

# PREDICTING THE HOUSE PRICE IN KING COUNTY, USA

## 1. Project objective

The main goal of the project is to construct a predicting model for the house prices in King County, USA. Whether we are going to buy or sell a house, we need to estimate its price to make a better decision. And Orange data mining software can give us an accurate estimate.

## 2. Data understanding

The dataset contains house sale prices for King County, which includes Seattle. It includes homes sold between May 2014 and May 2015.

Data source: Kaggle (<https://www.kaggle.com/harlfoxem/housesalesprediction/home>)

Data description: 21600 records with 14 attributes

- id = a notation for a house
- **date** = Date house was sold (Categorical)
- price = Price is prediction target
- bedrooms = Number of Bedrooms/House
- bathrooms = Number of bathrooms
- sqft\_living = square footage of the home
- sqft\_lot = square footage of the lot
- floors = Total floors (levels) in house
- **waterfront** = House which has a view to a waterfront (categorical)
- view = Has been viewed
- condition = How good the condition is overall
- grade = overall grade given to the housing unit, based on King County grading system
- sqft\_above = square footage of house apart from basement
- sqft\_basement = square footage of the basement
- yr\_built = Built Year
- yr\_renovated = Year when house was renovated
- **zipcode** = zipcode (categorical)
- lat = Latitude coordinate
- long = Longitude coordinate
- sqft\_living15 = Living room area in 2015(implies– some renovations) This might or might not have affected the lotsize area
- sqft\_lot15 = lotSize area in 2015 (implies– some renovations)

## 3. Data Preparation

- Convert Yr\_built and Yr\_renovated to House\_age and House\_NewAge in Excel
- Statistics features: checking missing value, min, max. There is no missing value in the data set. But I noticed some weird values (33 bedrooms in one house and no bathrooms in some houses....)
- Select row: I eliminated the records with wrong values

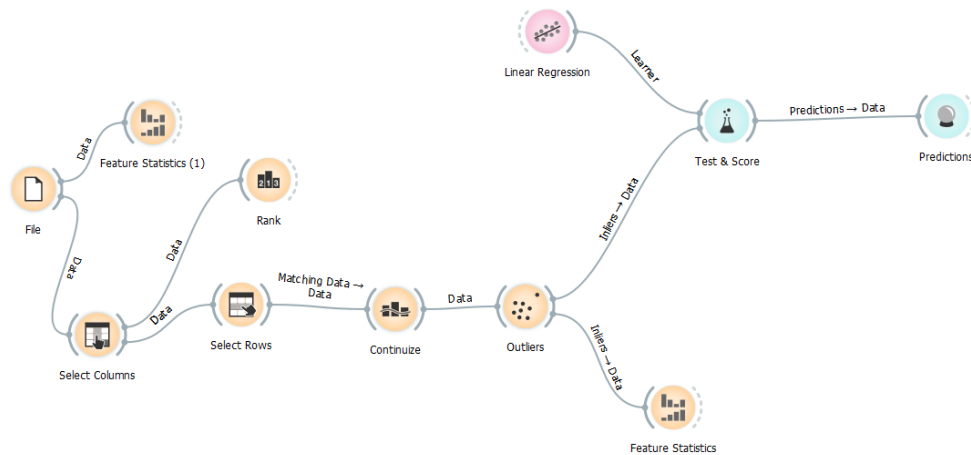
- Select column: this function helped me set role for the target feature (price) and eliminate some unnecessary attributes (Id and Date)
- Rank: using this widget to score the attributes according to their correlation with the price.

| Input  |      |              |                      |
|--|------|--------------|----------------------|
| <b>Features:</b> bedrooms, bathrooms, sqft_living, sqft_lot, floors, waterfront, view, condition, grade, sqft_above, sqft_basement, zipcode, sqft_living15, sqft_lot15, long, New_Age, Age_of_the_house, lat<br>(total: 18 features)<br><b>Target:</b> price |      |              |                      |
| Ranks  |      |              |                      |
|  | #    | Univar. reg. | RReliefF             |
| view   |      | nan          | 0.14788673991310056  |
| sqft_living15  |      | nan          | 0.08882213694560973  |
| zipcode  | 70.0 | nan          | 0.08143295789368377  |
| sqft_basement  |      | nan          | 0.08137431467649377  |
| bathrooms  |      | nan          | 0.08051113964939055  |
| floors   |      | nan          | 0.07708178908375866  |
| grade  |      | nan          | 0.075462770782035    |
| Age_of_the_house   |      | nan          | 0.0726465365809526   |
| New_Age  |      | nan          | 0.07261949166508619  |
| sqft_above   |      | nan          | 0.061685578029879236 |
| condition  |      | nan          | 0.05914658535841037  |
| sqft_living  |      | nan          | 0.053595897660015275 |
| lat  |      | nan          | 0.02789047775672913  |
| bedrooms   |      | nan          | 0.021016466587666947 |
| sqft_lot   |      | nan          | 0.019111711635617833 |
| long   |      | nan          | 0.013373059635296821 |
| waterfront   | 2.0  | nan          | 0.008965271270909259 |
| sqft_lot15   |      | nan          | 0.006083786452192738 |
| Output   |      |              |                      |
| <b>Features:</b> waterfront, zipcode, date, id, bedrooms, bathrooms, sqft_living, sqft_lot, floors, view (total: 10 features)<br><b>Target:</b> price  |      |              |                      |

- Continuize: to convert the categorical variables to dummies variables. In this case, the water front has 2 dummies variables and the zipcode has 70 variables.
- Outliers: helped me delete 217 outliers. Now, the data set has 21385 instances

## 4. Modeling

As the goal of this project is to predict how much a house should be sold, I chose Linear regression because it outputs the value of the variable as its prediction. The logistics regression can not be used in this case as it only outputs the probability of occurrence of an event as its prediction, for example, it can answer either Yes or No when being questioned whether a house should be sold at certain amount.



## 5. Results

| Model             | Details                               | MSE             | RMSE            | MAE        | R2    |
|-------------------|---------------------------------------|-----------------|-----------------|------------|-------|
| Linear Regression | with 12 attributes filtered from Rank | 27974455439.306 | 27974455439.306 | 101265.260 | 0.788 |
| Linear Regression | all selected features                 | 25970596539.379 | 161153.953      | 96320.299  | 0.807 |
| Ridge Regression  | alpha = 1                             | 25966489724.253 | 161141.211      | 96278.304  | 0.807 |
| Ridge Regression  | alpha = 100                           | 29202276362.621 | 170886.735      | 101017.186 | 0.783 |
| Ridge Regression  | alpha = 1000                          | 40696507192.143 | 201733.753      | 124411.262 | 0.697 |
| Lasso Regression  | alpha = 1                             | 25965721164.449 | 161138.826      | 96272.732  | 0.807 |
| Lasso Regression  | alpha = 100                           | 26067523286.259 | 161454.400      | 96179.150  | 0.806 |
| Lasso Regression  | alpha = 1000                          | 30667578590.013 | 175121.611      | 107794.491 | 0.772 |

Note:

- Sampling: using cross validation with number of folds: 10
- Lasso regression minimizes a penalized version of the least squares loss function with L1-norm penalty and Ridge regularization with L2-norm penalty.
- Alpha is the regularization strength. Regularization is designed to address the problem of overfitting and underfitting. To start with the overfitting, it means high variance and it is usually caused by a complicated function that creates a lot of unnecessary curves and angles unrelated to the data. This function fits to training data well but might cause poor results for the test set. On the

other hand, underfitting means low variance and a very simple model. This might also cause poor results too.

## **6. Reflection**

What went well

- The data is quite in good condition, no missing data, most of them are numeric
- Orange tutorials on YouTube, the Orange blog, and the Kaggel

What did not go Well:

- Statistics: As I took the statistics class 4-5 years ago and almost forgot anything
- The Zip Code: numeric/categorical value
- Pick a dataset: I tried so many datasets before coming up with the King County House Price Prediction. For example, the LA restaurants violations, USA Name Datasets, Credit Card Fraud Detection, CryptoCurrencyPrice .... Honestly I find it difficult to both learn about the Orange tools and the new dataset with unfamiliar business problem at the same time.