In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import math
from pandas.api.types import CategoricalDtype
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, roc_curve, roc_a
uc_score
from sklearn.model_selection import GridSearchCV, KFold
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [2]:
```
train_set = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-databa
ses/adult/adult.data', header = None)
test_set = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-databas
es/adult/adult.test' , skiprows = 1, header = None)
col_labels = ['age', 'workclass', 'fnlwgt', 'education', 'education_num', 'mar
ital_status', 'occupation', 'relationship',
              'race', 'sex', 'capital_gain', 'capital_loss', 'hours_per_week',
'native_country', 'wage_class']
train_set.columns = col_labels
test_set.columns = col_labels
```

In [3]:
```
print('Train size:: {}'.format(train_set.shape))
print('Test size:: {}'.format(test_set.shape))
```

```
Train size:: (32561, 15)
Test size:: (16281, 15)
```

In [4]:
```
train_set.head()
```

Out[4]:

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationship
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife

In [5]:
```
test_set.head()
```

Out[5]:

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationship
0	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband
3	44	Private	160323	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband
4	18	?	103497	Some-college	10	Never-married	?	Own-child

In [6]:
```
train_set.describe()
```

Out[6]:

	age	fnlwgt	education_num	capital_gain	capital_loss	hours_per_week
count	32561.000000	3.256100e+04	32561.000000	32561.000000	32561.000000	32561.000000
mean	38.581647	1.897784e+05	10.080679	1077.648844	87.303830	40.437456
std	13.640433	1.055500e+05	2.572720	7385.292085	402.960219	12.347429
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1.000000
25%	28.000000	1.178270e+05	9.000000	0.000000	0.000000	40.000000
50%	37.000000	1.783560e+05	10.000000	0.000000	0.000000	40.000000
75%	48.000000	2.370510e+05	12.000000	0.000000	0.000000	45.000000
max	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000	99.000000

In [7]:
```
train_set.isna().sum()
```

Out[7]:
```
age               0
workclass         0
fnlwgt            0
education         0
education_num     0
marital_status    0
occupation        0
relationship      0
race              0
sex               0
capital_gain      0
capital_loss      0
hours_per_week    0
native_country    0
wage_class        0
dtype: int64
```

In [8]:
```
train_set.describe(include=["object"]).T
```

Out[8]:

	count	unique	top	freq
workclass	32561	9	Private	22696
education	32561	16	HS-grad	10501
marital_status	32561	7	Married-civ-spouse	14976
occupation	32561	15	Prof-specialty	4140
relationship	32561	6	Husband	13193
race	32561	5	White	27816
sex	32561	2	Male	21790
native_country	32561	42	United-States	29170
wage_class	32561	2	<=50K	24720

In [9]:
```
test_set.describe(include=["object"]).T
```

Out[9]:

	count	unique	top	freq
workclass	16281	9	Private	11210
education	16281	16	HS-grad	5283
marital_status	16281	7	Married-civ-spouse	7403
occupation	16281	15	Prof-specialty	2032
relationship	16281	6	Husband	6523
race	16281	5	White	13946
sex	16281	2	Male	10860
native_country	16281	41	United-States	14662
wage_class	16281	2	<=50K.	12435

In [10]:
```
# Check if duplicate data exist
check_dup = train_set.duplicated().any()
print("Are there any duplicated values in data? ",check_dup)

if check_dup:
    train_set = train_set.drop_duplicates()
else:
    print("There are not duplicated values in data.")

check_dup_test = test_set.duplicated().any()
print("Are there any duplicated values in data? ",check_dup)

if check_dup:
    test_set = test_set.drop_duplicates()
else:
    print("There are not duplicated values in data.")
```

```
Are there any duplicated values in data?  True
Are there any duplicated values in data?  True
```

In [11]:
```
object_columns=train_set.select_dtypes(include=["object"]).columns
for i in range(len(object_columns)):
    print("----- {}-----".format(object_columns[i]))
    print(train_set[object_columns[i]].value_counts())
```

```
----- workclass-----
 Private             22673
 Self-emp-not-inc     2540
 Local-gov            2093
 ?                    1836
 State-gov            1298
 Self-emp-inc         1116
 Federal-gov           960
 Without-pay            14
 Never-worked            7
Name: workclass, dtype: int64
----- education-----
 HS-grad         10494
 Some-college     7282
 Bachelors        5353
 Masters          1722
 Assoc-voc        1382
 11th             1175
 Assoc-acdm       1067
 10th              933
 7th-8th           645
 Prof-school       576
 9th               514
 12th              433
 Doctorate         413
 5th-6th           332
 1st-4th           166
 Preschool          50
Name: education, dtype: int64
----- marital_status-----
 Married-civ-spouse       14970
 Never-married            10667
 Divorced                  4441
 Separated                 1025
 Widowed                    993
 Married-spouse-absent      418
 Married-AF-spouse           23
Name: marital_status, dtype: int64
----- occupation-----
 Prof-specialty       4136
 Craft-repair         4094
 Exec-managerial      4065
 Adm-clerical         3768
 Sales                3650
 Other-service        3291
 Machine-op-inspct    2000
 ?                    1843
 Transport-moving     1597
 Handlers-cleaners    1369
 Farming-fishing       992
 Tech-support          927
 Protective-serv       649
 Priv-house-serv       147
 Armed-Forces            9
Name: occupation, dtype: int64
----- relationship-----
 Husband           13187
```

```
 Not-in-family      8292
 Own-child          5064
 Unmarried          3445
 Wife               1568
 Other-relative      981
Name: relationship, dtype: int64
----- race-----
 White                 27795
 Black                  3122
 Asian-Pac-Islander     1038
 Amer-Indian-Eskimo      311
 Other                   271
Name: race, dtype: int64
----- sex-----
 Male      21775
 Female    10762
Name: sex, dtype: int64
----- native_country-----
 United-States                 29153
 Mexico                          639
 ?                               582
 Philippines                     198
 Germany                         137
 Canada                          121
 Puerto-Rico                     114
 El-Salvador                     106
 India                           100
 Cuba                             95
 England                          90
 Jamaica                          81
 South                            80
 China                            75
 Italy                            73
 Dominican-Republic               70
 Vietnam                          67
 Guatemala                        62
 Japan                            62
 Poland                           60
 Columbia                         59
 Taiwan                           51
 Haiti                            44
 Iran                             43
 Portugal                         37
 Nicaragua                        34
 Peru                             31
 France                           29
 Greece                           29
 Ecuador                          28
 Ireland                          24
 Hong                             20
 Trinadad&Tobago                  19
 Cambodia                         19
 Thailand                         18
 Laos                             18
 Yugoslavia                       16
 Outlying-US(Guam-USVI-etc)       14
 Hungary                          13
```

```
 Honduras                          13
 Scotland                          12
 Holand-Netherlands                 1
Name: native_country, dtype: int64
----- wage_class-----
 <=50K    24698
 >50K      7839
Name: wage_class, dtype: int64
```

In [12]:
```
train_set.replace([' ?'], np.nan, inplace=True)
test_set.replace([' ?'], np.nan, inplace=True)
```

In [13]:
```
train_set.isnull().sum()
```

Out[13]:
```
age                  0
workclass         1836
fnlwgt               0
education            0
education_num        0
marital_status       0
occupation        1843
relationship         0
race                 0
sex                  0
capital_gain         0
capital_loss         0
hours_per_week       0
native_country     582
wage_class           0
dtype: int64
```

In [14]:
```
test_set.isnull().sum()
```

Out[14]:
```
age                 0
workclass         963
fnlwgt              0
education           0
education_num       0
marital_status      0
occupation        966
relationship        0
race                0
sex                 0
capital_gain        0
capital_loss        0
hours_per_week      0
native_country    274
wage_class          0
dtype: int64
```

In [15]:
```
object_columns=train_set.select_dtypes(include=["object"]).columns
for i in range(len(object_columns)):
    print("----- {}-----".format(object_columns[i]))
    print(train_set[object_columns[i]].value_counts())
```

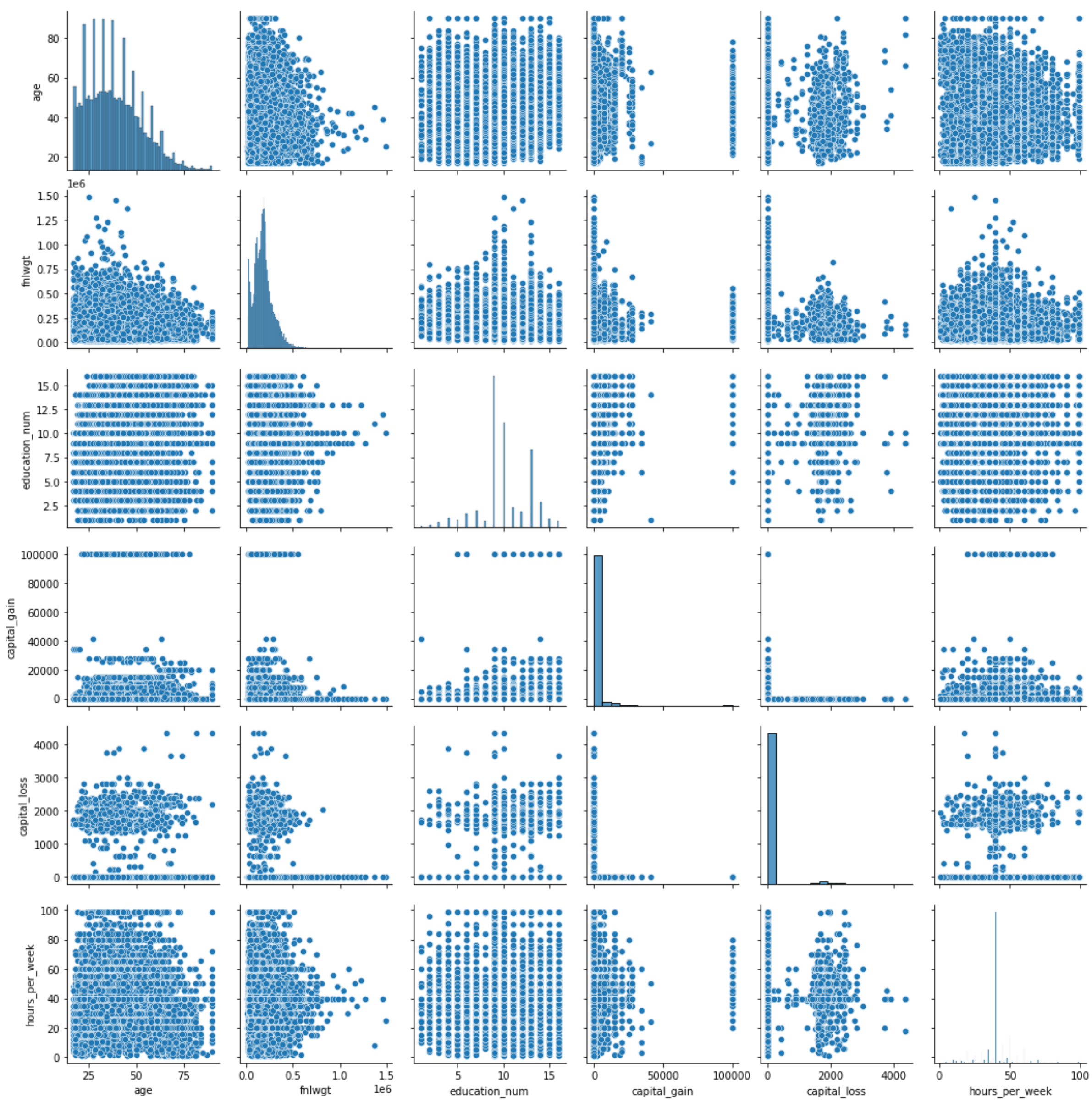
```
----- workclass-----
 Private             22673
 Self-emp-not-inc     2540
 Local-gov            2093
 State-gov            1298
 Self-emp-inc         1116
 Federal-gov           960
 Without-pay            14
 Never-worked            7
Name: workclass, dtype: int64
----- education-----
 HS-grad         10494
 Some-college     7282
 Bachelors        5353
 Masters          1722
 Assoc-voc        1382
 11th             1175
 Assoc-acdm       1067
 10th              933
 7th-8th           645
 Prof-school       576
 9th               514
 12th              433
 Doctorate         413
 5th-6th           332
 1st-4th           166
 Preschool          50
Name: education, dtype: int64
----- marital_status-----
 Married-civ-spouse       14970
 Never-married            10667
 Divorced                  4441
 Separated                 1025
 Widowed                    993
 Married-spouse-absent      418
 Married-AF-spouse           23
Name: marital_status, dtype: int64
----- occupation-----
 Prof-specialty       4136
 Craft-repair         4094
 Exec-managerial      4065
 Adm-clerical         3768
 Sales                3650
 Other-service        3291
 Machine-op-inspct    2000
 Transport-moving     1597
 Handlers-cleaners    1369
 Farming-fishing       992
 Tech-support          927
 Protective-serv       649
 Priv-house-serv       147
 Armed-Forces            9
Name: occupation, dtype: int64
----- relationship-----
 Husband          13187
 Not-in-family     8292
 Own-child         5064
```

```
 Unmarried          3445
 Wife               1568
 Other-relative      981
Name: relationship, dtype: int64
----- race-----
 White                 27795
 Black                  3122
 Asian-Pac-Islander     1038
 Amer-Indian-Eskimo      311
 Other                   271
Name: race, dtype: int64
----- sex-----
 Male      21775
 Female    10762
Name: sex, dtype: int64
----- native_country-----
 United-States                 29153
 Mexico                          639
 Philippines                     198
 Germany                         137
 Canada                          121
 Puerto-Rico                     114
 El-Salvador                     106
 India                           100
 Cuba                             95
 England                          90
 Jamaica                          81
 South                            80
 China                            75
 Italy                            73
 Dominican-Republic               70
 Vietnam                          67
 Japan                            62
 Guatemala                        62
 Poland                           60
 Columbia                         59
 Taiwan                           51
 Haiti                            44
 Iran                             43
 Portugal                         37
 Nicaragua                        34
 Peru                             31
 Greece                           29
 France                           29
 Ecuador                          28
 Ireland                          24
 Hong                             20
 Cambodia                         19
 Trinadad&Tobago                  19
 Thailand                         18
 Laos                             18
 Yugoslavia                       16
 Outlying-US(Guam-USVI-etc)       14
 Hungary                          13
 Honduras                         13
 Scotland                         12
 Holand-Netherlands                1
```

```
Name: native_country, dtype: int64
----- wage_class-----
 <=50K    24698
 >50K      7839
Name: wage_class, dtype: int64
```

In [16]:
```
sns.pairplot(train_set)
```

Out[16]:
```
<seaborn.axisgrid.PairGrid at 0x214feef3048>
```



In [17]:
```
train_set.education.value_counts()
```

Out[17]:
```
HS-grad         10494
Some-college     7282
Bachelors        5353
Masters          1722
Assoc-voc        1382
11th             1175
Assoc-acdm       1067
10th              933
7th-8th           645
Prof-school       576
9th               514
12th              433
Doctorate         413
5th-6th           332
1st-4th           166
Preschool          50
Name: education, dtype: int64
```

In [18]:
```
train_set.education_num.value_counts()
```

Out[18]:
```
9     10494
10     7282
13     5353
14     1722
11     1382
7      1175
12     1067
6       933
4       645
15      576
5       514
8       433
16      413
3       332
2       166
1        50
Name: education_num, dtype: int64
```

In [19]:
```
## As education and education_num are same, we are dropping education column
train_set.drop(columns=['education'], inplace=True)
test_set.drop(columns=['education'], inplace=True)
```

In [20]:
```
train_set["education_num"]=train_set["education_num"].astype(CategoricalDtype(
ordered=True)) #ordinal data.
test_set["education_num"]=test_set["education_num"].astype(CategoricalDtype(or
dered=True))
train_set["education_num"].head()
```

Out[20]:
```
0    13
1    13
2     9
3     7
4    13
Name: education_num, dtype: category
Categories (16, int64): [1 < 2 < 3 < 4 ... 13 < 14 < 15 < 16]
```

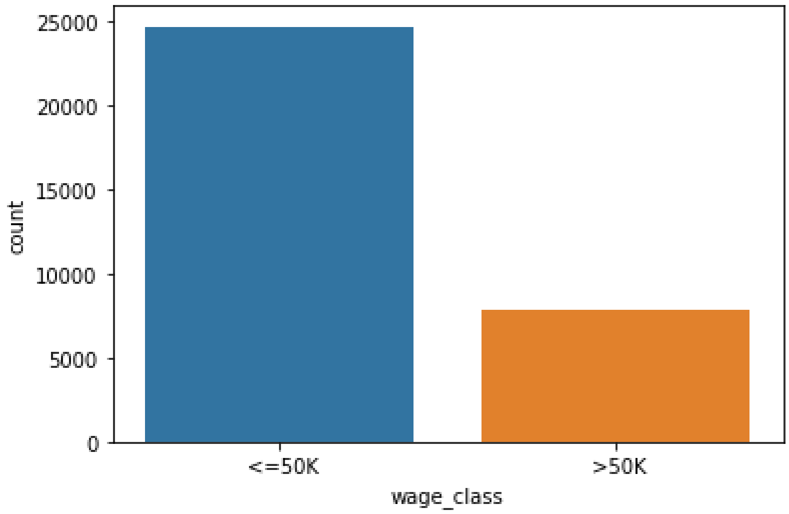
In [21]:
```
train_set.education_num.value_counts()
```

Out[21]:
```
9     10494
10     7282
13     5353
14     1722
11     1382
7      1175
12     1067
6       933
4       645
15      576
5       514
8       433
16      413
3       332
2       166
1        50
Name: education_num, dtype: int64
```

In [22]:
```
sns.countplot(train_set.wage_class)
```

```
C:\Users\Urvi\AppData\Roaming\Python\Python37\site-packages\seaborn\_decorato
rs.py:43: FutureWarning: Pass the following variable as a keyword arg: x. Fro
m version 0.12, the only valid positional argument will be `data`, and passin
g other arguments without an explicit keyword will result in an error or misi
nterpretation.
  FutureWarning
```

Out[22]:
```
<AxesSubplot:xlabel='wage_class', ylabel='count'>
```

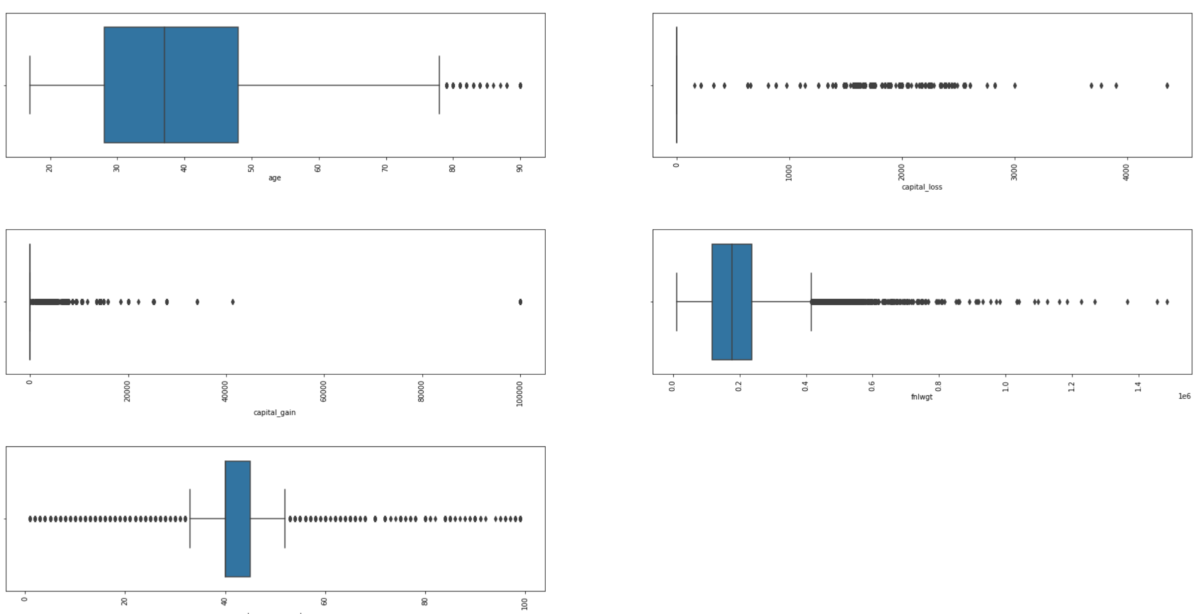


In [23]:
```
train_set.skew()
```

Out[23]:
```
age                0.557663
fnlwgt             1.447703
capital_gain      11.949403
capital_loss       4.592702
hours_per_week     0.228759
dtype: float64
```

In [24]:
```
plt.figure(figsize=(30,15))

plt.subplot(321)
sns.boxplot(train_set["age"])
plt.xticks(rotation=90)

plt.subplot(322)
sns.boxplot(train_set["capital_loss"])
plt.xticks(rotation=90)

plt.subplot(323)
sns.boxplot(train_set["capital_gain"])
plt.xticks(rotation=90)

plt.subplot(324)
sns.boxplot(train_set["fnlwgt"])
plt.xticks(rotation=90)

plt.subplot(325)
sns.boxplot(train_set["hours_per_week"])
plt.xticks(rotation=90)

plt.subplots_adjust(hspace=0.5)
plt.show()
```

```
C:\Users\Urvi\AppData\Roaming\Python\Python37\site-packages\seaborn\_decorato
rs.py:43: FutureWarning: Pass the following variable as a keyword arg: x. Fro
m version 0.12, the only valid positional argument will be `data`, and passin
g other arguments without an explicit keyword will result in an error or misi
nterpretation.
  FutureWarning
C:\Users\Urvi\AppData\Roaming\Python\Python37\site-packages\seaborn\_decorato
rs.py:43: FutureWarning: Pass the following variable as a keyword arg: x. Fro
m version 0.12, the only valid positional argument will be `data`, and passin
g other arguments without an explicit keyword will result in an error or misi
nterpretation.
  FutureWarning
C:\Users\Urvi\AppData\Roaming\Python\Python37\site-packages\seaborn\_decorato
rs.py:43: FutureWarning: Pass the following variable as a keyword arg: x. Fro
m version 0.12, the only valid positional argument will be `data`, and passin
g other arguments without an explicit keyword will result in an error or misi
nterpretation.
  FutureWarning
C:\Users\Urvi\AppData\Roaming\Python\Python37\site-packages\seaborn\_decorato
rs.py:43: FutureWarning: Pass the following variable as a keyword arg: x. Fro
m version 0.12, the only valid positional argument will be `data`, and passin
g other arguments without an explicit keyword will result in an error or misi
nterpretation.
  FutureWarning
C:\Users\Urvi\AppData\Roaming\Python\Python37\site-packages\seaborn\_decorato
rs.py:43: FutureWarning: Pass the following variable as a keyword arg: x. Fro
m version 0.12, the only valid positional argument will be `data`, and passin
g other arguments without an explicit keyword will result in an error or misi
nterpretation.
  FutureWarning
```

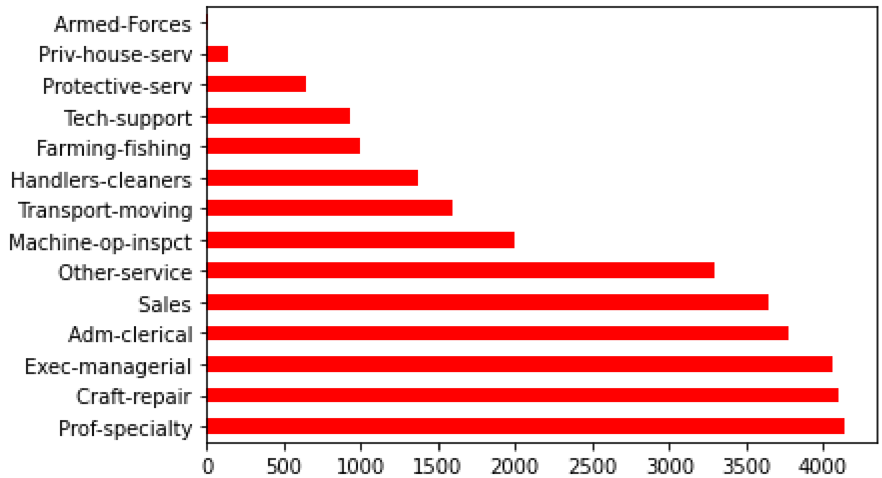


In [25]:
```
numeric_columns=list(train_set.select_dtypes(include=["int64"]).columns) #nume
ric columns
numeric_columns
```

Out[25]:
```
['age', 'fnlwgt', 'capital_gain', 'capital_loss', 'hours_per_week']
```

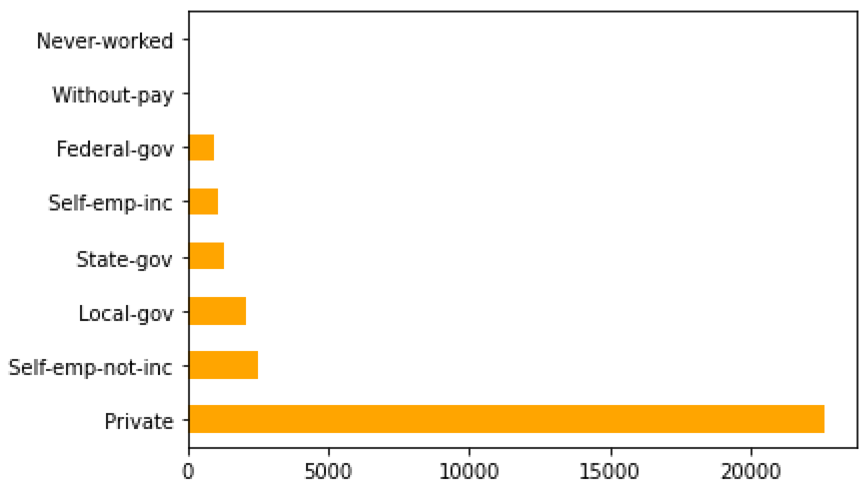
In [26]:
```
train_set["occupation"].value_counts().plot.barh(color="red")
```

Out[26]: <AxesSubplot:>



In [27]:
```
train_set["workclass"].value_counts().plot.barh(color="orange")
```

Out[27]: <AxesSubplot:>



In [28]:
```
train_set.native_country.value_counts()
```

Out[28]:
```
United-States                 29153
Mexico                          639
Philippines                     198
Germany                         137
Canada                          121
Puerto-Rico                     114
El-Salvador                     106
India                           100
Cuba                             95
England                          90
Jamaica                          81
South                            80
China                            75
Italy                            73
Dominican-Republic               70
Vietnam                          67
Japan                            62
Guatemala                        62
Poland                           60
Columbia                         59
Taiwan                           51
Haiti                            44
Iran                             43
Portugal                         37
Nicaragua                        34
Peru                             31
Greece                           29
France                           29
Ecuador                          28
Ireland                          24
Hong                             20
Cambodia                         19
Trinadad&Tobago                  19
Thailand                         18
Laos                             18
Yugoslavia                       16
Outlying-US(Guam-USVI-etc)       14
Hungary                          13
Honduras                         13
Scotland                         12
Holand-Netherlands                1
Name: native_country, dtype: int64
```

In [29]:
```
for i in ["occupation","workclass","native_country"]:
    train_set[i].fillna(train_set[i].mode()[0],inplace=True)
    test_set[i].fillna(test_set[i].mode()[0],inplace=True)
```

In [30]:
```
train_set.isnull().sum()
```

Out[30]:
```
age               0
workclass         0
fnlwgt            0
education_num     0
marital_status    0
occupation        0
relationship      0
race              0
sex               0
capital_gain      0
capital_loss      0
hours_per_week    0
native_country    0
wage_class        0
dtype: int64
```

In [31]:
```
test_set.isnull().sum()
```

Out[31]:
```
age               0
workclass         0
fnlwgt            0
education_num     0
marital_status    0
occupation        0
relationship      0
race              0
sex               0
capital_gain      0
capital_loss      0
hours_per_week    0
native_country    0
wage_class        0
dtype: int64
```

In [32]:
```
#Assigning the numeric values to the string type variables
number = LabelEncoder()
train_set['workclass'] = number.fit_transform(train_set['workclass'])
train_set['marital_status'] = number.fit_transform(train_set['marital_status'
])
train_set['occupation'] = number.fit_transform(train_set['occupation'])
train_set['relationship'] = number.fit_transform(train_set['relationship'])
train_set['race'] = number.fit_transform(train_set['race'])
train_set['sex'] = number.fit_transform(train_set['sex'])
train_set['native_country'] = number.fit_transform(train_set['native_country'
])
train_set['wage_class'] = number.fit_transform(train_set['wage_class'])

test_set['workclass'] = number.fit_transform(test_set['workclass'])
test_set['marital_status'] = number.fit_transform(test_set['marital_status'])
test_set['occupation'] = number.fit_transform(test_set['occupation'])
test_set['relationship'] = number.fit_transform(test_set['relationship'])
test_set['race'] = number.fit_transform(test_set['race'])
test_set['sex'] = number.fit_transform(test_set['sex'])
test_set['native_country'] = number.fit_transform(test_set['native_country'])
test_set['wage_class'] = number.fit_transform(test_set['wage_class'])
```

In [33]:
```
train_set['age_bin'] = pd.cut(train_set['age'], 20)
test_set['age_bin'] = pd.cut(test_set['age'], 20)
```

In [34]:
```
train_set['hours-per-week_bin'] = pd.cut(train_set['hours_per_week'], 10)
test_set['hours-per-week_bin'] = pd.cut(test_set['hours_per_week'], 10)
```

In [35]:
```
train_set[['wage_class', 'age']].groupby(['wage_class'], as_index=False).mean
().sort_values(by='age', ascending=False)
```

Out[35]:

	wage_class	age
1	1	44.250925
0	0	36.787392

In [36]:
```
train_set = train_set.apply(LabelEncoder().fit_transform)
train_set.head()
```

Out[36]:

	age	workclass	fnlwgt	education_num	marital_status	occupation	relationship	race	sex
0	22	6	2671	12	4	0	1	4	1
1	33	5	2926	12	2	3	0	4	1
2	21	3	14086	8	0	5	1	4	1
3	36	3	15336	6	2	5	0	2	1
4	11	3	19355	12	2	9	5	2	0

In [37]:
```
test_set = test_set.apply(LabelEncoder().fit_transform)
test_set.head()
```

Out[37]:

	age	workclass	fnlwgt	education_num	marital_status	occupation	relationship	race	sex	c
0	8	3	8931	6	4	6	3	2	1	
1	21	3	1888	8	2	4	0	4	1	
2	11	1	11540	11	2	10	0	4	1	
3	27	3	5146	9	2	6	0	2	1	
4	1	3	2450	9	4	9	3	4	0	

In [38]:
```
train_x = train_set.drop(columns=['wage_class', 'age', 'hours_per_week'])
test_x = test_set.drop(columns=['wage_class', 'age', 'hours_per_week'])
train_y = train_set.wage_class
test_y = test_set.wage_class
```

Checking VIF

In [39]:
```
scalar = StandardScaler()
X_scaled = scalar.fit_transform(train_x)
```

In [40]:
```
vif = pd.DataFrame()
vif["vif"] = [variance_inflation_factor(X_scaled,i) for i in range(X_scaled.sh
ape[1])]
vif["Features"] = train_x.columns

#let's check the values
vif
```

Out[40]:

	vif	Features
0	1.010422	workclass
1	1.014561	fnlwgt
2	1.076122	education_num
3	1.123101	marital_status
4	1.009878	occupation
5	1.678307	relationship
6	1.032643	race
7	1.558542	sex
8	1.056592	capital_gain
9	1.022096	capital_loss
10	1.025766	native_country
11	1.165779	age_bin
12	1.118631	hours-per-week_bin

XGBoost Classifier

In [41]:
```
# fit model no training data
model = XGBClassifier(objective='binary:logistic')
model.fit(train_x, train_y)
```

Out[41]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=0, num_parallel_tree=1,
              objective='binary:logistic', random_state=0, reg_alpha=0,
              reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)
```

In [42]:
```
# cheking training accuracy
y_pred = model.predict(train_x)
predictions = [round(value) for value in y_pred]
accuracy = accuracy_score(train_y,predictions)
accuracy
```

Out[42]:
```
0.9019270369118234
```

In [43]:
```
# cheking initial test accuracy
y_pred = model.predict(test_x)
predictions = [round(value) for value in y_pred]
accuracy = accuracy_score(test_y,predictions)
accuracy
```

Out[43]:
```
0.854939788645859
```

In [44]:
```
param_grid={
    'learning_rate': [1, 0.5, 0.1, 0.01, 0.001],
    'max_depth': [3, 5, 10, 20],
    'n_estimators': [10, 50, 100, 200]
}
```

In [45]:
```
grid= GridSearchCV(XGBClassifier(objective='binary:logistic'), param_grid)
```

In [46]:
```
grid.fit(train_x, train_y)
```

Out[46]:
```
GridSearchCV(cv=None, error_score=nan,
             estimator=XGBClassifier(base_score=None, booster=None,
                                     colsample_bylevel=None,
                                     colsample_bynode=None,
                                     colsample_bytree=None, gamma=None,
                                     gpu_id=None, importance_type='gain',
                                     interaction_constraints=None,
                                     learning_rate=None, max_delta_step=None,
                                     max_depth=None, min_child_weight=None,
                                     missing=nan, monotone_constraints=None,
                                     n_es...
                                     random_state=None, reg_alpha=None,
                                     reg_lambda=None, scale_pos_weight=None,
                                     subsample=None, tree_method=None,
                                     validate_parameters=None, verbosity=Non
e),
             iid='deprecated', n_jobs=None,
             param_grid={'learning_rate': [1, 0.5, 0.1, 0.01, 0.001],
                         'max_depth': [3, 5, 10, 20],
                         'n_estimators': [10, 50, 100, 200]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

In [47]:
```
grid.best_params_
```

Out[47]:
```
{'learning_rate': 0.1, 'max_depth': 5, 'n_estimators': 200}
```

In [48]:
```
# Create new model using the same parameters
new_model=XGBClassifier(learning_rate= 0.1, max_depth= 5, n_estimators= 200)
new_model.fit(train_x, train_y)
```

Out[48]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.1, max_delta_step=0, max_depth=5,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=200, n_jobs=0, num_parallel_tree=1,
              objective='binary:logistic', random_state=0, reg_alpha=0,
              reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)
```

In [49]:
```
y_pred_new = new_model.predict(test_x)
predictions_new = [round(value) for value in y_pred_new]
accuracy_new_xgboost = accuracy_score(test_y,predictions_new)
accuracy_new_xgboost
```

Out[49]:
```
0.8597321209142296
```

In [50]:
```
new_model.get_booster().get_score(importance_type="gain")
```

Out[50]:
```
{'relationship': 128.6458774135325,
 'education_num': 41.5177175380451,
 'capital_gain': 37.861184960465046,
 'capital_loss': 18.21865458632269,
 'age_bin': 15.75366145925717,
 'occupation': 9.55463262210465,
 'hours-per-week_bin': 12.643608384179403,
 'fnlwgt': 3.129041437650815,
 'marital_status': 38.846798557440955,
 'sex': 9.694870202,
 'race': 4.3695650333863645,
 'workclass': 5.375567432009281,
 'native_country': 3.365511446216217}
```

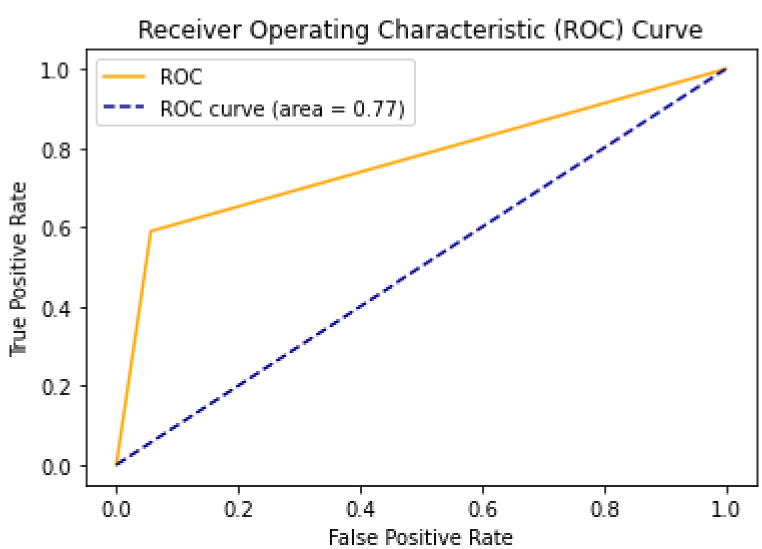
Features relationship, education_num, marital_status, capital_gain, capital_loss, age_bin, sex, hours-per-week_bin has more importance as compared to other variables

In [51]:
```
y_pred_xgboost = new_model.predict(test_x)
```

In [52]:
```
conf_mat_xgboost = confusion_matrix(test_y, y_pred_xgboost)
true_positive_xgboost = conf_mat_xgboost[0][0]
false_positive_xgboost = conf_mat_xgboost[0][1]
false_negative_xgboost = conf_mat_xgboost[1][0]
true_negative_xgboost = conf_mat_xgboost[1][1]
Accuracy_xgboost = (true_positive_xgboost + true_negative_xgboost) / (true_pos
itive_xgboost +false_positive_xgboost + false_negative_xgboost + true_negative
_xgboost)
Precision_xgboost = true_positive_xgboost/(true_positive_xgboost+false_positiv
e_xgboost)
Recall_xgboost = true_positive_xgboost/(true_positive_xgboost+false_negative_x
gboost)
F1_Score_xgboost = 2*(Recall_xgboost * Precision_xgboost) / (Recall_xgboost +
Precision_xgboost)
auc_xgboost = roc_auc_score(test_y, y_pred_xgboost)
fpr_xgboost, tpr_xgboost, thresholds_xgboost = roc_curve(test_y, y_pred_xgboos
t)
print('Accuracy:: ', Accuracy_xgboost)
print('Precision:: ', Precision_xgboost)
print('Recall:: ', Recall_xgboost)
print('F1 Score:: ', F1_Score_xgboost)
print('AUC:: ', auc_xgboost)
```

```
Accuracy::  0.8597321209142296
Precision::  0.9432823813354787
Recall::  0.8813801398180862
F1 Score::  0.9112812342128784
AUC::  0.7664929847395022
```

In [53]:
```
plt.plot(fpr_xgboost, tpr_xgboost, color='orange', label='ROC')
plt.plot([0, 1], [0, 1], color='darkblue', linestyle='--', label='ROC curve (a
rea = %0.2f)' % auc_xgboost)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()
```



Logistic Regression

In [54]:
```
log_reg = LogisticRegression(max_iter=300)
log_reg.fit(train_x, train_y)
```

Out[54]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=300,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [55]:
```
accuracy_score(train_y, log_reg.predict(train_x))
```

Out[55]:
```
0.8101238589913022
```

In [56]:
```
y_pred_log = log_reg.predict(test_x)
```

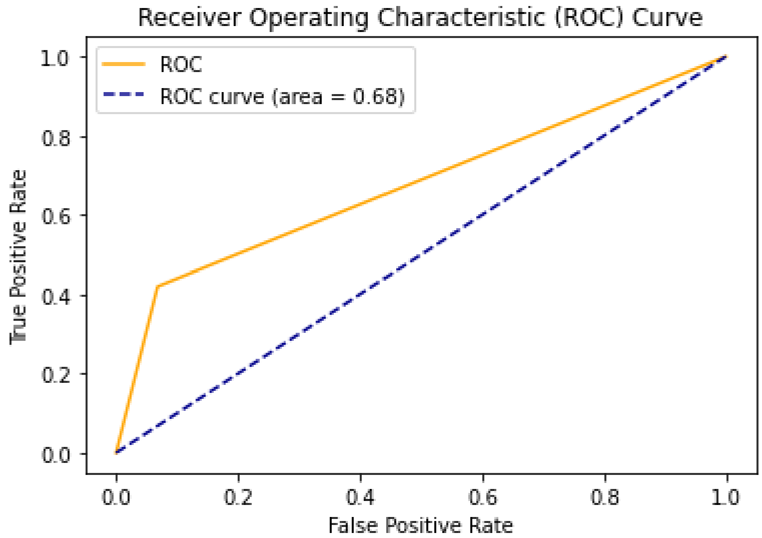
In [57]:
```
accuracy_score(test_y, y_pred_log)
```

Out[57]:
```
0.8109486360285082
```

In [58]:
```
conf_mat = confusion_matrix(test_y, y_pred_log)
true_positive = conf_mat[0][0]
false_positive = conf_mat[0][1]
false_negative = conf_mat[1][0]
true_negative = conf_mat[1][1]
Accuracy = (true_positive + true_negative) / (true_positive +false_positive +
false_negative + true_negative)
Precision = true_positive/(true_positive+false_positive)
Recall = true_positive/(true_positive+false_negative)
F1_Score = 2*(Recall * Precision) / (Recall + Precision)
auc = roc_auc_score(test_y, y_pred_log)
fpr_log, tpr_log, thresholds_log = roc_curve(test_y, y_pred_log)
print('Accuracy:: ', Accuracy)
print('Precision:: ', Precision)
print('Recall:: ', Recall)
print('F1 Score:: ', F1_Score)
print('AUC:: ', auc)
```

```
Accuracy::  0.8109486360285082
Precision::  0.9320193081255028
Recall::  0.838459868278208
F1 Score::  0.882767554387168
AUC::  0.6758380471984768
```

In [59]:
```
plt.plot(fpr_log, tpr_log, color='orange', label='ROC')
plt.plot([0, 1], [0, 1], color='darkblue', linestyle='--', label='ROC curve (a
rea = %0.2f)' % auc)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()
```



Decision Tree Classifier

In [60]:
```
clf = DecisionTreeClassifier()
clf.fit(train_x, train_y)
```

Out[60]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                       max_depth=None, max_features=None, max_leaf_nodes=Non
e,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

In [61]:
```
clf.score(train_x, train_y)
```

Out[61]:
```
0.9998770630359284
```

In [62]:
```
y_pred_dtc = clf.predict(test_x)
```

In [63]:
```
clf.score(test_x, test_y)
```

Out[63]:
```
0.8078151880068813
```

In [64]:
```
grid_param_dt = {
    'criterion': ['gini', 'entropy'],
    'max_depth' : range(2,32,1),
    'min_samples_leaf' : range(1,10,1),
    'min_samples_split': range(2,10,1),
    'splitter' : ['best', 'random']
}
```

In [65]:
```
grid_search_decision = GridSearchCV(estimator = clf, param_grid = grid_param_d
t, cv = 5, n_jobs = -1)
```

In [66]:
```
grid_search_decision.fit(train_x, train_y)
```

Out[66]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=DecisionTreeClassifier(ccp_alpha=0.0, class_weight=Non
e,
                                              criterion='gini', max_depth=Non
e,
                                              max_features=None,
                                              max_leaf_nodes=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              presort='deprecated',
                                              random_state=None,
                                              splitter='best'),
             iid='deprecated', n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': range(2, 32),
                         'min_samples_leaf': range(1, 10),
                         'min_samples_split': range(2, 10),
                         'splitter': ['best', 'random']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

In [67]:
```
grid_search_decision.best_params_
```

Out[67]:
```
{'criterion': 'gini',
 'max_depth': 8,
 'min_samples_leaf': 8,
 'min_samples_split': 2,
 'splitter': 'best'}
```

In [68]:
```
clf = DecisionTreeClassifier(criterion='entropy', max_depth=14, min_samples_le
af=2, min_samples_split=9, splitter='random')
clf.fit(train_x, train_y)
```

Out[68]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='entropy',
                       max_depth=14, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=2, min_samples_split=9,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='random')
```

In [69]:
```
clf.score(test_x, test_y)
```

Out[69]:
```
0.8492872941754731
```

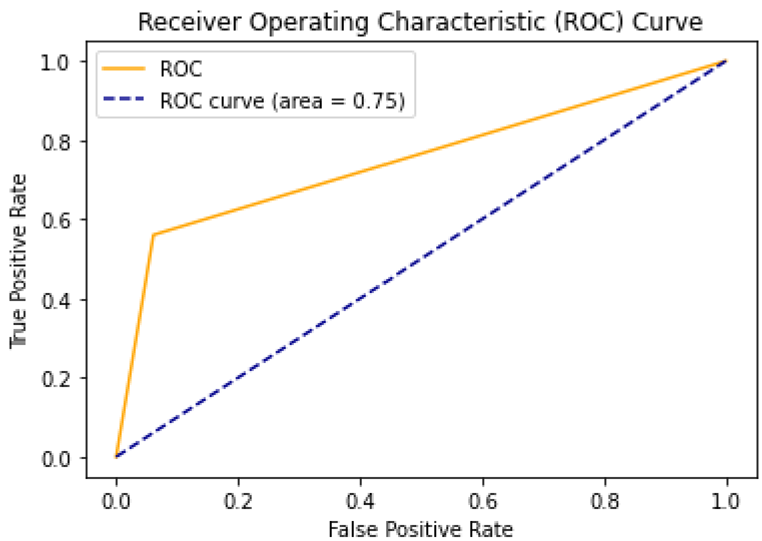
In [70]:
```
y_pred_dt = clf.predict(test_x)
accuracy_score(test_y, y_pred_dt)
```

Out[70]:
```
0.8492872941754731
```

In [71]:
```
conf_mat_dt = confusion_matrix(test_y, y_pred_dt)
true_positive_dt = conf_mat_dt[0][0]
false_positive_dt = conf_mat_dt[0][1]
false_negative_dt = conf_mat_dt[1][0]
true_negative_dt = conf_mat_dt[1][1]
Accuracy_dt = (true_positive_dt + true_negative_dt) / (true_positive_dt + fals
e_positive_dt + false_negative_dt + true_negative_dt)
Precision_dt = true_positive_dt / (true_positive_dt + false_positive_dt)
Recall_dt = true_positive_dt / (true_positive_dt + false_negative_dt)
F1_Score_dt = 2 * (Recall_dt * Precision_dt) / (Recall_dt + Precision_dt)
auc_dt = roc_auc_score(test_y, y_pred_dt)
fpr_dt, tpr_dt, thresholds_dt = roc_curve(test_y, y_pred_dt)
print('Accuracy:: ', Accuracy_dt)
print('Precision:: ', Precision_dt)
print('Recall:: ', Recall_dt)
print('F1 Score:: ', F1_Score_dt)
print('AUC:: ', auc_dt)
```

```
Accuracy::  0.8492872941754731
Precision::  0.9387771520514884
Recall::  0.8733627722475863
F1 Score::  0.9048893024698538
AUC::  0.7494197772737942
```

In [72]:
```
plt.plot(fpr_dt, tpr_dt, color='orange', label='ROC')
plt.plot([0, 1], [0, 1], color='darkblue', linestyle='--', label='ROC curve (a
rea = %0.2f)' % auc_dt)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()
```



KNN Classifier

In [73]:
```
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(train_x, train_y)
knn.score(test_x, test_y)
```

Out[73]: 0.7767879085770459

In [74]:
```
y_pred_knn = knn.predict(test_x)
```

In [75]:
```
print("The accuracy score is : ", accuracy_score(test_y, y_pred_knn))
```

```
The accuracy score is :  0.7767879085770459
```

In [76]:
```
param_grid_knn = {'algorithm' : ['ball_tree', 'kd_tree', 'brute'],
              'leaf_size' : [18, 20, 25, 27, 30, 32, 34],
              'n_neighbors' : [3, 5, 7, 9, 10, 11, 12, 13]
             }
```

In [103]:
```
gridsearch_knn = GridSearchCV(knn, param_grid_knn)
```

In [104]:
```
gridsearch_knn.fit(train_x, train_y)
```

Out[104]:
```
GridSearchCV(cv=None, error_score=nan,
             estimator=KNeighborsClassifier(algorithm='ball_tree', leaf_size=
18,
                                            metric='minkowski',
                                            metric_params=None, n_jobs=None,
                                            n_neighbors=13, p=2,
                                            weights='uniform'),
             iid='deprecated', n_jobs=None,
             param_grid={'algorithm': ['ball_tree', 'kd_tree', 'brute'],
                         'leaf_size': [18, 20, 25, 27, 30, 32, 34],
                         'n_neighbors': [3, 5, 7, 9, 10, 11, 12, 13]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

In [80]:
```
gridsearch_knn.best_params_
```

Out[80]:
```
{'algorithm': 'ball_tree', 'leaf_size': 18, 'n_neighbors': 13}
```

In [81]:
```
knn = KNeighborsClassifier(algorithm = 'ball_tree', leaf_size =18, n_neighbors
=13)
```

In [83]:
```
knn.fit(train_x, train_y)
```

Out[83]:
```
KNeighborsClassifier(algorithm='ball_tree', leaf_size=18, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=13, p=2,
                     weights='uniform')
```

In [84]:
```
knn.score(train_x, train_y)
```

Out[84]:
```
0.8110151519808219
```

In [85]:
```
knn.score(test_x, test_y)
```

Out[85]:
```
0.7970631604816908
```

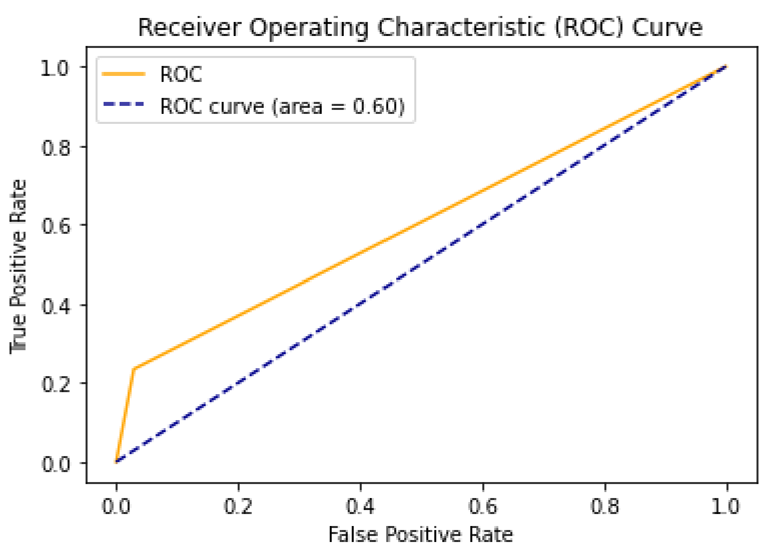
In [86]:
```
y_pred_knn = knn.predict(test_x)
accuracy_score(test_y, y_pred_knn)
```

Out[86]:
```
0.7970631604816908
```

In [87]:
```
conf_mat_knn = confusion_matrix(test_y, y_pred_knn)
true_positive_knn = conf_mat_knn[0][0]
false_positive_knn = conf_mat_knn[0][1]
false_negative_knn = conf_mat_knn[1][0]
true_negative_knn = conf_mat_knn[1][1]
Accuracy_knn = (true_positive_knn + true_negative_knn) / (true_positive_knn +
false_positive_knn + false_negative_knn + true_negative_knn)
Precision_knn = true_positive_knn / (true_positive_knn + false_positive_knn)
Recall_knn = true_positive_knn / (true_positive_knn + false_negative_knn)
F1_Score_knn = 2 * (Recall_knn * Precision_knn) / (Recall_knn + Precision_knn)
auc_knn = roc_auc_score(test_y, y_pred_knn)
fpr_knn, tpr_knn, thresholds_knn = roc_curve(test_y, y_pred_knn)
print('Accuracy:: ', Accuracy_knn)
print('Precision:: ', Precision_knn)
print('Recall:: ', Recall_knn)
print('F1 Score:: ', F1_Score_knn)
print('AUC:: ', auc_knn)
```

```
Accuracy::  0.7970631604816908
Precision::  0.9710378117457763
Recall::  0.8039698927596083
F1 Score::  0.8796414386182267
AUC::  0.6029136016607196
```

In [88]:
```
plt.plot(fpr_knn, tpr_knn, color='orange', label='ROC')
plt.plot([0, 1], [0, 1], color='darkblue', linestyle='--', label='ROC curve (a
rea = %0.2f)' % auc_knn)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()
```



Random Forest Classifier

In [89]:
```
rand_clf = RandomForestClassifier(random_state=6)
```

In [90]:
```
rand_clf.fit(train_x, train_y)
```

Out[90]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=None, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=None, oob_score=False, random_state=6, verbose=
0,
                       warm_start=False)
```

In [91]:
```
rand_clf.score(test_x, test_y)
```

Out[91]:
```
0.8489800933890391
```

In [92]:
```
grid_param_rdf = {
    "n_estimators" : [90,100,115],
    'criterion': ['gini', 'entropy'],
    'min_samples_leaf' : [1,2,3,4,5],
    'min_samples_split': [4,5,6,7,8],
    'max_features' : ['auto','log2']
}
```

In [105]:
```
grid_search_rdf = GridSearchCV(estimator=rand_clf, param_grid=grid_param_rdf,
cv=5, n_jobs=-1)
```

In [106]:
```
grid_search_rdf.fit(train_x, train_y)
```

Out[106]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                                              class_weight=None,
                                              criterion='entropy',
                                              max_depth=None,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              max_samples=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=3,
                                              min_samples_split=7,
                                              min_weight_fraction_leaf=0.0,
                                              n_estimators=100, n_jobs=None,
                                              oob_score=False,
                                              random_state=None, verbose=0,
                                              warm_start=False),
             iid='deprecated', n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_features': ['auto', 'log2'],
                         'min_samples_leaf': [1, 2, 3, 4, 5],
                         'min_samples_split': [4, 5, 6, 7, 8],
                         'n_estimators': [90, 100, 115]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

In [95]:
```
grid_search_rdf.best_params_
```

Out[95]:
```
{'criterion': 'entropy',
 'max_features': 'auto',
 'min_samples_leaf': 3,
 'min_samples_split': 7,
 'n_estimators': 100}
```

In [96]:
```
rand_clf = RandomForestClassifier(criterion= 'entropy', max_features = 'auto', min_samples_leaf = 3, min_samples_split= 7,
                                  n_estimators = 100)
```

In [97]:
```
rand_clf.fit(train_x, train_y)
```

Out[97]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='entropy', max_depth=None, max_features='aut
o',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=3, min_samples_split=7,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

In [98]:
```
rand_clf.score(test_x, test_y)
```

Out[98]:
```
0.8585647579257802
```

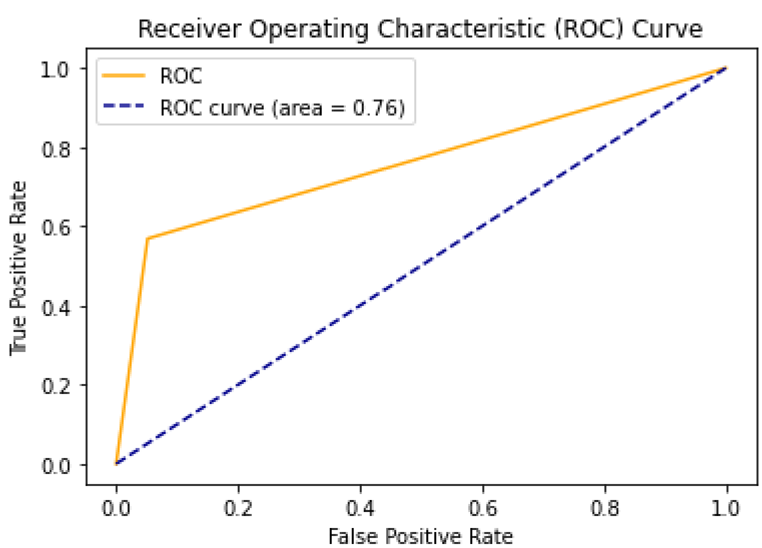
In [99]:
```
y_pred_rdf = rand_clf.predict(test_x)
accuracy_score(test_y, y_pred_rdf)
```

Out[99]: 0.8585647579257802

In [100]:
```
conf_mat_rdf = confusion_matrix(test_y, y_pred_rdf)
true_positive_rdf = conf_mat_rdf[0][0]
false_positive_rdf = conf_mat_rdf[0][1]
false_negative_rdf = conf_mat_rdf[1][0]
true_negative_rdf = conf_mat_rdf[1][1]
Accuracy_rdf = (true_positive_rdf + true_negative_rdf) / (true_positive_rdf +
false_positive_rdf + false_negative_rdf + true_negative_rdf)
Precision_rdf = true_positive_rdf / (true_positive_rdf + false_positive_rdf)
Recall_rdf = true_positive_rdf / (true_positive_rdf + false_negative_rdf)
F1_Score_rdf = 2 * (Recall_rdf * Precision_rdf) / (Recall_rdf + Precision_rdf)
auc_rdf = roc_auc_score(test_y, y_pred_rdf)
fpr_rdf, tpr_rdf, thresholds_rdf = roc_curve(test_y, y_pred_rdf)
print('Accuracy:: ', Accuracy_rdf)
print('Precision:: ', Precision_rdf)
print('Recall:: ', Recall_rdf)
print('F1 Score:: ', F1_Score_rdf)
print('AUC:: ', auc_rdf)
```

```
Accuracy::  0.8585647579257802
Precision::  0.9483507642799678
Recall::  0.8765615704937537
F1 Score::  0.9110441301491614
AUC::  0.7583667497946901
```

In [101]:
```
plt.plot(fpr_rdf, tpr_rdf, color='orange', label='ROC')
plt.plot([0, 1], [0, 1], color='darkblue', linestyle='--', label='ROC curve (a
rea = %0.2f)' % auc_rdf)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()
```



Comparing scores of different classification models

In [102]:
```
print('Score of Logistic Regression::', F1_Score)
print('Score of Decision Tree::      ', F1_Score_dt)
print('Score of Random Forest::      ', F1_Score_rdf)
print('Score of K-Nearest Neighbors::', F1_Score_knn)
print('Score of XGBoost::            ', F1_Score_xgboost)
```

```
Score of Logistic Regression:: 0.882767554387168
Score of Decision Tree::       0.9048893024698538
Score of Random Forest::       0.9110441301491614
Score of K-Nearest Neighbors:: 0.8796414386182267
Score of XGBoost::             0.9112812342128784
```

After comparing the scores, we see that xgboost model is performing better as compared to others

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In [ ]: