

# Capstone Project - The Battle of Neighborhoods

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Capstone Project - The Battle of Neighborhoods

Munich vs. Berlin

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## 0.2 1. Introduction/Business Problem

### 0.3 1.1 Problem description

Two of Germany’s most wanted cities are Berlin and Munich. The first cities that come to everybody’s mind, when thinking about diversity and a place to be. However, if you think about having agony of choice to pick a restaurant, what would be your first thought? Exactly, - where can I find a restaurant? - which restaurants have the highest user ratings? - and of course, can I afford that?

### 0.4 1.2 focus and compromise

In this analysis, we will focus on picking the right borough to find a suitable restaurant. If you do not use any Foursquare premium API requests, this will be the compromise to select your destination. Afterwards you can easily search the right restaurant via your mobile app and get the missing information. We use free *explore* requests to communicate with Foursquare database. As we decide for one borough, we will start one free premium request for *trending* venues.

## 0.5 1.3 approach and target

First we'll have a look at different venue categories offered by Foursquare. Second, we will create an array for relevant restaurants categories. So data of both cities are quite comparable as we start to evaluate amount of suitable restaurant categories. In addition, we will use the  $k$ -means clustering algorithm to split restaurant into clusters according to venue categories by Foursquare. Finally, we will use the Folium library to visualize the neighborhoods in Berlin and Munich and their emerging clusters. Based on the results, my wife can decide whether she will have dinner in Munich or Berlin and to which borough I have to navigate her. Anyway, she will only decide with her stomach. Rational evaluation of Foursquare data would exceed my competencies and is going to be outvoted. But as soon as we arrive, we will look for the places with the highest foot traffic. So let's do that and get the trending venues around.

## 0.6 1.5 define restaurant categories

Since we like to eat in different restaurants and experience new kitchens, we just need the number of restaurants for the first step, regardless of quality, price or user rating. To be comparable, here's a list of venue categories, we would like to compare the cities:

```
[2]: restaurants = ['American Restaurant',
                    'Asian Restaurant',
                    'Argentinian Restaurant',
                    'Fast Food Restaurant',
                    'Bavarian Restaurant',
                    'Chinese Restaurant',
                    'Eastern European Restaurant',
                    'English Restaurant',
                    'Falafel Restaurant',
                    'German Restaurant',
                    'Greek Restaurant',
                    'Indian Restaurant',
                    'Israeli Restaurant',
                    'Italian Restaurant',
                    'Mediterranean Restaurant',
                    'Mexican Restaurant',
                    'Middle Eastern Restaurant',
                    'Modern European Restaurant',
                    'Restaurant',
                    'Seafood Restaurant',
                    'Sushi Restaurant',
                    'Thai Restaurant',
                    'Theme Restaurant',
                    'Vegetarian / Vegan Restaurant',
                    'Vietnamese Restaurant',
                    'Beer Garden',
                    'Bistro',
                    'Burger Joint',
                    'Burrito Place',
```

```
'Creperie',
'Fried Chicken Joint',
'Pizza Place',
'Steakhouse']
```

```
[3]: #munich_venues.to_csv('venue_categories_munich.csv', sep=';', decimal=',',
      ↪index=True)
      #berlin_venues.to_csv('venue_categories_berlin.csv', sep=';', decimal=',',
      ↪index=True)
```

## 0.7 2. Munich: Data import and cleaning

### 0.8 2.1 library import

```
[4]: import pandas as pd
import numpy as np

!pip install BeautifulSoup4
from bs4 import BeautifulSoup
import requests

!pip install lxml
!pip install geopandas
!pip install geopy
import geopy as geo
import geopandas as gpd

import folium
from sklearn.cluster import KMeans

import matplotlib.cm as cm
import matplotlib.colors as colors

pd.options.mode.chained_assignment = None # default='warn'
print('Done!')
```

Collecting BeautifulSoup4

Downloading <https://files.pythonhosted.org/packages/d1/41/e6495bd7d3781cee623ce23ea6ac73282a373088fcd0ddc809a047b18eae/beautifulsoup4-4.9.3-py3-none-any.whl> (115kB)

| 122kB 5.4MB/s eta 0:00:01

Collecting soupsieve>1.2; python\_version >= "3.0" (from BeautifulSoup4)

Downloading <https://files.pythonhosted.org/packages/02/fb/1c65691a9aeb7bd6ac2aa505b84cb8b49ac29c976411c6ab3659425e045f/soupsieve-2.1-py3-none-any.whl>

Installing collected packages: soupsieve, BeautifulSoup4

Successfully installed BeautifulSoup4-4.9.3 soupsieve-2.1

Collecting lxml

```

    Downloading https://files.pythonhosted.org/packages/bd/78/56a7c88a57d0d1
4945472535d0df9fb4bbad7d34ede658ec7961635c790e/lxml-4.6.2-cp36-cp36m-manylinux1_
x86_64.whl (5.5MB)
      |                               | 5.5MB 8.5MB/s eta 0:00:01
Installing collected packages: lxml
Successfully installed lxml-4.6.2
Collecting geopandas
  Downloading https://files.pythonhosted.org/packages/f7/a4/e66aafbefcbb71
7813bf3a355c8c4fc3ed04ea1dd7feb2920f2f4f868921/geopandas-0.8.1-py2.py3-none-
any.whl (962kB)
      |                               | 972kB 6.4MB/s eta 0:00:01
Collecting shapely (from geopandas)
  Downloading https://files.pythonhosted.org/packages/9d/18/557d4f55453fe0
0f59807b111cc7b39ce53594e13ada88e16738fb4ff7fb/Shapely-1.7.1-cp36-cp36m-manylinu
x1_x86_64.whl (1.0MB)
      |                               | 1.0MB 20.0MB/s eta 0:00:01
Collecting fiona (from geopandas)
  Downloading https://files.pythonhosted.org/packages/37/94/4910fd55246c1d
963727b03885ead6ef1cd3748a465f7b0239ab25dfc9a3/Fiona-1.8.18-cp36-cp36m-manylinux
1_x86_64.whl (14.8MB)
      |                               | 14.8MB 38.8MB/s eta 0:00:01
      |                               | 3.5MB 9.1MB/s eta 0:00:02
      |                               | 12.4MB 38.8MB/s eta 0:00:01
Collecting pyproj>=2.2.0 (from geopandas)
  Downloading https://files.pythonhosted.org/packages/e4/ab/280e80a67cfc10
9d15428c0ec56391fc03a65857b7727cf4e6e6f99a4204/pyproj-3.0.0.post1-cp36-cp36m-man
ylinux2010_x86_64.whl (6.4MB)
      |                               | 6.5MB 8.6MB/s eta 0:00:01
      |                               | 6.0MB 8.6MB/s eta 0:00:01
Requirement already satisfied: pandas>=0.23.0 in
/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages (from geopandas)
(1.1.5)
Requirement already satisfied: six>=1.7 in
/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages (from
fiona->geopandas) (1.15.0)
Collecting cligj>=0.5 (from fiona->geopandas)
  Downloading https://files.pythonhosted.org/packages/42/1e/947eadf10d6804bf276e
b8a038bd5307996dceaaa41cfd21b7a15ec62f5d/cligj-0.7.1-py3-none-any.whl
Collecting click-plugins>=1.0 (from fiona->geopandas)
  Downloading https://files.pythonhosted.org/packages/e9/da/824b92d9942f4e472702
488857914bdd50f73021efea15b4cad9aca8ecef/click_plugins-1.1.1-py2.py3-none-
any.whl
Requirement already satisfied: certifi in
/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages (from
fiona->geopandas) (2020.12.5)
Collecting munch (from fiona->geopandas)
  Downloading https://files.pythonhosted.org/packages/cc/ab/85d8da5c9a45e072301b
eb37ad7f833cd344e04c817d97e0cc75681d248f/munch-2.5.0-py2.py3-none-any.whl

```

```

Requirement already satisfied: click<8,>=4.0 in
/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages (from
fiona->geopandas) (7.1.2)
Requirement already satisfied: attrs>=17 in
/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages (from
fiona->geopandas) (20.3.0)
Requirement already satisfied: pytz>=2017.2 in
/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages (from
pandas>=0.23.0->geopandas) (2020.4)
Requirement already satisfied: python-dateutil>=2.7.3 in
/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages (from
pandas>=0.23.0->geopandas) (2.8.1)
Requirement already satisfied: numpy>=1.15.4 in
/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages (from
pandas>=0.23.0->geopandas) (1.19.4)
Installing collected packages: shapely, cligj, click-plugins, munch, fiona,
pyproj, geopandas
  Found existing installation: pyproj 1.9.6
    Uninstalling pyproj-1.9.6:
      Successfully uninstalled pyproj-1.9.6
Successfully installed click-plugins-1.1.1 cligj-0.7.1 fiona-1.8.18
geopandas-0.8.1 munch-2.5.0 pyproj-3.0.0.post1 shapely-1.7.1
Collecting geopy
  Downloading https://files.pythonhosted.org/packages/0c/67/915668d0e286ca
a21a1da82a85ffe3d20528ec7212777b43ccd027d94023/geopy-2.1.0-py3-none-any.whl
(112kB)
    |                                     | 112kB 7.1MB/s eta 0:00:01
Collecting geographiclib<2,>=1.49 (from geopy)
  Downloading https://files.pythonhosted.org/packages/8b/62/26ec95a98ba642991631
99e95ad1b0e34ad3f4e176e221c40245f211e425/geographiclib-1.50-py3-none-any.whl
Installing collected packages: geographiclib, geopy
Successfully installed geographiclib-1.50 geopy-2.1.0
Done!

```

```
[ ]:
```

## 0.9 2.2 Munich Data import with BeautifulSoup

```

[5]: url='http://www.places-in-germany.com/
      ↪21179-places-within-a-radius-of-15km-around-muenchen.html'
      req=requests.get(url)
      soup=BeautifulSoup(req.text,"html.parser")
      table = soup.find_all('table')
      df=pd.read_html(str(table), header=0)[0]

```

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

```
[6]:
```

	Distance	Route	Postal code / Place	Population
0	3.4 km (2.1 miles)	NaN	81675 Bogenhausen	-
1	4.3 km (2.7 miles)	NaN	81671 Berg am Laim	-
2	5.1 km (3.2 miles)	NaN	80796 Milbertshofen-Am Hart	-
3	6.7 km (4.2 miles)	NaN	80634 Moosach	-
4	8.7 km (5.4 miles)	NaN	85774 Unterföhring	7553

```
[7]: df.rename({'Postal code / Place': 'Borough'}, axis=1, inplace=True)
munich=df.Borough.str.split(" ",n=1,expand=True)
munich.rename({0: 'postalcode', 1: 'borough'}, axis=1, inplace=True)
munich.shape
```

```
[7]: (88, 2)
```

test for NaN values

```
[8]: if munich['borough'].isnull().sum() > 0:
    munich.dropna(axis=0, inplace=True)
    print('NaN values deleted')
else:
    print('no NaN values')
```

no NaN values

web adresse offers data with same postal code and borough name but different distances to our search request. Therefore we will *drop duplicates()*

```
[9]: munich.drop_duplicates(keep='first', inplace=True)
munich.shape
```

```
[9]: (82, 2)
```

## 0.10 2.3 Folium Map Munich

```
[10]: from geopy.geocoders import Nominatim
from geopy.extra.rate_limiter import RateLimiter

lat=[]
lon=[]

geolocator = Nominatim(user_agent='Couserera')

for line, borough in munich.iterrows():

    try:
        adress= borough[0], ' München ', borough[1]
        location = geolocator.geocode(adress)
        #print(location)
```

```

        lat.append(location.latitude)
        lon.append(location.longitude)
    except:
        lat.append(np.nan)
        lon.append(np.nan)

munich['latitude']=lat
munich['longitude']=lon

```

```

[11]: munich.dropna(axis=0, inplace=True)
      munich.shape

```

```

[11]: (67, 4)

```

```

[12]: munich

```

```

[12]:   postalcode      borough  latitude  longitude
0      81675      Bogenhausen  48.158487   11.636682
1      81671      Berg am Laim  48.123483   11.633451
2      80796  Milbertshofen-Am Hart  48.182385   11.575043
3      80634      Moosach      48.179895   11.510571
4      85774      Unterföhring  48.190718   11.644580
..      ...
79     82110      Neugermering  48.127735   11.363372
82     85764      Mittenheim    48.263084   11.557159
83     82065      Baierbrunn    48.020477   11.486546
85     85630      Neukeferloh   48.096429   11.760195
86     85737      Fischerhäuser  48.251850   11.695184

```

```

[67 rows x 4 columns]

```

**add city center to dataset** Folium Map shows, that there's no entry for the searched geo tag itself. It just returns positions around the search tag. So let's add it manually to the results of [www.places-in-germany.com](http://www.places-in-germany.com).

```

[13]: df_city = pd.DataFrame({"postalcode":['80331', '80335'], "borough":['Zentrum_
      ↪Marienplatz', 'Hauptbahnhof'], "latitude":[48.137187, 48.140458], ↪
      ↪"longitude":[11.575501, 11.557766]})
      df_city

```

```

[13]:   postalcode      borough  latitude  longitude
0      80331  Zentrum Marienplatz  48.137187   11.575501
1      80335      Hauptbahnhof  48.140458   11.557766

