Animal Boarding Services

Exploring best location for animal boarding service in Toronto

Using Data Science

By Richard Inniss
July 7, 2020

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1. Introduction

1.1 Background

Pets play a vital role in our lives. They are loyal companions, they keep us active, they make us laugh and occasionally they make us cry. Pet ownership contributes to improved mental and physical well-being – it reduces stress and blood pressure, improves our immunity and can even prevent allergies. No one can deny that the special relationship we share with our pets contributes to our quality of life.

From 2016 to 2018, the Canadian dog population has continued to grow. Dog population figures for 2018 increased to 8.2 million, up from 7.6 million in 2016.

As many of us live active and busy lives, we all feel a need to take time off and take a vacation somewhere nice and warm, far away from our daily and hectic lives. Unfortunately, for many of us pet owners, this creates a problem as the logistics of leaving our pet behind, even if only for a week or two, can be quite a challenge. Hence, there is an ever growing need for Pet owners to have access to a reliable and reputable animal boarding service (or animal hotel) where their pets can bee safe and the owner can feel confident that they can enjoy some good vacation time without having to worry about their animal's well-being.

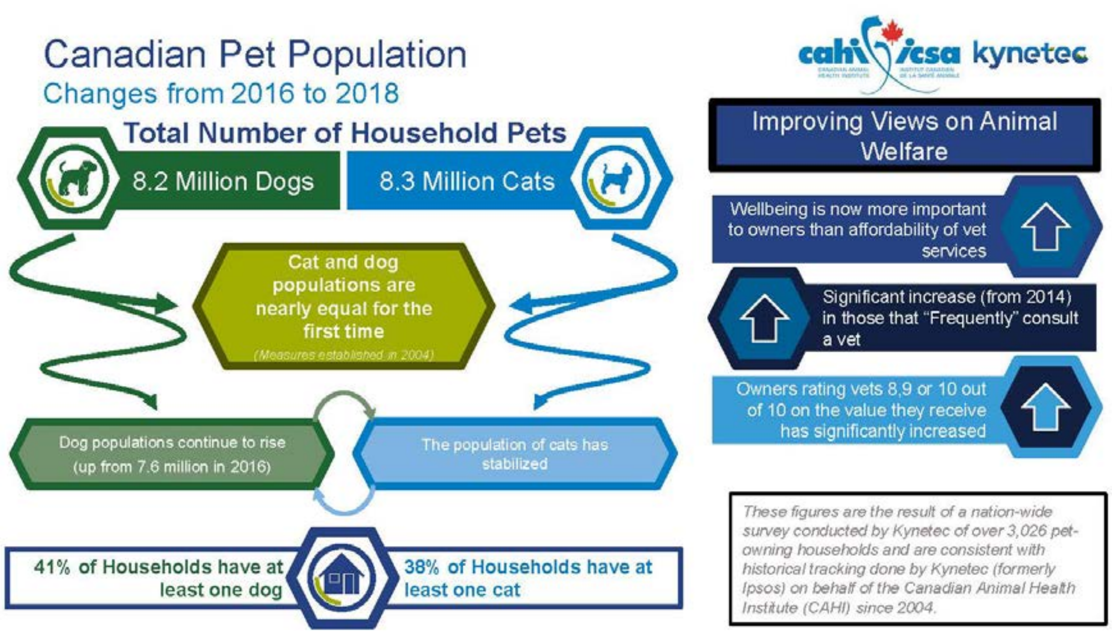


Figure 1 - Canadian Pet Population (source: Canadian Animal Health Institute webpage)

1.2 Business problem

The business problem we face is trying to ascertain for our stakeholders what would be the best location for an Animal Boarding Service in Toronto in order to maximize the number of clients.

I will attempt to leverage several of the tools discovered during the IBM Data Science Professional Certificate program, first by creating neighborhoods around Toronto by scraping some publically available web data on postal codes. Then, I will leverage services via API's from Foursquares to explore and identify pet stores, pet services, pet cafes, veterinarians and animal shelters contained in each of these neighborhoods.

Finally, using geopy, folium and K-mean clustering, I will locate all the venues on a map and find the ideal location to maximize the size of the clientele. This method will be based on the assumption that the above mentioned Pet Services are located in areas of high demand.

2. Data acquisition and cleaning

2.1 Data sources

For this exercise, the first data source I decided to use was the publically available postal code data for Toronto postal code from the following Wikipedia page:

https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M.

This data contains postal codes as well as the boroughs and neighborhoods for the greater Toronto area (GTA) and will be scrapped and entered into a panda's dataframe.

The second source of data I decided to use was a publically available csv file found at http://cocl.us/Geospatial_data using the pd.read_csv feature. The Latitude & Longitude data points it contains will be appended to the previously mentioned dataframe. Finally, the third data source I will use will be from Foursquares by using an API call to explore specific venue types with the categoryId function. Specifically, the categoryId's I will be searching for in each of the previously mentioned neighborhoods are:

Category Name	Category ID
Pet Stores	4bf58dd8d48988d100951735
Pet Services	5032897c91d4c4b30a586d69
Pet Cafes	56aa371be4b08b9a8d573508
Veterinarians	4d954af4a243a5684765b473
Animal Shelters	4e52d2d203646f7c19daa8ae

2.2 Data cleaning

The postal code data contains missing information for some of the boroughs as well as some of the neighborhoods. We therefore needed to clean this by removing those postal codes having missing data.

We also needed to clean some of the data acquired from Foursquares as some of the venues were duplicates based on the radius and proximity of certain neighborhoods. I used the following line of code to accomplish this:

```
toronto_venues=toronto_venues.drop_duplicates(subset='Venue Id', keep='first')
```

The original number of venues was 839, once the duplicates were eliminated the number of unique venues was 263, therefore there were quite a few duplicated in our original dataframe.

3. Methodology

3.1 First, we imported all required libraries

After we created our notebook instance, we needed to install software that our notebook depends on. We installed these dependencies by adding install commands in our notebook.

Here is a list of the libraries and dependencies we needed for our notebook:

```
import numpy as np # library to handle data in a vectorized manner
import pandas as pd # library for data analsysis
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
import json # library to handle JSON files
!pip install geopy
from geopy.geocoders import Nominatim # convert an address into latitude and longitude values
import requests # library to handle requests
from bs4 import BeautifulSoup # used for scraping data from a webpage
from pandas.io.json import json_normalize # tranform JSON file into a pandas dataframe
import matplotlib.cm as cm
import matplotlib.colors as colors
import math # This module provides access to the mathematical functions
from sklearn.cluster import KMeans
!pip install folium
import folium # map rendering library
```

Another advantage of adding install commands in a file like this is that, when we share our notebook, the commands to install the dependencies have been saved with the notebook and are available to users that we share the notebook with.

3.2 Second, we scraped the Toronto region postal code, borough and Neighborhood data from wiki page URL and created a dataframe

We used “BeautifulSoup” to scrape the wiki webpage on Toronto "M" postal codes, neighborhoods and boroughs. Beautiful Soup is a Python library for getting data out of HTML, XML, and other markup languages. Say you’ve found some webpages that display data relevant to your research, such as in our case; postal codes, neighborhoods and boroughs, but that do not provide any way of downloading the data directly. Beautiful Soup helps you pull particular content from a webpage, remove the HTML markup, and save the information. It is a tool for web scraping that helps you clean up and parse the documents you have pulled down from the web.

In our case, I also added a print(req.status_code) to confirm whether or not the page was successfully retrieved. If the resulting htnl status code is 200, this means the content is present and response is ok, a 404 status code means the content was not present.

As the resulting dataframe contains certain neighborhoods or borough containing values of “Not assigned”, we removed them from the dataframe.

3.3 Third, we merged the neighborhood dataframe with coordinates from the csv file

Using an existing csv file available here: http://cocl.us/Geospatial_data, we used the following code to both read the csv file and merge it to our existing dataframe:

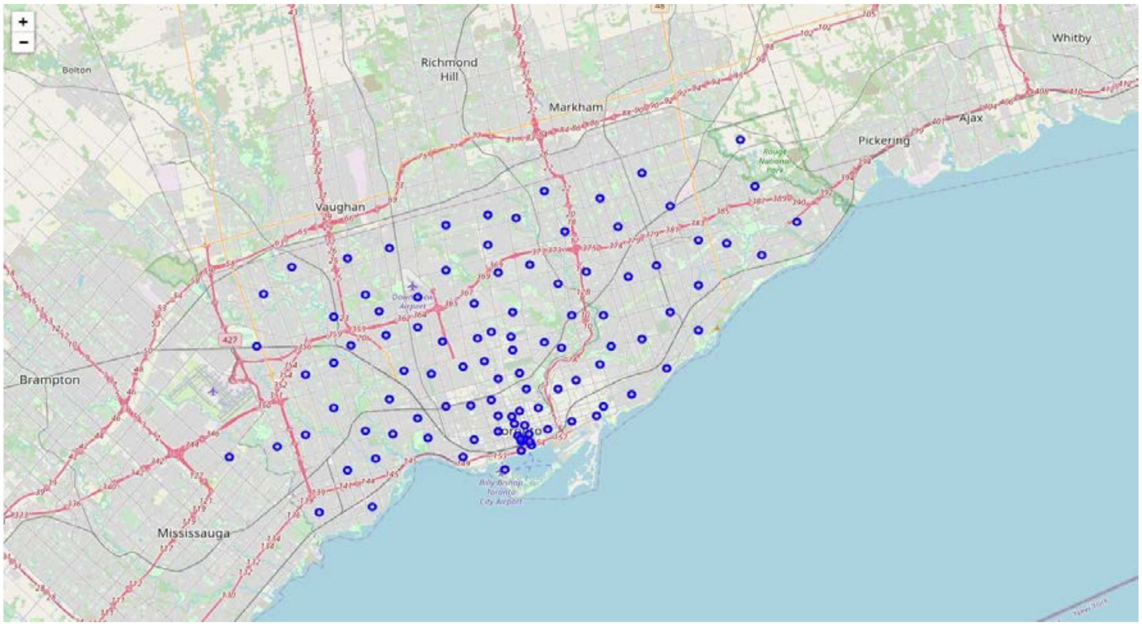
```
geo_df = pd.read_csv('http://cocl.us/Geospatial_data')
neighborhood_coord = pd.merge(neighborhood, geo_df)
neighborhood_coord.head()
```

Here are the first 5 lines of the resulting dataframe:

	Postal Code	Borough	Neighborhood	Latitude	Longitude
0	M3A	North York	Parkwoods	43.753259	-79.329656
1	M4A	North York	Victoria Village	43.725882	-79.315572
2	M5A	Downtown Toronto	Regent Park, Harbourfront	43.654260	-79.360636
3	M6A	North York	Lawrence Manor, Lawrence Heights	43.718518	-79.464763
4	M7A	Downtown Toronto	Queen's Park, Ontario Provincial Government	43.662301	-79.389494

3.4 Fourth, we explored the neighborhoods in Toronto and generated map

We started by using geopy in order to obtain the lat/long coordinates for the city of Toronto. Then, using folium we generated a map of Toronto and added a marker for each one of the neighborhoods in our dataframe. The resulting map can be seen bellow:



3.5 Fifth, we extracted specific categoryId's from Foursquare for each of our neighborhoods.

Once the credentials were setup, a function was defined to extract specific categoryId's from Foursquare for each of our neighborhoods in Toronto susceptible of creating client traffic for Pet owners. Specifically, the categories I have researched from Foursquares are Pet shops, Pet services, Veterinarians, Animal shelters and Pet cafes which can be found at the following URL: https://developer.foursquare.com/docs/build-with-foursquare/categories/

The following table shows the first 10 of 839 venues found by Foursquares based on a radius of 2000 meters for each neighborhood.

	Neighborhood	Venue	Venue Id	Vlatitude	Vlongitude	Venue Category
0	Parkwoods	Fab Fido Dog Grooming Spaw	575025d0498e76286719d2ca	43.760547	-79.325212	Pet Service
1	Parkwoods	Romeo & Paw Dog Grooming	59805bd2123a193a9e585603	43.760271	-79.318117	Pet Service
2	Parkwoods	Pet Valu @Parkway mall	4ea1de29be7ba4918e019152	43.757930	-79.313445	Pet Store
3	Parkwoods	Pet Valu	4d03e73754d0236aebeaebd5	43.757972	-79.312664	Pet Store
4	Parkwoods	Paws of Joy	5acd1b1a2387067b7497a126	43.759557	-79.309278	Pet Service
5	Parkwoods	Global Pet Foods	5ef144334eeed3000828b72c	43.759556	-79.309715	Pet Store
6	Victoria Village	Personal Paws	54de636b498e03fa29ad51dd	43.724390	-79.308764	Pet Service
7	Victoria Village	Pet Valu	4e342de3b0fb17f64f8affa0	43.726178	-79.302960	Pet Store
8	Victoria Village	Global Pet Foods	4b5a1ef3f964a52094ae28e3	43.727234	-79.292997	Pet Store
9	Victoria Village	Ren's Pet Depot	5a5262f960d11b7530fce57a	43.725628	-79.291600	Pet Store

As we will base on decisions going forward on the location of the venues, we added the coordinated of the venues (Vlatittude and Vlongitude) and dropped the neighborhood Latitude and Longitude information as we will no longer need them for the next analysis.

Also, as some of the venues might be duplicates based on our radius of 2000 meters and the proximity of certain neighborhoods to each other, we removed any duplicates that might exist in our dataframe by using the following line of code:

```
toronto_venues=toronto_venues.drop_duplicates(subset='Venue Id', keep='first')
```

The original number of venues was 839, once the duplicates were removed, the number of unique venues was 263, therefore there were quite a few duplicated in our dataframe.

We then generated a map of Toronto using folium, this time adding markers for all the unique venues we had discovered (see map bellow):

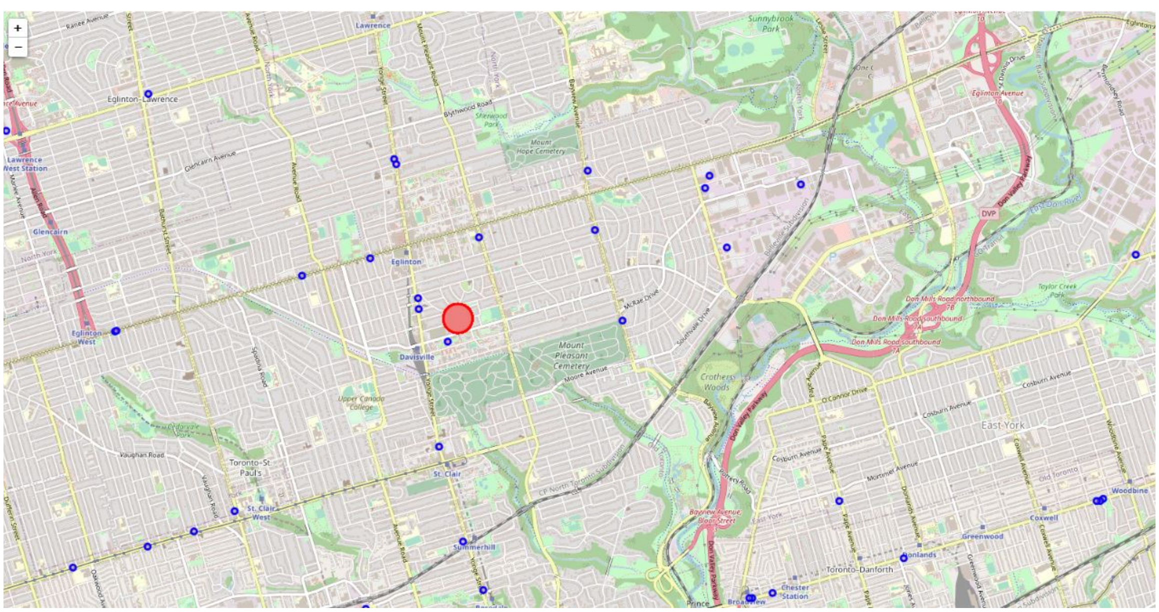
3.6 Analysis

Earlier, we added the import math as part of our required libraries in order to provide access to mathematical functions. We then used these functions to find the optimal location of our Animal Boarding Service by locating the most central point "Centroid" based on all of the 263 venue latitudes and longitudes obtained from Foursquares.

The following code was therefore used to calculate the central latitude and central longitude:

```
x = 0.0
y = 0.0
z = 0.0
for i, coord in toronto_venues.iterrows():
    Latitude = math.radians(coord.Vlatitude)
    Longitude = math.radians(coord.Vlongitude)
    x += math.cos(Latitude) * math.cos(Longitude)
    y += math.cos(Latitude) * math.sin(Longitude)
    z += math.sin(Latitude)
total = len(toronto_venues)
x = x / total
y = y / total
z = z / total
central_Longitude = math.atan2(y, x)
central_square_root = math.sqrt(x * x + y * y)
central_Latitude = math.atan2(z, central_square_root)
mean_location = {
    'Latitude': math.degrees(central_Latitude),
    'Longitude': math.degrees(central_Longitude)
    }
central_Latitude = math.degrees(central_Latitude)
central_Longitude = math.degrees(central_Longitude)
```

We then generated the map of Toronto with markers for all the unique venues once again, but this time added a large red marker to indicate the ideal location for our Animal Boarding Service and zoomed in a little closer so we can see street names:



Based on our calculation of the central latitude and central longitude, the ideal location for our Animal Boarding Service was determined to be just a few blocks south of Eglington, east of Yonge. This location has the potential of maximizing the size of the clientele as it is the most centrally located based on all of the related animal care services in Toronto.

4. Results and Discussion

The ideal location having been identified for our Animal Boarding Service, we decided to further explore the neighborhoods to see what other insights we could uncover by using K-Means clustering.

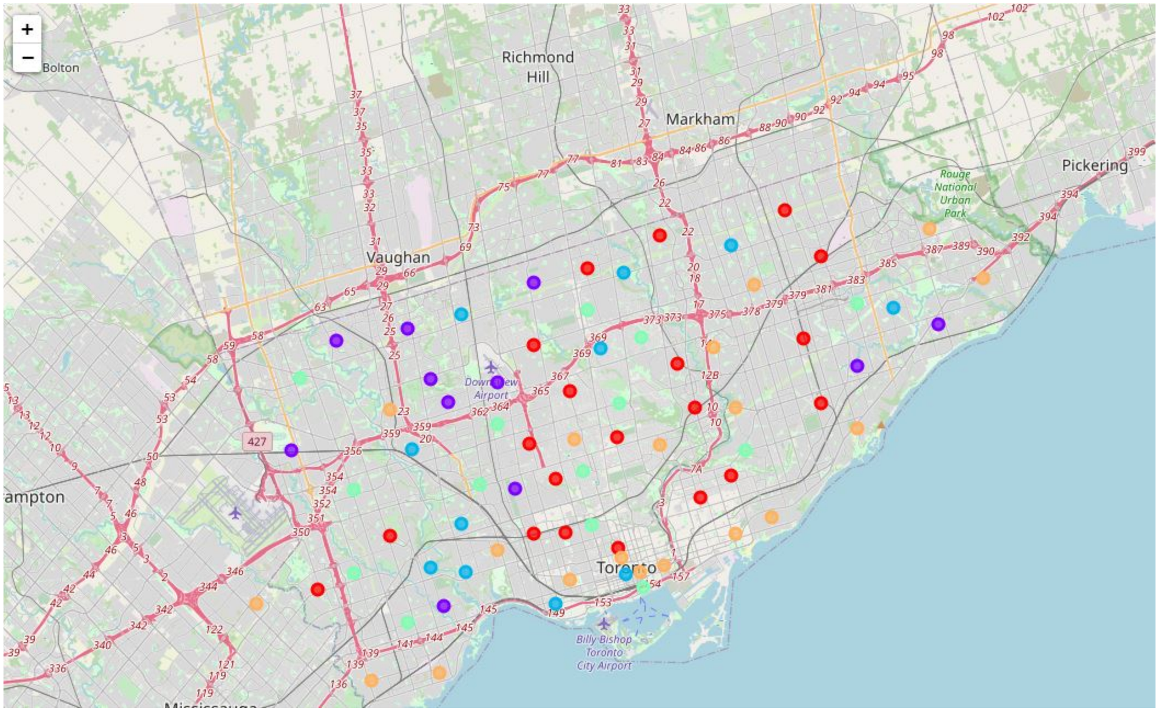
We first analyzed how many unique categories exist in each of the neighborhoods and then grouped rows by neighborhood taking the mean of the frequency of occurrence of each category. We then establish the 5 most common venues in each neighborhood. Finally, we created a new dataframe called neighborhoods_venues_sorted containing the top 5 venues for each neighborhood as per the following table:

	Neighborhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
0	Agincourt	Veterinarian	Pet Store	Medical Center	Pet Service	Hospital
1	Alderwood, Long Branch	Pet Store	Pet Service	Veterinarian	Medical Center	Hospital
2	Bathurst Manor, Wilson Heights, Downsview North	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
3	Bayview Village	Veterinarian	Pet Service	Pet Store	Medical Center	Hospital
4	Bedford Park, Lawrence Manor East	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital

We then ran *k*-means to cluster the neighborhood into 5 clusters. The following is the new resulting dataframe which includes the cluster label as well as the top 5 venues for each neighborhood.

	Postal Code	Borough	Neighborhood	Latitude	Longitude	ClusterLabels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
0	M3A	North York	Parkwoods	43.753259	-79.329656	4.0	Pet Store	Pet Service	Veterinarian	Medical Center	Hospital
1	M4A	North York	Victoria Village	43.725882	-79.315572	4.0	Pet Store	Pet Service	Veterinarian	Medical Center	Hospital
2	M5A	Downtown Toronto	Regent Park, Harbourfront	43.654260	-79.360636	4.0	Pet Store	Pet Service	Animal Shelter	Veterinarian	Medical Center
3	M6A	North York	Lawrence Manor, Lawrence Heights	43.718518	-79.464763	3.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
4	M7A	Downtown Toronto	Queen's Park, Ontario Provincial Government	43.662301	-79.389494	0.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
5	M9A	Etobicoke	Islington Avenue, Humber Valley Village	43.667856	-79.532242	0.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
6	M1B	Scarborough	Malvern, Rouge	43.806686	-79.194353	4.0	Pet Store	Animal Shelter	Veterinarian	Pet Service	Medical Center
7	M3B	North York	Don Mills	43.745906	-79.352188	0.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
8	M4B	East York	Parkview Hill, Woodbine Gardens	43.706397	-79.309937	3.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
10	M6B	North York	Glencairn	43.709577	-79.445073	0.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital

Finally, we generated the map to visualize the resulting clusters:



We can gain valuable insights by further examining each one of the clusters in greater detail in order to see if we can detect any patterns or anomalies which could help us in the future.

Let's start with the first Cluster, Cluster 0:

```
In [35]: toronto_merged.loc[toronto_merged['ClusterLabels'] == 0, toronto_merged.columns[[1] + list(range(5, toronto_merged.shape[1]))]]
```

Out[35]:

	Borough	ClusterLabels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
4	Downtown Toronto	0.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
5	Etobicoke	0.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
7	North York	0.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
10	North York	0.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
13	North York	0.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
14	East York	0.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
16	York	0.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
17	Etobicoke	0.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
25	Downtown Toronto	0.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
27	North York	0.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
28	North York	0.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
31	West Toronto	0.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
35	East York	0.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
38	Scarborough	0.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
52	North York	0.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
55	North York	0.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
65	Scarborough	0.0	Pet Store	Veterinarian	Medical Center	Pet Service	Hospital
67	Central Toronto	0.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
78	Scarborough	0.0	Veterinarian	Pet Store	Medical Center	Pet Service	Hospital
85	Scarborough	0.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital

At first glance, Cluster 0 has a group of 20 neighborhoods within 8 boroughs. Of these 20, the first most common at 65% (13) is Veterinarians, followed by Pet Shop at 35% (7). So it's safe to say that Cluster 0 is leaning towards Veterinarians.

Let's now examine Cluster 1:

```
In [37]: toronto_merged.loc[toronto_merged['ClusterLabels'] == 1, toronto_merged.columns[[1] + list(range(5, toronto_merged.shape[1]))]]
```

Out[37]:

	Borough	ClusterLabels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
18	Scarborough	1.0	Pet Service	Pet Store	Veterinarian	Medical Center	Hospital
21	York	1.0	Pet Service	Veterinarian	Pet Store	Medical Center	Hospital
32	Scarborough	1.0	Veterinarian	Pet Service	Pet Store	Medical Center	Hospital
40	North York	1.0	Pet Service	Veterinarian	Pet Store	Medical Center	Hospital
46	North York	1.0	Pet Service	Veterinarian	Pet Store	Medical Center	Hospital
50	North York	1.0	Pet Service	Pet Store	Veterinarian	Medical Center	Hospital
53	North York	1.0	Pet Service	Veterinarian	Pet Store	Medical Center	Hospital
60	North York	1.0	Pet Service	Veterinarian	Pet Store	Medical Center	Hospital
72	North York	1.0	Pet Service	Veterinarian	Pet Store	Medical Center	Hospital
94	Etobicoke	1.0	Pet Service	Veterinarian	Pet Store	Medical Center	Hospital
101	Etobicoke	1.0	Pet Service	Pet Store	Veterinarian	Medical Center	Hospital

This cluster groups 11 neighborhoods within 4 boroughs. Of these 11, the first most common at 91% (10) is Pet Services, followed by Veterinarians at 9% (1). So clearly this Cluster is mostly about Pet Services.

And now let's take a look at Cluster 2:

```
In [38]: toronto_merged.loc[toronto_merged['ClusterLabels'] == 2, toronto_merged.columns[[1] + list(range(5, toronto_merged.shape[1]))]]
```

Out[38]:

	Borough	ClusterLabels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
22	Scarborough	2.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
30	Downtown Toronto	2.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
34	North York	2.0	Veterinarian	Pet Service	Pet Store	Medical Center	Hospital
39	North York	2.0	Veterinarian	Pet Service	Pet Store	Medical Center	Hospital
43	West Toronto	2.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
63	York	2.0	Veterinarian	Pet Service	Pet Store	Medical Center	Hospital
64	York	2.0	Veterinarian	Pet Service	Pet Store	Medical Center	Hospital
66	North York	2.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
81	West Toronto	2.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
90	Scarborough	2.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital
98	Etobicoke	2.0	Veterinarian	Pet Store	Pet Service	Medical Center	Hospital

This cluster also groups 11 neighborhoods but in this case within 6 boroughs. Of these 11, the first most common at 100% (11) is Veterinarians. Therefore, even more so then Cluster 0, this cluster is entirely grouping Veterinarians.

And how about Cluster 3:

```
In [39]: toronto_merged.loc[toronto_merged['ClusterLabels'] == 3, toronto_merged.columns[[1] + list(range(5, toronto_merged.shape[1]))]]
```

Out[39]:

	Borough	ClusterLabels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
3	North York	3.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
8	East York	3.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
11	Etobicoke	3.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
20	Downtown Toronto	3.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
26	Scarborough	3.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
45	North York	3.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
56	York	3.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
59	North York	3.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
61	Central Toronto	3.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
68	Central Toronto	3.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
74	Central Toronto	3.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
77	Etobicoke	3.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
89	Etobicoke	3.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
102	Etobicoke	3.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital

This cluster groups 14 neighborhoods within 7 boroughs. Of these 14, the first most common at 100% (14) is Pet Stores. Therefore, this cluster is entirely grouping Pet Stores and has a little bit more of a retail flavor to it. The other interesting aspect of this cluster is that the second most common venue is 100% Veterinarians, the third most common venue 100% Pet Services. So this cluster is very cleanly separated across all venues.

And finally, let's take a look at Cluster 4:

```
In [40]: toronto_merged.loc[toronto_merged['ClusterLabels'] == 4, toronto_merged.columns[[1] + list(range(5, toronto_merged.shape[1]))]]
```

Out[40]:

	Borough	ClusterLabels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
0	North York	4.0	Pet Store	Pet Service	Veterinarian	Medical Center	Hospital
1	North York	4.0	Pet Store	Pet Service	Veterinarian	Medical Center	Hospital
2	Downtown Toronto	4.0	Pet Store	Pet Service	Animal Shelter	Veterinarian	Medical Center
6	Scarborough	4.0	Pet Store	Animal Shelter	Veterinarian	Pet Service	Medical Center
12	Scarborough	4.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
15	Downtown Toronto	4.0	Pet Store	Event Space	Veterinarian	Pet Service	Medical Center
19	East Toronto	4.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
23	East York	4.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
24	Downtown Toronto	4.0	Pet Store	Hospital	Veterinarian	Pet Service	Medical Center
37	West Toronto	4.0	Pet Store	Pet Service	Veterinarian	Medical Center	Hospital
47	East Toronto	4.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
51	Scarborough	4.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
57	North York	4.0	Pet Store	Pet Service	Veterinarian	Medical Center	Hospital
62	Central Toronto	4.0	Pet Store	Pet Service	Veterinarian	Medical Center	Hospital
69	West Toronto	4.0	Pet Store	Veterinarian	Pet Service	Medical Center	Hospital
76	Mississauga	4.0	Pet Store	Pet Service	Veterinarian	Medical Center	Hospital
82	Scarborough	4.0	Pet Store	Animal Shelter	Veterinarian	Pet Service	Medical Center
88	Etobicoke	4.0	Pet Store	Pet Service	Veterinarian	Medical Center	Hospital
93	Etobicoke	4.0	Pet Store	Pet Service	Veterinarian	Medical Center	Hospital

Cluster 4 has a group of 19 neighborhoods within 9 boroughs. Of these 19, the first most common at 100% (13) is Pet Stores, therefore somewhat similar to Cluster 3, however it does not have the same characteristics of being very cleanly separate across all venues for the 2nd, 3rd, 4th and 5th most common venues as Cluster 3 does.

4. Conclusion

The purpose of this project was to identify the best location of our Animal Boarding Service in order to in order to aid stakeholders in narrowing down the search for optimal location in Toronto. By calculating Pet services density distribution from Foursquare data we have first identified exact locations for all Veterinarians, Pet Stores, Pet Services, Pet Cafes and Animal Shelters and then generated a map of all unique locations. Mathematical calculations were then performed in order to find the most central location of all these services in order to maximize the potential client traffic. We then performed some additional exploration of our data to see what other insights we can uncover by using K-Means clustering. This was performed in order to create major zones of interest to be used as additional insights for exploration by stakeholders. Even do our ideal location might be located outside some of these clusters, the insight we gather for each of these clusters could be used for our stakeholders marketing efforts in order to fine tune the advertising of the Animal Boarding Service with each of these clusters.

For example, in clusters 3 and 4, the dominant venue is clearly Pet Stores, therefore we could concentrate our advertising efforts within these cluster to these types of venues. In cluster 2, the most common venue is exclusively Veterinarians. We can therefore concentrate our promotion efforts to these venues within this cluster.

The final decision on optimal Animal Boarding Service location can be made by stakeholders based on either the optimal central location as calculated previously, or by specific characteristics of neighborhoods and locations in each of the clusters, taking into consideration additional factors like attractiveness of each location (proximity to Veterinarians for example), Pet Services, etc.