

Data Science Problem

Objective: Predict the price of housing in Ames, with higher accuracy and more features

We are a team of data scientists engaged by a real estate company to create a Machine Learning model that predicts the sale price of residential properties in Ames, Iowa with higher accuracy and more features as compared to available apps in the market and deploy it on an Application Programming Interface (API) for their agents.

Dataset Used for Prediction

80 explanatory variables

- Qualitative Features (eg quality and condition)
- Area specific Features (eg porches, bath, kitchen)
- Size Related Features (eg. total basement in sq ft, above grade (ground) living area, garage area)
- Location (eg. ms zoning and neighbourhood)
- Date-related (eg. year built, garage year built, year sold)

The features are also classified into the following data types:

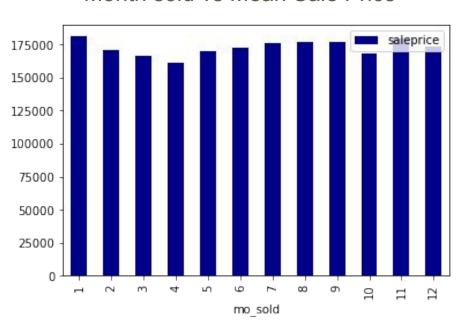
- Numerical (eg total basement square feet)
- Categorical (Ordinal) (eg overall condition)
- Categorical (Nominal) (eg. house style)

Overall Trend of Dataset Observations

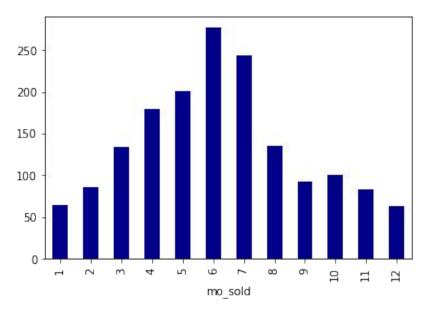


Overall Trend of Dataset Observations

Month sold vs Mean Sale Price

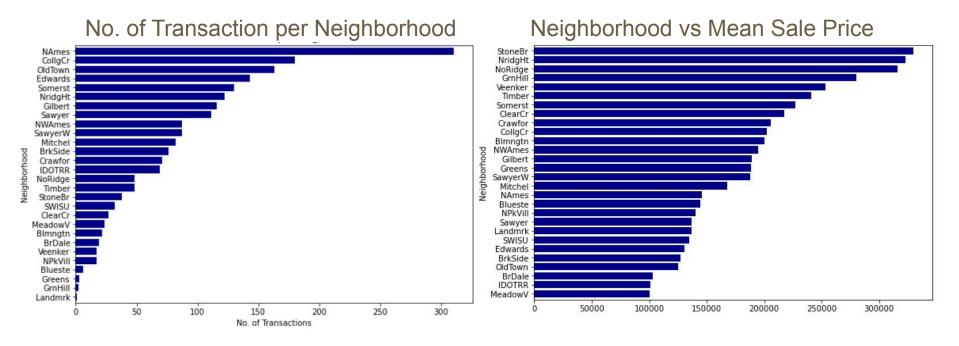


Month vs No. of Transaction



- Higher amount of transactions during summer
- Does not affect mean Sale Price

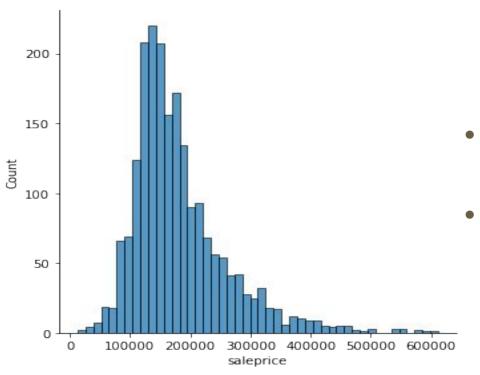
Overall Trend of Dataset Observations



- Northwest Ames has the high amount of transactions
- Most of the sales happened for residential low and medium density area

Visualizing target variable - Sale Price

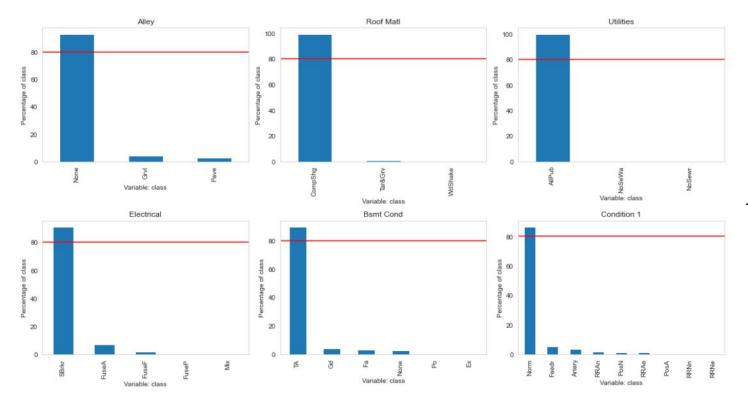
Sale Price Distribution



Majority data capture between 100k to 330k

Right-skewed, potential outliers

Feature Selection: High Frequency Class



Threshold set at 80%

Features Selection

Correlation Matrix for Ames House Prediction data

```
saleprice -
  overall qual -
    exter qual -0.720.72
    bsmt qual -0.630.640.57
   bsmt cond -0.25 0.3 0.2 0.64
   heating gc -0.480.480.520.43 0
  kitchen qual -0.690.67 0.72 0.51 0.2 0.51
               0 140 180 110 17 0 20 0910 1
  fireplace gu -0.530.460.340.290.12 0.2 0.340.04
  garage qual - 0.3 0.3 0.230.190.130.16 0.210.083
  garage cond -0.290.29 0.210.190.140.15 0.210.0980.21 0.96
     electrical -0.280.29 0.23 0.29 0.21 0.26 0.250 0530 17 0.17 0.1
 wood deck sf -0.330.260.220.250.120.130.2800061210.120.110.1
 total bsmt sf -0.640.540.450.580.410.270.420.07(0.320.170.170.210.2
   gr liv area -0.680.530.390.310.070.26 0.40.050.440.140.130.140.240.37
  garage area -0.660.54 0.5 0.4 0.12 0.31 0.47 0.07 0.31 0.58 0.57 0.23 0.24 0.45 0.44
 mas vnr area -0.440.39 0.320.270.0990 17 0.270 08 0 28 0 14 0 13 0 14 0 14 0.33 0.29 0.32
totrms abvgrd -0.450.33 0.210 19 0049 15 0.220 0470.3 0.03 0.02 0.0730 170 23 0.8 0.29 0.1
bsmt_full_bath_-0.260.150.130.240.170.0660.150.03D.0870.08D.0730.140.160.29.0046.16.0.1-0.07
     full bath -0.550.51 0.460.35) 0520.31 0.410.0150.27 0.10.0820.170.16 0.33 0.61 0.38 0.23 0.5 0.03
    fireplaces -0.460.380.230.230.120.120.24.003 8.870.220.210.160.230.280.410.260.240.260.130.1
  garage cars -0.660.57 0.510.44 0.14 0.33 0.47 007 0.35 0.59 0.58 0.24 0.24 0.43 0.46 0.9 0.32 0.33 0.13 0.44 0.29
                                                         garage_qua
```

 Selection based on top few correlated features (corr >0.50)

- 0.8

- 0.6

- 0.2

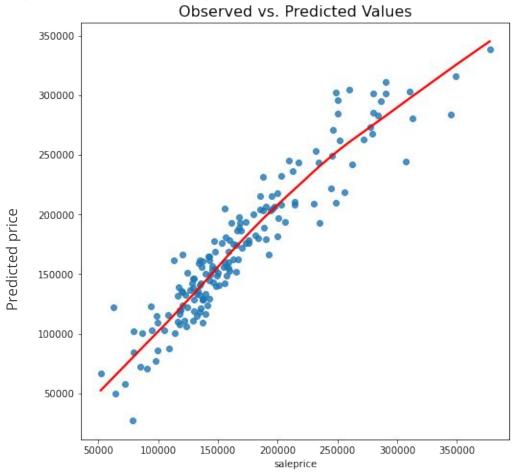
Features in the prediction model

Categorical (Ordinal)	- 'Overall_qual' - 'Fireplace_qu'
Categorical (Nominal)	 'Lot_config', 'Lot_shape', 'Land_slope', 'Land_contour' 'Ms_zoning', 'Neighborhood', 'Bldg_type' 'Street', 'House_style', 'Roof_style', 'Exterior_1st', 'Exterior_2nd', 'Mas_vnr_type', 'Foundation' 'Central_air', 'Paved_drive' 'Sale_type'
Numerical	 'Lot_frontage' 'Lot_area', 'Garage_area', 'Mas_vnr_area' 'Total_bsmt_sf', 'Gr_liv_area' 'Fireplaces', 'Full_bath' 'Age'

Model Selection & Performance

	Linear Regression	Ridge (alpha = 1)	Lasso (alpha = 1)	Elastic Net (alpha = 0.01, l1_ratio = 0.4444)
MSE (Train)	453705780.33	455767752.73	453838558.22	470576542.68
MSE (Test)	461692464.30	429791086.29	452407612.99	421405745.57
Percentage difference	-1.76%	5.69%	0.32%	10.44%

Actual VS Predicted Sale Price



Deployment of ML Model

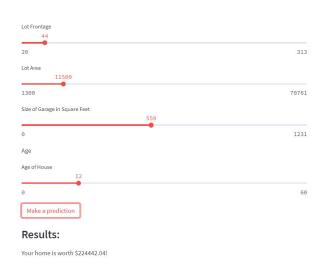
Web based deployment using **Streamlit**.

Process:

- Load and apply saved feature engineering
- Load and apply saved the best model
- Select each value of features using a slider window
- Make prediction button

Let's try out our prediction webpage!





Demo Time

Limitations of the model

- Developed using data on houses sold between 2006 2010 (4 years)
 - Not enough to capture annual changes in Sale Price
- Housing prices at present (in 2022) may have also changed as a result of inflation
- Only specific to houses in Ames, model may not be applied to other city or country
- Prices do not take into consideration of social factors (i.e. crime rates, demographics in the neighborhood)
- Assumption of independence variables
- Good at predicting the price of properties within the range of \$70,000 to \$225,000

Conclusion

- Current application in the market: Zillow.com, Trulia
 - Provides estimates on the market value of property
- Our model is specifically build for Ames, lowa
- More features as compared to others
- Complimentary tool on top of Comparative Market Analysis (CMA) reports
 - More confident in their proposed prices with improved accuracy based on more features
- Recommendation
 - Use better model such as XGBoost
- Future project consideration
 - Feature importance from the model, see which coef are greater and identify those features.
 - o Property survey portfolio: Property surveyor to evaluate the price of houses.
 - Extend to banks to establish the asset value of the houses