Import

Dataset Link

https://archive.ics.uci.edu/ml/machine-learning-databases/adult/
(https://archive.ics.uci.edu/ml/machine-learning-databases/adult/)

- **Problem 1:**

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

- **Problem 2:**

Which factors are important

- **Problem 3:**

Which algorithms are best for this dataset

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

Dataset Training Url

In [2]:
```
url = 'https://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.data
```

Dataset columns

In [3]:
```
columns = ['age','workclass','fnlwgt','education','education-num','marital-status
```

Loading Data with Pandas

In [4]:
```
df = pd.read_csv(url,names=columns)
```

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

Out[5]:

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

Dataset Info

In [6]:
```
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
```

Dataset Shape

In [7]:
```
df.shape
```
Out[7]:
```
(32561, 15)
```

Dataset Description

In [8]:
```
df.describe()
```
Out[8]:

	age	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week
count	32561.000000	3.256100e+04	32561.000000	32561.000000	32561.000000	32561.000000
mean	38.581647	1.897784e+05	10.080679	1077.648844	87.303830	40.437456
std	13.640433	1.055500e+05	2.572720	7385.292085	402.960219	12.347429
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1.000000
25%	28.000000	1.178270e+05	9.000000	0.000000	0.000000	40.000000
50%	37.000000	1.783560e+05	10.000000	0.000000	0.000000	40.000000
75%	48.000000	2.370510e+05	12.000000	0.000000	0.000000	45.000000
max	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000	99.000000

In [9]:
```
df.size
```
Out[9]:
```
488415
```

Feature Engineering

Checking for null Values

In [10]:
```
df.isnull().sum()
```
Out[10]:
```
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
```

In [11]:
```
df.workclass.unique()
```

Out[11]:
```
array([' State-gov', ' Self-emp-not-inc', ' Private', ' Federal-gov',
       ' Local-gov', ' ?', ' Self-emp-inc', ' Without-pay',
       ' Never-worked'], dtype=object)
```

Replacing ' ?' with Nan for data cleaning

In [12]:
```
df.replace(' ?',np.nan,inplace=True)
```

In [13]:
```
df.isnull().sum()
```

Out[13]:
```
age                  0
workclass         1836
fnlwgt               0
education            0
education-num        0
marital-status       0
occupation        1843
relationship         0
race                 0
sex                  0
capital-gain         0
capital-loss         0
hours-per-week       0
native-country     583
salary               0
dtype: int64
```

In [14]:
```
df.dtypes
```

Out[14]:
```
age                int64
workclass         object
fnlwgt             int64
education         object
education-num      int64
marital-status    object
occupation        object
relationship      object
race              object
sex               object
capital-gain       int64
capital-loss       int64
hours-per-week     int64
native-country    object
salary            object
dtype: object
```

Salary

In [15]:
```
df.salary.unique()
```

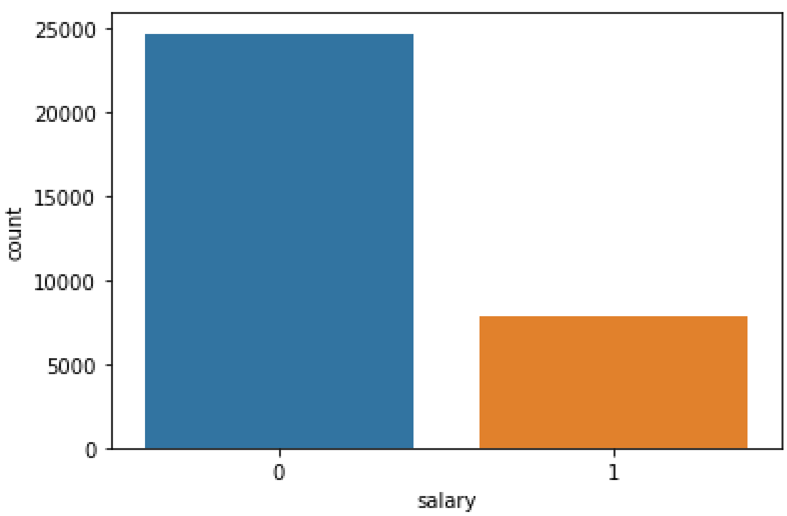
Out[15]:
```
array([' <=50K', ' >50K'], dtype=object)
```

In [16]:
```
df = df.replace({' <=50K':0,' >50K':1})
```

In [17]:
```
sns.countplot(df['salary'])
```

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

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



In [18]:
```
df['salary'].value_counts()
```

Out[18]:
```
0    24720
1     7841
Name: salary, dtype: int64
```

Workclass

In [19]:
```
df.workclass.unique()
```

Out[19]:
```
array([' State-gov', ' Self-emp-not-inc', ' Private', ' Federal-gov',
       ' Local-gov', nan, ' Self-emp-inc', ' Without-pay',
       ' Never-worked'], dtype=object)
```

In [20]:
```
df['workclass'].value_counts()
```

Out[20]:
```
 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
```

In [21]:
```
df= df.replace(' Without-pay', ' Never-worked')
```

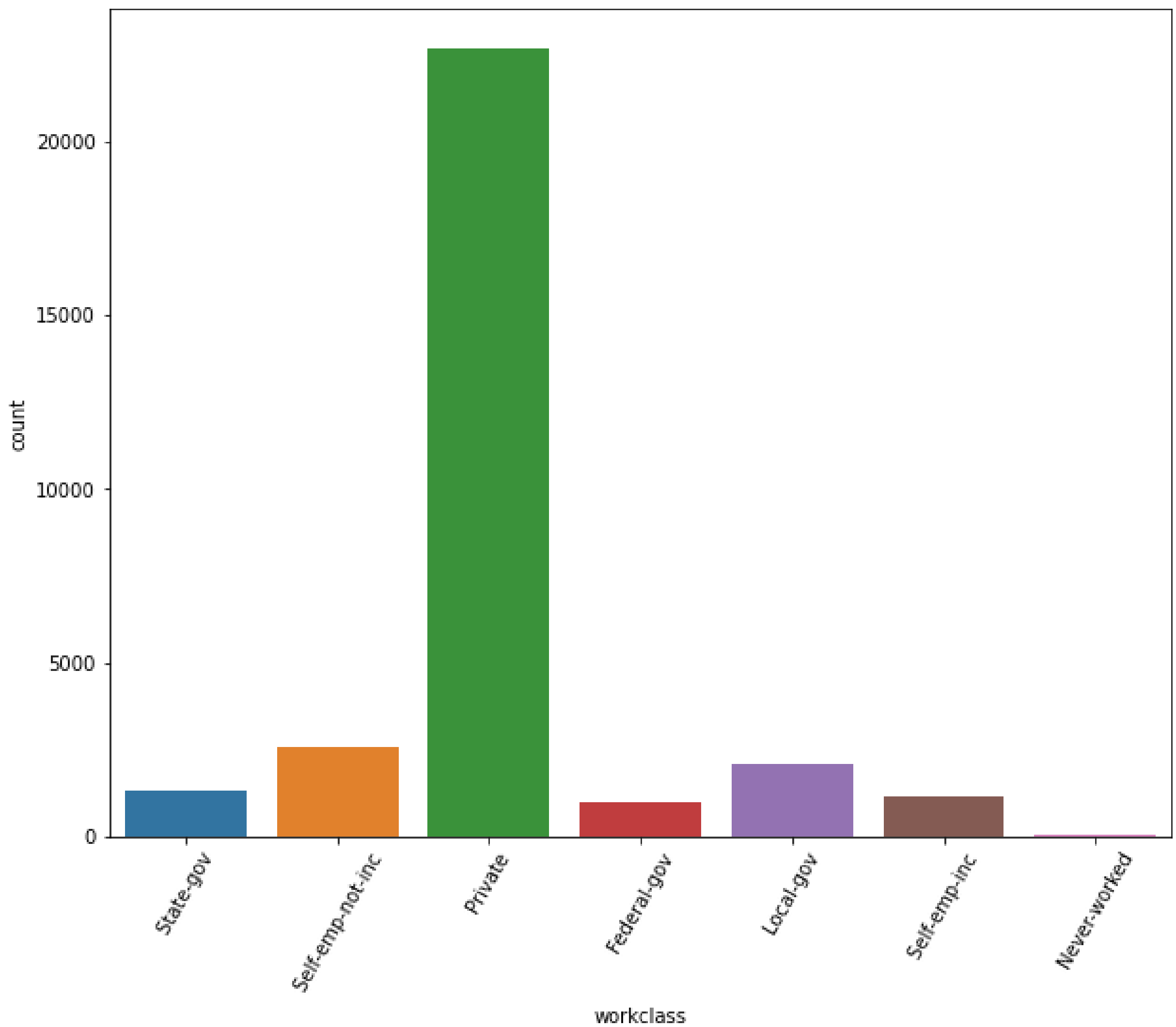
In [22]:
```
df['workclass'].value_counts()
```

