XGBoost_Salary_Classifier

December 26, 2020

[1]:
```
import pandas as pd
import numpy as np
import scipy.stats as st
from sklearn.ensemble import GradientBoostingClassifier
```

[2]:
```
train_set=pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-databases/
↪adult/adult.data',header=None)
```

[91]:
```
test_set=pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-databases/
↪adult/adult.test',skiprows=1,header=None)
```

[92]:
```
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']
```

[93]:
```
train_set.columns=col_labels
test_set.columns=col_labels
```

[94]:
```
#Getting a glimpse of train data
train_set.head()
```

[94]:
```
   age         workclass  fnlwgt   education  education_num  \
0   39         State-gov   77516   Bachelors             13
1   50  Self-emp-not-inc   83311   Bachelors             13
2   38           Private  215646     HS-grad              9
3   53           Private  234721        11th              7
4   28           Private  338409   Bachelors             13

       marital_status         occupation   relationship   race  sex  \
0       Never-married       Adm-clerical  Not-in-family  White    1
1  Married-civ-spouse    Exec-managerial        Husband  White    1
2            Divorced  Handlers-cleaners  Not-in-family  White    1
3  Married-civ-spouse  Handlers-cleaners        Husband  Black    1
4  Married-civ-spouse     Prof-specialty           Wife  Black    0

   capital_gain  capital_loss  hours_per_week  native_country  wage_class
```

```
0        2174         0          40          1          1
1           0         0          13          1          1
2           0         0          40          1          1
3           0         0          40          1          1
4           0         0          40          0          1
```

[95]:
```
#Getting a Glimpse of test data
test_set.head()
```

[95]:
```
   age   workclass  fnlwgt      education  education_num       marital_status  \
0   25     Private  226802           11th              7        Never-married
1   38     Private   89814        HS-grad              9   Married-civ-spouse
2   28   Local-gov  336951     Assoc-acdm             12   Married-civ-spouse
3   44     Private  160323   Some-college             10   Married-civ-spouse
4   18           ?  103497   Some-college             10        Never-married

          occupation relationship    race      sex  capital_gain  \
0  Machine-op-inspct    Own-child   Black     Male             0
1    Farming-fishing      Husband   White     Male             0
2    Protective-serv      Husband   White     Male             0
3  Machine-op-inspct      Husband   Black     Male          7688
4                  ?    Own-child   White   Female             0

   capital_loss  hours_per_week  native_country wage_class
0             0              40   United-States     <=50K.
1             0              50   United-States     <=50K.
2             0              40   United-States      >50K.
3             0              40   United-States      >50K.
4             0              30   United-States     <=50K.
```

[8]:
```
#Getting shape details of both train and test data
print('Train Dataset Shape: ',train_set.shape)
print('Test Dataset Shape: ',test_set.shape)
```

```
Train Dataset Shape:  (32561, 15)
Test Dataset Shape:  (16281, 15)
```

[9]:
```
#Checking for NULL values
print('\n************************** TRAIN SET ***************************\n')
print(train_set.info())

print('\n************************** TEST SET ***************************\n')
print(test_set.info())
```

```
************************** TRAIN SET ***************************

<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             32561 non-null  int64
 1   workclass       32561 non-null  object
 2   fnlwgt          32561 non-null  int64
 3   education       32561 non-null  object
 4   education_num   32561 non-null  int64
 5   marital_status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital_gain    32561 non-null  int64
 11  capital_loss    32561 non-null  int64
 12  hours_per_week  32561 non-null  int64
 13  native_country  32561 non-null  object
 14  wage_class      32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
None

************************** TEST SET ***************************

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16281 entries, 0 to 16280
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             16281 non-null  int64
 1   workclass       16281 non-null  object
 2   fnlwgt          16281 non-null  int64
 3   education       16281 non-null  object
 4   education_num   16281 non-null  int64
 5   marital_status  16281 non-null  object
 6   occupation      16281 non-null  object
 7   relationship    16281 non-null  object
 8   race            16281 non-null  object
 9   sex             16281 non-null  object
 10  capital_gain    16281 non-null  int64
 11  capital_loss    16281 non-null  int64
 12  hours_per_week  16281 non-null  int64
 13  native_country  16281 non-null  object
 14  wage_class      16281 non-null  object
dtypes: int64(6), object(9)
memory usage: 1.9+ MB
None
```

No NULL values are present in train and test dataset, hence no need for imputation techniques.

[10]:
```
#Getting an idea of values distribution in train dataset
train_set.describe()
```

[10]:
```
                age        fnlwgt  education_num  capital_gain  capital_loss  \
count  32561.000000  3.256100e+04   32561.000000  32561.000000  32561.000000
mean      38.581647  1.897784e+05      10.080679   1077.648844     87.303830
std       13.640433  1.055500e+05       2.572720   7385.292085    402.960219
min       17.000000  1.228500e+04       1.000000      0.000000      0.000000
25%       28.000000  1.178270e+05       9.000000      0.000000      0.000000
50%       37.000000  1.783560e+05      10.000000      0.000000      0.000000
75%       48.000000  2.370510e+05      12.000000      0.000000      0.000000
max       90.000000  1.484705e+06      16.000000  99999.000000   4356.000000

       hours_per_week
count    32561.000000
mean        40.437456
std         12.347429
min          1.000000
25%         40.000000
50%         40.000000
75%         45.000000
max         99.000000
```

[11]:
```
#Checking the type of output variable and identifying the type of problem
train_set['wage_class'].value_counts()
```

[11]:
```
 <=50K    24720
 >50K      7841
Name: wage_class, dtype: int64
```

Above is a binary classification problem

[12]:
```
train_set['workclass'].value_counts()
```

[12]:
```
 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
```

[13]:
```
train_set['occupation'].value_counts()
```

[13]:
```
 Prof-specialty       4140
 Craft-repair         4099
 Exec-managerial      4066
 Adm-clerical         3770
 Sales                3650
 Other-service        3295
 Machine-op-inspct    2002
 ?                    1843
 Transport-moving     1597
 Handlers-cleaners    1370
 Farming-fishing       994
 Tech-support          928
 Protective-serv       649
 Priv-house-serv       149
 Armed-Forces            9
Name: occupation, dtype: int64
```

Seems like few of the missing details are denoted by ?, so replacing the same with np.nan

[14]:
```
train_set.replace('\?',np.nan,regex=True,inplace=True)
```

[15]:
```
train_set['workclass'].value_counts()
```

[15]:
```
 Private             22696
 Self-emp-not-inc     2541
 Local-gov            2093
 State-gov            1298
 Self-emp-inc         1116
 Federal-gov           960
 Without-pay            14
 Never-worked            7
Name: workclass, dtype: int64
```

[16]:
```
train_set.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             32561 non-null  int64
 1   workclass       30725 non-null  object
 2   fnlwgt          32561 non-null  int64
 3   education       32561 non-null  object
 4   education_num   32561 non-null  int64
```

```
 5   marital_status  32561 non-null  object
 6   occupation      30718 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital_gain    32561 non-null  int64
 11  capital_loss    32561 non-null  int64
 12  hours_per_week  32561 non-null  int64
 13  native_country  31978 non-null  object
 14  wage_class      32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

[17]:
```
#Three columns workclass,occupation,native_country seems to have NULL values.␣
↪Lets get the percentage of NaN values in data.
```

[18]:
```
nan_cnt=train_set[(train_set.workclass.isna())|(train_set.occupation.
↪isna())|(train_set.native_country.isna())].count().max()
```

[19]:
```
per_nan=nan_cnt/train_set.shape[0] * 100
print('Percentage of NaN values in dataset: ',per_nan,'%')
```

```
Percentage of NaN values in dataset:  7.367709836921471 %
```

[20]:
```
#Null Values dropped
train_set.dropna(inplace=True)
```

[21]:
```
train_set.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30162 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             30162 non-null  int64
 1   workclass       30162 non-null  object
 2   fnlwgt          30162 non-null  int64
 3   education       30162 non-null  object
 4   education_num   30162 non-null  int64
 5   marital_status  30162 non-null  object
 6   occupation      30162 non-null  object
 7   relationship    30162 non-null  object
 8   race            30162 non-null  object
 9   sex             30162 non-null  object
 10  capital_gain    30162 non-null  int64
 11  capital_loss    30162 non-null  int64
 12  hours_per_week  30162 non-null  int64
 13  native_country  30162 non-null  object
```

```
 14  wage_class      30162 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

Working with categorical and non numeric data

[22]:
```
#Sex Feature
```

[23]:
```
train_set.sex.value_counts()
```

[23]:
```
 Male      20380
 Female     9782
Name: sex, dtype: int64
```

[24]:
```
train_set['sex']=train_set['sex'].str.strip()
#label encoding
train_set['sex']=train_set['sex'].map({'Male':1,'Female':0})
```

[25]:
```
train_set.sex.value_counts()
```

[25]:
```
1    20380
0     9782
Name: sex, dtype: int64
```

[26]:
```
#Feature: workclass
```

[27]:
```
train_set['workclass']=train_set['workclass'].str.strip()
train_set.workclass.value_counts()
```

[27]:
```
Private             22286
Self-emp-not-inc     2499
Local-gov            2067
State-gov            1279
Self-emp-inc         1074
Federal-gov           943
Without-pay            14
Name: workclass, dtype: int64
```

[28]:
```
df_workclass=pd.
 ↪get_dummies(train_set['workclass'],drop_first=True,prefix='workclass',prefix_sep='_')
```

[29]:
```
df_workclass.head()
```

[29]:
```
   workclass_Local-gov  workclass_Private  workclass_Self-emp-inc  \
0                    0                  0                       0
1                    0                  0                       0
2                    0                  1                       0
3                    0                  1                       0
```

```
4                    0                  1                        0

   workclass_Self-emp-not-inc  workclass_State-gov  workclass_Without-pay
0                           0                    1                      0
1                           1                    0                      0
2                           0                    0                      0
3                           0                    0                      0
4                           0                    0                      0
```

[30]:
```python
#Feature: marital_status
```

[31]:
```python
train_set['marital_status']=train_set['marital_status'].str.strip()
train_set['marital_status'].value_counts()
```

[31]:
```
Married-civ-spouse       14065
Never-married             9726
Divorced                  4214
Separated                  939
Widowed                    827
Married-spouse-absent      370
Married-AF-spouse           21
Name: marital_status, dtype: int64
```

[32]:
```python
df_maritalst=pd.get_dummies(train_set['marital_status'],drop_first=True)
```

[33]:
```python
df_maritalst.head()
```

[33]:
```
   Married-AF-spouse  Married-civ-spouse  Married-spouse-absent  \
0                  0                   0                      0
1                  0                   1                      0
2                  0                   0                      0
3                  0                   1                      0
4                  0                   1                      0

   Never-married  Separated  Widowed
0              1          0        0
1              0          0        0
2              0          0        0
3              0          0        0
4              0          0        0
```

[34]:
```python
#Feature: relationship
```

[35]:
```python
train_set['relationship']=train_set['relationship'].str.strip()
train_set['relationship'].value_counts()
```

[35]:
```
Husband           12463
Not-in-family      7726
Own-child          4466
Unmarried          3212
Wife               1406
Other-relative      889
Name: relationship, dtype: int64
```

[36]:
```python
df_rel=pd.get_dummies(train_set['relationship'],drop_first=True)
```

[37]:
```python
df_rel.head()
```

[37]:
```
   Not-in-family  Other-relative  Own-child  Unmarried  Wife
0              1               0          0          0     0
1              0               0          0          0     0
2              1               0          0          0     0
3              0               0          0          0     0
4              0               0          0          0     1
```

[38]:
```python
#Feature: occupation
train_set['occupation']=train_set['occupation'].str.strip()
train_set['occupation'].value_counts()
```

[38]:
```
Prof-specialty       4038
Craft-repair         4030
Exec-managerial      3992
Adm-clerical         3721
Sales                3584
Other-service        3212
Machine-op-inspct    1966
Transport-moving     1572
Handlers-cleaners    1350
Farming-fishing       989
Tech-support          912
Protective-serv       644
Priv-house-serv       143
Armed-Forces            9
Name: occupation, dtype: int64
```

[39]:
```python
df_occ=pd.get_dummies(train_set['occupation'],drop_first=True)
```

[40]:
```python
df_occ.head()
```

[40]:
```
   Armed-Forces  Craft-repair  Exec-managerial  Farming-fishing  \
0             0             0                0                0
1             0             0                1                0
2             0             0                0                0
```

```
3              0             0                0                0
4              0             0                0                0

   Handlers-cleaners  Machine-op-inspct  Other-service  Priv-house-serv  \
0                  0                  0              0                0
1                  0                  0              0                0
2                  1                  0              0                0
3                  1                  0              0                0
4                  0                  0              0                0

   Prof-specialty  Protective-serv  Sales  Tech-support  Transport-moving
0               0                0      0             0                 0
1               0                0      0             0                 0
2               0                0      0             0                 0
3               0                0      0             0                 0
4               1                0      0             0                 0
```

[41]:
```
#Feature: race
train_set['race']=train_set['race'].str.strip()
train_set['race'].value_counts()
```

[41]:
```
White                 25933
Black                  2817
Asian-Pac-Islander      895
Amer-Indian-Eskimo      286
Other                   231
Name: race, dtype: int64
```

[42]:
```
df_race=pd.
 ↪get_dummies(train_set['race'],drop_first=True,prefix='race',prefix_sep='_')
```

[43]:
```
df_race.head()
```

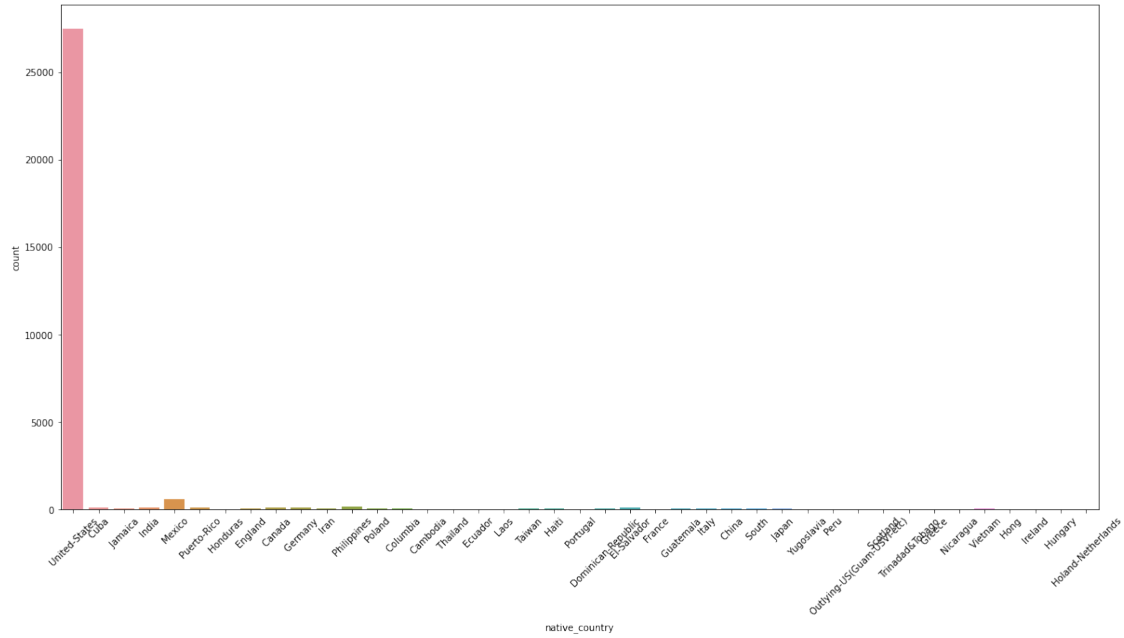
[43]:
```
   race_Asian-Pac-Islander  race_Black  race_Other  race_White
0                        0           0           0           1
1                        0           0           0           1
2                        0           0           0           1
3                        0           1           0           0
4                        0           1           0           0
```

[44]:
```
#Feature: native_country
```

[46]:
```
import seaborn as sns
import matplotlib.pyplot as plt
```

[47]:
```
plt.figure(figsize=(20,10))
x=sns.countplot(x=train_set['native_country'])
```

```
x.set_xticklabels(labels=x.get_xticklabels(),rotation=45)
plt.show()
```



[48]:
```
#Seems like native_country has ditribution of US much higher than other hence␣
↪dividing it into US and Non-US and label encoding the same.
```

[49]:
```
train_set['native_country']=train_set['native_country'].str.strip()
train_set['native_country']=train_set['native_country'].apply(lambda x:x␣
↪if('United-States' in x) else 'Non-US')
```

[50]:
```
train_set['native_country'].value_counts()
```

[50]:
```
United-States    27504
Non-US            2658
Name: native_country, dtype: int64
```

[51]:
```
train_set['native_country']=train_set['native_country'].map({'United-States':
↪1,'Non-US':0})
```

[52]:
```
train_set['native_country'].value_counts()
```

[52]:
```
1    27504
0     2658
Name: native_country, dtype: int64
```

[53]:
```
#Feature: wage_class
```

[54]:
```
train_set['wage_class'].value_counts()
```

[54]:
```
 <=50K    22654
 >50K      7508
Name: wage_class, dtype: int64
```

[55]:
```
train_set['wage_class']=train_set['wage_class'].str.strip()
```

[56]:
```
train_set['wage_class']=train_set['wage_class'].map({'<=50K':1,'>50K':0})
```

[57]:
```
train_set['wage_class'].value_counts()
```

[57]:
```
1    22654
0     7508
Name: wage_class, dtype: int64
```

[58]:
```
train_set.head()
```

[58]:
```
   age         workclass  fnlwgt   education  education_num  \
0   39         State-gov   77516   Bachelors             13
1   50  Self-emp-not-inc   83311   Bachelors             13
2   38           Private  215646     HS-grad              9
3   53           Private  234721        11th              7
4   28           Private  338409   Bachelors             13

       marital_status         occupation   relationship   race  sex  \
0       Never-married       Adm-clerical  Not-in-family  White    1
1  Married-civ-spouse    Exec-managerial        Husband  White    1
2            Divorced  Handlers-cleaners  Not-in-family  White    1
3  Married-civ-spouse  Handlers-cleaners        Husband  Black    1
4  Married-civ-spouse     Prof-specialty           Wife  Black    0

   capital_gain  capital_loss  hours_per_week  native_country  wage_class
0          2174             0              40               1           1
1             0             0              13               1           1
2             0             0              40               1           1
3             0             0              40               1           1
4             0             0              40               0           1
```

[59]:
```
#Appending all new columns
new_df=pd.
 ↪concat([train_set,df_workclass,df_maritalst,df_rel,df_occ,df_race],axis=1)
```

[60]:
```
new_df.columns
```

[60]:
```
Index(['age', 'workclass', 'fnlwgt', 'education', 'education_num',
       'marital_status', 'occupation', 'relationship', 'race', 'sex',
```

```
       'capital_gain', 'capital_loss', 'hours_per_week', 'native_country',
       'wage_class', 'workclass_Local-gov', 'workclass_Private',
       'workclass_Self-emp-inc', 'workclass_Self-emp-not-inc',
       'workclass_State-gov', 'workclass_Without-pay', 'Married-AF-spouse',
       'Married-civ-spouse', 'Married-spouse-absent', 'Never-married',
       'Separated', 'Widowed', 'Not-in-family', 'Other-relative', 'Own-child',
       'Unmarried', 'Wife', 'Armed-Forces', 'Craft-repair', 'Exec-managerial',
       'Farming-fishing', 'Handlers-cleaners', 'Machine-op-inspct',
       'Other-service', 'Priv-house-serv', 'Prof-specialty', 'Protective-serv',
       'Sales', 'Tech-support', 'Transport-moving', 'race_Asian-Pac-Islander',
       'race_Black', 'race_Other', 'race_White'],
      dtype='object')
```

[61]:
```
new_df=new_df.
 ↪drop(columns=['workclass','education','marital_status','occupation','relationship','race'])
```

[62]:
```
print(new_df.columns)
new_df.head()
```

```
Index(['age', 'fnlwgt', 'education_num', 'sex', 'capital_gain', 'capital_loss',
       'hours_per_week', 'native_country', 'wage_class', 'workclass_Local-gov',
       'workclass_Private', 'workclass_Self-emp-inc',
       'workclass_Self-emp-not-inc', 'workclass_State-gov',
       'workclass_Without-pay', 'Married-AF-spouse', 'Married-civ-spouse',
       'Married-spouse-absent', 'Never-married', 'Separated', 'Widowed',
       'Not-in-family', 'Other-relative', 'Own-child', 'Unmarried', 'Wife',
       'Armed-Forces', 'Craft-repair', 'Exec-managerial', 'Farming-fishing',
       'Handlers-cleaners', 'Machine-op-inspct', 'Other-service',
       'Priv-house-serv', 'Prof-specialty', 'Protective-serv', 'Sales',
       'Tech-support', 'Transport-moving', 'race_Asian-Pac-Islander',
       'race_Black', 'race_Other', 'race_White'],
      dtype='object')
```

[62]:

	age	fnlwgt	education_num	sex	capital_gain	capital_loss	\
0	39	77516	13	1	2174	0	
1	50	83311	13	1	0	0	
2	38	215646	9	1	0	0	
3	53	234721	7	1	0	0	
4	28	338409	13	0	0	0	

	hours_per_week	native_country	wage_class	workclass_Local-gov	…	\
0	40	1	1	0	…	
1	13	1	1	0	…	
2	40	1	1	0	…	
3	40	1	1	0	…	
4	40	0	1	0	…	

```
   Priv-house-serv  Prof-specialty  Protective-serv  Sales  Tech-support  \
0                0               0                0      0             0
1                0               0                0      0             0
2                0               0                0      0             0
3                0               0                0      0             0
4                0               1                0      0             0

   Transport-moving  race_Asian-Pac-Islander  race_Black  race_Other  \
0                 0                        0           0           0
1                 0                        0           0           0
2                 0                        0           0           0
3                 0                        0           1           0
4                 0                        0           1           0

   race_White
0           1
1           1
2           1
3           0
4           0

[5 rows x 43 columns]
```

All features are now converted to numerical once

[96]:
```
test_set.replace('\?',np.nan,regex=True,inplace=True)
test_set.dropna(inplace=True)

test_set['workclass']=test_set['workclass'].str.strip()
test_set['marital_status']=test_set['marital_status'].str.strip()
test_set['relationship']=test_set['relationship'].str.strip()
test_set['occupation']=test_set['occupation'].str.strip()
test_set['race']=test_set['race'].str.strip()

test_set['sex']=test_set['sex'].str.strip()
#label encoding
test_set['sex']=test_set['sex'].map({'Male':1,'Female':0})

df_workclass=pd.
 ↪get_dummies(test_set['workclass'],drop_first=True,prefix='workclass',prefix_sep='_')

df_maritalst=pd.get_dummies(test_set['marital_status'],drop_first=True)
df_rel=pd.get_dummies(test_set['relationship'],drop_first=True)
df_occ=pd.get_dummies(test_set['occupation'],drop_first=True)
df_race=pd.
 ↪get_dummies(test_set['race'],drop_first=True,prefix='race',prefix_sep='_')
test_set['native_country']=test_set['native_country'].str.strip()
```

```
test_set['native_country']=test_set['native_country'].apply(lambda x:x␣
↪if('United-States' in x) else 'Non-US')
test_set['native_country']=test_set['native_country'].map({'United-States':
↪1,'Non-US':0})
test_set['wage_class']=test_set['wage_class'].str.strip()
print(test_set.head())
test_set['wage_class']=test_set['wage_class'].map({'<=50K.':1,'>50K.':0})
test_df=pd.
↪concat([test_set,df_workclass,df_maritalst,df_rel,df_occ,df_race],axis=1)

test_df=test_df.
↪drop(columns=['workclass','education','marital_status','occupation','relationship','race'])
```

```
   age  workclass  fnlwgt      education  education_num      marital_status  \
0   25    Private  226802           11th              7       Never-married
1   38    Private   89814        HS-grad              9  Married-civ-spouse
2   28  Local-gov  336951     Assoc-acdm             12  Married-civ-spouse
3   44    Private  160323   Some-college             10  Married-civ-spouse
5   34    Private  198693           10th              6       Never-married

          occupation   relationship   race  sex  capital_gain  capital_loss  \
0  Machine-op-inspct      Own-child  Black    1             0             0
1    Farming-fishing        Husband  White    1             0             0
2    Protective-serv        Husband  White    1             0             0
3  Machine-op-inspct        Husband  Black    1          7688             0
5      Other-service  Not-in-family  White    1             0             0

   hours_per_week  native_country wage_class
0              40               1     <=50K.
1              50               1     <=50K.
2              40               1      >50K.
3              40               1      >50K.
5              30               1     <=50K.
```

[97]:
```
test_df.columns
```

[97]:
```
Index(['age', 'fnlwgt', 'education_num', 'sex', 'capital_gain', 'capital_loss',
       'hours_per_week', 'native_country', 'wage_class', 'workclass_Local-gov',
       'workclass_Private', 'workclass_Self-emp-inc',
       'workclass_Self-emp-not-inc', 'workclass_State-gov',
       'workclass_Without-pay', 'Married-AF-spouse', 'Married-civ-spouse',
       'Married-spouse-absent', 'Never-married', 'Separated', 'Widowed',
       'Not-in-family', 'Other-relative', 'Own-child', 'Unmarried', 'Wife',
       'Armed-Forces', 'Craft-repair', 'Exec-managerial', 'Farming-fishing',
       'Handlers-cleaners', 'Machine-op-inspct', 'Other-service',
       'Priv-house-serv', 'Prof-specialty', 'Protective-serv', 'Sales',
       'Tech-support', 'Transport-moving', 'race_Asian-Pac-Islander',
```

```
       'race_Black', 'race_Other', 'race_White'],
      dtype='object')
```

[98]:
```
test_df.head()
```

[98]:
```
   age  fnlwgt  education_num  sex  capital_gain  capital_loss  \
0   25  226802              7    1             0             0
1   38   89814              9    1             0             0
2   28  336951             12    1             0             0
3   44  160323             10    1          7688             0
5   34  198693              6    1             0             0

   hours_per_week  native_country  wage_class  workclass_Local-gov  …  \
0              40               1           1                    0  …
1              50               1           1                    0  …
2              40               1           0                    1  …
3              40               1           0                    0  …
5              30               1           1                    0  …

   Priv-house-serv  Prof-specialty  Protective-serv  Sales  Tech-support  \
0                0               0                0      0             0
1                0               0                0      0             0
2                0               0                1      0             0
3                0               0                0      0             0
5                0               0                0      0             0

   Transport-moving  race_Asian-Pac-Islander  race_Black  race_Other  \
0                 0                        0           1           0
1                 0                        0           0           0
2                 0                        0           0           0
3                 0                        0           1           0
5                 0                        0           0           0

   race_White
0           0
1           1
2           1
3           0
5           1

[5 rows x 43 columns]
```

[65]:
```
new_df.columns
```

[65]:
```
Index(['age', 'fnlwgt', 'education_num', 'sex', 'capital_gain', 'capital_loss',
       'hours_per_week', 'native_country', 'wage_class', 'workclass_Local-gov',
       'workclass_Private', 'workclass_Self-emp-inc',
```

```
       'workclass_Self-emp-not-inc', 'workclass_State-gov',
       'workclass_Without-pay', 'Married-AF-spouse', 'Married-civ-spouse',
       'Married-spouse-absent', 'Never-married', 'Separated', 'Widowed',
       'Not-in-family', 'Other-relative', 'Own-child', 'Unmarried', 'Wife',
       'Armed-Forces', 'Craft-repair', 'Exec-managerial', 'Farming-fishing',
       'Handlers-cleaners', 'Machine-op-inspct', 'Other-service',
       'Priv-house-serv', 'Prof-specialty', 'Protective-serv', 'Sales',
       'Tech-support', 'Transport-moving', 'race_Asian-Pac-Islander',
       'race_Black', 'race_Other', 'race_White'],
      dtype='object')
```

[99]:
```
train_x=new_df.drop(columns=['wage_class'])
train_y=new_df['wage_class']
test_x=test_df.drop(columns=['wage_class'])
test_y=test_df['wage_class']
```

[100]:
```
#Applying models on machine learning
```

[101]:
```
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.metrics import accuracy_score, confusion_matrix, roc_curve,␣
 ↪roc_auc_score
import xgboost as xgb
```

[102]:
```
#Fitting model on training data
model = xgb.XGBClassifier(objective='binary:logistic')
model.fit(train_x, train_y)
```

[102]:
```
XGBClassifier()
```

[103]:
```
# cheking training accuracy
y_pred = model.predict(train_x)
predictions = [round(value) for value in y_pred]
accuracy = accuracy_score(train_y,predictions)
accuracy
```

[103]:
```
0.8634374378356873
```

[104]:
```
# checking initial test accuracy
y_pred = model.predict(test_x)
predictions = [round(value) for value in y_pred]
accuracy = accuracy_score(test_y,predictions)
accuracy
```

[104]:
```
0.8638778220451527
```

Model seems not be overfitting as test and train data accuracy is almost same.

[105]:
```
from sklearn.model_selection import GridSearchCV
```

[106]:
```
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]

}
```

[110]:
```
grid= GridSearchCV(xgb.XGBClassifier(objective='binary:logistic'),param_grid,␣
 ↪verbose=3, n_jobs=-1)
```

[111]:
```
grid.fit(train_x,train_y)
```

```
Fitting 5 folds for each of 80 candidates, totalling 400 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  16 tasks      | elapsed:   15.7s
[Parallel(n_jobs=-1)]: Done 112 tasks      | elapsed:  3.6min
[Parallel(n_jobs=-1)]: Done 272 tasks      | elapsed:  8.5min
[Parallel(n_jobs=-1)]: Done 400 out of 400 | elapsed: 13.2min finished
```

[111]:
```
GridSearchCV(estimator=XGBClassifier(), n_jobs=-1,
             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]},
             verbose=3)
```

[112]:
```
# To find the parameters giving maximum accuracy
grid.best_params_
```

[112]:
```
{' learning_rate': 1, 'max_depth': 5, 'n_estimators': 200}
```

[122]:
```
# Create new model using the same parameters
new_model=xgb.XGBClassifier(learning_rate= 1, max_depth= 5, n_estimators= 50)
new_model.fit(train_x, train_y)
```

[122]:
```
XGBClassifier(learning_rate=1, max_depth=5, n_estimators=50)
```

[123]:
```
y_pred_new = new_model.predict(test_x)
predictions_new = [round(value) for value in y_pred_new]
accuracy_new = accuracy_score(test_y,predictions_new)
accuracy_new
```

[123]:
```
0.8602921646746348
```

[124]:
```python
# cheking training accuracy
y_pred = new_model.predict(train_x)
predictions = [round(value) for value in y_pred]
accuracy = accuracy_score(train_y,predictions)
accuracy
```

[124]: 0.9017306544658842

[125]:
```python
# As we have increased the accuracy of the model, we'll save this model
import pickle
filename = 'xgboost_model.pickle'
pickle.dump(new_model, open(filename, 'wb'))
```