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, Exec-managerial, 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, El-Salvador, 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/machine-learning- (http://archive.ics.uci.edu/ml/machine-learning-) databases/adult/adult.data', header = None)

test_set = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning- (http://archive.ics.uci.edu/ml/machine-learning-) databases/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]:
```
#code to load required libraries and data:
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')

train_set = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.data', header = None)

test_set = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-databases/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 [2]:
```
train_set.shape,test_set.shape
```

Out[2]:
```
((32561, 15), (16281, 15))
```

In [3]:
```
# View training and test data sample
train_set.sample(4, random_state = 42)
```

Out[3]:

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationsh
14160	27	Private	160178	Some-college	10	Divorced	Adm-clerical	Not-in-fam
27048	45	State-gov	50567	HS-grad	9	Married-civ-spouse	Exec-managerial	W
28868	29	Private	185908	Bachelors	13	Married-civ-spouse	Exec-managerial	Husba
5667	30	Private	190040	Bachelors	13	Never-married	Machine-op-inspct	Not-in-fam

In [4]:
```
test_set.sample(4, random_state = 42)
```

Out[4]:

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationsl
13633	29	Private	189346	HS-grad	9	Never-married	Transport-moving	Unmarri
1921	31	Private	137076	Bachelors	13	Married-civ-spouse	Protective-serv	Husba
12140	52	Federal-gov	35546	HS-grad	9	Married-civ-spouse	Tech-support	Husba
9933	54	Local-gov	116428	10th	6	Married-civ-spouse	Exec-managerial	Husba

In [5]:
```
# Checking null values in training and test data sets
train_set.isnull().sum()
```

Out[5]:
```
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 [6]:
```
test_set.isnull().sum()
```

Out[6]:
```
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 [7]:
```
pd.DataFrame([train_set.dtypes, test_set.dtypes], index = ['train_set','test_set']).T
```

Out[7]:

	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 [8]:
```
# 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 [9]:
```
train_set.workclass.value_counts()
```

Out[9]:
```
 Private             22696
 Self-emp-not-inc     2541
 Local-gov            2093
 ?                    1836
 State-gov            1298
 Self-emp-inc         1116
 Federal-gov           960
 Without-pay            14
 Never-worked            7
Name: workclass, dtype: int64
```

In [10]:
```
train_set
```

Out[10]:

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationsh
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-fam
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husba
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-fam
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husba
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	W
5	37	Private	284582	Masters	14	Married-civ-spouse	Exec-managerial	W
6	49	Private	160187	9th	5	Married-spouse-absent	Other-service	Not-in-fam
7	52	Self-emp-not-inc	209642	HS-grad	9	Married-civ-spouse	Exec-managerial	Husba
8	31	Private	45781	Masters	14	Never-married	Prof-specialty	Not-in-fam
9	42	Private	159449	Bachelors	13	Married-civ-spouse	Exec-managerial	Husba
10	37	Private	280464	Some-college	10	Married-civ-spouse	Exec-managerial	Husba
11	30	State-gov	141297	Bachelors	13	Married-civ-spouse	Prof-specialty	Husba
12	23	Private	122272	Bachelors	13	Never-married	Adm-clerical	Own-ch
13	32	Private	205019	Assoc-acdm	12	Never-married	Sales	Not-in-fam
14	40	Private	121772	Assoc-voc	11	Married-civ-spouse	Craft-repair	Husba
15	34	Private	245487	7th-8th	4	Married-civ-spouse	Transport-moving	Husba
16	25	Self-emp-not-inc	176756	HS-grad	9	Never-married	Farming-fishing	Own-ch
17	32	Private	186824	HS-grad	9	Never-married	Machine-op-inspct	Unmarri
18	38	Private	28887	11th	7	Married-civ-spouse	Sales	Husba
19	43	Self-emp-not-inc	292175	Masters	14	Divorced	Exec-managerial	Unmarri
20	40	Private	193524	Doctorate	16	Married-civ-spouse	Prof-specialty	Husba
21	54	Private	302146	HS-grad	9	Separated	Other-service	Unmarri

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationsh
22	35	Federal-gov	76845	9th	5	Married-civ-spouse	Farming-fishing	Husba
23	43	Private	117037	11th	7	Married-civ-spouse	Transport-moving	Husba
24	59	Private	109015	HS-grad	9	Divorced	Tech-support	Unmarri
25	56	Local-gov	216851	Bachelors	13	Married-civ-spouse	Tech-support	Husba
26	19	Private	168294	HS-grad	9	Never-married	Craft-repair	Own-ch
27	54	?	180211	Some-college	10	Married-civ-spouse	?	Husba
28	39	Private	367260	HS-grad	9	Divorced	Exec-managerial	Not-in-fam
29	49	Private	193366	HS-grad	9	Married-civ-spouse	Craft-repair	Husba
...	...	...	...	...	...	...	...	
32531	30	?	33811	Bachelors	13	Never-married	?	Not-in-fam
32532	34	Private	204461	Doctorate	16	Married-civ-spouse	Prof-specialty	Husba
32533	54	Private	337992	Bachelors	13	Married-civ-spouse	Exec-managerial	Husba
32534	37	Private	179137	Some-college	10	Divorced	Adm-clerical	Unmarri
32535	22	Private	325033	12th	8	Never-married	Protective-serv	Own-ch
32536	34	Private	160216	Bachelors	13	Never-married	Exec-managerial	Not-in-fam
32537	30	Private	345898	HS-grad	9	Never-married	Craft-repair	Not-in-fam
32538	38	Private	139180	Bachelors	13	Divorced	Prof-specialty	Unmarri
32539	71	?	287372	Doctorate	16	Married-civ-spouse	?	Husba
32540	45	State-gov	252208	HS-grad	9	Separated	Adm-clerical	Own-ch
32541	41	?	202822	HS-grad	9	Separated	?	Not-in-fam
32542	72	?	129912	HS-grad	9	Married-civ-spouse	?	Husba
32543	45	Local-gov	119199	Assoc-acdm	12	Divorced	Prof-specialty	Unmarri
32544	31	Private	199655	Masters	14	Divorced	Other-service	Not-in-fam
32545	39	Local-gov	111499	Assoc-acdm	12	Married-civ-spouse	Adm-clerical	W

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationsh
32546	37	Private	198216	Assoc-acdm	12	Divorced	Tech-support	Not-in-fam
32547	43	Private	260761	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husba
32548	65	Self-emp-not-inc	99359	Prof-school	15	Never-married	Prof-specialty	Not-in-fam
32549	43	State-gov	255835	Some-college	10	Divorced	Adm-clerical	Oth relat
32550	43	Self-emp-not-inc	27242	Some-college	10	Married-civ-spouse	Craft-repair	Husba
32551	32	Private	34066	10th	6	Married-civ-spouse	Handlers-cleaners	Husba
32552	43	Private	84661	Assoc-voc	11	Married-civ-spouse	Sales	Husba
32553	32	Private	116138	Masters	14	Never-married	Tech-support	Not-in-fam
32554	53	Private	321865	Masters	14	Married-civ-spouse	Exec-managerial	Husba
32555	22	Private	310152	Some-college	10	Never-married	Protective-serv	Not-in-fam
32556	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	W
32557	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husba
32558	58	Private	151910	HS-grad	9	Widowed	Adm-clerical	Unmarri
32559	22	Private	201490	HS-grad	9	Never-married	Adm-clerical	Own-ch
32560	52	Self-emp-inc	287927	HS-grad	9	Married-civ-spouse	Exec-managerial	W

32561 rows × 15 columns

In [11]:
```
train_set.relationship.value_counts()
```

Out[11]:
```
 Husband           13193
 Not-in-family      8305
 Own-child          5068
 Unmarried          3446
 Wife               1568
 Other-relative      981
Name: relationship, dtype: int64
```

In [12]:
```
train_set.workclass.nunique(),train_set.education.nunique(),train_set.marital_
status.nunique(),train_set.native_country.nunique()
```

Out[12]:
```
(9, 16, 7, 42)
```

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 to numeric 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_sex,dict_education,dict_wage_class,dict_native_country,dict_race,dict_occ
upation ,dict_marital_status
```

Out[18]:
```
({' Male': 0, ' Female': 1},
 {' 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,
  ' Prof-school': 10,
  ' 5th-6th': 11,
  ' 10th': 12,
  ' 1st-4th': 13,
  ' Preschool': 14,
  ' 12th': 15},
 {' <=50K': 0, ' >50K': 1},
 {' United-States': 0,
  ' Cuba': 1,
  ' Jamaica': 2,
  ' India': 3,
  ' ?': 4,
  ' Mexico': 5,
  ' South': 6,
  ' Puerto-Rico': 7,
  ' Honduras': 8,
  ' England': 9,
  ' Canada': 10,
  ' Germany': 11,
  ' Iran': 12,
  ' Philippines': 13,
  ' Italy': 14,
  ' Poland': 15,
  ' Columbia': 16,
  ' Cambodia': 17,
  ' Thailand': 18,
  ' Ecuador': 19,
  ' Laos': 20,
  ' Taiwan': 21,
  ' Haiti': 22,
  ' Portugal': 23,
  ' Dominican-Republic': 24,
  ' El-Salvador': 25,
  ' France': 26,
  ' Guatemala': 27,
  ' China': 28,
  ' Japan': 29,
  ' Yugoslavia': 30,
  ' Peru': 31,
  ' Outlying-US(Guam-USVI-etc)': 32,
  ' Scotland': 33,
  ' Trinadad&Tobago': 34,
  ' Greece': 35,
  ' Nicaragua': 36,
  ' Vietnam': 37,
  ' Hong': 38,
```

```
 ' Ireland': 39,
 ' Hungary': 40,
 ' Holand-Netherlands': 41},
{' White': 0,
 ' Black': 1,
 ' Asian-Pac-Islander': 2,
 ' Amer-Indian-Eskimo': 3,
 ' Other': 4},
{' Adm-clerical': 0,
 ' Exec-managerial': 1,
 ' Handlers-cleaners': 2,
 ' Prof-specialty': 3,
 ' Other-service': 4,
 ' Sales': 5,
 ' Craft-repair': 6,
 ' Transport-moving': 7,
 ' Farming-fishing': 8,
 ' Machine-op-inspct': 9,
 ' Tech-support': 10,
 ' ?': 11,
 ' Protective-serv': 12,
 ' Armed-Forces': 13,
 ' Priv-house-serv': 14},
{' Never-married': 0,
 ' Married-civ-spouse': 1,
 ' Divorced': 2,
 ' Married-spouse-absent': 3,
 ' Separated': 4,
 ' Married-AF-spouse': 5,
 ' Widowed': 6})
```

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

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

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

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

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
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

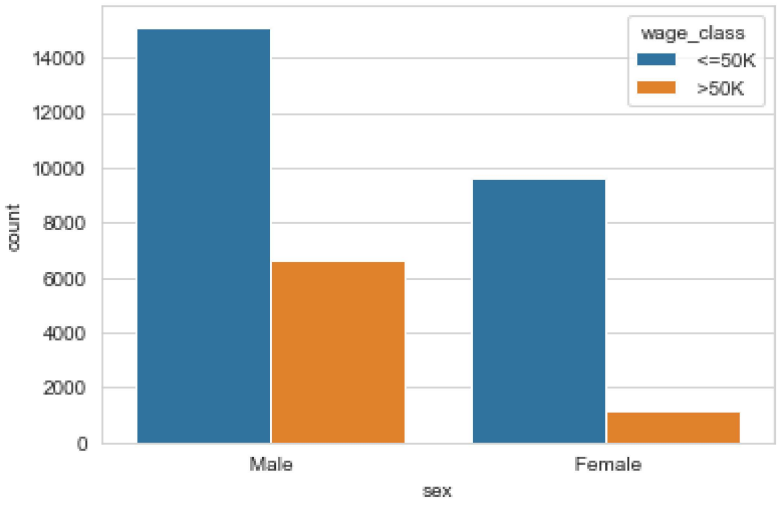
In [28]:
```
X_test.describe()
```

Out[28]:

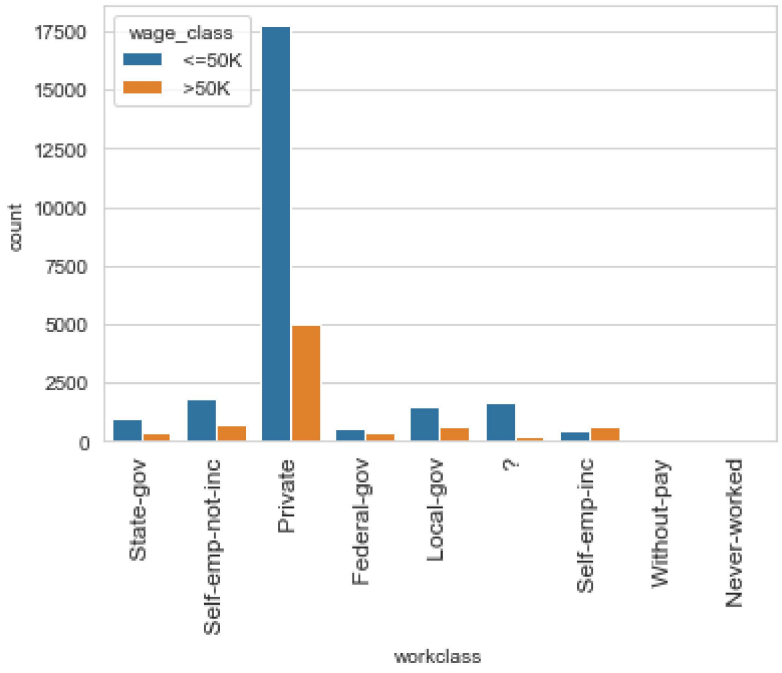
	age	workclass	fnlwgt	education	education_num	marital_status
count	16281.000000	16281.000000	1.628100e+04	16281.000000	16281.000000	16281.000000
mean	38.767459	2.315030	1.894357e+05	3.386954	10.072907	1.084270
std	13.849187	1.246499	1.057149e+05	3.440725	2.567545	1.269622
min	17.000000	0.000000	1.349200e+04	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]:
```
# Performing annual income visual analysis
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(40,20))
sns.set_style('whitegrid')
%matplotlib inline
sns.countplot('sex',data=train_set,hue='wage_class')
```

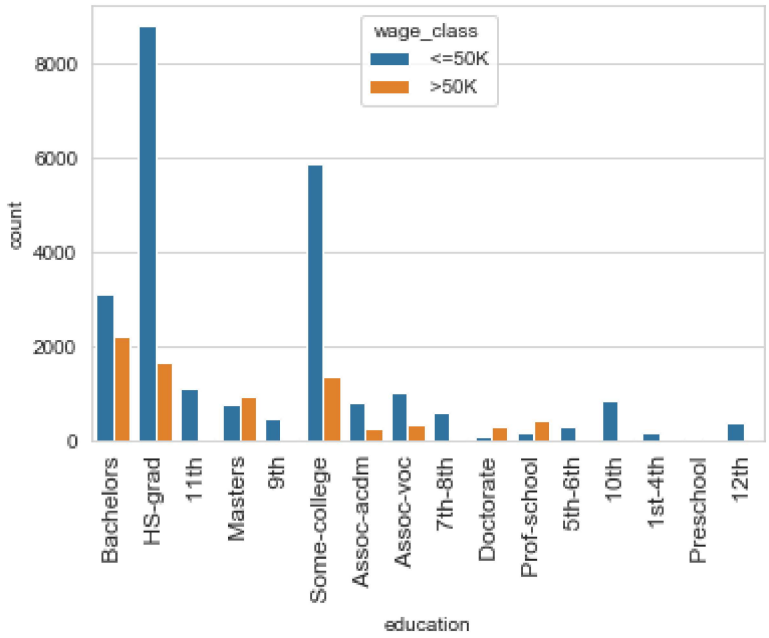
Out[29]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x24a9b5e9a90>
```



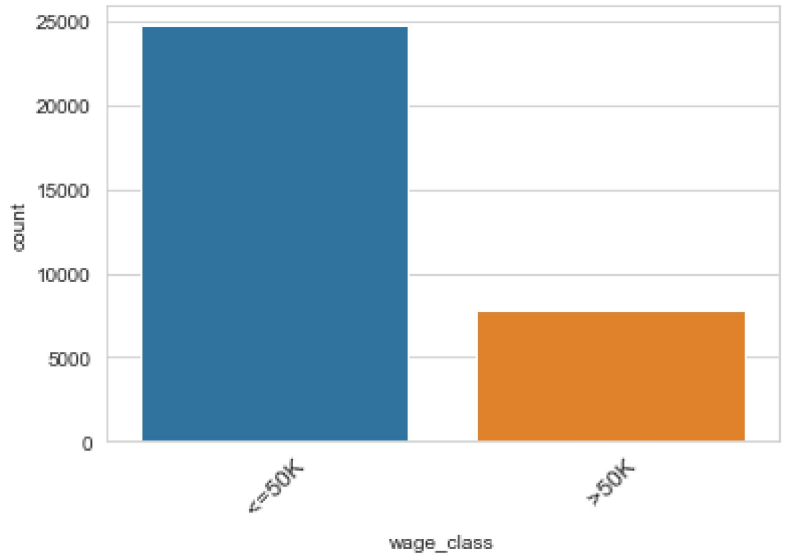
In [32]:
```
g = sns.countplot('workclass',data=train_set,hue='wage_class')
g.set_xticklabels(g.get_xticklabels(), rotation = 90, fontsize = 12)
plt.show()
```



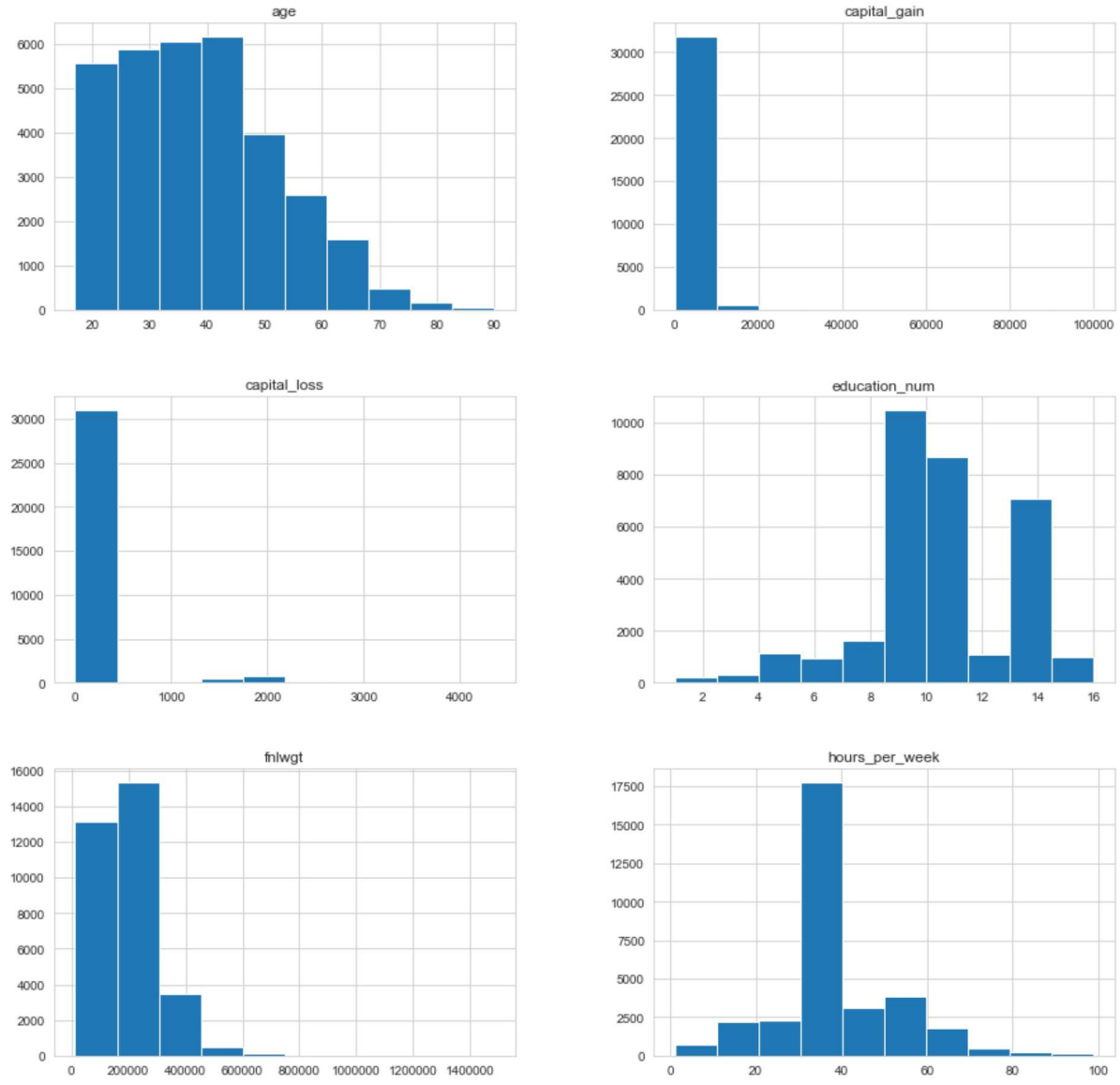
In [33]:
```
g = sns.countplot('education',data=train_set,hue='wage_class')
g.set_xticklabels(g.get_xticklabels(), rotation = 90, fontsize = 12)
plt.show()
```



In [34]:
```
g = sns.countplot('wage_class',data=train_set)
g.set_xticklabels(g.get_xticklabels(), rotation = 45, fontsize = 12)
plt.show()
```



In [35]:
```
pd.DataFrame.hist(train_set,figsize = [15,15])
plt.show()
```



In [36]:
```
x_train = X_train.drop('wage_class',axis=1)
y_train = X_train['wage_class']

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

In [37]:
```
X = x_train.values
Y = y_train.values
Xtest = x_test.values
Ytest = y_test.values
```

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]:
```
Xtest
```

Out[39]:
```
array([[    25,      2, 226802, ...,      0,     40,      0],
       [    38,      2,  89814, ...,      0,     50,      0],
       [    28,      4, 336951, ...,      0,     40,      0],
       ...,
       [    38,      2, 374983, ...,      0,     50,      0],
       [    44,      2,  83891, ...,      0,     40,      0],
       [    35,      6, 182148, ...,      0,     60,      0]], dtype=int64)
```

In [40]:
```
# Using boosting method of ensemble model for predicting the annual income

from xgboost.sklearn import XGBClassifier
#set the parameters for the xgbosst model
params = {
    'objective': 'binary:logistic',
    'max_depth': 2,
    'learning_rate': 1.0,
    'silent': 1.0,
    'n_estimators': 5
}
params['eval_metric'] = ['logloss', 'auc']
```

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

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

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

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

Out[43]:
```
array([[0.9862895 , 0.01371049],
       [0.6448917 , 0.35510832],
       [0.8749048 , 0.1250952 ],
       ...,
       [0.282     , 0.718     ],
       [0.71667016, 0.28332984],
       [0.17598617, 0.8240138 ]], dtype=float32)
```

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

acc = accuracy_score(Ytest, preds)

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

```
Predicted correctly: 13897/16281
Accuracy Score :0.8536
Error: 0.1464
```

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

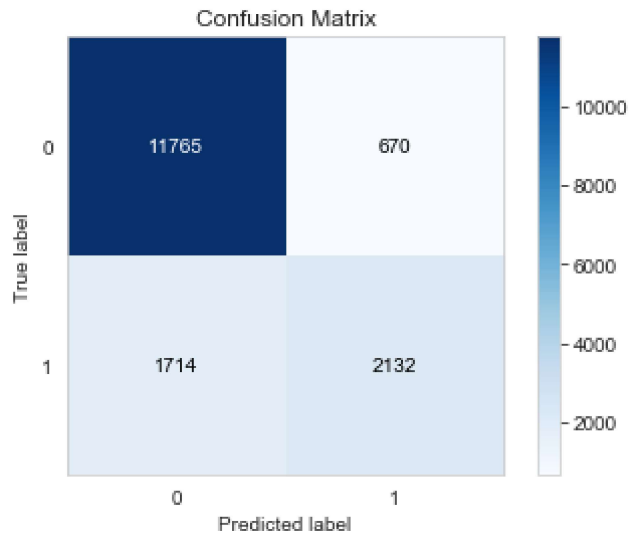
```
              precision    recall  f1-score   support

           0       0.87      0.95      0.91     12435
           1       0.76      0.55      0.64      3846

   micro avg       0.85      0.85      0.85     16281
   macro avg       0.82      0.75      0.77     16281
weighted avg       0.85      0.85      0.85     16281
```

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

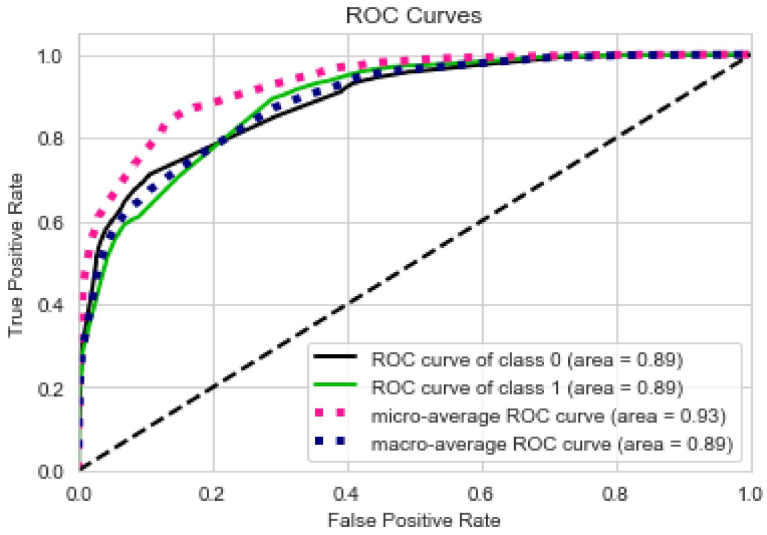
Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0x24a9d644860>



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

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:77: D
eprecationWarning: Function plot_roc_curve is deprecated; This will be remove
d in v0.5.0. Please use scikitplot.metrics.plot_roc instead.
  warnings.warn(msg, category=DeprecationWarning)
```

Out[47]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x24a9d6c8710>
```



In [48]:
```
# Comapring the ensemble model with single random Logistic Regression model
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
lr.fit(X,Y)
```

Out[48]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)
```

In [49]:
```
pred_lr = lr.predict(Xtest)
pred_lr
```

Out[49]:
```
array([0, 0, 0, ..., 0, 1, 0], dtype=int64)
```

In [50]:
```
pred_lr_proba = lr.predict_proba(Xtest)
pred_lr_proba
```

Out[50]:
```
array([[0.80955138, 0.19044862],
       [0.71918966, 0.28081034],
       [0.87925836, 0.12074164],
       ...,
       [0.89229153, 0.10770847],
       [0.26855158, 0.73144842],
       [0.79149081, 0.20850919]])
```

In [51]:
```
print('Accuracy Score :{:.4f}'.format(accuracy_score(Ytest,pred_lr)))
```

```
Accuracy Score :0.8003
```

In [52]:
```
print(classification_report(Ytest,pred_lr))
```

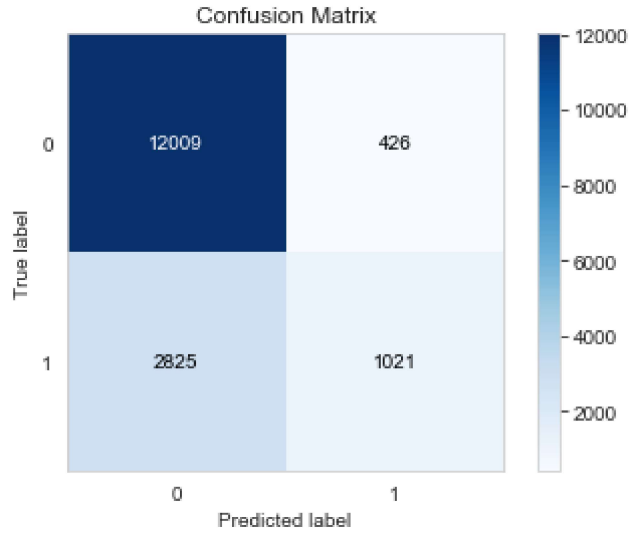
```
              precision    recall  f1-score   support

           0       0.81      0.97      0.88     12435
           1       0.71      0.27      0.39      3846

   micro avg       0.80      0.80      0.80     16281
   macro avg       0.76      0.62      0.63     16281
weighted avg       0.79      0.80      0.76     16281
```

In [53]:
```
#Confusion matrix
import scikitplot
scikitplot.metrics.plot_confusion_matrix(Ytest, pred_lr)
```

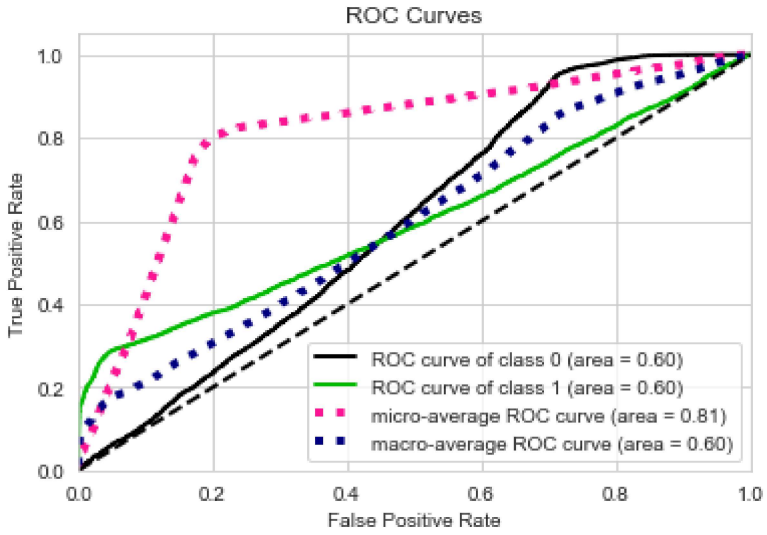
Out[53]: <matplotlib.axes._subplots.AxesSubplot at 0x24a9d7573c8>



In [54]:
```
# ROC
scikitplot.metrics.plot_roc_curve(Ytest,pred_lr_proba)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:77: D
eprecationWarning: Function plot_roc_curve is deprecated; This will be remove
d in v0.5.0. Please use scikitplot.metrics.plot_roc instead.
  warnings.warn(msg, category=DeprecationWarning)
```

Out[54]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x24a9d7c4710>
```



In [55]:
```
# Using Bagging Method of Ensemble model and base model as Logistic Regression

from sklearn.ensemble import BaggingClassifier
bag_LR = BaggingClassifier(LogisticRegression(),
                           n_estimators=10, max_samples=0.5,
                           bootstrap=True, random_state=3)
```

In [56]:
```
bag_LR.fit(X,Y)
```

Out[56]:
```
BaggingClassifier(base_estimator=LogisticRegression(C=1.0, class_weight=None,
dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False),
         bootstrap=True, bootstrap_features=False, max_features=1.0,
         max_samples=0.5, n_estimators=10, n_jobs=None, oob_score=False,
         random_state=3, verbose=0, warm_start=False)
```

In [57]:
```
# Predictions by the Bagging Ensemble model
bag_preds = bag_LR.predict(Xtest)
bag_preds
```

Out[57]:
```
array([0, 0, 0, ..., 0, 1, 0], dtype=int64)
```

In [58]:
```
bag_preds_proba = bag_LR.predict_proba(Xtest)
bag_preds_proba
```

Out[58]:
```
array([[0.81156283, 0.18843717],
       [0.73510814, 0.26489186],
       [0.87842468, 0.12157532],
       ...,
       [0.87698788, 0.12301212],
       [0.26852472, 0.73147528],
       [0.78501132, 0.21498868]])
```

In [59]:
```
# Score of the bagging ensemble model
bag_LR.score(Xtest,Ytest)
```

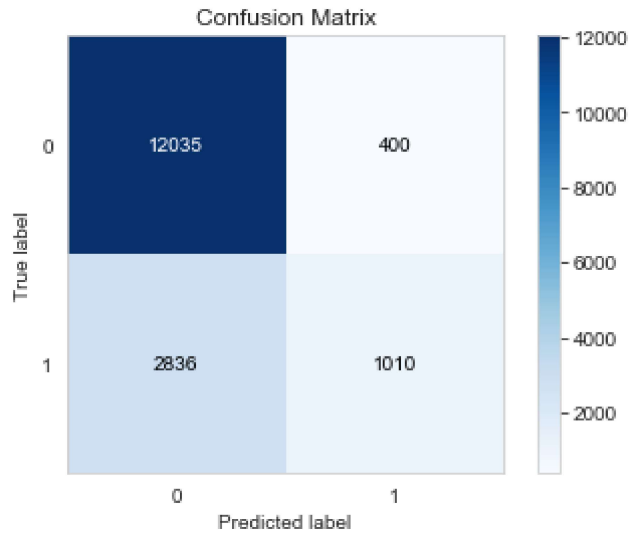
Out[59]:
```
0.8012407100300964
```

In [60]:
```
print(accuracy_score(Ytest,bag_preds))
```

```
0.8012407100300964
```

In [61]:
```
# Confusion matrix
scikitplot.metrics.plot_confusion_matrix(Ytest,bag_preds)
```

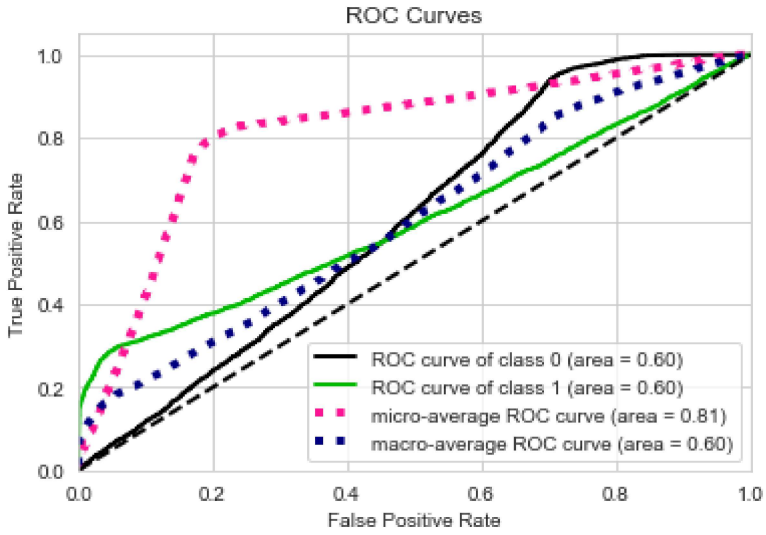
Out[61]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x24a9b8e5b70>
```



In [62]:
```
# ROC
scikitplot.metrics.plot_roc_curve(Ytest,bag_preds_proba)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:77: D
eprecationWarning: Function plot_roc_curve is deprecated; This will be remove
d in v0.5.0. Please use scikitplot.metrics.plot_roc instead.
  warnings.warn(msg, category=DeprecationWarning)
```

Out[62]: <matplotlib.axes._subplots.AxesSubplot at 0x24a9b633978>



In [63]:
```
# CONCLUSION
# The boosting Classifier method yields a better performance in this scenario
 as compared to single random Binary
# classifier and bagging method.
```