

# Exploratory Data Analysis of Airbnb Listings in Berlin

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# Outline

## Introduction

## Spatial data

- Districts/Neighbourhoods

- VBB Areas

## Airbnb data

- Variables

- Functions

## Drivers of price

- Correlation

## ShinyApp

## Objectives

- Airbnb is a website where private people, and commercial entities, can rent apartments, or part of them.
- Aim of the project:
  - ▶ Answer the following questions:
    - How are the Airbnb properties distributed in Berlin?
    - Which variables drive the property price?
  - ▶ Display the information through a ShinyApp

## Creating Polygons for the districts and neighbourhoods

- Loading the shapefile of Berlin neighbourhoods:  
(downloaded from [www.statistik-berlin-brandenburg.de](http://www.statistik-berlin-brandenburg.de))
- For the neighbourhoods we just need to transform the SpatialPolygonsDataFrame into an sf object.

```
1 berlin_neighbourhood_sf <- berlin %>%  
2   sf::st_as_sf() %>%  
3   sf::st_set_crs(proj4string(berlin)) %>%  
4   dplyr::rename(id      = Name,  
5                 group = BEZNAME) %>%  
6   dplyr::select(id, group, geometry) %>%  
7   dplyr::arrange(group) %>%  
8   dplyr::mutate(view = "Neighbourhoods")
```

- The neighbourhood Buckow is composed of two separate parts, which we unite by grouping the neighbourhoods by their id.

```
1 berlin_neighbourhood_singlebuckow_sf <-  
  berlin_neighbourhood_sf %>%  
2   dplyr::group_by(id, group, view) %>%  
3   dplyr::summarize(do_union = TRUE) %>%  
4   dplyr::arrange(group)
```

- To get the districts we unite the neighbourhoods by their district (group).

```
1 berlin_district_sf <- berlin_neighbourhood_sf %>%  
2   dplyr::group_by(group, view) %>%  
3   dplyr::summarize(do_union = TRUE) %>%  
4   dplyr::mutate(id      = group,  
5                 view    = "Districts")
```

# Mapping the polygons

## □ Districts:

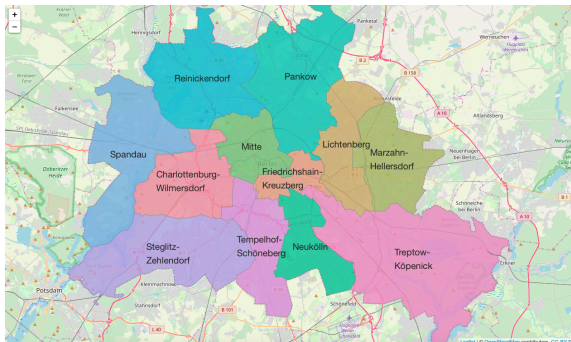


Figure 1: Leaflet map of Berlin Districts

## □ Neighbourhoods:

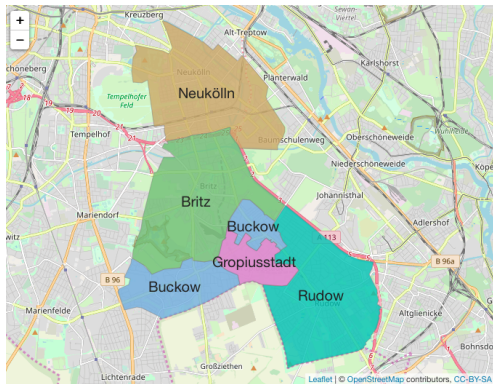


Figure 2: Leaflet map of Neukölln's Neighbourhoods

## Creating Polygons of the VBB Areas

- Loading the shapefile of the stations and stops in Berlin:  
(downloaded from [www.geofabrik.de](http://www.geofabrik.de))
- Create dataframe with the information for train/subway stations.

```
1 bahn_stations_df <- stations %>%  
2   base::as.data.frame() %>%  
3   dplyr::filter(fclass %like% "railway") %>%  
4   dplyr::rename(id      = name ,  
5                 long   = coords.x1 ,  
6                 lat    = coords.x2) %>%
```



```
1  dplyr::mutate(id      = gsub("Berlin ", "", id),
2                id      = gsub("Berlin-", "", id),
3                id      = gsub(" *\\(.*?\\) *", "",
4                               id),
5                s_bahn  = ifelse(startsWith(id,
6                               "S "), TRUE, FALSE),
7                u_bahn  = ifelse(startsWith(id,
8                               "U "), TRUE, FALSE),
9                id      = gsub("S ", "", id),
10               id      = gsub("U ", "", id)) %>%
11  dplyr::group_by(id) %>%
12  dplyr::summarize(long  = mean(long),
13                  lat   = mean(lat),
14                  s_bahn = any(s_bahn),
15                  u_bahn = any(u_bahn))
```

- Create dataframe with names and order position of stations that form the Ringbahn (VBB Area A).

```
1 ringbahn_names_df <- base::data.frame(  
2   id = c("Südkreuz", "Schöneberg",  
3         "Innsbrucker Platz", "Bundesplatz",  
4         "Heidelberger Platz", "Hohenzollerndamm",  
5         "Halensee", "Westkreuz", "Messe Nord/ICC",  
6         "Westend", "Jungfernheide",  
7         "Beusselstraße", "Westhafen", "Wedding",  
8         "Gesundbrunnen", "Schönhauser Allee",  
9         "Prenzlauer Allee", "Greifswalder Straße",  
10        "Landsberger Allee", "Storkower Straße",  
11        "Frankfurter Allee", "Ostkreuz",  
12        "Treptower Park", "Sonnenallee",  
13        "Neukölln", "Hermannstraße",  
14        "Tempelhof", "Südkreuz"),  
15   stringsAsFactors = FALSE) %>%
```

```
1 tibble::rownames_to_column(var = "order") %>%  
2 dplyr::mutate(order = as.numeric(order))
```

- Create the sf object of the VBB Areas by binding the Area A with the complete-Berlin polygon and finding their interaction.

```
1 vbb_AB_sf <- bahn_stations_df %>%  
2   dplyr::right_join(ringbahn_names_df ,  
3                     by = "id") %>%  
4   dplyr::arrange(order) %>%  
5   dplyr::select(long, lat) %>%  
6   base::as.matrix() %>%  
7   base::list() %>%  
8   sf::st_polygon() %>%  
9   sf::st_sfc() %>%  
10  sf::st_sf(crs = proj4string(berlin)) %>%
```

```
1 base::rbind(berlin_all_sf) %>%  
2 sf::st_intersection() %>%
```

- ▣ Area A: interaction ( $n.overlaps > 1$ )
- ▣ Area B: no interaction ( $n.overlaps = 1$ )

```
1 dplyr::mutate(id      = ifelse(n.overlaps > 1,  
2                               "A", "B"),  
3               view    = "VBB Areas",  
4               group   = id) %>%  
5 dplyr::select(-n.overlaps, -origins) %>%  
6 dplyr::arrange(desc(id))
```

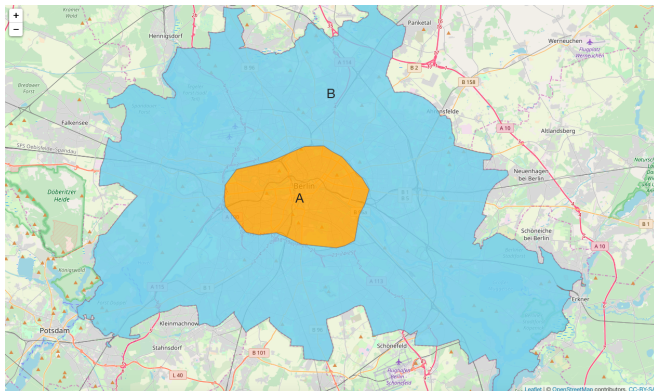


Figure 3: Leaflet map of VBB Areas

## Initial variables

- ▣ Loading the following files (downloaded from [www.insideairbnb.com](http://www.insideairbnb.com)):
  - ▶ *listings.csv.gz*: Detailed Listings data for Berlin
  - ▶ *listings.csv*: Summary information and metrics for listings in Berlin
  - ▶ *calendar.csv.gz*: Detailed Calendar Data for listings in Berlin
- ▣ Last update: 7th November 2018
- ▣ Keeping the following variables:
  - ▶ *id*: Reference to the listing
  - ▶ *long*, *lat*: Coordinates of the listing
  - ▶ *price*: Price per night in dollars
  - ▶ *security\_deposit\_yn*, *cleaning\_fee\_yn*: If extra money will be asked as deposit and/or for cleaning
  - ▶ *property\_type*, *room\_type*: Type of accommodation

- ▶ *accommodates, bedrooms, beds*: Important for the number of people who could stay in the property
- ▶ *minimum\_nights*: How many night at least a person has to book
- ▶ *reviewed\_yn, number\_of\_reviews, review\_scores\_rating*: If a listing has been reviewed, by how many people and what its average scoring is
- ▶ *availability\_30, availability\_60, availability\_90, availability\_365*: Availability in days in the next 30, 60, 90 and 365 days
- ▶ *listing\_url*: Website of the specific listing

## New variables

- ▣ district, neighbourhood, vbb\_area:

```
1 listings <- point_in_polygons(  
2     points_df = listings ,  
3     polys_sf  = berlin_neighbourhood_sf ,  
4     var_name  = "neighbourhood")
```

- ▣ station\_count, station\_dist, attraction\_count, attraction\_dist:

```
1 listings <- distance_count(  
2     main      = listings ,  
3     reference = bahn_stations_df ,  
4     var_name  = "station",  
5     distance  = 1000)
```



## Functions

□ point\_in\_polygons:

```
1 point_in_polygons <-  
2   function(points_df, polys_sf, var_name) {  
3     is_in <- data.frame(  
4       matrix(ncol = nrow(polys_sf),  
5             nrow = nrow(points_df)))  
6     is_in[,var_name] <- NA  
7     coordinates <- as.data.frame(st_coordinates(  
8       polys_sf))  
9     name <- polys_sf$id
```

```
1   for (k in 1:nrow(polys_sf)) {  
2       is_in[,k] <- sp::point.in.polygon(  
3           point.x = points_df$long,  
4           point.y = points_df$lat,  
5           pol.x    = coordinates$X  
6                   [coordinates$L2 == k],  
7           pol.y    = coordinates$Y  
8                   [coordinates$L2 == k])  
9       is_in[,var_name][is_in[,k] == 1] <- name[k]  
10  }  
11  is_in <- is_in %>%  
12  dplyr::select(var_name) %>%  
13  dplyr::mutate(id = points_df$id)  
14  points_df <- dplyr::full_join(points_df, is_in,  
15                               by = "id")  
16  return(points_df)  
17 }
```

### distance\_count:

```
1 distance_count <- function(main, reference,
2                             var_name, distance) {
3   var_name_count <- paste(var_name, "count",
4                             sep = "_")
5   var_name_dist <- paste(var_name, "dist",
6                             sep = "_")
7   point_distance <- geosphere::dism(
8     x = main %>%
9       dplyr::select(long,
10                     lat),
11     y = reference %>%
12       dplyr::select(long,
13                     lat),
14     fun = distHaversine) %>%
15     as.data.frame() %>%
16     data.table::setnames(as.character(reference$id))
```

```
1 point_distance[,var_name_count] <- rowSums(  
  point_distance <= distance)  
2 point_distance[,var_name_dist] <- apply(  
3   point_distance[, -ncol(point_distance)],  
4   MARGIN = 1, FUN = min) %>% round(0)  
5 main <- point_distance %>%  
6   dplyr::mutate(id = main$id) %>%  
7   dplyr::select(id,  
8     var_name_count, var_name_dist) %>%  
9   dplyr::right_join(main, by = "id")  
10 return(main)  
11 }
```

## Correlation with price

- Correlation of each variable with price.

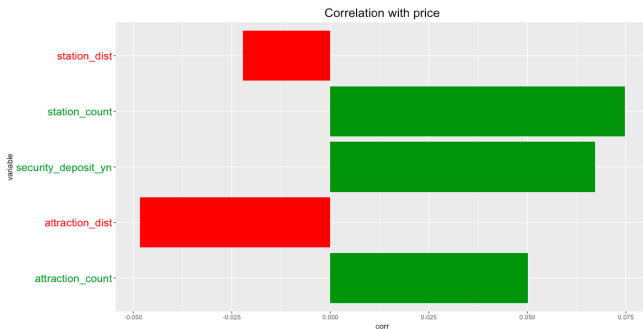


Figure 4: Correlation plot

# Tab Berlin map

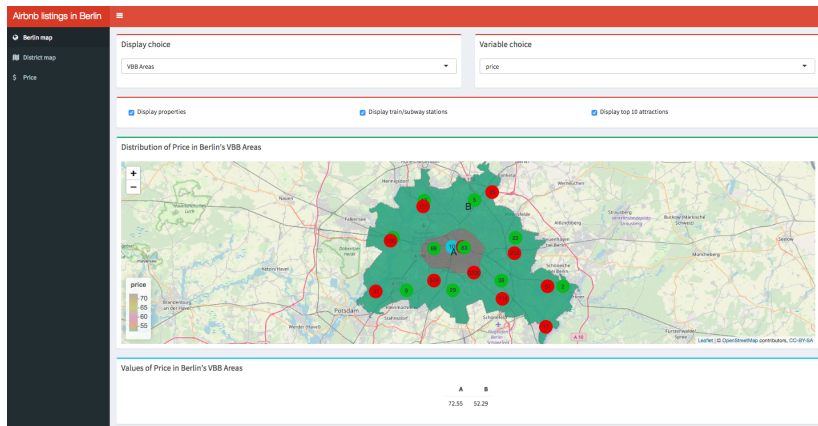


Figure 5: Tab Berlin map  
EDA of Berlin Airbnb Listings

# Tab District map

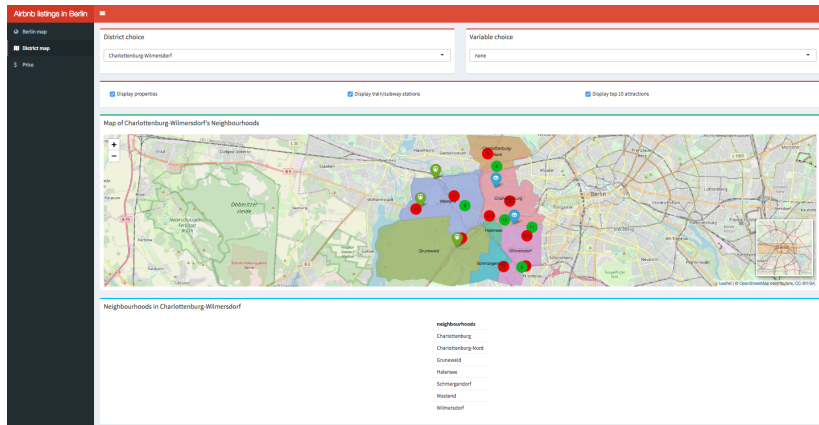


Figure 6: Tab District map

# Tab Price

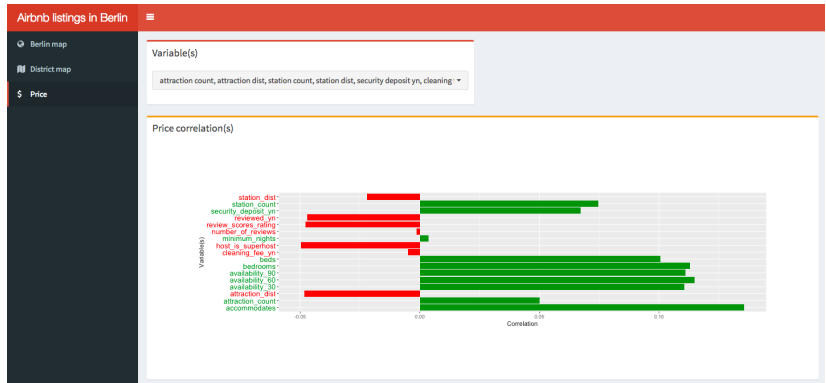


Figure 7: Tab Price