Report Capstone Project

January 18, 2021

1 The battle of neighbourhoods - Report

1.1 Introduction: the business problem

The client is a big hotel chain who wants to estabilish itself in the city of Munich. The current subdivision of Munich in neighbourhood, while historically grounded, fails to mirror the internal subdivision of the city. The client is interested in getting a picture of the predominant activities in the different sectors of the city, so as to understand where to open which kind of hotel: a family resort would be ideally placed in an area with parks rather than an industrial area, a more hostel-kind of accomodation close to cafes and pubs, and so on.

It is a typical clustering problem, where we are both interested in geographical proximity of points - neighbourhood should be connected - and some kind of "cultural" proximity, i.e. similar kind of activities. This report summarizes the full notebook, to which we refer for details.

1.2 Data

We review the situation as-is, i.e. the historical neighbourhood/postal codes subdivision:

[2]:
```
pc_mun = pd.read_csv("postal_codes_munich.csv")
pc_mun.head()
```

[2]:

	zipcode	Neighbourhood	latitude	longitude
0	80331	Altstadt-Lehel	48.1345	11.5710
1	80333	Altstadt-Lehel	48.1452	11.5668
2	80333	Maxvorstadt	48.1452	11.5668
3	80335	Altstadt-Lehel	48.1427	11.5552
4	80335	Ludwigsvorstadt-Isarvorstadt	48.1427	11.5552

It contains 25 different neighbourhoods and 74 different postal codes:

[393]:
```
print("Unique neighbourhoods: " + str(len(pc_mun["Neighbourhood"].unique())))
print("Unique postal codes: " + str(len(pc_mun["zipcode"].unique())))
```

```
Unique neighbourhoods: 25
Unique postal codes: 74
```

The tragic fact here is that postal codes aren't a refinement of the neighbourhoods, as can already be seen from the first rows of the dataset - 80333 corresponds to both Altstadt-Lehel and Maxvorstadt, covering two areas which we would expect to see in different clusters.

So we build a grid over Munich and then cluster the points of the grid:

[394]:
```
latitudes = np.linspace(start = 48.09, stop = 48.20, num = 20)
longitudes = np.linspace(start = 11.48, stop = 11.65, num = 20)

grid = pd.DataFrame(index = pd.MultiIndex.from_product([latitudes, longitudes],␣
↪names = ["Latitude", "Longitude"])).reset_index()
grid["Neighbourhood"] = grid.index
grid.head()
```

[394]:

	Latitude	Longitude	Neighbourhood
0	48.09	11.480000	0
1	48.09	11.488947	1
2	48.09	11.497895	2
3	48.09	11.506842	3
4	48.09	11.515789	4

Neat, right? Now let's do the clustering.

1.3 Methodology

We set up the classification algorithm and let it run, just like in the previous course assignments. We take around every element of the grid a circle of radius 75% the distance between the points, so that we cover all of the map, at the cost of counting some element twice.

We can load the activities for each grid point from Foursquare and obtain a dataframe like this:

[287]:
```
munich_venues.head()
```

[287]:

```
   Neighborhood  Neighborhood Latitude  Neighborhood Longitude  \
0             0                  48.09                   11.48
1             0                  48.09                   11.48
2             0                  48.09                   11.48
3             0                  48.09                   11.48
4             0                  48.09                   11.48

                          Venue  Venue Latitude  Venue Longitude  \
0                      Rossmann       48.087505        11.484407
1               Schweizer Platz       48.088626        11.479916
2                          REWE       48.089149        11.480729
3                  Ratschiller's       48.089207        11.480467
4  Wochenmarkt am Schweizer Platz       48.089108        11.480147

   Venue Category
```

```
0        Drugstore
1            Plaza
2      Supermarket
3           Bakery
4   Farmers Market
```

[288]:

```
print('There are {} uniques categories.'.format(len(munich_venues['Venue␣
↪Category'].unique())))
```

```
There are 320 uniques categories.
```

And now for the clustering - we drop the Neighbourhood ID for the dataset, since we don't want the algorithm to use it:

[366]:

```
# set number of clusters
kclusters = 28

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

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

[366]:

```
array([12, 12, 12, 12, 12, 12, 12, 10, 10,  7,  7,  7], dtype=int32)
```

Now we have the clusters and we can merge everything back in the original dataframe. We add columns with the most common venues per grid point, which will help us analyse the results later:

[367]:

```
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'] = munich_grouped['Neighborhood']

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.insert(0, 'Cluster Labels', kmeans.labels_)

munich_merged = grid

munich_merged = munich_merged.merge(neighborhoods_venues_sorted.
 ↪set_index('Neighborhood'), left_on='Neighbourhood', right_on =␣
 ↪"Neighborhood")

munich_merged.head() # check the last columns!
```

[367]:

```
    Latitude  Longitude  Neighbourhood  Cluster Labels 1st Most Common Venue  \
0  48.095789  11.488947             21              12     German Restaurant
1  48.095789  11.497895             22              12           Supermarket
2  48.095789  11.506842             23              12  Gym / Fitness Center
3  48.095789  11.515789             24              12                 Hotel
4  48.095789  11.524737             25              12                Bakery

  2nd Most Common Venue   3rd Most Common Venue 4th Most Common Venue  \
0            Playground      Italian Restaurant                Castle
1      Asian Restaurant           Bowling Alley                Bakery
2                 Hotel  Furniture / Home Store             Pet Store
3                  Bank                    Café           Supermarket
4  Gym / Fitness Center        Greek Restaurant           Supermarket

         5th Most Common Venue 6th Most Common Venue 7th Most Common Venue  \
0            Accessories Store     Outdoor Sculpture       Organic Grocery
1                          Spa        Massage Studio             Drugstore
2  Modern European Restaurant           Supermarket       Organic Grocery
3                    Pet Store             Drugstore           Pizza Place
4             Doner Restaurant   Rental Car Location                  Café

         8th Most Common Venue 9th Most Common Venue 10th Most Common Venue
0                 Optical Shop           Opera House                 Office
1                Metro Station             Nightclub           Optical Shop
2                    Drugstore      Asian Restaurant      Electronics Store
3  Construction & Landscaping      Greek Restaurant          Ice Cream Shop
4                 Noodle House       Organic Grocery           Optical Shop
```

1.4 Results

Here's the number of points per cluster:

[404]:

```
munich_merged.groupby("Cluster Labels").agg({"Cluster Labels":"count"})
```

[404]:

```
                Cluster Labels
Cluster Labels
```

```
0                             18
1                             12
2                             14
3                              3
4                             12
5                             25
6                             17
7                             22
8                             19
9                              5
10                             3
11                             1
12                            24
13                             6
14                            13
15                            20
16                            17
17                             1
18                            10
19                             2
20                            23
21                             1
22                             4
23                            16
24                             1
25                             6
26                            11
27                            16
```

Of course, it's so much better to visualize this on a map - take a look at the notebook for an interactive map.

1.5 Discussion

The city center is divided in four parts, corresponding to clusters 0, 8, 20 and 6 - let's look at them one by one as an example.

1.5.1 Cluster 0 - Maxvorstadt and Schwabing West

These are the point in the cluster:

[397]:
```
munich_merged.loc[munich_merged['Cluster Labels'] == 0, munich_merged.
 ↪columns[list(range(2, munich_merged.shape[1]))]]
```

[397]:
```
     Neighbourhood  Cluster Labels  1st Most Common Venue  \
153            190               0             Restaurant
```

154	191	0	Café
170	209	0	Café
171	210	0	Café
172	211	0	Café
173	212	0	Café
188	229	0	Café
189	230	0	Café
190	231	0	Bar
191	232	0	Ice Cream Shop
206	249	0	Bar
207	250	0	Italian Restaurant
208	251	0	Italian Restaurant
209	252	0	Bar
225	270	0	Vietnamese Restaurant
226	271	0	Vietnamese Restaurant
227	272	0	Bar
244	291	0	Plaza

	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue \
153	Plaza	Café	German Restaurant
154	Plaza	Boutique	French Restaurant
170	Asian Restaurant	Middle Eastern Restaurant	Theater
171	History Museum	Art Museum	Italian Restaurant
172	Italian Restaurant	Ice Cream Shop	Breakfast Spot
173	Italian Restaurant	Ice Cream Shop	Surf Spot
188	Asian Restaurant	Steakhouse	Bar
189	Bar	Bakery	Italian Restaurant
190	Café	Italian Restaurant	Ice Cream Shop
191	Irish Pub	Beer Garden	Café
206	Supermarket	Café	Trattoria/Osteria
207	Café	Vietnamese Restaurant	Plaza
208	Café	Ice Cream Shop	Breakfast Spot
209	Café	Trattoria/Osteria	Italian Restaurant
225	Japanese Restaurant	Bar	Indian Restaurant
226	Pizza Place	Plaza	Supermarket
227	Italian Restaurant	Organic Grocery	Bakery
244	Café	Bus Stop	Bakery

	5th Most Common Venue	6th Most Common Venue \
153	Church	Tram Station
154	Cocktail Bar	Clothing Store
170	History Museum	Restaurant
171	Japanese Restaurant	Plaza
172	Bar	Cocktail Bar
173	River	Eastern European Restaurant
188	Bakery	German Restaurant
189	Mediterranean Restaurant	Vietnamese Restaurant

190	Asian Restaurant	German Restaurant
191	Restaurant	Optical Shop
206	Pool	Bavarian Restaurant
207	Greek Restaurant	Bar
208	Vietnamese Restaurant	Pizza Place
209	Burger Joint	German Restaurant
225	Supermarket	Mexican Restaurant
226	Thai Restaurant	Indian Restaurant
227	Café	Burger Joint
244	Taverna	Drugstore

	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue \
153	Botanical Garden	Nightclub	Shopping Mall
154	Bar	Hotel	Restaurant
170	Salad Place	Coffee Shop	Sushi Restaurant
171	Sushi Restaurant	Peruvian Restaurant	Event Space
172	Bakery	Restaurant	Burger Joint
173	Frozen Yogurt Shop	Snack Place	Nightclub
188	Falafel Restaurant	Ramen Restaurant	Doner Restaurant
189	Spanish Restaurant	Gastropub	Cocktail Bar
190	Restaurant	Steakhouse	Burger Joint
191	Bagel Shop	Steakhouse	Bar
206	Thai Restaurant	Cocktail Bar	Restaurant
207	Trattoria/Osteria	Mediterranean Restaurant	Ice Cream Shop
208	German Restaurant	Beer Store	Sushi Restaurant
209	Breakfast Spot	Vietnamese Restaurant	Hotel
225	Thai Restaurant	Hotel	Café
226	Italian Restaurant	Café	Bar
227	Liquor Store	Vietnamese Restaurant	Hotel
244	Tram Station	Metro Station	Bank

	10th Most Common Venue
153	Middle Eastern Restaurant
154	Italian Restaurant
170	Steakhouse
171	Field
172	Plaza
173	Beer Garden
188	Bookstore
189	French Restaurant
190	Breakfast Spot
191	Monument / Landmark
206	Coworking Space
207	Thai Restaurant
208	Supermarket
209	Thai Restaurant
225	Italian Restaurant

```
226                     Bakery
227                    Theater
244         Italian Restaurant
```

This is where we'd build the youth hostel - look at the amount of cafes and bars in the top three. Maxvorstadt and Schwabing are indeed known to be hip neighbourhoods.

1.5.2 Cluster 8 - Altstadt-Lehel and Au-Haidhausen

These are the points in the cluster:

[398]:
```
munich_merged.loc[munich_merged['Cluster Labels'] == 8, munich_merged.
 ↪columns[list(range(2, munich_merged.shape[1]))]]
```

[398]:
```
     Neighbourhood  Cluster Labels 1st Most Common Venue  \
101            132               8                 Plaza
102            133               8    Italian Restaurant
103            134               8                 Hotel
104            135               8              Bus Stop
118            151               8                  Café
119            152               8     Indian Restaurant
120            153               8    Italian Restaurant
121            154               8     German Restaurant
122            155               8    Italian Restaurant
136            171               8                  Café
137            172               8     Indian Restaurant
138            173               8                  Café
139            174               8     Indian Restaurant
140            175               8             Drugstore
155            192               8    Italian Restaurant
156            193               8     German Restaurant
157            194               8    Italian Restaurant
174            213               8    Italian Restaurant
175            214               8                 Plaza

    2nd Most Common Venue  3rd Most Common Venue 4th Most Common Venue  \
101                 Hotel           Burger Joint                Bakery
102                 Plaza      French Restaurant            Restaurant
103  Gym / Fitness Center           Climbing Gym                   Pub
104                   Pub         Discount Store        Shipping Store
118   Bavarian Restaurant            Coffee Shop           Cocktail Bar
119        Ice Cream Shop           Pizza Place           Concert Hall
120                  Café                  Plaza                Bakery
121                 Hotel     Italian Restaurant                  Café
122                 Hotel  Portuguese Restaurant     Indian Restaurant
136   Bavarian Restaurant            Coffee Shop                 Hotel
137                 Beach     Italian Restaurant           Supermarket
```

138	Plaza	French Restaurant	Beer Garden
139	Italian Restaurant	Supermarket	Burger Joint
140	Gym / Fitness Center	Supermarket	Greek Restaurant
155	Japanese Restaurant	German Restaurant	Hotel
156	Italian Restaurant	Art Museum	Restaurant
157	Restaurant	Tram Station	Plaza
174	German Restaurant	River	Supermarket
175	Bakery	Italian Restaurant	German Restaurant

	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	\
101	Beer Garden	Supermarket	Greek Restaurant	
102	Café	Supermarket	Turkish Restaurant	
103	Nightclub	Beach Bar	Beer Bar	
104	Beach Bar	Liquor Store	Nightclub	
118	Pizza Place	Bookstore	German Restaurant	
119	Science Museum	Supermarket	Hotel	
120	German Restaurant	Indian Restaurant	Bar	
121	Plaza	Indian Restaurant	Spanish Restaurant	
122	Home Service	Pizza Place	Doner Restaurant	
136	Plaza	Bookstore	Pizza Place	
137	Bakery	Beer Garden	Snack Place	
138	Ice Cream Shop	Italian Restaurant	German Restaurant	
139	Gym / Fitness Center	Mexican Restaurant	Greek Restaurant	
140	Sushi Restaurant	Bar	Gourmet Shop	
155	Bar	Cocktail Bar	Plaza	
156	Indian Restaurant	Tram Station	Monument / Landmark	
157	Café	Indian Restaurant	Pool	
174	Surf Spot	Bakery	Gourmet Shop	
175	Restaurant	Post Office	Japanese Restaurant	

	8th Most Common Venue	9th Most Common Venue	\
101	Brewery	Café	
102	Organic Grocery	German Restaurant	
103	Gym	Supermarket	
104	Austrian Restaurant	Turkish Restaurant	
118	Theater	Tea Room	
119	Doner Restaurant	Afghan Restaurant	
120	Ice Cream Shop	French Restaurant	
121	Vegetarian / Vegan Restaurant	Bakery	
122	Coffee Shop	Restaurant	
136	German Restaurant	Clothing Store	
137	Bookstore	Doner Restaurant	
138	Taverna	Seafood Restaurant	
139	Steakhouse	German Restaurant	
140	Pastry Shop	Electronics Store	
155	Restaurant	Mediterranean Restaurant	
156	Sushi Restaurant	Gourmet Shop	

```
157                             Hotel             Skating Rink
174                       Pizza Place                   Garden
175                Sporting Goods Shop                 Bus Stop

    10th Most Common Venue
101           Tram Station
102               Bus Stop
103     Fried Chicken Joint
104      German Restaurant
118                 Bistro
119           Gourmet Shop
120           Concert Hall
121             Donut Shop
122           Climbing Gym
136     Italian Restaurant
137             Steakhouse
138    Bavarian Restaurant
139                  Plaza
140            Coffee Shop
155     Mexican Restaurant
156                    Bar
157           Gourmet Shop
174    Japanese Restaurant
175           Gourmet Shop
```

This is a more residential area - we often see drugstores and supermarkets in the first positions. It's still central, but looking at the amount of restaurants vs bars we can tell that the target is different. Hotels are also more common.

1.5.3 Cluster 20 - Ludwigsvorstadt-Isarvorstadt and Sendling

These are the points in the cluster:

[399]:
```python
munich_merged.loc[munich_merged['Cluster Labels'] == 20, munich_merged.
 ↪columns[list(range(2, munich_merged.shape[1]))]]
```

[399]:
```
     Neighbourhood  Cluster Labels 1st Most Common Venue  \
43             68              20                 Plaza
44             69              20                  Park
61             88              20                 Plaza
62             89              20     Athletics & Sports
63             90              20               Taverna
78            107              20     German Restaurant
79            108              20    Italian Restaurant
80            109              20                   Bar
81            110              20     German Restaurant
82            111              20    Italian Restaurant
```

94	125	20	Basketball Stadium
95	126	20	Park
96	127	20	Seafood Restaurant
97	128	20	Italian Restaurant
98	129	20	Italian Restaurant
99	130	20	Bar
100	131	20	Italian Restaurant
113	146	20	Italian Restaurant
114	147	20	Café
115	148	20	Italian Restaurant
116	149	20	Italian Restaurant
117	150	20	Café
135	170	20	Café

	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue \
43	Turkish Restaurant	Soccer Field	Construction & Landscaping
44	Beach	Gastropub	Café
61	Italian Restaurant	German Restaurant	Turkish Restaurant
62	Restaurant	Park	Trail
63	Plaza	Drugstore	Bus Line
78	Doner Restaurant	Bank	Gastropub
79	Supermarket	Market	Food & Drink Shop
80	Café	Italian Restaurant	Supermarket
81	Drugstore	Soccer Field	Plaza
82	Bar	Plaza	Pizza Place
94	Tunnel	Tennis Court	Lounge
95	Playground	Italian Restaurant	Café
96	Café	Vietnamese Restaurant	Indian Restaurant
97	Café	Seafood Restaurant	Grocery Store
98	Café	Bar	Bakery
99	Café	Italian Restaurant	Asian Restaurant
100	Café	Pub	Bus Stop
113	Café	Music Venue	Bus Stop
114	Indian Restaurant	Asian Restaurant	Bavarian Restaurant
115	Burger Joint	Café	Grocery Store
116	Vietnamese Restaurant	Café	German Restaurant
117	Coffee Shop	Bar	Italian Restaurant
135	Italian Restaurant	Plaza	German Restaurant

	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue \
43	Hotel	Bakery	Beer Garden
44	Rest Area	Seafood Restaurant	Beer Garden
61	Gas Station	Bakery	Park
62	Gas Station	Soccer Field	Beach
63	Spa	Bus Stop	Café
78	Bus Stop	Vietnamese Restaurant	Café
79	Gastropub	Grocery Store	Falafel Restaurant

80	Turkish Restaurant	Park	Bakery
81	Cupcake Shop	Gastropub	Bar
82	German Restaurant	Café	Bakery
94	Soccer Field	Bus Stop	Gym
95	Music Venue	Supermarket	Rock Club
96	Gym	Currywurst Joint	Restaurant
97	Supermarket	Vietnamese Restaurant	Hotel
98	Indian Restaurant	Pub	Seafood Restaurant
99	German Restaurant	Bakery	French Restaurant
100	Pizza Place	Brewery	Cocktail Bar
113	German Restaurant	Lounge	Thai Restaurant
114	Outdoor Sculpture	Burger Joint	Bar
115	Vietnamese Restaurant	Hostel	German Restaurant
116	Ice Cream Shop	Pharmacy	Sushi Restaurant
117	Pizza Place	Bakery	Asian Restaurant
135	Hotel	Cocktail Bar	Nightclub

	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
43	BBQ Joint	Climbing Gym	Greek Restaurant
44	Accessories Store	Nightclub	Optical Shop
61	Supermarket	Organic Grocery	Hotel
62	Rest Area	Newsstand	Optical Shop
63	German Restaurant	Greek Restaurant	Gym
78	Italian Restaurant	Drugstore	Spanish Restaurant
79	Gym Pool	Bar	Bus Stop
80	Cocktail Bar	Food Court	Trail
81	Beach	Beer Garden	Taverna
82	Drugstore	Brewery	Doner Restaurant
94	Park	Café	Beer Garden
95	Restaurant	Accessories Store	Nightclub
96	Rock Club	Ethiopian Restaurant	Organic Grocery
97	Nightclub	Caucasian Restaurant	Greek Restaurant
98	German Restaurant	Greek Restaurant	Spanish Restaurant
99	Track	Restaurant	Ice Cream Shop
100	Fair	Farmers Market	Fast Food Restaurant
113	Gym / Fitness Center	Sushi Restaurant	Greek Restaurant
114	Middle Eastern Restaurant	Bagel Shop	Salad Place
115	Supermarket	Sushi Restaurant	Falafel Restaurant
116	Bookstore	Grocery Store	Greek Restaurant
117	Cocktail Bar	Bavarian Restaurant	Ice Cream Shop
135	Burger Joint	Bavarian Restaurant	Indie Movie Theater

Yet another cafe area - it probably got separated from Cluster 0 because the algorithm tends to prefer circular neighbourhoods.

1.5.4 Cluster 6 - Schwantalerhöhe and Neuhausen

[409]:
```
munich_merged.loc[munich_merged['Cluster Labels'] == 18, munich_merged.
 ↪columns[list(range(2, munich_merged.shape[1]))]]
```

[409]:
```
     Neighbourhood  Cluster Labels 1st Most Common Venue  \
192            233              18              Bus Stop
193            234              18                  Bank
210            253              18                   Bar
211            254              18          Bathing Area
212            255              18          Bathing Area
228            273              18                 Hotel
229            274              18    Photography Studio
231            276              18              Bus Stop
247            294              18               Stadium
248            295              18         Indie Theater

    2nd Most Common Venue 3rd Most Common Venue 4th Most Common Venue  \
192    Monument / Landmark            Hotel Pool   Bavarian Restaurant
193                 Bakery           Supermarket                  Park
210                 Tunnel               Dog Run          Comedy Club
211    Bavarian Restaurant          Tennis Court                  Café
212      Trattoria/Osteria              Bus Stop     Accessories Store
228      German Restaurant                   Bar     Afghan Restaurant
229           Bathing Area   Bavarian Restaurant                  Park
231       Asian Restaurant           Gas Station                Bakery
247        Bed & Breakfast                 Trail           Beer Garden
248                   Lake                  Park          Bathing Area

    5th Most Common Venue 6th Most Common Venue 7th Most Common Venue  \
192             Restaurant           Beer Garden           Snack Place
193           Gourmet Shop    Athletics & Sports                Hostel
210      Trattoria/Osteria           Boat Rental     German Restaurant
211      Accessories Store           Noodle House       Organic Grocery
212              Newsstand       Organic Grocery          Optical Shop
228               Bus Stop     Trattoria/Osteria             Nightclub
229           Tennis Court       Volleyball Court           Beer Garden
231                Theater                   Bar    Italian Restaurant
247          Moving Target             Newsstand          Optical Shop
248                Dog Run            Skate Park           Music Venue

    8th Most Common Venue    9th Most Common Venue 10th Most Common Venue
192      Recreation Center      Athletics & Sports                  Hotel
193      German Restaurant         Organic Grocery               Bus Stop
210            Snack Place      Convenience Store             Beer Garden
211           Optical Shop             Opera House                 Office
212            Opera House                  Office           Noodle House
```

228	Outlet Store	Outdoor Sculpture	Organic Grocery
229	Newsstand	Opera House	Office
231	Music Store	Opera House	Outlet Store
247	Mountain	Opera House	Office
248	Nature Preserve	New American Restaurant	Newsstand

This is the area around the central station - look at how many hotels!

1.5.5 Other clusters

The algorithm caught some other interesting features, for example the industrial area northwest (Cluster 9), the zoo in the south (Cluster 10) and the park (Cluster 18).

1.6 Conclusion

The algorithm provides a new rationale for the subdivision of the city, grouping and splitting old neighbourhoods into new ones.