In this assignment students need to predict whether a person makes over 50K per year or not from classic adult dataset using XGBoost.

The description of the dataset is as follows:

Data Set Information:

Extraction was done by Barry Becker from the 1994 Census database. A set of reasonably clean records was extracted using the following conditions: ((AAGE>16) && (AGI>100) && (AFNLWGT>1)&& (HRSWK>0))

Attribute Information:

Listing of attributes: >50K, <=50K.

age: continuous. workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.

fnlwgt: continuous.

education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool. education-num: continuous.

marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.
occupation: Tech-support, Craft-repair, Other-service, Sales, Execmanagerial, Prof-specialty, Handlers-cleaners, Machine-op- inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces. relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.

race: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.

sex: Female, Male.

capital-gain: continuous.

capital-loss: continuous.

hours-per-week: continuous.

native-country: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, ElSalvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.

Following is the code to load required libraries and data:

import numpy as np

import pandas as pd

train_set = pd.read_csv('http://archive.ics.uci.edu/ml/machinelearning-databases/adult/adult.dat (http://archive.ics.uci.edu/ml/machinelearning-databases/adult/adult.dat) a', header = None)

test_set = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learningdatabases/adult/adult.test' (http://archive.ics.uci.edu/ml/machine-learningdatabases/adult/adult.test') , skiprows = 1, header = None)

col_labels = ["age", 'workclass', 'fnlwgt', 'education', 'education_num', 'marital_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 [1]:
```
#importing libraries
import numpy as np
import pandas as pd
```

In [2]:
```
train_set = pd.read_csv('adult.data', header = None)
train_set.head()
```

Out[2]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40

In [3]:
```
test_set = pd.read_csv('adult.test', skiprows = 1, header = None)
test_set.head()
```

Out[3]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	
0	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	0	0	40	Un St
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0	0	50	Un St
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	0	0	40	Un St
3	44	Private	160323	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	7688	0	40	Un St
4	18	?	103497	Some-college	10	Never-married	?	Own-child	White	Female	0	0	30	Un St

In [4]:
```
col_labels = ["age", 'workclass', 'fnlwgt', 'education', 'education_num', 'marita
train_set.columns = col_labels
test_set.columns = col_labels
```

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

Out[5]:

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

In [6]:
```
test_set.head()
```

Out[6]:

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

In [7]:
```
train_set.columns == test_set.columns
```

Out[7]:
```
array([ True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True,  True,  True,  True,  True])
```

In [8]:
```
#checking is there any missing values or not ?
train_set.isnull().sum()
```

Out[8]:
```
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 [9]:
```
#checking is there any missing values or not ?
test_set.isnull().sum()
```

Out[9]:
```
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 [10]:
```
df = pd.DataFrame([train_set.dtypes , test_set.dtypes ],index = ['train_set' , 't
df
```

Out[10]:

	train_set	test_set
age	int64	int64
workclass	object	object
fnlwgt	int64	int64
education	object	object
education_num	int64	int64
marital_status	object	object
occupation	object	object
relationship	object	object
race	object	object
sex	object	object
capital_gain	int64	int64
capital_loss	int64	int64
hours_per_week	int64	int64
native_country	object	object
wage_class	object	object

In [11]:
```
#Finding columns with data types as object
for i in train_set.columns:
    if train_set[i].dtypes=='object':
        print(i)
```

```
workclass
education
marital_status
occupation
relationship
race
sex
native_country
wage_class
```

In [12]:
```
print('(',train_set.workclass.nunique(),',' ,train_set.education.nunique(),',', t
train_set.relationship.nunique() ,',',train_set.race.nunique(),',', train_set.sex
train_set.wage_class.nunique() ,')')
```

```
( 9 , 16 , 7 , 15 , 6 , 5 , 2 , 42 , 2 )
```

In [13]:
```
x_train = train_set.copy()
x_test = test_set.copy()
```

In [14]:
```
x_train.columns
```

Out[14]:
```
Index(['age', 'workclass', 'fnlwgt', 'education', 'education_num',
       'marital_status', 'occupation', 'relationship', 'race', 'sex',
       'capital_gain', 'capital_loss', 'hours_per_week', 'native_country',
       'wage_class'],
      dtype='object')
```

In [15]:
```
#converting categorical values into numerical values
dict_sex = {}
count = 0
for i in x_train.sex.unique():
    dict_sex[i]= count
    count+=1
```

In [16]:
```
dict_workclass = {}
count = 0
for i in x_train.workclass.unique():
    dict_workclass[i]= count
    count+=1
```

In [17]:
```
dict_education = {}
count = 0
for i in x_train.education.unique():
    dict_education[i]= count
    count+=1


dict_marital_status = {}
count = 0
for i in x_train.marital_status.unique():
    dict_marital_status[i]= count
    count+=1


dict_occupation = {}
count = 0
for i in x_train.occupation.unique():
    dict_occupation[i]= count
    count+=1



dict_relationship = {}
count = 0
for i in x_train.relationship.unique():
    dict_relationship[i]= count
    count+=1



dict_race = {}
count = 0
for i in x_train.race.unique():
    dict_race[i]= count
    count+=1


dict_native_country = {}
count = 0
for i in x_train.native_country.unique():
    dict_native_country[i]= count
    count+=1



dict_wage_class = {}
count = 0
for i in x_train.wage_class.unique():
    dict_wage_class[i]= count
    count+=1
```

In [18]:
```
dict_workclass,dict_education,dict_marital_status,dict_occupation,dict_relationsh
```

Out[18]:
```
({' State-gov': 0,
  ' Self-emp-not-inc': 1,
  ' Private': 2,
  ' Federal-gov': 3,
  ' Local-gov': 4,
  ' ?': 5,
  ' Self-emp-inc': 6,
  ' Without-pay': 7,
  ' Never-worked': 8},
 {' Bachelors': 0,
  ' HS-grad': 1,
  ' 11th': 2,
  ' Masters': 3,
  ' 9th': 4,
  ' Some-college': 5,
  ' Assoc-acdm': 6,
  ' Assoc-voc': 7,
  ' 7th-8th': 8,
  ' Doctorate': 9,
```

In [19]:
```
x_train["workclass"]=x_train["workclass"].map(dict_workclass)
x_train['education']=x_train["education"].map(dict_education)
x_train['marital_status']=x_train['marital_status'].map(dict_marital_status)
x_train['occupation']=x_train['occupation'].map(dict_occupation)
x_train['relationship']=x_train['relationship'].map(dict_relationship)
x_train['race']=x_train['race'].map(dict_race)
x_train['sex']=x_train['sex'].map(dict_sex)
x_train['native_country']=x_train['native_country'].map(dict_native_country)
x_train['wage_class']=x_train['wage_class'].map(dict_wage_class)
```

In [20]:
```
x_train.isnull().sum()
```

Out[20]:
```
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 [21]:
```
xtrain = x_train.astype(int)
```

In [22]:
```
x_train.head()
```

Out[22]:

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationship	rac
0	39	0	77516	0	13	0	0	0	
1	50	1	83311	0	13	1	1	1	
2	38	2	215646	1	9	2	2	0	
3	53	2	234721	2	7	1	2	1	
4	28	2	338409	0	13	1	3	2	

In [23]:
```
x_train.describe()
```

Out[23]:

	age	workclass	fnlwgt	education	education_num	marital_status	
count	32561.000000	32561.000000	3.256100e+04	32561.000000	32561.000000	32561.000000	325
mean	38.581647	2.309972	1.897784e+05	3.424465	10.080679	1.083781	
std	13.640433	1.225728	1.055500e+05	3.453582	2.572720	1.251381	
min	17.000000	0.000000	1.228500e+04	0.000000	1.000000	0.000000	
25%	28.000000	2.000000	1.178270e+05	1.000000	9.000000	0.000000	
50%	37.000000	2.000000	1.783560e+05	2.000000	10.000000	1.000000	
75%	48.000000	2.000000	2.370510e+05	5.000000	12.000000	1.000000	
max	90.000000	8.000000	1.484705e+06	15.000000	16.000000	6.000000	

In [24]:
```
dict_native_country = {}
count = 0
for i in x_test.native_country.unique():
    dict_native_country[i]= count
    count+=1



dict_wage_class = {}
count = 0
for i in x_test.wage_class.unique():
    dict_wage_class[i]= count
    count+=1
```

In [25]:
```
x_test["workclass"]=x_test["workclass"].map(dict_workclass)
x_test['education']=x_test["education"].map(dict_education)
x_test['marital_status']=x_test['marital_status'].map(dict_marital_status)
x_test['occupation']=x_test['occupation'].map(dict_occupation)
x_test['relationship']=x_test['relationship'].map(dict_relationship)
x_test['race']=x_test['race'].map(dict_race)
x_test['sex']=x_test['sex'].map(dict_sex)
x_test['native_country']=x_test['native_country'].map(dict_native_country)
x_test['wage_class']=x_test['wage_class'].map(dict_wage_class)
```

In [26]:
```
dict_wage_class
```

Out[26]:
```
{' <=50K.': 0, ' >50K.': 1}
```

In [27]:
```
x_test.head()
```

Out[27]:

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationship	rac
0	25	2	226802	2	7	0	9	3	
1	38	2	89814	1	9	1	8	1	
2	28	4	336951	6	12	1	12	1	
3	44	2	160323	5	10	1	9	1	
4	18	5	103497	5	10	0	11	3	

In [28]:
```
x_test.describe()
```

Out[28]:

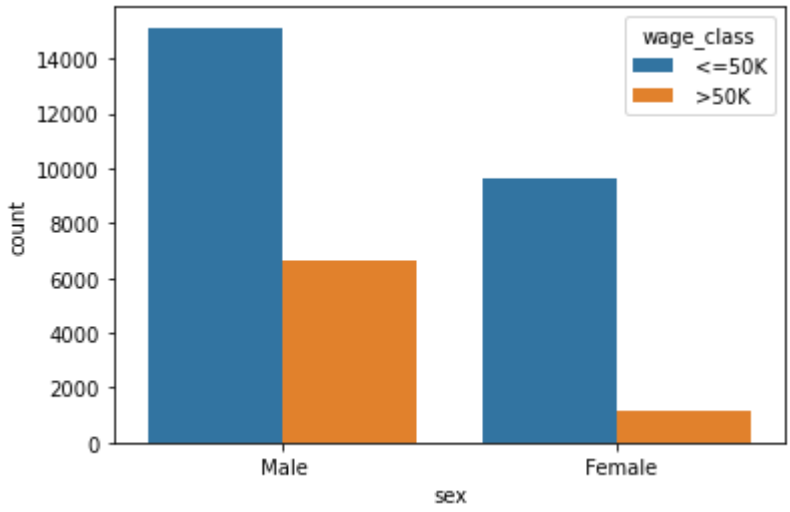
	age	workclass	fnlwgt	education	education_num	marital_status	c
count	16281.000000	16281.000000	1.628100e+04	16281.000000	16281.000000	16281.000000	162
mean	38.767459	2.315030	1.894357e+05	3.386954	10.072907	1.084270	
std	13.849187	1.246499	1.057149e+05	3.440725	2.567545	1.269622	
min	17.000000	0.000000	1.349200e+04	0.000000	1.000000	0.000000	
25%	28.000000	2.000000	1.167360e+05	1.000000	9.000000	0.000000	
50%	37.000000	2.000000	1.778310e+05	2.000000	10.000000	1.000000	
75%	48.000000	2.000000	2.383840e+05	5.000000	12.000000	1.000000	
max	90.000000	8.000000	1.490400e+06	15.000000	16.000000	6.000000	

In [29]:
```
import seaborn as sns
import matplotlib.pyplot as plt
```

In [30]:
```
sns.countplot('sex',data = train_set , hue = "wage_class")
```

```
C:\Users\idofa\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWar
ning: Pass the following variable as a keyword arg: x. From version 0.12, the o
nly valid positional argument will be `data`, and passing other arguments witho
ut an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

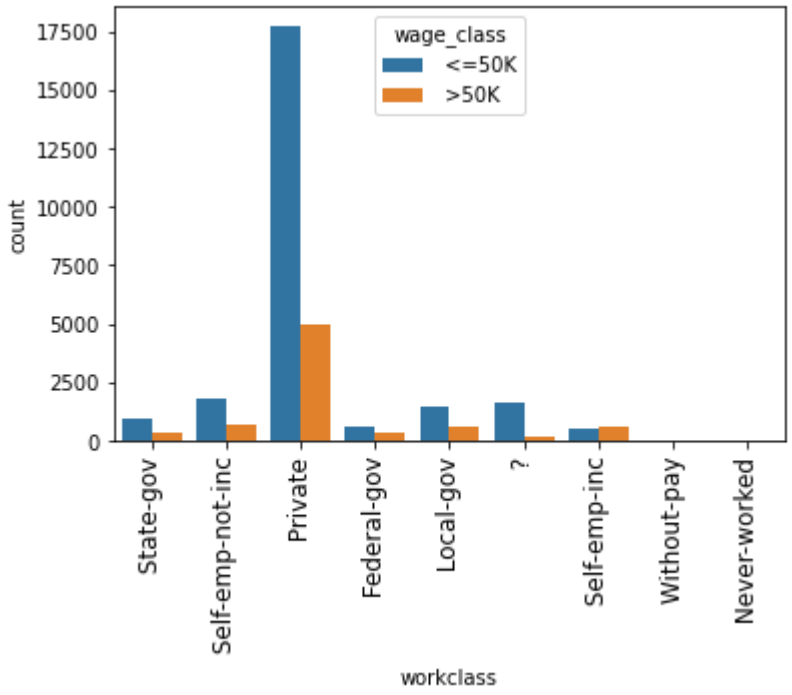
Out[30]:
```
<AxesSubplot:xlabel='sex', ylabel='count'>
```



In [31]:
```
g = sns.countplot('workclass',data = train_set , hue = "wage_class")
g.set_xticklabels(g.get_xticklabels() , rotation =90 , fontsize = 12)
```

```
C:\Users\idofa\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWar
ning: Pass the following variable as a keyword arg: x. From version 0.12, the o
nly valid positional argument will be `data`, and passing other arguments witho
ut an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

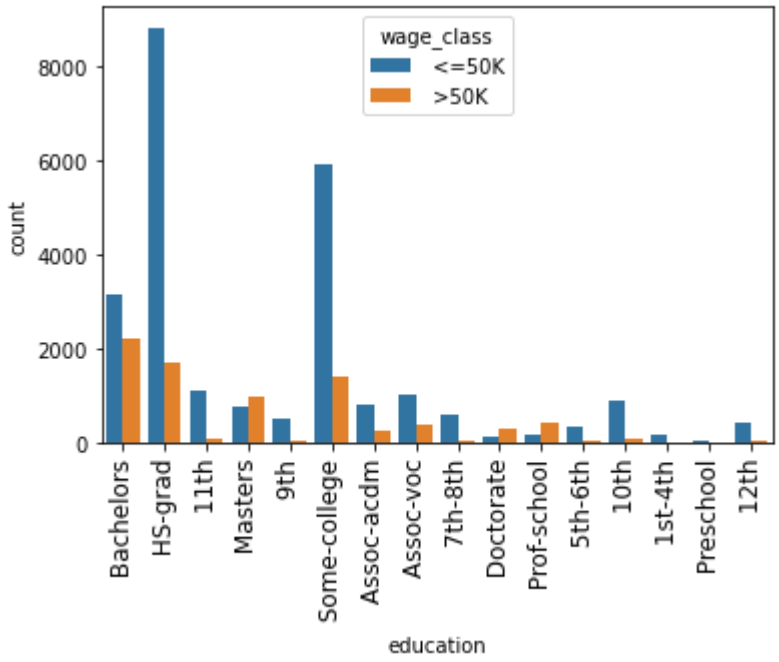
Out[31]:
```
[Text(0, 0, ' State-gov'),
 Text(1, 0, ' Self-emp-not-inc'),
 Text(2, 0, ' Private'),
 Text(3, 0, ' Federal-gov'),
 Text(4, 0, ' Local-gov'),
 Text(5, 0, ' ?'),
 Text(6, 0, ' Self-emp-inc'),
 Text(7, 0, ' Without-pay'),
 Text(8, 0, ' Never-worked')]
```



In [32]:
```
g = sns.countplot('education',data = train_set , hue = "wage_class")
g.set_xticklabels(g.get_xticklabels() , rotation =90 , fontsize = 12)
```

```
C:\Users\idofa\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWar
ning: Pass the following variable as a keyword arg: x. From version 0.12, the o
nly valid positional argument will be `data`, and passing other arguments witho
ut an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[32]:
```
[Text(0, 0, ' Bachelors'),
 Text(1, 0, ' HS-grad'),
 Text(2, 0, ' 11th'),
 Text(3, 0, ' Masters'),
 Text(4, 0, ' 9th'),
 Text(5, 0, ' Some-college'),
 Text(6, 0, ' Assoc-acdm'),
 Text(7, 0, ' Assoc-voc'),
 Text(8, 0, ' 7th-8th'),
 Text(9, 0, ' Doctorate'),
 Text(10, 0, ' Prof-school'),
 Text(11, 0, ' 5th-6th'),
 Text(12, 0, ' 10th'),
 Text(13, 0, ' 1st-4th'),
 Text(14, 0, ' Preschool'),
 Text(15, 0, ' 12th')]
```



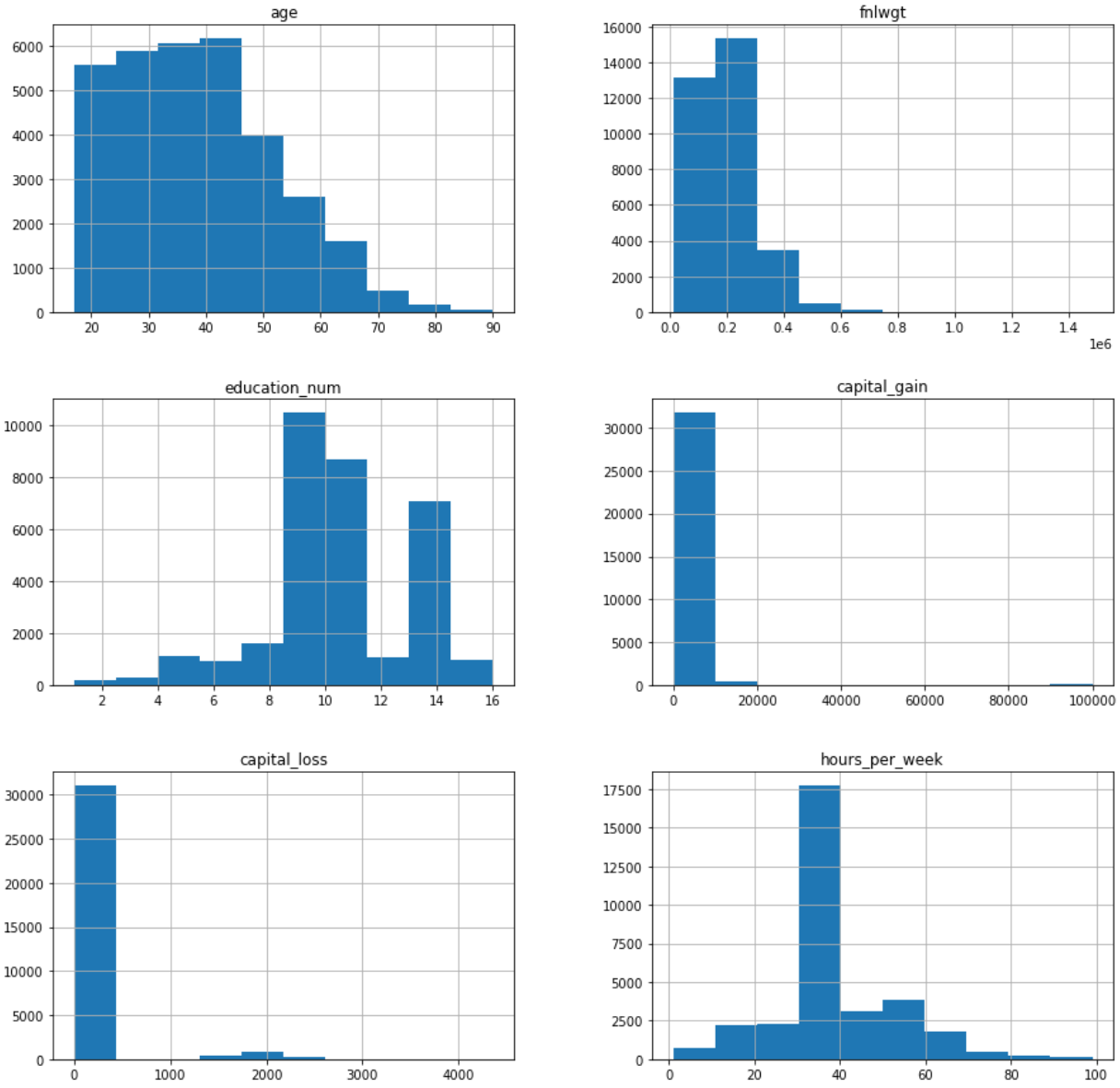
In [33]:
```
g = sns.countplot("wage_class",data = train_set , )
g.set_xticklabels(g.get_xticklabels() , rotation =90 , fontsize = 12)
```

```
C:\Users\idofa\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWar
ning: Pass the following variable as a keyword arg: x. From version 0.12, the o
nly valid positional argument will be `data`, and passing other arguments witho
ut an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[33]:
```
[Text(0, 0, ' <=50K'), Text(1, 0, ' >50K')]
```

In [34]:
```
pd.DataFrame.hist(train_set , figsize=[15,15])
```

Out[34]:
```
array([[<AxesSubplot:title={'center':'age'}>,
        <AxesSubplot:title={'center':'fnlwgt'}>],
       [<AxesSubplot:title={'center':'education_num'}>,
        <AxesSubplot:title={'center':'capital_gain'}>],
       [<AxesSubplot:title={'center':'capital_loss'}>,
        <AxesSubplot:title={'center':'hours_per_week'}>]], dtype=object)
```



In [35]:
```
y_train = x_train['wage_class']
x_train = x_train.drop('wage_class',axis =1 )

y_test = x_test['wage_class']
x_test = x_test.drop('wage_class',axis =1)
```

In [36]:
```
X = x_train.values
Y = y_train.values
Xtest = x_test.values
Ytest = y_test.values
```

In [37]:
```
x_train.head()
```

Out[37]:

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationship	rac
0	39	0	77516	0	13	0	0	0	
1	50	1	83311	0	13	1	1	1	
2	38	2	215646	1	9	2	2	0	
3	53	2	234721	2	7	1	2	1	
4	28	2	338409	0	13	1	3	2	

In [38]:
```
x_train.shape , y_train.shape , X.shape , Y.shape , Xtest.shape , Ytest.shape
```

Out[38]:
```
((32561, 14), (32561,), (32561, 14), (32561,), (16281, 14), (16281,))
```

In [39]:
```
from xgboost.sklearn import XGBClassifier
```

In [40]:
```
#set the parameter for XGBoost model
params = {
    "objective": "binary:logistic",
    'max_depth':2,
    'learning_rate':1.0,
    'silent':1.0,
    'n_estimstor':5
}
params['eval_metric'] = ['logloss','auc']
```

In [41]:
```
#Train the XGBoost model classifier
bst = XGBClassifier(**params).fit(X,Y)
```

```
C:\Users\idofa\anaconda3\lib\site-packages\xgboost\sklearn.py:892: UserWarning:
The use of label encoder in XGBClassifier is deprecated and will be removed in
a future release. To remove this warning, do the following: 1) Pass option use_
label_encoder=False when constructing XGBClassifier object; and 2) Encode your
labels (y) as integers starting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)

[09:52:06] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.
0/src/learner.cc:541:
Parameters: { n_estimstor, silent } might not be used.

  This may not be accurate due to some parameters are only used in language bin
dings but
  passed down to XGBoost core.  Or some parameters are not used but slip throug
h this
  verification. Please open an issue if you find above cases.
```

In [42]:
```
#predicting the annual income
pred = bst.predict(Xtest)
pred
```

Out[42]:
```
array([0, 0, 0, ..., 1, 0, 1], dtype=int64)
```

In [43]:
```
pred_prob = bst.predict_proba(Xtest)
pred_prob
```

Out[43]:
```
array([[9.9924290e-01, 7.5711834e-04],
       [8.0084783e-01, 1.9915217e-01],
       [6.3513732e-01, 3.6486265e-01],
       ...,
       [2.4961776e-01, 7.5038224e-01],
       [9.0756387e-01, 9.2436157e-02],
       [2.9993576e-01, 7.0006424e-01]], dtype=float32)
```

In [44]:
```
#measure the accuracy of this model
correct = 0
from sklearn.metrics import accuracy_score
for i in range(len(pred)):
    if(y_test[i]==pred[i]):
        correct+=1

acc = accuracy_score(Ytest , pred)


print("Predicted correctly :-",correct , '/',len(pred))
print("Accuracy score :-{:.4f}".format(acc))
print("Error:- {0:.4f}".format(1-acc))
```

```
Predicted correctly :- 14196 / 16281
Accuracy score :-0.8719
Error:- 0.1281
```

In [45]:
```
from sklearn.metrics import classification_report
print(classification_report(Ytest,pred))
```

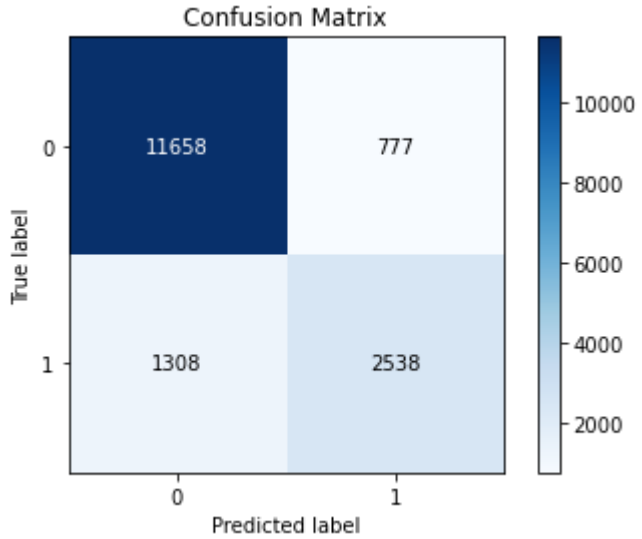
```
              precision    recall  f1-score   support

           0       0.90      0.94      0.92     12435
           1       0.77      0.66      0.71      3846

    accuracy                           0.87     16281
   macro avg       0.83      0.80      0.81     16281
weighted avg       0.87      0.87      0.87     16281
```

In [46]:
```
#Creating confusion matrix
import scikitplot
scikitplot.metrics.plot_confusion_matrix(Ytest , pred)
```

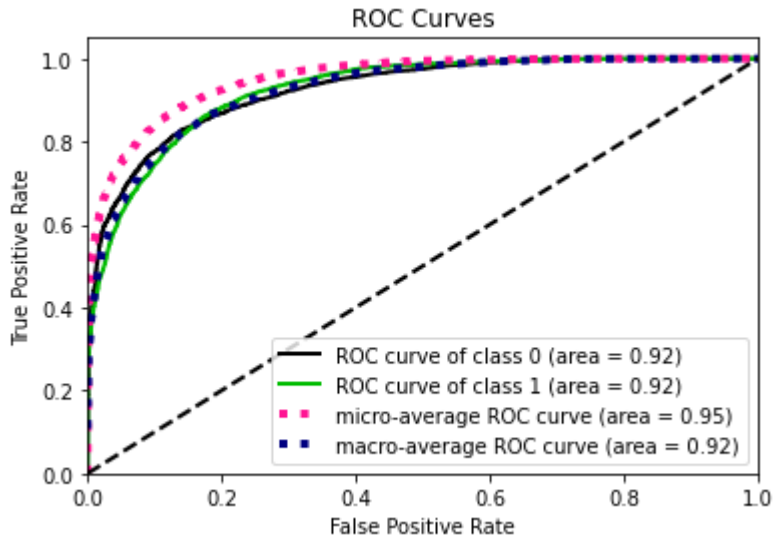
Out[46]:
```
<AxesSubplot:title={'center':'Confusion Matrix'}, xlabel='Predicted label', yla
bel='True label'>
```



In [47]:
```
#Creating ROC
scikitplot.metrics.plot_roc_curve(Ytest , pred_prob)
```

```
C:\Users\idofa\anaconda3\lib\site-packages\sklearn\utils\deprecation.py:86: Fut
ureWarning: Function plot_roc_curve is deprecated; This will be removed in v0.
5.0. Please use scikitplot.metrics.plot_roc instead.
  warnings.warn(msg, category=FutureWarning)
```

Out[47]:
```
<AxesSubplot:title={'center':'ROC Curves'}, xlabel='False Positive Rate', ylabe
l='True Positive Rate'>
```



In [ ]:
```
pip install scikitplot
```

In [ ]:
```
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
lr.fit(X , Y)
```

In [ ]:
```
pred_lr = lr.predict(Xtest)
pred_lr
```

In [ ]:
```
pred_lr_prob = lr.predict_proba(Xtest)
pred_lr_prob
```

In [ ]:
```
print("Accuracy score :-{:.4f}".format(accuracy_score(Ytest , pred_lr)))
```

In [ ]:
```
print(classification_report(Ytest,pred_lr))
```

In [ ]:
```
import scikitplot
scikitplot.metrics.plot_confusion_matrix(Ytest , pred_lr)
```

In [ ]:
```
#Creating ROC
scikitplot.metrics.plot_roc_curve(Ytest , pred_lr_prob)
```

In [ ]:
```
#Using bagging method and base method as logistic regression
from sklearn.ensemble import BaggingClassifier
bag_LR = BaggingClassifier(LogisticRegression() , n_estimators=10,max_samples=0.5
```

In [ ]:
```
bag_LR.fit(X,Y)
```

In [ ]:
```
#Prediction by bagging ensemble technique
bag_pred = bag_LR.predict(Xtest)
bag_pred
```

In [ ]:
```
bag_pred_prob = bag_LR.predict_proba(Xtest)
bag_pred_prob
```

In [ ]:
```
#Score of the bagging ensemble model
bag_LR.score(Xtest ,Ytest)
```

In [ ]:
```
print("Accuracy score :-{:.4f}".format(accuracy_score(Ytest , bag_pred)))
```

In [ ]:
```
print(classification_report(Ytest,bag_pred))
```

In [ ]:
```
#Creating ROC
scikitplot.metrics.plot_roc_curve(Ytest , bag_pred_prob)
```

In [ ]:
```
#CONCLUSION
#The boosting classifier method yields a better performance in this scenario as c
#classifier and bagging method
```

In [ ]:
```

```

In [ ]:
```

```