CSE 4020 - MACHINE LEARNING

Lab 29+30

Multi Layer Perceptron

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MLP

Question:

To train a Multi-Layer Perceptron (MLP) model to classify the network traffic record whether it is a normal or attack…

1. Read and parse the dataset.

2. Create Multi-Layer Perceptron Model (MLP)

3. Train and evaluate a Multi-Layer Perceptron (MLP) model

Dataset Used:

NSL KDD – Intrusion Detection Dataset
https://www.unb.ca/cic/datasets/nsl.html

Procedure:

-Using pandas, we first import the dataset into our workspace.

-Assign the column names to our dataset as it doesn't have one.

- Pick out and encode our specific variable.

- After encoding the specific variable, we want to dummy encode them on the way to keep away from ordinality among nominal information.

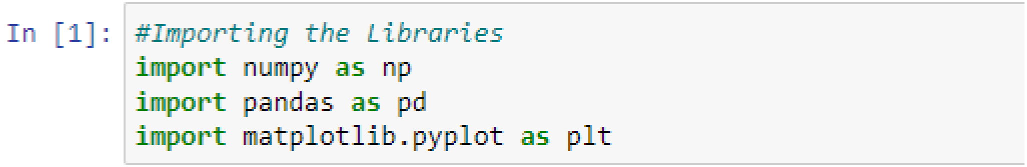
- We then want to re-assign our label information. All labels different than ordinary are assigned as attacks.

- We then want to divide the schooling set and check set information into set of structured attributes and impartial attributes.

- Next, we lay down the Multi-Layer Perceptron and byskip our enter records into enter layer of our neural network.

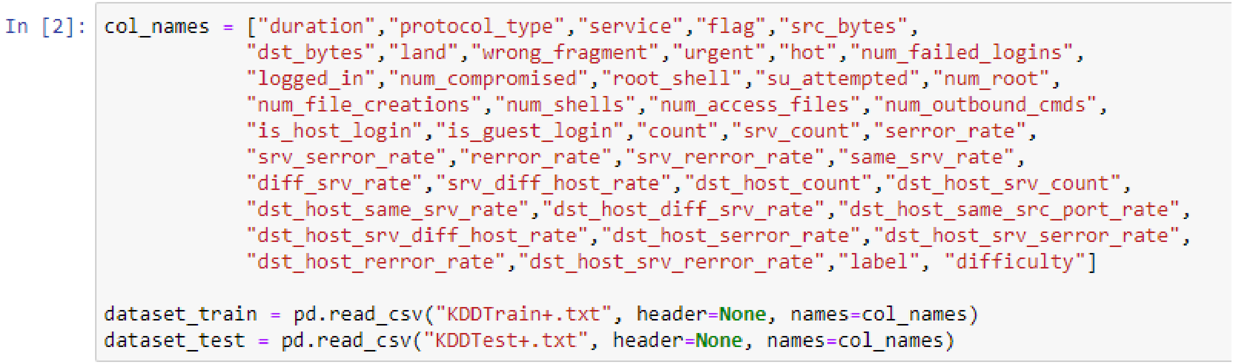
- Finally, we generate our check set consequences and evaluation metrices.

Code Snippets and Explanation:



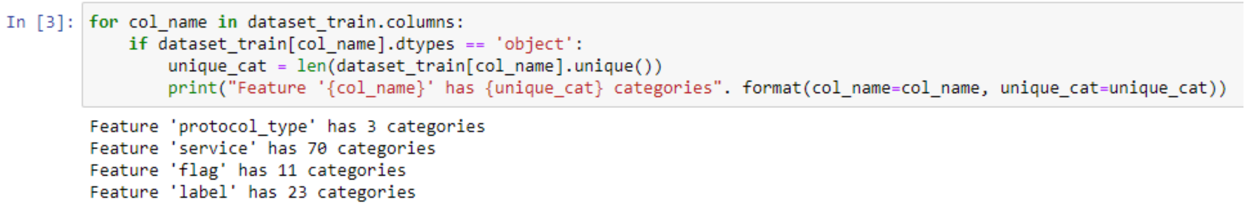
```
In [1]: #Importing the Libraries
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
```

Here we are importing the necessary libraries in our workspace.

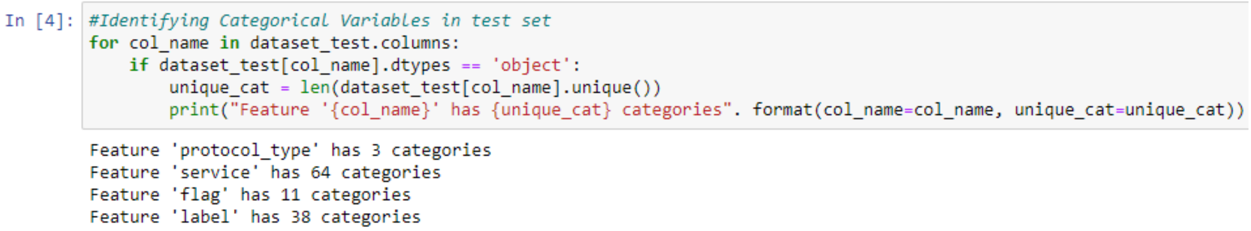


```
In [2]: col_names = ["duration","protocol_type","service","flag","src_bytes",
                    "dst_bytes","land","wrong_fragment","urgent","hot","num_failed_logins",
                    "logged_in","num_compromised","root_shell","su_attempted","num_root",
                    "num_file_creations","num_shells","num_access_files","num_outbound_cmds",
                    "is_host_login","is_guest_login","count","srv_count","serror_rate",
                    "srv_serror_rate","rerror_rate","srv_rerror_rate","same_srv_rate",
                    "diff_srv_rate","srv_diff_host_rate","dst_host_count","dst_host_srv_count",
                    "dst_host_same_srv_rate","dst_host_diff_srv_rate","dst_host_same_src_port_rate",
                    "dst_host_srv_diff_host_rate","dst_host_serror_rate","dst_host_srv_serror_rate",
                    "dst_host_rerror_rate","dst_host_srv_rerror_rate","label", "difficulty"]

        dataset_train = pd.read_csv("KDDTrain+.txt", header=None, names=col_names)
        dataset_test = pd.read_csv("KDDTest+.txt", header=None, names=col_names)
```

Here **we're uploading** the dataset into our workspace and are assigning them with the column names **because it isn't always** pre-**blanketed** in the given dataset.

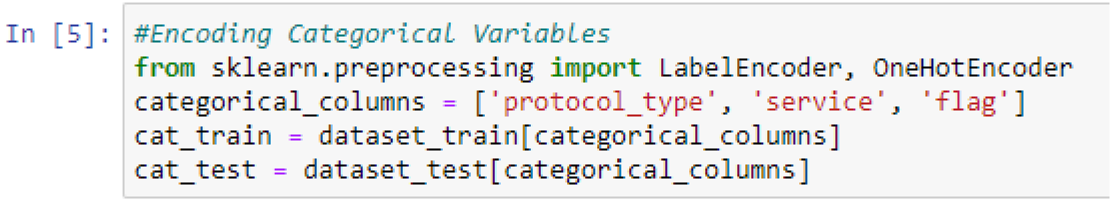


```
In [3]: for col_name in dataset_train.columns:
            if dataset_train[col_name].dtypes == 'object':
                unique_cat = len(dataset_train[col_name].unique())
                print("Feature '{col_name}' has {unique_cat} categories". format(col_name=col_name, unique_cat=unique_cat))

        Feature 'protocol_type' has 3 categories
        Feature 'service' has 70 categories
        Feature 'flag' has 11 categories
        Feature 'label' has 23 categories
```



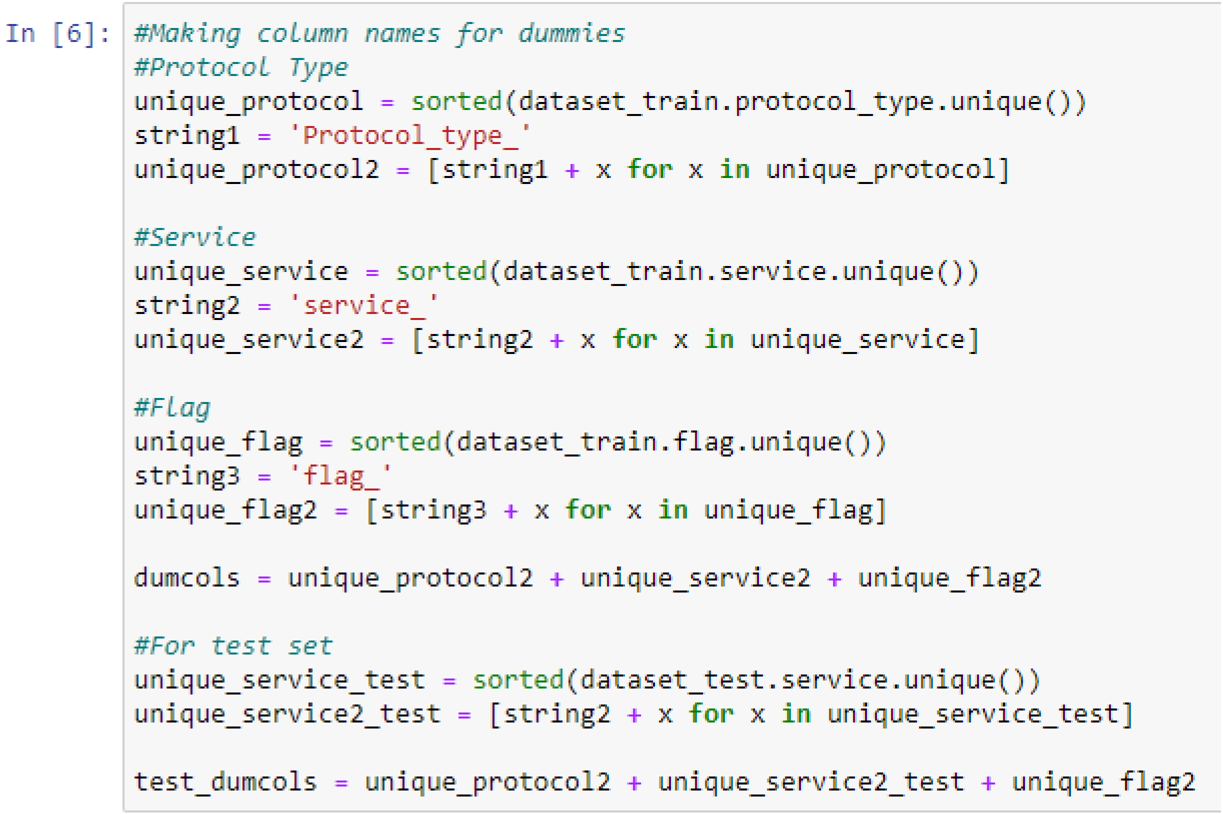
```
In [4]: #Identifying Categorical Variables in test set
        for col_name in dataset_test.columns:
            if dataset_test[col_name].dtypes == 'object':
                unique_cat = len(dataset_test[col_name].unique())
                print("Feature '{col_name}' has {unique_cat} categories". format(col_name=col_name, unique_cat=unique_cat))

        Feature 'protocol_type' has 3 categories
        Feature 'service' has 64 categories
        Feature 'flag' has 11 categories
        Feature 'label' has 38 categories
```

Here **we've identified all of the express** attributes in our training set and **take a look at** set. We have **additionally identified** the **range of** classes inculcating inside every attribute



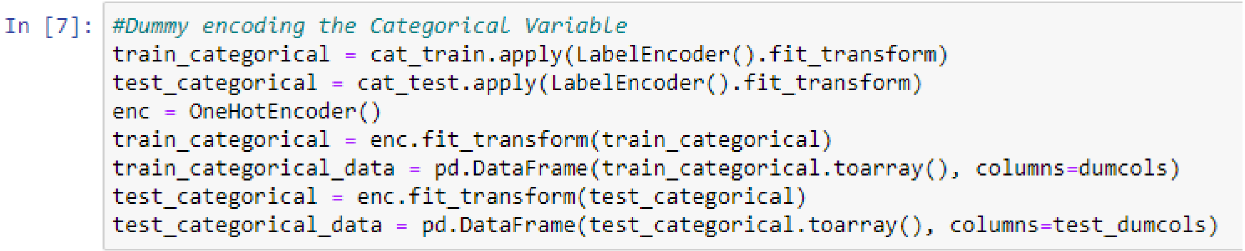
```
In [5]: #Encoding Categorical Variables
        from sklearn.preprocessing import LabelEncoder, OneHotEncoder
        categorical_columns = ['protocol_type', 'service', 'flag']
        cat_train = dataset_train[categorical_columns]
        cat_test = dataset_test[categorical_columns]
```

Here we have created 2 dummy data frames to include the categorical attributes in them



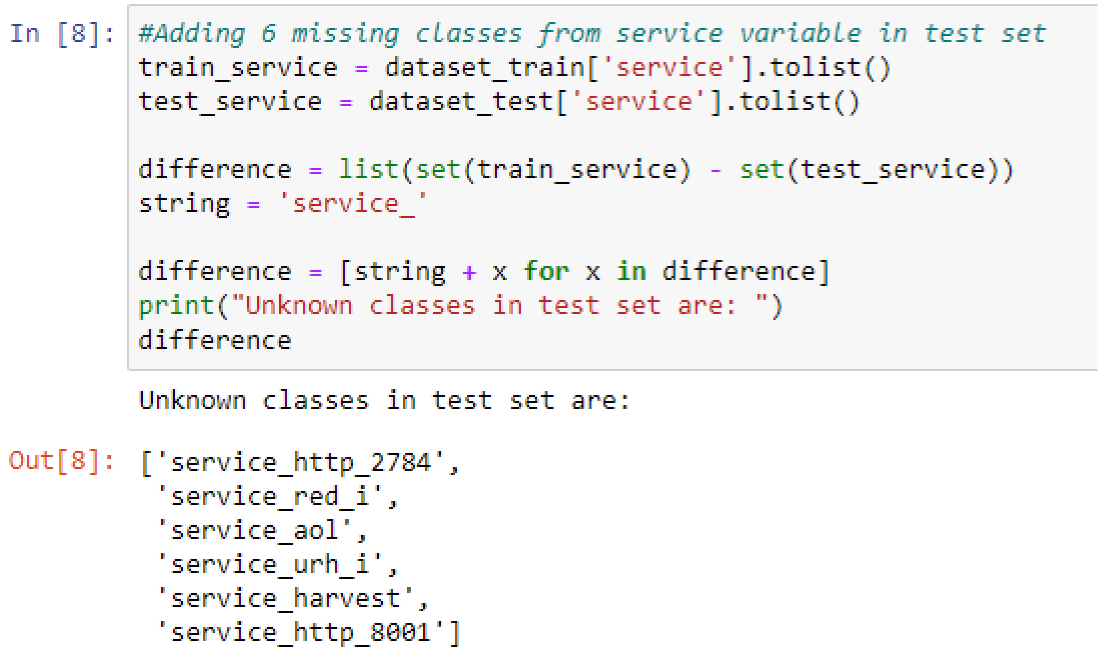
```
In [6]: #Making column names for dummies
        #Protocol Type
        unique_protocol = sorted(dataset_train.protocol_type.unique())
        string1 = 'Protocol_type_'
        unique_protocol2 = [string1 + x for x in unique_protocol]

        #Service
        unique_service = sorted(dataset_train.service.unique())
        string2 = 'service_'
        unique_service2 = [string2 + x for x in unique_service]

        #Flag
        unique_flag = sorted(dataset_train.flag.unique())
        string3 = 'flag_'
        unique_flag2 = [string3 + x for x in unique_flag]

        dumcols = unique_protocol2 + unique_service2 + unique_flag2

        #For test set
        unique_service_test = sorted(dataset_test.service.unique())
        unique_service2_test = [string2 + x for x in unique_service_test]

        test_dumcols = unique_protocol2 + unique_service2_test + unique_flag2
```

Here we've created the dummy attributes to keep away from the ordinal introduction among those nominal specific attributes.



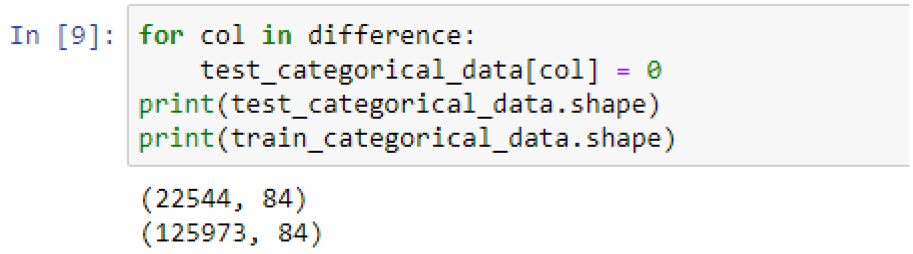
```
In [7]: #Dummy encoding the Categorical Variable
        train_categorical = cat_train.apply(LabelEncoder().fit_transform)
        test_categorical = cat_test.apply(LabelEncoder().fit_transform)
        enc = OneHotEncoder()
        train_categorical = enc.fit_transform(train_categorical)
        train_categorical_data = pd.DataFrame(train_categorical.toarray(), columns=dumcols)
        test_categorical = enc.fit_transform(test_categorical)
        test_categorical_data = pd.DataFrame(test_categorical.toarray(), columns=test_dumcols)
```

Here we've used the label encoder to fill withinside the dummy attributes in every of the specific attributes.



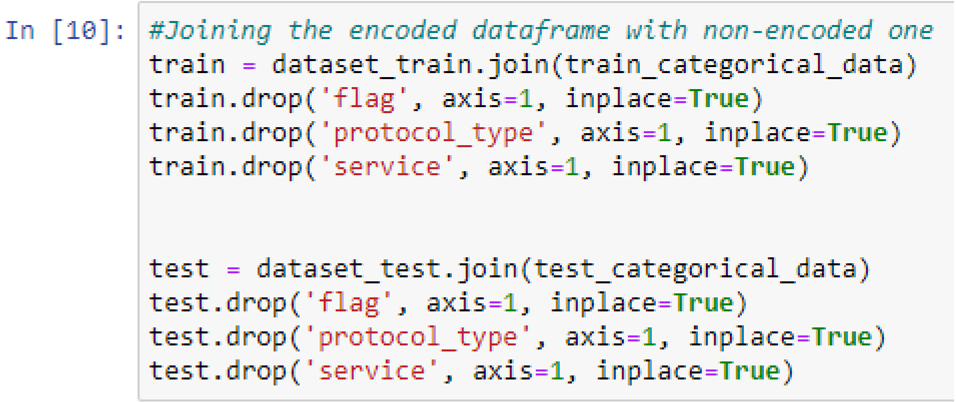
```
In [8]: #Adding 6 missing classes from service variable in test set
        train_service = dataset_train['service'].tolist()
        test_service = dataset_test['service'].tolist()

        difference = list(set(train_service) - set(test_service))
        string = 'service_'

        difference = [string + x for x in difference]
        print("Unknown classes in test set are: ")
        difference

        Unknown classes in test set are:

Out[8]: ['service_http_2784',
         'service_red_i',
         'service_aol',
         'service_urh_i',
         'service_harvest',
         'service_http_8001']
```

While checking the specific variables we noticed that service characteristic in check set has 70 training whilst schooling set has sixty four training. Hence, we want to encompass the ones 6 dummy attributes with zero fee in every our schooling set. This is what we've got diagnosed and achieved here.



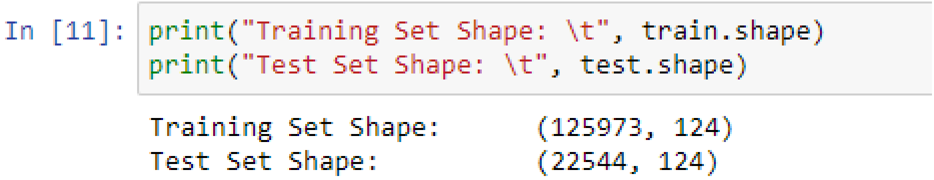
```
In [9]: for col in difference:
            test_categorical_data[col] = 0
        print(test_categorical_data.shape)
        print(train_categorical_data.shape)

        (22544, 84)
        (125973, 84)
```

Here we have finalised our data frames with the dummy values of categorical attributes.



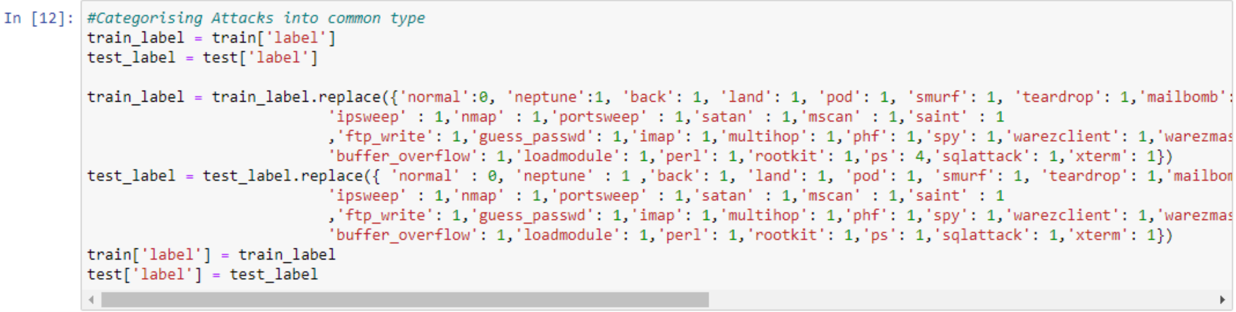
```
In [10]: #Joining the encoded dataframe with non-encoded one
         train = dataset_train.join(train_categorical_data)
         train.drop('flag', axis=1, inplace=True)
         train.drop('protocol_type', axis=1, inplace=True)
         train.drop('service', axis=1, inplace=True)


         test = dataset_test.join(test_categorical_data)
         test.drop('flag', axis=1, inplace=True)
         test.drop('protocol_type', axis=1, inplace=True)
         test.drop('service', axis=1, inplace=True)
```

Next, we've got combined our original dataset with dummy attributes that we acquired in our specific assignment. Also right here we've got dropped the original specific attributes for you to inculcate only the non-specific attributes.



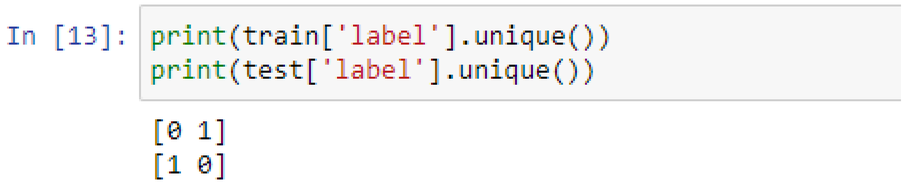
```
In [11]: print("Training Set Shape: \t", train.shape)
         print("Test Set Shape: \t", test.shape)

         Training Set Shape:      (125973, 124)
         Test Set Shape:          (22544, 124)
```

Here we have checked the number of attributes in both the training set and test set to see if they are equal… we can see that they have 124 attributes each and hence are compatible.

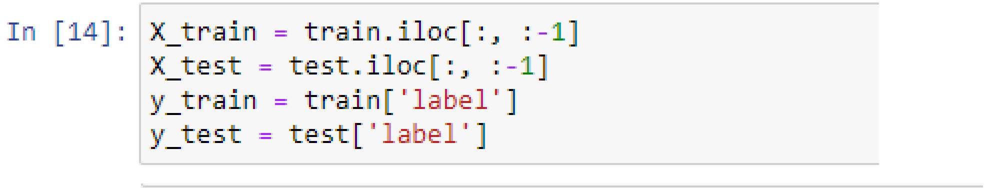


```
In [12]: #Categorising Attacks into common type
         train_label = train['label']
         test_label = test['label']

         train_label = train_label.replace({'normal':0, 'neptune':1, 'back': 1, 'land': 1, 'pod': 1, 'smurf': 1, 'teardrop': 1,'mailbomb':
                                  'ipsweep' : 1,'nmap' : 1,'portsweep' : 1,'satan' : 1,'mscan' : 1,'saint' : 1
                                 ,'ftp_write': 1,'guess_passwd': 1,'imap': 1,'multihop': 1,'phf': 1,'spy': 1,'warezclient': 1,'warezmas
                                  'buffer_overflow': 1,'loadmodule': 1,'perl': 1,'rootkit': 1,'ps': 4,'sqlattack': 1,'xterm': 1})
         test_label = test_label.replace({ 'normal' : 0, 'neptune' : 1 ,'back': 1, 'land': 1, 'pod': 1, 'smurf': 1, 'teardrop': 1,'mailbom
                                  'ipsweep' : 1,'nmap' : 1,'portsweep' : 1,'satan' : 1,'mscan' : 1,'saint' : 1
                                 ,'ftp_write': 1,'guess_passwd': 1,'imap': 1,'multihop': 1,'phf': 1,'spy': 1,'warezclient': 1,'warezmas
                                  'buffer_overflow': 1,'loadmodule': 1,'perl': 1,'rootkit': 1,'ps': 1,'sqlattack': 1,'xterm': 1})
         train['label'] = train_label
         test['label'] = test_label
```

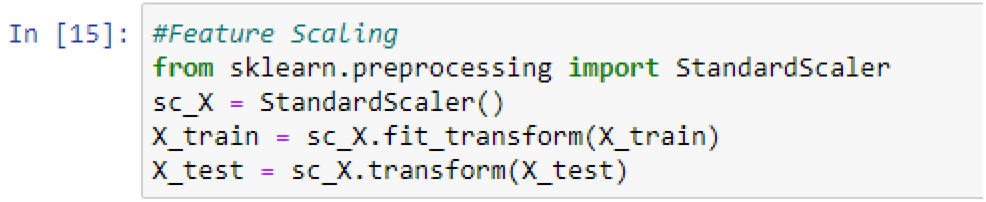
Here we have categorised each of the label attribute either as “normal” or an “attack”. All the labels which are normal are given a label of 0 and all those that indicate an attack are labelled as 1.



```
In [13]: print(train['label'].unique())
         print(test['label'].unique())

         [0 1]
         [1 0]
```

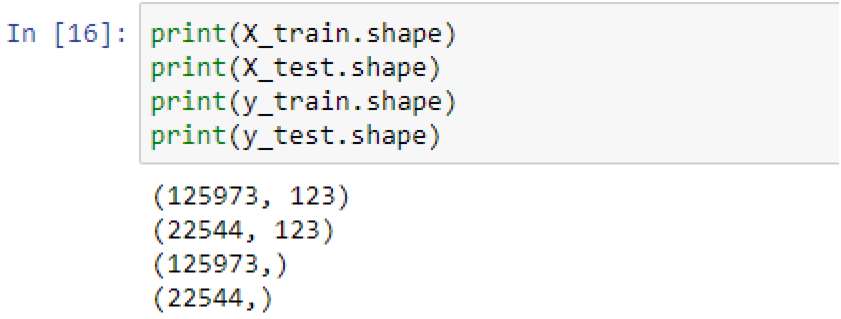


```
In [14]: X_train = train.iloc[:, :-1]
         X_test = test.iloc[:, :-1]
         y_train = train['label']
         y_test = test['label']
```



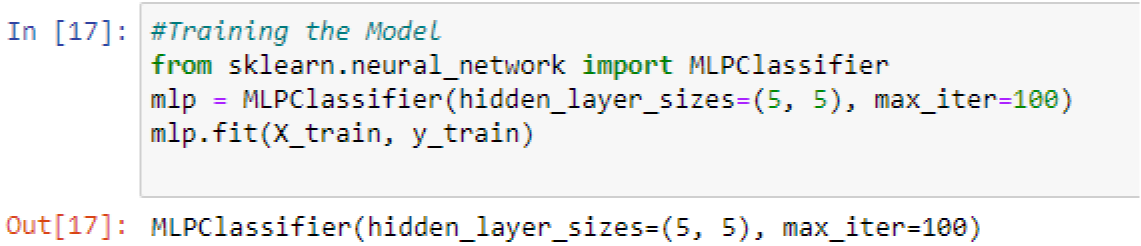
```
In [15]: #Feature Scaling
         from sklearn.preprocessing import StandardScaler
         sc_X = StandardScaler()
         X_train = sc_X.fit_transform(X_train)
         X_test = sc_X.transform(X_test)
```

Since all the attributes in our dataset don’t follow a common scale, we need to feature scale the dataset in order to avoid any preassumed weight amongst them. We have used standard scalar to do this and it scales down each attribute to a range in -1 to 1.



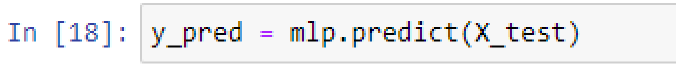
```
In [16]: print(X_train.shape)
         print(X_test.shape)
         print(y_train.shape)
         print(y_test.shape)

         (125973, 123)
         (22544, 123)
         (125973,)
         (22544,)
```

Here we have assigned the set of dependent and independent attributes. Also, we have printed the shape of each category that we have in order to check if they are compatible with each other.

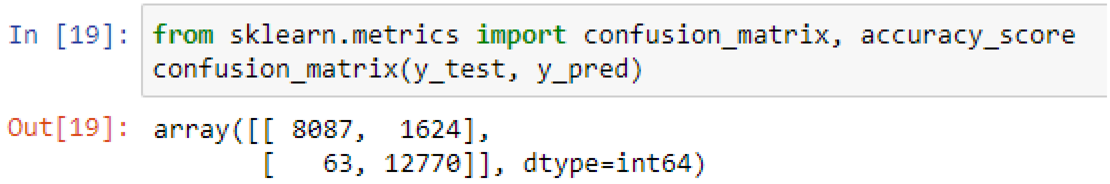


```
In [17]: #Training the Model
         from sklearn.neural_network import MLPClassifier
         mlp = MLPClassifier(hidden_layer_sizes=(5, 5), max_iter=100)
         mlp.fit(X_train, y_train)

Out[17]: MLPClassifier(hidden_layer_sizes=(5, 5), max_iter=100)
```

Here we have laid our neural network and then passed our input and output set to it in-order for it to adjust the weight biases.

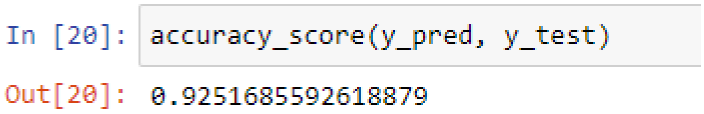


```
In [18]: y_pred = mlp.predict(X_test)
```



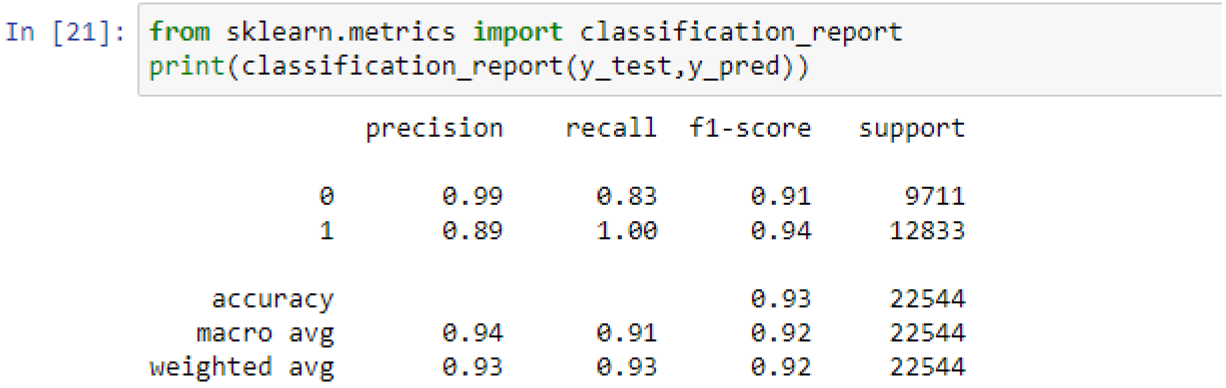
```
In [19]: from sklearn.metrics import confusion_matrix, accuracy_score
         confusion_matrix(y_test, y_pred)

Out[19]: array([[ 8087,  1624],
                [   63, 12770]], dtype=int64)
```

Here we have generated a vector y_pred that stores the result as predicted by our mlp classifier on test set. We have also generated the confusion matrix to check the performance of our classifier.



```
In [20]: accuracy_score(y_pred, y_test)

Out[20]: 0.9251685592618879
```

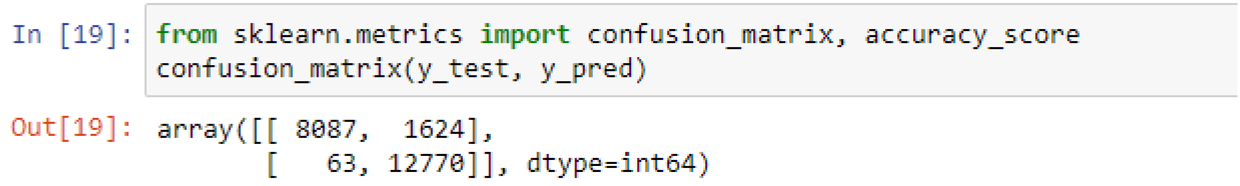
we have printed the accuracy of our model and printed the classification reported to finally check the performance of our model. We can see that the accuracy of the model is 92.51%.



```
In [21]: from sklearn.metrics import classification_report
         print(classification_report(y_test,y_pred))

              precision    recall  f1-score   support

           0       0.99      0.83      0.91      9711
           1       0.89      1.00      0.94     12833

    accuracy                           0.93     22544
   macro avg       0.94      0.91      0.92     22544
weighted avg       0.93      0.93      0.92     22544
```

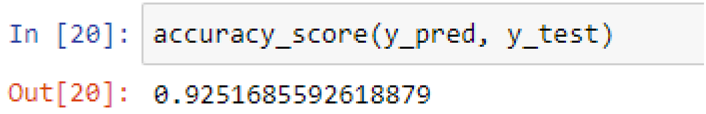
Result and Conclusion:

Confusion Matrix:



```
In [19]: from sklearn.metrics import confusion_matrix, accuracy_score
         confusion_matrix(y_test, y_pred)

Out[19]: array([[ 8087,  1624],
                [   63, 12770]], dtype=int64)
```

Accuracy:



```
In [20]: accuracy_score(y_pred, y_test)

Out[20]: 0.9251685592618879
```

Accuracy:92.51%.

- ✓ Identified Normal = 9711
- ✓ Actual Normal = 9362
- ✓ Identified Attack = 12833
- ✓ Actual Attack = 13182
- ✓ True Normal = 8087
- ✓ True Attack = 12770
- ✓ False Normal = 1624
- ✓ False Attack = 63
- ✓ Precision Normal = 0.99
- ✓ Precision Attack = 0.89
- ✓ Recall Normal = 0.83
- ✓ Recall Attack = 1.00