Out[22]:
```
 Private             22696
 Self-emp-not-inc     2541
 Local-gov            2093
 State-gov            1298
 Self-emp-inc         1116
 Federal-gov           960
 Never-worked           21
Name: workclass, dtype: int64
```

In [23]:
```
plt.figure(figsize=(10,8))
sns.countplot(df['workclass'])
plt.xticks(rotation=60)
```

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

Out[23]:
```
(array([0, 1, 2, 3, 4, 5, 6]),
 [Text(0, 0, ' State-gov'),
  Text(1, 0, ' Self-emp-not-inc'),
  Text(2, 0, ' Private'),
  Text(3, 0, ' Federal-gov'),
  Text(4, 0, ' Local-gov'),
  Text(5, 0, ' Self-emp-inc'),
  Text(6, 0, ' Never-worked')])
```

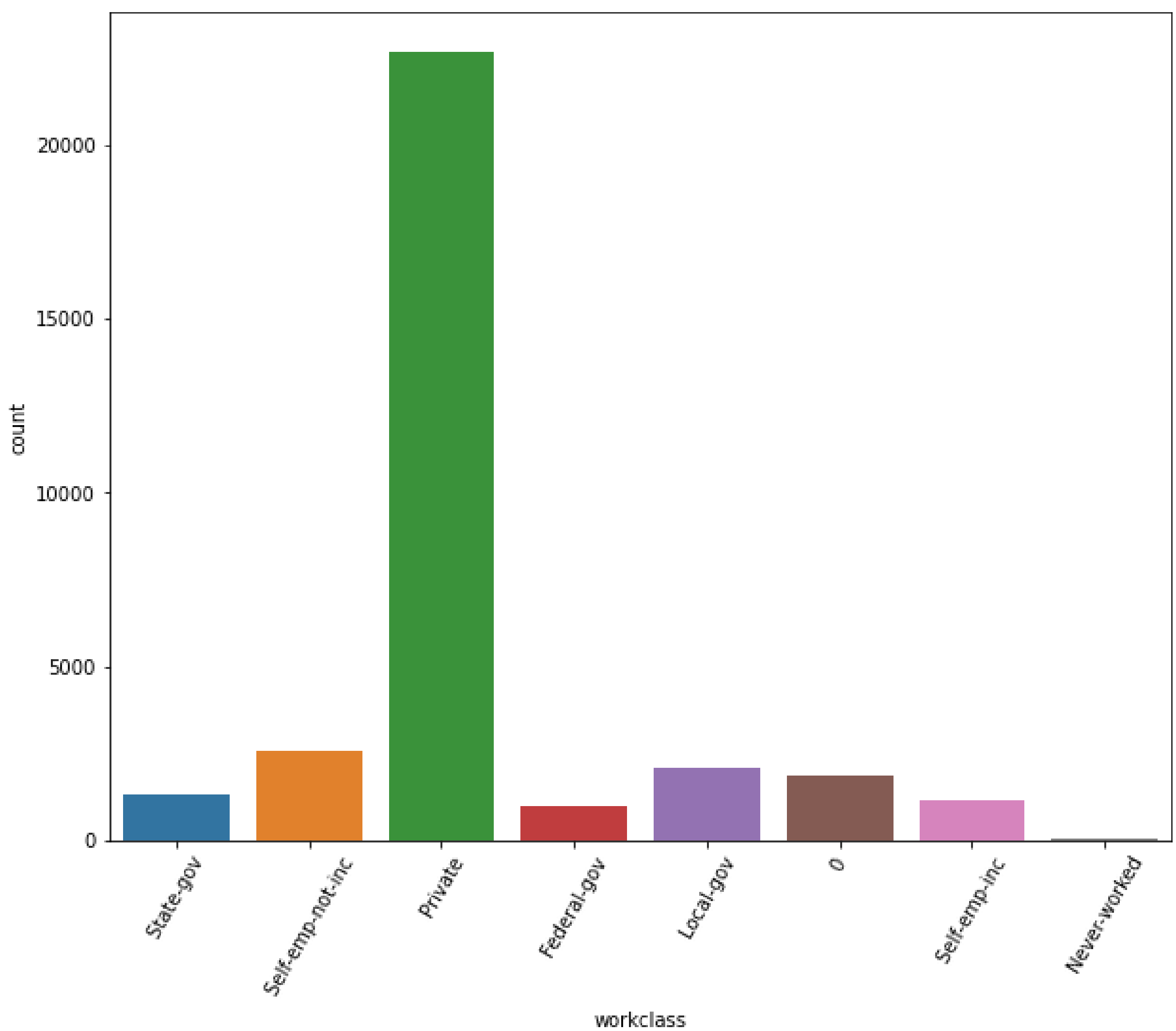


In [24]:
```
df['workclass'].fillna('0',inplace=True)
```

In [25]:
```
plt.figure(figsize=(10,8))
sns.countplot(df['workclass'])
plt.xticks(rotation=60)
```

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

Out[25]:
```
(array([0, 1, 2, 3, 4, 5, 6, 7]),
 [Text(0, 0, ' State-gov'),
  Text(1, 0, ' Self-emp-not-inc'),
  Text(2, 0, ' Private'),
  Text(3, 0, ' Federal-gov'),
  Text(4, 0, ' Local-gov'),
  Text(5, 0, '0'),
  Text(6, 0, ' Self-emp-inc'),
  Text(7, 0, ' Never-worked')])
```



Fnlwgt

In [26]:
```
df['fnlwgt'].describe()
```

Out[26]:
```
count    3.256100e+04
mean     1.897784e+05
std      1.055500e+05
min      1.228500e+04
25%      1.178270e+05
50%      1.783560e+05
75%      2.370510e+05
max      1.484705e+06
Name: fnlwgt, dtype: float64
```

In [27]:
```
df['fnlwgt'] = df['fnlwgt'].apply(lambda x :np.log1p(x))

df['fnlwgt'].describe()
```

Out[27]:
```
count    32561.000000
mean        11.983778
std          0.630738
min          9.416216
25%         11.676981
50%         12.091542
75%         12.376035
max         14.210727
Name: fnlwgt, dtype: float64
```

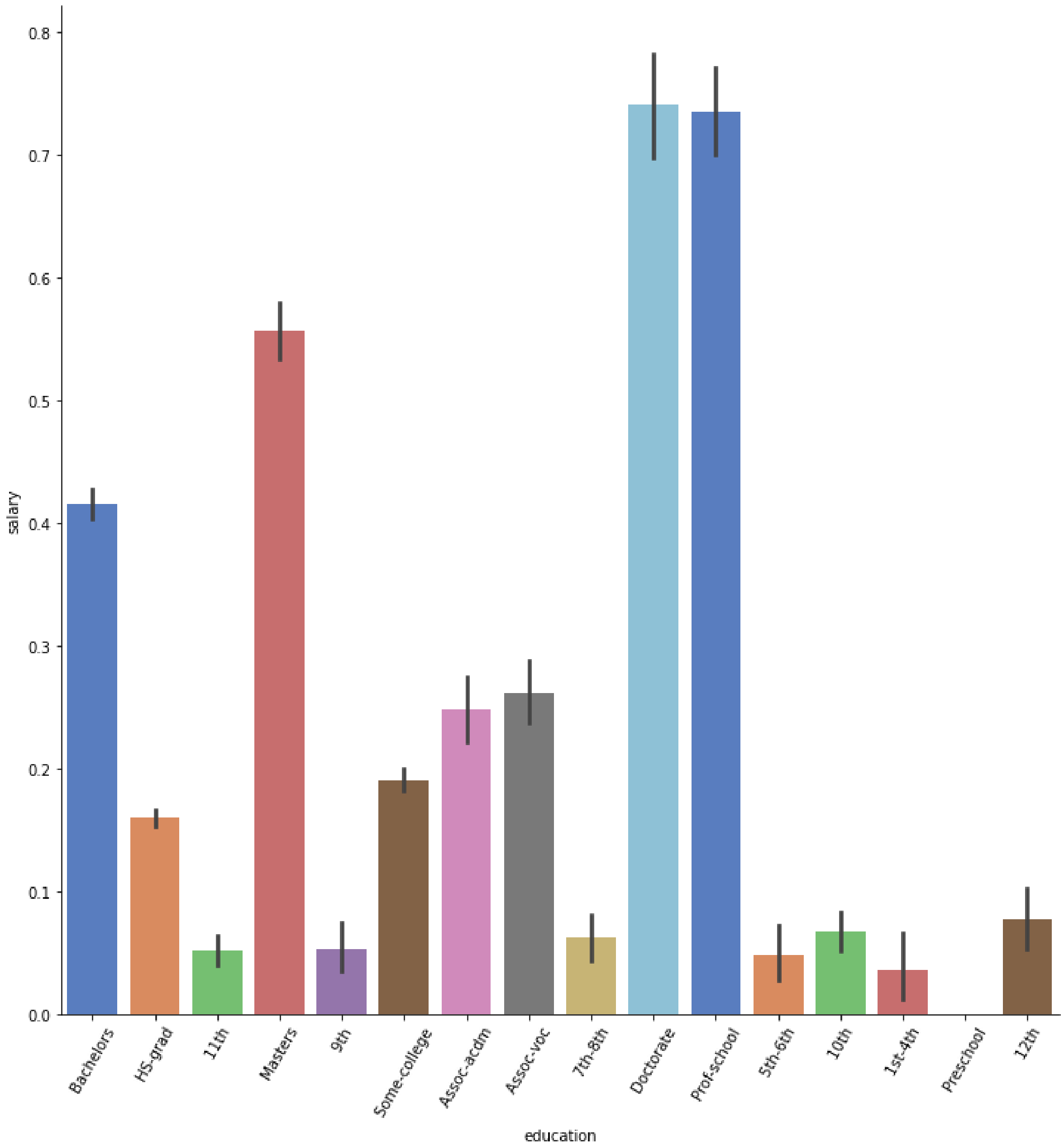
Education

In [28]:
```
df['education'].value_counts()
```

Out[28]:
```
 HS-grad         10501
 Some-college     7291
 Bachelors        5355
 Masters          1723
 Assoc-voc        1382
 11th             1175
 Assoc-acdm       1067
 10th              933
 7th-8th           646
 Prof-school       576
 9th               514
 12th              433
 Doctorate         413
 5th-6th           333
 1st-4th           168
 Preschool          51
Name: education, dtype: int64
```

In [29]:
```
sns.catplot(x='education',y='salary',data=df,height=10,palette='muted',kind='bar'
plt.xticks(rotation=60)
```

Out[29]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15]),
 [Text(0, 0, ' Bachelors'),
  Text(1, 0, ' HS-grad'),
  Text(2, 0, ' 11th'),
  Text(3, 0, ' Masters'),
  Text(4, 0, ' 9th'),
  Text(5, 0, ' Some-college'),
  Text(6, 0, ' Assoc-acdm'),
  Text(7, 0, ' Assoc-voc'),
  Text(8, 0, ' 7th-8th'),
  Text(9, 0, ' Doctorate'),
  Text(10, 0, ' Prof-school'),
  Text(11, 0, ' 5th-6th'),
  Text(12, 0, ' 10th'),
  Text(13, 0, ' 1st-4th'),
  Text(14, 0, ' Preschool'),
  Text(15, 0, ' 12th')])
```

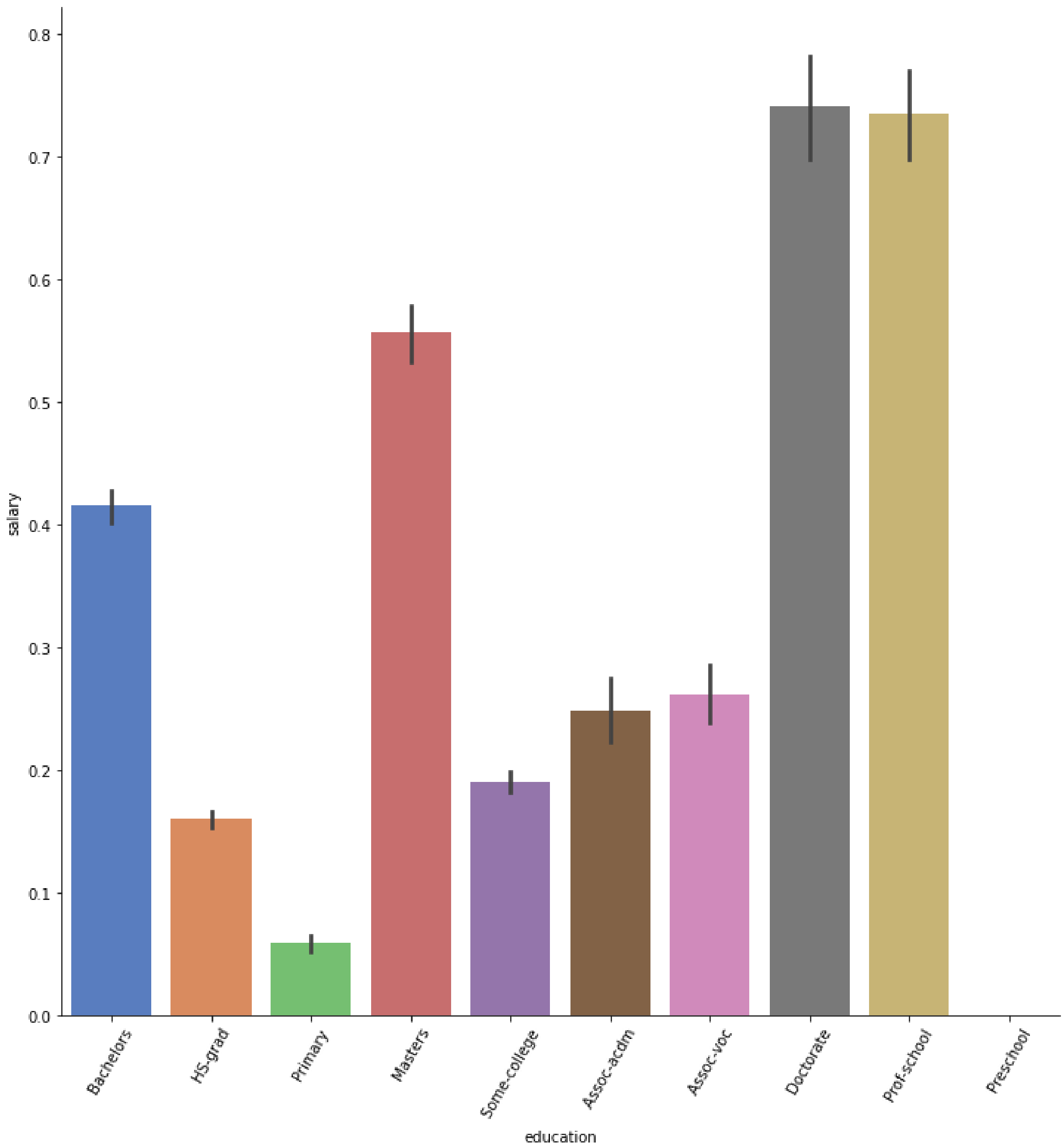


In [30]:
```
def primary(x):
    if x in [' 1st-4th', ' 5th-6th', ' 7th-8th', ' 9th', ' 10th', ' 11th', ' 12th
        return 'Primary'
    else:
        return x
```

In [31]:
```
df['education'] = df['education'].apply(primary)
```

In [32]:
```
sns.catplot(x='education',y='salary',data=df,height=10,palette='muted',kind='bar'
plt.xticks(rotation=60)
```

Out[32]:
```
(array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
 [Text(0, 0, ' Bachelors'),
  Text(1, 0, ' HS-grad'),
  Text(2, 0, 'Primary'),
  Text(3, 0, ' Masters'),
  Text(4, 0, ' Some-college'),
  Text(5, 0, ' Assoc-acdm'),
  Text(6, 0, ' Assoc-voc'),
  Text(7, 0, ' Doctorate'),
  Text(8, 0, ' Prof-school'),
  Text(9, 0, ' Preschool')])
```



Marital-status

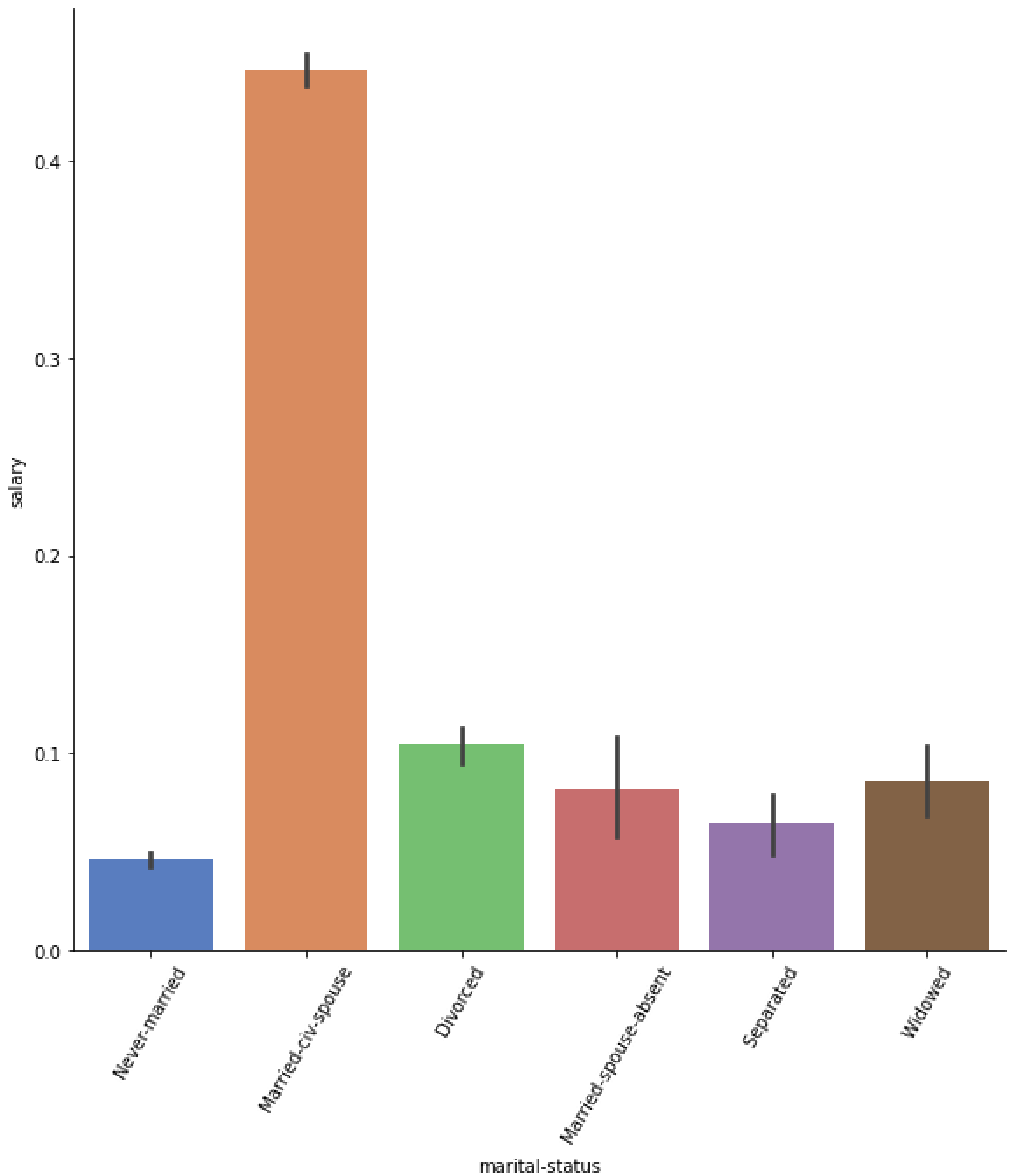
In [33]:
```
df['marital-status'].value_counts()
```

Out[33]:
```
 Married-civ-spouse       14976
 Never-married            10683
 Divorced                  4443
 Separated                 1025
 Widowed                    993
 Married-spouse-absent      418
 Married-AF-spouse           23
Name: marital-status, dtype: int64
```

In [34]:
```
df['marital-status'].replace(' Married-AF-spouse', ' Married-civ-spouse',inplace=
```

In [35]:
```
sns.catplot(x='marital-status',y='salary',data=df,palette='muted',kind='bar',heig
plt.xticks(rotation=60)
```

Out[35]:
```
(array([0, 1, 2, 3, 4, 5]),
 [Text(0, 0, ' Never-married'),
  Text(1, 0, ' Married-civ-spouse'),
  Text(2, 0, ' Divorced'),
  Text(3, 0, ' Married-spouse-absent'),
  Text(4, 0, ' Separated'),
  Text(5, 0, ' Widowed')])
```



Occupation

In [36]:
```
df['occupation'].fillna('0',inplace=True)

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

Out[36]:
```
 Prof-specialty       4140
 Craft-repair         4099
 Exec-managerial      4066
 Adm-clerical         3770
 Sales                3650
 Other-service        3295
 Machine-op-inspct    2002
0                     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
```

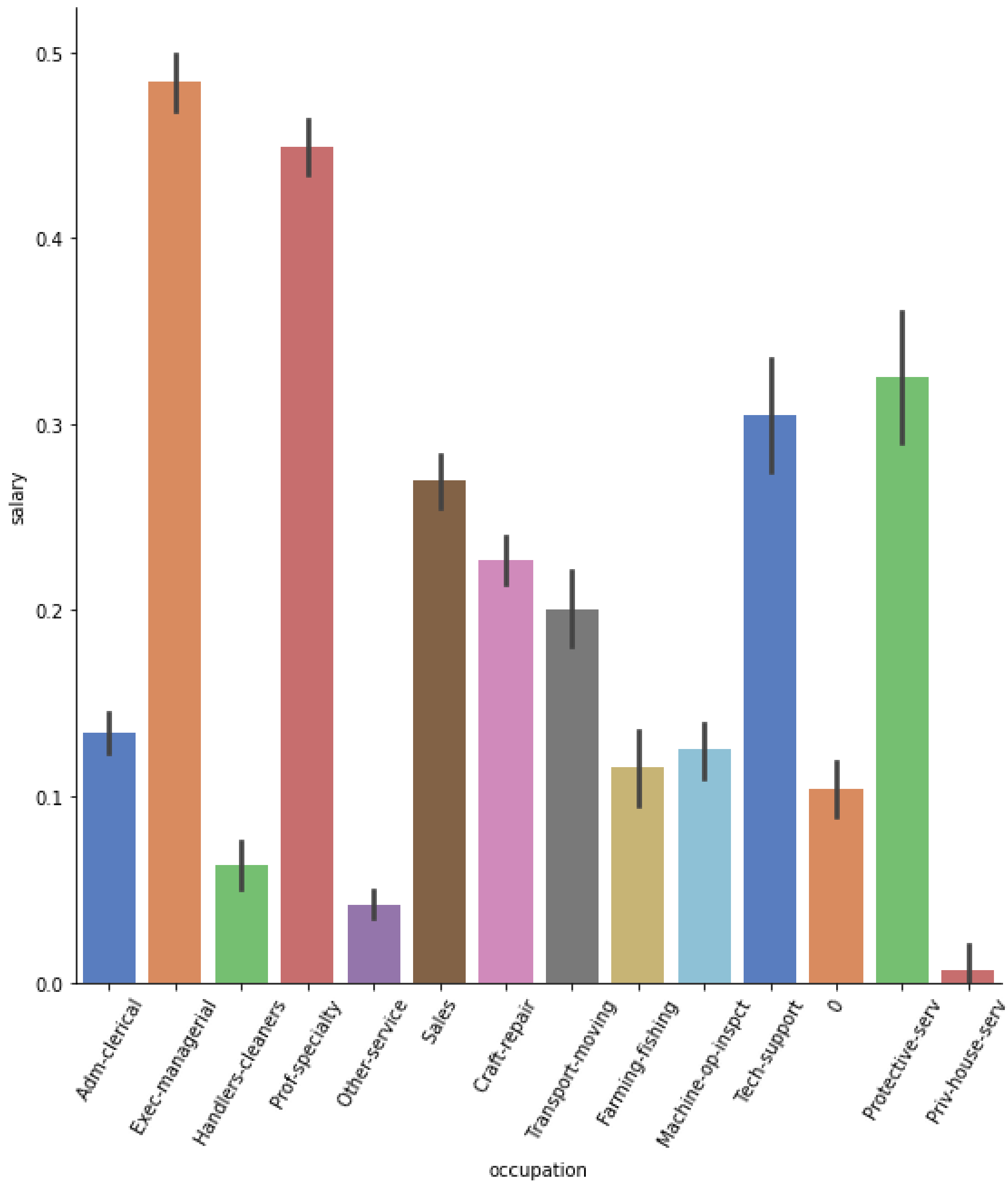
In [37]:
```
df['occupation'].replace(' Armed-Forces','0',inplace=True)

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

Out[37]:
```
 Prof-specialty       4140
 Craft-repair         4099
 Exec-managerial      4066
 Adm-clerical         3770
 Sales                3650
 Other-service        3295
 Machine-op-inspct    2002
0                     1852
 Transport-moving     1597
 Handlers-cleaners    1370
 Farming-fishing       994
 Tech-support          928
 Protective-serv       649
 Priv-house-serv       149
Name: occupation, dtype: int64
```

In [38]:
```
sns.catplot(x='occupation',y='salary',data=df,palette='muted',kind='bar',height=8
plt.xticks(rotation=60)
```

Out[38]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13]),
 [Text(0, 0, ' Adm-clerical'),
  Text(1, 0, ' Exec-managerial'),
  Text(2, 0, ' Handlers-cleaners'),
  Text(3, 0, ' Prof-specialty'),
  Text(4, 0, ' Other-service'),
  Text(5, 0, ' Sales'),
  Text(6, 0, ' Craft-repair'),
  Text(7, 0, ' Transport-moving'),
  Text(8, 0, ' Farming-fishing'),
  Text(9, 0, ' Machine-op-inspct'),
  Text(10, 0, ' Tech-support'),
  Text(11, 0, '0'),
  Text(12, 0, ' Protective-serv'),
  Text(13, 0, ' Priv-house-serv')])
```



Relationship

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

Out[39]:
```
 Husband           13193
 Not-in-family      8305
 Own-child          5068
 Unmarried          3446
 Wife               1568
 Other-relative      981
Name: relationship, dtype: int64
```

Race

In [40]:
```
df['race'].value_counts()
```

Out[40]:
```
 White                 27816
 Black                  3124
 Asian-Pac-Islander     1039
 Amer-Indian-Eskimo      311
 Other                   271
Name: race, dtype: int64
```

Sex

In [41]:
```
df['sex'].value_counts()
```

Out[41]:
```
 Male      21790
 Female    10771
Name: sex, dtype: int64
```

In [42]:
```
df.columns
```

Out[42]:
```
Index(['age', 'workclass', 'fnlwgt', 'education', 'education-num',
       'marital-status', 'occupation', 'relationship', 'race', 'sex',
       'capital-gain', 'capital-loss', 'hours-per-week', 'native-country',
       'salary'],
      dtype='object')
```

Native-Country

In [43]:
```
df['native-country'].unique()
```

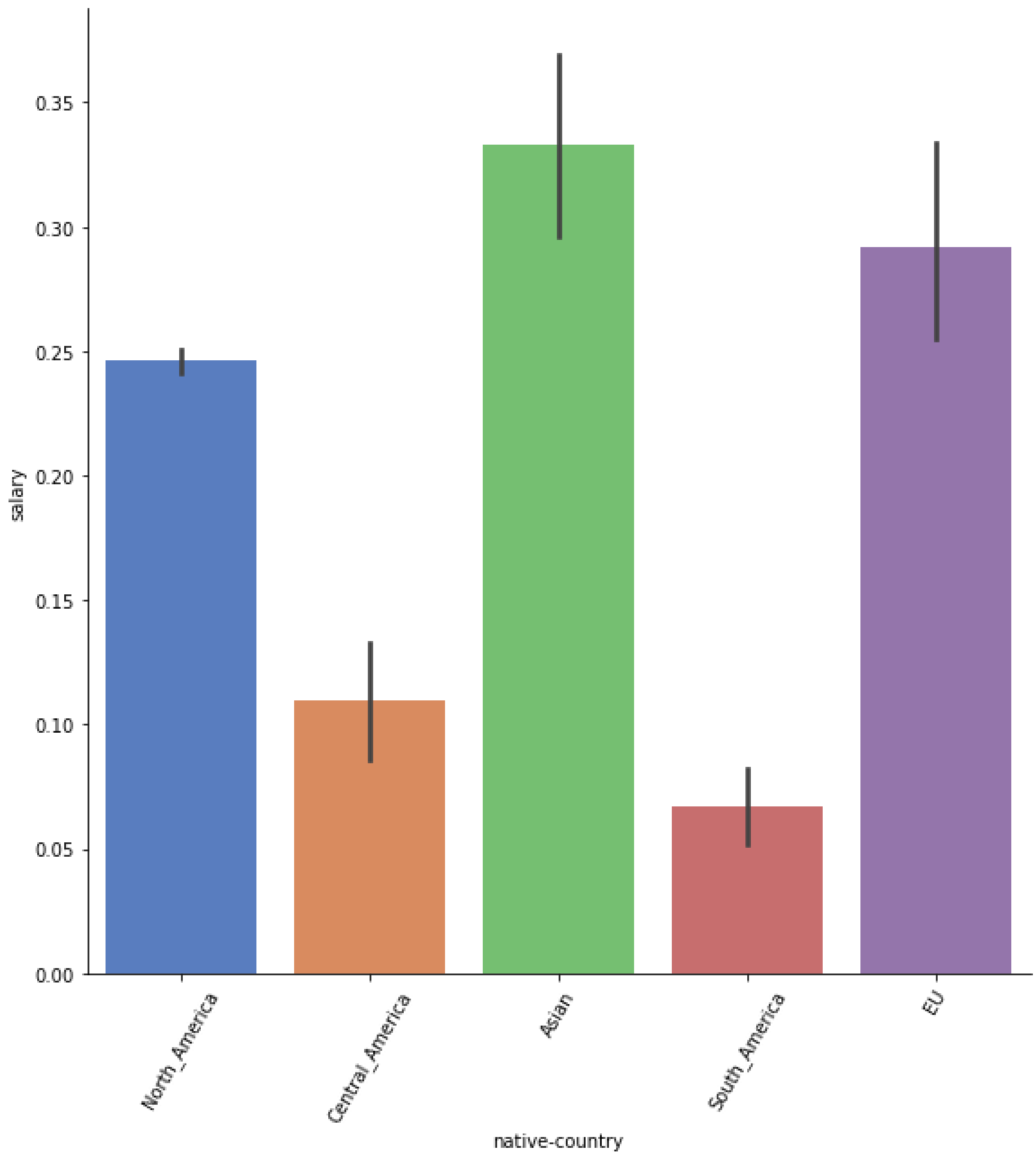
Out[43]:
```
array([' United-States', ' Cuba', ' Jamaica', ' India', nan, ' Mexico',
       ' South', ' Puerto-Rico', ' Honduras', ' England', ' Canada',
       ' Germany', ' Iran', ' Philippines', ' Italy', ' Poland',
       ' Columbia', ' Cambodia', ' Thailand', ' Ecuador', ' Laos',
       ' Taiwan', ' Haiti', ' Portugal', ' Dominican-Republic',
       ' El-Salvador', ' France', ' Guatemala', ' China', ' Japan',
       ' Yugoslavia', ' Peru', ' Outlying-US(Guam-USVI-etc)', ' Scotland',
       ' Trinadad&Tobago', ' Greece', ' Nicaragua', ' Vietnam', ' Hong',
       ' Ireland', ' Hungary', ' Holand-Netherlands'], dtype=object)
```

In [44]:
```
def native(country):
    if country in [' United-States',' Canada']:
        return 'North_America'
    elif country in [' Puerto-Rico',' El-Salvador',' Cuba',' Jamaica',' Dominican
        return 'Central_America'
    elif country in [' Mexico',' Columbia',' Vietnam',' Peru',' Ecuador',' South'
        return 'South_America'
    elif country in [' Germany',' England',' Italy',' Poland',' Portugal',' Greec
        return 'EU'
    elif country in [' India',' Iran',' China',' Japan',' Thailand',' Hong',' Can
        return 'Asian'
    else:
        return country
```

In [45]:
```
df['native-country'] = df['native-country'].apply(native)
```

In [46]:
```
sns.catplot(x='native-country',y='salary',data=df,palette='muted',kind='bar',heig
plt.xticks(rotation=60)
```

Out[46]:
```
(array([0, 1, 2, 3, 4]),
 [Text(0, 0, 'North_America'),
  Text(1, 0, 'Central_America'),
  Text(2, 0, 'Asian'),
  Text(3, 0, 'South_America'),
  Text(4, 0, 'EU')])
```



Let's check our data's correlation with the help of Heatmap

In [47]:
```
corr = df.corr()
plt.figure(figsize=(10,12))
sns.heatmap(corr,annot=True)
```

Out[47]: <AxesSubplot:>

As we can see that corr values of fnlwgt are very low, Hence we can drop it safely.

In [48]:
```
df.drop('fnlwgt',axis=1,inplace=True)
```

In [49]:
```
df.head()
```

Out[49]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	sex	capita gai
0	39	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	217
1	50	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	
2	38	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	
3	53	Private	Primary	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	
4	28	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	

Dividing Data into 'X' and 'y'

In [50]:
```
X = df.drop('salary',axis=1)
y = df['salary']
```

In [51]:
```
X.columns
```

Out[51]:
```
Index(['age', 'workclass', 'education', 'education-num', 'marital-status',
       'occupation', 'relationship', 'race', 'sex', 'capital-gain',
       'capital-loss', 'hours-per-week', 'native-country'],
      dtype='object')
```

Converting Categorical data into Numerical Data

In [52]:
```
X_d = pd.get_dummies(X)
```

In [53]:
```
X_d.head()
```

Out[53]:

	age	education-num	capital-gain	capital-loss	hours-per-week	workclass_Federal-gov	workclass_Local-gov	workclass_Never-worked	workclass_Private	wor Se
0	39	13	2174	0	40	0	0	0	0	
1	50	13	0	0	13	0	0	0	0	
2	38	9	0	0	40	0	0	0	1	
3	53	7	0	0	40	0	0	0	1	
4	28	13	0	0	40	0	0	0	1	

5 rows × 61 columns

Train_Test_Split

In [54]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(X_d,y,test_size=0.3,random_state
```

In [55]:
```
x_train.shape
```

Out[55]:
```
(22792, 61)
```

In [56]:
```
y_train.shape
```

Out[56]:
```
(22792,)
```

On Applying Algorithms & Evaluating the Models

1. Logistic Regression

In [57]:
```
from sklearn.linear_model import LogisticRegression
Lr = LogisticRegression()
Lr.fit(x_train,y_train)
```

```
C:\Users\idofa\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:76
2: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(
```

Out[57]:
```
LogisticRegression()
```

Applying Hyperparams for LogReg model to get best model score

In [58]:
```
penalty = ['l1', 'l2']
# C is the inverese of regularization parameter
C = np.logspace(0, 4, 10)
random_state=[0]
# creating a dictionary of hyperparameters
hyperparameters = dict(C=C, penalty=penalty,
                  random_state=random_state)
```

GridSearchCV for LogReg

In [59]:
```
from sklearn.model_selection import GridSearchCV
gsvLogReg = GridSearchCV(Lr,param_grid=hyperparameters,cv=5,verbose=3,n_jobs=-1)
gsvLogReg.fit(x_train,y_train)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed:    7.8s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:   20.2s finished
C:\Users\idofa\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:76
2: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-
learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on)
  n_iter_i = _check_optimize_result(
```

Out[59]:
```
GridSearchCV(cv=5, estimator=LogisticRegression(), n_jobs=-1,
             param_grid={'C': array([1.00000000e+00, 2.78255940e+00, 7.74263683
e+00, 2.15443469e+01,
       5.99484250e+01, 1.66810054e+02, 4.64158883e+02, 1.29154967e+03,
       3.59381366e+03, 1.00000000e+04]),
                         'penalty': ['l1', 'l2'], 'random_state': [0]},
             verbose=3)
```

Best_params

In [60]:
```
gsvLogReg.best_params_
```

Out[60]:
```
{'C': 2.7825594022071245, 'penalty': 'l2', 'random_state': 0}
```

In [61]:
```
lr_tuned = LogisticRegression(C=2.7825594022071245,penalty='l2',random_state=0)
```

In [62]:
```
lr_tuned.fit(x_train,y_train)
```

```
C:\Users\idofa\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:76
2: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-
learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on)
  n_iter_i = _check_optimize_result(
```

Out[62]:
```
LogisticRegression(C=2.7825594022071245, random_state=0)
```

In [63]:
```
Log_Reg =lr_tuned.score(x_test,y_test)
```

In [64]:
```
lr_y_pred = lr_tuned.predict(x_test)
```

In [65]:
```
lr_y_pred
```

Out[65]:
```
array([0, 0, 0, ..., 0, 0, 0], dtype=int64)
```

Logistic Regression Model Evaluation

In [67]:
```
from sklearn.metrics import accuracy_score,classification_report,confusion_matrix
print(f"Accuracy_Score:{accuracy_score(y_test,lr_y_pred)}")
print('*'*50)
print(f"Classification_Report:{classification_report(y_test,lr_y_pred)}")
print('*'*50)
print(f"Confusion_Matrix:\n{confusion_matrix(y_test,lr_y_pred)}")
```

```
Accuracy_Score:0.8280274337189067
**************************************************
Classification_Report:              precision    recall  f1-score   support

           0       0.86      0.93      0.89      7436
           1       0.68      0.52      0.59      2333

    accuracy                           0.83      9769
   macro avg       0.77      0.72      0.74      9769
weighted avg       0.82      0.83      0.82      9769

**************************************************
Confusion_Matrix:
[[6879  557]
 [1123 1210]]
```

2. Decision Tree

In [68]:
```
from sklearn.tree import DecisionTreeClassifier
dtc = DecisionTreeClassifier()
dtc.fit(x_train,y_train)
```

Out[68]:
```
DecisionTreeClassifier()
```

Applying grid_params with GridsearchCv for DTC model to get best model score

In [69]:
```
grid_paramDT = {
    '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']

}
```

In [70]:
```
gsvDT = GridSearchCV(dtc,param_grid=grid_paramDT,cv=5,verbose=3,n_jobs=-1)
gsvDT.fit(x_train,y_train)
```

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

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed:    1.1s
[Parallel(n_jobs=-1)]: Done 120 tasks      | elapsed:    5.1s
[Parallel(n_jobs=-1)]: Done 280 tasks      | elapsed:   11.8s
[Parallel(n_jobs=-1)]: Done 504 tasks      | elapsed:   21.5s
[Parallel(n_jobs=-1)]: Done 792 tasks      | elapsed:   34.7s
[Parallel(n_jobs=-1)]: Done 1144 tasks      | elapsed:   53.4s
[Parallel(n_jobs=-1)]: Done 1560 tasks      | elapsed:  1.3min
[Parallel(n_jobs=-1)]: Done 2040 tasks      | elapsed:  1.8min
[Parallel(n_jobs=-1)]: Done 2584 tasks      | elapsed:  2.5min
[Parallel(n_jobs=-1)]: Done 3192 tasks      | elapsed:  3.3min
[Parallel(n_jobs=-1)]: Done 3864 tasks      | elapsed:  4.4min
[Parallel(n_jobs=-1)]: Done 4600 tasks      | elapsed:  5.7min
[Parallel(n_jobs=-1)]: Done 5400 tasks      | elapsed:  7.3min
[Parallel(n_jobs=-1)]: Done 6264 tasks      | elapsed:  9.0min
[Parallel(n_jobs=-1)]: Done 7192 tasks      | elapsed: 10.0min
[Parallel(n_jobs=-1)]: Done 8184 tasks      | elapsed: 10.9min
[Parallel(n_jobs=-1)]: Done 9240 tasks      | elapsed: 12.2min
[Parallel(n_jobs=-1)]: Done 10360 tasks      | elapsed: 13.9min
[Parallel(n_jobs=-1)]: Done 11544 tasks      | elapsed: 16.0min
[Parallel(n_jobs=-1)]: Done 12792 tasks      | elapsed: 18.4min
[Parallel(n_jobs=-1)]: Done 12960 out of 12960 | elapsed: 18.7min finished
```

Out[70]:
```
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=3)
```

Bestparams

In [71]:
```
gsvDT.best_params_
```

Out[71]:
```
{'criterion': 'gini',
 'max_depth': 10,
 'min_samples_leaf': 6,
 'min_samples_split': 7,
 'splitter': 'best'}
```

In [84]:
```
dtc_tuned = DecisionTreeClassifier(criterion='gini',max_depth=10,min_samples_leaf
```

In [85]:
```
dtc_tuned.fit(x_train,y_train)
```

Out[85]:
```
DecisionTreeClassifier(max_depth=10, min_samples_leaf=6, min_samples_split=7)
```

In [86]:
```
Dtc = dtc_tuned.score(x_test,y_test)
Dtc
```

Out[86]:
```
0.8594533729143208
```

Decision Tree Classifier Model Evaluation

In [87]:
```
dtc_y_pred = dtc_tuned.predict(x_test)
```

In [88]:
```
print(f"Accuracy_Score:{accuracy_score(y_test,dtc_y_pred)}")
print('*'*50)
print(f"Classification_Report:{classification_report(y_test,dtc_y_pred)}")
print('*'*50)
print(f"Confusion_Matrix:{confusion_matrix(y_test,dtc_y_pred)}")
```

```
Accuracy_Score:0.8594533729143208
**************************************************
Classification_Report:              precision    recall  f1-score   support

           0       0.88      0.95      0.91      7436
           1       0.77      0.58      0.66      2333

    accuracy                           0.86      9769
   macro avg       0.83      0.76      0.79      9769
weighted avg       0.85      0.86      0.85      9769

**************************************************
Confusion_Matrix:[[7043  393]
 [ 980 1353]]
```

3. Random Forest Classifier

In [72]:
```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier()
rfc.fit(x_train,y_train)
```

Out[72]:
```
RandomForestClassifier()
```

Applying grid_params with GridsearchCv for RFC model to get best model score

In [73]:
```
grid_paramsRF = {"n_estimators" : [10,15,25,30],
              "max_depth" : range(1,10,2),
              "min_samples_leaf" : range(1,10,1),
              "min_samples_split" : range(2,10,1),
              "max_features" : ['auto','log2']
              }
```

In [74]:
```
gsvRF = GridSearchCV(rfc,param_grid=grid_paramsRF,cv=5,n_jobs=-1,verbose=3)
gsvRF.fit(x_train,y_train)
```

```
Fitting 5 folds for each of 2880 candidates, totalling 14400 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed:    2.1s
[Parallel(n_jobs=-1)]: Done 120 tasks      | elapsed:   11.1s
[Parallel(n_jobs=-1)]: Done 280 tasks      | elapsed:   25.7s
[Parallel(n_jobs=-1)]: Done 504 tasks      | elapsed:   45.9s
[Parallel(n_jobs=-1)]: Done 792 tasks      | elapsed:  1.2min
[Parallel(n_jobs=-1)]: Done 1144 tasks      | elapsed:  1.7min
[Parallel(n_jobs=-1)]: Done 1560 tasks      | elapsed:  2.4min
[Parallel(n_jobs=-1)]: Done 2040 tasks      | elapsed:  3.1min
[Parallel(n_jobs=-1)]: Done 2584 tasks      | elapsed:  3.9min
[Parallel(n_jobs=-1)]: Done 3192 tasks      | elapsed:  5.0min
[Parallel(n_jobs=-1)]: Done 3864 tasks      | elapsed:  6.2min
[Parallel(n_jobs=-1)]: Done 4600 tasks      | elapsed:  7.6min
[Parallel(n_jobs=-1)]: Done 5400 tasks      | elapsed:  9.2min
[Parallel(n_jobs=-1)]: Done 6264 tasks      | elapsed: 11.4min
[Parallel(n_jobs=-1)]: Done 7192 tasks      | elapsed: 13.8min
[Parallel(n_jobs=-1)]: Done 8184 tasks      | elapsed: 15.9min
[Parallel(n_jobs=-1)]: Done 9240 tasks      | elapsed: 18.7min
[Parallel(n_jobs=-1)]: Done 10360 tasks      | elapsed: 21.9min
[Parallel(n_jobs=-1)]: Done 11544 tasks      | elapsed: 24.9min
[Parallel(n_jobs=-1)]: Done 12792 tasks      | elapsed: 28.4min
[Parallel(n_jobs=-1)]: Done 14104 tasks      | elapsed: 31.5min
[Parallel(n_jobs=-1)]: Done 14400 out of 14400 | elapsed: 32.1min finished
```

Out[74]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(), n_jobs=-1,
             param_grid={'max_depth': range(1, 10, 2),
                         'max_features': ['auto', 'log2'],
                         'min_samples_leaf': range(1, 10),
                         'min_samples_split': range(2, 10),
                         'n_estimators': [10, 15, 25, 30]},
             verbose=3)
```

In [75]:
```
gsvRF.best_params_
```

Out[75]:
```
{'max_depth': 9,
 'max_features': 'auto',
 'min_samples_leaf': 1,
 'min_samples_split': 3,
 'n_estimators': 30}
```

In [79]:
```
rfc_tuned = RandomForestClassifier(max_depth=9,max_features='auto',min_samples_le
```

In [80]:
```
rfc_tuned.fit(x_train,y_train)
```

Out[80]:
```
RandomForestClassifier(max_depth=9, min_samples_split=3, n_estimators=30)
```

In [81]:
```
RFC = rfc_tuned.score(x_test,y_test)
```

RandomForest Classifier Model Evaluation

In [82]:
```
rfc_y_pred = rfc_tuned.predict(x_test)
```

In [83]:
```
print(f"Accuracy_Score:{accuracy_score(y_test,rfc_y_pred)}")
print('*'*50)
print(f"Classification_Report:{classification_report(y_test,rfc_y_pred)}")
print('*'*50)
print(f"Confusion_Matrix:\n{confusion_matrix(y_test,rfc_y_pred)}")
```

```
Accuracy_Score:0.8610912068789026
**************************************************
Classification_Report:              precision    recall  f1-score   support

           0       0.87      0.95      0.91      7436
           1       0.79      0.57      0.66      2333

    accuracy                           0.86      9769
   macro avg       0.83      0.76      0.79      9769
weighted avg       0.86      0.86      0.85      9769

**************************************************
Confusion_Matrix:
[[7093  343]
 [1014 1319]]
```

4. KNN Classifier

In [76]:
```
from sklearn.neighbors import KNeighborsClassifier
knc = KNeighborsClassifier()
knc.fit(x_train,y_train)
```

Out[76]:
```
KNeighborsClassifier()
```

In [77]:
```
param_gridKNN = { 'algorithm' : ['ball_tree', 'kd_tree', 'brute'],
               'leaf_size' : [18,25,27,30],
               'n_neighbors' : [3,7,9,11]
              }
```

In [89]:
```
gsvKNN = GridSearchCV(knc,param_grid=param_gridKNN,verbose=3)
gsvKNN.fit(x_train,y_train)
```

```
5s
[CV] algorithm=brute, leaf_size=27, n_neighbors=11 ..................
[CV]  algorithm=brute, leaf_size=27, n_neighbors=11, score=0.844, total=   2.
6s
[CV] algorithm=brute, leaf_size=27, n_neighbors=11 ..................
[CV]  algorithm=brute, leaf_size=27, n_neighbors=11, score=0.846, total=   2.
5s
[CV] algorithm=brute, leaf_size=27, n_neighbors=11 ..................
[CV]  algorithm=brute, leaf_size=27, n_neighbors=11, score=0.845, total=   2.
7s
[CV] algorithm=brute, leaf_size=27, n_neighbors=11 ..................







[CV]  algorithm=brute, leaf_size=27, n_neighbors=11, score=0.845, total=   2.
7s
```

In [90]:
```
gsvKNN.best_params_
```

Out[90]:
```
{'algorithm': 'kd_tree', 'leaf_size': 18, 'n_neighbors': 11}
```

In [92]:
```
knc_tuned = KNeighborsClassifier(algorithm='kd_tree',leaf_size=18,n_neighbors=11)
knc_tuned.fit(x_train,y_train)
```

Out[92]:
```
KNeighborsClassifier(algorithm='kd_tree', leaf_size=18, n_neighbors=11)
```

In [93]:
```
KNN = knc_tuned.score(x_test,y_test)
```

In [94]:
```
knc_y_pred = knc_tuned.predict(x_test)
```

KNN Classifier Model Evaluation

In [95]:
```
print(f"Accuracy_Score:{accuracy_score(y_test,knc_y_pred)}")
print('*'*50)
print(f"Classification_Report:{classification_report(y_test,knc_y_pred)}")
print('*'*50)
print(f"Confusion_Matrix:\n{confusion_matrix(y_test,knc_y_pred)}")
```

```
Accuracy_Score:0.8523902139420616
**************************************************
Classification_Report:              precision    recall  f1-score   support

           0       0.89      0.92      0.90      7436
           1       0.72      0.63      0.67      2333

    accuracy                           0.85      9769
   macro avg       0.80      0.78      0.79      9769
weighted avg       0.85      0.85      0.85      9769

**************************************************
Confusion_Matrix:
[[6852  584]
 [ 858 1475]]
```

5. XGBoost Classifier

In [96]:
```
from xgboost import XGBClassifier
xbc = XGBClassifier()
xbc.fit(x_train,y_train)
```

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

[12:23:14] 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 'loglos
s'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

Out[96]:
```
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=4, 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)
```

In [97]:
```
param_gridXG={
    ' learning_rate':[1,0.5,0.1,0.01,0.001],
    'max_depth': [3,5,7,9,11,15],
    'n_estimators':[10,50,100,200,300]
}
```

In [98]:
```
gsvXGBoost = GridSearchCV(xbc,param_grid=param_gridXG,verbose=3)
gsvXGBoost.fit(x_train,y_train)
```

```
                                     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=4,
                                     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),
             param_grid={' learning_rate': [1, 0.5, 0.1, 0.01, 0.001],
                         'max_depth': [3, 5, 7, 9, 11, 15],
                         'n_estimators': [10, 50, 100, 200, 300]},
             verbose=3)
```

In [99]:
```
gsvXGBoost.best_params_
```

Out[99]:
```
{' learning_rate': 1, 'max_depth': 3, 'n_estimators': 200}
```

In [100]:
```
xbc_tuned = XGBClassifier(learning_rate=1,max_depth=3,n_estimators=200)
xbc_tuned.fit(x_train,y_train)
```

```
[13:10:26] 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 'loglos
s'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

Out[100]:
```
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=1, max_delta_step=0, max_depth=3,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=200, n_jobs=4, 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)
```

In [101]:
```python
XBc = xbc_tuned.score(x_test,y_test)
print(XBc)
```

```
0.8686661889650936
```

XGBoost_Classifier Model Evaluation

In [102]:
```python
xbc_y_pred = xbc_tuned.predict(x_test)
```

In [103]:
```python
print(f"Accuracy_Score:{accuracy_score(y_test,rfc_y_pred)}")
print('*'*50)
print(f"Classification_Report:{classification_report(y_test,rfc_y_pred)}")
print('*'*50)
print(f"Confusion_Matrix:\n{confusion_matrix(y_test,rfc_y_pred)}")
```

```
Accuracy_Score:0.8610912068789026
**************************************************
Classification_Report:              precision    recall  f1-score   support

           0       0.87      0.95      0.91      7436
           1       0.79      0.57      0.66      2333

    accuracy                           0.86      9769
   macro avg       0.83      0.76      0.79      9769
weighted avg       0.86      0.86      0.85      9769

**************************************************
Confusion_Matrix:
[[7093  343]
 [1014 1319]]
```

Lets compare all the Models with its Model score by a table

In [104]:
```python
df = {'Models':['Logistic_Reg','Decision Tree','Random Forest','KNN','XGBoost_Cla
Result =pd.DataFrame(df)
```

In [105]:
```python
Result
```

Out[105]:

	Models	Model_Scores
0	Logistic_Reg	0.828027
1	Decision Tree	0.859453
2	Random Forest	0.861091
3	KNN	0.852390
4	XGBoost_Classifier	0.868666

In [ ]:

```

```

From Above table we can come to conclusion that XG boost classifier is the best as it gives high model scores when compared to other models