Digital Economy and Decision Analytics - Blockchain and Cryptocurrency Seminar (WS 21/22)

C.A.S.E.
CENTER FOR APPLIED STATISTICS AND ECONOMICS

Spatial Analysis of Berlin Rent Prices and Landlord Premiums

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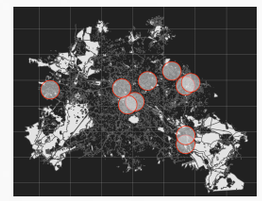
HUMBOLDT-UNIVERSITÄT ZU BERLIN

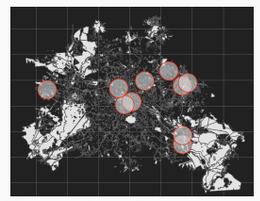
Outline

1. Motivation
2. Developing the spatial framework
3. Modeling the rent prices
4. Geocoding
5. Distance measurement and normalization
6. Evaluating landlord premiums



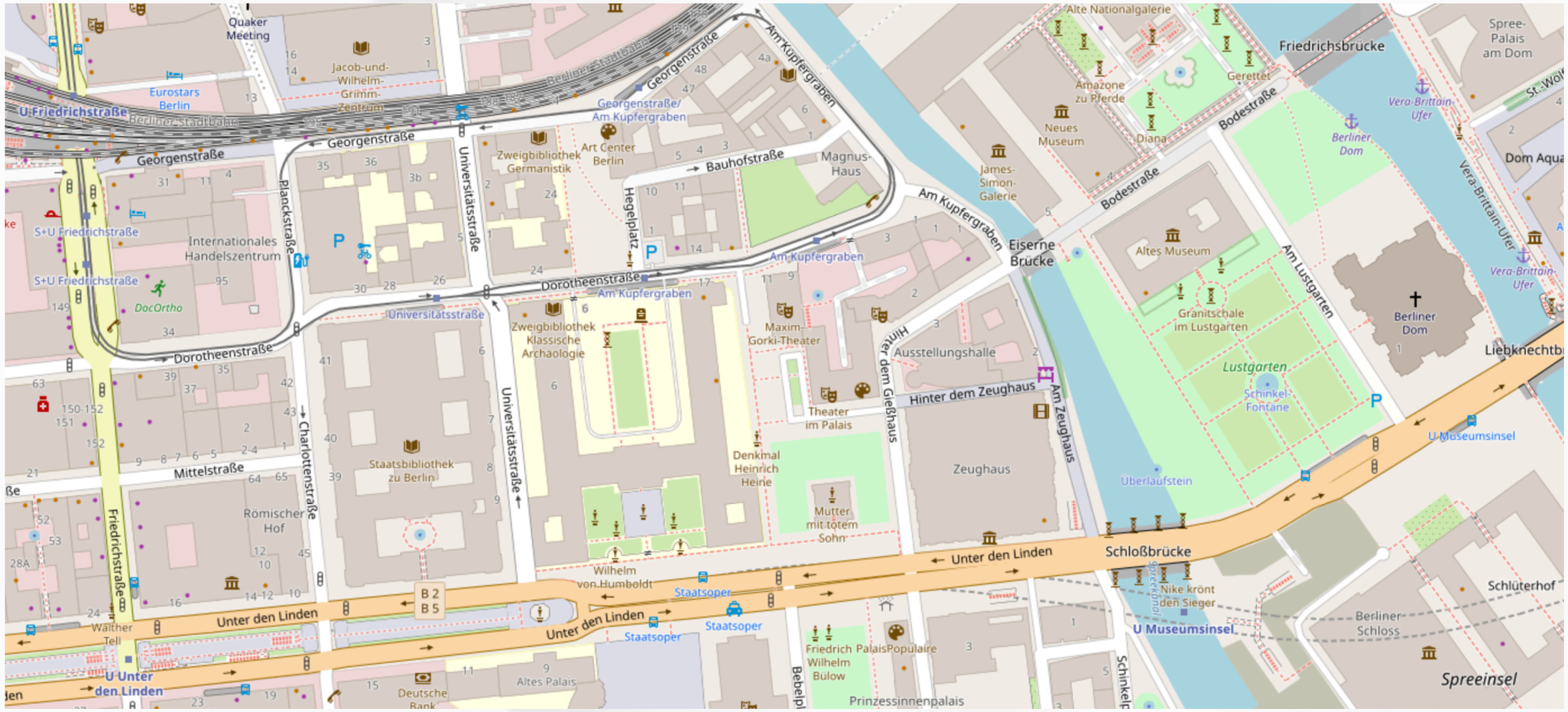
Motivation

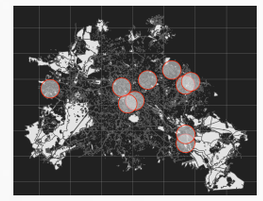
- Rent prices differ a lot between the same type of apartments
- Rent prices differ a lot between neighbourhoods
- Usually people “feel” these prices out of their own experiences
- Always a long term investment
- No easy way to create a benchmark



Part 1: developing the spatial framework

Cartographical data is taken from **OpenStreetMap**, which is is a collaborative project to create a free editable geographic database of the world.



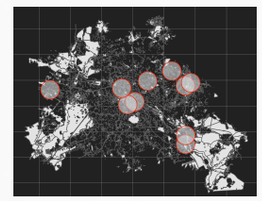


What does the data look like?

```
a_ber_poi_multipolygon = Table: 18,246 x 5 ... View Table
a_ber_poi_polygon = Table: 75,859 x 5 ... View Table
b_ber_landuse_multipolygon = Table: 33,291 x 5 ... View Table
c_ber_transport_polygon = Table: 36 x 5 ... View Table
d_ber_water_multipolygons = Table: 1,910 x 5 ... View Table
e_ber_map = Table: 109 x 6 ... View Table
```

```
> a_ber_poi_polygon
Simple feature collection with 75859 features and 4 fields
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 13.08407 ymin: 52.33794 xmax: 13.76027 ymax: 52.6727
Geodetic CRS:  WGS 84
# A tibble: 75,859 × 5
   osm_id    code fclass             name                  geometry
   <chr>    <int> <chr>              <chr>              <POINT [°]>
 1 16541597  2907 camera_surveillance Aral          (13.34544 52.54644)
 2 26735749  2301 restaurant         Aida           (13.32282 52.50691)
 3 26735753  2006 telephone          NA             (13.32214 52.50645)
 4 26735759  2301 restaurant         Madame Ngo     (13.31808 52.50621)
 5 26735763  2301 restaurant         Thanh Long     (13.32078 52.50732)
 6 26754448  2701 tourist_info       NA             (13.37075 52.52329)
 7 26865440  2307 biergarten         Spinnerbrücke  (13.19073 52.43336)
 8 26867409  2031 recycling_glass    NA             (13.29683 52.50133)
 9 26972366  2724 memorial           Konrad Zuse    (13.34722 52.52277)
10 27318009  2307 biergarten         Loretta        (13.17635 52.42009)
# … with 75,849 more rows
```

```
> b_ber_landuse_multipolygon
Simple feature collection with 33291 features and 4 fields
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: 13.05376 ymin: 52.32824 xmax: 13.76513 ymax: 52.68608
Geodetic CRS:  WGS 84
# A tibble: 33,291 × 5
   osm_id   code fclass     name                                    geometry
   <chr>   <int> <chr>      <chr>                            <MULTIPOLYGON [°]>
 1 4401982  7206 cemetery   Friedhof Wilmers… (((13.30865 52.48411, 13.30885 52.48…
 2 4413796  7202 park       Preußenpark       (((13.31033 52.49362, 13.31039 52.49…
 3 4440110  7202 park       NA                (((13.39298 52.39897, 13.39326 52.39…
 4 4535352  7206 cemetery   Städtischer Frie… (((13.32128 52.47605, 13.32128 52.47…
 5 4537560  7201 forest     NA                (((13.2787 52.5447, 13.28131 52.5447…
 6 4582178  7207 allotments Kleingartenkolon… (((13.30467 52.48664, 13.30539 52.48…
 7 4582243  7202 park       Volkspark Wilmer… (((13.30852 52.48381, 13.30862 52.48…
 8 4582244  7202 park       Volkspark Wilmer… (((13.31376 52.48316, 13.31378 52.48…
 9 4585104  7218 grass      NA                (((13.36668 52.47268, 13.3667 52.472…
10 1657757  7202 park       Fritz-Schloß-Park (((13.35311 52.53125, 13.35319 52.53…
# … with 33,281 more rows
```



Cleaning the data:

Next step is to clean the data and leave out the things that are not related to factors that could have an impact on rent prices. That is excluding such factors as police stations and hydrants.

OpenStreetMap Data in Layered GIS Format

Free shapefiles – 2021-07-08

Frederik Ramm <frederik.ramm@geofabrik.de>

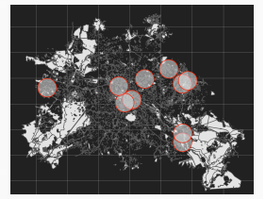
Table of Contents

4.2 Points of Interest

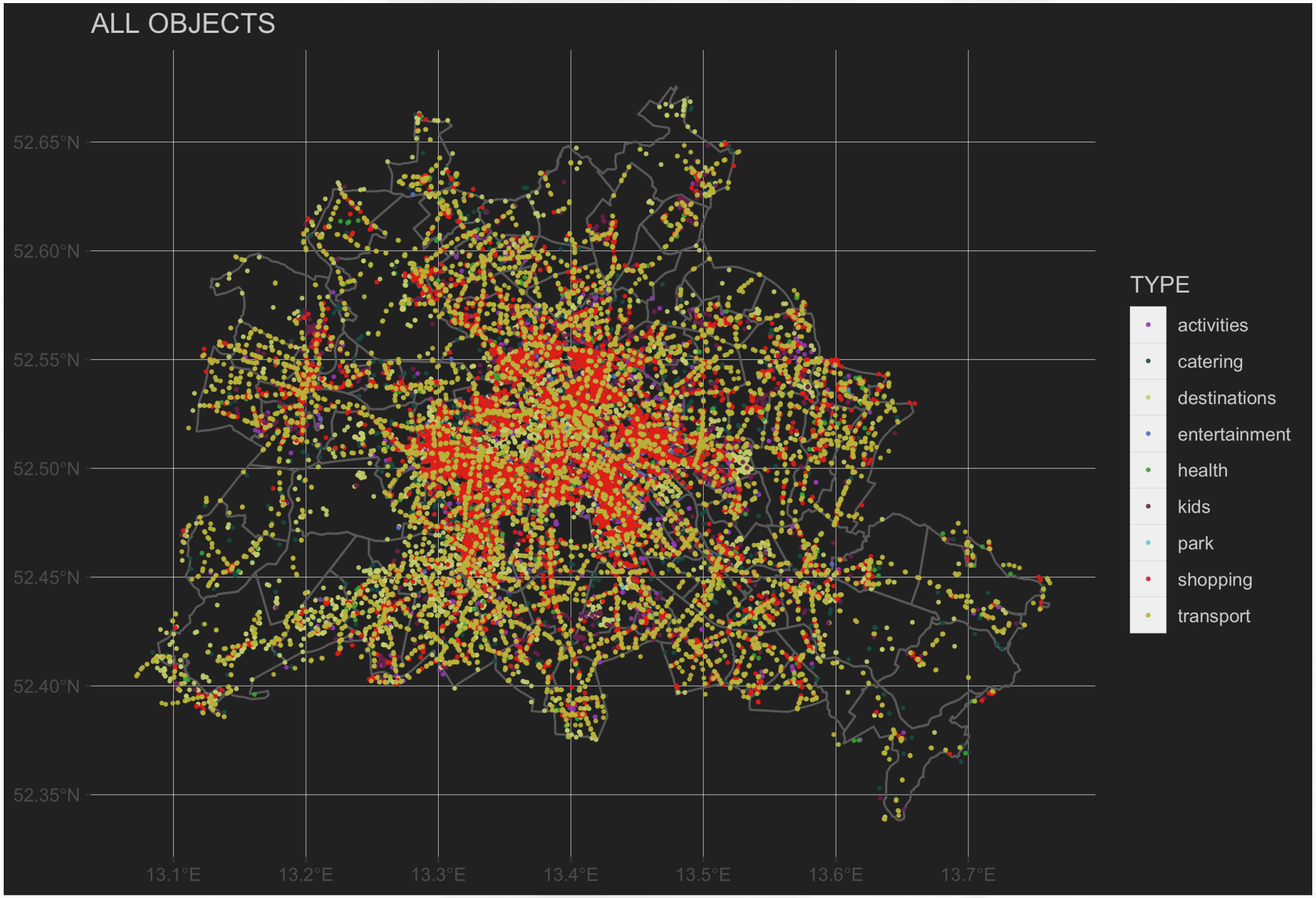
This layer has an associated area layer (see section 2.8).

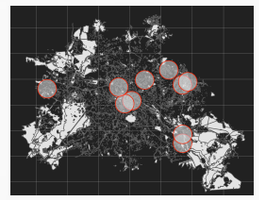
The following feature classes exist in this layer:

code	layer	fclass	Description	OSM Tags
20xx	**public**			
2001		police	A police post or station.	amenity=police
2002		fire_station	A fire station.	amenity=fire_station
2004		post_box	A post box (for letters).	amenity=post_box
2005		post_office	A post office.	amenity=post_office
2006		telephone	A public telephone booth.	amenity=telephone
2007		library	A library.	amenity=library
2008		town_hall	A town hall.	amenity=townhall
2009		courthouse	A court house.	amenity=courthouse
2010		prison	A prison.	amenity=prison
2011		embassy	An embassy or consulate.	amenity=embassy or office=diplomatic

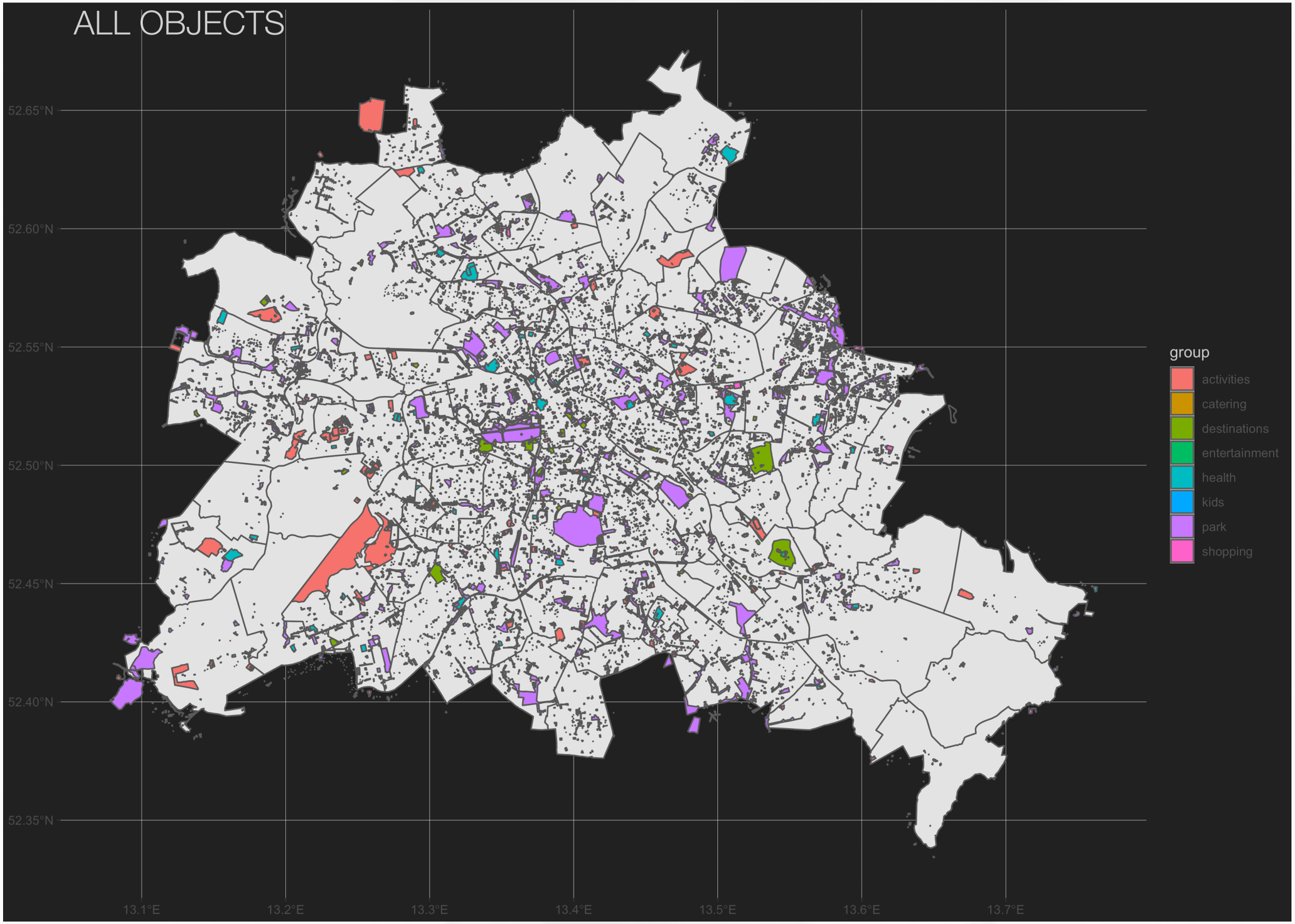


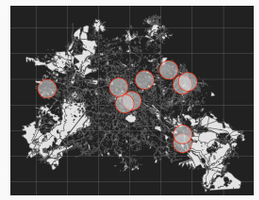
How the data looks like (polygons)



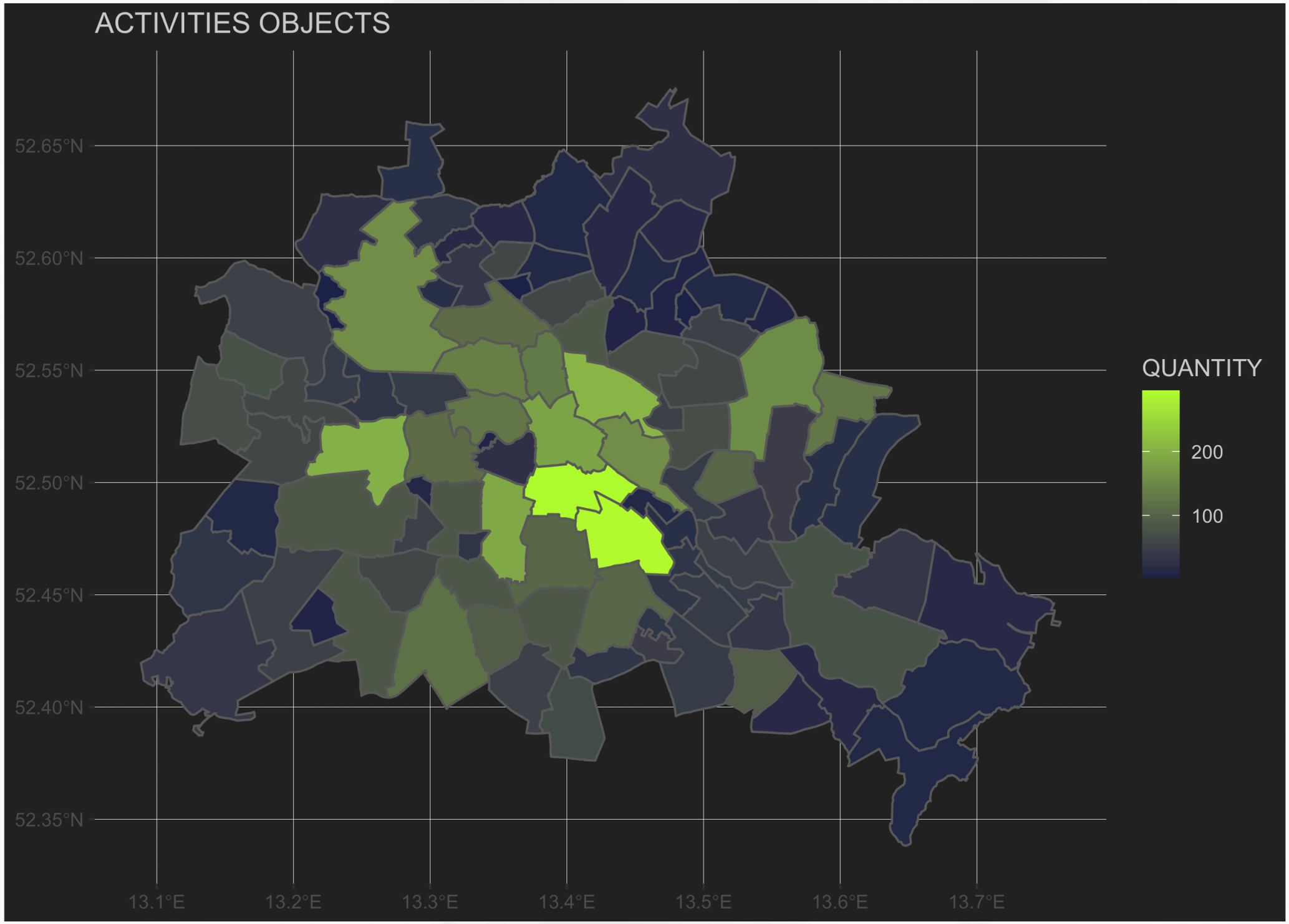


How the data looks like (multipolygons)





More maps: gyms, sports objects, etc.



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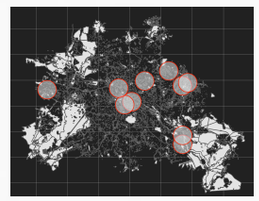
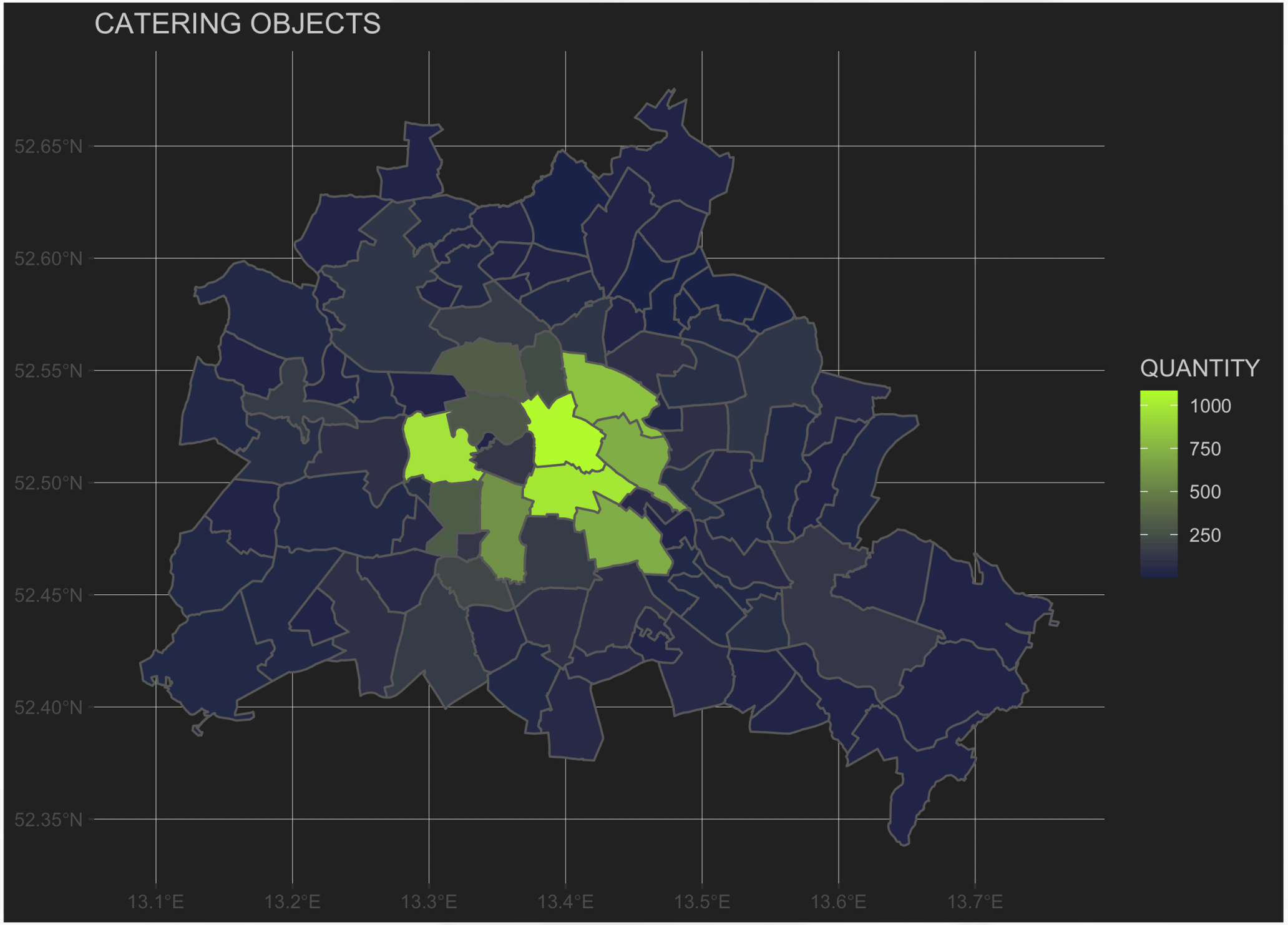


More maps: restaurants, bars, etc.



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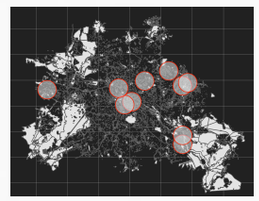
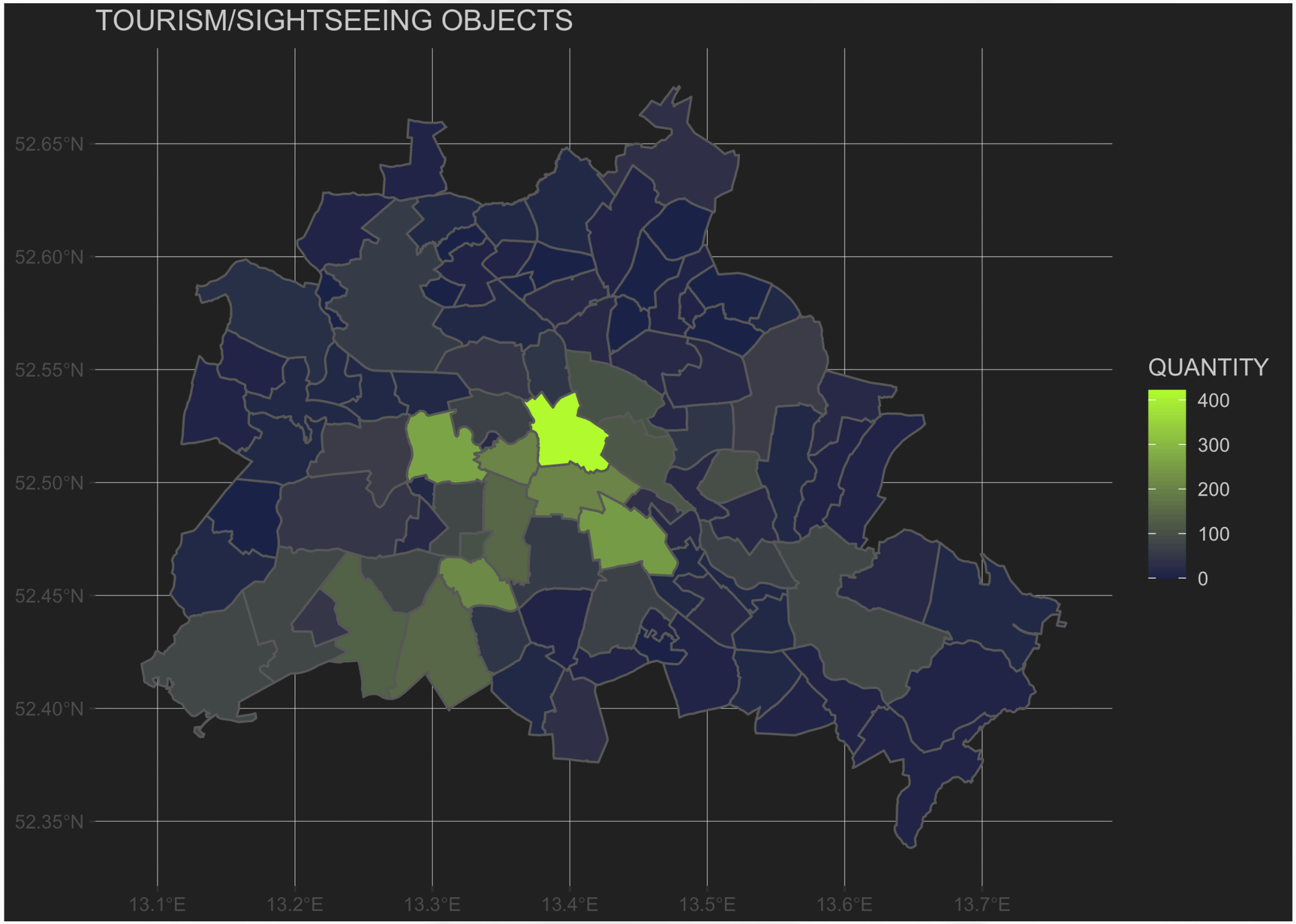


More maps: sightseeing, museums, etc.



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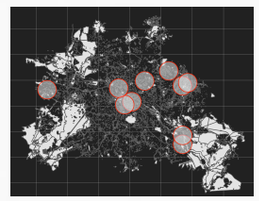
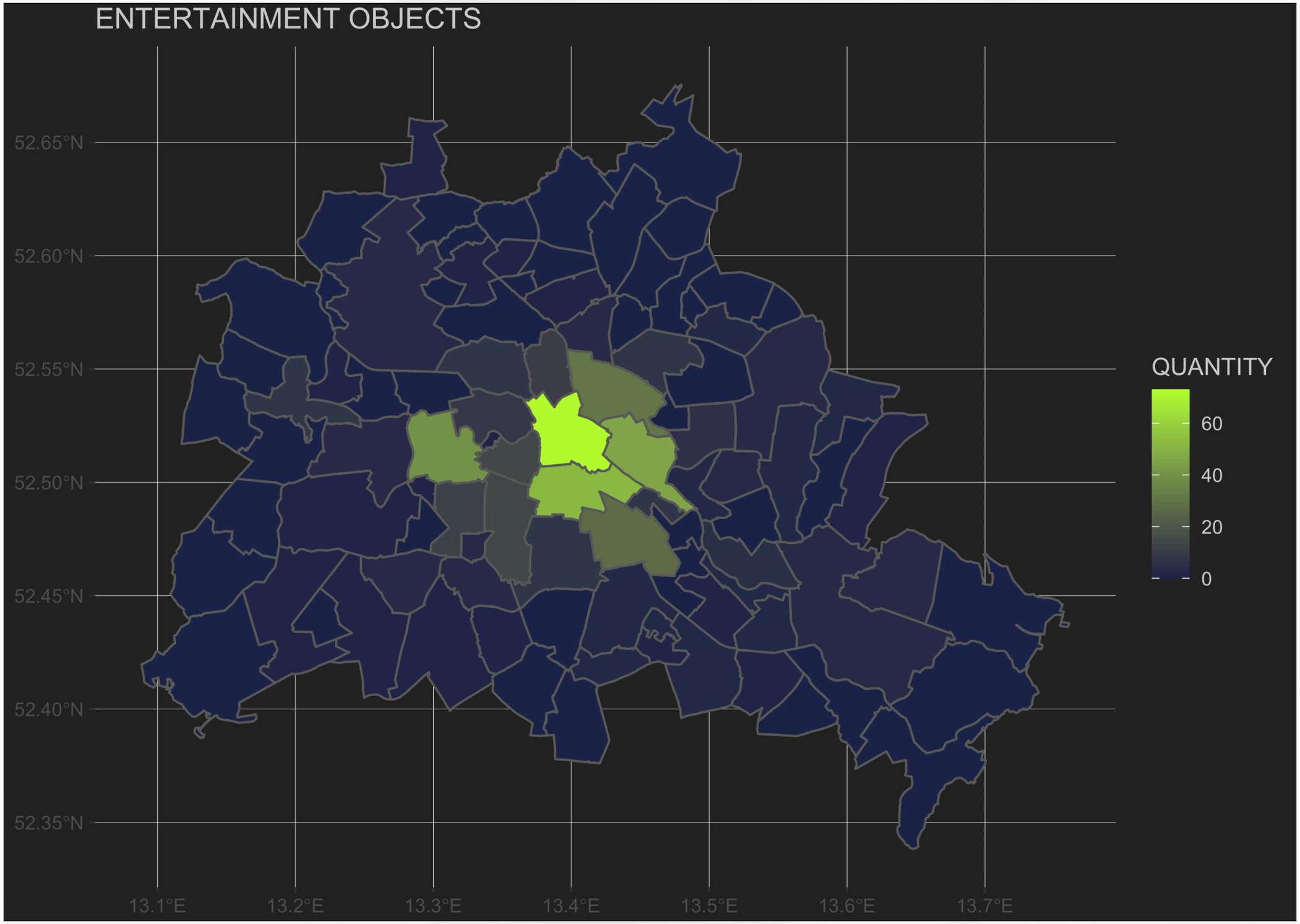


More maps: cinemas, night clubs, etc.



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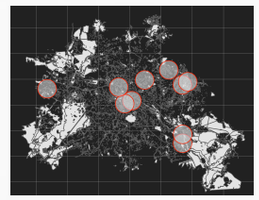
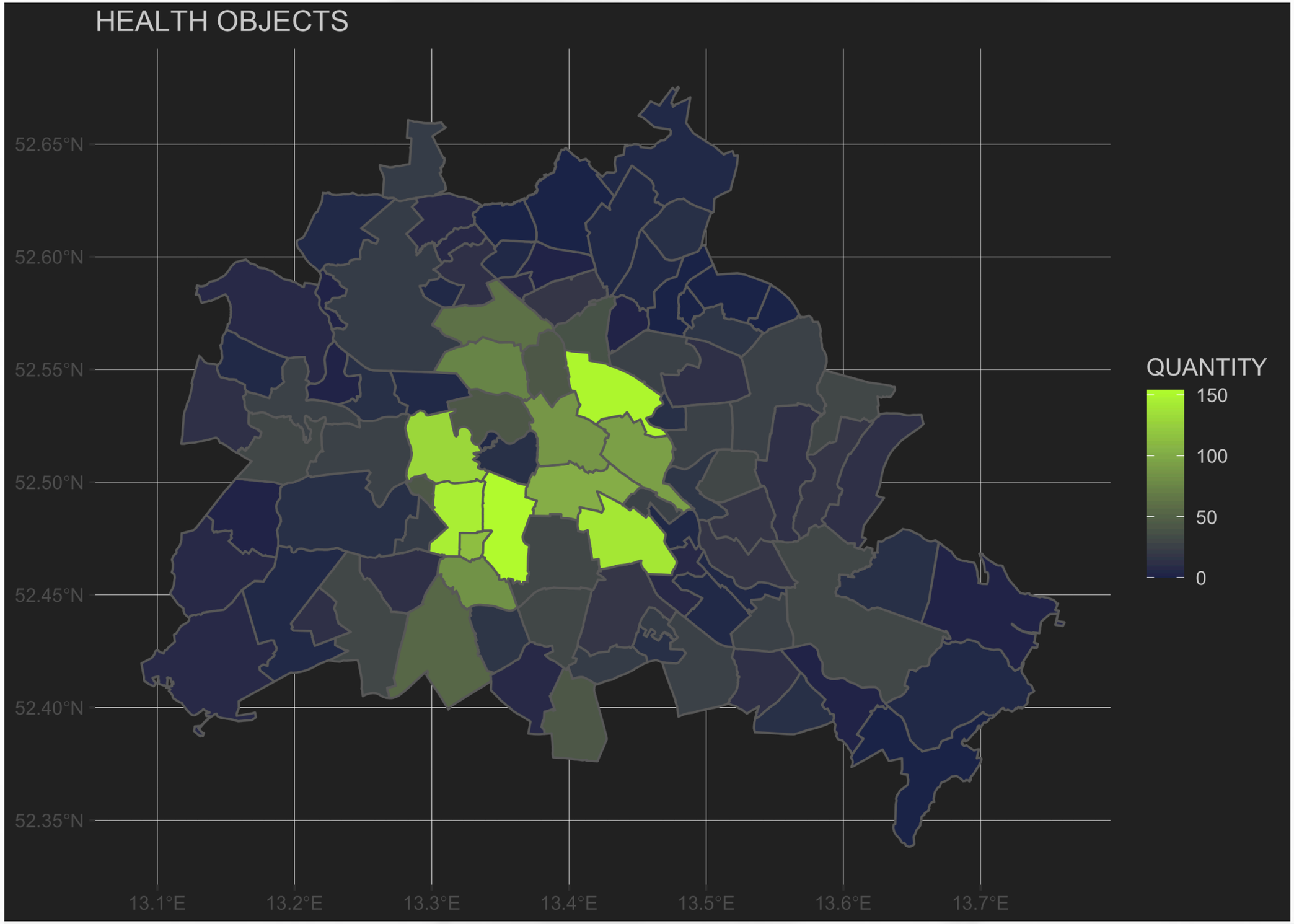


More maps: doctors, pharmacies, etc.



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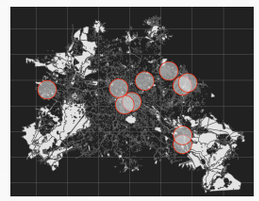
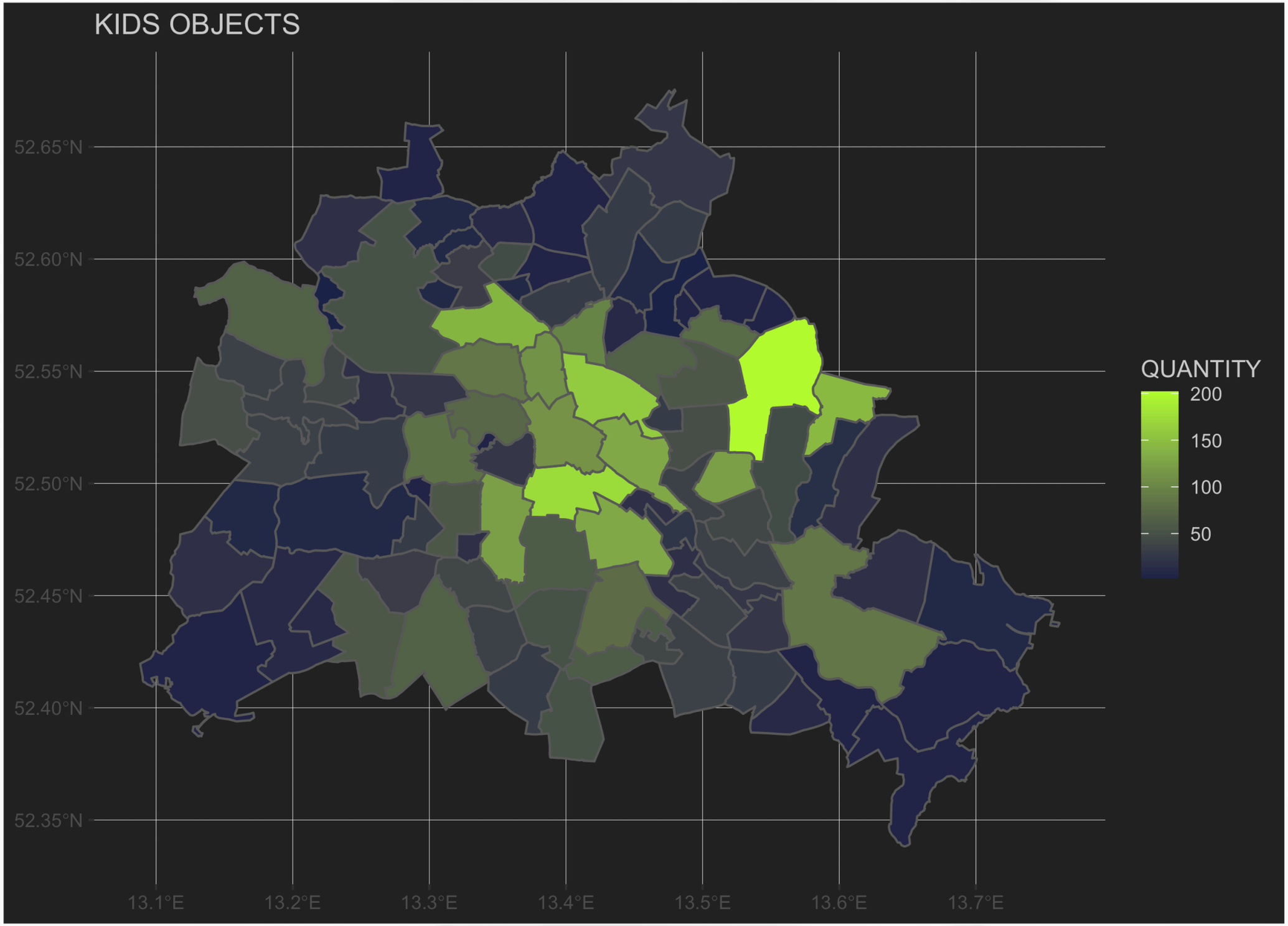


More maps: kitas, playgrounds, etc.



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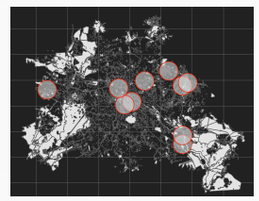
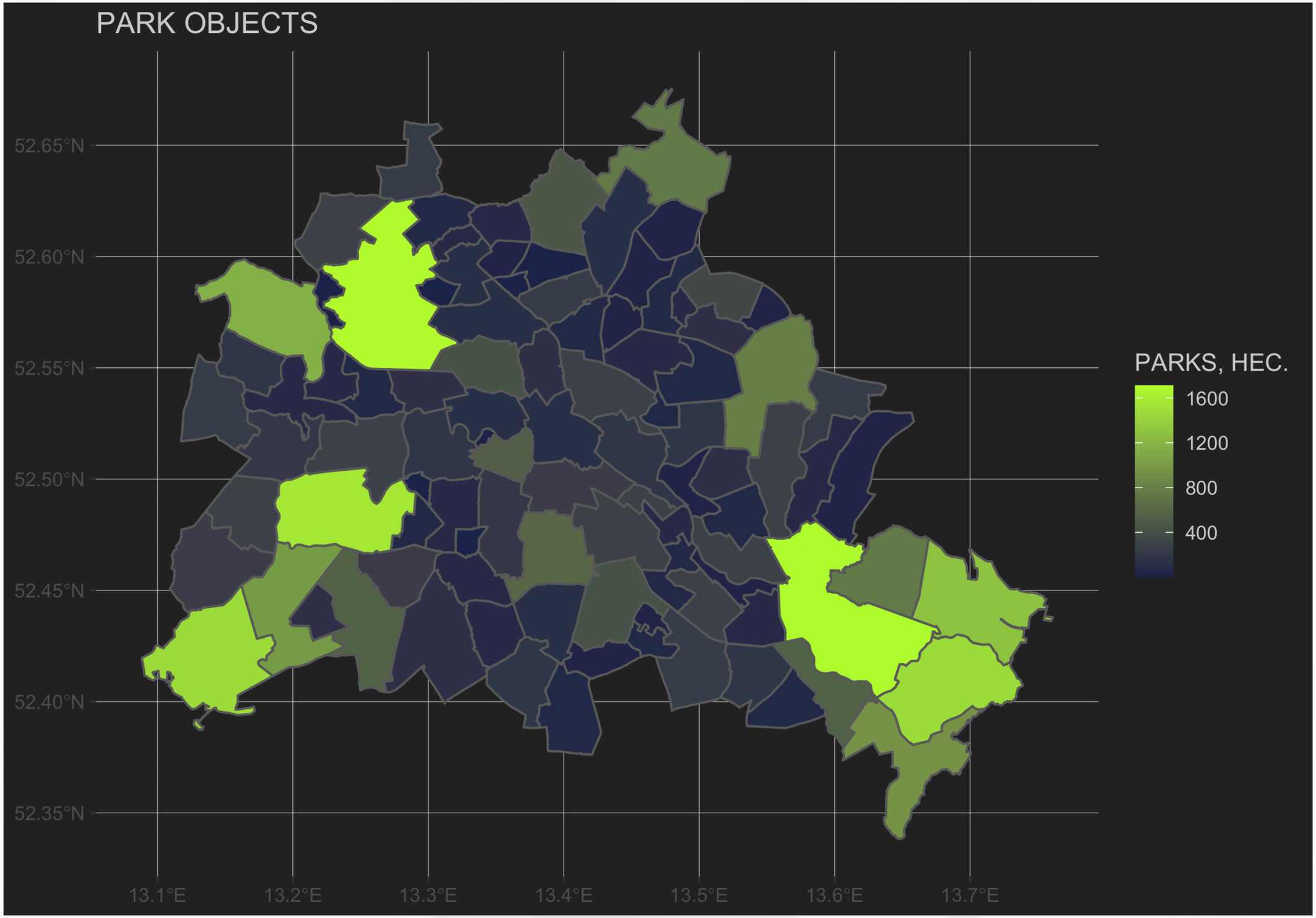


More maps: parks, dog parks, etc.



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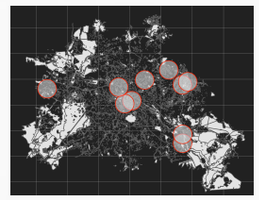
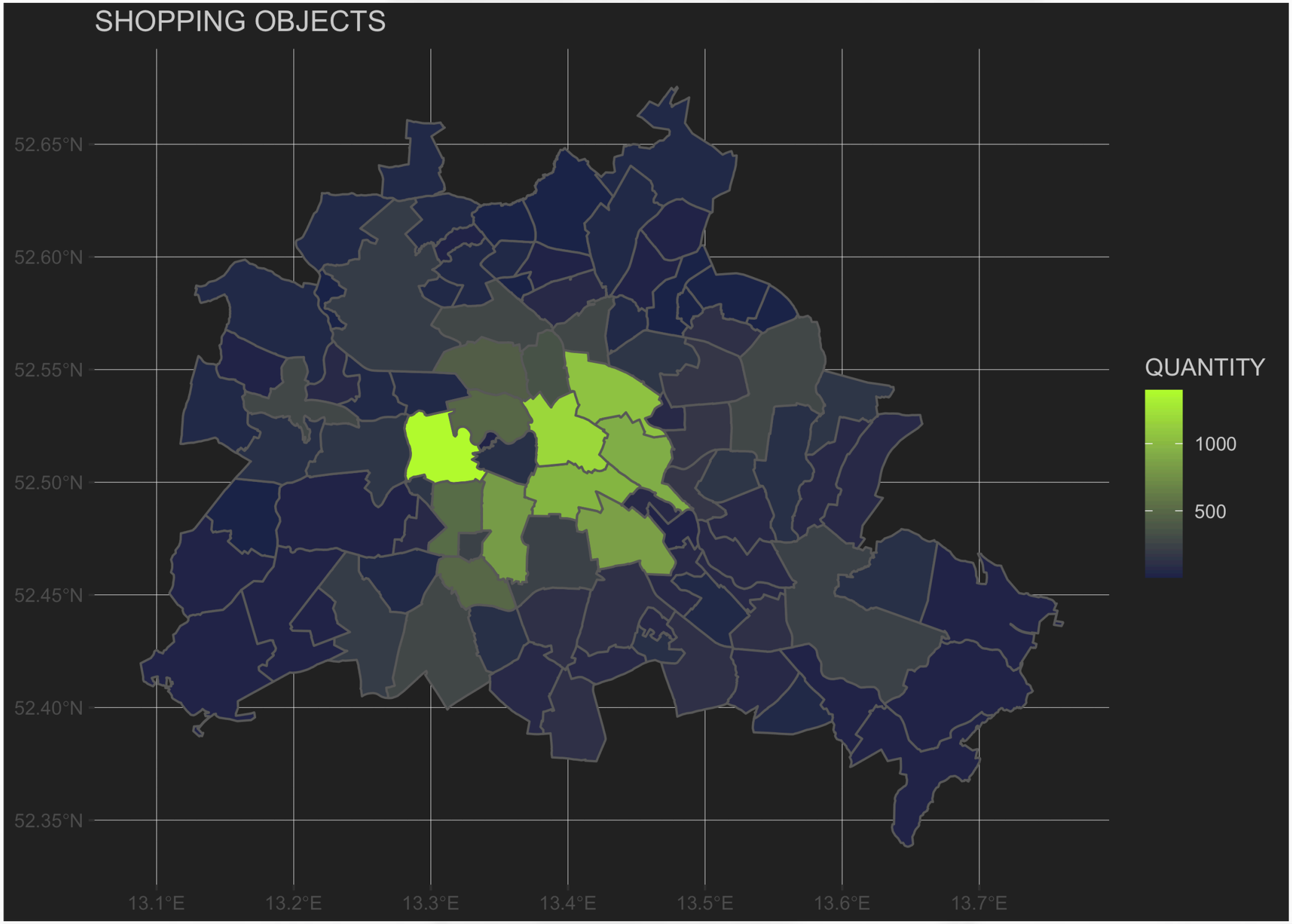


More maps: shops, grocery stores, etc.



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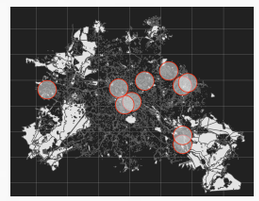
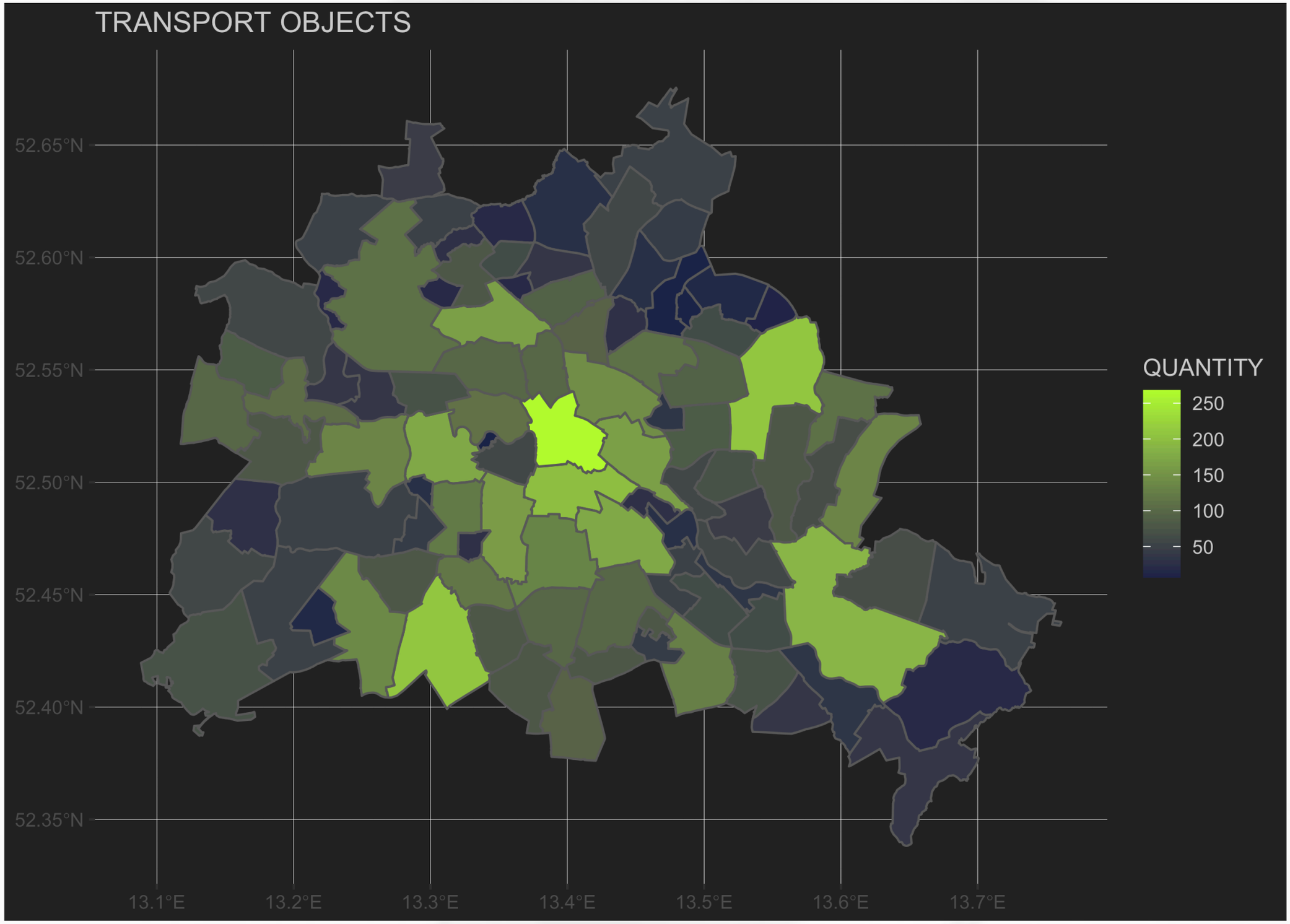


More maps: S-Bahn, U-Bahn, etc.



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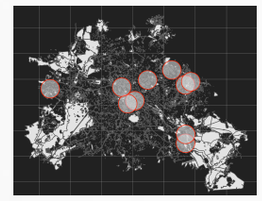
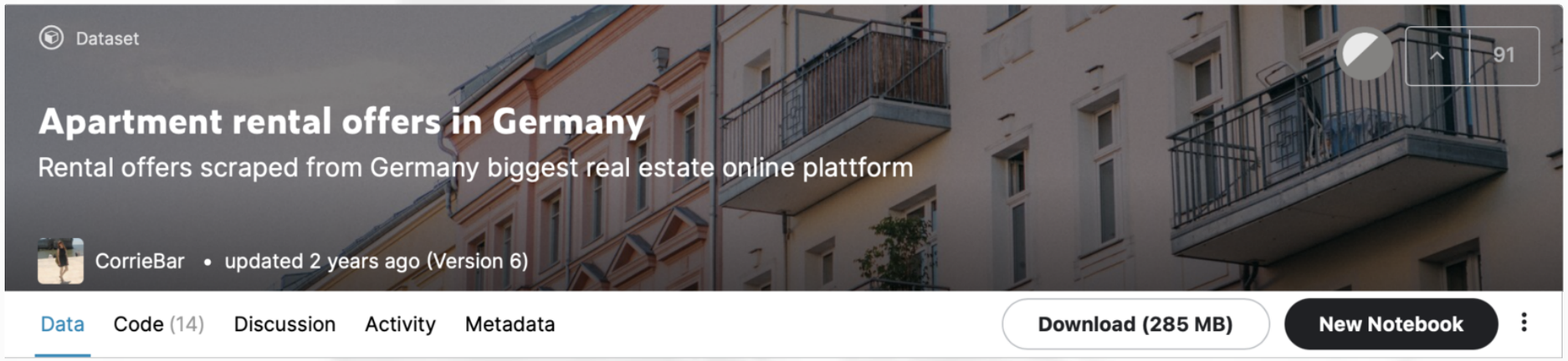
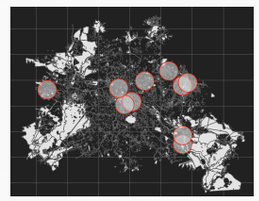


Modeling the rent prices

Data taken from Kaggle, dataset scraped from Immobilienscout24:



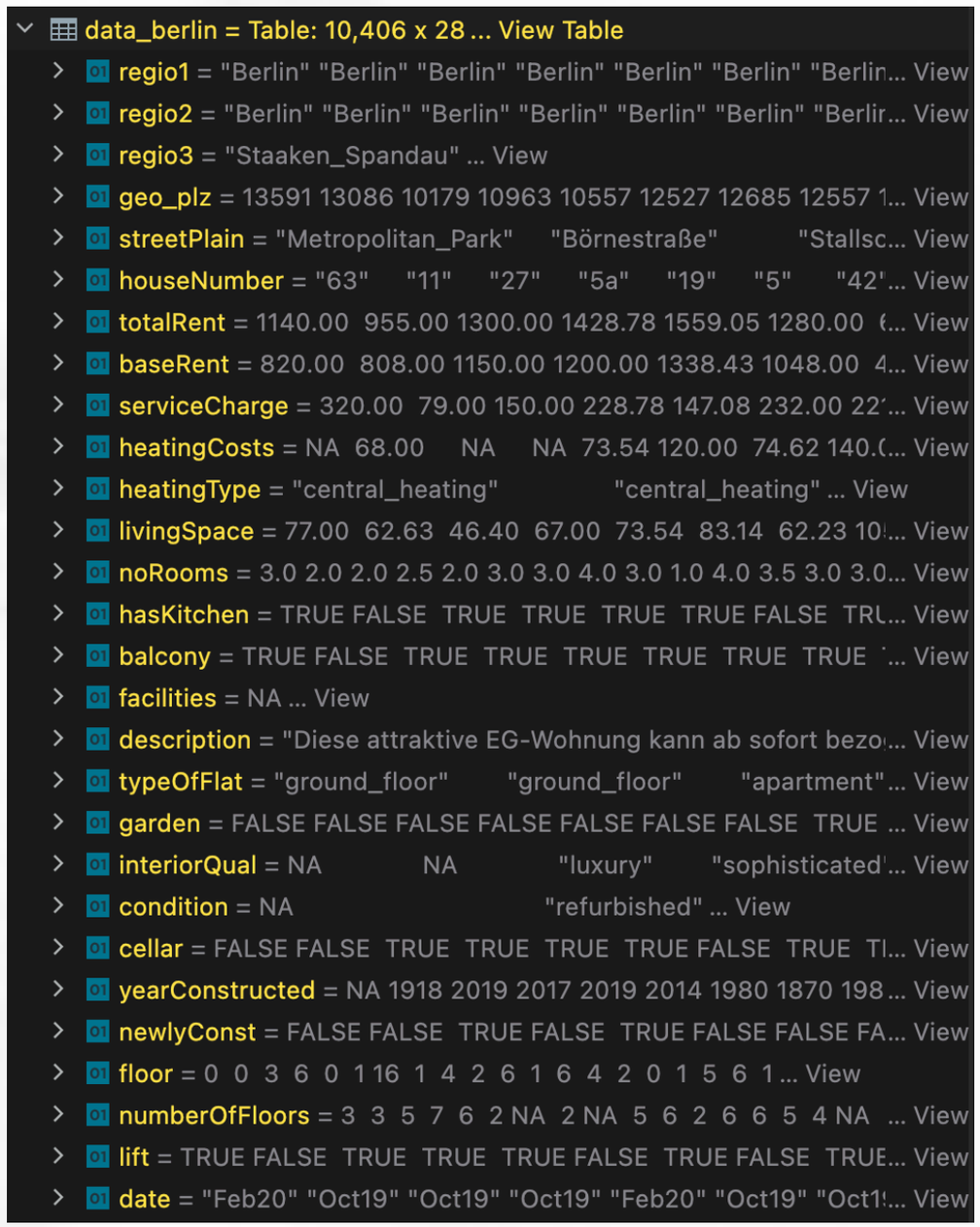
https://www.kaggle.com/corrieaar/apartment-rental-offers-in-germany/version/6



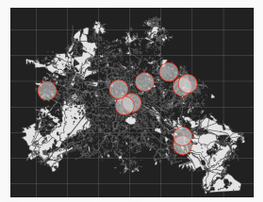
The data and data clearing

Extract Berlin from all the areas in Germany, filter the other columns

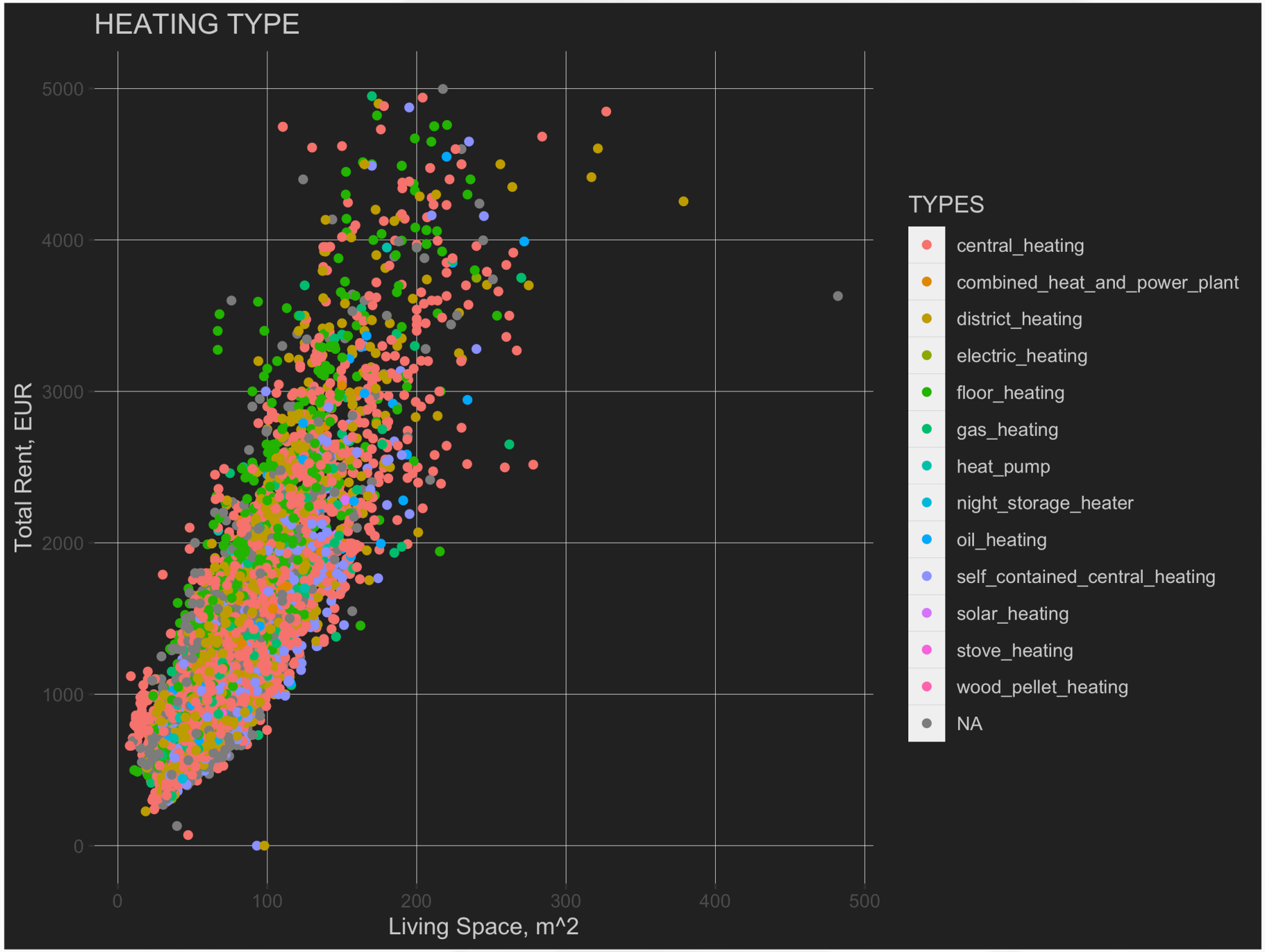
Baden_Württemberg	Bayern	Berlin
16091	21609	10406
Brandenburg	Bremen	Hamburg
6954	2965	3759
Hessen	Mecklenburg_Vorpommern	Niedersachsen
17845	6634	16593
Nordrhein_Westfalen	Rheinland_Pfalz	Saarland
62863	8368	1429
Sachsen	Sachsen_Anhalt	Schleswig_Holstein
58154	20124	6668
Thüringen		
8388		

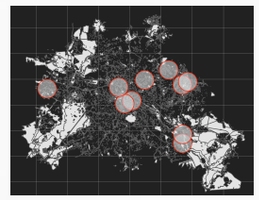


...and more cleaning



EDA example


HEATING TYPE
Total Rent, EUR
Living Space, m^2
0
1000
2000
3000
4000
5000
0
100
200
300
400
500
TYPES
central_heating
combined_heat_and_power_plant
district_heating
electric_heating
floor_heating
gas_heating
heat_pump
night_storage_heater
oil_heating
self_contained_central_heating
solar_heating
stove_heating
wood_pellet_heating
NA



The first model:

```
Call:
lm(formula = price ~ ., data = data_berlin_model_alltime)

Residuals:
    Min      1Q  Median      3Q     Max
-3046.9  -190.8   -14.3   160.9  7377.8

Coefficients:
                                          Estimate Std. Error t value             Pr(>|t|)
(Intercept)                               747.4011   365.1490   2.047             0.040745 *
heatingTypecombined_heat_and_power_plant   -4.3181    50.7278  -0.085             0.932168
heatingTypedistrict_heating                61.0344    19.2824   3.165             0.001562 **
heatingTypeelectric_heating              -154.7923   152.0269  -1.018             0.308654
heatingTypefloor_heating                   95.7866    21.9377   4.366       0.000012984780 ***
heatingTypegas_heating                    -22.6382    34.1480  -0.663             0.507407
heatingTypeheat_pump                      -34.9088    91.9724  -0.380             0.704296
heatingTypenight_storage_heater          -158.6878    92.0323  -1.724             0.084745 .
heatingTypeoil_heating                    -18.1057    47.6448  -0.380             0.703957
heatingTypeself_contained_central_heating -77.9583    24.6960  -3.157             0.001608 **
heatingTypesolar_heating                 -192.3944   201.8725  -0.953             0.340628
heatingTypestove_heating                   50.1163   302.2937   0.166             0.868334
heatingTypewood_pellet_heating            -59.3090   284.2205  -0.209             0.834716
livingSpace                                20.2205     0.3171  63.763 < 0.0000000000000002 ***
noRooms                                  -118.1389    11.3543 -10.405 < 0.0000000000000002 ***
hasKitchenTRUE                            135.7235    15.6967   8.647 < 0.0000000000000002 ***
extrawcTRUE                               -33.3685    21.1164  -1.580             0.114143
balconyTRUE                               -37.4643    18.3682  -2.040             0.041459 *
geschirrspTRUE                             -4.5796    49.8428  -0.092             0.926798
washingmTRUE                               57.7797    16.6531   3.470             0.000527 ***
typeOfFlatground_floor                     10.7332    25.7367   0.417             0.676675
typeOfFlathalf_basement                  -166.8751   201.2550  -0.829             0.407061
typeOfFlatloft                            166.2761    69.5983   2.389             0.016940 *
typeOfFlatmaisonette                     -126.3728    37.3286  -3.385             0.000718 ***
typeOfFlatother                          -111.4576    57.3925  -1.942             0.052210 .
typeOfFlatpenthouse                        84.4989    42.7761   1.975             0.048300 *
typeOfFlatraised_ground_floor             -24.3540    45.8593  -0.531             0.595409
typeOfFlatroof_storey                     -45.6478    23.8133  -1.917             0.055328 .
typeOfFlatterraced_flat                    14.8045    48.7432   0.304             0.761354
gardenTRUE                                -24.5034    17.8980  -1.369             0.171063
interiorQualnormal                       -504.8291    27.2210 -18.546 < 0.0000000000000002 ***
interiorQualsimple                       -485.9461   103.4259  -4.698       0.000002716618 ***
interiorQualsophisticated                -420.6247    20.6580 -20.361 < 0.0000000000000002 ***
conditionfirst_time_use_after_refurbishment  -48.7411    32.4277  -1.503             0.132906
conditionfully_renovated                 -216.7090    35.8141  -6.051       0.000000001584 ***
conditionmint_condition                   -62.0443    29.8743  -2.077             0.037885 *
conditionmodernized                      -195.8406    38.2705  -5.117       0.000000325828 ***
conditionneed_of_renovation              -170.3806    95.6920  -1.781             0.075075 .
conditionnegotiable                      -211.5881    90.8647  -2.329             0.019934 *
conditionrefurbished                     -104.2009    35.4655  -2.938             0.003323 **
conditionwell_kept                       -206.3251    33.0845  -6.236       0.000000000499 ***
cellarTRUE                                 -4.8510    14.7192  -0.330             0.741744
yearConstructed                            -0.2045     0.1868  -1.095             0.273721
newlyConstTRUE                             13.8662    29.6351   0.468             0.639886
floor                                      14.2858     4.8651   2.936             0.003341 **
numberOfFloors                              9.6770     4.4361   2.181             0.029217 *
liftTRUE                                  111.4863    18.8175   5.925       0.000000003418 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 399.9 on 3682 degrees of freedom
  (5433 observations deleted due to missingness)
Multiple R-squared:  0.8253,    Adjusted R-squared:  0.8231
F-statistic: 378.1 on 46 and 3682 DF,  p-value: < 0.00000000000000022
```

Heating types

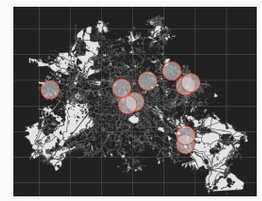
Apartment items

Type of apartment

Interior quality

Apartment conditions

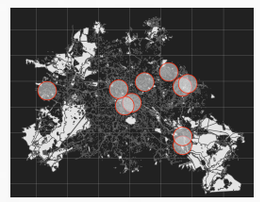
House parameters



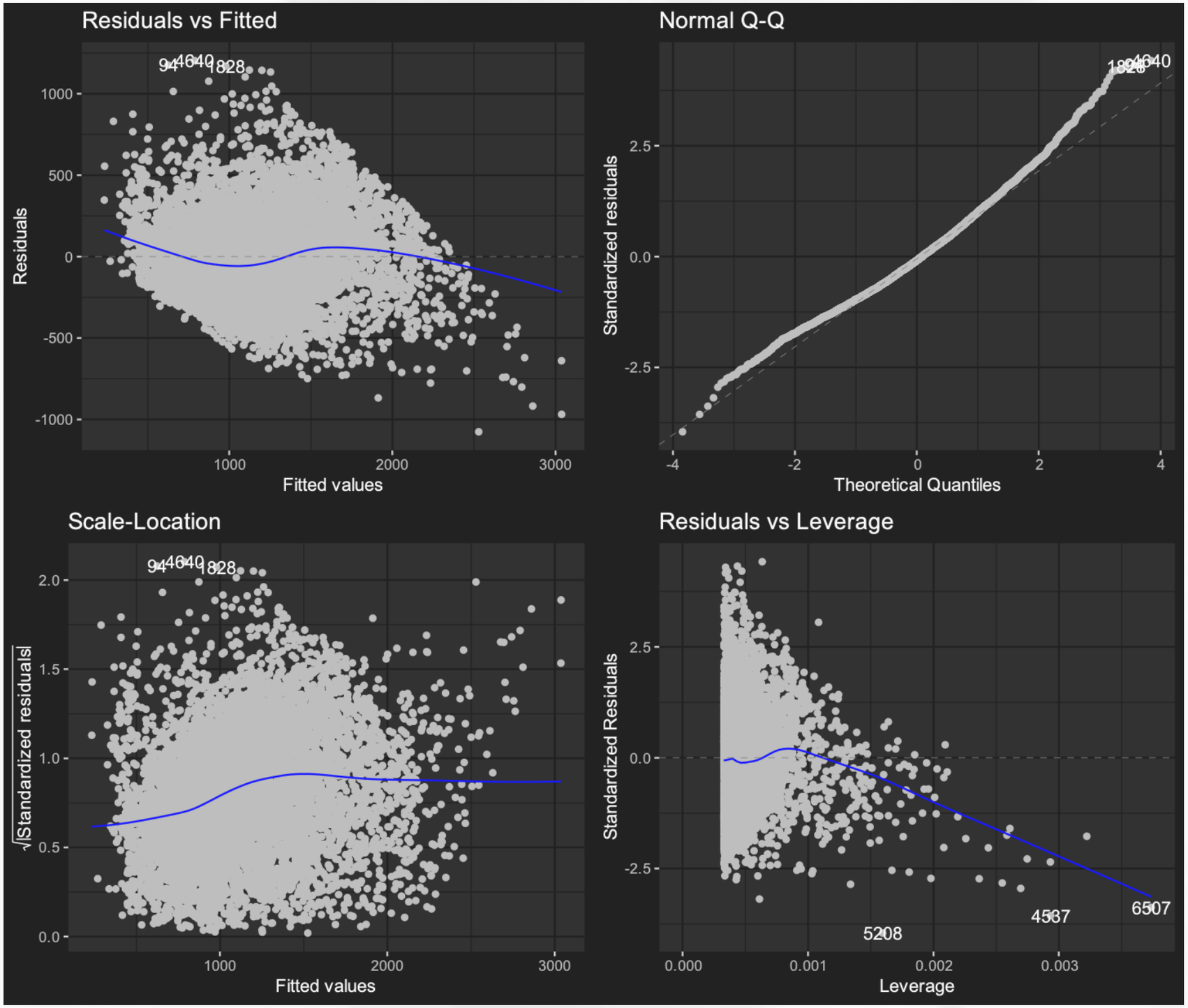
The general model:

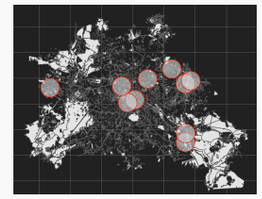
After multiple backward selection iterations and making a 90% percentile cutoff for the rent price at 2400 EUR:

```
Call:
lm(formula = price ~ livingSpace + hasKitchen + lift, data = data_berlin_model_filter)

Residuals:
     Min       1Q   Median       3Q      Max
-1075.76  -195.87   -23.61   168.52  1202.85

Coefficients:
              Estimate Std. Error t value             Pr(>|t|)
(Intercept)     24.446      9.138   2.675              0.00749 **
livingSpace     13.160      0.109 120.754 < 0.0000000000000002 ***
hasKitchenTRUE 217.212      6.119  35.498 < 0.0000000000000002 ***
liftTRUE       150.700      6.094  24.730 < 0.0000000000000002 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 272.2 on 8238 degrees of freedom
Multiple R-squared:  0.6792,    Adjusted R-squared:  0.6791
F-statistic:  5813 on 3 and 8238 DF,  p-value: < 0.00000000000000022
```



Diagnostic plots:





Geocoding

Apartments are geographically represented with a physical address. In order to work with that data spatially what we would need is to geocode those addresses to latitudes and longitudes. How?

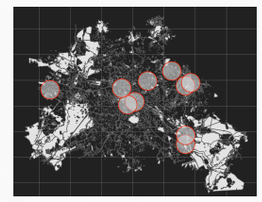
Via OpenStreenMap API Nominatim:

Nominatim API

Nominatim indexes named (or numbered) features within the OpenStreetMap (OSM) dataset and a subset of other unnamed features (pubs, hotels, churches, etc).

Its API has the following endpoints for querying the data:

- **/search** - search OSM objects by name or type
- **/reverse** - search OSM object by their location
- **/lookup** - look up address details for OSM objects by their ID
- **/status** - query the status of the server
- **/deletable** - list objects that have been deleted in OSM but are held back in Nominatim in case the deletion was accidental
- **/polygons** - list of broken polygons detected by Nominatim
- **/details** - show internal details for an object (for debugging only)



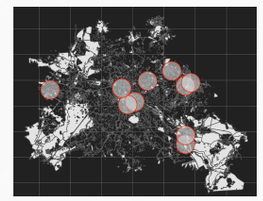
Distance measurement, scoring and normalization

The distance measurement chosen for this project is the Euclidian distance. The following formula was used to calculate the scores:

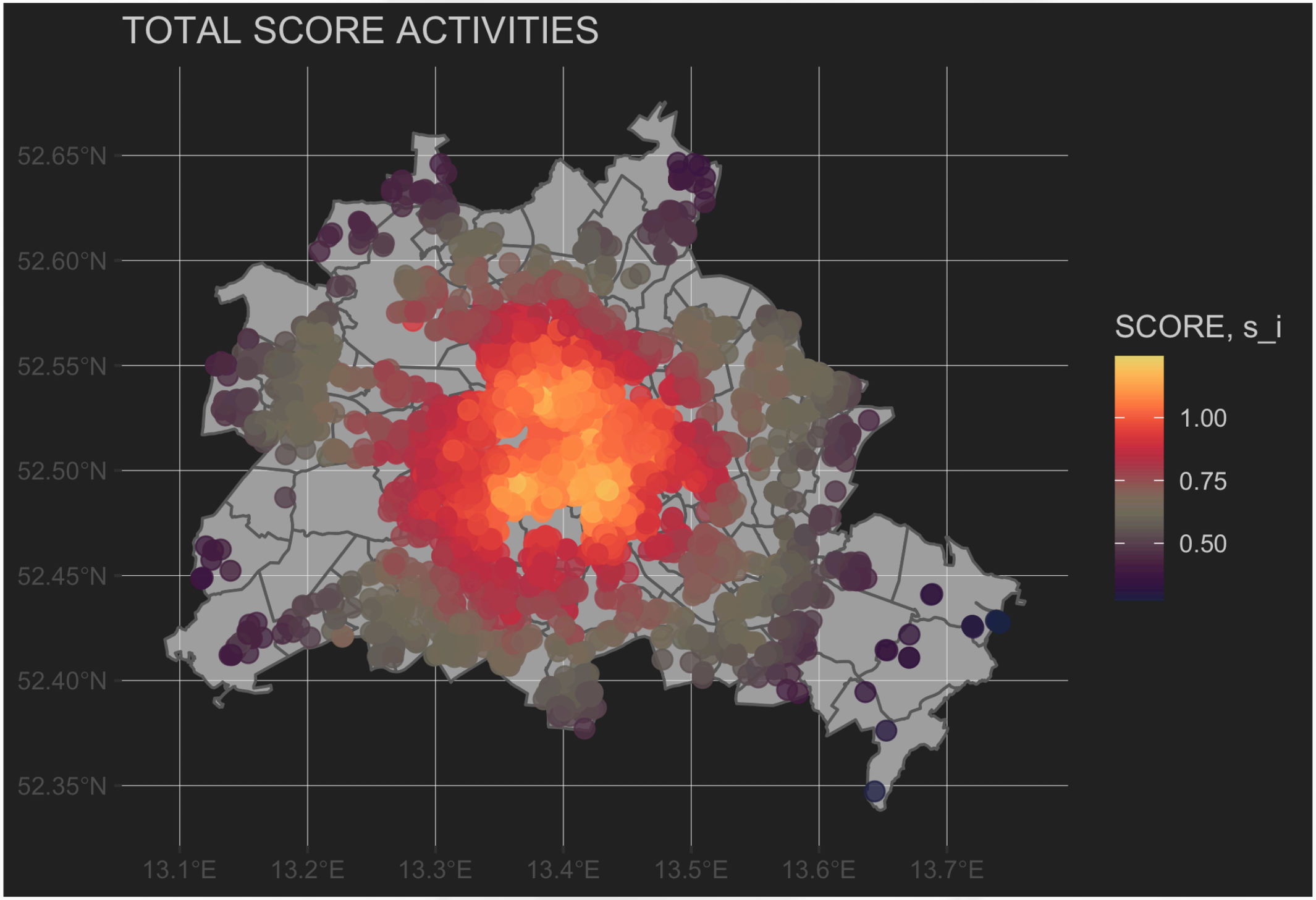
$$s_{i,k}^{dist} = \sum_{j=1}^{n} \left(\sqrt{\left(x_{A_i} - x_{O_{j,k}}\right)^2 + \left(y_{A_i} - y_{O_{j,k}}\right)^2} + 10 \right)^{-1}$$

Where x_{A_i}, y_{A_i} are the geographical coordinates of the apartment and x_{O_j}, y_{O_j} represent the infrastructure object coordinates.
i — apartment subscript, j — infrastructure object subscript,
k — category of infrastructural object subscript

Here 10 units (meters) are added to the distance in order to set the maximum score achievable for the measurement.



More maps: gyms, sports objects, etc.



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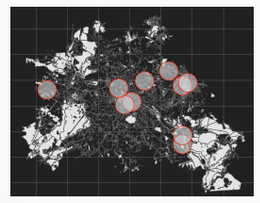
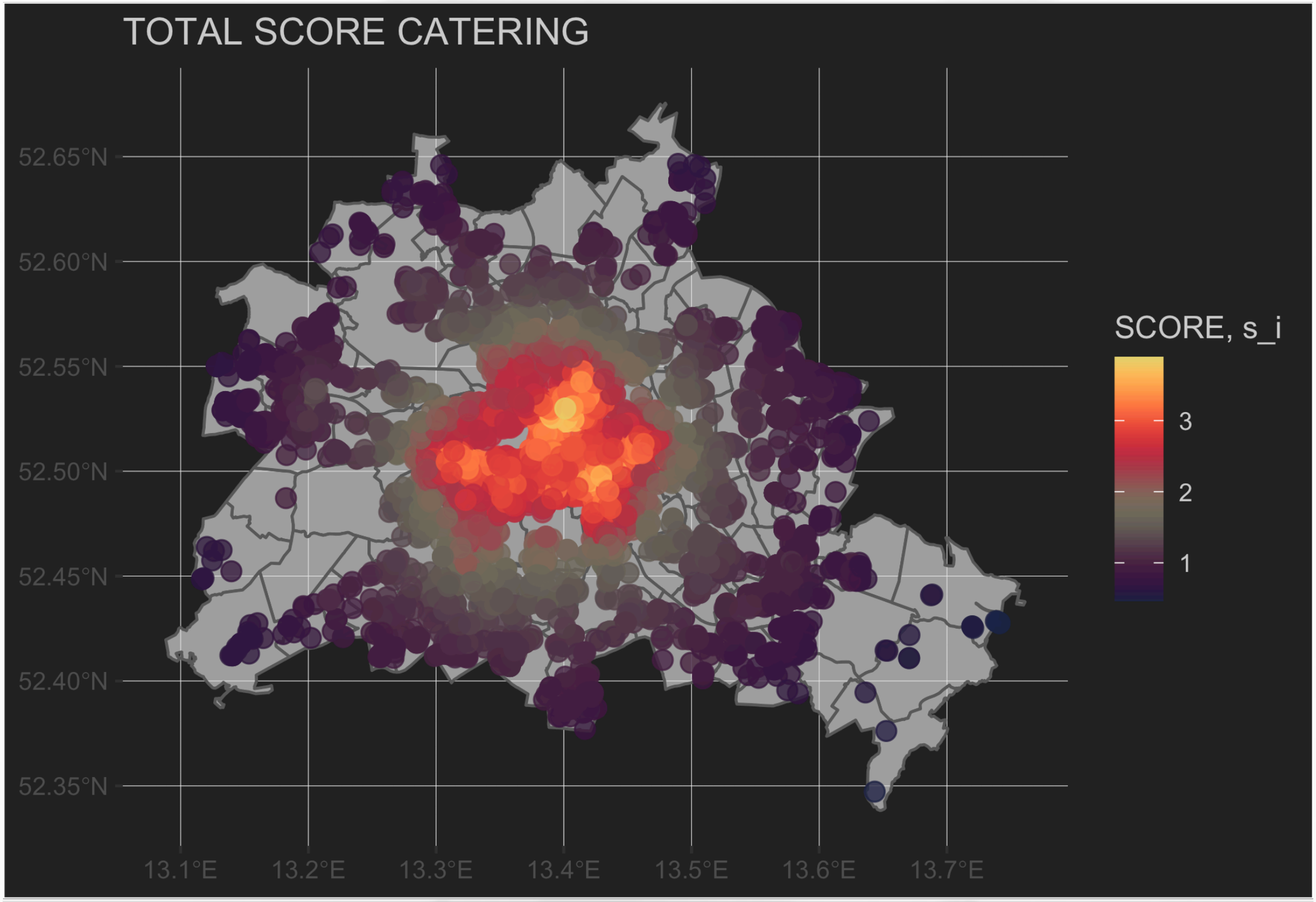


More maps: restaurants, bars, etc.



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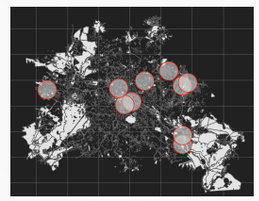
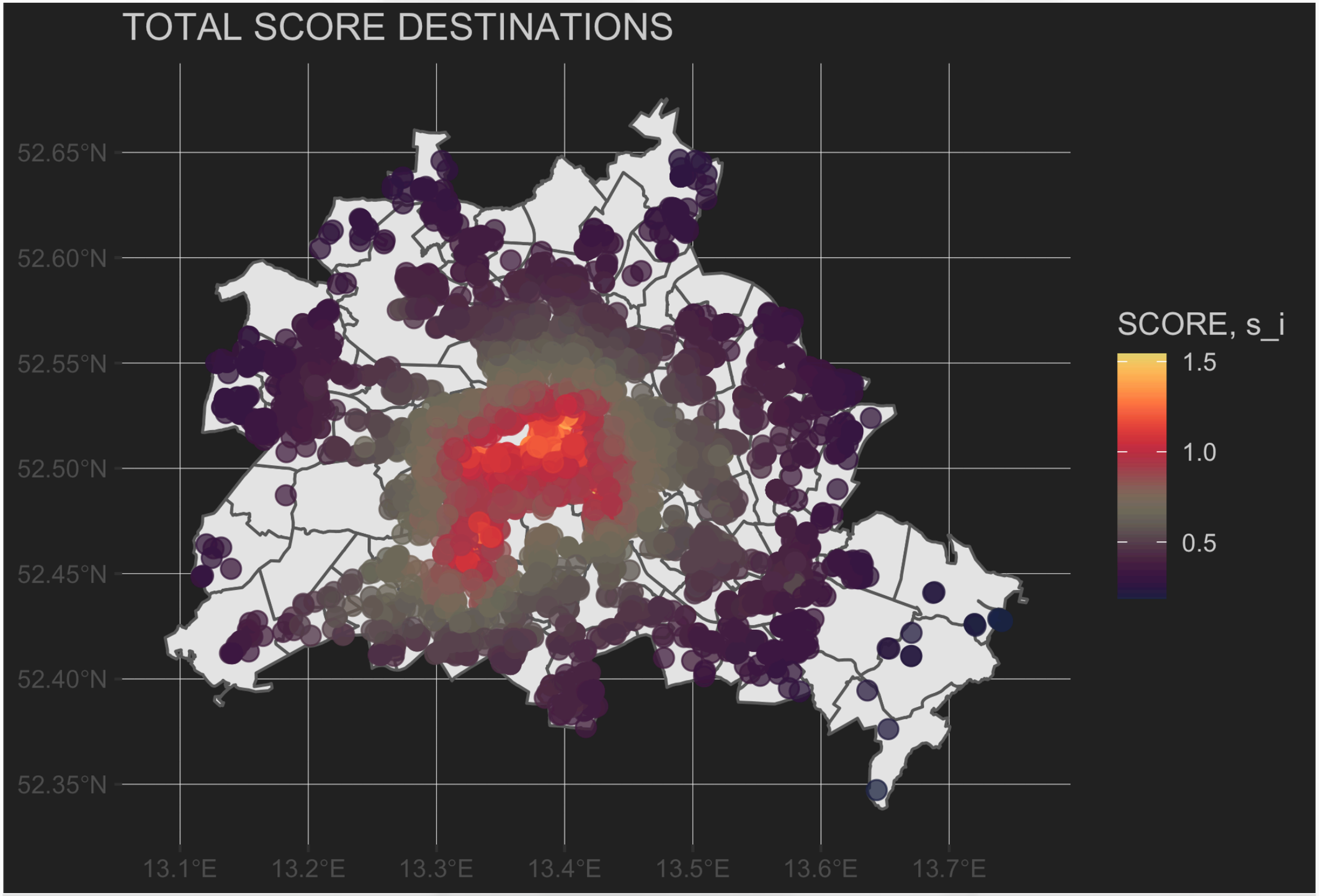


More maps: sightseeing, museums, etc.



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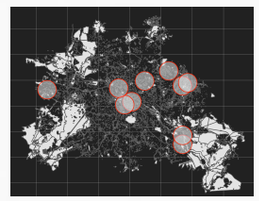
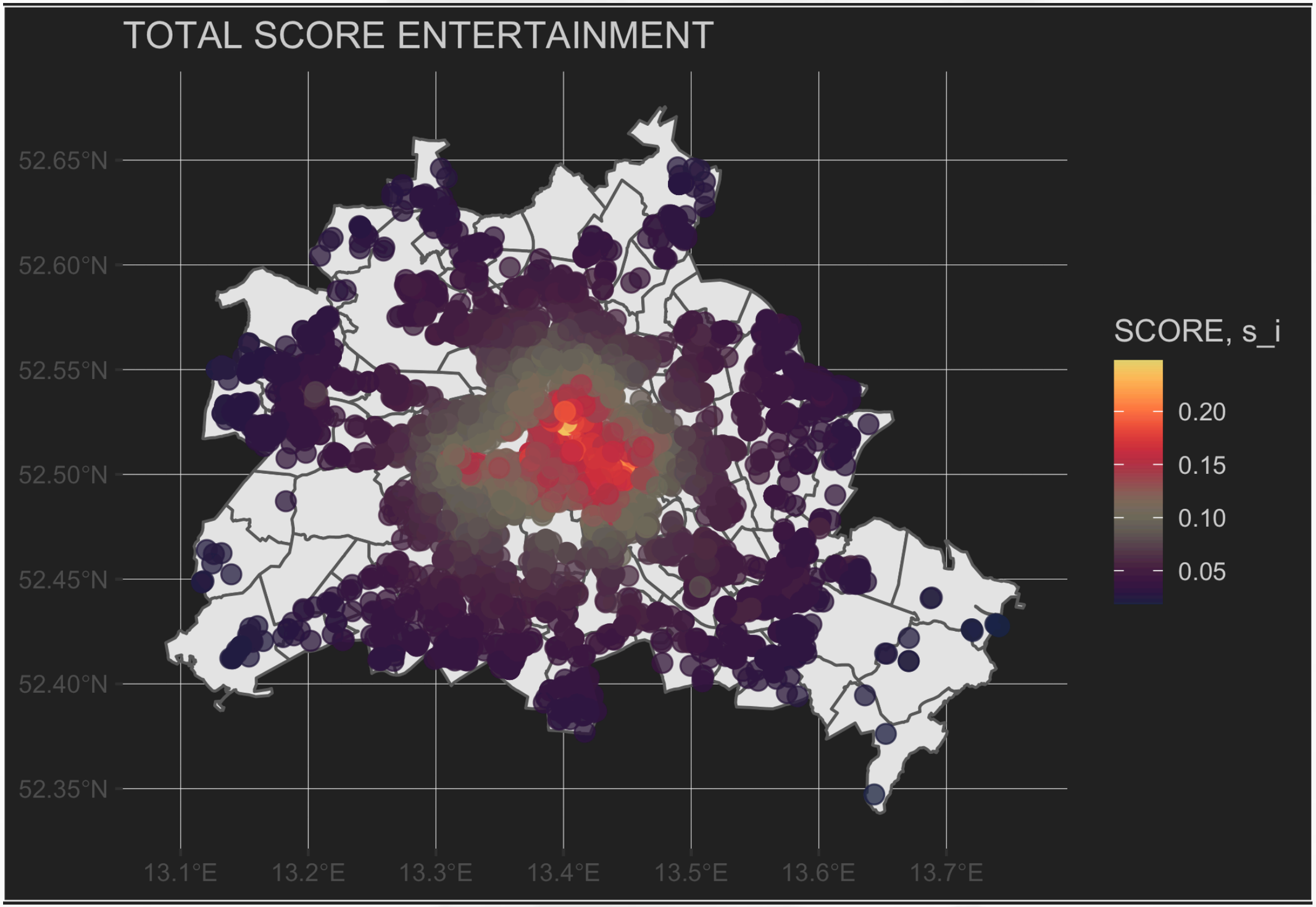


More maps: cinemas, night clubs, etc.



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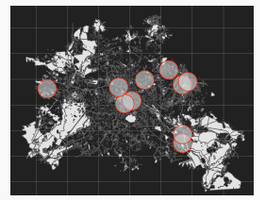
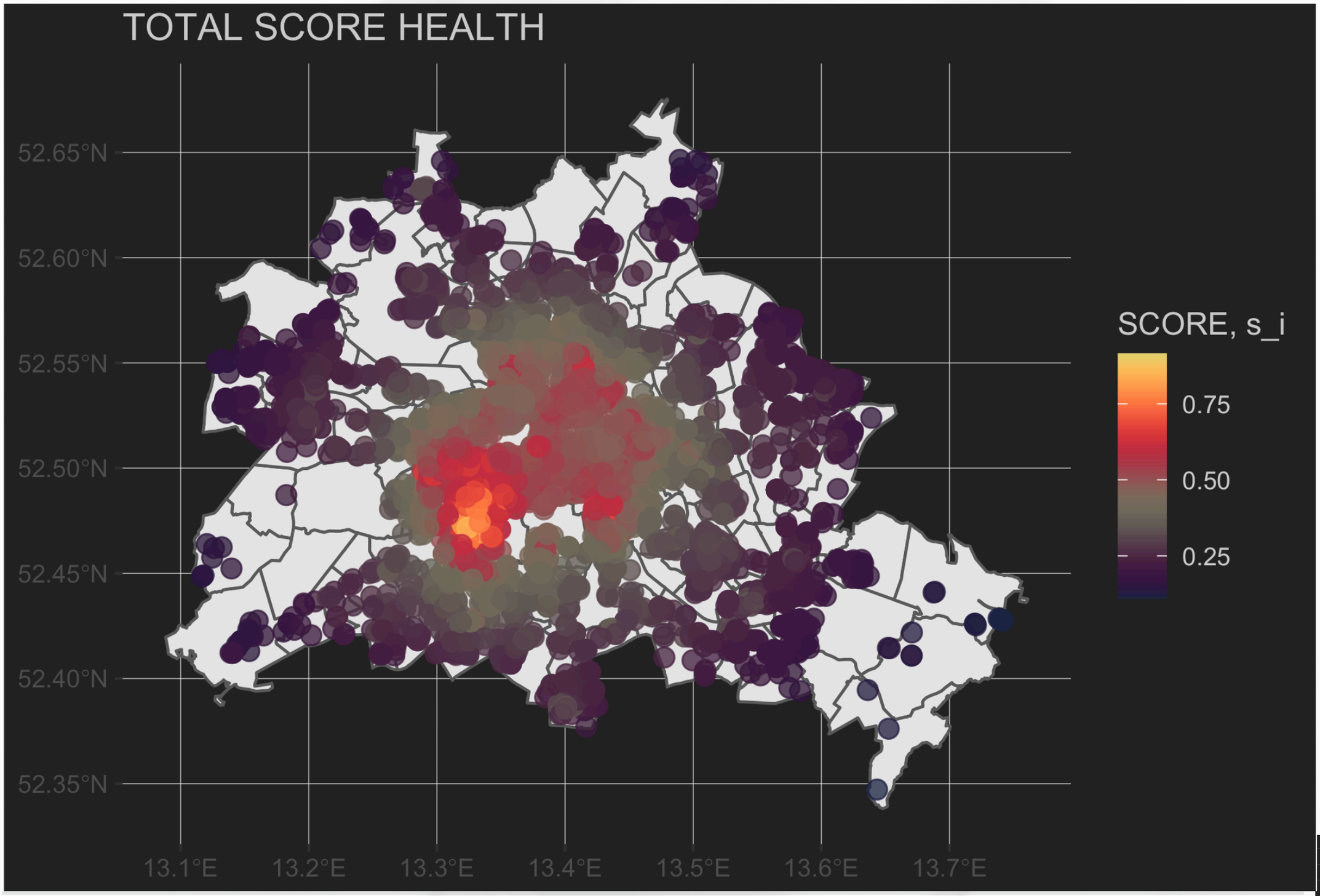


More maps: doctors, pharmacies, etc.



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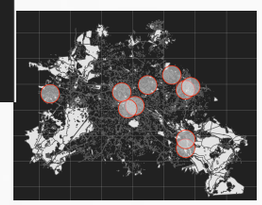
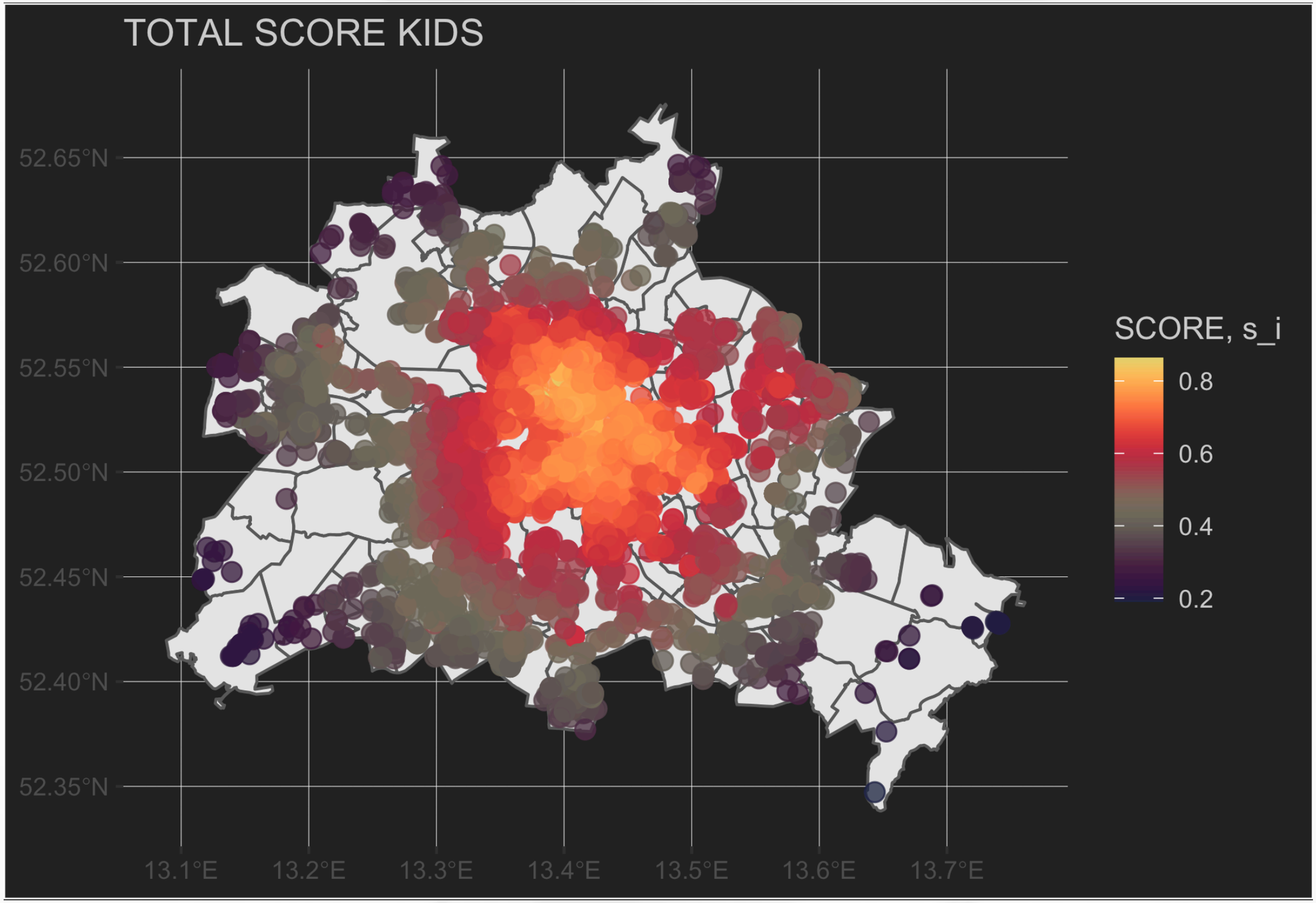


More maps: kitas, playgrounds, etc.



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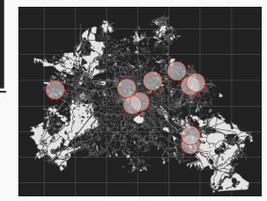
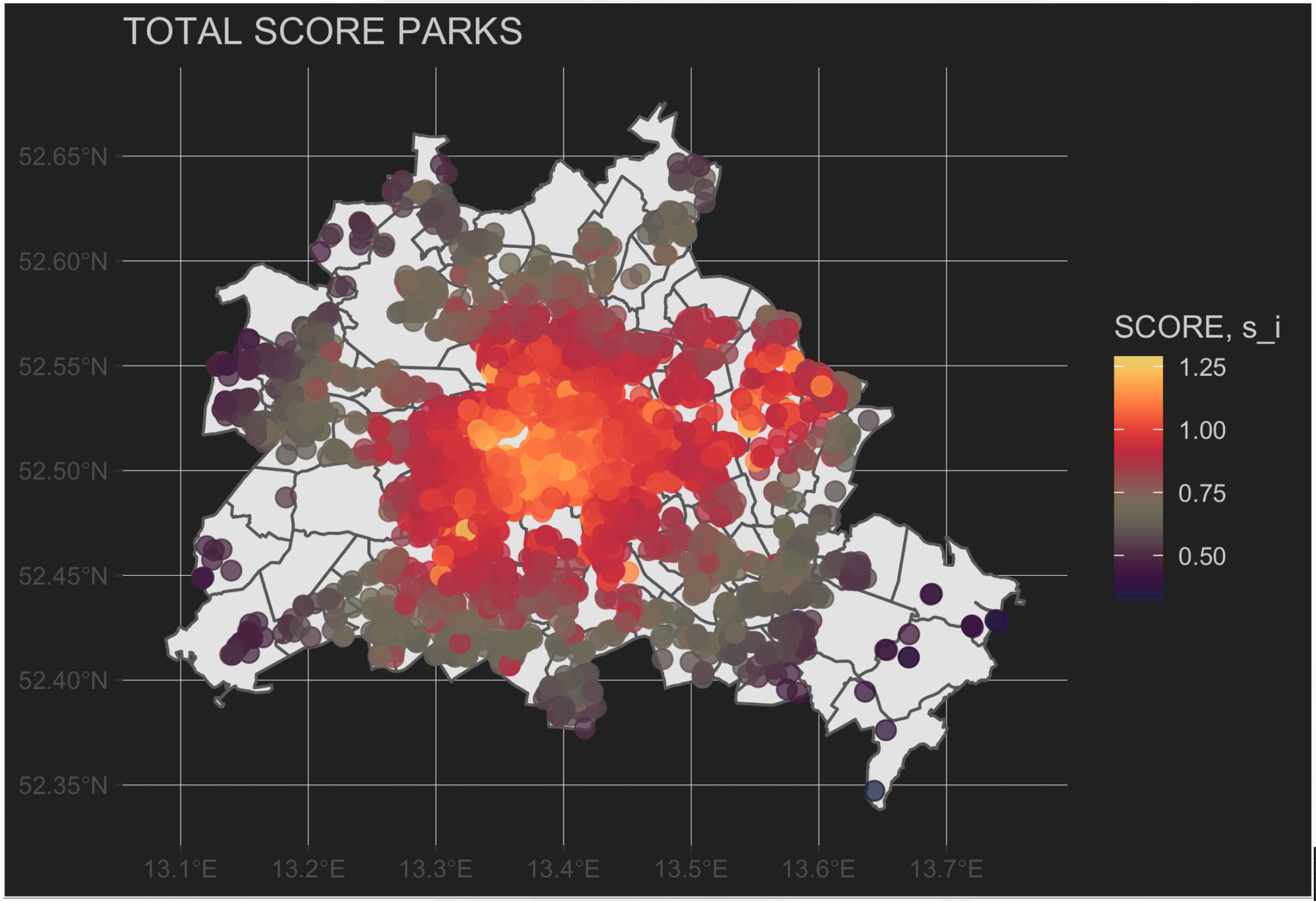


More maps: parks, dog parks, etc.



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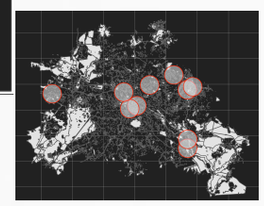
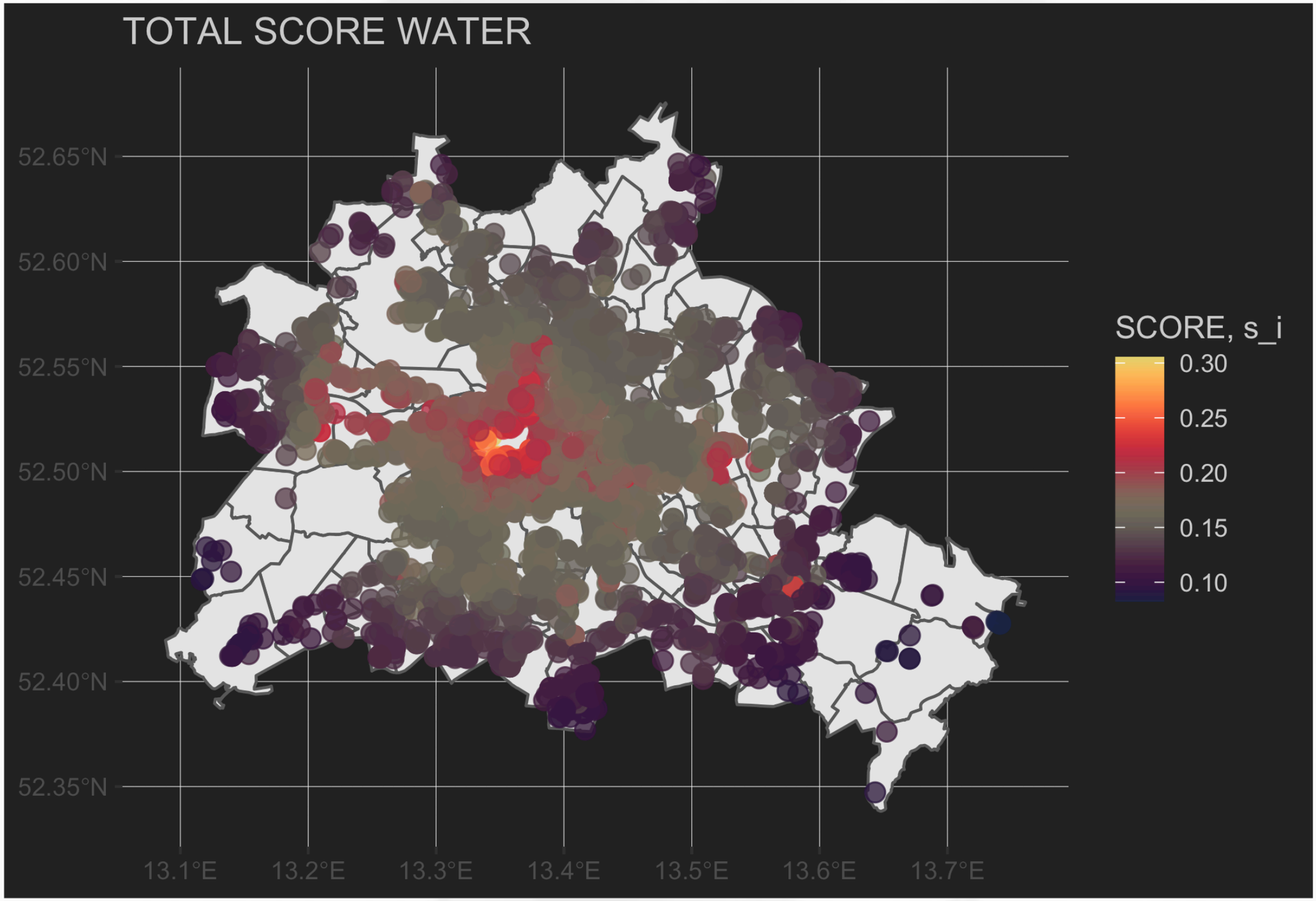


More maps: rivers, lakes etc.



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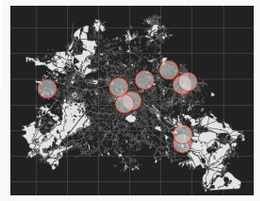
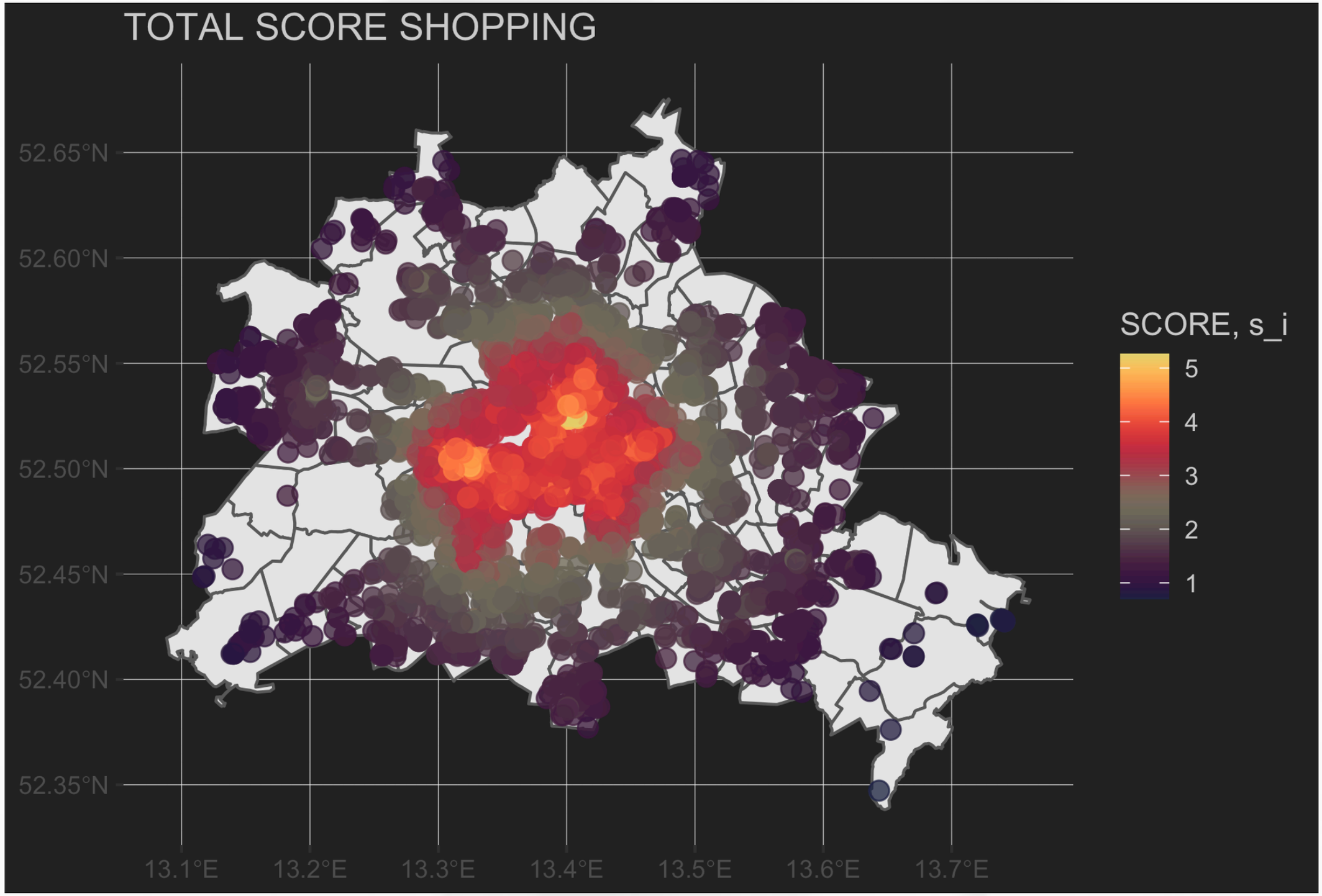


More maps: shops, grocery stores, etc.



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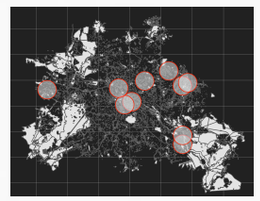
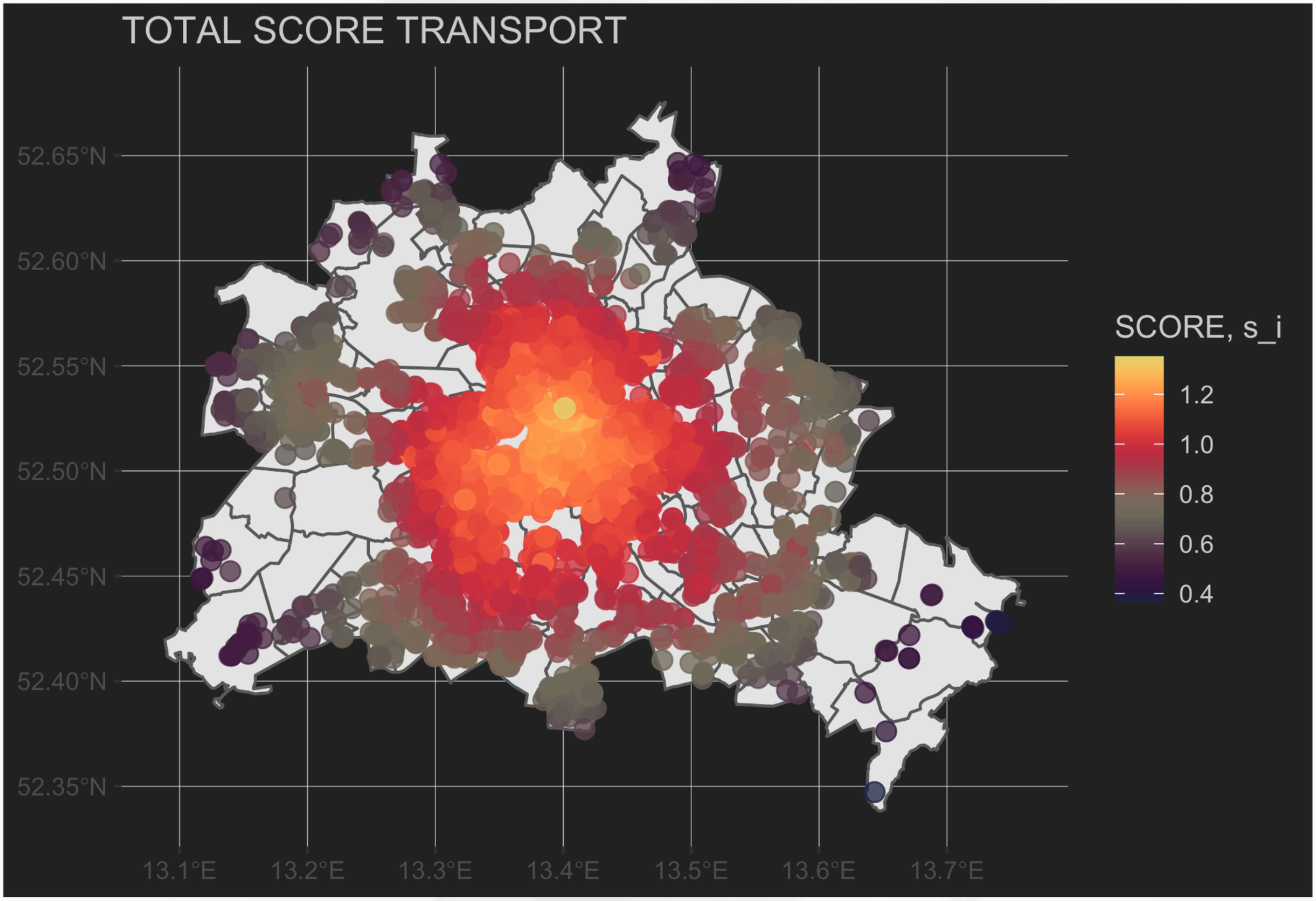


More maps: S-Bahn, U-Bahn, etc.



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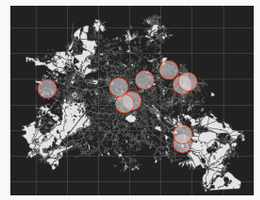


Distance measurement, scoring and normalization

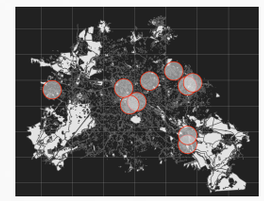
After that the scores are rescaled via min-max normalisation in order to get the weights:

$$s_{i,k}^{norm} = \frac{s_{i,k}^{dist} - \min s_k^{dist}}{\max s_k^{dist} - \min s_k^{dist}}$$

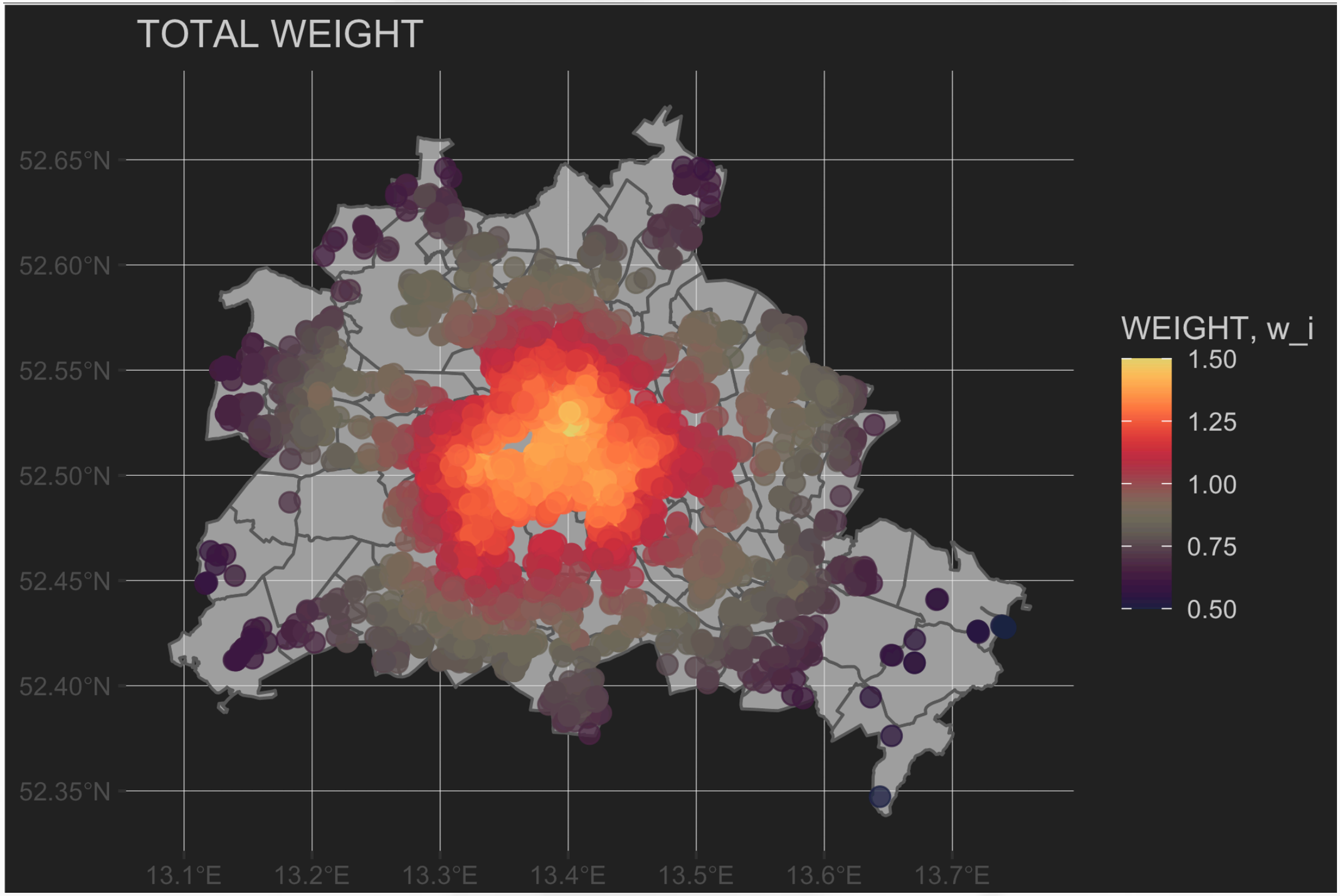
$$s_i^{norm} = \sum_k s_{i,k}^{norm}$$

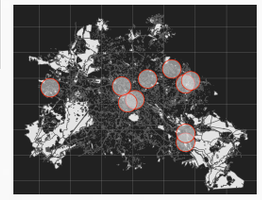
$$w_i = \frac{s_i^{norm} - \min s^{norm}}{\max s^{norm} - \min s^{norm}} + \frac{1}{2}$$

Here $\frac{1}{2}$ is added in order to make the minimum weight 0.5 and the maximum 1.5 (half-price discount or an extra payment)



Weights


TOTAL WEIGHT
52.65°N
52.60°N
52.55°N
52.50°N
52.45°N
52.40°N
52.35°N
13.1°E
13.2°E
13.3°E
13.4°E
13.5°E
13.6°E
13.7°E
WEIGHT, w_i
1.50
1.25
1.00
0.75
0.50



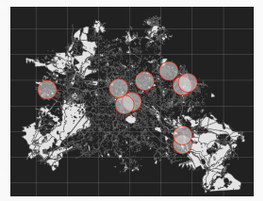
Evaluating landlord premiums

$$P_i = w_i \cdot \hat{P}_i + \varepsilon_i$$

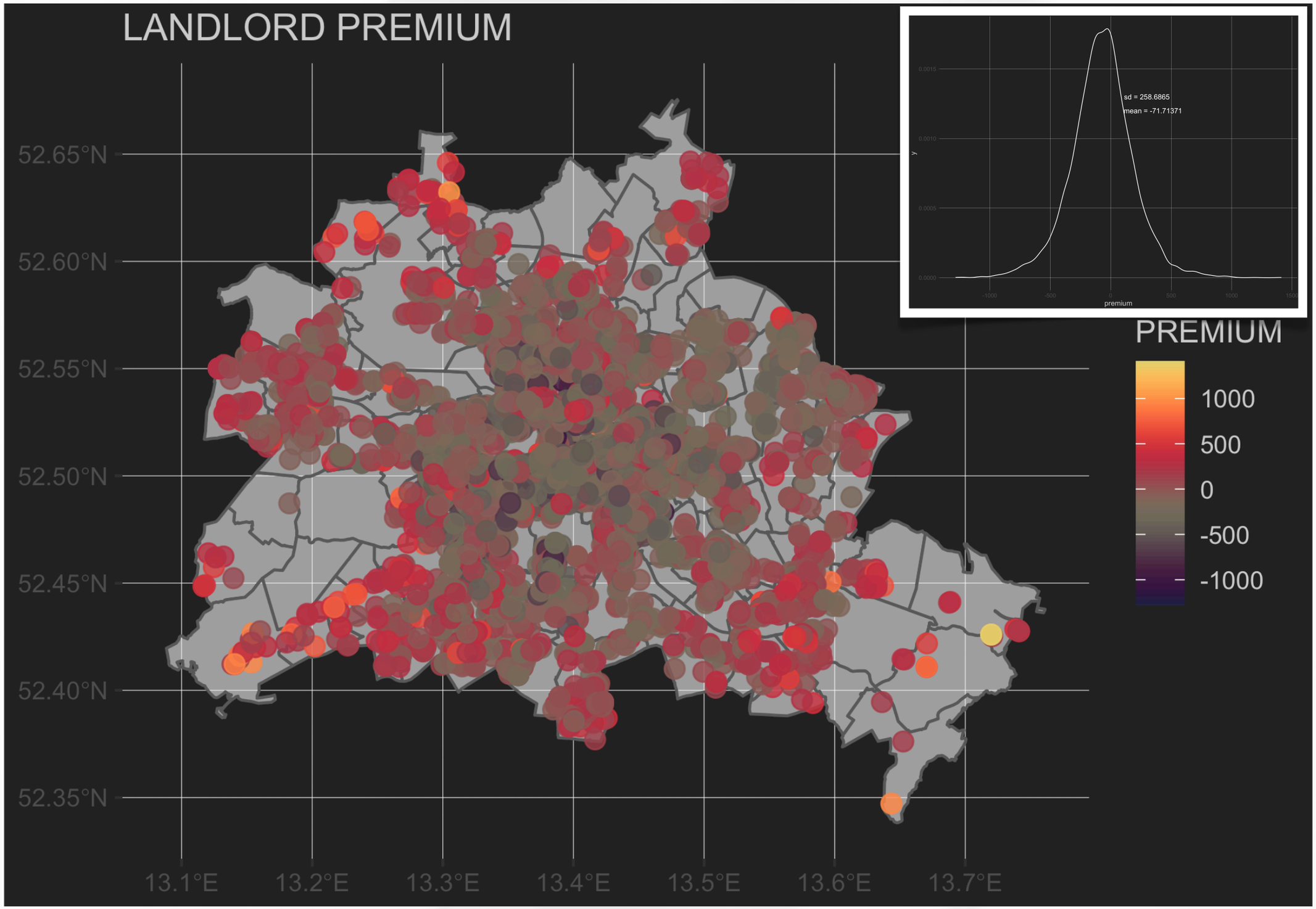
Market price — Discount-weight — Model price — Residuals

Landlord premium: property/area overvaluation/underevaluation

Find the distribution

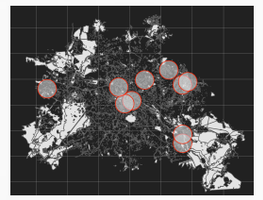


Premiums


LANDLORD PREMIUM
52.65°N
52.60°N
52.55°N
52.50°N
52.45°N
52.40°N
52.35°N
13.1°E
13.2°E
13.3°E
13.4°E
13.5°E
13.6°E
13.7°E
sd = 258.6865
mean = -71.71371
premium
y
PREMIUM
1000
500
0
-500
-1000

Key takeaways:

- The size of the apartment, the presence of a kitchen, and a lift can be used as a solid foundation for a price check for the rent prices of apartments
- Infrastructural-wise Berlin tends to be a very single-centroid oriented city with few other areas of concentration emerging from different infrastructural objects
- Overall in Berlin, rent prices are not under- or overvalued based on the model used in this research, landlord premiums seem to be fairly and normally distributed
- Overvalued properties seem to be more concentrated further outside the city centre and the more undervalued properties are located closer to the city center which can point to the lack of prestige living in the centre of the city



Sources and code

- https://daten.berlin.de/datensaetze/openstreetmap-daten-für-berlin
- https://www.kaggle.com/corrieaar/apartment-rental-offers-in-germany/version/6
- https://nominatim.org/release-docs/latest/api/Overview/
- https://github.com/IvanKotik/Spatial-Price-Analytics-Research-Project