Classification Machine Learning Problem

Data Description:

The data is related with direct marketing campaigns of a Portuguese banking institution. The marketing campaigns were based on phone calls. Often, more than one contact to the same client was required, in order to access if the product (bank term deposit) would be ('yes') or not ('no') subscribed.

Context:

Leveraging customer information is paramount for most businesses. In the case of a bank, attributes of customers like the ones mentioned below can be crucial in strategizing a marketing campaign when launching a new product.

Objective:

We need to check the overall performence of the Bank Dataset and will use different Machine Learning Algorithms -

Random Forrest
K Nearest Neighbors
SVM
Naive Baise
Decision Tree
Random Forrest
Gradient Boost
XG Boost

to predict that a client will subscribe (yes/no) a term deposit (variable y) with best Accuracy.

Bank client data

1. age (numeric)
2. job : type of job (categorical: 'admin.','blue- collar', 'entrepreneur', 'housemaid', 'management', 'retired','self-employed', 'services', 'student', 'technicia n', 'unemployed', 'unknown')

3. marital : marital status (categorical:'divorced', 'married', 'single', 'unknown'; note: 'divorced' means divorced or widowed)

4. education (categorical: 'basic.4y', 'basic.6y', 'basic.9y', 'high.school', 'illiterate', 'professional.course', 'university.degree', 'unknown')
5. default: has credit in default? (categorical: 'no','yes','unknown')
6. balance: average yearly balance, in euros (numeric)
7. housing: has housing loan? (categorical: 'no','yes','unknown')
8. loan: has personal loan? (categorical: 'no','yes','unknown')
9. contact: contact communication type (categorical: 'cellular','telephone')
10. day: last contact day of the month (numeric 1 -31)

11. month: last contact month of year (categorical: 'jan', 'feb', 'mar', ..., 'nov', 'dec')
12. duration: last contact duration, in seconds (numeric)
13. campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact)
14. pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)
15. 15.previous: number of contacts performed before this campaign and for this client (numeric)
16. poutcome: outcome of the previous marketing campaign (categorical: 'failure','nonexistent','success')
17. 17.target: has the client subscribed a term deposit? (binary: "yes","no")

Importing Nescessary Data Analysis Librarys

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

Reading the Dataset

In [2]:

```
bank = pd.read_csv('G:/TCS Study/TCS Git Hub Projects/Classification Project/bank-full.
bank.head()
```

Out[2]:

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

Exploratory Data Analysis

Take a look at the type, number of columns, entries, null values etc.

In [3]:

```
bank.info()
bank.isnull().any() # To search for null values
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   age        45211 non-null  int64
 1   job        45211 non-null  object
```

```
 2   marital    45211 non-null  object
 3   education  45211 non-null  object
 4   default    45211 non-null  object
 5   balance    45211 non-null  int64
 6   housing    45211 non-null  object
 7   loan       45211 non-null  object
 8   contact    45211 non-null  object
 9   day        45211 non-null  int64
 10  month      45211 non-null  object
 11  duration   45211 non-null  int64
 12  campaign   45211 non-null  int64
 13  pdays      45211 non-null  int64
 14  previous   45211 non-null  int64
 15  poutcome   45211 non-null  object
 16  Target     45211 non-null  object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
```

Out[3]:

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

As per observation there is no missing value in the data.

In [4]:

```
bank.columns
```

Out[4]:

```
Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housing',
       'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'Target'],
      dtype='object')
```

As per the nature of data, entire data set can be classified as follows

Bank client data:

Age

Job

Marital

Education

Default

Balance

Housing

Loan

Related with the last contact of the current campaign:

Contact

Month

Day

Duration

Other attributes:

Campaign

Pdays

Previous

Poutcome

Traget Variable:

Target

Bank client data Analysis and Categorical Treatment

Work with the atributes related to bank clients

To make things more clear, we'll going to creat a new datasets that contains just this part of data

In [5]:

```
bank_client = bank.iloc[: , 0:8]
bank_client.head()
```

Out[5]:

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

Knowing the Categorical Variables

In [6]:

```
print('Jobs:\n', bank_client['job'].unique())
print('Marital:\n', bank_client['marital'].unique())
print('Education:\n', bank_client['education'].unique())
print('Default:\n', bank_client['default'].unique())
print('Housing:\n', bank_client['housing'].unique())
print('Loan:\n', bank_client['loan'].unique())
```

```
Jobs:
 ['management' 'technician' 'entrepreneur' 'blue-collar' 'unknown'
 'retired' 'admin.' 'services' 'self-employed' 'unemployed' 'housemaid'
 'student']
Marital:
 ['married' 'single' 'divorced']
Education:
 ['tertiary' 'secondary' 'unknown' 'primary']
Default:
```

```
 ['no' 'yes']
Housing:
 ['yes' 'no']
Loan:
 ['no' 'yes']
```

Trying to find some insights crossing those Continuous Variables: Age, Balance

Age

Trying to find null values

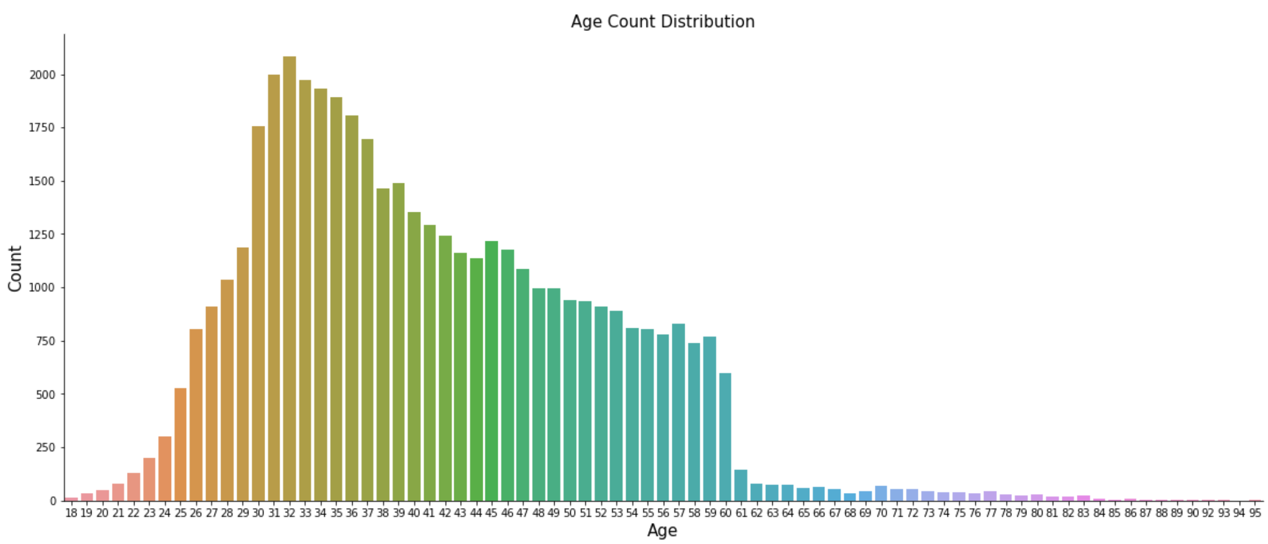
In [7]:

```
print('Min age: ', bank_client['age'].min())
print('Max age: ', bank_client['age'].max())
print('Null Values: ', bank_client['age'].isnull().any())
```

```
Min age:  18
Max age:  95
Null Values:  False
```

In [8]:

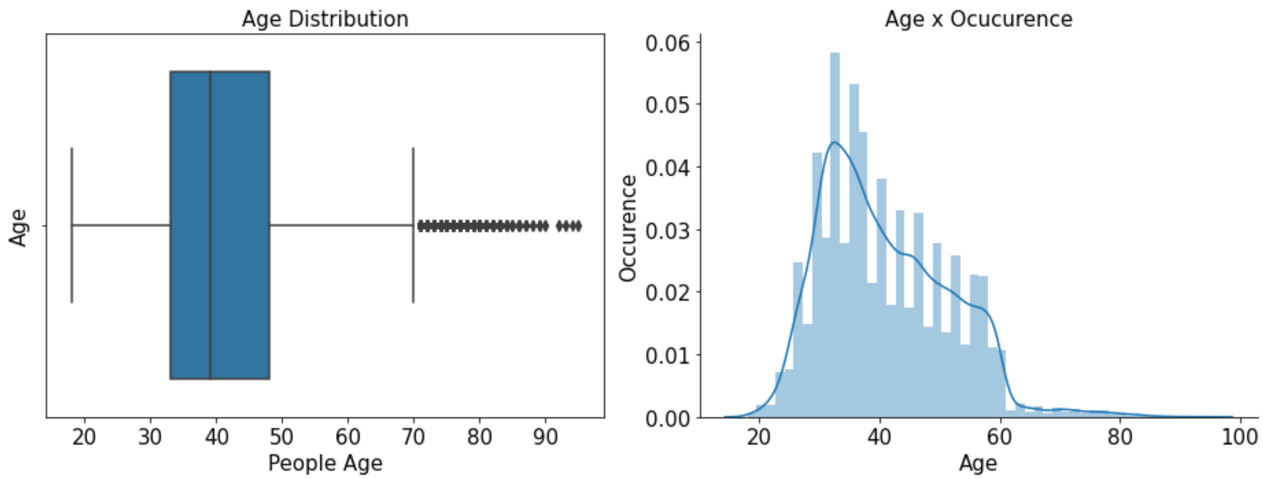
```
fig, ax = plt.subplots()
fig.set_size_inches(20, 8)
sns.countplot(x = 'age', data = bank_client)
ax.set_xlabel('Age', fontsize=15)
ax.set_ylabel('Count', fontsize=15)
ax.set_title('Age Count Distribution', fontsize=15)
sns.despine()
```



In [9]:

```
fig, (ax1, ax2) = plt.subplots(nrows = 1, ncols = 2, figsize = (13, 5))
sns.boxplot(x = 'age', data = bank_client, orient = 'v', ax = ax1)
ax1.set_xlabel('People Age', fontsize=15)
ax1.set_ylabel('Age', fontsize=15)
ax1.set_title('Age Distribution', fontsize=15)
ax1.tick_params(labelsize=15)

sns.distplot(bank_client['age'], ax = ax2)
sns.despine(ax = ax2)
ax2.set_xlabel('Age', fontsize=15)
ax2.set_ylabel('Occurence', fontsize=15)
ax2.set_title('Age x Ocucurence', fontsize=15)
ax2.tick_params(labelsize=15)
```

```
plt.subplots_adjust(wspace=0.5)
plt.tight_layout()
```



In [10]:

```
# Quartiles:
print('1º Quartile: ', bank_client['age'].quantile(q = 0.25))
print('2º Quartile: ', bank_client['age'].quantile(q = 0.50))
print('3º Quartile: ', bank_client['age'].quantile(q = 0.75))
print('4º Quartile: ', bank_client['age'].quantile(q = 1.00))
# Calculate the outliers:
# Interquartile range, IQR = Q3 - Q1
# lower 1.5*IQR whisker = Q1 - 1.5 * IQR
# Upper 1.5*IQR whisker = Q3 + 1.5 * IQR

print('Ages above: ', bank_client['age'].quantile(q = 0.75) +
                      1.5*(bank_client['age'].quantile(q = 0.75) - bank_client['age'].q
```

```
1º Quartile:  33.0
2º Quartile:  39.0
3º Quartile:  48.0
4º Quartile:  95.0
Ages above:  70.5 are outliers
```

In [11]:

```
print('Numerber of outliers: ', bank_client[bank_client['age'] > 69.6]['age'].count())
print('Number of clients: ', len(bank_client))
# Outliers in %
print('Outliers are:', round(bank_client[bank_client['age'] > 69.6]['age'].count()*100/
```

```
Numerber of outliers:  554
Number of clients:  45211
Outliers are: 1.23 %
```

In [12]:

```
# Calculating some values to evaluete this independent variable
print('MEAN:', round(bank_client['age'].mean(), 1))
# A low standard deviation indicates that the data points tend to be close to the mean
# A high standard deviation indicates that the data points are scattered
print('STD :', round(bank_client['age'].std(), 1))
# I thing the best way to give a precisly insight about dispersion is using the CV (coe
# cv < 15%, low dispersion
# cv > 30%, high dispersion
print('CV  :',round(bank_client['age'].std()*100/bank_client['age'].mean(), 1), ', High
```

```
MEAN: 40.9
STD : 10.6
CV  : 25.9 , High middle dispersion
```

Conclusion: About AGE - Due to almost high dispersion and just looking at this graph we cannot conclude if age have a high effect to our variable Target, need to keep searching for some pattern.
High middle dispersion means we have people with all ages and maybe all of them can subscript a term deposit, or not. The outliers was calculated, the model can be fitted with and without AGE.

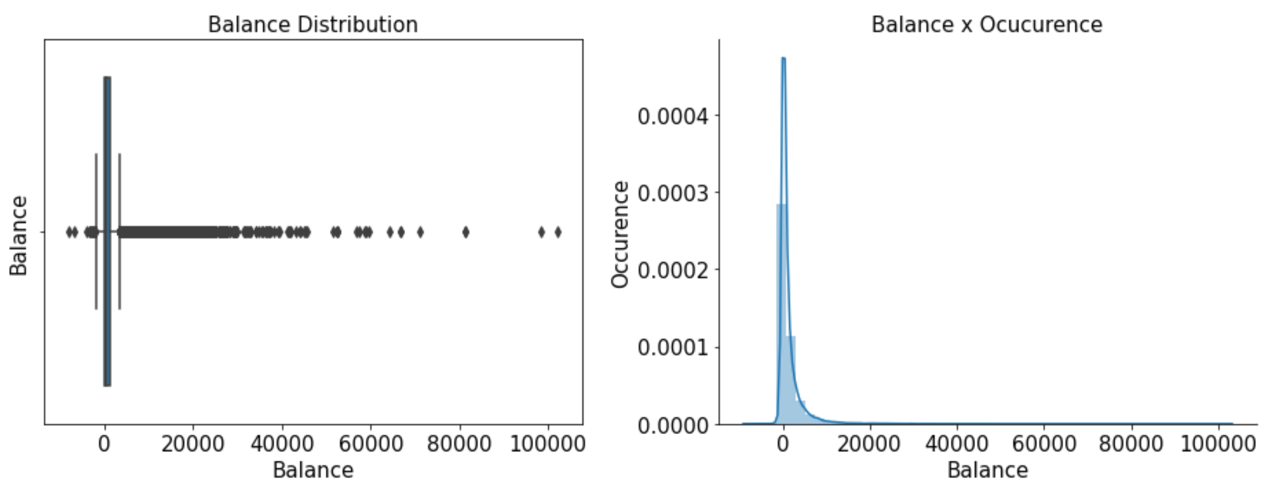
In [13]:

```
# Balance
# Trying to find null values
print('Min balance: ', bank_client['balance'].min())
print('Max balance: ', bank_client['balance'].max())
print('Null Values: ', bank_client['balance'].isnull().any())
```

```
Min balance:  -8019
Max balance:  102127
Null Values:  False
```

In [14]:

```
fig, (ax1, ax2) = plt.subplots(nrows = 1, ncols = 2, figsize = (13, 5))
sns.boxplot(x = 'balance', data = bank_client, orient = 'v', ax = ax1)
ax1.set_xlabel('Balance', fontsize=15)
ax1.set_ylabel('Balance', fontsize=15)
ax1.set_title('Balance Distribution', fontsize=15)
ax1.tick_params(labelsize=15)

sns.distplot(bank_client['balance'], ax = ax2)
sns.despine(ax = ax2)
ax2.set_xlabel('Balance', fontsize=15)
ax2.set_ylabel('Occurence', fontsize=15)
ax2.set_title('Balance x Ocucurence', fontsize=15)
ax2.tick_params(labelsize=15)

plt.subplots_adjust(wspace=0.5)
plt.tight_layout()
```



In [15]:

```
# Quartiles:
print('1º Quartile: ', bank_client['balance'].quantile(q = 0.25))
print('2º Quartile: ', bank_client['balance'].quantile(q = 0.50))
```

```
print('3º Quartile: ', bank_client['balance'].quantile(q = 0.75))
print('4º Quartile: ', bank_client['balance'].quantile(q = 1.00))
# Calculate the outliers:
# Interquartile range, IQR = Q3 - Q1
# lower 1.5*IQR whisker = Q1 - 1.5 * IQR
# Upper 1.5*IQR whisker = Q3 + 1.5 * IQR

print('Balance above: ', bank_client['balance'].quantile(q = 0.75) +
                      1.5*(bank_client['balance'].quantile(q = 0.75) - bank_client['bal
```

```
1º Quartile:  72.0
2º Quartile:  448.0
3º Quartile:  1428.0
4º Quartile:  102127.0
Balance above:  3462.0 are outliers
```

In [16]:

```
print('Numerber of outliers: ', bank_client[bank_client['balance'] > 69.6]['balance'].c
print('Number of clients: ', len(bank_client))
# Outliers in %
print('Outliers are:', round(bank_client[bank_client['balance'] > 69.6]['balance'].coun
```

```
Numerber of outliers:  34018
Number of clients:  45211
Outliers are: 75.24 %
```

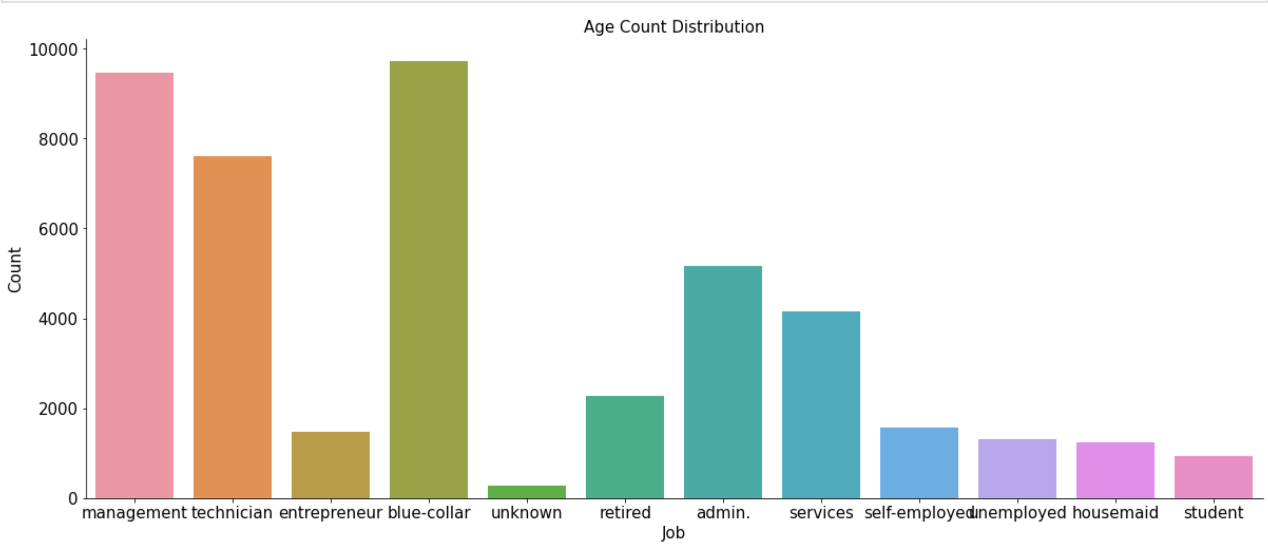
Conclusion: About Balance- As the number of Outlier is very high in dataset, so we'll exclude Balance variable from model building.

Relation of the Categorical Variables with Age in bank_client Data

JOBS

In [17]:

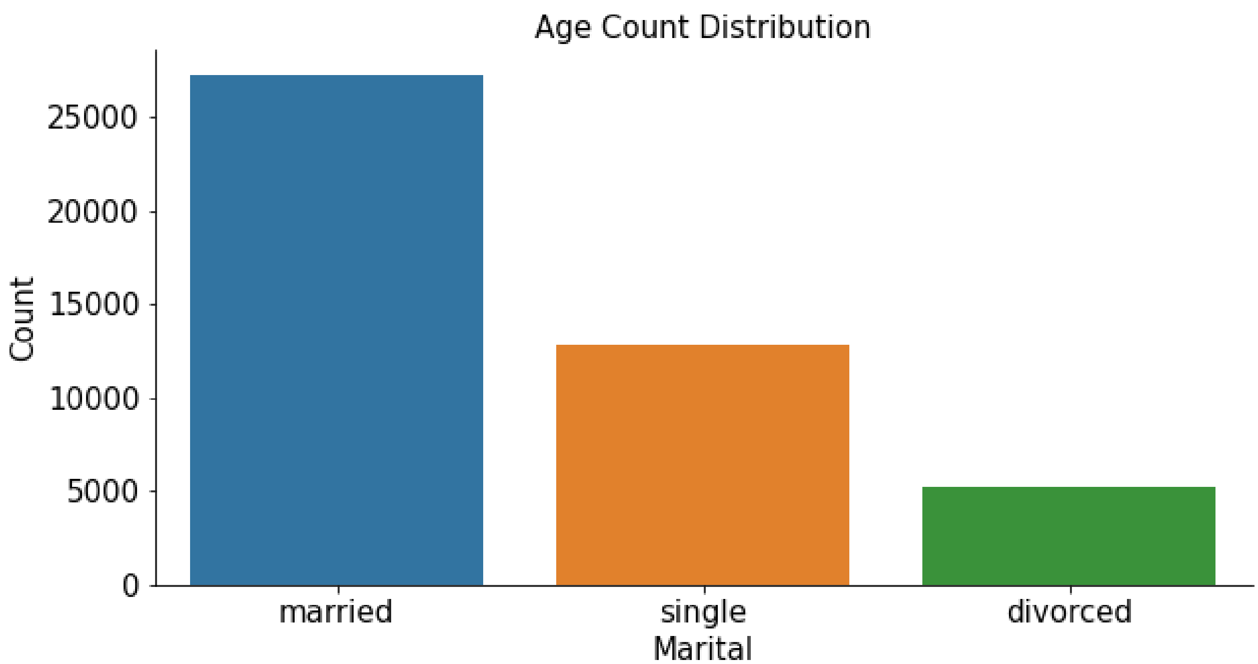
```
# What kind of jobs clients this bank have, if you cross jobs with default, loan or hou
fig, ax = plt.subplots()
fig.set_size_inches(20, 8)
sns.countplot(x = 'job', data = bank_client)
ax.set_xlabel('Job', fontsize=15)
ax.set_ylabel('Count', fontsize=15)
ax.set_title('Age Count Distribution', fontsize=15)
ax.tick_params(labelsize=15)
sns.despine()
```



MARITAL

In [18]:

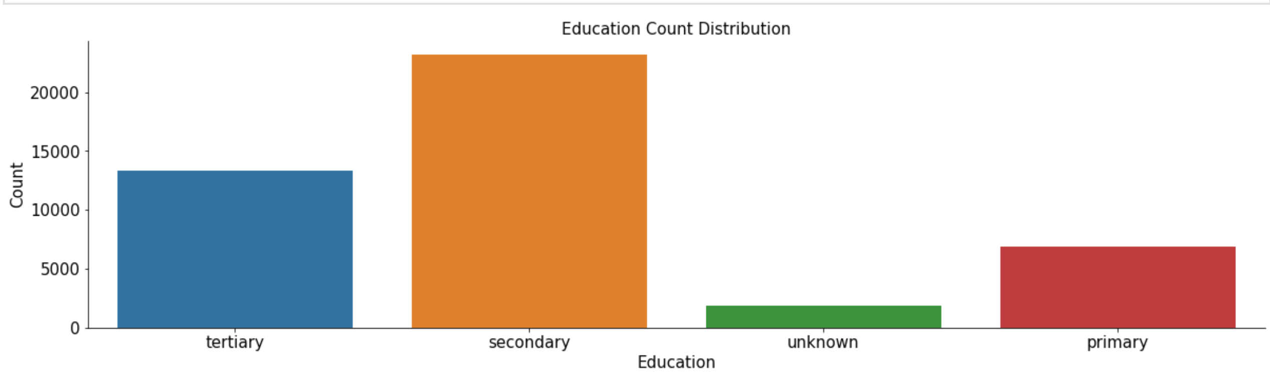
```
# What kind of 'marital clients' this bank have, if you cross marital with default, loa
fig, ax = plt.subplots()
fig.set_size_inches(10, 5)
sns.countplot(x = 'marital', data = bank_client)
ax.set_xlabel('Marital', fontsize=15)
ax.set_ylabel('Count', fontsize=15)
ax.set_title('Age Count Distribution', fontsize=15)
ax.tick_params(labelsize=15)
sns.despine()
```



EDUCATION

In [19]:

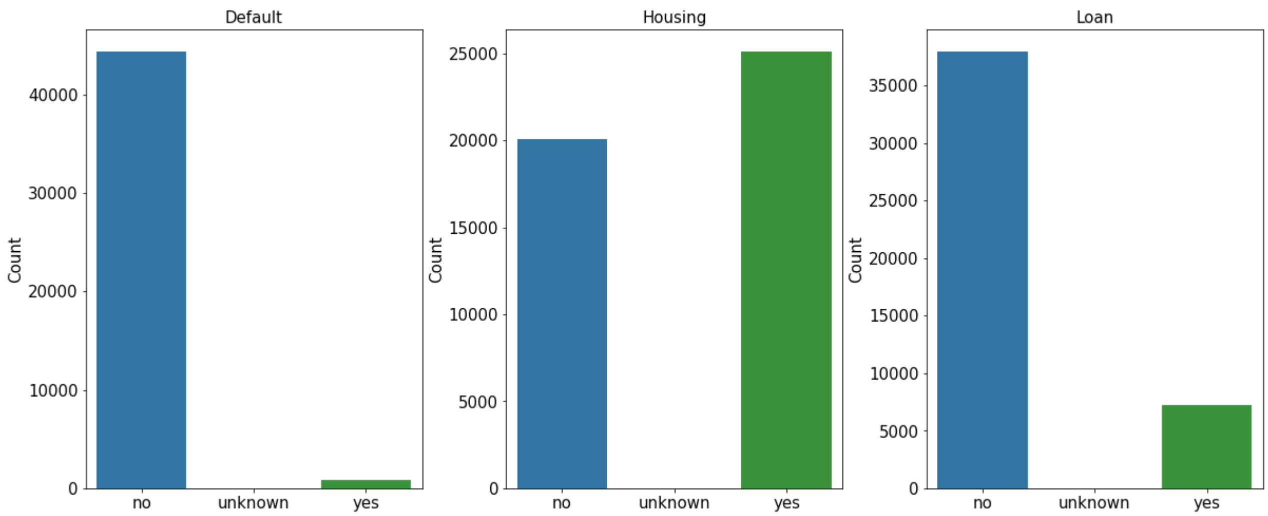
```
# What kind of 'education clients this bank have, if you cross education with default,
fig, ax = plt.subplots()
fig.set_size_inches(20, 5)
sns.countplot(x = 'education', data = bank_client)
ax.set_xlabel('Education', fontsize=15)
ax.set_ylabel('Count', fontsize=15)
ax.set_title('Education Count Distribution', fontsize=15)
ax.tick_params(labelsize=15)
sns.despine()
```



DEFAULT, HOUSING, LOAN

In [20]:

```
# Default, has credit in default ?
fig, (ax1, ax2, ax3) = plt.subplots(nrows = 1, ncols = 3, figsize = (20,8))
sns.countplot(x = 'default', data = bank_client, ax = ax1, order = ['no', 'unknown', 'y
ax1.set_title('Default', fontsize=15)
ax1.set_xlabel('')
ax1.set_ylabel('Count', fontsize=15)
ax1.tick_params(labelsize=15)

# Housing, has housing loan ?
sns.countplot(x = 'housing', data = bank_client, ax = ax2, order = ['no', 'unknown', 'y
ax2.set_title('Housing', fontsize=15)
ax2.set_xlabel('')
ax2.set_ylabel('Count', fontsize=15)
ax2.tick_params(labelsize=15)

# Loan, has personal loan ?
sns.countplot(x = 'loan', data = bank_client, ax = ax3, order = ['no', 'unknown', 'yes'
ax3.set_title('Loan', fontsize=15)
ax3.set_xlabel('')
ax3.set_ylabel('Count', fontsize=15)
ax3.tick_params(labelsize=15)

plt.subplots_adjust(wspace=0.25)
```



In [21]:

```
print('Default:\n No credit in default:'     , bank_client[bank_client['default'] == 'n
              '\n Unknown credit in default:', bank_client[bank_client['default'] == 'u
              '\n Yes to credit in default:' , bank_client[bank_client['default'] == 'y
```

```
Default:
 No credit in default: 44396
 Unknown credit in default: 0
 Yes to credit in default: 815
```

In [22]:

```
print('Housing:\n No housing in loan:'     , bank_client[bank_client['housing'] == 'no'
              '\n Unknown housing in loan:', bank_client[bank_client['housing'] == 'unk
              '\n Yes to housing in loan:' , bank_client[bank_client['housing'] == 'yes
```

```
Housing:
 No housing in loan: 20081
```

```
Unknown housing in loan: 0
Yes to housing in loan: 25130
```

In [23]:

```python
print('Housing:\n No to personal loan:'     , bank_client[bank_client['loan'] == 'no']
              '\n Unknown to personal loan:', bank_client[bank_client['loan'] == 'unkno
              '\n Yes to personal loan:'    , bank_client[bank_client['loan'] == 'yes']
```

```
Housing:
 No to personal loan: 37967
 Unknown to personal loan: 0
 Yes to personal loan: 7244
```

BANK CLIENTS CONCLUSION:

The AGEs don't mean to much, has a medium dispersion.

Jobs, Marital and Education will be the best analysis, that are just the count of each variables, if we relate with the other ones. It will be not conclusive, all this kind of variables has yes, unknown and no for loan, default and housing.

As the number of Outlier is very high in dataset, so we'll exclude Balance variable from model building.

Default, loan and housing, its just to see the distribution of people.

Bank Client Categorical Treatment
Jobs, Marital, Education, Default, Housing, Loan.
Converting to continuous due the feature scaling with Label Encoder.

In [24]:

```python
# Label encoder order is alphabetical
from sklearn.preprocessing import LabelEncoder
labelencoder_X = LabelEncoder()
bank_client['job']      = labelencoder_X.fit_transform(bank_client['job'])
bank_client['marital']  = labelencoder_X.fit_transform(bank_client['marital'])
bank_client['education']= labelencoder_X.fit_transform(bank_client['education'])
bank_client['default']  = labelencoder_X.fit_transform(bank_client['default'])
bank_client['housing']  = labelencoder_X.fit_transform(bank_client['housing'])
bank_client['loan']     = labelencoder_X.fit_transform(bank_client['loan'])
```

Segregation the AGE to different groups to make it as a Categorical Variable

In [25]:

```python
# function to creat group of ages, this helps because we have 78 differente values here
def age(dataframe):
    dataframe.loc[dataframe['age'] <= 32, 'age'] = 1
    dataframe.loc[(dataframe['age'] > 32) & (dataframe['age'] <= 47), 'age'] = 2
    dataframe.loc[(dataframe['age'] > 47) & (dataframe['age'] <= 70), 'age'] = 3
    dataframe.loc[(dataframe['age'] > 70) & (dataframe['age'] <= 98), 'age'] = 4

    return dataframe

age(bank_client);
```

In [26]:

```python
bank_client = bank_client.drop(['balance'], axis=1) # Removing Balance due to high perc
bank_client.head()
```

Out[26]:

	age	job	marital	education	default	housing	loan
0	3	4	1	2	0	1	0
1	2	9	2	1	0	1	0
2	2	2	1	1	0	1	1
3	2	1	1	3	0	1	0
4	2	11	2	3	0	0	0

Related with the last contact of the current campaign

Treat Categorical, see those values

Group Continuous Variables if necessary

In [27]:

```
# Slicing DataFrame to treat separately, make things more easy
bank_related = bank.iloc[: , 8:12]
bank_related.head()
```

Out[27]:

	contact	day	month	duration
0	unknown	5	may	261
1	unknown	5	may	151
2	unknown	5	may	76
3	unknown	5	may	92
4	unknown	5	may	198

In [28]:

```
bank_related.isnull().any()
```

Out[28]:

```
contact     False
day         False
month       False
duration    False
dtype: bool
```

In [29]:

```
print("Kind of Contact: \n", bank_related['contact'].unique())
print("\nWhich monthis this campaing work: \n", bank_related['month'].unique())
print("\nWhich days of week this campaing work: \n", bank_related['day'].unique())
```

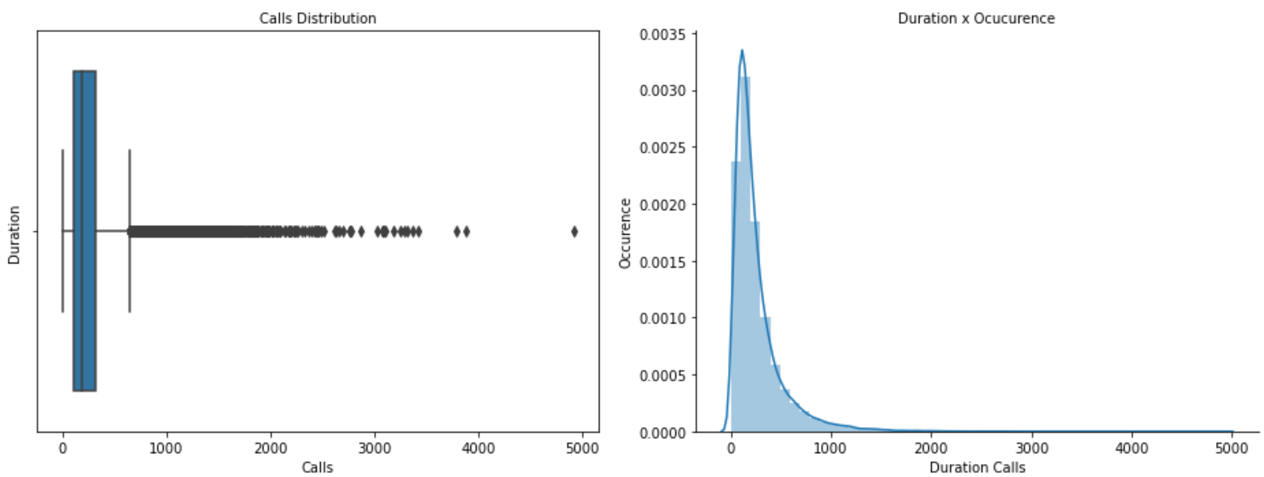
```
Kind of Contact: 
 ['unknown' 'cellular' 'telephone']

Which monthis this campaing work: 
 ['may' 'jun' 'jul' 'aug' 'oct' 'nov' 'dec' 'jan' 'feb' 'mar' 'apr' 'sep']

Which days of week this campaing work: 
 [ 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]
```

Duration

In [30]:

```
fig, (ax1, ax2) = plt.subplots(nrows = 1, ncols = 2, figsize = (13, 5))
```

```
sns.boxplot(x = 'duration', data = bank_related, orient = 'v', ax = ax1)
ax1.set_xlabel('Calls', fontsize=10)
ax1.set_ylabel('Duration', fontsize=10)
ax1.set_title('Calls Distribution', fontsize=10)
ax1.tick_params(labelsize=10)

sns.distplot(bank_related['duration'], ax = ax2)
sns.despine(ax = ax2)
ax2.set_xlabel('Duration Calls', fontsize=10)
ax2.set_ylabel('Occurence', fontsize=10)
ax2.set_title('Duration x Ocucurence', fontsize=10)
ax2.tick_params(labelsize=10)

plt.subplots_adjust(wspace=0.5)
plt.tight_layout()
```



In [31]:

```
print("Max duration  call in minutes:  ", round((bank_related['duration'].max()/60),1))
print("Min duration  call in minutes:   ", round((bank_related['duration'].min()/60),1)
print("Mean duration call in minutes:   ", round((bank_related['duration'].mean()/60),1
print("STD duration  call in minutes:   ", round((bank_related['duration'].std()/60),1)
# Std close to the mean means that the data values are close to the mean
```

```
Max duration  call in minutes:   82.0
Min duration  call in minutes:    0.0
Mean duration call in minutes:    4.3
STD duration  call in minutes:    4.3
```

In [32]:

```
print('1º Quartile: ', bank_related['duration'].quantile(q = 0.25))
print('2º Quartile: ', bank_related['duration'].quantile(q = 0.50))
print('3º Quartile: ', bank_related['duration'].quantile(q = 0.75))
print('4º Quartile: ', bank_related['duration'].quantile(q = 1.00))
#Calculate the outliers:
  # Interquartile range, IQR = Q3 - Q1
  # lower 1.5*IQR whisker = Q1 - 1.5 * IQR
  # Upper 1.5*IQR whisker = Q3 + 1.5 * IQR

print('Duration calls above: ', bank_related['duration'].quantile(q = 0.75) +
                      1.5*(bank_related['duration'].quantile(q = 0.75) - bank_related['
```

```
1º Quartile:  103.0
2º Quartile:  180.0
3º Quartile:  319.0
```

```
4º Quartile:  4918.0
Duration calls above:  643.0 are outliers
```

In [33]:

```
print('Numerber of outliers: ', bank_related[bank_related['duration'] > 644.5]['duratio
print('Number of clients: ', len(bank_related))
#Outliers in %
print('Outliers are:', round(bank_related[bank_related['duration'] > 644.5]['duration']
```

```
Numerber of outliers:  3222
Number of clients:  45211
Outliers are: 7.13 %
```

In [34]:

```
# Look, if the call duration is iqual to 0, then is obviously that this person didn't s
# THIS LINES NEED TO BE EXCLUDED LATER
bank[(bank['duration'] == 0)]
```

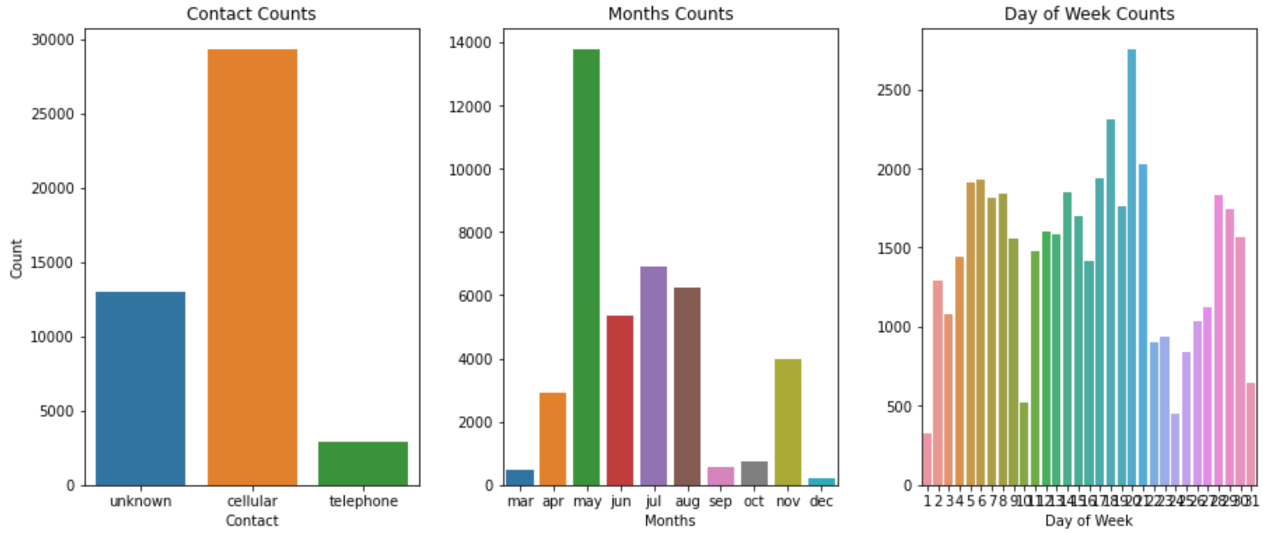
Out[34]:

	age	job	marital	education	default	balance	housing	loan	contact	day	montl
6424	53	management	married	primary	no	351	yes	no	unknown	27	ma
22937	35	technician	married	secondary	no	5535	no	no	cellular	26	au
36425	31	entrepreneur	married	secondary	no	162	yes	yes	cellular	11	ma

Contact, Month, Day of Week

In [35]:

```
fig, (ax1, ax2, ax3) = plt.subplots(nrows = 1, ncols = 3, figsize = (15,6))
sns.countplot(bank_related['contact'], ax = ax1)
ax1.set_xlabel('Contact', fontsize = 10)
ax1.set_ylabel('Count', fontsize = 10)
ax1.set_title('Contact Counts')
ax1.tick_params(labelsize=10)

sns.countplot(bank_related['month'], ax = ax2, order = ['mar', 'apr', 'may', 'jun', 'ju
ax2.set_xlabel('Months', fontsize = 10)
ax2.set_ylabel('')
ax2.set_title('Months Counts')
ax2.tick_params(labelsize=10)

sns.countplot(bank_related['day'], ax = ax3)
ax3.set_xlabel('Day of Week', fontsize = 10)
ax3.set_ylabel('')
ax3.set_title('Day of Week Counts')
ax3.tick_params(labelsize=10)

plt.subplots_adjust(wspace=0.25)
```



In [36]:

```
print('Duration above: ', bank_related['duration'].quantile(q = 0.75) +
                      1.5*(bank_related['duration'].quantile(q = 0.75) - bank_related['
```

```
Duration above:  643.0 are outliers
```

In [37]:

```
bank_related[bank_related['duration'] > 640].count()
```

Out[37]:

```
contact     3272
day         3272
month       3272
duration    3272
dtype: int64
```

Contact, Month, Day of Week treatment

In [38]:

```
# Label encoder order is alphabetical
from sklearn.preprocessing import LabelEncoder
labelencoder_X = LabelEncoder()
bank_related['contact']     = labelencoder_X.fit_transform(bank_related['contact'])
bank_related['month']       = labelencoder_X.fit_transform(bank_related['month'])
bank_related['day'] = labelencoder_X.fit_transform(bank_related['day'])
```

In [39]:

```
bank_related.head()
```

Out[39]:

	contact	day	month	duration
0	2	4	8	261
1	2	4	8	151
2	2	4	8	76
3	2	4	8	92
4	2	4	8	198

In [40]:

```
def duration(data):
```

```
    data.loc[data['duration'] <= 102, 'duration'] = 1
    data.loc[(data['duration'] > 102) & (data['duration'] <= 180)  , 'duration']    = 2
    data.loc[(data['duration'] > 180) & (data['duration'] <= 319)  , 'duration']   = 3
    data.loc[(data['duration'] > 319) & (data['duration'] <= 644.5), 'duration'] = 4
    data.loc[data['duration']  > 644.5, 'duration'] = 5

    return data
duration(bank_related);
# Excluded the lines where call duration is zero
```

In [41]:

```
bank_related.head()
```

Out[41]:

	contact	day	month	duration
0	2	4	8	3
1	2	4	8	2
2	2	4	8	1
3	2	4	8	1
4	2	4	8	3

Other attributes

In [42]:

```
bank_o = bank.loc[: , ['campaign', 'pdays','previous', 'poutcome']]
bank_o.head()
```

Out[42]:

	campaign	pdays	previous	poutcome
0	1	-1	0	unknown
1	1	-1	0	unknown
2	1	-1	0	unknown
3	1	-1	0	unknown
4	1	-1	0	unknown

In [43]:

```
bank_o['poutcome'].unique()
```

Out[43]:

```
array(['unknown', 'failure', 'other', 'success'], dtype=object)
```

In [44]:

```
bank_o['poutcome'].replace(['unknown','other', 'failure', 'success'], [0,1,2,3], inplac
```

In [45]:

```
bank_final= pd.concat([bank_client, bank_related, bank_o], axis = 1)
bank_final = bank_final[['age', 'job', 'marital', 'education', 'default', 'housing', 'l
                     'contact', 'day', 'month', 'duration', 'campaign', 'pdays', 'previ
bank_final.shape
```

Out[45]:

```
(45211, 15)
```

4. Model Building

In [46]:
```
# Train Test Split
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score
y = pd.get_dummies(bank['Target'], columns = ['Target'], prefix = ['Target'], drop_firs
X_train, X_test, y_train, y_test = train_test_split(bank_final, y, test_size = 0.20, ra

from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix, accuracy_score
k_fold = KFold(n_splits=10, shuffle=True, random_state=0)
```

In [47]:
```
X_train.head()
```

Out[47]:

	age	job	marital	education	default	housing	loan	contact	day	month	duration	campaig
3734	1	1	2	0	0	1	0	2	15	8	1	
28119	2	4	1	2	0	0	0	0	27	4	2	
36942	2	9	1	1	0	1	0	0	11	8	5	
4710	1	1	1	0	0	1	0	2	19	8	4	
26402	2	2	1	2	0	0	0	0	19	9	3	

In [48]:
```
from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler()
X_train = sc_X.fit_transform(X_train)
X_test = sc_X.transform(X_test)
```

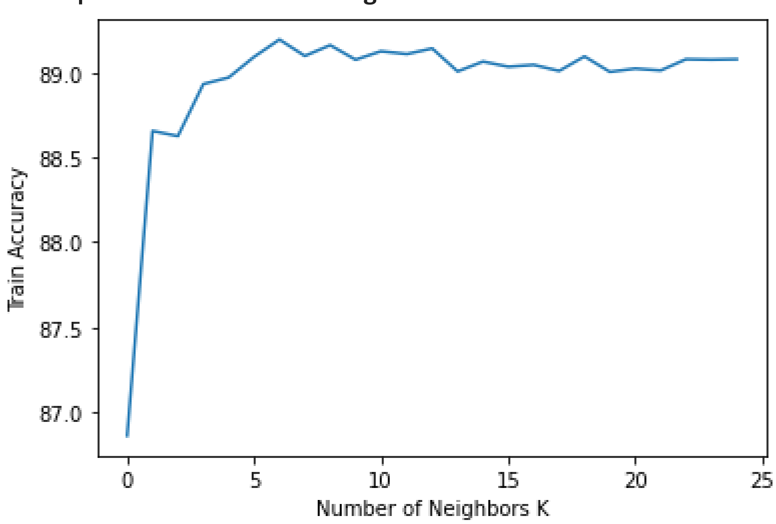
5. Standard Classification Algorithms

In [49]:
```
from sklearn.linear_model import LogisticRegression
logmodel = LogisticRegression()
logmodel.fit(X_train,y_train)
logpred = logmodel.predict(X_test)
LOGCV = (cross_val_score(logmodel, X_train, y_train, cv=k_fold, n_jobs=1, scoring = 'ac
```

In [50]:
```
from sklearn import model_selection
from sklearn.neighbors import KNeighborsClassifier

X_trainK, X_testK, y_trainK, y_testK = train_test_split(bank_final, y, test_size = 0.2,

#Neighbors
neighbors = np.arange(0,25)

#Create empty list that will hold cv scores
cv_scores = []

#Perform 10-fold cross validation on training set for odd values of k:
for k in neighbors:
```

```
    k_value = k+1
    knn = KNeighborsClassifier(n_neighbors = k_value, weights='uniform', p=2, metric='e
    kfold = model_selection.KFold(n_splits=10, random_state=123, shuffle=True)
    scores = model_selection.cross_val_score(knn, X_trainK, y_trainK, cv=kfold, scoring
    cv_scores.append(scores.mean()*100)
    print("k=%d %0.2f (+/- %0.2f)" % (k_value, scores.mean()*100, scores.std()*100))

optimal_k = neighbors[cv_scores.index(max(cv_scores))]
print ("The optimal number of neighbors is %d with %0.1f%%" % (optimal_k, cv_scores[opt

plt.plot(neighbors, cv_scores)
plt.xlabel('Number of Neighbors K')
plt.ylabel('Train Accuracy')
plt.show()
```

```
k=1 86.86 (+/- 0.71)
k=2 88.66 (+/- 0.55)
k=3 88.63 (+/- 0.52)
k=4 88.93 (+/- 0.55)
k=5 88.97 (+/- 0.51)
k=6 89.09 (+/- 0.59)
k=7 89.19 (+/- 0.52)
k=8 89.10 (+/- 0.59)
k=9 89.16 (+/- 0.66)
k=10 89.08 (+/- 0.55)
k=11 89.13 (+/- 0.56)
k=12 89.11 (+/- 0.54)
k=13 89.14 (+/- 0.54)
k=14 89.01 (+/- 0.52)
k=15 89.06 (+/- 0.52)
k=16 89.03 (+/- 0.56)
k=17 89.05 (+/- 0.45)
k=18 89.01 (+/- 0.52)
k=19 89.10 (+/- 0.51)
k=20 89.00 (+/- 0.51)
k=21 89.02 (+/- 0.49)
k=22 89.01 (+/- 0.51)
k=23 89.08 (+/- 0.46)
k=24 89.08 (+/- 0.47)
k=25 89.08 (+/- 0.46)
The optimal number of neighbors is 6 with 89.2%
```



In [51]:

```
from sklearn.neighbors import KNeighborsClassifier
```

```
knn = KNeighborsClassifier(n_neighbors=22)
knn.fit(X_train, y_train)
knnpred = knn.predict(X_test)
KNNCV = (cross_val_score(knn, X_train, y_train, cv=k_fold, n_jobs=1, scoring = 'accurac
```

In [52]:

```
from sklearn.svm import SVC
svc= SVC(kernel = 'sigmoid')
svc.fit(X_train, y_train)
svcpred = svc.predict(X_test)
SVCCV = (cross_val_score(svc, X_train, y_train, cv=k_fold, n_jobs=1, scoring = 'accurac
```

In [54]:

```
from sklearn.tree import DecisionTreeClassifier
dtree = DecisionTreeClassifier(criterion='gini') #criterion = entopy, gini
dtree.fit(X_train, y_train)
dtreepred = dtree.predict(X_test)
DTREECV = (cross_val_score(dtree, X_train, y_train, cv=k_fold, n_jobs=1, scoring = 'acc
```

In [55]:

```
from sklearn.naive_bayes import GaussianNB
gaussiannb= GaussianNB()
gaussiannb.fit(X_train, y_train)
gaussiannbpred = gaussiannb.predict(X_test)
probs = gaussiannb.predict(X_test)
GAUSIAN = (cross_val_score(gaussiannb, X_train, y_train, cv=k_fold, n_jobs=1, scoring =
```

In [56]:

```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier(n_estimators = 200)#criterion = entopy,gini
rfc.fit(X_train, y_train)
rfcpred = rfc.predict(X_test)
RFCCV = (cross_val_score(rfc, X_train, y_train, cv=k_fold, n_jobs=1, scoring = 'accurac
```

In [57]:

```
from xgboost import XGBClassifier
xgb = XGBClassifier()
xgb.fit(X_train, y_train)
xgbprd = xgb.predict(X_test)
XGB = (cross_val_score(estimator = xgb, X = X_train, y = y_train, cv = 10).mean())
```

```
[08:07:55] WARNING: ..\src\learner.cc:1061: Starting in XGBoost 1.3.0, the default evalu
ation metric used with the objective 'binary:logistic' was changed from 'error' to 'logl
oss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[08:07:57] WARNING: ..\src\learner.cc:1061: Starting in XGBoost 1.3.0, the default evalu
ation metric used with the objective 'binary:logistic' was changed from 'error' to 'logl
oss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[08:08:00] WARNING: ..\src\learner.cc:1061: Starting in XGBoost 1.3.0, the default evalu
ation metric used with the objective 'binary:logistic' was changed from 'error' to 'logl
oss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[08:08:02] WARNING: ..\src\learner.cc:1061: Starting in XGBoost 1.3.0, the default evalu
ation metric used with the objective 'binary:logistic' was changed from 'error' to 'logl
oss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[08:08:04] WARNING: ..\src\learner.cc:1061: Starting in XGBoost 1.3.0, the default evalu
ation metric used with the objective 'binary:logistic' was changed from 'error' to 'logl
oss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[08:08:07] WARNING: ..\src\learner.cc:1061: Starting in XGBoost 1.3.0, the default evalu
ation metric used with the objective 'binary:logistic' was changed from 'error' to 'logl
oss'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

```
[08:08:09] WARNING: ..\src\learner.cc:1061: Starting in XGBoost 1.3.0, the default evalu
ation metric used with the objective 'binary:logistic' was changed from 'error' to 'logl
oss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[08:08:11] WARNING: ..\src\learner.cc:1061: Starting in XGBoost 1.3.0, the default evalu
ation metric used with the objective 'binary:logistic' was changed from 'error' to 'logl
oss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[08:08:14] WARNING: ..\src\learner.cc:1061: Starting in XGBoost 1.3.0, the default evalu
ation metric used with the objective 'binary:logistic' was changed from 'error' to 'logl
oss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[08:08:16] WARNING: ..\src\learner.cc:1061: Starting in XGBoost 1.3.0, the default evalu
ation metric used with the objective 'binary:logistic' was changed from 'error' to 'logl
oss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[08:08:19] WARNING: ..\src\learner.cc:1061: Starting in XGBoost 1.3.0, the default evalu
ation metric used with the objective 'binary:logistic' was changed from 'error' to 'logl
oss'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

In [59]:

```python
from sklearn.ensemble import GradientBoostingClassifier
gbk = GradientBoostingClassifier()
gbk.fit(X_train, y_train)
gbkpred = gbk.predict(X_test)
GBKCV = (cross_val_score(gbk, X_train, y_train, cv=k_fold, n_jobs=1, scoring = 'accurac
```

In [60]:

```python
models = pd.DataFrame({
                'Models': ['Random Forest Classifier', 'Decision Tree Classifier', 'Sup
                           'K-Near Neighbors', 'Logistic Model', 'Gausian NB', 'Gradien
                'Score':  [RFCCV, DTREECV, SVCCV, KNNCV, LOGCV, GAUSIAN, GBKCV, XGB]})

models.sort_values(by='Score', ascending=False)
```

Out[60]:

	Models	Score
7	XG Boost	0.906713
6	Gradient Boosting	0.903423
0	Random Forest Classifier	0.899276
4	Logistic Model	0.894409
3	K-Near Neighbors	0.894161
1	Decision Tree Classifier	0.875056
2	Support Vector Machine	0.839223
5	Gausian NB	0.825205

As per the K-Fold Cross Validation, Ensemble Learnings are providing best results for the accuracy score.

Accuracy is also measured by the area under the ROC curve. An area of 1 represents a perfect test; an area of .5 represents a worthless test.

A rough guide for classifying the accuracy of a diagnostic test is the traditional academic point system:

.90-1 = excellent (A)

.80-.90 = good (B)

.70-.80 = fair (C)

.60-.70 = poor (D)

.50-.60 = fail (F)

As per the test result, Ensemble Learnings are providing exellent (A) results whereas remaining other classifications are providing good (B) result.

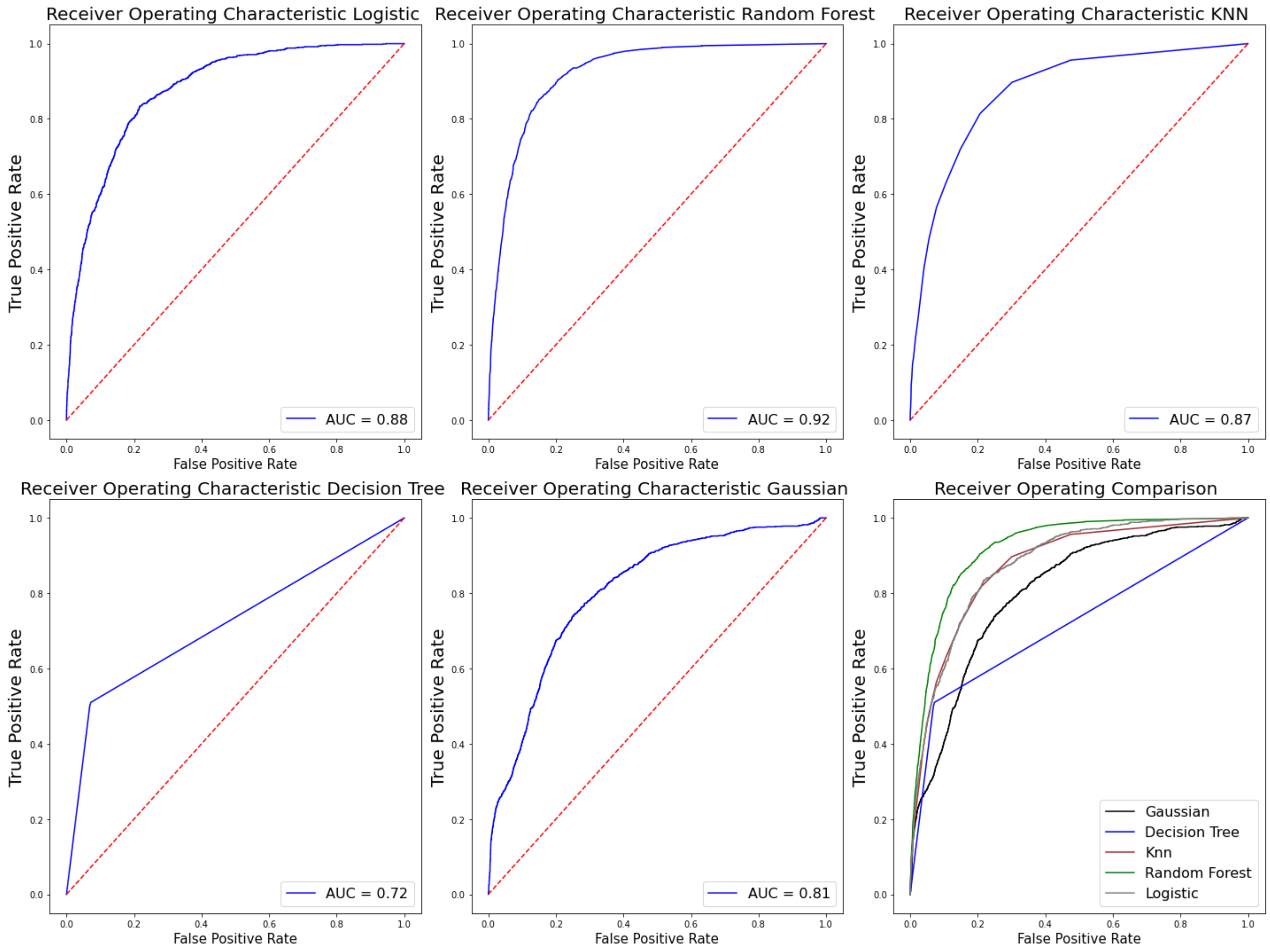
7. Comparing the perfromances for all Models

ROC/ AUC , BEST MODEL

In [61]:

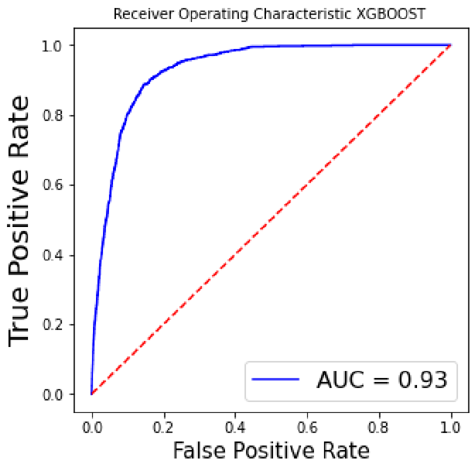
```
from sklearn import metrics
#fig, (ax1, ax2, ax3, ax4, ax5) = plt.subplots(nrows = 2, ncols = 3, figsize = (15, 4))
fig, ax_arr = plt.subplots(nrows = 2, ncols = 3, figsize = (20,15))

#LOGMODEL
probs = logmodel.predict_proba(X_test)
preds = probs[:,1]
fprlog, tprlog, thresholdlog = metrics.roc_curve(y_test, preds)
roc_auclog = metrics.auc(fprlog, tprlog)

ax_arr[0,0].plot(fprlog, tprlog, 'b', label = 'AUC = %0.2f' % roc_auclog)
ax_arr[0,0].plot([0, 1], [0, 1],'r--')
ax_arr[0,0].set_title('Receiver Operating Characteristic Logistic ',fontsize=20)
ax_arr[0,0].set_ylabel('True Positive Rate',fontsize=20)
ax_arr[0,0].set_xlabel('False Positive Rate',fontsize=15)
ax_arr[0,0].legend(loc = 'lower right', prop={'size': 16})

#RANDOM FOREST --------------------
probs = rfc.predict_proba(X_test)
preds = probs[:,1]
fprrfc, tprrfc, thresholdrfc = metrics.roc_curve(y_test, preds)
roc_aucrfc = metrics.auc(fprrfc, tprrfc)

ax_arr[0,1].plot(fprrfc, tprrfc, 'b', label = 'AUC = %0.2f' % roc_aucrfc)
ax_arr[0,1].plot([0, 1], [0, 1],'r--')
ax_arr[0,1].set_title('Receiver Operating Characteristic Random Forest ',fontsize=20)
ax_arr[0,1].set_ylabel('True Positive Rate',fontsize=20)
ax_arr[0,1].set_xlabel('False Positive Rate',fontsize=15)
ax_arr[0,1].legend(loc = 'lower right', prop={'size': 16})

#KNN----------------------
probs = knn.predict_proba(X_test)
preds = probs[:,1]
fprknn, tprknn, thresholdknn = metrics.roc_curve(y_test, preds)
roc_aucknn = metrics.auc(fprknn, tprknn)

ax_arr[0,2].plot(fprknn, tprknn, 'b', label = 'AUC = %0.2f' % roc_aucknn)
ax_arr[0,2].plot([0, 1], [0, 1],'r--')
ax_arr[0,2].set_title('Receiver Operating Characteristic KNN ',fontsize=20)
ax_arr[0,2].set_ylabel('True Positive Rate',fontsize=20)
ax_arr[0,2].set_xlabel('False Positive Rate',fontsize=15)
ax_arr[0,2].legend(loc = 'lower right', prop={'size': 16})
```

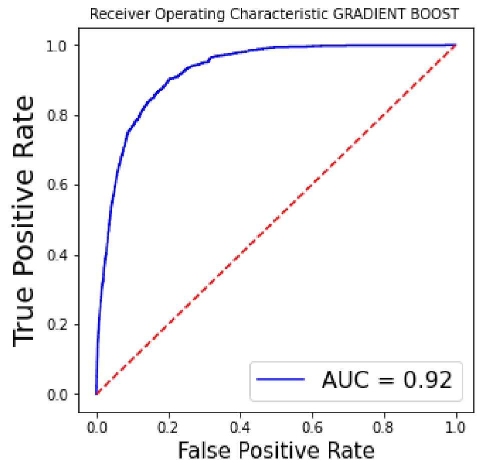
```
#DECISION TREE ---------------------
probs = dtree.predict_proba(X_test)
preds = probs[:,1]
fprdtree, tprdtree, thresholddtree = metrics.roc_curve(y_test, preds)
roc_aucdtree = metrics.auc(fprdtree, tprdtree)

ax_arr[1,0].plot(fprdtree, tprdtree, 'b', label = 'AUC = %0.2f' % roc_aucdtree)
ax_arr[1,0].plot([0, 1], [0, 1],'r--')
ax_arr[1,0].set_title('Receiver Operating Characteristic Decision Tree ',fontsize=20)
ax_arr[1,0].set_ylabel('True Positive Rate',fontsize=20)
ax_arr[1,0].set_xlabel('False Positive Rate',fontsize=15)
ax_arr[1,0].legend(loc = 'lower right', prop={'size': 16})

#GAUSSIAN ---------------------
probs = gaussiannb.predict_proba(X_test)
preds = probs[:,1]
fprgau, tprgau, thresholdgau = metrics.roc_curve(y_test, preds)
roc_aucgau = metrics.auc(fprgau, tprgau)

ax_arr[1,1].plot(fprgau, tprgau, 'b', label = 'AUC = %0.2f' % roc_aucgau)
ax_arr[1,1].plot([0, 1], [0, 1],'r--')
ax_arr[1,1].set_title('Receiver Operating Characteristic Gaussian ',fontsize=20)
ax_arr[1,1].set_ylabel('True Positive Rate',fontsize=20)
ax_arr[1,1].set_xlabel('False Positive Rate',fontsize=15)
ax_arr[1,1].legend(loc = 'lower right', prop={'size': 16})

#ALL PLOTS ----------------------------------
ax_arr[1,2].plot(fprgau, tprgau, 'b', label = 'Gaussian', color='black')
ax_arr[1,2].plot(fprdtree, tprdtree, 'b', label = 'Decision Tree', color='blue')
ax_arr[1,2].plot(fprknn, tprknn, 'b', label = 'Knn', color='brown')
ax_arr[1,2].plot(fprrfc, tprrfc, 'b', label = 'Random Forest', color='green')
ax_arr[1,2].plot(fprlog, tprlog, 'b', label = 'Logistic', color='grey')
ax_arr[1,2].set_title('Receiver Operating Comparison ',fontsize=20)
ax_arr[1,2].set_ylabel('True Positive Rate',fontsize=20)
ax_arr[1,2].set_xlabel('False Positive Rate',fontsize=15)
ax_arr[1,2].legend(loc = 'lower right', prop={'size': 16})

plt.subplots_adjust(wspace=0.2)
plt.tight_layout()
```



In [62]:

```
# XGBOOST ROC/ AUC , BEST MODEL

fig, (ax, ax1) = plt.subplots(nrows = 1, ncols = 2, figsize = (15,5))
probs = xgb.predict_proba(X_test)
preds = probs[:,1]
fprxgb, tprxgb, thresholdxgb = metrics.roc_curve(y_test, preds)
roc_aucxgb = metrics.auc(fprxgb, tprxgb)

ax.plot(fprxgb, tprxgb, 'b', label = 'AUC = %0.2f' % roc_aucxgb)
ax.plot([0, 1], [0, 1],'r--')
ax.set_title('Receiver Operating Characteristic XGBOOST ',fontsize=10)
ax.set_ylabel('True Positive Rate',fontsize=20)
ax.set_xlabel('False Positive Rate',fontsize=15)
ax.legend(loc = 'lower right', prop={'size': 16})

#Gradient
probs = gbk.predict_proba(X_test)
preds = probs[:,1]
fprgbk, tprgbk, thresholdgbk = metrics.roc_curve(y_test, preds)
roc_aucgbk = metrics.auc(fprgbk, tprgbk)

ax1.plot(fprgbk, tprgbk, 'b', label = 'AUC = %0.2f' % roc_aucgbk)
ax1.plot([0, 1], [0, 1],'r--')
ax1.set_title('Receiver Operating Characteristic GRADIENT BOOST ',fontsize=10)
ax1.set_ylabel('True Positive Rate',fontsize=20)
ax1.set_xlabel('False Positive Rate',fontsize=15)
ax1.legend(loc = 'lower right', prop={'size': 16})

plt.subplots_adjust(wspace=1)
```





ANALYZING THE RESULTS: </br>

So now we have to decide which one is the best model, and we have two types of wrong values:

False Positive, means the client do NOT SUBSCRIBED to term deposit, but the model thinks he did.

False Negative, means the client SUBSCRIBED to term deposit, but the model said he dont.

Considering the Objective, "The classification goal is to predict if the client will subscribe (yes/no) a term deposit (variable y)."

As we know:

From K-Fold Cross Validation Accurcy Score and ROC Curve, Ensemble Learnings (Random Forrest, Geadient Boostand XG Boost) are giving best results.

We are extending the process with Confusion Matrix and Classification Reports for Different Models.

Conusion Matrix

In [63]:
```
from sklearn.metrics import classification_report
```

In [64]:
```
print('KNN Confusion Matrix\n', confusion_matrix(y_test, knnpred))
print('KNN Reports\n',classification_report(y_test, knnpred))
```

```
KNN Confusion Matrix
 [[7861   83]
 [ 912  187]]
KNN Reports
               precision    recall  f1-score   support

           0       0.90      0.99      0.94      7944
           1       0.69      0.17      0.27      1099

    accuracy                           0.89      9043
   macro avg       0.79      0.58      0.61      9043
```

```
weighted avg       0.87      0.89      0.86      9043
```

In [65]:

```python
print('LOGR Confusion Matrix\n', confusion_matrix(y_test, logpred))
print('LOGR Reports\n',classification_report(y_test, logpred))
```

```
LOGR Confusion Matrix
 [[7794  150]
 [ 800  299]]
LOGR Reports
               precision    recall  f1-score   support

           0       0.91      0.98      0.94      7944
           1       0.67      0.27      0.39      1099

    accuracy                           0.89      9043
   macro avg       0.79      0.63      0.66      9043
weighted avg       0.88      0.89      0.87      9043
```

In [66]:

```python
print('SVC Confusion Matrix\n', confusion_matrix(y_test, svcpred))
print('SVC Reports\n',classification_report(y_test, svcpred))
```

```
SVC Confusion Matrix
 [[7227  717]
 [ 801  298]]
SVC Reports
               precision    recall  f1-score   support

           0       0.90      0.91      0.90      7944
           1       0.29      0.27      0.28      1099

    accuracy                           0.83      9043
   macro avg       0.60      0.59      0.59      9043
weighted avg       0.83      0.83      0.83      9043
```

In [67]:

```python
print('DTREE Confusion Matrix\n', confusion_matrix(y_test, dtreepred))
print('DTREE Reports\n',classification_report(y_test, dtreepred))
```

```
DTREE Confusion Matrix
 [[7398  546]
 [ 550  549]]
DTREE Reports
               precision    recall  f1-score   support

           0       0.93      0.93      0.93      7944
           1       0.50      0.50      0.50      1099

    accuracy                           0.88      9043
   macro avg       0.72      0.72      0.72      9043
weighted avg       0.88      0.88      0.88      9043
```

In [68]:

```python
print('RFC Confusion Matrix\n', confusion_matrix(y_test, rfcpred))
print('RFC Reports\n',classification_report(y_test, rfcpred))
```

```
RFC Confusion Matrix
```

```
 [[7701  243]
 [ 650  449]]
RFC Reports
               precision    recall  f1-score   support

           0       0.92      0.97      0.95      7944
           1       0.65      0.41      0.50      1099

    accuracy                           0.90      9043
   macro avg       0.79      0.69      0.72      9043
weighted avg       0.89      0.90      0.89      9043
```

In [69]:

```
print('GAUSSIAN Confusion Matrix\n', confusion_matrix(y_test, gaussiannbpred))
print('GAUSSIAN Reports\n',classification_report(y_test, gaussiannbpred))
```

```
GAUSSIAN Confusion Matrix
 [[6914 1030]
 [ 554  545]]
GAUSSIAN Reports
               precision    recall  f1-score   support

           0       0.93      0.87      0.90      7944
           1       0.35      0.50      0.41      1099

    accuracy                           0.82      9043
   macro avg       0.64      0.68      0.65      9043
weighted avg       0.86      0.82      0.84      9043
```

In [70]:

```
print('GRADIENT BOOST Confusion Matrix\n', confusion_matrix(y_test, gbkpred))
print('GRADIENT BOOST Reports\n',classification_report(y_test, gbkpred))
```

```
GRADIENT BOOST Confusion Matrix
 [[7754  190]
 [ 681  418]]
GRADIENT BOOST Reports
               precision    recall  f1-score   support

           0       0.92      0.98      0.95      7944
           1       0.69      0.38      0.49      1099

    accuracy                           0.90      9043
   macro avg       0.80      0.68      0.72      9043
weighted avg       0.89      0.90      0.89      9043
```

In [71]:

```
print('XG BOOST Confusion Matrix\n', confusion_matrix(y_test, xgbprd))
print('XG BOOST Reports\n',classification_report(y_test, xgbprd))
```

```
XG BOOST Confusion Matrix
 [[7667  277]
 [ 599  500]]
XG BOOST Reports
               precision    recall  f1-score   support

           0       0.93      0.97      0.95      7944
           1       0.64      0.45      0.53      1099
```

```
    accuracy                           0.90      9043
   macro avg       0.79      0.71      0.74      9043
weighted avg       0.89      0.90      0.90      9043
```

Conclusion:

From the above Performance Comparison for different Models we found out that Ensemble Learnings (Random Forrest, Geadient Boostand XG Boost) are giving the best results

In [ ]: