# Prediction Of Housing Sale Price Using The Ames Housing Data Set

DSI-23: Project 2

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# Mispricing Of Housing Units: A $39B Problem

**An information asymmetry & moral hazard problem**: Real estate agents exploit info advantage and convince clients to sell their houses too cheaply

- Levitt & Syverson (2008) found that homes owned by real estate agents sold for **3.7% more than other houses**!

The U.S. housing market in 2010 at a glance...

| | | | |
|---|---|---|---|
| **$278,000** | **$10,000** | **4.18 mil** | **$39 bil** |
| Average Sale Price of Houses Sold | Est. Cost of Imperfect Info | Houses Sold in the U.S. in 2010 | Loss in Housing Value assuming 95% of Homes Sold were not Property Agent Owned |

Sources:

1. https://ideas.repec.org/a/tpr/restat/v90y2008i4p599-611.html
2. https://fred.stlouisfed.org/series/ASPUS
3. https://www.statista.com/statistics/226144/us-existing-home-sales/

# Problem Statement

We want to help **uninformed home sellers** understand what constitute as fair housing prices by developing a regression model to **predict the sale prices of houses**. Specifically, we use linear models, i.e. ordinary least squares (OLS), Ridge and Lasso regressions.

A successful housing price prediction model should be able to predict housing prices with error term or **root mean squared error that is ideally lower than $10,000** (i.e. the cost of imperfection information in the housing market).

# Data Sets Obtained From Kaggle

Housing sales data in Ames, Iowa from 2006 to 2010

- Contains a range of categorical, ordinal and continuous variables to capture unit-specific housing features (e.g. lot area, overall quality, neighbourhood)
- Data is randomly split into the train and the test sets:

| Train Set | Test Set |
| --- | --- |
| • 2051 observations<br>• 80 features<br>• 1 target variable: sale price | • 878 observations<br>• 80 features (same as train) |

# Methodology

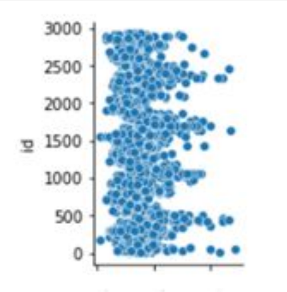
| | | |
|---|---|---|
| 01 | **Features Selection** | • Avoid overfitting<br>• Easily understandable model<br>• Use pair plots to identify variables with linear r/s to sale price |
| 02 | **Data Cleaning** | • Impute missing values<br>• Remove outliers |
| 03 | **Features Engineering** | • Engineer custom features<br>• Add interaction features<br>• Assign numerical rank values for ordinal variables<br>• Dummify categorical variables |
| 04 | **Model Preparation** | • Train-test split<br>• Scaling |
| 05 | **Model Selection & Deployment** | • OLS, Ridge and Lasso Regressions<br>• Cross Validation<br>• Model Evaluation using R2 scores |

# Selection Of Features For Model Using Pair Plots

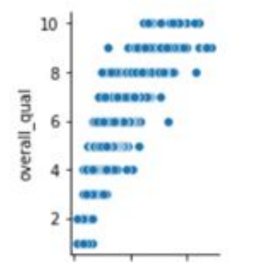
Pair plots are useful to provide visualisations to help us assess:

1. Whether variable has a **linear relationship** with target sale prices
2. The **amount of variations** within each variable
3. Possible **collinearity and relationship** between similar variables

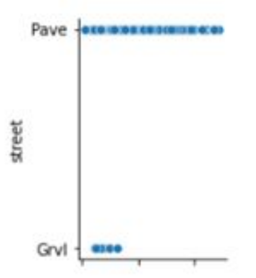
Sample Pair Plots of Independent Variables with Target (i.e. Housing Sale Prices)



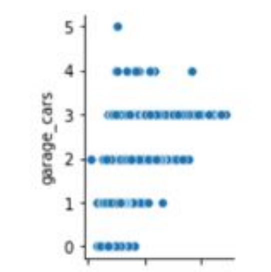

Non-linear

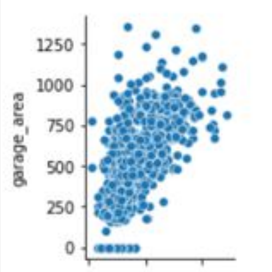



Linear




Feature with low variation



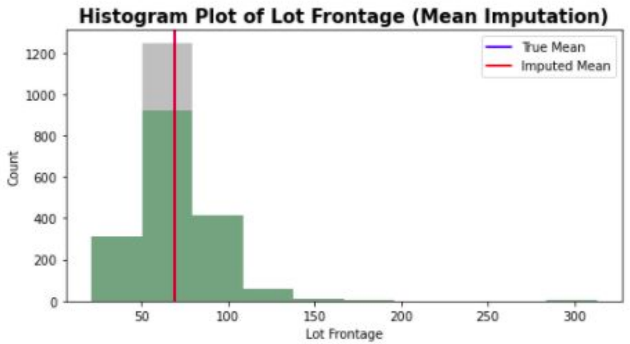

Related variables

# Data Cleaning - Missing Values

| | Missing Values |
|---|---|
| LotFrontage | 330 |
| BsmtQual | 55 |
| BsmtCond | 55 |
| TotalBsmtSF | 1 |
| BsmtFullBath | 2 |
| BsmtHalfBath | 2 |
| FireplaceQu | 1000 |
| GarageArea | 1 |
| GarageQual | 114 |
| GarageCond | 114 |

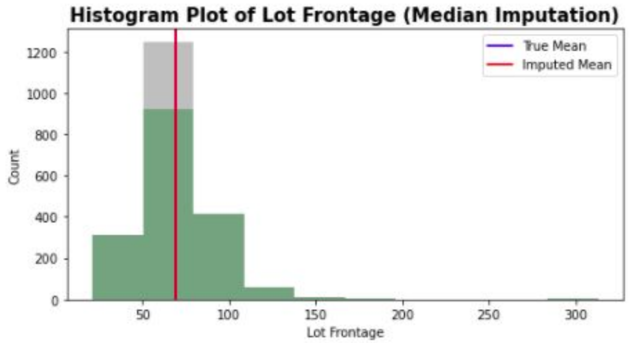
Method 1:
Imputation with **Mean**

```
Mean Lot Frontage Before Mean Imputation: 69.05520046484602
Mean Lot Frontage After Mean Imputation: 69.05520046484634
```




Method 2:
Imputation with **Median**

```
Mean Lot Frontage Before Median Imputation: 69.05520046484602
Mean Lot Frontage After Median Imputation: 68.88542174549
```



# Data Cleaning - Missing Values

| | Missing Values |
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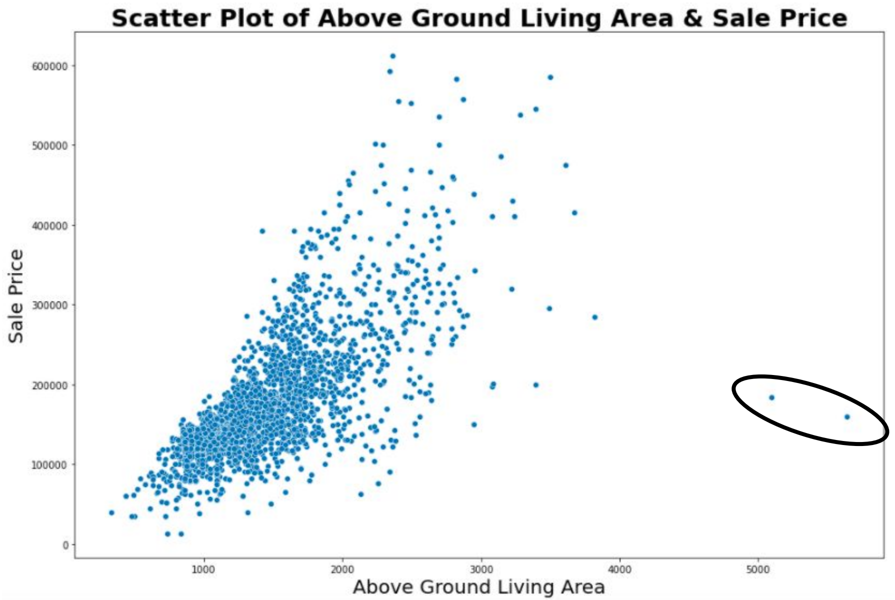
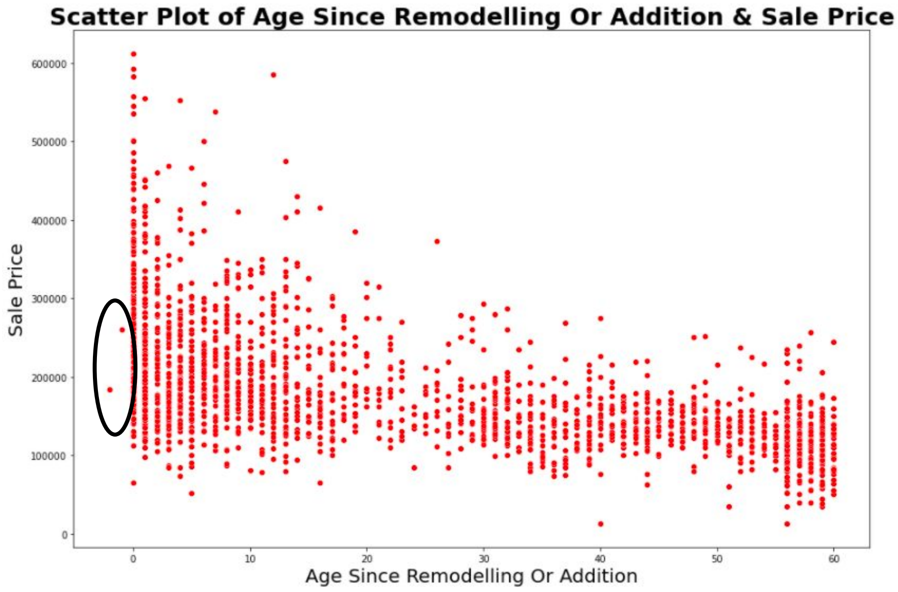
| FireplaceQu | 1000 |
| GarageArea | 1 |
| GarageQual | 114 |
| GarageCond | 114 |

- Missing values were actually ‘NA’ values
- ‘NA’ values arised due to the absence of that feature
  - Basement
  - Fireplace
  - Garage
- ‘NA’ values were replaced with 0

# Data Cleaning - Outliers



# Feature Engineering

| Custom Features | |
| --- | --- |
| Age Since Remodelling or Addition | **= Year Sold - Year Remodelled or Added** |
| Total Rooms | **= Bathrooms + Bedrooms + Kitchen** |
| Porch Area | **= Open Porch + Enclosed Porch + 3 Season Porch + Screen Porch** |
| Neighbourhood Score | **= (to be explained later)** |

| Interaction Features |
| --- |
| Overall Quality Condition |
| Exterior Quality Condition |
| Basement Quality Condition |
| Garage Quality Condition |

**= Quality x Condition**

# Feature Engineering

| Ordinal Features |
| --- |
| Exterior Quality<br>Exterior Condition<br>Basement Quality<br>Basement Condition<br>Garage Quality<br>Garage Condition |

**Mapped strings with numerals**

| | |
| --- | --- |
| Ex | 5 |
| Gd | 4 |
| TA | 3 |
| Fa | 2 |
| Po | 1 |

| Nominal Features |
| --- |
| Lot Shape<br>Lot Configuration<br>Land Contour<br>Land Slope<br>Year Sold |

**One-hot encoded (Dropped first level)**

# Feature Engineering - Neighbourhood Score

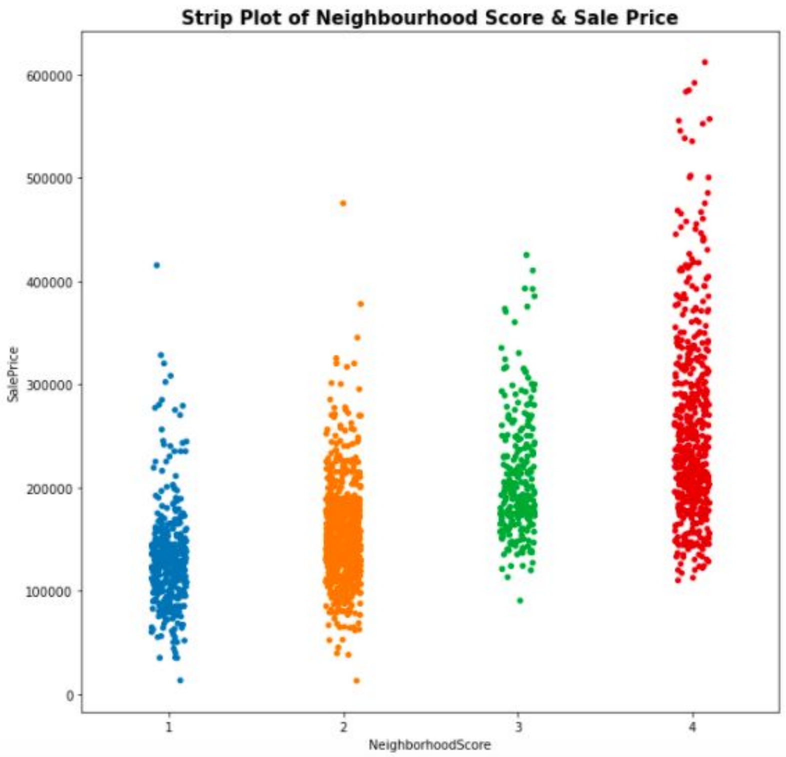
Context: Price of a house is determined not only by property-specific traits but also by **neighbourhood-specific traits** (i.e. the environment within which the house resides in) (e.g. crime rate, pollution level)

Idea: The more favourable the neighbourhood, the higher the price with which the house can be sold for

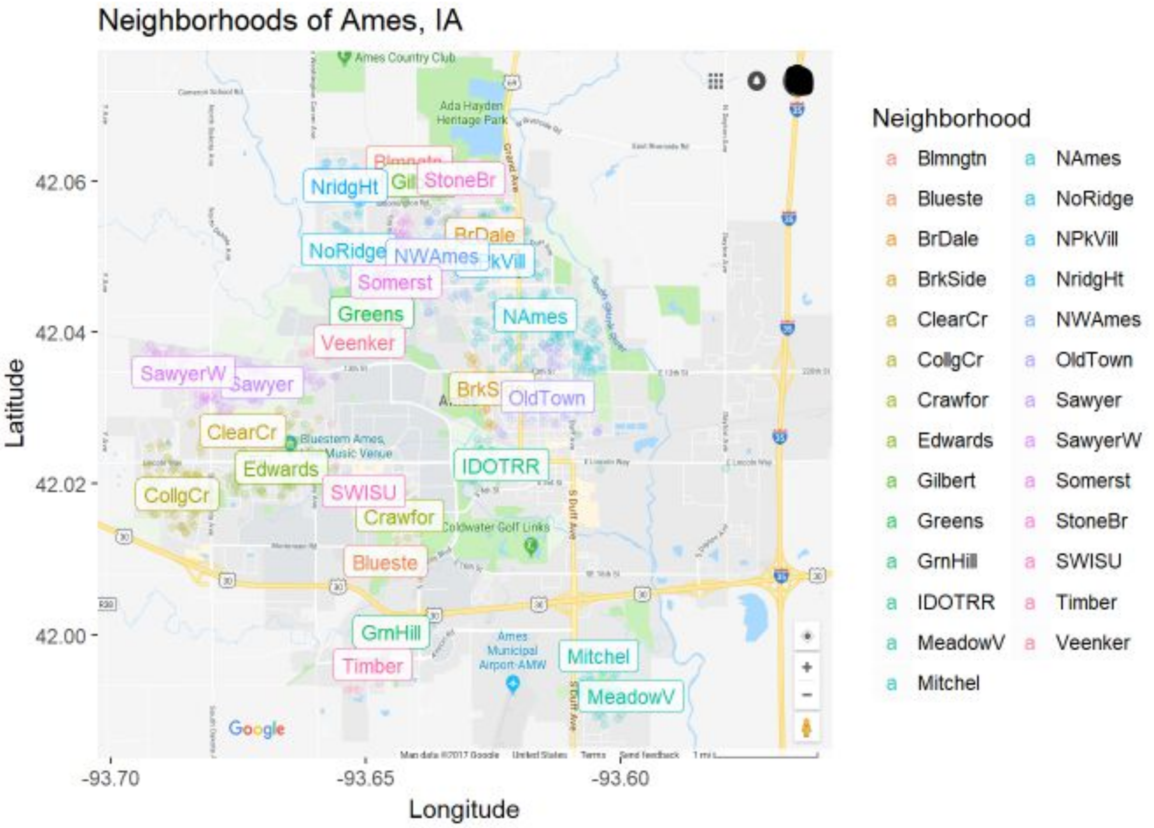
Data: Lack of features that could be considered neighbourhood-specific traits → **Had to improvise**

Theory: A more desirable neighbourhood would have:

1. Positive off-site features (e.g. park, greenbelt)
2. Typical, non-damaged, non-deducted houses
3. Higher overall quality and condition houses
4. Higher exterior quality and condition houses



# Neighbourhoods In Ames, Iowa



# Checking For Multicollinearity

What is Multicollinearity

- It is when a variable can be linearly predicted from the one or more variables with a substantial degree of accuracy

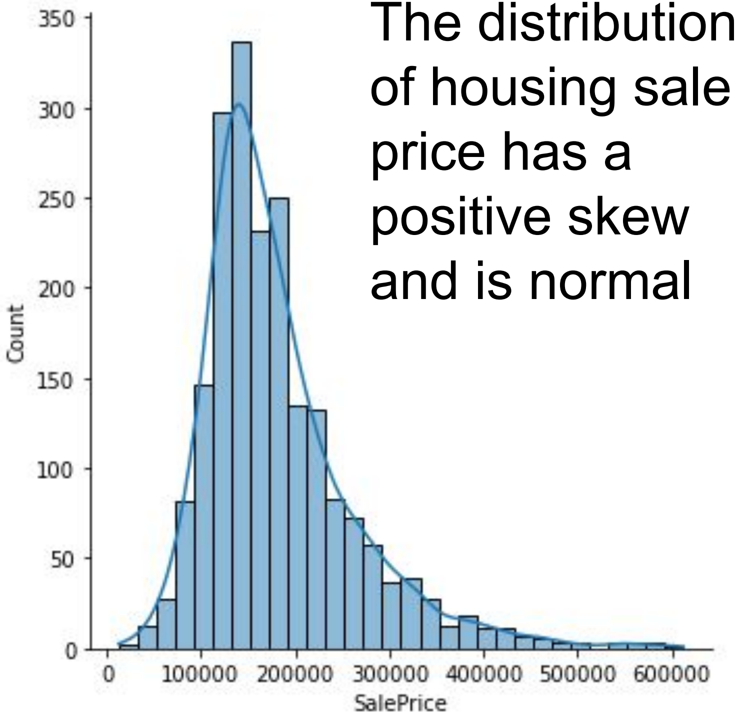
Issues of Multicollinearity

- Undermines the statistical significance of an independent variable.

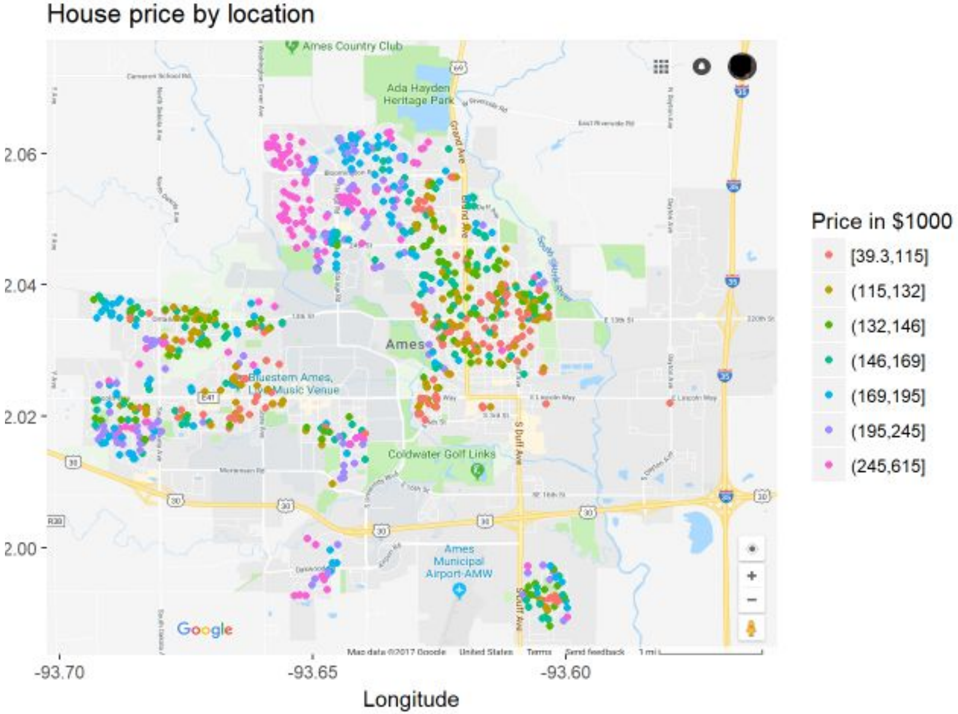
Threshold Selected = 0.8

| **Kept** | **Dropped** (on the basis they are less correlated with sale price) |
| --- | --- |
| Age Since Remodeling or Addition | Year Remodelled or Added |
| Exterior Quality | Exterior Quality Condition |
| Fireplace Quality | Fireplaces |
| Garage Quality | Garage Condition |
| Pool Quality | Pool Area |

# Distribution Of Sale Price



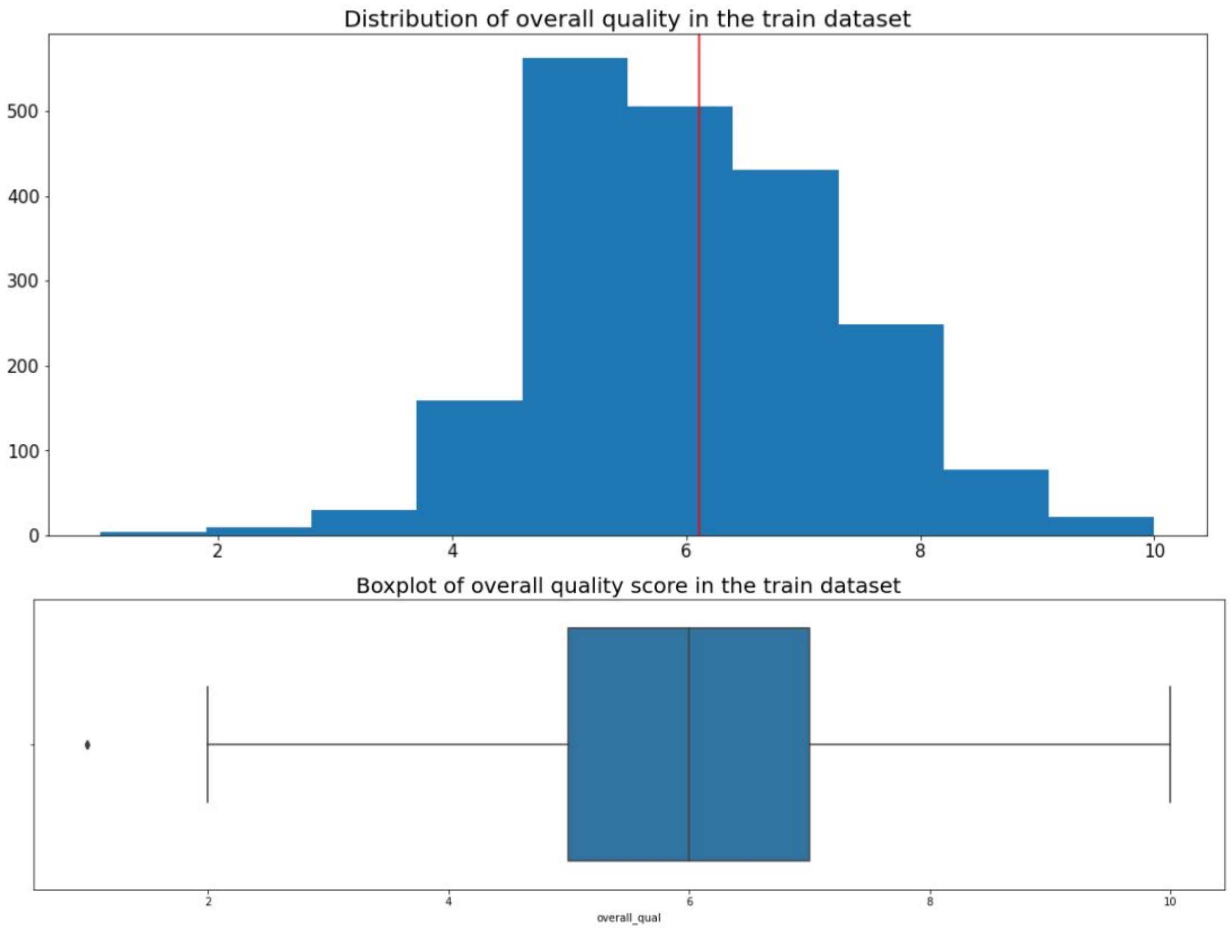

The distribution of housing sale price has a positive skew and is normal



# Distribution Of Overall Quality
(variable most correlated with Sale Price)

Similarly, normally distributed with a positive skew (but less so)

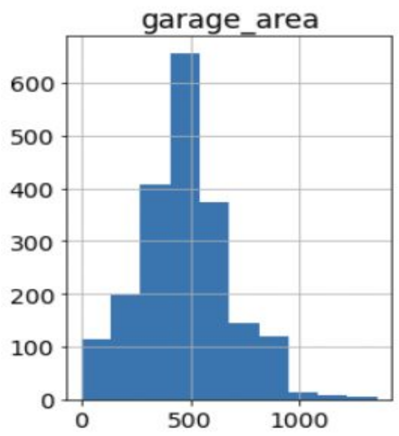
```
The mean overall quality is 6.11  out of 10 (see red line below).
```

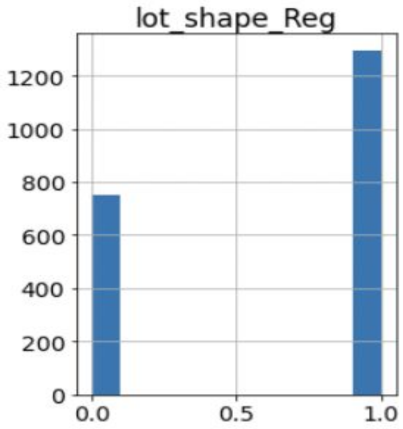


# Model Preparation

- Dependent variable: **Sale Price**
- Independent variables: **49 variables** such as garage_area, overall_qual, lot_shape etc

- Train-test-split of **70-30**
  - Aligned with industry norms
- **Scaling** so that model is not impacted because of variables with large magnitude



# Model Evaluation

| | Linear Regression | LassoCV | RidgeCV |
|---|---|---|---|
| Cross Validation | 0.8794 | 0.8798 | 0.8795 |
| Train $R^2$ | 0.8886 | 0.8878 | 0.8884 |
| Test $R^2$ | 0.8612 | 0.8520 | 0.8618 |
| Difference in $R^2$ | 0.0274 | 0.0258 | 0.0266 |

- Selected the LassoCV as it has the
    - highest cross validation score; and
    - smallest difference in $R^2$ between the train and test set

**The higher the $R^2$ the better*

# Model Selected: Lasso Model

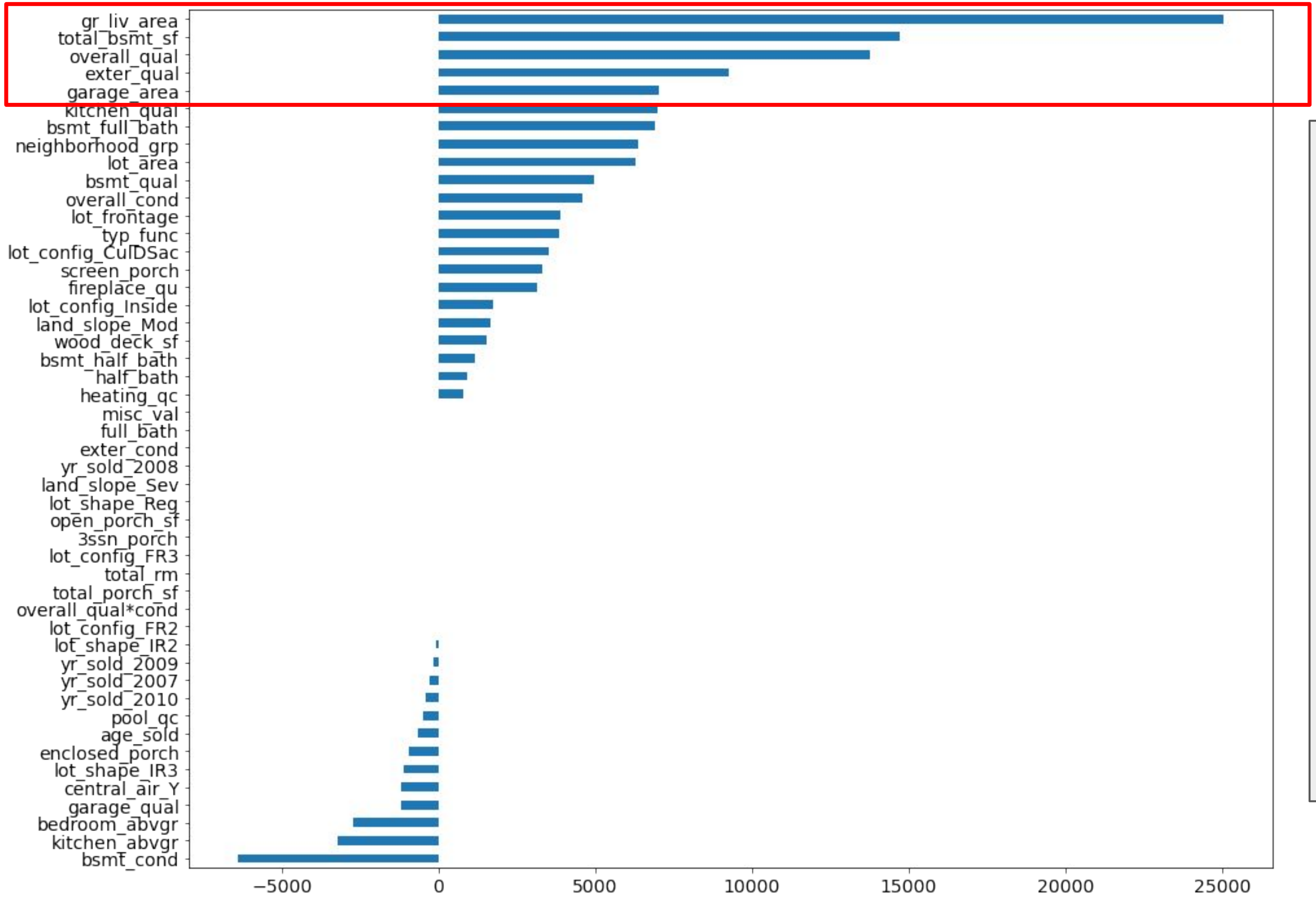
Lasso RMSE
40,427

<

Baseline RMSE
77,737

- Shrinks coefficient estimates towards zero (i.e. eliminating irrelevant variables) to make the model less complex

# Primary Findings




**Size and quality of the house are important**

- Above Ground Living Area
- Total Basement Area
- Overall Quality
- Exterior Quality
- Garage Area

# Recommendations

- Sellers to pay attention to housing quality and size when setting sale price
- In addition, some of the key factors to note are as follows:
  - **Above ground living area** and **total basement area** will influence the sale price more so than the lot area and garage area
  - The **quality** of the overall, exterior, garage, etc has a larger effect on sale price than the condition
  - Houses situated in **neighborhoods** with higher scores can sell at a slight premium

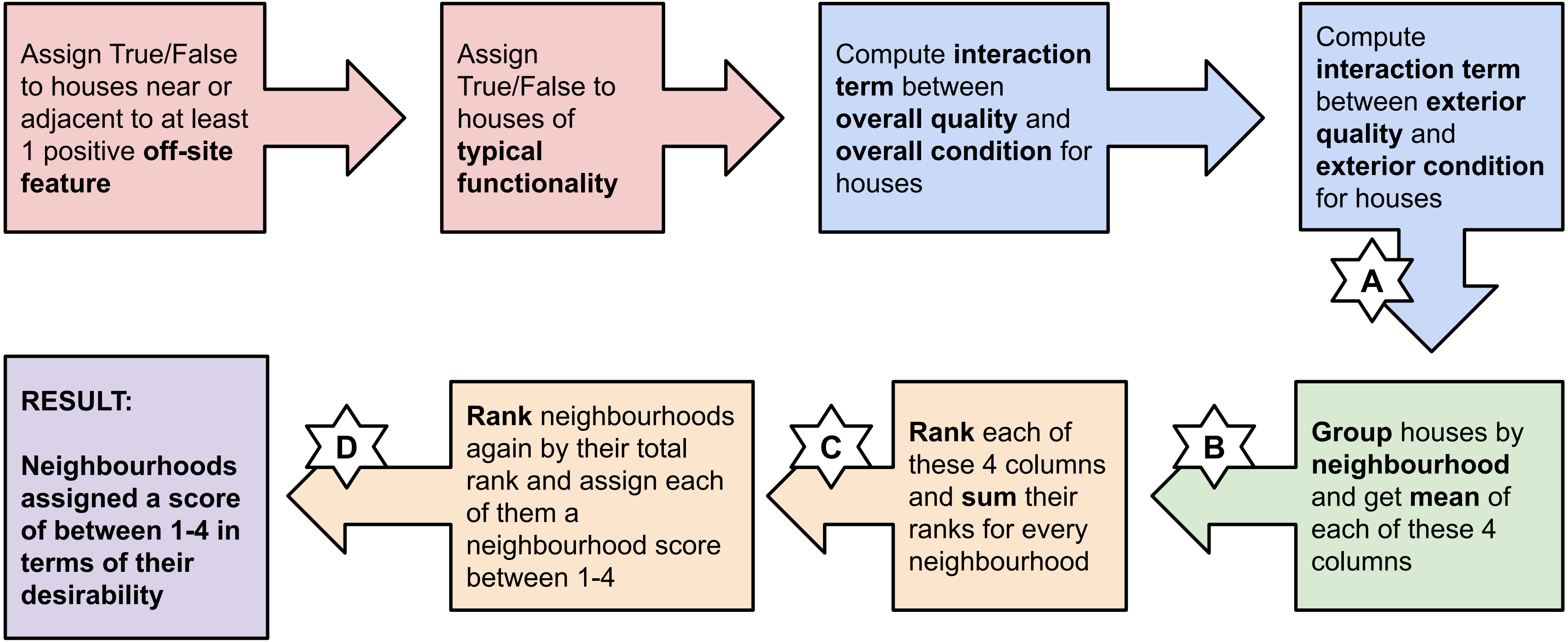
# Conclusion

- Model RMSE is ~$40,000 > $10,000 (cost of imperfection information in the housing market) → **model can be improved**
- Consider including all variables and use lasso regularization to identify the variables

**Next Steps:** Consider gathering housing data of other states so that the model can be expanded to other parts of the US instead of limiting to Iowa

# Annex

# Feature Engineering - Neighbourhood Score



# Feature Engineering - Neighbourhood Score

A

| | Neighborhood | PosOffSiteFeature | TypFunctional | OverallQualCond | ExterQualCond |
|---|---|---|---|---|---|
| 0 | Sawyer | 0 | 1 | 48 | 12 |
| 1 | SawyerW | 0 | 1 | 35 | 12 |
| 2 | NAmes | 0 | 1 | 35 | 12 |
| 3 | Timber | 0 | 1 | 25 | 9 |
| 4 | SawyerW | 0 | 1 | 48 | 9 |

B

| | Neighborhood | PosOffSiteFeature | TypFunctional | OverallQualCond | ExterQualCond |
|---|---|---|---|---|---|
| 0 | Blmngtn | 0.000000 | 1.000000 | 35.909091 | 12.000000 |
| 1 | Blueste | 0.000000 | 1.000000 | 38.666667 | 11.000000 |
| 2 | BrDale | 0.000000 | 0.947368 | 31.105263 | 9.000000 |
| 3 | BrkSide | 0.013158 | 0.894737 | 33.078947 | 9.407895 |
| 4 | ClearCr | 0.000000 | 0.740741 | 33.407407 | 10.259259 |

C

| | Neighborhood | PosOffSiteFeatureRank | TypFunctionalRank | OverallQualCondRank | ExterQualCondRank | TotalRank | FinalRank |
|---|---|---|---|---|---|---|---|
| 0 | Blmngtn | 9.0 | 24.5 | 18.0 | 22.0 | 73.5 | 21.5 |
| 1 | Blueste | 9.0 | 24.5 | 22.0 | 17.0 | 72.5 | 19.0 |
| 2 | BrDale | 9.0 | 13.0 | 7.0 | 3.5 | 32.5 | 5.0 |
| 3 | BrkSide | 19.0 | 7.0 | 11.0 | 7.0 | 44.0 | 10.0 |
| 4 | ClearCr | 9.0 | 1.0 | 13.0 | 14.0 | 37.0 | 6.0 |

D

| | Neighborhood | FinalRank | DesirabilityScore |
|---|---|---|---|
| 0 | IDOTRR | 1.0 | 1.0 |
| 1 | Edwards | 2.0 | 1.0 |
| 2 | MeadowV | 3.0 | 1.0 |
| 3 | SWISU | 4.0 | 1.0 |
| 4 | BrDale | 5.0 | 1.0 |