Vienna Supermarket Analysis

Introduction and Motivation

This section provides a description of the analysis conducted in this report. The problem beeing analysed will be described and the motivation for the work conducted will be given. This report is focused on the analysis of the 23 neighborhoods of the city of Vienna, Austria. Foursquare location data of Vienna is combined with data from an official gouvernmental website in order to identify neighborhoods where a lot of people live but certain venues are very sparse. The analysis conducted can be applied to any city-venue combination one can think of. This report however analyses the 23 neighborhoods of Vienna and identifies neighborhoods lacking of stores where people can buy grocerys. Supermarketes could use the findings of his analysis to identify places to open a new store thereby optimizing their potential earnings as well as upgrading a neighborhood by providing the convenience of an additional place to by food nearby.

Data Analysis and Methodology

This section describes the data that was used as well as the methodology of the analysis steps. Using a simple html parser from the BeautifulSoup library and pandas, a dataframe was built containing the 23 district names as well as their postal codes and the number of people living there. The pgeocode package was subsequently used to get the latitude and longitude values of each district by postal code. 160 unique venue categories could be retrieved from Foursquare by exploring those neighborhoods. Some exploratory data analysis was conducted such as exploring each neighborhood's top 10 venues and their density with respect to different venues. Applying k-means clustering 4 different clusters could be identified based on the similarity of the top 10 venues per neighborhood. The rest of the analysis focuses on calculating the ratio between number of people and density of existing supermarkets and grocery stores. A simple barplot visualizes those ratios per neighborhood and thereby clearly identifies neighborhoods with a possible lack of places for people to buy food in their close neighborhood.

In [2]:

```
import numpy as np # library to handle data in a vectorized manner

import pandas as pd # library for data analsysis
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)

import json # library to handle JSON files

from geopy.geocoders import Nominatim # convert an address into latitude and longitude
 values

import requests # library to handle requests
from pandas.io.json import json_normalize # tranform JSON file into a pandas dataframe

# Matplotlib and associated plotting modules
import matplotlib.cm as cm
import matplotlib.colors as colors

# import k-means from clustering stage
from sklearn.datasets.samples_generator import make_blobs
from sklearn.cluster import KMeans

import folium # map rendering library
import webbrowser
from bs4 import BeautifulSoup
import requests
import pgeocode
import unicodedata
print('Libraries imported.')
```

```
C:\Users\benno\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:14
4: FutureWarning: The sklearn.datasets.samples_generator module is  deprec
ated in version 0.22 and will be removed in version 0.24. The correspondin
g classes / functions should instead be imported from sklearn.datasets. An
ything that cannot be imported from sklearn.datasets is now part of the pr
ivate API.
  warnings.warn(message, FutureWarning)

Libraries imported.
```

Vienna can be clustered into 23 districts. The first step in the analysis is to retrieve those districts from a gouvernment official website and load them into a pandas dataframe.

In [3]:

```
source = requests.get("https://www.vienna.at/features/bezirke-wien")
soup = BeautifulSoup(source.content,"html.parser")
data = soup.find_all("ul", {"id": "bezirke"})
lis = data[0].find_all('li')
for li in lis:
    newsoup = BeautifulSoup(str(li), 'html.parser')
table_bezirke = []
for li in lis:
    table_bezirke.append(li.text)
```

In [4]:

```
df = pd.DataFrame(table_bezirke)
df[0] = df[0].astype("string")
df= df[0].str.split("\n",expand=True)
df.drop(columns = [0,4,5],inplace=True)
df.head()
```

Out[4]:

	1	2	3
0	1.	Innere Stadt	1010 Wien
1	2.	Leopoldstadt	1020 Wien
2	3.	Landstraße	1030 Wien
3	4.	Wieden	1040 Wien
4	5.	Margareten	1050 Wien

In [5]:

```
df.columns=["district_number","district_name","postalcode"]
df["postalcode"] = df["postalcode"].str.replace(" Wien","")
df["district_number"] = df["district_number"].str.replace(".","")
df.head()
```

Out[5]:

	district_number	district_name	postalcode
0	1	Innere Stadt	1010
1	2	Leopoldstadt	1020
2	3	Landstraße	1030
3	4	Wieden	1040
4	5	Margareten	1050

