A New Charging Station for Düsseldorf

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Outline

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Background

- electric vehicles (EVs) are an old concept (born 1827) with new relevance (Tesla etc)
- market share is increasing, a lot of future potential
- EVs require infrastructure in the form of a network of charging stations
- how to determine the best placement for a new charging station?
- use city of Düsseldorf (population $\approx$ 600,000) as example

Data Sources

- Foursquare: coordinates of existing charging stations $\rightarrow$ accessed via Foursquare API
- OpenStreetMap: district boundaries $\rightarrow$ OSM relations accessed via `https://nominatim.openstreetmap.org`
- Wikipedia: population density for each city district $\rightarrow$ read and entered into pandas dataframe

Data Cleaning

- data on charging station positions acquired from Foursquare API in large radius around city centre
- $\rightarrow$ yielded five stations, one of them outside of Düsseldorf
- this station was dropped from further analysis
- data also incomplete: additional charging stations found with `https://nominatim.openstreetmap.org`
- for real project, further digging would be required at this point

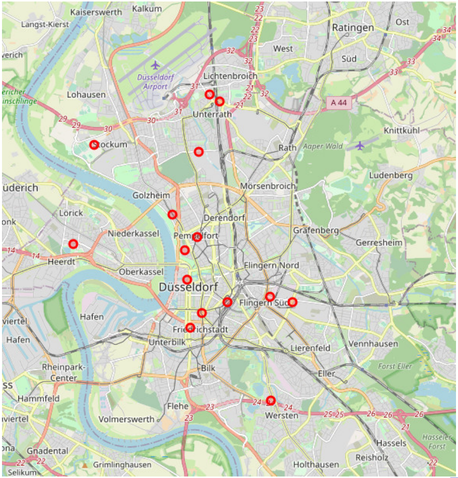
Final List of Charging Stations

	Name	Latitude	Longitude	City District
0	Stromtanke	51.2372	6.72549	NaN
1	Ladestation E-mobil NRW	51.2647	6.73449	NaN
2	Ladesäule Stadwerke Düsseldorf	51.2226	6.81245	NaN
3	Parkhaus Kunsthalle	51.2273	6.77595	NaN
4	Stadtwerke Düsseldorf	51.2766	6.79034	NaN
5	Stadtwerke Düsseldorf	51.218	6.78237	NaN
6	EON	51.2354	6.77466	NaN
7	Mennekes	51.2211	6.82248	NaN
8	DB Energie GmbH	51.2211	6.79354	NaN
9	Stadtwerke Düsseldorf	51.239	6.78032	NaN
10	Parsevalstr	51.2788	6.78575	NaN
11	Stadtwerke Düsseldorf	51.2454	6.76943	NaN
12	Aldi Süd	51.2627	6.78089	NaN
13	Stadtwerke Düsseldorf	51.2139	6.77703	NaN
14	Stadtwerke Düsseldorf	51.1938	6.81292	NaN

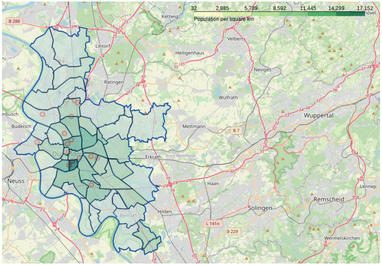
District Borders

- OSM relations for city districts of Düsseldorf obtained via `https://nominatim.openstreetmap.org`
- use of ’JOSM’ editor to obtain bare geometrical polygons as geojson files
- for two districts, a superfluous individual point had to be removed from these files as relations were broken

Exploratory Data Analysis: Current Charging Stations



Population Density by District



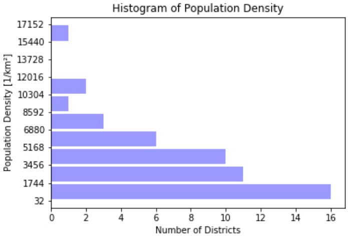


Figure: *Left:* Choropleth map of the different districts of Düsseldorf. Color intensity denotes population density as per the Wikipedia data. Charging stations marked in red.
Right: Histogram of population density in city districts.

Population Density by District - Summary

- 40 / 50 city districts have a population density $< 7000\,\mathrm{km}^{-2}$
- Friedrichstadt district has by far the highest population density: $> 15000\,\mathrm{km}^{-2}$

Assumptions behind Algorithm for Station Placement

- required data: positioning of current stations as well as information on population density distribution
- basic model assumption: Each station has an area of influence from where it pulls customers
- approximate radius of influence as average distance to closest neighboring station
- we want as many customers as possible $\Rightarrow$ maximize the **average available population density** in the area of influence of the new station

Current Stations with Areas of Influence

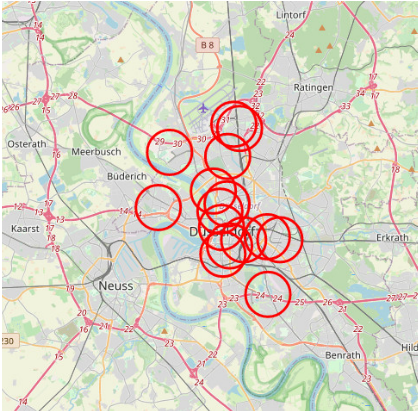


Figure: $r \approx 1.2\,\mathrm{km}$

Ingredients for Algorithm

1. **function** that gives avg. 'available population density' within circle of influence around given point, taking into account influence of existing stations.
2. **grid of points** over entire city for which to apply said function
3. for each district, find the optimal coordinates by **maximizing function ouput**, then find 'best of the best' for city $\Rightarrow$ optimal placement

Output

	City District	Geometry	Type	Population Density [1/km^2]	Polygon	Optimal Coordinates (lon,lat)	Available Population Density [1/km²]
0	Hafen	{'type': 'FeatureCollection', 'generator': 'JO...	<class 'geojson.feature.FeatureCollection'>	32	POLYGON ((6.730208 51.208949, 6.729931 51.2094...	[6.762843, 51.217879727272724]	2983.603604
1	Ludenberg	{'type': 'FeatureCollection', 'generator': 'JO...	<class 'geojson.feature.FeatureCollection'>	1077	POLYGON ((6.879068 51.261155, 6.878906 51.2604...	[6.832740421052632, 51.24189557142857]	4292.504505
2	Carlstadt	{'type': 'FeatureCollection', 'generator': 'JO...	<class 'geojson.feature.FeatureCollection'>	4804	POLYGON ((6.775664 51.225005, 6.775456 51.2249...	[6.76653125, 51.221308]	2725.098198
3	Holthausen	{'type': 'FeatureCollection', 'generator': 'JO...	<class 'geojson.feature.FeatureCollection'>	2276	POLYGON ((6.853443 51.17138, 6.853407 51.17129...	[6.8463386, 51.18835926315789]	4186.639640
4	Itter	{'type': 'FeatureCollection', 'generator': 'JO...	<class 'geojson.feature.FeatureCollection'>	749	POLYGON ((6.826055 51.157212, 6.823194 51.1611...	[6.811434714285714, 51.1737073125]	2074.171429

Figure: The first five rows of the pandas dataframe with the results. The final two columns show optimal coordinates and max 'available population density'. Grid point distance: 200 m.

Available Population Density by District

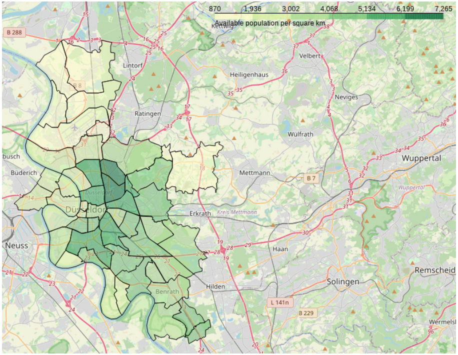


Figure: Color intensity indicates maximum available population density for each city district.

Where to Put the New Station?

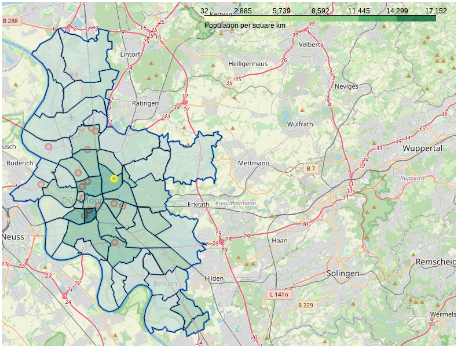


Figure: Optimal position, found at 6.181247° longitude and 51.241458° latitude, marked with a yellow circle. Background map shows population density and previous station placement.

Conclusion

- method was presented to determine optimal placement of a new charging station for electric vehicles in Düsseldorf.
- requires spatially resolved information on population density and previous network of charging stations
- gives a plausible result (no exact verification possible, as we do not know the optimal placement beforehand)
- can easily be adapted to different cities