```

```

[14]: munich = munich.append(df_city, ignore_index=True)

```

```
[15]: address = 'munich'

geolocator = Nominatim(user_agent="Couser")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print('geo-coordinates of Munich {}, {}'.format(latitude, longitude))

# Creating Folium Map
map_munich = folium.Map(location=[latitude, longitude], zoom_start=11)

# add markers to map
for lat, lng, borough in zip(munich['latitude'], munich['longitude'],
    ↪munich['borough']):
    label = '{}'.format(borough)
    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(map_munich)

map_munich
```

geo-coordinates of Munich 48.1371079, 11.5753822.

```
[15]: <folium.folium.Map at 0x7f70e5a15c88>
```

```
[ ]:
```

## 0.11 2.4 Explore Venues with 4square

```
[16]: CLIENT_ID = 'MIXA2M5FTBG1IILFL5ATNOBSNUP4BU4J1BUOGIM03E1UJOBE' # your
    ↪Foursquare ID
CLIENT_SECRET = 'ETQCTK31Z04IOFVKYEEHGM0JGLOG4DCLQ1R1ECOOPHX33D' # your
    ↪Foursquare Secret
VERSION = '20180604'
LIMIT = 100
radius = 500
print("ID loaded")
```



ID loaded

```
[17]: 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={}&client_secret={}&v={}&ll={},{}&radius={}&limit={}'.format(
            CLIENT_ID,
            CLIENT_SECRET,
            VERSION,
            lat,
            lng,
            radius,
            LIMIT)

        # make the GET request
        results = requests.get(url).json()["response"]['groups'][0]['items']

        # 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_
    ↪in venue_list])
    nearby_venues.columns = ['borough',
                            'Latitude',
                            'Longitude',
                            'Venue',
                            'Venue Latitude',
                            'Venue Longitude',
                            'Venue Category']

    return(nearby_venues)
```

```
[18]: munich_venues = getNearbyVenues(names=munich['borough'],
                                       latitudes=munich['latitude'],
                                       longitudes=munich['longitude'])
```

)

Bogenhausen  
Berg am Laim  
Milbertshofen-Am Hart  
Moosach  
Unterföhring  
Dornach  
Neuherberg  
Pasing  
Neubiberg  
Pullach  
Gronsdorf, Kreis München  
Winning, Kreis München  
Taufkirchen, Kreis München  
Gräfelfing  
Martinsried  
Großhesselohe, Isartal  
Pullach im Isartal  
Ottobrunn  
Westerham  
Salmdorf, Kreis München  
Unterhaching  
Hochmutting  
Oedenstockach  
Steinkirchen  
Solalinden  
Taufkirchen  
Aschheim  
Dirnismaning bei München  
Feldkirchen  
Pötzham, Kreis München  
Gerblinghausen  
Kreuzpullach  
Laufzorn  
Oberbiberg  
Oberhaching bei München  
Ödenpullach  
Karlsfeld bei München  
Putzbrunn  
Ottendichl, Kreis München  
Haar bei München  
Planegg  
Lustheim  
Oberschleißheim  
Hochbrück bei München  
Badersfeld

Eglfing, Kreis München  
Waldbrunn  
Deisenhofen bei München  
Ismaning  
Buchenhain, Isartal  
Hohenbrunn  
Riemerling  
Krailling  
Garching  
Garching bei München  
Kirchheim bei München  
Kirchheim  
Grasbrunn  
Frundsbergerhöhe  
Kirchstockach, Kreis München  
Rothschwaige  
Harthaus  
Neugermerring  
Mittenheim  
Baierbrunn  
Neukeferloh  
Fischerhäuser  
Zentrum Marienplatz  
Hauptbahnhof

```
[19]: print('4square provided', munich_venues.shape , 'venues')
munich_venues.head(5)
```

4square provided (697, 7) venues

```
[19]:
```

	borough	Latitude	Longitude	Venue	Venue Latitude	\
0	Bogenhausen	48.158487	11.636682	Martinelli	48.155396	
1	Bogenhausen	48.158487	11.636682	dm-drogerie markt	48.159468	
2	Bogenhausen	48.158487	11.636682	Pyrsos	48.154944	
3	Bogenhausen	48.158487	11.636682	Rossmann	48.157856	
4	Bogenhausen	48.158487	11.636682	Bäckerei Wimmer	48.158156	

  

	Venue Longitude	Venue Category
0	11.637115	Italian Restaurant
1	11.643064	Drugstore
2	11.637708	Greek Restaurant
3	11.641590	Drugstore
4	11.641109	Bakery

```
[20]: print('There are {} uniques categories.'.format(len(munich_venues['Venue_
→Category'].unique()))
munich_venues.groupby('Venue Category').Venue.count()
```

There are 163 unique categories.

```
[20]: Venue Category
      American Restaurant      1
      Argentinian Restaurant   1
      Art Museum               1
      Arts & Crafts Store      1
      Asian Restaurant         11
      ..
      Trattoria/Osteria       4
      Vegetarian / Vegan Restaurant 1
      Vietnamese Restaurant    5
      Warehouse Store         1
      Wine Bar                 2
      Name: Venue, Length: 163, dtype: int64
```

## 0.12 3. Analyze Boroughs of Munich

```
[21]: munich_restaurants = munich_venues[munich_venues['Venue Category'].str.
      ↪contains('|'.join(restaurants))]
```

```
[22]: munich_restaurants.head()
```

```
[22]:
```

	borough	Latitude	Longitude	Venue	Venue Latitude	\
0	Bogenhausen	48.158487	11.636682	Martinelli	48.155396	
2	Bogenhausen	48.158487	11.636682	Pysos	48.154944	
20	Milbertshofen-Am Hart	48.182385	11.575043	Rabiang Thai	48.180777	
21	Milbertshofen-Am Hart	48.182385	11.575043	Synantisis	48.179632	
23	Milbertshofen-Am Hart	48.182385	11.575043	Wolfs-Burger	48.184465	

  

	Venue Longitude	Venue Category
0	11.637115	Italian Restaurant
2	11.637708	Greek Restaurant
20	11.571211	Thai Restaurant
21	11.570367	Greek Restaurant
23	11.571378	Burger Joint

## 0.13 3.1 Frequency of occurrence

```
[23]: # one hot encoding
      munich_onehot = pd.get_dummies(munich_restaurants[['Venue Category']],
      ↪prefix="", prefix_sep="")

      # add neighborhood column back to dataframe
      munich_onehot['borough'] = munich_restaurants['borough']

      # move neighborhood column to the first column
```

```
fixed_columns = [munich_onehot.columns[-1]] + list(munich_onehot.columns[:-1])
munich_onehot = munich_onehot[fixed_columns]

munich_onehot.head()
```

```
[23]:
```

	borough	American Restaurant	Argentinian Restaurant	\
0	Bogenhausen	0	0	
2	Bogenhausen	0	0	
20	Milbertshofen-Am Hart	0	0	
21	Milbertshofen-Am Hart	0	0	
23	Milbertshofen-Am Hart	0	0	

  

	Asian Restaurant	Bavarian Restaurant	Beer Garden	Bistro	Burger Joint	\
0	0	0	0	0	0	
2	0	0	0	0	0	
20	0	0	0	0	0	
21	0	0	0	0	0	
23	0	0	0	0	1	

  

	Burrito Place	Chinese Restaurant	...	Modern European Restaurant	\
0	0	0	...	0	
2	0	0	...	0	
20	0	0	...	0	
21	0	0	...	0	
23	0	0	...	0	

  

	Pizza Place	Restaurant	Seafood Restaurant	Steakhouse	Sushi Restaurant	\
0	0	0	0	0	0	
2	0	0	0	0	0	
20	0	0	0	0	0	
21	0	0	0	0	0	
23	0	0	0	0	0	

  

	Thai Restaurant	Theme Restaurant	Vegetarian / Vegan Restaurant	\
0	0	0	0	
2	0	0	0	
20	1	0	0	
21	0	0	0	
23	0	0	0	

  

	Vietnamese Restaurant
0	0
2	0
20	0
21	0
23	0

[5 rows x 33 columns]

[ ]:

group rows by neighborhood and mean frequency of occurrence of each category

```
[24]: print('Size of One Hot is ', munich_onehot.shape, '.')
munich_grouped = munich_onehot.groupby('borough').mean().reset_index()
munich_grouped.head()
```

Size of One Hot is (183, 33) .

```
[24]:
```

	borough	American Restaurant	Argentinian Restaurant	\
0	Aschheim	0.0	0.0	
1	Baierbrunn	0.0	0.0	
2	Bogenhausen	0.0	0.0	
3	Buchenhain, Isartal	0.0	0.0	
4	Deisenhofen bei München	0.0	0.0	

  

	Asian Restaurant	Bavarian Restaurant	Beer Garden	Bistro	Burger Joint	\
0	0.333333	0.0	0.0	0.0	0.0	
1	0.000000	0.0	0.0	0.0	0.0	
2	0.000000	0.0	0.0	0.0	0.0	
3	0.000000	1.0	0.0	0.0	0.0	
4	0.500000	0.0	0.0	0.0	0.0	

  

	Burrito Place	Chinese Restaurant	...	Modern European Restaurant	\
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	

  

	Pizza Place	Restaurant	Seafood Restaurant	Steakhouse	Sushi Restaurant	\
0	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	

  

	Thai Restaurant	Theme Restaurant	Vegetarian / Vegan Restaurant	\
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	

	Vietnamese Restaurant
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0

[5 rows x 33 columns]

```
[25]: print('confirm the new size:', munich_grouped.shape)
```

confirm the new size: (50, 33)

Let's print each neighborhood along with the top 5 most common venues

```
[26]: num_top_venues = 5

for hood in munich_grouped['borough']:
    print("----"+hood+"----")
    temp = munich_grouped[munich_grouped['borough'] == hood].T.reset_index()
    temp.columns = ['venue', 'freq']
    temp = temp.iloc[1:]
    temp['freq'] = temp['freq'].astype(float)
    temp = temp.round({'freq': 2})
    print(temp.sort_values('freq', ascending=False).reset_index(drop=True).
    →head(num_top_venues))
    print('\n')
```

----Aschheim----

	venue	freq
0	Greek Restaurant	0.33
1	Asian Restaurant	0.33
2	Italian Restaurant	0.33
3	Indian Restaurant	0.00
4	Vegetarian / Vegan Restaurant	0.00

----Baierbrunn----

	venue	freq
0	German Restaurant	1.0
1	American Restaurant	0.0
2	Indian Restaurant	0.0
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Bogenhausen----

	venue	freq
--	-------	------

0	Greek Restaurant	0.5
1	Italian Restaurant	0.5
2	Argentinian Restaurant	0.0
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Buchenhain, Isartal----

	venue	freq
0	Bavarian Restaurant	1.0
1	American Restaurant	0.0
2	Indian Restaurant	0.0
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Deisenhofen bei München----

	venue	freq
0	Greek Restaurant	0.5
1	Asian Restaurant	0.5
2	Indian Restaurant	0.0
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Dornach----

	venue	freq
0	Thai Restaurant	0.33
1	Italian Restaurant	0.33
2	German Restaurant	0.33
3	American Restaurant	0.00
4	Indian Restaurant	0.00

----Eglfing, Kreis München----

	venue	freq
0	Italian Restaurant	1.0
1	American Restaurant	0.0
2	Argentinian Restaurant	0.0
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Feldkirchen----

	venue	freq
0	Greek Restaurant	0.25
1	German Restaurant	0.25
2	Italian Restaurant	0.25



3	Asian Restaurant	0.25
4	Vegetarian / Vegan Restaurant	0.00

----Garching----

	venue	freq
0	Greek Restaurant	0.22
1	German Restaurant	0.22
2	Italian Restaurant	0.22
3	Steakhouse	0.11
4	Indian Restaurant	0.11

----Garching bei München----

	venue	freq
0	Greek Restaurant	0.22
1	German Restaurant	0.22
2	Italian Restaurant	0.22
3	Steakhouse	0.11
4	Indian Restaurant	0.11

----Gronsdorf, Kreis München----

	venue	freq
0	Vietnamese Restaurant	0.33
1	Bistro	0.33
2	Italian Restaurant	0.33
3	Indian Restaurant	0.00
4	Vegetarian / Vegan Restaurant	0.00

----Gräfelfing----

	venue	freq
0	Italian Restaurant	1.0
1	American Restaurant	0.0
2	Argentinian Restaurant	0.0
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Haar bei München----

	venue	freq
0	Bistro	0.5
1	Italian Restaurant	0.5
2	American Restaurant	0.0
3	Indian Restaurant	0.0
4	Vegetarian / Vegan Restaurant	0.0

----Hauptbahnhof----

	venue	freq
0	Middle Eastern Restaurant	0.18
1	Mediterranean Restaurant	0.09
2	Asian Restaurant	0.09
3	Bavarian Restaurant	0.09
4	German Restaurant	0.09

----Hochbrück bei München----

	venue	freq
0	Italian Restaurant	1.0
1	American Restaurant	0.0
2	Argentinian Restaurant	0.0
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Hohenbrunn----

	venue	freq
0	Italian Restaurant	0.5
1	German Restaurant	0.5
2	American Restaurant	0.0
3	Indian Restaurant	0.0
4	Vegetarian / Vegan Restaurant	0.0

----Ismaning----

	venue	freq
0	German Restaurant	0.33
1	Indian Restaurant	0.17
2	Thai Restaurant	0.17
3	Restaurant	0.17
4	Italian Restaurant	0.17

----Kirchheim----

	venue	freq
0	German Restaurant	1.0
1	American Restaurant	0.0
2	Indian Restaurant	0.0
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Kirchheim bei München----

	venue	freq
--	-------	------

0	German Restaurant	1.0
1	American Restaurant	0.0
2	Indian Restaurant	0.0
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Krailling----

	venue	freq
0	Italian Restaurant	0.50
1	Greek Restaurant	0.25
2	Beer Garden	0.25
3	Indian Restaurant	0.00
4	Vegetarian / Vegan Restaurant	0.00

----Lustheim----

	venue	freq
0	German Restaurant	1.0
1	American Restaurant	0.0
2	Indian Restaurant	0.0
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Martinsried----

	venue	freq
0	Greek Restaurant	0.25
1	Indian Restaurant	0.25
2	Italian Restaurant	0.25
3	German Restaurant	0.25
4	Vegetarian / Vegan Restaurant	0.00

----Milbertshofen-Am Hart----

	venue	freq
0	Greek Restaurant	0.4
1	German Restaurant	0.2
2	Thai Restaurant	0.2
3	Burger Joint	0.2
4	Pizza Place	0.0

----Mittenheim----

	venue	freq
0	Chinese Restaurant	1.0
1	American Restaurant	0.0
2	Indian Restaurant	0.0

3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Moosach----

	venue	freq
0	American Restaurant	0.25
1	German Restaurant	0.25
2	Italian Restaurant	0.25
3	Asian Restaurant	0.25
4	Vegetarian / Vegan Restaurant	0.00

----Neubiberg----

	venue	freq
0	Restaurant	0.33
1	Italian Restaurant	0.33
2	German Restaurant	0.33
3	American Restaurant	0.00
4	Indian Restaurant	0.00

----Neugermerring----

	venue	freq
0	Asian Restaurant	0.2
1	German Restaurant	0.2
2	Burger Joint	0.2
3	Italian Restaurant	0.2
4	Pizza Place	0.2

----Neukeferloh----

	venue	freq
0	Bavarian Restaurant	1.0
1	American Restaurant	0.0
2	Indian Restaurant	0.0
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Oberbiberg----

	venue	freq
0	German Restaurant	1.0
1	American Restaurant	0.0
2	Indian Restaurant	0.0
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Oberhaching bei München----

	venue	freq
0	Greek Restaurant	0.5
1	Asian Restaurant	0.5
2	Indian Restaurant	0.0
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Oberschleißheim----

	venue	freq
0	Vietnamese Restaurant	0.25
1	German Restaurant	0.25
2	Chinese Restaurant	0.25
3	Italian Restaurant	0.25
4	Theme Restaurant	0.00

----Ottendichl, Kreis München----

	venue	freq
0	Restaurant	1.0
1	American Restaurant	0.0
2	Argentinian Restaurant	0.0
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Ottobrunn----

	venue	freq
0	Italian Restaurant	0.29
1	Sushi Restaurant	0.14
2	German Restaurant	0.14
3	Indian Restaurant	0.14
4	Vietnamese Restaurant	0.14

----Pasing----

	venue	freq
0	Italian Restaurant	0.17
1	Fast Food Restaurant	0.11
2	German Restaurant	0.11
3	Vietnamese Restaurant	0.11
4	Theme Restaurant	0.06

----Planegg----

	venue	freq
--	-------	------

0	German Restaurant	0.67
1	Italian Restaurant	0.33
2	American Restaurant	0.00
3	Indian Restaurant	0.00
4	Vegetarian / Vegan Restaurant	0.00

----Pötzham, Kreis München----

	venue	freq
0	Italian Restaurant	0.67
1	Doner Restaurant	0.33
2	American Restaurant	0.00
3	Indian Restaurant	0.00
4	Vegetarian / Vegan Restaurant	0.00

----Pullach----

	venue	freq
0	Italian Restaurant	0.33
1	Asian Restaurant	0.33
2	German Restaurant	0.33
3	Restaurant	0.00
4	Mediterranean Restaurant	0.00

----Pullach im Isartal----

	venue	freq
0	Italian Restaurant	0.33
1	Asian Restaurant	0.33
2	German Restaurant	0.33
3	Restaurant	0.00
4	Mediterranean Restaurant	0.00

----Putzbrunn----

	venue	freq
0	Italian Restaurant	0.5
1	German Restaurant	0.5
2	American Restaurant	0.0
3	Indian Restaurant	0.0
4	Vegetarian / Vegan Restaurant	0.0

----Riemerling----

	venue	freq
0	Asian Restaurant	1.0
1	American Restaurant	0.0
2	Indian Restaurant	0.0

3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Rothschwaige----

	venue	freq
0	Greek Restaurant	1.0
1	Argentinian Restaurant	0.0
2	Vegetarian / Vegan Restaurant	0.0
3	Theme Restaurant	0.0
4	Thai Restaurant	0.0

----Salmdorf, Kreis München----

	venue	freq
0	Steakhouse	1.0
1	American Restaurant	0.0
2	Argentinian Restaurant	0.0
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Solalinden----

	venue	freq
0	German Restaurant	1.0
1	American Restaurant	0.0
2	Indian Restaurant	0.0
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Taufkirchen----

	venue	freq
0	German Restaurant	1.0
1	American Restaurant	0.0
2	Indian Restaurant	0.0
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Taufkirchen, Kreis München----

	venue	freq
0	Italian Restaurant	0.67
1	Doner Restaurant	0.33
2	American Restaurant	0.00
3	Indian Restaurant	0.00
4	Vegetarian / Vegan Restaurant	0.00

----Unterföhring----

	venue	freq
0	Italian Restaurant	1.0
1	American Restaurant	0.0
2	Argentinian Restaurant	0.0
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Unterhaching----

	venue	freq
0	Greek Restaurant	0.50
1	Pizza Place	0.25
2	German Restaurant	0.25
3	Indian Restaurant	0.00
4	Vegetarian / Vegan Restaurant	0.00

----Westerham----

	venue	freq
0	Doner Restaurant	1.0
1	American Restaurant	0.0
2	Indian Restaurant	0.0
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Winning, Kreis München----

	venue	freq
0	Chinese Restaurant	0.4
1	Italian Restaurant	0.4
2	Doner Restaurant	0.2
3	Vegetarian / Vegan Restaurant	0.0
4	Theme Restaurant	0.0

----Zentrum Marienplatz----

	venue	freq
0	Bavarian Restaurant	0.21
1	German Restaurant	0.21
2	Pizza Place	0.08
3	Italian Restaurant	0.08
4	Restaurant	0.08



Let's put that into a *pandas* dataframe

```
[27]: # First, let's write a function to sort the venues in descending order.
```

```
def return_most_common_venues(row, num_top_venues):
    row_categories = row.iloc[1:]
    row_categories_sorted = row_categories.sort_values(ascending=False)

    return row_categories_sorted.index.values[0:num_top_venues]
```

create the new dataframe and display top 5 venues

```
[28]: num_top_venues = 5

indicators = ['st', 'nd', 'rd']

# create columns according to number of top venues
columns = ['borough']
for ind in np.arange(num_top_venues):
    try:
        columns.append('{}-{} Most Common Venue'.format(ind+1, indicators[ind]))
    except:
        columns.append('{}th Most Common Venue'.format(ind+1))

# create a new dataframe
neighborhoods_venues_sorted = pd.DataFrame(columns=columns)
neighborhoods_venues_sorted['borough'] = munich_grouped['borough']

for ind in np.arange(munich_grouped.shape[0]):
    neighborhoods_venues_sorted.iloc[ind, 1:] = ↵
    ↪return_most_common_venues(munich_grouped.iloc[ind, :], num_top_venues)

neighborhoods_venues_sorted.head()
```

```
[28]:
```

	borough	1st Most Common Venue \	2nd Most Common Venue	3rd Most Common Venue \
0	Aschheim	Greek Restaurant	Asian Restaurant	Italian Restaurant
1	Baierbrunn	German Restaurant	Vegetarian / Vegan Restaurant	Argentinian Restaurant
2	Bogenhausen	Greek Restaurant	Italian Restaurant	Vietnamese Restaurant
3	Buchenhain, Isartal	Bavarian Restaurant	Vietnamese Restaurant	Vegetarian / Vegan Restaurant
4	Deisenhofen bei München	Asian Restaurant	Greek Restaurant	Vietnamese Restaurant

	4th Most Common Venue	5th Most Common Venue
0	Vietnamese Restaurant	Chinese Restaurant
1	Asian Restaurant	Bavarian Restaurant
2	Chinese Restaurant	Falafel Restaurant
3	Argentinian Restaurant	Asian Restaurant
4	Fried Chicken Joint	Argentinian Restaurant

## 0.14 3.2 Cluster Borough with k-means

```
[29]: # set number of clusters
kclusters = 10

munich_grouped_clustering = munich_grouped.drop('borough', 1)

# run k-means clustering
kmeans = KMeans(n_clusters=kclusters, random_state=0).
↳fit(munich_grouped_clustering)

# check cluster labels generated for each row in the dataframe
kmeans.labels_[0:50]
```

```
[29]: array([0, 1, 0, 3, 0, 8, 2, 0, 7, 7, 7, 2, 2, 7, 2, 8, 7, 1, 1, 7, 1, 7,
          0, 5, 7, 8, 7, 3, 1, 0, 7, 6, 7, 7, 8, 2, 8, 8, 8, 0, 0, 4, 1, 1,
          2, 2, 0, 9, 7, 7], dtype=int32)
```

create dataframe

```
[30]: # add clustering labels
neighborhoods_venues_sorted.insert(0, 'Cluster Labels', kmeans.labels_)

munich_merged = munich

# merge manhattan_grouped with manhattan_data to add latitude/longitude for
↳each neighborhood
# munich_merged = munich_merged.join(neighborhoods_venues_sorted.
↳set_index('borough'), on='borough')

munich_merged = munich_merged.merge(neighborhoods_venues_sorted.
↳set_index('borough'), on='borough')

munich_merged
```

```
[30]:   postalcode      borough  latitude  longitude \
0      81675      Bogenhausen  48.158487  11.636682
1      80796  Milbertshofen-Am Hart  48.182385  11.575043
2      80634      Moosach      48.179895  11.510571
3      85774  Unterföhring      48.190718  11.644580
```

4	85609	Dornach	48.153899	11.689900
5	81241	Pasing	48.147785	11.460701
6	85579	Neubiberg	48.076994	11.661514
7	82049	Pullach	48.058962	11.521841
8	85540	Gronsdorf, Kreis München	48.108961	11.719957
9	82024	Winning, Kreis München	48.052210	11.605970
10	82024	Taufkirchen, Kreis München	48.048506	11.604389
11	82166	Gräfelfing	48.121204	11.429978
12	82152	Martinsried	48.108804	11.454734
13	82049	Pullach im Isartal	48.055612	11.521745
14	85521	Ottobrunn	48.064382	11.667504
15	82024	Westerham	48.051219	11.613601
16	85540	Salmdorf, Kreis München	48.130636	11.716920
17	82008	Unterhaching	48.066225	11.610224
18	85640	Solalinden	48.092209	11.706879
19	82024	Taufkirchen	48.045996	11.615190
20	85609	Aschheim	48.171348	11.716035
21	85622	Feldkirchen	48.147577	11.729921
22	82024	Potzham, Kreis München	48.048506	11.604389
23	82041	Oberbiberg	47.979905	11.571268
24	82041	Oberhaching bei München	48.021887	11.584537
25	85640	Putzbrunn	48.075308	11.715627
26	85540	Ottendichl, Kreis München	48.116420	11.741950
27	85540	Haar bei München	48.111625	11.725762
28	82152	Planegg	48.103742	11.422003
29	85764	Lustheim	48.251939	11.575141
30	85764	Oberschleißheim	48.254938	11.554606
31	85748	Hochbrück bei München	48.252378	11.634927
32	85540	Eglfing, Kreis München	48.110630	11.728781
33	82032	Deisenhofen bei München	48.019312	11.587387
34	85737	Ismaning	48.227225	11.676879
35	82065	Buchenhain, Isartal	48.029018	11.496768
36	85662	Hohenbrunn	48.048083	11.702163
37	85521	Riemerling	48.059283	11.680674
38	82152	Krailling	48.099184	11.417221
39	85748	Garching	48.251388	11.650966
40	85748	Garching bei München	48.251388	11.650966
41	85551	Kirchheim bei München	48.180638	11.752985
42	85551	Kirchheim	48.180638	11.752985
43	85757	Rothschwaige	48.183882	11.499586
44	82110	Neugermering	48.127735	11.363372
45	85764	Mittenheim	48.263084	11.557159
46	82065	Baierbrunn	48.020477	11.486546
47	85630	Neukeferloh	48.096429	11.760195
48	80331	Zentrum Marienplatz	48.137187	11.575501
49	80335	Hauptbahnhof	48.140458	11.557766

