multiclass_classification

October 31, 2018

1 Package imports

```
In [1]: import pandas as pd
        import numpy as np
        import sklearn
        from sklearn.datasets import load_breast_cancer
        import matplotlib.pyplot as plt

        import L_layer_nn as lnn
```

2 Dataset Import and Manipulation

Dataset chosen for analysis is covtype dataset which defines 7 types of forest cover types each labeled a number from the set {1,2,3,4,5,6,7}.

The dataset contains *581,012* observations from which: - first *11,340* records used for training data subset - next *3,780* records used for validation data subset - last *565,892* records used for testing data subset

The dataset has 12 measures, but 54 columns of data (10 quantitative variables, 4 binary wilderness areas and 40 binary soil type variables)

Name	Data Type	Measurement	Description
Elevation	quantitative	meters	Elevation in meters
Aspect	quantitative	azimuth	Aspect in degrees azimuth
Slope	quantitative	degrees	Slope in degrees

Name	Data Type	Measurement	Description
Horizontal_Distance_To_Hydrology	quantitative	meters	Horz Dist to nearest surface water features
Vertical_Distance_To_Hydrology	quantitative	meters	Vert Dist to nearest surface water features
Horizontal_Distance_To_Roadways	quantitative	meters	Horz Dist to nearest roadway
Hillshade_9am	quantitative	0 to 255 index	Hillshade index at 9am, summer solstice
Hillshade_Noon	quantitative	0 to 255 index	Hillshade index at noon, summer soltice

Name	Data Type	Measurement	Description
Hillshade_3pm	quantitative	0 to 255 index	Hillshade index at 3pm, summer solstice
Horizontal_Distance_To_Fire_Points	quantitative	meters	Horz Dist to nearest wildfire ignition points
Wilderness_Area (4 binary columns)	qualitative	0 (absence) or 1 (presence)	Wilderness area designation
Soil_Type (40 binary columns)	qualitative	0 (absence) or 1 (presence)	Soil Type designation
Cover_Type (7 types)	Integer	1 to 7	Forest Cover Type designation

2.0.1 Importing Dataset

Import the dataset from the file `covtype.data`.

If you don't have the dataset run the following commands and also replace the `pd.read_csv` command

```
!wget archive.ics.uci.edu/ml/machine-learning-databases/covtype/covtype.data.gz
dataset = pd.read_csv("covtype.data.gz", compression = "gzip")
```

```
In [2]: from sklearn.datasets import fetch_covtype
        dataset = pd.read_csv("covtype.data")
```

```
In [3]: dataset.head()
```

```
Out[3]:    2596   51   3  258    0   510  221  232  148  6279 ...  0.34  0.35  0.36  \
        0  2590   56   2  212   -6   390  220  235  151  6225 ...     0     0     0
        1  2804  139   9  268   65  3180  234  238  135  6121 ...     0     0     0
        2  2785  155  18  242  118  3090  238  238  122  6211 ...     0     0     0
        3  2595   45   2  153   -1   391  220  234  150  6172 ...     0     0     0
        4  2579  132   6  300  -15    67  230  237  140  6031 ...     0     0     0

           0.37  0.38  0.39  0.40  0.41  0.42  5
        0     0     0     0     0     0     0  5
        1     0     0     0     0     0     0  2
        2     0     0     0     0     0     0  2
        3     0     0     0     0     0     0  5
        4     0     0     0     0     0     0  2

        [5 rows x 55 columns]
```

2.0.2 Extract the labels from the dataset

There are 7 unique values of Cover_type in the dataset which determines the forest cover type.
It is the last column in the dataset with column name `'5'`

```
In [4]: # Unique labels by frequency
        dataset['5'].value_counts().sort_values()
```

```
Out[4]: 4      2747
        5      9492
        6     17367
        7     20510
        3     35754
        1    211840
        2    283301
        Name: 5, dtype: int64
```

```
In [5]: y = dataset.pop('5')
```

2.0.3 Normalize the Dataset

The dataset needs to be normalized before feeding it into any machine learning algorithm.

> The normalization method used is **min-max normalization**. `MinMaxScaler` function is used from the sklearn library.

It automatically handles the case of *divide by zero* when then min and the max in any data-column are the same.

```
In [6]: from sklearn.preprocessing import MinMaxScaler
        scaler = MinMaxScaler()
        dataset = pd.DataFrame(scaler.fit_transform(dataset))
```

```
In [7]: dataset.head()
```

```
Out[7]:          0         1         2         3         4         5         6  \
        0  0.365683  0.155556  0.030303  0.151754  0.215762  0.054798  0.866142
        1  0.472736  0.386111  0.136364  0.191840  0.307494  0.446817  0.921260
        2  0.463232  0.430556  0.272727  0.173228  0.375969  0.434172  0.937008
        3  0.368184  0.125000  0.030303  0.109520  0.222222  0.054939  0.866142
        4  0.360180  0.366667  0.090909  0.214746  0.204134  0.009414  0.905512

                 7         8         9 ...    44   45   46   47   48   49   50   51  \
        0  0.925197  0.594488  0.867838 ...  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
        1  0.937008  0.531496  0.853339 ...  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
        2  0.937008  0.480315  0.865886 ...  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
        3  0.921260  0.590551  0.860449 ...  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
        4  0.933071  0.551181  0.840792 ...  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0

            52   53
        0  0.0  0.0
        1  0.0  0.0
        2  0.0  0.0
        3  0.0  0.0
        4  0.0  0.0

        [5 rows x 54 columns]
```

2.0.4 Train and Test Split

The dataset contains 581,012 observations from which:

- first 11,340 records used for training data subset
- next 3,780 records used for testing data subset

```
In [8]: X_train = dataset.iloc[0:11340,:]
        y_train = y.iloc[0:11340]
        X_test = dataset.iloc[11341:15121,:]
        y_test = y.iloc[11341:15121]

        print ('The shape of X_train is: ' + str(X_train.shape))
        print ('The shape of y_train is: ' + str(y_train.shape))
        print ('The shape of X_train is: ' + str(X_test.shape))
        print ('The shape of y_train is: ' + str(y_test.shape))
```

```
The shape of X_train is: (11340, 54)
The shape of y_train is: (11340,)
The shape of X_train is: (3780, 54)
The shape of y_train is: (3780,)
```

3 Classification using Logistic Regression

`LogisticRegression` in sklearn has by default the value for `multi_class` attribute set to `ovr`.

This just means that the classifier generated uses by Defalut One-vs-Rest logistic regression (OVR) in which a separate model is trained for each class predicted whether an observation is that class or not (thus making it a binary classification problem). It assumes that each classification problem (e.g. class 0 or not) is independent.

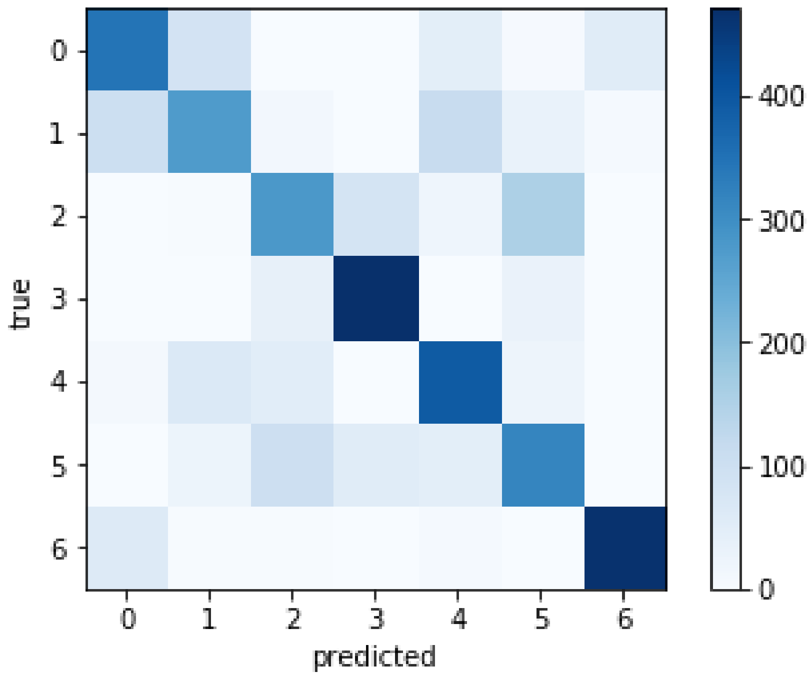
```
In [9]: from sklearn.linear_model import LogisticRegression

        # Fit the classifier on training data
        classifier = LogisticRegression().fit(X_train, y_train)

        print(classifier)
```

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

```
In [10]: # Calculate the accuracy on test data
         acc_lr_train = classifier.score(X_train, y_train)

         # Calculate the accuracy on test data
         acc_lr_test = classifier.score(X_test, y_test)

         print(f'Accuracy on Train data = {acc_lr_train * 100}')
         print(f'Accuracy on Test data = {acc_lr_test * 100}')
```

```
Accuracy on Train data = 66.37566137566138
Accuracy on Test data = 67.4074074074074
```

```
In [11]: from sklearn.metrics import confusion_matrix

         lr_predictions = classifier.predict(X_test)

         cm = confusion_matrix(y_test, lr_predictions)

         plt.imshow(cm, cmap='Blues', interpolation='nearest')
         plt.colorbar()
         plt.grid(False)
         plt.ylabel('true')
         plt.xlabel('predicted');
```



4 Classification using Support Vector Machines

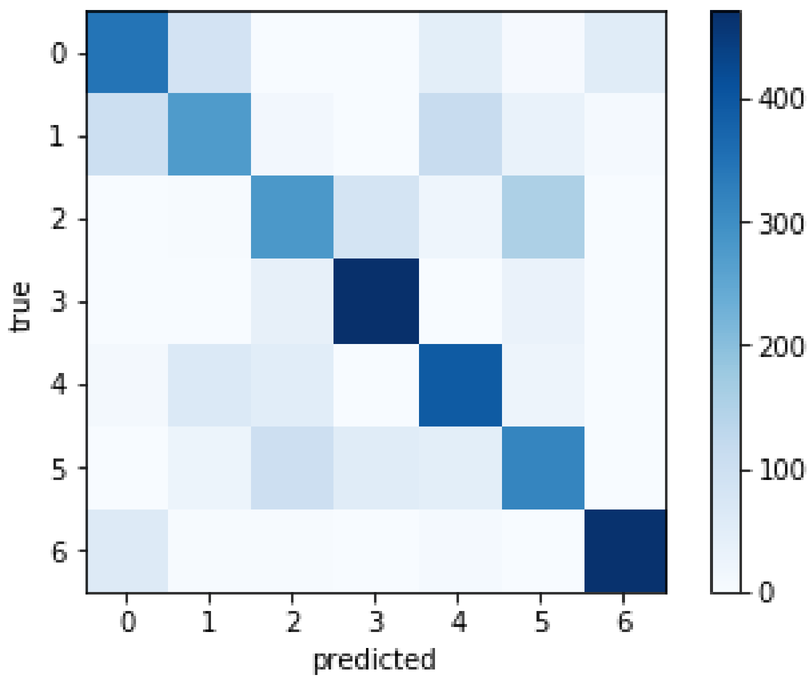
```
In [12]: from sklearn.svm import SVC
         svm_model_linear = SVC(kernel = 'linear', C = 1).fit(X_train, y_train)

         print(svm_model_linear)
```

```
SVC(C=1, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='linear',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

```
In [13]: # Calculate the accuracy on test data
         acc_lr_train = svm_model_linear.score(X_train, y_train)

         # Calculate the accuracy on test data
         acc_lr_test = svm_model_linear.score(X_test, y_test)

         print(f'Accuracy on Train data = {acc_lr_train * 100}')
         print(f'Accuracy on Test data = {acc_lr_test * 100}')
```

```
Accuracy on Train data = 69.94708994708995
Accuracy on Test data = 71.26984126984127
```

```
In [14]: svm_predictions = classifier.predict(X_test)

         cm = confusion_matrix(y_test, svm_predictions)

         plt.imshow(cm, cmap='Blues', interpolation='nearest')
         plt.colorbar()
         plt.grid(False)
         plt.ylabel('true')
         plt.xlabel('predicted');
```



4.1 Analysis

Accuracy scores from above two classifications show that our models have very high bias. To rectify that what we can do is exploratory data analysis. While that is a good option, it is a lengthy process and requires a fundamental understanding of the dataset.

What we can do is use a deep neural network to analyze it further.

5 2-layer Neural Network

5.1 Reshape data for Neural Network

```
In [15]: X_train = X_train.values
         X_train = X_train.T
         X_test = X_test.values
```

```
X_test = X_test.T

y_train = y_train.values
y_train = y_train.reshape(y_train.shape[0],1)
y_train = y_train.T

y_test = y_test.values
y_test = y_test.reshape(y_test.shape[0],1)
y_test = y_test.T

print ('The shape of X_train is: ' + str(X_train.shape))
print ('The shape of y_train is: ' + str(y_train.shape))
print ('The shape of X_test is: ' + str(X_test.shape))
print ('The shape of y_test is: ' + str(y_test.shape))
```

```
The shape of X_train is: (54, 11340)
The shape of y_train is: (1, 11340)
The shape of X_test is: (54, 3780)
The shape of y_test is: (1, 3780)
```

5.2 One-Hot Encoding the labels

```
In [16]: def oneHotEncoding(data, nb_classes):
             #targets = np.array(data).reshape(-1)
             data = data - 1
             return np.eye(nb_classes)[data]
```

```
In [17]: temp = oneHotEncoding(y_train, 7)
         temp = temp[0, :, :]
         y_train_single = y_train
         y_train = temp.T
         print(y_train.shape)

         temp = oneHotEncoding(y_test, 7)
         temp = temp[0, :, :]
         y_test_single = y_test
         y_test = temp.T
         print(y_test.shape)
```

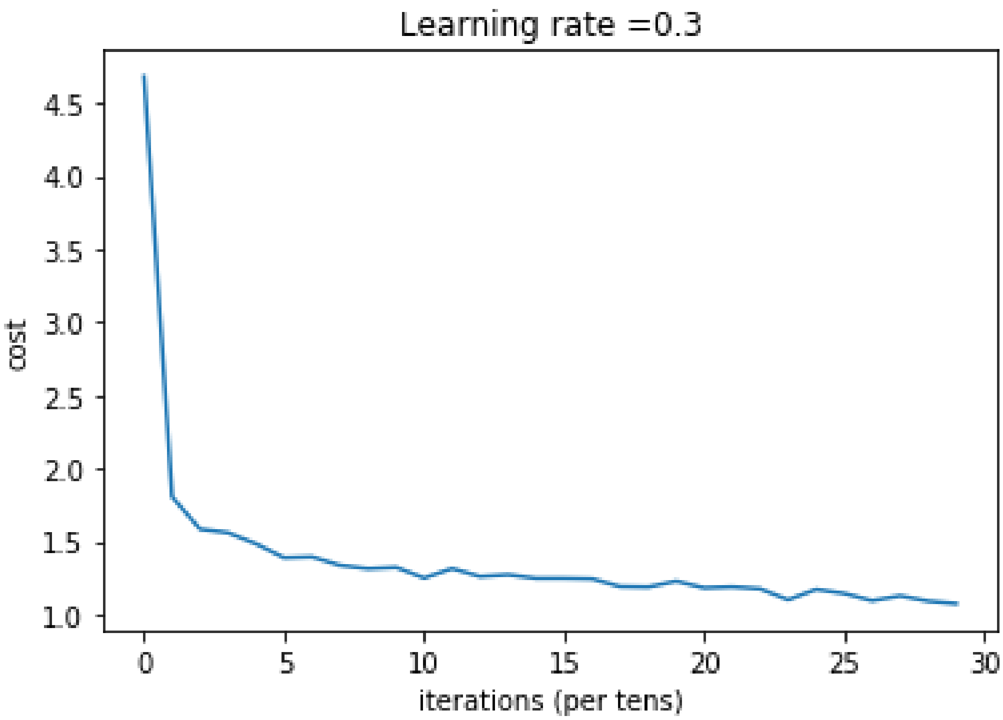
```
(7, 11340)
(7, 3780)
```

6 Training

```
In [18]: #Dimensions of each layer in our network
         layer_dims = [X_train.shape[0],20,20,10,y_train.shape[0]]
```

```
activation_functions = ["relu","relu","relu","sigmoid"]
alpha = 0.3
parameters = lnn.L_layer_model(X_train, y_train, layer_dims, activation_functions, lear
```

```
Cost after iteration 100: 4.681843
Cost after iteration 200: 1.806372
Cost after iteration 300: 1.584562
Cost after iteration 400: 1.560319
Cost after iteration 500: 1.484558
Cost after iteration 600: 1.388990
Cost after iteration 700: 1.395138
Cost after iteration 800: 1.337093
Cost after iteration 900: 1.314223
Cost after iteration 1000: 1.323225
Cost after iteration 1100: 1.250309
Cost after iteration 1200: 1.314965
Cost after iteration 1300: 1.260756
Cost after iteration 1400: 1.272822
Cost after iteration 1500: 1.247831
Cost after iteration 1600: 1.247774
Cost after iteration 1700: 1.244352
Cost after iteration 1800: 1.191837
Cost after iteration 1900: 1.188592
Cost after iteration 2000: 1.228667
Cost after iteration 2100: 1.182293
Cost after iteration 2200: 1.189142
Cost after iteration 2300: 1.176286
Cost after iteration 2400: 1.100950
Cost after iteration 2500: 1.172504
Cost after iteration 2600: 1.144521
Cost after iteration 2700: 1.095018
Cost after iteration 2800: 1.127667
Cost after iteration 2900: 1.091935
Cost after iteration 3000: 1.074326
```



7 Predictions and Accuracy

```
In [19]: activations = ["relu","relu","relu","sigmoid"]
         predictions = lnn.predict(parameters, X_test, activations)
         match_bool = np.equal(predictions,y_test_single).astype('int')
         accuracy = float(np.count_nonzero(match_bool == 1)) / float(y_test_single.size) * 100
         print(f'Accuracy: {round(accuracy,2)}%')
```

```
Accuracy: 71.01%
```

```
In [20]: activations = ["tanh","tanh","sigmoid"]
         layer_dims = [X_train.shape[0],20,10,y_train.shape[0]]
         parameters = lnn.L_layer_model(X_train, y_train, layer_dims, activation_functions, lear
         predictions = lnn.predict(parameters, X_test, activations)
         match_bool = np.equal(predictions,y_test_single).astype('int')
         accuracy = float(np.count_nonzero(match_bool == 1)) / float(y_test_single.size) * 100
         print(f'Accuracy: {round(accuracy,2)}%')
```

```
/home/chrx/Documents/DUCS/multi_layer_nn/L_layer_nn.py:251: RuntimeWarning: divide by zero encou
  dAL = - (np.divide(Y, AL) - np.divide(1 - Y, 1 - AL))
/home/chrx/Documents/DUCS/multi_layer_nn/L_layer_nn.py:251: RuntimeWarning: invalid value encoun
  dAL = - (np.divide(Y, AL) - np.divide(1 - Y, 1 - AL))
```

```
/home/chrx/Documents/DUCS/multi_layer_nn/L_layer_nn.py:153: RuntimeWarning: invalid value encoun
  cost =  (-1./m) * np.sum(np.multiply(np.log(AL+epsilon),Y) + np.multiply(np.log(1-AL+epsilon),

Accuracy: 14.29%
```

```
In [21]: activations = ["relu","tanh","sigmoid"]
         parameters = lnn.L_layer_model(X_train, y_train, layer_dims, activation_functions, lear
         predictions = lnn.predict(parameters, X_test, activations)
         match_bool = np.equal(predictions,y_test_single).astype('int')
         accuracy = float(np.count_nonzero(match_bool == 1)) / float(y_test_single.size) * 100
         print(f'Accuracy: {round(accuracy,2)}%')
```

```
/home/chrx/Documents/DUCS/multi_layer_nn/L_layer_nn.py:251: RuntimeWarning: divide by zero encou
  dAL = - (np.divide(Y, AL) - np.divide(1 - Y, 1 - AL))
/home/chrx/Documents/DUCS/multi_layer_nn/L_layer_nn.py:251: RuntimeWarning: invalid value encoun
  dAL = - (np.divide(Y, AL) - np.divide(1 - Y, 1 - AL))
/home/chrx/Documents/DUCS/multi_layer_nn/L_layer_nn.py:153: RuntimeWarning: invalid value encoun
  cost =  (-1./m) * np.sum(np.multiply(np.log(AL+epsilon),Y) + np.multiply(np.log(1-AL+epsilon),

Accuracy: 14.29%

/home/chrx/Documents/DUCS/multi_layer_nn/activation_utils.py:53: RuntimeWarning: invalid value e
  A = (np.exp(Z) - np.exp(-Z)) / (np.exp(Z) + np.exp(-Z))
```

```
In [22]: activations = ["tanh","relu","sigmoid"]
         parameters = lnn.L_layer_model(X_train, y_train, layer_dims, activation_functions, lear
         predictions = lnn.predict(parameters, X_test, activations)
         match_bool = np.equal(predictions,y_test_single).astype('int')
         accuracy = float(np.count_nonzero(match_bool == 1)) / float(y_test_single.size) * 100
         print(f'Accuracy: {round(accuracy,2)}%')
```

```
/home/chrx/Documents/DUCS/multi_layer_nn/L_layer_nn.py:251: RuntimeWarning: divide by zero encou
  dAL = - (np.divide(Y, AL) - np.divide(1 - Y, 1 - AL))
/home/chrx/Documents/DUCS/multi_layer_nn/L_layer_nn.py:251: RuntimeWarning: invalid value encoun
  dAL = - (np.divide(Y, AL) - np.divide(1 - Y, 1 - AL))
/home/chrx/Documents/DUCS/multi_layer_nn/L_layer_nn.py:153: RuntimeWarning: invalid value encoun
  cost =  (-1./m) * np.sum(np.multiply(np.log(AL+epsilon),Y) + np.multiply(np.log(1-AL+epsilon),

Accuracy: 14.29%
```