Website Phishing

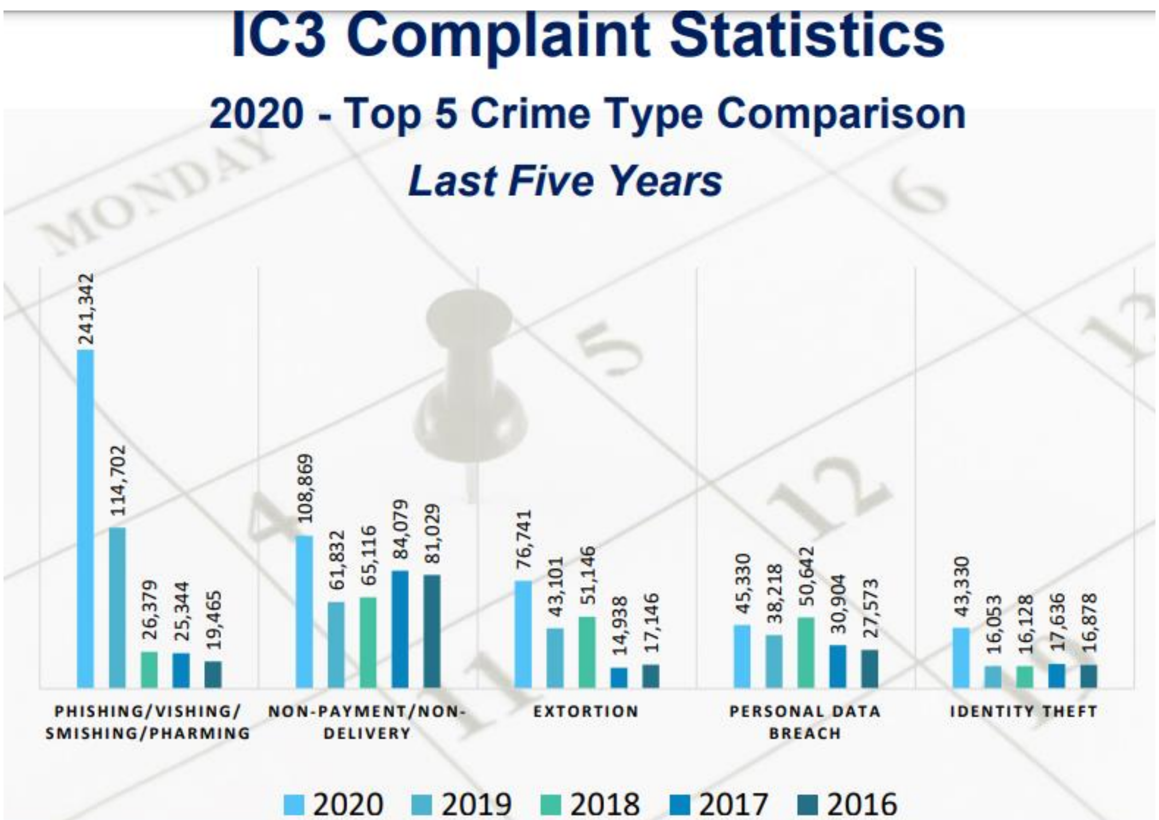
Introduction

Phishing is the fraudulent attempt to obtain sensitive information or data, such as usernames, passwords, credit card numbers, or other sensitive details by impersonating oneself as a trustworthy entity in a digital communication. Typically carried out by email spoofing, instant messaging, and text messaging, phishing often directs users to enter personal information at a fake website which matches the look and feel of the legitimate site.

Phishing is by far the most common attack performed by cyber-criminals, recording over twice as many incidents of phishing than any other type of computer crime.

As per Data by FBI, crime related to phishing increased rapidly.

Comparison for the top five reported crime types of 2020 for the years of 2016 to 2020:



Websites Phishing using Supervised and Unsupervised Machine Learning Algorithm

The main idea of this project is to how website phishing attacks can be prevented using supervised and unsupervised machine learning technique. In this project I am going to train the model using Logistic Regression, Neural Network, K-means and K-modes with the UCI Phishing Websites Data Set and see how accurate our model differentiates between Phishing and Legitimate website.

In this project we are going to use UCI Phishing Websites Data Set, which contains 11055 instances and 31 attributes.

First, we will import the dataset and see the dataset.

```
from scipy.io import arff
import pandas as pd
import numpy as np
```

```
df=pd.read_csv('D:/Security/Project/Phishing Dataset/csv_result-Training Dataset.csv')
```

```
df.head().T
```

	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
Links_pointing_to_page	1	1	0	-1	1
Statistical_report	-1	1	-1	1	1
Result	-1	-1	-1	-1	1

Checking all columns in the dataset:

```
df.columns
```

```
Index(['having_IP_Address', 'URL_Length', 'Shortining_Service',
       'having_At_Symbol', 'double_slash_redirecting', 'Prefix_Suffix',
       'having_Sub_Domain', 'SSLfinal_State', 'Domain_registeration_length',
       'Favicon', 'port', 'HTTPS_token', 'Request_URL', 'URL_of_Anchor',
       'Links_in_tags', 'SFH', 'Submitting_to_email', 'Abnormal_URL',
       'Redirect', 'on_mouseover', 'RightClick', 'popUpWidnow', 'Iframe',
       'age_of_domain', 'DNSRecord', 'web_traffic', 'Page_Rank',
       'Google_Index', 'Links_pointing_to_page', 'Statistical_report',
       'Class'],
      dtype='object')
```

Now we will check the total number of observations and classes in the dataset:

```
from collections import Counter
```

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

```
[(1, 6157), (-1, 4898)]
```

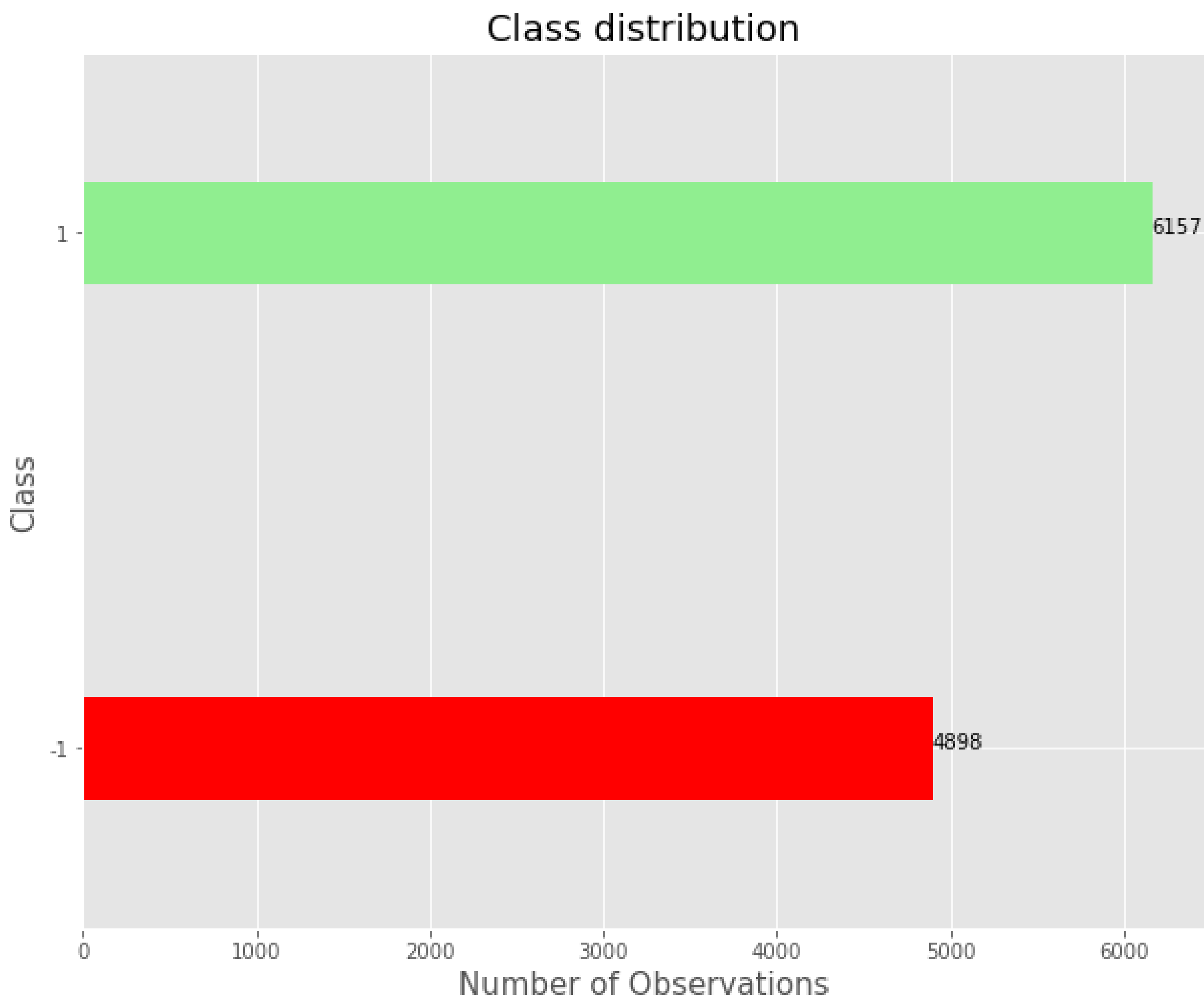
```
class_distribution = pd.DataFrame(classes.most_common(), columns=['Class', 'Number of Observations'])
class_distribution
```

	Class	Number of Observations
0	1	6157
1	-1	4898

As result dataset contains 4898 observation from -1 class shows Phishing data and 6157 observations from 1 class shows Legitimate data.

Plotting Class vs Number of Observations:

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

plot = class_distribution.groupby('Class')['Number of Observations'].sum().plot(kind='barh', width=0.2, figsize=(10,8))

plot.set_title('Class distribution', fontsize = 18)
plot.set_xlabel('Number of Observations', fontsize = 15)
plot.set_ylabel('Class', fontsize = 15)

for i in plot.patches:
    plot.text(i.get_width()+0.1, i.get_y()+0.1,str(i.get_width()), fontsize=10)
```


Class distribution
1
-1
Class
6157
4898
0
1000
2000
3000
4000
5000
6000
Number of Observations

Descriptive Statistics Summary of the dataset:

	count	mean	std	min	25%	50%	75%	max
having_IP_Address	11055.0	0.313795	0.949534	-1.0	-1.0	1.0	1.0	1.0
URL_Length	11055.0	-0.633198	0.766095	-1.0	-1.0	-1.0	-1.0	1.0
Shortining_Service	11055.0	0.738761	0.673998	-1.0	1.0	1.0	1.0	1.0
having_At_Symbol	11055.0	0.700588	0.713598	-1.0	1.0	1.0	1.0	1.0
double_slash_redirecting	11055.0	0.741474	0.671011	-1.0	1.0	1.0	1.0	1.0
Prefix_Suffix	11055.0	-0.734962	0.678139	-1.0	-1.0	-1.0	-1.0	1.0
having_Sub_Domain	11055.0	0.063953	0.817518	-1.0	-1.0	0.0	1.0	1.0
SSLfinal_State	11055.0	0.250927	0.911892	-1.0	-1.0	1.0	1.0	1.0
Domain_registeration_length	11055.0	-0.336771	0.941629	-1.0	-1.0	-1.0	1.0	1.0
Favicon	11055.0	0.628584	0.777777	-1.0	1.0	1.0	1.0	1.0
port	11055.0	0.728268	0.685324	-1.0	1.0	1.0	1.0	1.0
HTTPS_token	11055.0	0.675079	0.737779	-1.0	1.0	1.0	1.0	1.0
Request_URL	11055.0	0.186793	0.982444	-1.0	-1.0	1.0	1.0	1.0
URL_of_Anchor	11055.0	-0.076526	0.715138	-1.0	-1.0	0.0	0.0	1.0
Links_in_tags	11055.0	-0.118137	0.763973	-1.0	-1.0	0.0	0.0	1.0
SFH	11055.0	-0.595749	0.759143	-1.0	-1.0	-1.0	-1.0	1.0
Submitting_to_email	11055.0	0.635640	0.772021	-1.0	1.0	1.0	1.0	1.0
Abnormal_URL	11055.0	0.705292	0.708949	-1.0	1.0	1.0	1.0	1.0
Redirect	11055.0	0.115694	0.319872	0.0	0.0	0.0	0.0	1.0
on_mouseover	11055.0	0.762099	0.647490	-1.0	1.0	1.0	1.0	1.0
RightClick	11055.0	0.913885	0.405991	-1.0	1.0	1.0	1.0	1.0
popUpWidnow	11055.0	0.613388	0.789818	-1.0	1.0	1.0	1.0	1.0
Iframe	11055.0	0.816915	0.576784	-1.0	1.0	1.0	1.0	1.0
age_of_domain	11055.0	0.061239	0.998168	-1.0	-1.0	1.0	1.0	1.0
DNSRecord	11055.0	0.377114	0.926209	-1.0	-1.0	1.0	1.0	1.0
web_traffic	11055.0	0.287291	0.827733	-1.0	0.0	1.0	1.0	1.0
Page_Rank	11055.0	-0.483673	0.875289	-1.0	-1.0	-1.0	1.0	1.0
Google_Index	11055.0	0.721574	0.692369	-1.0	1.0	1.0	1.0	1.0
Links_pointing_to_page	11055.0	0.344007	0.569944	-1.0	0.0	0.0	1.0	1.0
Statistical_report	11055.0	0.719584	0.694437	-1.0	1.0	1.0	1.0	1.0
Result	11055.0	0.113885	0.993539	-1.0	-1.0	1.0	1.0	1.0

Concise summary of the dataset data type:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11055 entries, 0 to 11054
Data columns (total 31 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   having_IP_Address            11055 non-null  int64
 1   URL_Length                   11055 non-null  int64
 2   Shortining_Service           11055 non-null  int64
 3   having_At_Symbol             11055 non-null  int64
 4   double_slash_redirecting     11055 non-null  int64
 5   Prefix_Suffix                11055 non-null  int64
 6   having_Sub_Domain            11055 non-null  int64
 7   SSLfinal_State               11055 non-null  int64
 8   Domain_registeration_length  11055 non-null  int64
 9   Favicon                      11055 non-null  int64
 10  port                         11055 non-null  int64
 11  HTTPS_token                  11055 non-null  int64
 12  Request_URL                  11055 non-null  int64
 13  URL_of_Anchor                11055 non-null  int64
 14  Links_in_tags                11055 non-null  int64
 15  SFH                          11055 non-null  int64
 16  Submitting_to_email          11055 non-null  int64
 17  Abnormal_URL                 11055 non-null  int64
 18  Redirect                     11055 non-null  int64
 19  on_mouseover                 11055 non-null  int64
 20  RightClick                   11055 non-null  int64
 21  popUpWidnow                  11055 non-null  int64
 22  Iframe                       11055 non-null  int64
 23  age_of_domain                11055 non-null  int64
 24  DNSRecord                    11055 non-null  int64
 25  web_traffic                  11055 non-null  int64
 26  Page_Rank                    11055 non-null  int64
 27  Google_Index                 11055 non-null  int64
 28  Links_pointing_to_page       11055 non-null  int64
 29  Statistical_report           11055 non-null  int64
 30  Result                       11055 non-null  int64
dtypes: int64(31)
memory usage: 2.6 MB
```

Renaming "Result" to "Class" and Replacing -1 to 0:

```
df.rename(columns={'Result': 'Class'}, inplace=True)

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

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

Checking for NA values:

```
df.isna().sum()
```

```
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
Class                          0
dtype: int64
```

Logistic Regression

Now we are going to split the dataset into training and testing set with test size 20% and train size 80% to train the model

```
from sklearn.model_selection import train_test_split
```

```
X = df.iloc[:,0:30].values.astype(int)
y = df.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.seed(7))
```

Applying the Supervised Machine Learning Algorithm Logistic Regression and fitting the data into model

```
from sklearn.linear_model import LogisticRegression

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

```
LogisticRegression()
```

Now Predicting and checking accuracy on test data based on Logistic Regression algorithm

```
from sklearn.metrics import accuracy_score, classification_report
score = logistic_Regression.score(X_test, y_test)
print('Accuracy score ',score)
print('\n')
print('Accuracy score of the Logistic Regression Classifier {0:.2f}%'
      .format(accuracy_score(y_test, logistic_Regression.predict(X_test))*100.))
print('\n')
print('*****Classification report of the Logistic Regression classifier*****')
print('\n')
print(classification_report(y_test, logistic_Regression.predict(X_test),
                            target_names=['Phishing Websites', 'Normal Websites']))
```

```
Accuracy score  0.9371325192220714


Accuracy score of the Logistic Regression Classifier 93.71%


*****Classification report of the Logistic Regression classifier*****


                   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
```

As above prediction accuracy shows that 93%, which means our model is doing good prediction.

Now we will create the Confusion Matrix:

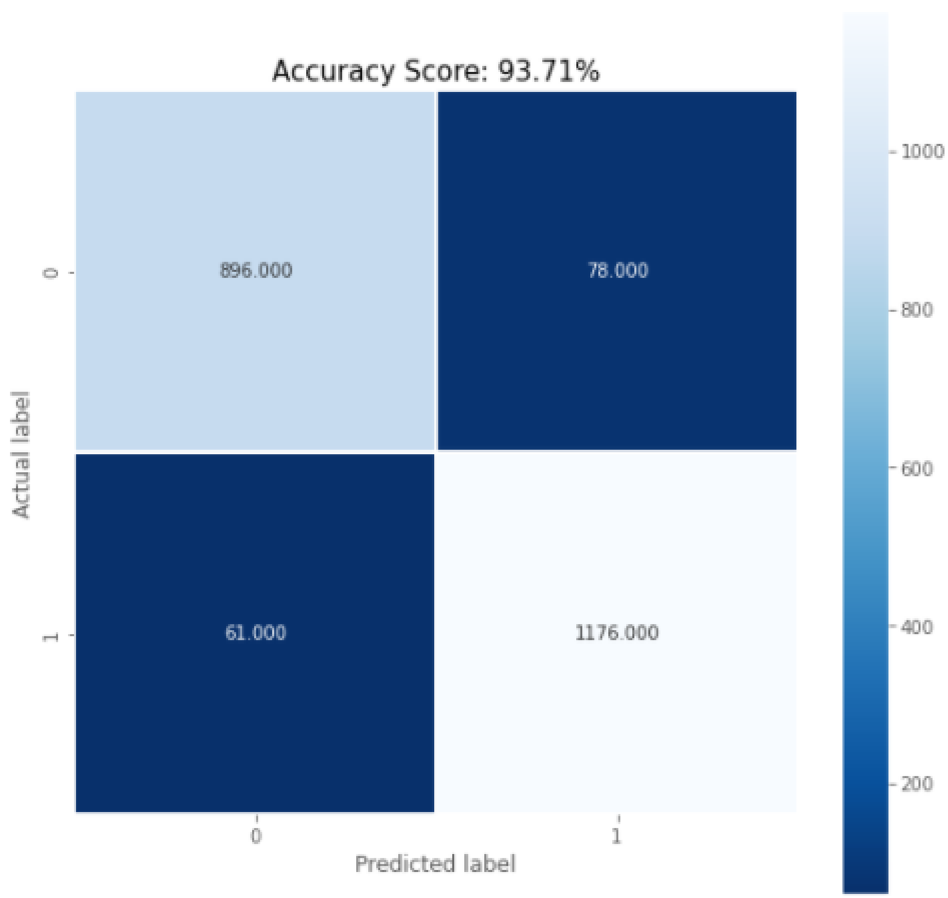
```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import metrics
```

```
confusion_matrix = metrics.confusion_matrix(y_test, logistic_Regression.predict(X_test))
print(confusion_matrix)
```

```
[[ 896   78]
 [  61 1176]]
```

Plotting Confusion Matrix:

```
plt.figure(figsize=(9,9))
sns.heatmap(confusion_matrix, annot=True, fmt=".3f", linewidths=.5, square = True, cmap = 'Blues_r');
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
all_sample_title = 'Accuracy Score: {0:.2f}%'.format(accuracy_score(y_test, logistic_Regression.predict(X_test))*100.)
plt.title(all_sample_title, size = 15);
```



The Confusion Matrix tells us the following:

- There are two possible predicted classes: **0** and **1**. If we were predicting that the website is, for example, 0 mean phishing, and 1 means legitimate.

- The classifier made a total of 2211 predictions.

- Out of those 2211 cases, the classifier predicted “0” 896 times, and “1” 1176 times.

- In reality, 1237 data are legitimate and 974 are phishing.

Basic terms related to Confusion matrix

- **True positives (TP):** These are cases in which we predicted one (legitimate), 1176

- **True negatives (TN):** We predicted zero(phishing) ,896

- **False positives (FP):** We predicted one they ***will*** legitimate, but they are not phishing. (Also known as a “Type I error.”) 78

- **False negatives (FN):** We predicted zero they are ***not*** legitimate, but they actually phishing (Also known as a “Type II error.”), 61

Accuracy: (TP+TN)/Total . Describes overall, how often the classifier correct. i.e. (896+1176)/2211

Neural Network

After splitting the data into train and test with test size 20%.

```
X = df.iloc[:,0:30].values.astype(int)
y = df.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.seed(7))
```

Training data with Neural Network having 3 layers Input layer, hidden layer and output layer with activation relu and sigmoid and compiling the model using binary_crossentropy and Adam optimizer

We build the Model using the Sequential API

```
model = Sequential()

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'))

model.compile(loss='binary_crossentropy', optimizer=Adam(), metrics=['accuracy'])
```

Model Summary:

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 40)                1240
_________________________________________________________________
dense_1 (Dense)              (None, 30)                1230
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 31
=================================================================
Total params: 2,501
Trainable params: 2,501
Non-trainable params: 0
_________________________________________________________________
```

Now we Fit the model on batch size=64, epochs=128 and get the accuracy of 95.75%:

```
# fit the keras model on the dataset
history = model.fit(X_train, y_train, batch_size=64, epochs=128,validation_split=0.05 ,verbose=1, callbacks=[es_cb])
scores = model.evaluate(X_test, y_test)
print('\nAccuracy score of the Neural Network is {0:.2f}%'.format(scores[1]*100))
```

```
132/132 [==============================] - 0s 2ms/step - loss: 0.0928 - accuracy: 0.9591 - val_loss: 0.1350 - val_accurac
y: 0.9413
Epoch 42/128
132/132 [==============================] - 0s 2ms/step - loss: 0.0934 - accuracy: 0.9592 - val_loss: 0.1354 - val_accurac
y: 0.9368
Epoch 43/128
132/132 [==============================] - 0s 2ms/step - loss: 0.0958 - accuracy: 0.9593 - val_loss: 0.1326 - val_accurac
y: 0.9413
Epoch 44/128
132/132 [==============================] - 0s 2ms/step - loss: 0.0969 - accuracy: 0.9586 - val_loss: 0.1372 - val_accurac
y: 0.9436
Epoch 45/128
132/132 [==============================] - 0s 2ms/step - loss: 0.0908 - accuracy: 0.9635 - val_loss: 0.1509 - val_accurac
y: 0.9278
Epoch 46/128
132/132 [==============================] - 0s 2ms/step - loss: 0.0974 - accuracy: 0.9597 - val_loss: 0.1416 - val_accurac
y: 0.9368
70/70 [==============================] - 0s 1ms/step - loss: 0.1141 - accuracy: 0.9575

Accuracy score of the Neural Network is 95.75%
```

Again, Fit the model on batch size=10, epochs=150 and get the accuracy score of 96.47%

```
# fit the keras model on the dataset
model.fit(X_train, y_train, batch_size=10, epochs=150, verbose=1, callbacks=[es_cb])
# make class predictions with the model
predictions = model.predict_classes(X_test)
# summarize the first 5 cases
for i in range(10):
    print('%s => %d (expected %d)' % (X_test[i].tolist(), predictions[i], y_test[i]))
scores = model.evaluate(X_test, y_test)
#print('\nAccuracy score of the Neural Network is {0:.2f}%'.format(scores[1]*100))
```

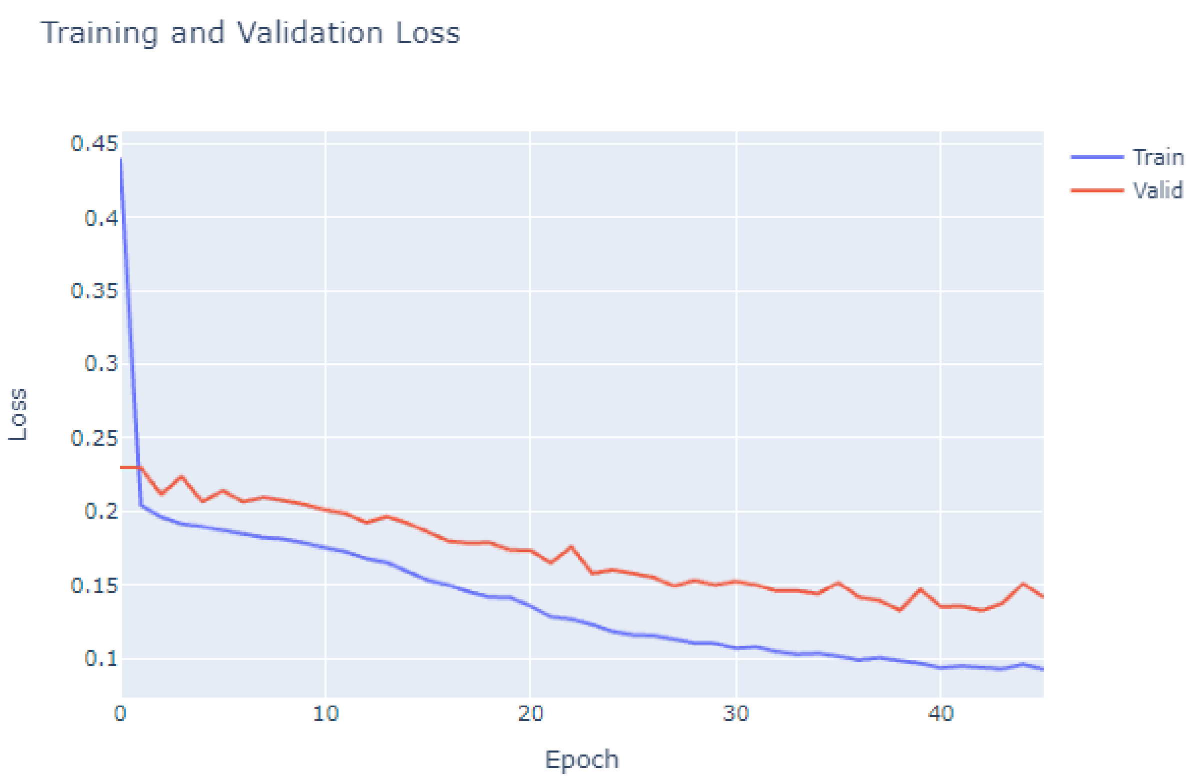
```
885/885 [==============================] - 2s 2ms/step - loss: 0.0465 - accuracy: 0.9783
Epoch 47/150
885/885 [==============================] - 2s 2ms/step - loss: 0.0465 - accuracy: 0.9782
Epoch 48/150
885/885 [==============================] - 2s 2ms/step - loss: 0.0453 - accuracy: 0.9803
Epoch 49/150
885/885 [==============================] - 2s 2ms/step - loss: 0.0465 - accuracy: 0.9793
Epoch 50/150
885/885 [==============================] - 2s 2ms/step - loss: 0.0447 - accuracy: 0.9803
[1, -1, 1, 1, 1, -1, -1, -1, 1, 1, 1, 1, -1, -1, -1, -1, 1, 1, 0, 1, 1, 1, 1, -1, 1, 0, 1, 1, 0, 1] => 0 (expected 0)
[-1, -1, 1, 1, 1, -1, 0, -1, -1, 1, 1, 1, 1, 0, -1, 1, 1, 1, 0, 1, 1, 1, 1, -1, 1, -1, 1, 1, 1, 1] => 0 (expected 0)
[1, -1, 1, -1, 1, -1, -1, -1, -1, 1, 1, 1, -1, 1, -1, -1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, -1, -1, 0, 1] => 0 (expected 0)
[-1, -1, -1, 1, -1, 1, -1, 1, -1, 1, 1, -1, -1, 0, 0, -1, 1, -1, 0, 1, 1, 1, 1, 1, -1, 1, -1, 1, 0, -1] => 1 (expected 1)
[-1, -1, -1, 1, -1, -1, 1, 1, 1, 1, 1, -1, -1, 0, -1, 1, 1, -1, 0, 1, 1, 1, 1, -1, -1, 1, -1, -1, 1, 1] => 1 (expected 1)
[1, -1, 1, 1, 1, 1, -1, 1, -1, -1, -1, 1, -1, 1, 0, -1, -1, 1, 0, 1, 1, -1, -1, -1, 1, -1, -1, 1, 0, 1] => 1 (expected 1)
[-1, -1, 1, 1, 1, 1, 1, 1, -1, 1, 1, 1, 1, 0, -1, 1, 1, 1, 0, 1, 1, 1, 1, -1, 1, 1, -1, 1, 1, 1] => 1 (expected 1)
[1, -1, 1, 1, 1, -1, -1, -1, 1, 1, 1, 1, 1, 0, 0, -1, 1, 1, 0, 1, 1, 1, 1, -1, 1, 1, -1, 1, 1, 1] => 0 (expected 0)
[-1, -1, -1, 1, -1, 1, 0, 1, -1, 1, 1, -1, 1, 0, 0, -1, 1, -1, 0, 1, 1, 1, 1, -1, -1, 1, -1, -1, 1, 1] => 1 (expected 1)
[-1, -1, 1, 1, 1, -1, 0, -1, 1, 1, 1, 1, -1, -1, -1, -1, 1, 1, 0, 1, 1, 1, 1, -1, 1, 0, -1, 1, 0, 1] => 0 (expected 0)
70/70 [==============================] - 0s 1ms/step - loss: 0.0997 - accuracy: 0.9647
```

```
print('\nAccuracy score of the Neural Network is {0:.2f}%'.format(scores[1]*100))
```

```
Accuracy score of the Neural Network is 96.47%
```

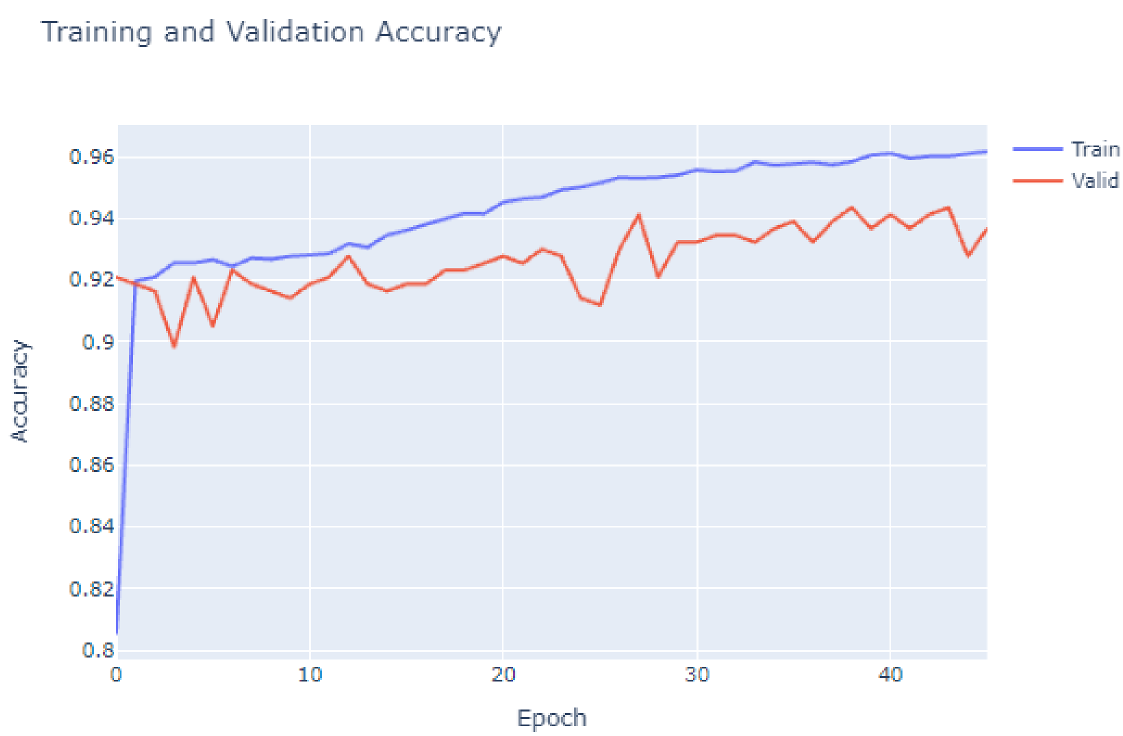
Plot for Training and Validation loss based on number of epoch

```python
import plotly.graph_objects as go
result_plot = go.Figure()
result_plot.add_trace(go.Scattergl(y=history.history['loss'],
                    name='Train'))

result_plot.add_trace(go.Scattergl(y=history.history['val_loss'],
                    name='Valid'))

result_plot.update_layout(height=500, width=700,
                  xaxis_title='Epoch',
                  yaxis_title='Loss',
                  title="Training and Validation Loss")

result_plot.show()
```



Plot for Accuracy Train vs Validation based on number of epoch

```
result_plot = go.Figure()
result_plot.add_trace(go.Scattergl(y=history.history['accuracy'],
                    name='Train'))
result_plot.add_trace(go.Scattergl(y=history.history['val_accuracy'],
                    name='Valid'))
result_plot.update_layout(height=500, width=700,
                  xaxis_title='Epoch',
                  yaxis_title='Accuracy',
                  title="Training and Validation Accuracy")

result_plot.show()
```



We can see that when we Fit the model on batch size=64, epochs=128, then we get 95.75% accuracy. Similarly, when we Fit the model on batch size=10, epochs=150, then we get 96.47% accuracy

K-Means Clustering

we are going to implement Unsupervised Machine Learning Algorithm i.e., K-Means Clustering algorithm.

Applying K-Means with cluster 2 on independent variables and dropping target column "Result" and fitting data on K means clustering model:

```
In [31]:  from sklearn.cluster import KMeans
          X_sup = df_unsup.drop(['Result'], axis=1)
          y_sup = df_unsup['Result']
          kmeans = KMeans(n_clusters=2, random_state=None)
          kmeans.fit(X_sup)

Out[31]: KMeans(n_clusters=2)
```

Comparing Predicted clustering group with original target column i.e. "Result"

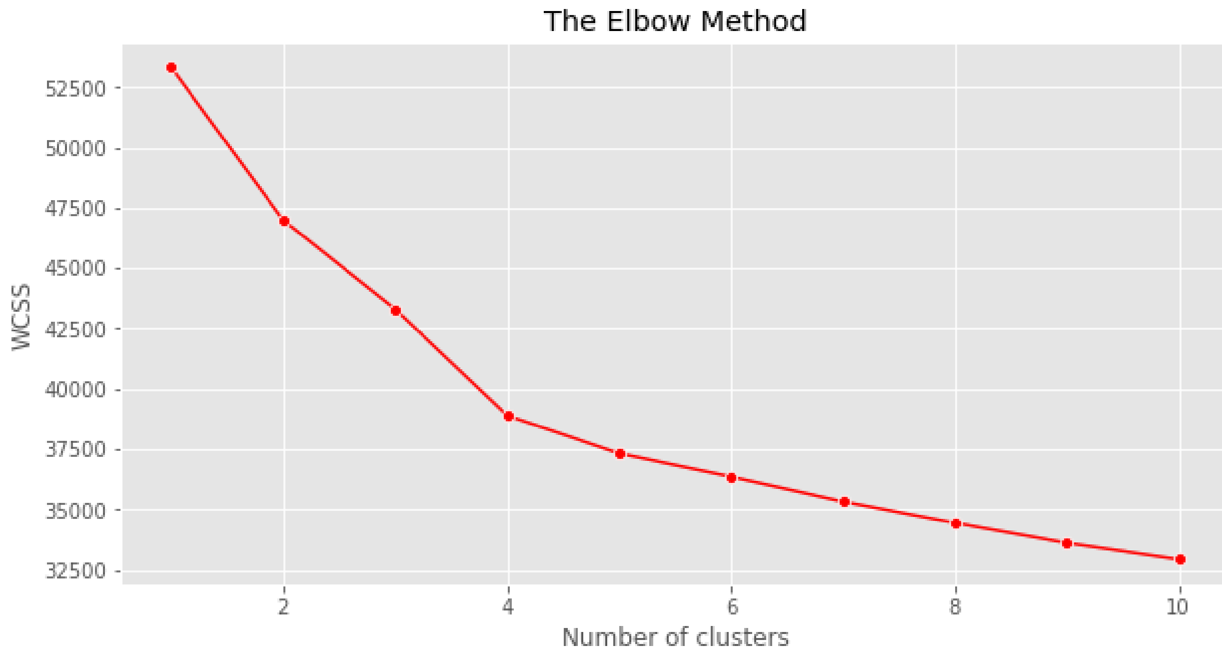
```
In [33]:  clusters = kmeans.predict(X_sup)

In [34]:  clusters

Out[34]: array([0, 1, 0, ..., 1, 0, 1])
```

Using the Elbow method to find the optimal number of clusters:

```
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
    kmeans.fit(X_sup)
    #inertia method returns wcss for that model
    wcss.append(kmeans.inertia_)
```

Plotting for Elbow Method below and we can see K=2 is an optimal value

```
plt.figure(figsize=(10,5))
sns.lineplot(range(1, 11), wcss,marker='o',color='red')
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



Fitting K-Means to the dataset for 2 clusters

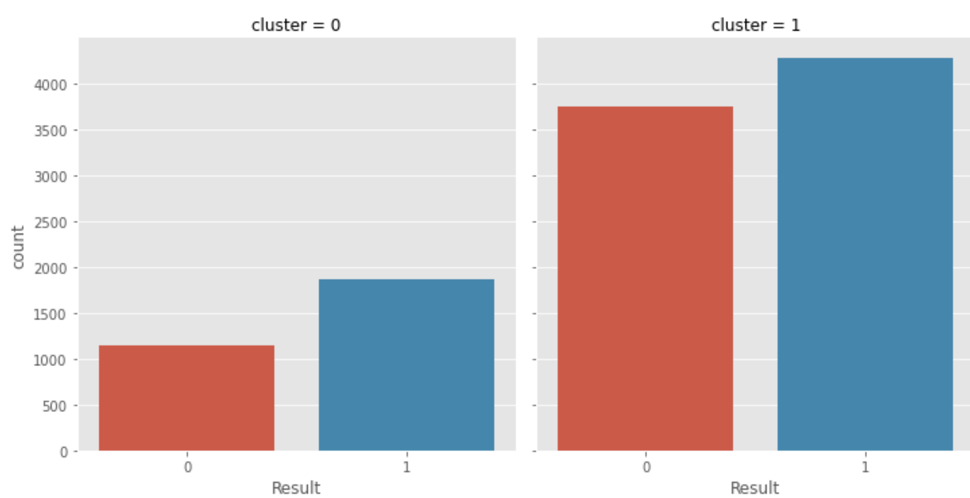
In [37]:

```
kmeans_2 = KMeans(n_clusters = 2, init = 'k-means++', random_state = 42)
y_kmean = kmeans_2.fit_predict(X_sup)
```

Plotting the Clusters:

As per below diagram there are 2 clusters and for each cluster, we have count of Result containing 0 and 1

For Cluster 0 we can see Result having 0 count is around 1200 while having 1 is around 1800
Similarly for Cluster 1 we can see Result having 0 count is 3700 while having 1 is around 4500

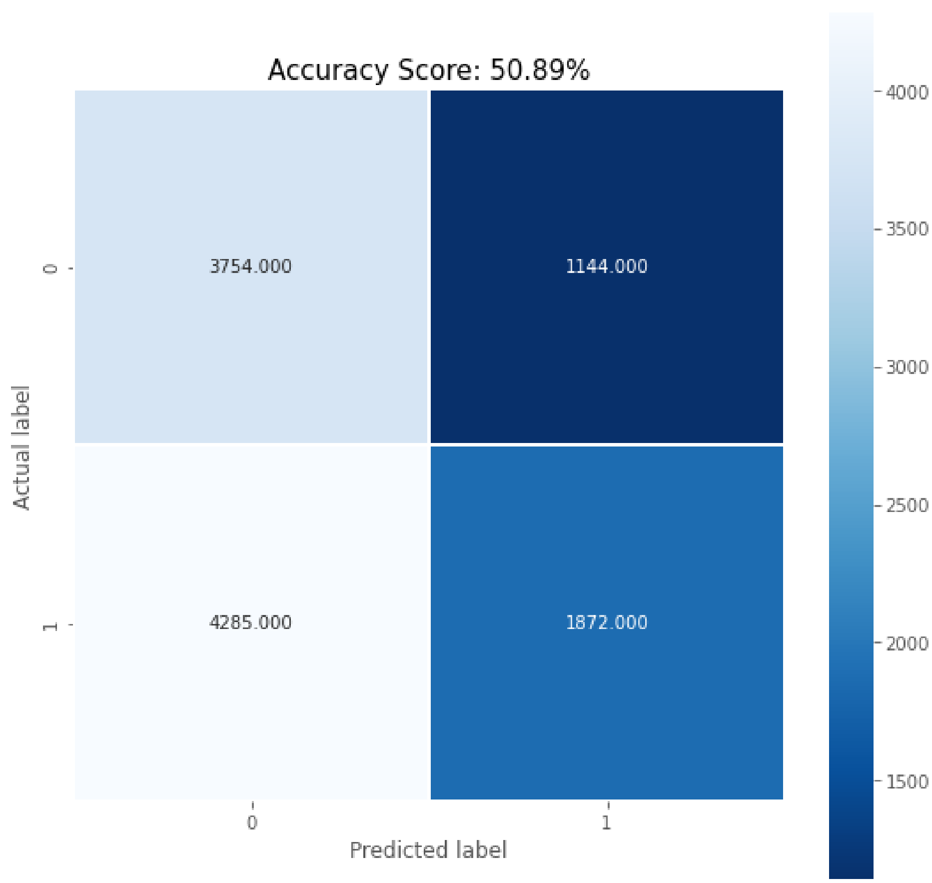


Calculate the Accuracy Score:

```
print('Accuracy Score: {0:.2f}%'.format(accuracy_score(y_sup, kmeans_2.fit_predict(X_sup))*100.))
print('\n')
print('Accuracy score of the K-Means Clustering Classifier {0:.2f}%'
      .format(accuracy_score(y_sup, kmeans_2.fit_predict(X_sup))*100.))
print('\n')
print('*****Classification report of the K-Means Clustering classifier*****')
print('\n')
print(classification_report(y_sup, kmeans_2.fit_predict(X_sup),target_names=['Phishing Websites', 'Normal Websites']))
```

```
Accuracy Score: 50.89%


Accuracy score of the K-Means Clustering Classifier 50.89%


*****Classification report of the K-Means Clustering classifier*****


                   precision    recall  f1-score   support

Phishing Websites       0.47      0.77      0.58      4898
  Normal Websites       0.62      0.30      0.41      6157

         accuracy                           0.51     11055
        macro avg       0.54      0.54      0.49     11055
     weighted avg       0.55      0.51      0.48     11055
```

Confusion Matrix:



The Confusion Matrix tells us the following:

• There are two possible predicted classes: 0 and 1. If we were predicting that the website is, for example, 0 mean phishing, and 1 means legitimate.

• The classifier made a total of 11055 predictions.

• Out of those 11055 cases, the classifier predicted “0” 3754 times, and “1” 1872 times.

• In reality, 6157 data are legitimate and 4898 are phishing.

Basic terms related to Confusion matrix:

- **True positives (TP):** These are cases in which we predicted one (legitimate), 1872
- **True negatives (TN):** We predicted zero(phishing), 3754
- **False positives (FP):** We predicted one they will legitimate, but they are not phishing. (Also known as a “Type I error.”), 1144
- **False negatives (FN):** We predicted zero they are not legitimate, but they actually phishing (Also known as a “Type II error.”), 4285

Accuracy: (TP+TN)/Total. Describes overall, how often the classifier correct. i.e. (3754+1872)/11055

Therefore, the accuracy score is 50.89%

Whenever we think about unsupervised machine learning algorithm, the first algorithm comes in our mind is K-means Clustering. As K-means clustering works efficiently only for numerical dataset. We don’t get proper results for the categorical data because of the improper spatial representation. K-means Clustering fails to find patterns in the categorical dataset. So, K-modes clustering comes into the picture.

In next step we are going to implement K-modes clustering algorithm.

K-Modes Clustering

K-modes is used for clustering categorical variables. It defines clusters based on the number of matching categories between data points. (This contrasts with the more well-known k-means algorithm, which clusters numerical data based on Euclidean distance.)

Implemented are:

• k-modes with initialization based on density Cao

• k-modes using Huang

Fitting K-Mode with "Cao" initialization with 2 Clusters

```
km_cao = KModes(n_clusters=2, init = "Cao", n_init = 1, verbose=1)
fitClusters_cao = km_cao.fit_predict(X_sup)
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 316, cost: 70230.0
Run 1, iteration: 2/100, moves: 161, cost: 70230.0
```

Fitting K-Mode with "Huang" initialization with 2 clusters

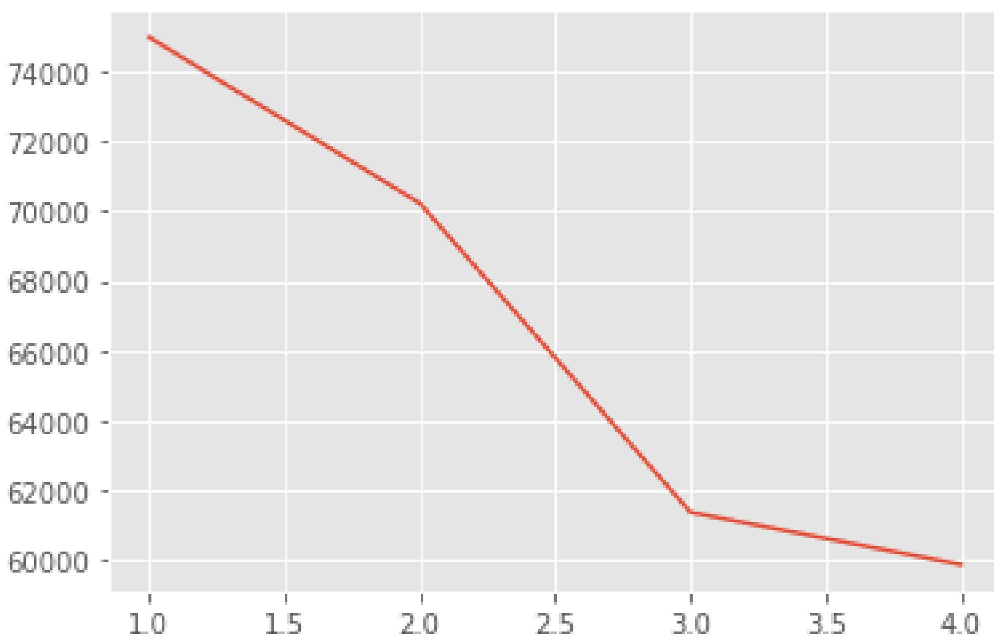
```
km_huang = KModes(n_clusters=2, init = "Huang", n_init = 1, verbose=1)
fitClusters_huang = km_huang.fit_predict(X_sup)
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 2291, cost: 76409.0
Run 1, iteration: 2/100, moves: 504, cost: 76409.0
```

Determining and plotting the optimum value of k using cost function by using "Cao" initialization

```
cost = []
for num_clusters in list(range(1,5)):
    kmode = KModes(n_clusters=num_clusters, init = "Cao", n_init = 1, verbose=1)
    kmode.fit_predict(X_sup)
    cost.append(kmode.cost_)
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 0, cost: 75004.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 316, cost: 70230.0
Run 1, iteration: 2/100, moves: 161, cost: 70230.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 1277, cost: 61352.0
Run 1, iteration: 2/100, moves: 307, cost: 61352.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 1510, cost: 59846.0
Run 1, iteration: 2/100, moves: 238, cost: 59846.0
```

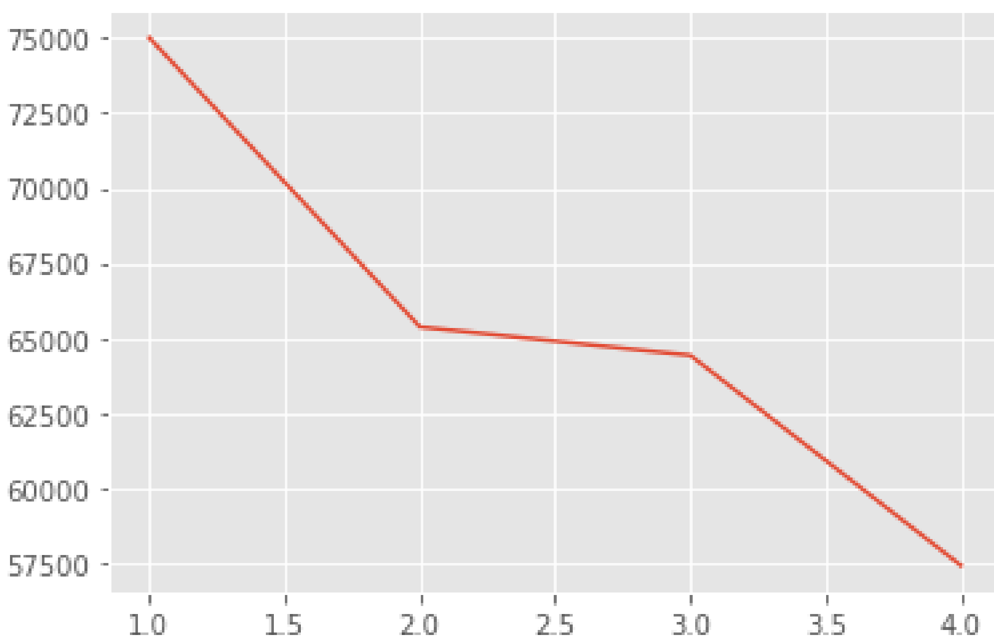


From above graph we can see that the optimum value of K is 2

Determining and plotting the optimum value of k using cost function by using " Huang" initialization

```python
cost_H = []
for num_clusters_H in list(range(1,5)):
    kmode_H = KModes(n_clusters=num_clusters_H, init = "Huang", n_init = 1, verbose=1)
    kmode_H.fit_predict(X_sup)
    cost_H.append(kmode_H.cost_)
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 0, cost: 75004.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 1963, cost: 66628.0
Run 1, iteration: 2/100, moves: 2221, cost: 65374.0
Run 1, iteration: 3/100, moves: 346, cost: 65374.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 1485, cost: 64426.0
Run 1, iteration: 2/100, moves: 193, cost: 64426.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 2620, cost: 57776.0
Run 1, iteration: 2/100, moves: 1357, cost: 57424.0
Run 1, iteration: 3/100, moves: 118, cost: 57424.0
```

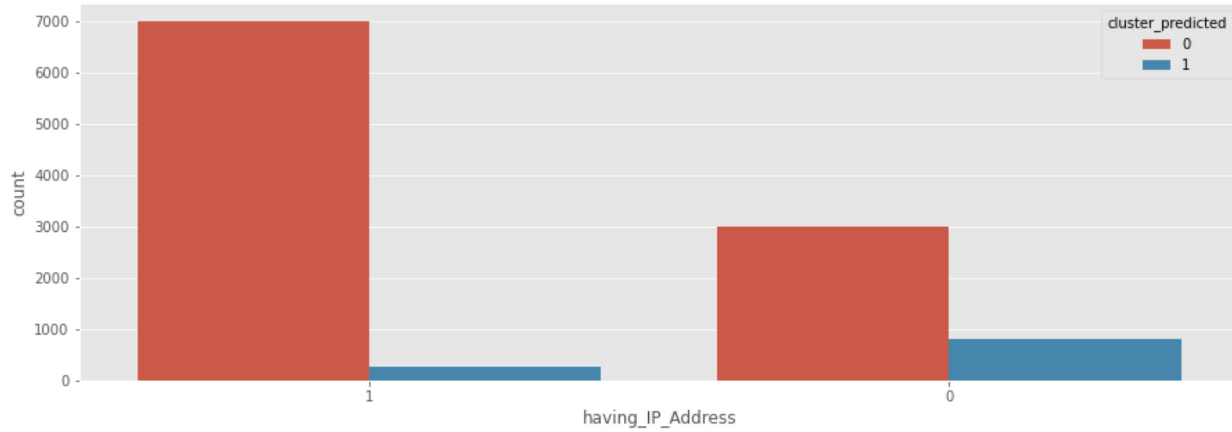


From above graph we can see that the optimum value of K is 2

Combining dataset for actual and predicted one for Cao Initialization:

```
clustersDf = pd.DataFrame(fitClusters_cao)
clustersDf.columns = ['cluster_predicted']
combinedDf = pd.concat([X_sup, clustersDf], axis = 1).reset_index()
combinedDf = combinedDf.drop(['index', 'level_0'], axis = 1)
```

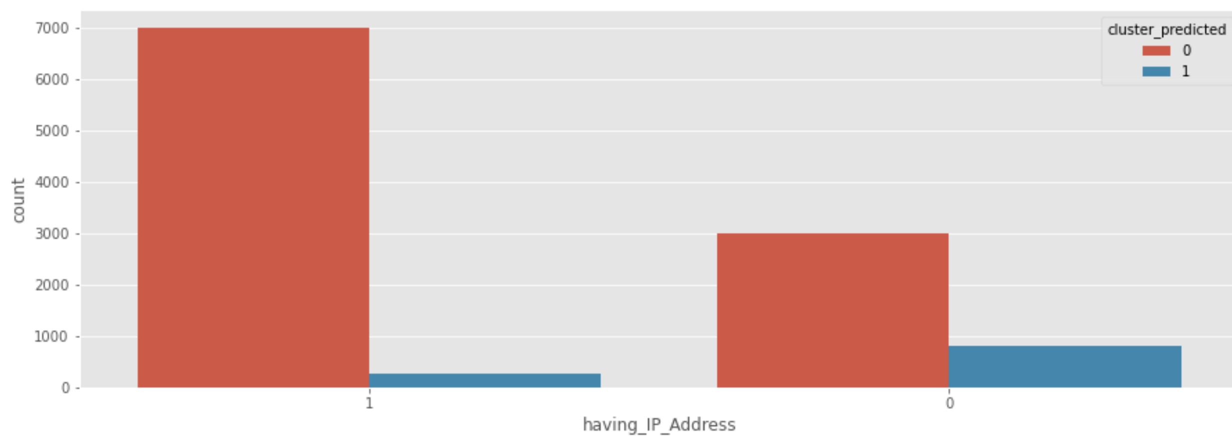
Plotting for cluster “having_IP_Address”:



Combining dataset for actual and predicted one for Cao Initialization:

```
clustersDf_H = pd.DataFrame(fitClusters_huang)
clustersDf_H.columns = ['cluster_predicted']
combinedDf_H = pd.concat([X_sup, clustersDf], axis = 1).reset_index()
combinedDf_H = combinedDf_H.drop(['index', 'level_0'], axis = 1)
```

Plotting for cluster “having_IP_Address”:



Accuracy Score for Cao Initialization:

```
print('Accuracy Score: {0:.2f}%'
      .format(accuracy_score(y_sup, km_cao.fit_predict(X_sup))*100.))
print('\n')
print('Accuracy Score: {0:.2f}%'
      .format(accuracy_score(y_sup, km_cao.fit_predict(X_sup))*100.))
print('\n')
print('*****Classification report of the K-Mode Clustering classifier*****')
print('\n')
print(classification_report(y_sup, km_cao.fit_predict(X_sup),
                            target_names=['Phishing Websites', 'Normal Websites']))
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 316, cost: 81283.0
Run 1, iteration: 2/100, moves: 161, cost: 81283.0
Accuracy Score: 41.61%


Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 316, cost: 81283.0
Run 1, iteration: 2/100, moves: 161, cost: 81283.0
Accuracy Score: 41.61%


*****Classification report of the K-Mode Clustering classifier*****


Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 316, cost: 81283.0
Run 1, iteration: 2/100, moves: 161, cost: 81283.0
                   precision    recall  f1-score   support

Phishing Websites       0.42      0.86      0.57      4898
  Normal Websites       0.36      0.06      0.11      6157

         accuracy                           0.42     11055
        macro avg       0.39      0.46      0.34     11055
     weighted avg       0.39      0.42      0.31     11055
```

Accuracy Score for Huang Initialization:

```
print('Accuracy Score: {0:.2f}%'
      .format(accuracy_score(y_sup, km_huang.fit_predict(X_sup))*100.))
print('\n')
print('Accuracy Score: {0:.2f}%'
      .format(accuracy_score(y_sup, km_huang.fit_predict(X_sup))*100.))
print('\n')
print('*****Classification report of the K-Mode Clustering classifier*****')
print('\n')
print(classification_report(y_sup, km_huang.fit_predict(X_sup),
                            target_names=['Phishing Websites', 'Normal Websites']))
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 2062, cost: 76444.0
Accuracy Score: 79.38%


Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 2604, cost: 82454.0
Accuracy Score: 49.24%


*****Classification report of the K-Mode Clustering classifier*****


Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 2660, cost: 76487.0
Run 1, iteration: 2/100, moves: 1233, cost: 76444.0
Run 1, iteration: 3/100, moves: 648, cost: 76444.0
                   precision    recall  f1-score   support

Phishing Websites       0.25      0.37      0.30      4898
  Normal Websites       0.19      0.12      0.14      6157

         accuracy                           0.23     11055
        macro avg       0.22      0.24      0.22     11055
     weighted avg       0.22      0.23      0.21     11055
```

Accuracy score of Cao Initialization clusters is 41.61%, and the Accuracy score of Huang Initialization clusters is 79.38%.

Comparison of the two phases:

We have implemented supervised as well as unsupervised machine learning algorithm, now we are evaluating which algorithm is giving accurate result.

SR No.	Algorithm	Supervised or Unsupervised	Accuracy
1.	Logistic Regression	Supervised	93.71%
2.	Neural Network	Supervised	96.47%
3.	K-Means Clustering	Unsupervised	50.89%
4.	K-Modes Clustering	Unsupervised	79.38%

In above table we can see that both supervised machine learning algorithm Logistic Regression and Neural network giving better accuracy than the unsupervised machine learning algorithms K-means and K-modes clustering.

Comparison with other researchers who have worked on the same dataset:

I learnt from the reference research Paper about assessment of features related to phishing using an automated technique. As per the researcher there are some characteristics that distinguish phishing websites from legitimate ones such as long URL, IP address in URL, adding prefix and suffix to domain and request URL adding prefix and suffix to domain and request URL, etc. In this paper they explore important features that are automatically extracted from websites using a new tool instead of relying on an experienced human in the extraction process and then judge on the features importance in deciding website legitimacy. I used machine learning technique which automatically predict is the website phishing or not considering by using website data to trained the model. Also, my model provide accuracy for the test data.

References:

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3. http://www.antiphishing.org/trendsreports/

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5.https://www.researchgate.net/publication/261081735_An_assessment_of_features_related_to_phishing_websites_using_an_automated_technique

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