510518079_Assignment3

September 21, 2021

1 Assignment 3 : Study on multiple datasets

1.1 Import Libraries

[ ]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import OneHotEncoder
from scipy.sparse import hstack
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import StandardScaler,MinMaxScaler
```

1.2 Titanic Dataset

Number of features = 26 , excluding passenger ID and 2urvived, but the actual number of features are 7, as we can remove the zero columns as they are in here for One Hot Encoding. Number of data rows = 1309 but two rows contain NaN values, so after dropping them we get 1307 rows Numerical Attributes = Age of the passenger, Fare paid, 'Parch' or # of parents/children, 'sibsp' or # of siblings/spouses Categorical Attributes = 'Pclass' or class of passenger, sex of the passenger, 'Embarked' the port of Embarkation

1.2.1 Reading Dataset and Pre processing

[ ]:
```
titanic = pd.read_csv('titanic.csv')
titanic.head()
```

[ ]:
```
   Passengerid   Age     Fare  Sex  sibsp  zero  zero.1  zero.2  zero.3  \
0            1  22.0   7.2500    0      1     0       0       0       0
1            2  38.0  71.2833    1      1     0       0       0       0
2            3  26.0   7.9250    1      0     0       0       0       0
3            4  35.0  53.1000    1      1     0       0       0       0
4            5  35.0   8.0500    0      0     0       0       0       0
```

```
   zero.4  …  zero.12  zero.13  zero.14  Pclass  zero.15  zero.16  Embarked  \
0       0  …        0        0        0       3        0        0       2.0
1       0  …        0        0        0       1        0        0       0.0
2       0  …        0        0        0       3        0        0       2.0
3       0  …        0        0        0       1        0        0       2.0
4       0  …        0        0        0       3        0        0       2.0

   zero.17  zero.18  2urvived
0        0        0         0
1        0        0         1
2        0        0         1
3        0        0         1
4        0        0         0

[5 rows x 28 columns]
```

[ ]:
```
titanic.describe()
```

[ ]:
```
       Passengerid          Age         Fare          Sex        sibsp  \
count  1309.000000  1309.000000  1309.000000  1309.000000  1309.000000
mean    655.000000    29.503186    33.281086     0.355997     0.498854
std     378.020061    12.905241    51.741500     0.478997     1.041658
min       1.000000     0.170000     0.000000     0.000000     0.000000
25%     328.000000    22.000000     7.895800     0.000000     0.000000
50%     655.000000    28.000000    14.454200     0.000000     0.000000
75%     982.000000    35.000000    31.275000     1.000000     1.000000
max    1309.000000    80.000000   512.329200     1.000000     8.000000

         zero  zero.1  zero.2  zero.3  zero.4  …  zero.12  zero.13  zero.14  \
count  1309.0  1309.0  1309.0  1309.0  1309.0  …   1309.0   1309.0   1309.0
mean      0.0     0.0     0.0     0.0     0.0  …      0.0      0.0      0.0
std       0.0     0.0     0.0     0.0     0.0  …      0.0      0.0      0.0
min       0.0     0.0     0.0     0.0     0.0  …      0.0      0.0      0.0
25%       0.0     0.0     0.0     0.0     0.0  …      0.0      0.0      0.0
50%       0.0     0.0     0.0     0.0     0.0  …      0.0      0.0      0.0
75%       0.0     0.0     0.0     0.0     0.0  …      0.0      0.0      0.0
max       0.0     0.0     0.0     0.0     0.0  …      0.0      0.0      0.0

            Pclass  zero.15  zero.16     Embarked  zero.17  zero.18  \
count  1309.000000   1309.0   1309.0  1307.000000   1309.0   1309.0
mean      2.294882      0.0      0.0     1.492731      0.0      0.0
std       0.837836      0.0      0.0     0.814626      0.0      0.0
min       1.000000      0.0      0.0     0.000000      0.0      0.0
25%       2.000000      0.0      0.0     1.000000      0.0      0.0
50%       3.000000      0.0      0.0     2.000000      0.0      0.0
75%       3.000000      0.0      0.0     2.000000      0.0      0.0
```

```
max       3.000000      0.0      0.0     2.000000      0.0      0.0

          2urvived
count  1309.000000
mean      0.261268
std       0.439494
min       0.000000
25%       0.000000
50%       0.000000
75%       1.000000
max       1.000000

[8 rows x 28 columns]
```

[ ]:
```python
titanic.columns
```

[ ]:
```
Index(['Passengerid', 'Age', 'Fare', 'Sex', 'sibsp', 'zero', 'zero.1',
       'zero.2', 'zero.3', 'zero.4', 'zero.5', 'zero.6', 'Parch', 'zero.7',
       'zero.8', 'zero.9', 'zero.10', 'zero.11', 'zero.12', 'zero.13',
       'zero.14', 'Pclass', 'zero.15', 'zero.16', 'Embarked', 'zero.17',
       'zero.18', '2urvived'],
      dtype='object')
```

[ ]:
```python
titanic = titanic.dropna()
```

[ ]:
```python
X = titanic.copy()
for fn in X.columns:
    if len(X[fn].unique()) == 1:
        X = X.drop(columns = [fn])
Y = titanic['2urvived']
X = X.drop(columns = ['Passengerid','2urvived'])
print(X.shape)
print(Y.shape)
X.head()
```

```
(1307, 7)
(1307,)
```

[ ]:

	Age	Fare	Sex	sibsp	Parch	Pclass	Embarked
0	22.0	7.2500	0	1	0	3	2.0
1	38.0	71.2833	1	1	0	1	0.0
2	26.0	7.9250	1	0	0	3	2.0
3	35.0	53.1000	1	1	0	1	2.0
4	35.0	8.0500	0	0	0	3	2.0

[ ]:
```python
scaler = MinMaxScaler()
```

