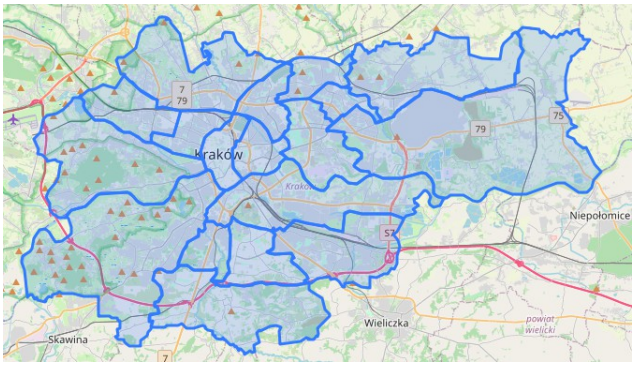
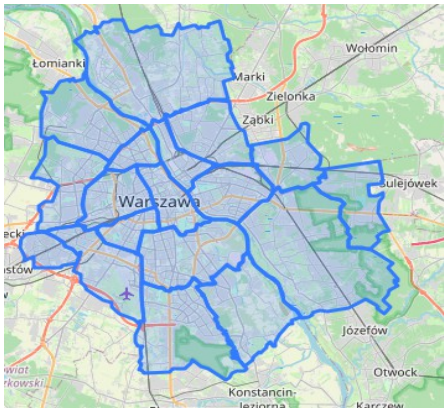
Warsaw and Krakow -districts analysis.





1. Introduction.

1.1. Project description and main goals.

In this project, I would like to explore two polish cities' districts -Warsaw and Krakow. Warsaw is the capital and largest city of Poland. The metropolis stands on the Vistula River in east-central Poland and its population is officially estimated at 1.8 million residents within a greater metropolitan area of 3.1 million residents, which makes Warsaw the 7th most-populous capital city in the European Union. City area is 517.24 km2 (199.71 sq mi).
Krakow, is the second largest and one of the oldest cities. Its population is estimated at 779 115 residents, and city area is 326.8 km2 (126.2 sq mi).

In the first place, I would like to create choroplets maps with most popular types of venues for both cities. This type of maps could be useful to quickly find similar districts, for example by tourists or investors.

Then, I would like to group districts into few cluster (no assumptions about the number), taking into consideration what kind of venues could be find there. This kind of data can be useful if, for example, someone is running business in one place, and wants find similar environment in different city. Also, this information could be used, for example, by travel agency to suggest clients new destination, similar to places he/she visited previously.

As an extra task, I will try to find correlation between different types of venues in districts (is number of Italian restaurants correlated with number of coffee shops?). Maybe I will find some interesting and surprising conclusions.

1.2. Data description.

Following data will be used to perform analysis:

a) Shapefiles of Warsaw and Krakow. The shapefile format is a geospatial vector data format for geographic information system (GIS) software. These files can be easily downloaded from web:
   - https://gis-support.pl/wp-content/uploads/dzielnice_Warszawy.zip
   - https://gis-support.pl/wp-content/uploads/dzielnice_Krakowa.zip

b) From shapefiles, with help of QGIS software, I will create GeoJSONs for both cities. GeoJSON is an open standard format designed for representing simple geographical features, along with their non-spatial attributes. It is based on the JSON format. When transforming .shp to geojson we intend to use with Folium, it is important to choose correct coordinate system: WGS 84. Generally speaking, GeoJSONs for both cities have different structure, but I will use mostly two informations: district name and shape of district (given by polygon coordinates).

