DDOS

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1 Machine Learning Model (Logistic Regression)

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1.1 1. Loading And Cleaning Data

Install necessary libraries First we will install the necessary libraries to run the following code.

[ ]:
```
#!pip install numpy
#!pip install pandas
#!pip install matplotlib
#!pip install seaborn
#!pip install sklearn
#!pip install --upgrade scikit-learn==0.23.1
#!pip install --upgrade imbalanced-learn==0.7.0
#!python -m pip install statsmodels
```

Importing libraries Then we will import the libraries we need to run the following code.

[1]:
```
import numpy as np

import pandas as pd
from scipy import stats
import pickle
import warnings

# Plotting libraries
import seaborn as sns
import math
import matplotlib.pyplot as plt

# Sklearn libraries
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import label_binarize
from sklearn.model_selection import train_test_split
```

```
from sklearn.decomposition import PCA
from sklearn.linear_model import LogisticRegression
from sklearn.cluster import DBSCAN, KMeans
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix

# Filter warnings
warnings.filterwarnings('ignore') #filter warnings
# Show plots inline
%matplotlib inline
```

Loading Data Here we load the CSV data collected from the Python script into pandas dataframe

[2]:
```
df = pd.read_csv('/home/larry/Desktop/DDOS/FlowStatistics.csv', index_col=False)
df.columns.str.split(',', expand=True)
# normal_df = pd.read_csv('/home/larry/Desktop/ML/csv/FlowStatistics(Normal).
↪csv')
# df = pd.concat([mixed_df, normal_df], ignore_index=True)
df.head()
```

[2]:

	Timestamp	SSIP	SSP	SDFP	SDFB	SFE	Status
0	2022-07-18_23:15:13.306651	0.4	1.6	0.5	27.0	1.6	0
1	2022-07-18_23:15:13.309375	0.4	1.6	0.5	27.0	1.6	0
2	2022-07-18_23:15:13.310084	0.4	1.6	0.5	27.0	1.6	0
3	2022-07-18_23:15:18.313410	0.4	3.6	0.5	27.0	3.6	0
4	2022-07-18_23:15:18.318547	0.4	3.6	0.5	27.0	3.6	0

[3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7558 entries, 0 to 7557
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Timestamp  7558 non-null   object
 1   SSIP       7558 non-null   float64
 2   SSP        7558 non-null   float64
 3   SDFP       7558 non-null   float64
 4   SDFB       7558 non-null   float64
 5   SFE        7558 non-null   float64
 6   Status     7558 non-null   int64
dtypes: float64(5), int64(1), object(1)
memory usage: 413.5+ KB
```

Cleaning Data Drop any rows that contain NaN (this happens when the training script ends abruptly)

Drop the Forward Packets, Forward Bytes, Reverse Packets, Reverse Bytes data. This data increases linearly and at a certain point in time can be any value so it is not helpful as a feature in the model.

[4]:
```
df.drop('Timestamp', axis=1, inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7558 entries, 0 to 7557
Data columns (total 6 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   SSIP    7558 non-null   float64
 1   SSP     7558 non-null   float64
 2   SDFP    7558 non-null   float64
 3   SDFB    7558 non-null   float64
 4   SFE     7558 non-null   float64
 5   Status  7558 non-null   int64
dtypes: float64(5), int64(1)
memory usage: 354.4 KB
```

Describing Data Now we have 5242 rows and 13 columns (12 features, 1 target)

1.2 2. Supervised Model - Logistic Regression

Now we will train a logistic regression model on this dataset by splitting it into a training and testing set.

Split dataset First we will split the dataset into features and targets.

[6]:
```
X = df.drop('Status',axis=1)
df['Status'] = df['Status'].astype('category')
y = df["Status"]
df.describe()
```

[6]:

	SSIP	SSP	SDFP	SDFB	SFE
count	7558.000000	7558.000000	7558.000000	7558.000000	7558.000000
mean	46.431437	49.321646	3.254849	580.195059	49.381635
std	47.525925	44.749889	30.030160	5186.131154	44.690282
min	0.200000	0.400000	0.000000	0.000000	0.400000
25%	0.400000	6.200000	0.064348	10.731554	6.400000
50%	0.600000	8.200000	0.500000	27.000000	8.400000
75%	96.200000	96.200000	2.151145	407.290363	96.200000
max	96.200000	96.200000	1563.216064	271999.595107	96.200000

[7]:
```
print(y)
```

```
0       0
1       0
2       0
3       0
4       0
       ..
7553    1
7554    1
7555    1
7556    1
7557    1
Name: Status, Length: 7558, dtype: category
Categories (2, int64): [0, 1]
```

[8]:
```
df["Status"].value_counts()
```

[8]:
```
0    3867
1    3691
Name: Status, dtype: int64
```

The challenge of working with imbalanced datasets is that most machine learning techniques will ignore, and in turn have poor performance on, the minority class, although typically it is performance on the minority class that is most important.

One approach to addressing imbalanced datasets is to oversample the minority class. The simplest approach involves duplicating examples in the minority class, although these examples don't add any new information to the model. #### Instead, new examples can be synthesized from the existing examples.

SMOTE (Synthetic Minority Oversampling Technique) If enabled this will cause our sample size to decrease during PCA Border Line graph so only run to create a more accurate model. If you want to see a visual display of data use it without SMOTE.

[9]:
```
# # Oversample and plot imbalanced dataset with SMOTE
# from collections import Counter
# from sklearn.datasets import make_classification
# from imblearn.over_sampling import SMOTE
# from matplotlib import pyplot
# from numpy import where

# os = SMOTE(random_state=0)

# # transform the dataset
# oversample = SMOTE()
# X, y = oversample.fit_resample(X, y)
# # summarize the new class distribution
# counter = Counter(y)
# print(counter)
```

Create training and testing sets We will use train_test_split with test size of 0.3 to put 70% of our data into training, and 30% into testing. The random_state is set so the results are repeatable.

[10]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y,test_size=0.5,␣
↪random_state=101)
```

RECURSIVE FEATURE ELIMINATION

[14]:
```
# This will take some time
from sklearn.pipeline import Pipeline
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.model_selection import cross_val_score
from sklearn.feature_selection import RFE
import numpy as np
from sklearn.ensemble import GradientBoostingClassifier

# create pipeline
# chosen algorithm specified via the “estimator”|
rfe = RFE(estimator=LogisticRegression(solver='liblinear'),␣
 ↪n_features_to_select=3)
# fit the model
rfe.fit(X_train,y_train)
for i in range(X.shape[1]):
    print('Column: %s, Selected %s, Rank: %.3f' % (X_train.columns[i], rfe.
 ↪support_[i],rfe.ranking_[i]))
print("The optimal number of features:", rfe.n_features_)
print("Best features:", X_train.columns[rfe.support_])
```

```
Column: SSIP, Selected True, Rank: 1.000
Column: SSP, Selected True, Rank: 1.000
Column: SDFP, Selected False, Rank: 2.000
Column: SDFB, Selected False, Rank: 3.000
Column: SFE, Selected True, Rank: 1.000
The optimal number of features: 3
Best features: Index(['SSIP', 'SSP', 'SFE'], dtype='object')
```

1.2.1 Train Model/ Model Building

Now we will create and train the model.

[13]:
```
# import the class
from sklearn.linear_model import LogisticRegression
# instantiate the model (using the default parameters)
logreg = LogisticRegression(solver='liblinear')
# fit the model with data
logreg.fit(X_train,y_train)
predictions = logreg.predict(X_test)
```

Make predictions Single prediction

[14]:
```
idx = 111 #random number
single_x_test = [df.iloc[idx].drop('Status').tolist()]
single_y_test = df.iloc[idx]['Status']
```

[15]:
```
single_prediction = logreg.predict(single_x_test)
print('For this sample, our model predicted %s and it was actually %s' %␣
↪(single_prediction[0], single_y_test))
```

```
For this sample, our model predicted 0 and it was actually 0.0
```

We can create a dataframe to see these in table form:

[16]:
```
resultsDF = pd.DataFrame({
        'true':y_test,
        'predicted':predictions
    })
resultsDF.head()
```

[16]:

	true	predicted
6637	1	1
4232	1	1
6144	1	1
634	0	0
6021	1	1

We see the model has a 99.68% accuracy

[17]:
```
print('Accuracy: %.2f%%' % (accuracy_score(predictions,y_test)*100))
```

```
Accuracy: 99.97%
```

We can save the model using the pickle library to use later in real-time

[18]:
```
print(pickle.format_version)
```

```
4.0
```

[19]:
```python
from platform import python_version
print(python_version())
```

```
3.8.10
```

[20]:
```python
pickle.dump(logreg,open('/home/larry/Desktop/TORONTO/trafficclassifier/
↪LogisticRegression','wb'))
```

1.2.2 Model Testing

Show the results of the prediction on a plot.

This phase is meant to be re-run again and again to re-train our model.

Confusion Matrix The confusion matrix allows you to see the numerical breakdown of the predictions by class:

[21]:
```
cm = confusion_matrix(predictions,y_test, labels=y.cat.categories)
print(cm)
```

```
[[1959    1]
 [   0 1819]]
```

To attach labels, we can view it as a dataframe:

[22]:
```
cmDF = pd.DataFrame()

for i, row in enumerate(y.cat.categories):
    temp = {}
    for j, col in enumerate(y.cat.categories):
        temp[col]=cm[i,j]
    cmDF = cmDF.append(pd.DataFrame.from_dict({row:temp}, orient='index'))

print(cmDF)
```

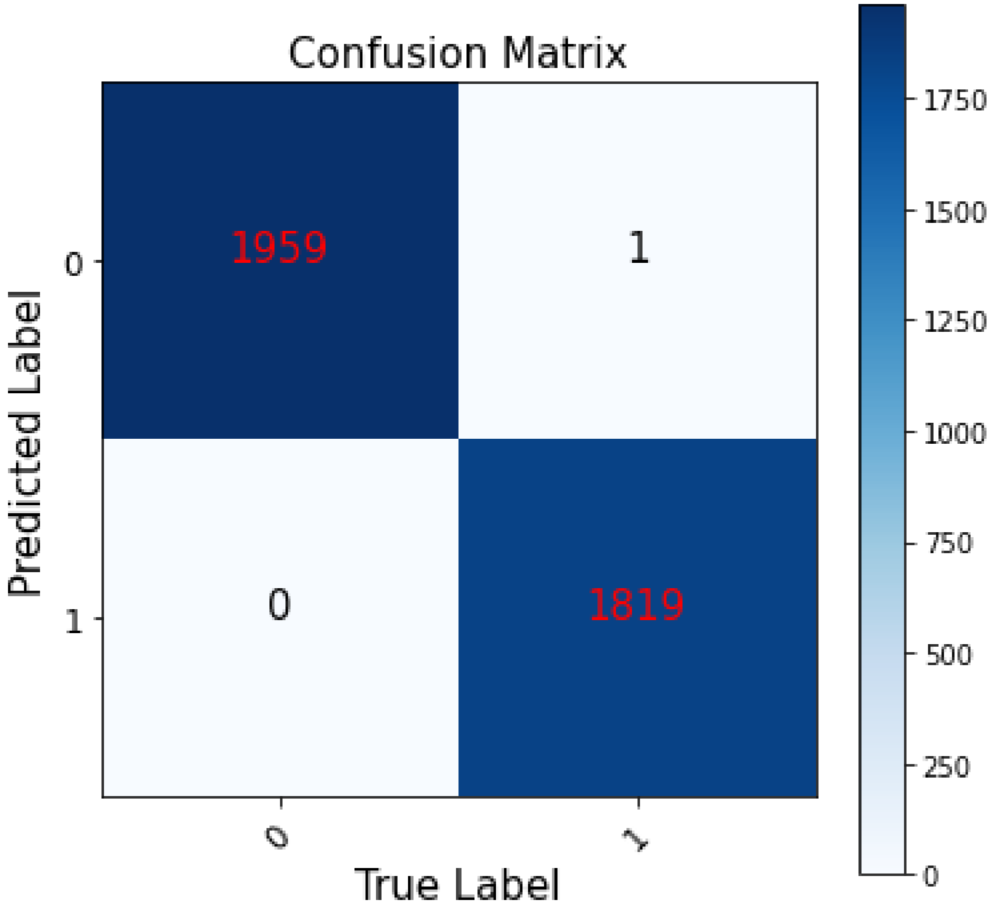
```
      0     1
0  1959     1
1     0  1819
```

We can also add a heatmap to better visualize it

[23]:
```
plt.figure(figsize=(6,6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix', fontsize=15)
plt.colorbar()
tick_marks = np.arange(len(y.unique()))
plt.xticks(tick_marks, y.unique(), rotation=45, fontsize=12)
plt.yticks(tick_marks, y.unique(), fontsize=12)
plt.xlabel('True Label', fontsize=15)
plt.ylabel('Predicted Label', fontsize=15)

for i in range(len(cm)):
    for j in range(len(cm[i])):
        color = 'black'
        if cm[i][j] > 5:
            color = 'red'
        plt.text(j, i, format(cm[i][j]),
```

```
                horizontalalignment='center',
                color=color, fontsize=15)
```



Precision: Precision is about being precise, i.e., how accurate your model is. In other words, you can say, when a model makes a prediction, how often it is correct. In your prediction case, when your Logistic Regression model predicted patients are going to suffer from diabetes, that patients have 76% of the time.

[24]:
```
# import the metrics class
from sklearn import metrics
print("Accuracy:",metrics.accuracy_score(y_test, predictions))
print("Precision:",metrics.precision_score(y_test, predictions))
print("Recall:",metrics.recall_score(y_test, predictions))
```

```
Accuracy: 0.9997353797300873
Precision: 1.0
Recall: 0.9994505494505495
```

1.2.3 Receiver Operating Characteristic(ROC)

Shows the tradeoff between specificity & sensitivity.

ROC is a plot of the true positive rate against the false positive rate.

The true-positive rate means recall, sensitivity or probability of detection.

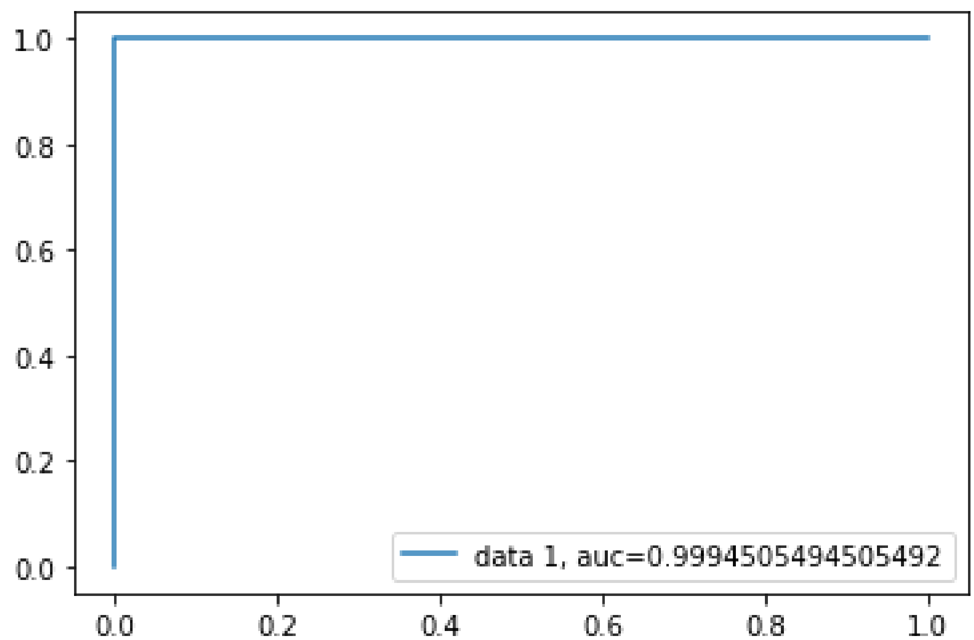
The false-positive rate means probability of false alarm.

The "AUC" ("area under curve") is important as we use this to rank a randomly chosen **positive instance** against a randomly chosen negative one.

This area equals to the probability that a classifier will choose **positive instance** over **negative instance** more.

In layman terms, we want this number as close to 1 as possible.

[25]:
```
y_pred_proba = logreg.predict_proba(X_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_proba)
auc = metrics.roc_auc_score(y_test, y_pred_proba)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



We can see the model works well for all classes.

1.2.4 Extension: Principal Component Analysis

A dimension reduction technique meant for large datsets.

Your data are broken down into principle components, each of which combines the features of the dataset by their correlation into components. These hold the dataset's variance (aka. spread of data)

Normalize data Now, the data must be scaled to fit inside the same range.

Meaning must scale the data so that they fall within the same range for PCA to function properly and determine the appropriate covariance among all the features.

By doing this, one feature won't be able to influence the final components more.

The `StandardScaler Class` from sklearn will remove the mean and scale the data so the have unit variance.

[26]:
```
df.drop('Status',axis=1).values[0:5]
```

[26]:
```
array([[ 0.4,  1.6,  0.5, 27. ,  1.6],
       [ 0.4,  1.6,  0.5, 27. ,  1.6],
       [ 0.4,  1.6,  0.5, 27. ,  1.6],
       [ 0.4,  3.6,  0.5, 27. ,  3.6],
       [ 0.4,  3.6,  0.5, 27. ,  3.6]])
```

Here are the means/std per feature.

[27]:
```
df.drop('Status',axis=1).values.mean(axis=0)
```

[27]:
```
array([ 46.43143689,  49.32164594,   3.25484949, 580.19505891,
        49.38163535])
```

[28]:
```
df.drop('Status',axis=1).values.std(axis=0)
```

[28]:
```
array([  47.52278128,   44.74692868,   30.02817366, 5185.78805379,
         44.68732537])
```

Here, we fit the scaler.

[29]:
```
scaler = StandardScaler()
scaler.fit(df.drop('Status',axis=1))
```

[29]:
```
StandardScaler()
```

[30]:
```
scaled_data = scaler.transform(df.drop('Status',axis=1))
scaled_data[0:5]
```

[30]:
```
array([[-0.96861833, -1.06647869, -0.09174216, -0.10667522, -1.06924357],
       [-0.96861833, -1.06647869, -0.09174216, -0.10667522, -1.06924357],
       [-0.96861833, -1.06647869, -0.09174216, -0.10667522, -1.06924357],
```

```
[-0.96861833, -1.02178289, -0.09174216, -0.10667522, -1.02448815],
[-0.96861833, -1.02178289, -0.09174216, -0.10667522, -1.02448815]])
```

Here are the new means and standard deviation per feature.

[31]:
```
scaled_data.mean(axis=0)
```

[31]:
```
array([-1.20335367e-16, -2.40670733e-16,  2.72634815e-17,  9.40120053e-19,
       -1.20335367e-16])
```

[32]:
```
scaled_data.std(axis=0)
```

[32]:
```
array([1., 1., 1., 1., 1.])
```

Now we will fit PCA model to the data. We will specify n_components=2, because we only want the first 2 principal components.

[33]:
```
pca = PCA(n_components=2)
pca.fit(scaled_data)
```

[33]:
```
PCA(n_components=2)
```

[34]:
```
scaled_data.shape
```

[34]:
```
(7558, 5)
```

[35]:
```
x_pca = pca.transform(scaled_data)
```

[36]:
```
x_pca.shape
```

[36]:
```
(7558, 2)
```

Explained Variance

[37]:
```
pca.explained_variance_ratio_
```

[37]:
```
array([0.60040491, 0.39938545])
```

[38]:
```
pca.explained_variance_ratio_.sum()*100
```

[38]:
```
99.97903588545655
```

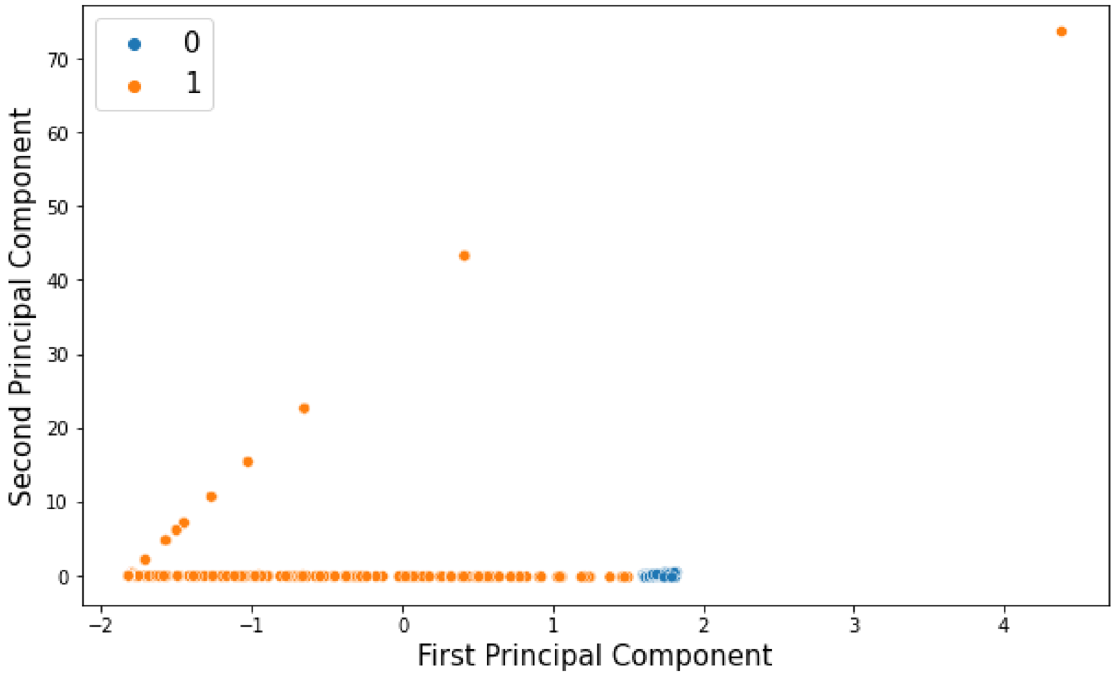
From above you can see that our first 2 principal components explain 99.97% of the variance in our data. We can get higher variance explained by increasing the number of principal components to a maximum of 100% with n_components = n_features.

Plotting the principal components

[39]:
```
fig = plt.figure(figsize=(10,6))
sns.scatterplot(x_pca[:,0], x_pca[:,1], hue=df['Status'])
plt.xlabel('First Principal Component', fontsize=15)
```

```python
plt.ylabel('Second Principal Component', fontsize=15)
plt.legend(fontsize=15)
```

[39]: <matplotlib.legend.Legend at 0x7f3f1b6d89d0>



From this plot, we can see DDOS and ping are easy to identify using first 2 principle components.

Decision Boundary w/ PCA Where the model transitions from forecasting one class to another is known as the decision boundary. We shall once more employ the principle components obtained above for training for visual representational purposes.

In this manner, we are able to train a model with only two features and see the decision boundary in two dimensions. However, since the actual model would make use of all the features, the decision boundary can change.

We will follow the same steps as above for training a model. We use the coded y as the contour plot that we use below prefers numerical values.

[40]:
```python
X_train, X_test, y_train, y_test = train_test_split(x_pca,y.cat.
    ↪codes,test_size=0.3, random_state=101)
```

[41]:
```python
model = LogisticRegression()
model.fit(X_train,y_train)
```

[41]: LogisticRegression()

As discussed above, the accuracy value is lower when we only use the first 2 principle components as opposed to the full set of features. Again, this is just for visualization purposes.

[42]:
```
predictions = model.predict(X_test)
print('Accuracy: %.2f%%' % (accuracy_score(predictions,y_test)*100))
```

```
Accuracy: 99.74%
```

Plotting We will first generate a grid of x[0] and x[1] values that we will use to make predictions with.

[43]:
```
x_min = x_pca[:,0].min()
x_max = x_pca[:,0].max()
y_min = x_pca[:,1].min()
y_max = x_pca[:,1].max()
spacing = 0.01
```

[44]:
```
xx, yy = np.meshgrid(np.arange(x_min, x_max, spacing), np.arange(y_min, y_max,␣
↪spacing))
```

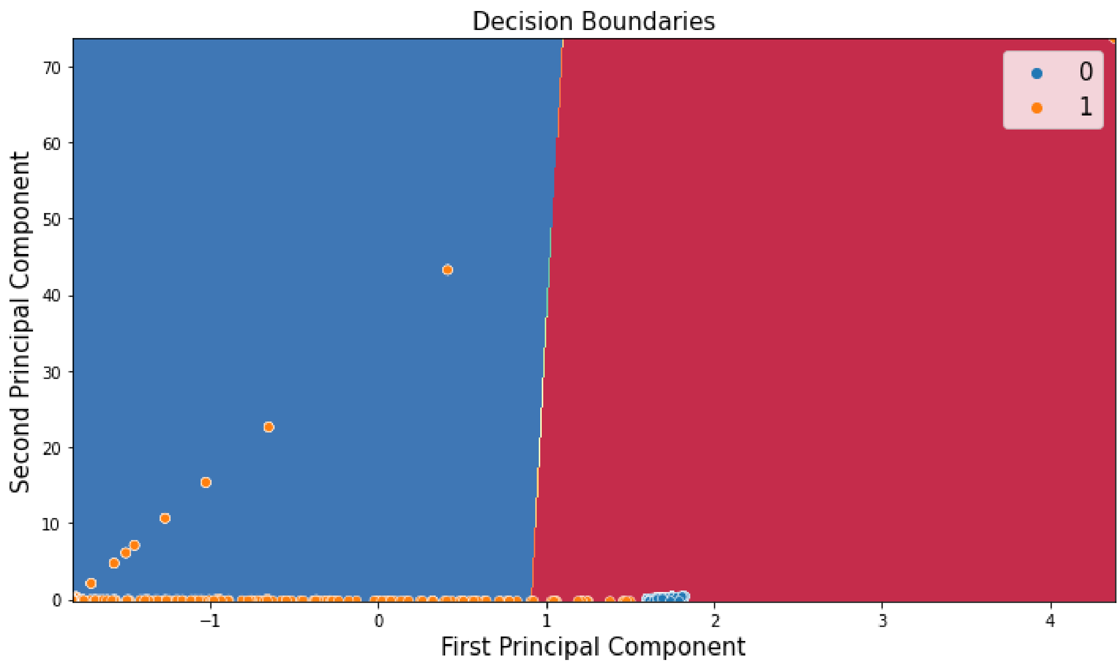
Now we will make predictions on the grid that we created. The `ravel` function just makes the 2D array that we have above into a 1D array. We will reshape the predictions Z into a 2D array afterwards for plotting

[45]:
```
Z = model.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)
```

Now we will plot the data, and the decision boundaries.

[46]:
```
plt.figure(figsize=(10,6))
plt.contourf(xx, yy, Z, cmap=plt.cm.Spectral)
sns.scatterplot(x_pca[:,0], x_pca[:,1], hue=df['Status'], cmap=plt.cm.Spectral)
plt.title('Decision Boundaries', fontsize=15)
plt.xlabel('First Principal Component', fontsize=15)
plt.ylabel('Second Principal Component', fontsize=15)
plt.tight_layout()
plt.xlim([x_min,x_max])
plt.ylim([y_min,y_max])
plt.legend(fontsize=15)
```

[46]:
```
<matplotlib.legend.Legend at 0x7f3f1952ffd0>
```



There is an equal decision split, shocasing clear distinction in classification using 2 principal Components.