MSDS 422_Assignment 2

April 24, 2022

0.1 Part 1: Regularized Regression Methods

[147]:
```
#Import useful libraries
import os
import numpy as np
import pandas as pd
import math
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import preprocessing
from sklearn.compose import ColumnTransformer
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn import metrics
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNet
%matplotlib inline
```

0.1.1 1.1: Data Cleaning, EDA

[148]:
```
train = pd.read_csv("housing_train.csv")
test = pd.read_csv("housing_test.csv")

train.columns = train.columns.str.replace(' ', '')
test.columns = test.columns.str.replace(' ', '')
```

[149]:
```
#Check that data loaded correctly
print(train.shape)
print(test.shape)
```

```
(1460, 81)
(1459, 80)
```

[151]:
```
#Save ID Column
train_ID = train['Id']
test_ID = test['Id']
```

```
#Drop ID column for prediction
train.drop("Id", axis = 1, inplace = True)
test.drop("Id", axis = 1, inplace = True)
```

[152]:
```
#Create training and validation data sets
np.random.seed(42)

Y = train["SalePrice"]
X = train.drop("SalePrice",axis=1)

#Split data into training and validation sets using sklearn with an 80/20 split
X_train, X_val, Y_train, Y_val = train_test_split(X, Y, train_size=0.8,␣
↪random_state=42)
```

In the last assignment, we focused on 12 features to base predictions on: "OverallQual", "GrLivArea", "GarageArea", "YearRemodAdd", "FullBath", "YearBuilt", "1stFlrSF", "Neighborhood","OverallCond", "BsmtFinType1", "HouseStyle", "SaleCondition".

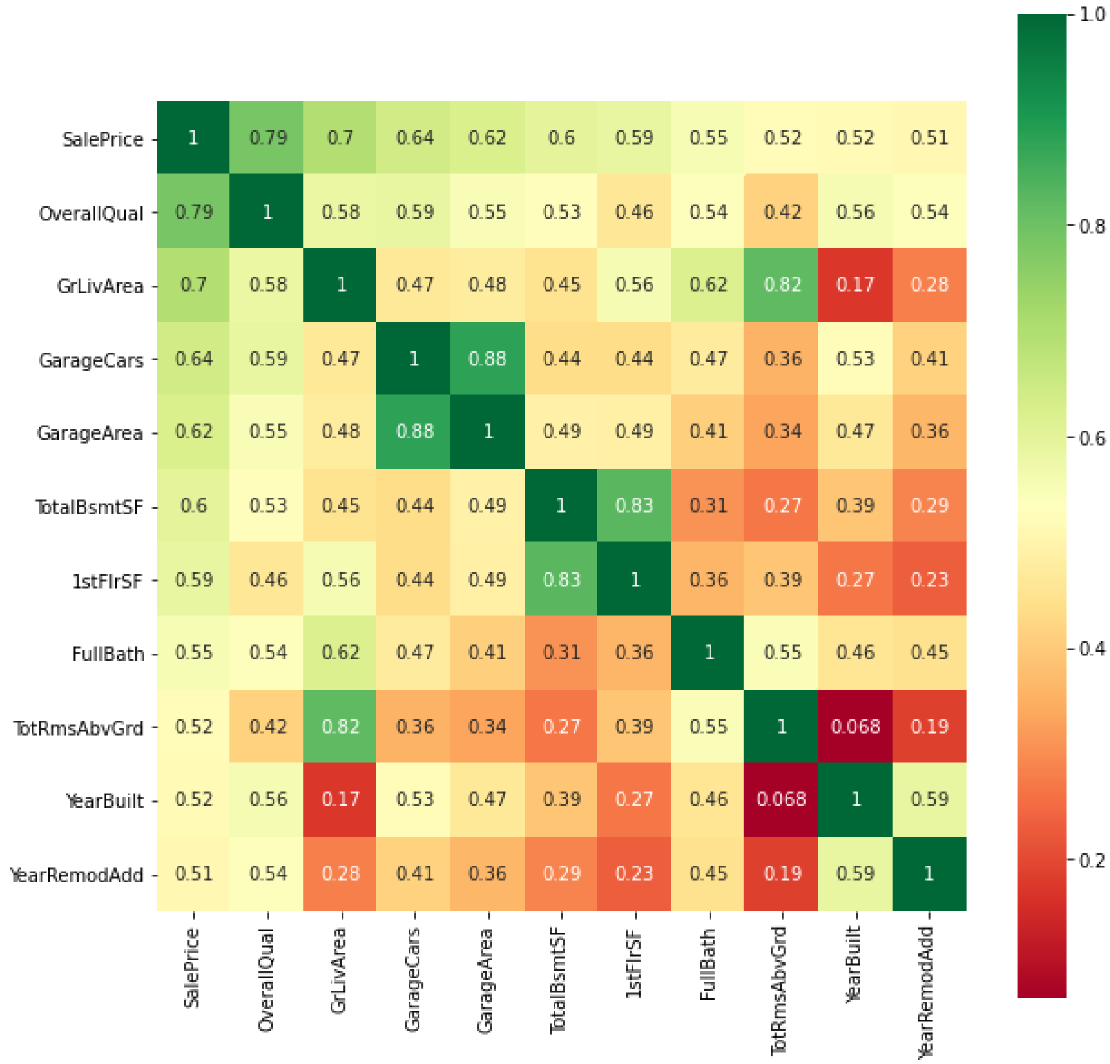
Let's double check to see if we should keep these features or add/replace them with additional features not used in the assignment 1 analysis

[153]:
```
#In assignment 1 correlations were determined using Pearson's coeff with the␣
↪the following identified as important features
copy = X_train.copy()
copy["SalePrice"] = Y_train.astype(float)
copy.corr()["SalePrice"].sort_values(ascending=False).head(11)
```

[153]:
```
SalePrice       1.000000
OverallQual     0.785555
GrLivArea       0.695652
GarageCars      0.640991
GarageArea      0.624139
TotalBsmtSF     0.597766
1stFlrSF        0.587883
FullBath        0.552546
TotRmsAbvGrd    0.520388
YearBuilt       0.516501
YearRemodAdd    0.508593
Name: SalePrice, dtype: float64
```

[154]:
```
#With corresponding corr matrix:
fig, ax = plt.subplots(figsize=(10, 10))
corr_matrix = copy.corr()
cols = corr_matrix.nlargest(11, 'SalePrice')['SalePrice'].index
cm = np.corrcoef(copy[cols].values.T)
sns.heatmap(cm, cbar=True, cmap='RdYlGn', annot=True, square=True,␣
↪yticklabels=cols.values, xticklabels=cols.values)
```

[154]: <matplotlib.axes._subplots.AxesSubplot at 0x2ae4f051880>



Pearson's coefficient evaluates linear relationships between continuous variables. We note that some of these features are configured as ranked choice (OverallQual, GarageCars). With these types of variables it is preferred to use Spearman's Correlation coefficient because it can detect nonlinear relationships and works better for ranking-type data.

[155]:
```
copy.corr(method='spearman')["SalePrice"].sort_values(ascending=False).head(11)
```

[155]:
```
SalePrice       1.000000
OverallQual     0.801016
GrLivArea       0.723435
GarageCars      0.686763
YearBuilt       0.643216
```

```
GarageArea      0.638676
FullBath        0.625567
TotalBsmtSF     0.595014
GarageYrBlt     0.581821
1stFlrSF        0.566305
YearRemodAdd    0.562948
Name: SalePrice, dtype: float64
```

Some of the coefficient values have changed but the identified features remain the same between the two types of coefficients. For assignment 1, categorical features were chosen based on intuition considering the condition of the home.

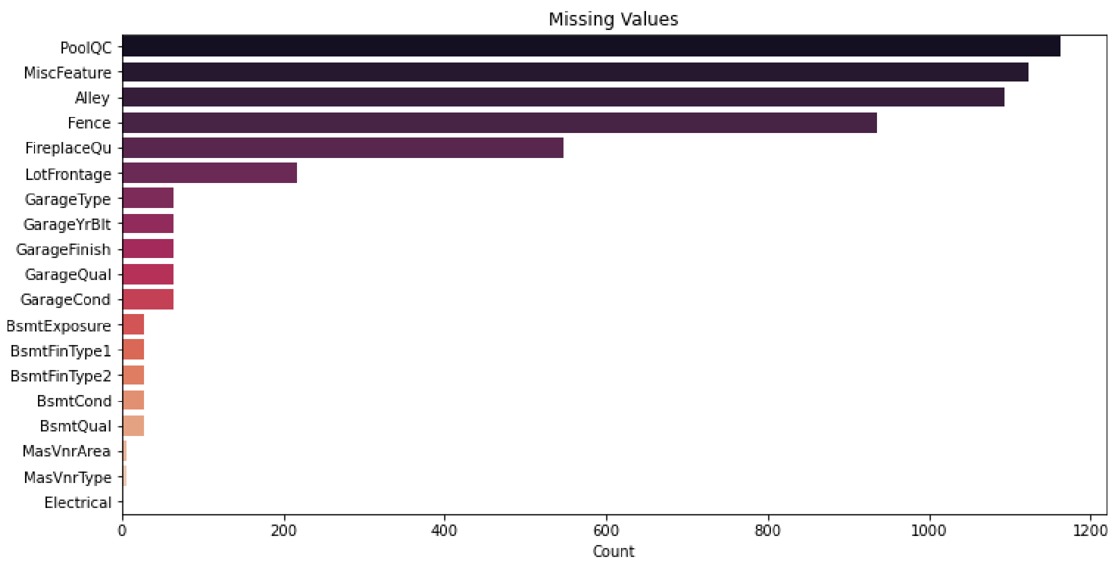
In this assignment we will try a different approach. Instead of selecting a few variables, the entire dataset will be cleaned up as much as possible and used for analysis. We will see if this approach gives better results given the lowered risk of data loss associated with removing variables.

[156]:
```
#Our first step is to deal with any missing values
missing_data_count = X_train.isnull().sum()
missing_data_percent = X_train.isnull().sum() / len(X) * 100

missing_data = pd.DataFrame({
    'Count': missing_data_count,
    'Percent': missing_data_percent
})
missing_data = missing_data[missing_data.Count > 0]
missing_data.sort_values(by='Count', ascending=False, inplace=True)

plt.figure(figsize=(12, 6))
sns.barplot(y=missing_data.index,
            x=missing_data.Count,
            palette="rocket")
title = plt.title("Missing Values")
missing_data
```

[156]:

	Count	Percent
PoolQC	1162	79.589041
MiscFeature	1122	76.849315
Alley	1094	74.931507
Fence	935	64.041096
FireplaceQu	547	37.465753
LotFrontage	217	14.863014
GarageType	64	4.383562
GarageYrBlt	64	4.383562
GarageFinish	64	4.383562
GarageQual	64	4.383562
GarageCond	64	4.383562
BsmtExposure	28	1.917808
BsmtFinType1	28	1.917808

```
BsmtFinType2     28   1.917808
BsmtCond         28   1.917808
BsmtQual         28   1.917808
MasVnrArea        6   0.410959
MasVnrType        6   0.410959
Electrical        1   0.068493
```



Missing values for most of these features indicate an absence of that given feature. If the feature is categorical, we will replace the NA values with "None". If the feature is numeric the NA will be replaced with a 0.

Three variables that stand out are LotFrontage, GarageYrBlt. Instead of replacing these with 0's we will replace the NAs of GarageYrBlt with the year the home was built and the NAs of LotFrontage with the median of lot frontage grouped by neighborhood. This will probably give a more representative result than replacing these values with 0.

[157]:
```
#Replace categorical NAs with None
cat_missing = [ 'PoolQC', 'MiscFeature', 'Alley', 'Fence', 'FireplaceQu',␣
↪'GarageType',
   'GarageFinish', 'GarageQual', 'GarageCond', 'BsmtQual', 'BsmtCond',
   'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2', 'MasVnrType',␣
↪'Electrical','MSZoning',
  ␣
↪'Functional','Utilities','SaleType','Exterior1st','Exterior2nd','KitchenQual']
X_train[cat_missing] = X_train[cat_missing].fillna("None")
X_val[cat_missing] = X_val[cat_missing].fillna("None")
test[cat_missing] = test[cat_missing].fillna("None")

#Replace numeric NAs with 0
```

```
num_missing = ['GarageArea', 'GarageCars', 'BsmtFinSF1', 'BsmtFinSF2',␣
↪'BsmtUnfSF',
    'TotalBsmtSF', 'BsmtFullBath', 'BsmtHalfBath', 'MasVnrArea']
X_train[num_missing] = X_train[num_missing].fillna(0)
X_val[num_missing] = X_val[num_missing].fillna(0)
test[num_missing] = test[num_missing].fillna(0)

#LotFrontage and GarageYrBlt
X_train["LotFrontage"] = X_train["LotFrontage"].fillna(X_train["LotFrontage"].
↪mean())
X_train["GarageYrBlt"] = X_train["GarageYrBlt"].fillna(X_train["YearBuilt"])

X_val["LotFrontage"] = X_val["LotFrontage"].fillna(X_val["LotFrontage"].mean())
X_val["GarageYrBlt"] = X_val["GarageYrBlt"].fillna(X_val["YearBuilt"])

test["LotFrontage"] = test["LotFrontage"].fillna(test["LotFrontage"].mean())
test["GarageYrBlt"] = test["GarageYrBlt"].fillna(test["YearBuilt"])
```

[158]:
```
#Check if missing values are gone
print(X_train.isna().values.any())
print(X_val.isna().values.any())
print(test.isna().values.any())
```

```
False
False
False
```

[159]:
```
#Separate dataset into categorical and numeric features
Xtrain_num = X_train.select_dtypes(include=["float","int64"]).columns
Xtrain_cat = X_train.select_dtypes(include=["object"]).columns

Xval_num = X_val.select_dtypes(include=["float","int64"]).columns
Xval_cat = X_val.select_dtypes(include=["object"]).columns

test_num = test.select_dtypes(include=["float","int64"]).columns
test_cat = test.select_dtypes(include=["object"]).columns
```

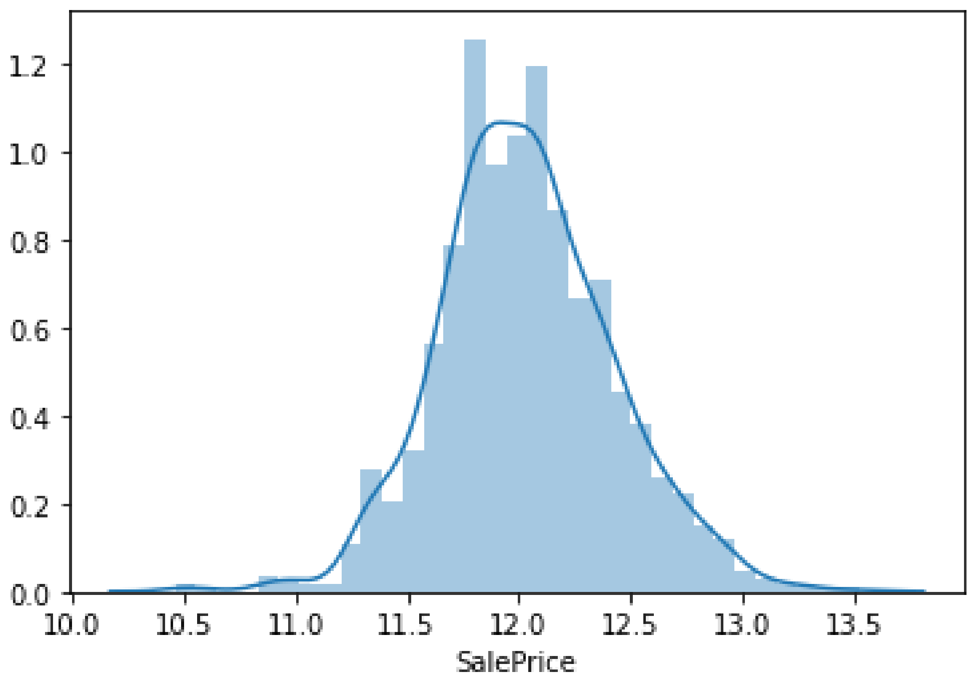
[160]:
```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder
numeric_transformer = Pipeline(steps=[('scaler',StandardScaler())])
categorical_transformer = Pipeline(steps=[("onehot",␣
↪OneHotEncoder(handle_unknown='ignore'))])

#Use Column transformer to perform scaling for numeric variables and one-hot␣
↪encoding for categorical variables
ct = ColumnTransformer(
    transformers=
```

```
    [('standardized',numeric_transformer,Xtrain_num),
       ('oneHotter', categorical_transformer,Xtrain_cat)])
```

From assignment 1, we saw that the target variable was skewed. We want to again perform a log transformation on SalePrice to give the target variable a normal distribution shape

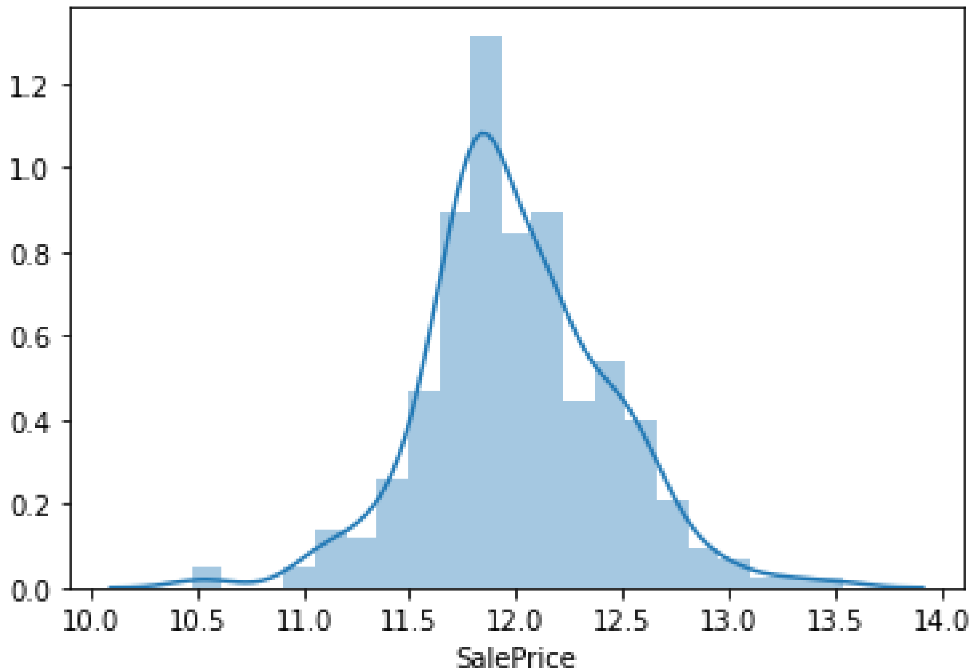
[161]:
```
y = np.log(Y_train)
sns.distplot(y)
print("Skewness: %f" % y.skew())
print("Kurtosis: %f" % y.kurt())
```

```
Skewness: 0.124880
Kurtosis: 0.700245
```



[162]:
```
#Perform the same log transformation on the validation set
y_val = np.log(Y_val)
sns.distplot(y_val)
print("Skewness: %f" % y_val.skew())
print("Kurtosis: %f" % y_val.kurt())
```

```
Skewness: 0.144873
Kurtosis: 1.050142
```



[163]:
```
#Lets check some of our features for high skew values (>0.75)
skewness = X_train.skew().sort_values(ascending=False)
skewness[abs(skewness) > 0.75]
```

[163]:
```
MiscVal          22.053579
PoolArea         14.396098
LotArea          11.958088
3SsnPorch         9.833911
LowQualFinSF      9.199456
KitchenAbvGr      4.445055
BsmtFinSF2        4.217895
ScreenPorch       4.090393
BsmtHalfBath      4.005786
EnclosedPorch     3.163946
LotFrontage       2.666498
OpenPorchSF       2.331890
MasVnrArea        2.294117
BsmtFinSF1        1.862132
TotalBsmtSF       1.723881
WoodDeckSF        1.587330
MSSubClass        1.438804
GrLivArea         1.425139
1stFlrSF          1.422162
BsmtUnfSF         0.910628
2ndFlrSF          0.801209
```

```
dtype: float64
```

[164]:
```
#We can perform a log transformation on these columns as well
#Remove MSSubClass/KitchenAbvGr/BsmtHalfBath because they are not a continuous␣
↪numeric)
skewed_cols = list(skewness[abs(skewness) > 0.75].index)

skewed_cols = [
    col for col in skewed_cols if col not in ['MSSubClass', 'KitchenAbvGr',␣
↪'BsmtHalfBath']
]

for col in skewed_cols:
    X_train[col] = np.log(1 + X_train[col])
    X_val[col] = np.log(1 + X_val[col])
    test[col] = np.log(1 + test[col])
```

[165]:
```
#check skew values
X_train[skewed_cols].skew().sort_values(ascending=False)
```

[165]:
```
PoolArea         13.874124
3SsnPorch         7.510573
LowQualFinSF      7.447547
MiscVal           5.004489
ScreenPorch       3.062578
BsmtFinSF2        2.561997
EnclosedPorch     2.179302
MasVnrArea        0.452588
2ndFlrSF          0.268476
WoodDeckSF        0.181798
1stFlrSF          0.026976
GrLivArea         0.007943
LotArea          -0.012599
OpenPorchSF      -0.064149
BsmtFinSF1       -0.622601
LotFrontage      -0.821789
BsmtUnfSF        -2.188927
TotalBsmtSF      -5.274632
dtype: float64
```

Still a few high values but overall there should be an improvement.

0.2 1.2: Model Training, Evaluation, and Comparison

[166]:
```
#We are going to use K-fold validation with 10 folds
kf=KFold(n_splits=10)

#Alpha values for hyperparameter testing
alphas=[0.001,0.01,0.1,1.0,10,100]
```

0.2.1 Ridge Regression

[167]:
```
#Use the processing loop from the getting started notebook
#This will perform the transformations and model fitting within each fold

resListofDicts=[]                               # a list of results in dicts
for alphVal in alphas:  # Outer processing loop
    fold = 0            # fold counter
    for trainNdx, testNdx in kf.split(X_train): # cv loop. should do it 10␣
↪times.
        fold+=1
        Xtr = ct.fit_transform(X_train.iloc[trainNdx])   # fit and transform X␣
↪training fold
        Xval = ct.transform(X_train.iloc[testNdx])       # transform X test fold
        regMod=Ridge(alpha=alphVal)  # instantiate regressor
        fitMod=regMod.fit(Xtr,y.iloc[trainNdx])          # fitted
        predtr = fitMod.predict(Xtr)             # training pred values
        predval = fitMod.predict(Xval)           # test pred values
        msetr = metrics.mean_squared_error(y.iloc[trainNdx],predtr)
        mseval = metrics.mean_squared_error(y.iloc[testNdx],predval)
        resDict={'alpha': alphVal,'fold': fold,
                 'trainMSE':msetr,'testMSE':mseval}
        resListofDicts.append(resDict)
```

[168]:
```
resultsDF=pd.DataFrame(resListofDicts)
resultsDF.shape
resultsDF.columns
```

[168]:
```
Index(['alpha', 'fold', 'trainMSE', 'testMSE'], dtype='object')
```

[169]:
```
#View results to see which alpha value has the lowest mean MSE for the test data
resultsSummaryDF=resultsDF.groupby(['alpha'],as_index=False).agg({'trainMSE':
↪['mean','std'],'testMSE':['mean','std']})
resultsSummaryDF
```

[169]:

	alpha	trainMSE		testMSE	
		mean	std	mean	std
0	0.001	0.007632	0.000383	0.021459	0.010698
1	0.010	0.007626	0.000399	0.021371	0.010663

```
2     0.100  0.007715  0.000381  0.020277  0.010288
3     1.000  0.008343  0.000398  0.018443  0.009712
4    10.000  0.010401  0.000562  0.017471  0.009172
5   100.000  0.013795  0.000774  0.018002  0.009144
```

It looks like an alpha value of 10 gives the lowest mean MSE for the test data. We will now refit a Ridge Regression Model with an alpha=10.

[170]:
```
#Save transformed data
X_final = ct.fit_transform(X_train)
X_final_val = ct.transform(X_val)
test_final = ct.transform(test)
print(X_final.shape)
print(X_final_val.shape)
print(test.shape)
```

```
(1168, 301)
(292, 301)
(1459, 79)
```

[71]:
```
#Fit and Predictions for Ridge Model
Ridge_model = Ridge(alpha=10)
Ridge_model.fit(X_final,y)

Ridge_predictions = Ridge_model.predict(X_final)
Ridge_predictions_val = Ridge_model.predict(X_final_val)

Ridge_R_squared = Ridge_model.score(X_final,y)
Ridge_R_squared_val = Ridge_model.score(X_final_val,y_val)

print(f'R-Squared for Ridge Regression (Training): {Ridge_R_squared.round(3)}')
print(f'R-Squared for Ridge Regression (Validation): {Ridge_R_squared_val.
 ↪round(3)}')
```

```
R-Squared for Ridge Regression (Training): 0.93
R-Squared for Ridge Regression (Validation): 0.909
```

0.2.2 Lasso Regression

[72]:
```
resListofDicts=[]                          # a list of results in dicts
for alphVal in alphas:  # Outer processing loop
    fold = 0            # fold counter
    for trainNdx, testNdx in kf.split(X_train): # cv loop. should do it 10␣
 ↪times.
        fold+=1
        Xtr = ct.fit_transform(X_train.iloc[trainNdx])   # fit and transform X␣
 ↪training fold
        Xval = ct.transform(X_train.iloc[testNdx])       # transform X test fold
```

```
        regMod=Lasso(alpha=alphVal)  # instantiate regressor
        fitMod=regMod.fit(Xtr,y.iloc[trainNdx])           # fitted
        predtr = fitMod.predict(Xtr)             # training pred values
        predval = fitMod.predict(Xval)           # test pred values
        msetr = metrics.mean_squared_error(y.iloc[trainNdx],predtr)
        mseval = metrics.mean_squared_error(y.iloc[testNdx],predval)
        resDict={'alpha': alphVal,'fold': fold,
                'trainMSE':msetr,'testMSE':mseval}
        resListofDicts.append(resDict)
```

[73]:
```
resultsDF=pd.DataFrame(resListofDicts)
resultsDF.shape
resultsDF.columns
```

[73]: Index(['alpha', 'fold', 'trainMSE', 'testMSE'], dtype='object')

[74]:
```
#View results to see which alpha value has the lowest mean MSE for the test data
resultsSummaryDF=resultsDF.groupby(['alpha'],as_index=False).agg({'trainMSE':
 ↪['mean','std'],'testMSE':['mean','std']})
resultsSummaryDF
```

[74]:

	alpha	trainMSE		testMSE	
		mean	std	mean	std
0	0.001	0.012447	0.000690	0.017096	0.009139
1	0.010	0.019002	0.000914	0.020668	0.008600
2	0.100	0.045974	0.000970	0.046775	0.012980
3	1.000	0.152432	0.003721	0.152624	0.033504
4	10.000	0.152432	0.003721	0.152624	0.033504
5	100.000	0.152432	0.003721	0.152624	0.033504

[75]:
```
#Fit and Predictions for Lasso Model
#Alpha value for lasso is 0.001

Lasso_model = Lasso(alpha=0.001)
Lasso_model.fit(X_final,y)

Lasso_predictions = Lasso_model.predict(X_final)
Lasso_predictions_val = Lasso_model.predict(X_final_val)

Lasso_R_squared = Lasso_model.score(X_final,y)
Lasso_R_squared_val = Lasso_model.score(X_final_val,y_val)

print(f'R-Squared for Lasso Regression (Training): {Lasso_R_squared.round(3)}')
print(f'R-Squared for Lasso Regression (Validation): {Lasso_R_squared_val.
 ↪round(3)}')
```

```
R-Squared for Lasso Regression (Training): 0.916
```

```
R-Squared for Lasso Regression (Validation): 0.906
```

0.2.3 ElasticNet Regression

[76]:
```python
resListofDicts=[]                              # a list of results in dicts
for alphVal in alphas:  # Outer processing loop
    fold = 0            # fold counter
    for trainNdx, testNdx in kf.split(X_train): # cv loop. should do it 10␣
↪times.
        fold+=1
        Xtr = ct.fit_transform(X_train.iloc[trainNdx])   # fit and transform X␣
↪training fold
        Xval = ct.transform(X_train.iloc[testNdx])       # transform X test fold
        regMod=ElasticNet(alpha=alphVal)  # instantiate regressor
        fitMod=regMod.fit(Xtr,y.iloc[trainNdx])            # fitted
        predtr = fitMod.predict(Xtr)             # training pred values
        predval = fitMod.predict(Xval)           # test pred values
        msetr = metrics.mean_squared_error(y.iloc[trainNdx],predtr)
        mseval = metrics.mean_squared_error(y.iloc[testNdx],predval)
        resDict={'alpha': alphVal,'fold': fold,
                'trainMSE':msetr,'testMSE':mseval}
        resListofDicts.append(resDict)
```

[77]:
```python
resultsDF=pd.DataFrame(resListofDicts)
resultsDF.shape
resultsDF.columns
```

[77]:
```
Index(['alpha', 'fold', 'trainMSE', 'testMSE'], dtype='object')
```

[78]:
```python
#View results to see which alpha value has the lowest mean MSE for the test data
resultsSummaryDF=resultsDF.groupby(['alpha'],as_index=False).agg({'trainMSE':
↪['mean','std'],'testMSE':['mean','std']})
resultsSummaryDF
```

[78]:

	alpha	trainMSE		testMSE	
		mean	std	mean	std
0	0.001	0.010576	0.000459	0.017053	0.009212
1	0.010	0.017321	0.000907	0.019669	0.008876
2	0.100	0.029473	0.000855	0.030541	0.009341
3	1.000	0.152432	0.003721	0.152624	0.033504
4	10.000	0.152432	0.003721	0.152624	0.033504
5	100.000	0.152432	0.003721	0.152624	0.033504

[79]:
```python
#Fit and Predictions for ElasticNet Model
#Alpha value for ElasticNet is 0.001

E_model = ElasticNet(alpha=0.001)
```

```
E_model.fit(X_final,y)

E_predictions = E_model.predict(X_final)
E_predictions_val = E_model.predict(X_final_val)

E_R_squared = E_model.score(X_final,y)
E_R_squared_val = E_model.score(X_final_val,y_val)

print(f'R-Squared for ElasticNet Regression (Training): {E_R_squared.round(3)}')
print(f'R-Squared for ElasticNet Regression (Validation): {E_R_squared_val.
↪round(3)}')
```

```
R-Squared for ElasticNet Regression (Training): 0.928
R-Squared for ElasticNet Regression (Validation): 0.914
```

0.3 1.3: Improve ElasticNet

We will try to improve the ElasticNet Model by performing hyperparameter tuning for the L1 ratio as well as the alpha values.

[83]:
```
from sklearn.model_selection import GridSearchCV
grid_param_elasticNet = {
     'alpha': [0.0001, 0.0003, 0.0006, 0.001, 0.003, 0.006, 0.01, 0.03, 0.06, 0.
↪1, 0.3, 0.6, 1, 3, 6],
     'l1_ratio': [0.1, 0.3, 0.5, 0.6, 0.7, 0.8, 0.85, 0.9, 0.95, 1]}

search_elasticNet = GridSearchCV(ElasticNet(), grid_param_elasticNet,␣
↪scoring='neg_mean_squared_error',
                           cv=10, n_jobs=-1, verbose=0).fit(X_final, y)
search_elasticNet.best_params_
```

[83]: {'alpha': 0.0006, 'l1_ratio': 1}

[84]:
```
E_model = ElasticNet(alpha=0.0006, l1_ratio = 1)
Efit = E_model.fit(X_final,y)

_predictions = E_model.predict(X_final)
E_predictions_val = E_model.predict(X_final_val)

E_R_squared = E_model.score(X_final,y)
E_R_squared_val = E_model.score(X_final_val,y_val)

print(f'R-Squared for ElasticNet Regression (Training): {E_R_squared.round(3)}')
print(f'R-Squared for ElasticNet Regression (Validation): {E_R_squared_val.
↪round(3)}')
```

```
R-Squared for ElasticNet Regression (Training): 0.928
R-Squared for ElasticNet Regression (Validation): 0.913
```

We don't see much of an improvement after using Gridsearch, but the performance of the model seems to be the same. Overall, it seems safe to use these hyperparameters because the R-squared of the model is still over 0.9 for both training and validation sets.

0.4 1.4: Model Comparison and Kaggle Predictions

[87]:
```
#Use model metrics function from assignment 1
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
def modMetrics(modName,predTrain,yTrain,predVal,yVal):

    resDict={'model':modName,
              'trainR2':r2_score(yTrain,predTrain),
              'valR2':r2_score(yVal,predVal),
              'trainMSE':mean_squared_error(yTrain,predTrain),
              'valMSE':mean_squared_error(yVal,predVal),
              'trainMAE':mean_absolute_error(yTrain,predTrain),
              'valMAE':mean_absolute_error(yVal,predVal)
            }
    return resDict
```

[90]:
```
Ridge_metrics = modMetrics("Ridge␣
↪Regression",Ridge_predictions,y,Ridge_predictions_val,y_val)
Lasso_metrics = modMetrics("Lasso␣
↪Regression",Lasso_predictions,y,Lasso_predictions_val,y_val)
Elastic_metrics = modMetrics("ElasticNet␣
↪Regression",E_predictions,y,E_predictions_val,y_val)
```

[93]:
```
modList=[]
modList.append(Ridge_metrics)
modList.append(Lasso_metrics)
modList.append(Elastic_metrics)
pd.DataFrame(modList)
```

[93]:
```
                   model   trainR2     valR2  trainMSE    valMSE  trainMAE  \
0       Ridge Regression  0.930367  0.909061  0.010615  0.016970  0.068543
1       Lasso Regression  0.915710  0.906326  0.012850  0.017481  0.074386
2  ElasticNet Regression  0.928150  0.913381  0.010953  0.016164  0.070616

     valMAE
0  0.087036
1  0.087217
2  0.084365
```

All 3 of our models performed very well on both the training data and validation data sets, with over 90% R-squared for each model on each set. For our final test data, the ElasticNet model will be used because it had slightly higher R-squared and slightly lower MSE and MAE on the validation set.

[172]:
```python
#ElasticNet Model predictions for the test set
Elastic_predictions = E_model.predict(test_final)

#Inverse Log the predicted values to reverse transformation
Elastic_predictions = np.expm1(Elastic_predictions)

#Create predictions dataframe
E_pred_df = pd.DataFrame()
E_pred_df["Id"] = test_ID
E_pred_df["SalePrice"] = Elastic_predictions

#Check
E_pred_df.head(10)
```

[172]:

	Id	SalePrice
0	1461	117738.225318
1	1462	152193.618683
2	1463	180729.547497
3	1464	192523.382050
4	1465	205588.555096
5	1466	173088.412503
6	1467	181705.063910
7	1468	160955.383083
8	1469	198653.626348
9	1470	117026.540556

[173]:
```python
#Export to CSV File
E_pred_df.to_csv("ElasticNet Predictions.csv",index=False)
```