

IBM_DS_Capstone_WK5_Final

December 30, 2018

1 IBM Data Science Specialztion Capstone by Coursera

1.0.1 Week 5 Project Final

```
In [1]: #Import necessary packacges & libraries
        !conda install -c conda-forge beautifulsoup4 --yes

        !conda install -c conda-forge geopy --yes

        !conda install -c conda-forge folium=0.5.0 --yes

        print('Libraries installed!')
```

Solving environment: done

All requested packages already installed.

Solving environment: done

All requested packages already installed.

Solving environment: done

All requested packages already installed.

Libraries installed!

```
In [2]: import numpy as np #library for computations and array manipulations
        import pandas as pd #library for tables
        pd.set_option('display.max_columns', None)
        pd.set_option('display.max_rows', None)

        import requests
        import json

        from bs4 import BeautifulSoup
```

```

from geopy.geocoders import Nominatim

import folium
%matplotlib inline
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import matplotlib.colors as colors

from sklearn.preprocessing import StandardScaler, normalize, scale
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.decomposition import PCA
from sklearn.metrics import mean_squared_error, r2_score

print('Libraries imported!')

```

Libraries imported!

1.1 I. Prepare the data:

1.1.1 1. Scrap CityRealty website for neighborhoods average prices:

URL: <https://www.cityrealty.com/nyc/market-insight/features/get-to-know/map-average-nyc-rent-prices-december-2018/26722>

```

In [8]: # Using BeautifulSoup to parse the website's html
data = requests.get('https://www.cityrealty.com/nyc/market-insight/features/get-to-know/
soup = BeautifulSoup(data, 'html.parser')

In [9]: # Scrap the website tables for average prices
areaList = []
neighborhoodList = []

for area in soup.find_all("div", class_="tile _quote _n1 _last"):
    areaText = area.find("a").text
    areaList.append(areaText)

for index, table in enumerate(soup.find_all("table", class_="table table-bordered table-
    for row in table.find_all("tr"):
        cells = row.find_all("td")
        if len(cells) > 0:
            neighborhoodName = cells[0].find("a").text.strip()
            avgPrice = cells[3].text.lstrip("$").strip()
            if "K" in avgPrice:
                avgPrice = float(avgPrice.rstrip("K")) * 1000
            else:
                if "M" in avgPrice:

```

```

        avgPrice = float(avgPrice.rstrip("M")) * 1000000

        neighborhoodList.append((
            areaList[index],
            neighborhoodName,
            avgPrice
        ))

In [10]: # Put the scrapped data into a dataframe
nyc_neighborhoods_df = pd.DataFrame(neighborhoodList)
nyc_neighborhoods_df.columns = ['Area', 'Neighborhood', 'AvgPrice']

In [11]: print(nyc_neighborhoods_df.shape)
nyc_neighborhoods_df.head()

(54, 3)

```

```

Out[11]:
      Area      Neighborhood  AvgPrice
0  Brooklyn  Bedford-Stuyvesant    750000
1  Brooklyn      Boerum Hill  1.69e+06
2  Brooklyn  Brooklyn Heights  2.15e+06
3  Brooklyn      Bushwick    967000
4  Brooklyn  Carroll Gardens  1.51e+06

```

1.1.2 2. Get the neighborhoods coordinate:

Free geodata is available free at: https://geo.nyu.edu/catalog/nyu_2451_34572
A copy has been downloaded and stored in IBM cloud

```

In [12]: # Download the geodata
!wget -q -O 'nyc_geo.json' https://ibm.box.com/shared/static/fbpwbovar7lf8p5sgddm06cgip
print('Data downloaded!')

Data downloaded!

```

```

In [13]: # Load the json file
with open('nyc_geo.json') as nyc_geo_json:
    nyc_geo_data = json.load(nyc_geo_json)

```

```

In [14]: # Get the neighborhoods list
nyc_geo_list = nyc_geo_data['features']

# Sample neighborhood node
nyc_geo_list[0]

```

```

Out[14]: {'type': 'Feature',
          'id': 'nyu_2451_34572.1',

```

```

'geometry': {'type': 'Point',
'coordinates': [-73.84720052054902, 40.89470517661]},
'geometry_name': 'geom',
'properties': {'name': 'Wakefield',
'stacked': 1,
'annoline1': 'Wakefield',
'annoline2': None,
'annoline3': None,
'annoangle': 0.0,
'borough': 'Bronx',
'bbox': [-73.84720052054902,
40.89470517661,
-73.84720052054902,
40.89470517661]}}

```

In [15]: *# Parse the json data into neighborhoods list*

```

neighborhood_geo_list = []
for data in nyc_geo_list:
    borough = neighborhood_name = data['properties']['borough']
    neighborhood_name = data['properties']['name']

    neighborhood_latlon = data['geometry']['coordinates']
    neighborhood_lat = neighborhood_latlon[1]
    neighborhood_lon = neighborhood_latlon[0]

    neighborhood_geo_list.append((
        borough, neighborhood_name, neighborhood_lat, neighborhood_lon
    ))

```

In [16]: *# Put into a dataframe*

```

neighborhood_geo_df = pd.DataFrame(neighborhood_geo_list)
neighborhood_geo_df.columns = ['Borough', 'Neighborhood', 'Latitude', 'Longitude']

# Avg price data is only available for Manhattan and Brooklyn
neighborhood_geo_df = neighborhood_geo_df[(neighborhood_geo_df['Borough'] == 'Manhattan'
| neighborhood_geo_df['Borough'] == 'Brooklyn')]

neighborhood_geo_df.reset_index(drop=True, inplace=True)

```

In [17]: `print(neighborhood_geo_df.shape)`

```
neighborhood_geo_df.head()
```

(110, 4)

```

Out[17]:
   Borough Neighborhood  Latitude  Longitude
0  Manhattan  Marble Hill  40.876551 -73.910660
1  Brooklyn    Bay Ridge  40.625801 -74.030621
2  Brooklyn  Bensonhurst  40.611009 -73.995180
3  Brooklyn  Sunset Park  40.645103 -74.010316
4  Brooklyn   Greenpoint  40.730201 -73.954241

```

1.1.3 3. Combine the two dataframes:

There are three problems here causing the number of neighborhoods doesn't match:

- First, avg price data isn't available to all neighborhoods. - Second, some neighborhoods name scrapped from the website is not same as their corresponding ones in the geo dataset. - Third, real estate market names some neighborhoods differently, or make up of new names. All for the purpose of sale.

Each line of price data will be considered, and suitable action will be performed: - If the names is different, decide which one to use after searching on the internet. - If the neighborhood is missing from the geo dataframe, add it's coordinate. - If the neighborhoods is makeup, combine them into the larger neighborhood which exist in the geo dataframe.

```
In [18]: # Bedford Stuyvesant missing a '-' in the middle
neighborhood_geo_df.at[18, 'Neighborhood'] = 'Bedford-Stuyvesant'

# Downtown is Downtown Brooklyn
neighborhood_geo_df.at[41, 'Neighborhood'] = 'Downtown Brooklyn'

# Dumbo should be DUMBO
neighborhood_geo_df.at[104, 'Neighborhood'] = 'DUMBO'

# Prospect Lefferts Gardens missing a '-' in the middle
nyc_neighborhoods_df.at[15, 'Neighborhood'] = 'Prospect-Lefferts Gardens'
neighborhood_geo_df.at[43, 'Neighborhood'] = 'Prospect-Lefferts Gardens'

# South Slope - Greenwood Heights is just South Slope
nyc_neighborhoods_df.at[17, 'Neighborhood'] = 'South Slope'
# South Slope coordinates is missing
neighborhood_geo_df = neighborhood_geo_df.append({'Borough': 'Brooklyn',
                                                    'Neighborhood': 'South Slope',
                                                    'Latitude': 40.662349,
                                                    'Longitude': -73.990350}, ignore_index=True)

# Park, Fifth Ave to 79th St is Upper East Side
nyc_neighborhoods_df.at[24, 'Neighborhood'] = 'Upper East Side'

# Flatiron/Union Square is just Flatiron
nyc_neighborhoods_df.at[29, 'Neighborhood'] = 'Flatiron District'
neighborhood_geo_df.at[99, 'Neighborhood'] = 'Flatiron District'

# Gramercy Park is just Gramercy
nyc_neighborhoods_df.at[30, 'Neighborhood'] = 'Gramercy'

# NOHO should be just NoHo
nyc_neighborhoods_df.at[33, 'Neighborhood'] = 'NoHo'
neighborhood_geo_df.at[88, 'Neighborhood'] = 'NoHo'

# NoLiTa/Little Italy is just NoLiTa
```

```

nyc_neighborhoods_df.at[34, 'Neighborhood'] = 'NoLiTa'
neighborhood_geo_df.at[76, 'Neighborhood'] = 'NoLiTa'

# SOHO should be just SoHo
nyc_neighborhoods_df.at[35, 'Neighborhood'] = 'SoHo'
neighborhood_geo_df.at[77, 'Neighborhood'] = 'SoHo'

# Stuyvesant Town / PCV is just Stuyvesant Town
nyc_neighborhoods_df.at[36, 'Neighborhood'] = 'Stuyvesant Town'

# Beekman/Sutton Place is just Sutton Place
nyc_neighborhoods_df.at[39, 'Neighborhood'] = 'Sutton Place'

# Midtown East and Midtown West will be combined into Midtown
nyc_neighborhoods_df.at[40, 'Neighborhood'] = 'Midtown'
midtown_avg = (nyc_neighborhoods_df.at[40, 'AvgPrice'] + nyc_neighborhoods_df.at[41, 'AvgPrice']) / 2
nyc_neighborhoods_df.at[40, 'AvgPrice'] = midtown_avg
nyc_neighborhoods_df.at[41, 'AvgPrice'] = '-'

# Turtle Bay/United Nations is just Turtle Bay
nyc_neighborhoods_df.at[43, 'Neighborhood'] = 'Turtle Bay'

# Central Harlem is Harlem
neighborhood_geo_df.at[60, 'Neighborhood'] = 'Harlem'

# Lincoln Center is Lincoln Square
nyc_neighborhoods_df.at[51, 'Neighborhood'] = 'Lincoln Square'

# Broadway Corridor, Central Park West and Riverside Dr./West End Ave. will be combined
nyc_neighborhoods_df.at[49, 'Neighborhood'] = 'Upper West Side'
midtown_avg = (nyc_neighborhoods_df.at[49, 'AvgPrice'] + nyc_neighborhoods_df.at[50, 'AvgPrice']) / 2
nyc_neighborhoods_df.at[49, 'AvgPrice'] = midtown_avg
nyc_neighborhoods_df.at[50, 'AvgPrice'] = '-'
nyc_neighborhoods_df.at[53, 'AvgPrice'] = '-'

# Drop the Red Hook row
nyc_neighborhoods_df.drop([16], inplace=True)

```

```

In [19]: # Inner join the two dataframes by Neighborhoods
nyc_neighborhood_price_df = pd.concat([nyc_neighborhoods_df.set_index('Neighborhood'),
neighborhood_geo_df.set_index('Neighborhood')], join='inner')
nyc_neighborhood_price_df.drop(columns=['Area', 'Borough'], inplace=True)
nyc_neighborhood_price_df.reset_index(inplace=True)

```

```

In [20]: # The joined dataframe
print(nyc_neighborhood_price_df.shape)
nyc_neighborhood_price_df.head()

```

```

(50, 4)

```

```
Out[20]:
```

	Neighborhood	AvgPrice	Latitude	Longitude
0	Bedford-Stuyvesant	750000	40.687232	-73.941785
1	Boerum Hill	1.69e+06	40.685683	-73.983748
2	Brooklyn Heights	2.15e+06	40.695864	-73.993782
3	Bushwick	967000	40.698116	-73.925258
4	Carroll Gardens	1.51e+06	40.680540	-73.994654

1.1.4 4. Visualize the data onto a map

```
In [21]: # for choropleth map, we need another geo data which contain the Polygon type Coordinates
!wget -q -O 'nyc_geo.geojson' http://data.beta.nyc//dataset/0ff93d2d-90ba-457c-9f7e-39e
print('Data downloaded!')
```

```
nyc_polygon_geo_data = r'nyc_geo.geojson'
latitude = 40.8021285
longitude = -73.9777254
```

Data downloaded!

```
In [22]: # Map without markers

# create a plain world map
nyc_map = folium.Map(location=[latitude, longitude], zoom_start=11)

# generate choropleth map
nyc_map.choropleth(
    geo_data=nyc_polygon_geo_data,
    data=nyc_neighborhood_price_df,
    columns=['Neighborhood', 'AvgPrice'],
    key_on='feature.properties.neighborhood',
    fill_color='YlOrRd',
    fill_opacity=0.7,
    line_opacity=0.2,
    legend_name='Average 2 bedrooms condo price in New York city'
)

# display map
nyc_map
```

```
Out[22]: <folium.folium.Map at 0x7f64bcd90320>
```

```
In [23]: # Map with markers

# create a plain world map
nyc_map = folium.Map(location=[latitude, longitude], zoom_start=11)

# generate choropleth map
nyc_map.choropleth(
```

```

        geo_data=nyc_polygon_geo_data,
        data=nyc_neighborhood_price_df,
        columns=['Neighborhood', 'AvgPrice'],
        key_on='feature.properties.neighborhood',
        fill_color='YlOrRd',
        fill_opacity=0.7,
        line_opacity=0.2,
        legend_name='Average 2 bedrooms condo price in New York city'
    )

    # add markers to map
    for lat, lng, neighborhood, price in zip(nyc_neighborhood_price_df['Latitude'], nyc_neighborhood_price_df['Longitude'], nyc_neighborhood_price_df['Neighborhood'], nyc_neighborhood_price_df['AvgPrice']):
        label = '{}, ${:3.0f}'.format(neighborhood, price)
        label = folium.Popup(label, parse_html=True)
        folium.CircleMarker(
            [lat, lng],
            radius=5,
            popup=label,
            color='blue',
            fill=True,
            fill_color='#3186cc',
            fill_opacity=0.7,
            parse_html=False).add_to(nyc_map)

    # display map
    nyc_map

```

Out[23]: <folium.folium.Map at 0x7f64bcb78d30>

1.1.5 5. Using FourSquare API to get surrounding venues:

```

In [24]: CLIENT_ID = 'XVEFCDBVHOQ1YTWQA54LAJ3Q515Y14CMKWEJHILHG3KP4104' # your Foursquare ID hidden in the browser's console
        CLIENT_SECRET = '2C52CNR5VN5LFGMQDHPHYNNCO3VCQCYXDMGH3RDO4Y1PNHY' # your Foursquare Secret key hidden in the browser's console
        VERSION = '20180605' # Foursquare API version

In [26]: # FourSquare parameters
        radius = 1000 # 1 km around the neighborhood center
        limit = 200

        venues = []

        for lat, long, neighborhood in zip(nyc_neighborhood_price_df['Latitude'], nyc_neighborhood_price_df['Longitude'], nyc_neighborhood_price_df['Neighborhood']):
            url = "https://api.foursquare.com/v2/venues/explore?client_id={}&client_secret={}&v={}&lat={}&lng={}&radius={}&limit={}&neighborhood={}"
            CLIENT_ID,
            CLIENT_SECRET,
            VERSION,
            lat,
            long,

```



```

        radius,
        limit)

results = requests.get(url).json()["response"]["groups"][0]["items"]

for venue in results:
    venues.append((
        neighborhood,
        lat,
        long,
        venue['venue']['name'],
        venue['venue']['location']['lat'],
        venue['venue']['location']['lng'],
        venue['venue']['categories'][0]['name']))

In [21]: # put the venues into a dataframe
venues_df = pd.DataFrame(venues)
venues_df.columns = ['Neighborhood', 'Latitude', 'Longitude', 'VenueName', 'VenueLatitude', 'VenueLongitude', 'VenueType']

# check the dataframe
print(venues_df.shape)
print('There are {} unique venue types.'.format(len(venues_df['VenueType'].unique())))
venues_df.head()

```

(4999, 7)

There are 327 unique venue types.

```

Out[21]:
   Neighborhood  Latitude  Longitude  VenueName \
0  Bedford-Stuyvesant  40.687232 -73.941785  Sincerely Tommy
1  Bedford-Stuyvesant  40.687232 -73.941785  Bed-Vyne Brew
2  Bedford-Stuyvesant  40.687232 -73.941785  Bed-Vyne Wine & Spirits
3  Bedford-Stuyvesant  40.687232 -73.941785  Anchor Coffee
4  Bedford-Stuyvesant  40.687232 -73.941785  Peaches HotHouse

   VenueLatitude  VenueLongitude  VenueType
0      40.686066      -73.944294  Boutique
1      40.684751      -73.944319  Bar
2      40.684668      -73.944363  Wine Shop
3      40.684145      -73.941015  Coffee Shop
4      40.683331      -73.943853  Fried Chicken Joint

```

```

In [22]: # one hot encoding
venues_type_onehot = pd.get_dummies(venues_df[['VenueType']], prefix="", prefix_sep="")

# add the neighborhood column

```

```

venues_type_onehot['Neighborhood'] = venues_df['Neighborhood']
fix_columns = list(venues_type_onehot.columns[-1:]) + list(venues_type_onehot.columns[:
venues_type_onehot = venues_type_onehot[fix_columns]

print(venues_type_onehot.shape)
venues_type_onehot.head()

```

(4999, 328)

```

Out[22]:
      Neighborhood  Accessories Store  Adult Boutique  African Restaurant \
0  Bedford-Stuyvesant                0                0                0
1  Bedford-Stuyvesant                0                0                0
2  Bedford-Stuyvesant                0                0                0
3  Bedford-Stuyvesant                0                0                0
4  Bedford-Stuyvesant                0                0                0

      American Restaurant  Animal Shelter  Antique Shop  Arcade \
0                        0                0                0      0
1                        0                0                0      0
2                        0                0                0      0
3                        0                0                0      0
4                        0                0                0      0

      Arepa Restaurant  Argentinian Restaurant  Art Gallery  Art Museum \
0                    0                        0                0          0
1                    0                        0                0          0
2                    0                        0                0          0
3                    0                        0                0          0
4                    0                        0                0          0

      Arts & Crafts Store  Asian Restaurant  Athletics & Sports  Auditorium \
0                        0                0                        0          0
1                        0                0                        0          0
2                        0                0                        0          0
3                        0                0                        0          0
4                        0                0                        0          0

      Australian Restaurant  Austrian Restaurant  BBQ Joint  Bagel Shop  Bakery \
0                        0                        0                0          0
1                        0                        0                0          0
2                        0                        0                0          0
3                        0                        0                0          0
4                        0                        0                0          0

      Bank  Bar  Baseball Field  Basketball Court  Basketball Stadium  Beach \
0      0    0                0                0                0      0
1      0    1                0                0                0      0

```

2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0

	Beer Bar	Beer Garden	Beer Store	Bike Trail	Bistro	Board Shop \
0	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0

	Boat or Ferry	Bookstore	Botanical Garden	Boutique	Boxing Gym \
0	0	0	0	1	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Brazilian Restaurant	Breakfast Spot	Brewery	Bridal Shop	Bridge \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Bubble Tea Shop	Buffet	Building	Burger Joint	Burrito Place	Butcher \
0	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0

	Cafeteria	Café	Cajun / Creole Restaurant	Cambodian Restaurant \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Candy Store	Caribbean Restaurant	Cemetery	Cheese Shop \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Chinese Restaurant	Chocolate Shop	Christmas Market	Church	Climbing Gym \
0	0	0	0	0	0

1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Clothing Store	Club House	Cocktail Bar	Coffee Shop	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	1	
4	0	0	0	0	

	College Academic Building	College Theater	Colombian Restaurant	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Comedy Club	Comfort Food Restaurant	Comic Shop	Community Center	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Concert Hall	Convenience Store	Cosmetics Shop	Coworking Space	Creperie	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Cuban Restaurant	Cupcake Shop	Cycle Studio	Czech Restaurant	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Dance Studio	Daycare	Deli / Bodega	Department Store	Design Studio	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Dessert Shop	Diner	Discount Store	Dive Bar	Dog Run	Donut Shop	\
--	--------------	-------	----------------	----------	---------	------------	---

0	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0

	Drugstore	Dumpling Restaurant	Eastern European Restaurant	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Electronics Store	Empanada Restaurant	English Restaurant	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Ethiopian Restaurant	Event Space	Exhibit	Factory	Falafel Restaurant	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Farm	Farmers Market	Fast Food Restaurant	Field	Filipino Restaurant	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Film Studio	Fish & Chips Shop	Fish Market	Flea Market	Flower Shop	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Food	Food & Drink Shop	Food Court	Food Truck	Fountain	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	French Restaurant	Fried Chicken Joint	Frozen Yogurt Shop	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	1	0	

	Fruit & Vegetable Store	Furniture / Home Store	Gaming Cafe	Garden	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Garden Center	Gas Station	Gastropub	Gay Bar	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	General College & University	General Entertainment	German Restaurant	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Gift Shop	Golf Driving Range	Gourmet Shop	Greek Restaurant	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Grocery Store	Gym	Gym / Fitness Center	Gymnastics Gym	Halal Restaurant	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Harbor / Marina	Hawaiian Restaurant	Health & Beauty Service	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Health Food Store	High School	Historic Site	History Museum	Hobby Shop \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Hookah Bar	Hot Dog Joint	Hotel	Hotel Bar	Ice Cream Shop \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Indian Restaurant	Indie Movie Theater	Indie Theater	Indoor Play Area \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Israeli Restaurant	Italian Restaurant	Japanese Curry Restaurant \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	Japanese Restaurant	Jazz Club	Jewelry Store	Jewish Restaurant \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Juice Bar	Karaoke Bar	Kids Store	Kitchen Supply Store \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Korean Restaurant	Kosher Restaurant	Lake	Laser Tag \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0

4	0	0	0	0
---	---	---	---	---

	Latin American Restaurant	Laundry Service	Lebanese Restaurant	Library	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Lighthouse	Lingerie Store	Liquor Store	Locksmith	Lounge	Market	\
0	0	0	0	0	0	0	
1	0	0	0	0	0	0	
2	0	0	0	0	0	0	
3	0	0	0	0	0	0	
4	0	0	0	0	0	0	

	Martial Arts Dojo	Massage Studio	Medical Center	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Mediterranean Restaurant	Memorial Site	Men's Store	Mexican Restaurant	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Middle Eastern Restaurant	Mini Golf	Miscellaneous Shop	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Mobile Phone Shop	Modern European Restaurant	\
0	0	0	
1	0	0	
2	0	0	
3	0	0	
4	0	0	

	Molecular Gastronomy Restaurant	Monument / Landmark	Moroccan Restaurant	\
0	0	0	0	
1	0	0	0	
2	0	0	0	

3		0		0		0
4		0		0		0

	Motorcycle Shop	Movie Theater	Museum	Music Store	Music Venue	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Nail Salon	New American Restaurant	Nightclub	Noodle House	Office	\
0	0		0	0	0	
1	0		0	0	0	
2	0		0	0	0	
3	0		0	0	0	
4	0		0	0	0	

	Opera House	Optical Shop	Organic Grocery	Other Great Outdoors	\
0	0	0	0		0
1	0	0	0		0
2	0	0	0		0
3	0	0	0		0
4	0	0	0		0

	Other Nightlife	Other Repair Shop	Outdoor Sculpture	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Outdoors & Recreation	Paella Restaurant	Pakistani Restaurant	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Paper / Office Supplies Store	Park	Performing Arts Venue	Perfume Shop	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Persian Restaurant	Peruvian Restaurant	Pet Café	Pet Service	Pet Store	\
0	0	0	0	0	0	
1	0	0	0	0	0	

2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Pharmacy	Piano Bar	Pie Shop	Pier	Pilates Studio	Pizza Place	\
0	0	0	0	0	0	0	
1	0	0	0	0	0	0	
2	0	0	0	0	0	0	
3	0	0	0	0	0	0	
4	0	0	0	0	0	0	

	Playground	Plaza	Polish Restaurant	Pool	Print Shop	Pub	Public Art	\
0	0	0		0	0	0	0	
1	0	0		0	0	0	0	
2	0	0		0	0	0	0	
3	0	0		0	0	0	0	
4	0	0		0	0	0	0	

	Ramen Restaurant	Record Shop	Recreation Center	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Residential Building (Apartment / Condo)	Resort	Rest Area	Restaurant	\
0		0	0	0	0
1		0	0	0	0
2		0	0	0	0
3		0	0	0	0
4		0	0	0	0

	Rock Club	Roof Deck	Russian Restaurant	Sake Bar	Salad Place	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Salon / Barbershop	Sandwich Place	Scenic Lookout	School	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Sculpture Garden	Seafood Restaurant	Shabu-Shabu Restaurant	\
0	0	0	0	

1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	Shipping Store	Shoe Store	Shopping Mall	Skating Rink	Smoke Shop \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Snack Place	Soba Restaurant	Soccer Field	Social Club	Soup Place \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	South American Restaurant	Southern / Soul Food Restaurant	Spa \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	Spanish Restaurant	Speakeasy	Sporting Goods Shop	Sports Bar \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Sports Club	State / Provincial Park	Steakhouse	Street Art \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Street Food Gathering	Strip Club	Supermarket	Supplement Shop \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Sushi Restaurant	Swiss Restaurant	Synagogue	Szechuan Restaurant \
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0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	TV Station	Taco Place	Tailor Shop	Taiwanese Restaurant	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Tapas Restaurant	Tattoo Parlor	Tea Room	Tech Startup	Tennis Court	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Thai Restaurant	Theater	Theme Park Ride / Attraction	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Thrift / Vintage Store	Tiki Bar	Tourist Information Center	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Toy / Game Store	Track	Trail	Train Station	Tram Station	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Turkish Restaurant	Udon Restaurant	Ukrainian Restaurant	Used Bookstore	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Vape Store	Vegetarian / Vegan Restaurant	Venezuelan Restaurant	\
0	0		0	0
1	0		0	0
2	0		0	0
3	0		0	0
4	0		0	0

	Veterinarian	Video Game Store	Video Store	Vietnamese Restaurant	\
0	0	0	0		0
1	0	0	0		0
2	0	0	0		0
3	0	0	0		0
4	0	0	0		0

	Volleyball Court	Waterfront	Whisky Bar	Wine Bar	Wine Shop	Wings Joint	\
0	0	0	0	0	0		0
1	0	0	0	0	0		0
2	0	0	0	0	1		0
3	0	0	0	0	0		0
4	0	0	0	0	0		0

	Women's Store	Yoga Studio
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0

```
In [23]: # get the occurrence of each venue type in each neighborhood
venue_count_df = venues_type_onehot.groupby(['Neighborhood']).sum().reset_index()

print(venue_count_df.shape)
venue_count_df.head()
```

(50, 328)

```
Out[23]:
```

	Neighborhood	Accessories Store	Adult Boutique	African Restaurant	\
0	Battery Park City	0	0		0
1	Bedford-Stuyvesant	0	0		0
2	Boerum Hill	0	0		0
3	Brooklyn Heights	0	0		0
4	Bushwick	0	0		0

	American Restaurant	Animal Shelter	Antique Shop	Arcade	\
0	3	0	0	0	
1	0	0	0	0	
2	1	0	0	0	

3	2	0	0	0
4	1	0	0	0

	Arepa Restaurant	Argentinian Restaurant	Art Gallery	Art Museum	\
0	0	0	0	0	
1	0	0	1	0	
2	0	0	1	0	
3	0	0	0	0	
4	1	0	1	0	

	Arts & Crafts Store	Asian Restaurant	Athletics & Sports	Auditorium	\
0	0	0	1	1	
1	0	0	0	0	
2	2	0	2	0	
3	0	1	1	0	
4	0	1	0	0	

	Australian Restaurant	Austrian Restaurant	BBQ Joint	Bagel Shop	Bakery	\
0	0	0	2	1	1	
1	0	0	1	1	1	
2	0	0	0	1	3	
3	0	0	0	2	2	
4	0	0	0	2	2	

	Bank	Bar	Baseball Field	Basketball Court	Basketball Stadium	Beach	\
0	0	0	0	0	0	0	
1	0	6	0	0	0	0	
2	0	6	0	0	1	0	
3	0	3	0	0	0	1	
4	0	17	0	0	0	0	

	Beer Bar	Beer Garden	Beer Store	Bike Trail	Bistro	Board Shop	\
0	0	0	0	0	0	0	
1	0	0	0	0	0	0	
2	0	0	0	0	0	1	
3	0	0	0	0	0	0	
4	0	0	0	0	0	0	

	Boat or Ferry	Bookstore	Botanical Garden	Boutique	Boxing Gym	\
0	0	2	0	0	1	
1	0	0	0	1	0	
2	0	2	0	1	0	
3	0	0	0	0	1	
4	0	1	0	0	0	

	Brazilian Restaurant	Breakfast Spot	Brewery	Bridal Shop	Bridge	\
0	0	0	0	0	0	
1	0	0	0	0	0	

2	0	0	1	0	0
3	0	0	0	0	0
4	0	0	1	0	0

	Bubble Tea Shop	Buffet	Building	Burger Joint	Burrito Place	Butcher \
0	0	0	1	2	1	0
1	0	0	0	0	0	0
2	0	0	0	3	1	0
3	0	0	0	2	0	0
4	0	0	0	0	0	0

	Cafeteria	Café	Cajun / Creole Restaurant	Cambodian Restaurant \
0	0	1	0	0
1	0	6	0	0
2	0	0	0	0
3	0	2	0	0
4	0	3	0	0

	Candy Store	Caribbean Restaurant	Cemetery	Cheese Shop \
0	0	0	0	0
1	0	4	0	0
2	0	0	0	1
3	0	0	0	0
4	0	0	0	0

	Chinese Restaurant	Chocolate Shop	Christmas Market	Church	Climbing Gym \
0	0	0	0	0	0
1	4	0	0	0	0
2	2	1	0	0	1
3	0	0	0	0	0
4	0	0	0	0	0

	Clothing Store	Club House	Cocktail Bar	Coffee Shop \
0	0	0	0	8
1	0	0	2	11
2	0	0	3	7
3	0	0	2	4
4	0	0	4	6

	College Academic Building	College Theater	Colombian Restaurant \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	Comedy Club	Comfort Food Restaurant	Comic Shop	Community Center \
0	0	0	0	0

1	0	1	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Concert Hall	Convenience Store	Cosmetics Shop	Coworking Space	Creperie \
0	0	0	0	0	0
1	0	1	0	0	0
2	1	0	1	0	0
3	0	0	2	0	0
4	0	0	0	0	0

	Cuban Restaurant	Cupcake Shop	Cycle Studio	Czech Restaurant \
0	0	1	1	0
1	0	0	0	0
2	0	0	0	0
3	0	0	1	0
4	0	0	0	0

	Dance Studio	Daycare	Deli / Bodega	Department Store	Design Studio \
0	0	0	0	1	0
1	0	0	4	0	0
2	3	0	0	2	0
3	0	0	1	0	0
4	0	0	3	0	0

	Dessert Shop	Diner	Discount Store	Dive Bar	Dog Run	Donut Shop \
0	0	0	0	0	2	0
1	0	1	1	0	1	0
2	0	1	0	0	0	0
3	0	1	0	0	2	0
4	0	0	0	3	1	0

	Drugstore	Dumpling Restaurant	Eastern European Restaurant \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	Electronics Store	Empanada Restaurant	English Restaurant \
0	1	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	Ethiopian Restaurant	Event Space	Exhibit	Factory	Falafel Restaurant \
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0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	1
4	0	0	0	0	0

	Farm	Farmers Market	Fast Food Restaurant	Field	Filipino Restaurant	\
0	0	0	0	0	0	
1	0	0	0	0	1	
2	0	0	0	0	0	
3	0	1	0	0	0	
4	0	0	0	0	0	

	Film Studio	Fish & Chips Shop	Fish Market	Flea Market	Flower Shop	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	2	
3	0	1	0	0	0	
4	0	0	0	0	0	

	Food	Food & Drink Shop	Food Court	Food Truck	Fountain	\
0	0	0	1	2	2	
1	1	0	0	1	0	
2	0	0	1	0	0	
3	0	0	0	1	0	
4	0	0	0	1	0	

	French Restaurant	Fried Chicken Joint	Frozen Yogurt Shop	\
0	0	0	0	
1	1	2	0	
2	2	0	0	
3	1	0	0	
4	2	0	0	

	Fruit & Vegetable Store	Furniture / Home Store	Gaming Cafe	Garden	\
0	0	1	0	0	
1	0	0	0	1	
2	0	1	0	0	
3	0	0	0	1	
4	0	0	0	0	

	Garden Center	Gas Station	Gastropub	Gay Bar	\
0	0	0	0	0	
1	1	0	0	0	
2	0	0	0	0	
3	0	0	1	0	
4	0	0	1	0	

	General College & University	General Entertainment	German Restaurant	\
0	0	0	0	
1	0	0	0	
2	0	0	1	
3	0	0	0	
4	0	0	0	

	Gift Shop	Golf Driving Range	Gourmet Shop	Greek Restaurant	\
0	1	0	0	0	
1	1	0	1	0	
2	2	0	0	0	
3	0	0	1	0	
4	0	0	2	0	

	Grocery Store	Gym	Gym / Fitness Center	Gymnastics Gym	Halal Restaurant	\
0	1	3	2	0	0	
1	1	1	0	0	0	
2	2	2	1	0	0	
3	3	2	1	0	0	
4	2	1	0	0	0	

	Harbor / Marina	Hawaiian Restaurant	Health & Beauty Service	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Health Food Store	High School	Historic Site	History Museum	Hobby Shop	\
0	0	0	0	0	0	
1	0	0	1	0	0	
2	0	0	0	1	0	
3	0	0	0	2	0	
4	0	0	0	0	0	

	Hookah Bar	Hot Dog Joint	Hotel	Hotel Bar	Ice Cream Shop	\
0	0	0	3	0	2	
1	0	0	0	0	0	
2	0	0	0	0	2	
3	0	0	2	0	2	
4	0	0	0	0	0	

	Indian Restaurant	Indie Movie Theater	Indie Theater	Indoor Play Area	\
0	0	0	0	0	
1	0	0	0	0	
2	0	1	0	1	
3	0	0	1	0	
4	0	0	0	0	

	Israeli Restaurant	Italian Restaurant	Japanese Curry Restaurant	\
0	0		1	0
1	0		0	0
2	0		1	0
3	0		5	0
4	0		3	0

	Japanese Restaurant	Jazz Club	Jewelry Store	Jewish Restaurant	\
0	1	0		1	0
1	1	0		0	0
2	2	0		0	0
3	2	0		0	0
4	1	0		0	0

	Juice Bar	Karaoke Bar	Kids Store	Kitchen Supply Store	\
0	1	0	2		0
1	3	0	0		0
2	0	0	0		0
3	0	0	0		0
4	1	0	0		0

	Korean Restaurant	Kosher Restaurant	Lake	Laser Tag	\
0	1		0	0	0
1	0		0	0	0
2	0		0	0	0
3	0		0	0	0
4	0		0	0	0

	Latin American Restaurant	Laundry Service	Lebanese Restaurant	Library	\
0		0		0	0
1		1		0	0
2		0		0	0
3		0		0	0
4		3		0	0

	Lighthouse	Lingerie Store	Liquor Store	Locksmith	Lounge	Market	\
0	0	1		0	0	2	
1	0	0		0	1	0	
2	0	0		0	0	1	
3	0	0		0	0	0	
4	0	0		0	0	0	

	Martial Arts Dojo	Massage Studio	Medical Center	\
0	0	0		0
1	0	0		0
2	1	0		0
3	0	0		1

4	0	0	0
---	---	---	---

	Mediterranean Restaurant	Memorial Site	Men's Store	Mexican Restaurant \
0	0	1	0	2
1	0	0	0	2
2	0	0	1	0
3	0	0	1	1
4	0	0	0	8

	Middle Eastern Restaurant	Mini Golf	Miscellaneous Shop \
0	0	0	0
1	0	0	0
2	1	0	0
3	1	0	0
4	1	0	0

	Mobile Phone Shop	Modern European Restaurant \
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0

	Molecular Gastronomy Restaurant	Monument / Landmark	Moroccan Restaurant \
0	0	1	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	Motorcycle Shop	Movie Theater	Museum	Music Store	Music Venue \
0	0	1	1	0	0
1	0	0	0	0	0
2	0	1	0	0	0
3	0	0	0	0	0
4	0	0	0	0	2

	Nail Salon	New American Restaurant	Nightclub	Noodle House	Office \
0	0	0	0	0	0
1	0	1	1	0	0
2	0	0	0	0	0
3	0	2	0	0	0
4	1	0	0	0	0

	Opera House	Optical Shop	Organic Grocery	Other Great Outdoors \
0	0	0	0	0
1	0	0	0	0
2	2	1	0	0

3	0	1	0	0
4	0	0	0	0

	Other Nightlife	Other Repair Shop	Outdoor Sculpture	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Outdoors & Recreation	Paella Restaurant	Pakistani Restaurant	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	1	

	Paper / Office Supplies Store	Park	Performing Arts Venue	Perfume Shop	\
0	0	7	2	0	
1	0	1	0	0	
2	0	0	2	0	
3	0	11	0	0	
4	0	1	0	0	

	Persian Restaurant	Peruvian Restaurant	Pet Café	Pet Service	Pet Store	\
0	0	0	0	0	1	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	1	1	
4	0	0	0	0	1	

	Pharmacy	Piano Bar	Pie Shop	Pier	Pilates Studio	Pizza Place	\
0	0	0	0	0	0	1	
1	0	0	0	0	0	5	
2	0	0	0	0	0	1	
3	0	0	0	1	0	4	
4	0	0	0	0	0	6	

	Playground	Plaza	Polish Restaurant	Pool	Print Shop	Pub	Public Art	\
0	1	3	0	0	0	1	1	
1	2	1	0	1	0	0	0	
2	0	0	0	0	0	0	0	
3	1	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	

	Ramen Restaurant	Record Shop	Recreation Center	\
0	0	0	0	
1	1	0	0	

2	0	0	0
3	0	0	0
4	0	1	0

	Residential Building (Apartment / Condo)	Resort	Rest Area	Restaurant \
0	0	0	0	0
1	0	0	0	1
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Rock Club	Roof Deck	Russian Restaurant	Sake Bar	Salad Place \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	1

	Salon / Barbershop	Sandwich Place	Scenic Lookout	School \
0	0	2	2	0
1	0	1	0	0
2	0	2	0	0
3	0	0	1	0
4	0	2	0	0

	Sculpture Garden	Seafood Restaurant	Shabu-Shabu Restaurant \
0	0	0	0
1	0	1	0
2	0	1	0
3	0	0	0
4	0	0	0

	Shipping Store	Shoe Store	Shopping Mall	Skating Rink	Smoke Shop \
0	0	0	2	0	1
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Snack Place	Soba Restaurant	Soccer Field	Social Club	Soup Place \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	1	0	0
4	0	0	0	0	0

	South American Restaurant	Southern / Soul Food Restaurant	Spa \
0	0	0	0

1		0		1	0
2		0		0	1
3		0		0	1
4		0		0	0

	Spanish Restaurant	Speakeasy	Sporting Goods Shop	Sports Bar	\
0	0	0	1	0	
1	0	1	0	1	
2	0	0	1	0	
3	0	0	0	0	
4	0	1	0	0	

	Sports Club	State / Provincial Park	Steakhouse	Street Art	\
0	0	0	2	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Street Food Gathering	Strip Club	Supermarket	Supplement Shop	\
0	0	1	0	0	
1	0	0	1	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Sushi Restaurant	Swiss Restaurant	Synagogue	Szechuan Restaurant	\
0	0	0	0	0	
1	0	0	0	0	
2	2	0	0	0	
3	1	0	0	0	
4	1	0	0	0	

	TV Station	Taco Place	Tailor Shop	Taiwanese Restaurant	\
0	0	0	0	0	
1	0	2	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	1	0	0	

	Tapas Restaurant	Tattoo Parlor	Tea Room	Tech Startup	Tennis Court	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	1	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

Thai Restaurant Theater Theme Park Ride / Attraction \

0	0	0	0
1	0	0	0
2	0	2	0
3	1	0	0
4	0	1	0

	Thrift / Vintage Store	Tiki Bar	Tourist Information Center	\
0	0	0	0	
1	2	0	0	
2	0	0	0	
3	0	0	0	
4	2	0	0	

	Toy / Game Store	Track	Trail	Train Station	Tram Station	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Turkish Restaurant	Udon Restaurant	Ukrainian Restaurant	Used Bookstore	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	1	

	Vape Store	Vegetarian / Vegan Restaurant	Venezuelan Restaurant	\
0	0	1	0	
1	0	0	0	
2	0	2	0	
3	0	0	0	
4	1	0	0	

	Veterinarian	Video Game Store	Video Store	Vietnamese Restaurant	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	2	
3	0	0	0	1	
4	0	0	0	0	

	Volleyball Court	Waterfront	Whisky Bar	Wine Bar	Wine Shop	Wings Joint	\
0	0	0	0	1	4	0	
1	0	0	0	1	6	0	
2	0	0	0	0	2	0	
3	0	0	0	1	4	0	
4	0	0	0	0	1	0	

	Women's Store	Yoga Studio
0	1	0
1	0	1
2	0	2
3	0	5
4	0	2

```
In [24]: # get the standardized neighborhoods' average prices
scaler = StandardScaler()
standardized_price = scaler.fit_transform(nyc_neighborhood_price_df[['AvgPrice']])

# add the normalized price to the dataframe
neighborhood_venues_withprice_df = pd.DataFrame(venue_count_df)
neighborhood_venues_withprice_df['StandardizedAvgPrice'] = standardized_price

print(neighborhood_venues_withprice_df.shape)
neighborhood_venues_withprice_df.head()
```

(50, 329)

```
Out[24]:
```

	Neighborhood	Accessories Store	Adult Boutique	African Restaurant	\
0	Battery Park City	0	0	0	
1	Bedford-Stuyvesant	0	0	0	
2	Boerum Hill	0	0	0	
3	Brooklyn Heights	0	0	0	
4	Bushwick	0	0	0	

	American Restaurant	Animal Shelter	Antique Shop	Arcade	\
0	3	0	0	0	
1	0	0	0	0	
2	1	0	0	0	
3	2	0	0	0	
4	1	0	0	0	

	Arepa Restaurant	Argentinian Restaurant	Art Gallery	Art Museum	\
0	0	0	0	0	
1	0	0	1	0	
2	0	0	1	0	
3	0	0	0	0	
4	1	0	1	0	

	Arts & Crafts Store	Asian Restaurant	Athletics & Sports	Auditorium	\
0	0	0	1	1	
1	0	0	0	0	
2	2	0	2	0	
3	0	1	1	0	
4	0	1	0	0	

	Australian Restaurant	Austrian Restaurant	BBQ Joint	Bagel Shop	Bakery	\
0	0	0	2	1	1	
1	0	0	1	1	1	
2	0	0	0	1	3	
3	0	0	0	2	2	
4	0	0	0	2	2	

	Bank	Bar	Baseball Field	Basketball Court	Basketball Stadium	Beach	\
0	0	0	0	0	0	0	
1	0	6	0	0	0	0	
2	0	6	0	0	1	0	
3	0	3	0	0	0	1	
4	0	17	0	0	0	0	

	Beer Bar	Beer Garden	Beer Store	Bike Trail	Bistro	Board Shop	\
0	0	0	0	0	0	0	
1	0	0	0	0	0	0	
2	0	0	0	0	0	1	
3	0	0	0	0	0	0	
4	0	0	0	0	0	0	

	Boat or Ferry	Bookstore	Botanical Garden	Boutique	Boxing Gym	\
0	0	2	0	0	1	
1	0	0	0	1	0	
2	0	2	0	1	0	
3	0	0	0	0	1	
4	0	1	0	0	0	

	Brazilian Restaurant	Breakfast Spot	Brewery	Bridal Shop	Bridge	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	1	0	0	
3	0	0	0	0	0	
4	0	0	1	0	0	

	Bubble Tea Shop	Buffet	Building	Burger Joint	Burrito Place	Butcher	\
0	0	0	1	2	1	0	
1	0	0	0	0	0	0	
2	0	0	0	3	1	0	
3	0	0	0	2	0	0	
4	0	0	0	0	0	0	

	Cafeteria	Café	Cajun / Creole Restaurant	Cambodian Restaurant	\
0	0	1	0	0	
1	0	6	0	0	
2	0	0	0	0	
3	0	2	0	0	

4	0	3	0	0
---	---	---	---	---

	Candy Store	Caribbean Restaurant	Cemetery	Cheese Shop	\
0	0	0	0	0	
1	0	4	0	0	
2	0	0	0	1	
3	0	0	0	0	
4	0	0	0	0	

	Chinese Restaurant	Chocolate Shop	Christmas Market	Church	Climbing Gym	\
0	0	0	0	0	0	
1	4	0	0	0	0	
2	2	1	0	0	1	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Clothing Store	Club House	Cocktail Bar	Coffee Shop	\
0	0	0	0	8	
1	0	0	2	11	
2	0	0	3	7	
3	0	0	2	4	
4	0	0	4	6	

	College Academic Building	College Theater	Colombian Restaurant	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Comedy Club	Comfort Food Restaurant	Comic Shop	Community Center	\
0	0	0	0	0	
1	0	1	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Concert Hall	Convenience Store	Cosmetics Shop	Coworking Space	Creperie	\
0	0	0	0	0	0	
1	0	1	0	0	0	
2	1	0	1	0	0	
3	0	0	2	0	0	
4	0	0	0	0	0	

	Cuban Restaurant	Cupcake Shop	Cycle Studio	Czech Restaurant	\
0	0	1	1	0	
1	0	0	0	0	
2	0	0	0	0	

3	0	0	1	0
4	0	0	0	0

	Dance Studio	Daycare	Deli / Bodega	Department Store	Design Studio \
0	0	0	0	1	0
1	0	0	4	0	0
2	3	0	0	2	0
3	0	0	1	0	0
4	0	0	3	0	0

	Dessert Shop	Diner	Discount Store	Dive Bar	Dog Run	Donut Shop \
0	0	0	0	0	2	0
1	0	1	1	0	1	0
2	0	1	0	0	0	0
3	0	1	0	0	2	0
4	0	0	0	3	1	0

	Drugstore	Dumpling Restaurant	Eastern European Restaurant \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	Electronics Store	Empanada Restaurant	English Restaurant \
0	1	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	Ethiopian Restaurant	Event Space	Exhibit	Factory	Falafel Restaurant \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	1
4	0	0	0	0	0

	Farm	Farmers Market	Fast Food Restaurant	Field	Filipino Restaurant \
0	0	0	0	0	0
1	0	0	0	0	1
2	0	0	0	0	0
3	0	1	0	0	0
4	0	0	0	0	0

	Film Studio	Fish & Chips Shop	Fish Market	Flea Market	Flower Shop \
0	0	0	0	0	0
1	0	0	0	0	0

2	0	0	0	0	2
3	0	1	0	0	0
4	0	0	0	0	0

	Food	Food & Drink Shop	Food Court	Food Truck	Fountain \
0	0	0	1	2	2
1	1	0	0	1	0
2	0	0	1	0	0
3	0	0	0	1	0
4	0	0	0	1	0

	French Restaurant	Fried Chicken Joint	Frozen Yogurt Shop \
0	0	0	0
1	1	2	0
2	2	0	0
3	1	0	0
4	2	0	0

	Fruit & Vegetable Store	Furniture / Home Store	Gaming Cafe	Garden \
0	0	1	0	0
1	0	0	0	1
2	0	1	0	0
3	0	0	0	1
4	0	0	0	0

	Garden Center	Gas Station	Gastropub	Gay Bar \
0	0	0	0	0
1	1	0	0	0
2	0	0	0	0
3	0	0	1	0
4	0	0	1	0

	General College & University	General Entertainment	German Restaurant \
0	0	0	0
1	0	0	0
2	0	0	1
3	0	0	0
4	0	0	0

	Gift Shop	Golf Driving Range	Gourmet Shop	Greek Restaurant \
0	1	0	0	0
1	1	0	1	0
2	2	0	0	0
3	0	0	1	0
4	0	0	2	0

	Grocery Store	Gym	Gym / Fitness Center	Gymnastics Gym	Halal Restaurant \
0	1	3	2	0	0

1	1	1	0	0	0
2	2	2	1	0	0
3	3	2	1	0	0
4	2	1	0	0	0

	Harbor / Marina	Hawaiian Restaurant	Health & Beauty Service	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Health Food Store	High School	Historic Site	History Museum	Hobby Shop	\
0	0	0	0	0	0	
1	0	0	1	0	0	
2	0	0	0	1	0	
3	0	0	0	2	0	
4	0	0	0	0	0	

	Hookah Bar	Hot Dog Joint	Hotel	Hotel Bar	Ice Cream Shop	\
0	0	0	3	0	2	
1	0	0	0	0	0	
2	0	0	0	0	2	
3	0	0	2	0	2	
4	0	0	0	0	0	

	Indian Restaurant	Indie Movie Theater	Indie Theater	Indoor Play Area	\
0	0	0	0	0	
1	0	0	0	0	
2	0	1	0	1	
3	0	0	1	0	
4	0	0	0	0	

	Israeli Restaurant	Italian Restaurant	Japanese Curry Restaurant	\
0	0	1	0	
1	0	0	0	
2	0	1	0	
3	0	5	0	
4	0	3	0	

	Japanese Restaurant	Jazz Club	Jewelry Store	Jewish Restaurant	\
0	1	0	1	0	
1	1	0	0	0	
2	2	0	0	0	
3	2	0	0	0	
4	1	0	0	0	

Juice Bar Karaoke Bar Kids Store Kitchen Supply Store \

0	1	0	2	0
1	3	0	0	0
2	0	0	0	0
3	0	0	0	0
4	1	0	0	0

	Korean Restaurant	Kosher Restaurant	Lake	Laser Tag	\
0	1	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Latin American Restaurant	Laundry Service	Lebanese Restaurant	Library	\
0	0	0	0	0	
1	1	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	3	0	0	0	

	Lighthouse	Lingerie Store	Liquor Store	Locksmith	Lounge	Market	\
0	0	1	0	0	0	2	
1	0	0	0	0	1	0	
2	0	0	0	0	0	1	
3	0	0	0	0	0	0	
4	0	0	0	0	0	0	

	Martial Arts Dojo	Massage Studio	Medical Center	\
0	0	0	0	
1	0	0	0	
2	1	0	0	
3	0	0	1	
4	0	0	0	

	Mediterranean Restaurant	Memorial Site	Men's Store	Mexican Restaurant	\
0	0	1	0	2	
1	0	0	0	2	
2	0	0	1	0	
3	0	0	1	1	
4	0	0	0	8	

	Middle Eastern Restaurant	Mini Golf	Miscellaneous Shop	\
0	0	0	0	
1	0	0	0	
2	1	0	0	
3	1	0	0	
4	1	0	0	

	Mobile Phone Shop	Modern European Restaurant	\
0	0	0	
1	0	0	
2	0	0	
3	0	0	
4	0	0	

	Molecular Gastronomy Restaurant	Monument / Landmark	Moroccan Restaurant	\
0	0	1	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Motorcycle Shop	Movie Theater	Museum	Music Store	Music Venue	\
0	0	1	1	0	0	
1	0	0	0	0	0	
2	0	1	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	2	

	Nail Salon	New American Restaurant	Nightclub	Noodle House	Office	\
0	0	0	0	0	0	
1	0	1	1	0	0	
2	0	0	0	0	0	
3	0	2	0	0	0	
4	1	0	0	0	0	

	Opera House	Optical Shop	Organic Grocery	Other Great Outdoors	\
0	0	0	0	0	
1	0	0	0	0	
2	2	1	0	0	
3	0	1	0	0	
4	0	0	0	0	

	Other Nightlife	Other Repair Shop	Outdoor Sculpture	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Outdoors & Recreation	Paella Restaurant	Pakistani Restaurant	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	1	

	Paper / Office Supplies Store	Park	Performing Arts Venue	Perfume Shop	\
0	0	7	2	0	
1	0	1	0	0	
2	0	0	2	0	
3	0	11	0	0	
4	0	1	0	0	

	Persian Restaurant	Peruvian Restaurant	Pet Café	Pet Service	Pet Store	\
0	0	0	0	0	1	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	1	1	
4	0	0	0	0	1	

	Pharmacy	Piano Bar	Pie Shop	Pier	Pilates Studio	Pizza Place	\
0	0	0	0	0	0	1	
1	0	0	0	0	0	5	
2	0	0	0	0	0	1	
3	0	0	0	1	0	4	
4	0	0	0	0	0	6	

	Playground	Plaza	Polish Restaurant	Pool	Print Shop	Pub	Public Art	\
0	1	3	0	0	0	1	1	
1	2	1	0	1	0	0	0	
2	0	0	0	0	0	0	0	
3	1	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	

	Ramen Restaurant	Record Shop	Recreation Center	\
0	0	0	0	
1	1	0	0	
2	0	0	0	
3	0	0	0	
4	0	1	0	

	Residential Building (Apartment / Condo)	Resort	Rest Area	Restaurant	\
0	0	0	0	0	
1	0	0	0	1	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Rock Club	Roof Deck	Russian Restaurant	Sake Bar	Salad Place	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	

4	0	0	0	0	1
---	---	---	---	---	---

	Salon / Barbershop	Sandwich Place	Scenic Lookout	School	\
0	0	2	2	0	
1	0	1	0	0	
2	0	2	0	0	
3	0	0	1	0	
4	0	2	0	0	

	Sculpture Garden	Seafood Restaurant	Shabu-Shabu Restaurant	\
0	0	0	0	
1	0	1	0	
2	0	1	0	
3	0	0	0	
4	0	0	0	

	Shipping Store	Shoe Store	Shopping Mall	Skating Rink	Smoke Shop	\
0	0	0	2	0	1	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Snack Place	Soba Restaurant	Soccer Field	Social Club	Soup Place	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	1	0	0	
4	0	0	0	0	0	

	South American Restaurant	Southern / Soul Food Restaurant	Spa	\
0	0	0	0	
1	0	1	0	
2	0	0	1	
3	0	0	1	
4	0	0	0	

	Spanish Restaurant	Speakeasy	Sporting Goods Shop	Sports Bar	\
0	0	0	1	0	
1	0	1	0	1	
2	0	0	1	0	
3	0	0	0	0	
4	0	1	0	0	

	Sports Club	State / Provincial Park	Steakhouse	Street Art	\
0	0	0	2	0	
1	0	0	0	0	
2	0	0	0	0	

3	0	0	0	0
4	0	0	0	0

	Street Food Gathering	Strip Club	Supermarket	Supplement Shop \
0	0	1	0	0
1	0	0	1	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Sushi Restaurant	Swiss Restaurant	Synagogue	Szechuan Restaurant \
0	0	0	0	0
1	0	0	0	0
2	2	0	0	0
3	1	0	0	0
4	1	0	0	0

	TV Station	Taco Place	Tailor Shop	Taiwanese Restaurant \
0	0	0	0	0
1	0	2	0	0
2	0	0	0	0
3	0	0	0	0
4	0	1	0	0

	Tapas Restaurant	Tattoo Parlor	Tea Room	Tech Startup	Tennis Court \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	1	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Thai Restaurant	Theater	Theme Park Ride / Attraction \
0	0	0	0
1	0	0	0
2	0	2	0
3	1	0	0
4	0	1	0

	Thrift / Vintage Store	Tiki Bar	Tourist Information Center \
0	0	0	0
1	2	0	0
2	0	0	0
3	0	0	0
4	2	0	0

	Toy / Game Store	Track	Trail	Train Station	Tram Station \
0	0	0	0	0	0
1	0	0	0	0	0

2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Turkish Restaurant	Udon Restaurant	Ukrainian Restaurant	Used Bookstore	\
0	0	0		0	0
1	0	0		0	0
2	0	0		0	0
3	0	0		0	0
4	0	0		0	1

	Vape Store	Vegetarian / Vegan Restaurant	Venezuelan Restaurant	\
0	0		1	0
1	0		0	0
2	0		2	0
3	0		0	0
4	1		0	0

	Veterinarian	Video Game Store	Video Store	Vietnamese Restaurant	\
0	0		0		0
1	0		0		0
2	0		0		2
3	0		0		1
4	0		0		0

	Volleyball Court	Waterfront	Whisky Bar	Wine Bar	Wine Shop	Wings Joint	\
0	0	0	0	1	4		0
1	0	0	0	1	6		0
2	0	0	0	0	2		0
3	0	0	0	1	4		0
4	0	0	0	0	1		0

	Women's Store	Yoga Studio	StandardizedAvgPrice
0	1	0	-1.303912
1	0	1	-0.418350
2	0	2	0.015011
3	0	5	-1.099479
4	0	2	-0.587926

This is the end of data collecting and preprocessing
neighborhood_venues_withprice_df will be the dataframe that will be used in the analyzing step below

1.2 III. Analyze the dataframe:

1.2.1 1. Check for correlation between occurrence of surrounding venues with real estate average price:

```
In [25]: # Using LinearRegression, we can get the list of coefficient correlations between each
lreg = LinearRegression(normalize=True)

X = neighborhood_venues_withprice_df.drop(columns=['Neighborhood', 'StandardizedAvgPrice'])
y = neighborhood_venues_withprice_df['StandardizedAvgPrice']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)

model = lreg.fit(X_train, y_train)

In [26]: # let's see how well Linear Regression fit the problem
y_pred = lreg.predict(X_test)

print('R2-score:', r2_score(y_test, y_pred)) # r2 score
print('Mean Squared Error:', mean_squared_error(y_test, y_pred)) # mse

print('Max positive coefs:', lreg.coef_[np.argsort(-lreg.coef_)[:10]])
print('Venue types with most postive effect:', X.columns[np.argsort(-lreg.coef_)[:10]])
print('Max negative coefs:', lreg.coef_[np.argsort(lreg.coef_)[:10]])
print('Venue types with most negative effect:', X.columns[np.argsort(lreg.coef_)[:10]])
coef_abs = abs(lreg.coef_)
print('Min coefs:', lreg.coef_[np.argsort(coef_abs)[:10]])
print('Venue types with least effect:', X.columns[np.argsort(coef_abs)[:10]].values)

R2-score: 0.273792308888
Mean Squared Error: 0.254179706388
Max positive coefs: [ 0.26348338  0.26213799  0.26213799  0.26213799  0.25818747  0.25818747
 0.25135936  0.24564842  0.23349638  0.22658134]
Venue types with most postive effect: ['Design Studio' 'Train Station' 'Jewish Restaurant' 'Reso
'Cafeteria' 'Colombian Restaurant' 'Dumpling Restaurant' 'Other Nightlife'
'Botanical Garden']
Max negative coefs: [-0.20813947 -0.20763403 -0.1798399  -0.1798399  -0.1798399  -0.17776278
-0.17776278 -0.17776278 -0.17776278 -0.17776278]
Venue types with most negative effect: ['Board Shop' 'Gay Bar' 'Supplement Shop' 'Rest Area' 'Li
'Flea Market' 'Golf Driving Range' 'Recreation Center'
'General Entertainment']
Min coefs: [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.]
Venue types with least effect: ['TV Station' 'Gas Station' 'Pakistani Restaurant' 'Volleyball Co
'Hookah Bar' 'Indoor Play Area' 'Laser Tag' 'Christmas Market' 'Cemetery'
'Mini Golf']
```

Looking back to our dataset, we can see that the features is much bigger than the samples. PCR (Principal Component Regression) will be used to reduce the number of features.

1.2.2 2. Applying PCR for better result:

PCR is a regression technique which is based on PCA (Principle Component Analysis).

It's a two steps process:

- First, perform PCA on the features set to obtain the principle components. Then select a subset for the next step.
- Second, use regression on the previous subset of principal components to get a list of coefficient correlations. (Linear Regression will be used)

```
In [27]: X = neighborhood_venues_withprice_df.drop(columns=['Neighborhood', 'StandardizedAvgPrice'])
        y = neighborhood_venues_withprice_df['StandardizedAvgPrice']
```

```
# First, apply PCA
pca = PCA(svd_solver='auto', random_state=0)
X_pca = pca.fit_transform(scale(X))
```

```
In [28]: n_component_list = range(1, 51)
        r2_list = []
        mse_list = []
```

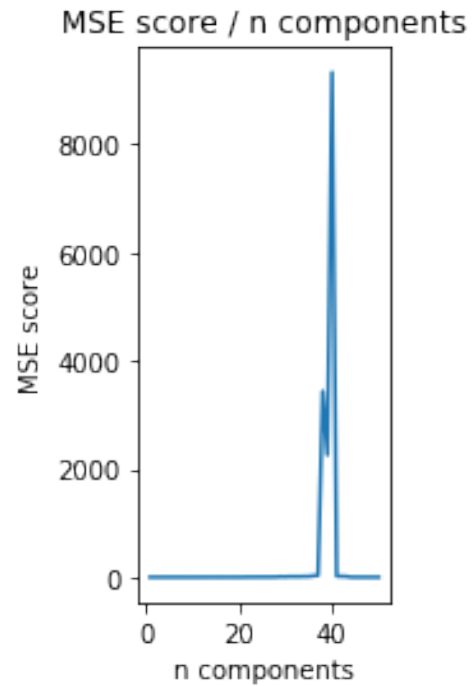
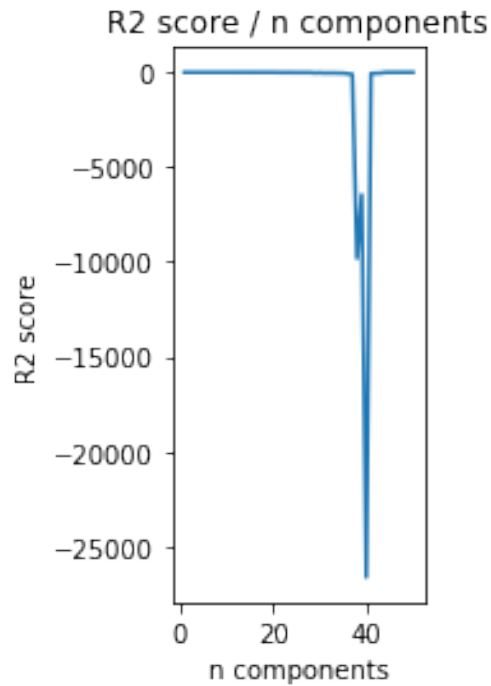
```
# Second, Linear Regression
for i in n_component_list:
    lreg = LinearRegression()
    X_train, X_test, y_train, y_test = train_test_split(X_pca[:, :i], y, test_size=0.2,
    model = lreg.fit(X_train, y_train)
    # check the result
    y_pred = lreg.predict(X_test)
    r2 = r2_score(y_test, y_pred) # r2 score
    mse = mean_squared_error(y_test, y_pred) # mse
    r2_list.append(r2)
    mse_list.append(mse)
```

```
scores_df = pd.DataFrame.from_dict(dict([('NComponents', n_component_list),
                                         ('R2', r2_list),
                                         ('MSE', mse_list)]))
scores_df.set_index('NComponents', inplace=True)
```

```
In [29]: # plot the scores to see the best n_components
plt.subplot(1, 3, 1)
scores_df['R2'].plot(kind='line')
plt.title('R2 score / n components')
plt.ylabel('R2 score')
plt.xlabel('n components')

plt.subplot(1, 3, 3)
scores_df['MSE'].plot(kind='line')
plt.title('MSE score / n components')
plt.ylabel('MSE score')
plt.xlabel('n components')

plt.show()
```



```
In [30]: r2_max = scores_df['R2'].idxmax()
print("Best n:", r2_max, "R2 score:", scores_df['R2'][r2_max])

mse_min = scores_df['MSE'].idxmin()
print("Best n:", mse_min, "MSE:", scores_df['MSE'][mse_min])
```

Best n: 50 R2 score: 0.454460324852

Best n: 50 MSE: 0.190944155714

```
In [31]: # Use the best n_components parameter
lreg = LinearRegression()
X_train, X_test, y_train, y_test = train_test_split(X_pca[:, :r2_max], y, test_size=0.2,
model = lreg.fit(X_train, y_train)

# check the result
y_pred = lreg.predict(X_test)
r2 = r2_score(y_test, y_pred) # r2 score
mse = mean_squared_error(y_test, y_pred) # mse
print("R2 score:", r2)
print("MSE:", mse)
```

R2 score: 0.454460324852

MSE: 0.190944155714

The result seems to improved compared to just using simple Linear Regression.

```
In [32]: # Let's try to project the coefs back to the original number of features
         eigenvectors = pca.components_
         pcr_coefs = eigenvectors[:r2_max, :].T @ lreg.coef_
```

```
         pcr_coefs.shape
```

```
Out[32]: (327,)
```

```
In [33]: # Let's check which venue types effect the most and least
         print('Max positive coefs:', pcr_coefs[np.argsort(-pcr_coefs)[:10]])
         print('Venue types with most positive effect:', X.columns[np.argsort(-pcr_coefs)[:10]].values)
         print('Max negative coefs:', pcr_coefs[np.argsort(pcr_coefs)[:10]])
         print('Venue types with most negative effect:', X.columns[np.argsort(pcr_coefs)[:10]].values)
         coef_abs = abs(pcr_coefs)
         print('Min coefs:', pcr_coefs[np.argsort(coef_abs)[:10]])
         print('Venue types with least effect:', X.columns[np.argsort(coef_abs)[:10]].values)
```

```
Max positive coefs: [ 0.07212567  0.0696754   0.06052737  0.0582199   0.05228078  0.05222561
 0.04901431  0.04597368  0.04465698  0.04399769]
```

```
Venue types with most positive effect: ['Dumpling Restaurant' 'Pilates Studio' 'Design Studio' '
'Southern / Soul Food Restaurant' 'Library' 'Sushi Restaurant' 'Resort'
'Korean Restaurant' 'Buffet']
```

```
Max negative coefs: [-0.05116074 -0.03897274 -0.03710211 -0.03457056 -0.03452567 -0.0345195
-0.03414522 -0.03304223 -0.03284579 -0.03284275]
```

```
Venue types with most negative effect: ['Market' 'Lingerie Store' 'Gay Bar' 'Kosher Restaurant'
'Food' 'Food Truck' 'Wine Bar' 'Food & Drink Shop' 'Climbing Gym']
```

```
Min coefs: [ -8.90366289e-06 -8.90366289e-06  4.09236430e-05 -4.99918920e-05
-5.87234477e-05  1.27322576e-04  1.27322576e-04  1.27322576e-04
 1.27322576e-04  1.41722883e-04]
```

```
Venue types with least effect: ['Christmas Market' 'TV Station' 'Cemetery' 'Event Space'
'Indoor Play Area' 'Modern European Restaurant' 'Mini Golf'
'Volleyball Court' 'Molecular Gastronomy Restaurant' 'Community Center']
```

1.3 IV. Conclusion:

Based on the observed coefficient correlations, fancy places like restaurants seem to boost real estate's value around the area the most.

In some ways, it's a logical conclusion. Neighborhoods that have many restaurants are most likely business areas such as downtown. It's where lots of people go to, lots of activities to enjoy, lots of other businesses cite their offices there. The kind of places that people like to live and work and as a result of high demand, the price will be higher than other cities away from the city center.

```
In [ ]:
```