



Ames Housing Price Prediction

Using Regression Models

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Scope

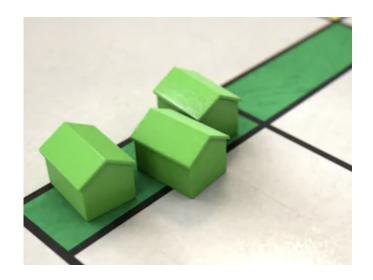
- Introduction
- Data Cleaning & Preprocessing
- EDA & Feature Engineering
- Target Engineering
- Regression Model
- Top Features
- Recommendations
- Limitations
- Conclusion

Introduction

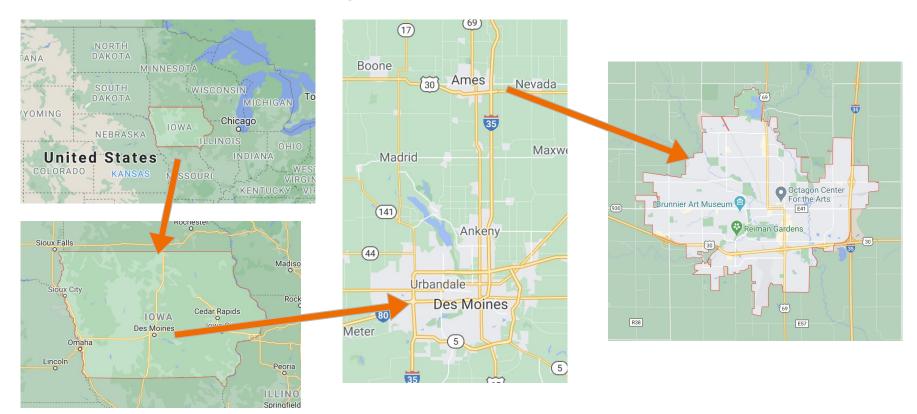
Introduction: Problem Statement

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.**

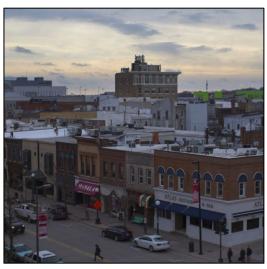


Introduction: Ames, Iowa



Introduction: Ames, Iowa







Introduction: Ames Dataset

The Ames dataset is a dataset built by **Dean De Cock**, a statistics professor from the Truman

State University, who was looking for an alternative to the well-used Boston housing dataset

Some features of the dataset:

- 2051 rows with 81 columns
- Some error correction was done
- Outliers/null values were not removed



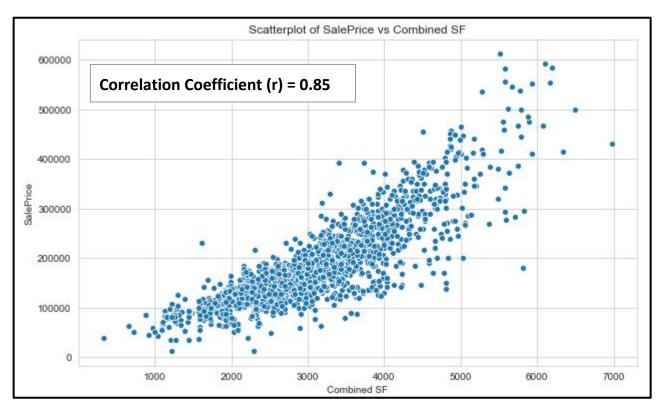
Data Cleaning & Preprocessing

Data Cleaning & Preprocessing

Missing Values **Eliminating Outliers** One Hot Encoding 26/82 features contain null Logic check Getting dummies for all the Extreme values Nominal features values - Replaced with 0 / string Missing value area but Data Rated with a scale -> ordinal presence with feature - replace features were mapped with a Cleaning with mean of feature range yrsold yearbuilt garageyrblt poolac 0.995612 miscfeature 0.968308 1699 2007 2006 2207.0 alley 0.931741 2007 2008 2008.0 1885 0.804973 fence Multicollinearity **New Features** Polynomial Features Age of building Features like Garage Cars and **Overall Quality** Combining of features [total sq Overall Sq Ft Garage Area Preft and total baths] garagecars garagearea processi 2.0 475.0 Total baths = Full bath + ng 2.0 559.0 (0.5 * Half Bath) 1.0 246.0 2.0 400.0 2.0 484.0

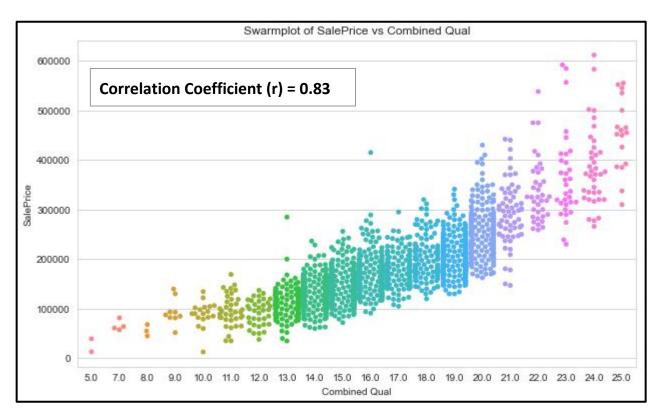
EDA & Feature Engineering

EDA & Feature Engineering: Total Area of House



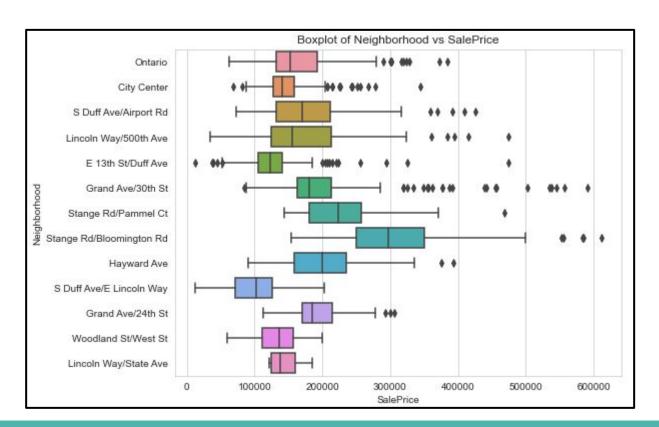
- Strong positive relationship between housing sale price and total area of the house
- Good indication of a linear relationship

EDA & Feature Engineering: Overall Quality



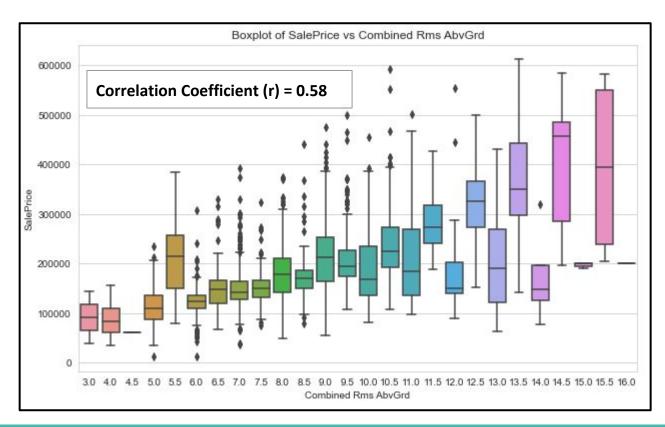
- Strong positive relationship between housing sale price and overall quality
- Clear linear relationship
- Largest number of houses within the overall quality range of 13-20

EDA & Feature Engineering: Neighborhood Regions



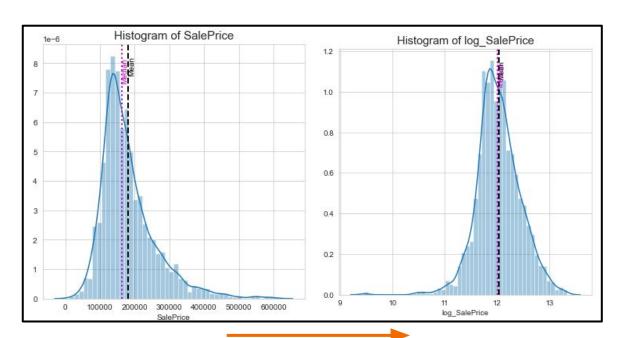
- Good variability in the data after grouping different neighborhoods into popular Ames regions
- Highest median of sale price within the Stange
 Rd/Bloomington Rd region
- Lowest median of sale price within the S Duff Ave/E Lincoln Way region

EDA & Feature Engineering: Number of Rooms



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

Target Engineering: Log Transformation

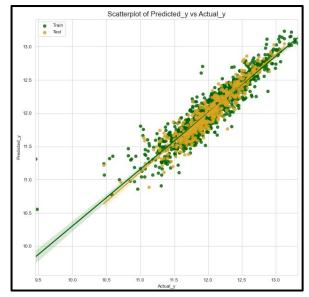


- The distribution of target variable is right(positive)-skewed
- Great improvement in normality after doing a log transformation on the target variable
- Correcting for the violation in normality assumption helps to improve predictions
- Achieve a more homoscedastic model

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



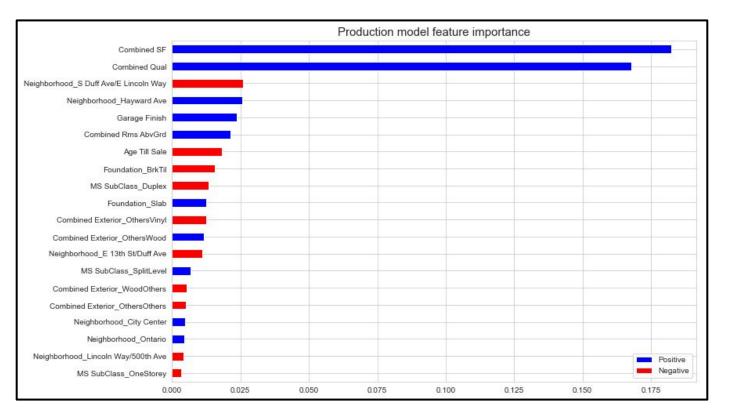
HIGHEST R²

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



Questions?



Did you know: The **mascot of Monopoly** is **Rich Uncle Pennybags**, Uncle Pennybags' full name was given as **Milburn Pennybags**. In large parts of the world he is known, additionally or exclusively, as the **Monopoly Man**, or **Mr. Monopoly**.

