Regression_PenalizedModel

April 9, 2022

[1]:
```python
import pandas as pd

data = pd.read_csv('C:\\Users\\MSI␣
↪Stealth\\Downloads\\BMEN415Project\\regression\\Volumetric_features.csv')

print(data.head())
```

```
   S.No  Left-Lateral-Ventricle  Left-Inf-Lat-Vent  \
0     1                 22916.9              982.7
1     2                 22953.2              984.5
2     3                 23320.4             1062.1
3     4                 24360.0             1000.5
4     5                 25769.4             1124.4

   Left-Cerebellum-White-Matter  Left-Cerebellum-Cortex  Left-Thalamus  \
0                       15196.7                 55796.4         6855.5
1                       15289.7                 55778.6         6835.1
2                       15382.1                 55551.2         7566.0
3                       14805.4                 54041.8         8004.6
4                       16331.1                 54108.6         6677.4

   Left-Caudate  Left-Putamen  Left-Pallidum  3rd-Ventricle  …  \
0        2956.4        4240.7         2223.9         2034.4  …
1        3064.2        4498.6         2354.1         1927.1  …
2        3231.7        4456.2         1995.4         2064.7  …
3        3137.3        4262.2         1983.4         2017.7  …
4        2964.4        4204.6         2409.7         2251.8  …

   rh_supramarginal_thickness  rh_frontalpole_thickness  \
0                       2.408                     2.629
1                       2.417                     2.640
2                       2.374                     2.601
3                       2.366                     2.639
4                       2.381                     2.555

   rh_temporalpole_thickness  rh_transversetemporal_thickness  \
0                      3.519                            2.009
1                      3.488                            2.111
```

```
2                      3.342                             2.146
3                      3.361                             2.056
4                      3.450                             2.052

   rh_insula_thickness  rh_MeanThickness_thickness  BrainSegVolNotVent.2  \
0                2.825                     2.33635               1093846
1                2.720                     2.34202               1099876
2                2.684                     2.31982               1097999
3                2.700                     2.29215               1070117
4                2.574                     2.30397               1075926

        eTIV.1  Age  dataset
0  1619602.965   85        1
1  1624755.130   85        1
2  1622609.518   86        1
3  1583854.236   87        1
4  1617375.362   89        1

[5 rows x 141 columns]
```

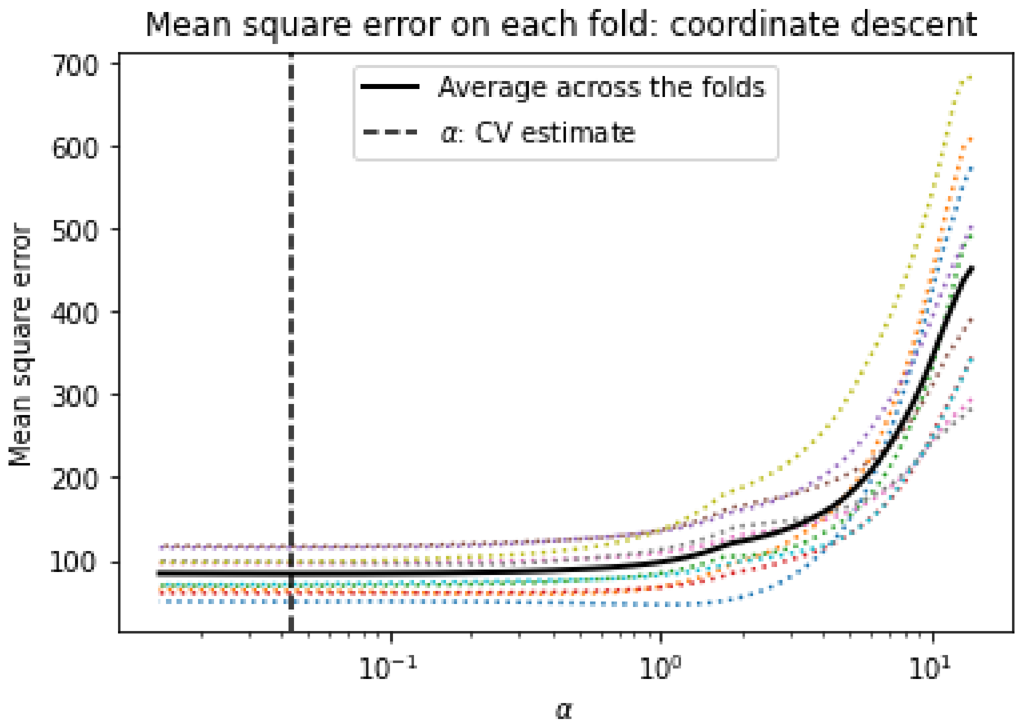
[2]:
```
# Separate Target Variable and Predictor Variables
y=data['Age'].values
X=data[['Left-Lateral-Ventricle', 'Left-Inf-Lat-Vent',
            'Left-Cerebellum-White-Matter', 'Left-Cerebellum-Cortex',
            'Left-Thalamus', 'Left-Caudate', 'Left-Putamen',
           'Left-Pallidum','3rd-Ventricle','4th-Ventricle',
           'Brain-Stem','Left-Hippocampus','Left-Amygdala',
           'CSF','Left-Accumbens-area','Left-VentralDC',
           'Left-vessel','Left-choroid-plexus','Right-Lateral-Ventricle',
           ␣
 ↪'Right-Inf-Lat-Vent','Right-Cerebellum-White-Matter','Right-Cerebellum-Cortex',
           'Right-Thalamus','Right-Caudate','Right-Putamen',
           ␣
 ↪'Right-Pallidum','Right-Hippocampus','Right-Amygdala','Right-Accumbens-area',
           'Right-VentralDC','Right-vessel','Right-choroid-plexus',
           '5th-Ventricle','WM-hypointensities','Left-WM-hypointensities',
           ␣
 ↪'Right-WM-hypointensities','non-WM-hypointensities','Left-non-WM-hypointensities',
           ␣
 ↪'Right-non-WM-hypointensities','Optic-Chiasm','CC_Posterior','CC_Mid_Posterior',
           ␣
 ↪'CC_Central','CC_Mid_Anterior','CC_Anterior','BrainSegVol','BrainSegVolNotVent']].
 ↪values
```

[3]:
```
train = data[:4000]
test = data[4000:]
X_test = X[4000:]
```

```
y_test = y[4000:]
X_train = X[:4000]
y_train = y[:4000]
```

[4]:
```
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from patsy import dmatrices, dmatrix
import matplotlib.pyplot as plt
import math

# Create a scaler object
sc = StandardScaler()

# Fit the scaler to the training data and transform
X_train_std = sc.fit_transform(X_train)

# Apply the scaler to the test data
X_test_std = sc.transform(X_test)
```

[5]:
```
from sklearn.linear_model import LassoCV, ElasticNetCV, RidgeCV
reg_lasso = LassoCV(cv=10).fit(X_train_std, y_train)

EPSILON = 1e-4  # This is to avoid division by zero while taking the base 10␣
 ↪logarithm
plt.figure()
plt.semilogx(reg_lasso.alphas_ + EPSILON, reg_lasso.mse_path_, ':')
plt.plot(reg_lasso.alphas_ + EPSILON, reg_lasso.mse_path_.mean(axis=-1), 'k',
         label='Average across the folds', linewidth=2)
plt.axvline(reg_lasso.alpha_ + EPSILON, linestyle='--', color='k',
            label=r'$\alpha$: CV estimate')
plt.legend()
plt.xlabel(r'$\alpha$')
plt.ylabel('Mean square error')
plt.title('Mean square error on each fold: coordinate descent ')
plt.axis('tight')
plt.show()
print ('Optimized alpha', reg_lasso.alphas_)
```




```
Optimized alpha [14.08755217 13.1380983  12.25263445 11.42684789 10.65671659
9.93848956
  9.26866863  8.64399138  8.06141529  7.51810288  7.01140791  6.53886248
  6.09816504  5.68716912  5.30387296  4.94640967  4.61303822  4.30213488
  4.01218539  3.74177752  3.48959424  3.25440727  3.03507111  2.83051747
  2.63975007  2.46183975  2.29591999  2.14118267  1.99687412  1.86229149
  1.73677928  1.61972617  1.51056204  1.40875522  1.31380983  1.22526344
  1.14268479  1.06567166  0.99384896  0.92686686  0.86439914  0.80614153
  0.75181029  0.70114079  0.65388625  0.6098165   0.56871691  0.5303873
  0.49464097  0.46130382  0.43021349  0.40121854  0.37417775  0.34895942
  0.32544073  0.30350711  0.28305175  0.26397501  0.24618398  0.229592
  0.21411827  0.19968741  0.18622915  0.17367793  0.16197262  0.1510562
  0.14087552  0.13138098  0.12252634  0.11426848  0.10656717  0.0993849
  0.09268669  0.08643991  0.08061415  0.07518103  0.07011408  0.06538862
  0.06098165  0.05687169  0.05303873  0.0494641   0.04613038  0.04302135
  0.04012185  0.03741778  0.03489594  0.03254407  0.03035071  0.02830517
  0.0263975   0.0246184   0.0229592   0.02141183  0.01996874  0.01862291
  0.01736779  0.01619726  0.01510562  0.01408755]
```

[6]:
```
from sklearn.linear_model import Lasso
reg = Lasso(alpha=0.01408755)
reg.fit(X_train_std, y_train)
```

```
Lasso(alpha=0.01408755)
print('R squared training set', round(reg.score(X_train_std, y_train)*100, 2))
print('R squared test set', round(reg.score(X_test_std, y_test)*100, 2))
```

```
R squared training set 81.59
R squared test set -89.09
```

[8]:
```
from sklearn.metrics import mean_squared_error
predictions = reg.predict(X_test_std)
total_cases = len(y_test) # size of validation set

avg = 0.0
SSres = 0.0
SStot = 0.0

for i in range(total_cases):
    value = y_test[i]
    predict = predictions[i]
    avg = (avg + value)/2
    SSres = SSres + (value - predict)**2
    SStot = SStot + (value - avg)**2
    #print(value, '--------- ' , predict)


Rsquared_cal = 1 - SStot/SSres

print('R squared: ', Rsquared_cal)
mse = mean_squared_error(y_test, reg.predict(X_test_std))
rmse = math.sqrt(mse)
print("The rooted mean squared error (MSE) on test set:{:.4f}", rmse)
```

```
R squared:  0.9084155078317926
The rooted mean squared error (MSE) on test set:{:.4f} 9.545207751552638
```

[ ]: