Naive Bayes Classification with Python and Scikit-Learn

In this project, I implement Naive Bayes Classification algorithm with Python and Scikit-Learn. I build a Naive Bayes Classifier to predict whether a person makes over 50K a year. I have used the **Adult Data Set** for this project. I have downloaded this dataset from the UCI Machine Learning Repository website.

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1. Introduction to Naive Bayes Classification algorithm

In machine learning, Naïve Bayes classification is a straightforward and powerful algorithm for the classification task. Naïve Bayes classification is based on applying Bayes' theorem with strong independence assumption between the features. Naïve Bayes classification produces good results when we use it for textual data analysis such as Natural Language Processing.

Naïve Bayes models are also known as `simple Bayes` or `independent Bayes`. All these names refer to the application of Bayes' theorem in the classifier's decision rule. Naïve Bayes classifier applies the Bayes' theorem in practice. This classifier brings the power of Bayes' theorem to machine learning.

2. Naive Bayes algorithm intuition

Naïve Bayes Classifier uses the Bayes' theorem to predict membership probabilities for each class such as the probability that given record or data point belongs to a particular class. The class with the highest probability is considered as the most likely class. This is also known as the **Maximum A Posteriori (MAP)**.

The **MAP for a hypothesis with 2 events A and B is**

MAP (A)

= max (P (A | B))

= max (P (B | A) * P (A))/P (B)

= max (P (B | A) * P (A))

Here, P (B) is evidence probability. It is used to normalize the result. It remains the same, So, removing it would not affect the result.

Naïve Bayes Classifier assumes that all the features are unrelated to each other. Presence or absence of a feature does not influence the presence or absence of any other feature.

In real world datasets, we test a hypothesis given multiple evidence on features. So, the calculations become quite complicated. To simplify the work, the feature independence approach is used to uncouple multiple evidence and treat each as an independent one.

3. The problem statement

In this project, I try to make predictions where the prediction task is to determine whether a person makes over 50K a year. I implement Naive Bayes Classification with Python and Scikit-Learn. So, to answer the question, I build a Naive Bayes classifier to predict whether a person makes over 50K a year.

4. Dataset description

I have used the **Adult Data Set** for this project. I have downloaded this dataset from the UCI Machine Learning Repository website. The data set can be found at the following url:-

https://archive.ics.uci.edu/ml/datasets/Adult

5. Import libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

```python
import warnings

warnings.filterwarnings('ignore')
```

6. Import dataset

```python
data = 'C:/datasets/adult.data'

df = pd.read_csv(data, header=None, sep=',\s')
```

7. Exploratory data analysis

Now, I will explore the data to gain insights about the data.

```python
# view dimensions of dataset

df.shape
```

```
(32561, 15)
```

We can see that there are 32561 instances and 15 attributes in the data set.

View top 5 rows of dataset

```python
# preview the dataset

df.head()
```

```
    0                 1       2          3   4                   5   \
0  39         State-gov   77516  Bachelors  13       Never-married
1  50  Self-emp-not-inc   83311  Bachelors  13  Married-civ-spouse
2  38           Private  215646    HS-grad   9            Divorced
3  53           Private  234721       11th   7  Married-civ-spouse
4  28           Private  338409  Bachelors  13  Married-civ-spouse

                   6              7      8       9     10  11  12  \
0       Adm-clerical  Not-in-family  White    Male  2174   0  40
1    Exec-managerial        Husband  White    Male     0   0  13
2  Handlers-cleaners  Not-in-family  White    Male     0   0  40
3  Handlers-cleaners        Husband  Black    Male     0   0  40
4     Prof-specialty           Wife  Black  Female     0   0  40

              13     14
0  United-States  <=50K
1  United-States  <=50K
2  United-States  <=50K
3  United-States  <=50K
4           Cuba  <=50K
```

Rename column names

We can see that the dataset does not have proper column names. The columns are merely labelled as 0,1,2.... and so on. We should give proper names to the columns. I will do it as follows:-

```
col_names = ['age', 'workclass', 'fnlwgt', 'education',
'education_num', 'marital_status', 'occupation', 'relationship',
             'race', 'sex', 'capital_gain', 'capital_loss',
'hours_per_week', 'native_country', 'income']

df.columns = col_names

df.columns

Index(['age', 'workclass', 'fnlwgt', 'education', 'education_num',
       'marital_status', 'occupation', 'relationship', 'race', 'sex',
       'capital_gain', 'capital_loss', 'hours_per_week',
'native_country',
       'income'],
      dtype='object')

# let's again preview the dataset

df.head()

   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
```

We can see that the column names are renamed. Now, the columns have meaningful names.

View summary of dataset

```
# view summary of dataset

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
age                  32561 non-null int64
workclass            32561 non-null object
fnlwgt               32561 non-null int64
education            32561 non-null object
education_num        32561 non-null int64
marital_status       32561 non-null object
occupation           32561 non-null object
relationship         32561 non-null object
race                 32561 non-null object
sex                  32561 non-null object
capital_gain         32561 non-null int64
capital_loss         32561 non-null int64
hours_per_week       32561 non-null int64
native_country       32561 non-null object
income               32561 non-null object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

We can see that there are no missing values in the dataset. I will confirm this further.

Types of variables

In this section, I segregate the dataset into categorical and numerical variables. There are a mixture of categorical and numerical variables in the dataset. Categorical variables have data type object. Numerical variables have data type int64.

First of all, I will explore categorical variables.

Explore categorical variables

```
# find categorical variables

categorical = [var for var in df.columns if df[var].dtype=='O']

print('There are {} categorical variables\n'.format(len(categorical)))

print('The categorical variables are :\n\n', categorical)
```

```
There are 9 categorical variables

The categorical variables are :

 ['workclass', 'education', 'marital_status', 'occupation',
'relationship', 'race', 'sex', 'native_country', 'income']
```

```
# view the categorical variables

df[categorical].head()
```

```
          workclass  education      marital_status         occupation  \
0         State-gov  Bachelors       Never-married       Adm-clerical

1  Self-emp-not-inc  Bachelors  Married-civ-spouse    Exec-managerial

2           Private    HS-grad            Divorced  Handlers-cleaners

3           Private       11th  Married-civ-spouse  Handlers-cleaners

4           Private  Bachelors  Married-civ-spouse     Prof-specialty


    relationship   race     sex native_country income
0  Not-in-family  White    Male  United-States  <=50K
1        Husband  White    Male  United-States  <=50K
2  Not-in-family  White    Male  United-States  <=50K
3        Husband  Black    Male  United-States  <=50K
4           Wife  Black  Female           Cuba  <=50K
```

Summary of categorical variables

- There are 9 categorical variables.
- The categorical variables are given by `workclass`, `education`, `marital_status`, `occupation`, `relationship`, `race`, `sex`, `native_country` and `income`.
- `income` is the target variable.

Explore problems within categorical variables

First, I will explore the categorical variables.

Missing values in categorical variables

```
# check missing values in categorical variables

df[categorical].isnull().sum()
```

```
workclass         0
education         0
```

```
marital_status    0
occupation        0
relationship      0
race              0
sex               0
native_country    0
income            0
dtype: int64
```

We can see that there are no missing values in the categorical variables. I will confirm this further.

Frequency counts of categorical variables

Now, I will check the frequency counts of categorical variables.