	Cluster Labels	1st Most Common Venue	2nd Most Common Venue \
0	0	Greek Restaurant	Italian Restaurant
1	0	Greek Restaurant	German Restaurant
2	7	German Restaurant	Italian Restaurant
3	2	Italian Restaurant	Vietnamese Restaurant
4	8	German Restaurant	Thai Restaurant
5	7	Italian Restaurant	Vietnamese Restaurant
6	8	German Restaurant	Italian Restaurant
7	8	German Restaurant	Asian Restaurant
8	7	Vietnamese Restaurant	Bistro
9	7	Chinese Restaurant	Italian Restaurant
10	2	Italian Restaurant	Doner Restaurant
11	2	Italian Restaurant	Vietnamese Restaurant
12	7	German Restaurant	Greek Restaurant
13	8	German Restaurant	Asian Restaurant
14	7	Italian Restaurant	Vietnamese Restaurant
15	9	Doner Restaurant	Vietnamese Restaurant
16	4	Steakhouse	Vietnamese Restaurant
17	0	Greek Restaurant	German Restaurant
18	1	German Restaurant	Vegetarian / Vegan Restaurant
19	1	German Restaurant	Vegetarian / Vegan Restaurant
20	0	Greek Restaurant	Asian Restaurant
21	0	German Restaurant	Greek Restaurant
22	2	Italian Restaurant	Doner Restaurant
23	1	German Restaurant	Vegetarian / Vegan Restaurant
24	0	Asian Restaurant	Greek Restaurant
25	8	German Restaurant	Italian Restaurant
26	6	Restaurant	Vietnamese Restaurant
27	2	Bistro	Italian Restaurant
28	8	German Restaurant	Italian Restaurant
29	1	German Restaurant	Vegetarian / Vegan Restaurant
30	7	Vietnamese Restaurant	Italian Restaurant
31	2	Italian Restaurant	Vietnamese Restaurant
32	2	Italian Restaurant	Vietnamese Restaurant
33	0	Asian Restaurant	Greek Restaurant
34	7	German Restaurant	Thai Restaurant
35	3	Bavarian Restaurant	Vietnamese Restaurant
36	8	German Restaurant	Italian Restaurant
37	0	Asian Restaurant	Vietnamese Restaurant
38	7	Italian Restaurant	Greek Restaurant
39	7	German Restaurant	Greek Restaurant
40	7	German Restaurant	Greek Restaurant
41	1	German Restaurant	Vegetarian / Vegan Restaurant
42	1	German Restaurant	Vegetarian / Vegan Restaurant
43	0	Greek Restaurant	Vietnamese Restaurant
44	7	German Restaurant	Burger Joint
45	5	Chinese Restaurant	Vietnamese Restaurant

46	1	German Restaurant	Vegetarian / Vegan Restaurant
47	3	Bavarian Restaurant	Vietnamese Restaurant
48	7	German Restaurant	Bavarian Restaurant
49	7	Middle Eastern Restaurant	German Restaurant

	3rd Most Common Venue	4th Most Common Venue \
0	Vietnamese Restaurant	Chinese Restaurant
1	Thai Restaurant	Burger Joint
2	Asian Restaurant	American Restaurant
3	Fried Chicken Joint	Argentinian Restaurant
4	Italian Restaurant	Burrito Place
5	Fast Food Restaurant	German Restaurant
6	Restaurant	Burrito Place
7	Italian Restaurant	Fried Chicken Joint
8	Italian Restaurant	Fried Chicken Joint
9	Doner Restaurant	Vietnamese Restaurant
10	Vietnamese Restaurant	Fried Chicken Joint
11	Fried Chicken Joint	Argentinian Restaurant
12	Indian Restaurant	Italian Restaurant
13	Italian Restaurant	Fried Chicken Joint
14	Beer Garden	Indian Restaurant
15	Vegetarian / Vegan Restaurant	Argentinian Restaurant
16	Fried Chicken Joint	Argentinian Restaurant
17	Pizza Place	Asian Restaurant
18	Argentinian Restaurant	Asian Restaurant
19	Argentinian Restaurant	Asian Restaurant
20	Italian Restaurant	Vietnamese Restaurant
21	Asian Restaurant	Italian Restaurant
22	Vietnamese Restaurant	Fried Chicken Joint
23	Argentinian Restaurant	Asian Restaurant
24	Vietnamese Restaurant	Fried Chicken Joint
25	Fried Chicken Joint	Argentinian Restaurant
26	Fried Chicken Joint	Argentinian Restaurant
27	Vietnamese Restaurant	Fried Chicken Joint
28	Fried Chicken Joint	Argentinian Restaurant
29	Argentinian Restaurant	Asian Restaurant
30	Chinese Restaurant	German Restaurant
31	Fried Chicken Joint	Argentinian Restaurant
32	Fried Chicken Joint	Argentinian Restaurant
33	Vietnamese Restaurant	Fried Chicken Joint
34	Indian Restaurant	Italian Restaurant
35	Vegetarian / Vegan Restaurant	Argentinian Restaurant
36	Fried Chicken Joint	Argentinian Restaurant
37	Vegetarian / Vegan Restaurant	Argentinian Restaurant
38	Beer Garden	Vietnamese Restaurant
39	Italian Restaurant	Chinese Restaurant
40	Italian Restaurant	Chinese Restaurant

41	Argentinian Restaurant	Asian Restaurant
42	Argentinian Restaurant	Asian Restaurant
43	Fried Chicken Joint	Argentinian Restaurant
44	Italian Restaurant	Pizza Place
45	Vegetarian / Vegan Restaurant	Argentinian Restaurant
46	Argentinian Restaurant	Asian Restaurant
47	Vegetarian / Vegan Restaurant	Argentinian Restaurant
48	Pizza Place	Italian Restaurant
49	Bavarian Restaurant	Eastern European Restaurant

#### 5th Most Common Venue

0	Falafel Restaurant
1	Asian Restaurant
2	Sushi Restaurant
3	Asian Restaurant
4	Falafel Restaurant
5	Theme Restaurant
6	Falafel Restaurant
7	Argentinian Restaurant
8	Argentinian Restaurant
9	Fried Chicken Joint
10	Argentinian Restaurant
11	Asian Restaurant
12	Chinese Restaurant
13	Argentinian Restaurant
14	German Restaurant
15	Asian Restaurant
16	Asian Restaurant
17	Bavarian Restaurant
18	Bavarian Restaurant
19	Bavarian Restaurant
20	Chinese Restaurant
21	Chinese Restaurant
22	Argentinian Restaurant
23	Bavarian Restaurant
24	Argentinian Restaurant
25	Asian Restaurant
26	Asian Restaurant
27	Argentinian Restaurant
28	Asian Restaurant
29	Bavarian Restaurant
30	Sushi Restaurant
31	Asian Restaurant
32	Asian Restaurant
33	Argentinian Restaurant
34	Restaurant
35	Asian Restaurant

```

36         Asian Restaurant
37     Bavarian Restaurant
38         Chinese Restaurant
39         Indian Restaurant
40         Indian Restaurant
41     Bavarian Restaurant
42     Bavarian Restaurant
43         Asian Restaurant
44         Asian Restaurant
45         Asian Restaurant
46     Bavarian Restaurant
47         Asian Restaurant
48             Restaurant
49         Italian Restaurant

```

### 0.15 3.3 Cluster Visualization

```

[31]: # create map
map_clusters = folium.Map(location=[latitude, longitude], zoom_start=11)

# set color scheme for the clusters
x = np.arange(kclusters)
ys = [i + x + (i*x)**2 for i in range(kclusters)]
colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
rainbow = [colors.rgb2hex(i) for i in colors_array]

# add markers to the map
markers_colors = []
for lat, lon, poi, cluster in zip(munich_merged['latitude'],
    ↪munich_merged['longitude'], munich_merged['borough'], munich_merged['Cluster_
    ↪Labels']):
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_clusters)

map_clusters

```

```

[31]: <folium.folium.Map at 0x7f70e400a668>

```

## 0.16 3.4 evaluate target criteria according to ‘munich\_restaurants’

```
[32]: munich_sum = pd.get_dummies(munich_restaurants[['Venue Category']], prefix="",
    ↪prefix_sep="")

munich_sum['borough'] = munich_restaurants['borough']

#Fix Column Order
fixed_columns = [munich_sum.columns[-1]] + list(munich_sum.columns[:-1])
munich_sum = munich_sum[fixed_columns]
```

Sum amount of each venues out of target definition ‘munich\_restaurants’

```
[82]: munich_sum['amount of restaurants']=munich_sum.sum(axis=1)
munich_sum = munich_sum.groupby('borough').sum().reset_index()
```

keep only sum as criteria and add it to overview ‘munich\_merged’ show only top5 boroughs according to amount of restaurants

```
[84]: munich_sum = munich_sum[['borough', 'amount of restaurants']]

munich_merged = pd.merge(munich_merged, munich_sum, on = 'borough')
munich_merged.sort_values(by=['amount of restaurants'], ascending=False,
    ↪inplace=True)
munich_merged.head(5)
```

```
[84]:  postalcode      borough  latitude  longitude  Cluster Labels  \
0      80331  Zentrum Marienplatz  48.137187  11.575501          7
1      81241          Pasing  48.147785  11.460701          7
2      80335  Hauptbahnhof  48.140458  11.557766          7
3      85748      Garching  48.251388  11.650966          7
4      85748  Garching bei München  48.251388  11.650966          7
```

```
      1st Most Common Venue  2nd Most Common Venue  3rd Most Common Venue  \
0      German Restaurant  Bavarian Restaurant  Pizza Place
1      Italian Restaurant  Vietnamese Restaurant  Fast Food Restaurant
2  Middle Eastern Restaurant  German Restaurant  Bavarian Restaurant
3      German Restaurant  Greek Restaurant  Italian Restaurant
4      German Restaurant  Greek Restaurant  Italian Restaurant
```

```
      4th Most Common Venue  5th Most Common Venue  Sum  \
0      Italian Restaurant  Restaurant  24
1      German Restaurant  Theme Restaurant  18
2  Eastern European Restaurant  Italian Restaurant  11
3      Chinese Restaurant  Indian Restaurant  9
4      Chinese Restaurant  Indian Restaurant  9
```

amount of restaurants



0	24
1	18
2	11
3	9
4	9

```
[ ]:
```

## 0.17 4. Berlin: Data import and cleaning

### 0.18 4.1 library import

If necessary, please run code line from '2. Munich'.

### 0.19 4.2 Berlin Data import with BeautifulSoup

```
[35]: url='http://www.places-in-germany.com/
↳14356-places-within-a-radius-of-15km-around-berlin.html'
req=requests.get(url)
soup=BeautifulSoup(req.text,"html.parser")
table = soup.find_all('table')
df=pd.read_html(str(table), header=0)[0]
```

```
[36]: df.head()
```

```
[36]:
```

	Distance	Route	Postal code / Place	Population
0	1.2 km (0.8 miles)	NaN	10115 Mitte	79582
1	2.1 km (1.3 miles)	NaN	10119 Prenzlauer Berg	140881
2	2.8 km (1.7 miles)	NaN	10115 Mitte	333534
3	2.9 km (1.8 miles)	NaN	13347 Gesundbrunnen	82110
4	3.3 km (2.0 miles)	NaN	10243 Friedrichshain-Kreuzberg	269398

delete double entry manually

```
[37]: df.drop(index=0, inplace=True)
df.shape
```

```
[37]: (97, 4)
```

```
[38]: df.rename({'Postal code / Place':'Borough'},axis=1, inplace=True)
berlin=df.Borough.str.split(" ",n=1,expand=True)
berlin.rename({0:'postalcode', 1:'borough'}, axis=1, inplace=True)
berlin
```

```
[38]:
```

	postalcode	borough
1	10119	Prenzlauer Berg
2	10115	Mitte
3	13347	Gesundbrunnen

4	10243	Friedrichshain-Kreuzberg
5	10243	Friedrichshain
..	...	...
93	12459	Köpenick
94	12524	Altglienicke
95	16341	Schwanebeck bei Bernau bei Berlin
96	12305	Lichtenrade
97	12157	Steglitz-Zehlendorf

[97 rows x 2 columns]

test for NaN values

```
[39]: if berlin['borough'].isnull().sum() > 0:
        berlin.dropna(axis=0, inplace=True)
        print('NaN values deleted. New size ',berlin.shape)
    else:
        print('no NaN values')
```

NaN values deleted. New size (96, 2)

## 0.20 4.3 Folium Map Berlin

```
[40]: from geopy.geocoders import Nominatim
        from geopy.extra.rate_limiter import RateLimiter

        lat=[]
        lon=[]

        geolocator = Nominatim(user_agent='Couserera')

        for line, borough in berlin.iterrows():

            try:
                adress= borough[0], ' Berlin ', borough[1]
                location = geolocator.geocode(adress)
                print(location)
                lat.append(location.latitude)
                lon.append(location.longitude)
            except:
                lat.append(np.nan)
                lon.append(np.nan)

        berlin['latitude']=lat
        berlin['longitude']=lon
```

Prenzlauer Berg, Winsviertel, Prenzlauer Berg, Pankow, Berlin, 10405, Deutschland

Mitte, Berlin, Deutschland  
Gesundbrunnen, Mitte, Berlin, Deutschland  
Friedrichshain-Kreuzberg, Berlin, Deutschland  
Friedrichshain, Friedrichshain-Kreuzberg, Berlin, Deutschland  
Tiergarten, Mitte, Berlin, Deutschland  
Wedding, Mitte, Berlin, Deutschland  
Moabit, Mitte, Berlin, Deutschland  
U Platz der Luftbrücke, Mehringdamm, Kreuzberg, Friedrichshain-Kreuzberg,  
Berlin, 10965, Deutschland  
Hansaviertel, Mitte, Berlin, Deutschland  
Fennpfuhl, Lichtenberg, Berlin, 10369, Deutschland  
Alt-Treptow, Treptow-Köpenick, Berlin, Deutschland  
Weißensee, Pankow, Berlin, Deutschland  
Pankow, Berlin, Deutschland  
Heinersdorf, Romain-Rolland-Straße, Heinersdorf, Pankow, Berlin, 13089,  
Deutschland  
Neukölln, Berlin, Deutschland  
Lichtenberg, Berlin, Deutschland  
Schöneberg, Tempelhof-Schöneberg, Berlin, Deutschland  
Lichtenberg, Berlin, Deutschland  
Rummelsburg, Lichtenberg, Berlin, Deutschland  
Niederschönhausen, Pankow, Berlin, 13156, Deutschland  
Tempelhof, Tempelhof-Schöneberg, Berlin, Deutschland  
Stadtrandsiedlung Malchow, Pankow, Berlin, Deutschland  
Reinickendorf, Berlin, Deutschland  
Plänterwald, Treptow-Köpenick, Berlin, 12435, Deutschland  
Charlottenburg, Charlottenburg-Wilmersdorf, Berlin, Deutschland  
Wilhelmsruh, Pankow, Berlin, Deutschland  
Alt-Hohenschönhausen, Lichtenberg, Berlin, Deutschland  
Wilmersdorf, Charlottenburg-Wilmersdorf, Berlin, Deutschland  
Charlottenburg-Nord, Charlottenburg-Wilmersdorf, Berlin, 13627, Deutschland  
Friedenau, Tempelhof-Schöneberg, Berlin, Deutschland  
Neu-Hohenschönhausen, Lichtenberg, Berlin, 13051, Deutschland  
Charlottenburg-Wilmersdorf, Berlin, Deutschland  
Friedrichsfelde, Lichtenberg, Berlin, Deutschland  
Malchow, Lichtenberg, Berlin, Deutschland  
Rosenthal, Pankow, Berlin, 13158, Deutschland  
Baumschulenweg, Treptow-Köpenick, Berlin, 12437, Deutschland  
Tempelhof-Schöneberg, Berlin, Deutschland  
Halensee, Charlottenburg-Wilmersdorf, Berlin, 10711, Deutschland  
Blankenburg, Pankow, Berlin, 13129, Deutschland  
Grunewald, Charlottenburg-Wilmersdorf, Berlin, Deutschland  
Märkisches Viertel, Reinickendorf, Berlin, 13439, Deutschland  
Britz, Neukölln, Berlin, Deutschland  
Steglitz, Steglitz-Zehlendorf, Berlin, Deutschland  
Westend, Charlottenburg-Wilmersdorf, Berlin, Deutschland  
Karlshorst, Lichtenberg, Berlin, 10318, Deutschland  
Wartenberg, Lichtenberg, Berlin, 13059, Deutschland

Schmargendorf, Charlottenburg-Wilmersdorf, Berlin, 14199, Deutschland  
 Wittenau, Reinickendorf, Berlin, Deutschland  
 Siemensstadt, Spandau, Berlin, 13629, Deutschland  
 Französisch Buchholz, Pankow, Berlin, 13127, Deutschland  
 Marzahn, Marzahn-Hellersdorf, Berlin, Deutschland  
 Mariendorf, Tempelhof-Schöneberg, Berlin, Deutschland  
 Biesdorf, Marzahn-Hellersdorf, Berlin, 12683, Deutschland  
 Falkenberg, Lichtenberg, Berlin, 13057, Deutschland  
 Tegel, Reinickendorf, Berlin, Deutschland  
 Niederschöneweide, Treptow-Köpenick, Berlin, 12439, Deutschland  
 Lübars, Reinickendorf, Berlin, Deutschland  
 Oberschöneweide, Treptow-Köpenick, Berlin, 12459, Deutschland  
 Waidmannslust, Reinickendorf, Berlin, 13469, Deutschland  
 Lankwitz, Steglitz-Zehlendorf, Berlin, Deutschland  
 Blankenfelde, Pankow, Berlin, 13159, Deutschland  
 Dahlem, Steglitz-Zehlendorf, Berlin, 14195, Deutschland  
 Karow, Pankow, Berlin, 13125, Deutschland  
 Johannisthal, Treptow-Köpenick, Berlin, 12487, Deutschland  
 Haselhorst, Spandau, Berlin, 13599, Deutschland  
 Gropiusstadt, Neukölln, Berlin, Deutschland  
 None  
 Buckow, Neukölln, Berlin, Deutschland  
 Lichterfelde, Steglitz-Zehlendorf, Berlin, Deutschland  
 Hermsdorf, Reinickendorf, Berlin, 13467, Deutschland  
 Kaulsdorf, Marzahn-Hellersdorf, Berlin, 12621, Deutschland  
 Marzahn-Hellersdorf, Berlin, Deutschland  
 Lübarser Weg, Schildow-Waldeck, Blankenfelde, Pankow, Berlin, 13159, Deutschland  
 Marienfelde, Tempelhof-Schöneberg, Berlin, Deutschland  
 Hellersdorf, Marzahn-Hellersdorf, Berlin, Deutschland  
 Ahrensfelde, Ahrensfelder Chaussee, Marzahn, Marzahn-Hellersdorf, Berlin, 12689, Deutschland  
 None  
 None  
 Verlauf der Berliner Mauer, Am Sandkrug, Entenschnabel, Glienicke/Nordbahn, Oberhavel, Brandenburg, 16548, Deutschland  
 Rudow, Neukölln, Berlin, Deutschland  
 Adlershof, Treptow-Köpenick, Berlin, 12489, Deutschland  
 Buch, Pankow, Berlin, Deutschland  
 Konradshöhe, Reinickendorf, Berlin, 13505, Deutschland  
 Zehlendorf, Steglitz-Zehlendorf, Berlin, Deutschland  
 Frohnau, Reinickendorf, Berlin, 13465, Deutschland  
 Spandau, Berlin, Deutschland  
 Mahlsdorf, Marzahn-Hellersdorf, Berlin, 12623, Deutschland  
 Treptow-Köpenick, Berlin, Deutschland  
 None  
 None  
 Köpenick, Treptow-Köpenick, Berlin, Deutschland  
 Altglienicke, Treptow-Köpenick, Berlin, 12524, Deutschland

None

Lichtenrade, Tempelhof-Schöneberg, Berlin, Deutschland

Steglitz-Zehlendorf, Berlin, Deutschland

```
[41]: berlin.dropna(axis=0, inplace=True)
      berlin.shape
```

```
[41]: (90, 4)
```

```
[42]: address = 'berlin'

geolocator = Nominatim(user_agent="Couser")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print('geo-coordinates of Berlin {}, {}'.format(latitude, longitude))

# Creating Folium Map
map_berlin = folium.Map(location=[latitude, longitude], zoom_start=11)

# add markers to map
for lat, lng, borough in zip(berlin['latitude'], berlin['longitude'],
↪berlin['borough']):
    label = '{}'.format(borough)
    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(map_berlin)

map_berlin
```

geo-coordinates of Berlin 52.5170365, 13.3888599.

```
[42]: <folium.folium.Map at 0x7f70e40415f8>
```

```
[ ]:
```

## 0.21 4.4 Explore Venues with 4square

```
[43]: CLIENT_ID = 'MIXA2M5FTBG1IILFL5ATNOBSNUP4BU4J1BUOGIM03E1UJOBE' # your ↵  
      ↪Foursquare ID  
      CLIENT_SECRET = 'ETQCTK31Z04IOFVKYEEH2MOJGLOG4DCLQ1R1ECOOPHX33D' # your ↵  
      ↪Foursquare Secret  
      VERSION = '20180604'  
      LIMIT = 100  
      radius = 500  
      print("ID loaded")
```

ID loaded

```
[44]: berlin_venues = getNearbyVenues(names=berlin['borough'],  
                                     latitudes=berlin['latitude'],  
                                     longitudes=berlin['longitude']  
                                     )
```

Prenzlauer Berg  
Mitte  
Gesundbrunnen  
Friedrichshain-Kreuzberg  
Friedrichshain  
Tiergarten  
Wedding  
Moabit  
Kreuzberg  
Hansaviertel  
Fennpfuhl  
Alt-Treptow  
Weißensee  
Pankow  
Heinersdorf  
Neukölln  
Lichtenberg  
Schöneberg  
Lichtenberg  
Rummelsburg  
Niederschönhausen  
Tempelhof  
Stadtrandsiedlung Malchow  
Reinickendorf  
Plänterwald  
Charlottenburg  
Wilhelmsruh  
Alt-Hohenschönhausen  
Wilmerdorf  
Charlottenburg-Nord

Friedenau  
Neu-Hohenschönhausen  
Charlottenburg-Wilmersdorf  
Friedrichsfelde  
Malchow  
Rosenthal  
Baumschulenweg  
Tempelhof-Schöneberg  
Halensee  
Blankenburg  
Grunewald  
Märkisches Viertel  
Britz  
Steglitz  
Westend  
Karlshorst  
Wartenberg  
Schmargendorf  
Wittenau  
Siemensstadt  
Französisch Buchholz  
Marzahn  
Mariendorf  
Biesdorf  
Falkenberg  
Tegel  
Niederschöneweide  
Lübars  
Oberschöneweide  
Waidmannslust  
Lankwitz  
Blankenfelde  
Dahlem  
Karow  
Johannisthal  
Haselhorst  
Gropiusstadt  
Buckow  
Lichterfelde  
Hermsdorf  
Kaulsdorf  
Marzahn-Hellersdorf  
Schildow  
Marienfelde  
Hellersdorf  
Ahrensfelde  
Glienicke / Nordbahn  
Rudow

Adlershof  
 Buch  
 Konradshöhe  
 Zehlendorf  
 Frohnau  
 Spandau  
 Mahlsdorf  
 Treptow-Köpenick  
 Köpenick  
 Altglienicke  
 Lichtenrade  
 Steglitz-Zehlendorf

```
[45]: print('4square provided', berlin_venues.shape , 'venues')
      berlin_venues.head(5)
```

4square provided (1483, 7) venues

```
[45]:
```

	borough	Latitude	Longitude	Venue \
0	Prenzlauer Berg	52.528634	13.420105	Bötzow Brauerei
1	Prenzlauer Berg	52.528634	13.420105	Soho House Cinema
2	Prenzlauer Berg	52.528634	13.420105	Cowshed Active
3	Prenzlauer Berg	52.528634	13.420105	The Store x Soho House Berlin
4	Prenzlauer Berg	52.528634	13.420105	Rooftop Soho House

  

	Venue	Latitude	Venue	Longitude	Venue	Category
0	52.530242		13.417293		Historic Site	
1	52.527359		13.415775		Movie Theater	
2	52.527378		13.415791	Gym /	Fitness Center	
3	52.527525		13.415868		Boutique	
4	52.527533		13.415599		Roof Deck	

```
[46]: print('There are {} uniques categories.'.format(len(berlin_venues['Venue_
      ↳Category'].unique()))
      berlin_venues.groupby('Venue Category').Venue.count()
```

There are 245 uniques categories.

```
[46]: Venue Category
```

ATM	2
Adult Boutique	1
African Restaurant	1
American Restaurant	2
Argentinian Restaurant	2
..	
Windmill	1
Wine Bar	2
Wine Shop	5



```

Yoga Studio                2
Zoo Exhibit                 2
Name: Venue, Length: 245, dtype: int64

```

## 0.22 5. Analyze Boroughs of Berlin

```

[47]: berlin_restaurants = berlin_venues[berlin_venues['Venue Category'].str.
      ↪contains('|'.join(restaurants))]

```

```

[48]: berlin_restaurants.head()

```

```

[48]:
      borough  Latitude  Longitude  Venue  Venue Latitude \
10  Prenzlauer Berg  52.528634  13.420105  The Store Kitchen  52.527506
11  Prenzlauer Berg  52.528634  13.420105  La Soupe Populaire  52.530595
12  Prenzlauer Berg  52.528634  13.420105  Mondo Sardo  52.531076
19  Prenzlauer Berg  52.528634  13.420105  Leibhaftig  52.531392
20  Prenzlauer Berg  52.528634  13.420105  MontRaw Restaurant  52.531860

      Venue Longitude  Venue Category
10      13.415744      Bistro
11      13.416777  Modern European Restaurant
12      13.422782  Italian Restaurant
19      13.416966  German Restaurant
20      13.415882  Israeli Restaurant

```

## 0.23 5.1 Frequency of occurrence

```

[49]: # one hot encoding
      berlin_onehot = pd.get_dummies(berlin_restaurants[['Venue Category']],
      ↪prefix="", prefix_sep="")

      # add neighborhood column back to dataframe
      berlin_onehot['borough'] = berlin_restaurants['borough']

      # move neighborhood column to the first column
      fixed_columns = [berlin_onehot.columns[-1]] + list(berlin_onehot.columns[:-1])
      berlin_onehot = berlin_onehot[fixed_columns]

      berlin_onehot.head()

```

```

[49]:
      borough  African Restaurant  American Restaurant \
10  Prenzlauer Berg              0                  0
11  Prenzlauer Berg              0                  0
12  Prenzlauer Berg              0                  0
19  Prenzlauer Berg              0                  0
20  Prenzlauer Berg              0                  0

```

	Argentinian Restaurant	Asian Restaurant	Austrian Restaurant	\
10	0	0	0	
11	0	0	0	
12	0	0	0	
19	0	0	0	
20	0	0	0	

  

	Bavarian Restaurant	Beer Garden	Bistro	Brazilian Restaurant	...	\
10	0	0	1	0	...	
11	0	0	0	0	...	
12	0	0	0	0	...	
19	0	0	0	0	...	
20	0	0	0	0	...	

  

	Silesian Restaurant	Spanish Restaurant	Steakhouse	Sushi Restaurant	\
10	0		0	0	
11	0		0	0	
12	0		0	0	
19	0		0	0	
20	0		0	0	

  

	Syrian Restaurant	Tapas Restaurant	Thai Restaurant	Turkish Restaurant	\
10	0	0	0	0	
11	0	0	0	0	
12	0	0	0	0	
19	0	0	0	0	
20	0	0	0	0	

  

	Vegetarian / Vegan Restaurant	Vietnamese Restaurant
10	0	0
11	0	0
12	0	0
19	0	0
20	0	0

[5 rows x 53 columns]

[ ]:

group rows by neighborhood and mean frequency of occurrence of each category

```
[50]: print('Size of One Hot is ', berlin_onehot.shape, '.')
      berlin_grouped = berlin_onehot.groupby('borough').mean().reset_index()
      berlin_grouped.head()
```

Size of One Hot is (392, 53) .

```

[50]:          borough African Restaurant American Restaurant \
0          Adlershof          0.0          0.0
1  Alt-Hohenschönhausen          0.0          0.0
2          Alt-Treptow          0.0          0.0
3          Blankenburg          0.0          0.0
4          Britz          0.0          0.0

          Argentinian Restaurant Asian Restaurant Austrian Restaurant \
0          0.0          0.00          0.0
1          0.0          0.25          0.0
2          0.0          0.00          0.0
3          0.0          0.00          0.0
4          0.0          0.00          0.0

          Bavarian Restaurant Beer Garden Bistro Brazilian Restaurant ... \
0          0.0          0.000000          0.0          0.0 ...
1          0.0          0.000000          0.0          0.0 ...
2          0.0          0.142857          0.0          0.0 ...
3          0.0          0.000000          0.0          0.0 ...
4          0.0          0.000000          0.0          0.0 ...

          Silesian Restaurant Spanish Restaurant Steakhouse Sushi Restaurant \
0          0.0          0.0          0.25          0.0
1          0.0          0.0          0.00          0.0
2          0.0          0.0          0.00          0.0
3          0.0          0.0          0.00          0.0
4          0.0          0.0          0.00          0.0

          Syrian Restaurant Tapas Restaurant Thai Restaurant Turkish Restaurant \
0          0.0          0.000000          0.0          0.0
1          0.0          0.000000          0.0          0.0
2          0.0          0.142857          0.0          0.0
3          0.0          0.000000          0.0          0.0
4          0.0          0.000000          0.0          0.0

          Vegetarian / Vegan Restaurant Vietnamese Restaurant
0          0.0          0.000000
1          0.0          0.000000
2          0.0          0.142857
3          0.0          0.000000
4          0.0          0.000000

[5 rows x 53 columns]

```

```

[51]: print('confirm the new size:', berlin_grouped.shape)

```

```
confirm the new size: (70, 53)
```

Let's print each neighborhood along with the top 5 most common venues

```
[52]: num_top_venues = 5

for hood in berlin_grouped['borough']:
    print("----"+hood+"----")
    temp = berlin_grouped[berlin_grouped['borough'] == hood].T.reset_index()
    temp.columns = ['venue', 'freq']
    temp = temp.iloc[1:]
    temp['freq'] = temp['freq'].astype(float)
    temp = temp.round({'freq': 2})
    print(temp.sort_values('freq', ascending=False).reset_index(drop=True).
    ↪head(num_top_venues))
    print('\n')
```

----Adlershof----

	venue	freq
0	Italian Restaurant	0.25
1	Greek Restaurant	0.25
2	Steakhouse	0.25
3	Pizza Place	0.25
4	Restaurant	0.00

----Alt-Hohenschönhausen----

	venue	freq
0	Doner Restaurant	0.25
1	Asian Restaurant	0.25
2	Indian Restaurant	0.25
3	Greek Restaurant	0.25
4	African Restaurant	0.00

----Alt-Treptow----

	venue	freq
0	Italian Restaurant	0.14
1	Beer Garden	0.14
2	Tapas Restaurant	0.14
3	Seafood Restaurant	0.14
4	Mexican Restaurant	0.14

----Blankenburg----

	venue	freq
0	Greek Restaurant	1.0
1	African Restaurant	0.0
2	Japanese Restaurant	0.0
3	Lebanese Restaurant	0.0

4 Mediterranean Restaurant 0.0

----Britz----

	venue	freq
0	German Restaurant	1.0
1	African Restaurant	0.0
2	Japanese Restaurant	0.0
3	Lebanese Restaurant	0.0
4	Mediterranean Restaurant	0.0

----Buch----

	venue	freq
0	Italian Restaurant	1.0
1	American Restaurant	0.0
2	Korean Restaurant	0.0
3	Lebanese Restaurant	0.0
4	Mediterranean Restaurant	0.0

----Buckow----

	venue	freq
0	Pizza Place	1.0
1	African Restaurant	0.0
2	American Restaurant	0.0
3	Korean Restaurant	0.0
4	Lebanese Restaurant	0.0

----Charlottenburg----

	venue	freq
0	Chinese Restaurant	0.20
1	Pizza Place	0.20
2	Italian Restaurant	0.13
3	Sushi Restaurant	0.07
4	Middle Eastern Restaurant	0.07

----Charlottenburg-Wilmersdorf----

	venue	freq
0	Italian Restaurant	0.50
1	Indian Restaurant	0.25
2	Pizza Place	0.25
3	Japanese Restaurant	0.00
4	Lebanese Restaurant	0.00

----Dahlem----

	venue	freq
0	German Restaurant	1.0
1	African Restaurant	0.0
2	Japanese Restaurant	0.0
3	Lebanese Restaurant	0.0
4	Mediterranean Restaurant	0.0

----Fennpfuhl----

	venue	freq
0	Italian Restaurant	0.5
1	Sushi Restaurant	0.5
2	Restaurant	0.0
3	Korean Restaurant	0.0
4	Lebanese Restaurant	0.0

----Französisch Buchholz----

	venue	freq
0	Chinese Restaurant	1.0
1	African Restaurant	0.0
2	Scandinavian Restaurant	0.0
3	Lebanese Restaurant	0.0
4	Mediterranean Restaurant	0.0

----Friedenau----

	venue	freq
0	Vietnamese Restaurant	0.25
1	Bistro	0.25
2	Korean Restaurant	0.25
3	Greek Restaurant	0.12
4	Burger Joint	0.12

----Friedrichsfelde----

	venue	freq
0	Restaurant	1.0
1	African Restaurant	0.0
2	American Restaurant	0.0
3	Korean Restaurant	0.0
4	Lebanese Restaurant	0.0

----Friedrichshain----

	venue	freq
0	Middle Eastern Restaurant	0.23

1	Doner Restaurant	0.23
2	Italian Restaurant	0.08
3	Vegetarian / Vegan Restaurant	0.08
4	Thai Restaurant	0.08

----Friedrichshain-Kreuzberg----

	venue	freq
0	Vietnamese Restaurant	0.14
1	Pizza Place	0.14
2	Falafel Restaurant	0.07
3	Indian Restaurant	0.07
4	Vegetarian / Vegan Restaurant	0.03

----Frohnau----

	venue	freq
0	Italian Restaurant	0.25
1	Pizza Place	0.25
2	Doner Restaurant	0.25
3	Restaurant	0.25
4	Japanese Restaurant	0.00

----Gesundbrunnen----

	venue	freq
0	Turkish Restaurant	0.36
1	Italian Restaurant	0.18
2	Halal Restaurant	0.09
3	Syrian Restaurant	0.09
4	Pakistani Restaurant	0.09

----Gropiusstadt----

	venue	freq
0	Restaurant	1.0
1	African Restaurant	0.0
2	American Restaurant	0.0
3	Korean Restaurant	0.0
4	Lebanese Restaurant	0.0

----Grunewald----

	venue	freq
0	German Restaurant	0.4
1	Italian Restaurant	0.2
2	Beer Garden	0.2
3	Eastern European Restaurant	0.2

4        Scandinavian Restaurant    0.0

----Halensee----

	venue	freq
0	Italian Restaurant	0.18
1	Spanish Restaurant	0.09
2	Japanese Restaurant	0.09
3	Mediterranean Restaurant	0.09
4	Greek Restaurant	0.09

----Hansaviertel----

	venue	freq
0	Turkish Restaurant	0.33
1	Mediterranean Restaurant	0.33
2	Bistro	0.33
3	African Restaurant	0.00
4	Scandinavian Restaurant	0.00

----Heinersdorf----

	venue	freq
0	Chinese Restaurant	1.0
1	African Restaurant	0.0
2	Scandinavian Restaurant	0.0
3	Lebanese Restaurant	0.0
4	Mediterranean Restaurant	0.0

----Hellersdorf----

	venue	freq
0	Greek Restaurant	0.5
1	Mexican Restaurant	0.5
2	African Restaurant	0.0
3	Japanese Restaurant	0.0
4	Lebanese Restaurant	0.0

----Hermsdorf----

	venue	freq
0	Sushi Restaurant	0.33
1	Seafood Restaurant	0.33
2	Chinese Restaurant	0.33
3	African Restaurant	0.00
4	Restaurant	0.00



----Johannisthal----

	venue	freq
0	Sushi Restaurant	0.33
1	Burger Joint	0.33
2	Pizza Place	0.33
3	African Restaurant	0.00
4	Scandinavian Restaurant	0.00

----Karlshorst----

	venue	freq
0	Italian Restaurant	0.38
1	Doner Restaurant	0.12
2	Argentinian Restaurant	0.12
3	Greek Restaurant	0.12
4	Sushi Restaurant	0.12

----Karow----

	venue	freq
0	Restaurant	1.0
1	African Restaurant	0.0
2	American Restaurant	0.0
3	Korean Restaurant	0.0
4	Lebanese Restaurant	0.0

----Konradshöhe----

	venue	freq
0	Italian Restaurant	0.5
1	Restaurant	0.5
2	American Restaurant	0.0
3	Korean Restaurant	0.0
4	Lebanese Restaurant	0.0

----Kreuzberg----

	venue	freq
0	Italian Restaurant	0.22
1	German Restaurant	0.22
2	Eastern European Restaurant	0.11
3	Vegetarian / Vegan Restaurant	0.11
4	Indian Restaurant	0.11

----Köpenick----

	venue	freq
0	Indian Restaurant	0.33

1	German Restaurant	0.33
2	Burger Joint	0.33
3	African Restaurant	0.00
4	Scandinavian Restaurant	0.00

----Lankwitz----

	venue	freq
0	German Restaurant	0.5
1	Fast Food Restaurant	0.5
2	African Restaurant	0.0
3	Restaurant	0.0
4	Lebanese Restaurant	0.0

----Lichtenrade----

	venue	freq
0	Doner Restaurant	1.0
1	African Restaurant	0.0
2	Japanese Restaurant	0.0
3	Lebanese Restaurant	0.0
4	Mediterranean Restaurant	0.0

----Lichterfelde----

	venue	freq
0	Italian Restaurant	0.50
1	Eastern European Restaurant	0.25
2	Chinese Restaurant	0.25
3	Scandinavian Restaurant	0.00
4	Lebanese Restaurant	0.00

----Lübars----

	venue	freq
0	Comfort Food Restaurant	1.0
1	Japanese Restaurant	0.0
2	Lebanese Restaurant	0.0
3	Mediterranean Restaurant	0.0
4	Mexican Restaurant	0.0

----Mahlsdorf----

	venue	freq
0	Italian Restaurant	0.5
1	Greek Restaurant	0.5
2	Japanese Restaurant	0.0
3	Lebanese Restaurant	0.0

4 Mediterranean Restaurant 0.0

----Malchow----

	venue	freq
0	German Restaurant	1.0
1	African Restaurant	0.0
2	Japanese Restaurant	0.0
3	Lebanese Restaurant	0.0
4	Mediterranean Restaurant	0.0

----Mariendorf----

	venue	freq
0	Greek Restaurant	0.25
1	German Restaurant	0.25
2	Steakhouse	0.25
3	Chinese Restaurant	0.25
4	African Restaurant	0.00

----Marienfelde----

	venue	freq
0	German Restaurant	0.2
1	Fast Food Restaurant	0.2
2	Pizza Place	0.2
3	Chinese Restaurant	0.2
4	Restaurant	0.2

