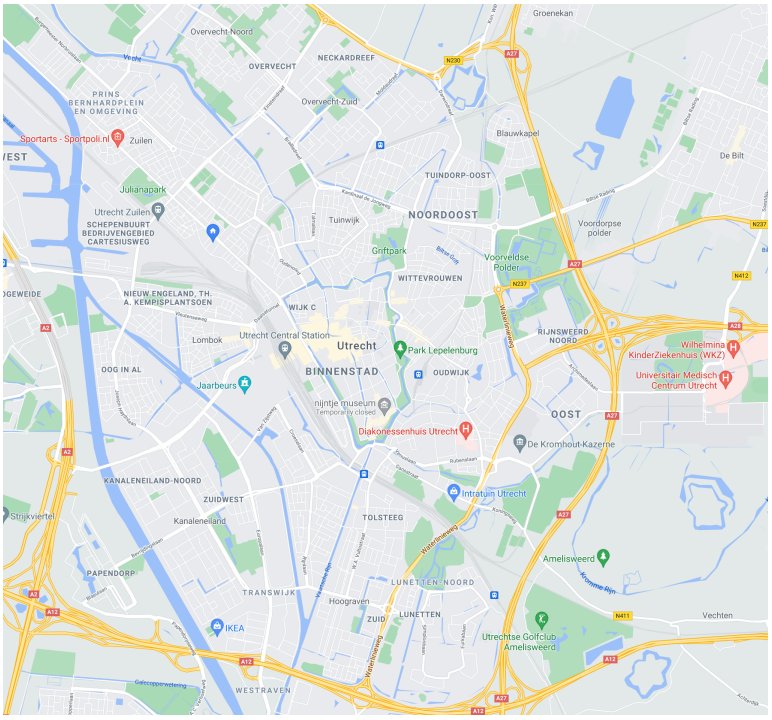
# Introduction:

Housing prices in Utrecht, Netherlands are high, this causes trouble for many people. A lack of transparency in pricing only makes this worse. People need to have the right information available when making these purchase decisions. However, for many it is unclear why prices are much higher in some areas than in others. Should this affect your purchase decision?




*The beautiful city of Utrecht, Netherlands*

Breaking down the price of housing in Utrecht allows people to understand this phenomena and act accordingly. Because neighbourhood data is used in this analysis, it could help when looking for new and upcoming areas to live or invest in. In this assignment I will combine Utrecht housing price data, Utrecht neighbourhood data, and Foursquare API data to compare housing prices in neighbourhoods in Utrecht.

Apart from the benefits to the Utrecht community, this information can help the government understand various factors influencing housing pricing on a local level which can lead to improvements in housing policies to combat the rise of unaffordable housing.

# Data:

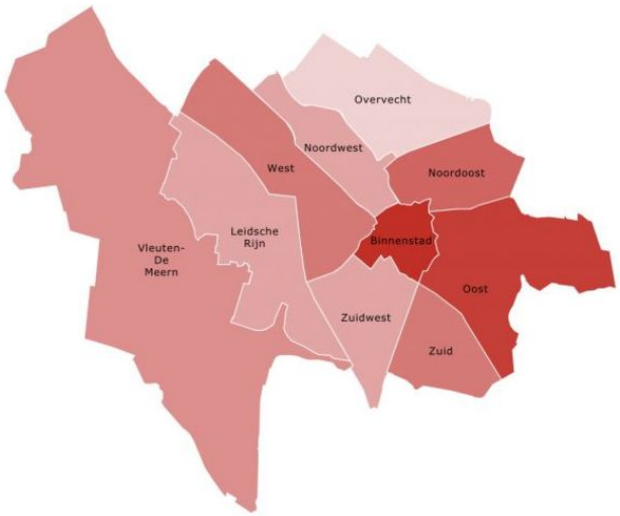
The data used in this analysis is from 3 sources. Utrecht neighbourhood data, Utrecht housing price data, and Foursquare API.

Utrecht neighbourhood data. The Dutch Central Bureau for Statistics (CBS) has a vast amount of data available on neighbourhoods. I have used the data set on neighbourhoods to find information on the number of inhabitants, children, addresses, neighbourhood size, and more. This data is available on various government levels. Initially, the idea was to use this data on 'Buurt' level (which is essentially a sub-neighbourhood), because utrecht has more than a 100 of those. However because of the lack of housing price data on such a small level of granularity, I had to make the choice to go with 'Wijk' level (large/parent neighbourhood). In the methodology section I will discuss the implications of that choice (significantly less data points).

| | ID | WijkenEnBuurten | Gemeentenaam_1 | SoortRegio_2 | Codering_3 | IndelingswijzigingWijkenEnBuurten_4 | AantalInwoners_5 | Mannen_6 | Vrouwen_7 | k_0T |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 14564 | Wijk 01 West | Utrecht | Wijk | WK034401 | 1 | 29270 | 14210 | 15055 | |
| 1 | 14576 | Wijk 02 Noordwest | Utrecht | Wijk | WK034402 | 1 | 45255 | 22060 | 23195 | |
| 2 | 14590 | Wijk 03 Overvecht | Utrecht | Wijk | WK034403 | 1 | 34295 | 17200 | 17095 | |
| 3 | 14601 | Wijk 04 Noordoost | Utrecht | Wijk | WK034404 | 1 | 39680 | 18780 | 20895 | |
| 4 | 14613 | Wijk 05 Oost | Utrecht | Wijk | WK034405 | 1 | 32080 | 14905 | 17170 | |
| 5 | 14627 | Wijk 06 Binnenstad | Utrecht | Wijk | WK034406 | 1 | 19165 | 9815 | 9345 | |
| 6 | 14639 | Wijk 07 Zuid | Utrecht | Wijk | WK034407 | 1 | 27895 | 13685 | 14210 | |
| 7 | 14648 | Wijk 08 Zuidwest | Utrecht | Wijk | WK034408 | 1 | 38620 | 19430 | 19190 | |
| 8 | 14656 | Wijk 09 Leidsche Rijn | Utrecht | Wijk | WK034409 | 1 | 41290 | 20685 | 20605 | |
| 9 | 14672 | Wijk 10 Vleuten-De Meern | Utrecht | Wijk | WK034410 | 1 | 49795 | 24465 | 25330 | |

10 rows × 118 columns

*General Neighbourhood data*




*Location and shape of each neighbourhood*

The next dataset is on housing prices in Utrecht's neighbourhoods. This data is from 2019, as the data from 2020 was not available at the time of this analysis. The data only includes transactions from 2019. The dataset was scraped from the web using the standard pandas scraping functionality (see notebook). This dataframe is merged with the already existing dataframe containing general neighbourhood data.

| | Neighbourhood | Price_2019Q3 | Price_per_m2 |
|---|---|---|---|
| 0 | West | 341.181 | 4.219 |
| 1 | Noordwest | 309.690 | 4.015 |
| 2 | Overvecht | 274.954 | 2.908 |
| 3 | Noordoost | 445.016 | 4.788 |
| 4 | Oost | 507.770 | 4.887 |
| 5 | Binnenstad | 434.747 | 5.091 |
| 6 | Zuid | 327.887 | 3.802 |
| 7 | Zuidwest | 313.324 | 3.661 |
| 8 | Leidsche rijn | 415.235 | 3.673 |
| 9 | Vleuten-De Meern | 428.002 | 3.562 |

*House prices table in euros*

The last dataset is coming from the Foursquare API. A central point was picked in each neighbourhood, and the coordinates of those points were added into the already existing dataset. Next, using the Foursquare API, all venues in a radius of 700m were identified. The 700 meter radius was chosen because 1) neighbourhood size is roughly 1.4km diameter, and 2) city centre reached the API return limit of 100 venues, so a bigger area would require multiple API calls. The returning values are transformed so that it represents the number of venues in that neighbourhood/area and appended to the existing dataset.

| Latitude | Longitude | Venue |
|---|---|---|
| 52.1091 | 5.0668 | 4 |
| 52.1108 | 5.0902 | 24 |
| 52.1180 | 5.1080 | 24 |
| 52.1035 | 5.1351 | 17 |
| 52.0840 | 5.1547 | 7 |
| 52.0889 | 5.1175 | 100 |
| 52.0641 | 5.1245 | 15 |
| 52.0758 | 5.1003 | 20 |
| 52.0954 | 5.0457 | 19 |
| 52.1002 | 5.0021 | 6 |

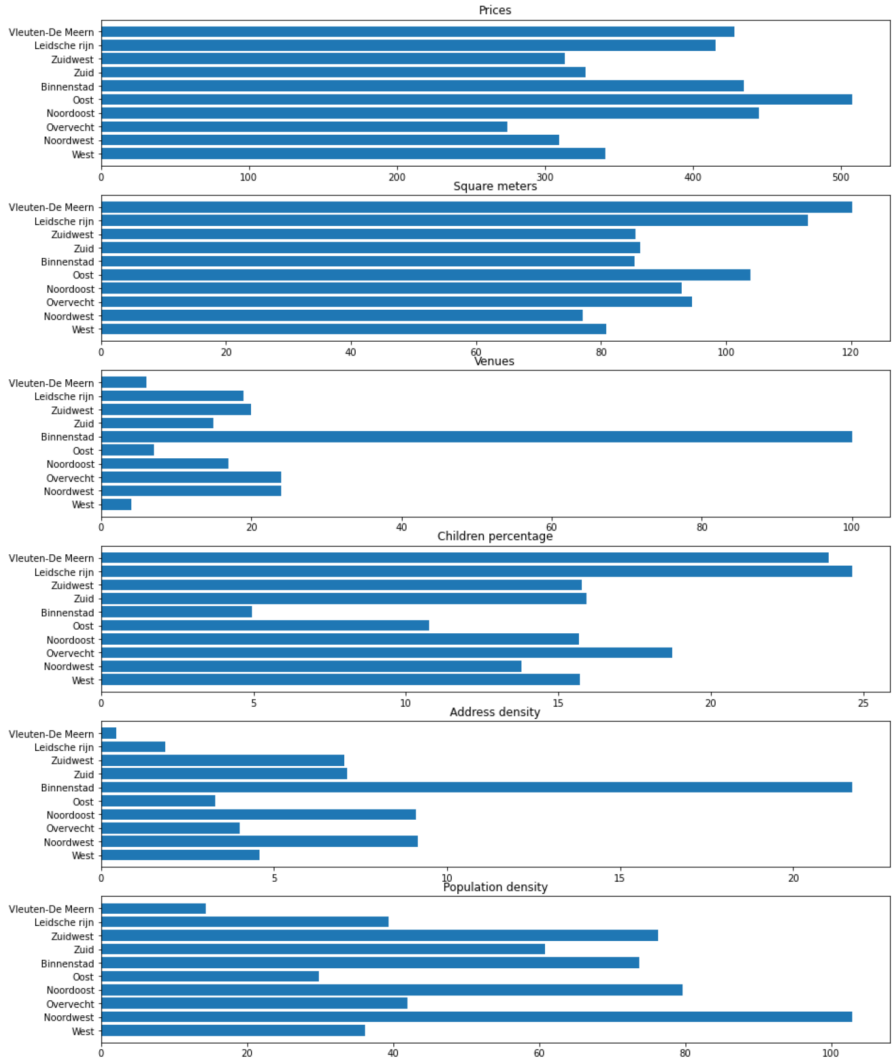
*Neighbourhoods coordinates and number of Foursquare venues*

# Methodology

Using these datasets described in the Data section, I created variables that are believed to be more meaningful than the variables already in the dataset. Variables like Inhabitants and Addresses, we cannot use on face value because these are inherently linked to the landmass of a neighbourhood. To accommodate for that the variables were transformed to density measures, instead of absolute numbers. New variables:

| | |
|---|---|
| Venues | = Count API results |
| Children_percentage | = Children / Inhabitants |
| Address_density | = Addresses / Landsurface |
| Population_density | = Inhabitants / Landsurface |
| Square_meters_2019 | = Price / Price per square meter |

Exploratory analysis consisted of comparing the variables above among neighbourhoods. The graph below shows some of the output:




*The difference among neighbourhoods in the key variables.*

Just from looking at these numbers, some similarities and differences can be discovered. For example, Vleuten-De Meern & Leidsche rijn are less populated, have more children, bigger surface area, medium price. This makes a lot of sense for neighbourhoods that are on the edge of Utrecht. To investigate this further, a cluster analysis will be discussed in the results section using K-means.

The main analysis on price, will be performed using multiple linear regression. This choice has been made because I do not just want to predict or estimate the average housing price, I also want to understand why the price is what it is. Many machine learning algorithms work as a black box, but this is not the case for regressions.

The variables are not standardized at all, therefore the choice has been made to normalize them using min-max feature scaling. This allows an apples to apples comparison because all variables are scaled to be in the 0 to 1 range.

# Results

### Clustering

The result of the k-means cluster analysis is 4 clusters:

| | Neighbourhood | Cluster |
|---|---|---|
| 0 | West | 1 |
| 1 | Noordwest | 1 |
| 2 | Overvecht | 1 |
| 3 | Noordoost | 0 |
| 4 | Oost | 0 |
| 5 | Binnenstad | 2 |
| 6 | Zuid | 1 |
| 7 | Zuidwest | 1 |
| 8 | Leidsche rijn | 3 |
| 9 | Vleuten-De Meern | 3 |

*Result of cluster analysis*

Based on the the data and the knowledge I have on Utrecht, this makes each cluster unique:

- Cluster 0: High prices, few children
- Cluster 1: Low prices, small surface area
- Cluster 2: High prices, few children, high address density, many venues
- Cluster 3: Large surface area, low address & population density, many children

### Regression

Results:

| | 0 | Coefs |
|---|---|---|
| 0 | Venue | -538.558745 |
| 1 | children_percentage | -203.656263 |
| 2 | address_density | 637.866379 |
| 3 | population_density | -52.330406 |
| 4 | square_meters_2019 | 338.110482 |

*Coefficient results of regression analysis*

Because the variables have been normalized using min-max scaling prior to the analysis, we can compare them on face value. The results seem to suggest the amount of venues has a negative effect on housing prices, and address density a positive effect. Important to note is that these variables are negatively correlated with each other (collinearity), therefore the actual effect is smaller because they cancel each other out.

# Discussion

So why are the results what they are? The density of children is negatively related to housing prices. This could have various reasons. Children are expensive, and so are houses, so people without children could perhaps afford more housing. Additionally, in general people in the city centre have less children, this is also where prices have risen the most in recent years. Population density is also slightly negatively correlated to price. This is a bit harder to explain, perhaps because population density is negatively correlated to square meters (surface area) of dwellings? This is definitely an area where more research is needed.

This brings me to the last point in this discussion. Obviously the sample size of this study is too small to make any conclusive statements. This is mainly due to data limitations and time limitations. However, this work could be used as a starting point, or a framework to expand on by including other cities, or digging up the data on a lower level of granularity in Utrecht. Sadly it seems that this data is only available through kadaster (paid).

# Conclusion

The results show that there the neighbourhoods can be clustered in four distinct groups based on the variables used in this study. Additionally, children have a large negative effect on housing prices, surface area obviously has a big positive effect. Population density has a slight negative effect.