Predicting Iowa House Prices (Linear Regression)

January 2, 2021

0.1 Predicting Iowa House Prices with Linear Regression and Regularization

This project predicted house prices in Ames, Iowa with 79 features (2006-2010). The training set had 1460 observations and the test set had 1459 observations.

I engineered features for linear regression models, and trained OLS, Lasso, Ridge, and Elastic Net in this notebook

Feature Engineering:

- Outliers
- Skewness
- Missing Values
- Categorical Variables (One-hot Encoding)

Models:

- OLS
- Lasso
- Ridge
- Elastic Net
- All with PCA

[40]:
```
#import libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from scipy.stats import norm, skew
from scipy import stats

#import libraries--feature engineering
from sklearn.preprocessing import LabelEncoder
from scipy.special import boxcox1p
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA

#import libraries--modeling
```

```
from sklearn.linear_model import LinearRegression, ElasticNet, Lasso, Ridge
from sklearn.kernel_ridge import KernelRidge
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import RobustScaler
from sklearn.model_selection import KFold, cross_val_score, train_test_split,␣
↪GridSearchCV
from sklearn.metrics import mean_squared_error
import os
import warnings
warnings.filterwarnings('ignore')
def ignore_warn(*args, **kwargs):
    pass
warnings.warn = ignore_warn #ignore warnings from sklearn and seaborn

#setup graphs
color = sns.color_palette()
sns.set_style('darkgrid')
%matplotlib inline
pd.set_option('display.float_format', lambda x: '{:.3f}'.format(x)) #Limiting␣
↪floats output to 3 decimal points
```

[41]:
```
#import datasets
train = pd.read_csv('/Users/qingchuanlyu/Documents/Application/Projects/Iowa␣
↪Housing/house-prices-advanced-regression-techniques/train.csv')
test = pd.read_csv('/Users/qingchuanlyu/Documents/Application/Projects/Iowa␣
↪Housing/house-prices-advanced-regression-techniques/test.csv')
train.shape, test.shape
```

[41]:
```
((1460, 81), (1459, 80))
```

Feature Engineering

[42]:
```
#fix outlier: YrSold is earlier than YrBuilt for the observation 1089 in the␣
↪test data
test.loc[1089]["YrSold"] = 2009
test.loc[1089]["YrActualAge"] = 0
```

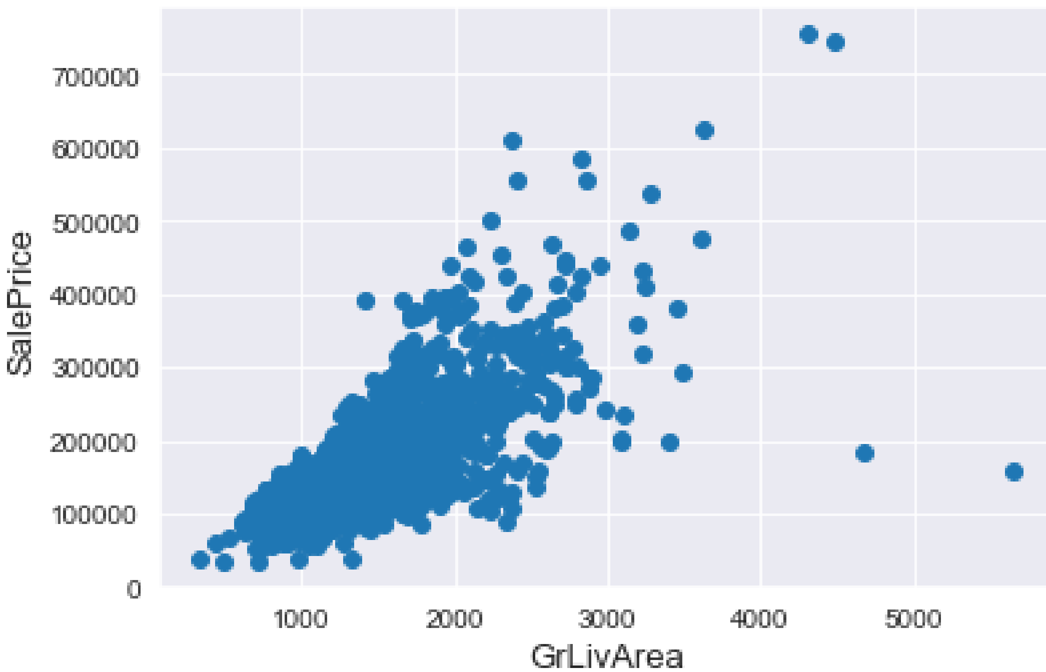
[43]:
```
#store the 'Id' column then drop it from original datasets--not used in modeling
#axis = 1 indicates col
train_ID = train['Id']
test_ID = test['Id']
train.drop("Id", axis = 1, inplace = True)
test.drop("Id", axis = 1, inplace = True)
```

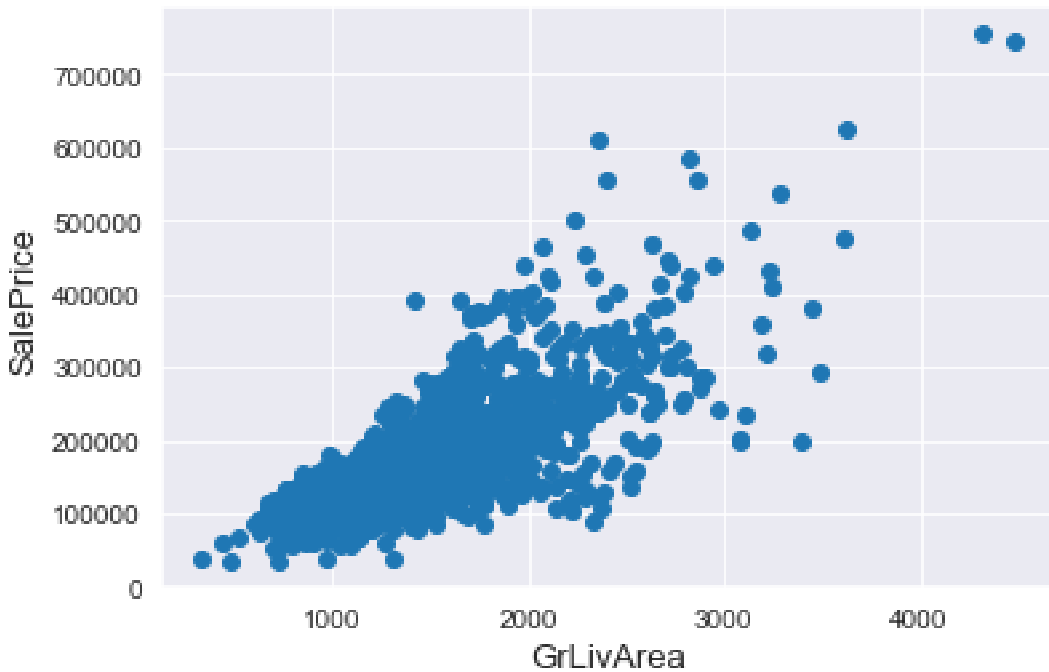
[44]:
```
###Outliers
```

```
#use a scatter plot to observation the relationshiop between living areas and␣
↪prices
fig, ax = plt.subplots()
ax.scatter(x = train['GrLivArea'], y = train['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('GrLivArea', fontsize=13)
plt.show()

#Delete outliers in the bottom-right corner of the scatter plot
train = train.drop(train[(train['GrLivArea']>4000) &␣
↪(train['SalePrice']<300000)].index)

#Check distribution again
fig, ax = plt.subplots()
ax.scatter(train['GrLivArea'], train['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('GrLivArea', fontsize=13)
plt.show()
```





[45]:
```
#Target variable
#Check the distribution of target variable: saleprice
sns.distplot(train['SalePrice'] , fit=norm);

#Get the fitted parameters used by the function
(mu, sigma) = norm.fit(train['SalePrice'])
print( '\n mu = {:.2f} and sigma = {:.2f}\n'.format(mu, sigma))

#Plot the distribution of salesprice
plt.legend(['Normal dist. ($\mu=$ {:.2f} and $\sigma=$ {:.2f} )'.format(mu,␣
↪sigma)],
            loc='best')
plt.ylabel('Frequency')
plt.title('SalePrice distribution')
```

```
mu = 180932.92 and sigma = 79467.79
```

[45]:
```
Text(0.5, 1.0, 'SalePrice distribution')
```

[46]:
```
# Label is a little right-skewed. Use log transformation to make it more␣
↪normally distributed.
#use the numpy fuction log1p to apply log(1+x): plus 1 to avoid -inf
train["SalePrice"] = np.log1p(train["SalePrice"])

#Check the new distribution
sns.distplot(train['SalePrice'] , fit=norm);

# Get the fitted parameters used by the function
(mu, sigma) = norm.fit(train['SalePrice'])
print( '\n mu = {:.2f} and sigma = {:.2f}\n'.format(mu, sigma))

#Now plot the distribution again
plt.legend(['Normal dist. ($\mu=$ {:.2f} and $\sigma=$ {:.2f} )'.format(mu,␣
↪sigma)],
            loc='best')
plt.ylabel('Frequency')
plt.title('SalePrice distribution')
```

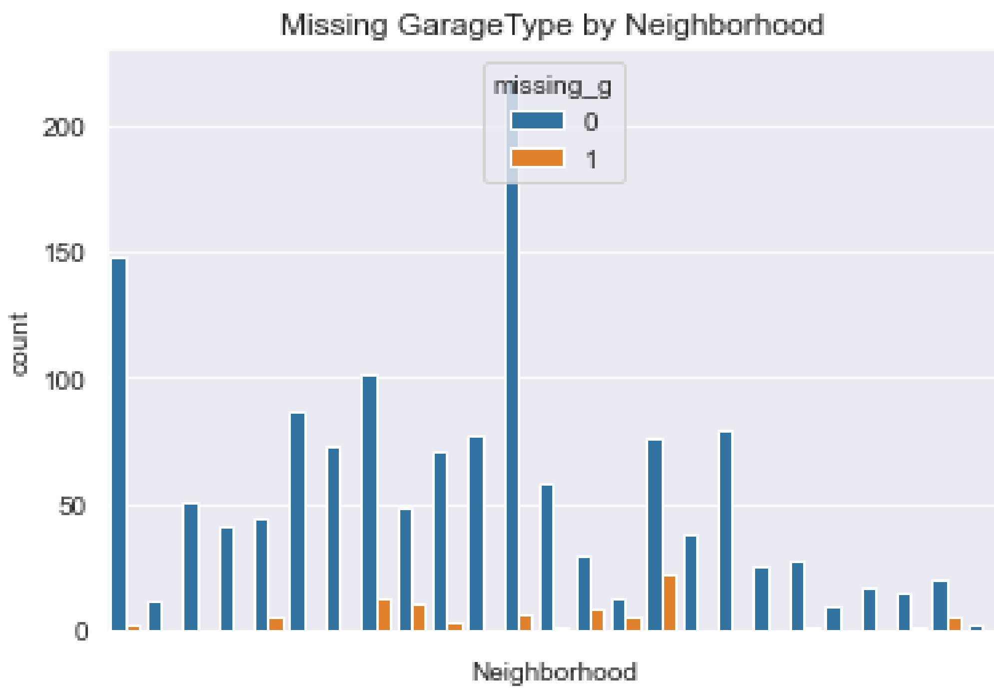
```
mu = 12.02 and sigma = 0.40
```

[46]:
```
Text(0.5, 1.0, 'SalePrice distribution')
```

[47]:
```
#predictors in the training set
y_train = train.SalePrice.values
```

[48]:
```
#check if missing values are Missing at Random, Missing completely at Random,
↪or Not Missing at Random
#Assign label "None" to missing values:
for col in ('MSSubClass', 'MasVnrType', 'BsmtQual', 'BsmtCond', 'BsmtExposure',
↪'BsmtFinType1', 'BsmtFinType2', 'PoolQC', 'MiscFeature', 'Alley', 'Fence',
↪'FireplaceQu', 'GarageType', 'GarageFinish', 'GarageQual', 'GarageCond'):
    train[col] = train[col].fillna('None')
#check if GarageType is missing completely at random
train['missing_g'] = np.where(train['GarageType']=="None", 1, 0)
#Check distribution of counts of each garage type with seaborn
ax = sns.countplot(x ='Neighborhood', hue = 'missing_g', data = train)
ax.set(xticklabels=[])
ax.set(title='Missing GarageType by Neighborhood')
#missing values of garage types spread across a few neighborhoods, so keep
↪"None"
```

[48]: [Text(0.5, 1.0, 'Missing GarageType by Neighborhood')]



[49]:
```
#check the number of missing values among all variables
train.isnull().sum()
```

[49]:
```
MSSubClass         0
MSZoning           0
LotFrontage      259
LotArea            0
Street             0
                 …
YrSold             0
SaleType           0
SaleCondition      0
SalePrice          0
missing_g          0
Length: 81, dtype: int64
```

[50]:
```
plt.scatter(train['LotFrontage'], train['SalePrice'])
```

[50]: <matplotlib.collections.PathCollection at 0x1257b9280>

[51]:
```
#saleprice increases with lotfrontage
#next, check if missing lotfrontage concentrate in larger or samller values
train.loc[train.LotFrontage.isnull() == True][['SalePrice']].mean()
```

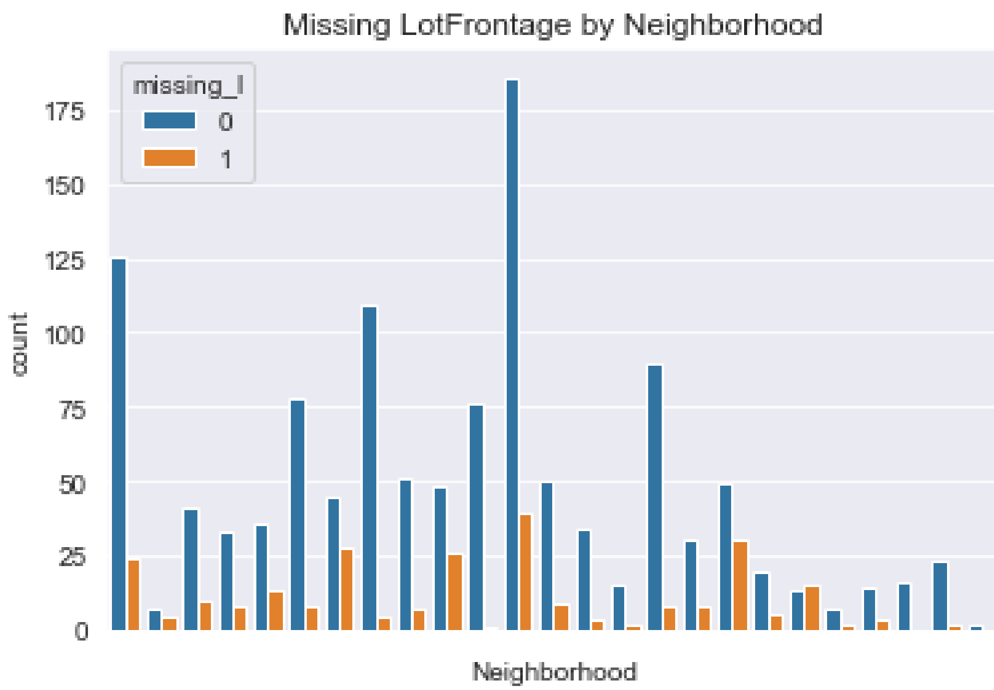
[51]:
```
SalePrice   12.062
dtype: float64
```

[52]:
```
train.loc[train.LotFrontage.isnull() == False][['SalePrice']].mean()
```

[52]:
```
SalePrice   12.016
dtype: float64
```

[53]:
```
#check if missing LotFrontage concentrate in a few neighborhoods
train['missing_l'] = np.where(train['LotFrontage'].isnull(), 1, 0)
ax = sns.countplot(x = 'Neighborhood', hue = 'missing_l', data = train)
ax.set(xticklabels=[])
ax.set(title='Missing LotFrontage by Neighborhood')
#missing LotFrontage spreads out across different neighborhoods
```

[53]:
```
[Text(0.5, 1.0, 'Missing LotFrontage by Neighborhood')]
```



[54]:
```
#check if mean and median of lotfrontage is different across neighborhoods
lotfrontage_by_ngh = train.groupby(['Neighborhood']).\
                    agg(mean_lotfrontage = ('LotFrontage', 'mean'), \
                        med_lotfrontage=('LotFrontage', 'median')).\
                    reset_index()
```

[55]:
```
lotfrontage_by_ngh.head(15)
```

[55]:

	Neighborhood	mean_lotfrontage	med_lotfrontage
0	Blmngtn	47.143	43.000
1	Blueste	24.000	24.000
2	BrDale	21.562	21.000
3	BrkSide	57.510	52.000
4	ClearCr	83.462	80.000
5	CollgCr	71.683	70.000
6	Crawfor	71.805	74.000
7	Edwards	64.811	64.500
8	Gilbert	79.878	65.000
9	IDOTRR	62.500	60.000
10	MeadowV	27.800	21.000
11	Mitchel	70.083	73.000
12	NAmes	76.462	73.000
13	NPkVill	32.286	24.000
14	NWAmes	81.289	80.000

[56]:
```
#Group by neighborhood and fill in missing value by the median LotFrontage of␣
↪all the neighborhood in the training set
#median, mean functions are not affected by missing values. first, obtain the␣
↪median of training data
nbh_lot = train.groupby(train.Neighborhood)[['LotFrontage']].median()
#med_lot = neigh_lot.groupby("Neighborhood")["LotFrontage"].transform("median")
#all["LotFrontage"] = all["LotFrontage"].fillna(med_lot)
#all.loc[all.Neighborhood.isin(neigh_lot.Neighborhood), ['LotFrontage']] =␣
↪neigh_lot['LotFrontage']
train = train.merge(nbh_lot, on=["Neighborhood"], how='left', suffixes=('','_'))
train['LotFrontage'] = train['LotFrontage'].fillna(train['LotFrontage_']).
↪astype(int)
train = train.drop('LotFrontage_', axis=1)
```

[57]:
```
#GarageYrBlt, GarageArea and GarageCars : Replacing missing data with 0 (Since␣
↪No garage = no cars in such garage.)
#BsmtFinSF1, BsmtFinSF2, BsmtUnfSF, TotalBsmtSF, BsmtFullBath and BsmtHalfBath :
↪ missing values are likely zero for having no basement
for col in ('MasVnrArea', 'GarageYrBlt', 'GarageArea', 'GarageCars',␣
↪'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF','TotalBsmtSF', 'BsmtFullBath',␣
↪'BsmtHalfBath'):
    train[col] = train[col].fillna(0)
#Remove "Utilities"-- For this categorical feature all records are "AllPub",␣
↪except for one "NoSeWa" and 2 NA .
train = train.drop(['Utilities'], axis=1)
#Functional : data description says NA means typical
train["Functional"] = train["Functional"].fillna("Typical")
#vars with only one NA value, use mode of this var in the training set to␣
↪prevent data leakage
for col in ('KitchenQual', 'Electrical', 'Exterior1st', 'Exterior2nd',␣
↪'MSZoning', 'SaleType'):
    train[col] = train[col].fillna(train[col].mode()[0])
```

[58]:
```
#Changing OverallCond into a categorical variable
train['OverallCond'] = train['OverallCond'].apply(str)

#Year and month sold are transformed into categorical features.
train['YrSold'] = train['YrSold'].astype(str)
train['MoSold'] = train['MoSold'].astype(str)
```

[59]:
```
# extract categorical variables
cates = train.select_dtypes(include=['object', 'category']).columns
# process columns, apply LabelEncoder to categorical features
for c in cates:
    lbl = LabelEncoder()
    lbl.fit(list(train[c].values))
```

```
    train[c] = lbl.transform(list(train[c].values))
```

[60]:
```
#use one-hot encoder to transfer categorical values to omit orders indicated by␣
↪label encoders and prepare for PCA
train = pd.get_dummies(train)
print(train.shape)
```

```
(1458, 81)
```

[61]:
```
###clean Skewed features
#extract numerical features
num_vars = train.dtypes[train.dtypes != "object"].index

# Check the skew of all numerical features
skewed_vars = train[num_vars].apply(lambda x: skew(x.dropna())).
↪sort_values(ascending=False)
skewness = pd.DataFrame({'Skew' :skewed_vars})
skewness.head(15)

# apply Box Cox Transformation to (highly) skewed features
skewness = skewness[abs(skewness) > 0.8]
skewed_features = skewness.index
lam = 0.25
for f in skewed_features:
    train[f] = boxcox1p(train[f], lam)
```

Modeling

[62]:
```
metric = 'neg_mean_squared_error'
kfold = KFold(n_splits=5, shuffle=True, random_state=1)
```

[63]:
```
#try a simple linear regression first
print(f"{np.sqrt(-cross_val_score(LinearRegression(), train, y_train, cv=kfold,␣
↪scoring=metric)).mean():.4f} Error")
```

```
0.0063 Error
```

[64]:
```
#Lasso
lasso = make_pipeline(RobustScaler(), Lasso(alpha= 0.003, random_state=1))
param_grid = {
    'lasso__alpha' : np.linspace(0.0001, 0.001, 10)
}
search = GridSearchCV(lasso, param_grid, cv=10, scoring=metric, n_jobs=-1)
search.fit(train, y_train)
print(f"{search.best_params_}")
print(f"{search.cv_results_['std_test_score'][search.best_index_]}")
print(f"{np.sqrt(-search.best_score_):.4}")
```

```
{'lasso__alpha': 0.0001}
1.5168099742979261e-05
0.006237
```

[65]:
```
#Ridge
ridge = make_pipeline(RobustScaler(), Ridge(alpha= 0.003, random_state=1))
param_grid = {
    'ridge__alpha' : np.linspace(0.0001, 0.001, 10)
}
search = GridSearchCV(ridge, param_grid, cv=10, scoring=metric, n_jobs=-1)
search.fit(train, y_train)
print(f"{search.best_params_}")
print(f"{np.sqrt(-search.best_score_):.4}")
```

```
{'ridge__alpha': 0.001}
0.006347
```

[66]:
```
#elastic net
elastic_net = make_pipeline(RobustScaler(), ElasticNet(alpha= 0.0005,
                                                      l1_ratio= 0.4,␣
 ↪random_state=1))
param_grid = {
    'elasticnet__alpha' : np.linspace(0.0001, 0.001, 10),
    'elasticnet__l1_ratio' : np.linspace(0.6, 0.95, 20),
}
search = GridSearchCV(elastic_net, param_grid, cv=10, scoring=metric, n_jobs=-1)
search.fit(train, y_train)
print(f"{search.best_params_}")
print(f"{search.cv_results_['std_test_score'][search.best_index_]}")
print(f"{np.sqrt(-search.best_score_):.4}")
```

```
{'elasticnet__alpha': 0.0001, 'elasticnet__l1_ratio': 0.6}
1.452325945216543e-05
0.0062
```

[67]:
```
### PCA
#standardize dataset -- preparing for PCA: too many features
scaler = StandardScaler()
#fit on training set only.
scaler.fit(train)
# Apply transform to both the training set and the test set.
train = scaler.transform(train)

#pca: reducing dimensionality of features; getting rid of collinear features
#choose the minimum number of principal components such that 95% of the␣
 ↪variance is retained
pca = PCA(.95)
```

```
pca.fit(train)
train = pca.transform(train)
```

[68]:
```
#OLS with PCA
#try a simple linear regression first
print(f"{np.sqrt(-cross_val_score(LinearRegression(), train, y_train, cv=kfold,␣
↪scoring=metric)).mean():.4f} Error")
```

```
0.1095 Error
```

[69]:
```
#Lasso with PCA
lasso_pca = make_pipeline(RobustScaler(), Lasso(alpha= 0.003, random_state=1))
param_grid = {
    'lasso__alpha' : np.linspace(0.0001, 0.001, 10)
}
search = GridSearchCV(lasso_pca, param_grid, cv=10, scoring=metric, n_jobs=-1)
search.fit(train, y_train)
print(f"{search.best_params_}")
print(f"{np.sqrt(-search.best_score_):.4}")
```

```
{'lasso__alpha': 0.0005}
0.1086
```

[70]:
```
#Ridge with PCA
ridge_pca = make_pipeline(RobustScaler(), Ridge(alpha= 0.003, random_state=1))
param_grid = {
    'ridge__alpha' : np.linspace(0.0001, 0.001, 10)
}
search = GridSearchCV(ridge_pca, param_grid, cv=10, scoring=metric, n_jobs=-1)
search.fit(train, y_train)
print(f"{search.best_params_}")
print(f"{np.sqrt(-search.best_score_):.4}")
```

```
{'ridge__alpha': 0.001}
0.1088
```

[71]:
```
#elastic net with PCA
elastic_net_pca = make_pipeline(RobustScaler(), ElasticNet(alpha= 0.0005,
                                                           l1_ratio= 0.4,␣
↪random_state=1))
param_grid = {
    'elasticnet__alpha' : np.linspace(0.0001, 0.001, 10),
    'elasticnet__l1_ratio' : np.linspace(0.6, 0.95, 20),
}
search = GridSearchCV(elastic_net_pca, param_grid, cv=10, scoring=metric,␣
↪n_jobs=-1)
search.fit(train, y_train)
```

```python
print(f"{search.best_params_}")
print(f"{search.cv_results_['std_test_score'][search.best_index_]}")
print(f"{np.sqrt(-search.best_score_):.4}")
```

```
{'elasticnet__alpha': 0.0006000000000000001, 'elasticnet__l1_ratio':
0.894736842105263}
0.002294992213406111
0.1086
```

Linear Models perform much better without PCA, but indeed run into overfitting issues with high collinear features, such as the area of a parking lot and the area of its house, according to the extremely small std dev of score. PCA partially solved this problem by combining collinear features together.