In machine learning, Naïve Bayes classification is a straightforward and powerful algorithm for the classification task. In this kernel, 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.

1. Introduction to Naive Bayes 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. Import libraries

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt # for data visualization purposes
import seaborn as sns # for statistical data visualization
%matplotlib inline
```

3. Import dataset

```
data = '/content/adult.csv'
```

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

```
<ipython-input-2-6bdc593ece69>:3: ParserWarning: Falling back to the 'python' engine because the 'c' engine does not support regex s
  df = pd.read_csv(data, header=None, sep=',\s')
```

4. Exploratory data analysis

```
# view dimensions of dataset
```

```
df.shape
```

```
(32561, 15)
```

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

```
# preview the dataset
```

```
df.head()
```

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3						Married-civ-	Handlers-							United-	

Next steps: Generate code with df View recommended plots

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	marital_status	occupation	relationship	race	sex	capital_gain	capital_l
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	

Next steps: Generate code with df View recommended plots

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):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32561 non-null  int64 
 1   workclass       32561 non-null  object
 2   fnlwgt          32561 non-null  int64 
 3   education       32561 non-null  object
 4   education_num   32561 non-null  int64 
 5   marital_status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital_gain    32561 non-null  int64 
 11  capital_loss    32561 non-null  int64 
 12  hours_per_week  32561 non-null  int64 
 13  native_country  32561 non-null  object
 14  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

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	relationship	race	sex	native_country	income
0	State-gov	Bachelors	Never-married	Adm-clerical	Not-in-family	White	Male	United-States	<=50K
1	Self-emp-not-inc	Bachelors	Married-civ-spouse	Exec-managerial	Husband	White	Male	United-States	<=50K
2	Private	HS-grad	Divorced	Handlers-cleaners	Not-in-family	White	Male	United-States	<=50K
3	Private	11th	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	United-States	<=50K
4	Private	Bachelors	Married-civ-spouse	Prof-specialty	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

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.

Frequency counts of categorical variables

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

for var in categorical:

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

```
Taiwan                        51
Haiti                         44
Iran                          43
Portugal                      37
Nicaragua                     34
Peru                          31
France                        29
Greece                        29
Ecuador                       28
Ireland                       24
Hong                          20
Cambodia                      19
Trinadad&Tobago               19
Laos                          18
Thailand                      18
Yugoslavia                    16
Outlying-US(Guam-USVI-etc)    14
Honduras                      13
Hungary                       13
Scotland                      12
Holand-Netherlands             1
Name: count, dtype: int64
income
<=50K    24720
>50K      7841
Name: count, dtype: int64
```

```
# view frequency distribution of categorical variables

for var in categorical:

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

```
>50K      0.24081
Name: count, 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().

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()
```

```
workclass
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: count, 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()
```

```
workclass
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: count, 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()
```

```
occupation
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: count, 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()
```

```
occupation
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: count, 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()
```

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

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

```
# 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.

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.

5. Declare feature vector and target variable

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

y = df['income']
```

6. 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))
```

7. 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
```

```
# 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 0.05598455598455984
occupation 0.05607230607230607
native_country 0.018164268164268166
```

```
# 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)
```

```
# 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
```

```
# 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
```

I will check for missing values in X_train and X_test once again.

```
# 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	relationship	race	sex	native_country
32098	Private	HS-grad	Married-civ-spouse	Craft-repair	Husband	White	Male	United-States
25206	State-gov	HS-grad	Divorced	Adm-clerical	Unmarried	White	Female	United-States
23491	Private	Some-college	Married-civ-spouse	Sales	Husband	White	Male	United-States
12367	Private	HS-grad	Never-married	Craft-repair	Not-in-family	White	Male	Guatemala
7054	Private	7th-8th	Never-married	Craft-repair	Not-in-family	White	Male	Germany

```
# import category encoders
!pip install category_encoders
import category_encoders as ce
```

```
Collecting category_encoders
  Downloading category_encoders-2.6.3-py2.py3-none-any.whl (81 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 81.9/81.9 kB 3.1 MB/s eta 0:00:00
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (1.25.2)
Requirement already satisfied: scikit-learn>=0.20.0 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (1.2.2)
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (1.11.4)
Requirement already satisfied: statsmodels>=0.9.0 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (0.14.2)
Requirement already satisfied: pandas>=1.0.5 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (2.0.3)
Requirement already satisfied: patsy>=0.5.1 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (0.5.6)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.0.5->category_enco
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.0.5->category_encoders) (202
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.0.5->category_encoders) (20
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from patsy>=0.5.1->category_encoders) (1.16.0)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.20.0->category_encoder
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.20.0->category_
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.10/dist-packages (from statsmodels>=0.9.0->category_encoder
Installing collected packages: category_encoders
Successfully installed category_encoders-2.6.3
```

```
# 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()
```

	age	workclass_1	workclass_2	workclass_3	workclass_4	workclass_5	workclass_6	workclass_7	workclass_8	fnlwgt	...	nat:
32098	45	1	0	0	0	0	0	0	0	170871	...	
25206	47	0	1	0	0	0	0	0	0	108890	...	
23491	48	1	0	0	0	0	0	0	0	187505	...	
12367	29	1	0	0	0	0	0	0	0	145592	...	
7054	23	1	0	0	0	0	0	0	0	203003	...	

5 rows × 105 columns

```
X_train.shape
```

```
(22792, 105)
```

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()
```

	age	workclass_1	workclass_2	workclass_3	workclass_4	workclass_5	workclass_6	workclass_7	workclass_8	fnlwgt	...	nat:
22278	27	1	0	0	0	0	0	0	0	177119	...	
8950	27	1	0	0	0	0	0	0	0	216481	...	
7838	25	1	0	0	0	0	0	0	0	256263	...	
16505	46	1	0	0	0	0	0	0	0	147640	...	
19140	45	1	0	0	0	0	0	0	0	172822	...	

5 rows × 105 columns

```
X_test.shape
```

```
(9769, 105)
```

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.

8. 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()
```

	age	workclass_1	workclass_2	workclass_3	workclass_4	workclass_5	workclass_6	workclass_7	workclass_8	fnlwgt	...	nati
0	0.40	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.058906	...	
1	0.50	-1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.578076	...	
2	0.55	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.080425	...	
3	-0.40	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.270650	...	
4	-0.70	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.210240	...	

5 rows × 105 columns

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

9. Model training

```
# 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
GaussianNB()
```

10. Predict the results

```
y_pred = gnb.predict(X_test)

y_pred
```

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

11. 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()
```

```
income
<=50K    7407
>50K     2362
Name: count, 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.

12. 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.

```
# 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
```

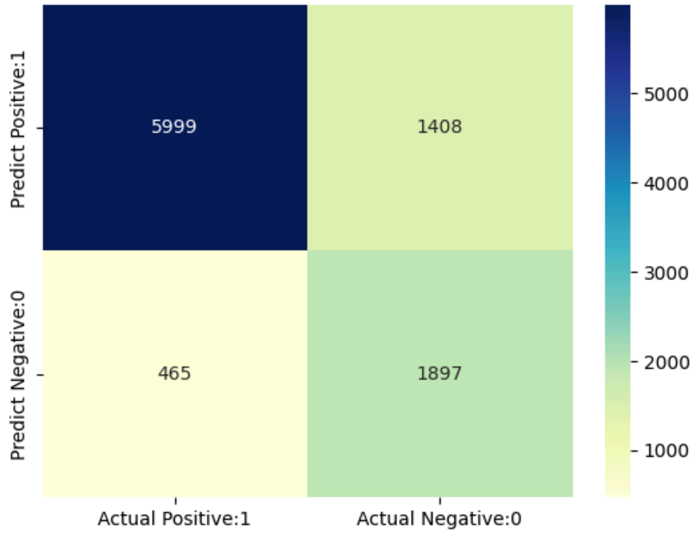
The confusion matrix shows 5999 + 1897 = 7896 correct predictions and 1408 + 465 = 1873 incorrect predictions.

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')
```

```
<Axes: >
```



