The Battle of Neighborhoods

Recommending the correct neighbourhood to a new home buyer

Introduction (Problem statement and discussion):

Selecting a good home is not just about owning a place, the user also needs to consider facilities and services offered in the nearby region, such as snack bars, hotels, theaters etc.

To make this process easy, this project aims to be a recommendation engine based on user's input of desired services, currently in Neighbourhoods of Toronto. The intended approach is to create feature vectors of neighbourhoods and use them to train classifier which gives out top place (neighbourhood) which is close to the user's requirements.

This can be used by home buyers directly as well as real estate agents who make suggestions to their customers.

Stakeholders: Home buyers and real estate agents

Description of data and its usage

Data required is the data for Neighbourhoods in Toronto and nearby venues.

- The neighbourhood data (PostalCodes mainly) will be scraped from public websites and then using FourSquare API, the corresponding venues and their categories will be extracted.
- The categories will then be converted to numerical features for all venues, and they will be mapped to the corresponding neighbourhoods. Using this, a kNN classifier will be trained. This can be treated as a classification with k=1 problem or as a Recommender system.
- For prediction, the user input will be converted to same features and a class will be extracted with probabilities, from that top 1 will be returned as suggestion.

Data Sample:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Parkwoods	43.753259	-79.329656	Brookbanks Park	43.751976	-79.332140	Park
1	Parkwoods	43.753259	-79.329656	KFC	43.754387	-79.333021	Fast Food Restaurant
2	Parkwoods	43.753259	-79.329656	Variety Store	43.751974	-79.333114	Food & Drink Shop
3	Victoria Village	43.725882	-79.315572	Victoria Village Arena	43.723481	-79.315635	Hockey Arena
4	Victoria Village	43.725882	-79.315572	Tim Hortons	43.725517	-79.313103	Coffee Shop
5	Victoria Village	43.725882	-79.315572	Portugril	43.725819	-79.312785	Portuguese Restaurant
6	Victoria Village	43.725882	-79.315572	Pizza Nova	43.725824	-79.312860	Pizza Place
7	Regent Park, Harbourfront	43.654260	-79.360636	Roselle Desserts	43.653447	-79.362017	Bakery
8	Regent Park, Harbourfront	43.654260	-79.360636	Tandem Coffee	43.653559	-79.361809	Coffee Shop
9	Regent Park, Harbourfront	43.654260	-79.360636	Cooper Koo Family YMCA	43.653249	-79.358008	Distribution Center

Methodology

The extracted mappings of venue categories and neighbourhood will be mapped to a feature space. Features will be a vector of 1's and 0's where 1 represents that venue belonging to that category exists in the neighborhood, and 0 means it does not.

For inference, since training set only has 1 neighbourhood as class, KNN model with k=1 will be used. Theis can be improved if user location is also served as input but that has not been included as of now.

For inference, distance will be calculated only for values of input features which are positive, otherwise, other positive dimensions of known datapoints can increase the distance.

Analysis and modeling

Step 1: Scrape data

In [1]:
```
import pandas as pd
import requests
from bs4 import BeautifulSoup
```

In [2]:
```
url = "https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M"
wiki_url = requests.get(url)
wiki_url
```

Out[2]: <Response [200]>

In [3]:
```
soup = BeautifulSoup(wiki_url.text)
table_contents=[]
table=soup.find('table')
for row in table.findAll('td'):
    cell = {}
    if row.span.text=='Not assigned':
        pass
    else:
        cell['PostalCode'] = row.p.text[:3]
        cell['Borough'] = (row.span.text).split('(')[0]
        cell['Neighborhood'] = (((((row.span.text).split('(')[1]).strip(')'))
        table_contents.append(cell)
```

```
# print(table_contents)
df=pd.DataFrame(table_contents)
```

In [4]:
```
df
```

Out[4]:

	PostalCode	Borough	Neighborhood
0	M3A	North York	Parkwoods
1	M4A	North York	Victoria Village
2	M5A	Downtown Toronto	Regent Park, Harbourfront
3	M6A	North York	Lawrence Manor, Lawrence Heights
4	M7A	Queen's Park	Ontario Provincial Government
...	...	...	...
98	M8X	Etobicoke	The Kingsway, Montgomery Road, Old Mill North
99	M4Y	Downtown Toronto	Church and Wellesley
100	M7Y	East TorontoBusiness reply mail Processing Cen...	Enclave of M4L
101	M8Y	Etobicoke	Old Mill South, King's Mill Park, Sunnylea, Hu...
102	M8Z	Etobicoke	Mimico NW, The Queensway West, South of Bloor,...

103 rows × 3 columns

In [5]:
```
df['Borough']=df['Borough'].replace({'Downtown TorontoStn A PO Boxes25 The Es
                                     'East TorontoBusiness reply mail
                                     'EtobicokeNorthwest':'Etobicoke
                                     'MississaugaCanada Post Gateway
```

In [6]:
```
df.head()
```

Out[6]:

	PostalCode	Borough	Neighborhood
0	M3A	North York	Parkwoods
1	M4A	North York	Victoria Village
2	M5A	Downtown Toronto	Regent Park, Harbourfront
3	M6A	North York	Lawrence Manor, Lawrence Heights
4	M7A	Queen's Park	Ontario Provincial Government

In [7]:
```
df = df.groupby(['PostalCode']).head()
```

In [8]:
```
df.Neighborhood.str.count("Not assigned").sum()
```

Out[8]:
```
0
```

Step 2: Get latitude and longitude using geocoder

In [9]:
```
!pip install geocoder
```

```
Collecting geocoder
  Downloading geocoder-1.38.1-py2.py3-none-any.whl (98 kB)
     |████████████████████████████████| 98 kB 5.3 MB/s
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages
(from geocoder) (1.15.0)
Requirement already satisfied: future in /usr/local/lib/python3.7/dist-packag
es (from geocoder) (0.16.0)
Collecting ratelim
  Downloading ratelim-0.1.6-py2.py3-none-any.whl (4.0 kB)
Requirement already satisfied: requests in /usr/local/lib/python3.7/dist-pack
ages (from geocoder) (2.23.0)
Requirement already satisfied: click in /usr/local/lib/python3.7/dist-package
s (from geocoder) (7.1.2)
Requirement already satisfied: decorator in /usr/local/lib/python3.7/dist-pac
kages (from ratelim->geocoder) (4.4.2)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.
7/dist-packages (from requests->geocoder) (2021.5.30)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /us
r/local/lib/python3.7/dist-packages (from requests->geocoder) (1.24.3)
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/
dist-packages (from requests->geocoder) (3.0.4)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-
packages (from requests->geocoder) (2.10)
Installing collected packages: ratelim, geocoder
Successfully installed geocoder-1.38.1 ratelim-0.1.6
```

In [10]:
```
import geocoder # import geocoder

lat_list = []
long_list = []
```

In [11]:
```
lat_long_df = pd.read_csv('https://cf-courses-data.s3.us.cloud-object-storage
```

In [12]:
```
lat_long_df
```

Out[12]:

	Postal Code	Latitude	Longitude
0	M1B	43.806686	-79.194353
1	M1C	43.784535	-79.160497
2	M1E	43.763573	-79.188711
3	M1G	43.770992	-79.216917
4	M1H	43.773136	-79.239476
...	...	...	...
98	M9N	43.706876	-79.518188
99	M9P	43.696319	-79.532242
100	M9R	43.688905	-79.554724
101	M9V	43.739416	-79.588437
102	M9W	43.706748	-79.594054

103 rows × 3 columns

In [13]:
```
lat_long_df.columns = ['PostalCode', 'Latitude','Longitude']
lat_long_df['PostalCode'] = lat_long_df['PostalCode'].astype(object)
df['PostalCode'] = df['PostalCode'].astype(object)
```

In [14]:
```
df = df.join(lat_long_df.set_index('PostalCode'), on='PostalCode')
```

In [15]:
```
df.head(10)
```

Out[15]:

	PostalCode	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	Queen's Park	Ontario Provincial Government	43.662301	-79.389494
5	M9A	Etobicoke	Islington Avenue	43.667856	-79.532242
6	M1B	Scarborough	Malvern, Rouge	43.806686	-79.194353
7	M3B	North York	Don Mills North	43.745906	-79.352188
8	M4B	East York	Parkview Hill, Woodbine Gardens	43.706397	-79.309937
9	M5B	Downtown Toronto	Garden District, Ryerson	43.657162	-79.378937

Step 3: Data preprocessing/wrangling and transformation

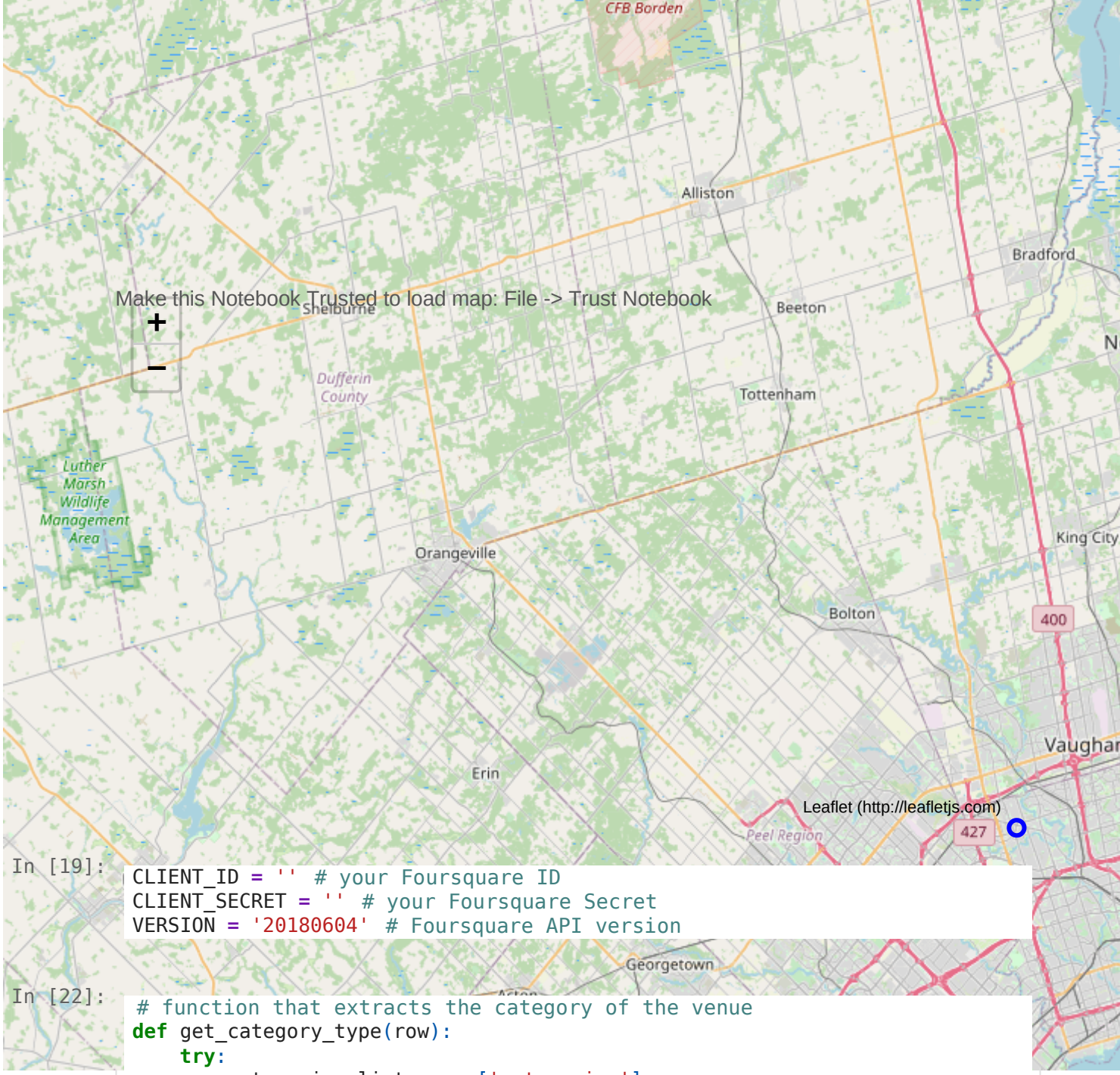
Extracting venue and categories using Foursquare API and geocoder

In [16]:
```
from geopy.geocoders import Nominatim
```

In [17]:
```
address = 'Toronto, Ontario'

geolocator = Nominatim(user_agent="toronto_explorer")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print("Toronto's coordinates: {}, {}.".format(latitude, longitude))
```

```
Toronto's coordinates: 43.6534817, -79.3839347.
```

In [18]:
```
import folium

# create map of Toronto using latitude and longitude values
map_Toronto = folium.Map(location=[latitude, longitude], zoom_start=10)

# add markers to map
for lat, lng, borough, neighborhood in zip(df['Latitude'], df['Longitude'], d
    label = '{}, {}'.format(neighborhood, borough)
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=5,
```



In [19]:
```
CLIENT_ID = ''  # your Foursquare ID
CLIENT_SECRET = ''  # your Foursquare Secret
VERSION = '20180604'  # Foursquare API version
```

In [22]:
```
# function that extracts the category of the venue
def get_category_type(row):
    try:
        categories_list = row['categories']
    except:
        categories_list = row['venue.categories']

    if len(categories_list) == 0:
        return None
    else:
        return categories_list[0]['name']
```

In [23]:
```
import json
from pandas import json_normalize

venues = results['response']['groups'][0]['items']

nearby_venues = json_normalize(venues)  # flatten JSON

# filter columns
filtered_columns = ['venue.name', 'venue.categories', 'venue.location.lat', '
nearby_venues =nearby_venues.loc[:, filtered_columns]

# filter the category for each row
nearby_venues['venue.categories'] = nearby_venues.apply(get_category_type, ax
```

```
# clean columns
nearby_venues.columns = [col.split(".")[-1] for col in nearby_venues.columns]

nearby_venues.head()
```

Out[23]:

	name	categories	lat	lng
0	Brookbanks Park	Park	43.751976	-79.332140
1	KFC	Fast Food Restaurant	43.754387	-79.333021
2	Variety Store	Food & Drink Shop	43.751974	-79.333114

In [24]:

```
def getNearbyVenues(names, latitudes, longitudes, radius=500):

    venues_list=[]
    for name, lat, lng in zip(names, latitudes, longitudes):
        # print(name)
        # create the API request URL
        url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&cli
            CLIENT_ID,
            CLIENT_SECRET,
            VERSION,
            lat,
            lng,
            radius,
            LIMIT)

        # make the GET request
        try:
            results = requests.get(url).json()["response"]['groups'][0]['item
        except:
            print(requests.get(url).json()["response"])
        # return only relevant information for each nearby venue
        venues_list.append([(
            name,
            lat,
            lng,
            v['venue']['name'],
            v['venue']['location']['lat'],
            v['venue']['location']['lng'],
            v['venue']['categories'][0]['name']) for v in results])

    nearby_venues = pd.DataFrame([item for venue_list in venues_list for item
    nearby_venues.columns = ['Neighborhood',
                  'Neighborhood Latitude',
                  'Neighborhood Longitude',
                  'Venue',
                  'Venue Latitude',
                  'Venue Longitude',
                  'Venue Category']

    return(nearby_venues)
```

In [25]:

```
toronto_venues = getNearbyVenues(names=df['Neighborhood'],
                                 latitudes=df['Latitude'],
                                 longitudes=df['Longitude']
                                )
```

In [26]:

```
toronto_venues.head(10)
```

Out[26]:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Parkwoods	43.753259	-79.329656	Brookbanks Park	43.751976	-79.332140	Park
1	Parkwoods	43.753259	-79.329656	KFC	43.754387	-79.333021	Fast Food Restaurant
2	Parkwoods	43.753259	-79.329656	Variety Store	43.751974	-79.333114	Food & Drink Shop
3	Victoria Village	43.725882	-79.315572	Victoria Village Arena	43.723481	-79.315635	Hockey Arena
4	Victoria Village	43.725882	-79.315572	Tim Hortons	43.725517	-79.313103	Coffee Shop
5	Victoria Village	43.725882	-79.315572	Portugril	43.725819	-79.312785	Portuguese Restaurant
6	Victoria Village	43.725882	-79.315572	Pizza Nova	43.725824	-79.312860	Pizza Place
7	Regent Park, Harbourfront	43.654260	-79.360636	Roselle Desserts	43.653447	-79.362017	Bakery
8	Regent Park, Harbourfront	43.654260	-79.360636	Tandem Coffee	43.653559	-79.361809	Coffee Shop
9	Regent Park, Harbourfront	43.654260	-79.360636	Cooper Koo Family YMCA	43.653249	-79.358008	Distribution Center

In [27]:
```
toronto_venues.groupby('Neighborhood')['Venue'].count()
```

Out[27]:
```
Neighborhood
Agincourt                                          4
Alderwood, Long Branch                             8
Bathurst Manor, Wilson Heights, Downsview North    21
Bayview Village                                    4
Bedford Park, Lawrence Manor East                  25
                                                   ..
Willowdale West                                    5
Willowdale, Newtonbrook                            1
Woburn                                             4
Woodbine Heights                                   8
York Mills West                                    3
Name: Venue, Length: 100, dtype: int64
```

In [237…
```
len(toronto_venues['Venue Category'].unique())
```

Out[237… 274

In [238…
```
toronto_venues
```

Out[238…

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Parkwoods	43.753259	-79.329656	Brookbanks Park	43.751976	-79.332140	Park
1	Parkwoods	43.753259	-79.329656	KFC	43.754387	-79.333021	Fast Food Restaurant

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
2	Parkwoods	43.753259	-79.329656	Variety Store	43.751974	-79.333114	Food & Drink Shop
3	Victoria Village	43.725882	-79.315572	Victoria Village Arena	43.723481	-79.315635	Hockey Arena
4	Victoria Village	43.725882	-79.315572	Tim Hortons	43.725517	-79.313103	Coffee Shop
...	...	...	...	...	...	...	...
2137	Mimico NW, The Queensway West, South of Bloor,...	43.628841	-79.520999	Jim & Maria's No Frills	43.631152	-79.518617	Grocery Store
2138	Mimico NW, The Queensway West, South of Bloor,...	43.628841	-79.520999	Islington Florist & Nursery	43.630156	-79.518718	Flower Shop
2139	Mimico NW, The Queensway West, South of Bloor,...	43.628841	-79.520999	Koala Tan Tanning Salon & Sunless Spa	43.631370	-79.519006	Tanning Salon
2140	Mimico NW, The Queensway West, South of Bloor,...	43.628841	-79.520999	Kingsway Boxing Club	43.627254	-79.526684	Gym
2141	Mimico NW, The Queensway West, South of Bloor,...	43.628841	-79.520999	Burrito Boyz	43.626657	-79.526349	Burrito Place

2142 rows × 7 columns

All 274 different venues will become features and Neighbourhood will become target

In [239…
```
toronto_venues_ohe = pd.get_dummies(toronto_venues[['Venue Category']], prefi
```

In [240…
```
# Add neighborhood
toronto_venues_ohe['Neighborhood'] = toronto_venues['Neighborhood']
```

In [241…
```
toronto_venues_ohe = toronto_venues_ohe[['Neighborhood'] + [i for i in toront
```

In [242…
```
toronto_venues_ohe.head()
```

Out[242…

	Neighborhood	Accessories Store	Adult Boutique	Airport	Airport Food Court	Airport Lounge	Airport Service	Airport Terminal	American Restaurant
0	Parkwoods	0	0	0	0	0	0	0	0

	Neighborhood	Accessories Store	Adult Boutique	Airport	Airport Food Court	Airport Lounge	Airport Service	Airport Terminal	American Restaurant
1	Parkwoods	0	0	0	0	0	0	0	0
2	Parkwoods	0	0	0	0	0	0	0	0
3	Victoria Village	0	0	0	0	0	0	0	0
4	Victoria Village	0	0	0	0	0	0	0	0

5 rows × 274 columns

Group all venues for a neighbour hood and aggregate all venue categories

In [245…
```
toronto_venues_ohe_grouped = toronto_venues_ohe.groupby('Neighborhood').sum()
```

In [246…
```
toronto_venues_ohe_grouped.head()
```

Out[246…

	Neighborhood	Accessories Store	Adult Boutique	Airport	Airport Food Court	Airport Lounge	Airport Service	Airport Terminal	American Restaurant
0	Agincourt	0	0	0	0	0	0	0	0
1	Alderwood, Long Branch	0	0	0	0	0	0	0	0
2	Bathurst Manor, Wilson Heights, Downsview North	0	0	0	0	0	0	0	0
3	Bayview Village	0	0	0	0	0	0	0	0
4	Bedford Park, Lawrence Manor East	0	0	0	0	0	0	0	1

5 rows × 274 columns

Venue categories are not just one hot encoded anymore, after sum, the values can be greater than one (Multiple venues of same category), which will also increase the distance from user's input vector. A good way to mitigate this will be clipping as average/scaling etc will reduce the score for available services.

In [247…
```
toronto_venues_ohe_grouped[[i for i in toronto_venues_ohe.columns if i!= 'Nei
```

```
/usr/local/lib/python3.7/dist-packages/pandas/core/generic.py:7358: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy
  return self._clip_with_scalar(lower, upper, inplace=inplace)
```

In [248…
```
toronto_venues_ohe_grouped.head()
```

Out[248…

	Neighborhood	Accessories Store	Adult Boutique	Airport	Airport Food Court	Airport Lounge	Airport Service	Airport Terminal	American Restaurant
0	Agincourt	0	0	0	0	0	0	0	0
1	Alderwood, Long Branch	0	0	0	0	0	0	0	0
2	Bathurst Manor, Wilson Heights, Downsview North	0	0	0	0	0	0	0	0
3	Bayview Village	0	0	0	0	0	0	0	0
4	Bedford Park, Lawrence Manor East	0	0	0	0	0	0	0	1

5 rows × 274 columns

Separate features and target (Neighborhood)

In [249…
```
neighborhood = toronto_venues_ohe_grouped[['Neighborhood']]
category_features = toronto_venues_ohe_grouped[[i for i in toronto_venues_ohe
```

In [250…
```
# Save order of categories (Features)
category_order = category_features.columns
```

In [250…
```
```

Step 4: Creating a model

In [251…
```
import numpy as np
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import recall_score, f1_score
```

In [252…
```
def distance_metric(x, y):
    """
    Only consider features which are non zero for
    x (input) and ignore other positive features of datapoint and
    then calculate euclidean distance.
    """
    x_mask = x!=0
    y = y*x_mask
    return np.linalg.norm(y-x, 1)
```

In [294…
```
clf = KNeighborsClassifier(n_neighbors=1, metric=distance_metric)
clf.fit(category_features, neighborhood)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: DataConversio
nWarning: A column-vector y was passed when a 1d array was expected. Please c
hange the shape of y to (n_samples, ), for example using ravel().
```

Out[294…
```
KNeighborsClassifier(algorithm='auto', leaf_size=30,
                     metric=<function distance_metric at 0x7f040c9d04d0>,
                     metric_params=None, n_jobs=None, n_neighbors=1, p=2,
                     weights='uniform')
```

Step 5: model testing and evaluation

We only need to consider services which are available

In [295…
```
outputs = clf.predict(category_features)
print("Recall score: ", recall_score(np.array(neighborhood).ravel(), np.array
print("F1 score: ", f1_score(np.array(neighborhood).ravel(), np.array(outputs
```

```
Recall score:  0.91
F1 score:  0.91
```

Test on ungrouped data

In [297…
```
test_neighbourhood = toronto_venues_ohe['Neighborhood']
test_features = toronto_venues_ohe[[i for i in toronto_venues_ohe.columns if
test_features = test_features[category_order]
outputs = clf.predict(test_features)
print("Recall score: ", recall_score(np.array(test_neighbourhood).ravel(), np
print("F1 score: ", f1_score(np.array(test_neighbourhood).ravel(), np.array(o
```

```
Recall score:  0.73697639214539
F1 score:  0.6930395072369206
```

Sample usage

Get categories from user and transform them

In [282…
```
# User input
input_categories = ["Women's Store",'American Restaurant', 'Airport', 'Wine B
input_vector = [1 if i in input_categories else 0 for i in category_order]
```

In [284…
```
len(input_vector)
```

Out[284…
```
273
```

In [285…
```
clf.predict([input_vector])
```

Out[285…
```
array(['Fairview, Henry Farm, Oriole'], dtype=object)
```

Results and Discussion

Test results are not as great compared to training results, this is due to the fact that selected features are not very expressive / are binary and number of samples for each class is 1. This can be improved by including location information, For example, instead of restaurant being scored as 1, it can be scaled to express the distance from user's location.

For this, user's location will be required as input.

Conclusion

The purpose of this project was to create a recommendation engine which recommends a neighborhood to user based on availability of given facilities.

Here, an approach based on classification is given for recommendation of a neighborhood that best provides the facilities required by the user.

Final decission on optimal location will be made by stakeholders based on specific characteristics of neighborhoods and locations in every recommended zone, taking into consideration additional factors like attractiveness of each location (proximity to park or water), levels of noise / proximity to major roads, real estate availability, prices, social and economic dynamics of every neighborhood etc.

In [ ]: