HW5 - Linear & Logistic regression

February 18, 2019

1 Data-X Spring 2019: Homework 05

1.0.1 Linear regression & Logistic regression

1.1 Name: Shrey Samdani

1.2 SID: 3032000414

In this homework, you will do some exercises on prediction using sklearn.

REMEMBER TO DISPLAY ALL OUTPUTS. If the question asks you to do something, make sure to print your results.

1.3 Part 1 - Regression

1.3.1 Data:

Data Source: Data file is uploaded to bCourses and is named: **Energy.csv** (Link in the Assignment details page on Bcourses)

The dataset was created by Angeliki Xifara (Civil/Structural Engineer) and was processed by Athanasios Tsanas, Oxford Centre for Industrial and Applied Mathematics, University of Oxford, UK).

Data Description:

The dataset contains eight attributes of a building (or features, denoted by X1...X8) and response being the heating load on the building, y1.

- X1 Relative Compactness
- X2 Surface Area
- X3 Wall Area
- X4 Roof Area
- X5 Overall Height
- X6 Orientation
- X7 Glazing Area
- X8 Glazing Area Distribution
- y1 Heating Load

Q1.1 Read the data file from the csv.

Print the count of NaN values for each attribute in the dataset.

Print the Range (min, max) and percentiles (25th, 50th, and 75th) of each attribute in the dataset

```
In [11]: import numpy as np
         import pandas as pd

         energy = pd.read_csv("energy.csv")
         print("# of NaN values:", energy.isnull().sum().sum())
         energy.describe()
```

```
# of NaN values: 0
```

```
Out[11]:                X1          X2          X3          X4         X5          X6  \
         count  768.000000  768.000000  768.000000  768.000000  768.00000  768.000000
         mean     0.764167  671.708333  318.500000  176.604167    5.25000    3.500000
         std      0.105777   88.086116   43.626481   45.165950    1.75114    1.118763
         min      0.620000  514.500000  245.000000  110.250000    3.50000    2.000000
         25%      0.682500  606.375000  294.000000  140.875000    3.50000    2.750000
         50%      0.750000  673.750000  318.500000  183.750000    5.25000    3.500000
         75%      0.830000  741.125000  343.000000  220.500000    7.00000    4.250000
         max      0.980000  808.500000  416.500000  220.500000    7.00000    5.000000

                        X7         X8          Y1
         count  768.000000  768.00000  768.000000
         mean     0.234375    2.81250   22.307201
         std      0.133221    1.55096   10.090196
         min      0.000000    0.00000    6.010000
         25%      0.100000    1.75000   12.992500
         50%      0.250000    3.00000   18.950000
         75%      0.400000    4.00000   31.667500
         max      0.400000    5.00000   43.100000
```

REGRESSION:

Using the data, we want to predict "Heating load". The output variable is continuous. Hence, we need to use a regression algorithm.

Q 1.2:

Split the dataset randomly into train and test. Train a **Linear Regression** model on 80% of the data (80-20 split). What is the intercept and coefficient values?

```
In [12]: from sklearn.model_selection import train_test_split

         X = energy.iloc[:,:-1]
         Y = energy['Y1']
         x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2)


         from sklearn import linear_model

         linearModel = linear_model.LinearRegression()
         linearModel.fit(x_train, y_train)
```

```
print("Intercept:",linearModel.intercept_)
print("Coefficients:", linearModel.coef_)
```

```
Intercept: 73.63857288273616
Coefficients: [-5.79848476e+01 -1.39460642e+11  1.39460642e+11  2.78921284e+11
  4.13473804e+00 -2.13875247e-02  1.98411253e+01  2.32395440e-01]
```

Q.1.3: Create a function which takes arrays of prediction and actual values of the output as parameters to calculate **'Root Mean Square error'** (RMSE) metric:

1. Use the function to calculate the training RMSE

2. Use the function to calculate the test RMSE

```
In [13]: # your code
         rmseCalc = lambda pred, actual: np.mean((pred-actual)**2)**0.5

         print("TRAINING RMSE:", rmseCalc(linearModel.predict(x_train), y_train))
         print("TEST RMSE:", rmseCalc(linearModel.predict(x_test), y_test))
```

```
TRAINING RMSE: 2.892919795496745
TEST RMSE: 3.03337797694144
```

Q1.4: Let's see the effect of amount of data on the performance of prediction model. Use varying amounts of data (100,200,300,400,500,all) from the training data you used previously to train different regression models. Report training error and test error in each case. Test data is the same as above for all these cases.

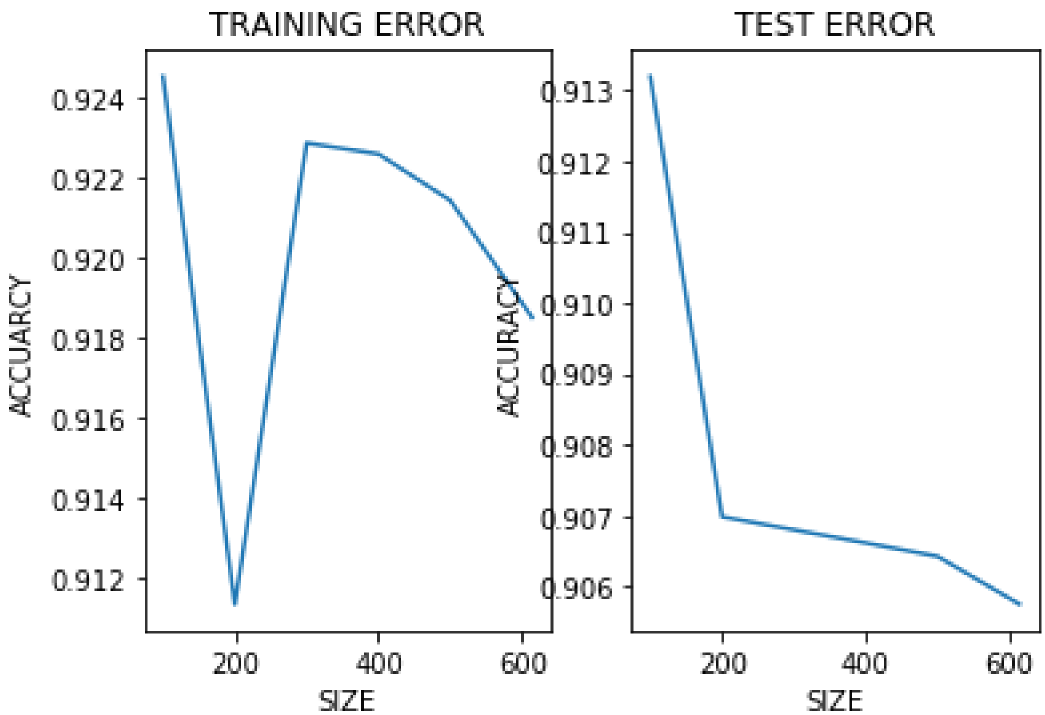
Plot error rates vs number of training examples. Both the training error and the test error should be plotted. Comment on the relationship you observe between the amount of data used to train the model and the test accuracy of the model.

Hint: Use array indexing to choose varying data amounts

```
In [14]: import matplotlib.pyplot as plt

         train_sizes = [100,200,300,400,500, len(x_train)]
         train_error, test_error = [], []

         for size in train_sizes:
             linearModel = linear_model.LinearRegression()
             linearModel.fit(x_train.iloc[:size,:], y_train.iloc[:size])
             train_error.append(linearModel.score(x_train.iloc[:size,:], y_train.iloc[:size]))
             test_error.append(linearModel.score(x_test.iloc[:size,:], y_test.iloc[:size]))

             print("SIZE:",size)
             print("TRAINING ACCURACY:",train_error[-1])
             print("TEST ACCURACY:",test_error[-1])
```

```
        print()

    plt.subplot(1, 2, 1)
    plt.plot(train_sizes, train_error)
    plt.title("TRAINING ERROR")
    plt.xlabel("SIZE")
    plt.ylabel("ACCUARCY")

    plt.subplot(1, 2, 2)
    plt.plot(train_sizes, test_error)
    plt.title("TEST ERROR")
    plt.xlabel("SIZE")
    plt.ylabel("ACCURACY")

    plt.show()
```

```
SIZE: 100
TRAINING ACCURACY: 0.9244997008930089
TEST ACCURACY: 0.9131949482613633

SIZE: 200
TRAINING ACCURACY: 0.9113355114015416
TEST ACCURACY: 0.9069831120301527

SIZE: 300
TRAINING ACCURACY: 0.922842847741354
TEST ACCURACY: 0.9067987723998217

SIZE: 400
TRAINING ACCURACY: 0.9225682273925364
TEST ACCURACY: 0.9066138628588658

SIZE: 500
TRAINING ACCURACY: 0.9214084886642311
TEST ACCURACY: 0.9064240862216149

SIZE: 614
TRAINING ACCURACY: 0.9184933052813427
TEST ACCURACY: 0.9057492207192306
```



It seems as the size increases, the accuracy goes down after a certain point, which could be explained by overfitting.

1.4 Part 2 - Classification

CLASSIFICATION: LABELS ARE DISCRETE VALUES.

Here the model is trained to classify each instance into a set of predefined discrete classes. On inputting a feature vector into the model, the trained model is able to predict a class of that instance.

Q2.1 Bucket the values of 'y1' i.e 'Heating Load' from the original dataset into 3 classes:

0: 'Low' ($<$ 14),
1: 'Medium' (14-28),
2: 'High' (>28)

HINT: Use pandas.cut

This converts the given dataset into a classification problem. Use this dataset with transformed 'heating load' to create a **logistic regression** classifiction model that predicts heating load type of a building. Split the data randomly into training and test set. Train the model on 80% of the data (80-20 split).

```
In [5]: bins = pd.IntervalIndex.from_tuples([(0, 1), (2, 3), (4, 5)])
        energy['Y_class'] = energy['Y1']
        Y = energy['Y_class']
        Y[Y < 14] = 0
```

```
    Y[(Y >= 14) & (Y<=28)] = 1
    Y[Y > 28] = 2

    x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2)
    linearModel = linear_model.LogisticRegression()
    linearModel.fit(x_train, y_train)
```

```
/Users/shreysamdani/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:4: SettingWith
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  after removing the cwd from sys.path.
/Users/shreysamdani/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:5: SettingWith
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  """
/Users/shreysamdani/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:6: SettingWith
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html

/Users/shreysamdani/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.py:433
  FutureWarning)
/Users/shreysamdani/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.py:460
  "this warning.", FutureWarning)
```

```
Out[5]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, max_iter=100, multi_class='warn',
                   n_jobs=None, penalty='l2', random_state=None, solver='warn',
                   tol=0.0001, verbose=0, warm_start=False)
```

Q2.2

- Print the training and test accuracies
- Print the confusion matrix
- Print the precision and recall numbers for all the classes

```
In [6]: # your code
        print("TRAINING ACCURACY:", linearModel.score(x_train, y_train))
        print("TEST ACCURACY:", linearModel.score(x_test, y_test))

        from sklearn.metrics import *
        predicted = linearModel.predict(x_test)
        print("CONFUSION MATRIX:",confusion_matrix(predicted,y_test))
        print("PRECISION NUMBERS:", precision_score(predicted,y_test, average = None))
        print("RECALL NUMBERS:", recall_score(predicted,y_test, average = None))
```

```
TRAINING ACCURACY: 0.7947882736156352
TEST ACCURACY: 0.7467532467532467
CONFUSION MATRIX: [[44 18  0]
 [ 2 24  0]
 [ 0 19 47]]
PRECISION NUMBERS: [0.95652174 0.39344262 1.        ]
RECALL NUMBERS: [0.70967742 0.92307692 0.71212121]
```

Q2.3

K Fold Cross Validation In k-fold cross-validation, the shuffled training data is partitioned into k disjoint sets and the model is trained on k 1 sets and validated on the kth set. This process is repeated k times with each set chosen as the validation set once. The cross-validation accuracy is reported as the average accuracy of the k iterations

Use 7-fold cross validation on the training data. Print the average accuracy

```
In [7]: # your code
        from sklearn.model_selection import cross_val_score

        linearModel = linear_model.LogisticRegression()
        print("AVERAGE ACCURACY:",cross_val_score(linearModel,x_train,y_train).mean())
```

```
AVERAGE ACCURACY: 0.7636857275837573
```

```
/Users/shreysamdani/anaconda3/lib/python3.7/site-packages/sklearn/model_selection/_split.py:205
  warnings.warn(CV_WARNING, FutureWarning)
/Users/shreysamdani/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.py:433
  FutureWarning)
/Users/shreysamdani/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.py:460
  "this warning.", FutureWarning)
/Users/shreysamdani/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.py:433
  FutureWarning)
/Users/shreysamdani/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.py:460
  "this warning.", FutureWarning)
/Users/shreysamdani/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.py:433
  FutureWarning)
/Users/shreysamdani/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.py:460
  "this warning.", FutureWarning)
```

Q2.4

One of the preprocessing steps in Data science is Feature Scaling i.e getting all our data on the same scale by setting same Min-Max of feature values. This makes training less sensitive to the scale of features . Scaling is important in algorithms that use distance functions as a part of classification. If we Scale features in the range [0,1] it is called unity based normalization.

Perform unity based normalization on the above dataset and train the model again, compare model performance in training and validation with your previous model.

refer:http://scikit-learn.org/stable/modules/preprocessing.html#preprocessing-scaler
more at: https://en.wikipedia.org/wiki/Feature_scaling

In [8]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaler.fit(X)

x_train, x_test, y_train, y_test = train_test_split(scaler.transform(X), Y, test_size=(
linearModel = linear_model.LogisticRegression()
linearModel.fit(x_train, y_train)

print("TRAINING ACCURACY:", linearModel.score(x_train, y_train))
print("TEST ACCURACY:", linearModel.score(x_test, y_test))
```

```
TRAINING ACCURACY: 0.8241042345276873
TEST ACCURACY: 0.8181818181818182
```

```
/Users/shreysamdani/anaconda3/lib/python3.7/site-packages/sklearn/preprocessing/data.py:323: Da
  return self.partial_fit(X, y)
/Users/shreysamdani/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.py:433
  FutureWarning)
/Users/shreysamdani/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.py:460
  "this warning.", FutureWarning)
```

The model performance is very similar in training and validation with the previous model.

In [ ]: