Apartment Rental Prediction System

Dr. Ivan S. Zapreev

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Contents

Introduction

Dataset overview

As stated on the webpage of the 'Apartment rental offers in Germany' dataset, it contains `198,379` rental offers scraped from the Germany's biggest real estate online platform ß ImmobilienScout24.

The data set consists of a single CSV file: *immo_data.csv* which only contains offers for rental properties. The data features important rental property attributes, such as the living area size, the rent (both base rent as well as total rent), the location, type of energy, and etc. The `date` column present in the data set defines the time of scraping, which was done on three distinct dates: *2018-09-22*, *2019-05-10* and *2019-10-08*.

The complete list of data set columns is extensive[1] and thus in this study we will use the following subset:

```
##  [1] "hasKitchen"           "heatingType"           "balcony"
##  [4] "lift"                 "garden"                "cellar"
##  [7] "noParkSpaces"         "livingSpace"           "typeOfFlat"
## [10] "noRooms"              "floor"                 "numberOfFloors"
## [13] "condition"            "newlyConst"            "interiorQual"
## [16] "yearConstructed"      "energyEfficiencyClass" "regio1"
## [19] "regio2"               "regio3"                "baseRent"
## [22] "electricityBasePrice" "heatingCosts"          "serviceCharge"
## [25] "totalRent"            "date"
```

This sub-selection reduces the number of considered data set columns[2] from 48 to 26 and is motivated by the personal preferences of the report's author and has no scientifically proven motivation. On the contrary, this column selection shall be seen as a part of problem statement. In other words, the task is to build an accurate[3] rental price prediction model based on the predictors from this set of columns.

The additional data preparation steps will be described in the *"Data wrangling"* section of this document.

Project goal

Execution plan

Let us now briefly outline the main steps to be performed to reach the previously formalized project goal:

1. **Prepare the data** – see the *"Data wrangling"* section:
   - Select, clean, and reshape relevant data; split it into training and validation sets; and etc.
2. **Analyze the dataset** – see the *"Dataset analysis"* section:
   - Perform data exploration and visualization; summarize insights on the data.
3. **Describe the modeling approach** – see the *"Modeling approach"* section:
   - Consider the insights of the data analysis; suggest the way for building the prediction model.
4. **Present modeling results** – see the *"Results"* section:
   - Train the model on the `modeling` set; analyze the training results; evaluate on the `validation` set.
5. **Provide concluding remarks** – see the *"Conclusions"* section:
   - Summarize the results; mention any approach limitations; outline possible future improvements.

[1] Please consider reading *"Appendix A"* for the complete list of the data set columns.
[2] Please consider reading *"Appendix B"* for the column descriptions.
[3] Please consider reading the *"Project goal"* section for an exact goal formulation.

Data wrangling

In this section we present cleaning, enriching, and restructuring the raw data taken from the 'Apartment rental offers in Germany' dataset.

This section will be organized as follows: First we explain how we cleaned the data and solved some of its inconsistencies, by enriching the data. Then we identify some structural changes done to the data. Further, we provide a summary of the wrangled data set. In the end, we explain how we split the entire data set into the `validation` and `modeling` sub-sets[4].

Data cleaning & enriching

Let us note that the number of data entries in the original data set is equal to 198332. This data is however not ready to be worked with as it is very dirty. It contains multiple `N/A` values; is inconsistent – has mismatching row values, e.g. `floor = 10` and `typeOfFlat = "roof_storey"`; and has multiple outliers in numerical/integer columns.

The rest of the section is organized as follows: First, we explain cleaning of `N/A` values. Second, we discuss stripping of the data from the outliers. Third, we outline filtering out and correcting some of the data inconsistencies.

Removing `N/A` values

Consider for example the next table summarizing the number of `N/A` values per data set column:

```
## # A tibble: 26 x 3
##    `Column name`          `N/A count` `N/A percent`
##    <chr>                        <int>         <dbl>
##  1 electricityBasePrice        151158         76.2
##  2 energyEfficiencyClass       143316         72.3
##  3 heatingCosts                135154         68.2
##  4 noParkSpaces                130405         65.8
##  5 interiorQual                 83002         41.8
##  6 numberOfFloors               71792         36.2
##  7 condition                    50318         25.4
##  8 yearConstructed              42293         21.3
##  9 floor                        37612         19.0
## 10 heatingType                  32605         16.4
## 11 totalRent                    29762         15.0
## 12 typeOfFlat                   27572         13.9
## 13 serviceCharge                 5110          2.58
## 14 hasKitchen                       1          0
## 15 lift                             1          0
## 16 garden                           1          0
## 17 cellar                           1          0
## 18 livingSpace                      1          0
## 19 noRooms                          1          0
## 20 regio2                           1          0
## 21 regio3                           1          0
## 22 baseRent                         1          0
## 23 date                             1          0
## 24 balcony                          0          0
```

[4]The latter will also be split into the `training` and `testing` set for the sake of model cross-validation.

```
## 25 newlyConst                        0          0
## 26 regio1                            0          0
```

As one can see, about $\frac{1}{2}$ of the columns has 2.5–80% `N/A`^{s}, whereas the other half has (almost) no `N/A`^{s}.

Cleaning the data from `N/A` values will be explained in the next steps:

1. We begin with the `totalRent` column as this is the value that we want to predict;
2. We proceed with the columns with the marginal ($< 1\%$) of `N/A` values;
3. We cover the remaining columns in the descending order of the number of `N/A` values.

The first steps

The `totalRent` column contains data that we want to predict. Therefore, the rows with `totalRent` == `N/A` are useless to us and shall be removed. Unfortunately, this will reduce the data set by 15.01%. There are also 13 columns with a marginal (0 to 1) number of `N/A` values. The latter can be seamlessly removed as even if all of these `N/A`^{s} appear in different rows, we will remove at most 13 entries which is just 0.0066% of data.

The main columns

Let us consider the columns one by one. Note that, some modifications we will do to the data to remove the `N/A` values may introduce bias. To for test that we would need a clean data set with no `N/A` values initially present and then to use such a data set for the trained model(s) validation. Due to the lack of time this will not be done in the case study.

Column: `electricityBasePrice` - 76.2% `N/A` values

We will set the electricity base price for the `N/A` values to zero. The motivation is that, since the number of `N/A` values is almost 80% and no other zero values are present:

```
x <- arog_data$selected_data %>% filter(!is.na(electricityBasePrice))
sum(x$electricityBasePrice == 0)
```

```
## [1] 0
```

it is likely that the `N/A` values were used to determine the fact that there is no electricity base price.

Column: `energyEfficiencyClass` - 72.3% `N/A` values

The energy efficiency factor levels are:

```
levels(arog_data$selected_data$energyEfficiencyClass)
```

```
##  [1] "A"              "A_PLUS"         "B"              "C"
##  [5] "D"              "E"              "F"              "G"
##  [9] "H"              "NO_INFORMATION"
```

So we shall naturally set all the `N/A` energy efficiency levels to `"NO_INFORMATION"`.

Column: `heatingCosts` - 68.2% `N/A` values

We will set the heating costs for the `N/A` values to zero as there are already 1989 zero-valued heating cost entries. It is unlikely that there are non-heated accommodations in Germany so *we assume that the* 0 *values, the same as* `N/A`^{s} *mean - "unknown".*

Column: `noParkSpaces` - 65.8% `N/A` values

We will set the number of parking places for the `N/A` values to zero as there is already 2850 zero-valued entries. By this step we assume that, `N/A` is interpreted as *"not applicable"* or *"no are available"*.

Column: `interiorQual` - 38.8% `N/A` values

The interior quality factor levels are:

```
levels(arog_data$selected_data$interiorQual)
```

```
## [1] "luxury"        "normal"        "simple"        "sophisticated"
```

So we shall introduce a new level for the `N/A` values, called `"unknown"`.

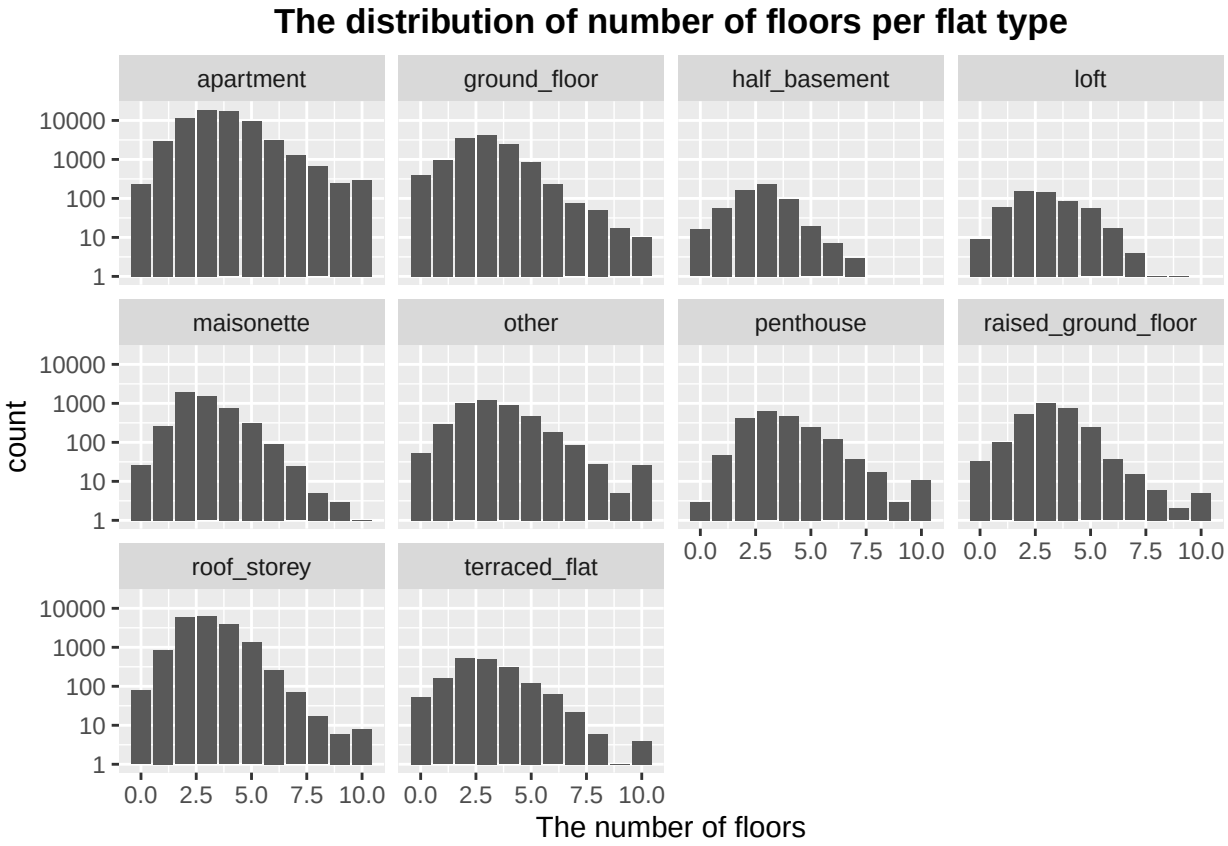
Column: `numberOfFloors` - 36.2% `N/A` values

Setting the `N/A` values for the floors shall be agreed with the apartment type, if we gather some number of floors statistics for each available apartment type we get the following:

Table 1: Type of flat vs. number of floors statistics

typeOfFlat	numberOfFloors				
	Count	Average	Standard error	Minimum	Maximum
apartment	66844	3.9	6.6	0	999
roof_storey	18450	3.1	6.7	0	800
ground_floor	12802	3	8.9	0	999
maisonette	4979	2.9	1.5	0	43
other	4284	3.6	5	0	301
raised_ground_floor	2779	3.4	7.3	0	370
penthouse	2011	3.7	2.2	0	33
terraced_flat	1760	3	1.5	0	14
half_basement	598	2.7	1.1	0	7
loft	542	3	1.5	0	15

From where we conclude that the data we have is very polluted. Clearly, one can not expect apartments with 99 floors and alike. See also on the large average (all `+/-` around 3 floors) and the huge standard error values. If we visualize the results (filtering out 1662 flats with more than 10 floors), we see that:



the data seems to be approximately normally distributed (except for the `apartment` type) with the mean values within 2.5 - 4.0 range. This makes us believe that this data is too much biased and polluted. So we will not rely on this column in our analysis.

Column: `condition` - 25.4% **`N/A` values**

The condition factor levels are:

```
##  [1] "first_time_use"                  "first_time_use_after_refurbishment"
##  [3] "fully_renovated"                 "mint_condition"
##  [5] "modernized"                      "need_of_renovation"
##  [7] "negotiable"                      "refurbished"
##  [9] "ripe_for_demolition"             "well_kept"
```

So we shall introduce a new level for the `N/A` values, called `"unknown"`.

Column: `yearConstructed` - 21.3% **`N/A` values**

There is no good default to replace the `N/A` values here. Yet, it is a significant amount of data which we do not want to exclude. Therefore drop this column from the analysis and just use the `newlyConst` flag column.

Column: `floor` - 19.0% **`N/A` values**

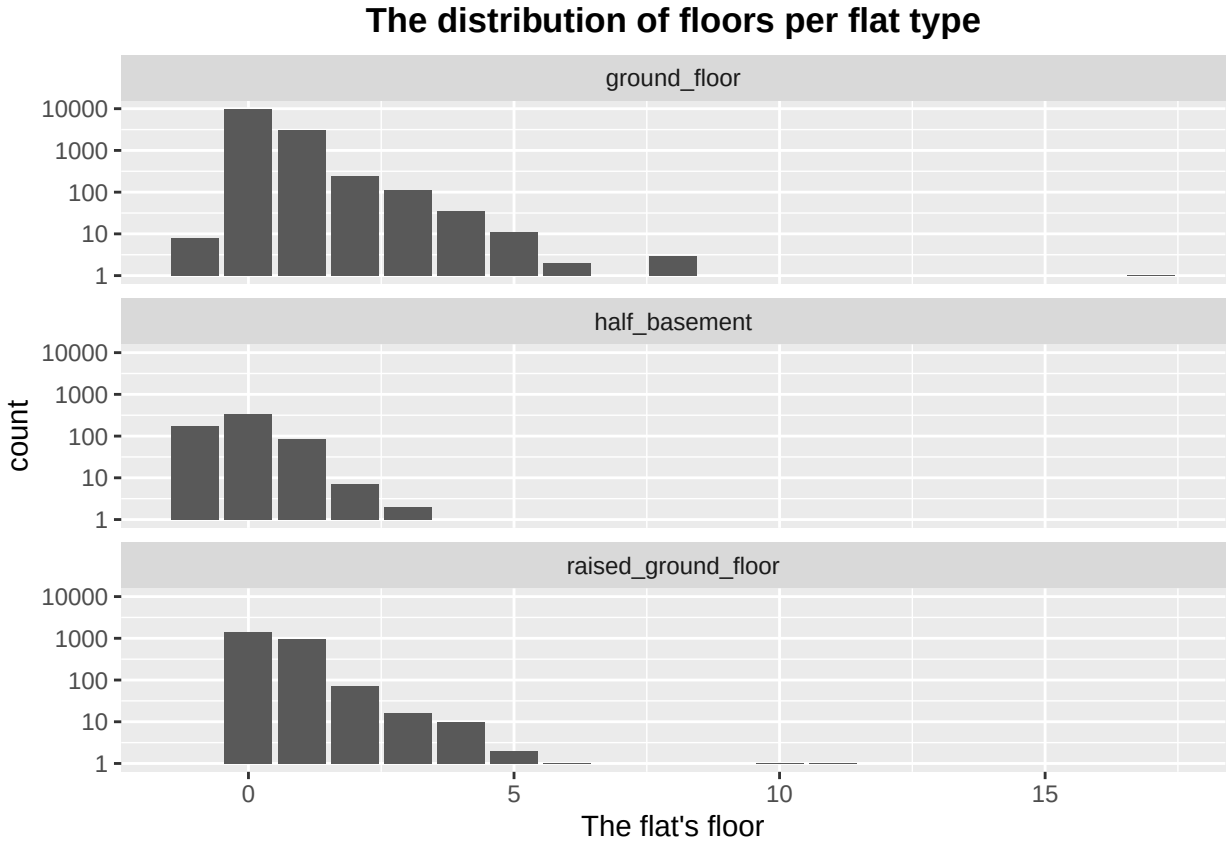
We could assign some `floor` values based on the flat types:

```
##  [1] "apartment"           "ground_floor"        "half_basement"
##  [4] "loft"                "maisonette"          "other"
##  [7] "penthouse"           "raised_ground_floor" "roof_storey"
## [10] "terraced_flat"
```

For example, we could consider assigning:

- `half_basement` – set `floor` to be the average half-basement floor value
- `ground_floor` – set `floor = 0`
- `raised_ground_floor` – set `floor` to be the average raised ground floor value

but, let us look at the floor values (filtering out 10 flats with `floor` > 100), for these flat types:



From the data above we see that we shall not only correct the `N/A` values but set all of the floor values for the considered flat types as follows:

- `half_basement` – set `floor = -1`
- `ground_floor` – set `floor = 0`
- `raised_ground_floor` – set `floor = 0`

If we do that then there will still be 20049 (10.1% of data) `N/A` floor values for the flat types for which we can not give any exact value. So we will just assign those to the mean floor value in the category.

Column: `heatingType` - 16.4% `N/A` values

The heating type factor levels are:

```
##  [1] "central_heating"                "combined_heat_and_power_plant"
##  [3] "district_heating"               "electric_heating"
##  [5] "floor_heating"                  "gas_heating"
##  [7] "heat_pump"                      "night_storage_heater"
##  [9] "oil_heating"                    "self_contained_central_heating"
## [11] "solar_heating"                  "stove_heating"
## [13] "wood_pellet_heating"
```

So we shall introduce a new level for the `N/A`, and `"H"` values, called `"unknown"`.

Column: `typeOfFlat` - 13.9% `N/A` values

The type of flat factor levels are:

```
##  [1] "apartment"           "ground_floor"        "half_basement"
##  [4] "loft"                "maisonette"          "other"
##  [7] "penthouse"           "raised_ground_floor" "roof_storey"
## [10] "terraced_flat"
```

So we shall introduce a new level for the `N/A` values, called `"unknown"`. Note that, we do not use the pre-defined level `"other"` here as we interpret it as known flat type which is just not on the list of available choices.

Column `serviceCharge` - 2.58% `N/A` values

We will set the service charges for the `N/A` values to zero. The motivation is that, there are:

```
x <- arog_data$selected_data %>% filter(!is.na(serviceCharge))
sum(x$serviceCharge == 0)
```

```
## [1] 2496
```

zero values present, so we interpret the `N/A` values as defining the fact of no additional service charges.

Filtering outliers

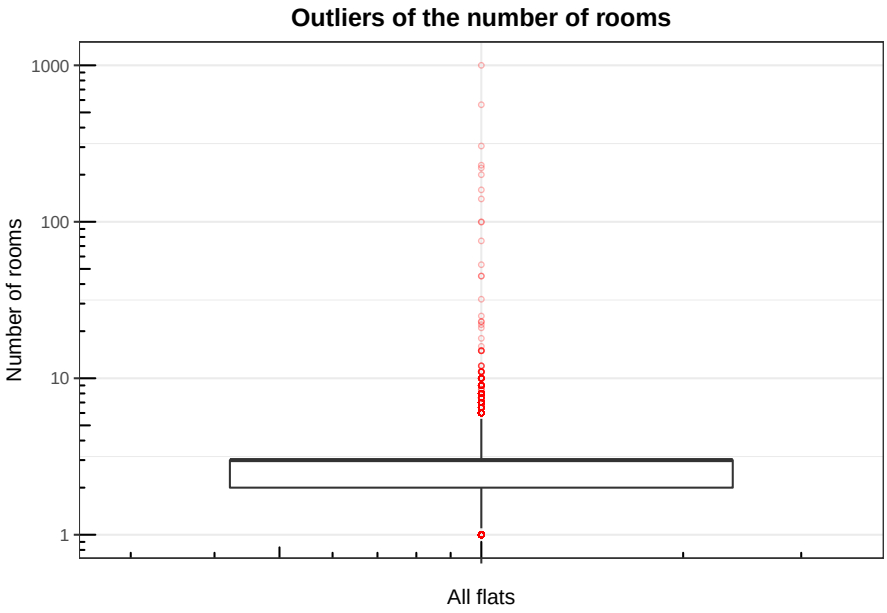
In this section we only considered the numeric/integer columns of the data set. The initial set of outliers per column is obtained using:

```
boxplot.stats(.)$out
```

However, not all of the obtained outlier values are the true outliers. It may be that some flats do stand out as examples of extraordinary property, and not due to owner input errors. This is why, for each of the column, the identified outliers are analyzed and it is then decided on how much of them is to be removed.

Column: `noRooms`

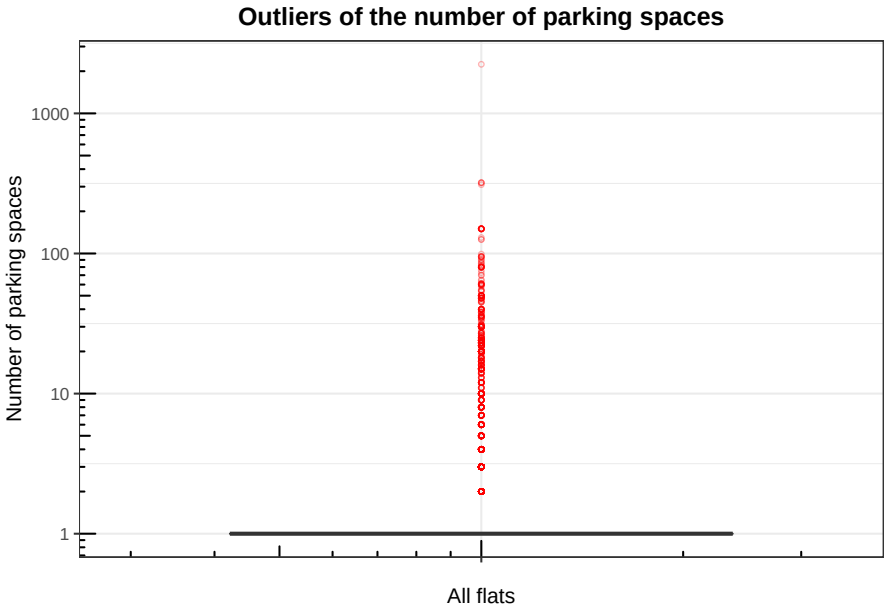
The `noRooms` column has 6038 outliers, see the plot:



We shall remove all the rows with `noRooms` outside the interval [1, 20].

Column: `noParkSpaces`

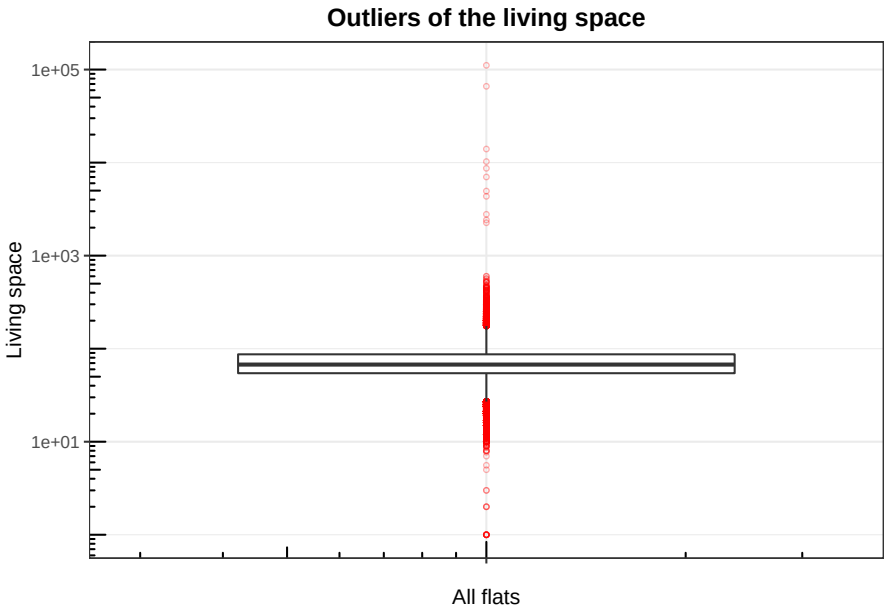
The `noParkSpaces` column has 10416 outliers, see the plot:



We shall remove all the rows with `noParkSpaces` outside the interval [0, 200].

Column: `livingSpace`

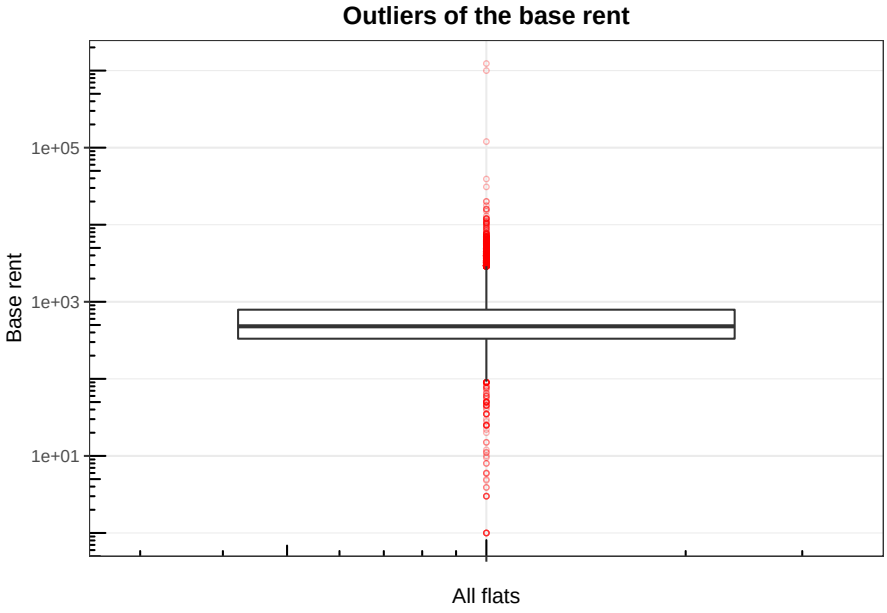
The `livingSpace` has 8830 outliers, see the plot:



We shall remove all the rows with `livingSpace` outside the interval [1, 1000].

Column: `baseRent`

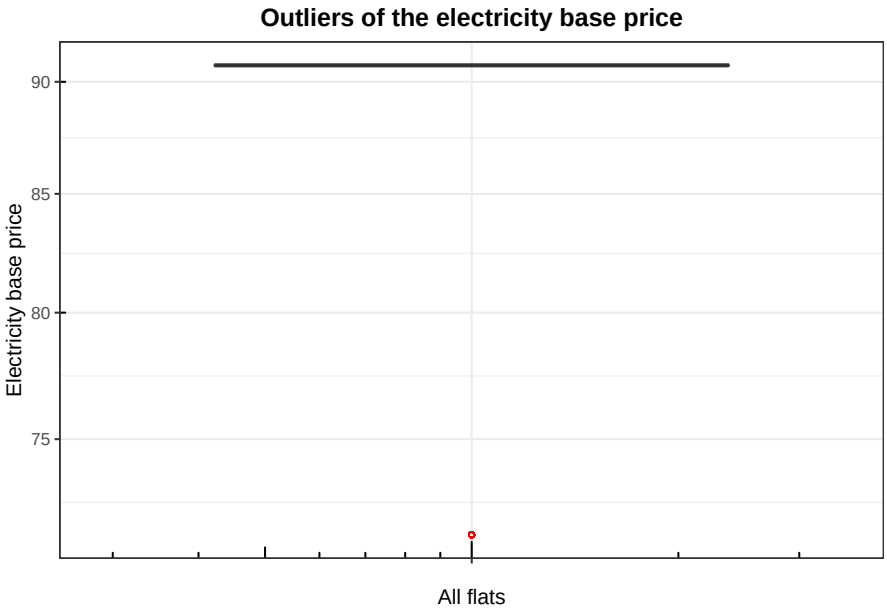
The `baseRent` has 10953 outliers, see the plot:



We shall remove all the rows with `baseRent` outside the interval $[100, 3 \times 10^4]$.

Column: `electricityBasePrice`

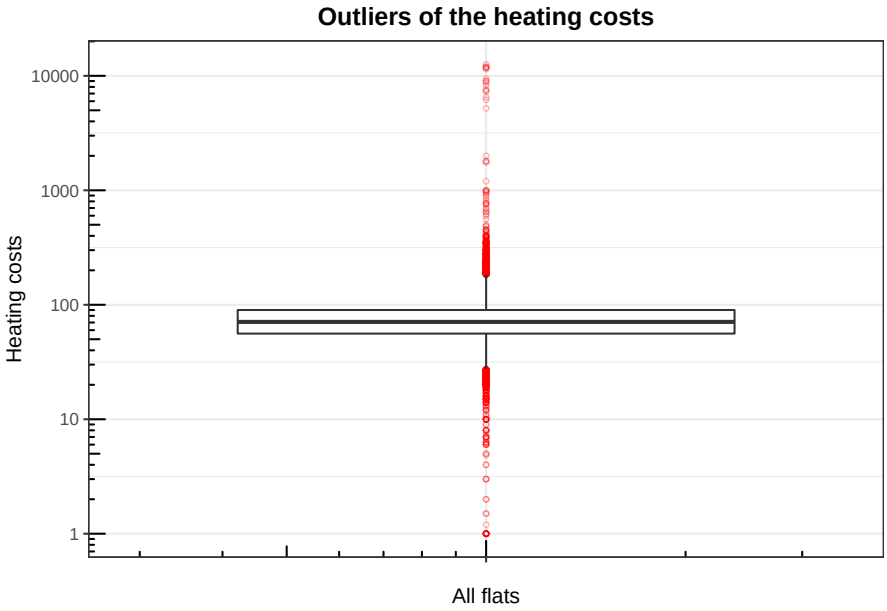
The `electricityBasePrice` has 4048 outliers, see the plot:



We shall remove all the rows with `electricityBasePrice` outside the interval [0, 100].

Column: `heatingCosts`

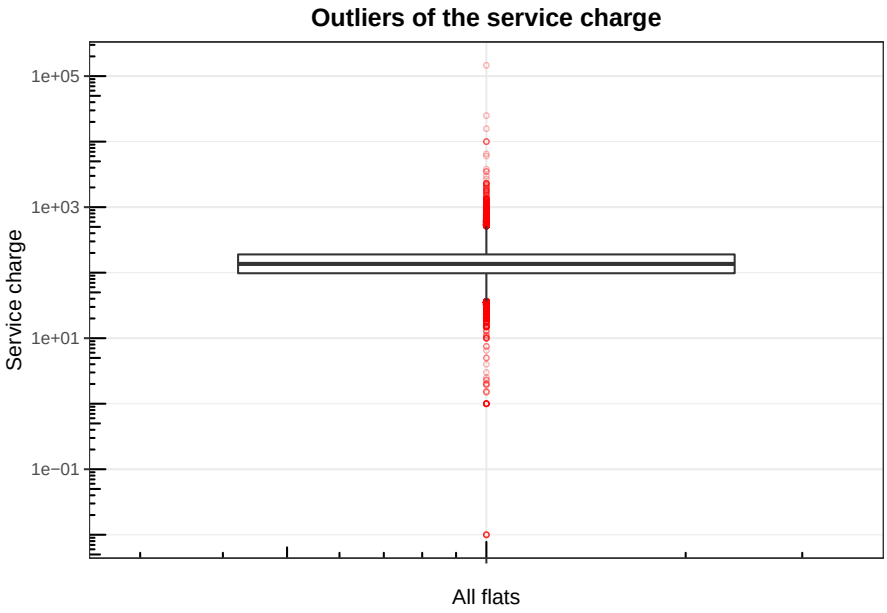
The `heatingCosts` has 4765 outliers, see the plot:



We shall remove all the rows with `heatingCosts` outside the interval [0, 3000].

Column: `serviceCharge`

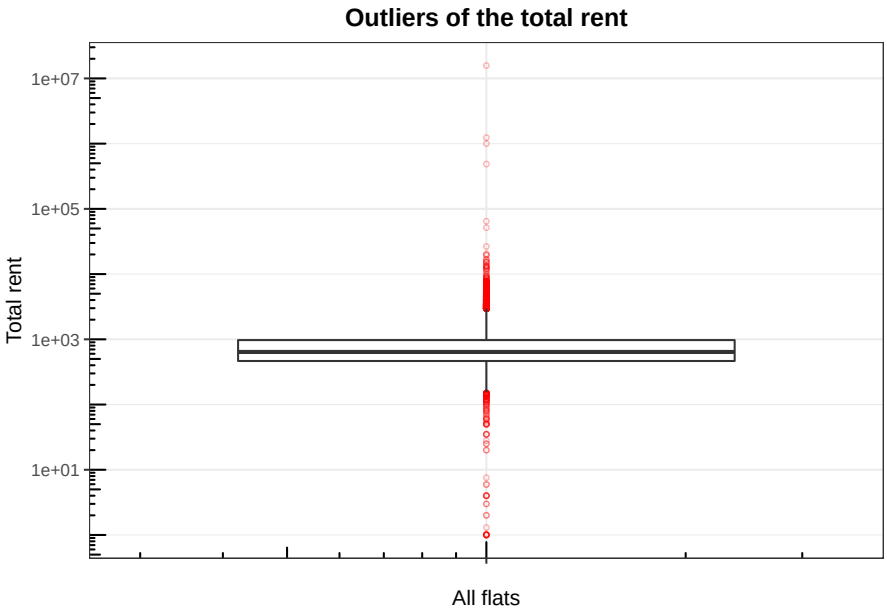
The `serviceCharge` has 6557 outliers, see the plot:



We shall remove all the rows with `serviceCharge` outside the interval $[10, 10^4]$.

Column: `totalRent`

The `totalRent` has 9366 outliers, see the plot:



We shall remove all the rows with `totalRent` outside the interval $[10, 10^5]$.

Fixing inconsistencies

In addition to the data alternations done above we have also done the following:

- Re-setting the number of floors:
  - `half_basement` –`floor` $= -1$
  - `ground_floor` – `floor` $= 0$

  - `raised_ground_floor` –`floor` = 0
- Filter out flats:
  - Other than `"half_basement"`, `"other"`, and `"unknown"`; but with `floor` < 0
  - With zero `totalRent` values (207 entries)
- Fix wrong and convert scraping dates:
  - `"Sep18"` changes into `ymd("2018-09-22")`[5]
  - `"May19"` changes into `ymd("2019-05-10")`
  - `"Oct19"` changes into `ymd("2019-10-08")`
- Made sure that the integer-valued ("floor", "noParkSpaces", "noRooms") columns are rounded.

There may be more inconsistencies present in the data, for example we expect that:

```
totalRent = baseRent + electricityBasePrice + heatingCosts + serviceCharge
```

which may not be the case. Unfortunately due to the lack of time these were not analyzed further and thus may potentially influence the "accuracy" of the trained statistical model.

Restructuring data

There data set at hand does not have any complex structure. However, because we want to be able to do predictions per city and avoid cities with the same names within different lands and regions we shall combine the `regio` columns into a new single one, as follows:

```
  clean_arog_data <- clean_arog_data %>%
    unite("location", c("regio1", "regio2", "regio3"), remove=FALSE) %>%
    select(-regio1, -regio2, -regio3)
```

The resulting columns have values constructed according to the following pattern:

```
location = regio1 + "_" + regio2 + "_" + regio3
```

For example:

```
arog_data$wrangled_data$location[1:5]
```

```
## [1] Nordrhein_Westfalen_Essen_Karnap
## [2] Nordrhein_Westfalen_Steinfurt_Kreis_Emsdetten
## [3] Nordrhein_Westfalen_Bottrop_Lehmkuhle
## [4] Sachsen_Anhalt_Salzlandkreis_Schönebeck_Elbe
## [5] Sachsen_Chemnitz_Bernsdorf
## 8087 Levels: Baden_Württemberg_Alb_Donau_Kreis_Allmendingen ...
```

In addition we have rounded and turned into integer columns all the integer-valued columns of the data set:

```
c("floor", "noParkSpaces", "noRooms")
```

```
## [1] "floor"        "noParkSpaces" "noRooms"
```

Wrangled data set

Let us now summarize the resulting clean data:

```
## # A tibble: 22 x 3
##    `Column name`          `N/A count` `N/A percent`
##    <chr>                        <int>         <dbl>
##  1 hasKitchen                       0             0
```

[5] The `ymd(.)` function is provided by the `lubridate` package.

```
##  2 heatingType                    0            0
##  3 balcony                        0            0
##  4 lift                           0            0
##  5 garden                         0            0
##  6 cellar                         0            0
##  7 noParkSpaces                   0            0
##  8 livingSpace                    0            0
##  9 typeOfFlat                     0            0
## 10 noRooms                        0            0
## 11 floor                          0            0
## 12 condition                      0            0
## 13 newlyConst                     0            0
## 14 interiorQual                   0            0
## 15 energyEfficiencyClass          0            0
## 16 location                       0            0
## 17 baseRent                       0            0
## 18 electricityBasePrice           0            0
## 19 heatingCosts                   0            0
## 20 serviceCharge                  0            0
## 21 totalRent                      0            0
## 22 date                           0            0
```

As one can notice, the dat set size has been reduced from 198332 to 162742. The major reason for that is excluding the rows with the `N/A` values of the `totalRent` column. Let us recall that the number of such raws was 15.01% of the data set, e.g. 29770 rows. It now remains to notice that $198332 - 29770 = 168562 > 162742$. The remaining delta of 5820 rows ($\approx 2.9\%$ of data) is explained by cleaning the `floor`/`typeOfFlat` columns, filtering-out outliers, and etc.

The data has been cleaned but we can expect that there is some noise in the data which we have not addressed. We might get more data-quality insights when we perform data analysis in the subsequent sections.

Splitting data

To facilitate supervised learning, the wrangled data is split into the `modeling`, 90% of data, and `validation`, 10% of data, sets. The former will be used for training statistical model(s) and the latter for the model(s) validation. Note that, for the sake of subsequent cross validation during modeling part, we further split the `modeling` set into the `training`, 80% thereof, and `testing`, 20% thereof, sets.

We split the data in the following steps:

1. The data is randomly split into to parts according to the specified ratio:

```
test_index <- createDataPartition(y = data_set$totalRent, times = 1,
                                  p = ratio, list = FALSE)
```

2. The `test_index` rows are the candidates for the `testing`/`validation` set rows
3. The factorized column values of the `testing`/`validation` set are considered:

```
str_data <- capture.output(str(arog_data$wrangled_data))
str_replace_all(str_subset(str_data, "Factor"), "levels.*","levels ...")
```

```
## [1] " $ heatingType          : Factor w/ 14 levels ..."
## [2] " $ typeOfFlat           : Factor w/ 11 levels ..."
## [3] " $ condition            : Factor w/ 11 levels ..."
## [4] " $ interiorQual         : Factor w/ 5 levels ..."
## [5] " $ energyEfficiencyClass: Factor w/ 10 levels ..."
## [6] " $ location             : Factor w/ 8087 levels ..."
```

4. The rows with the values not present in the `testing/modeling` set are dropped
5. The `testing/modeling` set consists of rows absent in the `testing/validation` set

The procedure above ensures that the `testing/validation` set can always be evaluated on a model trained on the `testing/modeling` set. For more details, see the `create_arog_data` and `split_train_test_sets` functions located in the `apartment_rental_project.R` script.

The resulting set sizes are as follows:

- `modeling` – 133902 rows, 82.3% of data
  - `training` – 117820 rows, 88% of `modeling` set
  - `testing` – 16082 rows, 12% of `modeling` set
- `validation` – 16082 rows, 9.9% of data

As expected, due to returning `testing/validation` set rows to the `testing/modeling` set for consistency, the desired set ratios are biased. The `validation` set size is almost as prescribed (10% of data), but the `testing` set size is affected more significantly[6]. Yet, we see no issue as the `testing` set is still $> 10\%$ of the `modeling` set, which should be enough for performing cross validation.

Data analysis

In this sections we analyze the `training` subset of the original data set only, as we assume that this is the only data available for building the prediction models. The motivation behind is that we want to avoid influencing the model testing and validation results. This is done under a, not-verified, assumption that the the `testing` set, follows the same probability distribution of the conditional probability of interest as the `validation` set. In the *"Results"* section we may come back to this assumption in case the accuracy of the developed statistical model(s) on the `validation` set will turn out to be insufficient.

In this section we shall use data visualization and other techniques to investigate the properties of the data we could use to build the prediction model. In the remainder of the section we analyze:

1. Possible `timing`/"scraping date" effects
2. Possible `flat count` effects
3. Possible `location` effects
4. Predictor's correlation and PCA

and conclude the section with a short summary of our findings.

Possible `timing`/"scraping date" effects

Let us consider any possible effects introduced by the scraping date. In essence, the goal of this section is to understand whether:

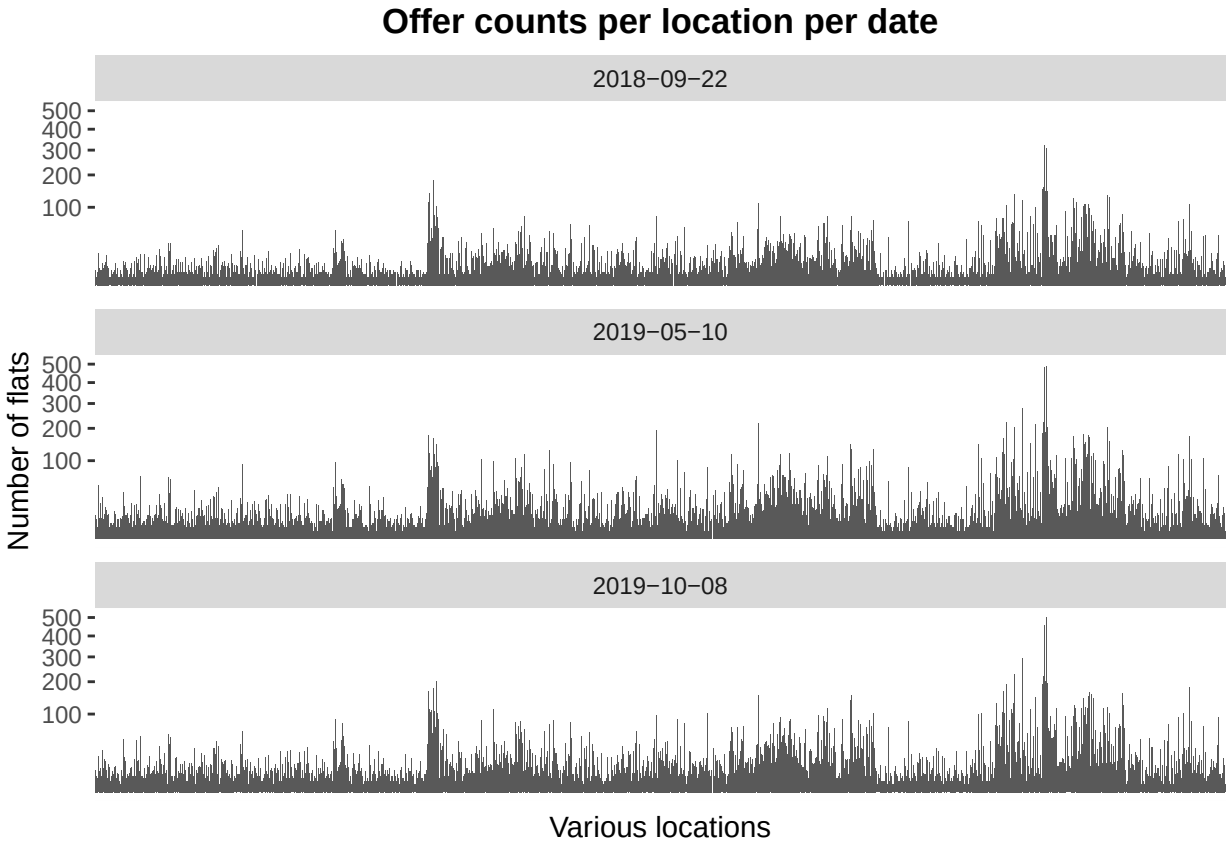
1. We shall keep the data scraped on different date distinct, and have the `date` column as a predictor, or
2. We could consider the combined statistics for all the data ignoring the `date` field as a predictor

We answer this question based on the analysis of "Flat offers per `date`", "Flat counts per `location` per `date`", and "Average `totalRent` per `date`"

Flat offers per `date`

Let us consider the number of flat offers per location per date:

[6]The requested `testing` set size was 20% of the `modeling` set.

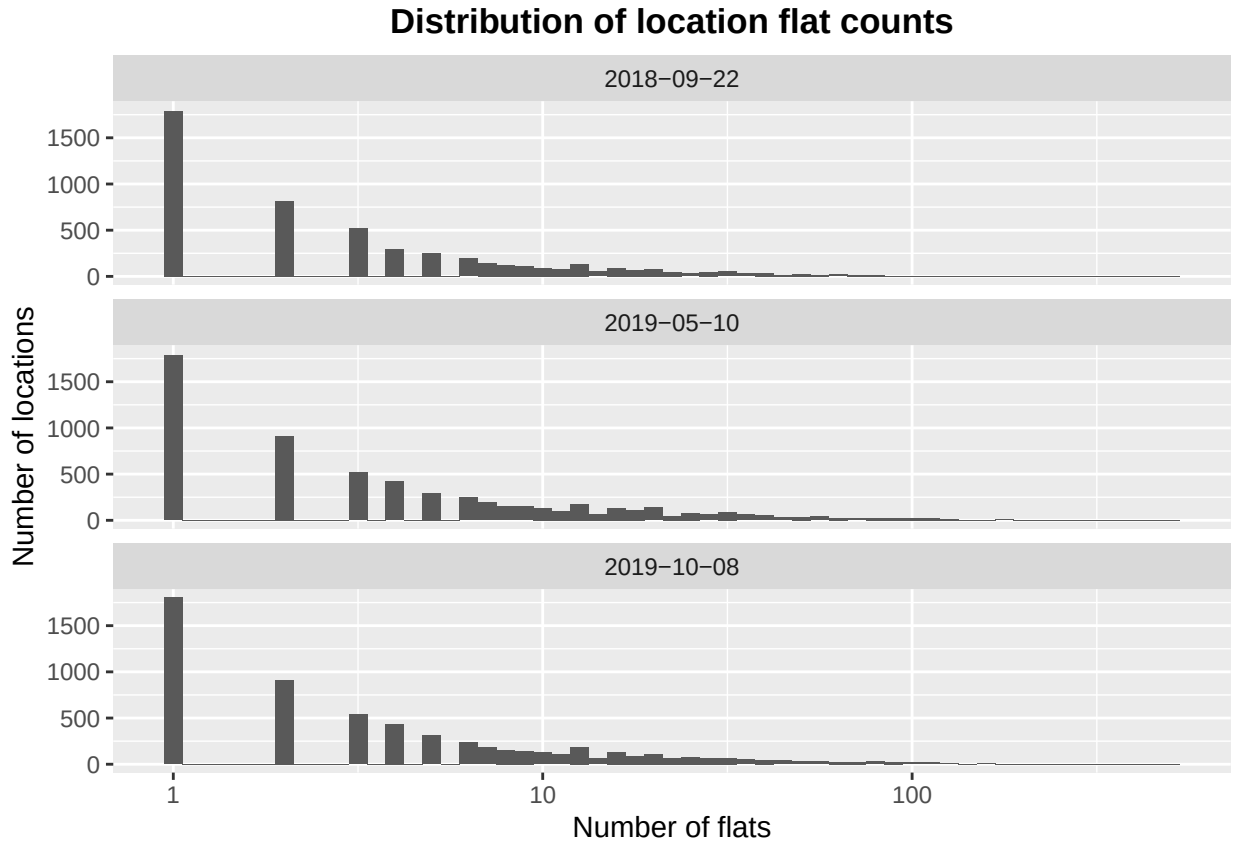


The number of flats listed by location seems to follow the same pattern on all of the three data scraping dates.

It seems like we may ignore the `date` column and consider the joint statistics. To have more solid grounds for that, let us investigate the flat counts per `location` per `date`.

Flat counts per `location` per `date`

The distribution of flat counts per `location` indicates that there are a lot of locations with just one flat. However, there are also a few locations with a "large" (> 100) number of flat offers.



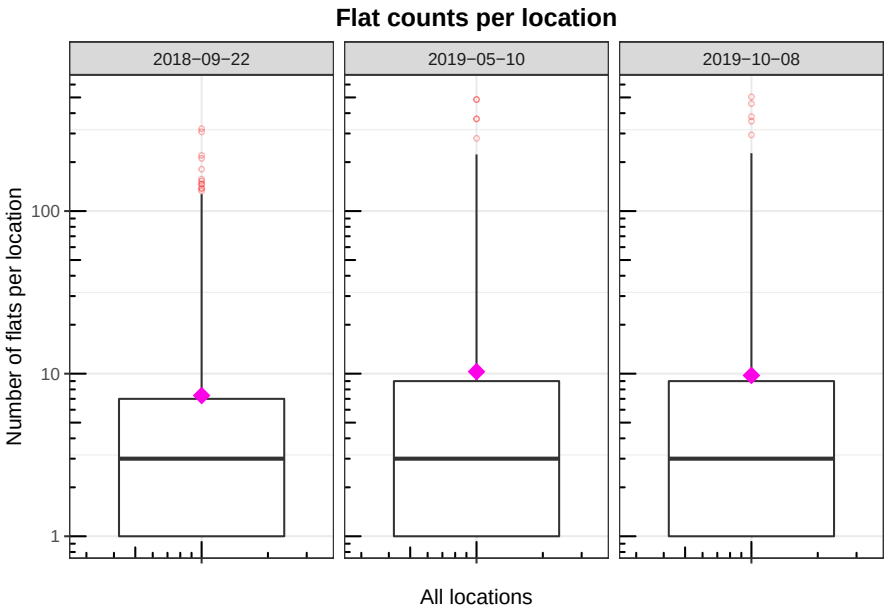
The median numbers of flats per location are equal for all the dates:

```
## # A tibble: 3 x 2
##   date       median
##   <date>      <dbl>
## 1 2018-09-22      3
## 2 2019-05-10      3
## 3 2019-10-08      3
```

The average numbers of flats per location for the last two scrapes are equal, and for the first one is somewhat smaller:

```
## # A tibble: 3 x 2
##   date       average
##   <date>       <dbl>
## 1 2018-09-22       7
## 2 2019-05-10      10
## 3 2019-10-08      10
```

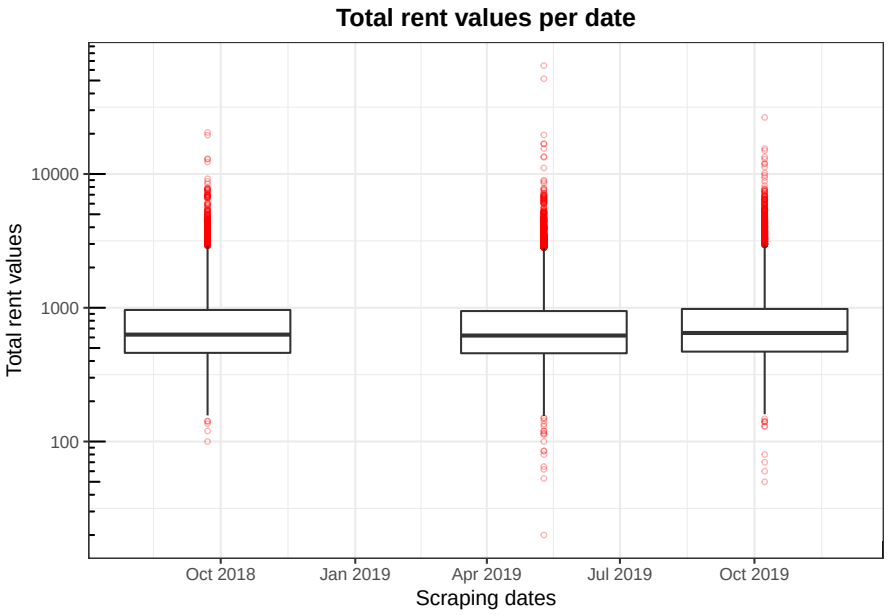
Overall, the number of flats per location seems to be stable from one date to another:



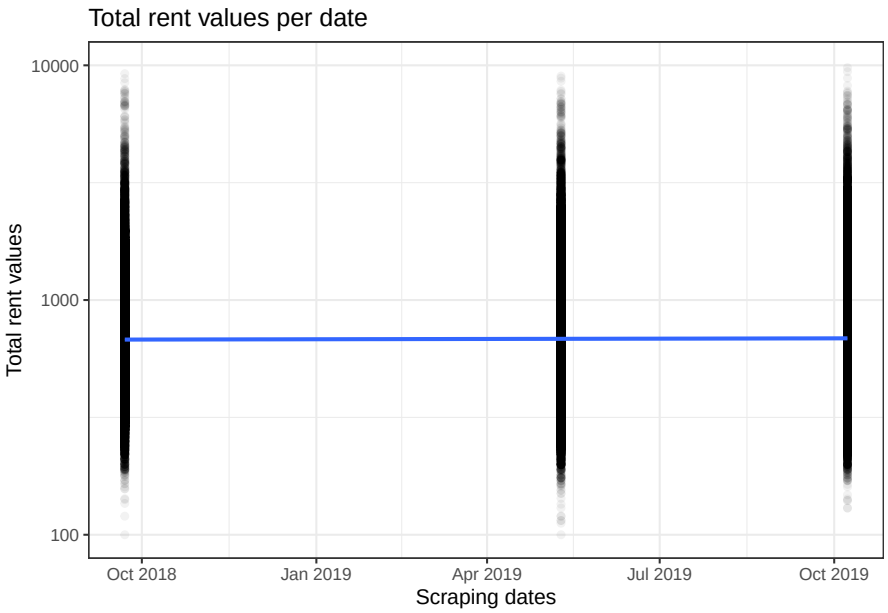
It seems like we may ignore the `date` column and consider the joint statistics. To have more solid grounds for that, let us investigate the average `totalRent` per `date`.

Average `totalRent` per `date`

Let us plot the `totalRent` per `date`:



As we see the data seems to be distributed similarly, moreover the does not seem to be any trend in average `totalRent` per `date`, as computed with `geom_smooth(method="lm")`:



There does not seem to be any global[7] `timing` effect in `totalRent` related to the scraping date.

Conclusion: We may ignore the `date` column and consider the joint statistics for all the dates.

Possible `location` effects

Let us consider any possible effects introduced by the location. In essence, the goal of this section is to understand whether:

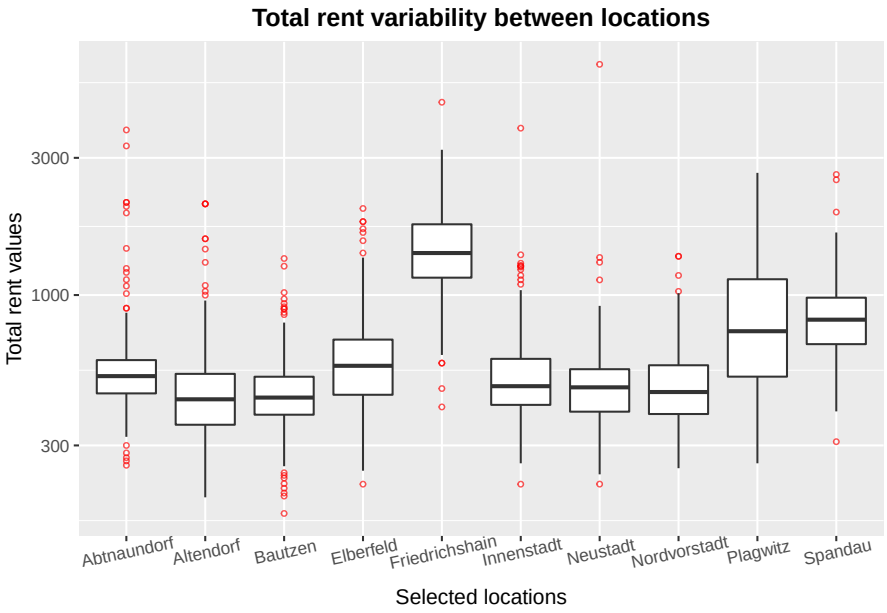
1. The `totalRent` values are `location` dependent
   - Suggests using the `location` column as a predictor
2. The offered flat counts per `location`:
   1. Have influence on the number of `totalRent` value outliers
      - Suggests using Regularization in statistical modeling
   2. Are correlated with the `totalRent` values
      - Facilitates using the `location` column as a predictor

We answer this question based on the analysis of "Average `totalRent` per `location`", "Min/Max `totalRent` per `location` flat count", and "Average `totalRent` per `location` flat count".

Average `totalRent` per `location`

Let us consider the variability of the `totalRent`, for several randomly chosen locations, with > 100 offers:

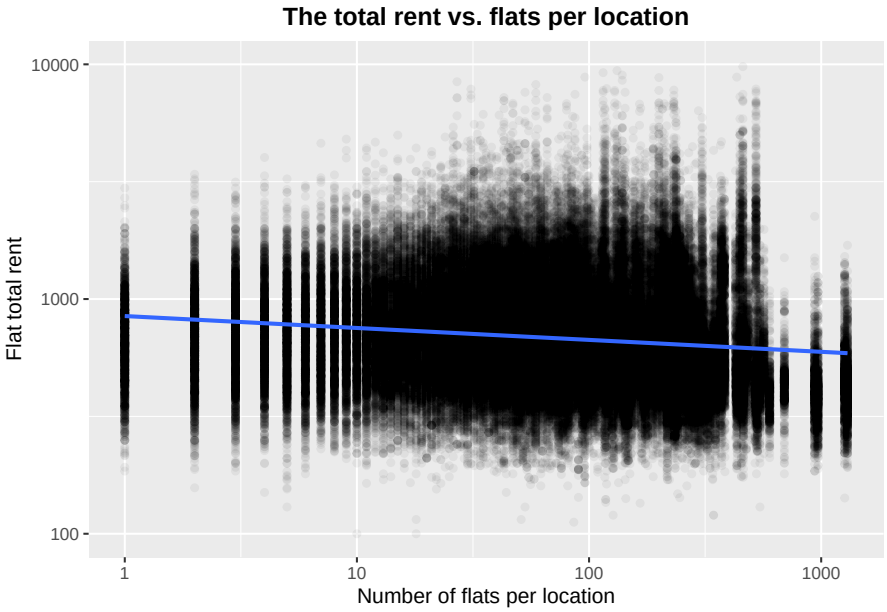
[7] There may be some location specific timing effects, but we do not consider them due to the lack of time.



Conclusion: Locations differ quite significantly in their `totalRent` – this is a `location` effect.

Average `totalRent` per `location` flat count

Let us plot the `totalRent` per location flat count, ordered by the count. Also to show the trend we will use `ggplot` with `geom_smooth(method = 'gam')`.



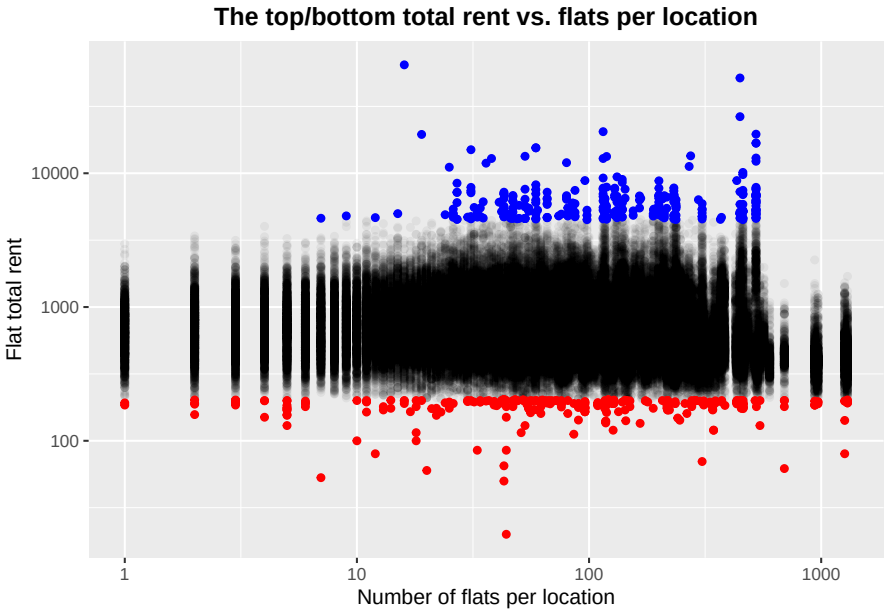
Conclusion: There is a trend in that the places with more flat offers have on-average lower `totalRent` values - this is a `number of offers` effect.

Min/Max `totalRent` per `location` flat count

Let us the maximum and minimum `totalRent` values relative to the flat count per `location`. In other words, each `location` has a number of flats offered. If we now combine the flat offers per location into a single

totally ordered *flat-offers range*, we can plot how many locations there are with that many orders. Or we can plot the `totalRent` values offered in locations with the same number of flats. The latter will help us to see if the extreme `totalRent` values, like 300 `top` and 300 `bottom` priced flats are more likely to be encountered in locations with lower or larger number of flat offers.

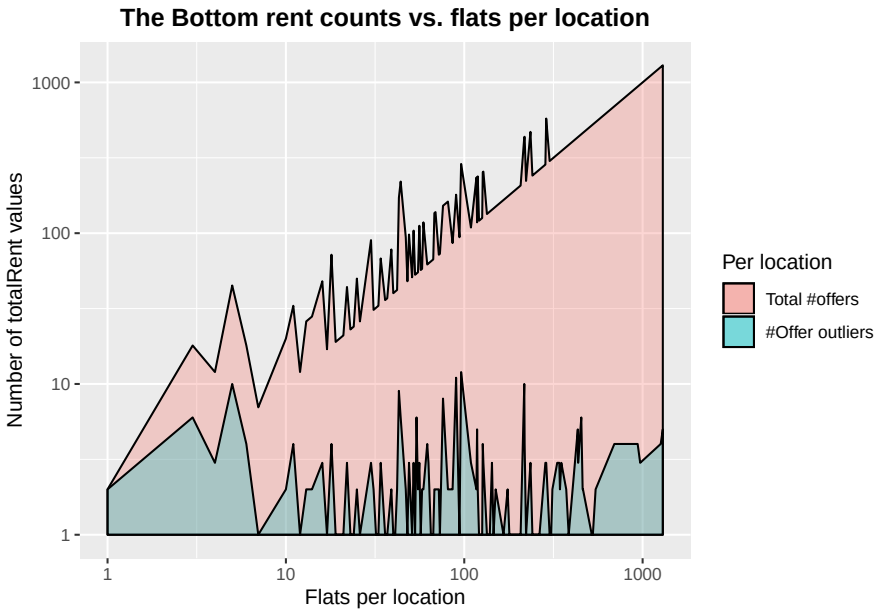
If we indicate `top` and `bottom` priced flats on the plot then we can observe:



that it seems that the `top`/`bottom` priced rentals are, almost uniformly, spread all over the *flat-offers range*.

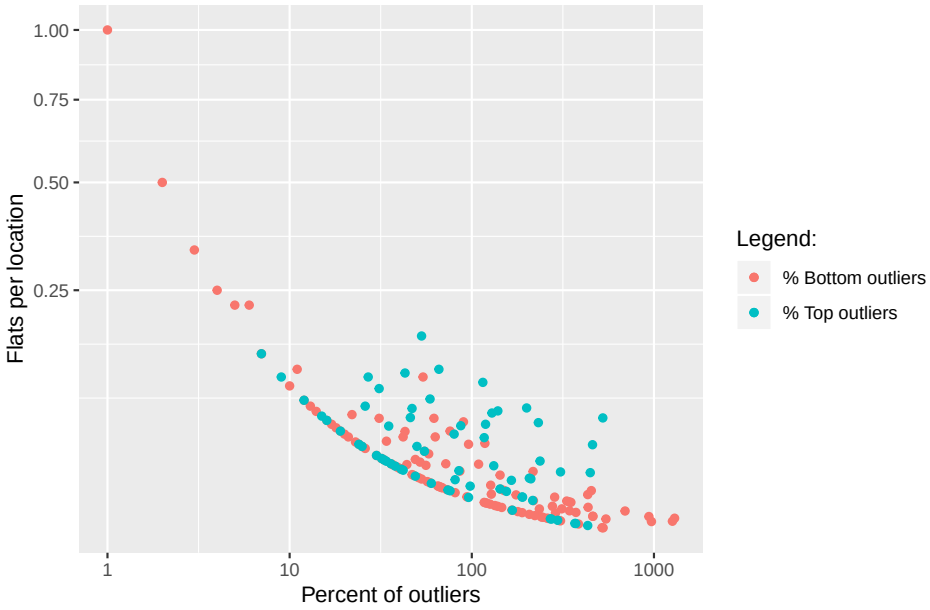
To get a better view on data, considering `top` and total `totalRent` counts versus the *flat-offers range*:

Considering `bottom` and total `totalRent` counts versus the *flat-offers range*:



The total count is computed as the sum of offers in the locations with the same number of offers. Effectively it is equal to `"number of offers in location"` × `"number of locations with this number of offers"`. This explains almost line-like behavior of the `"Total #offers"` plots. The irregularities are caused by having more than one location with the given number of flat offers (mind the `log10` scale of the y axis).

The number of `bottom` outliers is ≈ uniform across the *flat-offers range*. The number of `top` outliers looks somewhat biased to be larger for locations with more offers. Let us plot the outliers to total ratio:



The plot above has, even though contains quite some "noise" for 50-200 flats per location, indicates the common trend of having proportionally less outliers in locations with more rental offers.

Conclusion 1: It is less likely to have a cheap rentals in locations with large number of offers. **Conclusion 2:** It is less likely to have an expensive rentals in locations with a larger number of offers.

Predictor's correlation and PCA

In this case-study we have selected 21 potential predictors:

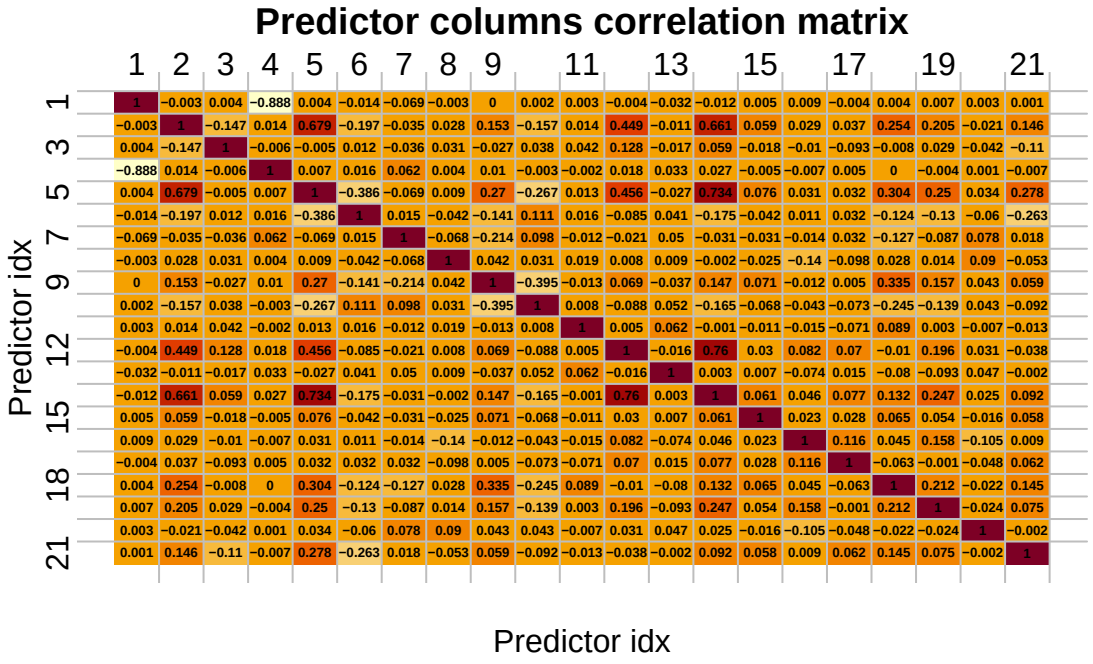
```
##  [1] "hasKitchen"           "heatingType"          "balcony"
##  [4] "lift"                 "garden"               "cellar"
##  [7] "noParkSpaces"         "livingSpace"          "typeOfFlat"
## [10] "noRooms"              "floor"                "condition"
## [13] "newlyConst"           "interiorQual"         "energyEfficiencyClass"
## [16] "location"             "baseRent"             "electricityBasePrice"
## [19] "heatingCosts"         "serviceCharge"        "date"
```

As we have discussed in the `timing` effects section the `date` column seems to be eligible for exclusion. However, to give this a more formal ground and also to reduce the number of predictors even further let us consider the correlation matrix of the training data columns:

```
#First create the predictors matrix, from the wrangled data
predictors_mtx <- arog_data$wrangled_data %>%
  select(-totalRent) %>%
  data.matrix(.)

#Next compute the correlations matrix and round off the values
corr_mtx <- predictors_mtx %>%
  cor(.) %>% round(., 3)
```

When visualized, we see that there is quite a few predictors with strong correlation:



For instance, `heatingType` (idx: 2) is strongly correlated with `garden` (idx: 5), `typeOfFlat` (idx: 9), `condition` (idx: 12), `interiorQual` (idx: 14), `electricityBasePrice` (idx: 18), and `date` (idx: 21).

Motivated by the correlation analysis, we can use the Principle Component Analysis (PCA) to see if we have a distance preserving transformation of our data that gives us a new feature-space basis in which most of the data variability is explained by fewer predictors:

```
pca_result <- prcomp(predictors_mtx)
summary(pca_result)
```

```
## Importance of components:
##                             PC1       PC2       PC3      PC4      PC5      PC6
## Standard deviation     2101.8878 459.05602 148.70605 68.76676 41.45316 19.46240
## Proportion of Variance    0.9485   0.04524   0.00475  0.00102  0.00037  0.00008
## Cumulative Proportion     0.9485   0.99371   0.99846  0.99947  0.99984  0.99992
##                            PC7  PC8   PC9  PC10  PC11  PC12  PC13  PC14   PC15
## Standard deviation     16.96046 4.49 3.968 3.475 3.463 2.446 2.242 1.343 0.6259
## Proportion of Variance  0.00006 0.00 0.000 0.000 0.000 0.000 0.000 0.000 0.0000
## Cumulative Proportion   0.99998 1.00 1.000 1.000 1.000 1.000 1.000 1.000 1.0000
##                           PC16   PC17   PC18   PC19   PC20   PC21
## Standard deviation     0.502 0.4409 0.4353 0.3871 0.3665 0.2265
## Proportion of Variance 0.000 0.0000 0.0000 0.0000 0.0000 0.0000
## Cumulative Proportion  1.000 1.0000 1.0000 1.0000 1.0000 1.0000
```

As one can see from the PCA summary above, according to Cumulative Proportion of Variance, it shall suffice to use the first two principle components (`PC1`, and `PC2`) to explain $\approx 99.3\%$ of the data.

Data analysis summary

...

Modeling approach

Results

Conclusions

Future work

Check for introducing any bias by data wrangling.

Appendix A: The complete list of data set columns

Hereby we present the complete list of columns from the original 'Apartment rental offers in Germany' dataset:

```
##  [1] "regio1"                   "serviceCharge"
##  [3] "heatingType"              "telekomTvOffer"
##  [5] "telekomHybridUploadSpeed" "newlyConst"
##  [7] "balcony"                  "electricityBasePrice"
##  [9] "picturecount"             "pricetrend"
## [11] "telekomUploadSpeed"       "totalRent"
## [13] "yearConstructed"          "electricityKwhPrice"
## [15] "scoutId"                  "noParkSpaces"
## [17] "firingTypes"              "hasKitchen"
## [19] "geo_bln"                  "cellar"
## [21] "yearConstructedRange"     "baseRent"
## [23] "houseNumber"              "livingSpace"
## [25] "geo_krs"                  "condition"
```

```
## [27] "interiorQual"             "petsAllowed"
## [29] "streetPlain"              "lift"
## [31] "baseRentRange"            "typeOfFlat"
## [33] "geo_plz"                  "noRooms"
## [35] "thermalChar"              "floor"
## [37] "numberOfFloors"           "noRoomsRange"
## [39] "garden"                   "livingSpaceRange"
## [41] "regio2"                   "regio3"
## [43] "description"              "facilities"
## [45] "heatingCosts"             "energyEfficiencyClass"
## [47] "lastRefurbish"            "date"
```

Appendix B: Data set column descriptions

Here is the list of the initially considered data set columns with the descriptions thereof:

1. `hasKitchen` – has a kitchen
2. `balcony` – does the object have a balcony
3. `cellar` – has a cellar
4. `lift` – is elevator available
5. `floor` – which floor is the flat on
6. `garden` – has a garden
7. `noParkSpaces` – number of parking spaces
8. `livingSpace` – living space in sqm
9. `condition` – condition of the flat
10. `interiorQual` – interior quality
11. `regio1` – Bundesland
12. `regio2` - District or Kreis, same as geo krs
13. `regio3` – City/town
14. `noRooms` – number of rooms
15. `numberOfFloors` – number of floors in the building
16. `typeOfFlat` – type of flat
17. `yearConstructed` – construction year
18. `newlyConst` – is the building newly constructed
19. `heatingType` – Type of heating
20. `energyEfficiencyClass` – energy efficiency class
21. `heatingCosts` – monthly heating costs in €
22. `serviceCharge` – auxiliary costs such as electricity or Internet in €
23. `electricityBasePrice` – monthly base price for electricity in €
24. `baseRent` – base rent without electricity and heating
25. `totalRent` – total rent (usually a sum of base rent, service charge and heating cost)

26. `date` – time of scraping