```python
# view frequency counts of values in categorical variables

for var in categorical:

    print(df[var].value_counts())
```

```
Private             22696
Self-emp-not-inc     2541
Local-gov            2093
?                    1836
State-gov            1298
Self-emp-inc         1116
Federal-gov           960
Without-pay            14
Never-worked            7
Name: workclass, dtype: int64
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
```

```
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
Prof-specialty       4140
Craft-repair         4099
Exec-managerial      4066
Adm-clerical         3770
Sales                3650
Other-service        3295
Machine-op-inspct    2002
?                    1843
Transport-moving     1597
Handlers-cleaners    1370
Farming-fishing       994
Tech-support          928
Protective-serv       649
Priv-house-serv       149
Armed-Forces            9
Name: occupation, dtype: int64
Husband           13193
Not-in-family      8305
Own-child          5068
Unmarried          3446
Wife               1568
Other-relative      981
Name: relationship, dtype: int64
White                 27816
Black                  3124
Asian-Pac-Islander     1039
Amer-Indian-Eskimo      311
Other                   271
Name: race, dtype: int64
Male      21790
Female    10771
Name: sex, dtype: int64
United-States                 29170
Mexico                          643
?                               583
Philippines                     198
Germany                         137
Canada                          121
Puerto-Rico                     114
El-Salvador                     106
India                           100
```

```
Cuba                                 95
England                              90
Jamaica                              81
South                                80
China                                75
Italy                                73
Dominican-Republic                   70
Vietnam                              67
Guatemala                            64
Japan                                62
Poland                               60
Columbia                             59
Taiwan                               51
Haiti                                44
Iran                                 43
Portugal                             37
Nicaragua                            34
Peru                                 31
France                               29
Greece                               29
Ecuador                              28
Ireland                              24
Hong                                 20
Trinadad&Tobago                      19
Cambodia                             19
Thailand                             18
Laos                                 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: income, dtype: int64
```

```python
# view frequency distribution of categorical variables

for var in categorical:

    print(df[var].value_counts()/np.float(len(df)))
```

```
Private             0.697030
Self-emp-not-inc    0.078038
Local-gov           0.064279
?                   0.056386
State-gov           0.039864
Self-emp-inc        0.034274
```

```
Federal-gov         0.029483
Without-pay         0.000430
Never-worked        0.000215
Name: workclass, dtype: float64
HS-grad         0.322502
Some-college    0.223918
Bachelors       0.164461
Masters         0.052916
Assoc-voc       0.042443
11th            0.036086
Assoc-acdm      0.032769
10th            0.028654
7th-8th         0.019840
Prof-school     0.017690
9th             0.015786
12th            0.013298
Doctorate       0.012684
5th-6th         0.010227
1st-4th         0.005160
Preschool       0.001566
Name: education, dtype: float64
Married-civ-spouse       0.459937
Never-married            0.328092
Divorced                 0.136452
Separated                0.031479
Widowed                  0.030497
Married-spouse-absent    0.012837
Married-AF-spouse        0.000706
Name: marital_status, dtype: float64
Prof-specialty       0.127146
Craft-repair         0.125887
Exec-managerial      0.124873
Adm-clerical         0.115783
Sales                0.112097
Other-service        0.101195
Machine-op-inspct    0.061485
?                    0.056601
Transport-moving     0.049046
Handlers-cleaners    0.042075
Farming-fishing      0.030527
Tech-support         0.028500
Protective-serv      0.019932
Priv-house-serv      0.004576
Armed-Forces         0.000276
Name: occupation, dtype: float64
Husband           0.405178
Not-in-family     0.255060
Own-child         0.155646
Unmarried         0.105832
```

```
Wife                 0.048156
Other-relative       0.030128
Name: relationship, dtype: float64
White                    0.854274
Black                    0.095943
Asian-Pac-Islander       0.031909
Amer-Indian-Eskimo       0.009551
Other                    0.008323
Name: race, dtype: float64
Male       0.669205
Female     0.330795
Name: sex, dtype: float64
United-States                  0.895857
Mexico                         0.019748
?                              0.017905
Philippines                    0.006081
Germany                        0.004207
Canada                         0.003716
Puerto-Rico                    0.003501
El-Salvador                    0.003255
India                          0.003071
Cuba                           0.002918
England                        0.002764
Jamaica                        0.002488
South                          0.002457
China                          0.002303
Italy                          0.002242
Dominican-Republic             0.002150
Vietnam                        0.002058
Guatemala                      0.001966
Japan                          0.001904
Poland                         0.001843
Columbia                       0.001812
Taiwan                         0.001566
Haiti                          0.001351
Iran                           0.001321
Portugal                       0.001136
Nicaragua                      0.001044
Peru                           0.000952
France                         0.000891
Greece                         0.000891
Ecuador                        0.000860
Ireland                        0.000737
Hong                           0.000614
Trinadad&Tobago                0.000584
Cambodia                       0.000584
Thailand                       0.000553
Laos                           0.000553
Yugoslavia                     0.000491
```

```
Outlying-US(Guam-USVI-etc)    0.000430
Honduras                      0.000399
Hungary                       0.000399
Scotland                      0.000369
Holand-Netherlands            0.000031
Name: native_country, dtype: float64
<=50K    0.75919
>50K     0.24081
Name: income, dtype: float64
```

Now, we can see that there are several variables like `workclass`, `occupation` and `native_country` which contain missing values. Generally, the missing values are coded as `NaN` and python will detect them with the usual command of `df.isnull().sum()`.

But, in this case the missing values are coded as `?`. Python fail to detect these as missing values because it do not consider `?` as missing values. So, I have to replace `?` with `NaN` so that Python can detect these missing values.

I will explore these variables and replace `?` with `NaN`.

Explore workclass variable

```
# check labels in workclass variable

df.workclass.unique()

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

# check frequency distribution of values in workclass variable

df.workclass.value_counts()

Private             22696
Self-emp-not-inc     2541
Local-gov            2093
?                    1836
State-gov            1298
Self-emp-inc         1116
Federal-gov           960
Without-pay            14
Never-worked            7
Name: workclass, dtype: int64
```

We can see that there are 1836 values encoded as `?` in workclass variable. I will replace these `?` with `NaN`.

```
# replace '?' values in workclass variable with `NaN`


df['workclass'].replace('?', np.NaN, inplace=True)

# again check the frequency distribution of values in workclass
variable

df.workclass.value_counts()
```

```
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
```

Now, we can see that there are no values encoded as `?` in the `workclass` variable.

I will adopt similar approach with `occupation` and `native_country` column.

Explore occupation variable

```
# check labels in occupation variable

df.occupation.unique()
```

```
array(['Adm-clerical', 'Exec-managerial', 'Handlers-cleaners',
       'Prof-specialty', 'Other-service', 'Sales', 'Craft-repair',
       'Transport-moving', 'Farming-fishing', 'Machine-op-inspct',
       'Tech-support', '?', 'Protective-serv', 'Armed-Forces',
       'Priv-house-serv'], dtype=object)
```

```
# check frequency distribution of values in occupation variable

df.occupation.value_counts()
```

```
Prof-specialty       4140
Craft-repair         4099
Exec-managerial      4066
Adm-clerical         3770
Sales                3650
Other-service        3295
Machine-op-inspct    2002
?                    1843
Transport-moving     1597
Handlers-cleaners    1370
Farming-fishing       994
```

```
Tech-support          928
Protective-serv       649
Priv-house-serv       149
Armed-Forces            9
Name: occupation, dtype: int64
```

We can see that there are 1843 values encoded as `?` in `occupation` variable. I will replace these `?` with `NaN`.

```
# replace '?' values in occupation variable with `NaN`

df['occupation'].replace('?', np.NaN, inplace=True)

# again check the frequency distribution of values in occupation
variable

df.occupation.value_counts()

Prof-specialty       4140
Craft-repair         4099
Exec-managerial      4066
Adm-clerical         3770
Sales                3650
Other-service        3295
Machine-op-inspct    2002
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
```

Explore native_country variable

```
# check labels in native_country variable

df.native_country.unique()

array(['United-States', 'Cuba', 'Jamaica', 'India', '?', '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)
```

```
# check frequency distribution of values in native_country variable

df.native_country.value_counts()
```

```
United-States                 29170
Mexico                          643
?                               583
Philippines                     198
Germany                         137
Canada                          121
Puerto-Rico                     114
El-Salvador                     106
India                           100
Cuba                             95
England                          90
Jamaica                          81
South                            80
China                            75
Italy                            73
Dominican-Republic               70
Vietnam                          67
Guatemala                        64
Japan                            62
Poland                           60
Columbia                         59
Taiwan                           51
Haiti                            44
Iran                             43
Portugal                         37
Nicaragua                        34
Peru                             31
France                           29
Greece                           29
Ecuador                          28
Ireland                          24
Hong                             20
Trinadad&Tobago                  19
Cambodia                         19
Thailand                         18
Laos                             18
Yugoslavia                       16
Outlying-US(Guam-USVI-etc)       14
Honduras                         13
Hungary                          13
Scotland                         12
Holand-Netherlands                1
Name: native_country, dtype: int64
```

We can see that there are 583 values encoded as `?` in `native_country` variable. I will replace these `?` with `NaN`.

```
# replace '?' values in native_country variable with `NaN`

df['native_country'].replace('?', np.NaN, inplace=True)

# again check the frequency distribution of values in native_country variable

df.native_country.value_counts()
```

```
United-States                 29170
Mexico                          643
Philippines                     198
Germany                         137
Canada                          121
Puerto-Rico                     114
El-Salvador                     106
India                           100
Cuba                             95
England                          90
Jamaica                          81
South                            80
China                            75
Italy                            73
Dominican-Republic               70
Vietnam                          67
Guatemala                        64
Japan                            62
Poland                           60
Columbia                         59
Taiwan                           51
Haiti                            44
Iran                             43
Portugal                         37
Nicaragua                        34
Peru                             31
France                           29
Greece                           29
Ecuador                          28
Ireland                          24
Hong                             20
Trinadad&Tobago                  19
Cambodia                         19
Thailand                         18
Laos                             18
Yugoslavia                       16
Outlying-US(Guam-USVI-etc)       14
Honduras                         13
```

```
Hungary                               13
Scotland                              12
Holand-Netherlands                     1
Name: native_country, dtype: int64
```

Check missing values in categorical variables again

```
df[categorical].isnull().sum()
```

```
workclass         1836
education            0
marital_status       0
occupation        1843
relationship         0
race                 0
sex                  0
native_country     583
income               0
dtype: int64
```

Now, we can see that `workclass`, `occupation` and `native_country` variable contains missing values.

Number of labels: cardinality

The number of labels within a categorical variable is known as **cardinality**. A high number of labels within a variable is known as **high cardinality**. High cardinality may pose some serious problems in the machine learning model. So, I will check for high cardinality.

```
# check for cardinality in categorical variables

for var in categorical:

    print(var, ' contains ', len(df[var].unique()), ' labels')
```

```
workclass  contains  9  labels
education  contains  16  labels
marital_status  contains  7  labels
occupation  contains  15  labels
relationship  contains  6  labels
race  contains  5  labels
sex  contains  2  labels
native_country  contains  42  labels
income  contains  2  labels
```

We can see that `native_country` column contains relatively large number of labels as compared to other columns. I will check for cardinality after train-test split.

Explore Numerical Variables

```
# find numerical variables

numerical = [var for var in df.columns if df[var].dtype!='O']

print('There are {} numerical variables\n'.format(len(numerical)))

print('The numerical variables are :', numerical)
```

```
There are 6 numerical variables

The numerical variables are : ['age', 'fnlwgt', 'education_num',
'capital_gain', 'capital_loss', 'hours_per_week']
```

```
# view the numerical variables

df[numerical].head()
```

```
   age  fnlwgt  education_num  capital_gain  capital_loss
hours_per_week
0   39   77516             13          2174             0
40
1   50   83311             13             0             0
13
2   38  215646              9             0             0
40
3   53  234721              7             0             0
40
4   28  338409             13             0             0
40
```

Summary of numerical variables

- There are 6 numerical variables.
- These are given by `age`, `fnlwgt`, `education_num`, `capital_gain`, `capital_loss` and `hours_per_week`.
- All of the numerical variables are of discrete data type.

Explore problems within numerical variables

Now, I will explore the numerical variables.

Missing values in numerical variables

```
# check missing values in numerical variables

df[numerical].isnull().sum()
```

```
age               0
fnlwgt            0
education_num     0
capital_gain      0
capital_loss      0
hours_per_week    0
dtype: int64
```

We can see that all the 6 numerical variables do not contain missing values.

8. Declare feature vector and target variable

```
X = df.drop(['income'], axis=1)

y = df['income']
```

9. Split data into separate training and test set

```
# split X and y into training and testing sets

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.3, random_state = 0)

# check the shape of X_train and X_test

X_train.shape, X_test.shape

((22792, 14), (9769, 14))
```

10. Feature Engineering

Feature Engineering is the process of transforming raw data into useful features that help us to understand our model better and increase its predictive power. I will carry out feature engineering on different types of variables.

First, I will display the categorical and numerical variables again separately.

```
# check data types in X_train

X_train.dtypes

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
dtype: object
```

```
# display categorical variables

categorical = [col for col in X_train.columns if X_train[col].dtypes
== 'O']

categorical
```

```
['workclass',
 'education',
 'marital_status',
 'occupation',
 'relationship',
 'race',
 'sex',
 'native_country']
```

```
# display numerical variables

numerical = [col for col in X_train.columns if X_train[col].dtypes !=
'O']

numerical
```

```
['age',
 'fnlwgt',
 'education_num',
 'capital_gain',
 'capital_loss',
 'hours_per_week']
```

Engineering missing values in categorical variables

```
# print percentage of missing values in the categorical variables in
training set

X_train[categorical].isnull().mean()
```

```
workclass         0.055985
education         0.000000
marital_status    0.000000
occupation        0.056072
```

```
relationship      0.000000
race              0.000000
sex               0.000000
native_country    0.018164
dtype: float64
```

```python
# print categorical variables with missing data

for col in categorical:
    if X_train[col].isnull().mean()>0:
        print(col, (X_train[col].isnull().mean()))
```

```
workclass 0.055984555984555984
occupation 0.05607230607230607
native_country 0.018164268164268166
```

```python
# impute missing categorical variables with most frequent value

for df2 in [X_train, X_test]:
    df2['workclass'].fillna(X_train['workclass'].mode()[0],
inplace=True)
    df2['occupation'].fillna(X_train['occupation'].mode()[0],
inplace=True)
    df2['native_country'].fillna(X_train['native_country'].mode()[0],
inplace=True)
```

```python
# check missing values in categorical variables in X_train

X_train[categorical].isnull().sum()
```

```
workclass         0
education         0
marital_status    0
occupation        0
relationship      0
race              0
sex               0
native_country    0
dtype: int64
```

```python
# check missing values in categorical variables in X_test

X_test[categorical].isnull().sum()
```

```
workclass         0
education         0
marital_status    0
occupation        0
relationship      0
race              0
sex               0
```

```
native_country    0
dtype: int64
```

As a final check, I will check for missing values in X_train and X_test.

```
# check missing values in X_train

X_train.isnull().sum()
```

```
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
dtype: int64
```

```
# check missing values in X_test

X_test.isnull().sum()
```

```
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
dtype: int64
```

We can see that there are no missing values in X_train and X_test.

Encode categorical variables

```
# print categorical variables

categorical

['workclass',
 'education',
 'marital_status',
 'occupation',
 'relationship',
 'race',
 'sex',
 'native_country']

X_train[categorical].head()

       workclass     education       marital_status    occupation  \
32098    Private       HS-grad  Married-civ-spouse  Craft-repair
25206  State-gov       HS-grad            Divorced  Adm-clerical
23491    Private  Some-college  Married-civ-spouse         Sales
12367    Private       HS-grad       Never-married  Craft-repair
7054     Private       7th-8th       Never-married  Craft-repair

        relationship   race     sex native_country
32098        Husband  White    Male  United-States
25206      Unmarried  White  Female  United-States
23491        Husband  White    Male  United-States
12367  Not-in-family  White    Male      Guatemala
7054   Not-in-family  White    Male        Germany

# import category encoders

import category_encoders as ce

# encode remaining variables with one-hot encoding

encoder = ce.OneHotEncoder(cols=['workclass', 'education',
'marital_status', 'occupation', 'relationship',
                                 'race', 'sex', 'native_country'])

X_train = encoder.fit_transform(X_train)

X_test = encoder.transform(X_test)

X_train.head()

       workclass_1  workclass_2  workclass_3  workclass_4  workclass_5
\
32098            1            0            0            0            0

25206            0            1            0            0            0
```

```
23491             1            0            0            0            0
12367             1            0            0            0            0
7054              1            0            0            0            0

       workclass_6  workclass_7  workclass_8  workclass_-1
education_1  \
32098            0            0            0             0
1
25206            0            0            0             0
1
23491            0            0            0             0
0
12367            0            0            0             0
1
7054             0            0            0             0
0

            ...        native_country_39  native_country_40  \
32098       ...                        0                  0
25206       ...                        0                  0
23491       ...                        0                  0
12367       ...                        0                  0
7054        ...                        0                  0

       native_country_41  native_country_-1  age  fnlwgt
education_num  \
32098                  0                  0   45  170871
9
25206                  0                  0   47  108890
9
23491                  0                  0   48  187505
10
12367                  0                  0   29  145592
9
7054                   0                  0   23  203003
4

       capital_gain  capital_loss  hours_per_week
32098          7298             0              60
25206          1831             0              38
23491             0             0              50
12367             0             0              40
7054              0             0              25

[5 rows x 113 columns]
```

```
X_train.shape
```

```
(22792, 113)
```

We can see that from the initial 14 columns, we now have 113 columns.

Similarly, I will take a look at the `X_test` set.

```
X_test.head()
```

```
       workclass_1  workclass_2  workclass_3  workclass_4  workclass_5  \
22278            1            0            0            0            0

8950             1            0            0            0            0

7838             1            0            0            0            0

16505            1            0            0            0            0

19140            1            0            0            0            0


       workclass_6  workclass_7  workclass_8  workclass_-1
education_1  \
22278            0            0            0             0
0
8950             0            0            0             0
0
7838             0            0            0             0
0
16505            0            0            0             0
0
19140            0            0            0             0
0

            ...         native_country_39  native_country_40  \
22278       ...                         0                  0
8950        ...                         0                  0
7838        ...                         0                  0
16505       ...                         0                  0
19140       ...                         0                  0

       native_country_41  native_country_-1  age  fnlwgt
education_num  \
22278                  0                  0   27  177119
10
8950                   0                  0   27  216481
13
7838                   0                  0   25  256263
```

```
12
16505                  0                  0   46   147640
3
19140                  0                  0   45   172822
7

       capital_gain  capital_loss  hours_per_week
22278             0             0              44
8950              0             0              40
7838              0             0              40
16505             0          1902              40
19140             0          2824              76

[5 rows x 113 columns]

X_test.shape

(9769, 113)
```

We now have training and testing set ready for model building. Before that, we should map all the feature variables onto the same scale. It is called `feature scaling`. I will do it as follows.

11. Feature Scaling

```
cols = X_train.columns

from sklearn.preprocessing import RobustScaler

scaler = RobustScaler()

X_train = scaler.fit_transform(X_train)

X_test = scaler.transform(X_test)

X_train = pd.DataFrame(X_train, columns=[cols])

X_test = pd.DataFrame(X_test, columns=[cols])

X_train.head()

  workclass_1 workclass_2 workclass_3 workclass_4 workclass_5
workclass_6  \
0         0.0         0.0         0.0         0.0         0.0
0.0
1        -1.0         1.0         0.0         0.0         0.0
0.0
2         0.0         0.0         0.0         0.0         0.0
0.0
3         0.0         0.0         0.0         0.0         0.0
0.0
4         0.0         0.0         0.0         0.0         0.0
```

```
0.0

  workclass_7 workclass_8 workclass_-1 education_1      ...        \
0         0.0         0.0          0.0         1.0      ...
1         0.0         0.0          0.0         1.0      ...
2         0.0         0.0          0.0         0.0      ...
3         0.0         0.0          0.0         1.0      ...
4         0.0         0.0          0.0         0.0      ...

  native_country_39 native_country_40 native_country_41
native_country_-1  \
0               0.0               0.0               0.0
0.0
1               0.0               0.0               0.0
0.0
2               0.0               0.0               0.0
0.0
3               0.0               0.0               0.0
0.0
4               0.0               0.0               0.0
0.0

    age    fnlwgt education_num capital_gain capital_loss
hours_per_week
0  0.40 -0.058906     -0.333333       7298.0          0.0
4.0
1  0.50 -0.578076     -0.333333       1831.0          0.0            -
0.4
2  0.55  0.080425      0.000000          0.0          0.0
2.0
3 -0.40 -0.270650     -0.333333          0.0          0.0
0.0
4 -0.70  0.210240     -2.000000          0.0          0.0            -
3.0

[5 rows x 113 columns]
```

We now have `X_train` dataset ready to be fed into the Gaussian Naive Bayes classifier. I will do it as follows.

12. Model training

```python
# train a Gaussian Naive Bayes classifier on the training set
from sklearn.naive_bayes import GaussianNB


# instantiate the model
gnb = GaussianNB()
```

```
# fit the model
gnb.fit(X_train, y_train)
```

```
GaussianNB(priors=None, var_smoothing=1e-09)
```

13. Predict the test set results

```
y_pred = gnb.predict(X_test)

y_pred
```

```
array(['<=50K', '<=50K', '>50K', ..., '>50K', '<=50K', '<=50K'],
      dtype='<U5')
```

14. Check accuracy score

```
from sklearn.metrics import accuracy_score

print('Model accuracy score: {0:0.4f}'. format(accuracy_score(y_test,
y_pred)))
```

```
Model accuracy score: 0.8083
```

Here, **y_test** are the true class labels and **y_pred** are the predicted class labels in the test-set.

Compare the train-set and test-set accuracy

Now, I will compare the train-set and test-set accuracy to check for overfitting.

```
y_pred_train = gnb.predict(X_train)

y_pred_train
```

```
array(['>50K', '<=50K', '>50K', ..., '<=50K', '>50K', '<=50K'],
      dtype='<U5')
```

```
print('Training-set accuracy score: {0:0.4f}'.
format(accuracy_score(y_train, y_pred_train)))
```

```
Training-set accuracy score: 0.8067
```

Check for overfitting and underfitting

```
# print the scores on training and test set

print('Training set score: {:.4f}'.format(gnb.score(X_train,
y_train)))

print('Test set score: {:.4f}'.format(gnb.score(X_test, y_test)))
```

```
Training set score: 0.8067
Test set score: 0.8083
```

The training-set accuracy score is 0.8067 while the test-set accuracy to be 0.8083. These two values are quite comparable. So, there is no sign of overfitting.

Compare model accuracy with null accuracy

So, the model accuracy is 0.8083. But, we cannot say that our model is very good based on the above accuracy. We must compare it with the **null accuracy**. Null accuracy is the accuracy that could be achieved by always predicting the most frequent class.

So, we should first check the class distribution in the test set.

```
# check class distribution in test set

y_test.value_counts()

<=50K    7407
>50K     2362
Name: income, dtype: int64
```

We can see that the occurences of most frequent class is 7407. So, we can calculate null accuracy by dividing 7407 by total number of occurences.

```
# check null accuracy score

null_accuracy = (7407/(7407+2362))

print('Null accuracy score: {0:0.4f}'. format(null_accuracy))

Null accuracy score: 0.7582
```

We can see that our model accuracy score is 0.8083 but null accuracy score is 0.7582. So, we can conclude that our Gaussian Naive Bayes Classification model is doing a very good job in predicting the class labels.

Now, based on the above analysis we can conclude that our classification model accuracy is very good. Our model is doing a very good job in terms of predicting the class labels.

But, it does not give the underlying distribution of values. Also, it does not tell anything about the type of errors our classifer is making.

We have another tool called `Confusion matrix` that comes to our rescue.

15. Confusion matrix

A confusion matrix is a tool for summarizing the performance of a classification algorithm. A confusion matrix will give us a clear picture of classification model performance and the types of errors produced by the model. It gives us a summary of correct and incorrect predictions broken down by each category. The summary is represented in a tabular form.

Four types of outcomes are possible while evaluating a classification model performance. These four outcomes are described below:-

True Positives (TP) – True Positives occur when we predict an observation belongs to a certain class and the observation actually belongs to that class.

True Negatives (TN) – True Negatives occur when we predict an observation does not belong to a certain class and the observation actually does not belong to that class.

False Positives (FP) – False Positives occur when we predict an observation belongs to a certain class but the observation actually does not belong to that class. This type of error is called **Type I error.**

False Negatives (FN) – False Negatives occur when we predict an observation does not belong to a certain class but the observation actually belongs to that class. This is a very serious error and it is called **Type II error.**

These four outcomes are summarized in a confusion matrix given below.

```
# Print the Confusion Matrix and slice it into four pieces

from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test, y_pred)

print('Confusion matrix\n\n', cm)

print('\nTrue Positives(TP) = ', cm[0,0])

print('\nTrue Negatives(TN) = ', cm[1,1])

print('\nFalse Positives(FP) = ', cm[0,1])

print('\nFalse Negatives(FN) = ', cm[1,0])
```

```
Confusion matrix

 [[5999 1408]
 [ 465 1897]]

True Positives(TP) =  5999

True Negatives(TN) =  1897

False Positives(FP) =  1408

False Negatives(FN) =  465
```

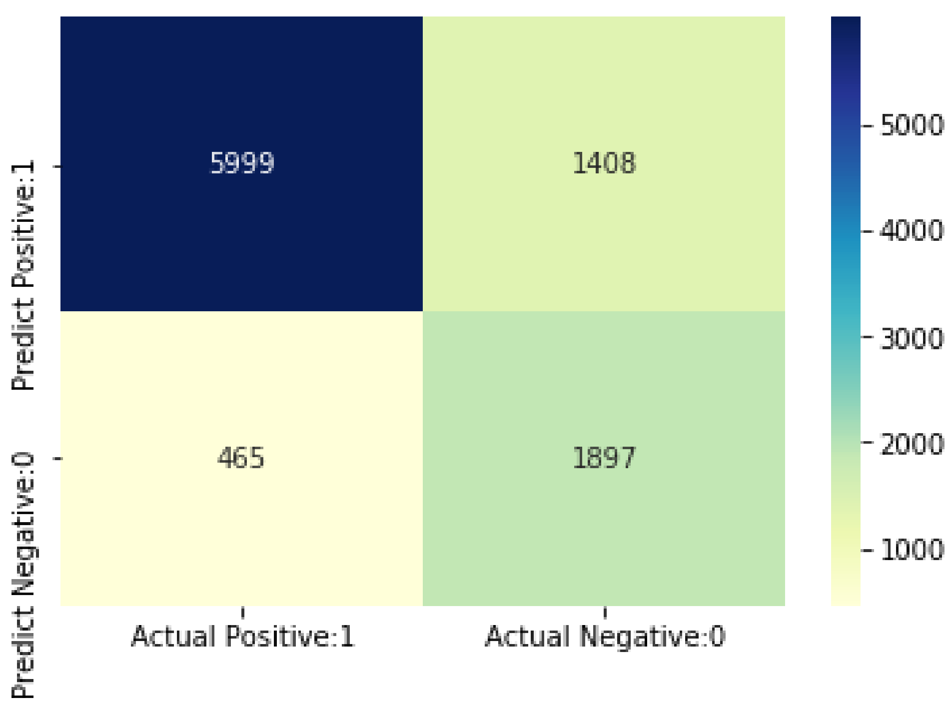
The confusion matrix shows `5999 + 1897 = 7896 correct predictions` and `1408 + 465 = 1873 incorrect predictions`.

In this case, we have

- `True Positives` (Actual Positive:1 and Predict Positive:1) - 5999
- `True Negatives` (Actual Negative:0 and Predict Negative:0) - 1897
- `False Positives` (Actual Negative:0 but Predict Positive:1) - 1408 `(Type I error)`
- `False Negatives` (Actual Positive:1 but Predict Negative:0) - 465 `(Type II error)`

```
# visualize confusion matrix with seaborn heatmap

cm_matrix = pd.DataFrame(data=cm, columns=['Actual Positive:1', 'Actual Negative:0'],
                                 index=['Predict Positive:1', 'Predict Negative:0'])

sns.heatmap(cm_matrix, annot=True, fmt='d', cmap='YlGnBu')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0xf202a9c6a0>
```



16. Classification metrices

Classification Report

Classification report is another way to evaluate the classification model performance. It displays the **precision**, **recall**, **f1** and **support** scores for the model. I have described these terms in later.

We can print a classification report as follows:-

```
from sklearn.metrics import classification_report

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

```
              precision    recall  f1-score   support

       <=50K       0.93      0.81      0.86      7407
        >50K       0.57      0.80      0.67      2362

   micro avg       0.81      0.81      0.81      9769
   macro avg       0.75      0.81      0.77      9769
weighted avg       0.84      0.81      0.82      9769
```

Classification accuracy

```
TP = cm[0,0]
TN = cm[1,1]
FP = cm[0,1]
FN = cm[1,0]

# print classification accuracy

classification_accuracy = (TP + TN) / float(TP + TN + FP + FN)

print('Classification accuracy :
{0:0.4f}'.format(classification_accuracy))

Classification accuracy : 0.8083
```

Classification error

```
# print classification error

classification_error = (FP + FN) / float(TP + TN + FP + FN)

print('Classification error : {0:0.4f}'.format(classification_error))

Classification error : 0.1917
```

Precision

Precision can be defined as the percentage of correctly predicted positive outcomes out of all the predicted positive outcomes. It can be given as the ratio of true positives (TP) to the sum of true and false positives (TP + FP).

So, **Precision** identifies the proportion of correctly predicted positive outcome. It is more concerned with the positive class than the negative class.

Mathematically, precision can be defined as the ratio of `TP to (TP + FP)`.

```
# print precision score

precision = TP / float(TP + FP)


print('Precision : {0:0.4f}'.format(precision))
```

```
Precision : 0.8099
```

Recall

Recall can be defined as the percentage of correctly predicted positive outcomes out of all the actual positive outcomes. It can be given as the ratio of true positives (TP) to the sum of true positives and false negatives (TP + FN). **Recall** is also called **Sensitivity**.

Recall identifies the proportion of correctly predicted actual positives.

Mathematically, recall can be given as the ratio of `TP to (TP + FN)`.

```
recall = TP / float(TP + FN)

print('Recall or Sensitivity : {0:0.4f}'.format(recall))
```

```
Recall or Sensitivity : 0.9281
```

True Positive Rate

True Positive Rate is synonymous with **Recall**.

```
true_positive_rate = TP / float(TP + FN)


print('True Positive Rate : {0:0.4f}'.format(true_positive_rate))
```

```
True Positive Rate : 0.9281
```

False Positive Rate

```
false_positive_rate = FP / float(FP + TN)
```

```python
print('False Positive Rate : {0:0.4f}'.format(false_positive_rate))
```

```
False Positive Rate : 0.4260
```

Specificity

```python
specificity = TN / (TN + FP)

print('Specificity : {0:0.4f}'.format(specificity))
```

```
Specificity : 0.5740
```

f1-score

f1-score is the weighted harmonic mean of precision and recall. The best possible **f1-score** would be 1.0 and the worst would be 0.0. **f1-score** is the harmonic mean of precision and recall. So, **f1-score** is always lower than accuracy measures as they embed precision and recall into their computation. The weighted average of `f1-score` should be used to compare classifier models, not global accuracy.

Support

Support is the actual number of occurrences of the class in our dataset.

17. Calculate class probabilities

```python
# print the first 10 predicted probabilities of two classes- 0 and 1

y_pred_prob = gnb.predict_proba(X_test)[0:10]

y_pred_prob
```

```
array([[9.99999426e-01, 5.74152436e-07],
       [9.99687907e-01, 3.12093456e-04],
       [1.54405602e-01, 8.45594398e-01],
       [1.73624321e-04, 9.99826376e-01],
       [8.20121011e-09, 9.99999992e-01],
       [8.76844580e-01, 1.23155420e-01],
       [9.99999927e-01, 7.32876705e-08],
       [9.99993460e-01, 6.53998797e-06],
       [9.87738143e-01, 1.22618575e-02],
       [9.99999996e-01, 4.01886317e-09]])
```

Observations

- In each row, the numbers sum to 1.
- There are 2 columns which correspond to 2 classes - `<=50K` and `>50K`.
  - Class 0 => <=50K - Class that a person makes less than equal to 50K.

- Class 1 => >50K - Class that a person makes more than 50K.

- Importance of predicted probabilities
  - We can rank the observations by probability of whether a person makes less than or equal to 50K or more than 50K.
- predict_proba process
  - Predicts the probabilities
  - Choose the class with the highest probability
- Classification threshold level
  - There is a classification threshold level of 0.5.
  - Class 0 => <=50K - probability of salary less than or equal to 50K is predicted if probability < 0.5.
  - Class 1 => >50K - probability of salary more than 50K is predicted if probability > 0.5.

```
# store the probabilities in dataframe

y_pred_prob_df = pd.DataFrame(data=y_pred_prob, columns=['Prob of -
<=50K', 'Prob of - >50K'])

y_pred_prob_df
```

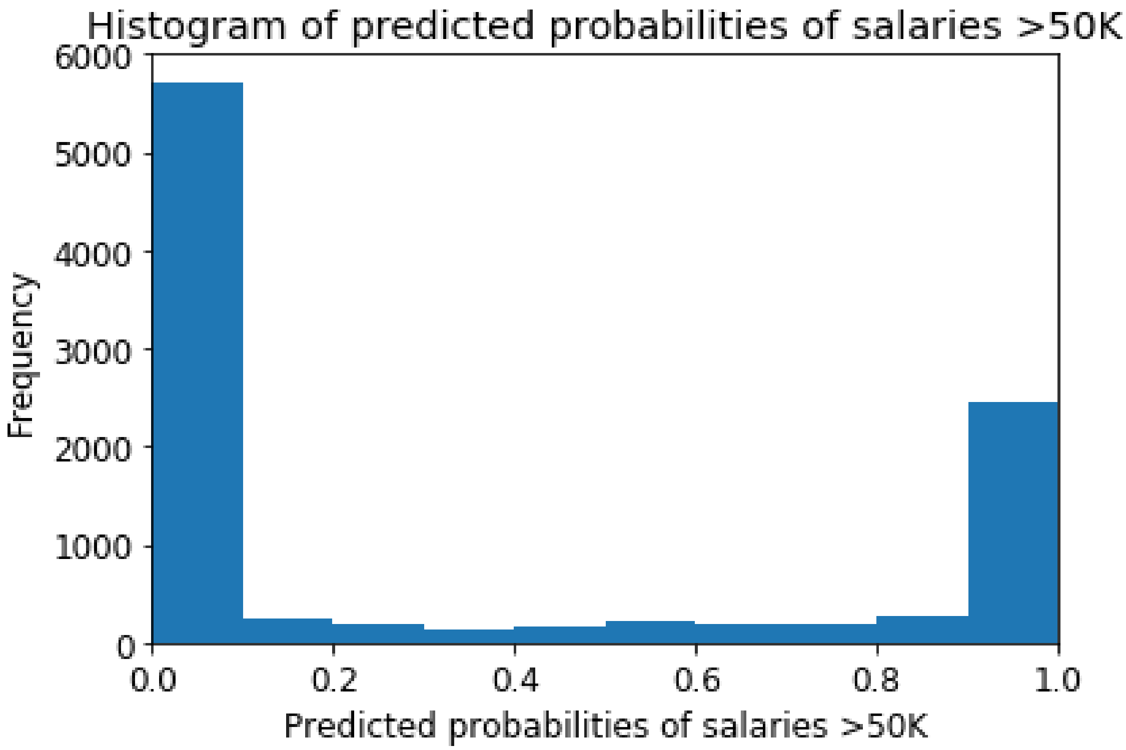
	Prob of - <=50K	Prob of - >50K
0	9.999994e-01	5.741524e-07
1	9.996879e-01	3.120935e-04
2	1.544056e-01	8.455944e-01
3	1.736243e-04	9.998264e-01
4	8.201210e-09	1.000000e+00
5	8.768446e-01	1.231554e-01
6	9.999999e-01	7.328767e-08
7	9.999935e-01	6.539988e-06
8	9.877381e-01	1.226186e-02
9	1.000000e+00	4.018863e-09

```
# print the first 10 predicted probabilities for class 1 - Probability
of >50K

gnb.predict_proba(X_test)[0:10, 1]
```

```
array([5.74152436e-07, 3.12093456e-04, 8.45594398e-01, 9.99826376e-01,
       9.99999992e-01, 1.23155420e-01, 7.32876705e-08, 6.53998797e-06,
       1.22618575e-02, 4.01886317e-09])
```

```
# store the predicted probabilities for class 1 - Probability of >50K

y_pred1 = gnb.predict_proba(X_test)[:, 1]

# plot histogram of predicted probabilities


# adjust the font size
plt.rcParams['font.size'] = 12


# plot histogram with 10 bins
plt.hist(y_pred1, bins = 10)


# set the title of predicted probabilities
plt.title('Histogram of predicted probabilities of salaries >50K')


# set the x-axis limit
plt.xlim(0,1)


# set the title
plt.xlabel('Predicted probabilities of salaries >50K')
plt.ylabel('Frequency')
```

```
Text(0,0.5,'Frequency')
```



Observations

- We can see that the above histogram is highly positive skewed.
- The first column tell us that there are approximately 5700 observations with probability between 0.0 and 0.1 whose salary is <=50K.
- There are relatively small number of observations with probability > 0.5.
- So, these small number of observations predict that the salaries will be >50K.
- Majority of observations predcit that the salaries will be <=50K.

18. ROC - AUC

ROC Curve

Another tool to measure the classification model performance visually is **ROC Curve**. ROC Curve stands for **Receiver Operating Characteristic Curve**. An **ROC Curve** is a plot which shows the performance of a classification model at various classification threshold levels.

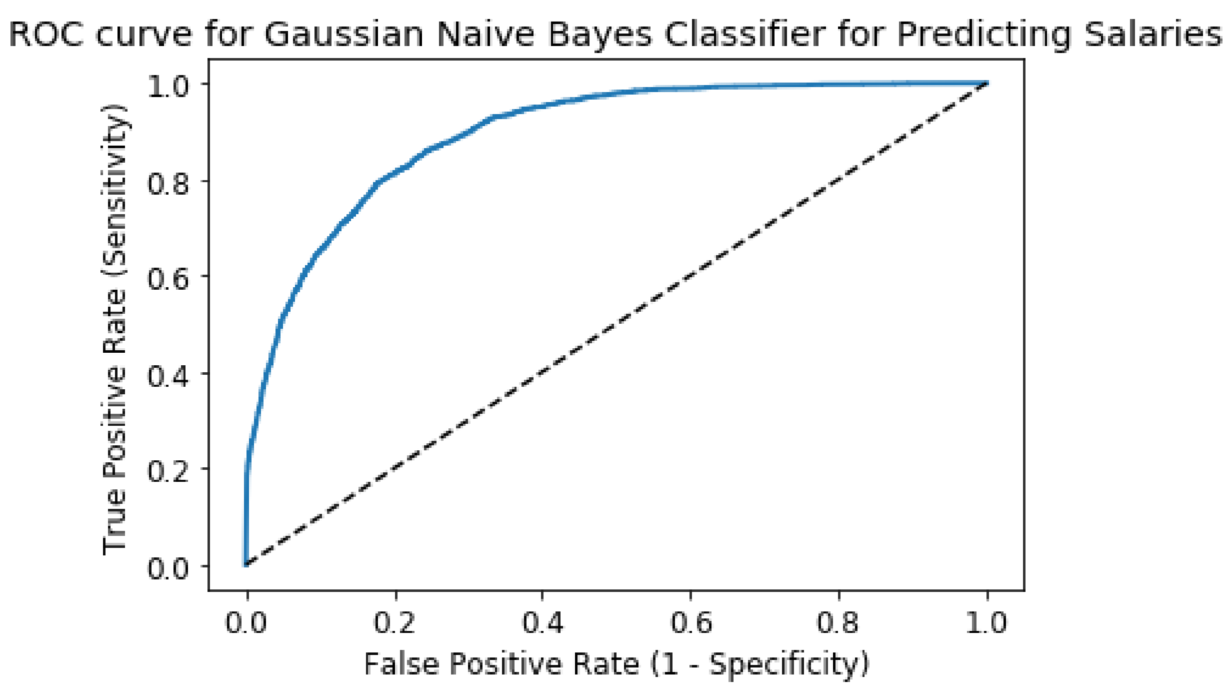
The **ROC Curve** plots the **True Positive Rate (TPR)** against the **False Positive Rate (FPR)** at various threshold levels.

True Positive Rate (TPR) is also called **Recall**. It is defined as the ratio of `TP to (TP + FN)`.

False Positive Rate (FPR) is defined as the ratio of `FP to (FP + TN)`.

In the ROC Curve, we will focus on the TPR (True Positive Rate) and FPR (False Positive Rate) of a single point. This will give us the general performance of the ROC curve which consists of the TPR and FPR at various threshold levels. So, an ROC Curve plots TPR vs FPR at different classification threshold levels. If we lower the threshold levels, it may result in more items being classified as positve. It will increase both True Positives (TP) and False Positives (FP).

```
# plot ROC Curve

from sklearn.metrics import roc_curve

fpr, tpr, thresholds = roc_curve(y_test, y_pred1, pos_label = '>50K')

plt.figure(figsize=(6,4))

plt.plot(fpr, tpr, linewidth=2)

plt.plot([0,1], [0,1], 'k--' )

plt.rcParams['font.size'] = 12

plt.title('ROC curve for Gaussian Naive Bayes Classifier for
Predicting Salaries')

plt.xlabel('False Positive Rate (1 - Specificity)')

plt.ylabel('True Positive Rate (Sensitivity)')

plt.show()
```



ROC curve help us to choose a threshold level that balances sensitivity and specificity for a particular context.

ROC AUC

ROC AUC stands for **Receiver Operating Characteristic - Area Under Curve**. It is a technique to compare classifier performance. In this technique, we measure the `area under the curve (AUC)`. A perfect classifier will have a ROC AUC equal to 1, whereas a purely random classifier will have a ROC AUC equal to 0.5.

So, **ROC AUC** is the percentage of the ROC plot that is underneath the curve.

```
# compute ROC AUC

from sklearn.metrics import roc_auc_score

ROC_AUC = roc_auc_score(y_test, y_pred1)

print('ROC AUC : {:.4f}'.format(ROC_AUC))

ROC AUC : 0.8941
```

Interpretation

- ROC AUC is a single number summary of classifier performance. The higher the value, the better the classifier.
- ROC AUC of our model approaches towards 1. So, we can conclude that our classifier does a good job in predicting whether it will rain tomorrow or not.

```
# calculate cross-validated ROC AUC

from sklearn.model_selection import cross_val_score

Cross_validated_ROC_AUC = cross_val_score(gnb, X_train, y_train, cv=5, 
scoring='roc_auc').mean()

print('Cross validated ROC AUC : 
{:.4f}'.format(Cross_validated_ROC_AUC))

Cross validated ROC AUC : 0.8938
```

19. k-Fold Cross Validation

```
# Applying 10-Fold Cross Validation

from sklearn.model_selection import cross_val_score

scores = cross_val_score(gnb, X_train, y_train, cv = 10, 
scoring='accuracy')
```

```
print('Cross-validation scores:{}'.format(scores))
```

```
Cross-validation scores:[0.81359649 0.80438596 0.81184211 0.80517771
0.79640193 0.79684072
 0.81044318 0.81175954 0.80210619 0.81035996]
```

We can summarize the cross-validation accuracy by calculating its mean.

```
# compute Average cross-validation score

print('Average cross-validation score: {:.4f}'.format(scores.mean()))
```

```
Average cross-validation score: 0.8063
```

Interpretation

- Using the mean cross-validation, we can conclude that we expect the model to be around 80.63% accurate on average.
- If we look at all the 10 scores produced by the 10-fold cross-validation, we can also conclude that there is a relatively small variance in the accuracy between folds, ranging from 81.35% accuracy to 79.64% accuracy. So, we can conclude that the model is independent of the particular folds used for training.
- Our original model accuracy is 0.8083, but the mean cross-validation accuracy is 0.8063. So, the 10-fold cross-validation accuracy does not result in performance improvement for this model.

20. Results and conclusion

1. In this project, I build a Gaussian Naïve Bayes Classifier model to predict whether a person makes over 50K a year. The model yields a very good performance as indicated by the model accuracy which was found to be 0.8083.
2. The training-set accuracy score is 0.8067 while the test-set accuracy to be 0.8083. These two values are quite comparable. So, there is no sign of overfitting.
3. I have compared the model accuracy score which is 0.8083 with null accuracy score which is 0.7582. So, we can conclude that our Gaussian Naïve Bayes classifier model is doing a very good job in predicting the class labels.
4. ROC AUC of our model approaches towards 1. So, we can conclude that our classifier does a very good job in predicting whether a person makes over 50K a year.
5. Using the mean cross-validation, we can conclude that we expect the model to be around 80.63% accurate on average.
6. If we look at all the 10 scores produced by the 10-fold cross-validation, we can also conclude that there is a relatively small variance in the accuracy between folds, ranging from 81.35% accuracy to 79.64% accuracy. So, we can conclude that the model is independent of the particular folds used for training.

7. Our original model accuracy is 0.8083, but the mean cross-validation accuracy is 0.8063. So, the 10-fold cross-validation accuracy does not result in performance improvement for this model.