----Marzahn----

	venue	freq
0	Asian Restaurant	0.5
1	German Restaurant	0.5
2	African Restaurant	0.0
3	Scandinavian Restaurant	0.0
4	Lebanese Restaurant	0.0

----Marzahn-Hellersdorf----

	venue	freq
0	Doner Restaurant	1.0
1	African Restaurant	0.0
2	Japanese Restaurant	0.0
3	Lebanese Restaurant	0.0
4	Mediterranean Restaurant	0.0

----Mitte----

	venue	freq
0	German Restaurant	0.67
1	Italian Restaurant	0.08
2	Spanish Restaurant	0.08
3	Restaurant	0.08
4	Vietnamese Restaurant	0.08

----Moabit----

	venue	freq
0	Doner Restaurant	0.15
1	German Restaurant	0.15
2	Burger Joint	0.15
3	Italian Restaurant	0.10
4	Vegetarian / Vegan Restaurant	0.10

----Märkisches Viertel----

	venue	freq
0	Italian Restaurant	0.67
1	American Restaurant	0.33
2	Korean Restaurant	0.00
3	Lebanese Restaurant	0.00
4	Mediterranean Restaurant	0.00

----Neukölln----

	venue	freq
0	Italian Restaurant	0.14
1	Bistro	0.14
2	Middle Eastern Restaurant	0.14
3	Vegetarian / Vegan Restaurant	0.09
4	Lebanese Restaurant	0.09

----Niederschöneweide----

	venue	freq
0	Italian Restaurant	0.2
1	Restaurant	0.2
2	Indian Restaurant	0.2
3	Greek Restaurant	0.2
4	Fast Food Restaurant	0.2

----Niederschönhausen----

	venue	freq
0	Italian Restaurant	0.5

1	Thai Restaurant	0.5
2	Restaurant	0.0
3	Korean Restaurant	0.0
4	Lebanese Restaurant	0.0

----Oberschöneweide----

	venue	freq
0	Burger Joint	0.29
1	Doner Restaurant	0.14
2	Asian Restaurant	0.14
3	German Restaurant	0.14
4	Pizza Place	0.14

----Pankow----

	venue	freq
0	Italian Restaurant	0.1
1	Eastern European Restaurant	0.1
2	Japanese Restaurant	0.1
3	Mexican Restaurant	0.1
4	Middle Eastern Restaurant	0.1

----Prenzlauer Berg----

	venue	freq
0	German Restaurant	0.29
1	Italian Restaurant	0.14
2	Israeli Restaurant	0.14
3	Thai Restaurant	0.14
4	Bistro	0.14

----Rosenthal----

	venue	freq
0	German Restaurant	1.0
1	African Restaurant	0.0
2	Japanese Restaurant	0.0
3	Lebanese Restaurant	0.0
4	Mediterranean Restaurant	0.0

----Rudow----

	venue	freq
0	Chinese Restaurant	0.5
1	Doner Restaurant	0.5
2	African Restaurant	0.0
3	Scandinavian Restaurant	0.0

4        Lebanese Restaurant    0.0

----Rummelsburg----

	venue	freq
0	Creperie	0.33
1	Indian Restaurant	0.33
2	German Restaurant	0.33
3	African Restaurant	0.00
4	Mediterranean Restaurant	0.00

----Schmargendorf----

	venue	freq
0	Italian Restaurant	0.67
1	Chinese Restaurant	0.33
2	Scandinavian Restaurant	0.00
3	Lebanese Restaurant	0.00
4	Mediterranean Restaurant	0.00

----Schöneberg----

	venue	freq
0	Italian Restaurant	0.11
1	Doner Restaurant	0.11
2	Restaurant	0.11
3	Vietnamese Restaurant	0.11
4	African Restaurant	0.05

----Spandau----

	venue	freq
0	Italian Restaurant	0.25
1	Restaurant	0.25
2	Doner Restaurant	0.12
3	Asian Restaurant	0.12
4	Bistro	0.12

----Stadtrandsiedlung Malchow----

	venue	freq
0	Restaurant	1.0
1	African Restaurant	0.0
2	American Restaurant	0.0
3	Korean Restaurant	0.0
4	Lebanese Restaurant	0.0

----Steglitz----

	venue	freq
0	Sushi Restaurant	0.29
1	Doner Restaurant	0.14
2	Korean Restaurant	0.07
3	Indian Restaurant	0.07
4	Mediterranean Restaurant	0.07

----Steglitz-Zehlendorf----

	venue	freq
0	Italian Restaurant	1.0
1	American Restaurant	0.0
2	Korean Restaurant	0.0
3	Lebanese Restaurant	0.0
4	Mediterranean Restaurant	0.0

----Tegel----

	venue	freq
0	Restaurant	0.21
1	Indian Restaurant	0.14
2	Italian Restaurant	0.07
3	Seafood Restaurant	0.07
4	Mediterranean Restaurant	0.07

----Tempelhof----

	venue	freq
0	Italian Restaurant	0.29
1	Doner Restaurant	0.29
2	Fried Chicken Joint	0.29
3	Vietnamese Restaurant	0.14
4	Austrian Restaurant	0.00

----Tiergarten----

	venue	freq
0	Scandinavian Restaurant	0.5
1	German Restaurant	0.5
2	Japanese Restaurant	0.0
3	Lebanese Restaurant	0.0
4	Mediterranean Restaurant	0.0

----Waidmannslust----

	venue	freq
0	Italian Restaurant	0.67

1	Fast Food Restaurant	0.33
2	Japanese Restaurant	0.00
3	Lebanese Restaurant	0.00
4	Mediterranean Restaurant	0.00

----Wartenberg----

	venue	freq
0	Indian Restaurant	0.5
1	German Restaurant	0.5
2	African Restaurant	0.0
3	Restaurant	0.0
4	Lebanese Restaurant	0.0

----Weißensee----

	venue	freq
0	Vietnamese Restaurant	0.5
1	German Restaurant	0.5
2	Japanese Restaurant	0.0
3	Lebanese Restaurant	0.0
4	Mediterranean Restaurant	0.0

----Westend----

	venue	freq
0	Italian Restaurant	1.0
1	American Restaurant	0.0
2	Korean Restaurant	0.0
3	Lebanese Restaurant	0.0
4	Mediterranean Restaurant	0.0

----Wilhelmsruh----

	venue	freq
0	Mexican Restaurant	1.0
1	African Restaurant	0.0
2	American Restaurant	0.0
3	Korean Restaurant	0.0
4	Lebanese Restaurant	0.0

----Wilmersdorf----

	venue	freq
0	Italian Restaurant	0.1
1	Burger Joint	0.1
2	French Restaurant	0.1
3	Doner Restaurant	0.1



4 Vietnamese Restaurant 0.1

----Wittenau----

	venue	freq
0	German Restaurant	0.4
1	Italian Restaurant	0.2
2	Restaurant	0.2
3	Eastern European Restaurant	0.2
4	Lebanese Restaurant	0.0

----Zehlendorf----

	venue	freq
0	Italian Restaurant	0.2
1	Doner Restaurant	0.2
2	Asian Restaurant	0.1
3	Middle Eastern Restaurant	0.1
4	German Restaurant	0.1

Let's put that into a *pandas* dataframe create the new dataframe and display top 5 venues

```
[53]: num_top_venues = 5

indicators = ['st', 'nd', 'rd']

# create columns according to number of top venues
columns = ['borough']
for ind in np.arange(num_top_venues):
    try:
        columns.append('{}{} Most Common Venue'.format(ind+1, indicators[ind]))
    except:
        columns.append('{}th Most Common Venue'.format(ind+1))

# create a new dataframe
berlin_neighborhoods_venues_sorted = pd.DataFrame(columns=columns)
berlin_neighborhoods_venues_sorted['borough'] = berlin_grouped['borough']

for ind in np.arange(berlin_grouped.shape[0]):
    berlin_neighborhoods_venues_sorted.iloc[ind, 1:] =
    ↪return_most_common_venues(berlin_grouped.iloc[ind, :], num_top_venues)

#pd.set_option('display.max_rows', None)
berlin_neighborhoods_venues_sorted.head()
```

```
[53]:
```

	borough	1st Most Common Venue	2nd Most Common Venue \
0	Adlershof	Greek Restaurant	Italian Restaurant
1	Alt-Hohenschönhausen	Indian Restaurant	Greek Restaurant
2	Alt-Treptow	Vietnamese Restaurant	Italian Restaurant
3	Blankenburg	Greek Restaurant	Vietnamese Restaurant
4	Britz	German Restaurant	Vietnamese Restaurant

  

	3rd Most Common Venue	4th Most Common Venue \
0	Steakhouse	Pizza Place
1	Asian Restaurant	Doner Restaurant
2	Tapas Restaurant	Beer Garden
3	Vegetarian / Vegan Restaurant	Halal Restaurant
4	Vegetarian / Vegan Restaurant	Halal Restaurant

  

	5th Most Common Venue
0	Chinese Restaurant
1	Comfort Food Restaurant
2	Seafood Restaurant
3	German Restaurant
4	Greek Restaurant

## 0.24 5.2 Cluster Borough with k-means

```
[54]: # set number of clusters
kclusters = 10

berlin_grouped_clustering = berlin_grouped.drop('borough', 1)

# run k-means clustering
kmeans = KMeans(n_clusters=kclusters, random_state=0).
    ↪fit(berlin_grouped_clustering)

# check cluster labels generated for each row in the dataframe
kmeans.labels_[0:50]
```

```
[54]: array([0, 0, 0, 9, 4, 2, 6, 0, 2, 4, 2, 8, 0, 1, 0, 0, 0, 0, 1, 3, 0, 0,
          8, 9, 0, 0, 0, 1, 2, 0, 3, 3, 5, 2, 7, 2, 4, 0, 0, 3, 5, 4, 0, 2,
          0, 0, 2, 0, 0, 0], dtype=int32)
```

create dataframe 'berlin\_merged'

```
[55]: # add clustering labels
berlin_neighborhoods_venues_sorted.insert(0, 'Cluster Labels', kmeans.labels_)
```

```
[56]: berlin_merged = berlin
```

```
# merge manhattan_grouped with manhattan_data to add latitude/longitude for
↳ each neighborhood
berlin_merged = berlin_merged.merge(berlin_neighborhoods_venues_sorted.
↳ set_index('borough'), on='borough')

#pd.set_option('display.max_rows', None)
berlin_merged
```

```
[56]:
```

	postalcode	borough	latitude	longitude	Cluster Labels	\
0	10119	Prenzlauer Berg	52.528634	13.420105	0	
1	10115	Mitte	52.517885	13.404060	4	
2	13347	Gesundbrunnen	52.550920	13.384846	0	
3	10243	Friedrichshain-Kreuzberg	52.501115	13.444285	0	
4	10243	Friedrichshain	52.512215	13.450290	0	
..	...	...	...	...	...	
65	13581	Spandau	52.535788	13.197792	0	
66	12623	Mahlsdorf	52.508699	13.613162	2	
67	12459	Köpenick	52.453910	13.576413	3	
68	12305	Lichtenrade	52.393456	13.402040	5	
69	12157	Steglitz-Zehlendorf	52.429205	13.229974	2	
	1st Most Common Venue	2nd Most Common Venue	\			
0	German Restaurant	Israeli Restaurant				
1	German Restaurant	Vietnamese Restaurant				
2	Turkish Restaurant	Italian Restaurant				
3	Vietnamese Restaurant	Pizza Place				
4	Middle Eastern Restaurant	Doner Restaurant				
..	...	...				
65	Restaurant	Italian Restaurant				
66	Italian Restaurant	Greek Restaurant				
67	Indian Restaurant	German Restaurant				
68	Doner Restaurant	Vietnamese Restaurant				
69	Italian Restaurant	Indian Restaurant				
	3rd Most Common Venue	4th Most Common Venue	\			
0	Italian Restaurant	Thai Restaurant				
1	Spanish Restaurant	Italian Restaurant				
2	Halal Restaurant	Syrian Restaurant				
3	Indian Restaurant	Falafel Restaurant				
4	Thai Restaurant	Vegetarian / Vegan Restaurant				
..	...	...				
65	Asian Restaurant	Bistro				
66	Indian Restaurant	Halal Restaurant				
67	Burger Joint	Comfort Food Restaurant				
68	Vegetarian / Vegan Restaurant	Halal Restaurant				
69	Halal Restaurant	Greek Restaurant				

```

    5th Most Common Venue
0          Bistro
1          Restaurant
2    Falafel Restaurant
3      Asian Restaurant
4    Italian Restaurant
..          ...
65 Fast Food Restaurant
66    German Restaurant
67      Halal Restaurant
68    Greek Restaurant
69    German Restaurant

```

```
[70 rows x 10 columns]
```

## 0.25 5.3 Cluster Visualization

```

[57]: # create map
map_clusters = folium.Map(location=[latitude, longitude], zoom_start=11)

# set color scheme for the clusters
x = np.arange(kclusters)
ys = [i + x + (i*x)**2 for i in range(kclusters)]
colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
rainbow = [colors.rgb2hex(i) for i in colors_array]

# add markers to the map
markers_colors = []
for lat, lon, poi, cluster in zip(berlin_merged['latitude'],
↳berlin_merged['longitude'], berlin_merged['borough'], berlin_merged['Cluster_
↳Labels']):
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_clusters)

map_clusters

```

```
[57]: <folium.folium.Map at 0x7f70dfbbf908>
```

## 0.26 5.4 evaluate target criteria according to 'berlin\_restaurants'

```
[58]: berlin_sum = pd.get_dummies(berlin_restaurants[['Venue Category']], prefix="",
    ↪ prefix_sep="")

berlin_sum['borough'] = berlin_restaurants['borough']

#Fix Column Order
#fixed_columns = [berlin_sum.columns[-1]] + list(berlin_sum.columns[:-1])
#berlin_sum = berlin_sum[fixed_columns]
berlin_sum
```

```
[58]:
```

	African Restaurant	American Restaurant	Argentinian Restaurant	\
10	0	0	0	
11	0	0	0	
12	0	0	0	
19	0	0	0	
20	0	0	0	
...	...	...	...	
1455	0	0	0	
1476	0	0	0	
1477	0	0	0	
1478	0	0	0	
1479	0	0	0	

  

	Asian Restaurant	Austrian Restaurant	Bavarian Restaurant	Beer Garden	\
10	0	0	0	0	
11	0	0	0	0	
12	0	0	0	0	
19	0	0	0	0	
20	0	0	0	0	
...	...	...	...	...	
1455	0	0	0	0	
1476	0	0	0	0	
1477	0	0	0	0	
1478	0	0	0	0	
1479	0	0	0	0	

  

	Bistro	Brazilian Restaurant	Burger Joint	...	Spanish Restaurant	\
10	1	0	0	...	0	
11	0	0	0	...	0	
12	0	0	0	...	0	
19	0	0	0	...	0	
20	0	0	0	...	0	
...	...	...	...	...	...	
1455	0	0	0	...	0	
1476	0	0	0	...	0	

1477	0	0	0 ...	0
1478	0	0	0 ...	0
1479	0	0	0 ...	0

	Steakhouse	Sushi Restaurant	Syrian Restaurant	Tapas Restaurant	\
10	0	0	0	0	
11	0	0	0	0	
12	0	0	0	0	
19	0	0	0	0	
20	0	0	0	0	
...	...	...	...	...	
1455	0	0	0	0	
1476	0	0	0	0	
1477	0	0	0	0	
1478	0	0	0	0	
1479	0	0	0	0	

	Thai Restaurant	Turkish Restaurant	Vegetarian / Vegan Restaurant	\
10	0	0	0	
11	0	0	0	
12	0	0	0	
19	0	0	0	
20	0	0	0	
...	...	...	...	
1455	0	0	0	
1476	0	0	0	
1477	0	0	0	
1478	0	0	0	
1479	0	0	0	

	Vietnamese Restaurant	borough
10	0	Prenzlauer Berg
11	0	Prenzlauer Berg
12	0	Prenzlauer Berg
19	0	Prenzlauer Berg
20	0	Prenzlauer Berg
...	...	...
1455	0	Köpenick
1476	0	Lichtenrade
1477	0	Steglitz-Zehlendorf
1478	0	Steglitz-Zehlendorf
1479	0	Steglitz-Zehlendorf

[392 rows x 53 columns]

Sum amount of each venues out of target definition 'berlin\_restaurants'

```
[59]: berlin_sum['amount of restaurants']=berlin_sum.sum(axis=1)
berlin_sum = berlin_sum.groupby('borough').sum().reset_index()
berlin_sum
```

```
[59]:
```

	borough	African Restaurant	American Restaurant	\
0	Adlershof	0	0	
1	Alt-Hohenschönhausen	0	0	
2	Alt-Treptow	0	0	
3	Blankenburg	0	0	
4	Britz	0	0	
..	...	...	...	
65	Westend	0	0	
66	Wilhelmsruh	0	0	
67	Wilmersdorf	0	0	
68	Wittenau	0	0	
69	Zehlendorf	0	0	

  

	Argentinian Restaurant	Asian Restaurant	Austrian Restaurant	\
0	0	0	0	
1	0	1	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	
..	...	...	...	
65	0	0	0	
66	0	0	0	
67	0	0	0	
68	0	0	0	
69	0	1	0	

  

	Bavarian Restaurant	Beer Garden	Bistro	Brazilian Restaurant	...	\
0	0	0	0	0	...	
1	0	0	0	0	...	
2	0	1	0	0	...	
3	0	0	0	0	...	
4	0	0	0	0	...	
..	...	...	...	...	...	
65	0	0	0	0	...	
66	0	0	0	0	...	
67	1	0	0	0	...	
68	0	0	0	0	...	
69	0	0	0	0	...	

  

	Spanish Restaurant	Steakhouse	Sushi Restaurant	Syrian Restaurant	\
0	0	1	0	0	
1	0	0	0	0	
2	0	0	0	0	

3	0	0	0	0
4	0	0	0	0
..	...	...	...	...
65	0	0	0	0
66	0	0	0	0
67	0	0	1	0
68	0	0	0	0
69	0	1	0	0

	Tapas Restaurant	Thai Restaurant	Turkish Restaurant	\
0	0	0	0	
1	0	0	0	
2	1	0	0	
3	0	0	0	
4	0	0	0	
..	...	...	...	
65	0	0	0	
66	0	0	0	
67	0	1	0	
68	0	0	0	
69	0	0	0	

	Vegetarian / Vegan Restaurant	Vietnamese Restaurant	\
0		0	
1		0	
2		1	
3		0	
4		0	
..	...	...	
65		0	
66		0	
67		2	
68		0	
69		0	

	amount of restaurants
0	4
1	4
2	7
3	1
4	1
..	...
65	1
66	1
67	20
68	5
69	10



[70 rows x 54 columns]

keep only sum as criteria and add it to overview 'berlin\_merged' show only top5 boroughs according to amount of restaurants

```
[60]: berlin_sum = berlin_sum[['borough', 'amount of restaurants']]

berlin_merged = pd.merge(berlin_merged, berlin_sum, on = 'borough')
berlin_merged.sort_values(by=['amount of restaurants'], ascending=False,
    inplace=True)
berlin_merged.head(5)
```

```
[60]:
```

	postalcode	borough	latitude	longitude	Cluster Labels	\
3	10243	Friedrichshain-Kreuzberg	52.501115	13.444285	0	
14	12043	Neukölln	52.481150	13.435350	0	
23	10707	Wilmerdsdorf	52.487115	13.320330	0	
6	10551	Moabit	52.530102	13.342542	0	
15	10777	Schöneberg	52.482157	13.355190	0	

  

	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	\
3	Vietnamese Restaurant	Pizza Place	Indian Restaurant	
14	Italian Restaurant	Middle Eastern Restaurant	Bistro	
23	Vietnamese Restaurant	Doner Restaurant	French Restaurant	
6	German Restaurant	Doner Restaurant	Burger Joint	
15	Vietnamese Restaurant	Restaurant	Doner Restaurant	

  

	4th Most Common Venue	5th Most Common Venue	\
3	Falafel Restaurant	Asian Restaurant	
14	Vegetarian / Vegan Restaurant	Lebanese Restaurant	
23	Italian Restaurant	Burger Joint	
6	Vegetarian / Vegan Restaurant	Italian Restaurant	
15	Italian Restaurant	Argentinian Restaurant	

  

	amount of restaurants
3	29
14	22
23	20
6	20
15	19

```
[ ]:
```

## 0.27 6. result and discussion

Now we've got a top5 list of each City with amount and most frequent kind of restaurant of restaurants:

### 0.27.1 6.1 Berlin

```
[61]: berlin_merged.head(5)
```

```
[61]:
```

	postalcode	borough	latitude	longitude	Cluster Labels	\
3	10243	Friedrichshain-Kreuzberg	52.501115	13.444285	0	
14	12043	Neukölln	52.481150	13.435350	0	
23	10707	Wilmerdorf	52.487115	13.320330	0	
6	10551	Moabit	52.530102	13.342542	0	
15	10777	Schöneberg	52.482157	13.355190	0	

  

	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	\
3	Vietnamese Restaurant	Pizza Place	Indian Restaurant	
14	Italian Restaurant	Middle Eastern Restaurant	Bistro	
23	Vietnamese Restaurant	Doner Restaurant	French Restaurant	
6	German Restaurant	Doner Restaurant	Burger Joint	
15	Vietnamese Restaurant	Restaurant	Doner Restaurant	

  

	4th Most Common Venue	5th Most Common Venue	\
3	Falafel Restaurant	Asian Restaurant	
14	Vegetarian / Vegan Restaurant	Lebanese Restaurant	
23	Italian Restaurant	Burger Joint	
6	Vegetarian / Vegan Restaurant	Italian Restaurant	
15	Italian Restaurant	Argentinian Restaurant	

  

	amount of restaurants
3	29
14	22
23	20
6	20
15	19

### 0.27.2 6.2 Munich

```
[85]: munich_merged.head(5)
```

```
[85]:
```

	postalcode	borough	latitude	longitude	Cluster Labels	\
0	80331	Zentrum Marienplatz	48.137187	11.575501	7	
1	81241	Pasing	48.147785	11.460701	7	
2	80335	Hauptbahnhof	48.140458	11.557766	7	
3	85748	Garching	48.251388	11.650966	7	
4	85748	Garching bei München	48.251388	11.650966	7	

  

	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	\
0	German Restaurant	Bavarian Restaurant	Pizza Place	
1	Italian Restaurant	Vietnamese Restaurant	Fast Food Restaurant	
2	Middle Eastern Restaurant	German Restaurant	Bavarian Restaurant	

3	German Restaurant	Greek Restaurant	Italian Restaurant
4	German Restaurant	Greek Restaurant	Italian Restaurant

	4th Most Common Venue	5th Most Common Venue	Sum \
0	Italian Restaurant	Restaurant	24
1	German Restaurant	Theme Restaurant	18
2	Eastern European Restaurant	Italian Restaurant	11
3	Chinese Restaurant	Indian Restaurant	9
4	Chinese Restaurant	Indian Restaurant	9

	amount of restaurants
0	24
1	18
2	11
3	9
4	9

Berlin - Friedrichshain-Kreuzberg has the highest number of restaurants of 29. But Munich - Marienplatz seems also to be a good choice with 24 different restaurants. So she will decide based on most common restaurants.

## 0.28 6.3 Explore Trending Venues

Since it's possible to get at least *one* premium request, we use *trending* API. Most probably she will pick Friedrichshain-Kreuzberg with the highest number of restaurants of 29. As soon as we arrive, we will look for the places with the highest foot traffic. So let's do that and get the trending venues around.

```
[78]: latitude = berlin_merged._get_value(3, 'latitude')
longitude = berlin_merged._get_value(3, 'longitude')
print("borough =", berlin_merged._get_value(3, 'borough'), ", latitude =",
      ↪latitude, ", longitude =", longitude)
```

```
borough = Friedrichshain-Kreuzberg , latitude = 52.5011154 , longitude =
13.4442848
```

```
[79]: # define URL
url = 'https://api.foursquare.com/v2/venues/trending?
      ↪client_id={}&client_secret={}&ll={},{&v={}'.format(CLIENT_ID,
      ↪CLIENT_SECRET, latitude, longitude, VERSION)

# send GET request and get trending venues
results = requests.get(url).json()
results
```

```
[79]: {'meta': {'code': 200, 'requestId': '5ffd6f19aca2493433cd08d3'},
      'response': {'venues': []}}
```

### 0.28.1 Check if any venues are trending at this time

```
[80]: if len(results['response']['venues']) == 0:
        trending_venues_df = 'No trending venues are available at the moment!'

    else:
        trending_venues = results['response']['venues']
        trending_venues_df = json_normalize(trending_venues)

        # filter columns
        columns_filtered = ['name', 'categories'] + ['location.distance', 'location.
        ↪city', 'location.postalCode', 'location.state', 'location.country', '
        ↪location.lat', 'location.lng']
        trending_venues_df = trending_venues_df.loc[:, columns_filtered]

        # filter the category for each row
        trending_venues_df['categories'] = trending_venues_df.
        ↪apply(get_category_type, axis=1)

[81]: # display trending venues
        trending_venues_df
```

```
[81]: 'No trending venues are available at the moment!'
```

Now, depending on when you run the above code, you might get different venues since the venues with the highest foot traffic are fetched live.

### 0.28.2 Visualize trending venues

```
[ ]: if len(results['response']['venues']) == 0:
        venues_map = 'Cannot generate visual as no trending venues are available at
        ↪the moment!'

    else:
        venues_map = folium.Map(location=[latitude, longitude], zoom_start=15) #
        ↪generate map centred around Ecco

        # add Ecco as a red circle mark
        folium.CircleMarker(
            [latitude, longitude],
            radius=10,
            popup='Ecco',
            fill=True,
            color='red',
            fill_color='red',
            fill_opacity=0.6
```

```
).add_to(venues_map)
```

```
# add the trending venues as blue circle markers
for lat, lng, label in zip(trending_venues_df['location.lat'],
↪ trending_venues_df['location.lng'], trending_venues_df['name']):
    folium.CircleMarker(
        [lat, lng],
        radius=5,
        popup=label,
        fill=True,
        color='blue',
        fill_color='blue',
        fill_opacity=0.6
    ).add_to(venues_map)
```

```
[ ]: # display map
venues_map
```

```
[ ]:
```

Section ??

```
[ ]:
```