

```
In [1]: 1 import numpy as np
        2 import pandas as pd
        3 import matplotlib.pyplot as plt
```

```
In [10]: 1 salary_train=pd.read_csv('SalaryData_Train.csv')
        2 salary_train
```

Out[10]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	sex	capitalgain	capitalloss	hoursperw
0	39	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	
1	50	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	
2	38	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	
3	53	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	
4	28	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	
...	
30156	27	Private	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	0	0	
30157	40	Private	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0	
30158	58	Private	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	0	0	
30159	22	Private	HS-grad	9	Never-married	Adm-clerical	Own-child	White	Male	0	0	
30160	52	Self-emp-inc	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	15024	0	

30161 rows × 14 columns



```
In [11]: 1 salary_test=pd.read_csv('SalaryData_Test.csv')
          2 salary_test
```

Out[11]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	sex	capitalgain	capitalloss	hourspe
0	25	Private	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	0	0	
1	38	Private	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0	0	
2	28	Local-gov	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	0	0	
3	44	Private	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	7688	0	
4	34	Private	10th	6	Never-married	Other-service	Not-in-family	White	Male	0	0	
...	
15055	33	Private	Bachelors	13	Never-married	Prof-specialty	Own-child	White	Male	0	0	
15056	39	Private	Bachelors	13	Divorced	Prof-specialty	Not-in-family	White	Female	0	0	
15057	38	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Husband	White	Male	0	0	
15058	44	Private	Bachelors	13	Divorced	Adm-clerical	Own-child	Asian-Pac-Islander	Male	5455	0	
15059	35	Self-emp-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	

15060 rows × 14 columns



```
In [12]: 1 salary_train.columns
          2 salary_test.columns
          3 string_columns=['workclass','education','maritalstatus','occupation','relationship','race','sex','native']
```

```
In [13]: 1 from sklearn import preprocessing
2 label_encoder=preprocessing.LabelEncoder()
3 for i in string_columns:
4     salary_train[i]=label_encoder.fit_transform(salary_train[i])
5     salary_test[i]=label_encoder.fit_transform(salary_test[i])
```

```
In [14]: 1 col_names=list(salary_train.columns)
2 train_X=salary_train[col_names[0:13]]
3 train_Y=salary_train[col_names[13]]
4 test_x=salary_test[col_names[0:13]]
5 test_y=salary_test[col_names[13]]
6
```

```
In [15]: 1 #Gaussian Naive Bayes
2
3 from sklearn.naive_bayes import GaussianNB
4 Gmodel=GaussianNB()
5 train_pred_gau=Gmodel.fit(train_X,train_Y).predict(train_X)
6 test_pred_gau=Gmodel.fit(train_X,train_Y).predict(test_x)
```

```
In [16]: 1 train_acc_gau=np.mean(train_pred_gau==train_Y)
2 test_acc_gau=np.mean(test_pred_gau==test_y)
```

```
In [17]: 1 train_acc_gau
```

Out[17]: 0.7953317197705646

```
In [18]: 1 test_acc_gau
```

Out[18]: 0.7946879150066402

```
In [19]: 1 #Multinomial Naive Bayes
          2
          3 from sklearn.naive_bayes import MultinomialNB
          4 Mmodel=MultinomialNB()
          5 train_pred_multi=Mmodel.fit(train_X,train_Y).predict(train_X)
          6 test_pred_multi=Mmodel.fit(train_X,train_Y).predict(test_x)
```

```
In [20]: 1 train_acc_multi=np.mean(train_pred_multi==train_Y)
          2 test_acc_multi=np.mean(test_pred_multi==test_y)
```

```
In [21]: 1 train_acc_multi
```

Out[21]: 0.7729186698053778

```
In [22]: 1 test_acc_multi
```

Out[22]: 0.7749667994687915

```
In [ ]: 1
```