Ames Housing Prices: Advanced Regression

Capstone Project Report

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Definition

Housing markets are incredibly competitive. Using a dataset of 79 characteristics (variables) of nearly 1500 homes in the Ames, Iowa area a potential home seller or buyer could possibly influence price negotiations of a house by examining more than just the number of bedrooms, number of bathrooms and square footage of a house. The Ames Housing dataset was compiled by Dean De Cock for use in data science education.

Problem Statement

The problem set forth is utilizing this housing dataset to its maximum potential by identifying optimal features to include in a model. The strategy to identify the optimal features using data exploration to identify patterns, correlations and feature engineering to determine the appropriate inputs for the model. The expected solution will involve a subset of the features in the dataset that best contribute to the 'SalePrice' of any given home.

Metrics

The performance metric best suited for this type of advanced regression model is Root-Mean-Squared-Error (RMSE). The RMSE is the square root of the variance of the residuals. It indicates the absolute fit of the model to the data–how close the observed data points are to the model's predicted values. Taking the RMSE between the logarithm of the predicted value and the logarithm of the observed sales price. Taking logs means that errors in predicting expensive houses and cheap houses will affect the result equally.

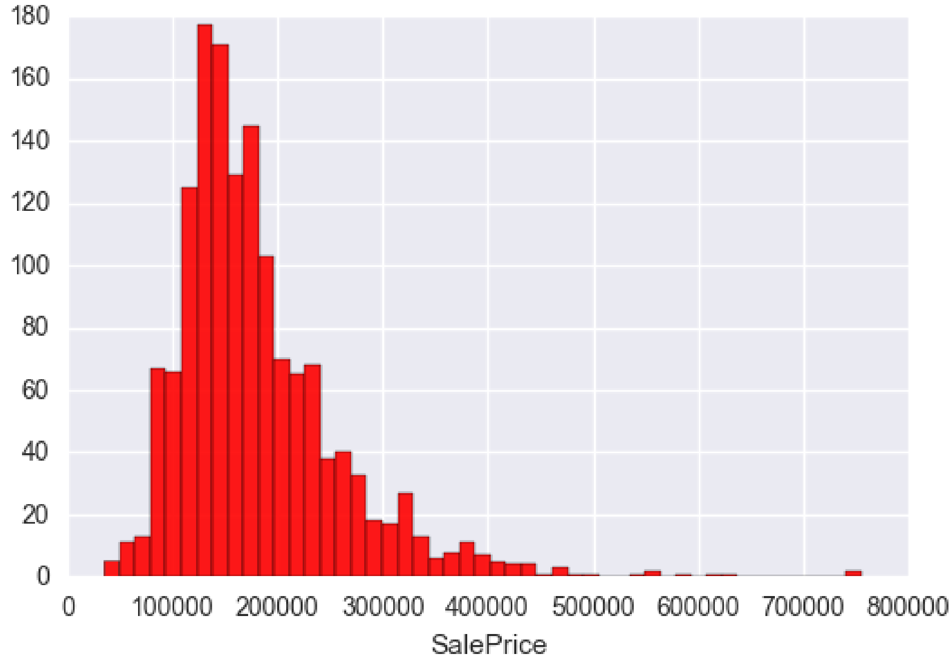
Analysis

Data Exploration

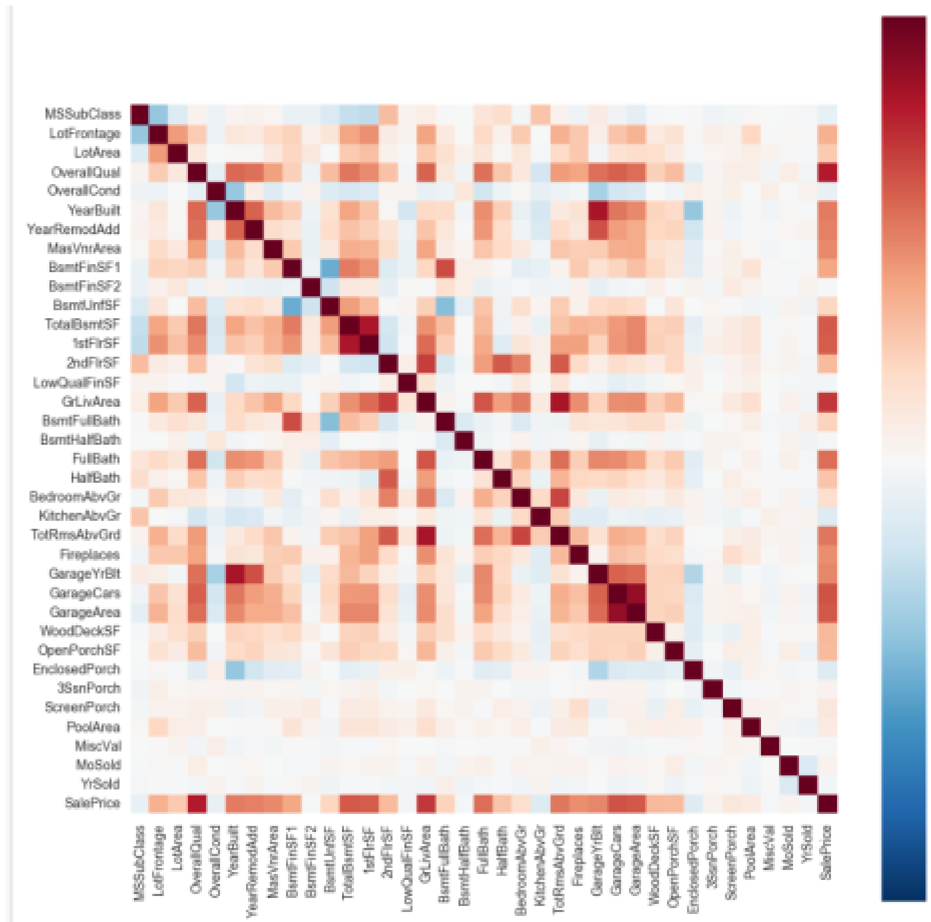
Given the problem domain is relative sale prices of homes based on a calculated subset of features, elementary statistics of the housing data will be useful to analyze various prediction results from the implemented model. Statistics to be calculated include minimum price, maximum price, mean price, median price and the standard deviation.

Exploratory Visualization

To better understand the target output value 'SalePrice', I have included some visualizations including a simple bar graph visualization of the values from the column labeled 'SalePrice' in the training dataset. As well as a heat map to get a high-level overview of which features in the dataset correlate highly with 'SalePrice' to guide further feature observation and engineering.



The average 'SalePrice' from the dataset is $180,921.20, while the min and max are $34,900.00 and $755,00.00 respectively. The are a few outliers but most the data is within one standard deviation of $79,442.50.



To better understand and use the heat map effectively for feature observation. A sorted dictionary was created that list the numerical features in descending order by their correlation with 'SalePrice'.

Feature Observation

- 'OverallQual' is the Rating of the overall material and finish of the house (1-10, Very Poor to Very Excellent)
- 'GrLiveArea' is above grade (ground) living area square feet
- 'GarageCars' is size of garage in car capacity
- 'GarageArea' is size of garage in square feet
- 'TotalBsmtSF' is total square feet of basement area
- '1stFlrSF' is first Floor square feet
- 'FullBath' is full bathrooms above grade
- 'TotRmsAbvGrd' is total rooms above grade (does not include bathrooms)
- 'YearBuilt' is the original construction date
- 'YearRemodAdd' is remodel date (same as construction date if no remodeling or additions)

Looking at the top 10 features that correlate most (>0.50) highly with 'SalePrice' several features are highly correlated amongst certain descriptive categories such as Garage space wich contains attributes 'GarageCars' and 'GarageArea'. The correlation graphs and data above along with my intuition and sampling of various physical real estate ads should allow for a initial reduction in the feature set for ease of analysis and model building. The features chosen for an initial analysis include 'OverallQual', 'GrLiveArea', 'GarageCars', 'FullBath' and 'TotRmsAbvGrd'.

Description of the features and their respective value ranges can be found in the data_description.txt file included with the project files.

Algorithms and Techniques

For this advanced regression type problem, the algorithm most suited for the characteristics of this problem are decision trees. The goal of a decision tree is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features. There are many advantages to using a decision tree for this problem because they are visual, simple to understand and easy to interpret. Additionally, to implement a decision tree there is little data preparation to do which allows for faster iterations and more nimble and adaptable analysis. Decision trees are also easy to refine by augmenting the minimum number of samples required at a leaf node or setting the maximum depth of the tree to avoid overfitting.

Benchmark

Additionally, to appropriately benchmark the output prediction values from the model using the testing data set a reasonable metric for assessing performance would be to look at the statistical attributes of the dataset. For this specific type of problem domain of predicting housing prices a good attribute to determine the robustness of the model would be the percent difference in the average 'SalePrice' from the training data compared to the predictions from the model using the test data.

To appropriately compare the performance of the model a benchmark result will be calculated using the Root-Mean-Squared-Error (RMSE). The benchmark results will be a score that indicates the absolute fit of the model to the data–how close the observed data points are to the model's predicted values. The benchmark will be comparing the average housing price from the subset of training data ('benchmark_avg') and comparing it against the actual housing prices from the subset of the training data ('y_train'). The average housing price is chosen as a benchmark because housing prices a historically grouped by geographic areas and pricing can be generally associated to regional trends in the market. For the purposes of this project's scope assessing performance against a benchmark scored against the average housing cost should be more than adequate. As for the model predicted results ('preds') that performance will be assessed directly from the known labels of the subset of the training data set that was split for testing ('y_test') the model performance. A percent difference < 10% could be classified as robust in terms of initial performance before any model tuning is applied.

Methodology

Data Preprocessing

In order to implement the decision tree model the training data has to be processed. The first step in processing the data is creating a new data structure only containing the features selected from the feature observation section above. There are no obvious abnormalities or characteristics about the training dataset that needs to be addressed.

	OverallQual	GrLivArea	GarageCars	FullBath	TotRmsAbvGrd
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000
mean	6.099315	1515.463699	1.767123	1.565068	6.517808
std	1.382997	525.480383	0.747315	0.550916	1.625393
min	1.000000	334.000000	0.000000	0.000000	2.000000
25%	5.000000	1129.500000	1.000000	1.000000	5.000000
50%	6.000000	1464.000000	2.000000	2.000000	6.000000
75%	7.000000	1776.750000	2.000000	2.000000	7.000000
max	10.000000	5642.000000	4.000000	3.000000	14.000000

All five features are described with numeric values and are present for all 1460 data points in the training dataset.

Implementation

To implement and train a model using the decision tree algorithm I followed several steps listed below:

- Imported 'GridSearchCV' from 'sklearn.metrics' to find the optimal 'max_depth' parameter for the decision tree. Grid search is a way of automatically testing multiple combinations of parameter tunes.
- Imported 'DecisionTreeRegressor' from 'sklearn.tree' to create a decision tree regressor object.
- Imported 'make_scorer' from 'sklearn.metrics' to create a scoring function object.
- Created a dictionary for 'max_depth' containing the values from 1 to 10.

Refinement

When the model is trained with a maximum depth of 1 it appears to suffer from high bias where it is underfit due to the model being too simple and unable to represent the complexity. When the model is trained with a maximum depth of 10 it appears to suffer from high variance where it is overfit because the decision tree is too large. At the maximum depth of 1 both the training and testing scores are low and at the maximum depth of 10 the training score is high while the testing score is low.

Parameter 'max_depth' is 5 for the optimal model.

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Results

Model Evaluation and Validation

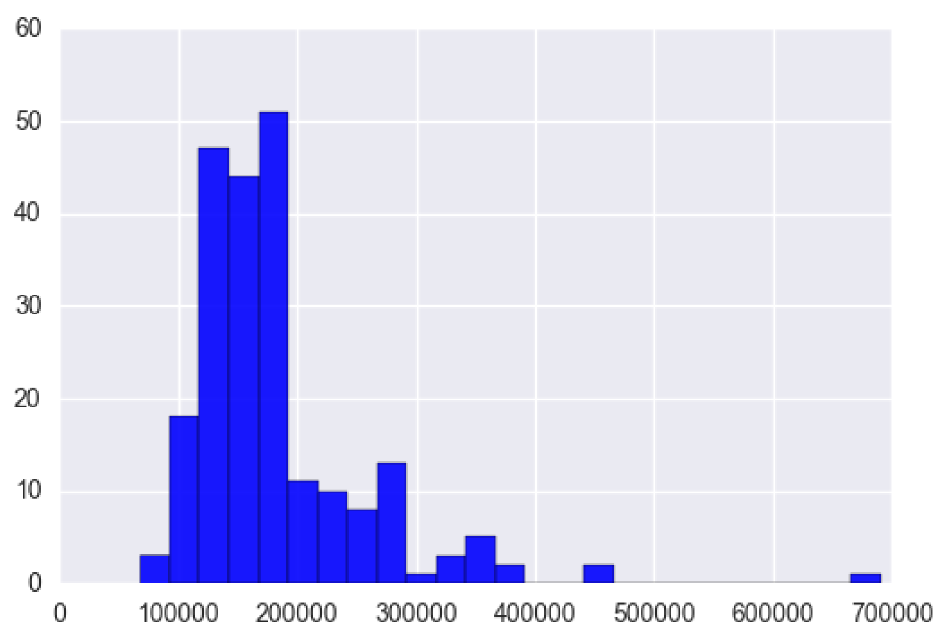
I think a maximum depth of 5 results in an model that best generalizes the unseen data because that appears to be the sweet spot that minimizes bias and variance due to model complexity. There is sufficient data to reduce bias and the error between the training and validation score is reasonable. At a maximum depth of 5 the training and validation scores are trending close enough together to predict a reasonable 'SalePrice' while also being able to provide a generalized model that is not to biased or over-fit to the training data and therfore I believe predicts useful results.

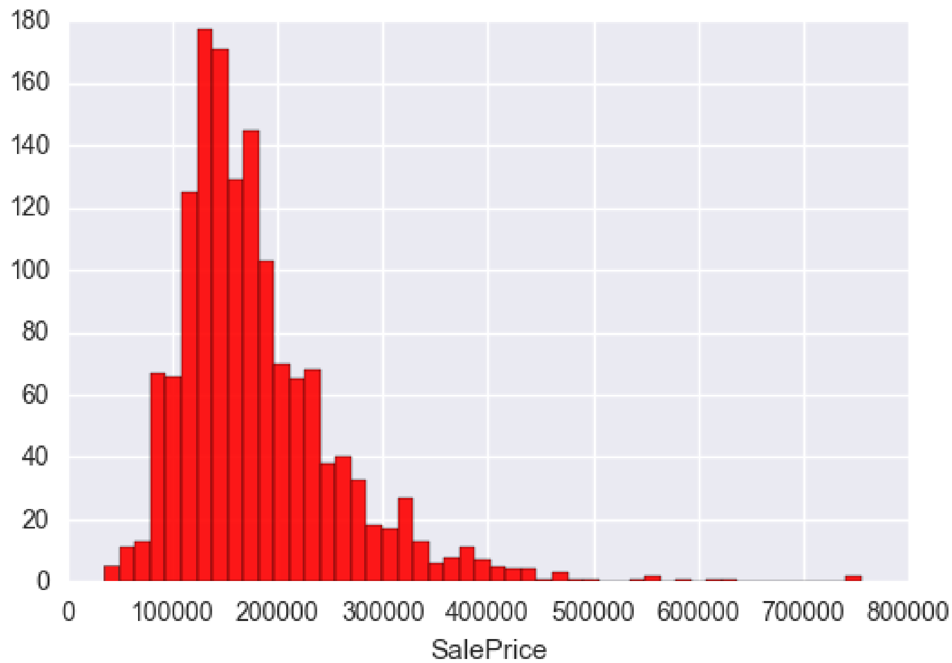
At this point there are diminishing returns from trying to replace a good learning algorithm with an exceptional one for this specific problem. Instead most of the improvements will come from feature engineering that will enable the learning system to extract more patterns and generalize more accurately.

Justification

Looking at the percent difference between the RMSE of the benchmark (training data and average house price values) and comparing them to the RSME of the prediction (actual house price and predicted values). The percent difference is small.

RSME – Benchmark	RSME – Prediction	Percent Difference
22.57	20.80	-7.842%





At a high-level, both 'SalePrice' graphs have a similar shape and trend. Overall I think the comparison of the two graphs represents a rough although robust model for predicting housing prices given a set of engineered features for analysis. The predictions graph in blue could have a bit more fidelity but as an initial survey of the data it well represents the high-level trends of the original red 'SalePrice' graph.

Reflection

Initially given a wide range of features that describe a given house it was relatively straight froward to identify and filter out the most relevant features that most highly correlated with the 'SalePrice' of the house. Determining a benchmark to assess and engineer a robust model was one of the more difficult tasks of this project. The implemented solution involves a comparison between a benchmark score and a prediction score. The benchmark score is calculated by doing an RSME between the average 'SalePrice' of a portion of the training set and comparing it to the actual 'SalePrice' data. I took this approach for this problem due to the clustering behavior of real estate markets in each geographical area. By comparing the average price to the actual price over a given geographical area you can get a baseline housing price range to gauge the robustness of the model's predictions. The score that is compared against the benchmark is calculated by looking at the output prediction from the model and comparing it to the actual 'SalePrice' of the home from the other portion of the train_test data split. The final analysis was done by comparing the raw scores from the benchmark results and the prediction results and assessing performance based on percent difference. Initially a 10% threshold was used a metric of a successful and robust model given most housing prices are negotiable within that range.

After completion of this project an analysis of the results it became clear that the most important features to determine a given houses' price are more physical in nature and can be easily referenced on a realtors' flyer posted outside the house for sale. Although there are many other factors a homebuyer may take into consideration such as location, neighborhood or school districts it is most beneficial to consider features such as overall quality, square footage, number of bedrooms and number bathrooms when trying to determine the 'SalePrice' of a house.

Improvement

One aspect of the implementation of the model that could be improved for further a nalysiswould be the use of something like a RandomForestRegressor in place of a heat map to determine optimal correlation of features to determine 'SalePrice'. A random forest is a pre-process estimator that fits several classifying decision trees on various sub-samples of the dataset and use averaging to improve the predictive accuracy and control over-fitting. I chose the heat map to determine correlation due to its visual nature and how easy it is to interpret. Going beyod the scope of this project a random forest could provide a richer analysis but lead to a similar outcome. A random forest could help with over-fitting and provide a wider range of prediction values given a more diverse feature set. I beleive the current implemtation of the model and feature set is robust enough to provide an initial set of reliable predictions.