a recommended NY neighborhood with a SL equals to 3 means that the NY neighborhood has a perfect match with the 1st, 2nd and 3th customer's most common venues.

With this information I was able to extract those NY neighborhoods with the highest SL score:

SL	Venue Type	Neighborhoods
1	Bus Stop	Starrett City, New Brighton, Woodrow, Arlington, Grasmere, Bulls Head, Elm Park, Willowbrook
2	Park	New Brighton

A this point it is easier to have a look at the results:



Results and Discussion

In the above map we can see the NY recommended neighborhoods. Here we have deferenciated some neighborhoods with different colors.

In this case, the intense red point represents the neighborhood with the highest SL to the actual customer's neighborhood. The other three light red points are those neighborhoods that are part of the cluster where the intense red point belongs to (which makes them good cantidates for recommendation).

The same applies for the purple points. The seven intense purple points are those neighborhoods with a SL equals to 1 and the light purple points are those who belongs to the same cluster.

Gray points are neighborhoods with zero SL (not recommended).

Now we can recommend neighborhoods to customer in a more easy and fast way reducing the opeartional cost by the company.

Conclusion

By using unsupervised clustering algorithms we were able to recommend specific neighborhoods but also whole clusters to our imaginary customer.

At this point we've done the prove of concept for a business problem reducing the operational cost and response time for recommending neighborhoods based on neighborhood's similarities were customer is used to live.

One next step should be our model's optimization by defining a proper clustering size based on F1-score, V-Measure, comparing performance between multiple unsupervised algorithms and so on.