```
X[['Age', 'Fare','Parch','sibsp']] = scaler.fit_transform(X[['Age',␣
↪'Fare','Parch','sibsp']])
X.head()
```

[ ]:

	Age	Fare	Sex	sibsp	Parch	Pclass	Embarked
0	0.273456	0.014151	0	0.125	0.0	3	2.0
1	0.473882	0.139136	1	0.125	0.0	1	0.0
2	0.323563	0.015469	1	0.000	0.0	3	2.0
3	0.436302	0.103644	1	0.125	0.0	1	2.0
4	0.436302	0.015713	0	0.000	0.0	3	2.0

[ ]:

```
pclass = X['Pclass'].values.reshape(-1, 1)
embarked = X['Embarked'].values.reshape(-1, 1)
sex = X['Sex'].values.reshape(-1, 1)

ohe = OneHotEncoder()

pclass_ohe = ohe.fit_transform(pclass)
embarked_ohe = ohe.fit_transform(embarked)
sex_ohe = ohe.fit_transform(sex)
```

[ ]:

```
t_n = X[['Age', 'Fare', 'Parch','sibsp']]
#t_n = scaler.fit_transform
X = hstack((t_n, embarked_ohe, sex_ohe, pclass_ohe))
print(X.shape)
```

```
(1307, 12)
```

[ ]:

```
x_train, x_test, y_train, y_test = train_test_split(X, Y, stratify = Y,␣
↪test_size = 0.2, random_state = 5)
print(x_train.shape, x_test.shape)
print(y_train.shape, y_test.shape)
```

```
(1045, 12) (262, 12)
(1045,) (262,)
```

1.2.2

First, I normalised all the numerical features. Then,I converted categorical features by using One Hot Encoder Combined them together to get a matrix of dimension, (1307,12) Split the data into testing and training part.

1.2.3 Logistic Regression

[ ]:

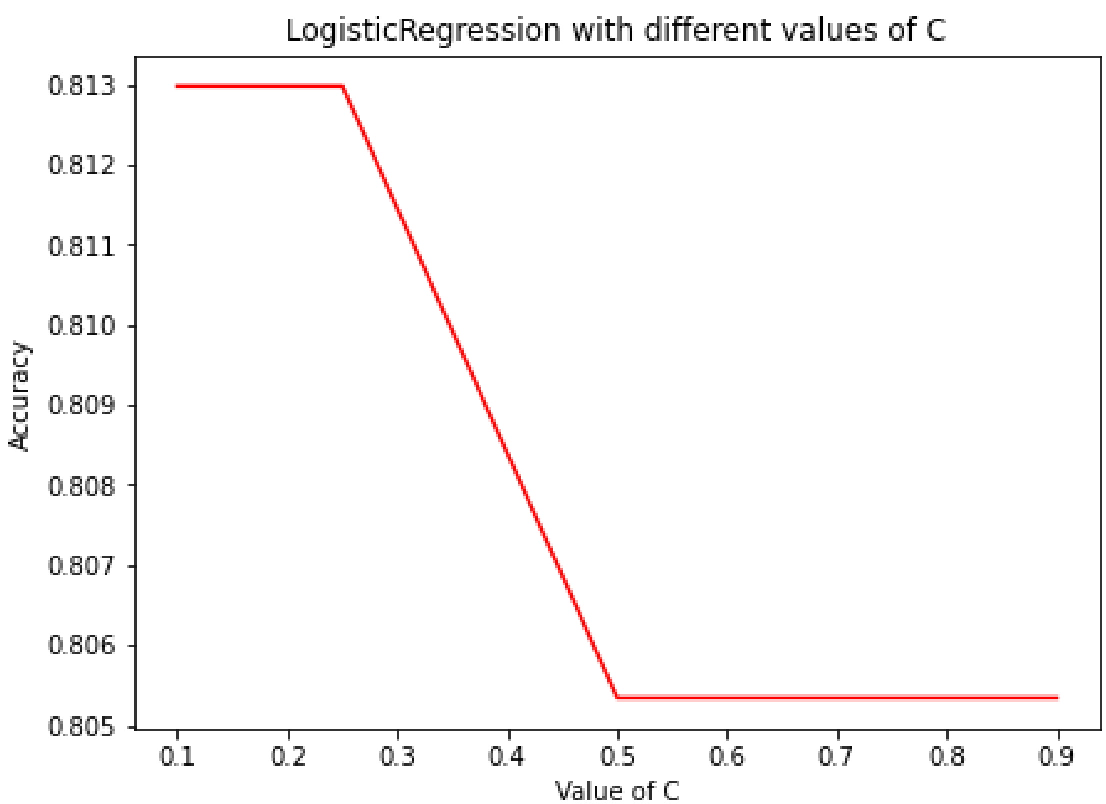
```
lr = LogisticRegression()
lr.fit(x_train, y_train)
y_pred = lr.predict(x_test)
lr_acc = accuracy_score(y_test, y_pred)
```

```
print(accuracy_score(y_test, y_pred))
```

0.8053435114503816

[ ]:
```
cs = [0.1, 0.25, 0.5, 0.75, 0.9]
coeffs = []
accs = []

for c in cs:
    lr = LogisticRegression(C = c)
    lr.fit(x_train, y_train)
    y_pred = lr.predict(x_test)
    coeffs.append(lr.coef_)
    lr_acc = accuracy_score(y_test, y_pred)
    accs.append(lr_acc)
```

[ ]:
```
plt.figure(figsize = (7, 5))
plt.title('LogisticRegression with different values of C')
plt.ylabel('Accuracy')
plt.xlabel('Value of C')
plt.plot(cs, accs, color = 'red')
plt.show()
```

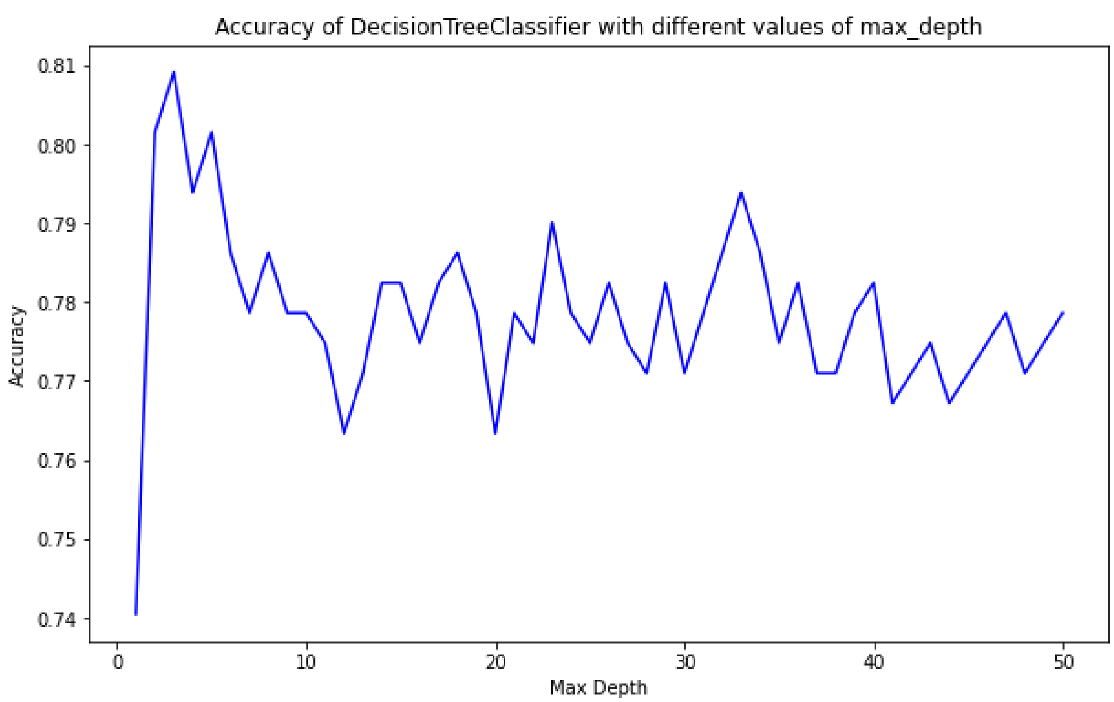


After, performing the above experiment, I can clearly observe that best accuracy is around 81.3% at C = 0.25.

1.2.4 Decision Tree Classifier

[ ]:
```
accs = []
for d in range(1,51,1):
    dt = DecisionTreeClassifier(max_depth = d)
    dt.fit(x_train, y_train)
    y_pred = dt.predict(x_test)
    dt_acc = accuracy_score(y_test, y_pred)
    accs.append(dt_acc)
```

[ ]:
```
ds = [i for i in range(1,51,1)]
plt.figure(figsize = (10, 6))
plt.title('Accuracy of DecisionTreeClassifier with different values of␣
 ↪max_depth')
plt.ylabel('Accuracy')
plt.xlabel('Max Depth')
plt.plot(ds, accs, color = 'blue')
plt.show()
```



I iterated from 1 to 50 and varied the max-depth in similar manner and from the following I can see that the best accuracy is at max depth 3, which is equal to ~81%. There is no trend that can be observed on the basis of max-depth.

1.2.5 Conclusion

The Logistic Regression model performed better in the case of Titanic Data set for classification of survivor as compared to Decision Tree Classifier, although marginally.

1.3 Forest Cover Type Dataset

Part 1

There are 54 attributes excluding the cover_type , and in total of 581012 data rows. There are 14 numerical attributes and 40 categorical attributes, which are essentially soil types.

Part 2

There are total of 2 attributes excluding the cover type and 530895 data rows. There are only 2 numerical attributes and no categorical attributes.

1.3.1 Reading dataset and data pre processing

[ ]:
```
forest = pd.read_csv("covtype.csv")
forest.head()
```

[ ]:
```
   Elevation  Aspect  Slope  Horizontal_Distance_To_Hydrology  \
0       2596      51      3                               258
1       2590      56      2                               212
2       2804     139      9                               268
3       2785     155     18                               242
4       2595      45      2                               153

   Vertical_Distance_To_Hydrology  Horizontal_Distance_To_Roadways  \
0                               0                              510
1                              -6                              390
2                              65                             3180
3                             118                             3090
4                              -1                              391

   Hillshade_9am  Hillshade_Noon  Hillshade_3pm  \
0            221             232            148
1            220             235            151
2            234             238            135
3            238             238            122
4            220             234            150

   Horizontal_Distance_To_Fire_Points  …  Soil_Type32  Soil_Type33  \
0                                6279  …            0            0
1                                6225  …            0            0
2                                6121  …            0            0
3                                6211  …            0            0
```

```
4                              6172  …            0            0

   Soil_Type34  Soil_Type35  Soil_Type36  Soil_Type37  Soil_Type38  \
0            0            0            0            0            0
1            0            0            0            0            0
2            0            0            0            0            0
3            0            0            0            0            0
4            0            0            0            0            0

   Soil_Type39  Soil_Type40  Cover_Type
0            0            0           5
1            0            0           5
2            0            0           2
3            0            0           2
4            0            0           5

[5 rows x 55 columns]
```

[ ]:
```
forest.describe()
```

[ ]:
```
           Elevation         Aspect          Slope  \
count  581012.000000  581012.000000  581012.000000
mean     2959.365301     155.656807      14.103704
std       279.984734     111.913721       7.488242
min      1859.000000       0.000000       0.000000
25%      2809.000000      58.000000       9.000000
50%      2996.000000     127.000000      13.000000
75%      3163.000000     260.000000      18.000000
max      3858.000000     360.000000      66.000000

       Horizontal_Distance_To_Hydrology  Vertical_Distance_To_Hydrology  \
count                     581012.000000                   581012.000000
mean                         269.428217                       46.418855
std                          212.549356                       58.295232
min                            0.000000                     -173.000000
25%                          108.000000                        7.000000
50%                          218.000000                       30.000000
75%                          384.000000                       69.000000
max                         1397.000000                      601.000000

       Horizontal_Distance_To_Roadways  Hillshade_9am  Hillshade_Noon  \
count                    581012.000000  581012.000000   581012.000000
mean                       2350.146611     212.146049      223.318716
std                        1559.254870      26.769889       19.768697
min                           0.000000       0.000000        0.000000
25%                        1106.000000     198.000000      213.000000
50%                        1997.000000     218.000000      226.000000
```

```
75%                      3328.000000     231.000000      237.000000
max                      7117.000000     254.000000      254.000000

       Hillshade_3pm  Horizontal_Distance_To_Fire_Points  …    Soil_Type32  \
count  581012.000000                       581012.000000  …  581012.000000
mean      142.528263                         1980.291226  …       0.090392
std        38.274529                         1324.195210  …       0.286743
min         0.000000                            0.000000  …       0.000000
25%       119.000000                         1024.000000  …       0.000000
50%       143.000000                         1710.000000  …       0.000000
75%       168.000000                         2550.000000  …       0.000000
max       254.000000                         7173.000000  …       1.000000

         Soil_Type33    Soil_Type34    Soil_Type35    Soil_Type36  \
count  581012.000000  581012.000000  581012.000000  581012.000000
mean        0.077716       0.002773       0.003255       0.000205
std         0.267725       0.052584       0.056957       0.014310
min         0.000000       0.000000       0.000000       0.000000
25%         0.000000       0.000000       0.000000       0.000000
50%         0.000000       0.000000       0.000000       0.000000
75%         0.000000       0.000000       0.000000       0.000000
max         1.000000       1.000000       1.000000       1.000000

         Soil_Type37    Soil_Type38    Soil_Type39    Soil_Type40  \
count  581012.000000  581012.000000  581012.000000  581012.000000
mean        0.000513       0.026803       0.023762       0.015060
std         0.022641       0.161508       0.152307       0.121791
min         0.000000       0.000000       0.000000       0.000000
25%         0.000000       0.000000       0.000000       0.000000
50%         0.000000       0.000000       0.000000       0.000000
75%         0.000000       0.000000       0.000000       0.000000
max         1.000000       1.000000       1.000000       1.000000

          Cover_Type
count  581012.000000
mean        2.051471
std         1.396504
min         1.000000
25%         1.000000
50%         2.000000
75%         2.000000
max         7.000000

[8 rows x 55 columns]
```

[ ]:
```
forest.columns
```

[ ]: Index(['Elevation', 'Aspect', 'Slope', 'Horizontal_Distance_To_Hydrology',
       'Vertical_Distance_To_Hydrology', 'Horizontal_Distance_To_Roadways',
       'Hillshade_9am', 'Hillshade_Noon', 'Hillshade_3pm',
       'Horizontal_Distance_To_Fire_Points', 'Wilderness_Area1',
       'Wilderness_Area2', 'Wilderness_Area3', 'Wilderness_Area4',
       'Soil_Type1', 'Soil_Type2', 'Soil_Type3', 'Soil_Type4', 'Soil_Type5',
       'Soil_Type6', 'Soil_Type7', 'Soil_Type8', 'Soil_Type9', 'Soil_Type10',
       'Soil_Type11', 'Soil_Type12', 'Soil_Type13', 'Soil_Type14',
       'Soil_Type15', 'Soil_Type16', 'Soil_Type17', 'Soil_Type18',
       'Soil_Type19', 'Soil_Type20', 'Soil_Type21', 'Soil_Type22',
       'Soil_Type23', 'Soil_Type24', 'Soil_Type25', 'Soil_Type26',
       'Soil_Type27', 'Soil_Type28', 'Soil_Type29', 'Soil_Type30',
       'Soil_Type31', 'Soil_Type32', 'Soil_Type33', 'Soil_Type34',
       'Soil_Type35', 'Soil_Type36', 'Soil_Type37', 'Soil_Type38',
       'Soil_Type39', 'Soil_Type40', 'Cover_Type'],
      dtype='object')

[ ]:
```
forest['Cover_Type'].value_counts()
```

[ ]:
```
2    283301
1    211840
3     35754
7     20510
6     17367
5      9493
4      2747
Name: Cover_Type, dtype: int64
```

[ ]:
```
forest['Soil_Type32'].value_counts()
```

[ ]:
```
0    528493
1     52519
Name: Soil_Type32, dtype: int64
```

[ ]:
```
X1 = forest.copy()
X1[['Elevation', 'Aspect', 'Slope', 'Horizontal_Distance_To_Hydrology',
       'Vertical_Distance_To_Hydrology', 'Horizontal_Distance_To_Roadways',
       'Hillshade_9am', 'Hillshade_Noon', 'Hillshade_3pm',
       'Horizontal_Distance_To_Fire_Points', 'Wilderness_Area1',
       'Wilderness_Area2', 'Wilderness_Area3', 'Wilderness_Area4']] = scaler.
 ↪fit_transform(X1[['Elevation', 'Aspect', 'Slope',␣
 ↪'Horizontal_Distance_To_Hydrology',
       'Vertical_Distance_To_Hydrology', 'Horizontal_Distance_To_Roadways',
       'Hillshade_9am', 'Hillshade_Noon', 'Hillshade_3pm',
       'Horizontal_Distance_To_Fire_Points', 'Wilderness_Area1',
       'Wilderness_Area2', 'Wilderness_Area3', 'Wilderness_Area4']])
X1 = X1.drop(columns = ['Cover_Type'])
```

```python
Y1 = forest['Cover_Type']
print(Y1.shape)
X1.head()
```

```
(581012,)
```

```
[ ]:    Elevation    Aspect     Slope  Horizontal_Distance_To_Hydrology  \
     0   0.368684  0.141667  0.045455                          0.184681
     1   0.365683  0.155556  0.030303                          0.151754
     2   0.472736  0.386111  0.136364                          0.191840
     3   0.463232  0.430556  0.272727                          0.173228
     4   0.368184  0.125000  0.030303                          0.109520

        Vertical_Distance_To_Hydrology  Horizontal_Distance_To_Roadways  \
     0                        0.223514                         0.071659
     1                        0.215762                         0.054798
     2                        0.307494                         0.446817
     3                        0.375969                         0.434172
     4                        0.222222                         0.054939

        Hillshade_9am  Hillshade_Noon  Hillshade_3pm  \
     0       0.870079        0.913386       0.582677
     1       0.866142        0.925197       0.594488
     2       0.921260        0.937008       0.531496
     3       0.937008        0.937008       0.480315
     4       0.866142        0.921260       0.590551

        Horizontal_Distance_To_Fire_Points  …  Soil_Type31  Soil_Type32  \
     0                            0.875366  …            0            0
     1                            0.867838  …            0            0
     2                            0.853339  …            0            0
     3                            0.865886  …            0            0
     4                            0.860449  …            0            0

        Soil_Type33  Soil_Type34  Soil_Type35  Soil_Type36  Soil_Type37  \
     0            0            0            0            0            0
     1            0            0            0            0            0
     2            0            0            0            0            0
     3            0            0            0            0            0
     4            0            0            0            0            0

        Soil_Type38  Soil_Type39  Soil_Type40
     0            0            0            0
     1            0            0            0
     2            0            0            0
     3            0            0            0
     4            0            0            0
```

```
[5 rows x 54 columns]
```

[ ]:
```python
forestx = forest[(forest['Cover_Type'] == 1) | (forest['Cover_Type'] == 2) |␣
↪(forest['Cover_Type'] == 3)]
print(forestx.shape)
forestx.head()
```

```
(530895, 55)
```

[ ]:
```
    Elevation  Aspect  Slope  Horizontal_Distance_To_Hydrology  \
2        2804     139      9                               268
3        2785     155     18                               242
5        2579     132      6                               300
11       2886     151     11                               371
12       2742     134     22                               150

    Vertical_Distance_To_Hydrology  Horizontal_Distance_To_Roadways  \
2                               65                             3180
3                              118                             3090
5                              -15                               67
11                              26                             5253
12                              69                             3215

    Hillshade_9am  Hillshade_Noon  Hillshade_3pm  \
2             234             238            135
3             238             238            122
5             230             237            140
11            234             240            136
12            248             224             92

    Horizontal_Distance_To_Fire_Points  …  Soil_Type32  Soil_Type33  \
2                                 6121  …            0            0
3                                 6211  …            0            0
5                                 6031  …            0            0
11                                4051  …            0            0
12                                6091  …            0            0

    Soil_Type34  Soil_Type35  Soil_Type36  Soil_Type37  Soil_Type38  \
2             0            0            0            0            0
3             0            0            0            0            0
5             0            0            0            0            0
11            0            0            0            0            0
12            0            0            0            0            0

    Soil_Type39  Soil_Type40  Cover_Type
2             0            0           2
```

```
3            0            0            2
5            0            0            2
11           0            0            2
12           0            0            2

[5 rows x 55 columns]
```

[ ]:
```
forestx = forestx[['Slope', 'Elevation', 'Cover_Type']]
print(forestx.shape)
```

```
(530895, 3)
```

[ ]:
```
X2 = forestx.copy()
X2[['Slope','Elevation']] = scaler.fit_transform(X2[['Slope','Elevation']])
X2 = X2.drop(columns = ['Cover_Type'])
Y2 = forestx['Cover_Type']

print(Y2.shape)
X2.head()
```

```
(530895,)
```

[ ]:

	Slope	Elevation
2	0.136364	0.517241
3	0.272727	0.506842
5	0.090909	0.394089
11	0.166667	0.562124
12	0.333333	0.483306

[ ]:
```
x_train1, x_test1, y_train1, y_test1 = train_test_split(X1, Y1, stratify = Y1,␣
↪test_size = 0.98, random_state = 42)
print(x_train1.shape, x_test1.shape)
print(y_train1.shape, y_test1.shape)
```

```
(11620, 54) (569392, 54)
(11620,) (569392,)
```

[ ]:
```
x_train2, x_test2, y_train2, y_test2 = train_test_split(X2, Y2,␣
↪stratify=Y2,test_size = 0.2)
print(x_train2.shape, x_test2.shape)
print(y_train2.shape, y_test2.shape)
```

```
(424716, 2) (106179, 2)
(424716,) (106179,)
```

Part 1

I normalised my numerical features, then kept 2% of the dataset for training and 98% for testing.

Part 2

I just normalised my data and then split the data into training and testing sets.

1.3.2 SVM

[ ]:
```
svc = SVC(verbose=True)
svc.fit(x_train1, y_train1)
y_pred1 = svc.predict(x_test1)
```

[ ]:
```
print(accuracy_score(y_test1, y_pred1))
```

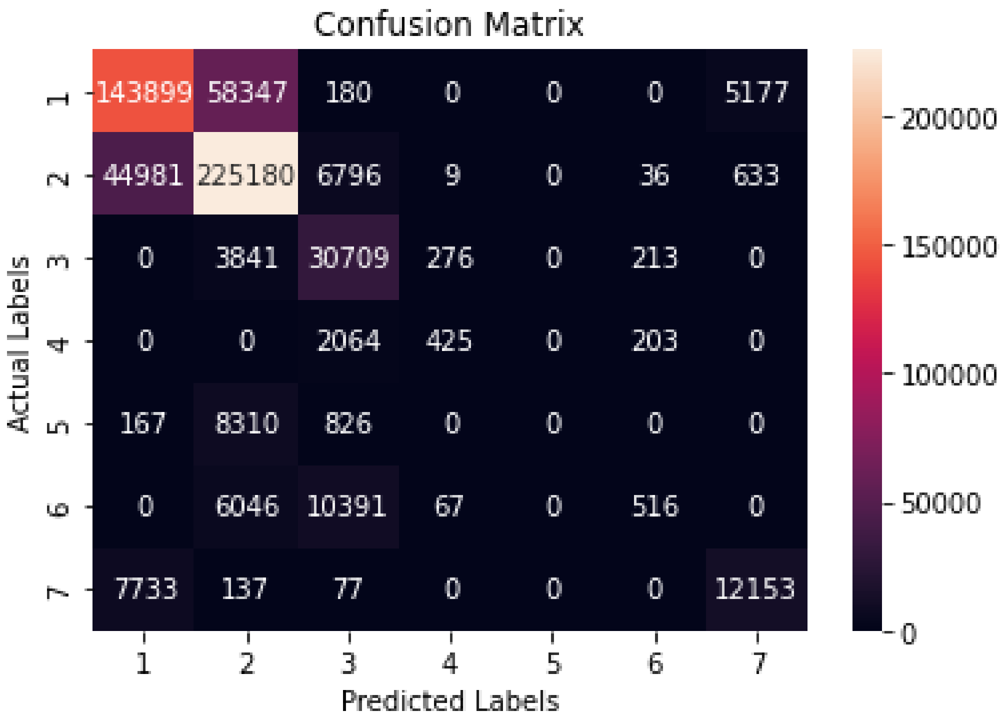
```
0.725127855677635
```

[ ]:
```
cm = confusion_matrix(y_test1,y_pred1,labels=svc.classes_)
print(cm)
```

```
[[143899  58347    180      0      0      0   5177]
 [ 44981 225180   6796      9      0     36    633]
 [     0   3841  30709    276      0    213      0]
 [     0      0   2064    425      0    203      0]
 [   167   8310    826      0      0      0      0]
 [     0   6046  10391     67      0    516      0]
 [  7733    137     77      0      0      0  12153]]
```

[ ]:
```
ax = sns.heatmap(cm, annot=True, fmt='g')
ax.set_title('Confusion Matrix')
ax.set_xlabel('Predicted Labels')
ax.set_ylabel('Actual Labels')
ax.xaxis.set_ticklabels(svc.classes_)
ax.yaxis.set_ticklabels(svc.classes_)
```

[ ]:
```
[Text(0, 0.5, '1'),
 Text(0, 1.5, '2'),
 Text(0, 2.5, '3'),
 Text(0, 3.5, '4'),
 Text(0, 4.5, '5'),
 Text(0, 5.5, '6'),
 Text(0, 6.5, '7')]
```



Above, I have plotted the confusion matrix from where I can observe number of points for each combination of original and predicted class. We can see that our model is not able to classify a single point of label 5 and the classification from label 4 onwards is pretty poor. The accuracy of the model is 72.5%.

1.3.3 Logistic Regression

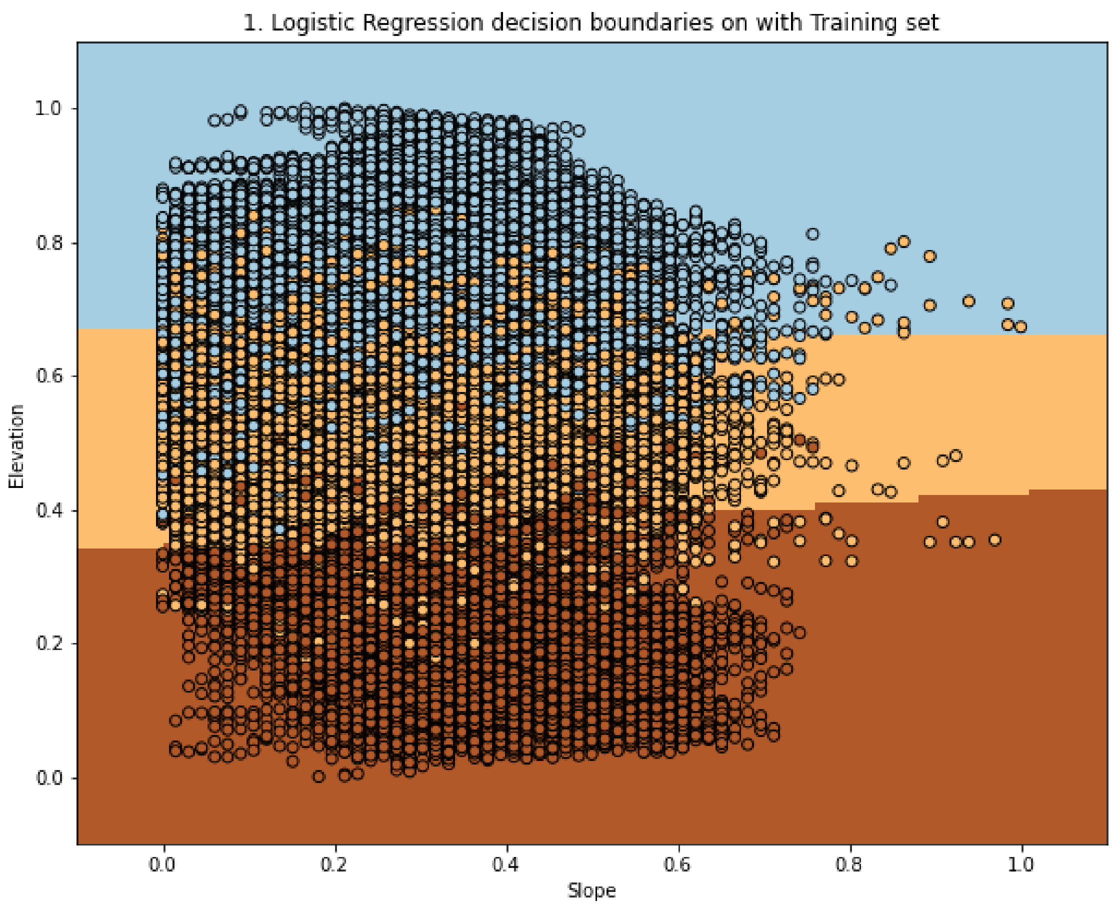
[ ]:
```
logreg = LogisticRegression()
logreg.fit(x_train2, y_train2)
```

[ ]:
```
LogisticRegression()
```

[ ]:
```
x_min, x_max = min(X2.values[:, 0]) - 0.1, max(X2.values[:, 0]) + 0.1
y_min, y_max = min(X2.values[:, 1]) - 0.1, max(X2.values[:, 1]) + 0.1
h = .01  # step size in the mesh
xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
Z = logreg.predict(np.c_[xx.ravel(), yy.ravel()])

# Put the result into a color plot
Z = Z.reshape(xx.shape)
plt.figure(1, figsize=(10, 8))
plt.pcolormesh(xx, yy, Z, cmap=plt.cm.Paired)

# Plot also the training points
```

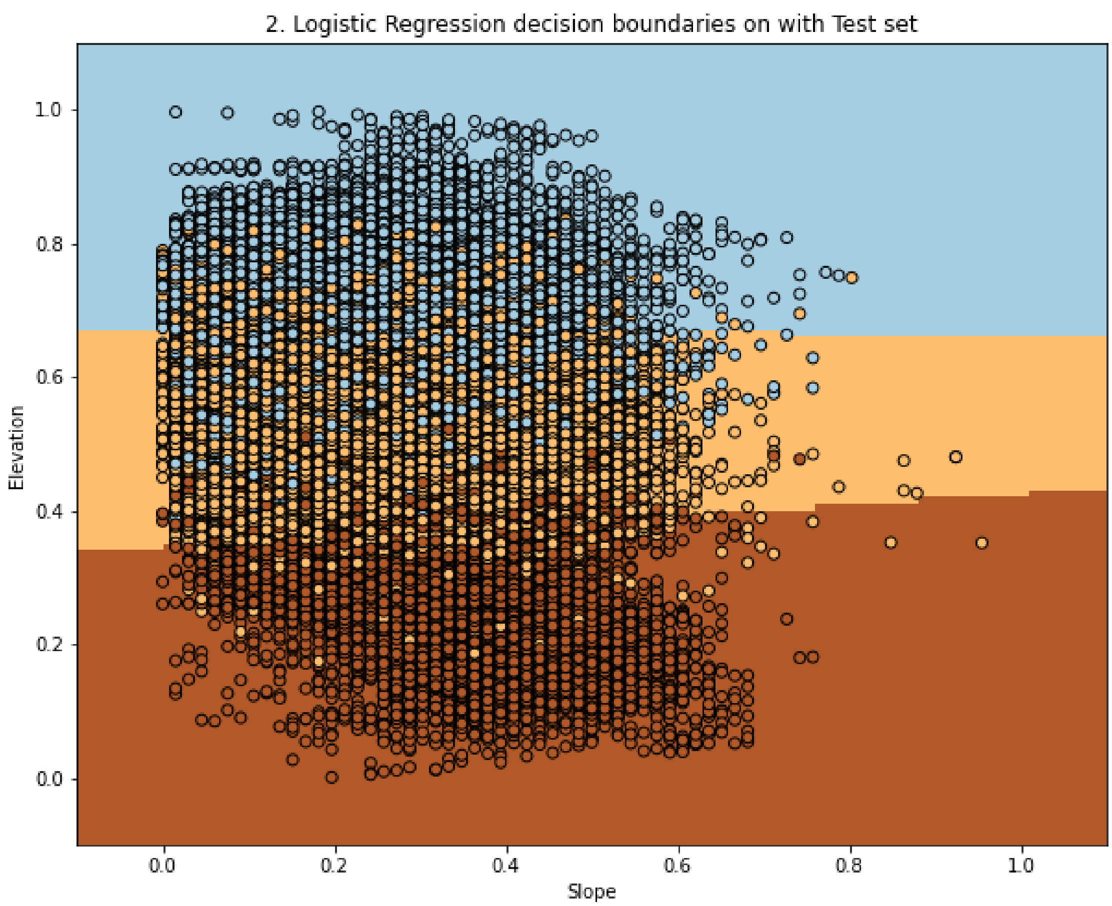
```
plt.title('1. Logistic Regression decision boundaries on with Training set')
plt.scatter(x_train2.values[:, 0], x_train2.values[:, 1], c=y_train2,␣
 ↪edgecolors='k', cmap=plt.cm.Paired)
plt.xlabel('Slope')
plt.ylabel('Elevation')

plt.xlim(xx.min(), xx.max())
plt.ylim(yy.min(), yy.max())

plt.show()
```

```
/tmp/ipykernel_4194/3129041014.py:10: MatplotlibDeprecationWarning:
shading='flat' when X and Y have the same dimensions as C is deprecated since
3.3.  Either specify the corners of the quadrilaterals with X and Y, or pass
shading='auto', 'nearest' or 'gouraud', or set rcParams['pcolor.shading'].  This
will become an error two minor releases later.
  plt.pcolormesh(xx, yy, Z, cmap=plt.cm.Paired)
```



[ ]:
```
plt.figure(1, figsize=(10, 8))
plt.pcolormesh(xx, yy, Z, cmap=plt.cm.Paired)

# Plot also the training points
plt.title('2. Logistic Regression decision boundaries on with Test set')
plt.scatter(x_test2.values[:, 0], x_test2.values[:, 1], c=y_test2,␣
↪edgecolors='k', cmap=plt.cm.Paired)
plt.xlabel('Slope')
plt.ylabel('Elevation')

plt.xlim(xx.min(), xx.max())
plt.ylim(yy.min(), yy.max())

plt.show()
```

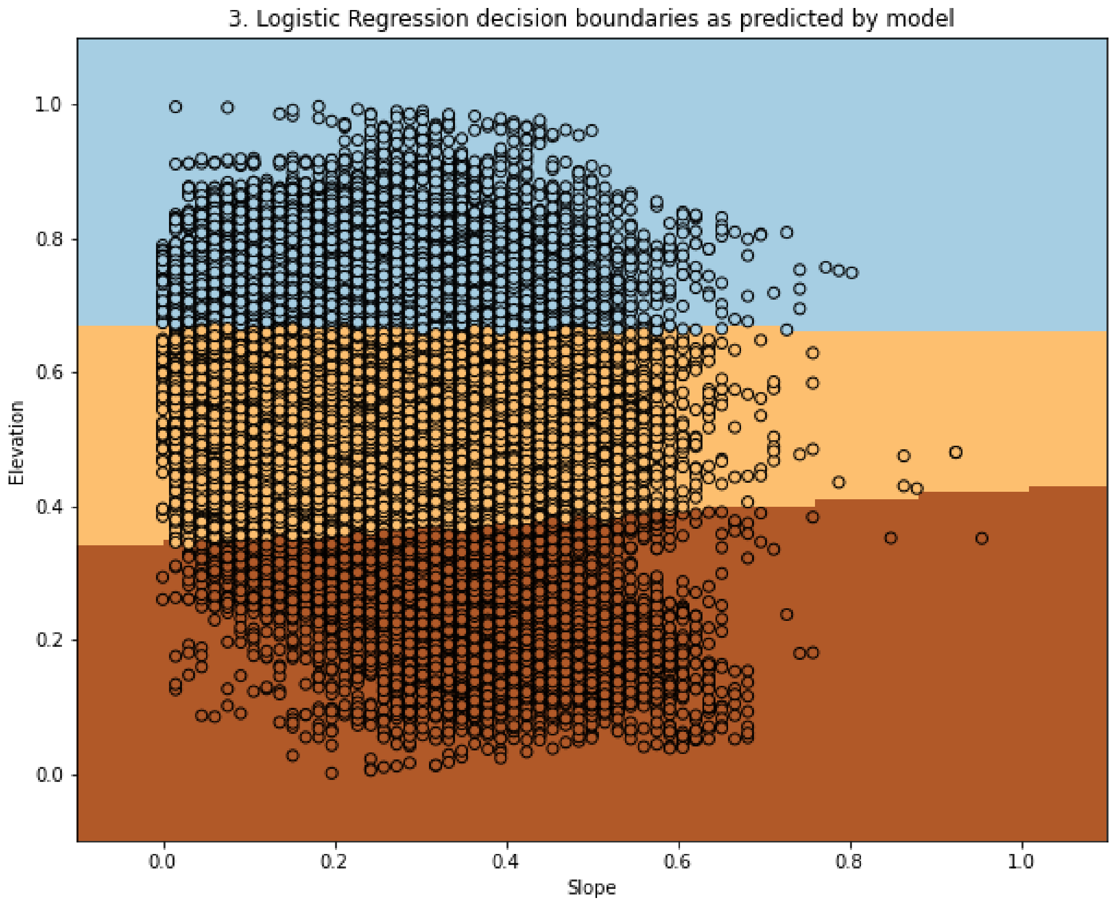
```
/tmp/ipykernel_4194/4182778859.py:2: MatplotlibDeprecationWarning:
shading='flat' when X and Y have the same dimensions as C is deprecated since
3.3.  Either specify the corners of the quadrilaterals with X and Y, or pass
shading='auto', 'nearest' or 'gouraud', or set rcParams['pcolor.shading'].  This
will become an error two minor releases later.
  plt.pcolormesh(xx, yy, Z, cmap=plt.cm.Paired)
```



[ ]:

```
y_pred2 = logreg.predict(x_test2)

plt.figure(1, figsize=(10, 8))
plt.pcolormesh(xx, yy, Z, cmap=plt.cm.Paired)

# Plot also the training points
plt.title('3. Logistic Regression decision boundaries as predicted by model')
plt.scatter(x_test2.values[:, 0], x_test2.values[:, 1], c=y_pred2,␣
 ↪edgecolors='k', cmap=plt.cm.Paired)
plt.xlabel('Slope')
plt.ylabel('Elevation')
plt.xlim(xx.min(), xx.max())
plt.ylim(yy.min(), yy.max())

plt.show()
```

```
/tmp/ipykernel_4194/3546256627.py:4: MatplotlibDeprecationWarning:
shading='flat' when X and Y have the same dimensions as C is deprecated since
3.3.  Either specify the corners of the quadrilaterals with X and Y, or pass
shading='auto', 'nearest' or 'gouraud', or set rcParams['pcolor.shading'].  This
will become an error two minor releases later.
  plt.pcolormesh(xx, yy, Z, cmap=plt.cm.Paired)
```




```
[ ]: print(accuracy_score(y_train2,logreg.predict(x_train2)))
     print(accuracy_score(y_test2,y_pred2))
```

```
0.7333041373529605
0.7345143578297026
```

From the plot 1, we can visualize the boundaries on the training data set. Plot 2 and Plot 3 gives us a Reality vs Expectation check for our model, where we can see what original distribution was and how are model perceived it. Also, we get a 73.3% accuracy on training dataset and 73.4% accuracy on testing data set.