Regression model

April 11, 2022

[1]:
```python
# Import packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sklearn as sk
import os
from scipy.stats import gaussian_kde
```

[2]:
```python
# Read in data, print info, and inspect columns visually
data = pd.read_csv("Volumetric_features.csv")
data.info()
data.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4226 entries, 0 to 4225
Columns: 141 entries, S.No to dataset
dtypes: float64(122), int64(19)
memory usage: 4.5 MB
```

[2]:
```
   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  …
```

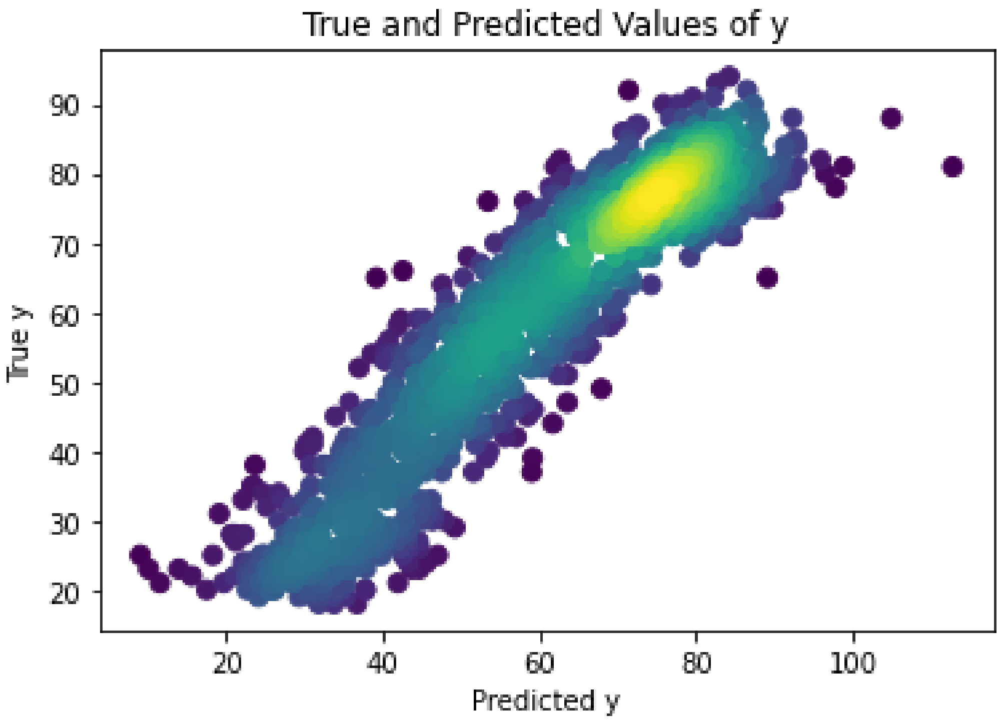
```
4        2964.4        4204.6         2409.7         2251.8  …

   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]
```

[3]:

```python
# Separate test predictor (age)
x = data.drop(["Age"], axis=1)
y = data.Age.values

# Drop poor/collinear predictors (based on group analysis)
data.drop('dataset', axis=1, inplace = True)
data.drop('Left-WM-hypointensities', axis=1, inplace = True)
data.drop('Right-WM-hypointensities', axis=1, inplace = True)
data.drop('Left-non-WM-hypointensities', axis=1, inplace = True)
data.drop('Right-non-WM-hypointensities', axis=1, inplace = True)

# Split testing/training data
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3,
 ↪random_state=42, shuffle = True)
```

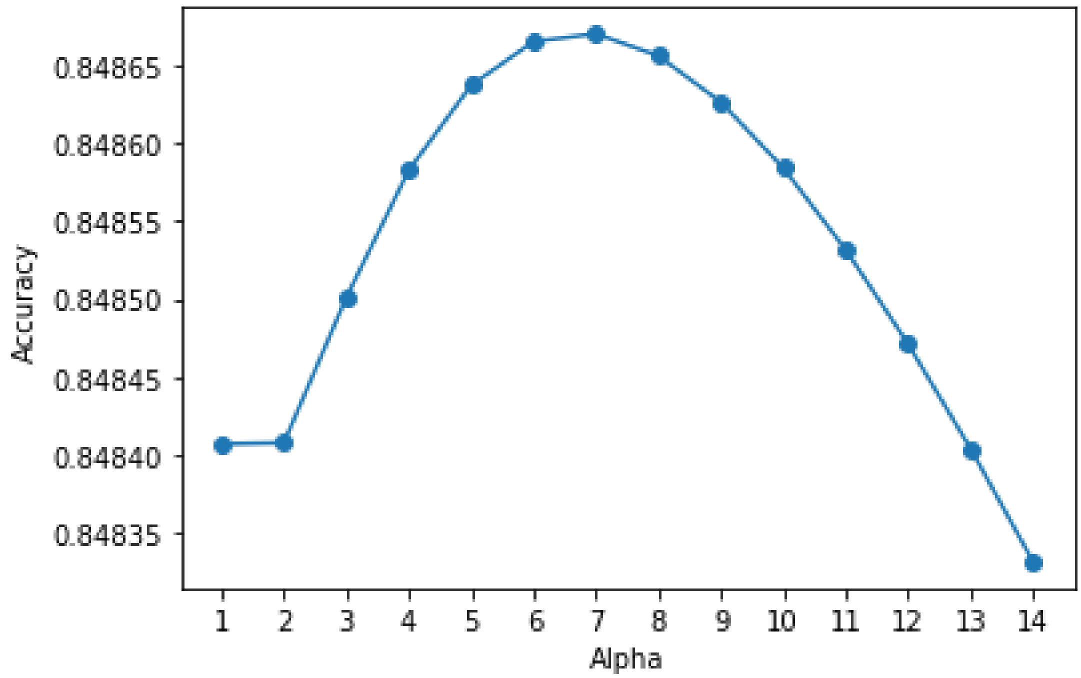
[6]:
```python
def plot_prediction(x, y):
    # This function creates a density scatter plot from x and y
    # Code adapted from:
    # https://stackoverflow.com/questions/20105364/
↪how-can-i-make-a-scatter-plot-colored-by-density-in-matplotlib

    # Get point density
    xy = np.vstack([x,y])
    z = gaussian_kde(xy)(xy)

    # Plot densest points on top by sorting
    idx = z.argsort()
    x, y, z = x[idx], y[idx], z[idx]

    # Plot
    plt.figure()
    plt.xlabel("Predicted y")
    plt.ylabel("True y")
    plt.title("True and Predicted Values of y")
    plt.scatter(x, y, c=z, s=50)
    plt.show()
```

[7]:
```python
# Penalized Model - Ridge Regression

from sklearn import linear_model

def Ridge(plot=True, **kwargs):

    # Training
    model = linear_model.Ridge(**kwargs)
    model = model.fit(x_train, y_train)
    y_predict = model.predict(x_test)

    # Test
    r2 = sk.metrics.r2_score(y_test, y_predict)
    rmse = np.sqrt(sk.metrics.mean_squared_error(y_test, y_predict))

    # Plotting
    if plot: # Option to disable plottig (for looping)
        plot_prediction(y_predict, y_test)

    return(r2, rmse)


Ridge(alpha=7)
```

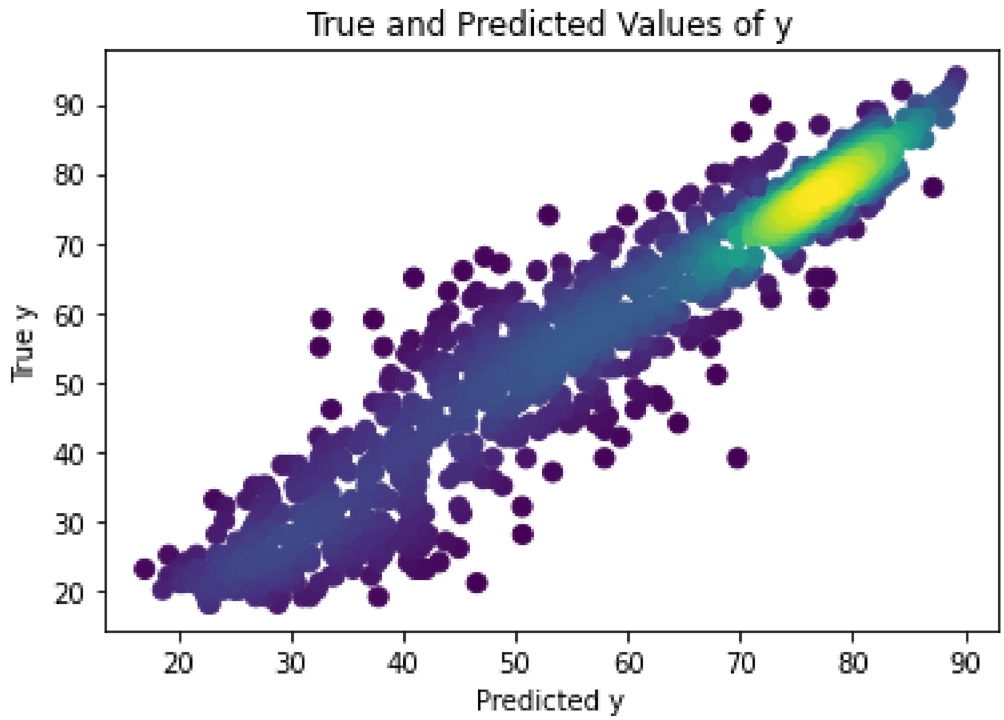


[7]: (0.8486697961085404, 7.781587237400794)

[8]:
```
# Loop for optimizing Ridge alpha parameter

# Initialize arrays
alpha = []
accs = []

# Loop over reasonable range of alpha, calculate acc, and append
for i in np.arange(1, 15):
    alpha.append(i)
    (acc, rmse) = Ridge(alpha=i, plot=False)
    accs.append(acc)

# Plot accuracy vs alpha
plt.plot(alpha, accs, '-o')
plt.xticks(np.arange(min(alpha), max(alpha)+1, 1.0))
plt.xlabel('Alpha')
plt.ylabel("Accuracy")
plt.show()
```



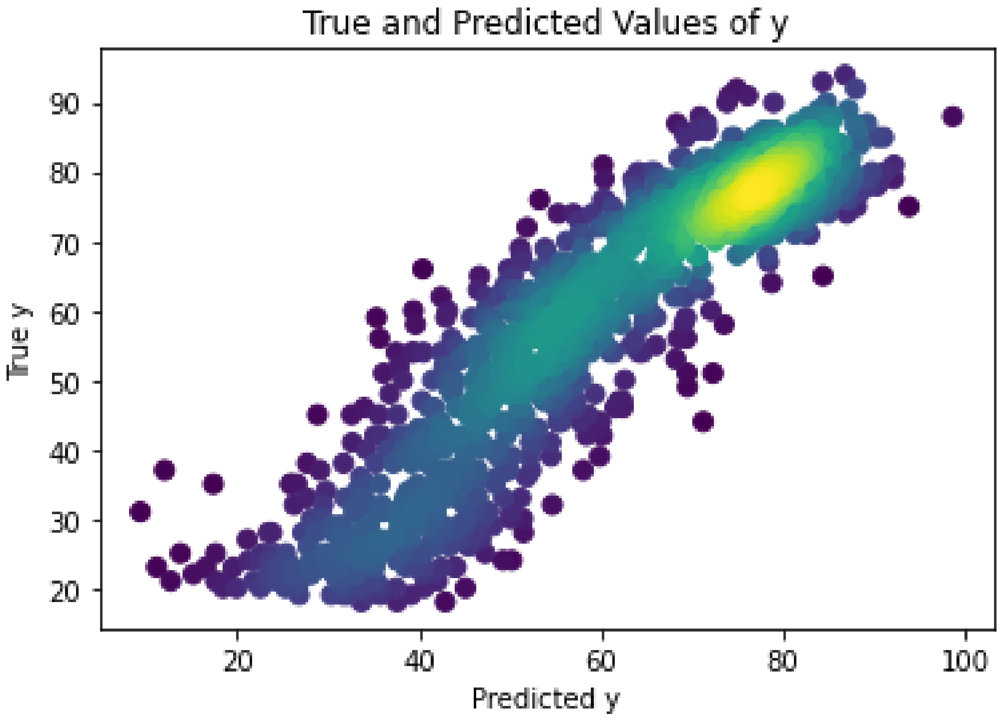
[17]:
```
# Boosted tree

# Hist seems to work better for some reason, despite n < 10000
from sklearn.ensemble import HistGradientBoostingRegressor

def Boosted(plot=True, **kwargs):
    # Train
    model = HistGradientBoostingRegressor(**kwargs)
    model = model.fit(x_train, y_train)
    y_predict = model.predict(x_test)

    # Test
    r2 = sk.metrics.r2_score(y_test, y_predict)
    rmse = np.sqrt(sk.metrics.mean_squared_error(y_test, y_predict))

    # Plotting
    if plot:
        plot_prediction(y_predict, y_test)

    return r2, rmse


Boosted(loss="squared_error")
```



[17]: (0.9050537601636167, 6.163739376062851)

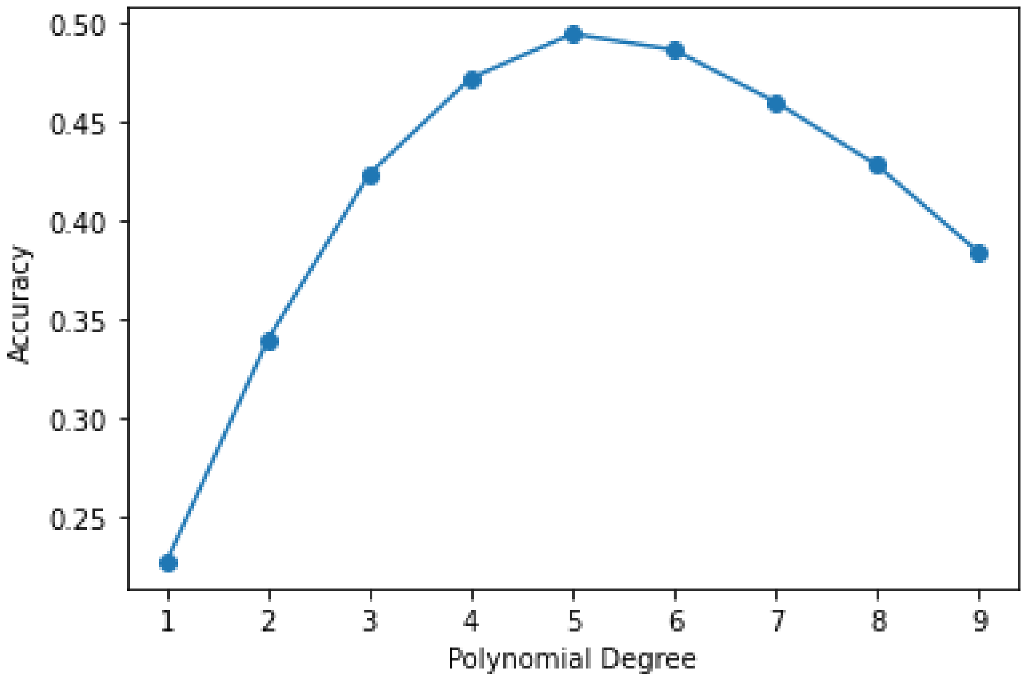
[10]:
```
# Support Vector Machine

from sklearn import svm

def SVM(plot=True, **kwargs):
    # Train
    model = svm.SVR(**kwargs)
    model = model.fit(x_train, y_train)
    y_predict = model.predict(x_test)

    # Test
    r2 = sk.metrics.r2_score(y_test, y_predict)
    rmse = np.sqrt(sk.metrics.mean_squared_error(y_test, y_predict))

    # Plotting
    if plot:
        plot_prediction(y_predict, y_test)

    return(r2, rmse)
```

```
SVM(kernel='poly', degree=5, coef0=23)
```



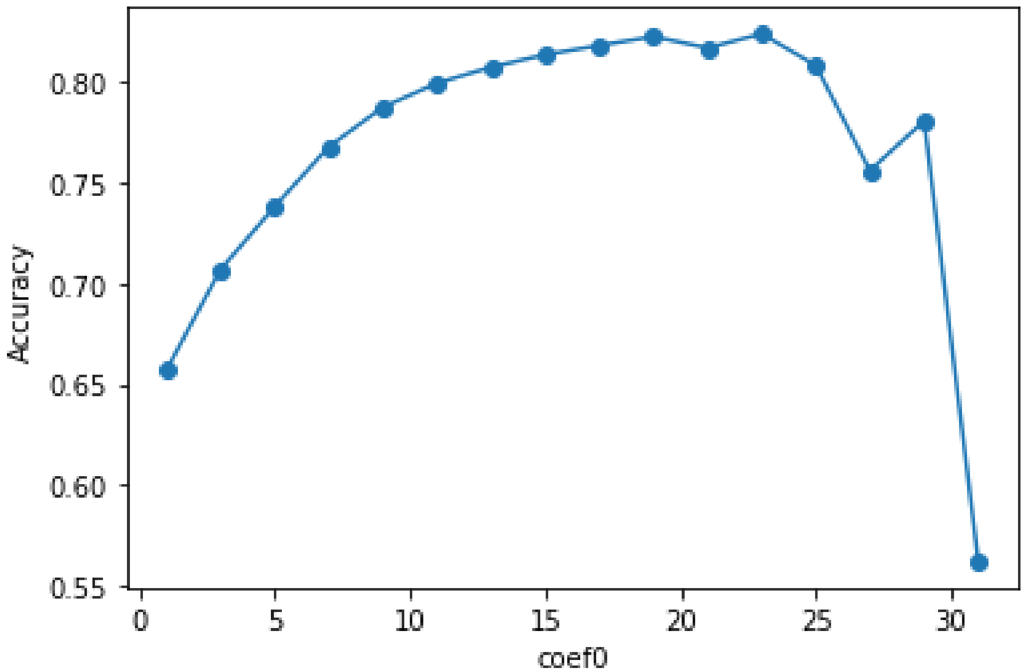
[10]: (0.8238630839227749, 8.395190899096825)

[11]:
```
# Loop for optimizing SVM polynomial degree

# Initialize arrays
degree = []
accs = []

# Loop over reasonable degree values, calculate accuracy, and append
for i in np.arange(1, 10):
    degree.append(i)
    (acc, rmse) = SVM(kernel='poly', degree=i, plot=False)
    accs.append(acc)

# Plot accuracy vs degree
plt.plot(degree, accs, '-o')
plt.xticks(np.arange(min(degree), max(degree)+1, 1.0))
plt.xlabel('Polynomial Degree')
plt.ylabel("Accuracy")
plt.show()
```



[13]:

```
# Loop for optimizing SVM polynomial coefficient

# Initialize arrays
coef0 = []
accs = []

# Loop over reasonable coef0 values, calculate accuracy, and append
for i in np.arange(1, 32, 2):
    coef0.append(i)
    (acc, rmse) = SVM(kernel='poly', degree=5, coef0=i, plot=False)
    accs.append(acc)

# Plot accuracy vs coef0
plt.plot(coef0, accs, '-o')
plt.xlabel('coef0')
plt.ylabel("Accuracy")
plt.show()
```


Accuracy
0.80
0.75
0.70
0.65
0.60
0.55
0
5
10
15
20
25
30
coef0