# Detecting Phishing Websites using Neural Networks

In [1]:

```
# Filter the uneccesary warnings
import warnings
warnings.filterwarnings("ignore")

#import Tensorflow and keras
import tensorflow as tf
from tensorflow import keras

# Import pandas and numpy
import pandas as pd
import numpy as np
```

In [2]:

```
myData =
pd.read_csv("C:\\Users\Whoopie\\Desktop\\School\\Spring_2020\\Knowledge_Based_Systems_APT_3020\\Ma
nning-Phishing-Websites-Detection-master\\Phishing.csv")

myData.head().T
```

Out[2]:

| | 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| having_IP_Address | -1 | 1 | 1 | 1 | 1 |
| URL_Length | 1 | 1 | 0 | 0 | 0 |
| Shortining_Service | 1 | 1 | 1 | 1 | -1 |
| having_At_Symbol | 1 | 1 | 1 | 1 | 1 |
| double_slash_redirecting | -1 | 1 | 1 | 1 | 1 |
| Prefix_Suffix | -1 | -1 | -1 | -1 | -1 |
| having_Sub_Domain | -1 | 0 | -1 | -1 | 1 |
| SSLfinal_State | -1 | 1 | -1 | -1 | 1 |
| Domain_registeration_length | -1 | -1 | -1 | 1 | -1 |
| Favicon | 1 | 1 | 1 | 1 | 1 |
| port | 1 | 1 | 1 | 1 | 1 |
| HTTPS_token | -1 | -1 | -1 | -1 | 1 |
| Request_URL | 1 | 1 | 1 | -1 | 1 |
| URL_of_Anchor | -1 | 0 | 0 | 0 | 0 |
| Links_in_tags | 1 | -1 | -1 | 0 | 0 |
| SFH | -1 | -1 | -1 | -1 | -1 |
| Submitting_to_email | -1 | 1 | -1 | 1 | 1 |
| Abnormal_URL | -1 | 1 | -1 | 1 | 1 |
| Redirect | 0 | 0 | 0 | 0 | 0 |
| on_mouseover | 1 | 1 | 1 | 1 | -1 |
| RightClick | 1 | 1 | 1 | 1 | 1 |
| popUpWidnow | 1 | 1 | 1 | 1 | -1 |
| Iframe | 1 | 1 | 1 | 1 | 1 |
| age_of_domain | -1 | -1 | 1 | -1 | -1 |
| DNSRecord | -1 | -1 | -1 | -1 | -1 |
| web_traffic | -1 | 0 | 1 | 1 | 0 |
| Page_Rank | -1 | -1 | -1 | -1 | -1 |
| Google_Index | 1 | 1 | 1 | 1 | 1 |

| | 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| **Links_pointing_to_page** | 1 | 1 | 0 | -1 | 1 |
| **Statistical_report** | -1 | 1 | -1 | 1 | 1 |
| **Result** | -1 | -1 | -1 | -1 | 1 |

In [3]:

```
# Data dimension
myData.shape
```

Out[3]:

```
(11055, 31)
```

### Finding out the distribution of the class labels and preparing a report

In [4]:

```
from collections import Counter

classes = Counter(myData['Result'].values)
classes.most_common()

class_dist = pd.DataFrame(classes.most_common(), columns=['Class', 'Num_Observations'])
class_dist
```

Out[4]:

| | Class | Num_Observations |
|---|---|---|
| **0** | 1 | 6157 |
| **1** | -1 | 4898 |

### Plot bar distribution

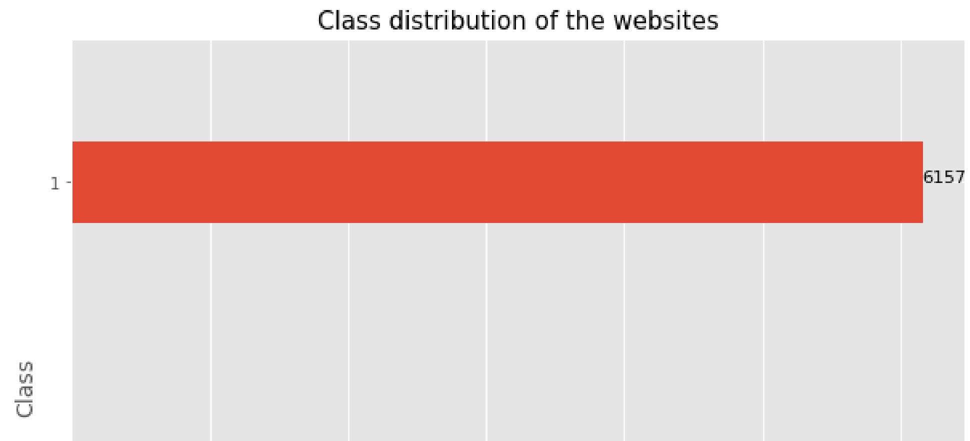
In [5]:

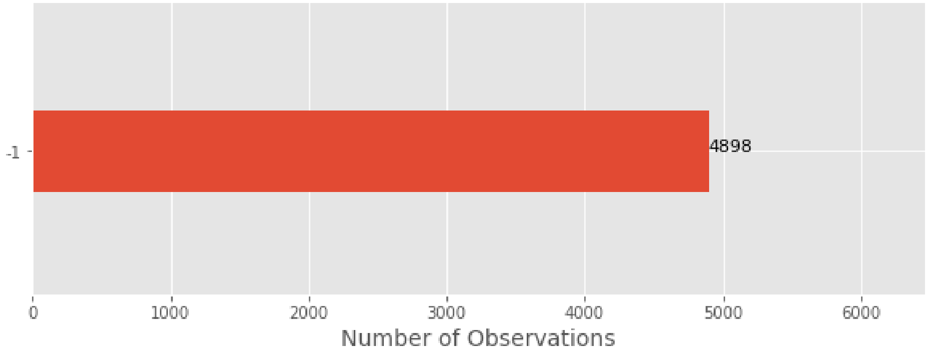
```
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('ggplot')

subplot = class_dist.groupby('Class')['Num_Observations'].sum().plot(kind='barh', width=0.2, figsiz
e=(10,8))

subplot.set_title('Class distribution of the websites', fontsize = 15)
subplot.set_xlabel('Number of Observations', fontsize = 14)
subplot.set_ylabel('Class', fontsize = 14)

for i in subplot.patches:
    subplot.text(i.get_width()+0.1, i.get_y()+0.1, \
            str(i.get_width()), fontsize=11)
```






In [6]:

```
#Find null
myData.isna().sum()
```

Out[6]:

```
having_IP_Address              0
URL_Length                     0
Shortining_Service             0
having_At_Symbol               0
double_slash_redirecting       0
Prefix_Suffix                  0
having_Sub_Domain              0
SSLfinal_State                 0
Domain_registeration_length    0
Favicon                        0
port                           0
HTTPS_token                    0
Request_URL                    0
URL_of_Anchor                  0
Links_in_tags                  0
SFH                            0
Submitting_to_email            0
Abnormal_URL                   0
Redirect                       0
on_mouseover                   0
RightClick                     0
popUpWidnow                    0
Iframe                         0
age_of_domain                  0
DNSRecord                      0
web_traffic                    0
Page_Rank                      0
Google_Index                   0
Links_pointing_to_page         0
Statistical_report             0
Result                         0
dtype: int64
```

### Mapping the -1 values to 0 in the class labels

In [7]:

```
myData.rename(columns={'Result': 'Class'}, inplace=True)
#When inplace = True is used, it performs operation on data and nothing is returned.
#When inplace=False is used, it performs operation on data and returns a new copy of data

myData['Class'] = myData['Class'].map({-1:0, 1:1})
myData['Class'].unique()
```

Out[7]:

```
array([0, 1], dtype=int64)
```

### Split data

In [8]:

```
from sklearn.model_selection import train_test_split

#iloc is integer index based, so it specifies rows and columns by their integer index
X = myData.iloc[:,0:30].values.astype(int)
y = myData.iloc[:,30].values.astype(int)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=np.random.see
d(7))
```

In [ ]:

```

```

**Fit training data to the Logistic Regression Classifier; suitable coz data is in -1, 0, 1.**

In [11]:

```
from sklearn.linear_model import LogisticRegression

logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

Out[11]:

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

## Find Accuracy

In [12]:

```
from sklearn.metrics import accuracy_score, classification_report

print('Accuracy score of the Logistic Regression classifier with default hyperparameter values {0:
.2f}%'.format(accuracy_score(y_test, logreg.predict(X_test))*100.))
print('\n')
print('----Classification report of the Logistic Regression classifier with default hyperparameter
value----')
print('\n')
print(classification_report(y_test, logreg.predict(X_test), target_names=['Phishing Websites',
'Normal Websites']))
```

```
Accuracy score of the Logistic Regression classifier with default hyperparameter values 93.71%


----Classification report of the Logistic Regression classifier with default hyperparameter value-
---


                   precision    recall  f1-score   support

Phishing Websites       0.94      0.92      0.93       974
  Normal Websites       0.94      0.95      0.94      1237

         accuracy                           0.94      2211
        macro avg       0.94      0.94      0.94      2211
     weighted avg       0.94      0.94      0.94      2211
```

## Hyperparameter tuning with random search

In [17]:

```
# Import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV

# Define the grid of values
#penalty : Used to specify the norm used in the penalization (regularization).
penalty = ['l1', 'l2']
C = [0.8, 0.9, 1.0]
tol = [0.01, 0.001 ,0.0001]

#max_iter : Maximum number of iterations taken to converge.
max_iter = [100, 150, 200, 250]

# Create a dictionary where tol and max_iter are keys and the lists of their values are the corres
ponding values
param_grid = dict(penalty=penalty, C=C, tol=tol, max_iter=max_iter)

# Instantiate RandomizedSearchCV with the required parameters
random_model = RandomizedSearchCV(estimator=logreg, param_distributions=param_grid, cv=5)

# Fit random_model to the data
random_model_result = random_model.fit(X_train, y_train)

# Summarize results
best_score, best_params = random_model_result.best_score_, random_model_result.best_params_
print("Best score: %.2f using %s" % (best_score*100., best_params))
```

```
Best score: 92.41 using {'tol': 0.0001, 'penalty': 'l2', 'max_iter': 250, 'C': 0.9}
```

### Use Neural networks

In [14]:

```
# Imports
from keras.models import Sequential
from keras.layers import Dense
from keras.optimizers import *
```

```
Using TensorFlow backend.
```

In [15]:

```
# Model building using the Sequential API
#provides linear stack of layers
model = Sequential()

#activation function introduces non-linearity into the output of a neuron
model.add(Dense(40, activation='relu', kernel_initializer='uniform',input_dim=X.shape[1]))
model.add(Dense(30, activation='relu', kernel_initializer='uniform'))
model.add(Dense(1,  activation='sigmoid', kernel_initializer='uniform'))

#loss measures how far from the true value the prediction is.
model.compile(loss='binary_crossentropy', optimizer=Adam(), metrics=['accuracy'])

model.summary()
```

```
WARNING:tensorflow:From C:\ProgramData\Anaconda3\lib\site-
packages\tensorflow\python\ops\resource_variable_ops.py:435: colocate_with (from
tensorflow.python.framework.ops) is deprecated and will be removed in a future version.
Instructions for updating:
Colocations handled automatically by placer.
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 40)                1240
_________________________________________________________________
dense_2 (Dense)              (None, 30)                1230
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 31
=================================================================
Total params: 2,501
Trainable params: 2,501
```

```
Non-trainable params: 0
_________________________________________________________________
```

In [16]:

```python
from keras import callbacks
#Callbacks can help get internal states and statistics of the model during training

es_cb = callbacks.EarlyStopping(monitor='loss', min_delta=0.001, patience=5)
#min-delta: minimum change in the monitored quantity to modify as an improvement
#patience: number of epochs with no improvement after which training will stop

history = model.fit(X_train, y_train, batch_size=64, epochs=128, verbose=1, callbacks=[es_cb])

scores = model.evaluate(X_test, y_test)
print('\nAccuracy score of the Neural Network with basic hyperparameter settings {0:.2f}%'.format(
scores[1]*100))
```

```
WARNING:tensorflow:From C:\ProgramData\Anaconda3\lib\site-
packages\tensorflow\python\ops\math_ops.py:3066: to_int32 (from tensorflow.python.ops.math_ops) is
deprecated and will be removed in a future version.
Instructions for updating:
Use tf.cast instead.
Epoch 1/128
8844/8844 [==============================] - 1s 81us/step - loss: 0.4172 - accuracy: 0.8272
Epoch 2/128
8844/8844 [==============================] - 0s 26us/step - loss: 0.2030 - accuracy: 0.9210
Epoch 3/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1944 - accuracy: 0.9233
Epoch 4/128
8844/8844 [==============================] - 0s 26us/step - loss: 0.1903 - accuracy: 0.9251
Epoch 5/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1859 - accuracy: 0.9274
Epoch 6/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1831 - accuracy: 0.9283
Epoch 7/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1786 - accuracy: 0.9271
Epoch 8/128
8844/8844 [==============================] - 0s 30us/step - loss: 0.1748 - accuracy: 0.9293
Epoch 9/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.1690 - accuracy: 0.9302
Epoch 10/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.1649 - accuracy: 0.9326
Epoch 11/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1600 - accuracy: 0.9331
Epoch 12/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1554 - accuracy: 0.9358
Epoch 13/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1507 - accuracy: 0.9376
Epoch 14/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.1477 - accuracy: 0.9384
Epoch 15/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1440 - accuracy: 0.9374
Epoch 16/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1390 - accuracy: 0.9418
Epoch 17/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1363 - accuracy: 0.9408
Epoch 18/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.1323 - accuracy: 0.9423
Epoch 19/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1311 - accuracy: 0.9453
Epoch 20/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1285 - accuracy: 0.9448
Epoch 21/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1276 - accuracy: 0.9445
Epoch 22/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1257 - accuracy: 0.9453
Epoch 23/128
8844/8844 [==============================] - 0s 29us/step - loss: 0.1213 - accuracy: 0.9460
Epoch 24/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.1205 - accuracy: 0.9464
Epoch 25/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1197 - accuracy: 0.9480
Epoch 26/128
8844/8844 [==============================] - 0s 29us/step - loss: 0.1172 - accuracy: 0.9480
```

```
Epoch 27/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.1142 - accuracy: 0.9479
Epoch 28/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.1164 - accuracy: 0.9482
Epoch 29/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.1131 - accuracy: 0.9504
Epoch 30/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.1113 - accuracy: 0.9516
Epoch 31/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1109 - accuracy: 0.9522
Epoch 32/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.1104 - accuracy: 0.9531
Epoch 33/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.1076 - accuracy: 0.9539
Epoch 34/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.1048 - accuracy: 0.9549
Epoch 35/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1059 - accuracy: 0.9551
Epoch 36/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1075 - accuracy: 0.9547
Epoch 37/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1046 - accuracy: 0.9545
Epoch 38/128
8844/8844 [==============================] - 0s 29us/step - loss: 0.1037 - accuracy: 0.9571
Epoch 39/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.1020 - accuracy: 0.9554
Epoch 40/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.0995 - accuracy: 0.9570
Epoch 41/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.0978 - accuracy: 0.9570
Epoch 42/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.0972 - accuracy: 0.9571
Epoch 43/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.0972 - accuracy: 0.9599
Epoch 44/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.0933 - accuracy: 0.9608
Epoch 45/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.0929 - accuracy: 0.9601
Epoch 46/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.0917 - accuracy: 0.9611
Epoch 47/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.0946 - accuracy: 0.9608
Epoch 48/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.0885 - accuracy: 0.9628
Epoch 49/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.0898 - accuracy: 0.9612
Epoch 50/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.0867 - accuracy: 0.9608
Epoch 51/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.0867 - accuracy: 0.9629
Epoch 52/128
8844/8844 [==============================] - 0s 29us/step - loss: 0.0853 - accuracy: 0.9630
Epoch 53/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.0860 - accuracy: 0.9633
Epoch 54/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.0826 - accuracy: 0.9657
Epoch 55/128
8844/8844 [==============================] - 0s 29us/step - loss: 0.0863 - accuracy: 0.9626
Epoch 56/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.0850 - accuracy: 0.9633
Epoch 57/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.0812 - accuracy: 0.9648
Epoch 58/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.0801 - accuracy: 0.9661
Epoch 59/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.0826 - accuracy: 0.9630
Epoch 60/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.0782 - accuracy: 0.9648
Epoch 61/128
8844/8844 [==============================] - 0s 27us/step - loss: 0.0762 - accuracy: 0.9675
Epoch 62/128
8844/8844 [==============================] - 0s 29us/step - loss: 0.0773 - accuracy: 0.9669
Epoch 63/128
8844/8844 [==============================] - 0s 29us/step - loss: 0.0775 - accuracy: 0.9657
Epoch 64/128
8844/8844 [==============================] - 0s 29us/step - loss: 0.0748 - accuracy: 0.9673
Epoch 65/128
```

```
8844/8844 [==============================] - 0s 27us/step - loss: 0.0764 - accuracy: 0.9678
Epoch 66/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.0708 - accuracy: 0.9699
Epoch 67/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.0743 - accuracy: 0.9689
Epoch 68/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.0711 - accuracy: 0.9689
Epoch 69/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.0753 - accuracy: 0.9680
Epoch 70/128
8844/8844 [==============================] - 0s 28us/step - loss: 0.0748 - accuracy: 0.9670
Epoch 71/128
8844/8844 [==============================] - 0s 29us/step - loss: 0.0721 - accuracy: 0.9700
2211/2211 [==============================] - 0s 66us/step

Accuracy score of the Neural Network with basic hyperparameter settings 96.25%
```

Evaluates model at the end of each epoch and gives performance. Accuracy has now improved as seen.

In [ ]:

```

```