Example of Warsaw geojson:


```
{
  "type": "FeatureCollection",
  "name": "warsaw_districts",
  "crs": {
    "type": "name",
    "properties": {
      "name": "urn:ogc:def:crs:OGC:1.3:CRS84"
    }
  },
  "features": [
    {
      "type": "Feature",
      "properties": {
        "nazwa_dzie": "Żoliborz",
        "style": {
          "weight": 1,
          "opacity": 0.9,
          "color": "black",
          "fillOpacity": 0.7,
          "fillColor": "#d9f0a3"
        },
        "highlight": {}
      },
      "geometry": {
        "type": "MultiPolygon",
        "coordinates": [
          [
            [
              [
                20.957550244360345,
                52.266927972075955
              ],
              [
                20.957595033280743,
                52.26712068328835
              ],
                 .....
            ]
          ]
        ]
      }
    }
  ]
}
```


Example of Cracow geojson:


```
{
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  "name": "cracow_districts",
  "crs": {
    "type": "name",
    "properties": {
      "name": "urn:ogc:def:crs:OGC:1.3:CRS84"
    }
  },
  "features": [
    {
      "type": "Feature",
      "properties": {
        "objectid": 1.0,
        "mslink": 1.0,
        "mapid": 3013.0,
        "id_dzielni": 1.0,
        "nr_dzielni": "I",
        "powierzchn": 5567646.0,
        "nazwa": "Stare Miasto",
        "nazwa_peln": "Dzielnica I Stare Miasto",
        "opis": "UCHWALA NR XCIX/1495/14 RADY MIASTA
KRAKOWA",
        "data_aktua": "2014/04/01",
        "st_area(sh": 5567646.1253,
        "st_length(": 11730.268840426876,
        "style": {},
        "highlight": {}
      },
      "geometry": {
        "type": "MultiPolygon",
        "coordinates": [
          [
            [
              [
                19.92376505386849,
                50.062551412466526
              ],
              [
                19.923769137430885,
                50.06260611760511
              ],
                 .....
            ]
          ]
        ]
      }
    }
  ]
}
```

From these GeoJSON files, the most important information was district geometry, defined as type of figure (MultiPolygon), and coordinates of its vertices. These data were used to:

- defining centers of districts
- calculating radius for defining searching area in Foursquare request
- verification if point with given coordinates is inside or outside district

c) For creating choroplet maps, data about districts areas were required. This type of data can be easily find in Wikipedia.

d) I used Foursquare API to get information about venues in different districts.

2. Methodology and results.

2.1. Creating choroplets maps

With help of previously mentioned data, I created dataframe and dictionaries with districts centers, radiuses (to use in Foursquare request), and geometries -to verify later if venues returned from Foursquare are inside district.

Dataframe with districts centers:

	District_center
Żoliborz	[52.2688536216614, 20.985135391429377]
Praga-Południe	[52.235168690871, 21.071138918572952]
Mokotów	[52.18866196405862, 21.052814696946914]
Wola	[52.22969762335711, 20.94634273758449]
Wilanów	[52.15030830502675, 21.091139416474352]

Dictionary with districts polygons:

```
{'Żoliborz': [[20.957550244360345, 52.266927972075955],
  [20.957595033280743, 52.26712068328835],
  [20.957577637116344, 52.26723607840504],
  [20.957537312295642, 52.26727740707875],
  [20.957761257322645, 52.267475395339645],
  [20.957815144778245, 52.267498512850246],
```

Districts radiuses to be used in Foursquare api:

```
{'Żoliborz': 2735,
 'Praga-Południe': 4228,
 'Mokotów': 4866,
 'Wola': 3791,
 'Wilanów': 5010,
 'Wesoła': 3668,
 'Wawer': 7006,
 'Włochy': 4599,
 'Ursynów': 4896,
 'Śródmieście': 4339,
 'Praga-Północ': 3133,
 'Ursus': 2402,
 'Targówek': 3617,
 'Rembertów': 3461,
 'Ochota': 2640,
 'Bielany': 4385,
 'Białołęka': 7513,
 'Bemowo': 3478}
```

With help of these informations, I prepared function for sending request to Foursquare API. Returned informations were used for creation of Dataframes for both cities with all venues in all districts:

	District	Name	Category	Lat	Lon	VenueId	Inside
0	Żoliborz	Park Żeromskiego	Park	52.268377	20.988747	4baf7aa5f964a52031033ce3	True
1	Żoliborz	Galeria Wypieków	Bakery	52.268523	20.986111	55508b67498e2dcf9038f190	True
2	Żoliborz	Plac zabaw w Parku Żeromskiego	Playground	52.267248	20.988827	4db2f35a4b226b343d6d0581	True
3	Żoliborz	Kino Wisła	Indie Movie Theater	52.269609	20.986743	4c14d3afa9c220a11e18589d	True
4	Żoliborz	Plac Wilsona	Plaza	52.268914	20.985587	4bb771276edc76b0a92e321c	True

...

Then, I grouped venues by category and prepared top 5 categories for Warsaw and Krakow:

```
warsaw_top5
```

Category	District	Name	Lat	Lon	VenueId
Café	179	179	179	179	179
Park	140	140	140	140	140
Coffee Shop	138	138	138	138	138
Italian Restaurant	117	117	117	117	117
Supermarket	84	84	84	84	84

```
cracow_top5
```

Category	District	Name	Lat	Lon	VenueId	Inside
Hotel	52	52	52	52	52	52
Supermarket	35	35	35	35	35	35
Italian Restaurant	31	31	31	31	31	31
Café	26	26	26	26	26	26
Park	24	24	24	24	24	24

Then I summed up top categories, to finally receive top 5 categories for further analysis:

```
['Café', 'Coffee Shop', 'Hotel', 'Italian Restaurant', 'Park']
```

Last step before creation of choroplets were counting venues of given categories in districts, and calculating densities [number of venues/km2]:

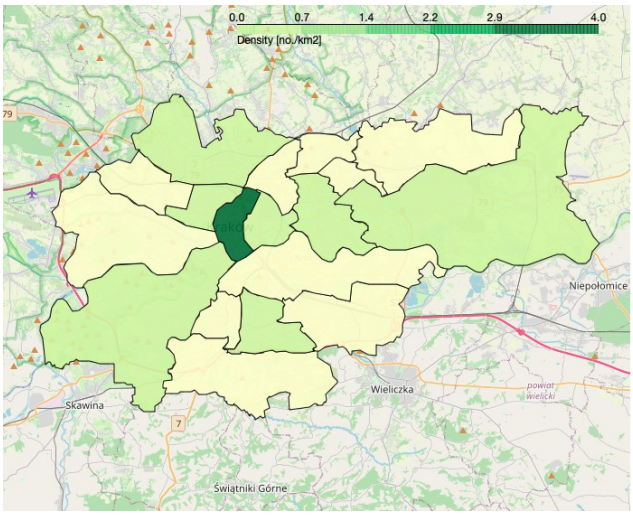
District	Category	Name	Lat	Lon	VenueId
Bemowo	Café	5	5	5	5
	Coffee Shop	3	3	3	3
	Italian Restaurant	4	4	4	4
	Park	8	8	8	8
Białołęka	Café	8	8	8	8

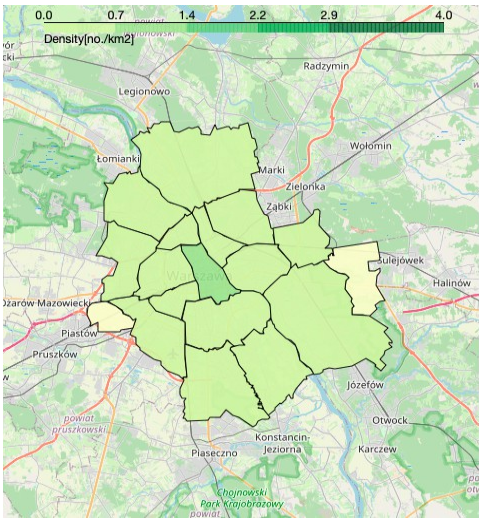
	Category	District	Category_density
0	Café	Bemowo	0.200401
1	Coffee Shop	Bemowo	0.120240
2	Italian Restaurant	Bemowo	0.160321
3	Park	Bemowo	0.320641
4	Café	Białołęka	0.109529
5	Coffee Shop	Białołęka	0.068456
6	Hotel	Białołęka	0.027382
7	Italian Restaurant	Białołęka	0.027382
8	Park	Białołęka	0.136911
9	Café	Bielany	0.278293

Having above data prepared, creating choroplet maps with Folium is straightforward. Below are results

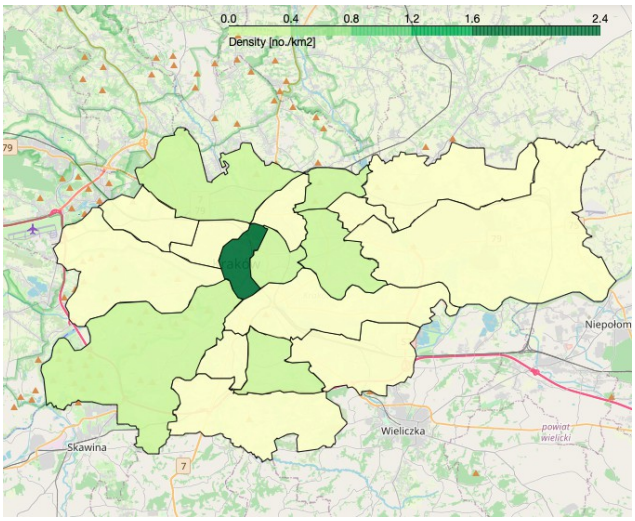
Krakow Warsaw

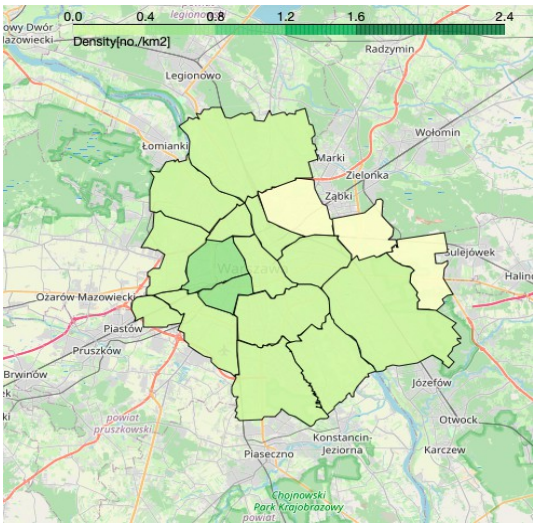
Cafe



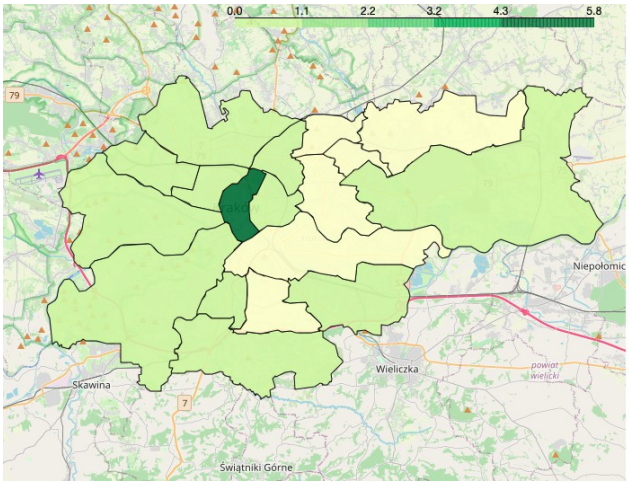


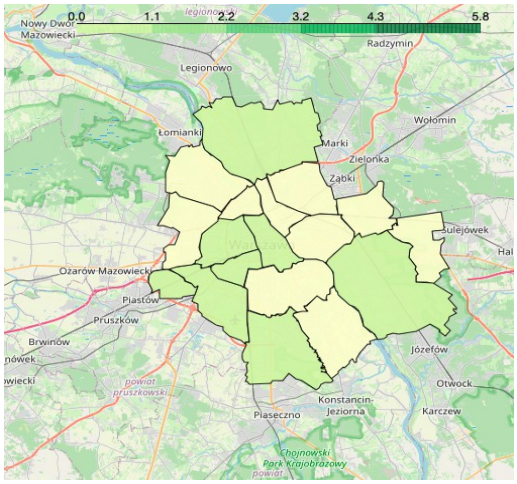
Coffee shops



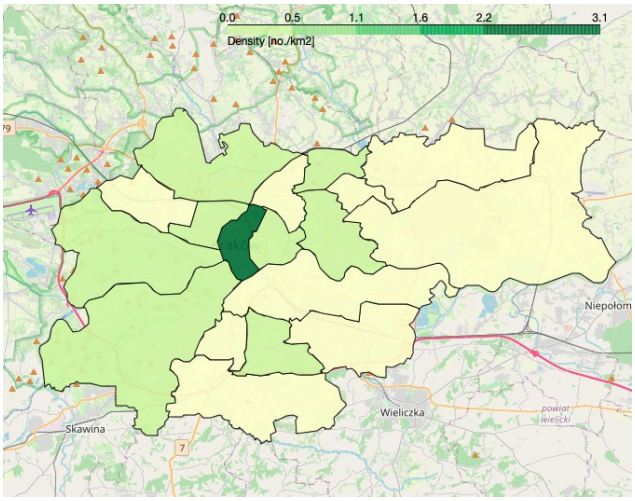


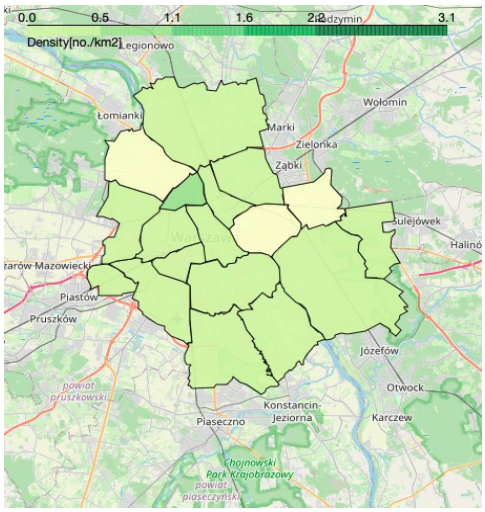
Hotels



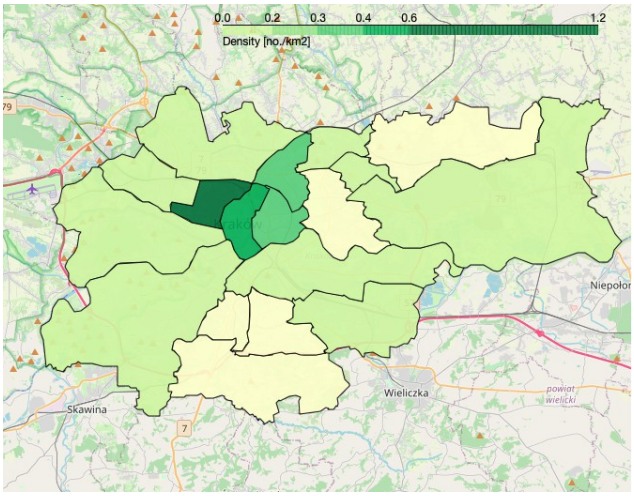


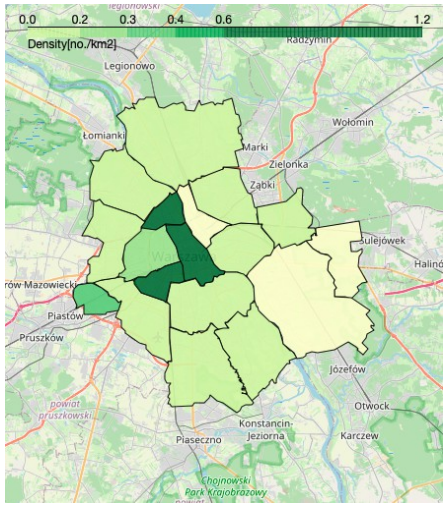
Italian restaurants





Parks





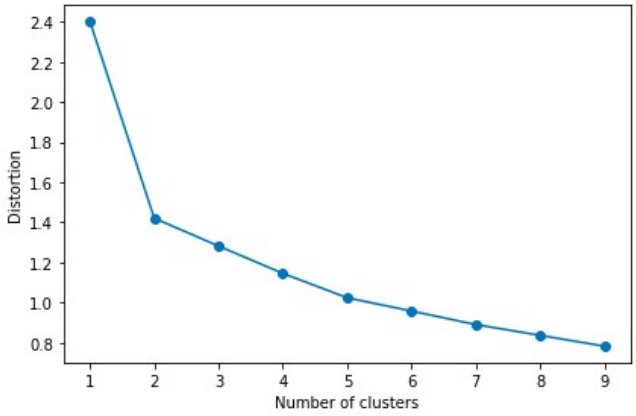
2.2. Clustering districts.

For further analysis, both cities venues dataframes were concatenated into one dataframe. Then I found top 10 categories for each district:

	District	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	Bemowo	Supermarket	Park	Italian Restaurant	Playground	Coffee Shop	Café	Shopping Mall	Grocery Store	Ski Area	Mobile Phone Shop
1	Białołęka	Supermarket	Shopping Mall	Hotel	Sporting Goods Shop	Bar	Multiplex	Neighborhood	Fast Food Restaurant	Farmers Market	Tennis Court
2	Bielany	Café	Grocery Store	Gym / Fitness Center	Park	Coffee Shop	Supermarket	Gym	Pizza Place	Indian Restaurant	Bookstore
3	Bieńczyce	Burger Joint	Lake	Soccer Field	Supermarket	Food & Drink Shop	Shopping Mall	Fast Food Restaurant	Farmers Market	Market	Park
4	Bieżanów-Prokocim	Bus Station	Pizza Place	Bakery	Field	Supermarket	Shoe Store	Go Kart Track	Park	Gym Pool	Tram Station

...

Then k-means algorithm was used to group districts into clusters. I used so called 'elbow method' to choose optimal number of clusters:



In this plot, elbow is located at k=2. Nevertheless, when algorithm was executed with k=2, almost all districts were classified to one cluster:

```
districts_venues_sorted.groupby('Cluster Labels').count()
```

Cluster Labels	District	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	35	35	35	35	35	35	35	35	35	35	35
1	1	1	1	1	1	1	1	1	1	1	1

I tested algorithm with different k, and most reasonable results were obtained for k=3:

```
districts_venues_sorted.groupby('Cluster Labels').count()
```

Cluster Labels	District	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	1	1	1	1	1	1	1	1	1	1	1
1	11	11	11	11	11	11	11	11	11	11	11
2	24	24	24	24	24	24	24	24	24	24	24

Only one district was labeled as cluster 0, so I will not perform its further analysis. For clusters 1 and 2, from top 10 types of venues in each district, I listed most popular. Below are most popular types of venues in clusters 1 and 2 and number of its appearances in top 10:

Cluster 1

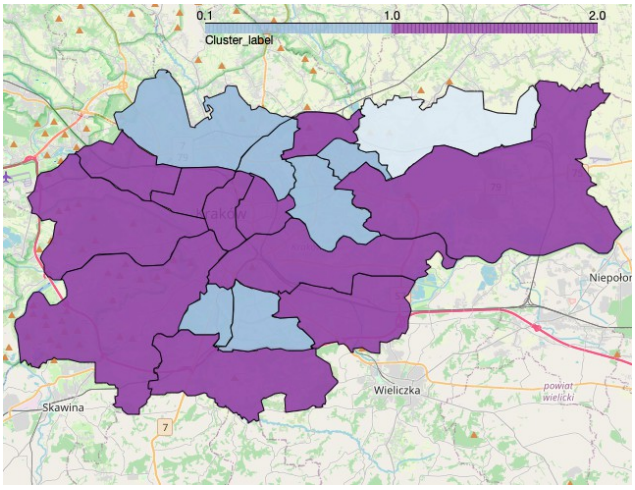
```
Supermarket              11
Fast Food Restaurant      7
Park                      6
Shopping Mall             6
Pizza Place               5
```

Cluster 2

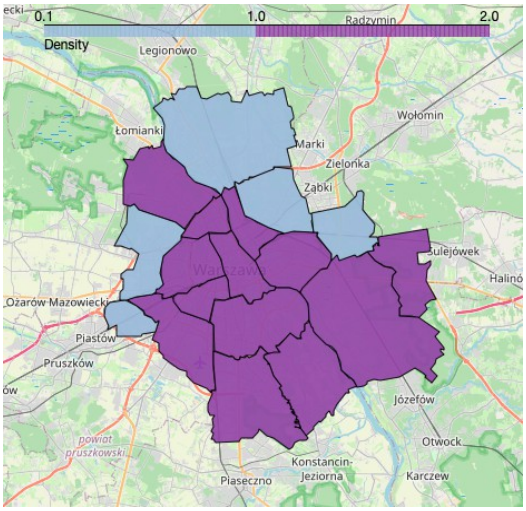
```
Park                  16
Italian Restaurant    15
Café                  13
Supermarket           11
Pizza Place           10
```

And here are maps with labels:

Krakow clusters

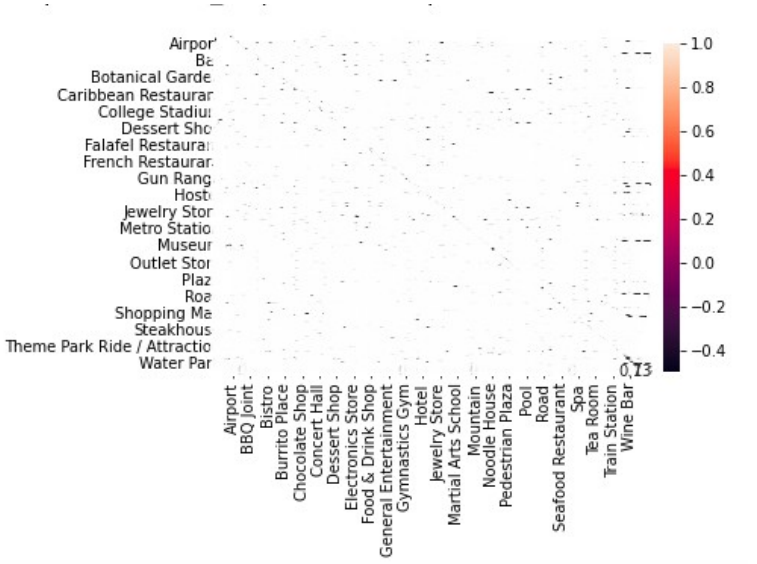


Warsaw clusters



2.3. *Correlations between different types of venues.*

My last aim was investigation of correlations between different types of venues. This can be easily done by creating correaltion matrix -in Pandas it can be done by calling corr() method on datafreame. As a result, desired matrix is obtained. It can be visualized -for example by so called heatmap:



Although heatmaps can be grat visualization tool, in this specific case it is not really useful -correlation matrix is too big (235x235), and it is almost impossible to find most correlated types of venues. Nevertheless, this matrix can be still useful for finding correlations. For example, here are places with highest correlation coefficient with Cafe:

Dessert Shop	0.546974
Indian Restaurant	0.452301
Beer Bar	0.414315
Ramen Restaurant	0.409367
Beach	0.404221
Vegetarian / Vegan Restaurant	0.392186
Food & Drink Shop	0.390660
Liquor Store	0.373259
Wine Bar	0.357540

3. Discussion.

Finally, all my goals were achieved. Below I present short discussion about result.

3.1. Choroplets.

Although received choroplet maps look attractive, they are not as informative as I expected. On most of them, there are only three groups of density values used. Possible reason of that problem is dividing scale into equal intervals from zero to maximum. Usually only one district fall into maximum interval, and all others into first and second minimum interval. Possible remedies for that could be different division of density scale. Second possible reason is fact, that Krakow centre is much more popular among english tourist than other districts of Krakow and Warsaw. Because of that, there is much more venues added in this area in Foursquare app.

3.2. Clustering.

So called elbow method was used to determine optimal number of clusters, but results were not satisfactory -almost all districts were cumulated in one cluster. The best results, in terms of distribution of districts in cluster, were achieved for k=3. Nevertheless, clusters do not seems to be internally coherent. This could be caused by small number of venues received from Foursquare. To verify this hypothesis, some other service could be used to compare numbers of venues.

3.3. Correlations.

Correlation matrix can be really useful for finding what kinds of places appear simultaneously in given area. This may be a hint of where to locate own business. But again, because of small number of venues in many districts, results should be compared with other service of similar functionality.