Module 3 Assignment 1: House Prices: Advanced Regression Techniques

Introduction

Developing a well-tuned predictive model (Ridge, Lasso, ElasticNet) can provide accurate estimates of home prices, benefiting real-estate industry stakeholders. Lasso or ElasticNet approaches may excel with many good predictors due to their cost functions. These methods offer advantages like regularization, reducing collinearities, and improving performance on unseen data. However, they might not be the best for variable selection due to the arbitrary selection in the presence of multicollinearity. This study evaluates these predictive models to identify predictors of home prices and determine the most suitable approach.

Method

Home sale prices data from Ames, Iowa, were sourced from Kaggle and analyzed using Jupyter Notebooks. Exploratory data analysis examined feature characteristics, associations, distributions, missingness, and outliers. Both bivariate (Pearson correlations, t-tests, ANOVAs, simple linear regressions) and multivariate analyses (OLS, Ridge, Lasso, and ElasticNet regression) were conducted using k-fold cross-validation. Model assumptions and metrics were examined throughout the analyses.

Results and Insights

Descriptive Statistics and Data Preparation:

- Sale prices ranged from $34,900 to $755,000 (M= $180,921

- Log transformation improved normality for subsequent analyses.
- Categorical variables were encoded into indicator, ordinal, and non-indicator variables, creating a larger dataset for analysis.

Bivariate Analyses:

- Significant predictors of Sale Price: central air ($t(1458) = 17.26$, $p < .001$), exterior quality ($F(3, 1456) = 443.33$, $p < .001$), and total square footage ($r = .82$, $p < .001$).
- Regression models (simple, piecewise, five-factor) showed R^2 values of .76, .82, and .84, respectively.

Model Comparisons:

- Lasso: Optimal alpha ~.005 with $R^2 = .90$; validation set $R^2 = .863$; Kaggle test RMSE = 0.16194.
- ElasticNet: alpha : 0.013, Best performance with $R^2 = .92$; Kaggle RMSE = 0.1365. Optimal alphas were .015 (limited data) and .009 (full data).

Feature Importance:

- ElasticNet's optimal model indicated that square footage, overall quality and condition, and year built were significant positive predictors of Sale Price.
- Negative predictors included years since last remodel and certain zoning classifications.

Kaggle Username:

Sunnysharma03

Screenshot of Kaggle Scores for 2 models:

salesprice_lasso_model.csv Complete · 14h ago	0.16194
salesprice_elastic_model.csv Complete · 14h ago	0.13658

Appendix – Python code and outputs:

Module 3 Assignment 1: House Prices: Advanced Regression Techniques (Kaggle)

Sachin Sharma

MSDS 422

6 July 2024

Import Modules

```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
from scipy import stats
from scipy.stats import ttest_ind, f_oneway
import statsmodels.api as sm
from IPython.core.interactiveshell import InteractiveShell
from sklearn.model_selection import train_test_split, KFold,
cross_validate
from numpy import mean, absolute
from sklearn.linear_model import Ridge, ElasticNet, LinearRegression,
Lasso, LassoCV
from sklearn.metrics import r2_score, get_scorer, mean_squared_error
from sklearn.decomposition import PCA
from sklearn.preprocessing import scale, StandardScaler,
PolynomialFeatures, LabelEncoder
import warnings
# Ignore all FutureWarnings
warnings.filterwarnings("ignore")
InteractiveShell.ast_node_interactivity = "all"
```

Data Preparation

```
housing_training_data = pd.read_csv('train.csv')
housing_training_data.shape
housing_training_data.head()

(1460, 81)

   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape
\
0   1          60       RL         65.0     8450   Pave   NaN      Reg

1   2          20       RL         80.0     9600   Pave   NaN      Reg

2   3          60       RL         68.0    11250   Pave   NaN      IR1

3   4          70       RL         60.0     9550   Pave   NaN      IR1
```

```
4   5           60        RL          84.0     14260    Pave    NaN       IR1


  LandContour Utilities  ... PoolArea PoolQC Fence MiscFeature MiscVal
MoSold  \
0         Lvl    AllPub  ...        0    NaN   NaN         NaN       0
2
1         Lvl    AllPub  ...        0    NaN   NaN         NaN       0
5
2         Lvl    AllPub  ...        0    NaN   NaN         NaN       0
9
3         Lvl    AllPub  ...        0    NaN   NaN         NaN       0
2
4         Lvl    AllPub  ...        0    NaN   NaN         NaN       0
12

  YrSold  SaleType  SaleCondition  SalePrice
0   2008        WD         Normal     208500
1   2007        WD         Normal     181500
2   2008        WD         Normal     223500
3   2006        WD        Abnorml     140000
4   2008        WD         Normal     250000

[5 rows x 81 columns]
```

Details on Dependent Variable

We can start analyzing the distribution of the dataset's dependent variable, sale price, by generating summary statistics.

```
housing_training_data['SalePrice'].describe()

count      1460.000000
mean     180921.195890
std       79442.502883
min       34900.000000
25%      129975.000000
50%      163000.000000
75%      214000.000000
max      755000.000000
Name: SalePrice, dtype: float64
```

We can also construct a histogram and a boxplot to visualize the distribution of the sale price variable in this dataframe.

```
plt.figure(figsize=(10, 6))
sns.boxplot(x=housing_training_data["SalePrice"], palette="pastel")
plt.title('Distribution of Sale Prices', fontsize=16)
```

```
plt.xlabel('Sale Price', fontsize=14)
plt.ylabel('Frequency', fontsize=14)
plt.xticks(rotation=45)
plt.grid(True)
plt.show();
```

Check for Missing Data and Outliers

```
# Calculate null counts, percentage of null values, and column types
null_count = housing_training_data.isnull().sum()
null_percentage = (null_count * 100) / len(housing_training_data)
column_type = housing_training_data.dtypes

# Combine the null counts, percentage, and column types into a summary
DataFrame
null_summary = pd.concat([null_count, null_percentage, column_type],
axis=1, keys=['Missing Count', 'Percentage Missing', 'Column Type'])

# Filter the summary to show only columns with missing values, sorted
by percentage of missing values
null_summary_with_missing = null_summary[null_count >
0].sort_values('Percentage Missing', ascending=False)
```

```
# Display the summary of columns with missing values
null_summary_with_missing
```

	Missing Count	Percentage Missing	Column Type
PoolQC	1453	99.520548	object
MiscFeature	1406	96.301370	object
Alley	1369	93.767123	object
Fence	1179	80.753425	object
MasVnrType	872	59.726027	object
FireplaceQu	690	47.260274	object
LotFrontage	259	17.739726	float64
GarageType	81	5.547945	object
GarageYrBlt	81	5.547945	float64
GarageFinish	81	5.547945	object
GarageQual	81	5.547945	object
GarageCond	81	5.547945	object
BsmtFinType2	38	2.602740	object
BsmtExposure	38	2.602740	object
BsmtFinType1	37	2.534247	object
BsmtCond	37	2.534247	object
BsmtQual	37	2.534247	object
MasVnrArea	8	0.547945	float64
Electrical	1	0.068493	object

We will address columns containing missing values in our exploratory data analysis by leveraging the percentage of null values, column types, and other available data columns that may offer insights useful for imputation.

We will remove columns with over 50% Null values.

```
# Drop columns with over 50% missing values: Alley, PoolQC, Fence,
MiscFeature
housing_training_data.drop(['Alley', 'PoolQC', 'Fence',
'MiscFeature'], axis=1, inplace=True)
housing_training_data.shape
```

```
(1460, 77)
```

We will assign null values

```
# List of non-numeric columns with more than one null value
columns_None = ['BsmtQual', 'BsmtCond', 'BsmtExposure',
'BsmtFinType1',
                'BsmtFinType2', 'GarageType', 'GarageFinish',
'GarageQual',
                'FireplaceQu', 'GarageCond', 'MasVnrType',
'Electrical']

# Fill null values in non-numeric columns with 'None'
```

```
housing_training_data[columns_None] =
housing_training_data[columns_None].fillna('None')
```

We establish the optimal null-handling approach for each numeric column. Null values in the Masonry veneer area are replaced with 0, nulls in Lot Frontage with the median, and nulls in Year Garage was built with the average of the year the garage was built and the year the house was built.

```
housing_training_data['MasVnrArea'].fillna(0, inplace=True)
lot_frontage_median = housing_training_data['LotFrontage'].median()
housing_training_data['LotFrontage'].fillna(lot_frontage_median,
inplace=True)
avg_years = round((housing_training_data['GarageYrBlt'] -
housing_training_data['YearBuilt']).mean())
# fill Nulls with avg bet year garage was built and year house was
built
housing_training_data['GarageYrBlt'].fillna(housing_training_data['Yea
rBuilt']+avg_years, inplace=True)
```

Let's check if there are any null values available

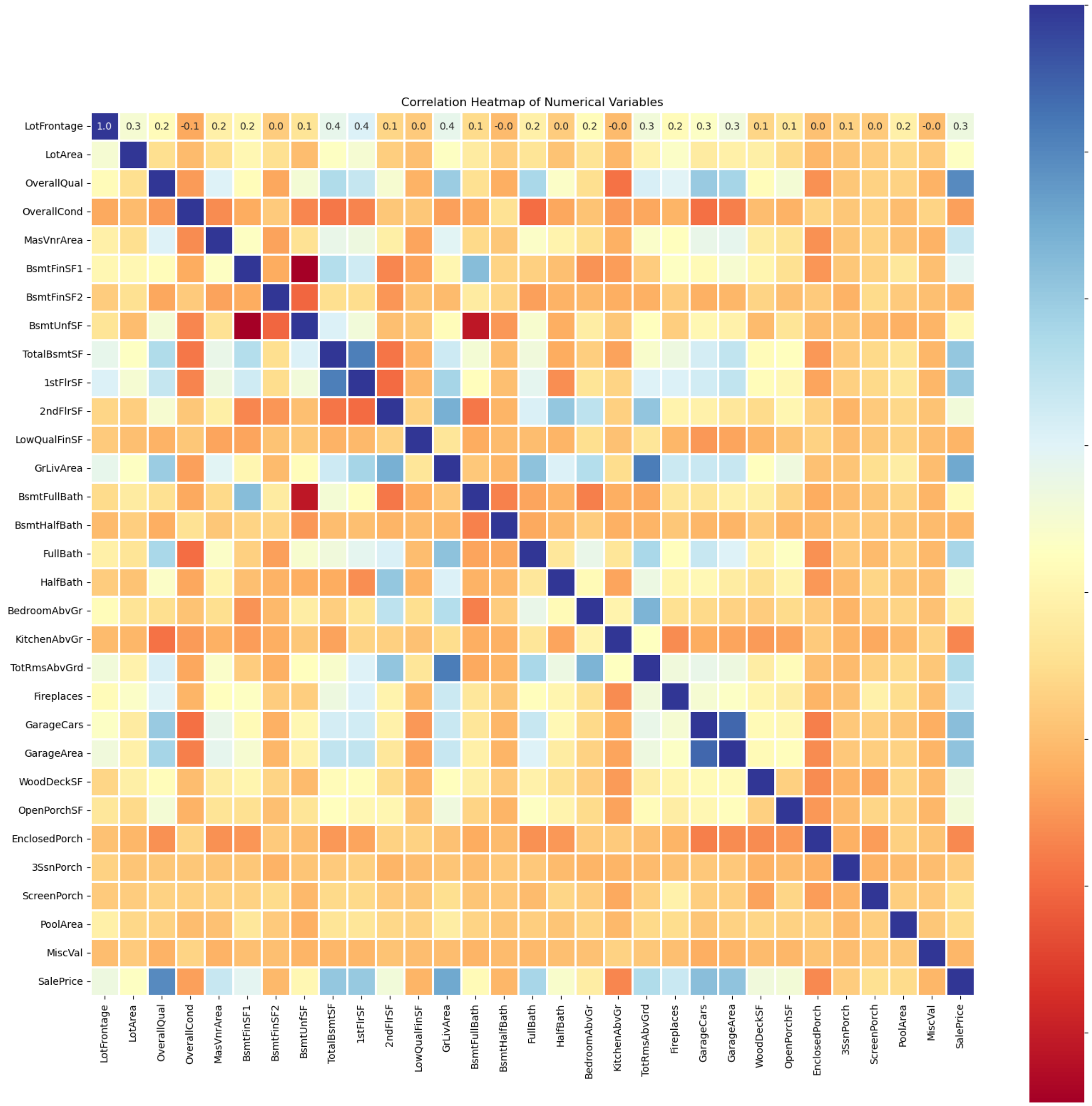
```
# check if there are no more missing values in the dataframe
null_count = housing_training_data.isnull().sum()
null_count[null_count != 0]
```

```
Series([], dtype: int64)
```

Heat Map between dependent and potential Predictor

```
# Select numerical variables
numerical_vars = ['LotFrontage', 'LotArea', 'OverallQual',
'OverallCond', 'MasVnrArea',
                  'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF',
'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
                  'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath',
'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr',
                  'TotRmsAbvGrd', 'Fireplaces', 'GarageCars',
'GarageArea', 'WoodDeckSF', 'OpenPorchSF',
                  'EnclosedPorch', '3SsnPorch', 'ScreenPorch',
'PoolArea', 'MiscVal', 'SalePrice']

# Create correlation matrix
df_corr_housing_training = housing_training_data[numerical_vars]
corrmat_housing_training = df_corr_housing_training.corr()

# Plot heatmap
plt.figure(figsize=(20, 20))
sns.heatmap(corrmat_housing_training, vmax=1, square=True, annot=True,
cmap='RdYlBu', linewidths=0.8, fmt=".1f")
```

```python
plt.title('Correlation Heatmap of Numerical Variables')
plt.show();
```

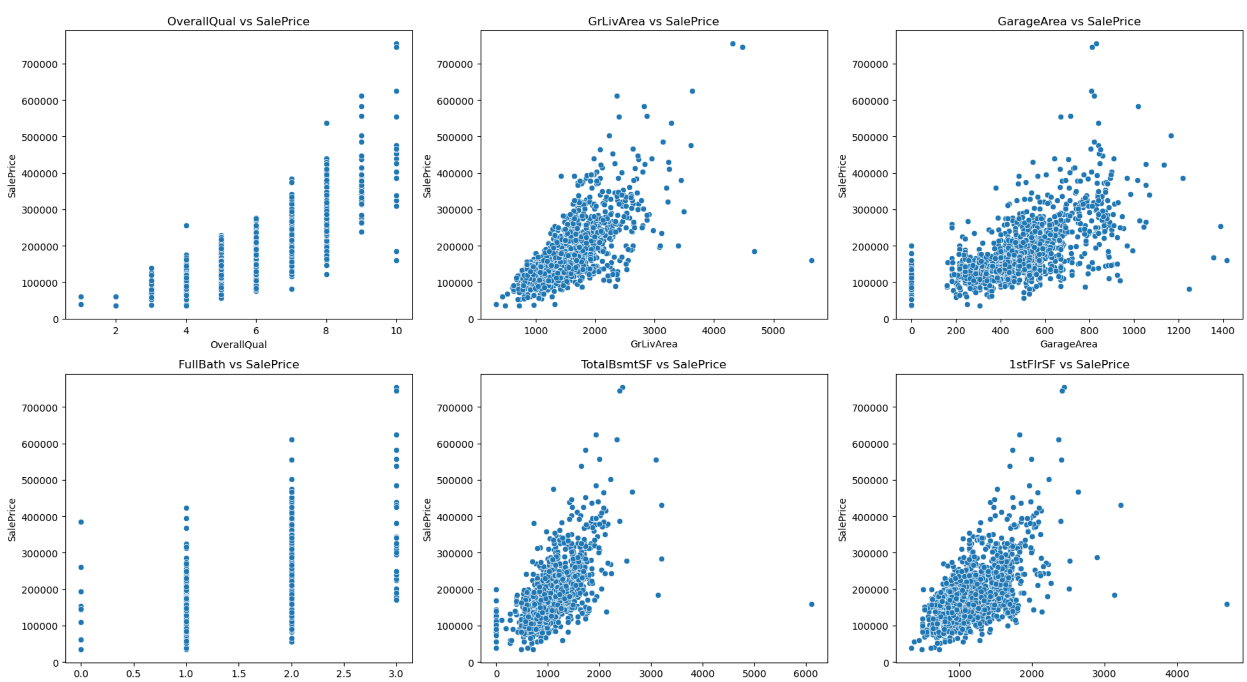



```python
# Determine the correlation between each feature and SalePrice
cor_target = cormat_housing_training["SalePrice"]
# Identify features with a correlation higher than 0.5
important_features = cor_target[cor_target > 0.5]
# Order the important features by correlation coefficient, highest
first
important_features = important_features.sort_values(ascending=False)
# Show the important features
important_features
```

```
SalePrice       1.000000
OverallQual     0.790982
GrLivArea       0.708624
GarageCars      0.640409
GarageArea      0.623431
TotalBsmtSF     0.613581
1stFlrSF        0.605852
FullBath        0.560664
TotRmsAbvGrd    0.533723
Name: SalePrice, dtype: float64
```

Below are plots that examine the relationship between variables of interest and sale price

```
variables_of_interest = ['OverallQual', 'GrLivArea', 'GarageArea', 
'FullBath', 'TotalBsmtSF', '1stFlrSF']

# Plotting relationships with SalePrice
fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(18, 10))
for ax, var in zip(axes.flatten(), variables_of_interest):
    sns.scatterplot(x=housing_training_data[var], 
y=housing_training_data['SalePrice'], ax=ax)
    ax.set_title(f'{var} vs SalePrice')
plt.tight_layout()
plt.show();
```

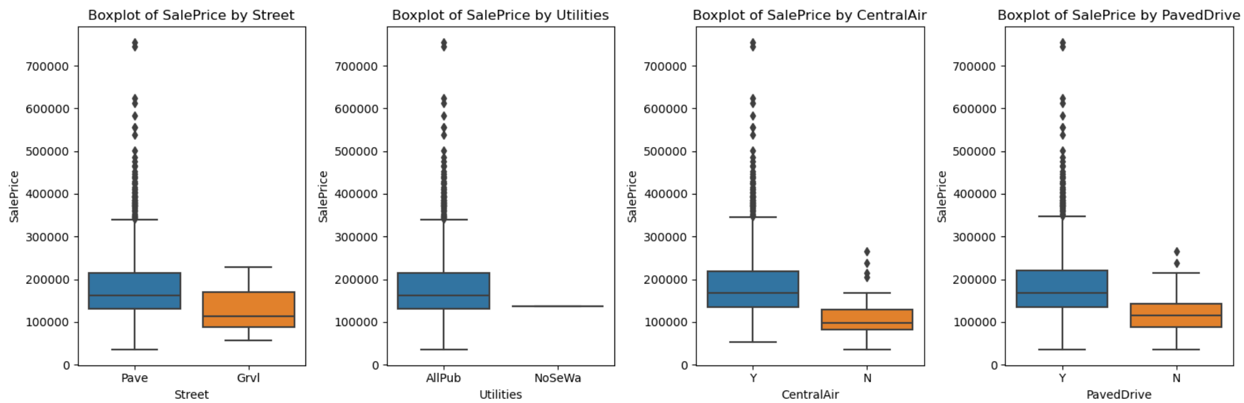


To identify the most predictive binary categorical variables for a regression model, we will utilize boxplots and conduct t-tests to assess which binary indicators exhibit the strongest correlation with home sale prices.

```
categorical_variables = ['MSZoning', 'Street', 'LotShape',
'LandContour', 'Utilities', 'LotConfig', 'LandSlope',
                         'Neighborhood', 'Condition1', 'Condition2',
'BldgType', 'HouseStyle', 'RoofStyle',  'RoofMatl',
                         'Exterior1st', 'Exterior2nd', 'MasVnrType',
'ExterQual', 'ExterCond', 'Foundation',
                         'BsmtQual', 'BsmtCond', 'BsmtExposure',
'BsmtFinType1', 'BsmtFinType2', 'Heating', 'HeatingQC',
                         'CentralAir', 'Electrical', 'KitchenQual',
'Functional', 'FireplaceQu', 'GarageType',
                         'GarageQual', 'GarageCond', 'PavedDrive',
'SaleType', 'SaleCondition','YearBuilt','GarageYrBlt',
                          'YrSold', 'MoSold']

# Calculate number of unique categories for each variable
category_counts = [len(housing_training_data[var].unique()) for var in
categorical_variables]

# Create a DataFrame to summarize categorical variables and their
category counts
categorical_variable_dictionary = {'Categorical Predictor':
categorical_variables, 'Number of Categories': category_counts}
categorical_var_df = pd.DataFrame(categorical_variable_dictionary)

# Identify indicator variables (binary categorical variables)
indicator_variables_df = categorical_var_df[categorical_var_df['Number
of Categories'] == 2]

# Identify non-indicator categorical variables (more than two
categories)
non_indicator_categorial_vars_df =
categorical_var_df[categorical_var_df['Number of Categories'] > 2]

# Display the results
print("Summary of Categorical Variables:")
print(", ".join(f"('{var}':
{len(housing_training_data[var].unique())})" for var in
categorical_variables))
print("\nIndicator Variables (Binary):")
print(", ".join(f"('{var}': {num})" for var, num in
zip(indicator_variables_df['Categorical Predictor'],
indicator_variables_df['Number of Categories'])))
# Print results for non_indicator_categorial_vars_df
print("\nNon-Indicator Categorical Variables (More than Two
Categories):")
print(", ".join(f"('{var}': {num})" for var, num in
zip(non_indicator_categorial_vars_df['Categorical Predictor'],
non_indicator_categorial_vars_df['Number of Categories'])))
```

```
Summary of Categorical Variables:
('MSZoning': 5), ('Street': 2), ('LotShape': 4), ('LandContour': 4),
('Utilities': 2), ('LotConfig': 5), ('LandSlope': 3), ('Neighborhood':
25), ('Condition1': 9), ('Condition2': 8), ('BldgType': 5),
('HouseStyle': 8), ('RoofStyle': 6), ('RoofMatl': 8), ('Exterior1st':
15), ('Exterior2nd': 16), ('MasVnrType': 4), ('ExterQual': 4),
('ExterCond': 5), ('Foundation': 6), ('BsmtQual': 5), ('BsmtCond': 5),
('BsmtExposure': 5), ('BsmtFinType1': 7), ('BsmtFinType2': 7),
('Heating': 6), ('HeatingQC': 5), ('CentralAir': 2), ('Electrical':
6), ('KitchenQual': 4), ('Functional': 7), ('FireplaceQu': 6),
('GarageType': 7), ('GarageQual': 6), ('GarageCond': 6),
('PavedDrive': 3), ('SaleType': 9), ('SaleCondition': 6),
('YearBuilt': 112), ('GarageYrBlt': 102), ('YrSold': 5), ('MoSold':
12)

Indicator Variables (Binary):
('Street': 2), ('Utilities': 2), ('CentralAir': 2)

Non-Indicator Categorical Variables (More than Two Categories):
('MSZoning': 5), ('LotShape': 4), ('LandContour': 4), ('LotConfig':
5), ('LandSlope': 3), ('Neighborhood': 25), ('Condition1': 9),
('Condition2': 8), ('BldgType': 5), ('HouseStyle': 8), ('RoofStyle':
6), ('RoofMatl': 8), ('Exterior1st': 15), ('Exterior2nd': 16),
('MasVnrType': 4), ('ExterQual': 4), ('ExterCond': 5), ('Foundation':
6), ('BsmtQual': 5), ('BsmtCond': 5), ('BsmtExposure': 5),
('BsmtFinType1': 7), ('BsmtFinType2': 7), ('Heating': 6),
('HeatingQC': 5), ('Electrical': 6), ('KitchenQual': 4),
('Functional': 7), ('FireplaceQu': 6), ('GarageType': 7),
('GarageQual': 6), ('GarageCond': 6), ('PavedDrive': 3), ('SaleType':
9), ('SaleCondition': 6), ('YearBuilt': 112), ('GarageYrBlt': 102),
('YrSold': 5), ('MoSold': 12)

# convert Paved Drive to dichotomous, indicator variable
housing_training_data['PavedDrive'] =
np.where(housing_training_data['PavedDrive'] == 'Y', 'Y', 'N')
housing_training_data['PavedDrive'].value_counts()

# view indicator variables
indicator_vars = ['Street', 'Utilities', 'CentralAir','PavedDrive']

# Create subplots for each indicator variable
fig, ax = plt.subplots(1, 4, figsize=(15, 5))

# Iterate through each indicator variable and create boxplots
for var, subplot in zip(indicator_vars, ax.flatten()):
    sns.boxplot(x=var, y='SalePrice', data=housing_training_data,
ax=subplot)
    subplot.set_title(f'Boxplot of SalePrice by {var}')
    subplot.set_xlabel(var)
    subplot.set_ylabel('SalePrice')
```

```python
# Adjust layout and display the plots
fig.tight_layout()
plt.show();
```




```python
# Run T-tests for each indicator variable
Street_t_test = ttest_ind(
    housing_training_data['SalePrice'][housing_training_data['Street']
== 'Pave'],
    housing_training_data['SalePrice'][housing_training_data['Street']
== 'Grvl'], equal_var=False
)

Utilities_t_test = ttest_ind(
    housing_training_data['SalePrice']
[housing_training_data['Utilities'] == 'AllPub'],
    housing_training_data['SalePrice']
[housing_training_data['Utilities'] == 'NoSeWa'], equal_var=False
)

Central_Air_t_test = ttest_ind(
    housing_training_data['SalePrice']
[housing_training_data['CentralAir'] == 'Y'],
    housing_training_data['SalePrice']
[housing_training_data['CentralAir'] == 'N'], equal_var=False
)

Paved_Drive_t_test = ttest_ind(
    housing_training_data['SalePrice']
[housing_training_data['PavedDrive'] == 'Y'],
    housing_training_data['SalePrice']
[housing_training_data['PavedDrive'] == 'N'], equal_var=False
)

# Compile T-test statistics and p-values into lists
Indicator_Variable_t_test_statistics = [Street_t_test[0],
```

```
Utilities_t_test[0], Central_Air_t_test[0], Paved_Drive_t_test[0]]
Indicator_Variable_t_test_p_values = [Street_t_test[1],
Utilities_t_test[1], Central_Air_t_test[1], Paved_Drive_t_test[1]]


indicator_var_t_tests = {
    'Indicator Variable':indicator_vars,
    'T-Test Statistic':Indicator_Variable_t_test_statistics,
    'P-Values':Indicator_Variable_t_test_p_values
}

# Create a DataFrame from the dictionary
Indicator_var_t_test_df = pd.DataFrame(indicator_var_t_tests)

# Apply background gradient to highlight values in the DataFrame
styled_df =
Indicator_var_t_test_df.style.background_gradient(cmap='Greens')

# Display the styled DataFrame
styled_df
```

```
<pandas.io.formats.style.Styler at 0x155c0d650>
```

Correlation with SalePrice: Calculate correlation coefficients (such as Pearson correlation) between encoded categorical variables and SalePrice. Higher absolute correlation coefficients suggest stronger relationships, which will guide our selection for ANOVA testing.

```
# dummy encode the Street, Central Air, Paved Drive indicator
variables, we will exclude Utilities from encoding since there is only

housing_training_data = pd.get_dummies(housing_training_data,
columns=['Street','CentralAir','PavedDrive'], drop_first=True)
```

To determine which categorical variables might be most useful for inclusion in a regression model (in the form of a dichotomous variable), we can create boxplots and run analyses of variance (ANOVA) to determine which non-binary categorical variables may have the strongest relationship with home sale prices.

We can create boxplots to visually display the distribution of sale prices disaggregated by the categories associated with each of the non-indicator categorical variables as well.

```
# Remove specified items from categorical_variables
categorical_variables_refine = [var for var in categorical_variables
if var not in ['Street', 'CentralAir', 'PavedDrive']]

# Encode the categorical variables
encoded_categorical_vars =
housing_training_data[categorical_variables_refine].apply(LabelEncoder
().fit_transform)
```

```python
# Calculate correlation with SalePrice
corr_with_saleprice =
encoded_categorical_vars.corrwith(housing_training_data['SalePrice'])

# Identify variables with high correlation (absolute value)
relevant_categorical_vars =
corr_with_saleprice[abs(corr_with_saleprice) > 0.4].index.tolist()

print("Categorical variables with high correlation with SalePrice:")
print(relevant_categorical_vars)
```

```
Categorical variables with high correlation with SalePrice:
['ExterQual', 'BsmtQual', 'HeatingQC', 'KitchenQual', 'GarageType',
'YearBuilt', 'GarageYrBlt']
```

It looks like we've identified `ExterQual`, `BsmtQual`, `HeatingQC`, `KitchenQual`, `GarageType`, `YearBuilt`, and `GarageYrBlt` as categorical variables that show high correlation with `SalePrice`. These variables are likely to be significant predictors in your analysis. If you need further assistance with analyzing these variables or any other aspect of your project, feel free to ask!

```python
# Define variables for ANOVA analysis
ANOVA_vars = ['ExterQual', 'BsmtQual', 'FireplaceQu', 'KitchenQual',
'GarageQual', 'GarageCond', 'HeatingQC']

# Perform ANOVA for ExterQual
exter_qual_groups = [housing_training_data['SalePrice']
[housing_training_data['ExterQual'] == level] for level in ['Gd',
'TA', 'Ex', 'Fa']]
anova_exter_qual = f_oneway(*exter_qual_groups)

# Perform ANOVA for BsmtQual
bsmt_qual_groups = [housing_training_data['SalePrice']
[housing_training_data['BsmtQual'] == level] for level in ['Gd', 'TA',
'Ex', 'None', 'Fa']]
anova_bsmt_qual = f_oneway(*bsmt_qual_groups)

# Perform ANOVA for FireplaceQu
fireplace_qu_groups = [housing_training_data['SalePrice']
[housing_training_data['FireplaceQu'] == level] for level in ['None',
'TA', 'Gd', 'Fa', 'Ex', 'Po']]
anova_fireplace_qu = f_oneway(*fireplace_qu_groups)

# Perform ANOVA for KitchenQual
kitchen_qual_groups = [housing_training_data['SalePrice']
[housing_training_data['KitchenQual'] == level] for level in ['Gd',
'TA', 'Ex', 'Fa']]
anova_kitchen_qual = f_oneway(*kitchen_qual_groups)

# Perform ANOVA for GarageQual
```

```
garage_qual_groups = [housing_training_data['SalePrice']
[housing_training_data['GarageQual'] == level] for level in ['None',
'TA', 'Gd', 'Fa', 'Ex', 'Po']]
anova_garage_qual = f_oneway(*garage_qual_groups)

# Perform ANOVA for GarageCond
garage_cond_groups = [housing_training_data['SalePrice']
[housing_training_data['GarageCond'] == level] for level in ['None',
'TA', 'Gd', 'Fa', 'Ex', 'Po']]
anova_garage_cond = f_oneway(*garage_cond_groups)

# Perform ANOVA for HeatingQC
heating_qc_groups = [housing_training_data['SalePrice']
[housing_training_data['HeatingQC'] == level] for level in ['TA',
'Gd', 'Fa', 'Ex', 'Po']]
anova_heating_qc = f_oneway(*heating_qc_groups)

# Collect ANOVA results
anova_stats = [anova_exter_qual.statistic, anova_bsmt_qual.statistic,
anova_fireplace_qu.statistic, anova_kitchen_qual.statistic,
               anova_garage_qual.statistic,
anova_garage_cond.statistic, anova_heating_qc.statistic]

anova_pvals = [anova_exter_qual.pvalue, anova_bsmt_qual.pvalue,
anova_fireplace_qu.pvalue, anova_kitchen_qual.pvalue,
               anova_garage_qual.pvalue, anova_garage_cond.pvalue,
anova_heating_qc.pvalue]

anova_results = {'Categorical Variable': ANOVA_vars, 'Test Statistic':
anova_stats, 'P-Values': anova_pvals}
anova_df = pd.DataFrame(anova_results)

# Style the DataFrame
anova_df.style.background_gradient(cmap='Greens')
```

```
<pandas.io.formats.style.Styler at 0x155ea4a90>
```

```
# for heatingQC excellent is the only value that is statistically
significant from the others, so we will encode this to be a binary
variable.
housing_training_data['HeatingEx'] =
np.where(housing_training_data['HeatingQC'] == 'Ex', 1, 0)
housing_training_data.drop(columns=['HeatingQC'],inplace=True)
```

Encode important categorical variables

```
# List of important categorical features
important_cats = ['ExterQual', 'BsmtQual', 'FireplaceQu',
'KitchenQual', 'GarageQual', 'GarageCond']
```

```
# Ordinal mapping for categorical features
ordinal_map = {'Ex': 4, 'Gd': 3, 'TA': 2, 'Fa': 1, 'None': 1, 'Po':
0 }

# Replace categorical values with ordinal rankings
for feature in important_cats:
    housing_training_data[feature] =
housing_training_data[feature].replace(ordinal_map)

# Display the shape of the data
print(f'Shape all_data: {housing_training_data.shape}')
```

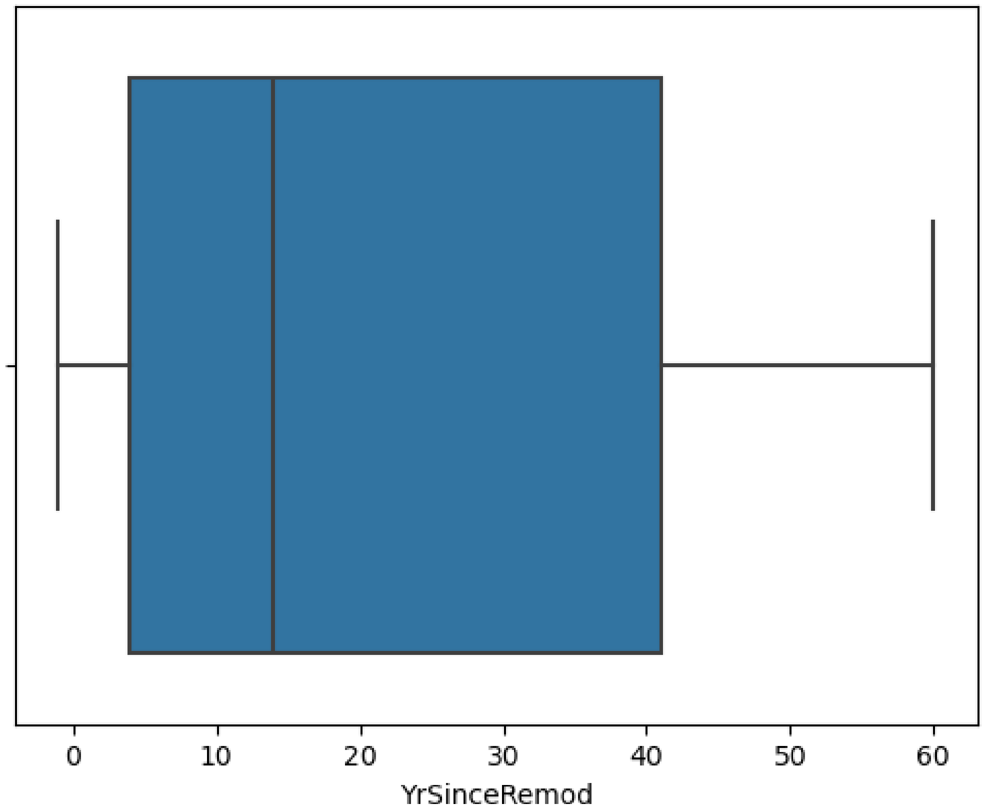
```
Shape all_data: (1460, 77)
```

Feature Creation

We will create a new feature to represent the number of years since a home was last remodeled, which may enhance the accuracy of our home sale price prediction models.

```
# Create a new variable: years since the house was remodeled from
selling date (use construction date if no remodeling or additions)
housing_training_data['YrSinceRemod'] =
housing_training_data['YrSold'] -
housing_training_data['YearRemodAdd'];

# Create a boxplot for YrSinceRemod
sns.boxplot(x='YrSinceRemod', data=housing_training_data);

# Compute Pearson correlation coefficient and p-value for SalePrice
and YrSinceRemod
correlation_coefficient, p_value =
stats.pearsonr(housing_training_data['YrSinceRemod'],
housing_training_data['SalePrice']);
print("Pearson correlation coefficient and p-value for SalePrice and
Years since House was remodeled/built:");
print("Correlation coefficient:", correlation_coefficient);
print("P-value:", p_value);
```

```
Pearson correlation coefficient and p-value for SalePrice and Years
since House was remodeled/built:
Correlation coefficient: -0.5090787380156276
P-value: 4.374855446379975e-97
```

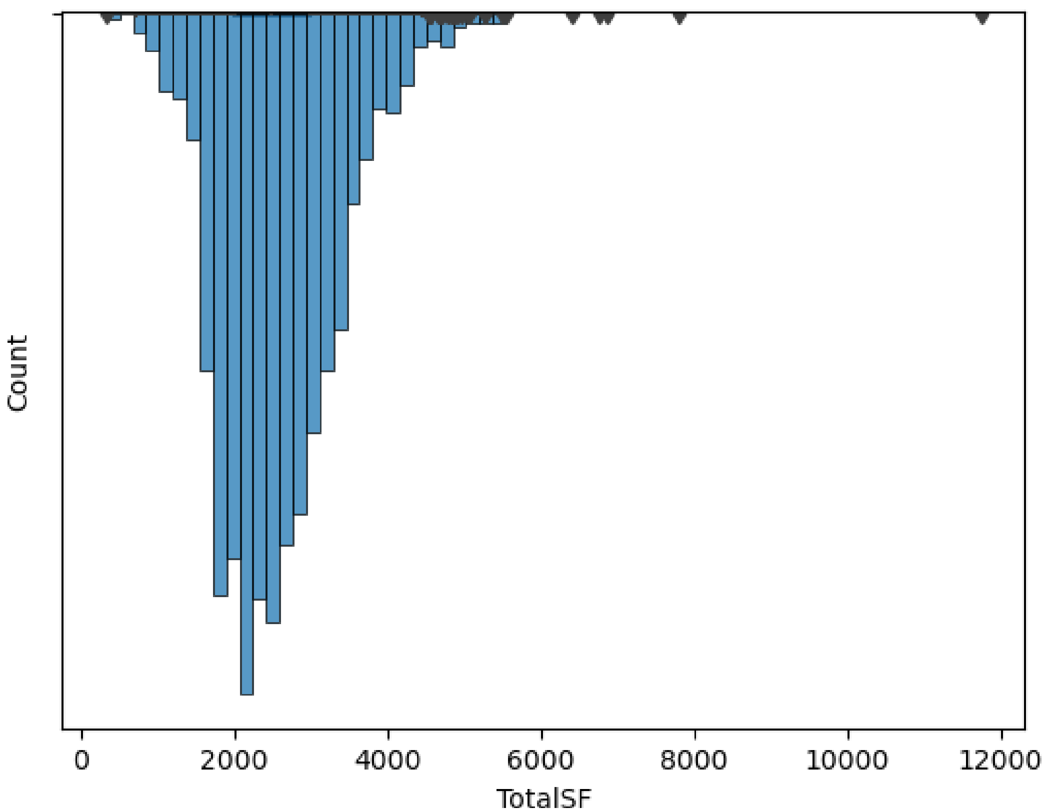


Additionally, we'll create a feature to represent the total square footage of the home, which can further contribute to our home sale price prediction models.

```
# Create a new variable: Total square feet (TotalSF)
housing_training_data['TotalSF'] =
housing_training_data['TotalBsmtSF'] +
housing_training_data['GrLivArea']

# Create a boxplot for TotalSF
sns.boxplot(x='TotalSF', data=housing_training_data);

# Drop large outliers from the dataframe
housing_training_data.drop(housing_training_data[housing_training_data
['TotalSF'] > 6000].index, inplace=True)

# Visualize distribution without extreme outliers
sns.histplot(data=housing_training_data, x="TotalSF");

# Compute Pearson correlation coefficient and p-value for SalePrice
and TotalSF
correlation_coefficient, p_value =
stats.pearsonr(housing_training_data['TotalSF'],
housing_training_data['SalePrice']);
print("Pearson correlation coefficient and p-value for SalePrice and
TotalSF (Total square feet - includes basement):");
```

```
print("Correlation coefficient:", correlation_coefficient);
print("P-value:", p_value);
```

```
Pearson correlation coefficient and p-value for SalePrice and TotalSF
(Total square feet - includes basement):
Correlation coefficient: 0.8199962912972798
P-value: 0.0
```



Dummy Encoding

Let's dummy encode the remaining categorical variables and create a new dataframe with these encoded columns and the original numeric columns.

```
# create new df with current numeric columns
housing_training_numeric_df =
pd.DataFrame(housing_training_data.select_dtypes(exclude=['object']))
housing_training_object_df =
pd.DataFrame(housing_training_data.select_dtypes(exclude=['uint8','int
','float']))
orig_object_cols = housing_training_object_df.columns
housing_training_data_dummy =
pd.get_dummies(housing_training_object_df, columns=orig_object_cols)
housing_training_data_large = pd.concat([housing_training_numeric_df,
housing_training_data_dummy], axis=1)
```

```
housing_training_data_large.head()
housing_training_data_large.shape

   Id  MSSubClass  LotFrontage  LotArea  OverallQual  OverallCond
YearBuilt  \
0   1          60         65.0     8450            7            5
2003
1   2          20         80.0     9600            6            8
1976
2   3          60         68.0    11250            7            5
2001
3   4          70         60.0     9550            7            5
1915
4   5          60         84.0    14260            8            5
2000

   YearRemodAdd  MasVnrArea  ExterQual  ...  SaleCondition_Alloca  \
0          2003       196.0          3  ...                 False
1          1976         0.0          2  ...                 False
2          2002       162.0          3  ...                 False
3          1970         0.0          2  ...                 False
4          2000       350.0          3  ...                 False

   SaleCondition_Family  SaleCondition_Normal
SaleCondition_Partial  \
0                 False                  True                  False

1                 False                  True                  False

2                 False                  True                  False

3                 False                 False                  False

4                 False                  True                  False


   Street_Pave_False  Street_Pave_True  CentralAir_Y_False
CentralAir_Y_True  \
0              False              True               False
True
1              False              True               False
True
2              False              True               False
True
3              False              True               False
True
4              False              True               False
True

   PavedDrive_Y_False  PavedDrive_Y_True
```

```
0                False                True
1                False                True
2                False                True
3                False                True
4                False                True

[5 rows x 262 columns]

(1455, 262)

# Calculate the correlation matrix
corrmat_housing_training = housing_training_data_large.corr()
cor_target = abs(corrmat_housing_training["SalePrice"])
relevant_features = cor_target[cor_target > 0.25]
feature_list = relevant_features.index
housing_training_data_large_subset =
housing_training_data_large[feature_list]
housing_training_data_large_subset.shape

(1455, 53)
```

We may use this dataframe later on in the analysis. For the start, we will investigate the relationship between SalePrice and a select number of features, like Total Square Feet.

Prepare Test Data

```
# load test data
housing_testing_data = pd.read_csv('test.csv')
```

Handle Null values, matches how we dealt with Nulls in the training dataset

```
# Find null counts, percentage of null values, and column type
null_count = housing_testing_data.isnull().sum()
null_percentage = housing_testing_data.isnull().sum() * 100 /
len(housing_testing_data)
column_type = housing_testing_data.dtypes
null_summary = pd.concat([null_count, null_percentage, column_type],
axis=1, keys=['Missing Count', 'Percentage Missing', 'Column Type'])
null_summary_only_missing = null_summary[null_count !=
0].sort_values('Percentage Missing', ascending=False)

# Remove columns with over 50% missing values
housing_testing_data.drop(['Alley', 'PoolQC', 'Fence', 'MiscFeature'],
axis=1, inplace=True)
columns_None = ['SaleType', 'BsmtCond', 'BsmtExposure',
'BsmtFinType1', 'BsmtFinType2', 'GarageType',
                'GarageFinish', 'GarageQual', 'MSZoning',
'FireplaceQu', 'Functional', 'Utilities', 'GarageCond',
                'MasVnrType', 'Exterior2nd', 'Exterior1st']
```

```
# Set Nulls in non-numeric columns to 'None'
housing_testing_data[columns_None] =
housing_testing_data[columns_None].fillna('None')
columns_zero = ['MasVnrArea', 'GarageArea', 'GarageCars',
'TotalBsmtSF', 'BsmtUnfSF', 'BsmtFinSF2',
                'BsmtFinSF1', 'BsmtHalfBath', 'BsmtFullBath',
'BsmtQual', 'KitchenQual']

housing_testing_data[columns_zero] =
housing_testing_data[columns_zero].fillna(0)
housing_testing_data['LotFrontage'].fillna(housing_testing_data['LotFr
ontage'].median(), inplace=True)
housing_testing_data['GarageYrBlt'].fillna(housing_testing_data['Garag
eYrBlt'].median(), inplace=True)

# Convert Paved Drive to dichotomous, indicator variable
housing_testing_data['PavedDrive'] =
np.where(housing_testing_data['PavedDrive'] == 'Y', 'Y', 'N')
housing_testing_data['PavedDrive'].value_counts()
housing_testing_data = pd.get_dummies(housing_testing_data,
columns=['Street', 'CentralAir', 'PavedDrive'], drop_first=True)
```

```
PavedDrive
Y    1301
N     158
Name: count, dtype: int64
```

```
# for heatingQC encode this to be a binary variable to match how we
encoded this column in training data
housing_testing_data['HeatingEx'] =
np.where(housing_testing_data['HeatingQC'] == 'Ex', 1, 0)
housing_testing_data.drop(columns=['HeatingQC'],inplace=True)

# encode categorical columns with ordinal values
important_categorical = ['ExterQual', 'BsmtQual', 'FireplaceQu',
'KitchenQual', 'GarageQual','GarageCond']

ordinal_mapping = { 'Ex': 4, 'Gd': 3, 'TA': 2, 'Fa': 1, 'None': 1,
'Po': 0 }

# process columns, replace to categorical features with ordinal
ranking
for i in important_categorical:
    housing_testing_data[i] =
housing_testing_data[i].replace(ordinal_mapping)

# shape
print('Shape all_data: {}'.format(housing_testing_data.shape))
```

```
Shape all_data: (1459, 76)
```

```
# create new variable TotalSF
housing_testing_data['TotalSF'] = housing_testing_data['TotalBsmtSF']
+ housing_testing_data['GrLivArea']
housing_testing_data['YrSinceRemod'] = housing_testing_data['YrSold']
- housing_testing_data['YearRemodAdd']
```

Dummy Encoding

```
# create new df with current numeric columns
housing_testing_numeric_data =
pd.DataFrame(housing_testing_data.select_dtypes(exclude=['object']))

# create new df with current categorical columns
housing_testing_object_data =
pd.DataFrame(housing_testing_data.select_dtypes(exclude=['uint8','int'
,'float']))
orig_object_cols = housing_testing_object_data.columns

# dummy encode the categorical columns
housing_testing_data_dummy =
pd.get_dummies(housing_testing_object_data, columns=orig_object_cols)

# create new df with original numeric and new dummy encoded columns
housing_testing_data_large = pd.concat([housing_testing_numeric_data,
housing_testing_data_dummy], axis=1)
housing_testing_data_large.shape
```

```
(1459, 252)
```

```
# create new dataframe with correlated variables with SalePrice
observed in the training data
feature_list = feature_list.drop('SalePrice')
housing_testing_data_large_subset =
housing_testing_data_large[feature_list]
housing_testing_data_large_subset.shape
```

```
(1459, 52)
```

```
# Find the common columns
common_columns =
housing_testing_data_large.columns.intersection(housing_training_data_
large.columns)
housing_testing_data_large_common =
housing_testing_data_large[common_columns]
housing_training_data_large_common =
housing_training_data_large[common_columns]
```

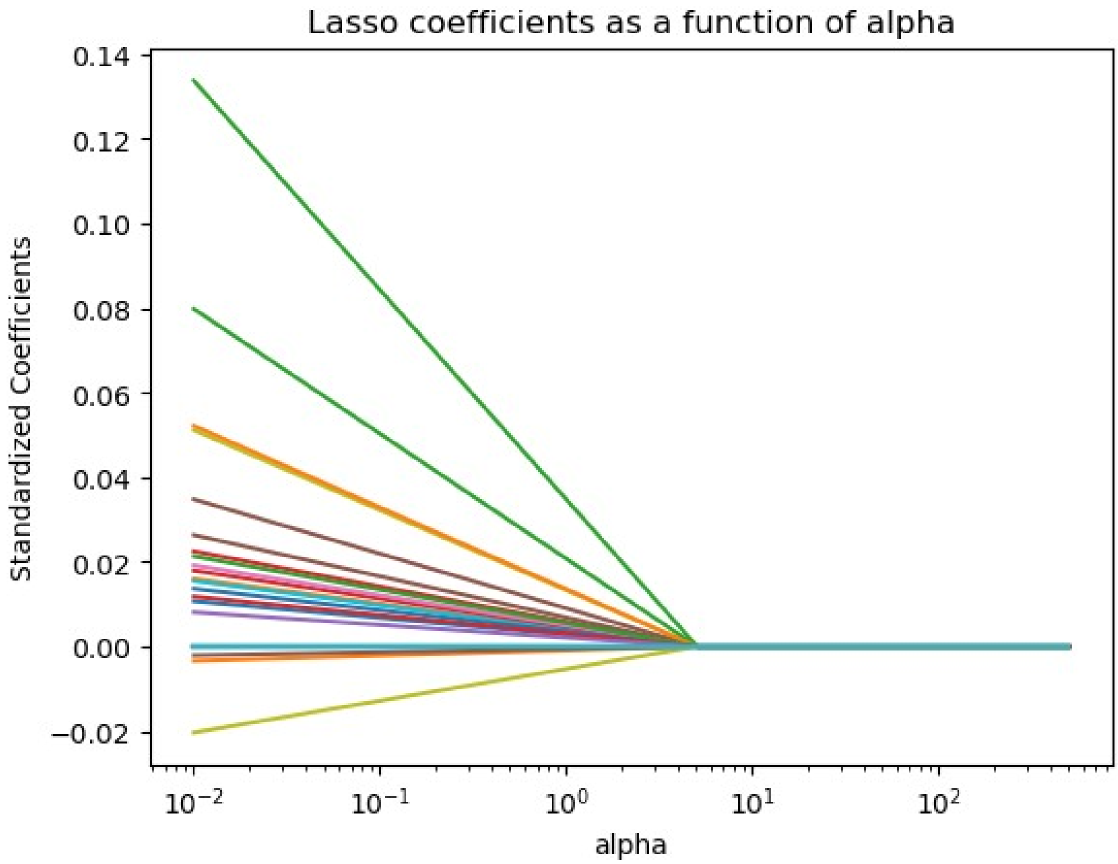
Constructing Models to Predict Home Prices

Lasso Regression

We will now try to fit a Lasso Regression to the housing sales dataframe.

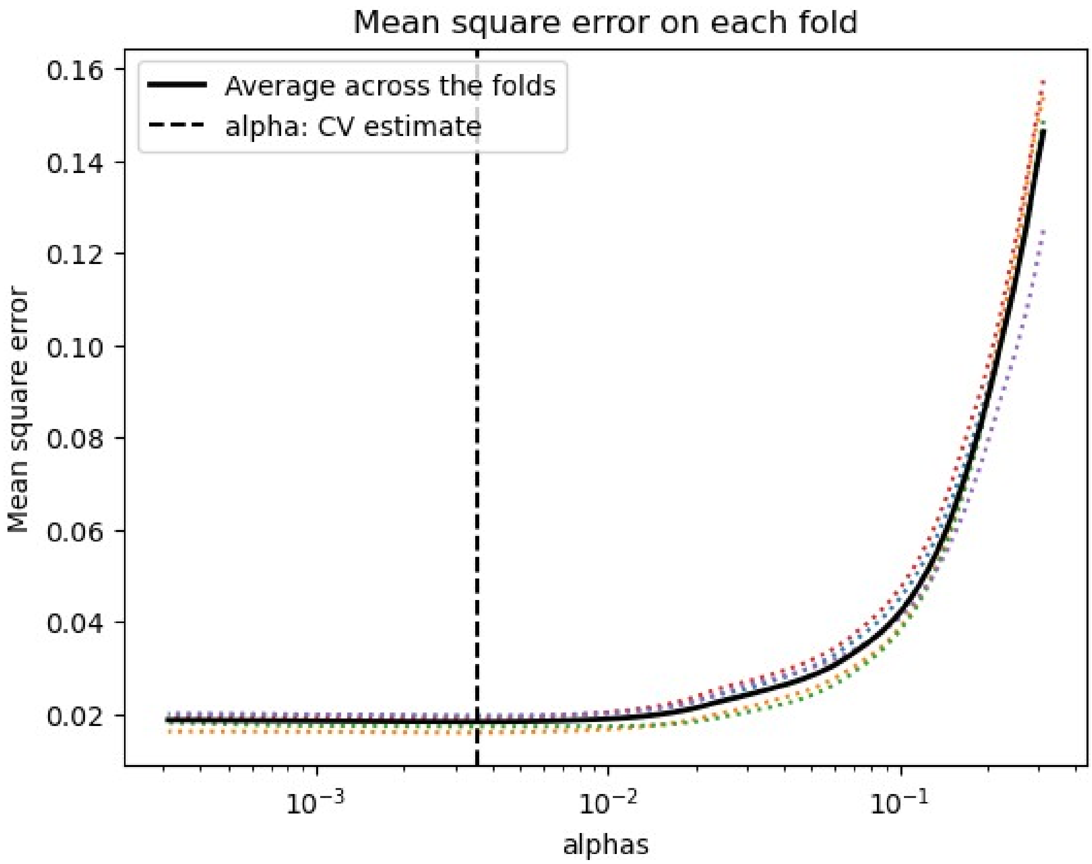
```
# Create dataframe that can be used for lasso.  Only keep variables
that aren't causing error messages
lasso_sandbox = housing_training_data[ ['LotFrontage', 'LotArea',
'OverallQual', 'OverallCond', 'MasVnrArea',
                  'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF',
'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
                  'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath',
'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr',
                  'TotRmsAbvGrd', 'Fireplaces', 'GarageCars',
'GarageArea', 'WoodDeckSF', 'OpenPorchSF',
                  'EnclosedPorch', '3SsnPorch', 'ScreenPorch',
'PoolArea', 'MiscVal', 'SalePrice']]

# Perform a Log Transformation on the outcome variable SalePrice and
drop the original variable
lasso_sandbox_log_saleprice =
np.log(housing_training_data['SalePrice'])
lasso_sandbox_x = lasso_sandbox.drop(columns=['SalePrice'])

# Split the dataset into training and testing dataframes
lasso_X_train, lasso_X_validation, lasso_y_train, lasso_y_validation =
train_test_split(lasso_sandbox_x,

lasso_sandbox_log_saleprice, test_size=0.3, random_state=1)

# Standardize the numeric predictors - which can help strengthen the
model fit
numerical_predictors = ['LotFrontage', 'LotArea', 'OverallQual',
'OverallCond', 'MasVnrArea',
                  'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF',
'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
                  'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath',
'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr',
                  'TotRmsAbvGrd', 'Fireplaces', 'GarageCars',
'GarageArea', 'WoodDeckSF', 'OpenPorchSF',
                  'EnclosedPorch', '3SsnPorch', 'ScreenPorch',
'PoolArea', 'MiscVal']

lasso_scaler =
StandardScaler().fit(lasso_X_train[numerical_predictors])
lasso_X_train[numerical_predictors] =
lasso_scaler.transform(lasso_X_train[numerical_predictors])
lasso_X_validation[numerical_predictors] =
```

```python
lasso_scaler.transform(lasso_X_validation[numerical_predictors])

alphas = np.linspace(0.01,500,100)
lasso = Lasso(max_iter=10000)
coefs = []

for a in alphas:
    lasso.set_params(alpha=a)
    lasso.fit(lasso_X_train, lasso_y_train)
    coefs.append(lasso.coef_)

ax = plt.gca();

ax.plot(alphas, coefs);
ax.set_xscale('log');
plt.axis('tight');
plt.xlabel('alpha');
plt.ylabel('Standardized Coefficients');
plt.title('Lasso coefficients as a function of alpha');

# Fit a Lasso Regression Model with ten-fold cross-validation
lasso_model = LassoCV(cv=5, random_state=1, max_iter = 10000)
lasso_model.fit(lasso_X_train, lasso_y_train);

# lasso_model.coef_
```



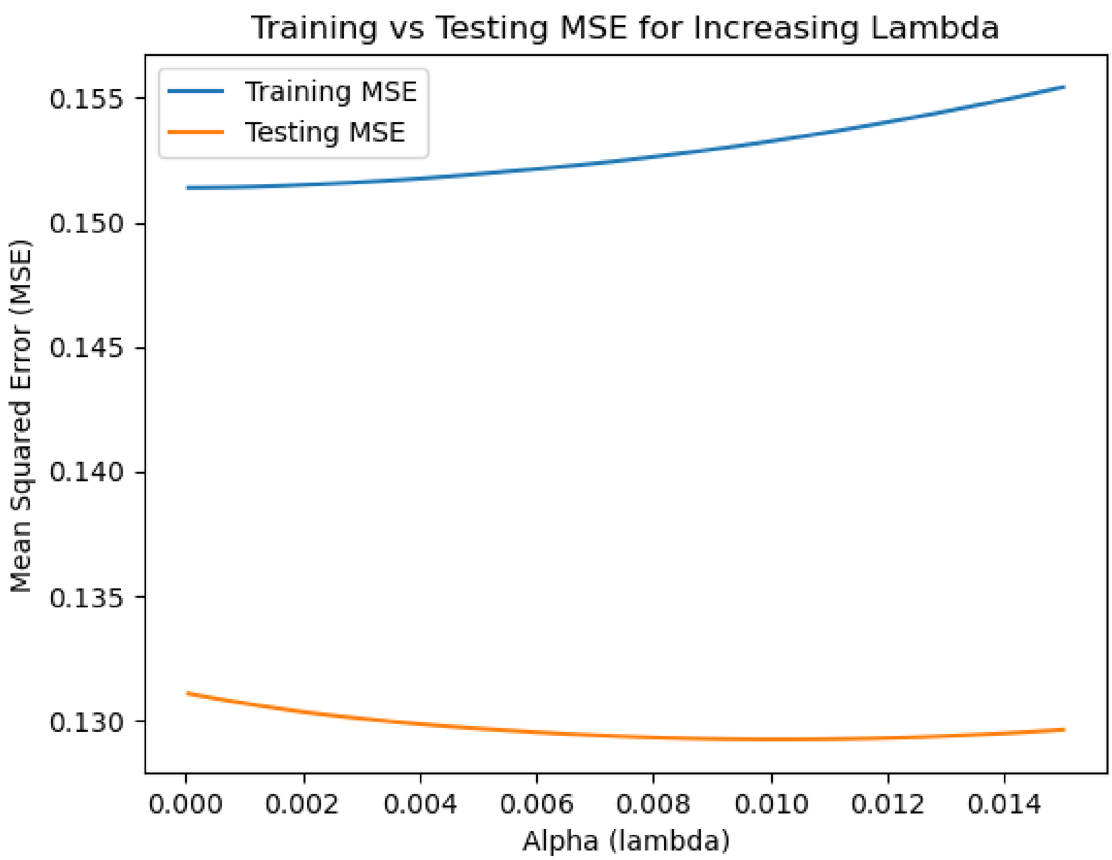
Let's plot the mean squared error as a function of our tuning parameter, alpha, from our cross-validation

```
plt.semilogx(lasso_model.alphas_, lasso_model.mse_path_, ":")
plt.plot(lasso_model.alphas_ , lasso_model.mse_path_.mean(axis=-1),
"k", label="Average across the folds", linewidth=2);
plt.axvline(lasso_model.alpha_, linestyle="--", color="k",
label="alpha: CV estimate" );

plt.legend();
plt.xlabel("alphas");
plt.ylabel("Mean square error");
plt.title("Mean square error on each fold");
plt.axis("tight");
```




```
# Initialize Lasso model
lasso = Lasso(max_iter=10000)

# Define alpha values (lambda values)
alphas = np.linspace(0.00005, 0.015, 100)

# Scale the predictors and target
scaler = StandardScaler()
lasso_x = scaler.fit_transform(lasso_sandbox_x)
lasso_y =
scaler.fit_transform(np.array(lasso_sandbox['SalePrice']).reshape(-1,
1))

# Split the dataset into training and testing dataframes
lasso_X_train, lasso_X_validation, lasso_y_train, lasso_y_validation =
train_test_split(lasso_x, lasso_y, test_size=0.3, random_state=1)

# Lists to store training and testing MSE
training_mse = []
testing_mse = []

# Loop through each alpha value
for a in alphas:
```

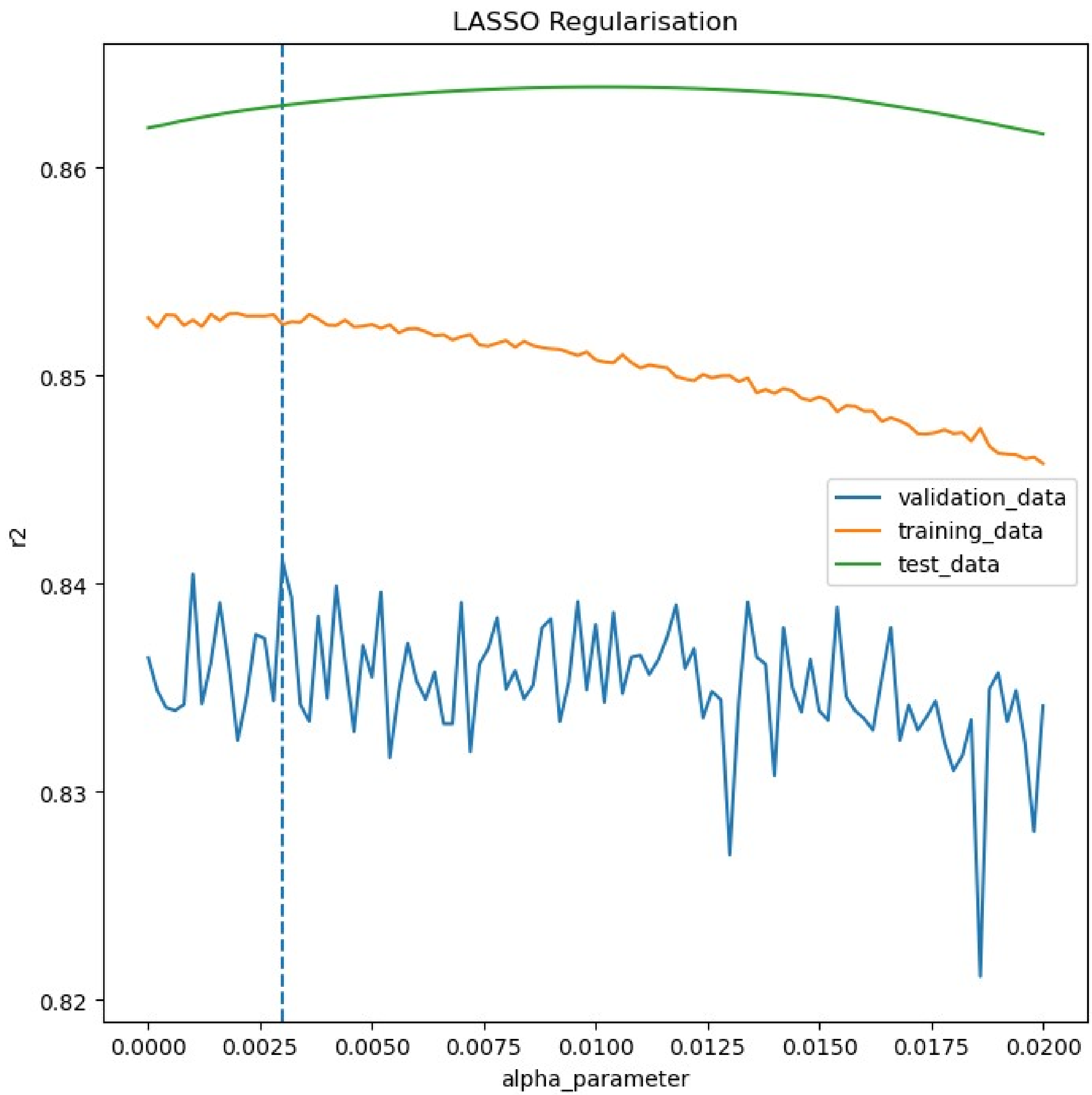
```
    lasso.set_params(alpha=a)
    lasso.fit(lasso_X_train, lasso_y_train)
    # Calculate MSE for training and testing sets
    training_mse.append(mean_squared_error(lasso_y_train,
lasso.predict(lasso_X_train)))
    testing_mse.append(mean_squared_error(lasso_y_validation,
lasso.predict(lasso_X_validation)))

# Plot training vs testing MSE for increasing lambda
plt.plot(alphas, training_mse, label='Training MSE')
plt.plot(alphas, testing_mse, label='Testing MSE')
plt.xlabel('Alpha (lambda)')
plt.ylabel('Mean Squared Error (MSE)')
plt.title('Training vs Testing MSE for Increasing Lambda')
plt.legend()
plt.show();
```




```
def regmodel_param_test(
    alphas_to_try, X, y, cv, scoring = 'r2',
    model_name = 'LASSO', X_test = None, y_test = None,
    draw_plot = False, filename = None):
```

```
    validation_scores = []
    train_scores = []
    results_list = []
    if X_test is not None:
        test_scores = []
        scorer = get_scorer(scoring)
    else:
        test_scores = None

    for curr_alpha in alphas_to_try:

        if model_name == 'LASSO':
            regmodel = Lasso(alpha = curr_alpha)
        elif model_name == 'Ridge':
            regmodel = Ridge(alpha = curr_alpha)
        elif model_name == 'ElasticNet':
            regmodel = ElasticNet(alpha = curr_alpha)
        else:
            return None

        results = cross_validate(
            regmodel, X, y, scoring=scoring, cv=cv,
            return_train_score = True)

        validation_scores.append(np.mean(results['test_score']))
        train_scores.append(np.mean(results['train_score']))
        results_list.append(results)

        if X_test is not None:
            regmodel.fit(X,y)
            y_pred = regmodel.predict(X_test)
            test_scores.append(scorer(regmodel, X_test, y_test))

    chosen_alpha_id = np.argmax(validation_scores)
    chosen_alpha = alphas_to_try[chosen_alpha_id]
    max_validation_score = np.max(validation_scores)
    if X_test is not None:
        test_score_at_chosen_alpha = test_scores[chosen_alpha_id]
    else:
        test_score_at_chosen_alpha = None

    if draw_plot:
        regmodel_param_plot(
            validation_scores, train_scores, alphas_to_try,
chosen_alpha,
            scoring, model_name, test_scores, filename)

    return chosen_alpha, max_validation_score,
test_score_at_chosen_alpha
```

```
def regmodel_param_plot(
    validation_score, train_score, alphas_to_try, chosen_alpha,
    scoring, model_name, test_score = None, filename = None):

    plt.figure(figsize = (8,8))
    sns.lineplot(y = validation_score, x = alphas_to_try, label =
'validation_data')
    sns.lineplot(y = train_score, x = alphas_to_try, label =
'training_data')
    plt.axvline(x=chosen_alpha, linestyle='--')
    if test_score is not None:
        sns.lineplot(y = test_score, x = alphas_to_try, label =
'test_data')
    plt.xlabel('alpha_parameter')
    plt.ylabel(scoring)
    plt.title(model_name + ' Regularisation')
    plt.legend()
    plt.show()

cv = KFold(n_splits=5, shuffle=True)

lasso_alphas = np.linspace(0, 0.02, 101)
chosen_alpha, max_validation_score, test_score_at_chosen_alpha = \
    regmodel_param_test( lasso_alphas, lasso_X_train, lasso_y_train,
cv, scoring = 'r2', model_name = 'LASSO',
        X_test = lasso_X_validation, y_test = lasso_y_validation,
draw_plot = True, filename = 'lasso_wide_search')
print("Chosen alpha: %.5f" %chosen_alpha)
print("Validation score: %.5f" %max_validation_score)
print("Test score at chosen alpha: %.5f" %test_score_at_chosen_alpha)
```




```
Chosen alpha: 0.00300
Validation score: 0.84110
Test score at chosen alpha: 0.86299
```

Let's evaluate the performance of the best Lasso model that we were able to construct

```
# Show best value of tuning parameter (alpha) chosen by cross
validation
print(f"The best value of the tuning parameter, alpha, chosen by
cross-validation is {lasso_model.alpha_}.")
lasso_best = Lasso(alpha=lasso_model.alpha_)
lasso_best.fit(lasso_X_train, lasso_y_train)
```

```
best_lasso_coeffs_data = (list(zip(lasso_X_train, lasso_best.coef_)))
best_lasso_coeffs_df = pd.DataFrame(best_lasso_coeffs_data, columns =
['Predictor', 'Best Lasso Coefficient'])
```

```
The best value of the tuning parameter, alpha, chosen by cross-
validation is 0.0035778259276540757.
```

```
Lasso(alpha=0.0035778259276540757)
```

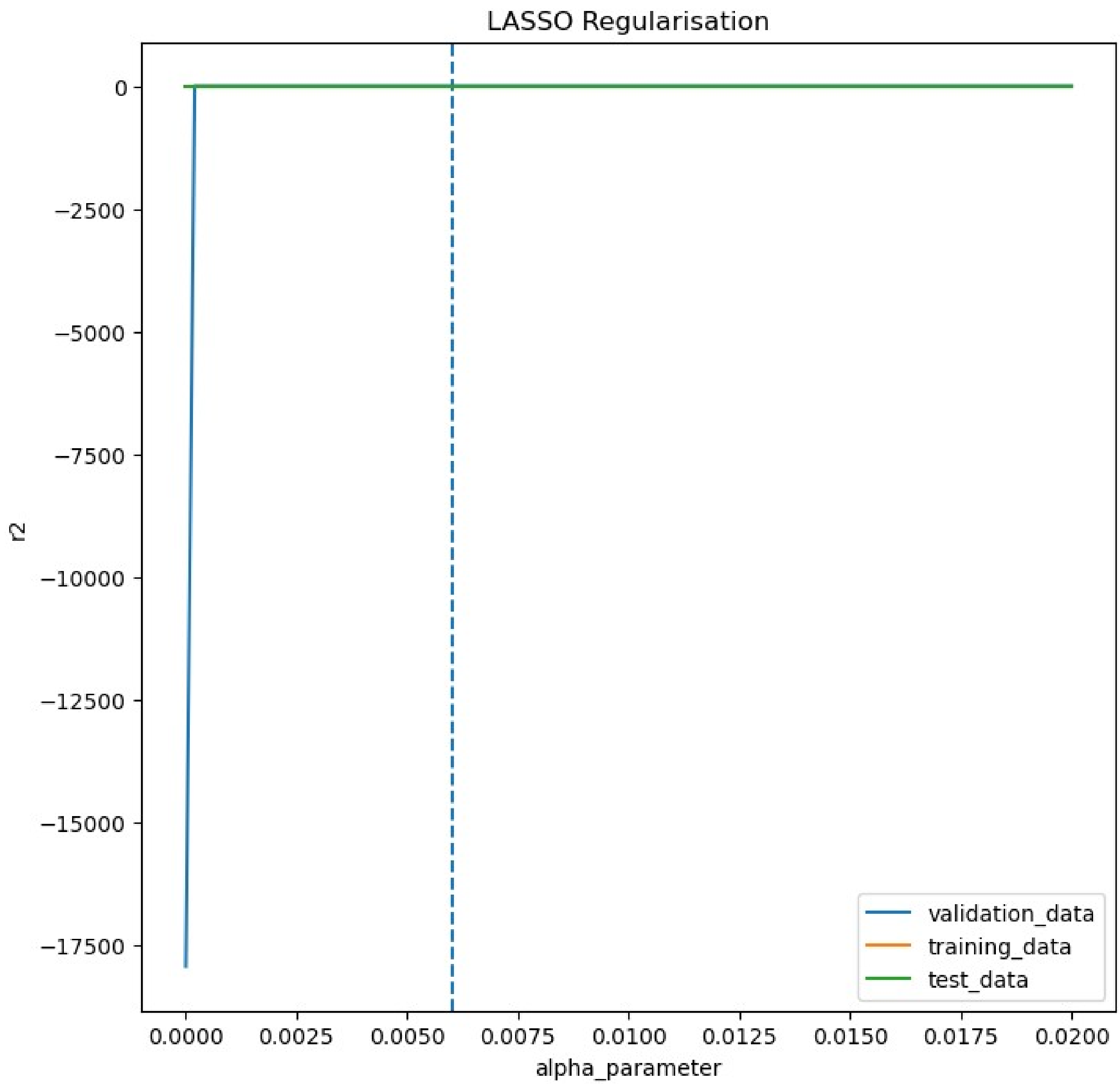
```
# Calculate the R squared for the training and validation datasets
lasso_r_squared_train = round(lasso_best.score(lasso_X_train,
lasso_y_train), 3)
lasso_r_squared_validation =
round(lasso_best.score(lasso_X_validation, lasso_y_validation), 3)
print(f"The R squared for the best Lasso model for the training set
is: {lasso_r_squared_train}.")
print(f"The R squared for the best Lasso model for the validation set
is: {lasso_r_squared_validation}.")
lasso_y_predictions_train = lasso_model.predict(lasso_X_train)
lasso_mse_train = mean_squared_error(lasso_y_train,
lasso_y_predictions_train)
print(f"The mean squared error of the Lasso Regression model's
predictions using the log home sale prices in the training dataset is
{lasso_mse_train}.")
lasso_y_predictions_validation =
lasso_model.predict(lasso_X_validation)
lasso_mse_validation = mean_squared_error(lasso_y_validation,
lasso_y_predictions_validation)
print(f"The mean squared error of the Lasso Regression model's
predictions using the log home sale prices in the validation dataset
is {lasso_mse_validation}.")
```

```
The R squared for the best Lasso model for the training set is: 0.851.
The R squared for the best Lasso model for the validation set is:
0.863.
The mean squared error of the Lasso Regression model's predictions
using the log home sale prices in the training dataset is
144.98172527888673.
The mean squared error of the Lasso Regression model's predictions
using the log home sale prices in the validation dataset is
146.1750136575638.
```

Rework LASSO analysis on full set of variables including encoded

```
# Split the dataset into training and testing dataframes
scaler = StandardScaler()
x_raw =
housing_training_data_large.select_dtypes(exclude=['object']).drop(col
umns = ['SalePrice'])
x_scale = scaler.fit_transform(x_raw)
```

```
y_scale =
scaler.fit_transform(np.array(housing_training_data['SalePrice']).resh
ape(-1,1))
y = housing_training_data_large['SalePrice']
new_lasso_X_train, new_lasso_X_validation, new_lasso_y_train,
new_lasso_y_validation = train_test_split(x_scale, y, test_size=0.3,
random_state=1)
cv = KFold(n_splits=5, shuffle=True)

lasso_alphas = np.linspace(0, 0.02, 101)

chosen_alpha, max_validation_score, test_score_at_chosen_alpha = \
    regmodel_param_test( lasso_alphas, x_scale, y_scale, cv, scoring =
'r2', model_name = 'LASSO',
        X_test = new_lasso_X_validation, y_test =
new_lasso_y_validation, draw_plot = True, filename =
'lasso_wide_search')
print("Chosen alpha: %.5f" % chosen_alpha)
print("Validation score: %.5f" % max_validation_score)
print("Test score at chosen alpha: %.5f" % test_score_at_chosen_alpha)
```




```
Chosen alpha: 0.00600
Validation score: 0.90326
Test score at chosen alpha: -5.52195
```

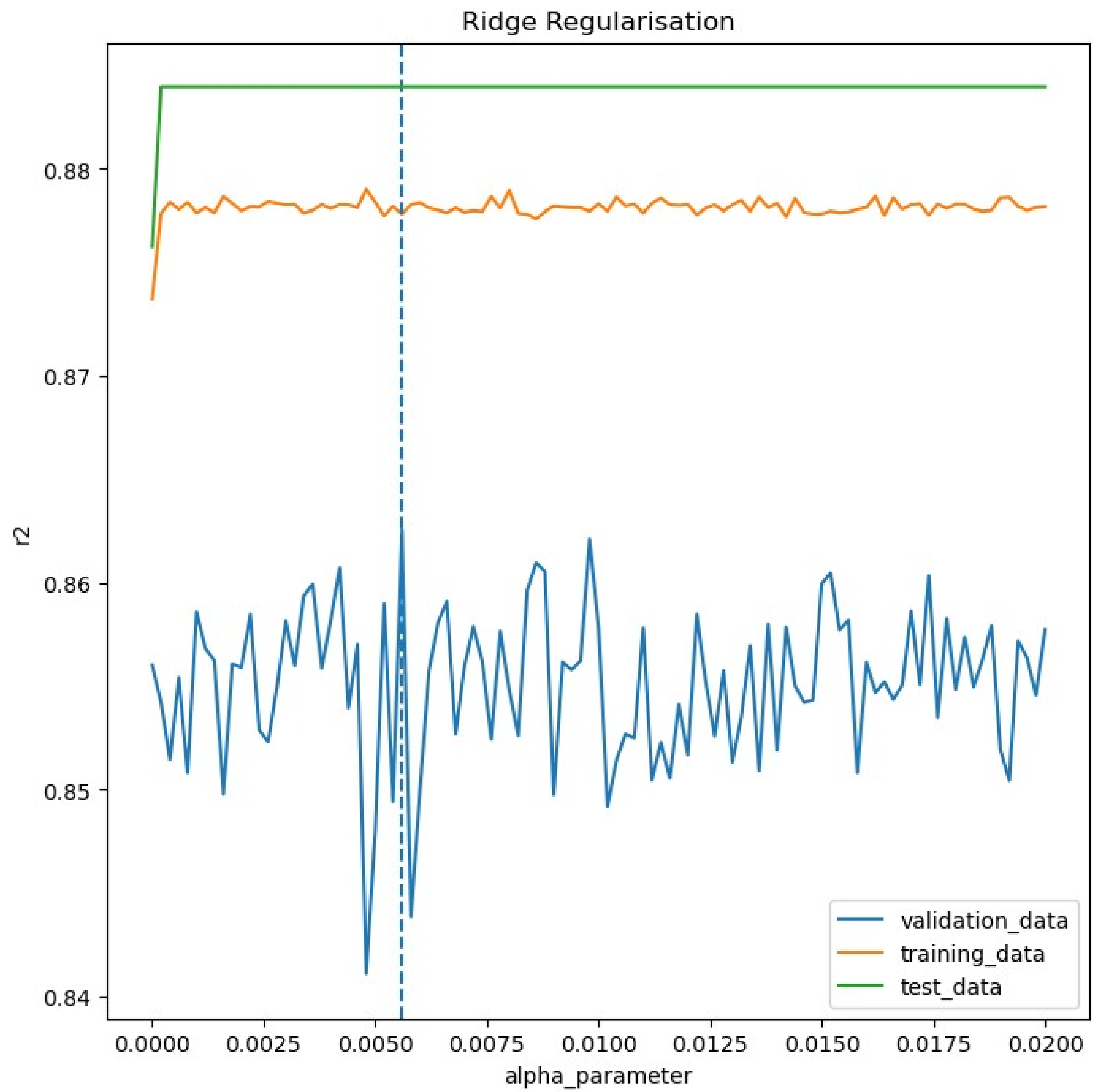
```
### BASED ON LASSOCV:
print(f"The best value of the tuning parameter, alpha, chosen by
cross-validation is {lasso_model.alpha_}.")
lasso_best = Lasso(alpha=lasso_model.alpha_)
lasso_best.fit(x_scale, y_scale)
# lasso_best.coef_
```

```
The best value of the tuning parameter, alpha, chosen by cross-
validation is 0.0035778259276540757.
```

```
Lasso(alpha=0.0035778259276540757)
```

repeat the process with RIDGE MODEL

```
# Split the dataset into training and testing dataframes
scaler = StandardScaler()
x_raw =
housing_training_data.select_dtypes(exclude=['object']).drop(columns =
['SalePrice'])
x_scale = scaler.fit_transform(x_raw)
y_scale = np.array(housing_training_data['SalePrice']).reshape(-1,1)

new_ridge_X_train, new_ridge_X_validation, new_ridge_y_train,
new_ridge_y_validation = train_test_split(x_scale, y_scale,
test_size=0.3, random_state=1)
cv = KFold(n_splits=5, shuffle=True)

lasso_alphas = np.linspace(0, 0.02, 101)

chosen_alpha, max_validation_score, test_score_at_chosen_alpha = \
    regmodel_param_test( lasso_alphas, new_ridge_X_train,
new_ridge_y_train, cv, scoring = 'r2', model_name = 'Ridge',
        X_test = new_ridge_X_validation, y_test =
new_ridge_y_validation, draw_plot = True, filename =
'ridge_wide_search')
print("Chosen alpha: %.5f" % chosen_alpha)
print("Validation score: %.5f" % max_validation_score)
print("Test score at chosen alpha: %.5f" % test_score_at_chosen_alpha)
```

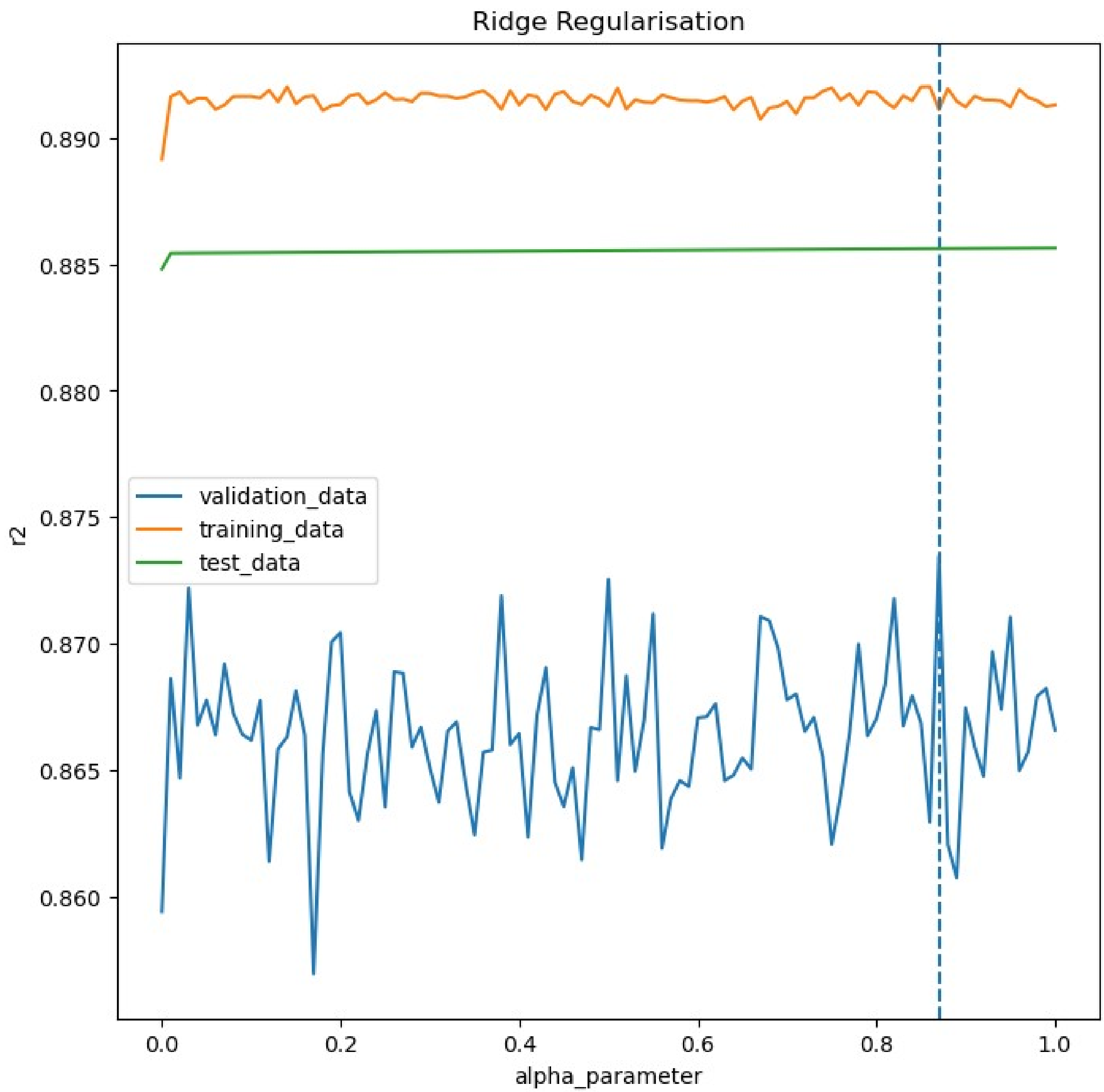



```
Chosen alpha: 0.00560
Validation score: 0.86254
Test score at chosen alpha: 0.88396
```

REPEAT WITH RIDGE USING SUBNET OF ENCODED VARIABLE SET

```
scaler = StandardScaler()
x_raw =
housing_training_data_large_subset.select_dtypes(exclude=['object']).d
rop(columns = ['SalePrice'])
x_scale = scaler.fit_transform(x_raw)
y_scale = np.array(housing_training_data['SalePrice']).reshape(-1,1)
```

```
new_ridge_X_train, new_ridge_X_validation, new_ridge_y_train,
new_ridge_y_validation = train_test_split(x_scale, y_scale,
test_size=0.3, random_state=1)
cv = KFold(n_splits=5, shuffle=True)

lasso_alphas = np.linspace(0, 1, 101)

chosen_alpha, max_validation_score, test_score_at_chosen_alpha = \
    regmodel_param_test( lasso_alphas, new_ridge_X_train,
new_ridge_y_train, cv, scoring = 'r2', model_name = 'Ridge',
        X_test = new_ridge_X_validation, y_test =
new_ridge_y_validation, draw_plot = True, filename =
'ridge_wide_search')
print("Chosen alpha: %.5f" %chosen_alpha)
print("Validation score: %.5f" %max_validation_score)
print("Test score at chosen alpha: %.5f" %test_score_at_chosen_alpha)
```

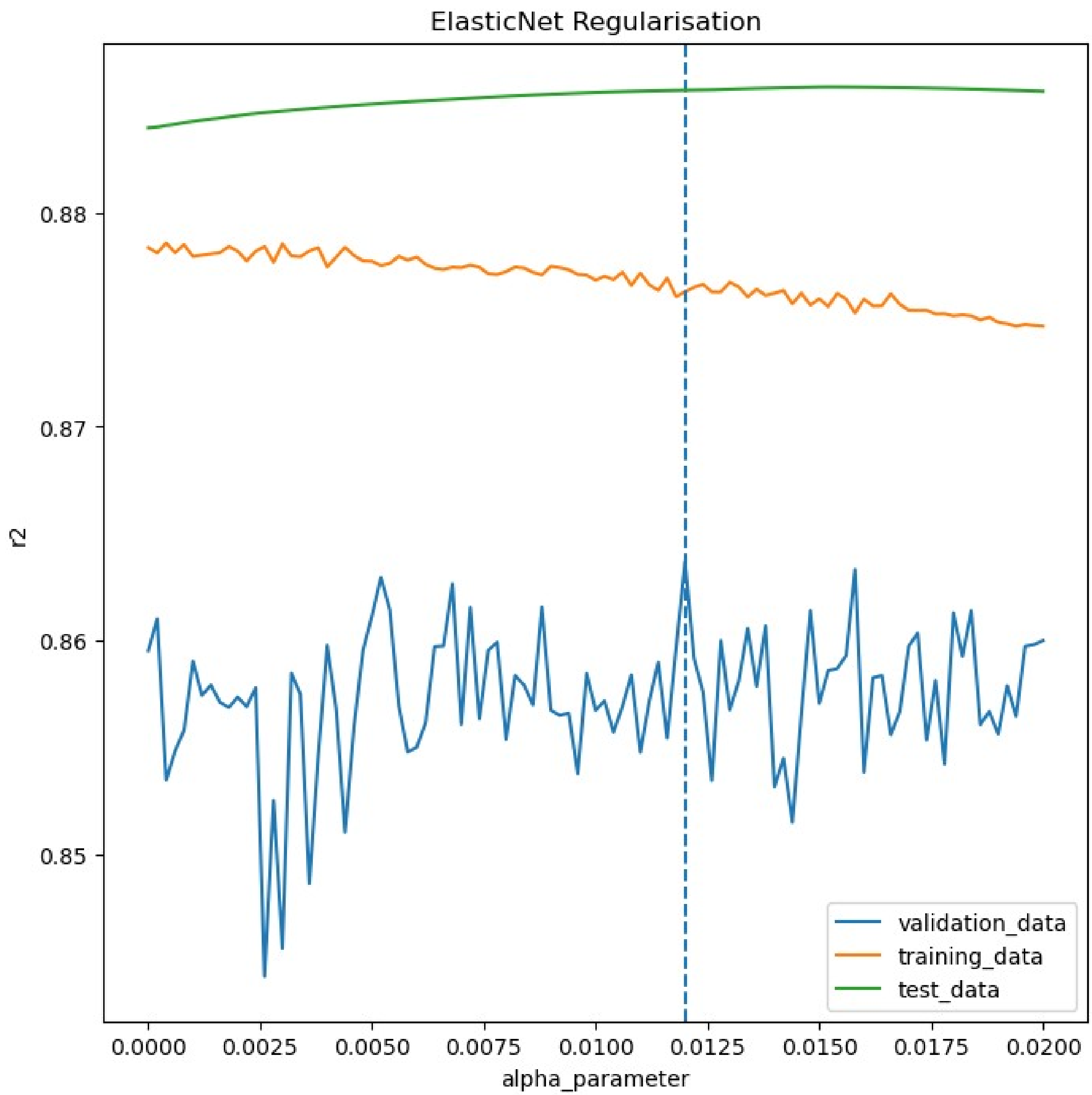



```
Chosen alpha: 0.87000
Validation score: 0.87345
Test score at chosen alpha: 0.88562
```

ElasticNet Model

```
# Split the dataset into training and testing dataframes
elasticscaler = StandardScaler()
x_raw =
housing_training_data.select_dtypes(exclude=['object']).drop(columns =
['SalePrice'])
x_scale = scaler.fit_transform(x_raw)
y_scale =
```

```
elasticscaler.fit_transform(np.array(housing_training_data['SalePrice'
]).reshape(-1,1))

new_elastic_X_train, new_elastic_X_validation, new_elastic_y_train,
new_elastic_y_validation = train_test_split(x_scale, y_scale,
test_size=0.3, random_state=1)
cv = KFold(n_splits=5, shuffle=True)

lasso_alphas = np.linspace(0, 0.02, 101)

chosen_alpha, max_validation_score, test_score_at_chosen_alpha = \
    regmodel_param_test(lasso_alphas, new_elastic_X_train,
new_elastic_y_train, cv, scoring = 'r2', model_name = 'ElasticNet',
        X_test = new_elastic_X_validation, y_test =
new_elastic_y_validation, draw_plot = True, filename =
'EN_wide_search')
print("Chosen alpha: %.5f" %chosen_alpha)
print("Validation score: %.5f" %max_validation_score)
print("Test score at chosen alpha: %.5f" %test_score_at_chosen_alpha)
```

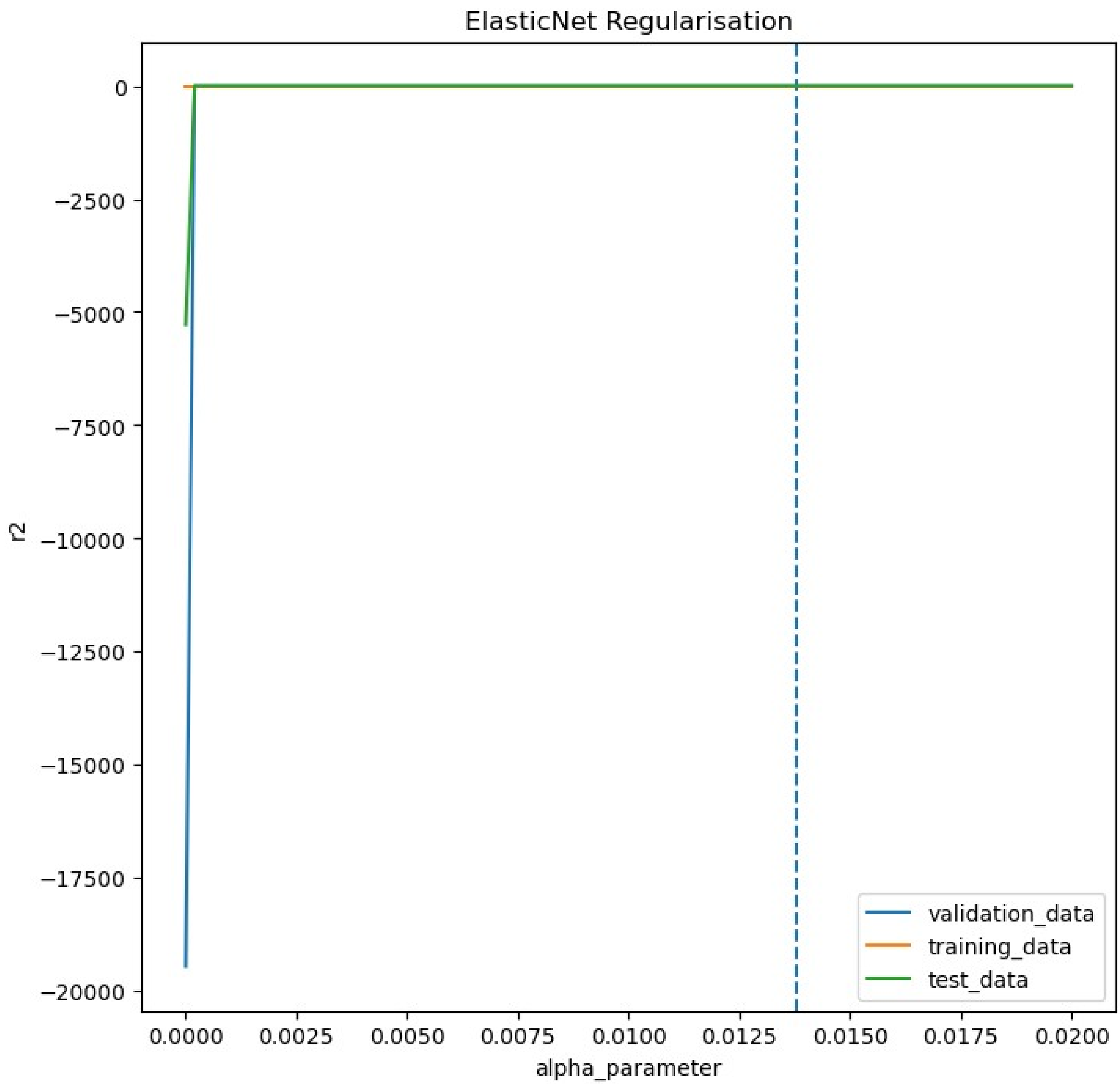



```
Chosen alpha: 0.01200
Validation score: 0.86371
Test score at chosen alpha: 0.88572
```

REPEAT WITH ELASTIC NET USING FULL ENCODED VARIABLE SET with LOG TRANSFORMED SALES PRICE

```
# Split the dataset into training and testing dataframes
elasticscaler = StandardScaler()
x_raw =
housing_training_data_large_common.select_dtypes(exclude=['object'])
x_scale = scaler.fit_transform(x_raw)
```

```
y_scale =
elasticscaler.fit_transform(np.array(np.log(housing_training_data['Sal
ePrice'])).reshape(-1,1))

new_elastic_X_train, new_elastic_X_validation, new_elastic_y_train,
new_elastic_y_validation = train_test_split(x_scale, y_scale,
test_size=0.3, random_state=1)
cv = KFold(n_splits=5, shuffle=True)
lasso_alphas = np.linspace(0, 0.02, 101)

chosen_alpha, max_validation_score, test_score_at_chosen_alpha = \
    regmodel_param_test( lasso_alphas, new_elastic_X_train,
new_elastic_y_train, cv, scoring = 'r2', model_name = 'ElasticNet',
        X_test = new_elastic_X_validation, y_test =
new_elastic_y_validation, draw_plot = True, filename =
'EN_wide_search')
print("Chosen alpha: %.5f" %chosen_alpha)
print("Validation score: %.5f" %max_validation_score)
print("Test score at chosen alpha: %.5f" %test_score_at_chosen_alpha)
```

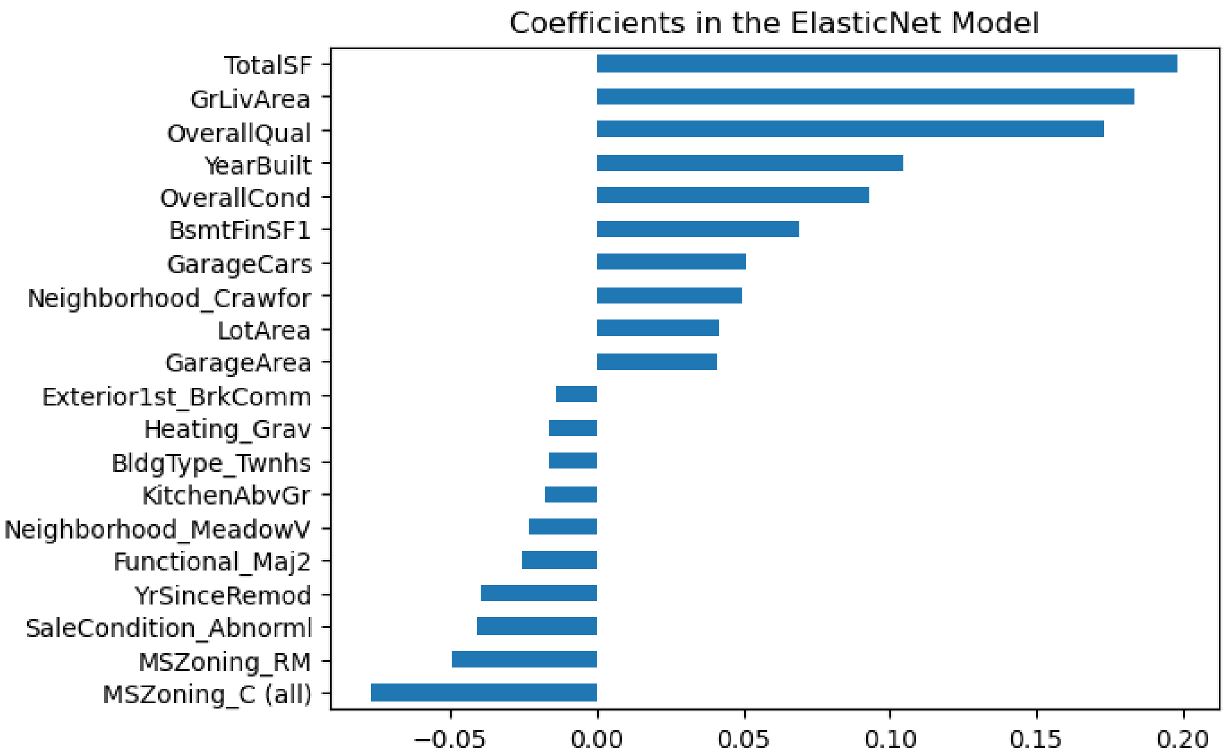



```
Chosen alpha: 0.01380
Validation score: 0.92382
Test score at chosen alpha: 0.90113
```

Let's check the coefficients to determine the important predictors in the model

```
regr = ElasticNet(alpha=chosen_alpha)
elastic_model = regr.fit(x_scale, y_scale)

coef = pd.Series(elastic_model.coef_, index = x_raw.columns)
important_features = pd.concat([coef.sort_values().head(10),
coef.sort_values().tail(10)])
```

```
important_features.plot(kind = "barh")
plt.title("Coefficients in the ElasticNet Model");
```



TotalSF, GrLivArea, and Overall Quality appear to have strong, positive effects on Sales Price.

Running Models on Test Data for Kaggle Predictions

Kaggle Results - Lasso Regression

```
# Set up Test dataframe for Lasso Regression Analysis
lasso_X_test = housing_testing_data.copy(deep=True)
lasso_X_test = lasso_X_test[ ['LotFrontage', 'LotArea', 'OverallQual',
'OverallCond', 'MasVnrArea',
                'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF',
'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
                'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath',
'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr',
                'TotRmsAbvGrd', 'Fireplaces', 'GarageCars',
'GarageArea', 'WoodDeckSF', 'OpenPorchSF',
                'EnclosedPorch', '3SsnPorch', 'ScreenPorch',
'PoolArea', 'MiscVal']]

lasso_X_test[numerical_predictors] =
lasso_scaler.transform(lasso_X_test[numerical_predictors])
```

```python
# Exponential transform the predictions (since the model output log transformed y-values)
lasso_y_predictions_test = lasso_model.predict(lasso_X_test)
y_predictions_final_lasso = np.exp(lasso_y_predictions_test)
predictiondf_lasso=pd.DataFrame(y_predictions_final_lasso, columns=['SalePrice'])
predictiondf_lasso.insert(0, 'Id', housing_testing_data['Id'])
predictiondf_lasso.to_csv('salesprice_lasso_model.csv', index=False)
```

Kaggle Results - Elastic Regression

```python
x_raw = housing_testing_data_large_common.select_dtypes(exclude=['object'])
x_scale = scaler.fit_transform(x_raw)
y_scale_elastic_pred = elastic_model.predict(x_scale)
if y_scale_elastic_pred.ndim == 1:
    y_scale_elastic_pred = y_scale_elastic_pred.reshape(-1, 1)

# transform the predictions (since the model output scaled y-values)
y_log_elastic_pred = elasticscaler.inverse_transform(y_scale_elastic_pred)
y_elastic_pred = np.exp(y_log_elastic_pred)

# Create a dataframe with the y predictions
predictiondf_elastic=pd.DataFrame(y_elastic_pred, columns=['SalePrice'])
predictiondf_elastic.insert(0, 'Id', housing_testing_data['Id'])
predictiondf_elastic.to_csv('salesprice_elastic_model.csv', index=False)
```