Get the number of inhibitants from each district from a differnt table on the same webseite and merge the dataframes, this will later be used for bubble-plotting the map of vienna and examine neighborhoods with many people living there

In [6]:

```
lis = data[2].find_all('li')
for li in lis:
    newsoup = BeautifulSoup(str(li), 'html.parser')
table_people = []
for li in lis:
    table_people.append(li.text)
df_people = pd.DataFrame(table_people)
df_people[0] = df_people[0].astype("string")
df_people = df_people[0].str.split("\n",expand=True)
df_people.drop(columns = [0,4,5],inplace=True)
df_people.columns=["district_number","district_name","people"]
df_people.drop(columns = ["district_number"],inplace=True)
df_people.head()
```

Out[6]:

	district_name	people
0	Innere Stadt	16.450
1	Leopoldstadt	105.574
2	Landstraße	90.712
3	Wieden	33.319
4	Margareten	55.640

Merge dfs on column "district_name" and convert "people" column to integer

In [8]:

```
df_merged = pd.merge(df,df_people,on="district_name")
df_merged["people"] = df_merged["people"].str.replace(".","")
df_merged["people"] = df_merged["people"].astype("int")
df_merged.dtypes
```

Out[8]:

```
district_number    string
district_name      string
postalcode         string
people              int32
dtype: object
```

In [9]:

```
df_merged.head()
```

Out[9]:

	district_number	district_name	postalcode	people
0	1	Innere Stadt	1010	16450
1	2	Leopoldstadt	1020	105574
2	3	Landstraße	1030	90712
3	4	Wieden	1040	33319
4	5	Margareten	1050	55640

Get Latitude and Longitude Values by postal codes

In [43]:

```
df_merged["Latitude"]=""
df_merged["Longitude"]=""

nomi = pgeocode.Nominatim("at")

for pc in df_merged.postalcode:
    nomidata=nomi.query_postal_code(pc)
    lat=nomidata.latitude
    lng=nomidata.longitude
    df_merged.loc[df_merged["postalcode"]==pc,"Latitude"]  = lat
    df_merged.loc[df_merged["postalcode"]==pc,"Longitude"] = lng

address = 'Vienna'

geolocator = Nominatim(user_agent="vienna_explorer")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print('The geograpical coordinate of Vienna are {}, {}.'.format(latitude, longitude))
```

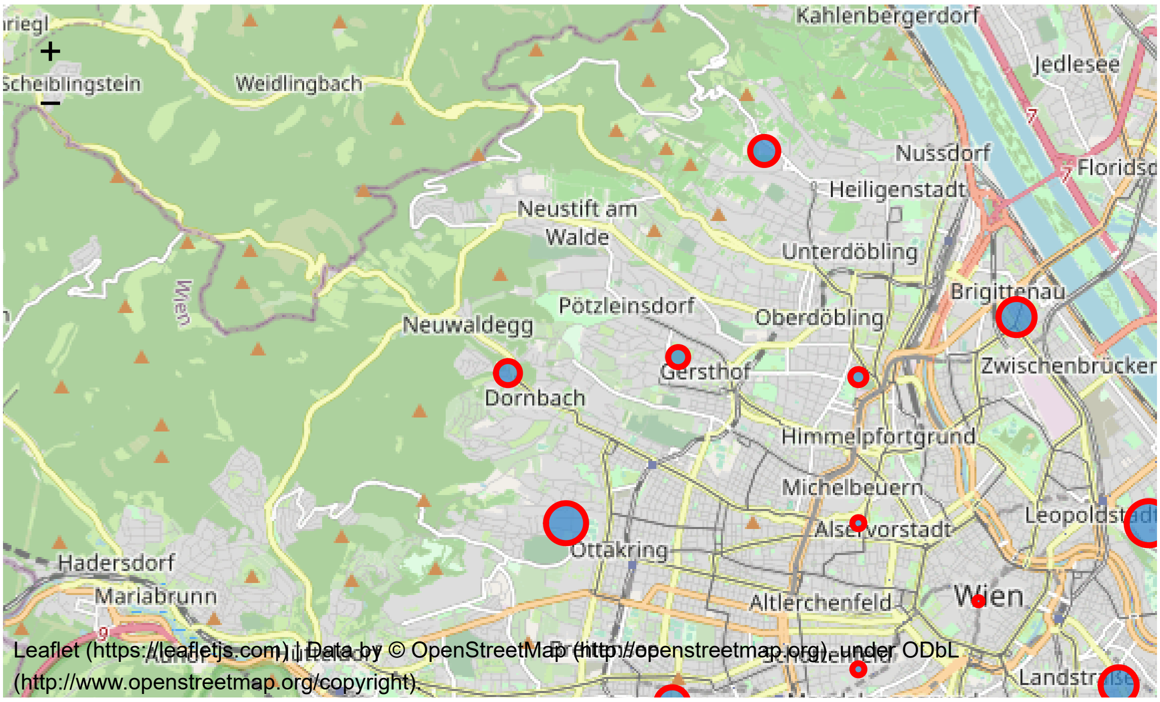
```
The geograpical coordinate of Vienna are 48.2083537, 16.3725042.
```

In [27]:

```
map_vienna = folium.Map(location=[latitude,longitude],zoom_start=12)

for lat, lng, district,people in zip(df_merged['Latitude'],
                                     df_merged['Longitude'],
                                     df_merged['district_name'],
                                     df_merged['people']):
    label = '{}'.format(district)
    label = folium.Popup(label, parse_html=True)
    people = people/10000
    folium.CircleMarker(
        [lat, lng],
        radius=people,
        popup=label,
        color='red',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_vienna)
map_vienna
```

Out[27]:



So far so good - all 23 districts of vienna are displayed on the map with their respective number of inhabitants displayed by the bubble sizes. Now lets explore those neighborhoods by extracting venues from Foursquare

In [28]:

```
CLIENT_ID = '' # your Foursquare ID
CLIENT_SECRET = '' # your Foursquare Secret
VERSION = '20180604'

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

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

#function to extract venues in neighborhoods
LIMIT = 100
radius = 500
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 = ['Neighborhood',
                  'Neighborhood Latitude',
                  'Neighborhood Longitude',
                  'Venue',
                  'Venue Latitude',
                  'Venue Longitude',
                  'Venue Category']
```

```
    return(nearby_venues)

vienna_venues = getNearbyVenues(names=df_merged['district_name'],
                                latitudes=df_merged['Latitude'],
                                longitudes=df_merged['Longitude'])

vienna_venues.head()
```

```
Innere Stadt
Leopoldstadt
Landstraße
Wieden
Margareten
Mariahilf
Neubau
Josefstadt
Alsergrund
Favoriten
Simmering
Meidling
Hietzing
Penzing
Rudolfsheim-Fünfhaus
Ottakring
Hernals
Währing
Döbling
Brigittenau
Floridsdorf
Donaustadt
Liesing
```

Out[28]:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venu Catego
0	Innere Stadt	48.2077	16.3705	Stephansplatz	48.208299	16.371880	Pla
1	Innere Stadt	48.2077	16.3705	Stephansdom	48.208626	16.372672	Chur
2	Innere Stadt	48.2077	16.3705	COS	48.209359	16.371591	Clothi Stc
3	Innere Stadt	48.2077	16.3705	Graben	48.208915	16.369379	Pedestri Pla
4	Innere Stadt	48.2077	16.3705	DO & CO Restaurant	48.208240	16.371758	Restaura

In [29]:

```
vienna_venues.groupby("Neighborhood").count()
print('There are {} uniques categories.'.format(len(vienna_venues['Venue Category'].uni
que())))
```

```
There are 160 uniques categories.
```

Analyze each Neighborhood

In [30]:

```
# one hot encoding
vienna_onehot = pd.get_dummies(vienna_venues[['Venue Category']], prefix="", prefix_sep
="")

# add neighborhood column back to dataframe
vienna_onehot['Neighborhood'] = vienna_venues['Neighborhood']

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

vienna_onehot.head()

#%%Next, let's group rows by neighborhood and by taking the mean of the frequency of oc
currence of each category
vienna_grouped = vienna_onehot.groupby("Neighborhood").mean().reset_index()
vienna_grouped.head()

#Let's print each neighborhood along with the top 5 most common venue
num_top_venues = 5

for hood in vienna_grouped['Neighborhood']:
    print("----"+hood+"----")
    temp = vienna_grouped[vienna_grouped['Neighborhood'] == 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')
```

```
----Alsergrund----
          venue  freq
0   Supermarket  0.10
1          Café  0.06
2  Tram Station  0.06
3     BBQ Joint  0.06
4   Beer Garden  0.03


----Brigittenau----
            venue  freq
0        Bus Stop  0.24
1           Plaza  0.14
2     Supermarket  0.10
3          Hostel  0.05
4  Cosmetics Shop  0.05


----Donaustadt----
               venue  freq
0        Supermarket  0.25
1     Hardware Store  0.25
2  Indian Restaurant  0.25
3         Restaurant  0.25
4              Motel  0.00


----Döbling----
                 venue  freq
0  Austrian Restaurant  0.27
1             Wine Bar  0.18
2           Restaurant  0.09
3                 Food  0.09
4                 Park  0.09


----Favoriten----
           venue  freq
0  Shopping Mall  0.17
1    Post Office  0.17
2  Metro Station  0.17
3     Smoke Shop  0.17
4  Grocery Store  0.17


----Floridsdorf----
            venue  freq
0     Supermarket   0.2
1  Discount Store   0.2
2        Vineyard   0.2
3      Restaurant   0.2
4   Shopping Mall   0.2


----Hernals----
                 venue  freq
0                 Pool  0.12
1         Tram Station  0.12
2               Bakery  0.12
3      Automotive Shop  0.12
4  Austrian Restaurant  0.12
```

```
----Hietzing----
                            venue  freq
0                  Scenic Lookout   1.0
1               Afghan Restaurant   0.0
2  Paper / Office Supplies Store   0.0
3                   Movie Theater   0.0
4                       Multiplex   0.0


----Innere Stadt----
                 venue  freq
0                 Café  0.09
1   Italian Restaurant  0.08
2           Restaurant  0.08
3                Plaza  0.07
4  Austrian Restaurant  0.06


----Josefstadt----
         venue  freq
0         Café  0.15
1   Restaurant  0.07
2        Hotel  0.07
3          Bar  0.07
4  Supermarket  0.07


----Landstraße----
                venue  freq
0                Café  0.15
1         Gourmet Shop  0.06
2  Italian Restaurant  0.06
3               Hotel  0.06
4           Irish Pub  0.03


----Leopoldstadt----
                           venue  freq
0  Theme Park Ride / Attraction  0.27
1                    Restaurant  0.08
2                          Café  0.06
3                         Hotel  0.06
4                     Gastropub  0.04


----Liesing----
                 venue  freq
0                Plaza  0.25
1        Grocery Store  0.25
2  Austrian Restaurant  0.25
3          Supermarket  0.25
4    Afghan Restaurant  0.00


----Margareten----
                venue  freq
0                 Bar  0.08
1               Hotel  0.08
2         Supermarket  0.08
```

```
3  Italian Restaurant  0.08
4                Park  0.08


----Mariahilf----
            venue  freq
0             Bar  0.07
1  Clothing Store  0.07
2      Restaurant  0.06
3    Cocktail Bar  0.06
4            Café  0.06


----Meidling----
                  venue  freq
0              Bus Stop  0.25
1    Light Rail Station  0.25
2  Gym / Fitness Center  0.25
3      Storage Facility  0.25
4     Afghan Restaurant  0.00


----Neubau----
                 venue  freq
0                  Bar  0.06
1       Clothing Store  0.06
2                 Café  0.06
3  Austrian Restaurant  0.06
4          Coffee Shop  0.05


----Ottakring----
                 venue  freq
0   Italian Restaurant   0.2
1                 Park   0.2
2             Wine Bar   0.2
3             Bus Stop   0.2
4  Austrian Restaurant   0.2


----Penzing----
               venue  freq
0        Sports Club  0.25
1               Café  0.25
2      Train Station  0.25
3              Motel  0.25
4  Afghan Restaurant  0.00


----Rudolfsheim-Fünfhaus----
                 venue  freq
0                Hotel  0.13
1   Chinese Restaurant  0.09
2     Asian Restaurant  0.09
3  Austrian Restaurant  0.09
4          Supermarket  0.09


----Simmering----
            venue  freq
0            Park  0.25
```

```
1      Playground  0.25
2  Farmers Market  0.25
3   Movie Theater  0.25
4           Plaza  0.00


----Wieden----
                venue  freq
0     Asian Restaurant  0.10
1                Hotel  0.08
2           Restaurant  0.08
3                 Café  0.08
4  Austrian Restaurant  0.06


----Währing----
                 venue  freq
0           Supermarket  0.18
1          Tram Station  0.18
2             Gastropub  0.09
3    Italian Restaurant  0.09
4  Hungarian Restaurant  0.09
```

In [31]:

```
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]

#%% Display the top 10 venues in each neighborhood
num_top_venues = 10

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

# create columns according to number of top venues
columns = ['Neighborhood']
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['Neighborhood'] = vienna_grouped['Neighborhood']

for ind in np.arange(vienna_grouped.shape[0]):
    neighborhoods_venues_sorted.iloc[ind, 1:] = return_most_common_venues(vienna_groupe
d.iloc[ind, :], num_top_venues)

neighborhoods_venues_sorted.head()
```

Out[31]:

	Neighborhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7 C
0	Alsergrund	Supermarket	BBQ Joint	Tram Station	Café	Middle Eastern Restaurant	Food & Drink Shop	
1	Brigittenau	Bus Stop	Plaza	Supermarket	Bakery	Ice Cream Shop	Kebab Restaurant	
2	Donaustadt	Indian Restaurant	Hardware Store	Restaurant	Supermarket	Hostel	Food	F Re
3	Döbling	Austrian Restaurant	Wine Bar	Light Rail Station	Winery	Gastropub	Park	
4	Favoriten	Metro Station	Post Office	Smoke Shop	Park	Shopping Mall	Grocery Store	

CLuster neighborhoods

In [32]:

```
#Run k-means to cluster the neighborhood into 5 clusters.
kclusters = 5

vienna_grouped_clustering = vienna_grouped.drop('Neighborhood', 1)

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

# check cluster labels generated for each row in the dataframe
kmeans.labels_[0:10]
```

Out[32]:

```
array([1, 1, 0, 1, 1, 1, 1, 3, 1, 1])
```

In [46]:

```
df_merged.head()
```

Out[46]:

	district_number	Neighborhood	postalcode	people	Latitude	Longitude
0	1	Innere Stadt	1010	16450	48.2077	16.3705
1	2	Leopoldstadt	1020	105574	48.2167	16.4
2	3	Landstraße	1030	90712	48.1981	16.3948
3	4	Wieden	1040	33319	48.192	16.3671
4	5	Margareten	1050	55640	48.1865	16.3549

In [47]:

```
neighborhoods_venues_sorted.head()
```

Out[47]:

	Cluster_Labels	Neighborhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Mos Commor Venue
0	1	Alsergrund	Supermarket	BBQ Joint	Tram Station	Café	Middle Easterr Restauran
1	1	Brigittenau	Bus Stop	Plaza	Supermarket	Bakery	Ice Cream Shop
2	0	Donaustadt	Indian Restaurant	Hardware Store	Restaurant	Supermarket	Hoste
3	1	Döbling	Austrian Restaurant	Wine Bar	Light Rail Station	Winery	Gastroput
4	1	Favoriten	Metro Station	Post Office	Smoke Shop	Park	Shopping Mal

Let's create a new dataframe that includes the cluster as well as the top 10 venues for each neighborhood.

In [45]:

```
df_merged.rename(columns={"district_name":"Neighborhood"},inplace=True)
```

In [48]:

```
# add clustering labels
neighborhoods_venues_sorted.insert(0, 'Cluster_Labels', kmeans.labels_)

df_merged=pd.merge(df_merged,neighborhoods_venues_sorted,on="Neighborhood")

#df_merged.drop("Cluster Labels",1,inplace=True)
df_merged.head()
```

Out[48]:

	district_number	Neighborhood	postalcode	people	Latitude	Longitude	Cluster_Labels
0	1	Innere Stadt	1010	16450	48.2077	16.3705	1
1	2	Leopoldstadt	1020	105574	48.2167	16.4	1
2	3	Landstraße	1030	90712	48.1981	16.3948	1
3	4	Wieden	1040	33319	48.192	16.3671	1
4	5	Margareten	1050	55640	48.1865	16.3549	1

Create the map

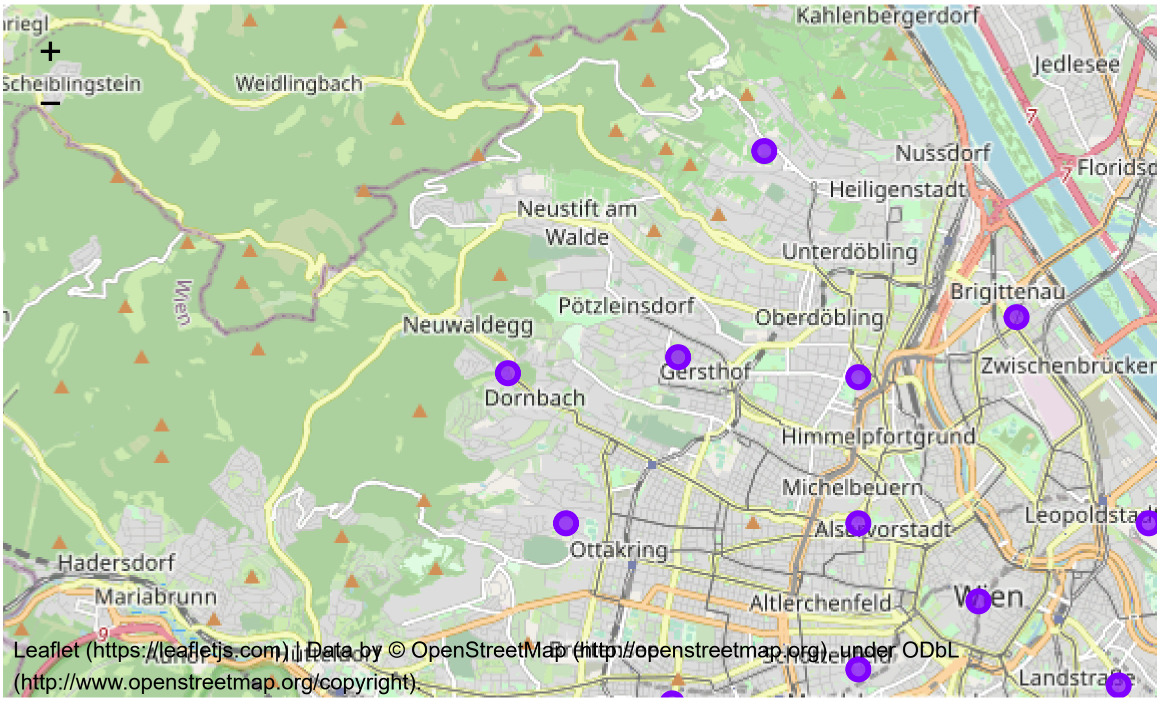
In [49]:

```
map_vienna_clusters = folium.Map(location=[latitude, longitude], zoom_start=12)

# 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(df_merged['Latitude'],
                                  df_merged['Longitude'],
                                  df_merged['Neighborhood'],
                                  df_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_vienna_clusters)
map_vienna_clusters
```

Out[49]:



Results of Supermarket analysis

Lets check out which districts have little or many places to buy food with respect to their inhabitants We will visualise the result and thereby identify possible districts where a new Supermarket opening might benefit the neighborhood

In [50]:

```
market_df = vienna_grouped[["Neighborhood","Supermarket"]]
market_df.rename(columns={"Neighborhood":"district_name"},inplace=True)
market_df = pd.merge(market_df,df_people,on="district_name")
market_df["groceryStore"] = vienna_grouped["Grocery Store"]
```

```
C:\Users\benno\Anaconda3\lib\site-packages\pandas\core\frame.py:4133: Sett
ingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  errors=errors,
```

Due to missing values in eighter of the two columns used, the combined grocery column will be built from the mean value of the two columns or, in case of missing values, from the maximum value in eigher of the two columns "Supermarket" or "grocery store"

In [51]:

```
market_df["grocery_combined"] = np.maximum( (market_df["Supermarket"]+market_df["grocer
yStore"]) /2, market_df[["groceryStore","Supermarket"]].max(axis=1) )
market_df.head()
market_df["people"] = market_df["people"].str.replace(".","")
market_df["people"] = market_df["people"].astype("int")
market_df["people_store_ratio"] = market_df["people"]*market_df["grocery_combined"]
market_df.head()
```

Out[51]:

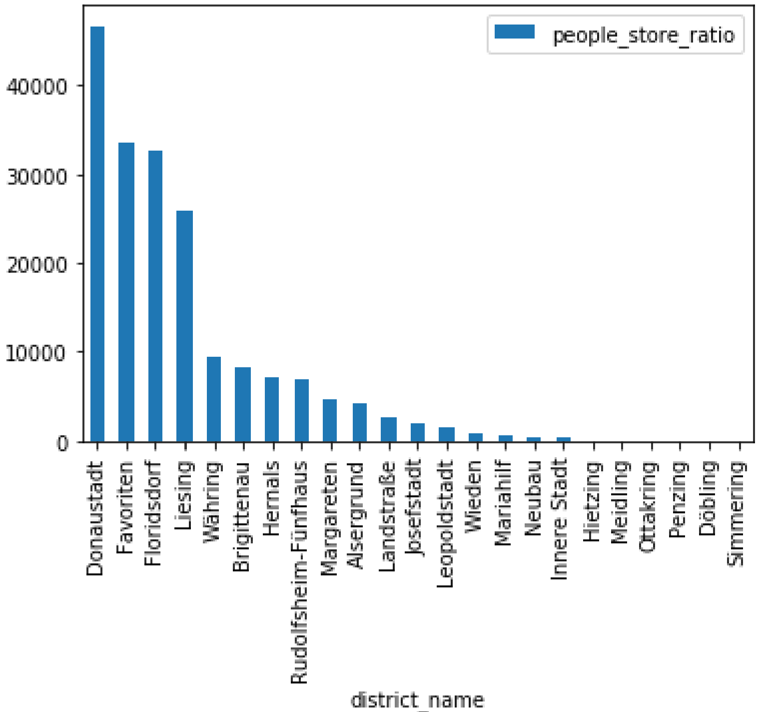
	district_name	Supermarket	people	groceryStore	grocery_combined	people_store_ratio
0	Alsergrund	0.096774	42547	0.000000	0.096774	4117.451613
1	Brigittenau	0.095238	87239	0.000000	0.095238	8308.476190
2	Donaustadt	0.250000	187007	0.000000	0.250000	46751.750000
3	Döbling	0.000000	72650	0.000000	0.000000	0.000000
4	Favoriten	0.000000	201882	0.166667	0.166667	33647.000000

In [52]:

```
market_df.sort_values("people_store_ratio",inplace=True,ascending=False)
market_df.plot(x="district_name",y="people_store_ratio",kind="bar")
```

Out[52]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x227ba1ec488>
```



Results Discussion and Conclusion:

Ignoring the districts "Penzing","Hietzing","Meidling","Ottakring","Döbling" and "Simmering" due to missing values, the plot above shows districts' people-to-store ratio. The data suggests that there are a lot of grocerystores per innhabitant in "Liesing" and quite a few stores where you can buy food in "Innere Stadt". With a little bit of backgroud information about the city of vienna, that makes a lot of sense because "innere Stadt" beeing the very heart of Vienna has a lot of malls, bars, restaurant and other shops mainly focused on tourists. Districts with a low people-to-store ratio are districts where many people live and work thereby creating the need of grocery stores and supermarkets. Future work might focus on identifying neighborhoods lacking of different venues such as stations or public transport. Identifying areas with a lot of people working and living might prove usefull in order to further optimize the public transport system of the city and thereby avoiding traffic jams.