13. 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

     accuracy                           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)


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

```
False Positive Rate : 0.4260
```

Specificity

```
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.

14. Calculate class probabilities

```
# 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

Next steps: Generate code with y_pred_prob_df View recommended plots

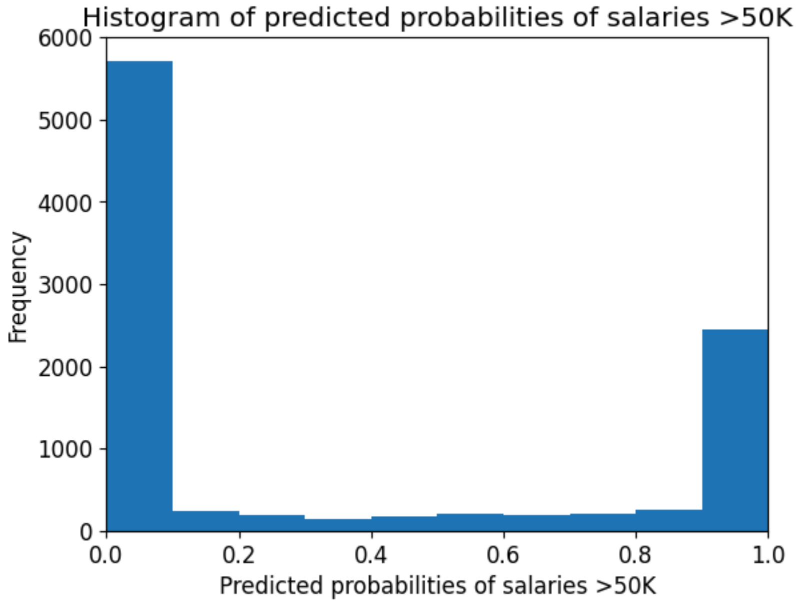
```
# print the first 10 predicted probabilities for class 1 - Probability of >50K

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]
```

```
# 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

14. 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.

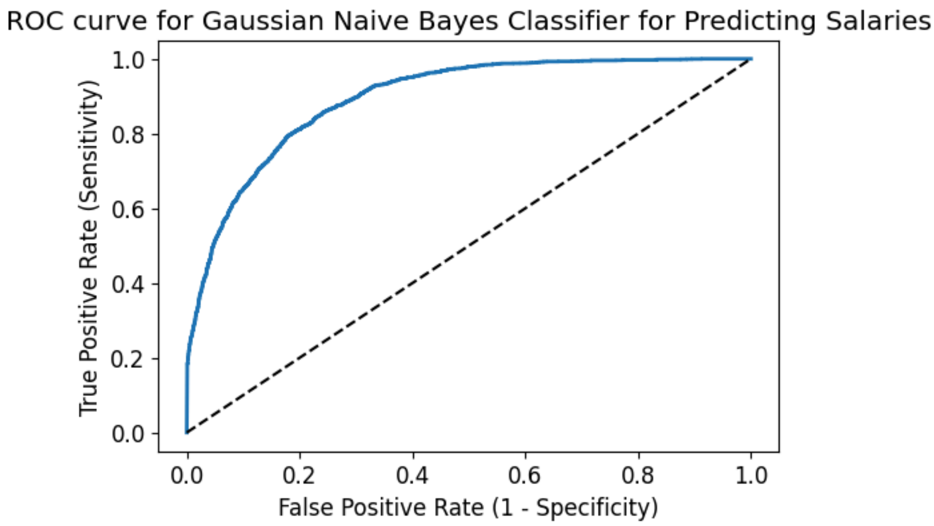
The ROC Curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold levels.

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.

16. 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')
```

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.

17. Results and conclusion

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. 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. 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. 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. 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.

18. References

The work done in this project is inspired from following websites:-

https://www.kaggle.com/datasets/qizarafzaal/adult-dataset