Project 3 : Prediction task is to determine whether a person makes over 50K a year.

In [1]:

```
# Importing the libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

In [2]:

```
# Importing the dataset
train = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.d
test = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.te
```

In [3]:

```
train.head(5)
```

Out[3]:

	0	1	2	3	4	5	6	7	8	9	10	11
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0

In [4]:

```
column_names = ['age', 'workclass', 'fnlwgt', 'education', 'educational_num','marital_statu
train.columns = column_names
test.columns = column_names
```

In [5]:

```
train.head(5)
```

Out[5]:

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

In [6]:

```
test.head(5)
```

Out[6]:

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

In [7]:

```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
age                32561 non-null int64
workclass          32561 non-null object
fnlwgt             32561 non-null int64
education          32561 non-null object
educational_num    32561 non-null int64
marital_status     32561 non-null object
occupation         32561 non-null object
relationship       32561 non-null object
race               32561 non-null object
gender             32561 non-null object
capital_gain       32561 non-null int64
capital_loss       32561 non-null int64
hours_per_week     32561 non-null int64
native_country     32561 non-null object
income             32561 non-null object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

In [8]:

```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16281 entries, 0 to 16280
Data columns (total 15 columns):
age                16281 non-null int64
workclass          16281 non-null object
fnlwgt             16281 non-null int64
education          16281 non-null object
educational_num    16281 non-null int64
marital_status     16281 non-null object
occupation         16281 non-null object
relationship       16281 non-null object
race               16281 non-null object
gender             16281 non-null object
capital_gain       16281 non-null int64
capital_loss       16281 non-null int64
hours_per_week     16281 non-null int64
native_country     16281 non-null object
income             16281 non-null object
dtypes: int64(6), object(9)
memory usage: 1.9+ MB
```

In [9]:

```
print(train.describe())
print('*'*100)
print(test.describe())
```

```
                age        fnlwgt  educational_num  capital_gain  \
count  32561.000000  3.256100e+04     32561.000000  32561.000000
mean      38.581647  1.897784e+05        10.080679   1077.648844
std       13.640433  1.055500e+05         2.572720   7385.292085
min       17.000000  1.228500e+04         1.000000      0.000000
25%       28.000000  1.178270e+05         9.000000      0.000000
50%       37.000000  1.783560e+05        10.000000      0.000000
75%       48.000000  2.370510e+05        12.000000      0.000000
max       90.000000  1.484705e+06        16.000000  99999.000000

       capital_loss  hours_per_week
count  32561.000000    32561.000000
mean      87.303830       40.437456
std      402.960219       12.347429
min        0.000000        1.000000
25%        0.000000       40.000000
50%        0.000000       40.000000
75%        0.000000       45.000000
max     4356.000000       99.000000
****************************************************************************
************************
                age        fnlwgt  educational_num  capital_gain  \
count  16281.000000  1.628100e+04     16281.000000  16281.000000
mean      38.767459  1.894357e+05        10.072907   1081.905104
std       13.849187  1.057149e+05         2.567545   7583.935968
min       17.000000  1.349200e+04         1.000000      0.000000
25%       28.000000  1.167360e+05         9.000000      0.000000
50%       37.000000  1.778310e+05        10.000000      0.000000
75%       48.000000  2.383840e+05        12.000000      0.000000
max       90.000000  1.490400e+06        16.000000  99999.000000

       capital_loss  hours_per_week
count  16281.000000    16281.000000
mean      87.899269       40.392236
std      403.105286       12.479332
min        0.000000        1.000000
25%        0.000000       40.000000
50%        0.000000       40.000000
75%        0.000000       45.000000
max     3770.000000       99.000000
```

From the primary data analysis, we can note that there are both numeric and object variables and there are ? values

In [10]:

```
train = train.replace(' ?',np.nan)
test = test.replace(' ?',np.nan)
```

In [11]:

```
print(train.isna().sum())
print('*'*100)
print(test.isna().sum())
```

```
age                  0
workclass         1836
fnlwgt               0
education            0
educational_num      0
marital_status       0
occupation        1843
relationship         0
race                 0
gender               0
capital_gain         0
capital_loss         0
hours_per_week       0
native_country     583
income               0
dtype: int64
****************************************************************************
************************
age                 0
workclass         963
fnlwgt              0
education           0
educational_num     0
marital_status      0
occupation        966
relationship        0
race                0
gender              0
capital_gain        0
capital_loss        0
hours_per_week      0
native_country    274
income              0
dtype: int64
```

In [12]:

```
# As there are large number of null values we will drop the null values
train = train.dropna()
test = test.dropna()
```

In [13]:

```
dataset = pd.concat([train,test],axis=0)
```

In [14]:

```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 45222 entries, 0 to 16280
Data columns (total 15 columns):
age                45222 non-null int64
workclass          45222 non-null object
fnlwgt             45222 non-null int64
education          45222 non-null object
educational_num    45222 non-null int64
marital_status     45222 non-null object
occupation         45222 non-null object
relationship       45222 non-null object
race               45222 non-null object
gender             45222 non-null object
capital_gain       45222 non-null int64
capital_loss       45222 non-null int64
hours_per_week     45222 non-null int64
native_country     45222 non-null object
income             45222 non-null object
dtypes: int64(6), object(9)
memory usage: 5.5+ MB
```

In [15]:

```
dataset.income.unique()
```

Out[15]:

```
array([' <=50K', ' >50K', ' <=50K.', ' >50K.'], dtype=object)
```

In [16]:

```
dataset['income'] = dataset.income.replace({' <=50K':' <=50K', ' >50K':' >50K', ' <=50K.':'
```

In [17]:

```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 45222 entries, 0 to 16280
Data columns (total 15 columns):
age                45222 non-null int64
workclass          45222 non-null object
fnlwgt             45222 non-null int64
education          45222 non-null object
educational_num    45222 non-null int64
marital_status     45222 non-null object
occupation         45222 non-null object
relationship       45222 non-null object
race               45222 non-null object
gender             45222 non-null object
capital_gain       45222 non-null int64
capital_loss       45222 non-null int64
hours_per_week     45222 non-null int64
native_country     45222 non-null object
income             45222 non-null object
dtypes: int64(6), object(9)
memory usage: 5.5+ MB
```

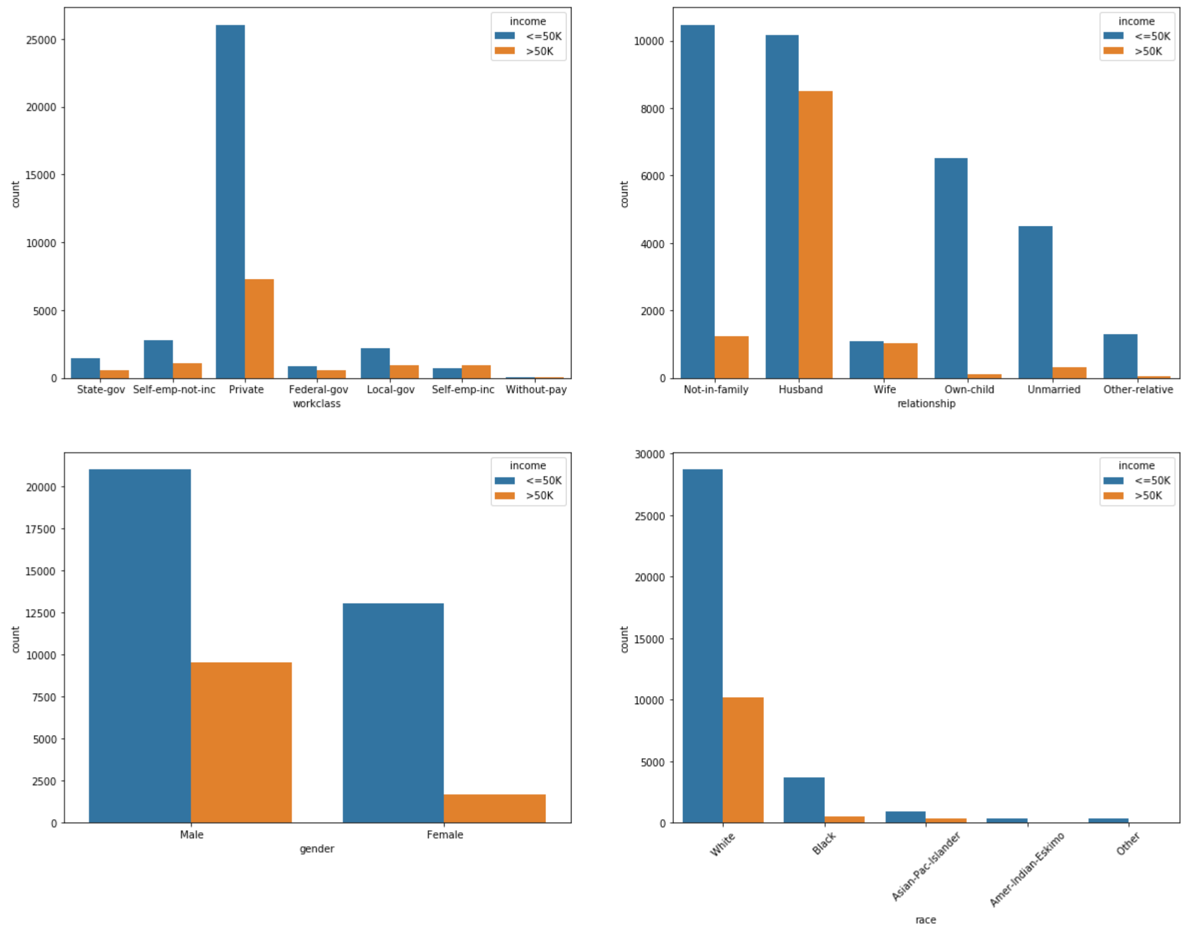
EDA

In [18]:

```
import seaborn as sns
fig, ((a,b),(c,d)) = plt.subplots(2,2,figsize=(20,15))
plt.xticks(rotation=45)
sns.countplot(dataset['workclass'],hue=dataset['income'],ax=a)
sns.countplot(dataset['relationship'],hue=dataset['income'],ax=b)
sns.countplot(dataset['gender'],hue=dataset['income'],ax=c)
sns.countplot(dataset['race'],hue=dataset['income'],ax=d)
```

Out[18]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x218a5eb2c50>
```

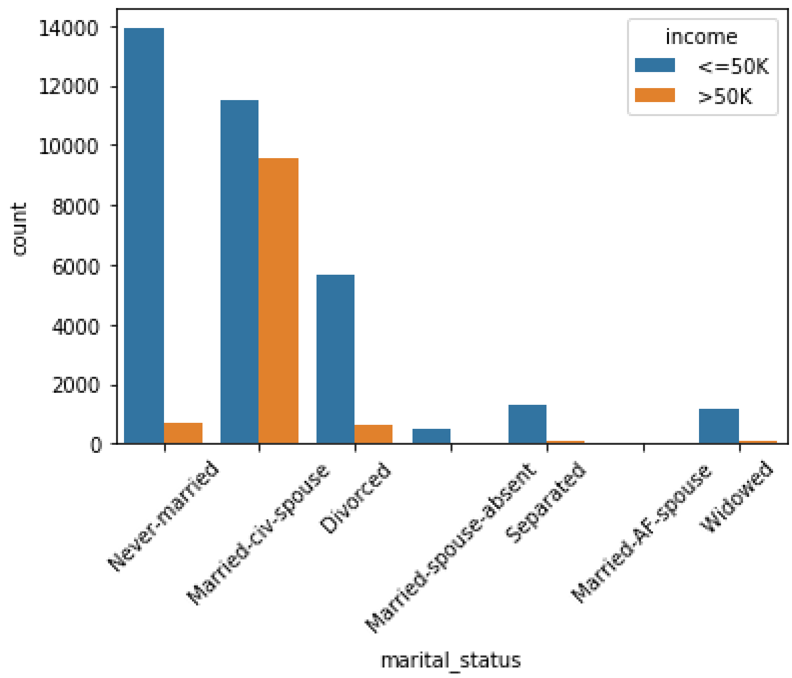


In [19]:

```
plt.xticks(rotation=45)
sns.countplot(dataset['marital_status'],hue=dataset['income'])
```

Out[19]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x218a66d7ac8>
```

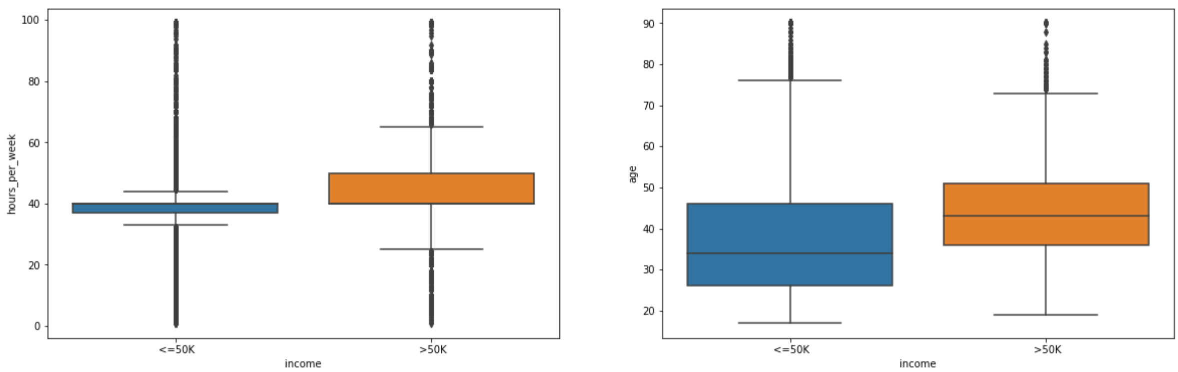


In [20]:

```
fig, (a,b)= plt.subplots(1,2,figsize=(20,6))
sns.boxplot(y='hours_per_week',x='income',data=dataset,ax=a)
sns.boxplot(y='age',x='income',data=dataset,ax=b)
```

Out[20]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x218a6a1a5c0>
```



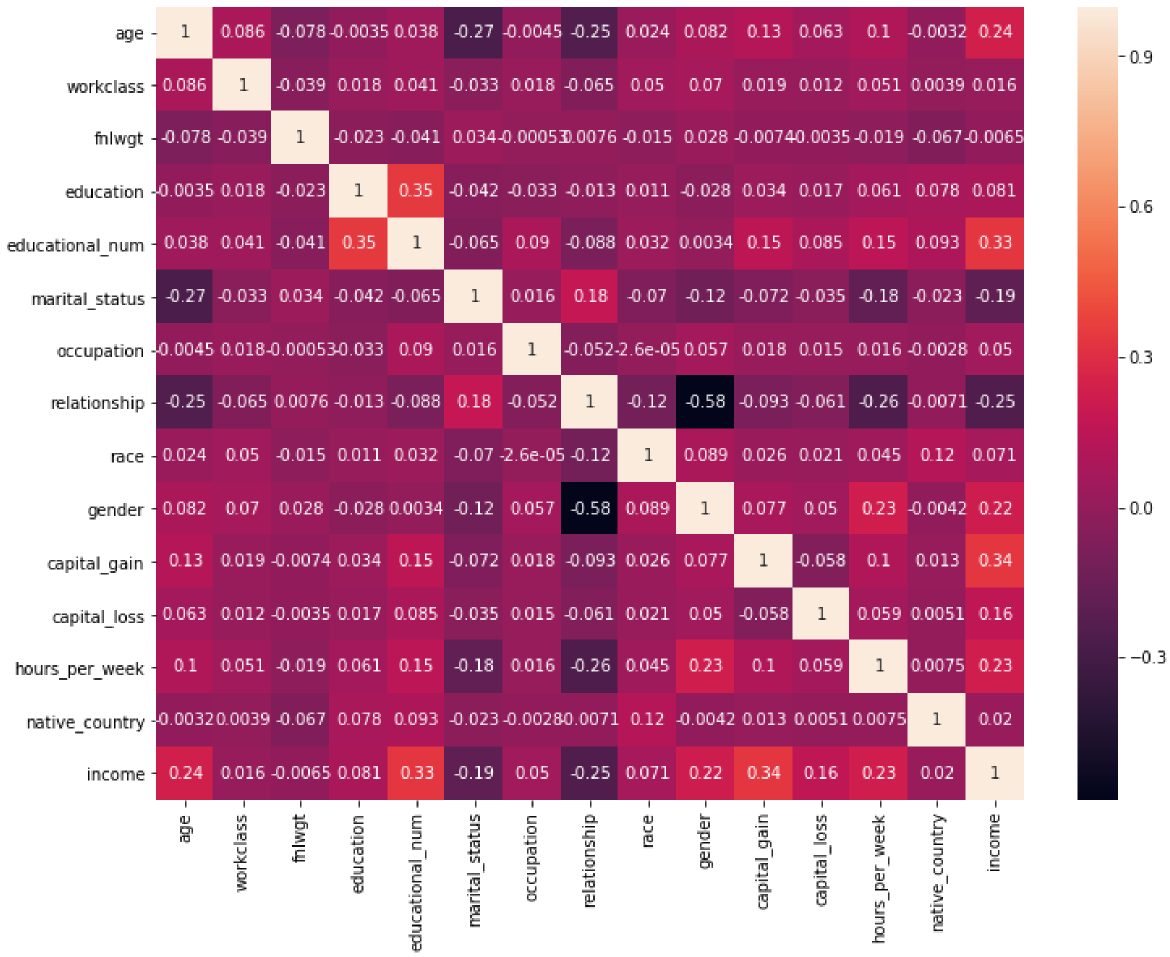
Data preprocessing

In [21]:

```
#Feature Engineering
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
for i in dataset.columns:
    dataset[i]=le.fit_transform(dataset[i])
```

In [22]:

```
hmap = dataset.corr()
plt.subplots(figsize=(12, 9))
sns.heatmap(hmap,annot=True);
```



In [23]:

```
#split the
X = dataset.iloc[:,:-1].values
y = dataset.iloc[:,14].values
X_train = X[:train.shape[0]] # Up to the last initial training set row
y_train = y[:train.shape[0]] # Up to the last initial training set row
X_test  = X[train.shape[0]:] # Past the last initial training set row
y_test  = y[train.shape[0]:] # Past the last initial training set row
```

In [24]:

```
print(X_train.shape,'**',y_train.shape,'**', X_test.shape,'**',y_test.shape)
```

```
(30162, 14) ** (30162,) ** (15060, 14) ** (15060,)
```

In [25]:

```
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

```
C:\Users\mallikarjuna.m\AppData\Local\Continuum\anaconda3\lib\site-packages
\sklearn\utils\validation.py:595: DataConversionWarning: Data with input dty
pe int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Users\mallikarjuna.m\AppData\Local\Continuum\anaconda3\lib\site-packages
\sklearn\utils\validation.py:595: DataConversionWarning: Data with input dty
pe int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Users\mallikarjuna.m\AppData\Local\Continuum\anaconda3\lib\site-packages
\sklearn\utils\validation.py:595: DataConversionWarning: Data with input dty
pe int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
```

Classification Models

Logistic Regression

In [26]:

```
# Fitting Logistic Regression to the Training set
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
logistic = LogisticRegression(random_state = 0)
logistic.fit(X_train, y_train)
y_pred = logistic.predict(X_test)
cm_log = confusion_matrix(y_test, y_pred)
Correct = cm_log [0,0] + cm_log [1,1]
Total =  cm_log [0,0] + cm_log [0,1]+ cm_log [1,0] + cm_log [1,1]
Logistic_accuracy = Correct / Total
print('Logistic_Regression_Accuracy : ', Logistic_accuracy*100,'%' )
```

```
C:\Users\mallikarjuna.m\AppData\Local\Continuum\anaconda3\lib\site-packages
\sklearn\linear_model\logistic.py:433: FutureWarning: Default solver will be
changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)

Logistic_Regression_Accuracy :  81.83266932270917 %
```

K-Nearest Neighbors (K-NN)

In [27]:

```
# Fitting K-NN to the Training set
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
knn = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
cm_knn = confusion_matrix(y_test, y_pred)
Correct = cm_knn[0,0] + cm_knn[1,1]
Total =  cm_knn[0,0] + cm_knn[0,1]+ cm_knn[1,0] + cm_knn[1,1]
knn_accuracy = Correct / Total
print('knn_Accuracy : ', knn_accuracy*100,'%' )
```

```
knn_Accuracy :  82.78884462151395 %
```

Support Vector Machine (SVM)

In [28]:

```
# Fitting SVM to the Training set
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix
svm = SVC(kernel = 'linear', random_state = 0)
svm.fit(X_train, y_train)
y_pred = svm.predict(X_test)
cm_svm = confusion_matrix(y_test, y_pred)
Correct = cm_svm [0,0] + cm_svm [1,1]
Total =  cm_svm [0,0] + cm_svm [0,1]+ cm_svm [1,0] + cm_svm [1,1]
svm_accuracy = Correct / Total
print('svm_Accuracy : ', svm_accuracy*100,'%')
```

```
svm_Accuracy :  80.37848605577689 %
```

Kernel SVM

In [29]:

```
# Fitting Kernel SVM to the Training set
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix
ksvm = SVC(kernel = 'rbf', random_state = 0)
ksvm.fit(X_train, y_train)
y_pred = ksvm.predict(X_test)
cm_ksvm = confusion_matrix(y_test, y_pred)
Correct = cm_ksvm [0,0] + cm_ksvm [1,1]
Total =  cm_ksvm [0,0] + cm_ksvm [0,1]+ cm_ksvm [1,0] + cm_ksvm [1,1]
ksvm_accuracy = Correct / Total
print('ksvm_Accuracy : ', ksvm_accuracy*100,'%' )
```

```
ksvm_Accuracy :  84.7011952191235 %
```

Naive Bayes

In [30]:

```
# Fitting Naive Bayes to the Training set
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix
nb = GaussianNB()
nb.fit(X_train, y_train)
y_pred = nb.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
Correct = cm[0,0] + cm[1,1]
Total =  cm[0,0] + cm[0,1]+ cm[1,0] + cm[1,1]
nb_accuracy = Correct / Total
print('nb_Accuracy : ', nb_accuracy*100,'%' )
```

```
nb_Accuracy :  81.28818061088977 %
```

Decision Tree Classification

In [31]:

```
# Fitting Decision Tree Classification to the Training set
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix
dt = DecisionTreeClassifier(criterion = 'entropy', random_state = 0)
dt.fit(X_train, y_train)
y_pred = dt.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
Correct = cm[0,0] + cm[1,1]
Total =  cm[0,0] + cm[0,1]+ cm[1,0] + cm[1,1]
dt_accuracy = Correct / Total
print('Decision_Tree_Accuracy : ', dt_accuracy*100,'%' )
```

```
Decision_Tree_Accuracy :  80.87649402390437 %
```

Random Forest Classification

In [32]:

```
# Fitting Random Forest Classification to the Training set
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix
rf = RandomForestClassifier(n_estimators = 10, criterion = 'entropy', random_state = 0)
rf.fit(X_train, y_train)
y_pred = rf.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
Correct = cm[0,0] + cm[1,1]
Total =  cm[0,0] + cm[0,1]+ cm[1,0] + cm[1,1]
rf_accuracy = Correct / Total
print('Random_Forest_Accuracy : ', rf_accuracy*100,'%' )
```

```
Random_Forest_Accuracy :  84.32934926958832 %
```

XGBoost

In [33]:

```
# Fitting XGBoost to the Training set
from xgboost import XGBClassifier
from sklearn.metrics import confusion_matrix
xgb = XGBClassifier()
xgb.fit(X_train, y_train)
y_pred = xgb.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
Correct = cm[0,0] + cm[1,1]
Total =  cm[0,0] + cm[0,1]+ cm[1,0] + cm[1,1]
xgb_accuracy = Correct / Total
print('XGBoost Accuracy : ', xgb_accuracy*100,'%' )
print(cm)
```

```
XGBoost Accuracy :  86.15537848605578 %
[[10785   575]
 [ 1510  2190]]
```

Visualising the Test set results

In [34]:

```
results = pd.DataFrame({
    'Model': ['Support Vector Machines','Kernel Support Vector Machine', 'KNN', 'Logistic R
              'Random Forest', 'Naive Bayes', 'Decision Tree','XGBoost'],
    'Score': [svm_accuracy, ksvm_accuracy, knn_accuracy, Logistic_accuracy, rf_accuracy, nb
result_df = results.sort_values(by='Score', ascending=False)
result_df = result_df.set_index('Score')
result_df.head(9)
```

Out[34]:

	Model
Score	
0.861554	XGBoost
0.847012	Kernel Support Vector Machine
0.843293	Random Forest
0.827888	KNN
0.818327	Logistic Regression
0.812882	Naive Bayes
0.808765	Decision Tree
0.803785	Support Vector Machines

Cross Validation

In [35]:

```
# Applying k-Fold Cross Validation
from sklearn.model_selection import cross_val_score
accuracies = cross_val_score(estimator = xgb, X = X_train, y = y_train, cv = 10)
print(accuracies.mean()*100)
print(accuracies.std())
```

```
85.97247279281186
0.004258902229655589
```

The best model that predict the income @ ~86% accuracy

Feature Importance

In [36]:

```
importances = list(zip(xgb.feature_importances_, dataset.columns))
importances.sort(reverse=True)
importances
```

Out[36]:

```
[(0.14985591, 'capital_gain'),
 (0.14985591, 'age'),
 (0.13400577, 'capital_loss'),
 (0.12391931, 'educational_num'),
 (0.093659945, 'relationship'),
 (0.0907781, 'hours_per_week'),
 (0.06916427, 'marital_status'),
 (0.06628242, 'occupation'),
 (0.0648415, 'fnlwgt'),
 (0.031700287, 'workclass'),
 (0.014409222, 'gender'),
 (0.007204611, 'race'),
 (0.0028818443, 'education'),
 (0.0014409221, 'native_country')]
```

In [ ]:

```

```