Predicting Real Estate Sale Prices

A Lecture on Linear Regression

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I. Problem Statement

For housing in AMES, Iowa:

- How can a house's information be used by Real Estate developers and clients to predict or increase a property's value?
- Moreover, how can a data scientist use a model to process all of this data?

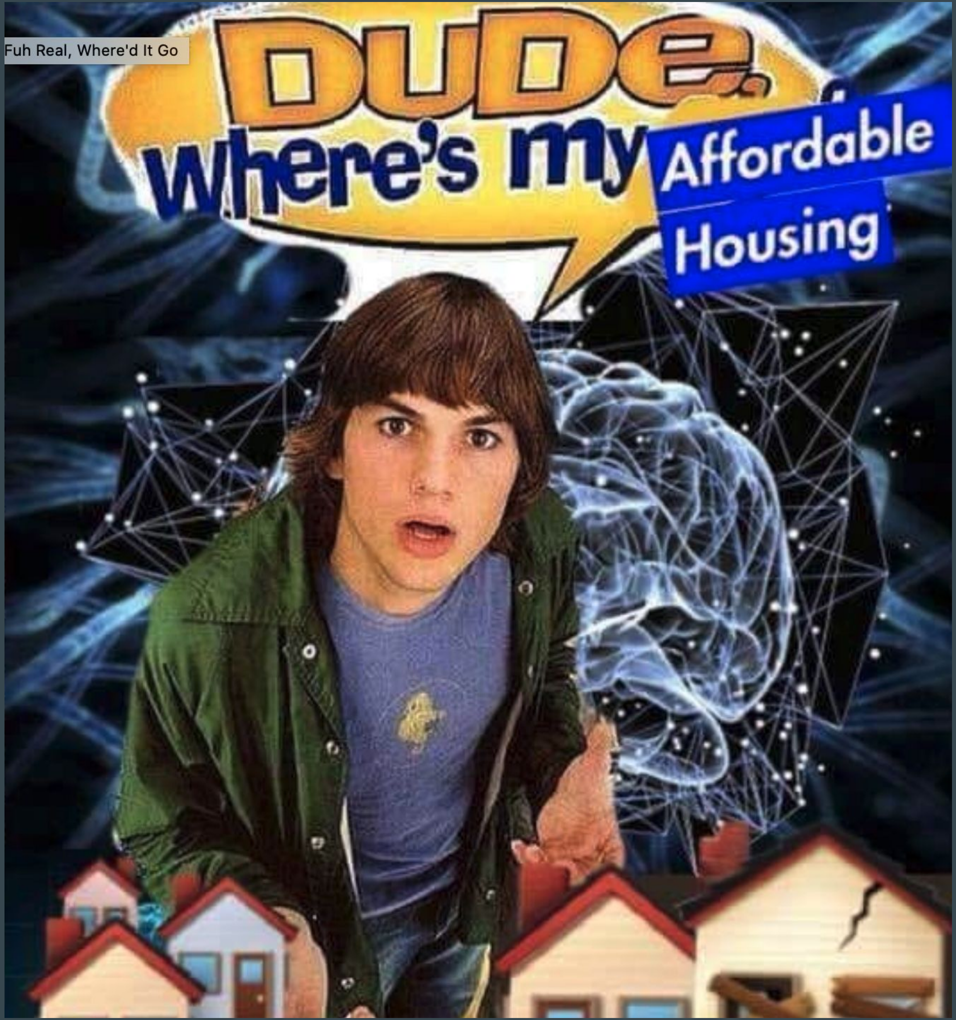
II. Executive Summary

By using the form of Machine Learning called **Linear Regression**, this project processes through a database of AMES Housing training data.

Then, linear regression predicts a house's **sale price** and **value** using the trends and properties of this training data.

Additionally, **regression techniques** (such as **feature engineering** and **selection**) enhance the quality of our predictions.

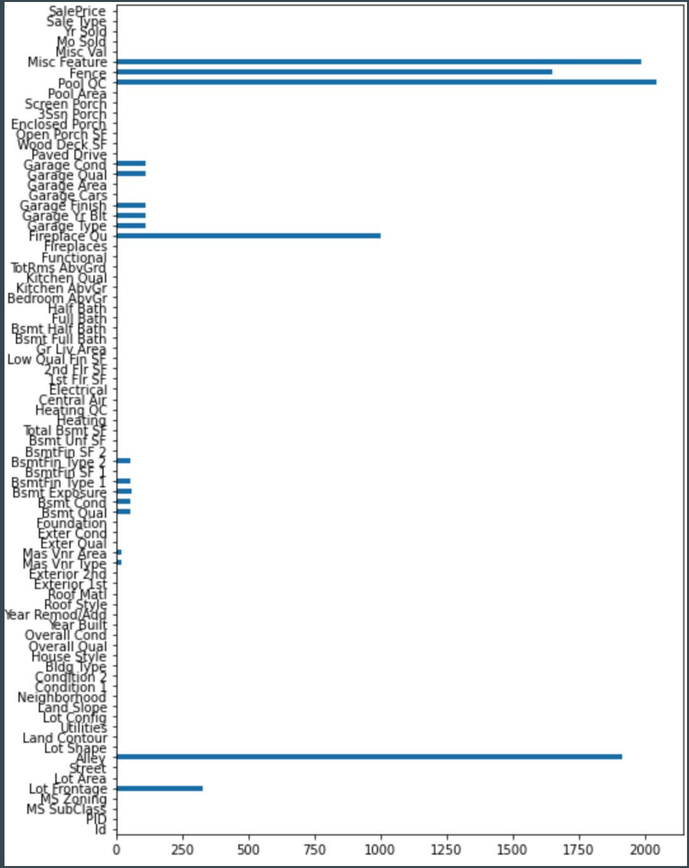
Fuh Real, Where'd It Go



III. Data Cleaning: Null Values

Replace **Null Values (NaNs)** with appropriate replacements using **.replace**

1. Categorical variables need ('NA') replacements
   a. These will later be one-hot-encoded (dummified)
2. Continuous variables need (Float) replacements
3. Discrete variables need (Int) replacements
4. Ordinal variables need ('NA') replacements
   a. These will later be mapped with hierarchical values



IV. Data Cleaning: One-Hot-Encoding/Mapping

Categorical variables (like 'Neighborhood') possess a lot of information but need to be made quantitative.

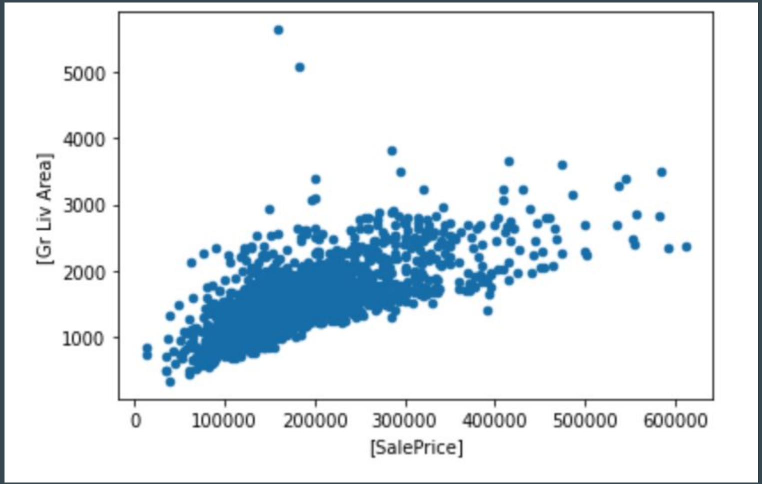
- One-hot-encoding gives each Neighborhood a column of binary (0/1) values for each neighborhood:
  - 0 value properties are not in that Neighborhood.
  - 1 properties are in that Neighborhood.
- We can interpret this data numerically now.

IV. Data Cleaning: One-Hot-Encoding/Mapping

Ordinal variables (like ‘Garage Quality’) possess a lot of information but need to be made quantitative. Additionally, these quantities need to have a hierarchy (e.g. ‘5 is more valuable than 2’).

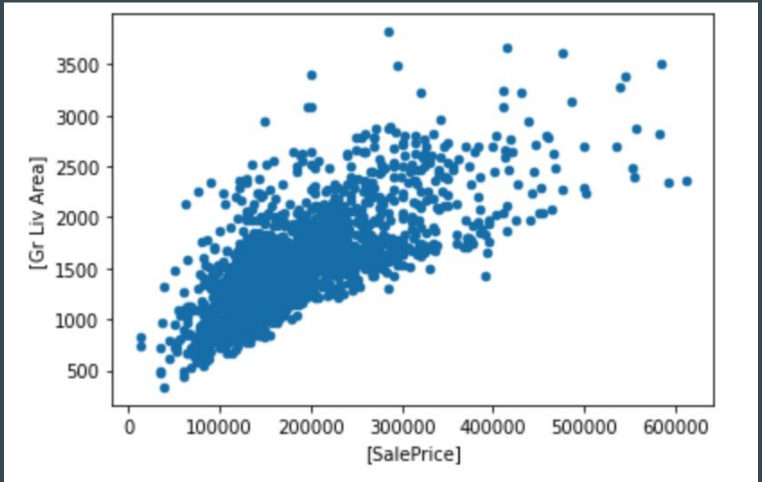
- **{'Lot Shape' : {'IR3' : 1, 'IR2' : 2, 'IR1' : 3, 'Reg' : 4},**
- **'Utilities': {'ELO' : 0, 'NoSeWa' : 1, 'NoSewr' : 2, 'AllPub' : 3},**
- **Etc. }**
- We can interpret this data numerically now.

V: Exploratory Data Analysis: Outlier Management



Gross Living Area vs Sale Price

BEFORE



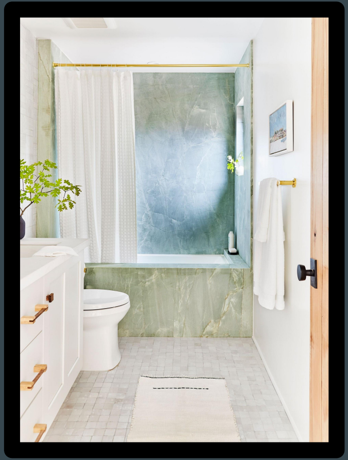
Gross Living Area vs Sale Price

AFTER

VI. Feature Engineering

- **# This code conglomerates the correlated data ‘Full Bath’ and ‘Half Bath’**
- **train_df['Bathroom Total'] = train_df['Full Bath'] + (0.5 * train_df['Half Bath'])**

Feature engineering lets us **express correlations** between features and **highlight** them in the model, **increasing the accuracy of the model’s predictions** for a house’s Sale Price.



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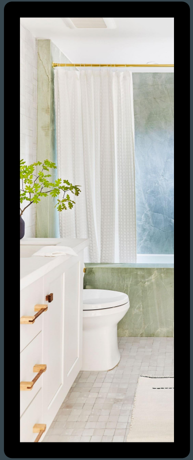

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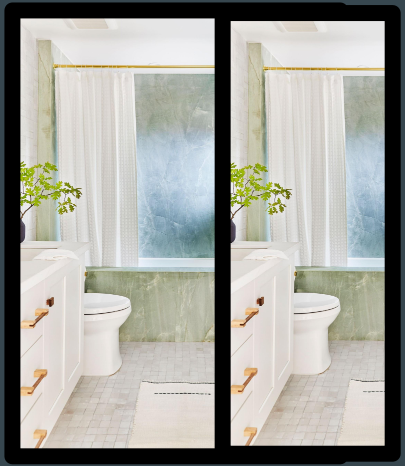
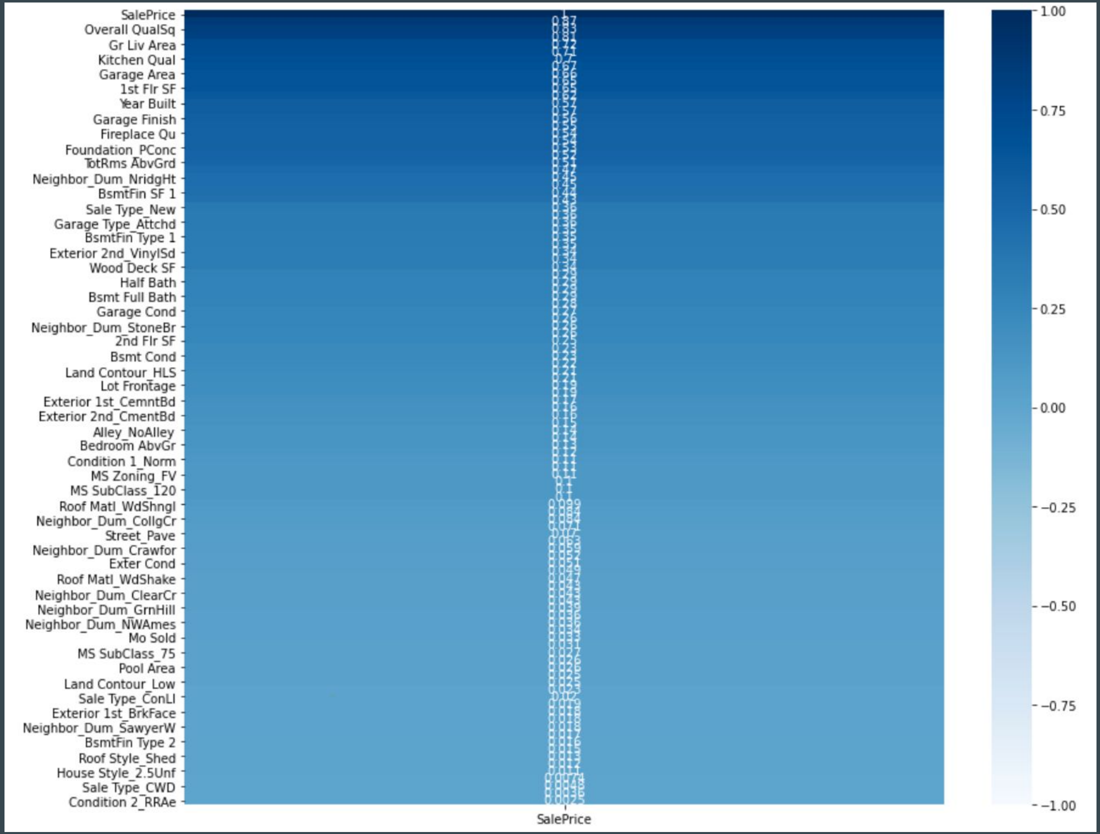


VII. Feature Selection



VIII. Ridge and LASSO Regularization

- First, I scaled the dataset with **StandardScaler**.
- Then, both Ridge and LASSO regularized the data set.
- Regularization:
    - reduces magnitude of coefficients
    - optimizes datasets
    - often increases R2 Values
    - improves accuracy

IX. RMSE and Evaluating Predictions

Root Mean Squared Error:

‘27,979’

- Meaning: Each prediction for Sale Price may be at most $27,979 from the actual Sale Price of each property.
- R2 = 90%

X. Recommendations for Real Estate Developers

One can use linear regression to greatly reduce errors and improve the performance of predicting sale price based on a variety of highly correlated factors.

Although, it seems that knowing which factors influence a house's price (such as Kitchen Quality and Bathroom Space) can often be more valuable than the predictive model itself.

As a result, even the basic method of Linear Regression can be incredibly useful for a firm's Real Estate pricing decisions.

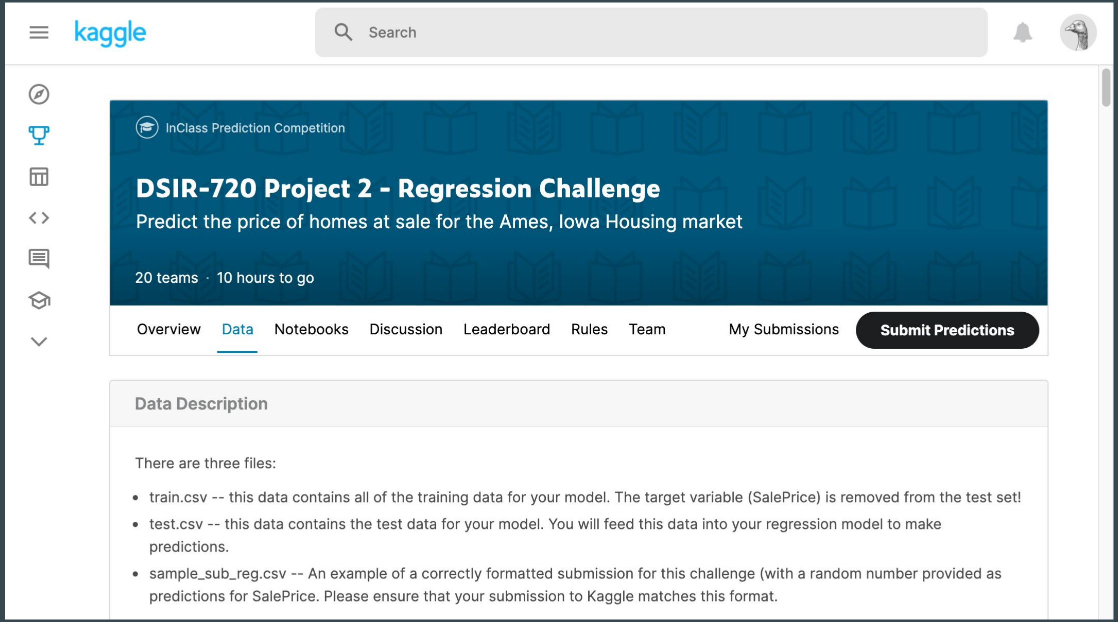
X. Recommendations for Real Estate Developers

Important Factors (Top 7):

1. Overall Quality
2. Gross Living Area
3. Kitchen Quality
4. Garage Area
5. 1ST Floor Square Footage
6. Year Built
7. Finished Garage

Questions?

XI. Data Source and Python Libraries



https://www.kaggle.com/c/dsir-720-project-2-regression-challenge/data
http://jse.amstat.org/v19n3/decock/DataDocumentation.txt

XI. Data Source and Python Libraries

- import pandas as pd
- import numpy as np
- import matplotlib.pyplot as plt
- import seaborn as sns

- from sklearn.linear_model import LinearRegression
- from sklearn import metrics
- from sklearn.model_selection import train_test_split, cross_val_score
- from sklearn.preprocessing import PolynomialFeatures, StandardScaler
- from sklearn.linear_model import Ridge, RidgeCV
- from sklearn.linear_model import Lasso, LassoCV