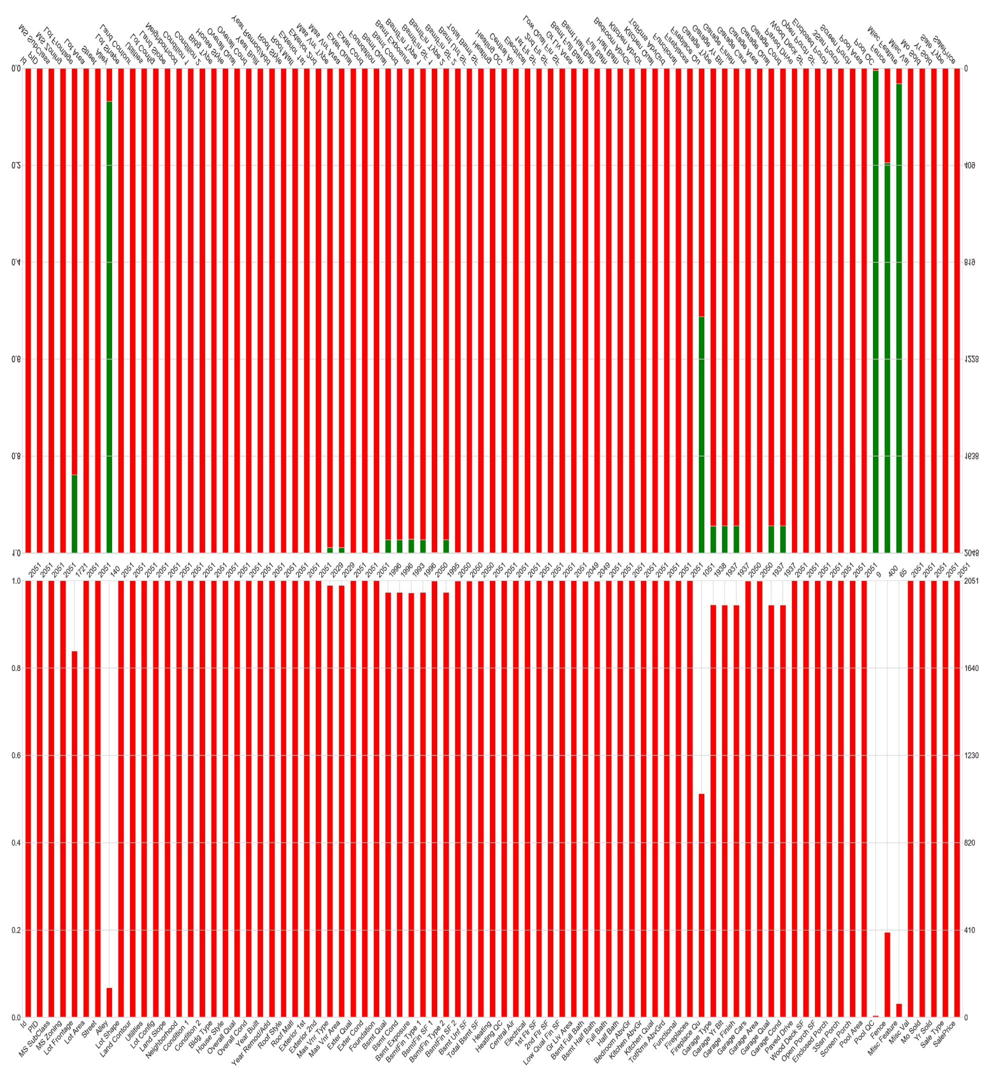
DSI Project 2

PREDICTION OF HOUSING PRICE IN AMES,IOWA

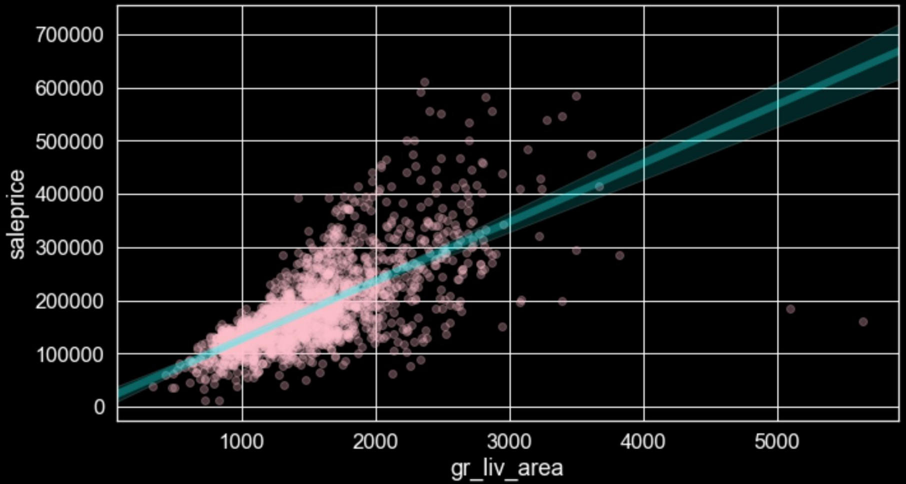
Presentation summary

1. Problem statement
2. Data Cleaning & Exploratory Data Analysis (EDA)
3. Pre-processing
4. Modelling
5. Model Evaluation
6. Conclusions & Recommendations



data

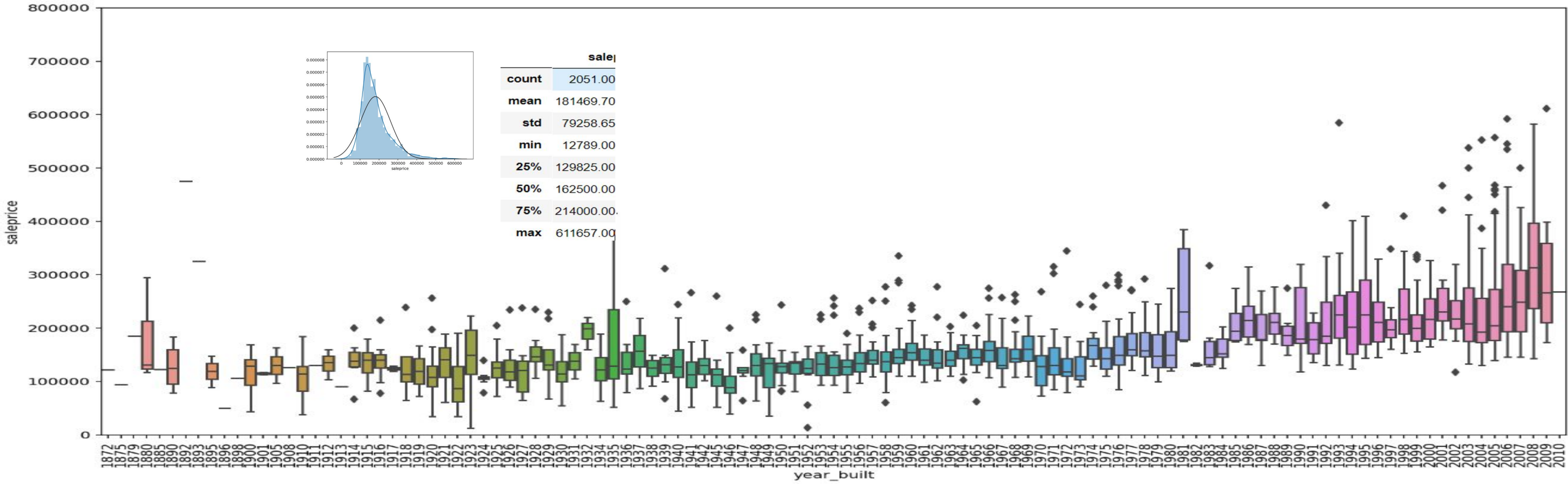
CLEANING



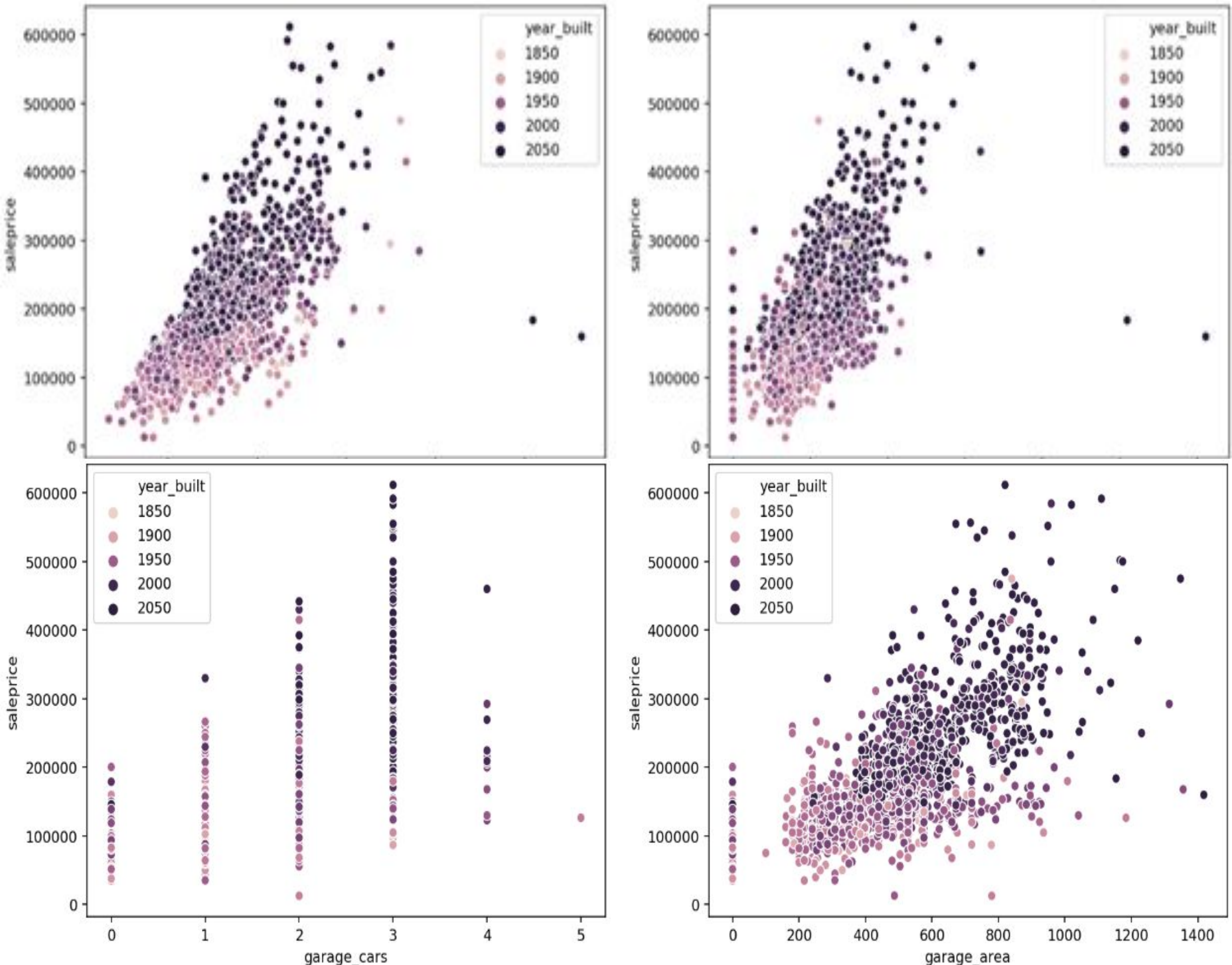
700000
600000
500000
400000
300000
200000
100000
0
saleprice
1000
2000
3000
4000
5000
gr_liv_area

EDA, Data Munching & Data Engineering

- Sales price is positively skewed and kurtosis show peakedness (ie. there are out'liars)
- Majority of the transactions were transacted between $130k to $250
- Sales has been increased steadily for more than century
- There are many features positively correlated to sales
- Some features exhibits unique characteristics



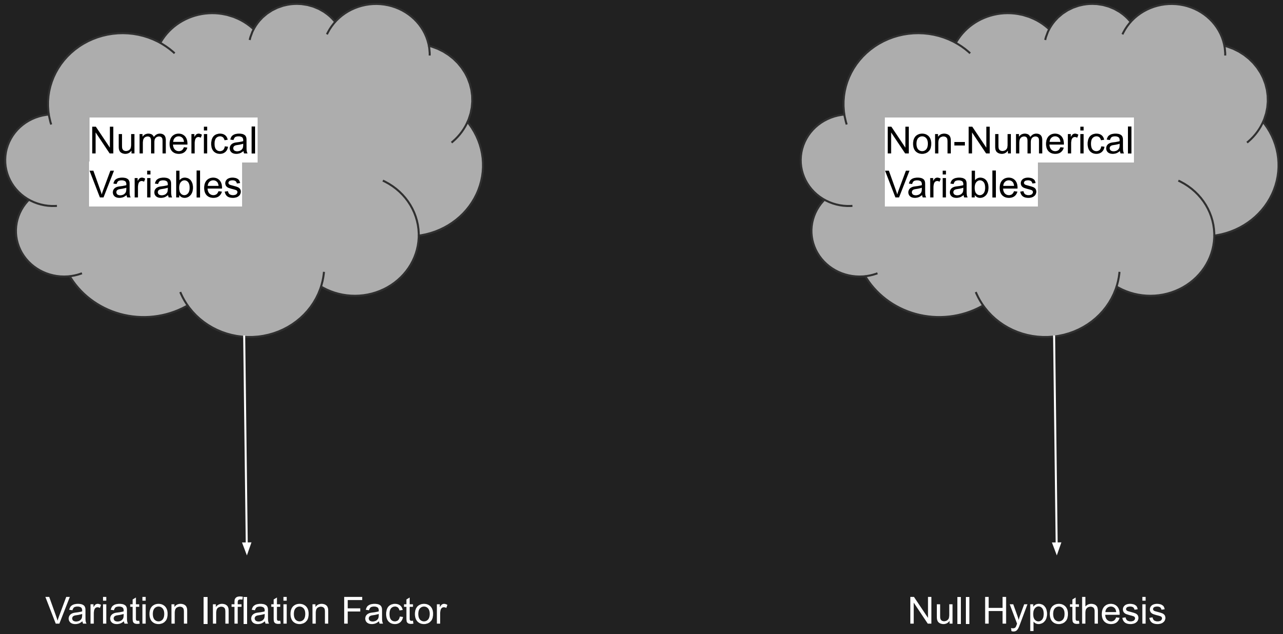
	sale
count	2051.00
mean	181469.70
std	79258.65
min	12789.00
25%	129825.00
50%	162500.00
75%	214000.00
max	611657.00



EDA, Data Munching & Data Engineering

Preprocessing

- Split training file into train/ validation sets to build an accurate model before scaling
- Apply one-hot encoding on selected categorical features
- Scale training and testing datasets excluding dummies ie. scaled numeric data only



Numerical Variables

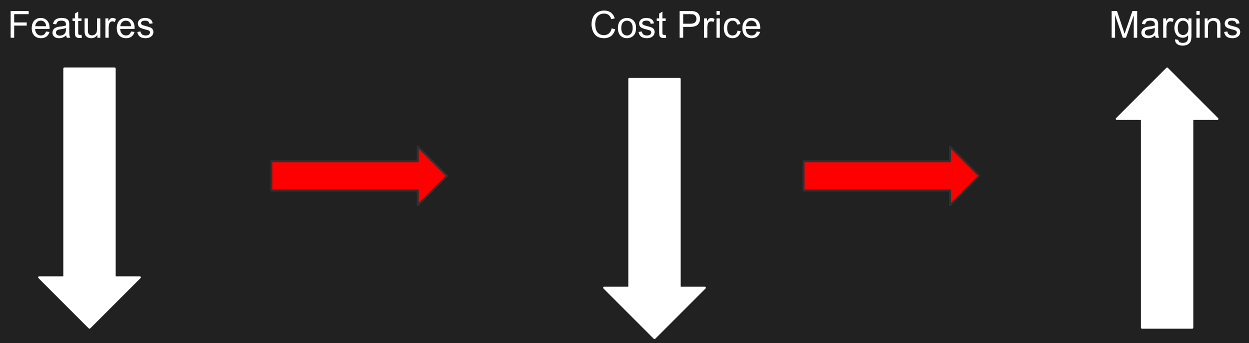
Variation Inflation Factor

Non-Numerical Variables

Null Hypothesis

Variation Inflation Factor

Goal: We want to drop features that are multicollinear

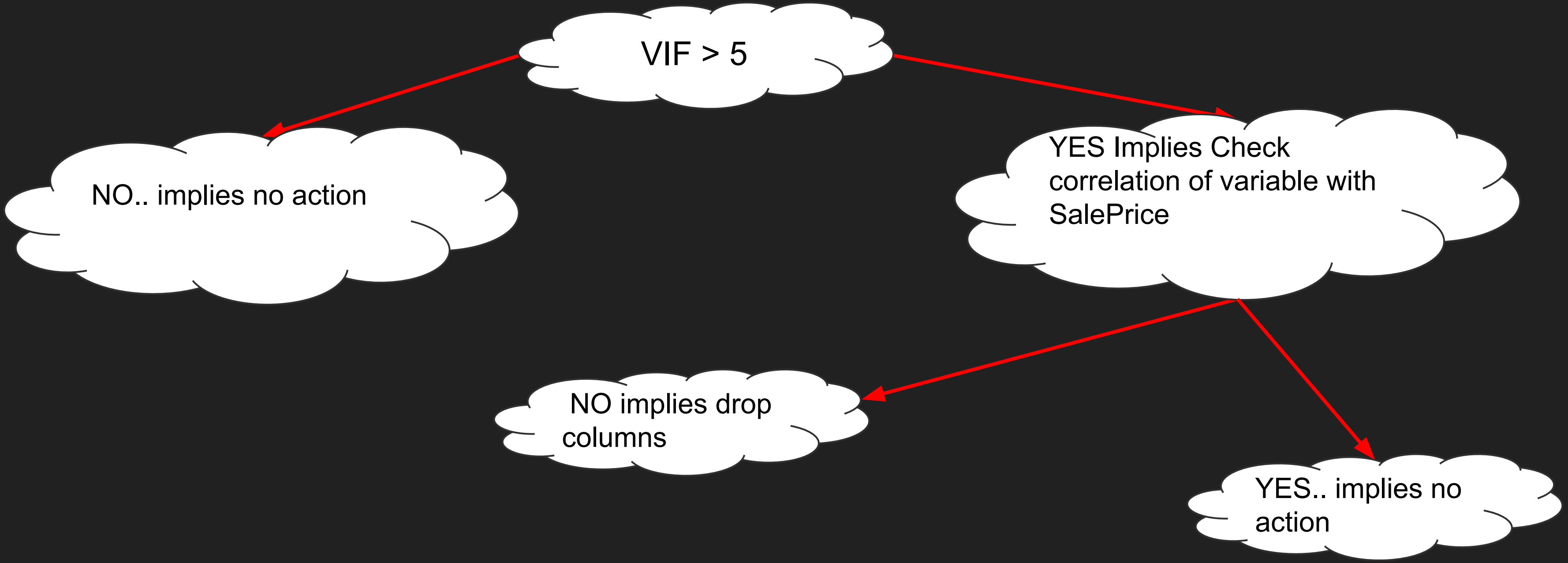


Features

Cost Price

Margins

Variation Inflation Factor



VIF > 5

NO.. implies no action

YES Implies Check correlation of variable with SalePrice

NO implies drop columns

YES.. implies no action

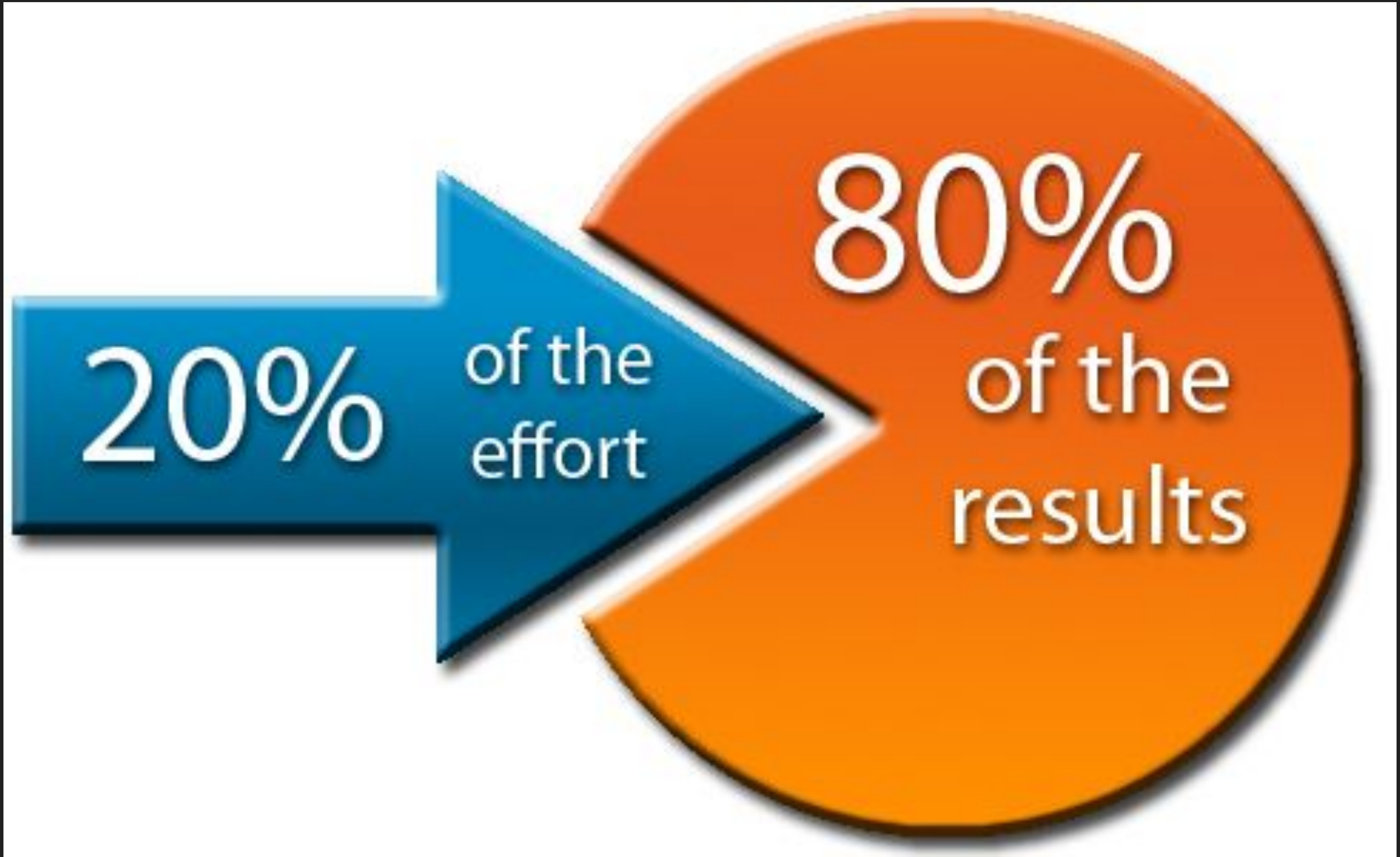
Chi Square Test

Null Hypothesis:

- **The selected feature has high multicollinearity with other variables and has to be discarded**

Alternate Hypothesis:

- **The selected feature has a low multicollinearity with other variables and it can be used for for our modelling**
  - **If p-value < 0.05 we reject the null hypothesis and include the feature in our modelling.**



20% of the effort

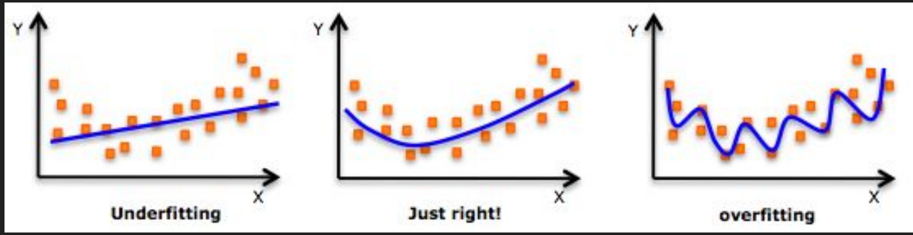
80% of the results

Feature selection

1. **Variation Inflation Factor(VIF)**
2. **Chi2 Test**
3. **Recursive Feature Elimination (RFE)**
4. **Built-in regularization from regression models**

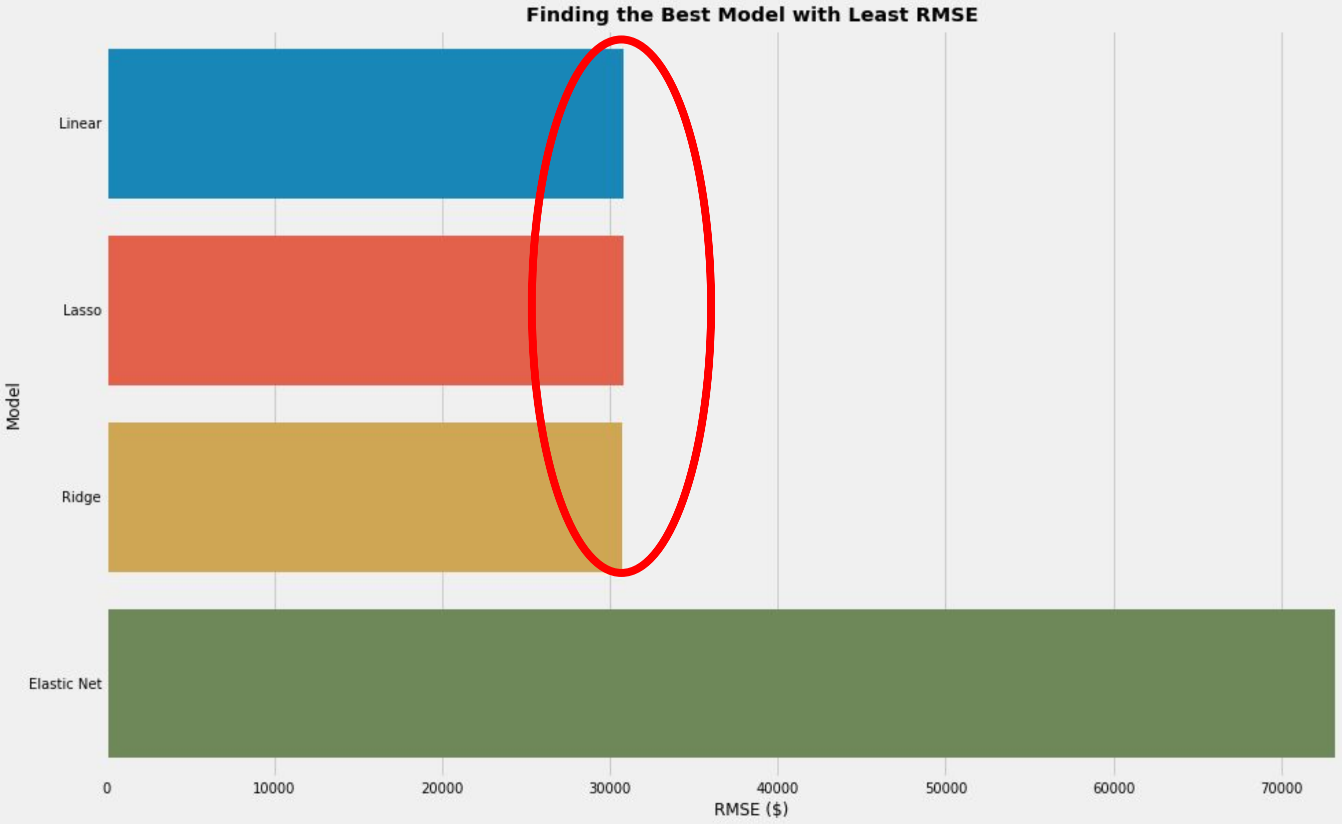
Modelling

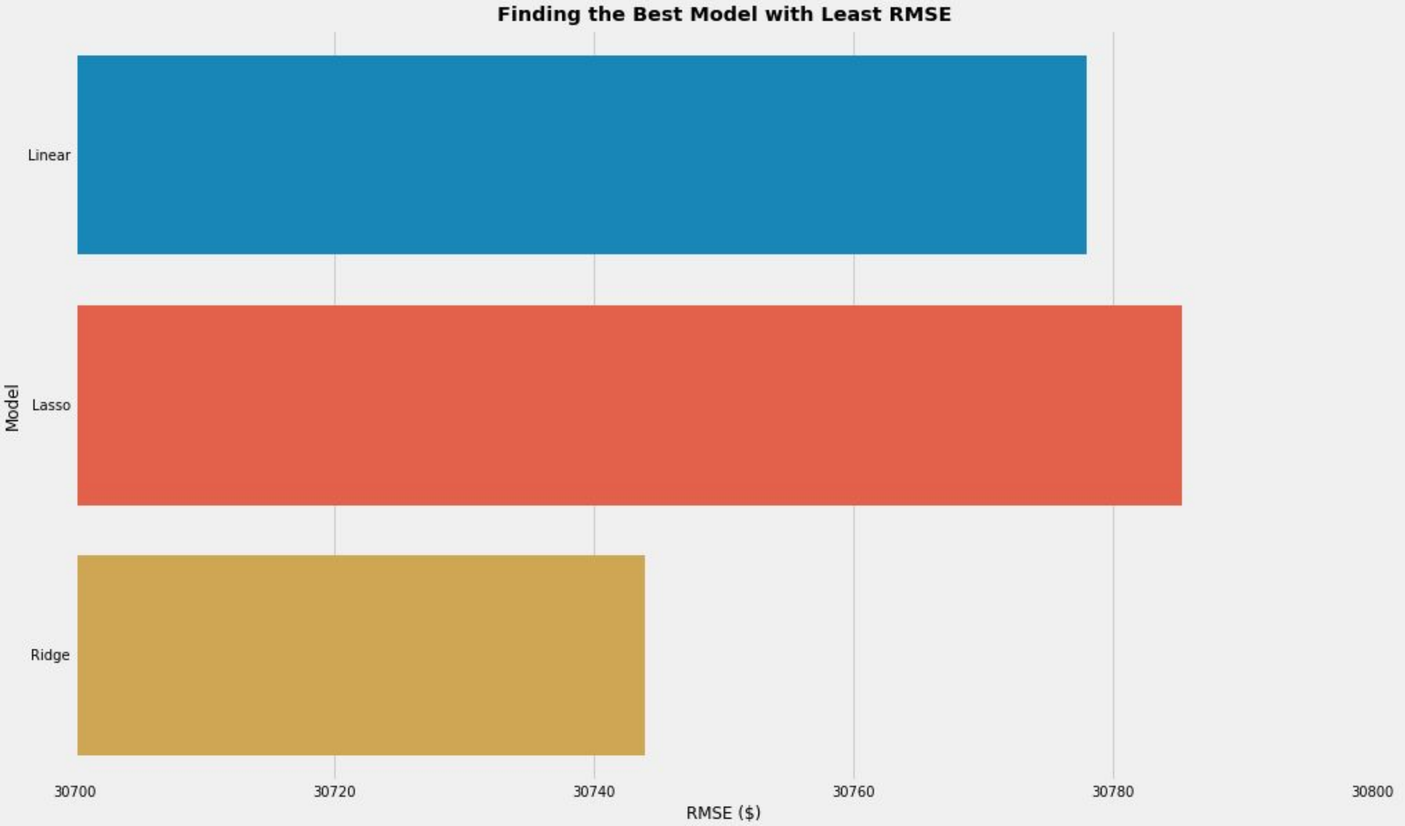
- ➢ **Linear Regression**
- ➢ **Lasso**
- ➢ **Ridge**
- ➢ **Elastic Net**

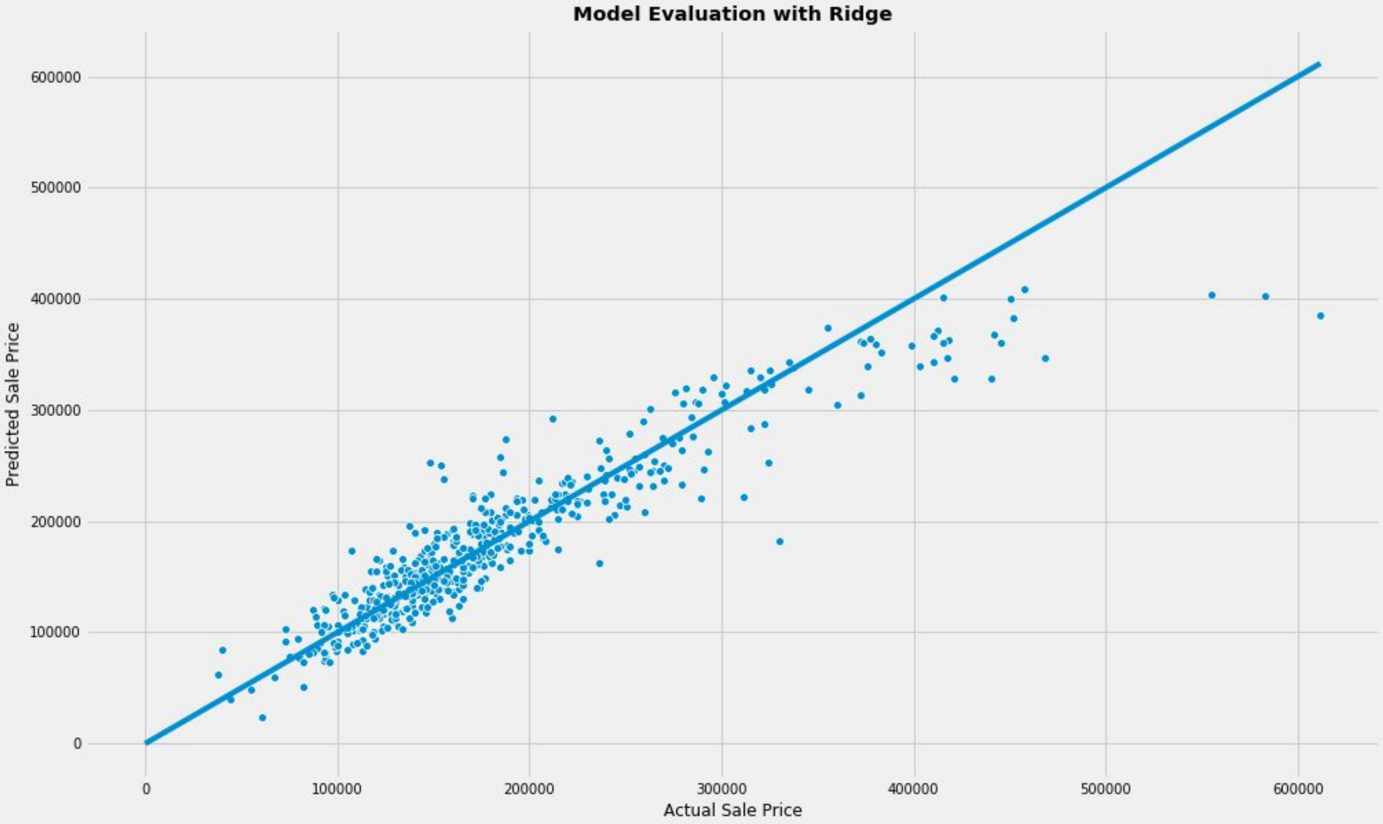


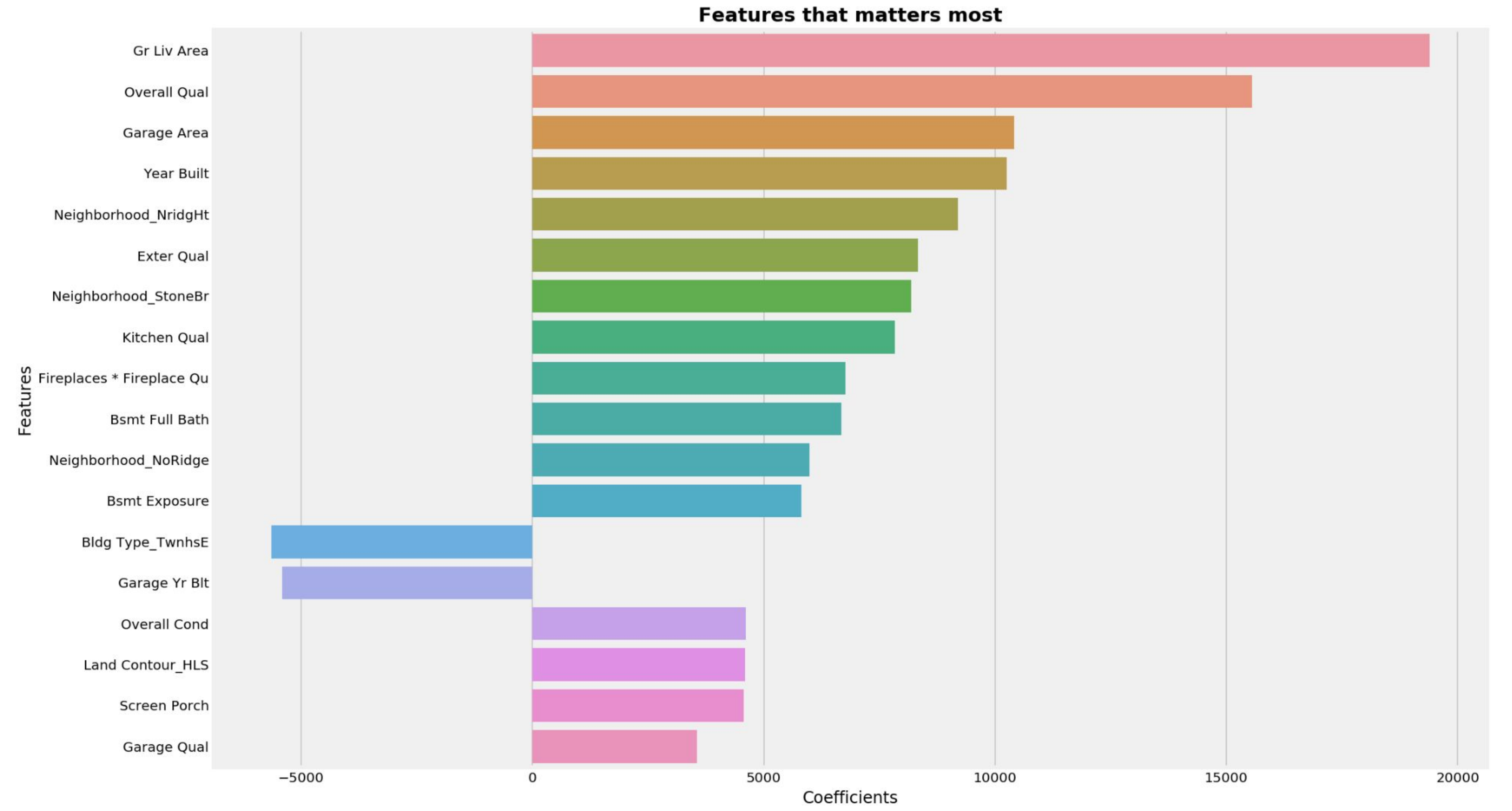
Baseline Score

$$RMSE(\mathbf{y}, \hat{\mathbf{y}}) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

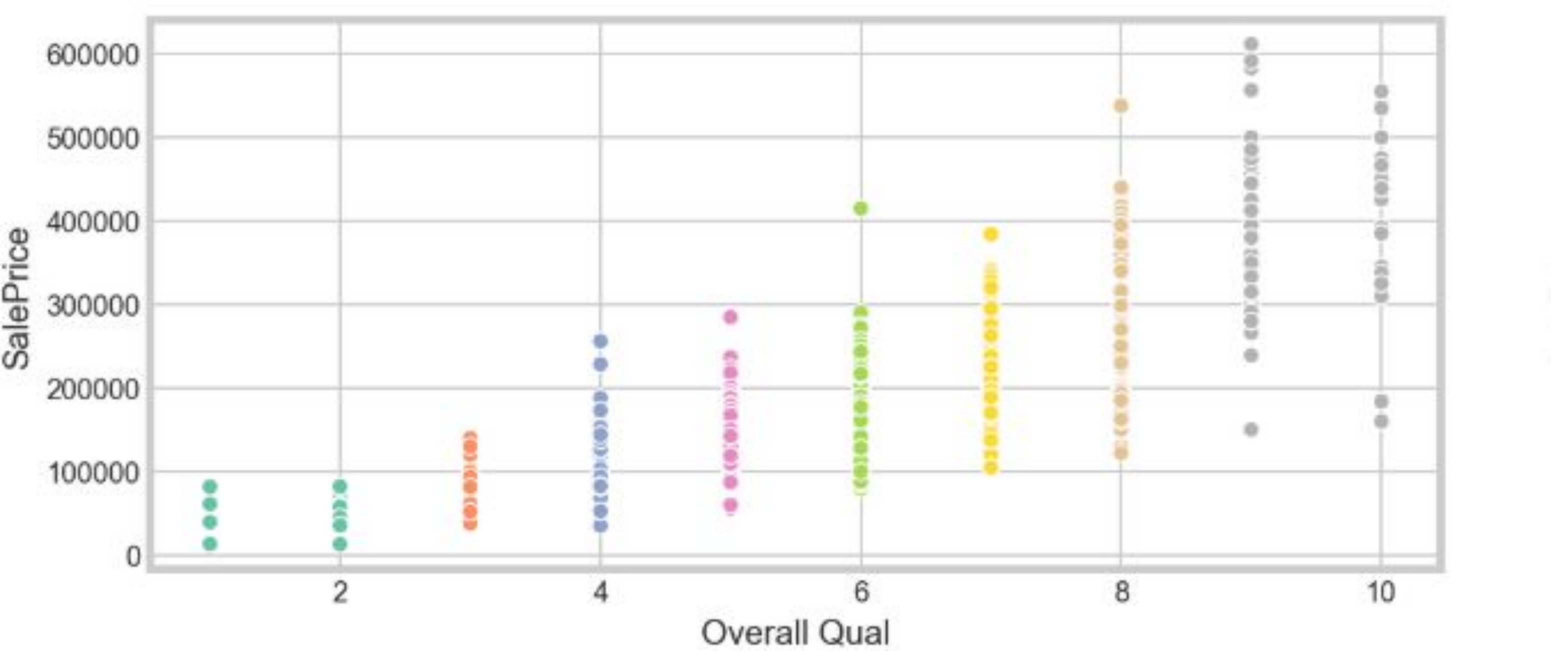

Finding the Best Model with Least RMSE
Model
Linear
Lasso
Ridge
Elastic Net
0
10000
20000
30000
40000
50000
60000
70000
RMSE ($)


Finding the Best Model with Least RMSE
Model
Linear
Lasso
Ridge
30700
30720
30740
30760
30780
30800
RMSE ($)

Model Evaluation with Ridge
Predicted Sale Price
0
100000
200000
300000
400000
500000
600000
Actual Sale Price
0
100000
200000
300000
400000
500000
600000


Features that matters most
Features
Gr Liv Area
Overall Qual
Garage Area
Year Built
Neighborhood_NridgHt
Exter Qual
Neighborhood_StoneBr
Kitchen Qual
Fireplaces * Fireplace Qu
Bsmt Full Bath
Neighborhood_NoRidge
Bsmt Exposure
Bldg Type_TwnhsE
Garage Yr Blt
Overall Cond
Land Contour_HLS
Screen Porch
Garage Qual
−5000
0
5000
10000
15000
20000
Coefficients

Conclusions



Conclusions

- Never compromise on quality
- Lesser number of features does not translate to lower selling price
- A larger floor area → higher price
- Newer the house → higher the price

Lets build smartly, the data science way!!!!