Problem statement

Adult Salary Prediction

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Our task is to analyze the dataset and predict whether the income of an adult will exceed 50k per year or not.

- We have been given 14 features.

  Adult dataset link : [http://archive.ics.uci.edu/ml/datasets/Adult (http://archive.ics.uci.edu/ml/datasets/Adult)](http://archive.ics.uci.edu/ml/datasets/Adult)

In [110]:

```
import numpy as np  # For mathematical calculations
import pandas as pd  # For data preprocessing
import matplotlib.pyplot as plt  # For data visualization
import seaborn as sns  # For data visualization
from sklearn.preprocessing import StandardScaler  # For feature scaling
from statsmodels.stats.outliers_influence import variance_inflation_factor  # For detect
from sklearn.model_selection import train_test_split  # For splitting data into training
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score, pre
from sklearn.tree import DecisionTreeClassifier  # For decision tree classification
from sklearn.ensemble import RandomForestClassifier  # For random forest classification
from sklearn.svm import SVC  # For support vector machine classification
from imblearn.over_sampling import SMOTE  # For oversampling the minority class
import warnings
warnings.filterwarnings("ignore")  # To ignore warnings for cleaner output
```

In [111]:

```
df = pd.read_csv("adult_data.csv")
df.head()
```

Out[111]:

	age	workclass	education	occupation	race	sex	capital-gain	capital-loss	hours-per-week	native-country
0	39	State-gov	Bachelors	Adm-clerical	White	Male	2174	0	40	United-States
1	50	Self-emp-not-inc	Bachelors	Exec-managerial	White	Male	0	0	13	United-States
2	38	Private	HS-grad	Handlers-cleaners	White	Male	0	0	40	United-States
3	53	Private	11th	Handlers-cleaners	Black	Male	0	0	40	United-States
4	28	Private	Bachelors	Prof-specialty	Black	Female	0	0	40	Cuba

In [112]:

```
df.columns
```

Out[112]:

```
Index(['age', ' workclass', ' education', ' occupation', ' race', ' sex',
       ' capital-gain', ' capital-loss', ' hours-per-week', ' native-count
ry',
       ' salary'],
      dtype='object')
```

In [113]:

```
len(df.columns)
```

Out[113]:

```
11
```

In [114]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32561 non-null  int64 
 1    workclass      32561 non-null  object
 2    education      32561 non-null  object
 3    occupation     32561 non-null  object
 4    race           32561 non-null  object
 5    sex            32561 non-null  object
 6    capital-gain   32561 non-null  int64 
 7    capital-loss   32561 non-null  int64 
 8    hours-per-week 32561 non-null  int64 
 9    native-country 32561 non-null  object
 10   salary         32561 non-null  object
dtypes: int64(4), object(7)
memory usage: 2.7+ MB
```

In [115]:

```
df.shape
```

Out[115]:

```
(32561, 11)
```

In [116]:

```
df.describe()
```

Out[116]:

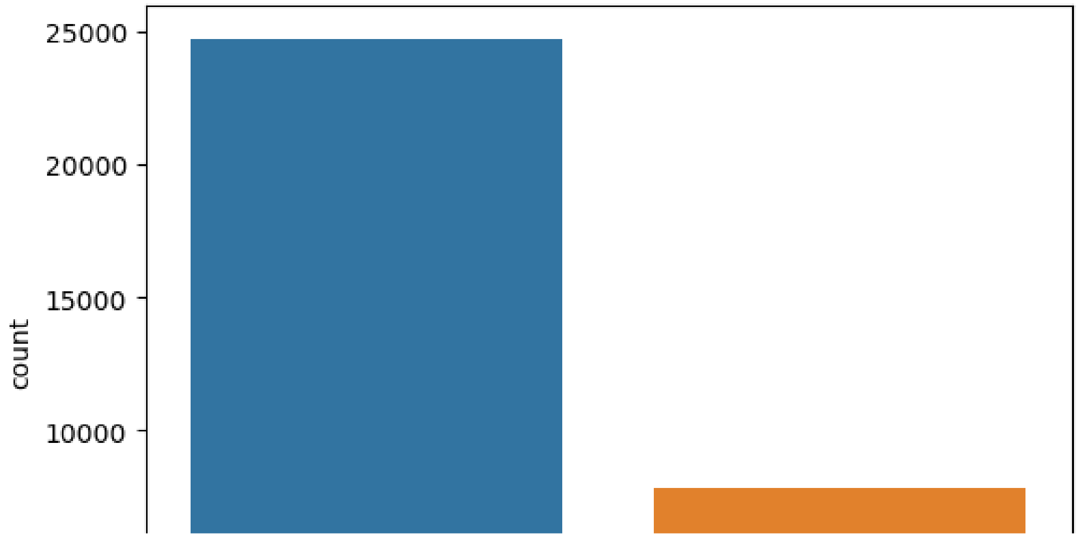
	age	capital-gain	capital-loss	hours-per-week
count	32561.000000	32561.000000	32561.000000	32561.000000
mean	38.581647	1077.648844	87.303830	40.437456
std	13.640433	7385.292085	402.960219	12.347429
min	17.000000	0.000000	0.000000	1.000000
25%	28.000000	0.000000	0.000000	40.000000
50%	37.000000	0.000000	0.000000	40.000000
75%	48.000000	0.000000	0.000000	45.000000
max	90.000000	99999.000000	4356.000000	99.000000

In [117]:

```
sns.countplot(x=' salary',data=df )
```

Out[117]:

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



In [118]:

```
df[" salary"].value_counts()
```

Out[118]:

```
 <=50K    24720
 >50K      7841
Name:  salary, dtype: int64
```

In [119]:

```
print(f"<= 50k : {round(24720 /32561 * 100 , 2)}")
print(f"> 50k : {round(7841 /32561 * 100 , 2)}")
```

```
<= 50k : 75.92
> 50k : 24.08
```

Exploratory data analysis and Feature Engineering

In [120]:

```
## Here we will check the missing values in our dataset
df.isnull().sum()
```

Out[120]:

```
age                0
 workclass         0
 education         0
 occupation        0
 race              0
 sex               0
 capital-gain      0
 capital-loss      0
 hours-per-week    0
 native-country    0
 salary            0
dtype: int64
```

In [121]:

```
numerical = [i for i in df.columns if df[i].dtypes != "O"]
```

In [122]:

```
numerical
```

Out[122]:

```
['age', ' capital-gain', ' capital-loss', ' hours-per-week']
```

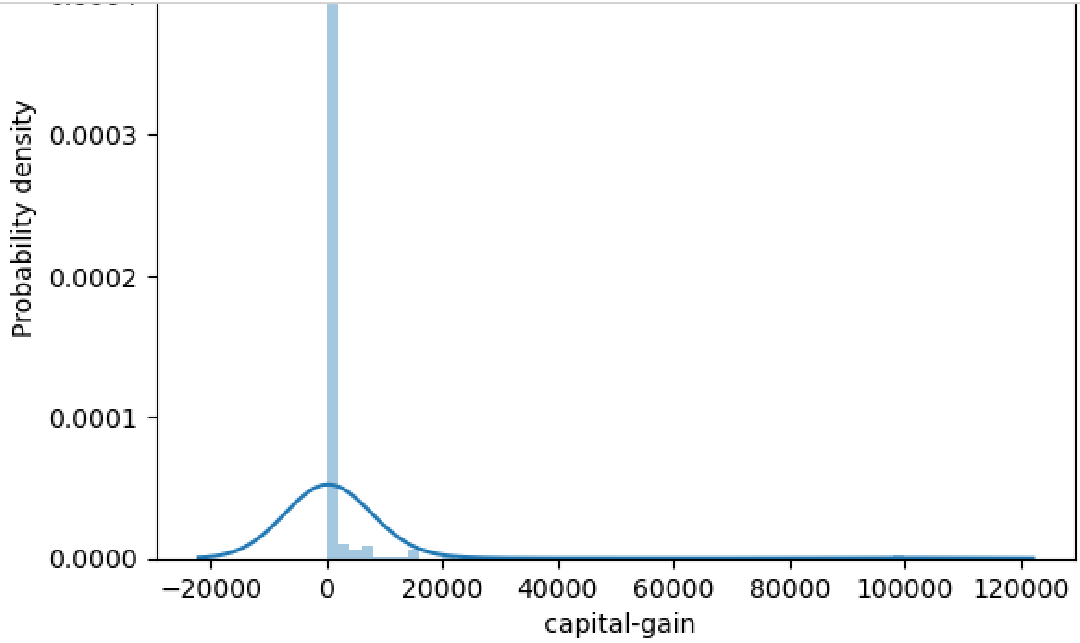
In [123]:

```
for i in numerical:
    print(f" {i}  :  {len(df[i].unique())}")
```

```
 age  :  73
  capital-gain  :  119
  capital-loss  :  92
  hours-per-week  :  94
```

In [124]:

```
for feature in numerical:
    bar = sns.distplot(df[feature] , kde_kws = {'bw' : 1})
    bar.legend(["Skewness: {:0.2f}".format(df[feature].skew())])
    plt.xlabel(feature)
    plt.ylabel("Probability density")
    plt.title(feature)
    plt.show()
```



In [125]:

```
df["age"] = np.log(df["age"])
```

In [126]:

```
df.columns
```

Out[126]:

```
Index(['age', ' workclass', ' education', ' occupation', ' race', ' sex',
       ' capital-gain', ' capital-loss', ' hours-per-week', ' native-count
ry',
       ' salary'],
      dtype='object')
```

Handling categorical data

In [127]:

```
categorical = [i for i in df.columns if df[i].dtypes == "O"]
```

In [128]:

```
for feature in categorical:
    print(f" {feature}  :  {len(df[feature].unique())}")
```

```
 workclass  :  9
 education  :  16
 occupation  :  15
 race  :  5
 sex  :  2
 native-country  :  42
 salary  :  2
```

In [129]:

```
for feature in  categorical:
    print(df[feature].value_counts())
    print("\n \n ")
```

```
 Cambodia                       19
 Trinadad&Tobago                19
 Laos                           18
 Thailand                       18
 Yugoslavia                     16
 Outlying-US(Guam-USVI-etc)     14
 Honduras                       13
 Hungary                        13
 Scotland                       12
 Holand-Netherlands              1
Name:  native-country, dtype: int64



 <=50K    24720
 >50K      7841
Name:  salary, dtype: int64
```

Handling missing values in categorical features

In [130]:

```
print(f"workclass : {round(2093 / 32561 , 4) *100}%")
print(f"occupation : {round(1843 / 32561 , 4) *100}%")
print(f"native-country : {round(583 / 32561 , 4) *100}%")
```

```
workclass : 6.43%
occupation : 5.66%
native-country : 1.79%
```

In [131]:

```
df[" occupation"].mode()[0]
```

Out[131]:

```
' Prof-specialty'
```

here we have less than 6 percent missing values so we can fill it with mode value

In [132]:

```
df[" workclass"] = df[' workclass'].str.replace('?', 'Private' )
df[' occupation'] = df[' occupation'].str.replace('?', 'Prof-specialty' )
df[' native-country'] = df[' native-country'].str.replace('?', 'United-States' )
```

In [133]:

```
# education Category
df[" education"].replace(['Preschool', '1st-4th', '5th-6th', '7th-8th', '9th','10th', '1
                        inplace = True , regex = True)
df[" education"].replace(['Assoc-voc', 'Assoc-acdm', 'Prof-school', 'Some-college'], 'hi
```

In [134]:

```
# income
df[" salary"] = df[" salary"].replace({'<=50K' : 0 , ">50K" : 1 } , regex = True)
```

In [135]:

```
df.head()
```

Out[135]:

	age	workclass	education	occupation	race	sex	capital-gain	capital-loss	hours-per-week	nat cou
0	3.663562	State-gov	Bachelors	Adm-clerical	White	Male	2174	0	40	Uni St
1	3.912023	Self-emp-not-inc	Bachelors	Exec-managerial	White	Male	0	0	13	Uni St
2	3.637586	Private	HS-grad	Handlers-cleaners	White	Male	0	0	40	Uni St
3	3.970292	Private	school	Handlers-cleaners	Black	Male	0	0	40	Uni St
4	3.332205	Private	Bachelors	Prof-specialty	Black	Female	0	0	40	C

In [136]:

```
for feature in categorical:
    print(f" {feature}  :  {len(df[feature].unique())}")
```

```
 workclass  :  8
 education  :  6
 occupation  :  14
 race  :  5
 sex  :  2
 native-country  :  41
 salary  :  2
```

In [137]:

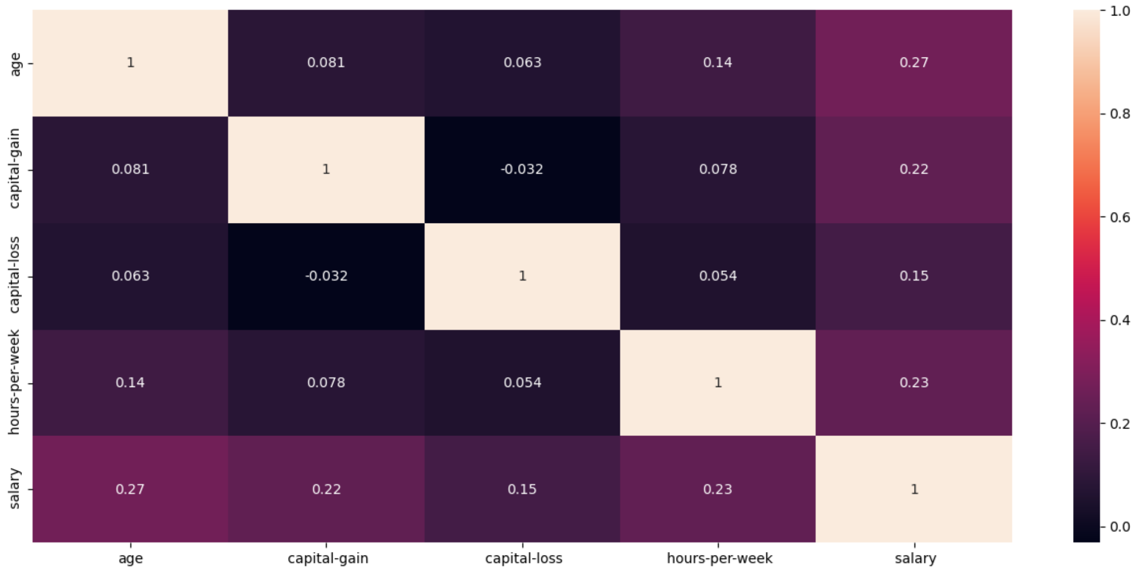
```
df[" education"].unique()
```

Out[137]:

```
array([' Bachelors', ' HS-grad', ' school', ' Masters', ' higher',
       ' Doctorate'], dtype=object)
```

In [138]:

```
plt.figure(figsize = (16 , 7))
sns.heatmap(df.corr(), annot=True);
```



In [139]:

```
from sklearn.preprocessing import  LabelEncoder
```

In [140]:

```
df = df.apply(LabelEncoder().fit_transform)
df .head()
```

Out[140]:

	age	workclass	education	occupation	race	sex	capital-gain	capital-loss	hours-per-week	native-country	sala
0	22	6	0	0	4	1	25	0	39	38	
1	33	5	0	3	4	1	0	0	12	38	
2	21	3	2	5	4	1	0	0	39	38	
3	36	3	5	5	2	1	0	0	39	38	
4	11	3	0	9	2	0	0	0	39	4	

Pre Processing

In [141]:

```
# Preprocess the data for machine learning
target_name = ' salary'
y = df[target_name]
x_train = df.drop(target_name, axis=1)
```

In [142]:

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x_res = sc.fit_transform(x_train)
```

In [143]:

```
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score
```

In [144]:

```
# Calculate variance inflation factor (VIF) for each feature
vif = pd.DataFrame()
vif["VIF Factor"] = [variance_inflation_factor(x_res, i) for i in range(x_res.shape[1])]
vif["features"] = x_train.columns
```

In [145]:

```
# Display VIF for each feature
print("Variance Inflation Factor (VIF):")
pd.DataFrame(vif)
```

```
Variance Inflation Factor (VIF):
```

Out[145]:

	VIF Factor	features
0	1.031483	age
1	1.008832	workclass
2	1.024136	education
3	1.003528	occupation
4	1.024756	race
5	1.079126	sex
6	1.036486	capital-gain
7	1.015167	capital-loss
8	1.084125	hours-per-week
9	1.016311	native-country

In [146]:

```
x_res.shape
```

Out[146]:

```
(32561, 10)
```

MODEL EVALUATION

1) Decision Tree Classifier

In [147]:

```
X_train, X_test, y_train, y_test = train_test_split(x_res, y, test_size=0.2, random_stat

# Print the shapes of training and testing sets
print("X_train.shape:", X_train.shape)
print("y_train.shape:", y_train.shape)
print("X_test.shape:", X_test.shape)
print("y_test.shape:", y_test.shape)
```

```
X_train.shape: (26048, 10)
y_train.shape: (26048,)
X_test.shape: (6513, 10)
y_test.shape: (6513,)
```

In [148]:

```
dt = DecisionTreeClassifier()
dt.fit(X_train, y_train)

# Predict on training and testing sets using Decision Tree Classifier
dt_train_pred = dt.predict(X_train)
dt_test_pred = dt.predict(X_test)
```

In [149]:

```
# Print accuracy scores and confusion matrix for Decision Tree Classifier
print('Train Accuracy:', accuracy_score(y_train, dt_train_pred) * 100)
print('Accuracy Score:', accuracy_score(y_test, dt_test_pred) * 100)
```

```
Train Accuracy: 95.98817567567568
Accuracy Score: 79.57930293259633
```

Confusion Matrix

In [150]:

```
print(confusion_matrix(y_test, dt_test_pred))
```

```
[[4330  621]
 [ 709  853]]
```

In [151]:

```
#Classfication_report
```

In [152]:

```
print(classification_report(y_test, dt_test_pred, digits=4))
```

```
              precision    recall  f1-score   support

           0     0.8593    0.8746    0.8669      4951
           1     0.5787    0.5461    0.5619      1562

    accuracy                         0.7958      6513
   macro avg     0.7190    0.7103    0.7144      6513
weighted avg     0.7920    0.7958    0.7937      6513
```

Precision Score

In [153]:

```
print('Precision score of macro is: ' , round(precision_score(y_test , dt_test_pred , av
print('Precision score of micro is: ' , round(precision_score(y_test , dt_test_pred , av
print('Precision score of weighted is: ' , round(precision_score(y_test , dt_test_pred ,
```

```
Precision score of macro is:  71.9
Precision score of micro is:  79.58
Precision score of weighted is:  79.2
```

Recall Score

In [154]:

```
print('recall_score score of macro is: ' , round(recall_score(y_test , dt_test_pred , av
print('recall_score score of micro is: ' , round(recall_score(y_test , dt_test_pred , av
print('recall_score score of weighted is: ' , round(recall_score(y_test , dt_test_pred ,
```

```
recall_score score of macro is:  71.03
recall_score score of micro is:  79.58
recall_score score of weighted is:  79.58
```

F1 Score

In [155]:

```
print('f1_score score of macro is: ' , round(f1_score(y_test , dt_test_pred , average =
print('f1_score score of micro is: ' , round(f1_score(y_test , dt_test_pred , average =
print('f1_score score of weighted is: ' , round(f1_score(y_test , dt_test_pred , average
```

```
f1_score score of macro is:  71.44
f1_score score of micro is:  79.58
f1_score score of weighted is:  79.37
```

2)Random Forest

In [156]:

```
from sklearn.ensemble import RandomForestClassifier
rf_classifier = RandomForestClassifier(n_estimators = 20, criterion = 'entropy' ,random_
rf_classifier.fit(X_train, y_train)
y_pred = rf_classifier.predict(X_test)
accuracy_score(y_test, y_pred)*100
```

Out[156]:

```
82.84968524489483
```

In [157]:

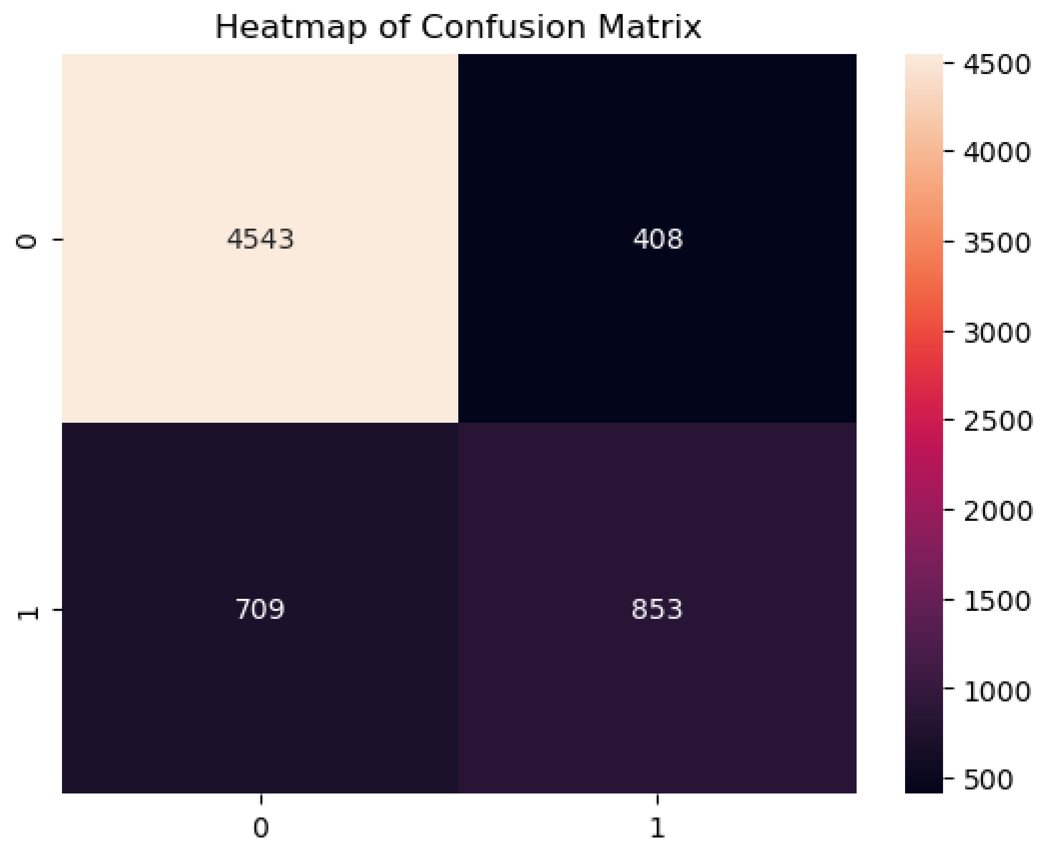
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.87      0.92      0.89      4951
           1       0.68      0.55      0.60      1562

    accuracy                           0.83      6513
   macro avg       0.77      0.73      0.75      6513
weighted avg       0.82      0.83      0.82      6513
```

Confusion Matrix

In [158]:

```
cm = confusion_matrix(y_test, y_pred )
plt.title('Heatmap of Confusion Matrix', fontsize = 12)
sns.heatmap(cm, annot = True ,  fmt = "d")
plt.show()
```



3)Support Vector Machine(SVM)

In [159]:

```
# Train Support Vector Classifier (SVC)
svc_model = SVC()
svc_model.fit(X_train, y_train)

# Predict on training and testing sets using SVC
svc_train_pred = svc_model.predict(X_train)
svc_test_pred = svc_model.predict(X_test)
```

In [160]:

```
# Print accuracy scores and confusion matrix for SVC
print('Train Accuracy:', accuracy_score(y_train, svc_train_pred) * 100)
print('Accuracy Score:', accuracy_score(y_test, svc_test_pred) * 100)
```

```
Train Accuracy: 82.8585687960688
Accuracy Score: 82.081989866421
```

Confusion Matrix

In [161]:

```
print(confusion_matrix(y_test, svc_test_pred))
```

```
[[4777  174]
 [ 993  569]]
```

Classification Report

In [66]:

```
print(classification_report(y_test, svc_test_pred, digits=4))
```

```
              precision    recall  f1-score   support

           0     0.8279    0.9649    0.8911      4951
           1     0.7658    0.3643    0.4937      1562

    accuracy                         0.8208      6513
   macro avg     0.7969    0.6646    0.6924      6513
weighted avg     0.8130    0.8208    0.7958      6513
```

Handling Imbalanced data

In [162]:

```
# Check value counts of y
print(y.value_counts())
```

```
0    24720
1     7841
Name:  salary, dtype: int64
```

In [163]:

```
# Apply SMOTE for handling imbalanced dataset
oversample = SMOTE(k_neighbors=4)
X_res1, y_res1 = oversample.fit_resample(x_res, y)
```

In [164]:

```
# Print shapes of resampled dataset
print("X_res1.shape:", X_res1.shape)
print("y_res1.shape:", y_res1.shape)
```

```
X_res1.shape: (49440, 10)
y_res1.shape: (49440,)
```

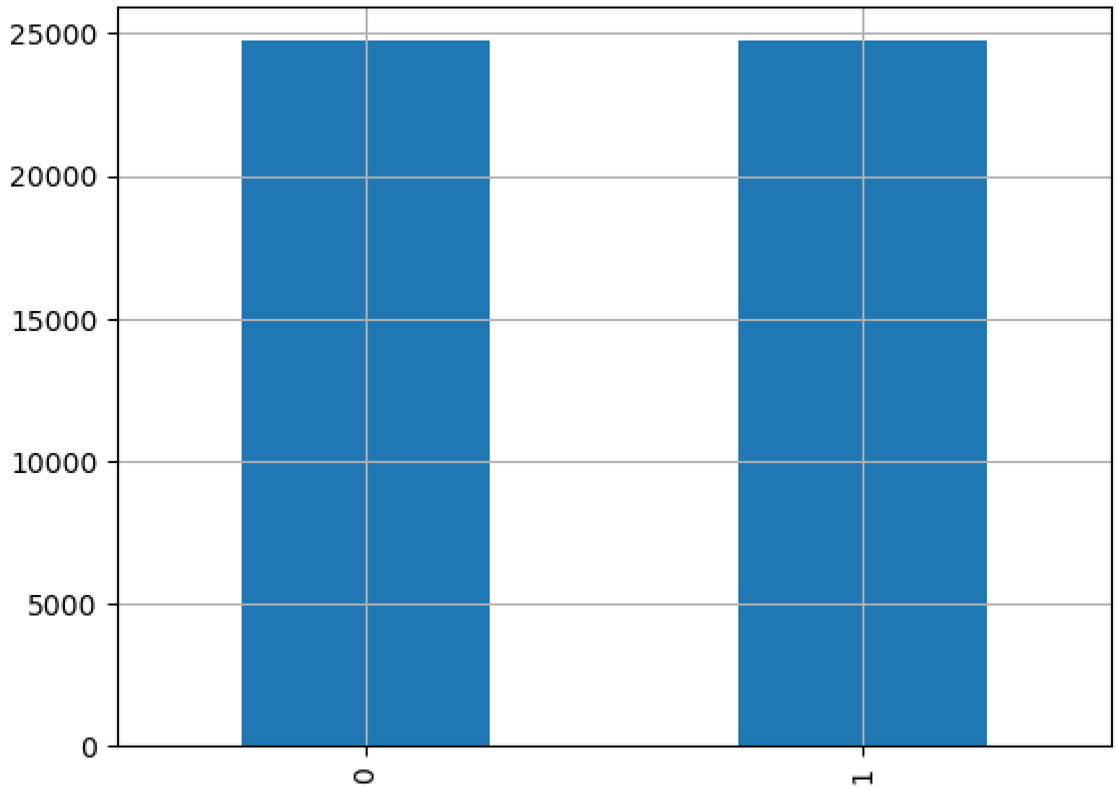
In [165]:

```
# Check value counts of original and resampled y
print("Original y value counts:")
print(y.value_counts())
print("Resampled y value counts:")
print(pd.Series(y_res1).value_counts())
```

```
Original y value counts:
0    24720
1     7841
Name:  salary, dtype: int64
Resampled y value counts:
0    24720
1    24720
Name:  salary, dtype: int64
```

In [166]:

```
# Plot bar chart of resampled y value counts
pd.Series(y_res1).value_counts().plot.bar()
plt.grid()
```



Retraining and Re-evaluation

1) Decision Tree Classifier

In [167]:

```
X_train, X_test, y_train, y_test = train_test_split(X_res1, y_res1, test_size=0.2, rando


print("X_train.shape:", X_train.shape)
print("y_train.shape:", y_train.shape)
print("X_test.shape:", X_test.shape)
print("y_test.shape:", y_test.shape)
```

```
X_train.shape: (39552, 10)
y_train.shape: (39552,)
X_test.shape: (9888, 10)
y_test.shape: (9888,)
```

In [168]:

```
# Decision Tree Classifier
dt = DecisionTreeClassifier()
dt.fit(X_train, y_train)

dt_train_pred = dt.predict(X_train)
dt_test_pred = dt.predict(X_test)
```

In [169]:

```
print('Decision Tree Classifier (after SMOTE) Train Accuracy: ', accuracy_score(y_train,
print('Decision Tree Classifier (after SMOTE) Accuracy Score: ', accuracy_score(y_test,
```

```
Decision Tree Classifier (after SMOTE) Train Accuracy:  96.93315129449837
Decision Tree Classifier (after SMOTE) Accuracy Score:  83.59627831715211
```

Confusion Matrix

In [170]:

```
print(confusion_matrix(y_test, dt_test_pred))
```

```
[[4224  723]
 [ 899 4042]]
```

Classfication Report

In [171]:

```
print(classification_report(y_test, dt_test_pred, digits=4))
```

```
              precision    recall  f1-score   support

           0     0.8245    0.8539    0.8389      4947
           1     0.8483    0.8181    0.8329      4941

    accuracy                         0.8360      9888
   macro avg     0.8364    0.8360    0.8359      9888
weighted avg     0.8364    0.8360    0.8359      9888
```

2) Random Forest

In [172]:

```
# Random Forest Classifier
from sklearn.ensemble import RandomForestClassifier
rf_classifier = RandomForestClassifier(n_estimators = 20, criterion = 'entropy' ,random_
rf_classifier.fit(X_train, y_train)
y_pred = rf_classifier.predict(X_test)
accuracy_score(y_test, y_pred)*100
```

Out[172]:

```
86.5796925566343
```

Classification Report

In [173]:

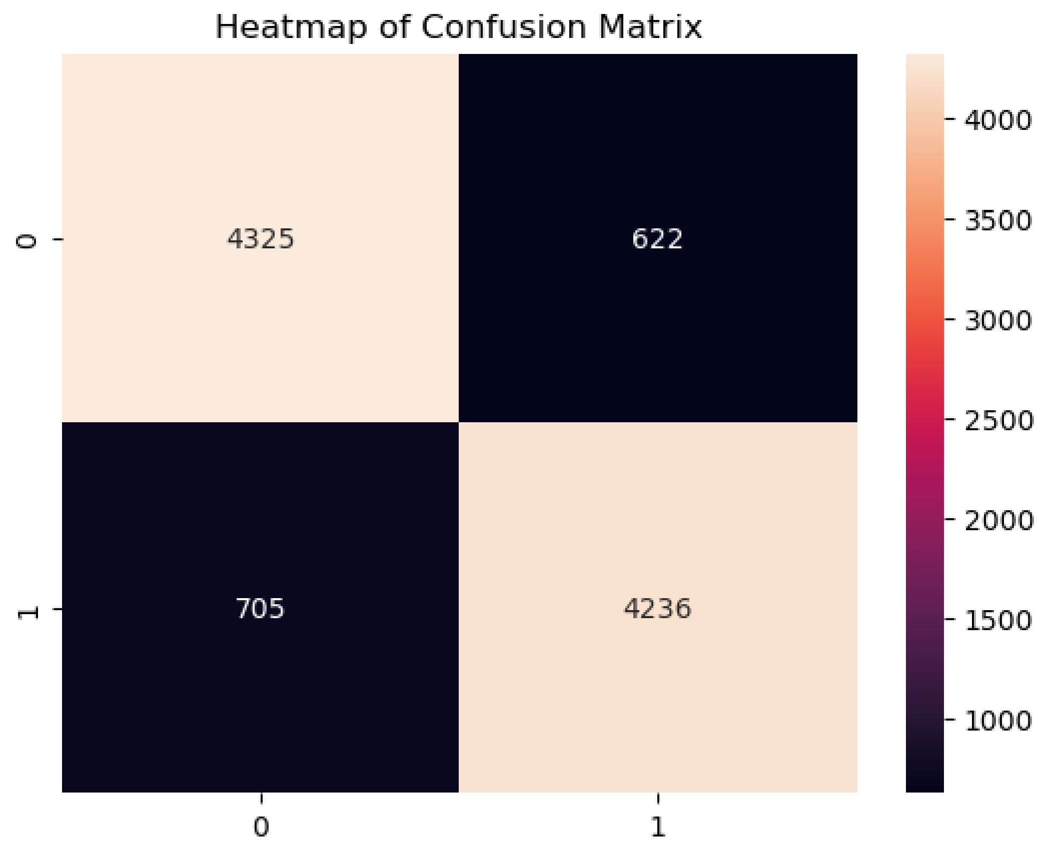
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.86      0.87      0.87      4947
           1       0.87      0.86      0.86      4941

    accuracy                           0.87      9888
   macro avg       0.87      0.87      0.87      9888
weighted avg       0.87      0.87      0.87      9888
```

Confusion Report

In [174]:

```
cm = confusion_matrix(y_test, y_pred )
plt.title('Heatmap of Confusion Matrix', fontsize = 12)
sns.heatmap(cm, annot = True ,  fmt = "d")
plt.show()
```



3)SVM

In [175]:

```
# Train Support Vector Classifier (SVC)
svc_model = SVC()
svc_model.fit(X_train, y_train)

# Predict on training and testing sets using SVC
svc_train_pred = svc_model.predict(X_train)
svc_test_pred = svc_model.predict(X_test)
```

In [176]:

```
# Print accuracy scores and confusion matrix for SVC
print('Train Accuracy:', accuracy_score(y_train, svc_train_pred) * 100)
print('Accuracy Score:', accuracy_score(y_test, svc_test_pred) * 100)
```

```
Train Accuracy: 78.85821197411003
Accuracy Score: 78.47896440129449
```

Confusion Report

In [177]:

```
print(confusion_matrix(y_test, svc_test_pred))
```

```
[[3752 1195]
 [ 933 4008]]
```

Classification Report

In [178]:

```
print(classification_report(y_test, svc_test_pred, digits=4))
```

```
              precision    recall  f1-score   support

           0     0.8009    0.7584    0.7791      4947
           1     0.7703    0.8112    0.7902      4941

    accuracy                         0.7848      9888
   macro avg     0.7856    0.7848    0.7846      9888
weighted avg     0.7856    0.7848    0.7846      9888
```

In [ ]: