Siddikov Boston Housing Assignment 3 Final

July 14, 2019

0.0.1 Introduction

The Boston Housing Study dataset has 506 observations and 13 columns. The response variable is the median value of homes in several neighborhoods. Neighborhood category variable was dropped when we prepared data for regression analysis. We need to use various regression models to determine the overall performance in terms of root-mean-squared error and recommend the best performer to management.

[1]:
```
# seed value for random number generators to obtain reproducible results
RANDOM_SEED = 1

# Expect fitted values to be close to zero
SET_FIT_INTERCEPT = True

# Execute the code line by line in jupyter-notebook
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"

# import base packages into the namespace for this program
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# modeling routines from Scikit Learn packages
import sklearn.linear_model
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, KFold, cross_val_score
from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet
from sklearn.metrics import mean_squared_error, r2_score
from math import sqrt  # for root mean-squared error calculation
```

[2]:
```
# read data for the Boston Housing Study
boston_input = pd.read_csv('boston.csv')
```

[3]:
```
# check the pandas DataFrame object boston_input
print('\nboston DataFrame (first five rows):')
boston_input.head()
```

```
boston DataFrame (first five rows):
```

[3]:
```
  neighborhood     crim    zn  indus  chas    nox  rooms   age     dis  rad  \
0       Nahant  0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1
1   Swampscott  0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2
2   Swanpscott  0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2
3   Marblehead  0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3
4   Marblehead  0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3

   tax  ptratio  lstat    mv
0  296     15.3   4.98  24.0
1  242     17.8   9.14  21.6
2  242     17.8   4.03  34.7
3  222     18.7   2.94  33.4
4  222     18.7   5.33  36.2
```

[4]:
```python
# look at the list of column names
# show the data types, missing values,
print('\nGeneral description of the boston_input DataFrame:')
boston_input.info()
```

```
General description of the boston_input DataFrame:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
neighborhood    506 non-null object
crim            506 non-null float64
zn              506 non-null float64
indus           506 non-null float64
chas            506 non-null int64
nox             506 non-null float64
rooms           506 non-null float64
age             506 non-null float64
dis             506 non-null float64
rad             506 non-null int64
tax             506 non-null int64
ptratio         506 non-null float64
lstat           506 non-null float64
mv              506 non-null float64
dtypes: float64(10), int64(3), object(1)
memory usage: 55.4+ KB
```

[5]:
```python
# drop neighborhood from the data being considered
# response variable is house median value
boston = boston_input.drop('neighborhood', 1)
```

[6]:
```
print('\nDescriptive statistics of the boston DataFrame:')
boston.describe()
```

```
Descriptive statistics of the boston DataFrame:
```

[6]:

	crim	zn	indus	chas	nox	rooms
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500
75%	3.677082	12.500000	18.100000	0.000000	0.624000	6.623500
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000

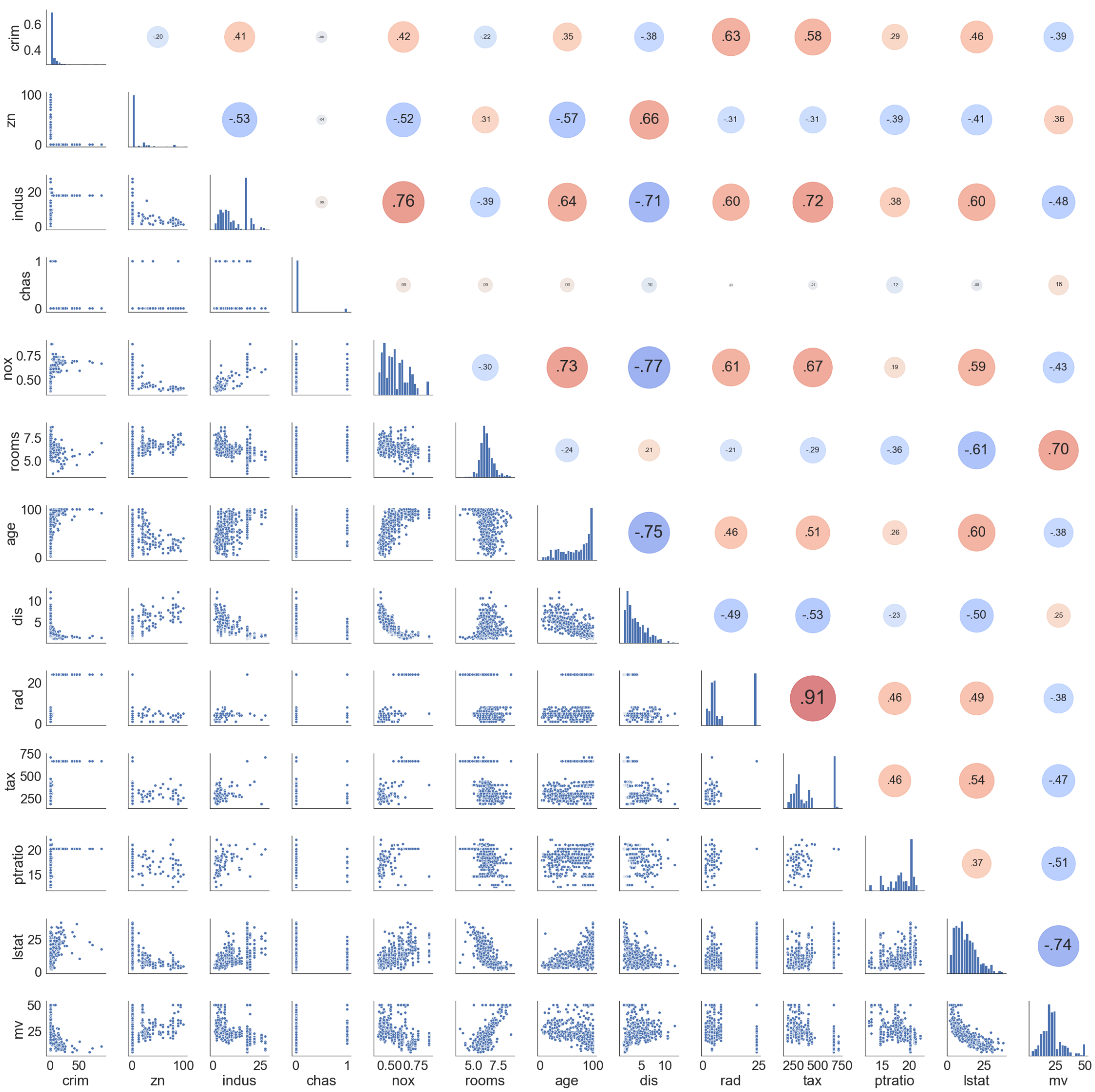
	age	dis	rad	tax	ptratio	lstat
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	68.574901	3.795043	9.549407	408.237154	18.455534	12.653063
std	28.148861	2.105710	8.707259	168.537116	2.164946	7.141062
min	2.900000	1.129600	1.000000	187.000000	12.600000	1.730000
25%	45.025000	2.100175	4.000000	279.000000	17.400000	6.950000
50%	77.500000	3.207450	5.000000	330.000000	19.050000	11.360000
75%	94.075000	5.188425	24.000000	666.000000	20.200000	16.955000
max	100.000000	12.126500	24.000000	711.000000	22.000000	37.970000

	mv
count	506.000000
mean	22.528854
std	9.182176
min	5.000000
25%	17.025000
50%	21.200000
75%	25.000000
max	50.000000

0.0.2 Data Exploration & Visualization

[7]:
```
# data correlation (scatterplot) and distribution (histogram)
## sns.set(font_scale = 1.5); sns.pairplot(boston, height = 2.5);

def corrdot(*args, **kwargs):
    corr_r = args[0].corr(args[1], 'pearson')
    corr_text = f"{corr_r:2.2f}".replace("0.", ".")
    ax = plt.gca()
    ax.set_axis_off()
    marker_size = abs(corr_r) * 10000
```

```python
    ax.scatter([.5], [.5], marker_size, [corr_r], alpha=0.6, cmap="coolwarm",
               vmin=-1, vmax=1, transform=ax.transAxes)
    font_size = abs(corr_r) * 40 + 5
    ax.annotate(corr_text, [.5, .5,],  xycoords="axes fraction",
                ha='center', va='center', fontsize=font_size)

sns.set(font_scale = 2.5, style='white')
g = sns.PairGrid(boston, diag_sharey=False)
g.map_lower(sns.scatterplot)
g.map_diag(plt.hist, bins = 20)
g.map_upper(corrdot);
```



Observed correlations: nox (air pollution) vs. age (pre-1940 built houses in perecentage): positive correlation 0.73 nox (air pollution) vs. dis (avg. commute to work): negative correlation -0.77

dis (avg. commute to work) vs. indus (industrial perecentage): negative correlation -0.71 dis (avg. commute to work) vs. nox (air pollution): negative correlation -0.77 rad (highway access) vs. tax (tax rate): positive correlation 0.91 rooms (number of avg. rooms) vs. lstat (poverty rate): negative correlation -0.61 *response veriable* mv (median house value) vs. lstat (poverty rate): negative correlation -0.74 mv (median house value) vs. rooms (number of avg. rooms): positive correlation 0.70

Observed distribution: The crime rate, zoned land lots, waterfront property (Charles River), average commute rate, and poverty rate have outliers, and they are right-skewed. There are less higher crime rates. Crime rates are concentrated around the low end. There are less zoned land lots. There are more shorter average commutes than longer ones. People leave closer to work.

0.0.3 Data Preparation for Modeling

[8]:
```
# set up preliminary data for data for fitting the models
# the first column is the median housing value response
# the remaining columns are the explanatory variables
prelim_model_data = np.array([boston.mv,\
    boston.crim,\
    boston.zn,\
    boston.indus,\
    boston.chas,\
    boston.nox,\
    boston.rooms,\
    boston.age,\
    boston.dis,\
    boston.rad,\
    boston.tax,\
    boston.ptratio,\
    boston.lstat]).T

# dimensions of the polynomial model X input and y response
# preliminary data before standardization
print('\nData dimensions:', prelim_model_data.shape)
```

```
Data dimensions: (506, 13)
```

[9]:
```
# standard scores for the columns... along axis 0
scaler = StandardScaler()
print(scaler.fit(prelim_model_data))
# show standardization constants being employed
scaler.mean_
scaler.scale_
```

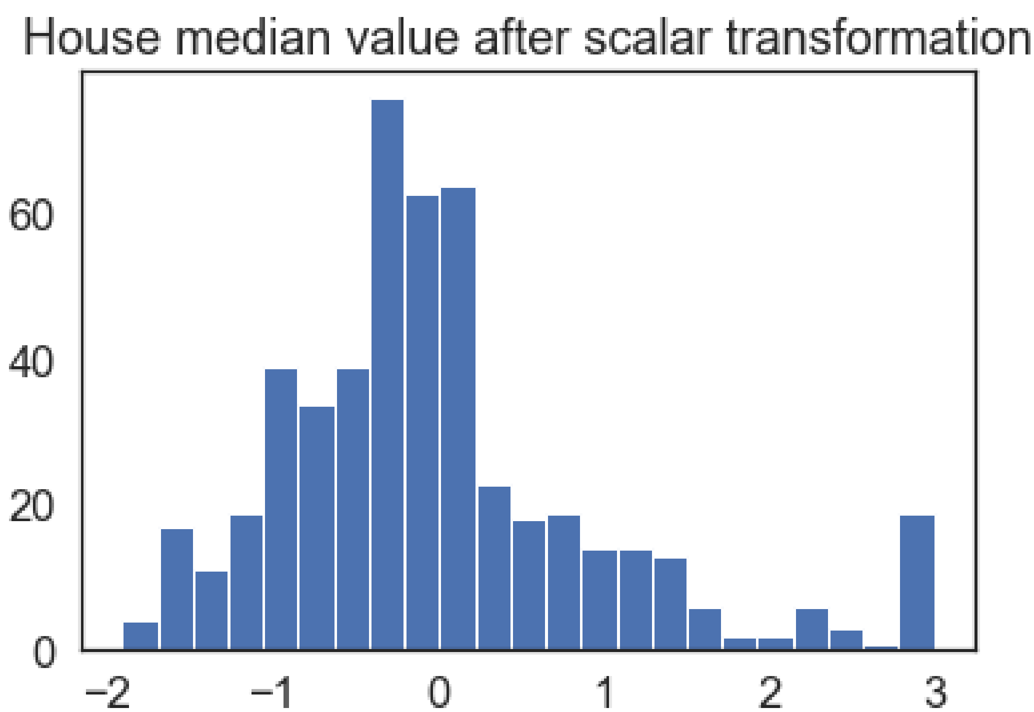
```
StandardScaler(copy=True, with_mean=True, with_std=True)
```

[9]: array([2.25288538e+01, 3.61352356e+00, 1.13636364e+01, 1.11367787e+01,
        6.91699605e-02, 5.54695059e-01, 6.28463439e+00, 6.85749012e+01,
        3.79504269e+00, 9.54940711e+00, 4.08237154e+02, 1.84555336e+01,
        1.26530632e+01])

[9]: array([9.17309810e+00, 8.59304135e+00, 2.32993957e+01, 6.85357058e+00,
        2.53742935e-01, 1.15763115e-01, 7.01922514e-01, 2.81210326e+01,
        2.10362836e+00, 8.69865112e+00, 1.68370495e+02, 2.16280519e+00,
        7.13400164e+00])

[10]:
```
# the model data will be standardized form of preliminary model data
model_data = scaler.fit_transform(prelim_model_data)

# dimensions of the polynomial model X input and y response
# all in standardized units of measure
print('\nDimensions for model_data:', model_data.shape)

# response veriable after scalar transformation
sns.set(font_scale = 1.5, style='white')
plt.hist(model_data[:,0], bins = 'auto')
plt.title('House median value after scalar transformation');
```

```
Dimensions for model_data: (506, 13)
```



0.0.4 Model Exploration

[11]:
```
# here we split our data into training and testing sets
X = model_data[:,1:] #changed to 1 until end, also changed from prelim_model to␣
↪model
y = model_data[:,0] #first column is responses, also changed from prelim_model␣
↪to model
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state = RANDOM_SEED)
```

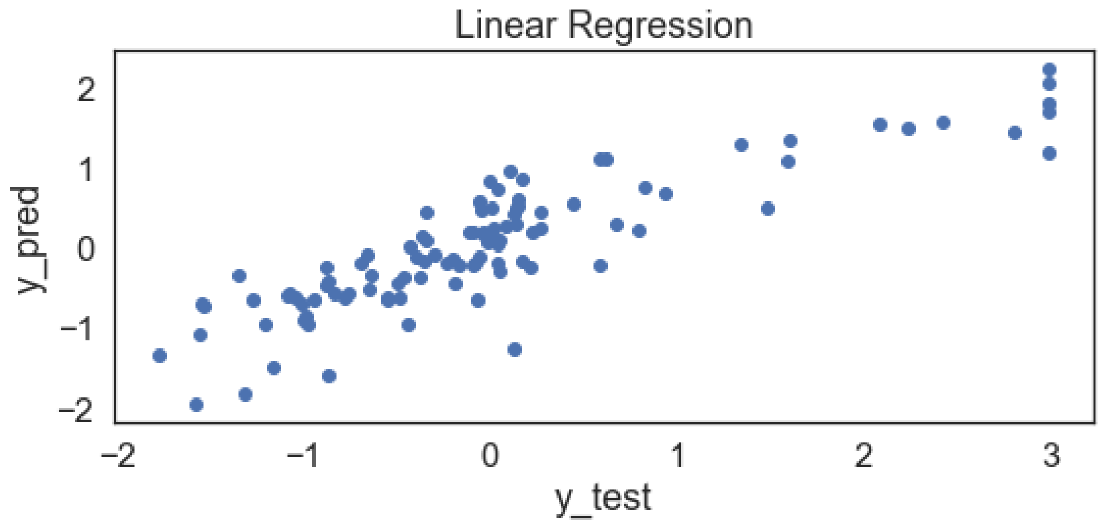
[12]:
```
# list of regression model names
names = ['Linear Regression', 'Ridge Regression: alpha = 1', 'Lasso Regression:␣
↪alpha = 0.1', 'ElasticNet Regression: alpha = 0.1']

# list of regressors
regressors = [LinearRegression(),
              Ridge(alpha = 1, solver = 'cholesky',
                    fit_intercept = True,
                    normalize = False,
                    random_state = RANDOM_SEED),
              Lasso(alpha = 0.1,
                    fit_intercept = True,
                    random_state = RANDOM_SEED),
              ElasticNet(alpha = 0.1,
                         fit_intercept = True,
                         normalize = False,
                         random_state = RANDOM_SEED),]
```

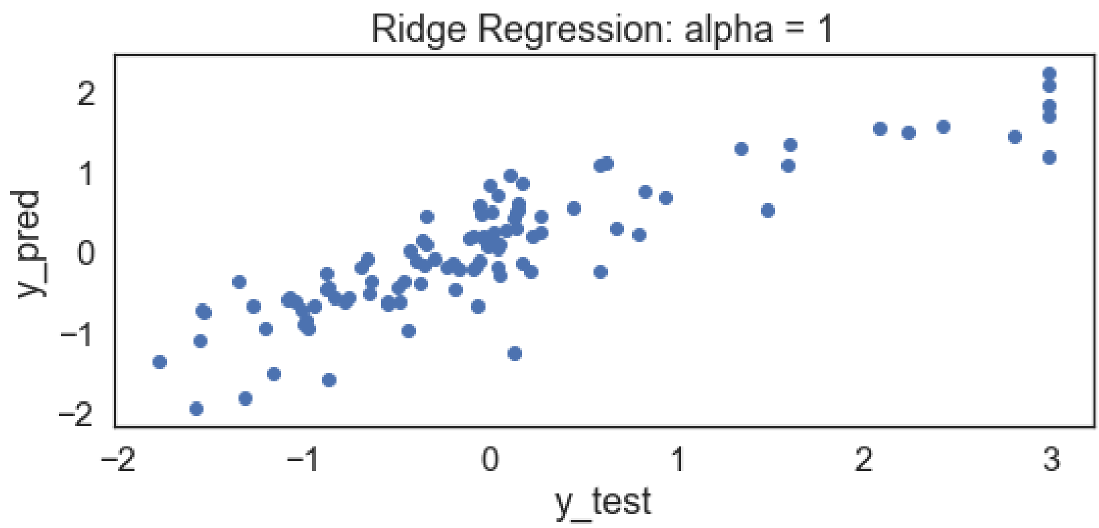
[13]:
```
# ten-fold cross-validation
# set up numpy array for storing results

perf_table = pd.DataFrame()

for name, reg_model in zip(names, regressors):

    # regression model and predict function
    model_fit = reg_model.fit(X_train, y_train) # fit on the train set for this␣
↪fold
    y_test_pred = reg_model.predict(X_test) # evaluate on the test set for this␣
↪fold

    # graph the regression model
    _=plt.figure(figsize=(8, 4))
    _=plt.scatter(y_test, y_test_pred)
    _=plt.xlabel('y_test')
    _=plt.ylabel('y_pred')
    _=plt.title(name)
    _=plt.tight_layout();
```

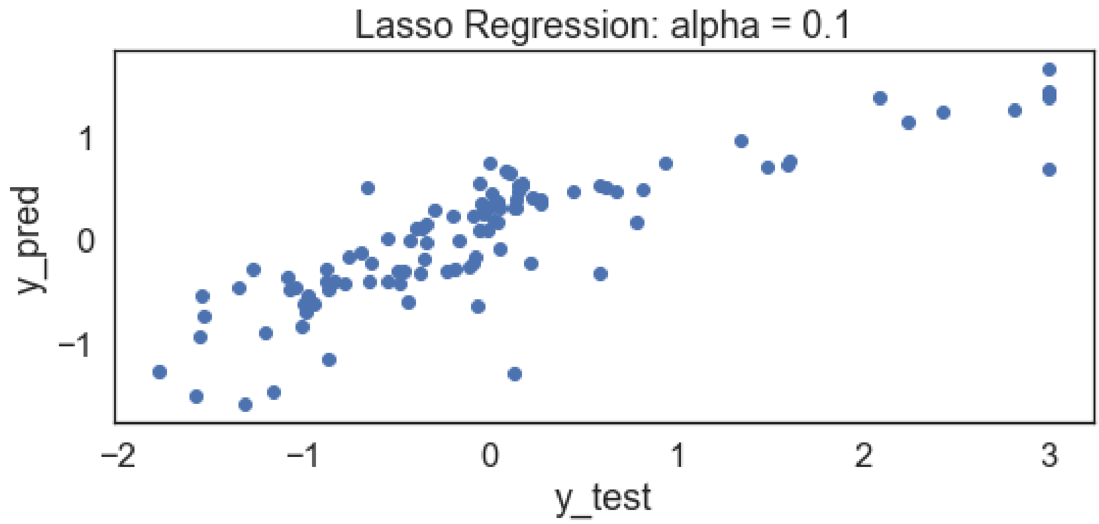
```
    # performance calculation
    ## rmse = np.round(np.sqrt(mean_squared_error(y_test, y_test_pred)),4)
    rmse_train = np.sqrt(-cross_val_score(model_fit, X_train, y_train, scoring␣
↪= "neg_mean_squared_error", cv = 10))
    rmse_test = np.sqrt(-cross_val_score(model_fit, X_test, y_test, scoring =␣
↪"neg_mean_squared_error", cv = 10))
    r2_train = cross_val_score(model_fit, X_train, y_train, scoring = "r2", cv␣
↪= 10)
    r2_test = cross_val_score(model_fit, X_test, y_test, scoring = "r2", cv =␣
↪10)

    # print performance
    pd.options.display.float_format = '{:,.3f}'.format
    perf = pd.DataFrame([name, np.mean(rmse_train), np.mean(rmse_test), np.
↪mean(r2_train), np.mean(r2_test)], columns = [''],
                        index = ['Regression','Training RMSE', 'Test RMSE',␣
↪'Training R-Square', 'Test R-Square']).T
    perf_table = pd.concat([perf_table, perf])

perf_table
```

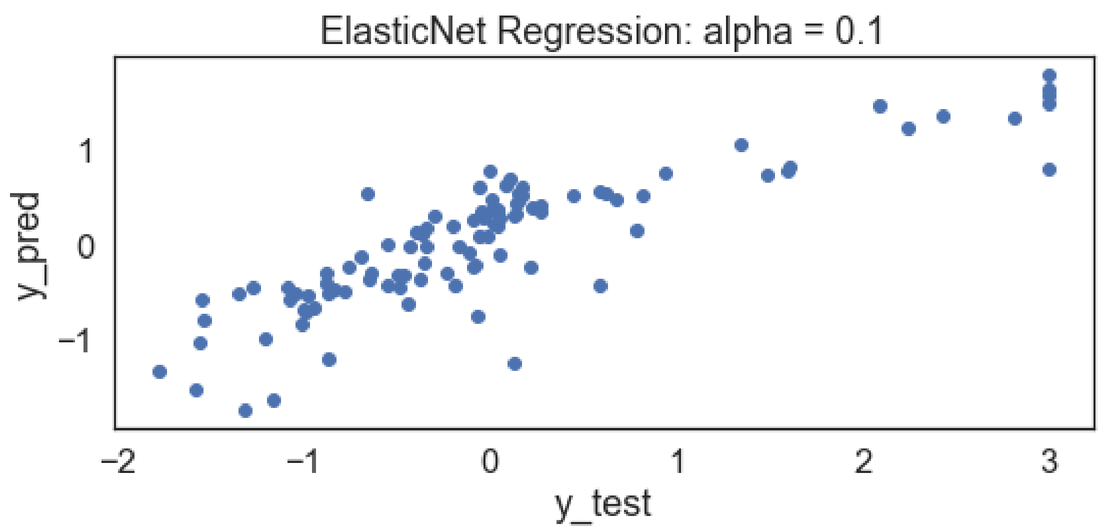
[13]:

```
                            Regression Training RMSE Test RMSE  \
                     Linear Regression         0.524     0.591
          Ridge Regression: alpha = 1          0.523     0.584
        Lasso Regression: alpha = 0.1          0.577     0.590
   ElasticNet Regression: alpha = 0.1          0.564     0.572

 Training R-Square Test R-Square
             0.682         0.417
             0.682         0.447
             0.626         0.638
             0.638         0.616
```


Linear Regression
y_pred
y_test
2
1
0
−1
−2
−2
−1
0
1
2
3


Ridge Regression: alpha = 1
y_pred
y_test
2
1
0
−1
−2
−2
−1
0
1
2
3





0.0.5 Summary

According to the performance summary chart, the ElasticNet and Ridge have the lowest RMSE test scores. The performance indicators were very close to each other. A relative comparison shows how tightly all four of these models were in terms of overall performance.