Airbnb Berlin Case Study: Project outline

**Business case**

**Who**

The client is a legal company which supports tenants in defending their right to a safe and affordable home.

**Why**

The client wants to see proof that short-term commercial rentals of apartments drive rental prices up and reduce the number of available apartments for permanent Berlin residents.

**What**

The storyboard will show the impact of commercial Airbnb hosts in Berlin on price and rental availability of apartments in Berlin.

**When**

It will be used when arguing with legislators for stricter regulations governing commercial short-term rentals with the aim to reduce and stabilize rental prices and availability for Berlin residents.

**Where**

Tableau Public.

**Data Source**

<http://insideairbnb.com/get-the-data.html>

Accessed on 16 September 2021.

Latest update of data set was on 12 July 2021.

The data is internal to Airbnb, therefore owned by them, but sourced from publicly available information from the Airbnb site. As such, it is as precise as it gets when it comes to data about Airbnb.

It is administrative data in the sense that it contains a directory of of information concerning rental rooms in Berlin as published on the Airbnb website.

It is licensed under [Creative Commons CC0 1.0 Universal (CC0 1.0) "Public Domain Dedication"](http://creativecommons.org/publicdomain/zero/1.0/) license and is therefore free to use.

The data contains 19095 observations of rooms for rent in Berlin, including

details on room description, location, prices, rental periods and reviews as of July 12, 2021.

**Data profile**

Columns: 16

Rows: 19095

**Categorical variables**

ID: property ID

name: property name

host\_id: host ID

host\_name: host name

room\_type: Entire place / private room / shared room

**Location variables**

neighbourhood\_group: City district the neighbourhood pertains to

neighbourhood: Neighbourhood as geocoded using the latitude and longitude against neighborhoods as defined by open or public digital shapefiles.

latitude: The neighbourhood group as geocoded using the latitude and longitude against neighborhoods as defined by open or public digital shapefiles.

longitude: The neighbourhood group as geocoded using the latitude and longitude against neighborhoods as defined by open or public digital shapefiles.

**Quantitative variables**

price: Daily price in local currency

minimum\_nights: Minimum number of nights stay for the listing

number\_of\_reviews: The number of reviews the listing has

last\_review: The date of the last / newest review

reviews\_per\_month: The number of reviews the listing has over the lifetime of the listing

calculated\_host\_listings

\_count: The number of listings the host has in the current scrape, in the city/region geography.

availability\_365: Availability\_x. The availability of the listing x days in the future as determined by the calendar. Note a listing may not be available because it has been booked by a guest or blocked by the host.

**Wrangling steps**

|  |  |  |  |
| --- | --- | --- | --- |
| Columns dropped | Columns renamed | Columns’s type changed | Comments |
|  |  | ID from int64 to str |  |
|  |  | Host\_id from int64 to str |  |
| Id |  |  | Not needed |
| Name |  |  | Not needed |
| Host\_id |  |  | Not needed |
| Host\_name |  |  | Not needed |
| Last\_review |  |  | Not needed |
| Neighbourhood |  |  | Not needed |
|  | Neighbourhood\_group |  | To match json |

**Consistency checks & cleaning**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | Missing values | Missing values treatment | Dups | Duplicates treatment | Mixed type columns | Mixed type columns treatment | Outliers | Outliers treatment |
| Listing\_  wrangled\_  cleaned | Name (30) | No change |  |  |  | Replaced NaN with “missing”, changed type to str |  |  |
| Listing\_  wrangled\_  cleaned | Host\_name (12) | No change |  |  |  | Replaced NaN with “missing”, changed type to str |  |  |
| Listing\_  wrangled\_  cleaned | Last\_review (4155) | No change |  |  |  | Replaced NaN with “0”, changed type to int64 |  |  |
| Listing\_  derived  columns | Reviews\_per\_month (4155) | Imputed mean |  |  |  |  |  |  |
| Listing\_  wrangled\_  cleaned |  |  |  |  |  |  | Price has 7 x value of 0 | Replaced with mean, 73,30 |
| Listing\_  wrangled\_  cleaned |  |  |  |  |  |  | Minimum\_nights has 13 x over 365 | Left them as they are. |
| Listing\_  wrangled\_  cleaned |  |  |  |  |  |  | Calculated\_host\_listings\_count has 583 x over 20 | Left them as they are. |
| Listing\_  derived  columns |  |  |  |  |  |  | Price has 3 x value of 8000 | Imputed with mean. |

**Summary statistics**

Before cleaning

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **latitude** | **longitude** | **price** | **minimum\_nights** | **number\_of\_reviews** | **reviews\_per\_month** | **calculated\_host\_listings\_count** | **availability\_365** |
| **count** | 19095.0 | 19095.0 | 19095.0 | 19095.0 | 19095.0 | 14940.0 | 19095.0 | 19095.0 |
| **mean** | 52.51021512931379 | 13.404654204095136 | 73.303221 | 9.105943964388583 | 21.63707776904949 | 0.7182737617135306 | 3.135847080387536 | 91.27169416077507 |
| **std** | 0.03239084494645433 | 0.06295250252312785 | 136.249622 | 33.63595600181032 | 48.67042696900742 | 1.4452721285482029 | 7.773246348000803 | 127.64533005331572 |
| **min** | 52.34007 | 13.09715 | 0.0 | 1.0 | 0.0 | 0.01 | 1.0 | 0.0 |
| **25 %** | 52.48971 | 13.36716 | 35.0 | 2.0 | 1.0 | 0.09 | 1.0 | 0.0 |
| **50 %** | 52.50995 | 13.41409 | 52.0 | 3.0 | 4.0 | 0.27 | 1.0 | 0.0 |
| **75 %** | 52.53332 | 13.4389 | 81.0 | 5.0 | 17.0 | 0.83 | 2.0 | 175.0 |
| **max** | 52.65611 | 13.75737 | 8000.0 | 1124.0 | 620.0 | 94.35 | 76.0 | 365.0 |

After cleaning

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **latitude** | **longitude** | **price** | **minimum\_nights** | **number\_of\_reviews** | **reviews\_per\_month** | **calculated\_host\_listings\_count** | **availability\_365** |
| **count** | 19095.0 | 19095.0 | 19095.0 | 19095.0 | 19095.0 | 14940.0 | 19095.0 | 19095.0 |
| **mean** | 52.51021512931379 | 13.404654204095136 | 73.33009282771243 | 9.105943964388583 | 21.63707776904949 | 0.7182737617135306 | 3.135847080387536 | 91.27169416077507 |
| **std** | 0.03239084494645433 | 0.06295250252312785 | 136.24238966411178 | 33.63595600181032 | 48.67042696900742 | 1.4452721285482029 | 7.773246348000803 | 127.64533005331572 |
| **min** | 52.34007 | 13.09715 | 8.0 | 1.0 | 0.0 | 0.01 | 1.0 | 0.0 |
| **25 %** | 52.48971 | 13.36716 | 35.0 | 2.0 | 1.0 | 0.09 | 1.0 | 0.0 |
| **50 %** | 52.50995 | 13.41409 | 52.0 | 3.0 | 4.0 | 0.27 | 1.0 | 0.0 |
| **75 %** | 52.53332 | 13.4389 | 81.0 | 5.0 | 17.0 | 0.83 | 2.0 | 175.0 |
| **max** | 52.65611 | 13.75737 | 8000.0 | 1124.0 | 620.0 | 94.35 | 76.0 | 365.0 |

**Derived columns**

|  |  |  |  |
| --- | --- | --- | --- |
| **Data set** | **New column** | **Column/s it was derived from** | **Conditions** |
| listing\_derivedcolumns | Price category | price | < 80 then “Low price” |
|  |  |  | >= 80 and < 300 then “Middle price” |
|  |  |  | >= 300 then “High price” |
| listing\_derivedcolumns | Rental availability | availability\_365 | <= 90 then “Short term” |
|  |  |  | > 90 and <= 180 then “Middle term” |
|  |  |  | > 180 then “Long term” |
| listing\_derivedcolumns | **host \_type** |  | > 180 then “Long term” |
|  |  |  | > 180 then “Long term” |

**Limitations**

In terms of limitations, it’s important to note that the travel industry has slumped because of Covid-19 and that as a result many hosts might not have updated their Airbnb listing for a while.

On the other hand, it might show the start of a “post-Covid-19” private rentals scenario, the beginning of a new reality for the travel industry.

Only time will tell if the period analysed in this project will constitute a stumbling stone or the beginning of a new era.

Further, it’s important to remember that this data is only of Airbnb properties and Airbnb is just one provider out of many of such services.

For these reasons this data set couldn’t be used to extrapolate results to other cities or the entire private property rental market in Berlin, as this would constitute a sample or exclusion bias.

**Recommendations**

* Conduct the same analysis with data from other short-term rental providers such as Wunderflats and 9flats,
* Compare, aggregate trends and aim to define the most precise number of misappropriated apartments in Berlin and what impact they have on the long-term rental market.