Income_Prediction_Project

January 26, 2021

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split,KFold
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import␣
↪LogisticRegression,LogisticRegressionCV,ElasticNetCV,LassoCV,RidgeCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

[2]:
```
import warnings

warnings.filterwarnings(action='ignore')
```

[3]:
```
#Loading data in pandas
df=pd.read_csv('https://archive.ics.uci.edu/ml/machine-learning-databases/adult/
↪adult.data',
names =␣
↪['age','workclass','fnlwgt','education','education-num','marital-status','occupation','rela
```

0.0.1 Basic dataframe details and stats

---

[4]:
```
df.head()
```

[4]:
```
   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    Male
1   Married-civ-spouse    Exec-managerial        Husband  White    Male
```

```
2             Divorced    Handlers-cleaners    Not-in-family   White     Male
3   Married-civ-spouse    Handlers-cleaners          Husband   Black     Male
4   Married-civ-spouse       Prof-specialty             Wife   Black   Female

   capital-gain  capital-loss  hours-per-week  native-country  salary
0          2174             0              40   United-States   <=50K
1             0             0              13   United-States   <=50K
2             0             0              40   United-States   <=50K
3             0             0              40   United-States   <=50K
4             0             0              40            Cuba   <=50K
```

[5]:
```python
#Getting an idea of total records and feature in dataframe
df.shape
```

[5]: (32561, 15)

[6]:
```python
#Checking datatypes and no of null values in df
df.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       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  salary          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

[7]:
```python
#Getting basic stats for numerical feature
df.describe().T
```

[7]:
```
                count       mean        std   min   25%  \
age           32561.0  38.581647  13.640433  17.0  28.0
```

```
fnlwgt          32561.0  189778.366512  105549.977697  12285.0  117827.0
education-num   32561.0      10.080679       2.572720      1.0       9.0
capital-gain    32561.0    1077.648844    7385.292085      0.0       0.0
capital-loss    32561.0      87.303830     402.960219      0.0       0.0
hours-per-week  32561.0      40.437456      12.347429      1.0      40.0

                     50%       75%        max
age                 37.0      48.0       90.0
fnlwgt          178356.0  237051.0  1484705.0
education-num       10.0      12.0       16.0
capital-gain         0.0       0.0    99999.0
capital-loss         0.0       0.0     4356.0
hours-per-week      40.0      45.0       99.0
```

[8]:
```
#Checking if any null values are present per column/feature
df.isna().sum()
```

[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
salary            0
dtype: int64
```

NULL values are not present in this data, hence no need for imputation techniques.

0.0.2 Exploratory Data Analysis

1. ***Exploring categorical features and checking how can same be converted to numrical features***

[9]:
```
#Custom Function for one hot encoding and after operations
def custom_encoding(df,col):
    dummies=pd.get_dummies(df[col],drop_first=True)
    df=df.drop(col,axis=1)
    df=pd.concat([df,dummies],axis=1)
    return df
```

[10]:
```
#Feature: workclass
```

[11]:
```
df['workclass'].value_counts()
```

[11]:
```
 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
```

[12]:
```
df.workclass=df.workclass.str.strip()
```

Found ? in many rows hence replacing the same with NaN for now.

[13]:
```
for x in␣
↪['workclass','education','marital-status','occupation','relationship','race','sex','native-
↪
    df[x]=df[x].str.strip()
    df[x]=df[x].replace(' ','')
```

[14]:
```
df=df.replace('?',np.nan).dropna()
```

[15]:
```
df.shape
```

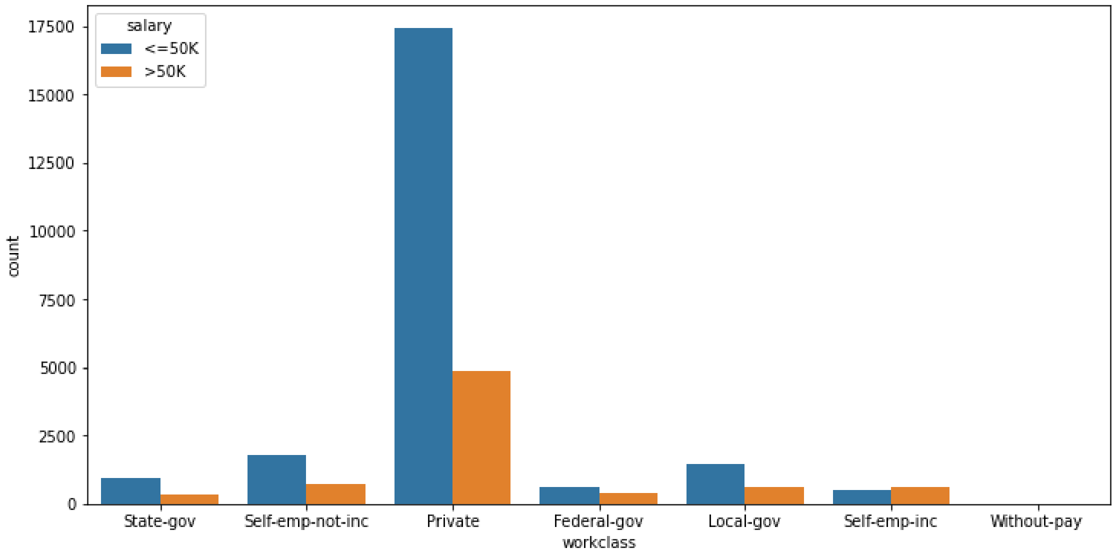
[15]:
```
(30162, 15)
```

[16]:
```
df['workclass'].isna().sum()
```

[16]:
```
0
```

[17]:
```
plt.figure(figsize=(12,6))
sns.countplot('workclass',data=df,hue='salary')
```

[17]:
```
<AxesSubplot:xlabel='workclass', ylabel='count'>
```



[18]:
```python
df=custom_encoding(df,'workclass')
```

[19]:
```python
df.columns
```

[19]:
```
Index(['age', 'fnlwgt', 'education', 'education-num', 'marital-status',
       'occupation', 'relationship', 'race', 'sex', 'capital-gain',
       'capital-loss', 'hours-per-week', 'native-country', 'salary',
       'Local-gov', 'Private', 'Self-emp-inc', 'Self-emp-not-inc', 'State-gov',
       'Without-pay'],
      dtype='object')
```

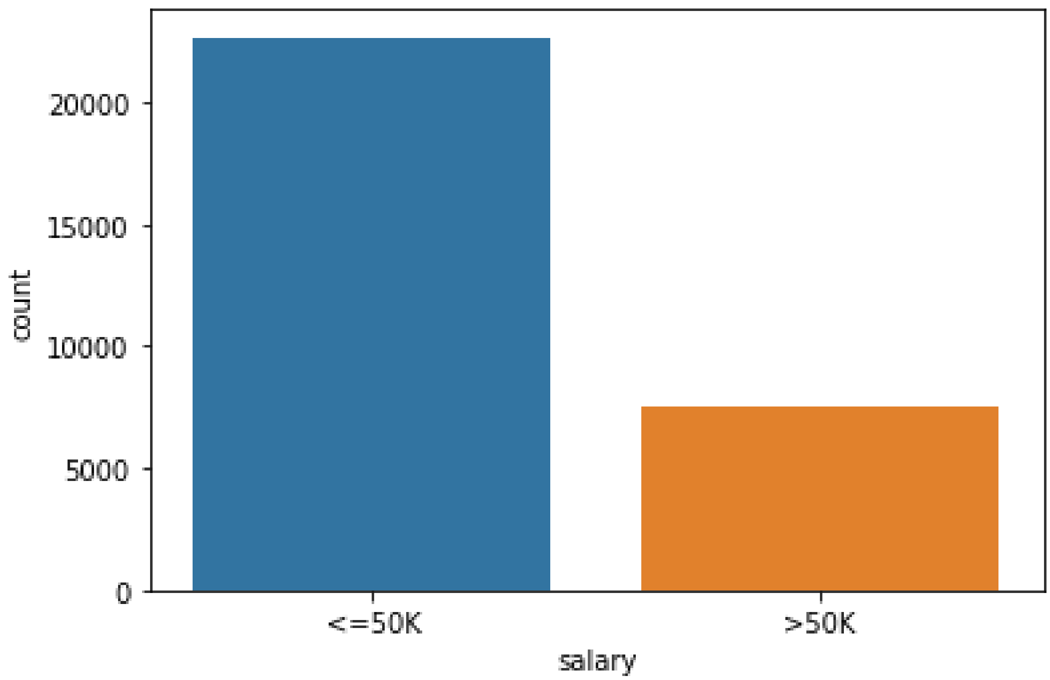
[20]:
```python
# Dependent Feature: salary
```

[21]:
```python
df['salary'].value_counts()
```

[21]:
```
<=50K    22654
>50K      7508
Name: salary, dtype: int64
```

[22]:
```python
sns.countplot('salary',data=df)
```

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



Seems like the dataset is imbalanced.

[23]:
```
#df.to_csv('tmp.csv',index=False)
```

[24]:
```
df['salary']=df['salary'].map({'<=50K':1,'>50K':0})
```

[25]:
```
# Feature: education & education-num
```

[26]:
```
df['education'].value_counts()
```

[26]:
```
HS-grad         9840
Some-college    6678
Bachelors       5044
Masters         1627
Assoc-voc       1307
11th            1048
Assoc-acdm      1008
10th             820
7th-8th          557
Prof-school      542
9th              455
12th             377
Doctorate        375
5th-6th          288
1st-4th          151
```

```
Preschool          45
Name: education, dtype: int64
```

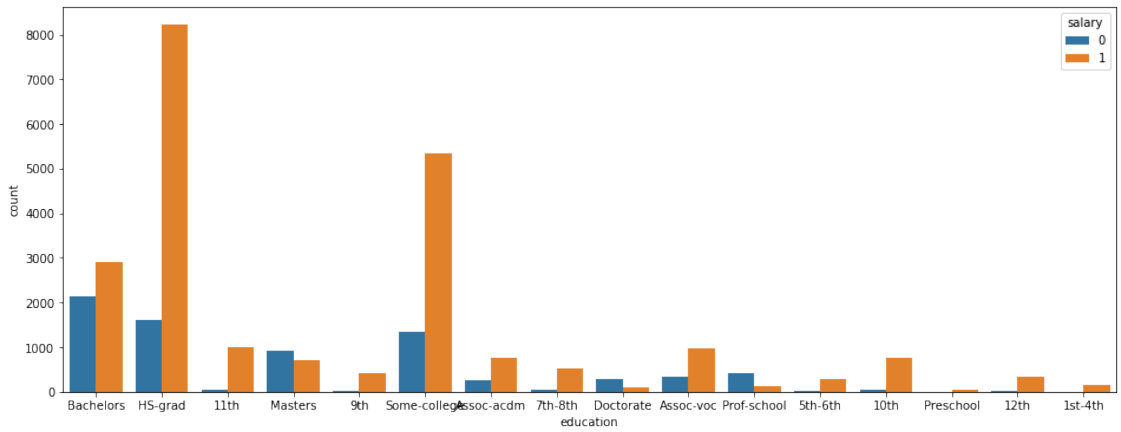
[27]:
```
df['education-num'].value_counts()
```

[27]:
```
9     9840
10    6678
13    5044
14    1627
11    1307
7     1048
12    1008
6      820
4      557
15     542
5      455
8      377
16     375
3      288
2      151
1       45
Name: education-num, dtype: int64
```

Features education and education-num seems to be same dropping education column

[28]:
```
plt.figure(figsize=(16,6))
sns.countplot('education',data=df,hue='salary')
```

[28]:
```
<AxesSubplot:xlabel='education', ylabel='count'>
```



[29]:
```
df=df.drop(columns=['education'])
```

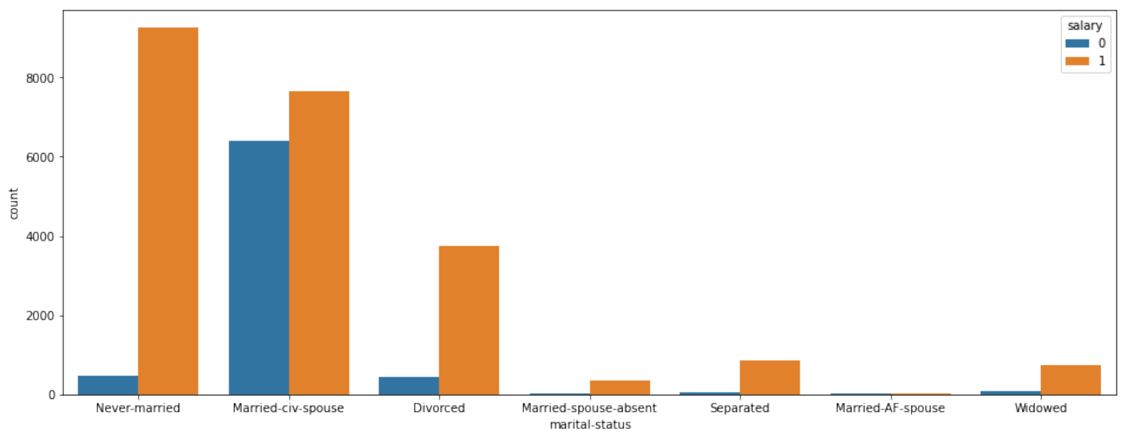
[30]:
```
#Feature: marital-status
```

[31]:
```
df['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]:
```
plt.figure(figsize=(16,6))
sns.countplot('marital-status',data=df,hue='salary')
```

[32]:
```
<AxesSubplot:xlabel='marital-status', ylabel='count'>
```



[33]:
```
df=custom_encoding(df,'marital-status')
```

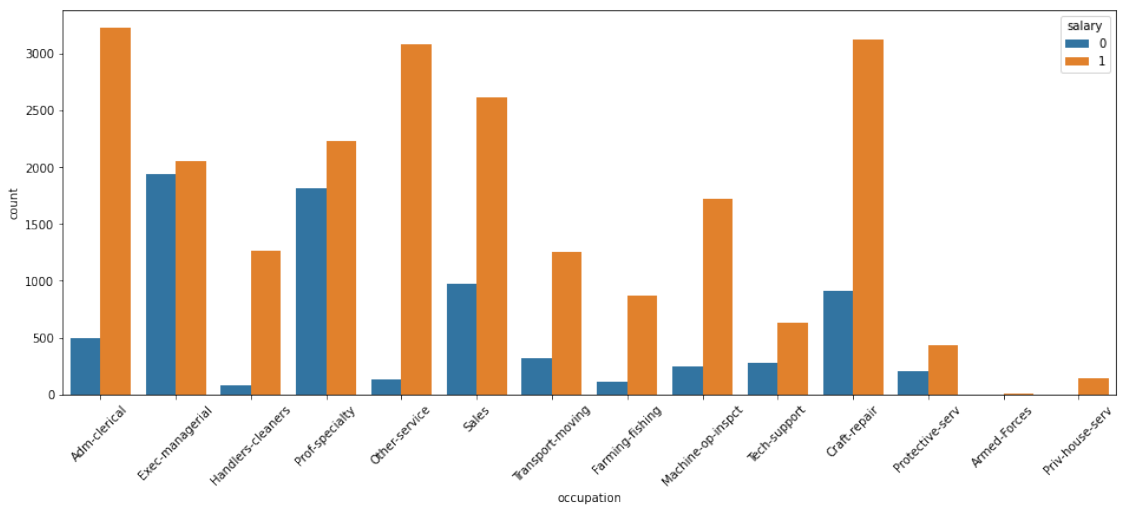
[34]:
```
# Feature:occupation
```

[35]:
```
df['occupation'].value_counts()
```

[35]:
```
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
```

[36]:
```
plt.figure(figsize=(16,6))
sns.countplot('occupation',data=df,hue='salary')
plt.xticks(rotation=45)
plt.show()
```



[37]:
```
df=custom_encoding(df,'occupation')
```

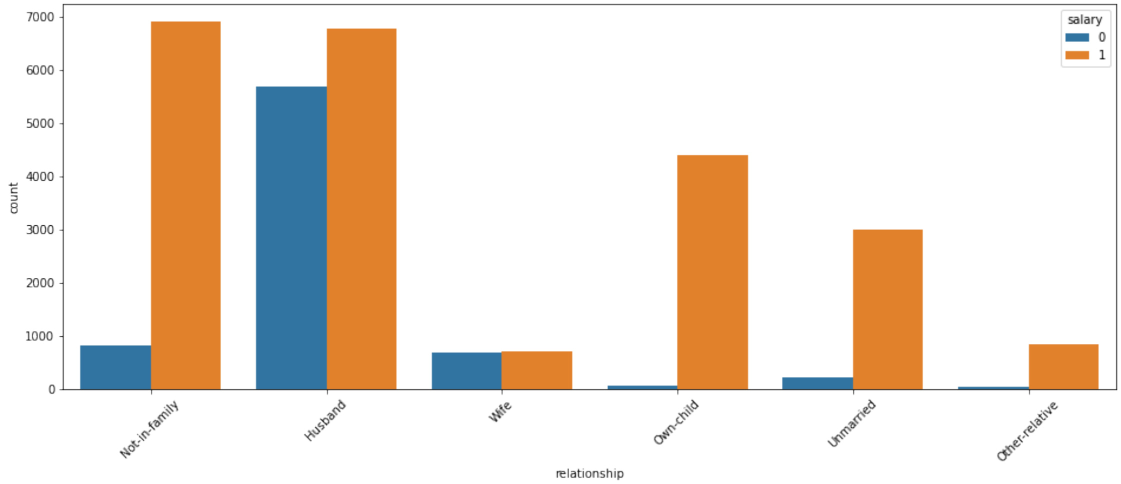
[38]:
```
# Feature: relationship
```

[39]:
```
df['relationship'].value_counts()
```

[39]:
```
Husband           12463
Not-in-family      7726
Own-child          4466
Unmarried          3212
Wife               1406
Other-relative      889
Name: relationship, dtype: int64
```

[40]:
```
plt.figure(figsize=(16,6))
sns.countplot('relationship',data=df,hue='salary')
plt.xticks(rotation=45)
```

```
plt.show()
```



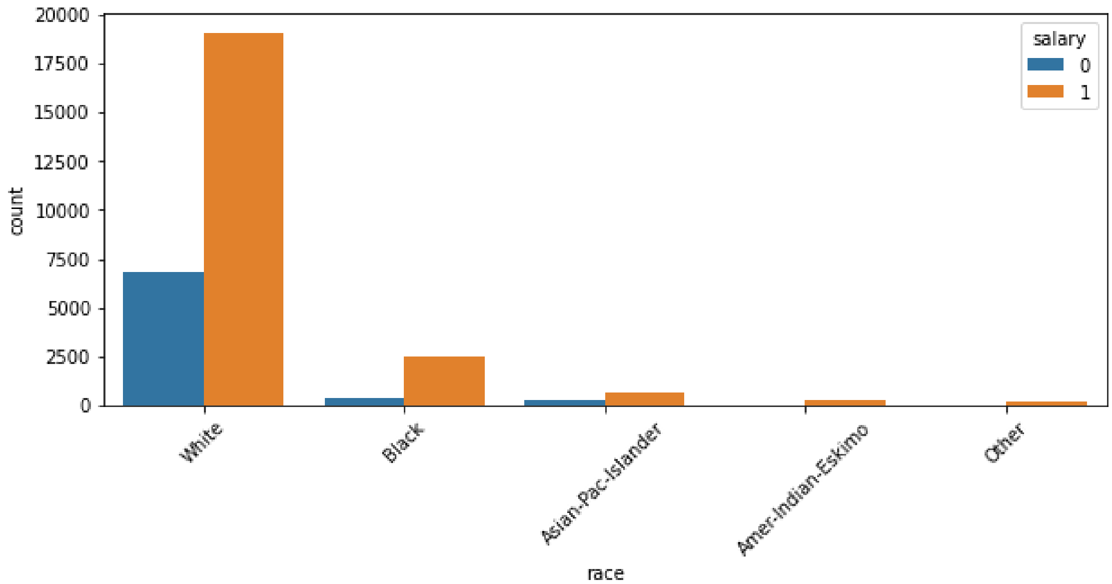
[41]:
```
df=custom_encoding(df,'relationship')
```

[42]:
```
# Feature:race
```

[43]:
```
df['race'].value_counts()
```

[43]:
```
White                 25933
Black                  2817
Asian-Pac-Islander      895
Amer-Indian-Eskimo      286
Other                   231
Name: race, dtype: int64
```

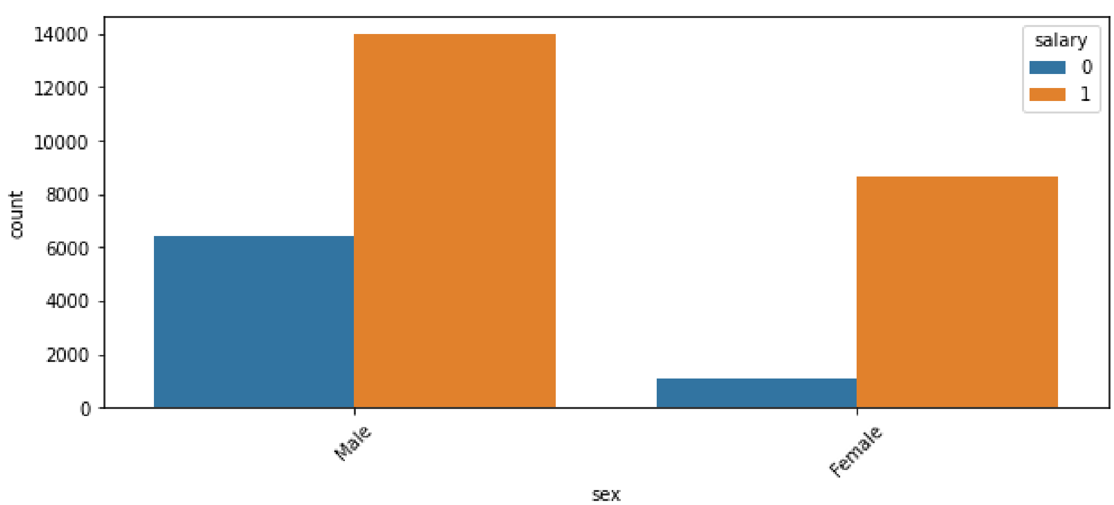
[44]:
```
plt.figure(figsize=(10,4))
sns.countplot('race',data=df,hue='salary')
plt.xticks(rotation=45)
plt.show()
```



[45]:
```
df=custom_encoding(df,'race')
```

[46]:
```
#Feature: sex
```

[47]:
```
plt.figure(figsize=(10,4))
sns.countplot('sex',data=df,hue='salary')
plt.xticks(rotation=45)
plt.show()
```



[48]:
```
df['sex']=df['sex'].map({'Male':0,'Female':1})
```

[49]:
```
#Feature: native-country
```

[50]:
```
df['native-country'].value_counts()
```

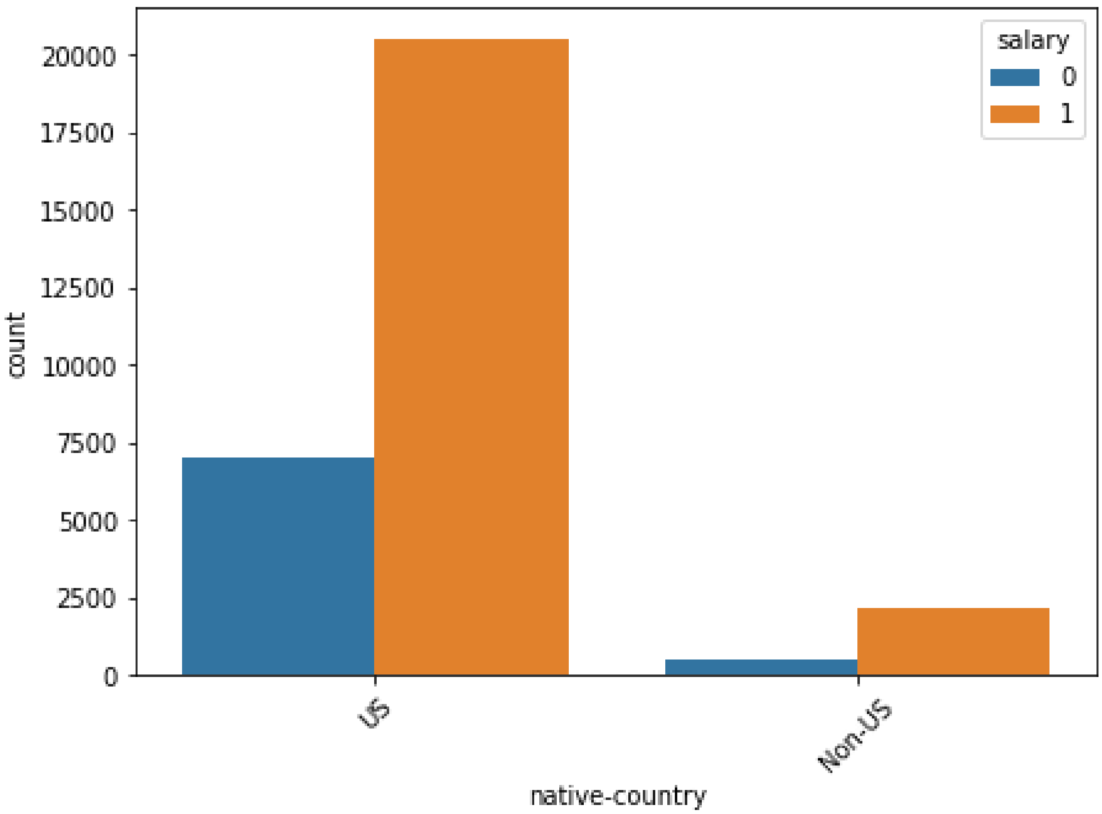
[50]:
```
United-States                 27504
Mexico                          610
Philippines                     188
Germany                         128
Puerto-Rico                     109
Canada                          107
India                           100
El-Salvador                     100
Cuba                             92
England                          86
Jamaica                          80
South                            71
Italy                            68
China                            68
Dominican-Republic               67
Vietnam                          64
Guatemala                        63
Japan                            59
Poland                           56
Columbia                         56
Taiwan                           42
Iran                             42
Haiti                            42
Portugal                         34
Nicaragua                        33
Peru                             30
Greece                           29
Ecuador                          27
France                           27
Ireland                          24
Hong                             19
Trinadad&Tobago                  18
Cambodia                         18
Laos                             17
Thailand                         17
Yugoslavia                       16
Outlying-US(Guam-USVI-etc)       14
Hungary                          13
Honduras                         12
Scotland                         11
Holand-Netherlands                1
Name: native-country, dtype: int64
```

[51]:
```
df['native-country']=df['native-country'].apply(lambda x:'US'␣
↪if('United-States' in x) else 'Non-US')
```

[52]:
```
df['native-country'].value_counts()
```

[52]:
```
US        27504
Non-US     2658
Name: native-country, dtype: int64
```

[53]:
```
plt.figure(figsize=(7,5))
sns.countplot('native-country',data=df,hue='salary')
plt.xticks(rotation=45)
plt.show()
```



[54]:
```
df['native-country']=df['native-country'].map({'US':0,'Non-US':1})
```

[55]:
```
df.columns
```

[55]:
```
Index(['age', 'fnlwgt', 'education-num', 'sex', 'capital-gain', 'capital-loss',
       'hours-per-week', 'native-country', 'salary', 'Local-gov', 'Private',
       'Self-emp-inc', 'Self-emp-not-inc', 'State-gov', 'Without-pay',
```

```
       'Married-AF-spouse', 'Married-civ-spouse', 'Married-spouse-absent',
       'Never-married', 'Separated', 'Widowed', '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', 'Not-in-family', 'Other-relative', 'Own-child',
       'Unmarried', 'Wife', 'Asian-Pac-Islander', 'Black', 'Other', 'White'],
      dtype='object')
```

[56]:
```
df.dtypes
```

[56]:
```
age                      int64
fnlwgt                   int64
education-num            int64
sex                      int64
capital-gain             int64
capital-loss             int64
hours-per-week           int64
native-country           int64
salary                   int64
Local-gov                uint8
Private                  uint8
Self-emp-inc             uint8
Self-emp-not-inc         uint8
State-gov                uint8
Without-pay              uint8
Married-AF-spouse        uint8
Married-civ-spouse       uint8
Married-spouse-absent    uint8
Never-married            uint8
Separated                uint8
Widowed                  uint8
Armed-Forces             uint8
Craft-repair             uint8
Exec-managerial          uint8
Farming-fishing          uint8
Handlers-cleaners        uint8
Machine-op-inspct        uint8
Other-service            uint8
Priv-house-serv          uint8
Prof-specialty           uint8
Protective-serv          uint8
Sales                    uint8
Tech-support             uint8
Transport-moving         uint8
Not-in-family            uint8
Other-relative           uint8
```

```
Own-child                 uint8
Unmarried                 uint8
Wife                      uint8
Asian-Pac-Islander        uint8
Black                     uint8
Other                     uint8
White                     uint8
dtype: object
```

0.0.3 Column Standardization

[57]:
```
X=df.drop('salary',axis=1)
y=df['salary']
```

[58]:
```
sc=StandardScaler()
```

[59]:
```
tmp_scaled=sc.
 ↪fit_transform(X[['age','fnlwgt','capital-gain','capital-loss','hours-per-week']])
```

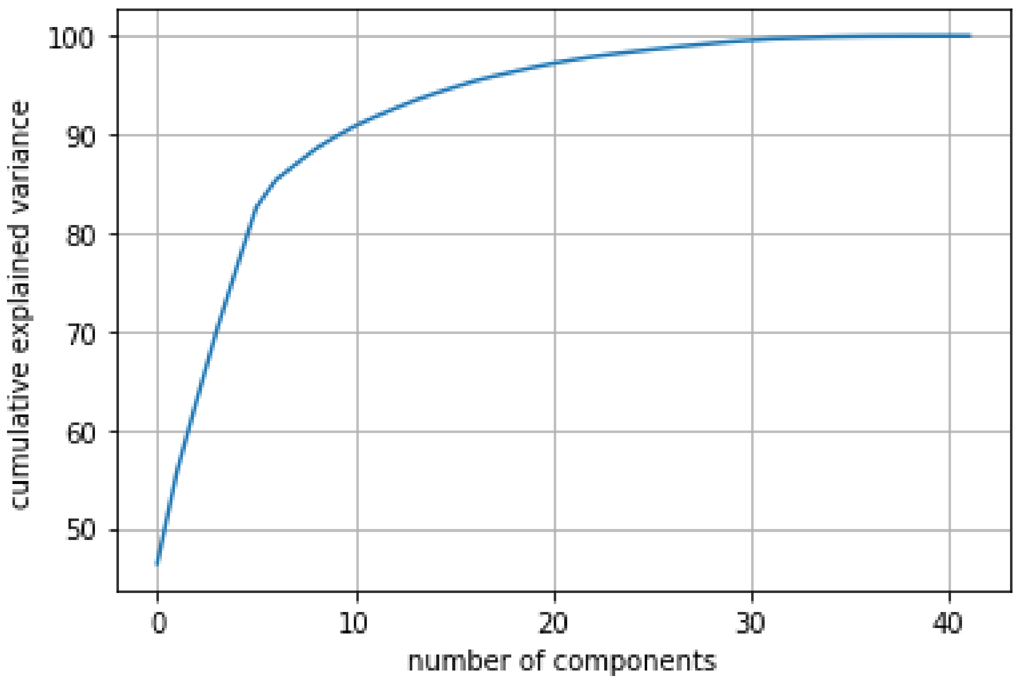
[60]:
```
X_tmp=X.copy()
```

[61]:
```
X_tmp[['age','fnlwgt','capital-gain','capital-loss','hours-per-week']]=tmp_scaled
```

[62]:
```
X_scaled=X_tmp.copy()
```

[63]:
```
X_scaled.to_csv('scaled_tmp.csv',index=False)
```

[64]:
```
from sklearn.decomposition import PCA
pca=PCA()
pca.fit(X_scaled)
#Plotting to get an idea regarding the count of components required to expained
 ↪the variance
plt.grid()
plt.plot(np.cumsum(pca.explained_variance_ratio_ * 100))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance');
```



0.0.4 Splitting data using train_test_split

[65]:
```
x_train,x_test,y_train,y_test = train_test_split(X_scaled,y,test_size=0.
↪25,random_state=365)
```

[66]:
```
x_train.shape
```

[66]: (22621, 42)

[67]:
```
x_test.shape
```

[67]: (7541, 42)

0.0.5 Logistic Regression

---

[68]:
```
regression=LogisticRegression()
```

[69]:
```
regression.fit(x_train,y_train)
```

[69]: LogisticRegression()

[70]:
```
print('Coeff Values: ',regression.coef_)
print('Intercept Value: ',regression.intercept_)
```

```
Coeff Values:  [[-0.32529997 -0.067151   -0.27930344  0.89672472 -2.41812277
-0.24229805
  -0.3465811   0.22944893  0.54610463  0.46265061  0.28811619  0.93117141
   0.73915593  0.30617891 -0.48539628 -1.02065423 -0.01866667  0.49389899
   0.07115522 -0.13471943  0.08696393  0.04624239 -0.74155424  1.16522722
   0.85339304  0.37650996  0.81813632  0.57071986 -0.53904173 -0.57245545
  -0.21069211 -0.69867144  0.15929075  0.6336106   1.18483874  1.63672013
   0.85199352 -1.30371899  0.14029241  0.32592346  0.63169834  0.14946232]]
Intercept Value:  [3.61952956]
```

[71]:
```
regression.score(x_train,y_train)
```

[71]: 0.8479731223199681

[72]:
```
regression.score(x_test,y_test)
```

[72]: 0.8510807585200901

[73]:
```
y_pred=regression.predict(x_test)
```

[74]:
```
y_test
```

[74]:
```
31565    1
15326    1
23763    0
31941    1
14139    1
        ..
16378    1
27319    1
7502     1
16579    1
30689    1
Name: salary, Length: 7541, dtype: int64
```

[75]:
```
y_pred
```

[75]: array([0, 0, 1, …, 1, 1, 0], dtype=int64)

Model does not seems to be overfitting

[76]:
```
from sklearn.metrics import classification_report,log_loss,confusion_matrix
```

[77]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.73      0.62      0.67      1834
```

```
           1       0.88      0.92      0.90      5707

    accuracy                           0.85      7541
   macro avg       0.81      0.77      0.79      7541
weighted avg       0.85      0.85      0.85      7541
```

[78]:
```
print(log_loss(y_test,y_pred))
```

```
5.143561863480152
```

[79]:
```
print(confusion_matrix(y_test,y_pred))
```

```
[[1141  693]
 [ 430 5277]]
```

[80]:
```
from sklearn.linear_model import SGDClassifier
sgdmodel=SGDClassifier(random_state=365)
```

[81]:
```
regression.fit(x_train,y_train)
```

[81]: LogisticRegression()

[82]:
```
print(regression.score(x_train,y_train))
print(regression.score(x_test,y_test))
```

```
0.8479731223199681
0.8510807585200901
```

[83]:
```
#Hypertuning SGD Classifier
```

[84]:
```
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.
for x in alpha:
    sgdmodel=SGDClassifier(alpha=x,random_state=365)
    sgdmodel.fit(x_train,y_train)
    print(x,': ',sgdmodel.score(x_train,y_train))
    print(x,': ',sgdmodel.score(x_test,y_test))
```

```
1e-05 :  0.6719420007957208
1e-05 :  0.66184856119878
0.0001 :  0.8477962954776536
0.0001 :  0.8494894576316139
0.001 :  0.8416957694177977
0.001 :  0.845245988595677
0.01 :  0.840855841916803
0.01 :  0.845245988595677
0.1 :  0.8297157508509792
0.1 :  0.8331786235247315
```

```
1 :  0.7539896556297246
1 :  0.7619679087654158
10 :  0.74917112417665
10 :  0.7567961808778677
```

0.0.6 Decision Tree

---

[85]:
```python
clf=DecisionTreeClassifier()
```

[86]:
```python
clf.fit(x_train,y_train)
```

[86]:
```
DecisionTreeClassifier()
```

[87]:
```python
print('Train Data Score: ',clf.score(x_train,y_train))
print('Test Data Score: ',clf.score(x_test,y_test))
```

```
Train Data Score:  1.0
Test Data Score:  0.8055960747911417
```

[88]:
```python
#Model is getting overfitted
```

[89]:
```python
grid_param = {
    'criterion': ['gini', 'entropy'],
    'max_depth' : range(2,20,2),
    'min_samples_leaf' : range(1,10,1),
    'min_samples_split': range(2,10,1),
    'splitter' : ['best', 'random']
}
```

[90]:
```python
from sklearn.model_selection import GridSearchCV
```

[91]:
```python
grid_search = GridSearchCV(clf,param_grid=grid_param,cv=5,verbose=5,n_jobs=-1)
grid_search.fit(x_train,y_train)
```

```
Fitting 5 folds for each of 2592 candidates, totalling 12960 fits
```

[91]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(), n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': range(2, 20, 2),
                         'min_samples_leaf': range(1, 10),
                         'min_samples_split': range(2, 10),
                         'splitter': ['best', 'random']},
             verbose=5)
```

[92]:
```python
best_dict=grid_search.best_params_
print(best_dict)
```

```
{'criterion': 'entropy', 'max_depth': 10, 'min_samples_leaf': 9,
'min_samples_split': 5, 'splitter': 'best'}
```

[93]:
```
clf1=DecisionTreeClassifier(criterion=best_dict['criterion'],max_depth=best_dict['max_depth'],
```

[94]:
```
clf1.fit(x_train,y_train)
```

[94]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=10, min_samples_leaf=9,
                       min_samples_split=5)
```

[95]:
```
print(clf1.score(x_train,y_train))
print(clf1.score(x_test,y_test))
```

```
0.8595994872021573
0.8566503116297574
```

0.0.7 RandomForest Classifier

---

[96]:
```
from sklearn.ensemble import RandomForestClassifier
```

[97]:
```
rf_clf=RandomForestClassifier()
```

[98]:
```
rf_clf.fit(x_train,y_train)
```

[98]:
```
RandomForestClassifier()
```

[99]:
```
print(rf_clf.score(x_train,y_train))
print(rf_clf.score(x_test,y_test))
```

```
0.9999557932894213
0.8492242408168678
```

[100]:
```
grid_params = {"n_estimators" : [30,70,110,150,190,230],
               "max_depth" : range(1,10,2),
               "min_samples_leaf" : range(1,10,1),
               "min_samples_split" : range(2,10,1)
               }
```

[101]:
```
grid_search =␣
 ↪GridSearchCV(rf_clf,param_grid=grid_params,cv=5,verbose=5,n_jobs=-1)
grid_search.fit(x_train,y_train)
```

```
Fitting 5 folds for each of 2160 candidates, totalling 10800 fits
```

[101]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(), n_jobs=-1,
             param_grid={'max_depth': range(1, 10, 2),
```

```
                              'min_samples_leaf': range(1, 10),
                              'min_samples_split': range(2, 10),
                              'n_estimators': [30, 70, 110, 150, 190, 230]},
             verbose=5)
```

[102]:
```
grid_search.best_params_
```

[102]:
```
{'max_depth': 9,
 'min_samples_leaf': 3,
 'min_samples_split': 6,
 'n_estimators': 70}
```

[103]:
```
rf_clf1=RandomForestClassifier(max_depth=9,max_features='auto',min_samples_leaf=3,min_samples_
```

[104]:
```
rf_clf1.fit(x_train,y_train)
```

[104]:
```
RandomForestClassifier(max_depth=9, min_samples_leaf=3, min_samples_split=6,
                       n_estimators=70)
```

[105]:
```
print(rf_clf1.score(x_train,y_train))
print(rf_clf1.score(x_test,y_test))
```

```
0.8588921798328987
0.8574459620739955
```

[107]:
```
import xgboost as xgb
```

[110]:
```
xgb_model=xgb.XGBClassifier()
```

[111]:
```
xgb_model.fit(x_train,y_train)
```

```
[13:17:43] WARNING: C:/Users/Administrator/workspace/xgboost-
win64_release_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default
evaluation metric used with the objective 'binary:logistic' was changed from
'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
```

[111]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=8, num_parallel_tree=1, random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)
```

[112]:
```
xgb_model.score(x_train,y_train)
```

[112]: 0.9050881923876044

[113]:
```
xgb_model.score(x_test,y_test)
```

[113]: 0.8656676833311232

[115]:
```
grid_params={
        'n_estimators': [70,90,110,130,150,190],
        'min_child_weight': [1, 5, 10],
        'gamma': [0.5, 1, 1.5, 2, 5],
        'subsample': [0.6, 0.8, 1.0],
        'colsample_bytree': [0.6, 0.8, 1.0],
        'max_depth': [3, 4, 5]
}
```

[116]:
```
grid_search =␣
 ↪GridSearchCV(xgb_model,param_grid=grid_params,cv=5,verbose=5,n_jobs=-1)
grid_search.fit(x_train,y_train)
```

```
Fitting 5 folds for each of 2430 candidates, totalling 12150 fits
[16:25:16] WARNING: C:/Users/Administrator/workspace/xgboost-
win64_release_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default
evaluation metric used with the objective 'binary:logistic' was changed from
'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
```

[116]:
```
GridSearchCV(cv=5,
             estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                     colsample_bylevel=1, colsample_bynode=1,
                                     colsample_bytree=1, gamma=0, gpu_id=-1,
                                     importance_type='gain',
                                     interaction_constraints='',
                                     learning_rate=0.300000012,
                                     max_delta_step=0, max_depth=6,
                                     min_child_weight=1, missing=nan,
                                     monotone_constraints='()',
                                     n_estimators=100, n_jobs=8,
                                     num_parallel_tree=1, random_state=0,
                                     reg_alpha=0, reg_lambda=1,
                                     scale_pos_weight=1, subsample=1,
                                     tree_method='exact', validate_parameters=1,
                                     verbosity=None),
             n_jobs=-1,
             param_grid={'colsample_bytree': [0.6, 0.8, 1.0],
                         'gamma': [0.5, 1, 1.5, 2, 5], 'max_depth': [3, 4, 5],
                         'min_child_weight': [1, 5, 10],
                         'n_estimators': [70, 90, 110, 130, 150, 190],
```

```
                            'subsample': [0.6, 0.8, 1.0]},
             verbose=5)
```

[117]:
```
grid_search.best_params_
```

[117]:
```
{'colsample_bytree': 1.0,
 'gamma': 5,
 'max_depth': 4,
 'min_child_weight': 1,
 'n_estimators': 90,
 'subsample': 0.8}
```

[119]:
```
xgb_model1=xgb.XGBClassifier(colsample_bytree=1.
 ↪0,gamma=5,max_depth=4,min_child_weight=1,n_estimators=90,subsample=0.8)
```

[120]:
```
xgb_model1.fit(x_train,y_train)
```

```
[17:29:25] WARNING: C:/Users/Administrator/workspace/xgboost-
win64_release_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default
evaluation metric used with the objective 'binary:logistic' was changed from
'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
```

[120]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1.0, gamma=5, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth=4,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=90, n_jobs=8, num_parallel_tree=1, random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=0.8,
              tree_method='exact', validate_parameters=1, verbosity=None)
```

[121]:
```
xgb_model1.score(x_train,y_train)
```

[121]:
```
0.878829406303877
```

[122]:
```
xgb_model1.score(x_test,y_test)
```

[122]:
```
0.8669937674048535
```

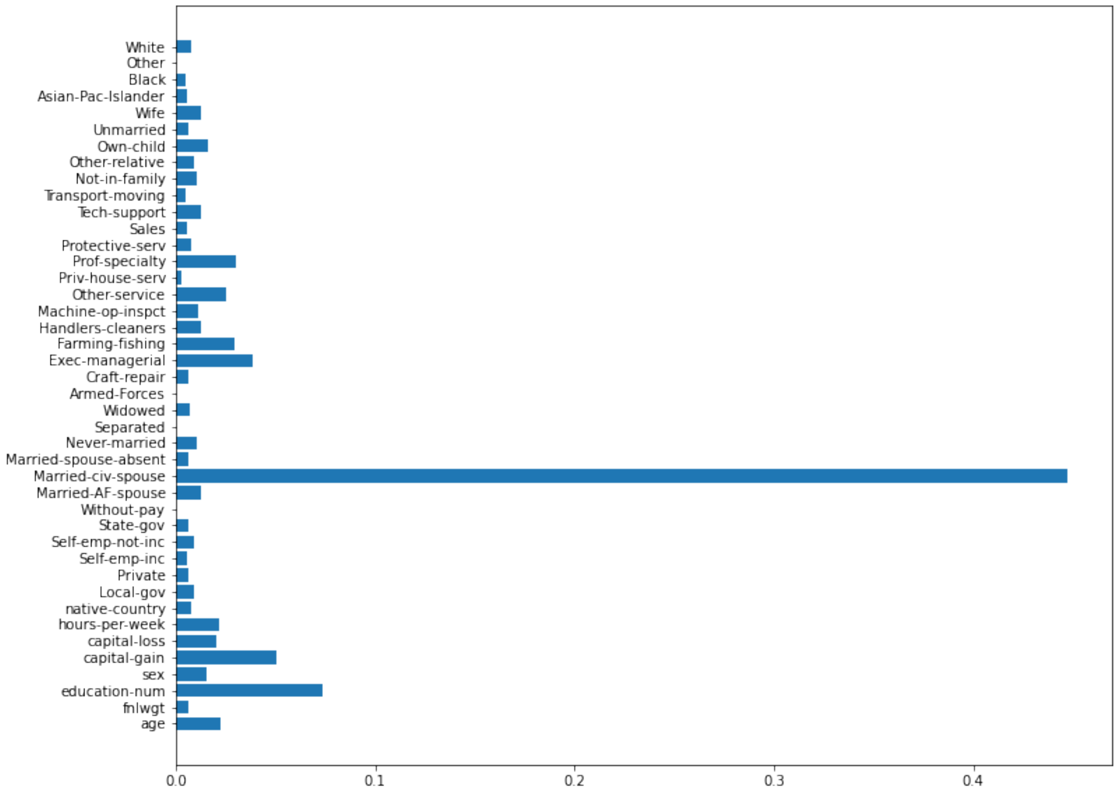
[124]:
```
xgb_model1.feature_importances_
```

[124]:
```
array([0.02251758, 0.00618192, 0.07329854, 0.01521296, 0.05028777,
       0.02037739, 0.02191892, 0.00789305, 0.00910249, 0.00637499,
       0.00584003, 0.00935466, 0.00622282, 0.        , 0.01247821,
       0.44706067, 0.00600868, 0.01045888, 0.        , 0.0072003 ,
       0.        , 0.00603016, 0.03890924, 0.02940442, 0.01283982,
```

```
0.01106759, 0.02547816, 0.00295946, 0.03034731, 0.00796404,
0.00588381, 0.01266422, 0.00504442, 0.01078747, 0.0090984 ,
0.01600897, 0.00662604, 0.01259239, 0.00557794, 0.00523698,
0.        , 0.00768929], dtype=float32)
```

[132]:
```python
#Features with importance are plotted
plt.figure(figsize=(12,10))
plt.barh(X_scaled.columns, xgb_model1.feature_importances_)
```

[132]: <BarContainer object of 42 artists>



[129]:
```python
y_pred=xgb_model1.predict(x_test)
```

[130]:
```python
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.76      0.66      0.71      1834
           1       0.90      0.93      0.91      5707

    accuracy                           0.87      7541
   macro avg       0.83      0.80      0.81      7541
```

```
weighted avg       0.86      0.87      0.86      7541
```

[131]:
```python
print(confusion_matrix(y_test,y_pred))
```

```
[[1211  623]
 [ 380 5327]]
```

[133]:
```python
from tabulate import tabulate
```

[134]:
```python
df_model=pd.DataFrame({'Model_Name':['LogisticRegression','SGDClassfier(Hinge␣
↪Loss)','DecisionTree','RandomForestClassifier','XGBoost'],
                      'Test Performance':[0.8510807585200901,0.
↪8494894576316139,0.8566503116297574,0.8574459620739955,0.8669937674048535]})
```

[136]:
```python
print(tabulate(df_model, headers='keys', tablefmt='psql'))
```

```
+----+--------------------------+--------------------+
|    | Model_Name               |   Test Performance |
|----+--------------------------+--------------------|
|  0 | LogisticRegression       |           0.851081 |
|  1 | SGDClassfier(Hinge Loss) |           0.849489 |
|  2 | DecisionTree             |           0.85665  |
|  3 | RandomForestClassifier   |           0.857446 |
|  4 | XGBoost                  |           0.866994 |
+----+--------------------------+--------------------+
```