

Real Estate Sales Pricing Prediction

Litter Box

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Are size, neighborhood the only key drivers of real estate sale prices? What's Missing?

Using the Ames Housing dataset which is an expanded and modernized version of the often cited Boston Housing dataset, we are tempted to address the question mentioned above.

Data Set and Background - Location of Sales



Data Set and Background

- Data Sourced in 2009

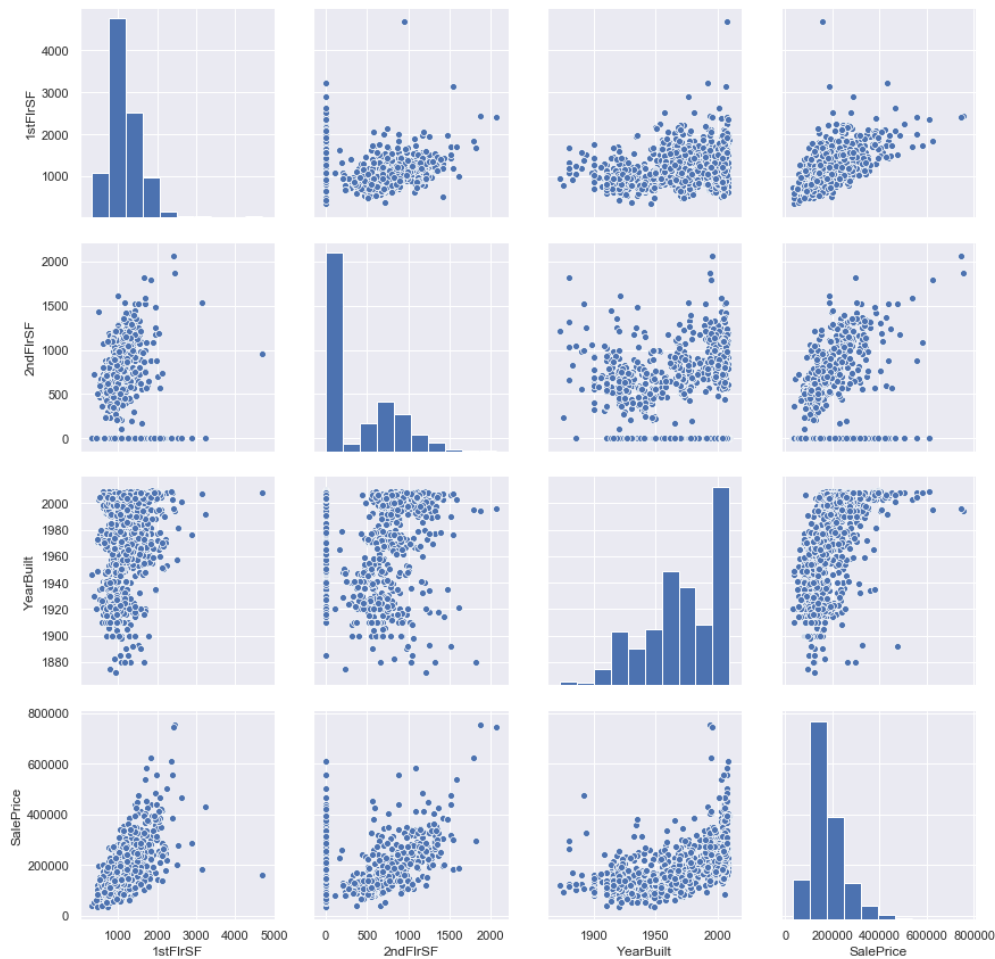
- Range of Sale Price: \$34,900 to \$755,000
- 36 Numerical Features
- 43 Categorical Features

Challenges

1. Too many features, better emphasis on the features that's important to improve accuracy.

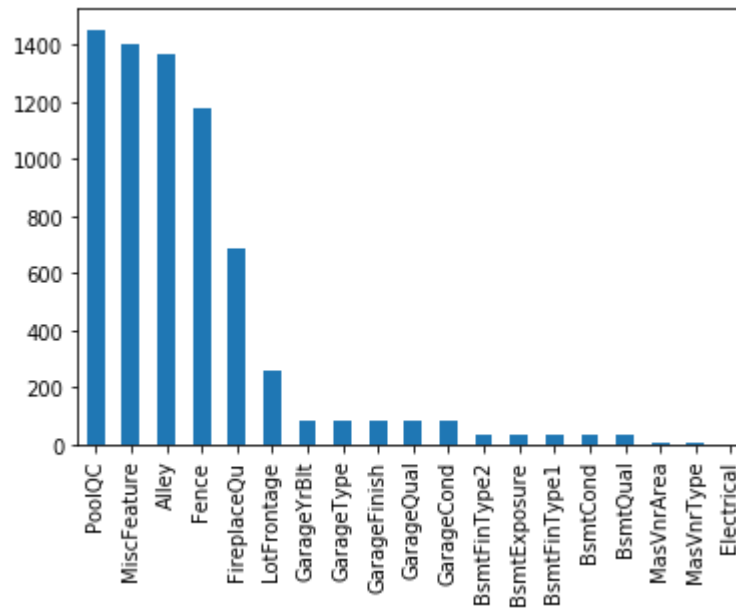
Challenges

2. Multicollinearity:



Data Processing

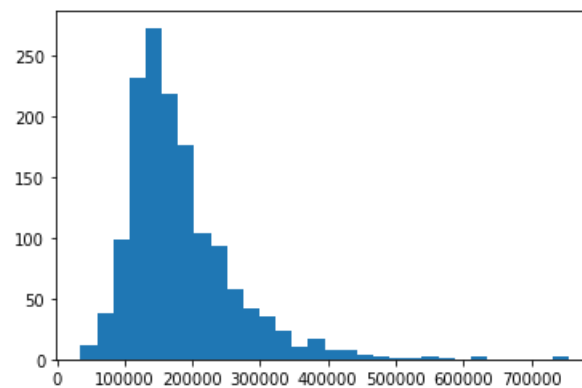
- Excluding features with more than 10% missing values



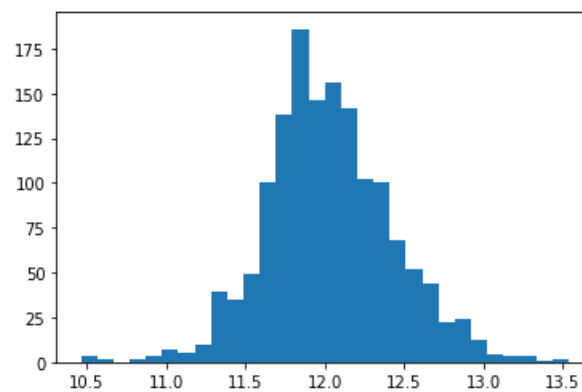
- Excluding categorical features with too many classes to avoid overfitting

Data Processing - Log Transformation of Target

- Sale Price



- $\log(\text{Sale Price})$



Pipeline

- **Numerical:** impute with median
- **Categorical:** impute with most common / one hot encoding.

Feature Selection

- **Naive selection** - selection includes squarefeet, neiborhood and housestyle, year built based on intuition.
- **Full Model** - all features included.
- **Reduced Model** - feature removed based on permutation importance score.

Modelling Approach

- Linear Regression (Lasso)
- Random Forest Regressor
- Graient Boosting Regressor

Model Evaluation Preliminary Results (Naive Selection):

Naive Feature Selection Training:

	MAE_train	MSE_train	R^2_train	MAPE_train	rmsle
RandomForestRegressor	0.08	0.03	0.83	0.937456	0.162844
Lasso	0.10	0.04	0.72	1.181609	0.210453
GradientBoostingRegressor	0.08	0.02	0.88	0.847233	0.137015

Naive Feature Selection Testing:

	MAE	MSE	R^2	MAPE	rmsle
RandomForestRegressor	0.09	0.04	0.79	1.084460	0.189584
Lasso	0.10	0.04	0.77	1.157128	0.197627
GradientBoostingRegressor	0.09	0.03	0.82	1.042674	0.176126

Model Evaluation Preliminary Results (Full Model):

Full Model Training:

	MAE_train	MSE_train	R^2_train	MAPE_train	rmsle
RandomForestRegressor	0.05	0.01	0.91	0.653651	0.119048
Lasso	0.07	0.03	0.80	0.953432	0.179829
GradientBoostingRegressor	0.05	0.01	0.96	0.496677	0.080476

Full Model Testing:

	MAE	MSE	R^2	MAPE	rmsle
RandomForestRegressor	0.07	0.02	0.86	0.869544	0.155604
Lasso	0.08	0.03	0.81	1.001921	0.179815
GradientBoostingRegressor	0.06	0.02	0.89	0.758071	0.139942

Permutation Importance

- Most Significant Features

Feature	Importance
Overall Quality	0.5543
Area above Basement	0.1611
Basement Area	0.0399
Basement Finished Area	0.0303
Size of Garage	0.0209
First Floor Area	0.0192
Second Floor Area	0.0166
Number of Rooms	0.0154
Lot Area	0.0120
Year Built	0.0111

Permutation Importance

- Least Significant

Feature	Importance
Kitchen Area	0.000325
Porch Area	0.000307
Swimming Pool Area	0.000279
Low Quality Finished Area	0.000081
Miscellaneous Feature Value	0.000078

Model Evaluation Preliminary Results (Reduced Model):

Reduced Model Training:

	MAE_train	MSE_train	R^2_train	MAPE_train	rmsle
RandomForestRegressor	0.05	0.01	0.91	0.653651	0.119048
Lasso	0.07	0.03	0.80	0.953432	0.179829
GradientBoostingRegressor	0.05	0.01	0.96	0.496677	0.080476

Reduced Model Testing:

	MAE	MSE	R^2	MAPE	rmsle
RandomForestRegressor	0.07	0.02	0.86	0.869544	0.155604
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Limitations

1. Not suited for broad applications, data is collected in one specific state.
2. Macros such as inflation, impact on the larger economic scale is difficult to gauge and be taken into account in the model.

Future Work

1. Hyperparameter fine-tuning
2. Further investigation in feature importance of categorical variable (Label Encoding, One hot encoding, Drop subset)
3. Dimension reduction and feature elimination for precision

THANK YOU!!



In []:

EDA

Graphs to be included placeholders (challenges to address in challenges)

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Modelling Approach

1. Linear Regression Lasso
2. Random Forest Regressor
3. Gradient Boosting Regressor

Data Cleaning and Pipeline

1. Numerical Data
2. Categorical Data

Load Data