Correlation between restaurants and socioeconomic factors in Lelystad

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Introduction

Lelystad is the capital of the Dutch province Flevoland, which is said to be one of the most multicultural diverse provinces of The Netherlands. Lelystad was initially designed around its boroughs, which means that most boroughs have their own shopping center and restaurants.

I have been fascinated with the restaurant business in Lelystad since my work at EetSmakelijk.nl. When I worked there, we were always looking to extend our reach. We also tried to understand why some restaurants did well in particular boroughs, while others did not. In this research, I will not focus on restaurant rating or popularity, since these are subjective and require surveying a large sample of citizens.

I will however, see if there is a correlation between the amount of restaurants in a certain borough and the demography of the boroughs - as well as finding the socioeconomic factors that seem to correlate most with the amount of restaurants that are located in a borough.

Finally, I will be presenting a list of boroughs where there are opportunities to start a restaurant based on my previous statistical analysis. If you were looking to open a restaurant in Lelystad: this might be the time.

Abstract

Restaurants are seemingly everywhere, but are they really? In this paper I find, using correlation and location-based clustering, that four socioeconomic factors show a strong correlation with the amount of

restaurants in a borough in Lelystad, a fast growing, multiculturally diverse city in The Netherlands. These are:

- The amount of people in a borough that have two parents who were born in The Netherlands
- The percentage of bought houses in a borough, and inversely, the percentage of rented houses in a borough
- The scale of addresses per square meter (expressed on a scale of 1 - low to 5 - high)

Overall I conclude that in Lelystad there is a certain correlation between socioeconomic factors and the amount of restaurants in a borough.

Data to be used

In order to find a relationship between demographic, socioeconomic variables and the type of and amount of restaurants in a borough, we will need the following data, collected from external resources:

- **Boroughs in Lelystad**, retrieved from https://www.metatopos.eu/flevoland2.html.
- **Socioeconomic data**, collected by the Central Bureau for Statistics in The Netherlands, retrieved as a .csv-file from https://www.cbs.nl/nl-nl/dossier/nederland-regionaal/geografische-data/gegevens-per-postcode.
- **Restaurants in Lelystad**, retrieved from the FourSquare API.

Data collection

In [173…

```
%%capture
# Remove this capture statement to debug pip installation
!pip install pandas
!pip install numpy
!pip install folium
!pip install bs4
!pip install simpledbf
!pip install SQLalchemy
!pip install matplotlib
# !pip install nbconvert
# !pip install pyppeteer
```

In [174…

```
import pandas as pd
import numpy as np
import folium
from bs4 import BeautifulSoup
import requests
import re
from simpledbf import Dbf5
import json
import matplotlib.pyplot as plt
from math import sin, cos, asin, sqrt
```

Boroughs of Lelystad

In [175…

```
flevoland_borough_web_data = requests.get('https://www.metatopos.eu/flevoland2.html').cont
flevoland_borough_soup = BeautifulSoup(flevoland_borough_web_data, 'html.parser')

lelystad_boroughs = pd.DataFrame(columns=['postal_code', 'borough', 'lat', 'lng'])
for index, row in enumerate(flevoland_borough_soup.find('table').find_all('tr')):
```

```
        if index == 0:
            # This is the table head, so let's not use it
            pass
        else:
            borough = {}
            cols = row.find_all('td')

            if cols[1].text == 'Lelystad':
                postal_code = cols[3].text
                borough = cols[4].text
                lat = re.search('@(.*?),', str(cols[3])).group(0)[1:][:-1]
                lng = re.search(',(.*?),', str(cols[3])).group(0)[1:][:-1]
                borough = {'postal_code': postal_code, 'borough': borough, 'lat': lat, 'lng':
                lelystad_boroughs = lelystad_boroughs.append(borough, ignore_index=True)

# Since we need to merge this later, we should cast the key for merge to an integer
lelystad_boroughs['postal_code'] = lelystad_boroughs['postal_code'].astype(int)
lelystad_boroughs['lat'] = lelystad_boroughs['lat'].astype(float)
lelystad_boroughs['lng'] = lelystad_boroughs['lng'].astype(float)

lelystad_boroughs
```

Out[175…

	postal_code	borough	lat	lng
0	8211	industrieterrein Oostervaart	52.538798	5.501941
1	8212	Wijngaard, Bongerd, Oostrandpark, Buitenplaats	52.514697	5.492923
2	8218	bedrijvenpark Larserpoort + ten zuiden van Lar...	52.440146	5.353604
3	8219	Edelhertweg, Runderweg, Dronterweg, Swifterrin...	52.515177	5.481707
4	8221	IJsselmeerdijk, Karperweg	52.569803	5.478124
5	8222	Biologisch Centrum; Groene Velden, Hazeleger, ...	52.538687	5.483483
6	8223	Gildenhof	52.523348	5.481777
7	8224	Lelycentre, Damrif, Kustrif	52.512792	5.477765
8	8225	Archipel, Wold, Horst, Kamp, Griend, Zoom	52.502910	5.486276
9	8226	Sont, Larserdreef	52.490578	5.487027
10	8231	De Stelling, De Schans, De Veste, Schouw, Kemp...	52.531211	5.455288
11	8232	De Gordiaan, Botter-oost, Tjalk	52.506531	5.459658
12	8233	De Doelen, Grietenij	52.496289	5.467008
13	8239	Lelystad-Zuid, bedrijventerrein Flevopoort I e...	52.469773	5.422923
14	8241	Birdielaan, Eaglelaan, Golfpark	52.537077	5.437665
15	8242	Boeier, Puner, Galjoen, Kogge, Gondel, Houtrib...	52.592990	5.234752
16	8243	Schoener, Botter-west, Jol, industrieterrein N...	52.505941	5.430568
17	8244	Lelystad-Haven	52.495409	5.404976
18	8245	Buizerdweg, Uilenweg	52.488722	5.423648

Socioeconomic data of Lelystad

The terms of the columns in this file are Dutch, because they have been provided by the Dutch Bureau of Statistics. I will try to comment usage of these columns as much as possible throughout the code. For more information, I highly recommend you read this piece of information provided by the CBS. Optionally, you could use a tool like Google Translate to translate the text.

In [176…

```python
dbf = Dbf5('./socioeconomic_data.dbf')
netherlands_socioeconomic = dbf.to_dataframe()
netherlands_socioeconomic.rename({'PC4': 'postal_code'}, axis=1, inplace=True)
lelystad_socioeconomic = lelystad_boroughs.merge(netherlands_socioeconomic)

# Remove values that are marked secret by CBS (-99997), as well as data we don't need here
# Also remove other data that is irrelevant for the socioeconomic data
# We remove WON_4564 (Houses built between 1945 and 1964) because the first houses in Lely
lelystad_socioeconomic.replace(-99997, np.nan, inplace=True)
lelystad_socioeconomic.drop(columns=['borough', 'lat', 'lng', 'WON_4564'], inplace=True)

lelystad_socioeconomic
```

Out[176…

	postal_code	INWONER	MAN	VROUW	INW_014	INW_1524	INW_2544	INW_4564	INW_65PL	P_NL_
0	8211	285.0	145.0	140.0	35.0	40.0	45.0	95.0	70.0	
1	8212	4550.0	2270.0	2280.0	715.0	465.0	990.0	1225.0	1150.0	
2	8218	225.0	125.0	95.0	55.0	35.0	50.0	65.0	20.0	
3	8219	2925.0	1510.0	1410.0	615.0	450.0	645.0	955.0	255.0	
4	8221	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
5	8222	185.0	90.0	90.0	20.0	15.0	15.0	65.0	70.0	
6	8223	4940.0	2550.0	2390.0	995.0	675.0	1335.0	1255.0	675.0	
7	8224	7135.0	3535.0	3595.0	1265.0	805.0	1795.0	1705.0	1570.0	
8	8225	8100.0	4110.0	3990.0	1390.0	965.0	2360.0	2085.0	1300.0	
9	8226	9630.0	4850.0	4780.0	1940.0	1315.0	2535.0	2740.0	1100.0	
10	8231	5145.0	2505.0	2640.0	1015.0	575.0	1310.0	1250.0	1000.0	
11	8232	7380.0	3575.0	3810.0	1255.0	730.0	2090.0	1685.0	1625.0	
12	8233	680.0	330.0	350.0	15.0	40.0	145.0	110.0	375.0	
13	8239	190.0	130.0	55.0	25.0	70.0	30.0	50.0	10.0	
14	8241	1465.0	750.0	715.0	230.0	140.0	225.0	505.0	365.0	
15	8242	6070.0	3035.0	3035.0	940.0	600.0	1370.0	1645.0	1515.0	
16	8243	9450.0	4695.0	4755.0	1700.0	1105.0	2480.0	2540.0	1630.0	
17	8244	4175.0	2175.0	2000.0	625.0	470.0	1035.0	1445.0	600.0	
18	8245	6055.0	3090.0	2965.0	1255.0	820.0	1570.0	1775.0	635.0	

19 rows × 35 columns

Restaurants in Lelystad

We can retrieve a list of all restaurants that can be found in Lelystad using the Foursquare API.

In [177…

```python
# Replace this with your own user and secret token
foursquare_api_user = 'MYRAWBC204ODSPK012UUUTKDZVL35YVFLPIBC11LFM5WQGGR'
foursquare_api_secret = 'JHW5AMMFRHXEQSM1H2C5ULPDR30S1DMUKHQSDBOD1GEBYRIF'
foursquare_base_url = f'https://api.foursquare.com/v2/venues/search?client_id={foursquare_

restaurants_lelystad = pd.DataFrame(columns=['name', 'category', 'lat', 'lng', 'borough'])

for _, entry in lelystad_boroughs.iterrows():
```

```
    foursquare_data = requests.get(f'{foursquare_base_url}&ll={entry["lat"]},{entry["lng"]
    foursquare_data = json.loads(foursquare_data)
    venues = foursquare_data['response']['venues']
    for venue in venues:
        try:
            if venue['location']['city'].lower() == 'lelystad':
                category = None
                for cat in venue['categories']:
                    if cat['primary'] is True:
                        category = cat['name']

                restaurants_lelystad = restaurants_lelystad.append({
                    'name': venue['name'],
                    'category': category,
                    'lat': venue['location']['lat'],
                        'lng': venue['location']['lng'],
                        'borough': None
                    }, ignore_index=True)
        except KeyError:
            pass
```

In [178…

```
restaurants_lelystad.drop_duplicates(inplace=True)
restaurants_lelystad
```

Out[178…

	name	category	lat	lng	borough
0	KFC	Fried Chicken Joint	52.482914	5.505881	None
1	McDonald's	Fast Food Restaurant	52.482354	5.505328	None
2	Aan Ut Water	Restaurant	52.551815	5.460253	None
3	PARAPARA Sushi & Grill Cafe	Sushi Restaurant	52.510146	5.476211	None
4	Restaurant Applaus	Restaurant	52.510884	5.475991	None
5	De Rede van Bataviahaven	Restaurant	52.519105	5.438982	None
6	Steak van de Keizer	Steakhouse	52.510215	5.476957	None
7	Le Passage	Café	52.509701	5.475661	None
8	Any Tyme - Snack & Dine	Diner	52.491499	5.483160	None
9	Gino Italiaanse Restaurant	Restaurant	52.502090	5.489030	None
10	La Place	Buffet	52.523160	5.436851	None
11	Bakker Bart	Bakery	52.507896	5.474241	None
12	McDonald's	Fast Food Restaurant	52.522800	5.438940	None
13	Trung Tien Vietnamees	Food Truck	52.510032	5.447958	None
14	Grieks restaurant Lemonakis	Greek Restaurant	52.519144	5.439341	None
15	Prego	Dessert Shop	52.503979	5.483926	None
16	koffie & thee FP	Café	52.507400	5.476178	None
17	Toko Atina	Food	52.502832	5.462334	None
18	dutch originals	Coffee Shop	52.523821	5.437461	None
19	Fashion Cafe	Café	52.523099	5.440457	None
20	Next	BBQ Joint	52.521677	5.438837	None
21	illy café	Café	52.523091	5.437837	None

	name	category	lat	lng	borough
22	Eetcafe@thebeach	Gastropub	52.547018	5.454643	None
23	Farinella Ristorante & Pizza Napoletana	Italian Restaurant	52.523869	5.439613	None
24	De Gordiaan Kitchen-Bar	Restaurant	52.510073	5.477390	None
25	Urker Visboer (voorhof)	Fish & Chips Shop	52.513849	5.502862	None
26	Starbucks	Coffee Shop	52.523320	5.439907	None
27	Uno	Restaurant	52.509373	5.474824	None
28	De Brass	Diner	52.529989	5.437901	None
29	Pizza Deal	Pizza Place	52.509987	5.476402	None
30	Bakkerij Scheunhage	Bakery	52.503016	5.462334	None
31	Prins	Bakery	52.517516	5.459906	None
32	Anadolu Turkish Bakery	Bakery	52.520258	5.484267	None
33	Intersnack	Bakery	52.503303	5.428760	None
34	Fusian Express - Wok2Go	Asian Restaurant	52.507268	5.476940	None
35	Banh Mi 101	Vietnamese Restaurant	52.522835	5.439387	None
36	Hajé De Taveerne	Deli / Bodega	52.471423	5.484383	None
37	Just Taste	Snack Place	52.498803	5.489889	None
38	Cafetaria Netwerk	Snack Place	52.500233	5.471400	None
39	Restaurant Silver Wine & Dine	Restaurant	52.505991	5.474223	None
40	SUBWAY®	Sandwich Place	52.522309	5.438616	None
47	Flantuas	Restaurant	52.454582	5.522275	None
80	Hajé de Aalscholver	Restaurant	52.435189	5.423217	None
81	Hajé de Lepelaar	Restaurant	52.433354	5.424527	None
82	Take Away	Coffee Shop	52.433770	5.425351	None
159	Restaurant Monica & Winston	Restaurant	52.507766	5.476100	None
161	Markt	Food Court	52.519814	5.485150	None

Visualizing our data

The next step to take, is to visualize the location of all restaurants, our boroughs and the categories. For this, we will mostly utilize the powerful Folium library for Python. To view these maps, you will have to run this notebook in trusted mode. Therefore, you are unable to view these maps on Github.

Map of restaurants

In [179…

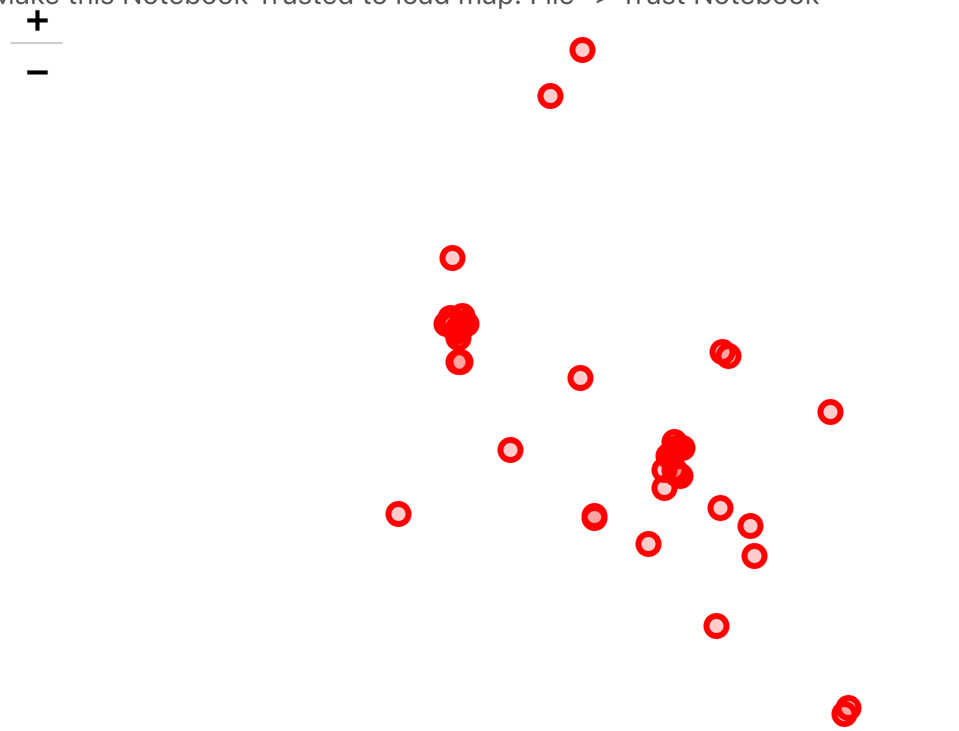
```
lelystad_coords = (52.518536 , 5.471422)
restaurant_map = folium.Map(location=list(lelystad_coords), zoom_start=12)

for lat, lng, name, category in zip(restaurants_lelystad['lat'], restaurants_lelystad['lng
    folium.CircleMarker(
        [lat, lng],
        radius = 5,
        popup=folium.Popup(f'{name}\n{category}'),
        color='red',
```

```
        fill=True,
        fill_color='red'
    ).add_to(restaurant_map)

restaurant_map
```

Out [179… Make this Notebook Trusted to load map: File -> Trust Notebook



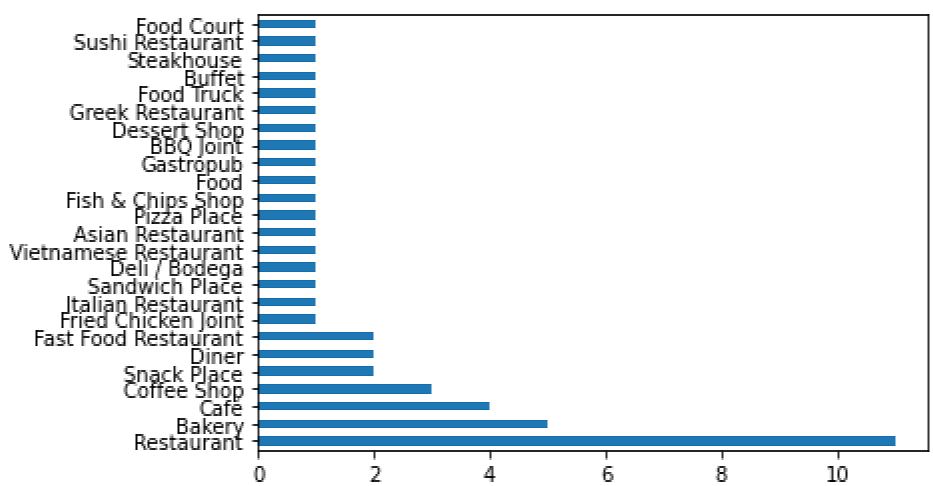
Leaflet (https://leafletjs.com) | Data by © OpenStreetMap (http://openstreetmap.org), under ODbL (http://www.openstreetmap.org/copyright).

As we can see, most restaurants are actually located in two places (the city center and Batavia Stad Fashion Outlet). We also see that next to the highway there are two places in which restaurants are located. These are most likely Fast Food restaurants and/or restaurants that belong to gas stations.

Restaurant categories

In [180…

```
category_graph = restaurants_lelystad['category'].value_counts().plot(kind='barh')
plt.show()
```



Most of the restaurants are classified by Foursquare as a generic restaurant, which does not give us a lot of information on the types of restaurant that are located in each borough.

Clustering our data into boroughs

In order for this data to be useful to our research, we will need some information about the types of restaurants located in each borough. To do so, we will cluster a restaurant to the closest borough, based on distance. We do this by implementing an iteration over all restaurants, iterating over all boroughs, using the Haversine formula.

In [181…

```
def haversine(A, B):
    """
    Calculates the distance between two points (A and B).

    Params:
        A (tuple): Coordinates in the form (float: lat, float: lng).
        B (tuple): Coordinates in the form (float: lat, float: lng).

    Returns:
        float: The distance between points A and B in meters.
    """
    A_lat, A_lng = A
    B_lat, B_lng = B
    distance_lat = B_lat - A_lat
    distance_lng = B_lng - A_lng
    a = sin(distance_lat/2)**2 + cos(A_lat) * cos(B_lat) * sin(distance_lng/2)**2
    c = 2 * asin(sqrt(a))
    return c * 6371000
```

In [182…

```
# Calculate the closest borough
for index, restaurant in restaurants_lelystad.iterrows():
    selected_borough = None
    restaurant_coords = (restaurant['lat'], restaurant['lng'])
    for n, borough in lelystad_boroughs.iterrows():
        borough_coords = (borough['lat'], borough['lng'])
        distance = haversine(restaurant_coords, borough_coords)
        if selected_borough is None or selected_borough[1] > distance:
            selected_borough = (n, distance)

    restaurants_lelystad.loc[index, 'borough'] = selected_borough[0]

restaurants_lelystad
```

Out[182…

	name	category	lat	lng	borough
0	KFC	Fried Chicken Joint	52.482914	5.505881	9
1	McDonald's	Fast Food Restaurant	52.482354	5.505328	9
2	Aan Ut Water	Restaurant	52.551815	5.460253	5
3	PARAPARA Sushi & Grill Cafe	Sushi Restaurant	52.510146	5.476211	7
4	Restaurant Applaus	Restaurant	52.510884	5.475991	7
5	De Rede van Bataviahaven	Restaurant	52.519105	5.438982	16
6	Steak van de Keizer	Steakhouse	52.510215	5.476957	7
7	Le Passage	Café	52.509701	5.475661	7
8	Any Tyme - Snack & Dine	Diner	52.491499	5.483160	9
9	Gino Italiaanse Restaurant	Restaurant	52.502090	5.489030	8
10	La Place	Buffet	52.523160	5.436851	14
11	Bakker Bart	Bakery	52.507896	5.474241	7
12	McDonald's	Fast Food Restaurant	52.522800	5.438940	10

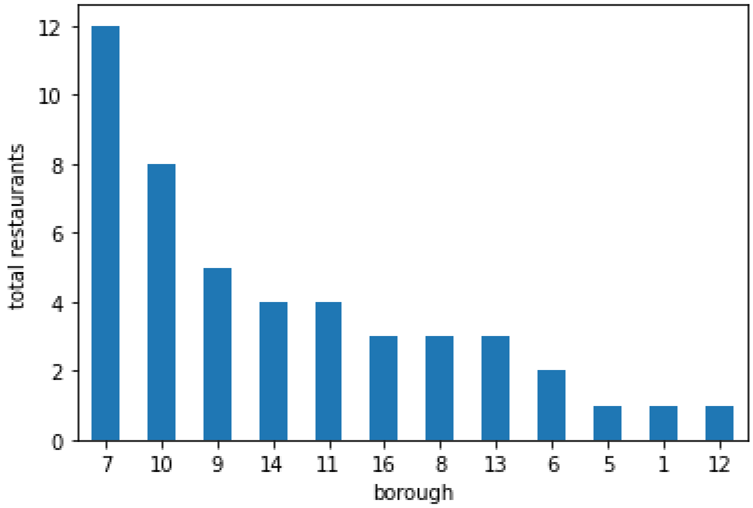
	name	category	lat	lng	borough
13	Trung Tien Vietnamees	Food Truck	52.510032	5.447958	11
14	Grieks restaurant Lemonakis	Greek Restaurant	52.519144	5.439341	16
15	Prego	Dessert Shop	52.503979	5.483926	8
16	koffie & thee FP	Café	52.507400	5.476178	7
17	Toko Atina	Food	52.502832	5.462334	11
18	dutch originals	Coffee Shop	52.523821	5.437461	14
19	Fashion Cafe	Café	52.523099	5.440457	10
20	Next	BBQ Joint	52.521677	5.438837	10
21	illy café	Café	52.523091	5.437837	10
22	Eetcafe@thebeach	Gastropub	52.547018	5.454643	14
23	Farinella Ristorante & Pizza Napoletana	Italian Restaurant	52.523869	5.439613	10
24	De Gordiaan Kitchen-Bar	Restaurant	52.510073	5.477390	7
25	Urker Visboer (voorhof)	Fish & Chips Shop	52.513849	5.502862	1
26	Starbucks	Coffee Shop	52.523320	5.439907	10
27	Uno	Restaurant	52.509373	5.474824	7
28	De Brass	Diner	52.529989	5.437901	14
29	Pizza Deal	Pizza Place	52.509987	5.476402	7
30	Bakkerij Scheunhage	Bakery	52.503016	5.462334	11
31	Prins	Bakery	52.517516	5.459906	11
32	Anadolu Turkish Bakery	Bakery	52.520258	5.484267	6
33	Intersnack	Bakery	52.503303	5.428760	16
34	Fusian Express - Wok2Go	Asian Restaurant	52.507268	5.476940	7
35	Banh Mi 101	Vietnamese Restaurant	52.522835	5.439387	10
36	Hajé De Taveerne	Deli / Bodega	52.471423	5.484383	9
37	Just Taste	Snack Place	52.498803	5.489889	8
38	Cafetaria Netwerk	Snack Place	52.500233	5.471400	12
39	Restaurant Silver Wine & Dine	Restaurant	52.505991	5.474223	7
40	SUBWAY®	Sandwich Place	52.522309	5.438616	10
47	Flantuas	Restaurant	52.454582	5.522275	9
80	Hajé de Aalscholver	Restaurant	52.435189	5.423217	13
81	Hajé de Lepelaar	Restaurant	52.433354	5.424527	13
82	Take Away	Coffee Shop	52.433770	5.425351	13
159	Restaurant Monica & Winston	Restaurant	52.507766	5.476100	7
161	Markt	Food Court	52.519814	5.485150	6

Visualizing clustered restaurants

In [183…

```
borough_graph = restaurants_lelystad['borough'].value_counts().plot.bar(rot=0, xlabel='bor
```

```
plt.show()
```



As we can see, not all boroughs actually have restaurants clustered to them. Let's see which boroughs that are:

In [184…

```
boroughs_with_restaurants = restaurants_lelystad['borough'].unique()
all_boroughs = np.array(lelystad_boroughs.index.tolist())
empty_boroughs = np.setdiff1d(all_boroughs, boroughs_with_restaurants)

boroughs_with_restaurants_dataframe = lelystad_boroughs.loc[set(lelystad_boroughs.index) -
boroughs_with_restaurants_dataframe['total'] = restaurants_lelystad['borough'].value_count
boroughs_with_restaurants_dataframe['total'].replace(np.nan, 0, inplace=True)
boroughs_with_restaurants_dataframe['total'] = boroughs_with_restaurants_dataframe['total'

empty_borough_dataframe = lelystad_boroughs.loc[set(lelystad_boroughs.index) - set(borough
```

Boroughs with restaurants

In [185…

```
boroughs_with_restaurants_dataframe
```

Out[185…

	postal_code	borough	lat	lng	total
1	8212	Wijngaard, Bongerd, Oostrandpark, Buitenplaats	52.514697	5.492923	1
5	8222	Biologisch Centrum; Groene Velden, Hazeleger, ...	52.538687	5.483483	1
6	8223	Gildenhof	52.523348	5.481777	2
7	8224	Lelycentre, Damrif, Kustrif	52.512792	5.477765	12
8	8225	Archipel, Wold, Horst, Kamp, Griend, Zoom	52.502910	5.486276	3
9	8226	Sont, Larserdreef	52.490578	5.487027	5
10	8231	De Stelling, De Schans, De Veste, Schouw, Kemp...	52.531211	5.455288	8
11	8232	De Gordiaan, Botter-oost, Tjalk	52.506531	5.459658	4
12	8233	De Doelen, Grietenij	52.496289	5.467008	1
13	8239	Lelystad-Zuid, bedrijventerrein Flevopoort I e...	52.469773	5.422923	3
14	8241	Birdielaan, Eaglelaan, Golfpark	52.537077	5.437665	4
16	8243	Schoener, Botter-west, Jol, industrieterrein N...	52.505941	5.430568	3

Boroughs without restaurants

In [186…

```
empty_borough_dataframe
```

Out[186…

	postal_code	borough	lat	lng
0	8211	industrieterrein Oostervaart	52.538798	5.501941
2	8218	bedrijvenpark Larserpoort + ten zuiden van Lar...	52.440146	5.353604
3	8219	Edelhertweg, Runderweg, Dronterweg, Swifterrin...	52.515177	5.481707
4	8221	IJsselmeerdijk, Karperweg	52.569803	5.478124
15	8242	Boeier, Puner, Galjoen, Kogge, Gondel, Houtrib...	52.592990	5.234752
17	8244	Lelystad-Haven	52.495409	5.404976
18	8245	Buizerdweg, Uilenweg	52.488722	5.423648

Finding correlation

Now we're at a stage that we can discover if there is any possible correlation between the socioeconomic data and the amount of restaurants that we find in a borough. I will not only find the values, but also graph them.

In [187…

```
correlation_dataframe = lelystad_socioeconomic.copy()
correlation_dataframe['restaurants'] = restaurants_lelystad['borough'].value_counts()
correlation_dataframe['restaurants'].replace(np.nan, 0, inplace=True)
correlation_dataframe['restaurants'] = correlation_dataframe['restaurants'].astype(int)
correlation_dataframe = correlation_dataframe.drop('postal_code', axis=1)
correlation_dataframe
```

Out[187…

	INWONER	MAN	VROUW	INW_014	INW_1524	INW_2544	INW_4564	INW_65PL	P_NL_ACHTG	P_WE
0	285.0	145.0	140.0	35.0	40.0	45.0	95.0	70.0	80.0	
1	4550.0	2270.0	2280.0	715.0	465.0	990.0	1225.0	1150.0	80.0	
2	225.0	125.0	95.0	55.0	35.0	50.0	65.0	20.0	90.0	
3	2925.0	1510.0	1410.0	615.0	450.0	645.0	955.0	255.0	80.0	
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
5	185.0	90.0	90.0	20.0	15.0	15.0	65.0	70.0	80.0	
6	4940.0	2550.0	2390.0	995.0	675.0	1335.0	1255.0	675.0	50.0	
7	7135.0	3535.0	3595.0	1265.0	805.0	1795.0	1705.0	1570.0	50.0	
8	8100.0	4110.0	3990.0	1390.0	965.0	2360.0	2085.0	1300.0	60.0	
9	9630.0	4850.0	4780.0	1940.0	1315.0	2535.0	2740.0	1100.0	60.0	
10	5145.0	2505.0	2640.0	1015.0	575.0	1310.0	1250.0	1000.0	70.0	
11	7380.0	3575.0	3810.0	1255.0	730.0	2090.0	1685.0	1625.0	60.0	
12	680.0	330.0	350.0	15.0	40.0	145.0	110.0	375.0	80.0	
13	190.0	130.0	55.0	25.0	70.0	30.0	50.0	10.0	50.0	
14	1465.0	750.0	715.0	230.0	140.0	225.0	505.0	365.0	80.0	
15	6070.0	3035.0	3035.0	940.0	600.0	1370.0	1645.0	1515.0	80.0	
16	9450.0	4695.0	4755.0	1700.0	1105.0	2480.0	2540.0	1630.0	70.0	

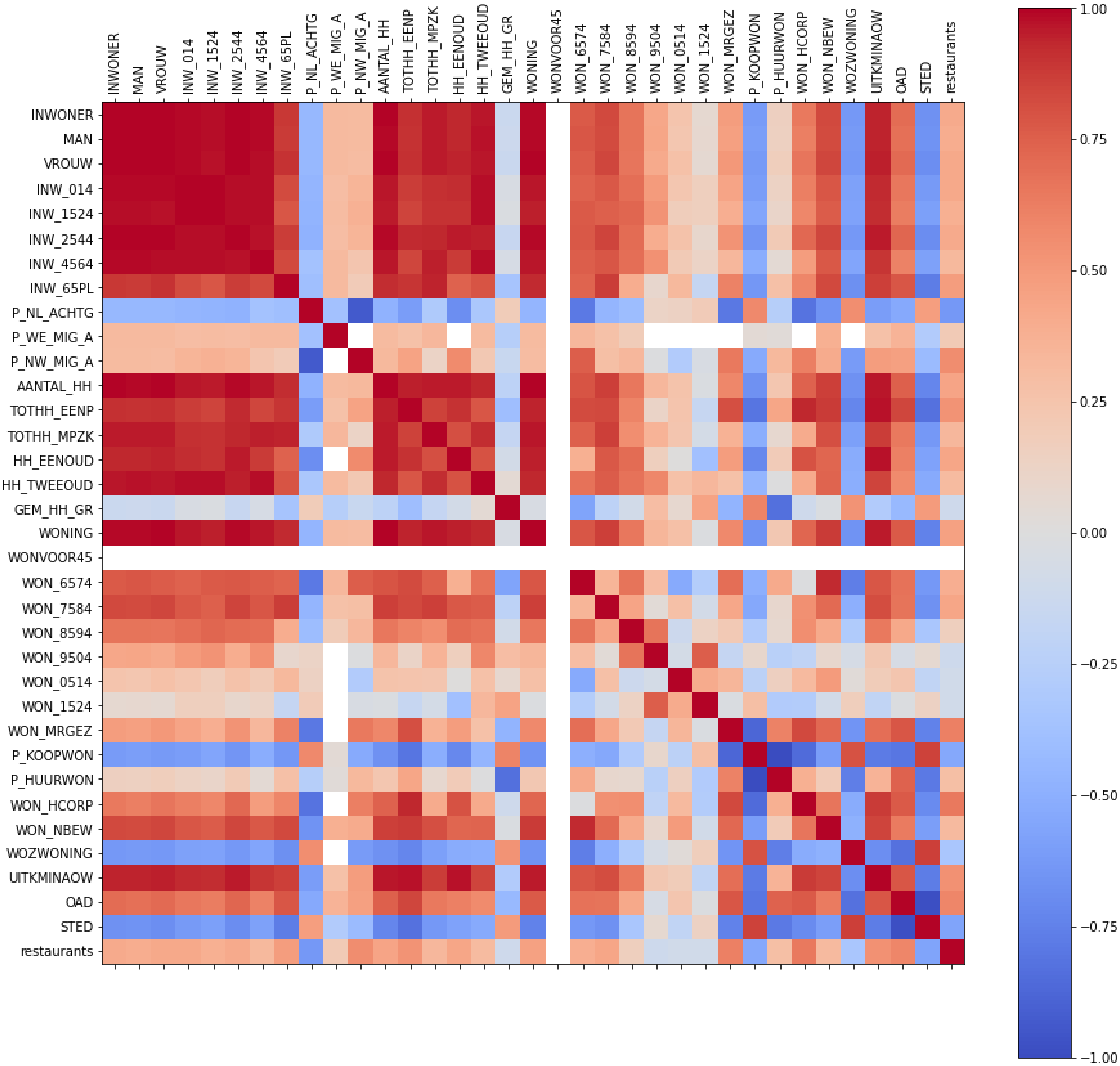
	INWONER	MAN	VROUW	INW_014	INW_1524	INW_2544	INW_4564	INW_65PL	P_NL_ACHTG	P_WE
17	4175.0	2175.0	2000.0	625.0	470.0	1035.0	1445.0	600.0	80.0	
18	6055.0	3090.0	2965.0	1255.0	820.0	1570.0	1775.0	635.0	80.0	

19 rows × 35 columns

In [188…

```
correlation = correlation_dataframe.corr()

# Visualization by https://medium.com/@sebastiannorena/finding-correlation-between-many-va
figure = plt.figure(figsize=(15, 15))
ax = figure.add_subplot(111)
cax = ax.matshow(correlation, cmap='coolwarm', vmin=-1, vmax=1)
figure.colorbar(cax)
ticks = np.arange(0, len(correlation_dataframe.columns), 1)
ax.set_xticks(ticks)
plt.xticks(rotation=90)
ax.set_yticks(ticks)
ax.set_xticklabels(correlation_dataframe.columns)
ax.set_yticklabels(correlation_dataframe.columns)
plt.show()
```



Correlation in words

For our research, only the final column (or row) is of good use. We now learn some interesting facts about the correlation between the socioeconomic factors and the amount of restaurants in a borough. For the sake of our research, let's look at the most striking correlations:

- There is a strong negative correlation between P_NL_ACHTG (The percentage of people in a borough with two parents who were born in The Netherlands) and the amount of restaurants in a borough.
- There is a negative correlation between P_KOOPWON (The percentage of bought houses in a borough) and the amount of restaurants in a borough. Vice-versa, there is an equally strong correlation between P_HUURWON (The percentage of rented houses in a borough) and the amount of restaurants in a borough.
- There is a negative correlation between STED (The density of addresses in a borough) and the amount of restaurants in a borough.

Finding opportunities

Now we know about the correlations in Lelystad between socioeconomic factors and the amount of restaurants in a borough, can we find a borough without restaurants that would fit the correlation? Let's have a look at the boroughs without restaurants again:

In [189…

```
empty_borough_dataframe
opportunity_dataframe = lelystad_socioeconomic.loc[set(lelystad_socioeconomic.index) - set
opportunity_dataframe[['P_NL_ACHTG', 'P_KOOPWON', 'P_HUURWON', 'STED']]
```

Out[189…

	P_NL_ACHTG	P_KOOPWON	P_HUURWON	STED
0	80.0	80.0	20.0	5
2	90.0	70.0	30.0	5
3	80.0	90.0	10.0	5
4	NaN	NaN	NaN	5
15	80.0	70.0	30.0	3
17	80.0	80.0	20.0	4
18	80.0	90.0	10.0	4

Without further analysis, we can already see how the correlation data lines up with the data from these boroughs and why there are no restaurants here:

1. The percentage of of people in the borough with two parents who were born in the Netherlands is very high.
2. The percentage of bought houses is very high, and as a result, the percentage of rented houses in these boroughs is very low.
3. The density of addresses in the borough is very high (the maximum score here is 5).

I would recommend that, all other factors being equal, you should not start a business in any of these boroughs since the correlation shows there is not much opportunity here.

Conclusion

The results I have found with this study of correlation between socioeconomic factors and the amount of restaurants in a borough is surprising to me. In this research I have shown the following correlations with the amount of restaurants in a borough:

- A positive correlation with the number of houses built between 1945 and 1964.
- A negative correlation with the percentage of people that have two parents who were born in The Netherlands.
- A negative correlation with the number of bought houses in a borough.
- Inversely, a positive correlation with the number of rented houses in a borough.
- A negative correlation with the density of addresses in a borough on a scale of 1 to 5.

I would say more study is needed to find why a restaurant is successful in a certain borough and why these factors are correlated in Lelystad. It might also be interesting to see if these correlations hold in other rapidly developing cities in The Netherlands (like Purmerend and Zoetermeer), if these correlations hold in other cities in Flevoland (most importantly: Almere) and if these correlations hold in the big cities in The Netherlands (For example Amsterdam, Rotterdam, Utrecht).