R00195793

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0.2 Establish Baseline

[1]:
```
import os
import numpy as np
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score,confusion_matrix
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn import svm
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier,␣
↪GradientBoostingClassifier, VotingClassifier, BaggingClassifier,␣
↪ExtraTreesClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import GridSearchCV, cross_val_score,␣
↪cross_val_predict, StratifiedKFold, learning_curve, train_test_split, KFold
# from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import RidgeClassifier
from sklearn.svm import SVC
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from imblearn.over_sampling import SMOTE
import seaborn as sb
```

```
from sklearn.pipeline import Pipeline
from sklearn.metrics import f1_score
```

[2]:
```
data = pd.read_csv('adult.csv',delimiter=",", names=["age", "workclass",␣
↪"fnlwgt",␣
↪"education","education-num","marital-status","occupation","relationship","race","sex","capi
```

[3]:
```
data.head()
```

[3]:
```
   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 income
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
```

0.2.1 Dealing with Missing values

[4]:
```
data.replace("?", np.nan, inplace = True)
data.head(5)
```

[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 income
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]:
```
data.isnull().sum()
```

[5]:
```
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
income               0
dtype: int64
```

[6]:
```
workclass_mode = data['workclass'].value_counts().idxmax()
occupation_mode = data['occupation'].value_counts().idxmax()
native_country_mode = data['native-country'].value_counts().idxmax()
```

0.3 Replace all null values into by most frequent value

[7]:
```
data.head()
```

[7]:
```
   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 income
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
```

[8]:
```python
data_man = data

data_man["workclass"].replace(np.nan, workclass_mode, inplace = True)
data_man["occupation"].replace(np.nan, occupation_mode, inplace = True)
data_man["native-country"].replace(np.nan, native_country_mode, inplace = True)
```

[9]:
```python
data.head()
```

[9]:
```
   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 income
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
```

[10]:
```python
data_man.isnull().sum()
```

[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
income            0
dtype: int64
```

0.4 Dealing with Outliers

[11]:
```
data.skew()
```

[11]:
```
age                0.558743
fnlwgt             1.446980
education-num     -0.311676
capital-gain      11.953848
capital-loss       4.594629
hours-per-week     0.227643
dtype: float64
```

[12]:
```
num_data = [i for i in data.columns if data[i].dtype != 'O']
format(len(num_data))
```

[12]:
```
'6'
```

[13]:
```
'The numerical variables are :', num_data
```

[13]:
```
('The numerical variables are :',
 ['age',
  'fnlwgt',
  'education-num',
  'capital-gain',
  'capital-loss',
  'hours-per-week'])
```

[14]:
```
data_loss_withoutzero=data.loc[data["capital-loss"]!=0,:]
data_loss_withoutzero.head()
```

[14]:
```
    age         workclass  fnlwgt    education  education-num  \
23   43           Private  117037         11th              7
32   45           Private  386940    Bachelors             13
52   47           Private   51835  Prof-school             15
93   30           Private  117747      HS-grad              9
96   48  Self-emp-not-inc  191277    Doctorate             16
```

```
       marital-status         occupation relationship                race  \
23  Married-civ-spouse  Transport-moving      Husband               White
32            Divorced   Exec-managerial    Own-child               White
52  Married-civ-spouse    Prof-specialty         Wife               White
93  Married-civ-spouse             Sales         Wife  Asian-Pac-Islander
96  Married-civ-spouse    Prof-specialty      Husband               White

       sex  capital-gain  capital-loss  hours-per-week native-country income
23    Male             0          2042              40  United-States  <=50K
32    Male             0          1408              40  United-States  <=50K
52  Female             0          1902              60       Honduras   >50K
93  Female             0          1573              35  United-States  <=50K
96    Male             0          1902              60  United-States   >50K
```

[15]:
```
data_gain_withoutzero=data.loc[data["capital-gain"]!=0,:]
data_gain_withoutzero.head()
```

[15]:
```
    age  workclass  fnlwgt  education  education-num      marital-status  \
0    39  State-gov   77516  Bachelors             13       Never-married
8    31    Private   45781    Masters             14       Never-married
9    42    Private  159449  Bachelors             13  Married-civ-spouse
59   30    Private  188146    HS-grad              9  Married-civ-spouse
60   30    Private   59496  Bachelors             13  Married-civ-spouse

           occupation   relationship   race     sex  capital-gain  \
0        Adm-clerical  Not-in-family  White    Male          2174
8      Prof-specialty  Not-in-family  White  Female         14084
9     Exec-managerial        Husband  White    Male          5178
59  Machine-op-inspct        Husband  White    Male          5013
60              Sales        Husband  White    Male          2407

    capital-loss  hours-per-week native-country income
0              0              40  United-States  <=50K
8              0              50  United-States   >50K
9              0              40  United-States   >50K
59             0              40  United-States  <=50K
60             0              40  United-States  <=50K
```

[16]:
```
num_col=list(data.select_dtypes(include=["int64"]).columns)
num_col
```

[16]:
```
['age',
 'fnlwgt',
 'education-num',
 'capital-gain',
 'capital-loss',
```

```
 'hours-per-week']
```

[17]:
```
l_limits=[]
u_limits=[]
QR_values=[]

for i in range(len(num_col)):

    q1=data[num_col[i]].quantile(0.25)
    q3=data[num_col[i]].quantile(0.75)
    QR=q3-q1
    QR_values.append(QR)
    l_limit=q1-(1.5*QR)
    l_limits.append(l_limit)
    u_limit=q3+1.5*QR
    u_limits.append(u_limit)
```

[18]:
```
QR=pd.DataFrame({"numeric_columns":num_col,"lower_limits":l_limits,
                        "upper_limits":u_limits,"IQR_values":QR_values})
QR
```

[18]:

	numeric_columns	lower_limits	upper_limits	IQR_values
0	age	-2.0	78.0	20.0
1	fnlwgt	-61009.0	415887.0	119224.0
2	education-num	4.5	16.5	3.0
3	capital-gain	0.0	0.0	0.0
4	capital-loss	0.0	0.0	0.0
5	hours-per-week	32.5	52.5	5.0

[19]:
```
Q1_loss=data[data["capital-loss"]!=0]["capital-loss"].quantile(0.25)
Q3_loss=data[data["capital-loss"]!=0]["capital-loss"].quantile(0.75)
IQR_loss=Q3_loss-Q1_loss
lower_limit_loss=Q1_loss-(1.5*IQR_loss)
upper_limit_loss=Q3_loss+(1.5*IQR_loss)
```

[20]:
```
"Capital-Loss Lower Limit :",lower_limit_loss
```

[20]:
```
('Capital-Loss Lower Limit :', 1214.5)
```

[21]:
```
"Capital-Loss Upper Limit :",upper_limit_loss
```

[21]:
```
('Capital-Loss Upper Limit :', 2434.5)
```

[22]:
```
Q1_gain=data[data["capital-gain"]!=0]["capital-gain"].quantile(0.25)
Q3_gain=data[data["capital-gain"]!=0]["capital-gain"].quantile(0.75)
IQR_gain=Q3_gain-Q1_gain
l_limit_gain=Q1_gain-(1.5*IQR_gain)
u_limit_gain=Q3_gain+(1.5*IQR_gain)
```

[23]:
```
print("outlier number for hours-per-week : {}".
↪format(data[(data["hours-per-week"]<(l_limits[4]))|(data["hours-per-week"]>(u_limits[4]))].
↪shape[0]))
```

```
outlier number for hours-per-week : 32561
```

[24]:
```
print("Final Weight Outlier Number :{}".
↪format(data[(data["fnlwgt"]<(l_limits[1]))|(data["fnlwgt"]>(u_limits[1]))].
↪shape[0]))
```

```
Final Weight Outlier Number :992
```

[25]:
```
data.drop(data[data["fnlwgt"]>900000].index,inplace=True)
```

[26]:
```
round(data[num_data].describe()), 2
```

[26]:
```
(            age    fnlwgt  education-num  capital-gain  capital-loss  \
 count  32541.0   32541.0        32541.0       32541.0       32541.0
 mean      39.0  189215.0           10.0        1078.0          87.0
 std       14.0  103014.0            3.0        7387.0         403.0
 min       17.0   12285.0            1.0           0.0           0.0
 25%       28.0  117791.0            9.0           0.0           0.0
 50%       37.0  178322.0           10.0           0.0           0.0
 75%       48.0  236879.0           12.0           0.0           0.0
 max       90.0  889965.0           16.0       99999.0        4356.0

        hours-per-week
 count         32541.0
 mean             40.0
 std              12.0
 min               1.0
 25%              40.0
 50%              40.0
 75%              45.0
 max              99.0  ,
 2)
```

0.4.1 Categorical Data

[27]:
```
data['sex'] = data['sex'].map({'Male': '1', 'Female': '0'})
data['income'] = data['income'].map({'<=50K': 0, '>50K': 1})
data['race'] = data['race'].map({'White': 1, 'Asian-Pac-Islander': 1, 'Black':
↪0, 'Amer-Indian-Eskimo':0, 'Other':0})
data['relationship'] = data['relationship'].map({'Not-in-family':0, 'Unmarried':
↪0, 'Own-child':0, 'Other-relative':0, 'Husband':1, 'Wife':1})

data.drop(['marital-status'], axis=1,inplace=True)
data.drop(['education'], axis=1,inplace=True)
```

0.4.2 LableEncoder

[28]:
```
data.head()
```

[28]:
```
   age         workclass  fnlwgt  education-num         occupation  \
0   39         State-gov   77516             13       Adm-clerical
1   50  Self-emp-not-inc   83311             13    Exec-managerial
2   38           Private  215646              9  Handlers-cleaners
3   53           Private  234721              7  Handlers-cleaners
4   28           Private  338409             13     Prof-specialty

   relationship  race  sex  capital-gain  capital-loss  hours-per-week  \
0             0     1    1          2174             0              40
1             1     1    1             0             0              13
2             0     1    1             0             0              40
3             1     0    1             0             0              40
4             1     0    0             0             0              40

  native-country  income
0  United-States       0
1  United-States       0
2  United-States       0
3  United-States       0
4           Cuba       0
```

[29]:
```
labels = ['workclass', 'occupation', 'native-country']
le = LabelEncoder()
for l in labels:
    data[l]=le.fit_transform(data[l])
data
```

[29]:
```
       age  workclass  fnlwgt  education-num  occupation  relationship  race  \
0       39          6   77516             13           0             0     1
1       50          5   83311             13           3             1     1
2       38          3  215646              9           5             0     1
3       53          3  234721              7           5             1     0
4       28          3  338409             13           9             1     0
…     …          …      …              …           …            …   …
32556   27          3  257302             12          12             1     1
32557   40          3  154374              9           6             1     1
32558   58          3  151910              9           0             0     1
32559   22          3  201490              9           0             0     1
32560   52          4  287927              9           3             1     1

       sex  capital-gain  capital-loss  hours-per-week  native-country  income
0        1          2174             0              40              38       0
1        1             0             0              13              38       0
2        1             0             0              40              38       0
```

```
3        1           0           0           40          38       0
4        0           0           0           40           4       0
…      ..        …           …           …           …       …
32556    0           0           0           38          38       0
32557    1           0           0           40          38       1
32558    0           0           0           40          38       0
32559    1           0           0           20          38       0
32560    0       15024           0           40          38       1

[32541 rows x 13 columns]
```

0.5 Scaling Data

[30]:
```python
X = StandardScaler().fit_transform(data.loc[:, data.columns != 'income'])
Y = data['income']
```

0.6 Handling imbalance data with using SMOTE

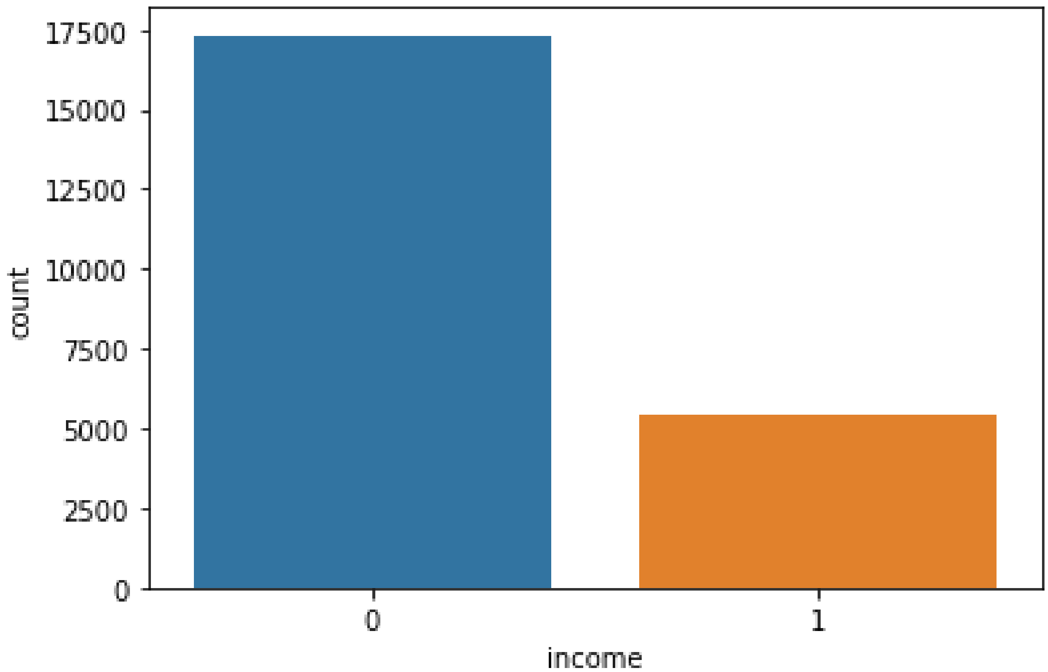
[31]:
```python
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.3,␣
↪random_state = 0)
```

[32]:
```python
Y_test.shape
```

[32]:
```
(9763,)
```

[33]:
```python
import seaborn as sb
plot_sb = sb.countplot(Y_train, label='Total')
greaterthan50, lessthan50 = Y_train.value_counts()
print('<=50K: ',lessthan50)
print('>50K : ',greaterthan50)
```

```
<=50K:  5441
>50K :  17337
```



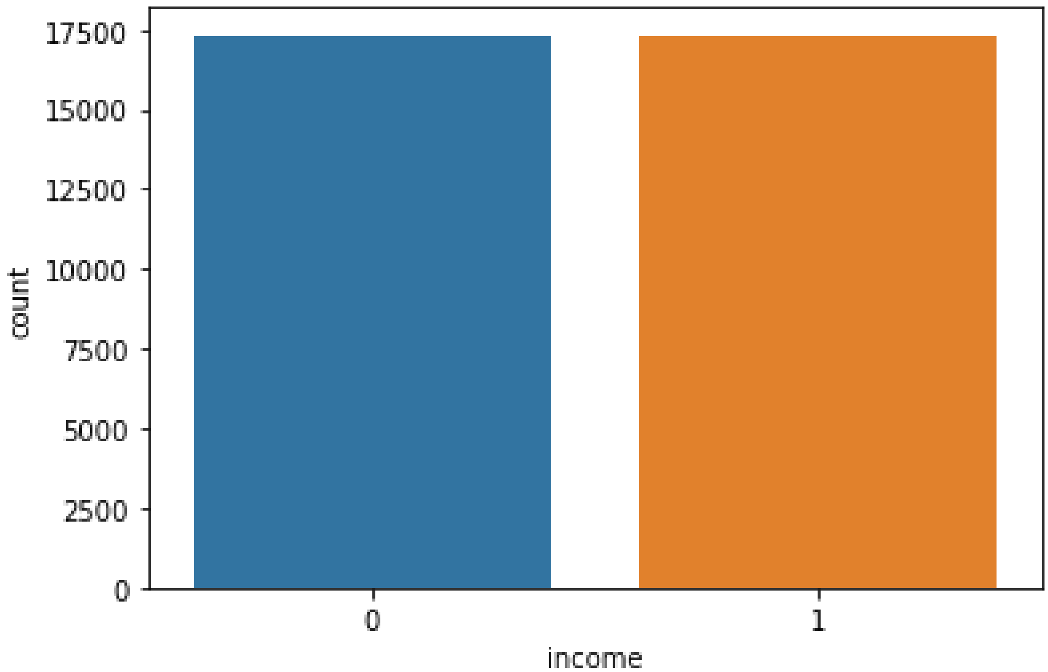
[34]:
```
print(X_train.shape)
print(Y_train.shape)
print(X_test.shape)
print(Y_test.shape)
```

```
(22778, 12)
(22778,)
(9763, 12)
(9763,)
```

[35]:
```
sm = SMOTE(random_state=0)
X_train, Y_train = sm.fit_sample(X_train, Y_train)
```

[36]:
```
plot_sb = sb.countplot(Y_train, label='Total')
greaterthan50, lessthan50 = Y_train.value_counts()
print('<=50K: ',lessthan50)
print('>50K : ',greaterthan50)
```

```
<=50K:  17337
>50K :  17337
```



0.6.1 Implementation of classifier

[37]:
```
classifiers = [LogisticRegression(solver='newton-cg'),
    KNeighborsClassifier(n_neighbors=17),
    LinearDiscriminantAnalysis(),
    GaussianNB(),
    RidgeClassifier(),GradientBoostingClassifier(),
    SVC(),RandomForestClassifier()]

for classifier in classifiers:
        print(type(classifier).__name__)
        pipe = Pipeline(steps=[('classifier', classifier)])
        pipe.fit(X_train, Y_train)
        Y_pred= pipe.predict(X_test)
        score = pipe.score(X_train, Y_train)
        print("F1 score: {:}".format(f1_score(Y_test,Y_pred)))
```

```
LogisticRegression
F1 score: 0.6743065935891049
KNeighborsClassifier
F1 score: 0.6535586610334742
LinearDiscriminantAnalysis
F1 score: 0.641818744200433
GaussianNB
```

```
F1 score: 0.5793438639125151
RidgeClassifier
F1 score: 0.641818744200433
GradientBoostingClassifier
F1 score: 0.7031814895155458
SVC
F1 score: 0.6694560669456067
RandomForestClassifier
F1 score: 0.6903160040774721
```

0.7 Hyperparameter tuning

Random Search

[38]:
```
from sklearn.model_selection import RandomizedSearchCV
# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 200, stop = 2000, num = 10)]

# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(10, 110, num = 11)]
max_depth.append(None)


objrandom_grid = {'n_estimators': n_estimators,
               'max_depth': max_depth,
               }
```

0.8 Random Forest Classifier with Hyper parameter tunning

[39]:
```
objrf = RandomForestClassifier()
objrf = RandomizedSearchCV(estimator = objrf,scoring= "f1", param_distributions␣
↪= objrandom_grid, n_iter = 10, cv = 3, verbose=2, random_state=42, n_jobs =␣
↪-1,)
objrf.fit(X_train, Y_train)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  23 out of  30 | elapsed:  1.4min remaining:   26.4s
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:  2.0min finished
```

[39]:
```
RandomizedSearchCV(cv=3, estimator=RandomForestClassifier(), n_jobs=-1,
                   param_distributions={'max_depth': [10, 20, 30, 40, 50, 60,
                                                      70, 80, 90, 100, 110,
                                                      None],
                                        'n_estimators': [200, 400, 600, 800,
                                                         1000, 1200, 1400, 1600,
                                                         1800, 2000]},
                   random_state=42, scoring='f1', verbose=2)
```

[40]:
```
objrf.best_estimator_
```

[40]:
```
RandomForestClassifier(max_depth=50, n_estimators=200)
```

[41]:
```
objrf.best_score_
```

[41]:
```
0.8908419875378314
```

[42]:
```
objrf = RandomForestClassifier(max_depth=50, n_estimators=200)
objrf.fit(X_train, Y_train)
y_pred = objrf.predict(X_test)
print(f1_score(Y_test,y_pred))
```

```
0.6940695296523517
```

0.9 GradientBoostingClassifier with hyper parameter tunning

[45]:
```
objrf = GradientBoostingClassifier()
objrf_random = RandomizedSearchCV(estimator = objrf,scoring= "f1",␣
↪param_distributions = objrandom_grid, n_iter = 10, cv = 3, verbose=2,␣
↪random_state=42, n_jobs = -1,)
objrf_random.fit(X_train, Y_train)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  23 out of  30 | elapsed: 17.5min remaining:  5.3min
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed: 25.1min finished
```

[45]:
```
RandomizedSearchCV(cv=3, estimator=GradientBoostingClassifier(), n_jobs=-1,
                   param_distributions={'max_depth': [10, 20, 30, 40, 50, 60,
                                                      70, 80, 90, 100, 110,
                                                      None],
                                        'n_estimators': [200, 400, 600, 800,
                                                         1000, 1200, 1400, 1600,
                                                         1800, 2000]},
                   random_state=42, scoring='f1', verbose=2)
```

[46]:
```
objrf_random.best_estimator_
```

[46]:
```
GradientBoostingClassifier(max_depth=20, n_estimators=200)
```

[47]:
```
objrf_random.best_score_
```

[47]:
```
0.8527389015815259
```

[48]:
```
objrf = GradientBoostingClassifier(max_depth=60,␣
↪max_features='sqrt',min_samples_split=5, n_estimators=200)
objrf_random.fit(X_train, Y_train)
```

```
y_pred = objrf_random.predict(X_test)
print(f1_score(Y_test,y_pred))
```

```
0.7186393780783727
```

0.10 Logistic Regression with hyper parameter tunning

[40]:
```
!pip install sklearn.learning_curve
```

```
ERROR: Could not find a version that satisfies the requirement
sklearn.learning_curve (from versions: none)
ERROR: No matching distribution found for sklearn.learning_curve
```

[49]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.model_selection import learning_curve, GridSearchCV
from sklearn.metrics import f1_score


C_param_range = [0.001,0.01,0.1,1,10,100]

sepal_acc_table = pd.DataFrame(columns = ['C_parameter','f1 score'])
sepal_acc_table['C_parameter'] = C_param_range


j = 0
for i in C_param_range:

    # Apply logistic regression model to training data
    lr = LogisticRegression(penalty = 'l2', C = i,random_state = 0)
    lr.fit(X_train,Y_train)

    # Predict using model
    y_pred = lr.predict(X_test)

    # Saving accuracy score in table
    sepal_acc_table.iloc[j,1] = f1_score(Y_test,y_pred)

    j += 1

print(max(sepal_acc_table['f1 score']))
```

```
0.6744186046511629
```

0.11 Basic Experimentation

[50]:
```
import numpy as np
import pandas as pd
import os
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score,confusion_matrix
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn import svm
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier,␣
↪GradientBoostingClassifier, VotingClassifier, BaggingClassifier,␣
↪ExtraTreesClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import GridSearchCV, cross_val_score,␣
↪cross_val_predict, StratifiedKFold, learning_curve, train_test_split, KFold
# from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import RidgeClassifier
from sklearn.svm import SVC
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.metrics import f1_score

data = pd.read_csv('adult.csv',delimiter=",", names=["age", "workclass",␣
↪"fnlwgt",␣
↪"education","education-num","marital-status","occupation","relationship","race","sex","capi


data.replace("?", np.nan, inplace = True)
data.head(5)

data.isnull().sum()
```

```
workclass_mode = data['workclass'].value_counts().idxmax()
occupation_mode = data['occupation'].value_counts().idxmax()
native_country_mode = data['native-country'].value_counts().idxmax()

data_man = data

data_man["workclass"].replace(np.nan, workclass_mode, inplace = True)
data_man["occupation"].replace(np.nan, occupation_mode, inplace = True)
data_man["native-country"].replace(np.nan, native_country_mode, inplace = True)

data_man.isnull().sum()

data.skew()

num_data = [i for i in data.columns if data[i].dtype != 'O']
format(len(num_data))

data_loss_withoutzero=data.loc[data["capital-loss"]!=0,:]
data_loss_withoutzero.head()

data_gain_withoutzero=data.loc[data["capital-gain"]!=0,:]
data_gain_withoutzero.head()

num_col=list(data.select_dtypes(include=["int64"]).columns)
num_col

lower_limits=[]
upper_limits=[]
IQR_values=[]

for i in range(len(num_col)):

    Q1=data[num_col[i]].quantile(0.25)
    Q3=data[num_col[i]].quantile(0.75)
    IQR=Q3-Q1
    IQR_values.append(IQR)
    lower_limit=Q1-(1.5*IQR)
    lower_limits.append(lower_limit)
    upper_limit=Q3+1.5*IQR
    upper_limits.append(upper_limit)

IQR_t=pd.DataFrame({"numeric_columns":num_col,"lower_limits":lower_limits,
                        "upper_limits":upper_limits,"IQR_values":IQR_values})
IQR_t

Q1_loss=data[data["capital-loss"]!=0]["capital-loss"].quantile(0.25)
```

```
Q3_loss=data[data["capital-loss"]!=0]["capital-loss"].quantile(0.75)
IQR_loss=Q3_loss-Q1_loss
lower_limit_loss=Q1_loss-(1.5*IQR_loss)
upper_limit_loss=Q3_loss+(1.5*IQR_loss)

Q1_gain=data[data["capital-gain"]!=0]["capital-gain"].quantile(0.25)
Q3_gain=data[data["capital-gain"]!=0]["capital-gain"].quantile(0.75)
IQR_gain=Q3_gain-Q1_gain
lower_limit_gain=Q1_gain-(1.5*IQR_gain)
upper_limit_gain=Q3_gain+(1.5*IQR_gain)

data.drop(data[data["fnlwgt"]>900000].index,inplace=True)

round(data[num_data].describe()), 2


data['sex'] = data['sex'].map({'Male': '1', 'Female': '0'})
data['income'] = data['income'].map({'<=50K': 0, '>50K': 1})
data['race'] = data['race'].map({'White': 1, 'Asian-Pac-Islander': 1, 'Black':
 ↪0, 'Amer-Indian-Eskimo':0, 'Other':0})
data['relationship'] = data['relationship'].map({'Not-in-family':0, 'Unmarried':
 ↪0, 'Own-child':0, 'Other-relative':0, 'Husband':1, 'Wife':1})

data.drop(['marital-status'], axis=1,inplace=True)
data.drop(['education'], axis=1,inplace=True)
data.head()
```

[50]:

```
   age         workclass  fnlwgt  education-num         occupation  \
0   39         State-gov   77516             13       Adm-clerical
1   50  Self-emp-not-inc   83311             13    Exec-managerial
2   38           Private  215646              9  Handlers-cleaners
3   53           Private  234721              7  Handlers-cleaners
4   28           Private  338409             13     Prof-specialty

   relationship  race sex  capital-gain  capital-loss  hours-per-week  \
0             0     1   1          2174             0              40
1             1     1   1             0             0              13
2             0     1   1             0             0              40
3             1     0   1             0             0              40
4             1     0   0             0             0              40

  native-country  income
0  United-States       0
1  United-States       0
2  United-States       0
3  United-States       0
4           Cuba       0
```

0.12 OneHot Encoder Implementation

[51]:
```
data=pd.get_dummies(data, columns=['workclass'], drop_first=True)
data=pd.get_dummies(data, columns=['occupation'], drop_first=True)
data=pd.get_dummies(data, columns=['native-country'], drop_first=True)
```

[52]:
```
data
```

[52]:
```
        age  fnlwgt  education-num  relationship  race sex  capital-gain  \
0        39   77516             13             0     1   1          2174
1        50   83311             13             1     1   1             0
2        38  215646              9             0     1   1             0
3        53  234721              7             1     0   1             0
4        28  338409             13             1     0   0             0
…     …     …            …            …    …   ..           …
32556    27  257302             12             1     1   0             0
32557    40  154374              9             1     1   1             0
32558    58  151910              9             0     1   0             0
32559    22  201490              9             0     1   1             0
32560    52  287927              9             1     1   0         15024

        capital-loss  hours-per-week  income  …  native-country_Portugal  \
0                  0              40       0  …                        0
1                  0              13       0  …                        0
2                  0              40       0  …                        0
3                  0              40       0  …                        0
4                  0              40       0  …                        0
…             …              …      …   …                      …
32556              0              38       0  …                        0
32557              0              40       1  …                        0
32558              0              40       0  …                        0
32559              0              20       0  …                        0
32560              0              40       1  …                        0

        native-country_Puerto-Rico  native-country_Scotland  \
0                                0                        0
1                                0                        0
2                                0                        0
3                                0                        0
4                                0                        0
…                             …                       …
32556                            0                        0
32557                            0                        0
32558                            0                        0
32559                            0                        0
32560                            0                        0
```

```
       native-country_South  native-country_Taiwan  native-country_Thailand  \
0                         0                      0                        0
1                         0                      0                        0
2                         0                      0                        0
3                         0                      0                        0
4                         0                      0                        0
…                       …                    …                      …
32556                     0                      0                        0
32557                     0                      0                        0
32558                     0                      0                        0
32559                     0                      0                        0
32560                     0                      0                        0

       native-country_Trinadad&Tobago  native-country_United-States  \
0                                   0                             1
1                                   0                             1
2                                   0                             1
3                                   0                             1
4                                   0                             0
…                                 …                           …
32556                               0                             1
32557                               0                             1
32558                               0                             1
32559                               0                             1
32560                               0                             1

       native-country_Vietnam  native-country_Yugoslavia
0                           0                          0
1                           0                          0
2                           0                          0
3                           0                          0
4                           0                          0
…                         …                        …
32556                       0                          0
32557                       0                          0
32558                       0                          0
32559                       0                          0
32560                       0                          0

[32541 rows x 70 columns]
```

[53]:
```
from sklearn import preprocessing
X = preprocessing.MinMaxScaler().fit_transform(data.loc[:, data.columns !=␣
 ↪'income'])
Y = data['income']
```

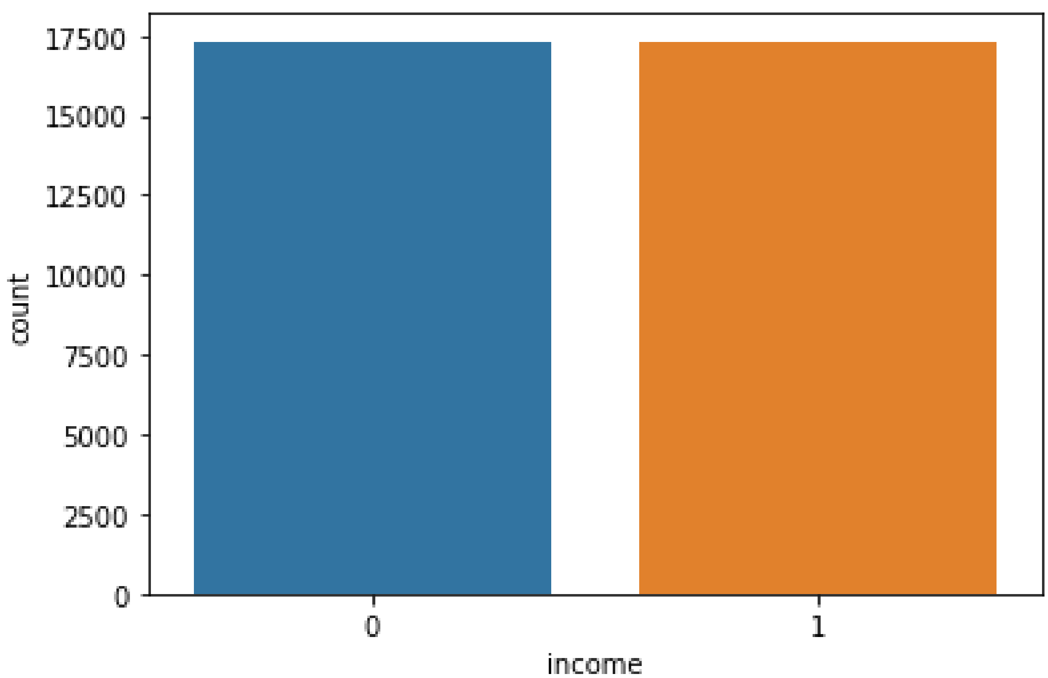
[54]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.3,␣
 ↪random_state = 0)
print(Y_train.head())
```

```
13016    0
26951    0
20919    0
30301    0
12368    0
Name: income, dtype: int64
```

[55]:
```
from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=0)
X_train, Y_train = sm.fit_sample(X_train, Y_train)
```

[56]:
```
import seaborn as sb
plot_sb = sb.countplot(Y_train, label='Total')
greaterthan50, lessthan50 = Y_train.value_counts()
print('<=50K: ',lessthan50)
print('>50K : ',greaterthan50)
```

```
<=50K:  17337
>50K :  17337
```



0.13 Feature selection techniques

[57]:
```
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier,␣
↪GradientBoostingClassifier, VotingClassifier, BaggingClassifier,␣
↪ExtraTreesClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier

from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import GridSearchCV, cross_val_score,␣
↪cross_val_predict, StratifiedKFold, learning_curve, train_test_split, KFold
# from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import RidgeClassifier
from sklearn.svm import SVC
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import GridSearchCV
```

0.13.1 SelectPercentile

[58]:
```
from sklearn.feature_selection import SelectPercentile, chi2
a = SelectPercentile(chi2, percentile=10).fit(X_train, Y_train)
X_train = a.transform(X_train)
X_test = a.transform(X_test)
```

[59]:
```
from sklearn.pipeline import Pipeline
from sklearn.metrics import f1_score
classifiers = [LogisticRegression(solver='newton-cg'),
    KNeighborsClassifier(n_neighbors=17), # Some trial and error I don't show␣
↪went into this hyperpa
    LinearDiscriminantAnalysis(),
    GaussianNB(),
    RidgeClassifier(),GradientBoostingClassifier(),
    SVC(),BaggingClassifier(),RandomForestClassifier()]

for classifier in classifiers:
        print(type(classifier).__name__)
        pipe = Pipeline(steps=[('classifier', classifier)])
        pipe.fit(X_train, Y_train)
        Y_pred= pipe.predict(X_test)
```

```
        score = pipe.score(X_train, Y_train)
        print("F1 score: {:.2f}".format(f1_score(Y_test,Y_pred)))
```

```
LogisticRegression
F1 score: 0.62
KNeighborsClassifier
F1 score: 0.61
LinearDiscriminantAnalysis
F1 score: 0.61
GaussianNB
F1 score: 0.52
RidgeClassifier
F1 score: 0.61
GradientBoostingClassifier
F1 score: 0.62
SVC
F1 score: 0.62
BaggingClassifier
F1 score: 0.63
RandomForestClassifier
F1 score: 0.63
```

0.14 Research

[2]:
```
data = pd.read_csv('adult.csv',delimiter=",", names=["age", "workclass",␣
 ↪"fnlwgt",␣
 ↪"education","education-num","marital-status","occupation","relationship","race","sex","capi



data.replace("?", np.nan, inplace = True)
data.head(5)

data.isnull().sum()

workclass_mode = data['workclass'].value_counts().idxmax()
occupation_mode = data['occupation'].value_counts().idxmax()
native_country_mode = data['native-country'].value_counts().idxmax()

data_man = data

data_man["workclass"].replace(np.nan, workclass_mode, inplace = True)
data_man["occupation"].replace(np.nan, occupation_mode, inplace = True)
data_man["native-country"].replace(np.nan, native_country_mode, inplace = True)

data_man.isnull().sum()

data.skew()
```

```
num_data = [i for i in data.columns if data[i].dtype != 'O']
format(len(num_data))

data_loss_withoutzero=data.loc[data["capital-loss"]!=0,:]
data_loss_withoutzero.head()

data_gain_withoutzero=data.loc[data["capital-gain"]!=0,:]
data_gain_withoutzero.head()

num_col=list(data.select_dtypes(include=["int64"]).columns)
num_col

lower_limits=[]
upper_limits=[]
IQR_values=[]

for i in range(len(num_col)):

    Q1=data[num_col[i]].quantile(0.25)
    Q3=data[num_col[i]].quantile(0.75)
    IQR=Q3-Q1
    IQR_values.append(IQR)
    lower_limit=Q1-(1.5*IQR)
    lower_limits.append(lower_limit)
    upper_limit=Q3+1.5*IQR
    upper_limits.append(upper_limit)

IQR_t=pd.DataFrame({"numeric_columns":num_col,"lower_limits":lower_limits,
                        "upper_limits":upper_limits,"IQR_values":IQR_values})
IQR_t

Q1_loss=data[data["capital-loss"]!=0]["capital-loss"].quantile(0.25)
Q3_loss=data[data["capital-loss"]!=0]["capital-loss"].quantile(0.75)
IQR_loss=Q3_loss-Q1_loss
lower_limit_loss=Q1_loss-(1.5*IQR_loss)
upper_limit_loss=Q3_loss+(1.5*IQR_loss)

Q1_gain=data[data["capital-gain"]!=0]["capital-gain"].quantile(0.25)
Q3_gain=data[data["capital-gain"]!=0]["capital-gain"].quantile(0.75)
IQR_gain=Q3_gain-Q1_gain
lower_limit_gain=Q1_gain-(1.5*IQR_gain)
upper_limit_gain=Q3_gain+(1.5*IQR_gain)

data.drop(data[data["fnlwgt"]>900000].index,inplace=True)

round(data[num_data].describe()), 2
```

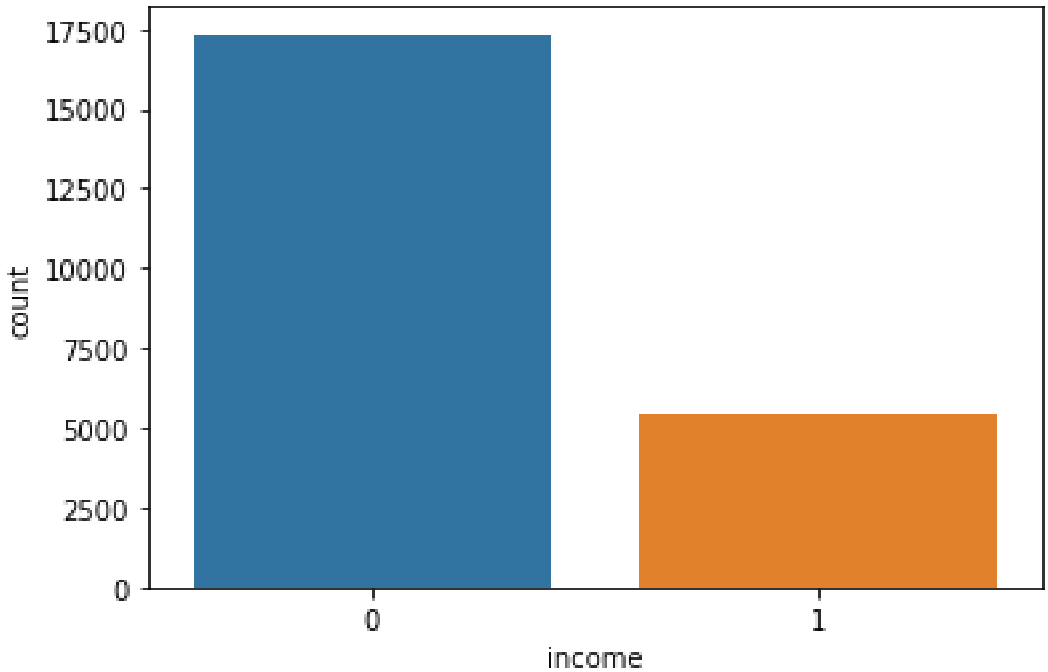
```
data['sex'] = data['sex'].map({'Male': '1', 'Female': '0'})
print(data['sex'])
data['income'] = data['income'].map({'<=50K': 0, '>50K': 1})
data['race'] = data['race'].map({'White': 1, 'Asian-Pac-Islander': 1, 'Black':
 ↪0, 'Amer-Indian-Eskimo':0, 'Other':0})
data['relationship'] = data['relationship'].map({'Not-in-family':0, 'Unmarried':
 ↪0, 'Own-child':0, 'Other-relative':0, 'Husband':1, 'Wife':1})

#relationship and marital.status contain the same information now, so one of␣
 ↪them can be removed
data.drop(['marital-status'], axis=1,inplace=True)

data.drop(['education'], axis=1,inplace=True)
data.head()

labels = ['workclass', 'occupation', 'native-country']

le = LabelEncoder()
for l in labels:
    data[l]=le.fit_transform(data[l])
data

X = StandardScaler().fit_transform(data.loc[:, data.columns != 'income'])
Y = data['income']

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.3,␣
 ↪random_state = 0)
print(Y_train.head())
```

```
0        1
1        1
2        1
3        1
4        0
        ..
32556    0
32557    1
32558    0
32559    1
32560    0
Name: sex, Length: 32541, dtype: object
13016    0
26951    0
20919    0
30301    0
```

```
12368    0
Name: income, dtype: int64
```

[3]:
```
plot_sb = sb.countplot(Y_train, label='Total')
greaterthan50, lessthan50 = Y_train.value_counts()
print('<=50K: ',lessthan50)
print('>50K : ',greaterthan50)
```

```
<=50K:  5441
>50K :  17337
```



[4]:
```
from imblearn.under_sampling import NearMiss
undersample = NearMiss(version=1, n_neighbors=3)
# transform the dataset
X_train, Y_train = undersample.fit_resample(X_train, Y_train)
```

[3]:
```
data.head()
```

[3]:

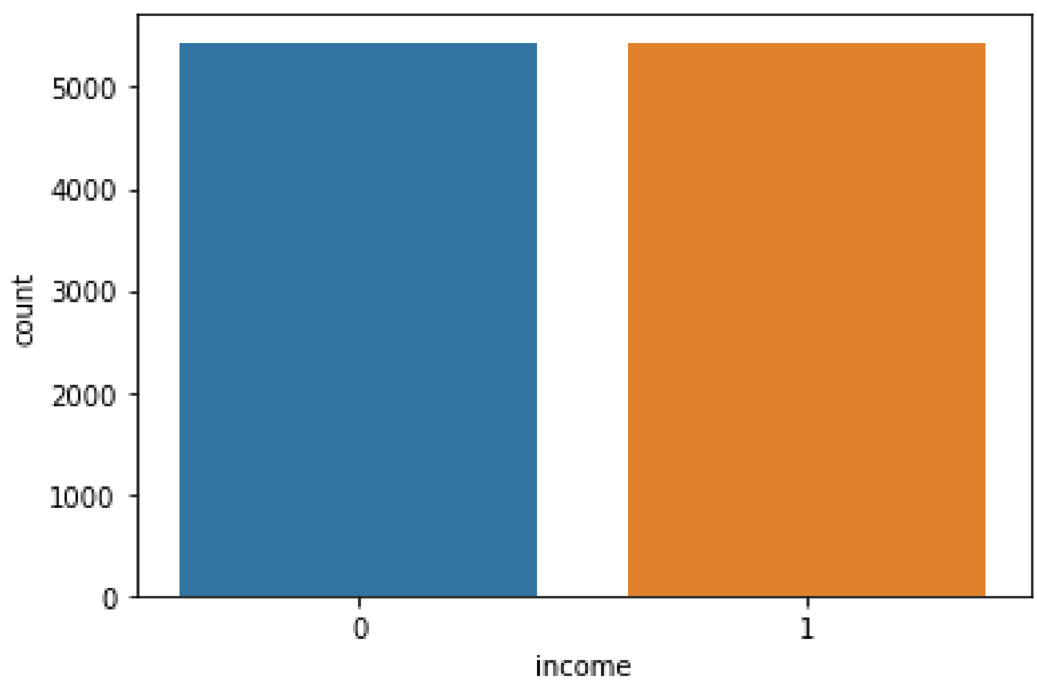
```
   age         workclass  fnlwgt  education  education-num  \
0   39         State-gov   77516  Bachelors             13
1   50  Self-emp-not-inc   83311  Bachelors             13
2   38           Private  215646    HS-grad              9
3   53           Private  234721       11th              7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

```
import seaborn as sb
plot_sb = sb.countplot(Y_train, label='Total')
greaterthan50, lessthan50 = Y_train.value_counts()
print('<=50K: ',lessthan50)
print('>50K : ',greaterthan50)
```

```
<=50K:  5441
>50K :  5441
```



[6]:

```
from sklearn.pipeline import Pipeline
from sklearn.metrics import f1_score
```

```
classifiers = [
    LogisticRegression()
    ]

for classifier in classifiers:
        print(type(classifier).__name__)
        pipe = Pipeline(steps=[('classifier', classifier)])
        pipe.fit(X_train, Y_train)
        Y_pred= pipe.predict(X_test)
        score = pipe.score(X_train, Y_train)
        print("F1 score: {:}".format(f1_score(Y_test,Y_pred)))
```

```
LogisticRegression
F1 score: 0.6189806678383127
```

0.14.1 NearMiss2

[7]:
```
data = pd.read_csv('adult.csv',delimiter=",", names=["age", "workclass",␣
↪"fnlwgt",␣
↪"education","education-num","marital-status","occupation","relationship","race","sex","capi


data.replace("?", np.nan, inplace = True)
data.head(5)

data.isnull().sum()

workclass_mode = data['workclass'].value_counts().idxmax()
occupation_mode = data['occupation'].value_counts().idxmax()
native_country_mode = data['native-country'].value_counts().idxmax()

data_man = data

data_man["workclass"].replace(np.nan, workclass_mode, inplace = True)
data_man["occupation"].replace(np.nan, occupation_mode, inplace = True)
data_man["native-country"].replace(np.nan, native_country_mode, inplace = True)

data_man.isnull().sum()

data.skew()

num_data = [i for i in data.columns if data[i].dtype != 'O']
format(len(num_data))

data_loss_withoutzero=data.loc[data["capital-loss"]!=0,:]
data_loss_withoutzero.head()

data_gain_withoutzero=data.loc[data["capital-gain"]!=0,:]
```

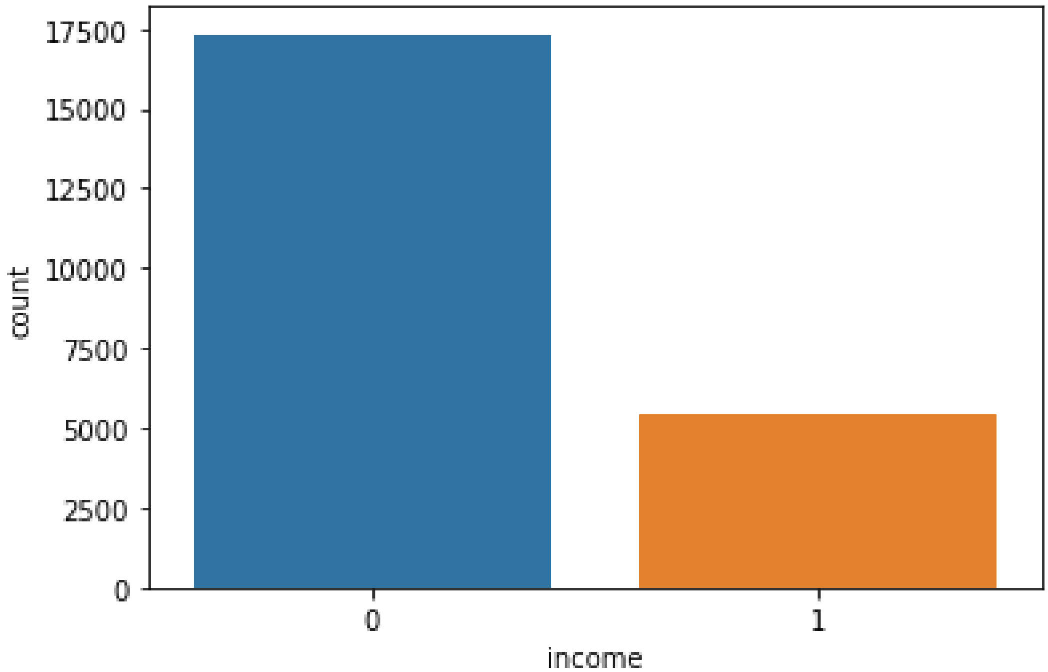
```
data_gain_withoutzero.head()

num_col=list(data.select_dtypes(include=["int64"]).columns)
num_col

lower_limits=[]
upper_limits=[]
IQR_values=[]

for i in range(len(num_col)):

    Q1=data[num_col[i]].quantile(0.25)
    Q3=data[num_col[i]].quantile(0.75)
    IQR=Q3-Q1
    IQR_values.append(IQR)
    lower_limit=Q1-(1.5*IQR)
    lower_limits.append(lower_limit)
    upper_limit=Q3+1.5*IQR
    upper_limits.append(upper_limit)

IQR_t=pd.DataFrame({"numeric_columns":num_col,"lower_limits":lower_limits,
                        "upper_limits":upper_limits,"IQR_values":IQR_values})
IQR_t

Q1_loss=data[data["capital-loss"]!=0]["capital-loss"].quantile(0.25)
Q3_loss=data[data["capital-loss"]!=0]["capital-loss"].quantile(0.75)
IQR_loss=Q3_loss-Q1_loss
lower_limit_loss=Q1_loss-(1.5*IQR_loss)
upper_limit_loss=Q3_loss+(1.5*IQR_loss)

Q1_gain=data[data["capital-gain"]!=0]["capital-gain"].quantile(0.25)
Q3_gain=data[data["capital-gain"]!=0]["capital-gain"].quantile(0.75)
IQR_gain=Q3_gain-Q1_gain
lower_limit_gain=Q1_gain-(1.5*IQR_gain)
upper_limit_gain=Q3_gain+(1.5*IQR_gain)

data.drop(data[data["fnlwgt"]>900000].index,inplace=True)

round(data[num_data].describe()), 2


data['sex'] = data['sex'].map({'Male': '1', 'Female': '0'})
print(data['sex'])
data['income'] = data['income'].map({'<=50K': 0, '>50K': 1})
data['race'] = data['race'].map({'White': 1, 'Asian-Pac-Islander': 1, 'Black':
 ↪0, 'Amer-Indian-Eskimo':0, 'Other':0})
```

```
data['relationship'] = data['relationship'].map({'Not-in-family':0, 'Unmarried':
↪0, 'Own-child':0, 'Other-relative':0, 'Husband':1, 'Wife':1})

#relationship and marital.status contain the same information now, so one of␣
↪them can be removed
data.drop(['marital-status'], axis=1,inplace=True)

data.drop(['education'], axis=1,inplace=True)
data.head()

labels = ['workclass', 'occupation', 'native-country']

le = LabelEncoder()
for l in labels:
    data[l]=le.fit_transform(data[l])
data

X = StandardScaler().fit_transform(data.loc[:, data.columns != 'income'])
Y = data['income']

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.3,␣
↪random_state = 0)
print(Y_train.head())
```

```
0        1
1        1
2        1
3        1
4        0
        ..
32556    0
32557    1
32558    0
32559    1
32560    0
Name: sex, Length: 32541, dtype: object
13016    0
26951    0
20919    0
30301    0
12368    0
Name: income, dtype: int64
```

[8]:
```
plot_sb = sb.countplot(Y_train, label='Total')
greaterthan50, lessthan50 = Y_train.value_counts()
print('<=50K: ',lessthan50)
print('>50K : ',greaterthan50)
```

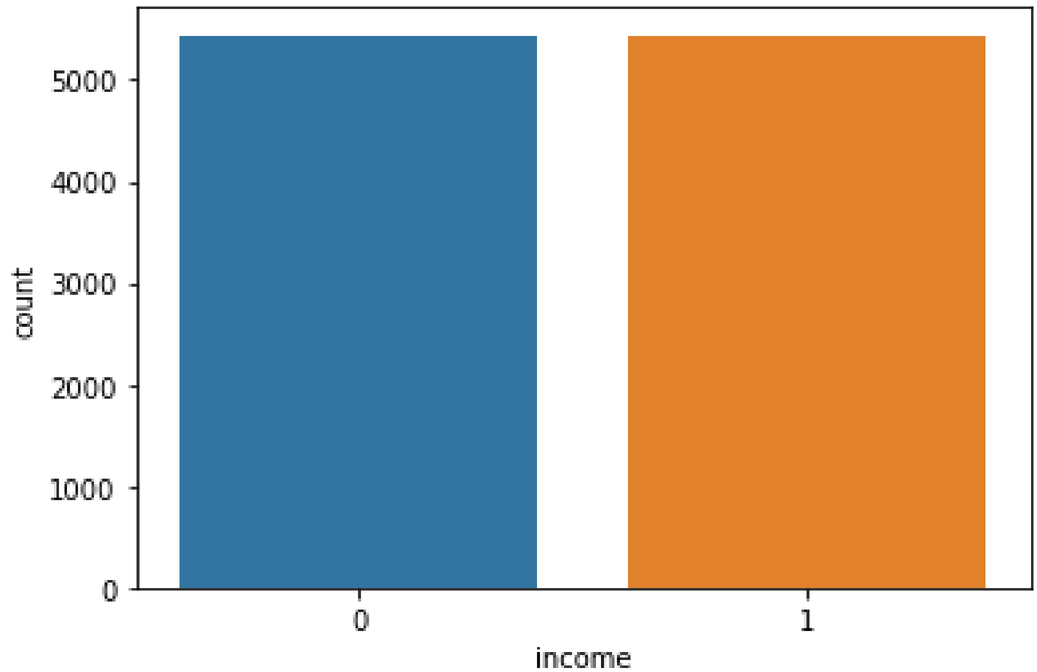
```
<=50K:  5441
>50K :  17337
```




```
[9]: from imblearn.under_sampling import NearMiss
undersample = NearMiss(version=2, n_neighbors=3)
# transform the dataset
X_train, Y_train = undersample.fit_resample(X_train, Y_train)
```

```
[10]: plot_sb = sb.countplot(Y_train, label='Total')
greaterthan50, lessthan50 = Y_train.value_counts()
print('<=50K: ',lessthan50)
print('>50K : ',greaterthan50)
```

```
<=50K:  5441
>50K :  5441
```



[11]:
```
from sklearn.pipeline import Pipeline
from sklearn.metrics import f1_score
classifiers = [
    LogisticRegression()
    ]

for classifier in classifiers:
        print(type(classifier).__name__)
        pipe = Pipeline(steps=[('classifier', classifier)])
        pipe.fit(X_train, Y_train)
        Y_pred= pipe.predict(X_test)
        score = pipe.score(X_train, Y_train)
        print("F1 score: {:}".format(f1_score(Y_test,Y_pred)))
```

```
LogisticRegression
F1 score: 0.6285090455396132
```

0.14.2 NearMiss3

[13]:
```
data = pd.read_csv('adult.csv',delimiter=",", names=["age", "workclass",␣
 ↪"fnlwgt",␣
 ↪"education","education-num","marital-status","occupation","relationship","race","sex","capi


data.replace("?", np.nan, inplace = True)
```

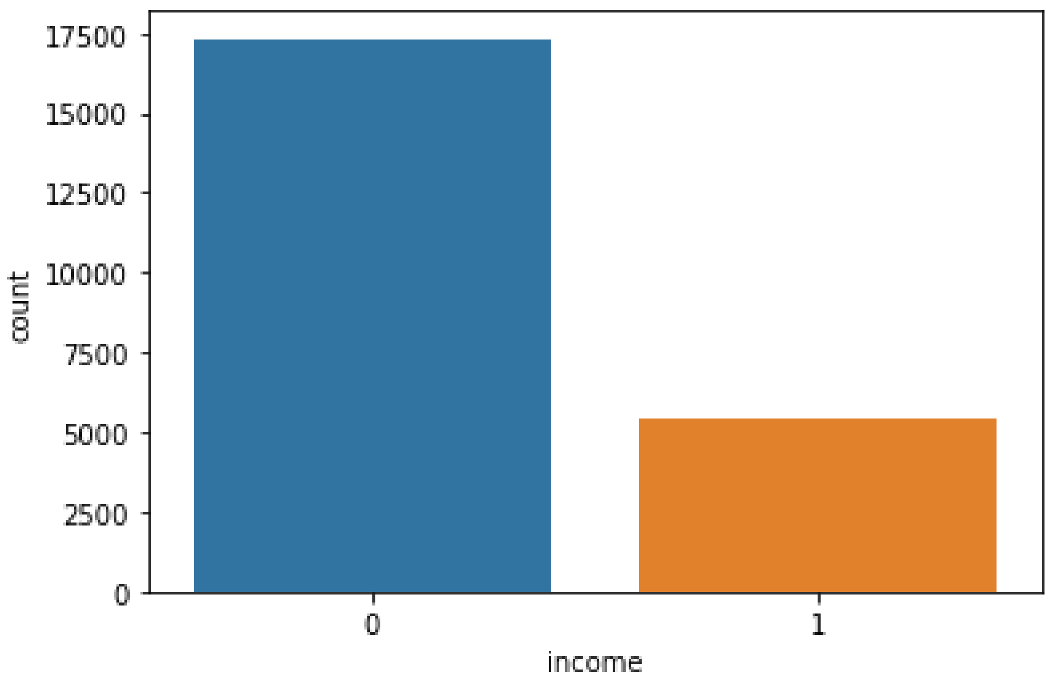
```python
data.head(5)

data.isnull().sum()

workclass_mode = data['workclass'].value_counts().idxmax()
occupation_mode = data['occupation'].value_counts().idxmax()
native_country_mode = data['native-country'].value_counts().idxmax()

data_man = data

data_man["workclass"].replace(np.nan, workclass_mode, inplace = True)
data_man["occupation"].replace(np.nan, occupation_mode, inplace = True)
data_man["native-country"].replace(np.nan, native_country_mode, inplace = True)

data_man.isnull().sum()

data.skew()

num_data = [i for i in data.columns if data[i].dtype != 'O']
format(len(num_data))

data_loss_withoutzero=data.loc[data["capital-loss"]!=0,:]
data_loss_withoutzero.head()

data_gain_withoutzero=data.loc[data["capital-gain"]!=0,:]
data_gain_withoutzero.head()

num_col=list(data.select_dtypes(include=["int64"]).columns)
num_col

lower_limits=[]
upper_limits=[]
IQR_values=[]

for i in range(len(num_col)):

    Q1=data[num_col[i]].quantile(0.25)
    Q3=data[num_col[i]].quantile(0.75)
    IQR=Q3-Q1
    IQR_values.append(IQR)
    lower_limit=Q1-(1.5*IQR)
    lower_limits.append(lower_limit)
    upper_limit=Q3+1.5*IQR
    upper_limits.append(upper_limit)

IQR_t=pd.DataFrame({"numeric_columns":num_col,"lower_limits":lower_limits,
                        "upper_limits":upper_limits,"IQR_values":IQR_values})
```

```
IQR_t

Q1_loss=data[data["capital-loss"]!=0]["capital-loss"].quantile(0.25)
Q3_loss=data[data["capital-loss"]!=0]["capital-loss"].quantile(0.75)
IQR_loss=Q3_loss-Q1_loss
lower_limit_loss=Q1_loss-(1.5*IQR_loss)
upper_limit_loss=Q3_loss+(1.5*IQR_loss)

Q1_gain=data[data["capital-gain"]!=0]["capital-gain"].quantile(0.25)
Q3_gain=data[data["capital-gain"]!=0]["capital-gain"].quantile(0.75)
IQR_gain=Q3_gain-Q1_gain
lower_limit_gain=Q1_gain-(1.5*IQR_gain)
upper_limit_gain=Q3_gain+(1.5*IQR_gain)

data.drop(data[data["fnlwgt"]>900000].index,inplace=True)

round(data[num_data].describe()), 2


data['sex'] = data['sex'].map({'Male': '1', 'Female': '0'})
print(data['sex'])
data['income'] = data['income'].map({'<=50K': 0, '>50K': 1})
data['race'] = data['race'].map({'White': 1, 'Asian-Pac-Islander': 1, 'Black':
 ↪0, 'Amer-Indian-Eskimo':0, 'Other':0})
data['relationship'] = data['relationship'].map({'Not-in-family':0, 'Unmarried':
 ↪0, 'Own-child':0, 'Other-relative':0, 'Husband':1, 'Wife':1})

#relationship and marital.status contain the same information now, so one of␣
 ↪them can be removed
data.drop(['marital-status'], axis=1,inplace=True)

data.drop(['education'], axis=1,inplace=True)
data.head()

labels = ['workclass', 'occupation', 'native-country']

le = LabelEncoder()
for l in labels:
    data[l]=le.fit_transform(data[l])
data

X = StandardScaler().fit_transform(data.loc[:, data.columns != 'income'])
Y = data['income']

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.3,␣
 ↪random_state = 0)
print(Y_train.head())
```

```
0        1
1        1
2        1
3        1
4        0
        ..
32556    0
32557    1
32558    0
32559    1
32560    0
Name: sex, Length: 32541, dtype: object
```

[14]:
```
plot_sb = sb.countplot(Y_train, label='Total')
greaterthan50, lessthan50 = Y_train.value_counts()
print('<=50K: ',lessthan50)
print('>50K : ',greaterthan50)
```

```
<=50K:  5441
>50K :  17337
```

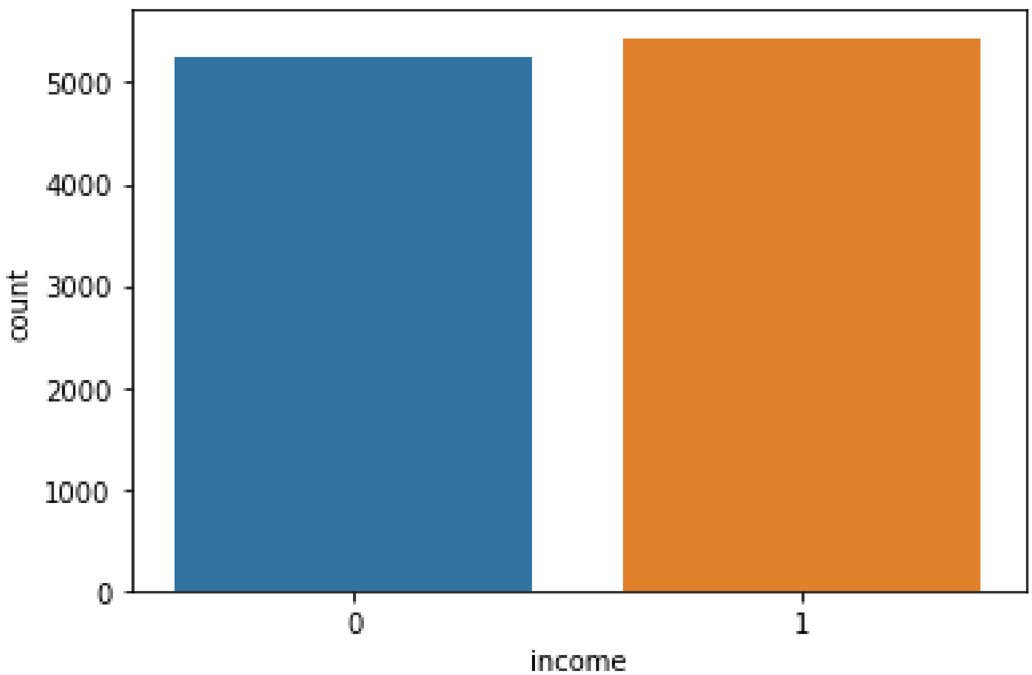


[15]:
```
from imblearn.under_sampling import NearMiss
undersample = NearMiss(version=3, n_neighbors=3)
# transform the dataset
X_train, Y_train = undersample.fit_resample(X_train, Y_train)
```

```
C:\Users\sanky\anaconda3\lib\site-
packages\imblearn\under_sampling\_prototype_selection\_nearmiss.py:177:
UserWarning: The number of the samples to be selected is larger than the number
of samples available. The balancing ratio cannot be ensure and all samples will
be returned.
  warnings.warn(
```

[16]:
```
plot_sb = sb.countplot(Y_train, label='Total')
greaterthan50, lessthan50 = Y_train.value_counts()
print('<=50K: ',lessthan50)
print('>50K : ',greaterthan50)
```

```
<=50K:  5259
>50K :  5441
```



[17]:
```
from sklearn.pipeline import Pipeline
from sklearn.metrics import f1_score
classifiers = [
    LogisticRegression()
    ]

for classifier in classifiers:
        print(type(classifier).__name__)
        pipe = Pipeline(steps=[('classifier', classifier)])
        pipe.fit(X_train, Y_train)
```

```python
Y_pred= pipe.predict(X_test)
score = pipe.score(X_train, Y_train)
print("F1 score: {:}".format(f1_score(Y_test,Y_pred)))
```

```
LogisticRegression
F1 score: 0.6702218430034129
```

[ ]:

```python

```