# Online shopping intention analysis

April 2, 2021

```
[58]: import pandas as pd
      import numpy as np
      import seaborn as sns
      import matplotlib.pyplot as plt
      import plotly as py
      import plotly.graph_objs as go
```

```
[59]: data= pd.read_csv('online_shoppers_intention.csv')
```

```
[60]: data.head()
```

```
[60]:    Administrative  Administrative_Duration  Informational  \
      0             0.0                      0.0            0.0
      1             0.0                      0.0            0.0
      2             0.0                     -1.0            0.0
      3             0.0                      0.0            0.0
      4             0.0                      0.0            0.0

         Informational_Duration  ProductRelated  ProductRelated_Duration  \
      0                     0.0             1.0                 0.000000
      1                     0.0             2.0                64.000000
      2                    -1.0             1.0                -1.000000
      3                     0.0             2.0                 2.666667
      4                     0.0            10.0               627.500000

         BounceRates  ExitRates  PageValues  SpecialDay Month  OperatingSystems  \
      0         0.20       0.20         0.0         0.0   Feb                 1
      1         0.00       0.10         0.0         0.0   Feb                 2
      2         0.20       0.20         0.0         0.0   Feb                 4
      3         0.05       0.14         0.0         0.0   Feb                 3
      4         0.02       0.05         0.0         0.0   Feb                 3

         Browser  Region  TrafficType        VisitorType  Weekend  Revenue
      0        1       1            1  Returning_Visitor    False    False
      1        2       1            2  Returning_Visitor    False    False
      2        1       9            3  Returning_Visitor    False    False
      3        2       2            4  Returning_Visitor    False    False
      4        3       1            4  Returning_Visitor     True    False
```

[61]:

```
data.shape
```

[61]:

```
(12330, 18)
```

[62]:

```
data.columns
```

[62]:

```
Index(['Administrative', 'Administrative_Duration', 'Informational',
       'Informational_Duration', 'ProductRelated', 'ProductRelated_Duration',
       'BounceRates', 'ExitRates', 'PageValues', 'SpecialDay', 'Month',
       'OperatingSystems', 'Browser', 'Region', 'TrafficType', 'VisitorType',
       'Weekend', 'Revenue'],
      dtype='object')
```

[63]:

```
missing =data.isnull().sum()
missing
```

[63]:

```
Administrative             14
Administrative_Duration    14
Informational              14
Informational_Duration     14
ProductRelated             14
ProductRelated_Duration    14
BounceRates                14
ExitRates                  14
PageValues                  0
SpecialDay                  0
Month                       0
OperatingSystems            0
Browser                     0
Region                      0
TrafficType                 0
VisitorType                 0
Weekend                     0
Revenue                     0
dtype: int64
```

[64]:

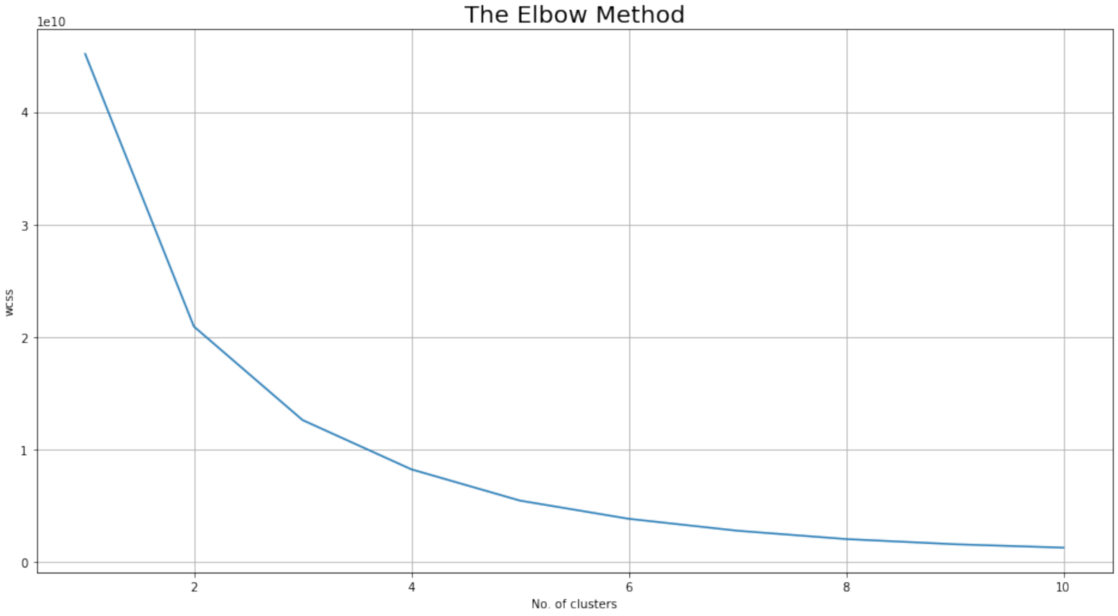
```
data.fillna(0,inplace=True)
```

[65]:

```
#Now have a look at product related bounce rates of customers:
x=data.iloc[:,[5,6]].values
```

[66]:

```
#Applying K-elbow method to determine the number of clustering groups

from sklearn.cluster import KMeans

wcss=[]  # with in cluster sum of squares
for i in range(1,11):
    km=KMeans(n_clusters= i, init␣
↪='k-means++',max_iter=300,n_init=10,random_state=0,algorithm='full',tol=0.
↪001)
    km.fit(x)
    labels=km.labels_
    wcss.append(km.inertia_)

plt.rcParams['figure.figsize']=(13,7)
plt.plot(range(1,11),wcss)
plt.grid()
plt.tight_layout()
plt.title('The Elbow Method',fontsize=20)
plt.xlabel('No. of clusters')
plt.ylabel('wcss')
plt.show()
```

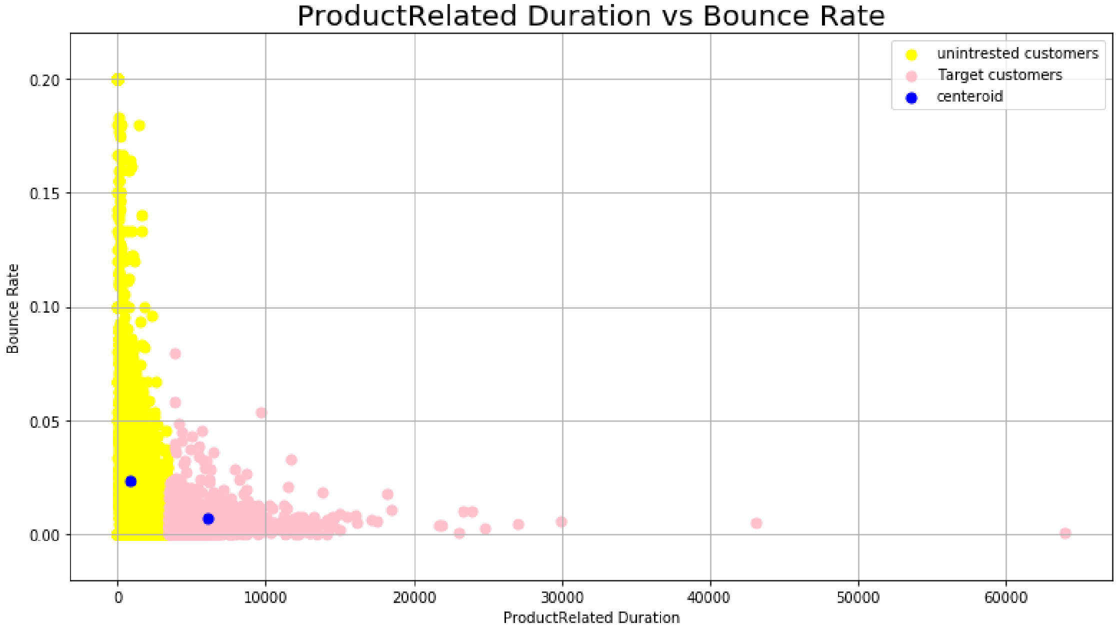


# 1 K Means Clustering

According to the graph above, the maximum curvature is at the second index, that is, the number of optimal clustering groups for the duration of the product and the bounce rates is 2. Once the number of clusterings determined, we apply the K Means method and plot the clusters:

```
[67]: km=KMeans(n_clusters=2,init='k-means++',max_iter=300,n_init=10,random_state=0)

      #get predicted customer index for  each sample:0,1,2
      y_means=km.fit_predict(x)
```

```
plt.scatter(x[y_means==0,0],x[y_means==0,1],s=50,c='yellow',label='unintrested␣
 ↪customers')
plt.scatter(x[y_means==1,0],x[y_means==1,1],s=50,c='pink',label='Target␣
 ↪customers')
plt.scatter(km.cluster_centers_[:,0],km.cluster_centers_[:
 ↪,1],s=50,c='blue',label='centeroid')

plt.title('ProductRelated Duration vs Bounce Rate',fontsize=20)
plt.grid()
plt.xlabel('ProductRelated Duration')
plt.ylabel('Bounce Rate')
plt.legend()
plt.show()
```



#Looking at this K Means grouping plot, we can say with certainty that customers who spent more time on a product-related website are very less likely to leave the website after viewing a single page.

Since K-Means is not a supervised learning method, we are adopting other ways of evaluating its clustering result. The leftmost column of the confusion matrix represents the actual label (True or False revenue), and the top row represents the expected clustering groups (uninterested customers or target customers):

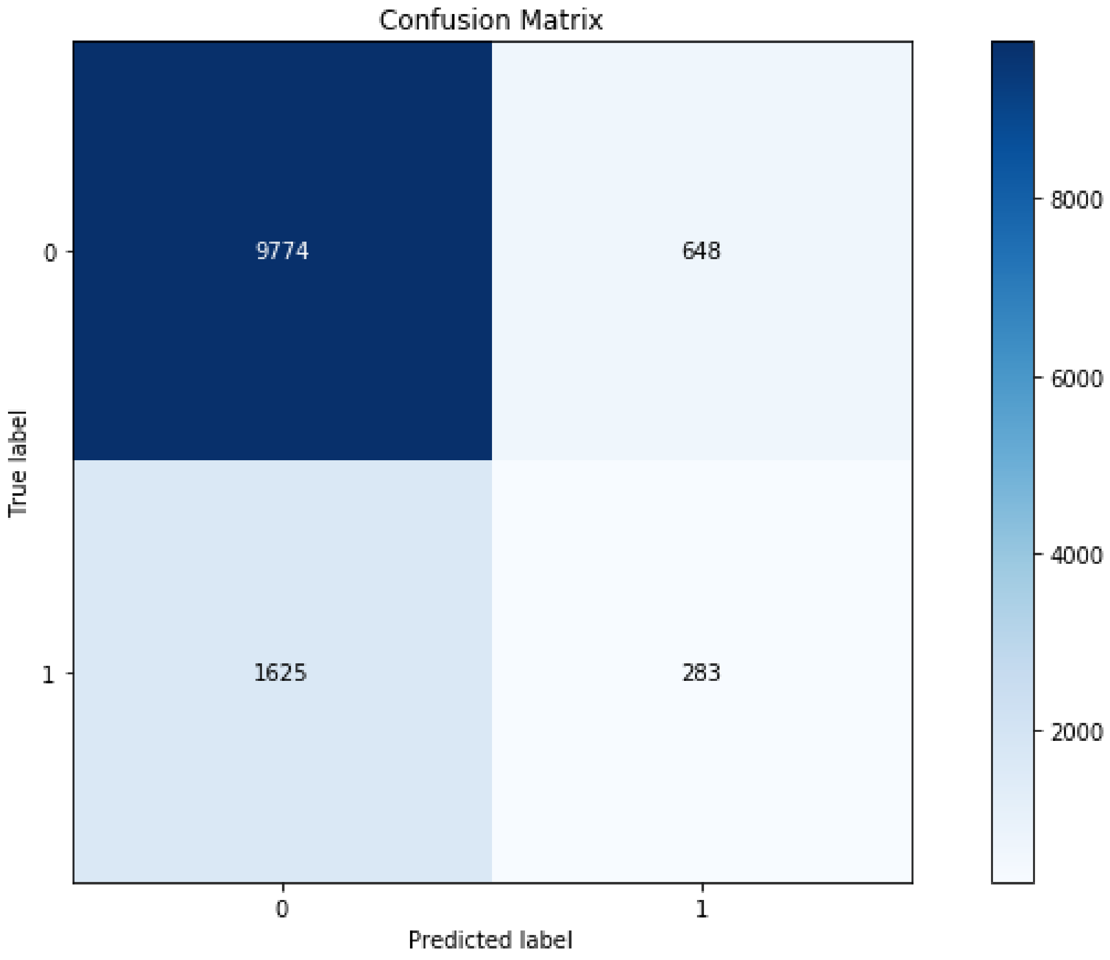
```
[68]: from sklearn.preprocessing import LabelEncoder
      le = LabelEncoder()
      labels_true=le.fit_transform(data['Revenue'])
```

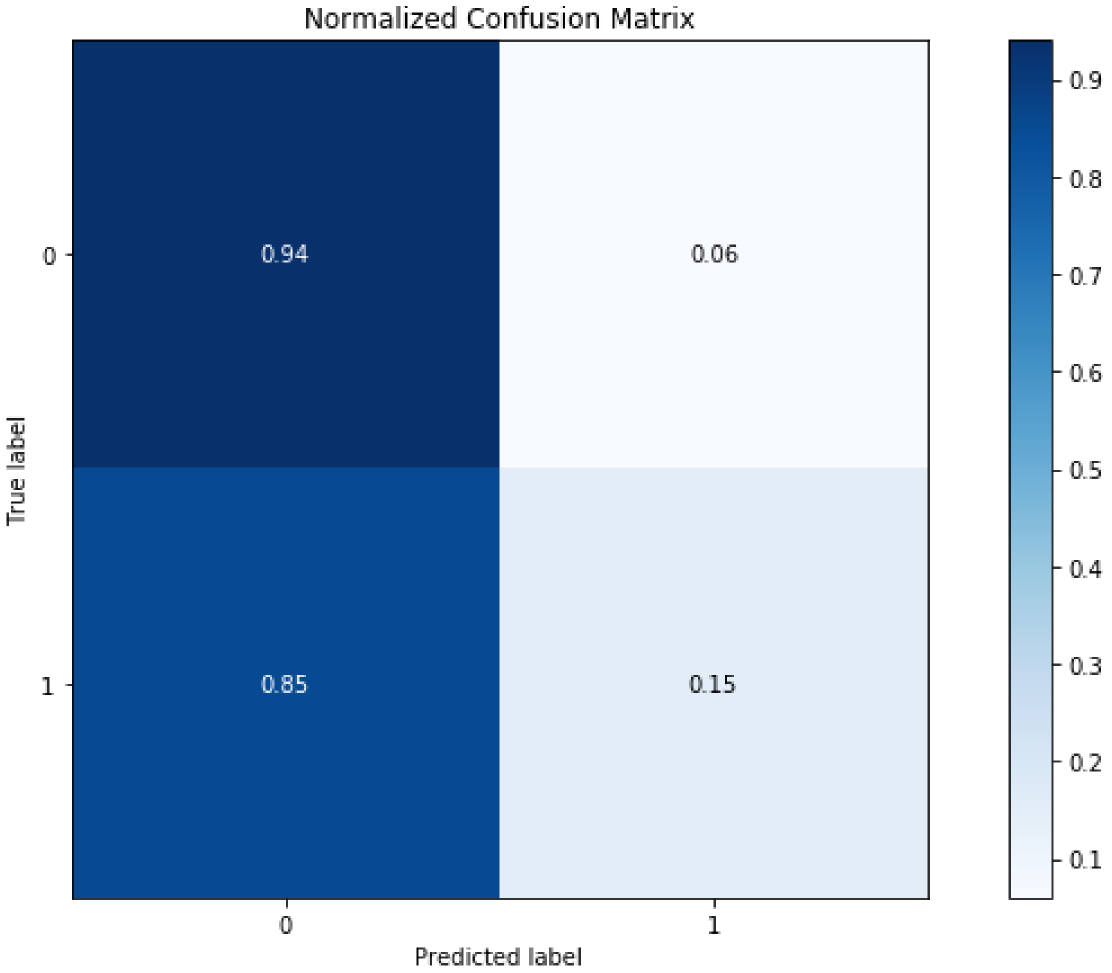
```
#get predicted clustering result label
labels_pred =y_means

# print adjusted rand index, which measures the similarity of the two␣
 ↪assignments
from sklearn import metrics
score = metrics.adjusted_rand_score(labels_true,labels_pred)
print('Adjusted rand index:')
print(score)
```

```
Adjusted rand index:
0.08359442469281109
```

[69]:

```
import scikitplot as skplt
plt_1 = skplt.metrics.plot_confusion_matrix(labels_true, labels_pred,␣
 ↪normalize=False)
plt_2 = skplt.metrics.plot_confusion_matrix(labels_true, labels_pred,␣
 ↪normalize=True)
```





## 2 Observations from above plots:

From the confusion matrix, we can see that out of 10,422 failed incomes, 9,769 are grouped into uninterested customers or 94%. However, out of 937 successful incomes, only 284 are grouped as target customers or 15%. Also, the adjusted index score is not very high

```
[ ]:
```