Analysis of data to explore marketing outcome

The objective of this analysis is to optimise the marketing efforts by determining the likelihood of customers purchasing term deposits based on the previous data, there by increasing the hit ratio.

We will import all the packages required for this analysis, at the outset.

In [117]:

```
%matplotlib inline
import numpy as np
import pandas as pd
from pandas import Series,DataFrame
import matplotlib.pyplot as plt
from scipy.stats import chi2_contingency
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn import model_selection, metrics, preprocessing
from sklearn.preprocessing import LabelEncoder
from sklearn.naive_bayes import GaussianNB


bank_df = pd.read_csv("bank-full.csv");
bank_df.head()
```

Out[117]:

	age	job	marital	education	default	balance	housing	loan	contact	day	mor
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	m
1	44	technician	single	secondary	no	29	yes	no	unknown	5	m
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	m
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	m
4	33	unknown	single	unknown	no	1	no	no	unknown	5	m

In [118]:

```
bank_df.dtypes
```

Out[118]:

```
age            int64
job           object
marital       object
education     object
default       object
balance        int64
housing       object
loan          object
contact       object
day            int64
month         object
duration       int64
campaign       int64
pdays          int64
previous       int64
poutcome      object
Target        object
dtype: object
```

As we can see, there are many non-numerical columns in the dataset. Let's ascertain the unique values in these columns inorder to understand the data.

In [119]:

```
for col in ['job', 'marital', 'education', 'default','housing',
            'loan','contact','day','month','poutcome','Target']:
    print(f'Unique values in column {col} are : {bank_df[col].unique()}\n')
```

```
Unique values in column job are : ['management' 'technician' 'entrep
reneur' 'blue-collar' 'unknown'
 'retired' 'admin.' 'services' 'self-employed' 'unemployed' 'housema
id'
 'student']

Unique values in column marital are : ['married' 'single' 'divorce
d']

Unique values in column education are : ['tertiary' 'secondary' 'unk
nown' 'primary']

Unique values in column default are : ['no' 'yes']

Unique values in column housing are : ['yes' 'no']

Unique values in column loan are : ['no' 'yes']

Unique values in column contact are : ['unknown' 'cellular' 'telepho
ne']

Unique values in column day are : [ 5  6  7  8  9 12 13 14 15 16 19
20 21 23 26 27 28 29 30  2  3  4 11 17
 18 24 25  1 10 22 31]

Unique values in column month are : ['may' 'jun' 'jul' 'aug' 'oct'
'nov' 'dec' 'jan' 'feb' 'mar' 'apr' 'sep']

Unique values in column poutcome are : ['unknown' 'failure' 'other'
'success']

Unique values in column Target are : ['no' 'yes']
```

While some of the column headings are evident, some are abstract. Let's explore what each of the column means in detail.

Description of the bank client data:

Data related to the customer

age (numeric) Age of the customer in years.

job : type of job the customer is in (categorical: 'management', 'technician', 'entrepreneur', 'blue-collar', 'unknown', 'retired', 'admin.', 'services', 'self-employed', 'unemployed', 'housemaid', 'student'

marital : marital status (categorical: married, single, divorced) (Widowed is not specified. We will presume it comes under single.)

education (categorical: primary, secondary, tertiary, unknown)

balance Average balance maintained in the account

default : Whether the customer has defaulted credit/loan previously? (categorical: yes,no)

housing: Whether the customer has housing loan? (categorical: yes,no)

loan: Whether the customer has personal loan? (categorical: yes,no)

Data related to current campaign

contact : contact communication type (categorical: 'cellular','telephone','unknown')

day : Day of the month of last contact

month : last contact month of year (categorical: jan to dec)

duration : last contact duration, in seconds (numeric).

campaign : number of contacts performed during this campaign and for this customer

Data related to previous campaign

pdays : number of days that passed by after the customer was last contacted from a previous campaign. -1 means the client was not contacted before.

previous: number of contacts performed before this campaign and for this customer

poutcome: Outcome of the previous marketing campaign (categorical: success, failure, unknown, other)

target Whether the customer could be successfully marketed to or not. In other words, whether or not the customer availed term deposit.

In [120]:

```
print(f"Maximum days lapsed since contact for previous campaign ", bank_df.pdays
.max())
print(f"Minimum days lapsed since contact for previous campaign ", bank_df.pdays
.min())

"""
Ascertaining the number of customers where the previous outcome
is unknown though a previous contact was made
"""
print("Number of customers where previous outcome is 'unknown' though contact wa
s made is ",bank_df['previous'][bank_df['poutcome'] == "unknown"][bank_df['previ
ous'] != 0].count())


"""
Ascertaining the number of customers where the previous outcome
is others though a previous contact was made
"""
print("Number of customers where previous outcome is 'other' though contact was
 made is ",bank_df['previous'][bank_df['poutcome'] == "other"][bank_df['previou
s'] != 0].count())
```

```
Maximum days lapsed since contact for previous campaign  871
Minimum days lapsed since contact for previous campaign  -1
Number of customers where previous outcome is 'unknown' though conta
ct was made is  5
Number of customers where previous outcome is 'other' though contact
was made is  1840
```

In [121]:

```
bank_df.dtypes
```

Out[121]:

```
age           int64
job          object
marital      object
education    object
default      object
balance       int64
housing      object
loan         object
contact      object
day           int64
month        object
duration      int64
campaign      int64
pdays         int64
previous      int64
poutcome     object
Target       object
dtype: object
```

In [122]:

```
bank_df.describe().transpose()
```

Out[122]:

	count	mean	std	min	25%	50%	75%	max
age	45211.0	40.936210	10.618762	18.0	33.0	39.0	48.0	95.0
balance	45211.0	1362.272058	3044.765829	-8019.0	72.0	448.0	1428.0	102127.0
day	45211.0	15.806419	8.322476	1.0	8.0	16.0	21.0	31.0
duration	45211.0	258.163080	257.527812	0.0	103.0	180.0	319.0	4918.0
campaign	45211.0	2.763841	3.098021	1.0	1.0	2.0	3.0	63.0
pdays	45211.0	40.197828	100.128746	-1.0	-1.0	-1.0	-1.0	871.0
previous	45211.0	0.580323	2.303441	0.0	0.0	0.0	0.0	275.0

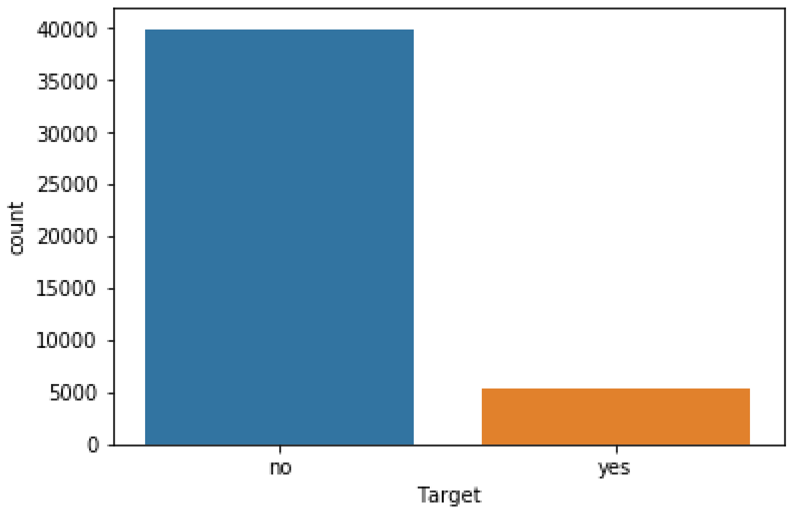
In [123]:

```
positive = len(bank_df.loc[bank_df['Target'] == 'yes'])
negative = len(bank_df.loc[bank_df['Target'] == 'no'])
print("Number of positive cases: {0} ".format(positive))
print("Number of negative cases: {0}".format(negative))

sns.countplot(bank_df['Target'])
```

```
Number of positive cases: 5289
Number of negative cases: 39922
```

Out[123]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a6a4e02b0>
```



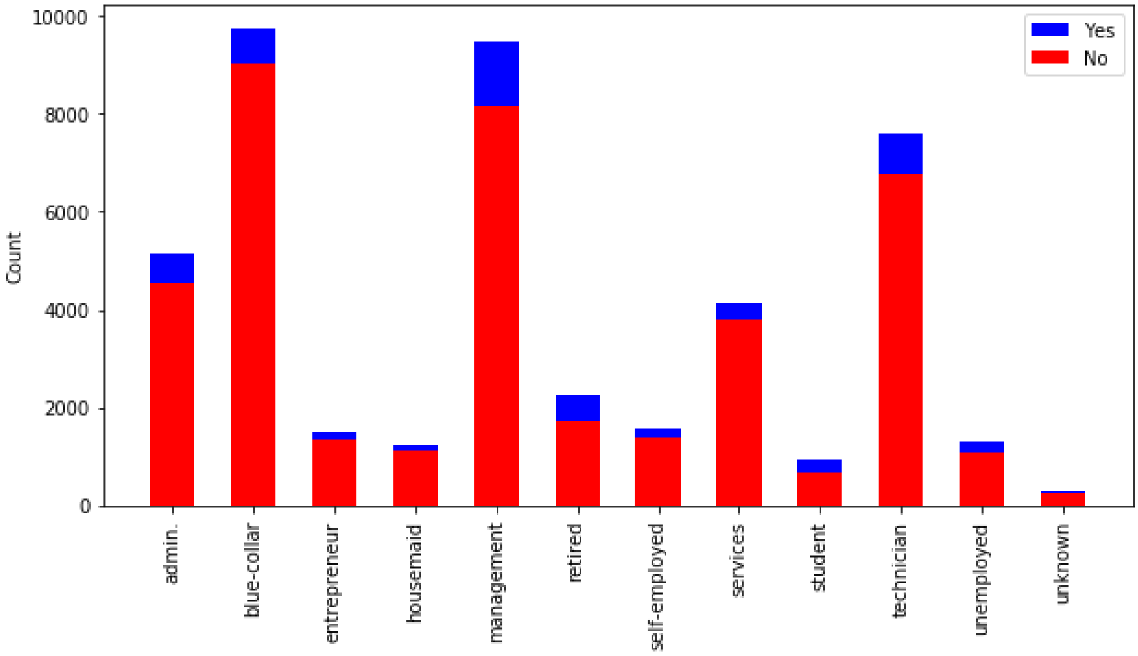
From the graph and the values printed above, it is evidently clear that the data set is highly imbalanced.

Before balancing the dataset, let's keep the dataset as is and explore it. The dataset has many values which are actually categorical. We will convert these in categorical type and then let's perform Chi square test between each of the categorical values and the outcome. The null hypothesis will be that the two are completely independent and there is no correlation between the two. But if the p value is less than .05, we have to reject the null hypothesis and infer that there is a correlation between the variables. We will create a copy of the original dataset to do all transformation and analysis.

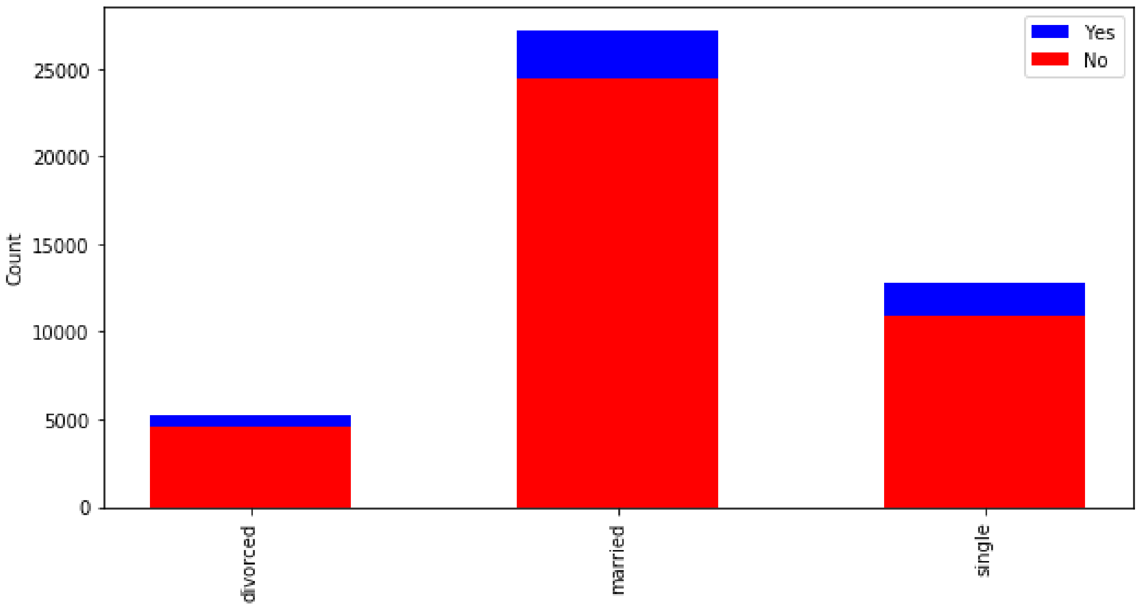
In [124]:

```
bank_df_workingcopy = bank_df.copy()

bank_df_workingcopy.columns = ["Age","Employment","MaritalStatus","Education","D
efaulter","Balance",
                   "HousingLoan","PersonalLoan","Contact","LastContact_DayOfMont
h",
                   "LastContact_Month","DurationOfCall","No.OfContactsMade",
                   "DaysSincePrevContact","TimesPreviouslyContacted","PreviousOu
tcome","Outcome"]


for col in ['Employment','MaritalStatus','Education','Defaulter','HousingLoan',
            'PersonalLoan','Contact','LastContact_Month','PreviousOutcome','Outc
ome']:
    bank_df_workingcopy[col] = bank_df_workingcopy[col].astype('category')
    if(col == "Outcome"):
        continue
    compare_table = pd.crosstab(bank_df_workingcopy['Outcome'],bank_df_workingco
py[col]);
    chi2,p,dof,expected = chi2_contingency(compare_table.values)
    if(p<0.5) :
        print("Null hyopthesis rejected. The p value is ",p,". \nThere is correl
ation between ",col," and outcome");
    else :
        print("Null hyopthesis accepted. The p value is ",p,". \nThere is no cor
relation between ",col," outcome");
    no_count = compare_table.iloc[0][:].values
    yes_count = compare_table.iloc[1][:].values

    #Plots the bar chart
    fig = plt.figure(figsize=(10, 5))
    categories = sorted(bank_df_workingcopy[col].unique())
    p1 = plt.bar(categories, no_count, 0.55, color='red', animated=True)
    p2 = plt.bar(categories, yes_count, 0.55, color = 'blue', bottom=no_count,an
imated=True)
    plt.legend((p2[0], p1[0]), ('Yes', 'No'))
    plt.ylabel('Count')
    plt.xticks(rotation='vertical')
    plt.show()
```

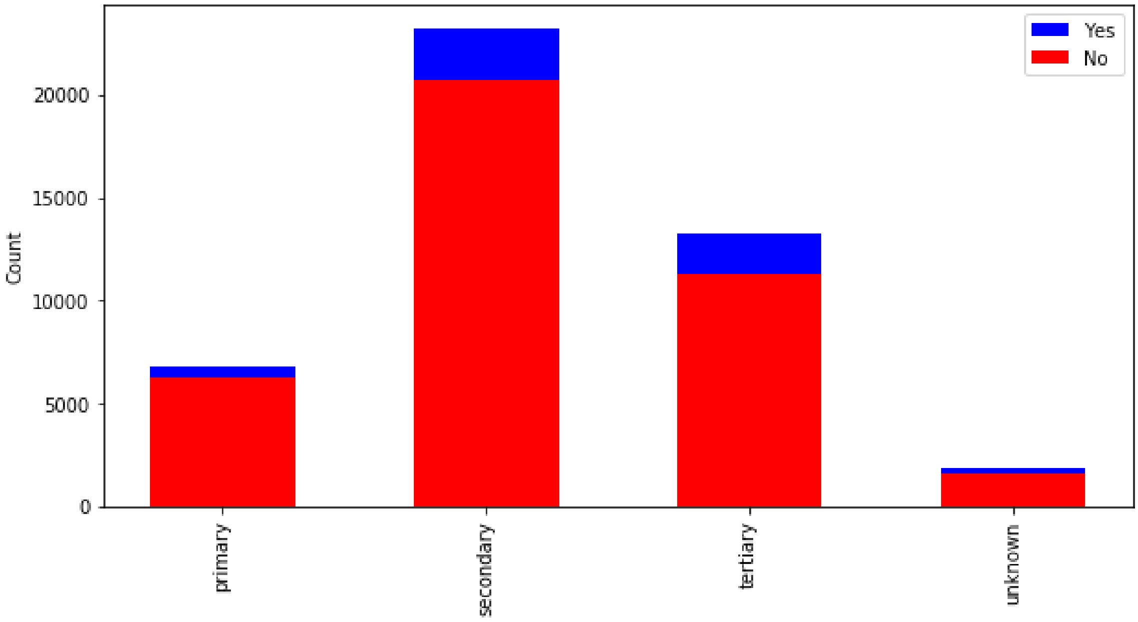
```
Null hyopthesis rejected. The p value is  3.337121944935502e-172 .
There is correlation between  Employment  and outcome
```



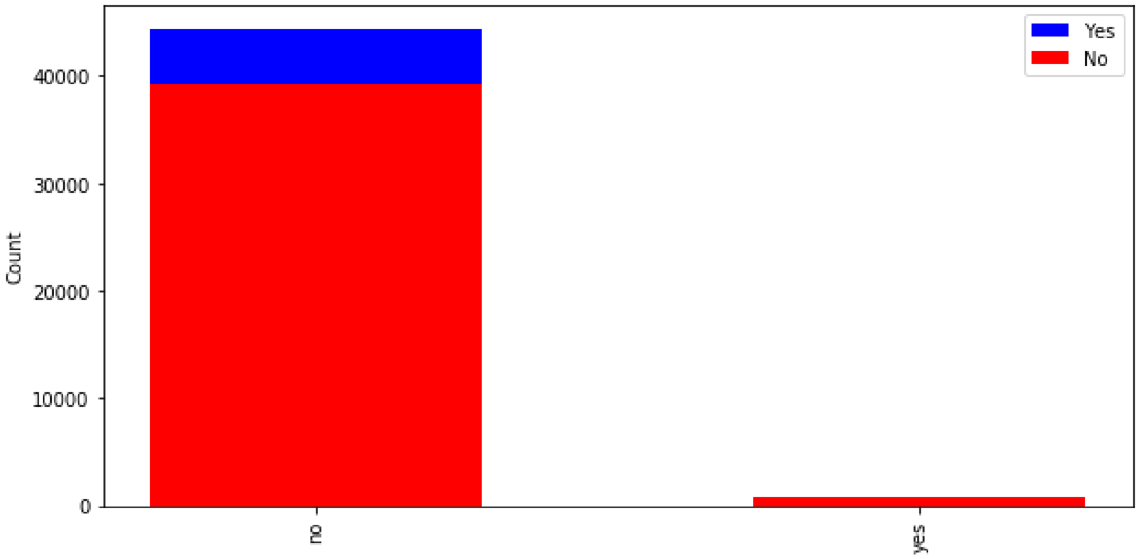

```
Null hyopthesis rejected. The p value is  2.1450999986791486e-43 .
There is correlation between  MaritalStatus  and outcome
```



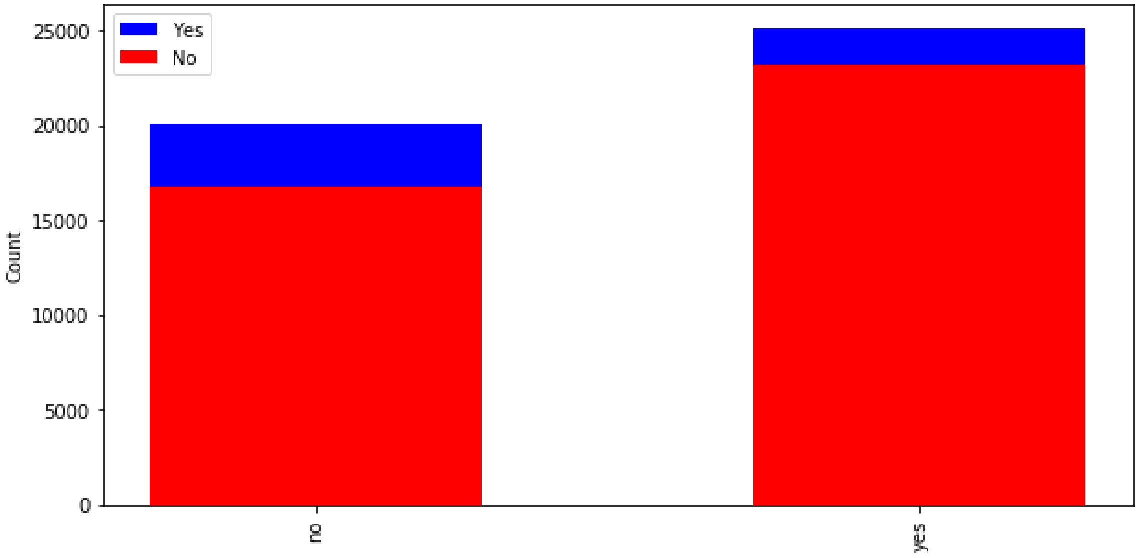

```
Null hyopthesis rejected. The p value is  1.6266562124072994e-51 .
There is correlation between  Education  and outcome
```



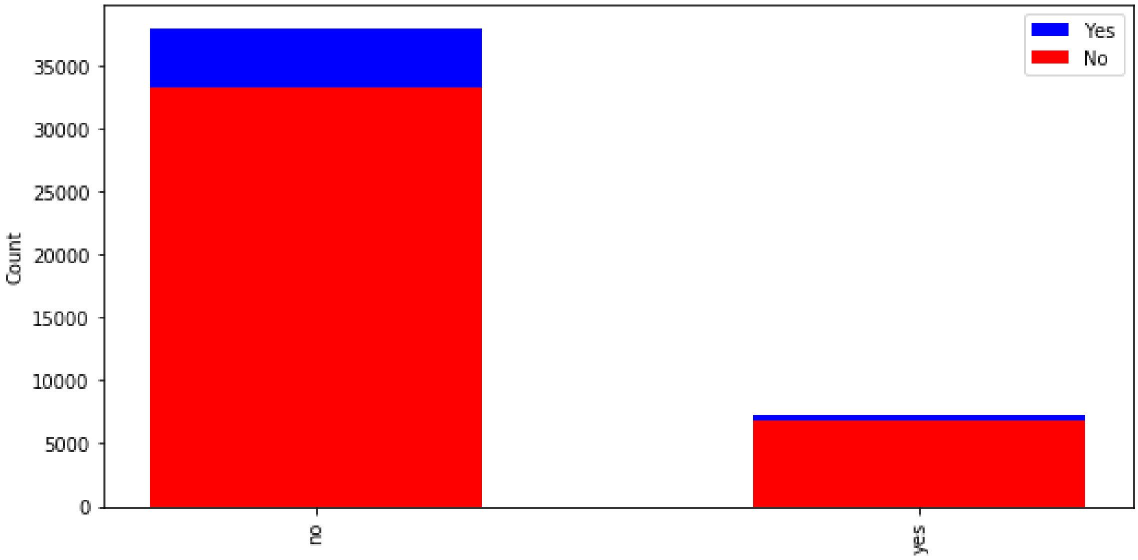

```
Null hyopthesis rejected. The p value is  2.4538606753508344e-06 .
There is correlation between  Defaulter  and outcome
```



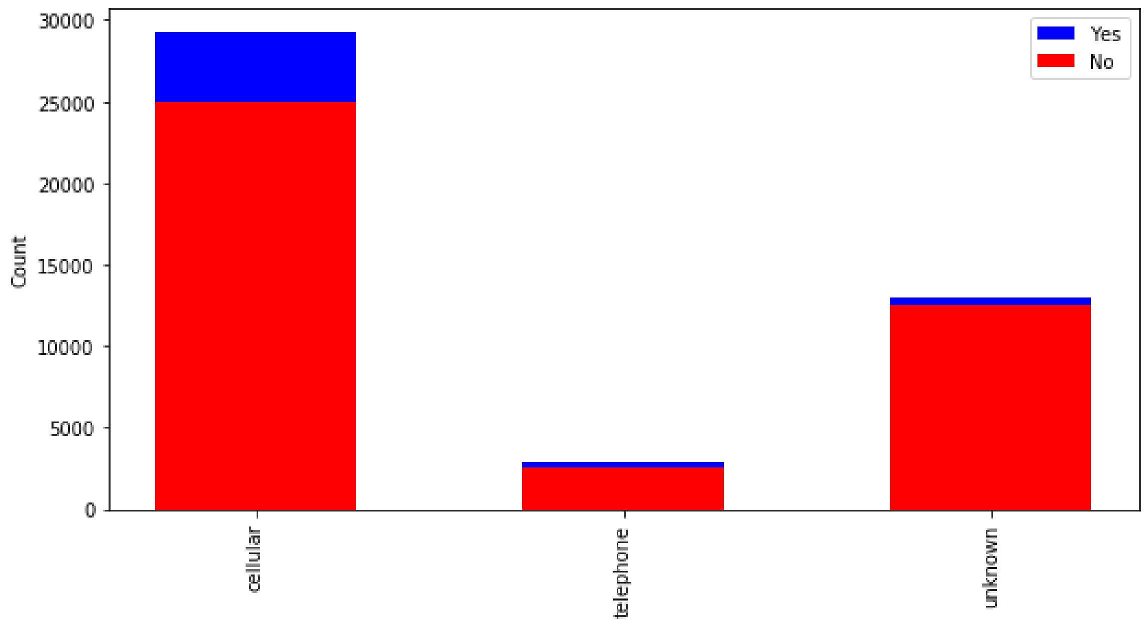

```
Null hyopthesis rejected. The p value is  2.918797605076633e-192 .
There is correlation between  HousingLoan  and outcome
```



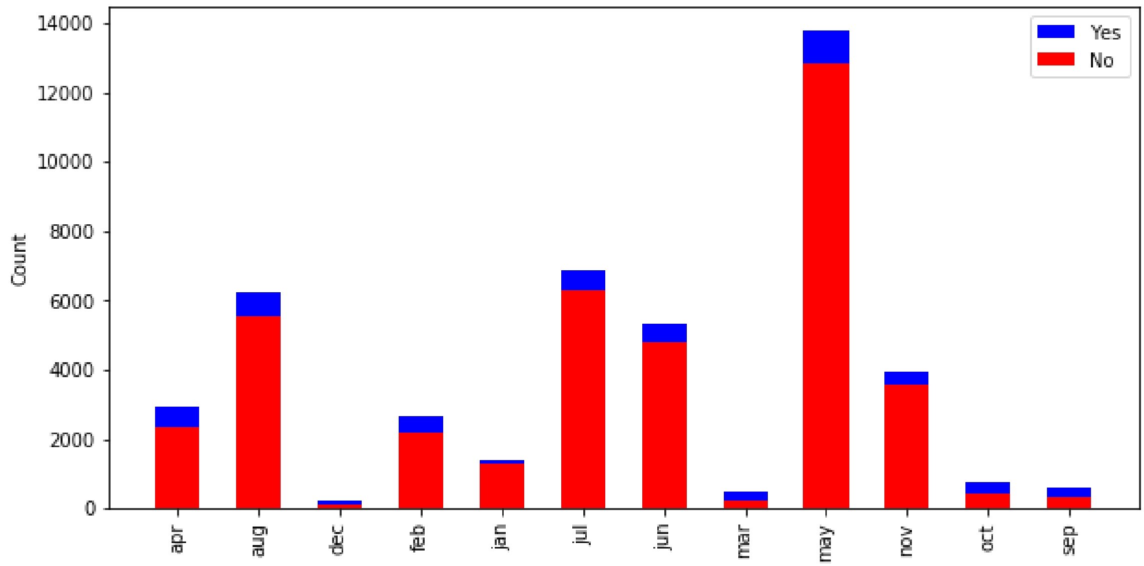

```
Null hyopthesis rejected. The p value is  1.665061163492756e-47 .
There is correlation between  PersonalLoan  and outcome
```



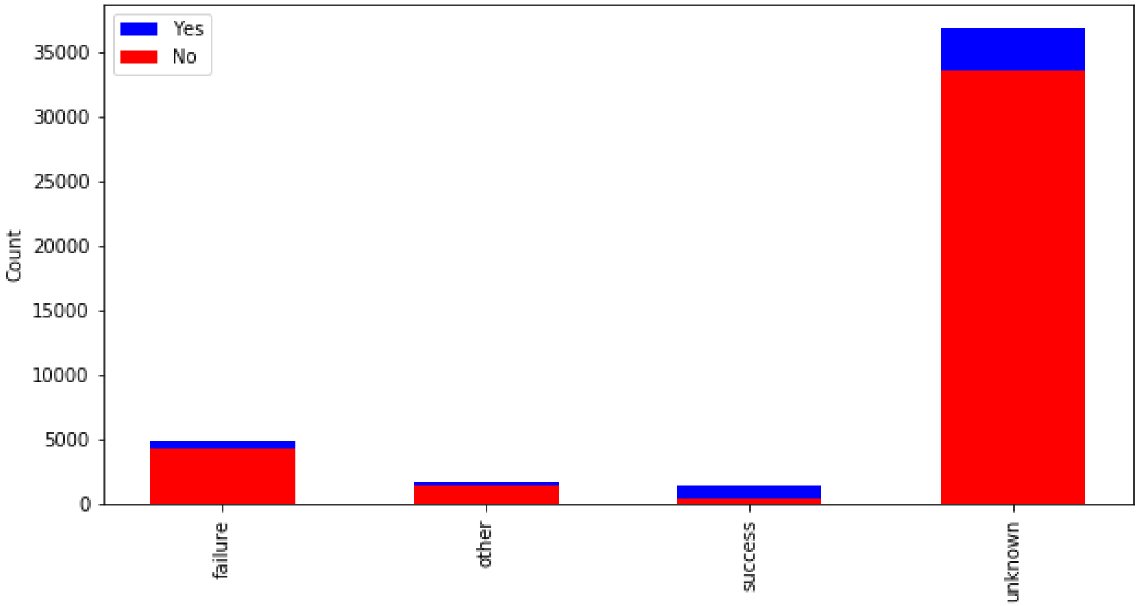

```
Null hyopthesis rejected. The p value is  1.2517383253404095e-225 .
There is correlation between  Contact  and outcome
```




```
Null hyopthesis rejected. The p value is  0.0 .
There is correlation between  LastContact_Month  and outcome
```




```
Null hyopthesis rejected. The p value is  0.0 .
There is correlation between  PreviousOutcome  and outcome
```



Based on the Chi square tests we can infer that most of the outcome is certainly dependent on the categorical variables Employment, MaritalStatus, Education, Defaulter, HousingLoan, PersonalLoan, Contact, LastContact_Month and PreviousOutcome. But since the target column values are highly imbalanced, using this dataset will not clearly indicate the possible outcome.

From the description of the dataset done above, it is evident that while some of the features which are continuously distributed are normal, some are not. The difference between their mean and median is too varied. Let's take a subset of the dataframe with just the continous features and pairplot them and observe the same.

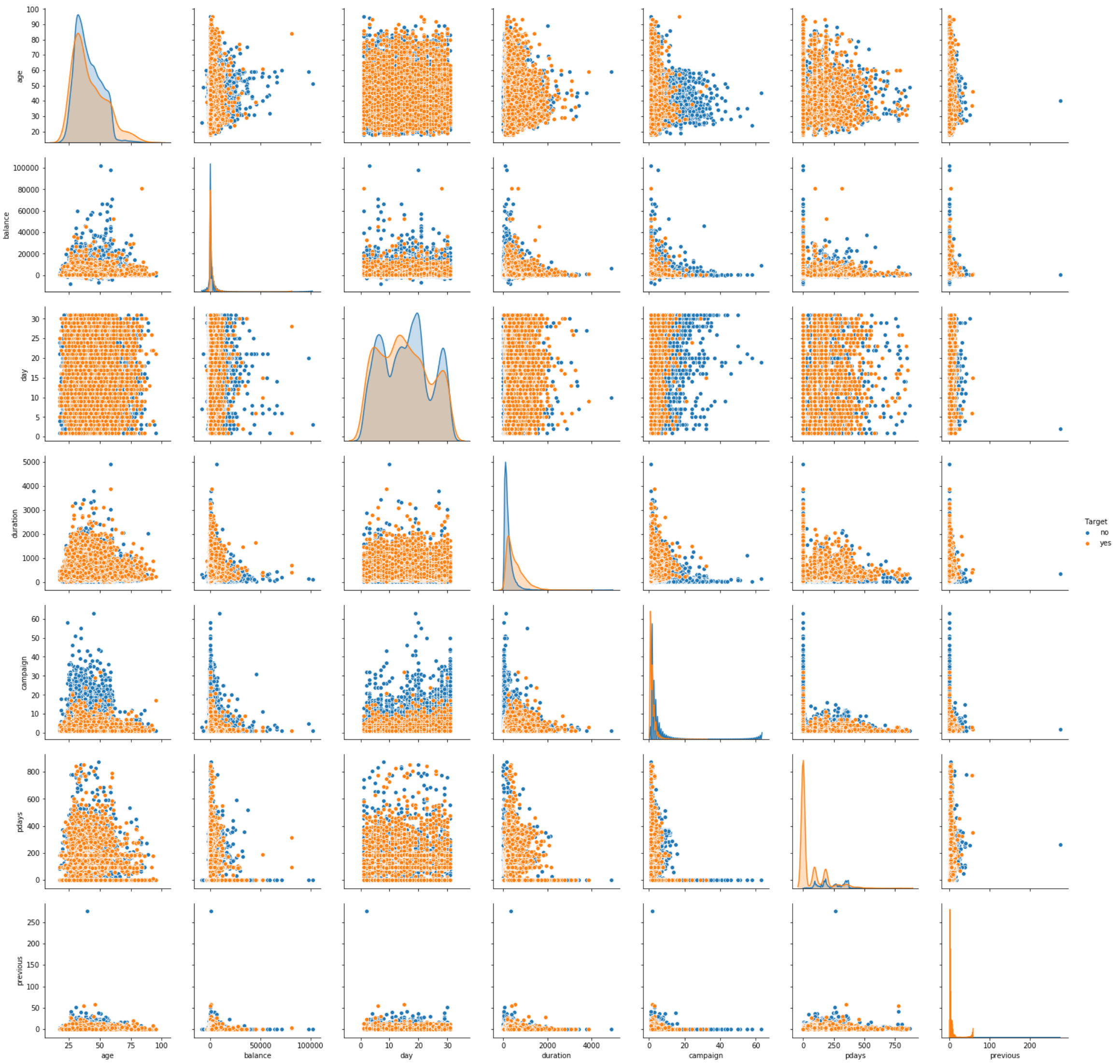
In [125]:

```
bank_df_transformed = bank_df.copy()

sns.pairplot(bank_df_transformed,hue="Target",height=3)
```

```
/Users/lavanyas/anaconda3/lib/python3.7/site-packages/scipy/stats/st
ats.py:1713: FutureWarning: Using a non-tuple sequence for multidime
nsional indexing is deprecated; use `arr[tuple(seq)]` instead of `ar
r[seq]`. In the future this will be interpreted as an array index, `
arr[np.array(seq)]`, which will result either in an error or a diffe
rent result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumva
l
```

Out[125]:

<seaborn.axisgrid.PairGrid at 0x1a6a510f98>



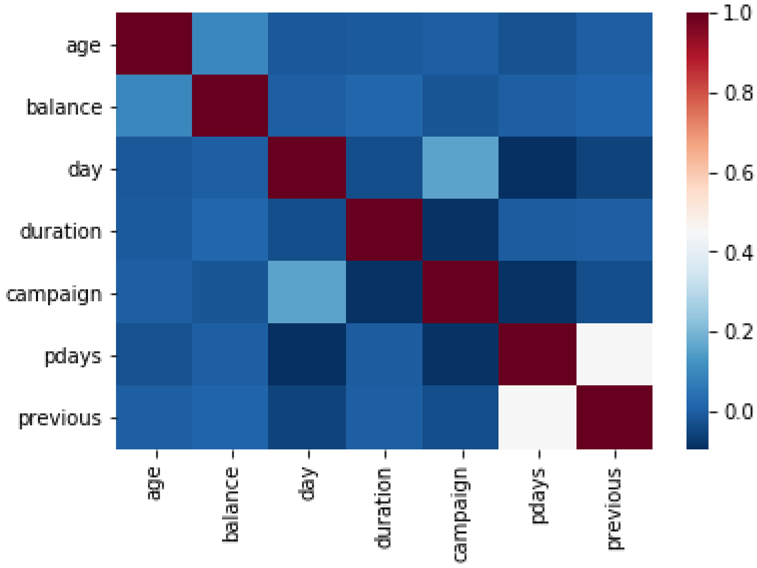
Let's heatmap the correlation between the features to understand it better.

In [126]:

```
sns.heatmap(bank_df_transformed.corr(),cmap="RdBu_r")
```

Out[126]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a487996d8>
```



From the heat plot, it appears like besides the duration of the call and previous contact made with the customer, no other feature which is continuous seems to influence the outcome much. It is obvious that any customer who has taken term deposit has been spoken to, but the vice versa is not true. We cannot conclude on the dependence or lack of it, especially given that the number of positive outcomes in the data set is way lesser than the number of negative outcome. Our objective is to find the likelihood of the customer who will be likely to avail term deposit given these features. Let's do supervised classification to ascertain the same.

To ensure that we consider all the features, let's convert all the values to numeric type and then scale it to explore further.

In [127]:

```
bank_df_workingcopy.dtypes
```

Out[127]:

```
Age                           int64
Employment                 category
MaritalStatus              category
Education                  category
Defaulter                  category
Balance                       int64
HousingLoan                category
PersonalLoan               category
Contact                    category
LastContact_DayOfMonth        int64
LastContact_Month          category
DurationOfCall                int64
No.OfContactsMade             int64
DaysSincePrevContact          int64
TimesPreviouslyContacted      int64
PreviousOutcome            category
Outcome                    category
dtype: object
```

In [128]:

```
bank_df_workingcopy['Education'].replace(['unknown','primary', 'secondary', 'ter
tiary'],[1,2,3,4],inplace = True);


bank_df_workingcopy['Employment'].replace(['unknown', 'unemployed', 'retired',
                                            'student', 'housemaid','services',
                                           'admin.','technician','blue-collar',
                                            'self-employed','management','entrepreneur'
],
                       [0,1,2,3,4,5,6,7,8,9,10,11],inplace = True);

bank_df_workingcopy['MaritalStatus'].replace(['single' ,'married' ,'divorced'],[
0,1,2],inplace = True);

bank_df_workingcopy['Defaulter'].replace(['no','yes'],[0,1],inplace = True);
bank_df_workingcopy['HousingLoan'].replace(['no','yes'],[0,1],inplace = True);
bank_df_workingcopy['PersonalLoan'].replace(['no','yes'],[0,1],inplace = True);
bank_df_workingcopy['Contact'].replace(['unknown','cellular', 'telephone'],[0,1,
2],inplace = True);
bank_df_workingcopy['LastContact_Month'].replace(['jan','feb','mar','apr','may',
'jun','jul','aug','sep','oct','nov','dec'],[1,2,3,4,5,6,7,8,9,10,11,12],inplace
= True);
bank_df_workingcopy['PreviousOutcome'].replace(['unknown', 'failure' ,'other',
'success'],[-1,0,2,1],inplace = True);
bank_df_workingcopy['Outcome'].replace(['no','yes'],[0,1],inplace = True);

bank_df_workingcopy.dtypes
```

Out[128]:

```
Age                          int64
Employment                   int64
MaritalStatus                int64
Education                    int64
Defaulter                    int64
Balance                      int64
HousingLoan                  int64
PersonalLoan                 int64
Contact                      int64
LastContact_DayOfMonth       int64
LastContact_Month            int64
DurationOfCall               int64
No.OfContactsMade            int64
DaysSincePrevContact         int64
TimesPreviouslyContacted     int64
PreviousOutcome              int64
Outcome                      int64
dtype: object
```

In [129]:

```
TD_outcome = bank_df_workingcopy['Outcome']
bank_df_workingcopy = bank_df_workingcopy.drop(labels='Outcome', axis = 1)

X = np.array(bank_df_workingcopy)
y = np.array(TD_outcome)

X_train, X_test,y_train,y_test = train_test_split(X,y, test_size = 0.30, random_
state=1)

clf = GaussianNB()
clf.fit(X_train,y_train)


clf.score(X_test, y_test)
test_prediction = clf.predict(X_test)
print("Model Accuracy with test data : ",metrics.accuracy_score(y_test, test_pre
diction))

print("Confusion Matrix")

confusion_matrix = metrics.confusion_matrix(y_test, test_prediction, labels=[1,
0])

print(confusion_matrix)
```

```
Model Accuracy with test data :  0.8468740784429372
Confusion Matrix
[[  809   742]
 [ 1335 10678]]
```

The above analysis is based on data which is not normalized. Let's do some scaling and run the test again.

In [130]:

```
X_scaled = preprocessing.scale(X_train)

X_test_scaled = preprocessing.scale(X_test)

clf.fit(X_scaled,y_train)
clf.score(X_test_scaled, y_test)
scaled_test_prediction = clf.predict(X_test_scaled)
print("Model Accuracy with test data : ",metrics.accuracy_score(y_test, scaled_t
est_prediction))

print("Confusion Matrix")

confusion_matrix = metrics.confusion_matrix(y_test, scaled_test_prediction, labe
ls=[1, 0])

print(confusion_matrix)
```

```
Model Accuracy with test data :  0.8473901503981126
Confusion Matrix
[[   831    720]
 [  1350 10663]]

/Users/lavanyas/anaconda3/lib/python3.7/site-packages/sklearn/utils/
validation.py:595: DataConversionWarning: Data with input dtype int6
4 was converted to float64 by the scale function.
  warnings.warn(msg, DataConversionWarning)
/Users/lavanyas/anaconda3/lib/python3.7/site-packages/sklearn/utils/
validation.py:595: DataConversionWarning: Data with input dtype int6
4 was converted to float64 by the scale function.
  warnings.warn(msg, DataConversionWarning)
```

The accuracy still seems to be of the same range and from the outcome we see that having an imbalanced data is not going to help us come to devise an optimal marketing plan based on predicted outcome. The issue with imbalanced data is biased predictions and misleading accuracy. Moving forward we will do our analysis using ensembling techniques. Let's first import all the modules required for this purpose and then use SMOTE (Synthetic Minority Over Sampling Technique) available in imblearn module, to do our classification.

In [131]:

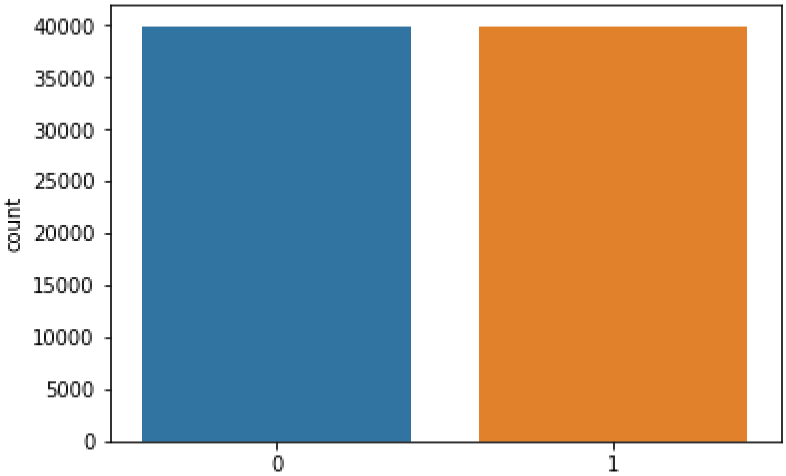
```
#pip install imblearn as this doesn't come with the default anaconda
from imblearn.over_sampling import SMOTE
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
```

In [132]:

```
sm = SMOTE(random_state=5)
X_res, y_res = sm.fit_resample(X, y)
sns.countplot(y_res)
```

Out[132]:

<matplotlib.axes._subplots.AxesSubplot at 0x1a46ddabe0>



We can see from the plot above that the dataset is now balanced with the help of the data sythesised.

Classification using DecisionTreeClassifier

In [133]:

```
X_res_train, X_res_test,y_res_train,y_res_test = train_test_split(X_res,y_res, t
est_size = 0.30, random_state=1)

dt_model = DecisionTreeClassifier(criterion = 'entropy' );

dtree = dt_model.fit(X_res_train, y_res_train);

y_res_predict = dt_model.predict(X_res_test);

print("Confusion Matrix")

confusion_matrix = metrics.confusion_matrix(y_res_test, y_res_predict, labels=[1
, 0])

print(confusion_matrix)

print("The performance score on test data is ",dt_model.score(X_test , y_test))
print("The performance score on training data is ",dt_model.score(X_train , y_tr
ain))
```

```
Confusion Matrix
[[10852  1077]
 [ 1481 10544]]
The performance score on test data is  0.9446328516661752
The performance score on training data is  0.9640724239264385
```

The accuracy of the outcome prediction on test data is 94%. But this could be a biassed result. Let's set some regularization parameters on the classifier and analyze the results.

Classification using generalized DecisionTreeClassifier

In [134]:

```
dt_model_gen = DecisionTreeClassifier(criterion = 'entropy' ,max_depth=5)

dt_model_gen.fit(X_res_train, y_res_train);

y_res_predict = dt_model_gen.predict(X_res_test);

print("Confusion Matrix")

confusion_matrix = metrics.confusion_matrix(y_res_test, y_res_predict, labels=[1
, 0])

print(confusion_matrix)

print("The performance score on test data is ",dt_model_gen.score(X_res_test , y
_res_test))
print("The performance score on training data is ",dt_model_gen.score(X_res_trai
n , y_res_train))
```

```
Confusion Matrix
[[10624  1305]
 [ 2577  9448]]
The performance score on test data is  0.8379393838189864
The performance score on training data is  0.8420647700840937
```

We can see that after regularization, the DecisionTreeClassifier's performance score has drastically dropped by more than 10%. We will apply some ensemble techniques and do the classification to minimize bias and variance.

Ensemble Techniques

Classification using GradientBoostingClassifier

In [135]:

```
from sklearn.ensemble import GradientBoostingClassifier
gbcl = GradientBoostingClassifier(n_estimators = 50, learning_rate = 0.05)
gbcl = gbcl.fit(X_res_train, y_res_train)

y_res_predict = gbcl.predict(X_res_test);

print("Confusion Matrix")

confusion_matrix = metrics.confusion_matrix(y_res_test, y_res_predict, labels=[1
, 0])

print(confusion_matrix)

print("The performance score on test data is ",gbcl.score(X_res_test , y_res_tes
t))
print("The performance score on training data is ",gbcl.score(X_res_train , y_re
s_train))
```

```
Confusion Matrix
[[10570  1359]
 [ 2181  9844]]
The performance score on test data is  0.8522167487684729
The performance score on training data is  0.8575415995705851
```

Classification using RandomForestClassifier

In [136]:

```
from sklearn.ensemble import RandomForestClassifier
rfcl = RandomForestClassifier(n_estimators = 50)
rfcl = rfcl.fit(X_res_train, y_res_train)

y_res_predict = rfcl.predict(X_res_test);

print("Confusion Matrix")

confusion_matrix = metrics.confusion_matrix(y_res_test, y_res_predict, labels=[1
, 0])

print(confusion_matrix)

print("The performance score on test data is ",rfcl.score(X_res_test , y_res_tes
t))
print("The performance score on training data is ",rfcl.score(X_res_train , y_re
s_train))
```

```
Confusion Matrix
[[11305   624]
 [ 1175 10850]]
The performance score on test data is  0.9248977206312098
The performance score on training data is  0.9998747539810342
```

Classification using Bagging Classifier

In [137]:

```
from sklearn.ensemble import BaggingClassifier

bgcl = BaggingClassifier(n_estimators=20, max_samples= .7, bootstrap=True)
bgcl = bgcl.fit(X_res_train, y_res_train)

y_res_predict = bgcl.predict(X_res_test);

print("Confusion Matrix")

confusion_matrix = metrics.confusion_matrix(y_res_test, y_res_predict, labels=[1
, 0])

print(confusion_matrix)

print("The performance score on test data is ",bgcl.score(X_res_test , y_res_tes
t))
print("The performance score on training data is ",bgcl.score(X_res_train , y_re
s_train))
```

```
Confusion Matrix
[[11227   702]
 [ 1227 10798]]
The performance score on test data is  0.9194706520831594
The performance score on training data is  0.9910717480765789
```

Classification using KNN as base estimator for Bagging

In [138]:

```
from sklearn.neighbors import KNeighborsClassifier
knn_clf = KNeighborsClassifier(5)
bgcl = BaggingClassifier(base_estimator=knn_clf, n_estimators=20)
bgcl = bgcl.fit(X_res_train, y_res_train)

y_res_predict = bgcl.predict(X_res_test);

print("Confusion Matrix")

confusion_matrix = metrics.confusion_matrix(y_res_test, y_res_predict, labels=[1
, 0])

print(confusion_matrix)

print("The performance score on test data is ",bgcl.score(X_res_test , y_res_tes
t))
print("The performance score on training data is ",bgcl.score(X_res_train , y_re
s_train))
```

```
Confusion Matrix
[[11359   570]
 [ 2678  9347]]
The performance score on test data is  0.864406779661017
The performance score on training data is  0.9088208981928789
```

Conclusion

Of all the ensemble classification methods used to explore the dataset after balancing, RandomForestClassifier has the highest accuracy with testing data and training data and this model's prediction can be used for marketing the term deposits by the bank.