Ames Housing Price Prediction

Using Regression Models

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Scope

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- Regression Model
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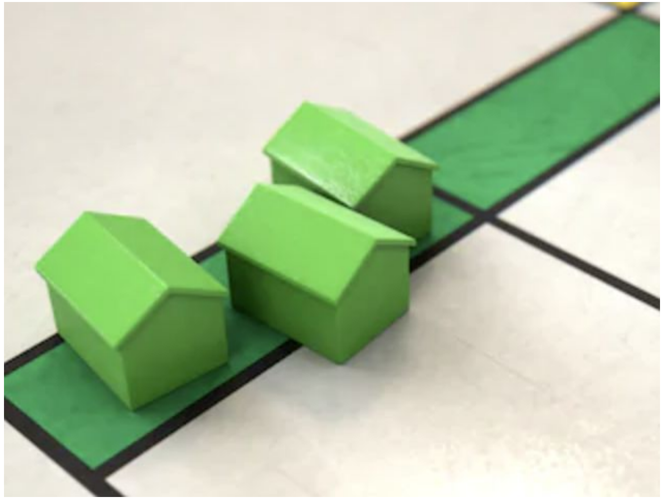
Introduction

Introduction: Problem Statement

As a team of data analysts, we have been tasked by a property agency to create a **linear regression model** based on the **Ames Housing Dataset** that will predict the rough price of a house at sale.

The agency has requested that the final production model be **easy to interpret** and make use of **no more than 20 features.**



Data Cleaning & Preprocessing

Data Cleaning & Preprocessing

Data Cleaning

Missing Values

- 26/82 features contain null values - Replaced with 0 / string
- Missing value area but presence with feature - replace with mean of feature

poolqc	0.995612
miscfeature	0.968308
alley	0.931741
fence	0.804973

Eliminating Outliers

- Logic check
- Extreme values

	yrsold	yearbuilt	garageyrblt
1699	2007	2006	2207.0
1885	2007	2008	2008.0

One Hot Encoding

- Getting dummies for all the Nominal features
- Rated with a scale -> ordinal features were mapped with a range

Pre-processing

Multicollinearity

- Features like Garage Cars and Garage Area

	garagecars	garagearea
0	2.0	475.0
1	2.0	559.0
2	1.0	246.0
3	2.0	400.0
4	2.0	484.0

New Features

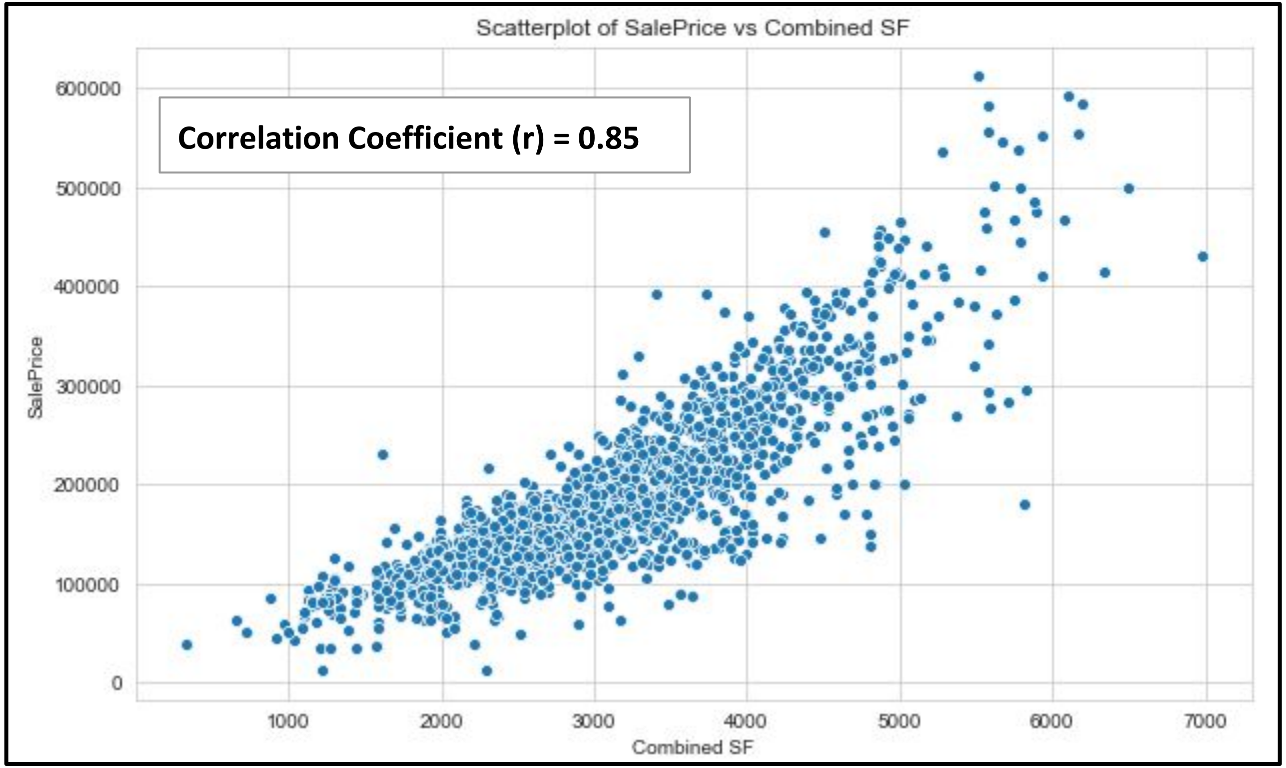
- Age of building
- Combining of features [total sq ft and total baths]
  - Total baths = Full bath + (0.5 * Half Bath)

Polynomial Features

- Overall Quality
- Overall Sq Ft

EDA & Feature Engineering

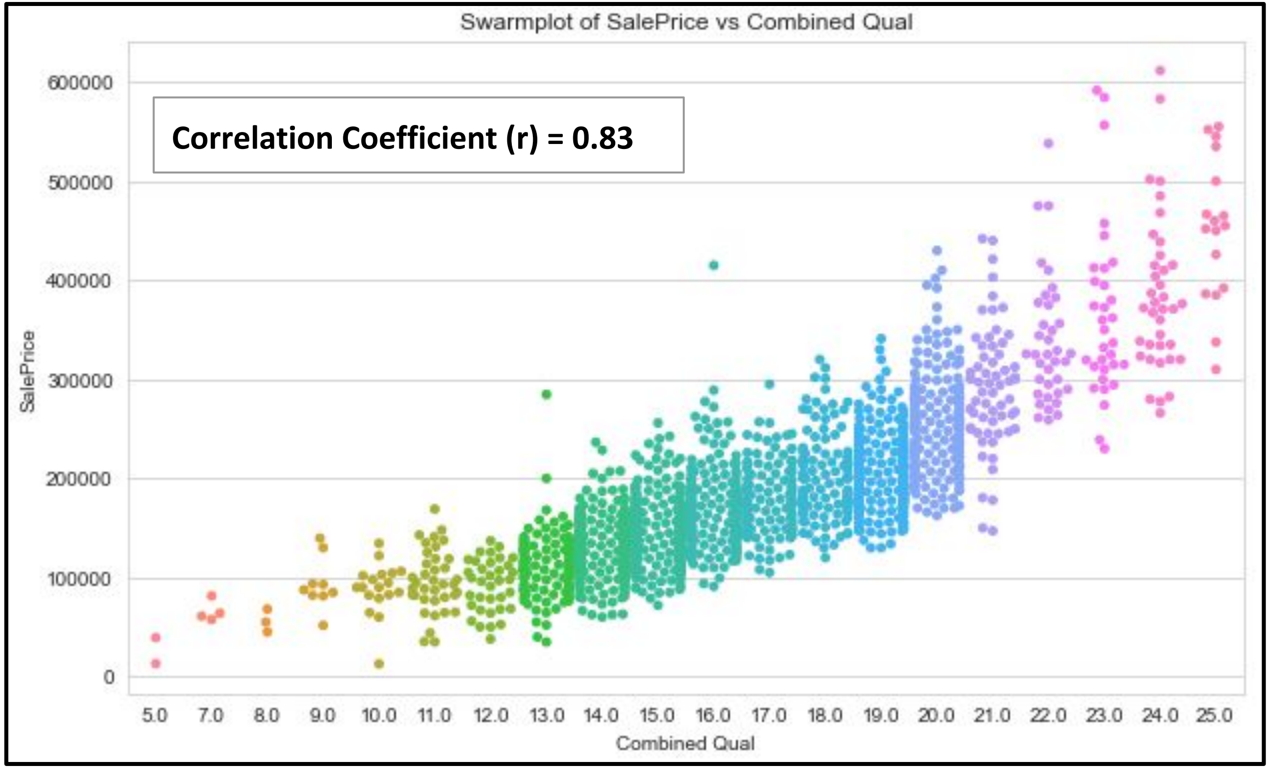
EDA & Feature Engineering: Total Area of House



Observations:

- **Strong positive relationship** between housing sale price and total area of the house
- Good indication of a linear relationship

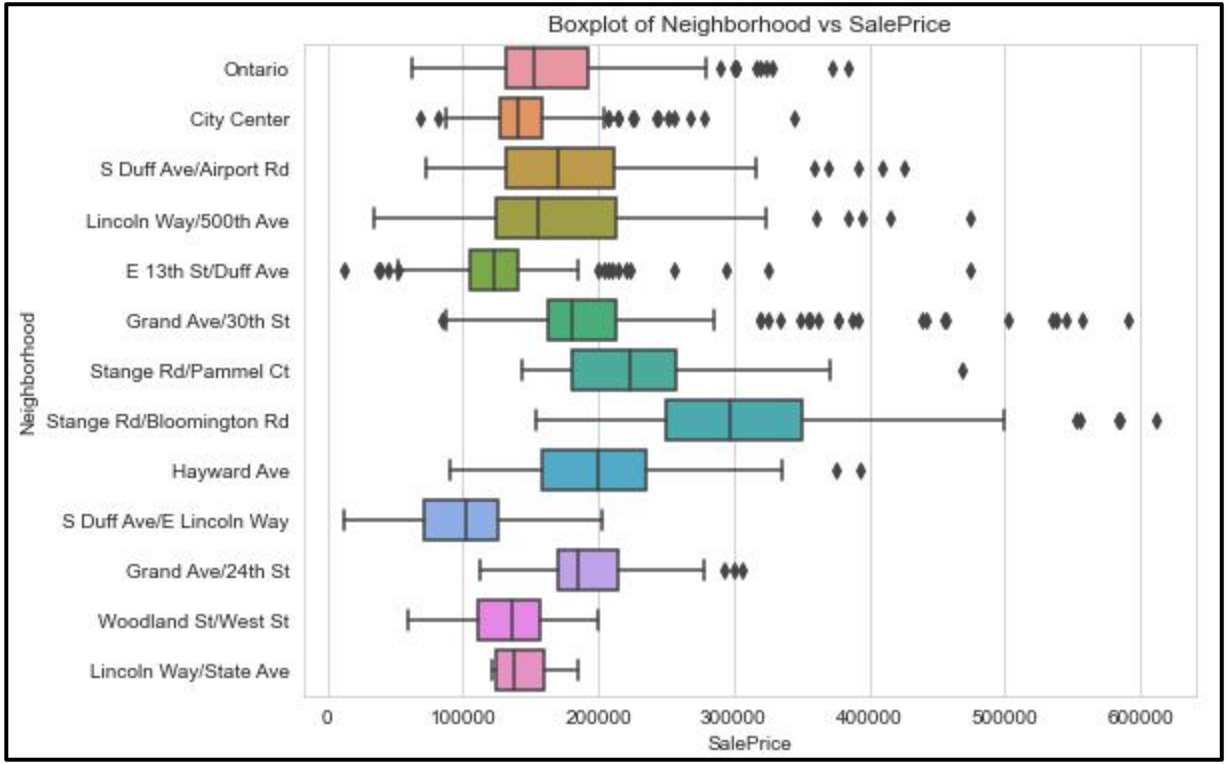
EDA & Feature Engineering: Overall Quality



Observations:

- **Strong positive relationship** between housing sale price and overall quality
- Clear linear relationship
- Largest number of houses within the overall quality range of 13-20

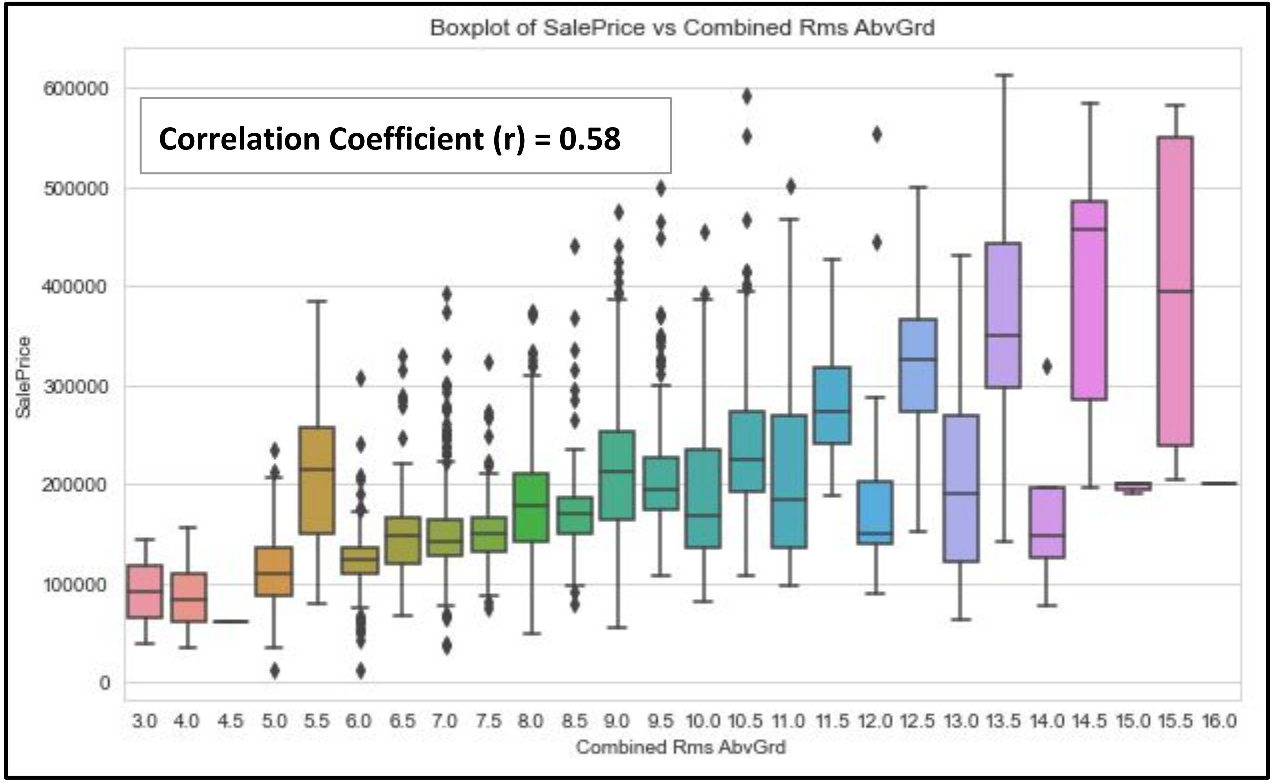
EDA & Feature Engineering: Neighborhood Regions



Observations:

- **Good variability** in the data after grouping different neighborhoods into popular Ames regions
- **Highest** median of sale price within the **Stange Rd/Bloomington Rd** region
- **Lowest** median of sale price within the **S Duff Ave/E Lincoln Way region**

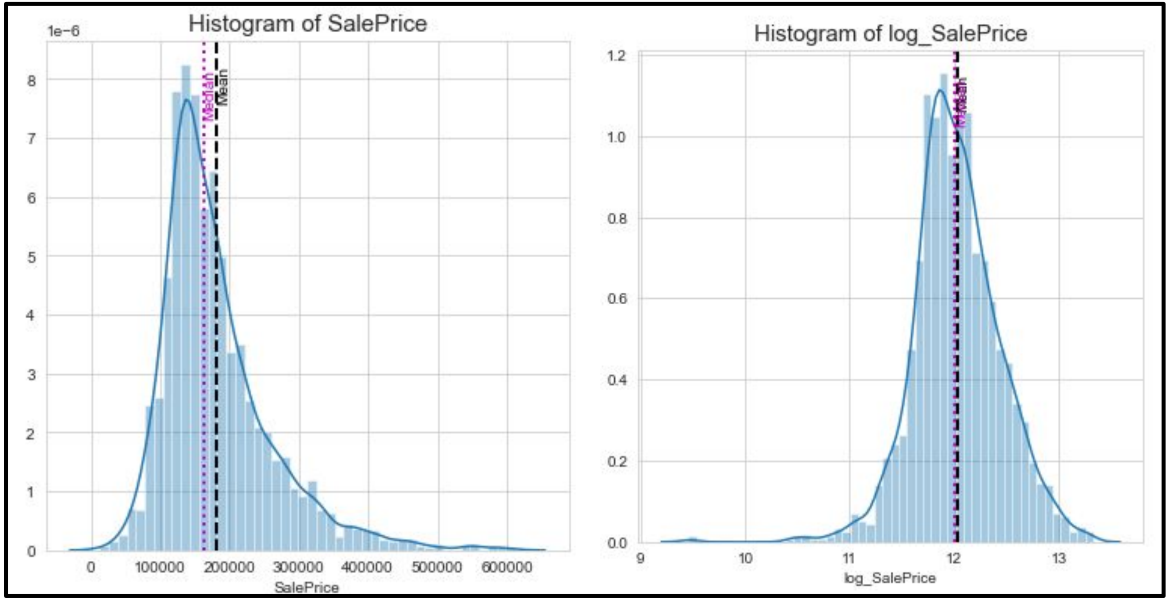
EDA & Feature Engineering: Number of Rooms



Observations:

- **Strong positive relationship** between housing sale price and total number of rooms
- Rooms include bedrooms and bathrooms
- Variability in data

Target Engineering: Log Transformation



Improvement in normality

Observations:

- The distribution of target variable is **right(positive)-skewed**
- Great improvement in normality after doing a **log transformation** on the target variable
- Correcting for the **violation in normality assumption** helps to improve predictions
- Achieve a more homoscedastic model

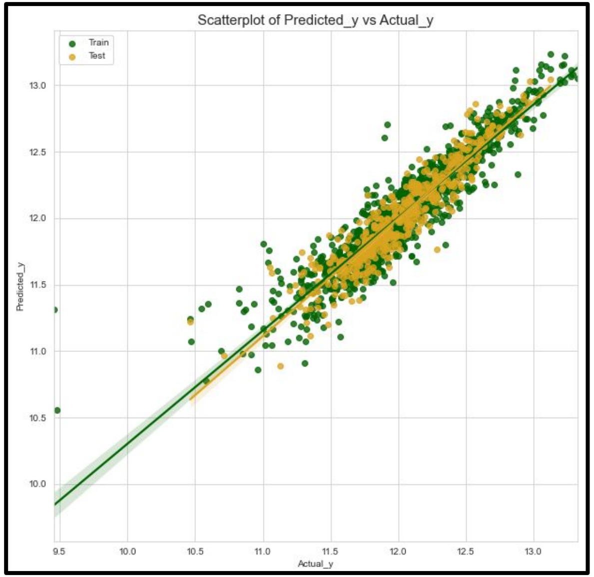
Regression Model & Top Features

Regression Model

	model	r2_train	r2_cv_estimate	adj_r2_train	adj_r2_cv_estimate	rmse_train	rmse_cv_estimate
0	Linear Regression	0.863296	0.850527	0.861491	0.848553	0.155803	0.162230
1	Ridge Regression	0.863268	0.850658	0.861463	0.848686	0.155819	0.162156
2	Lasso Regression	0.862256	0.851643	0.860438	0.849684	0.156394	0.161574
3	ElasticNet Regression	0.862257	0.851638	0.860439	0.849679	0.156394	0.161577

HIGHEST R^2

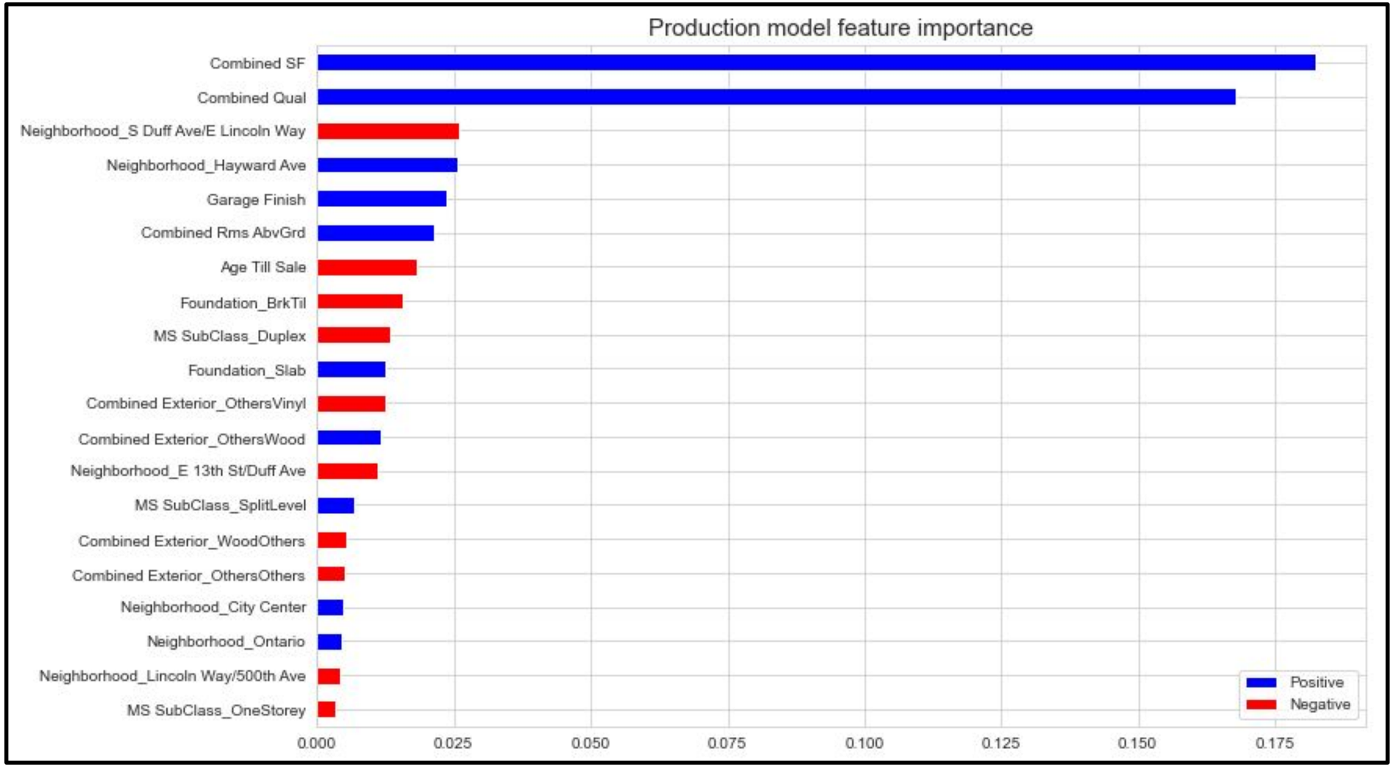
LOWEST RMSE



Lasso Regression Model

- **Strong linear relationship** between the predicted and actual sale price extracted from the train data
- Minimal difference between the best-fit lines of the train data and test(hold-out) data

Top Features



Discussion and Conclusion

Recommendations

1. **The more, the better!**
   - Add additional amenities (e.g. garage, fireplace, pool, masonry)
   - Add more bedrooms, add more bathrooms

2. **Quality is key**
   - Ensure the quality of condition of amenities

3. **Location, location, location!**
   - Houses in highly liveable social spaces (e.g. near parks, recreation, facilities) fetch higher prices
   - Less favourable environments include places near roads, petrol kiosks

Limitations

- **Dataset**
  - No data on demographics
  - No data on external factors such as government and external events (e.g. pandemic, disasters, subprime mortgage crisis from 2007-2010) and how it influenced decision making
  - Ill defined outliers

- **Model**
  - Not generalizable to other states or countries
  - May not be applicable to current year
  - Limited to Linear Regression
  - No of features limited, might be better to have more features to select

Conclusion

Among all the variables within the dataset, **variables measuring quality condition, number of amenities or age** are better predictors.

- Higher quality rating increases price
- Additional amenities (e.g. basement/garage) increases price
- As the building ages, the price gradually decreases