Q2-adult-census-income

March 8, 2021

0.1 Question 2

0.2 Census Income Data Set - Machine Learning Model

Data Source: https://www.kaggle.com/uciml/adult-census-income

0.2.1 Attribute Characteristics: Categorical, Integer

0.2.2 Data Set Characteristics: Multivariate

0.3 Prediction task is to determine whether a person makes over 50K a year.

1. Import the csv dataset from https://www.kaggle.com/uciml/adult-census-income (Links to an external site.) .
2. Identify the presence of missing values, fill the missing values with mean for numerical attributes and mode value for categorical attributes.
3. Extract X as all columns except the Income column and Y as Income column.
4. Split the data into training set and testing set.
5. Model the classifier using GaussianNB, BernoulliNB and MultinomialNB
6. Compute the accuracy and confusion matrix for each models.
7. Plot the decision boundary, visualize training and test results of all the models
8. Create an output .csv file consisting actual Test set values of Y (column name: Actual) and Predictions of Y(column name: Predicted).

Data Understanding:

- age: Continuous
- workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.
- fnlwgt: continuous.
- education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool.
- education-num: continuous.
- marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.

- occupation: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.
- relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.
- race: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.
- sex: Female, Male.
- capital-gain: continuous.
- capital-loss: continuous.
- hours-per-week: continuous.
- native-country: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.

0.4 Objective : To predict whether a given adult makes more than 50,000 a year based attributes such as:

age, workclass, fnlwgt, education, education.num, marital.status, occupation, relationship, race, sex, capital.gain, capital.loss, hours.per.week, native.country, income.

0.4.1 Common Libraries

[1]:
```python
import os
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import metrics
from scipy.stats import pointbiserialr, spearmanr
from mlxtend.plotting import plot_decision_regions
from sklearn.model_selection import cross_val_score
from sklearn.naive_bayes import GaussianNB, BernoulliNB, MultinomialNB
from sklearn.metrics import accuracy_score,confusion_matrix,␣
 ↪classification_report
cwd = os.getcwd()
```

0.4.2 1. Import the csv dataset from https://www.kaggle.com/uciml/adult-census-income

[2]:
```
ds=pd.read_csv('adult.csv',na_values='?')
print(ds.columns,'\n')
print(str.format('Number of Columns/Features: {0}',len(ds.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')

Number of Columns/Features: 15
```

- Get the the Data set using read_csv and replace '?' with NaN
- Understand the number of columns

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

[3]:
```
   age workclass  fnlwgt     education  education.num marital.status  \
0   90       NaN   77053       HS-grad              9        Widowed
1   82   Private  132870       HS-grad              9        Widowed
2   66       NaN  186061  Some-college             10        Widowed
3   54   Private  140359       7th-8th              4       Divorced
4   41   Private  264663  Some-college             10      Separated

          occupation   relationship   race     sex  capital.gain  \
0                NaN  Not-in-family  White  Female             0
1    Exec-managerial  Not-in-family  White  Female             0
2                NaN      Unmarried  Black  Female             0
3  Machine-op-inspct      Unmarried  White  Female             0
4     Prof-specialty      Own-child  White  Female             0

   capital.loss  hours.per.week native.country income
0          4356              40  United-States  <=50K
1          4356              18  United-States  <=50K
2          4356              40  United-States  <=50K
3          3900              40  United-States  <=50K
4          3900              40  United-States  <=50K
```

0.4.3 Understanding Number of Null values and outliers

[4]:
```
col_names=ds.columns
beforeDropTupleCount= len(ds)
len(ds.columns)
print(ds.info())
ds.isnull().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
age               32561 non-null int64
workclass         30725 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        30718 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    31978 non-null object
income            32561 non-null object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
None
```

[4]:
```
age                  0
workclass         1836
fnlwgt               0
education            0
education.num        0
marital.status       0
occupation        1843
relationship         0
race                 0
sex                  0
capital.gain         0
capital.loss         0
hours.per.week       0
native.country     583
income               0
dtype: int64
```

From above informaion null check, understood that 3 feature have null values

- workclass - string - 1836 null records
- occupation - string - 1843 null records
- native.country - string - 583 null records

0.5 2. Identify the presence of missing values, fill the missing values with mean for numerical attributes and mode value for categorical attributes.

[5]:
```
print('workclass mode:',ds['workclass'].mode().iloc[0])
print('occupation mode:',ds['occupation'].mode().iloc[0])
print('native.country mode:',ds['native.country'].mode().iloc[0])
ds['workclass']=ds['workclass'].fillna(ds['workclass'].mode().iloc[0])
ds['occupation']=ds['occupation'].fillna(ds['occupation'].mode().iloc[0])
ds['native.country']=ds['native.country'].fillna(ds['native.country'].mode().
 ↪iloc[0])
```

```
workclass mode: Private
occupation mode: Prof-specialty
native.country mode: United-States
```

[6]:
```
col_names=['age','workclass','fnlwgt','education','education.num','marital.
 ↪status','occupation','relationship','race','sex','capital.gain','capital.
 ↪loss','hours.per.week','native.country','income',]
col_names=ds.columns
beforeDropTupleCount= len(ds)
len(ds.columns)
print(ds.info())
ds.isnull().sum()
```

```
<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
None
```

[6]:
```
age               0
workclass         0
fnlwgt            0
education         0
education.num     0
marital.status    0
occupation        0
relationship      0
race              0
sex               0
capital.gain      0
capital.loss      0
hours.per.week    0
native.country    0
income            0
dtype: int64
```

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

[7]:
```
   age workclass  fnlwgt     education  education.num marital.status  \
0   90   Private   77053       HS-grad              9        Widowed
1   82   Private  132870       HS-grad              9        Widowed
2   66   Private  186061  Some-college             10        Widowed
3   54   Private  140359       7th-8th              4       Divorced
4   41   Private  264663  Some-college             10      Separated

          occupation   relationship   race     sex  capital.gain  \
0     Prof-specialty  Not-in-family  White  Female             0
1    Exec-managerial  Not-in-family  White  Female             0
2     Prof-specialty      Unmarried  Black  Female             0
3  Machine-op-inspct      Unmarried  White  Female             0
4     Prof-specialty      Own-child  White  Female             0

   capital.loss  hours.per.week native.country income
0          4356              40  United-States  <=50K
1          4356              18  United-States  <=50K
2          4356              40  United-States  <=50K
3          3900              40  United-States  <=50K
4          3900              40  United-States  <=50K
```

0.5.1 2.1 Below Null records are handled in above step

- workclass mode: Private
- occupation mode: Prof-specialty
- native.country mode: United-States

0.5.2 2.1.1 Data analysis

- Distinct Value on each Feature/Attributes

[8]:
```
print(ds.info())
Attribute_Wise_Count = pd.DataFrame(columns=['Attribute', 'Distinct_Count'])
for col_index in ds.columns:
    Attribute_Wise_Count = Attribute_Wise_Count.append(pd.
 ↪DataFrame({'Attribute': [col_index],'Distinct_Count': [len(ds[col_index].
 ↪unique())]}))
Attribute_Wise_Count.reset_index(drop=True).sort_values(by='Distinct_Count',␣
 ↪ascending=False)
```

```
<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
None
```

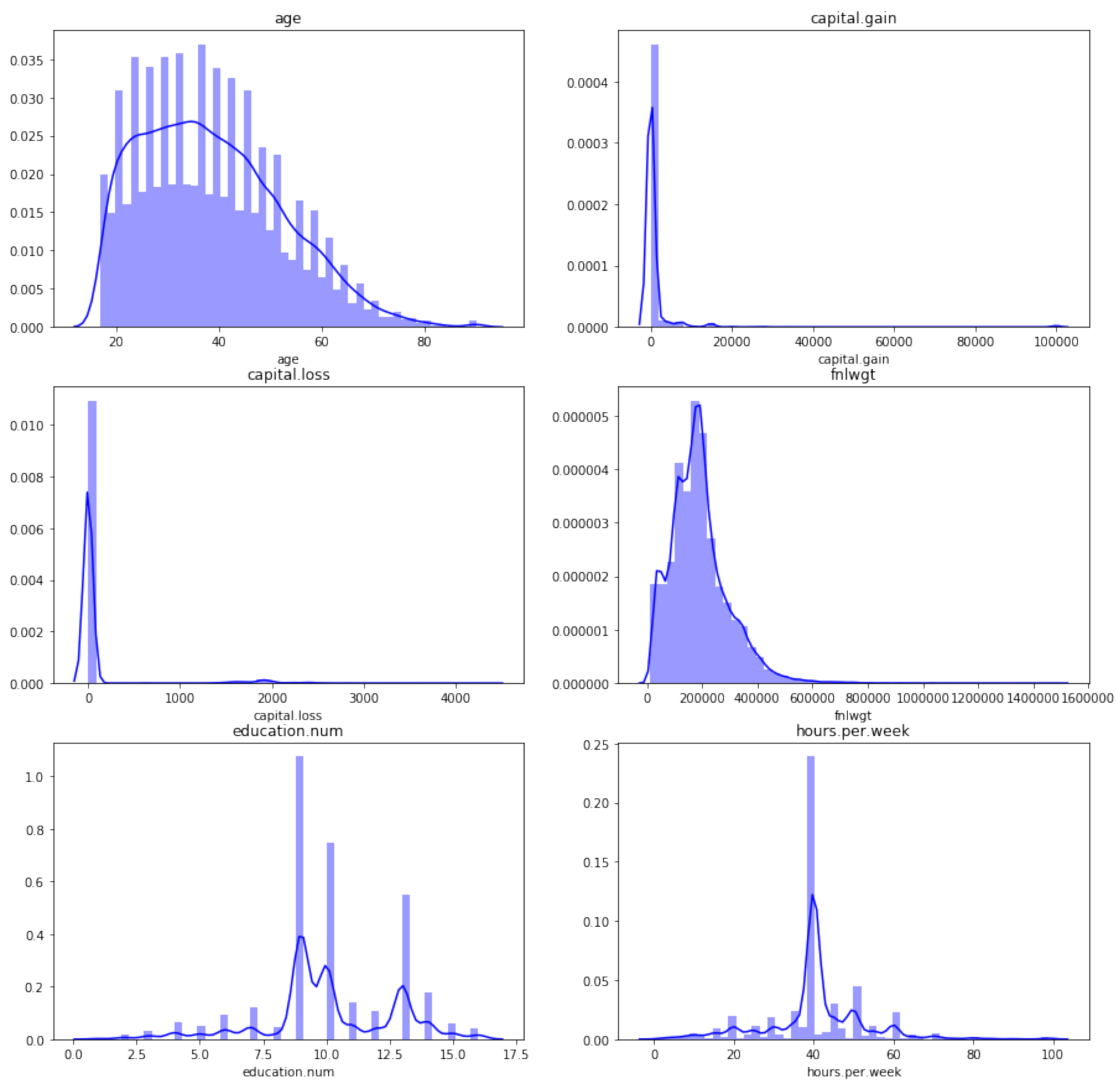
[8]:

	Attribute	Distinct_Count
2	fnlwgt	21648
10	capital.gain	119
12	hours.per.week	94
11	capital.loss	92
0	age	73
13	native.country	41
3	education	16
4	education.num	16
6	occupation	14
1	workclass	8
5	marital.status	7
7	relationship	6

```
8              race             5
9               sex             2
14           income             2
```

0.5.3 2.1.2 Numerical data visual interpretation

[9]:
```python
num_col=['age','capital.gain','capital.loss','fnlwgt','education.num','hours.
↪per.week']
fig,axes = plt.subplots(3,2,figsize=(15,15))
for idx,cat_col in enumerate(num_col):
    row,col = idx//2,idx%2
    sns.distplot(ds[cat_col],ax=axes[row,col], rug=False, color='b',␣
↪label="All").set_title(cat_col)
plt.subplots_adjust(hspace=.2)
```



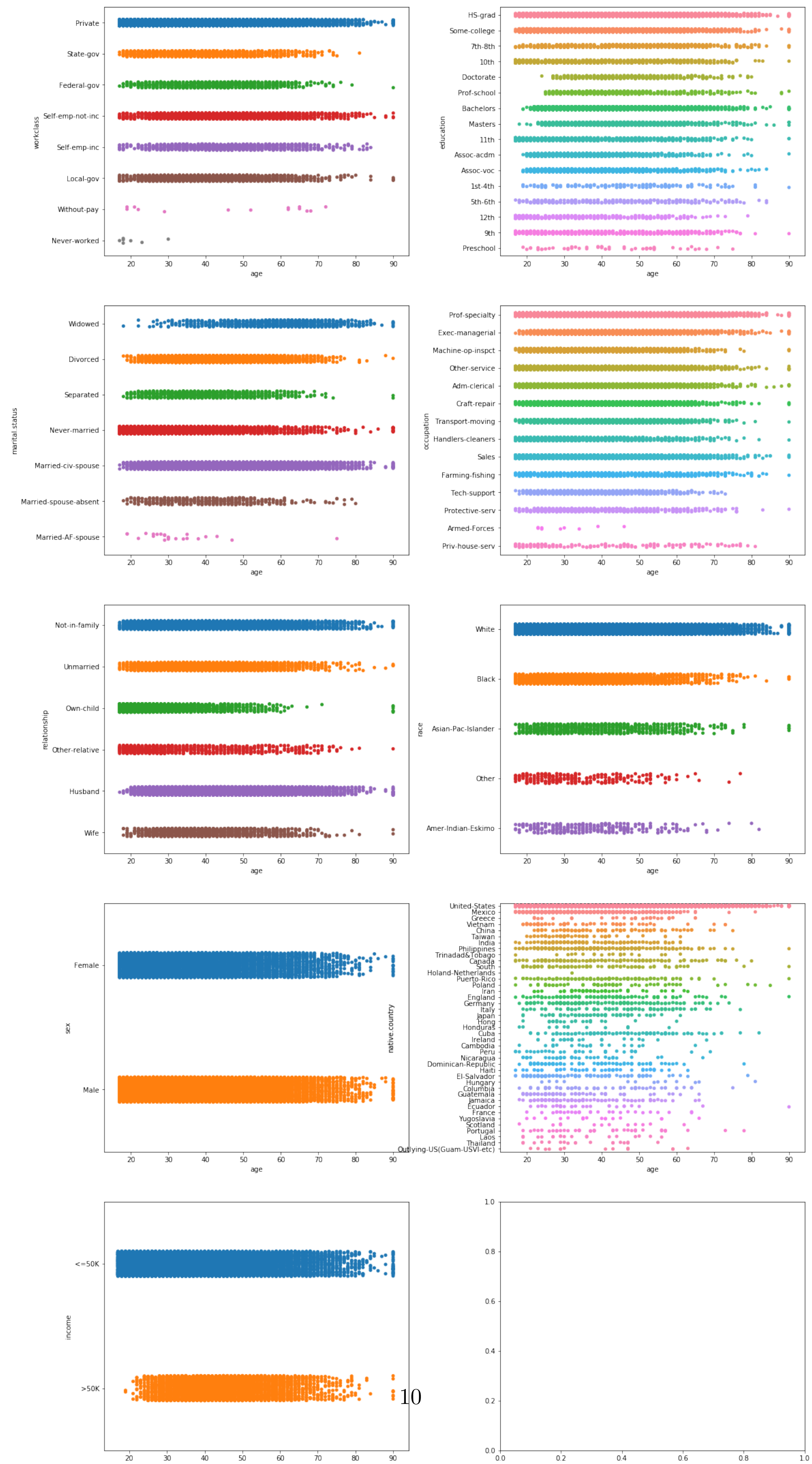
0.5.4 2.1.3 Correclation on numerical values

[10]:
```
X = ds[col_names]
X.corr()
```

[10]:
```
                     age   fnlwgt  education.num  capital.gain  capital.loss  \
age             1.000000 -0.076646       0.036527      0.077674      0.057775
fnlwgt         -0.076646  1.000000      -0.043195      0.000432     -0.010252
education.num   0.036527 -0.043195       1.000000      0.122630      0.079923
capital.gain    0.077674  0.000432       0.122630      1.000000     -0.031615
capital.loss    0.057775 -0.010252       0.079923     -0.031615      1.000000
hours.per.week  0.068756 -0.018768       0.148123      0.078409      0.054256

                hours.per.week
age                   0.068756
fnlwgt               -0.018768
education.num         0.148123
capital.gain          0.078409
capital.loss          0.054256
hours.per.week        1.000000
```

0.6 2.2 Categorical Visual Interpretation

[11]:
```
filtered = [(item) for item in ds.columns.tolist() if item not in num_col]
fig, axes = plt.subplots(nrows=5, ncols=2, figsize=(15, 30))
fig.tight_layout()
for idx,cat_col in enumerate(filtered):
    row,col = idx//2,idx%2
    g=sns.catplot(x='age', y=cat_col, data=ds, ax=axes[row,col])
    plt.title('cat_col')
    plt.close()
    plt.subplots_adjust(left=None, bottom=None, right=None, top=None, wspace=.
 ↪3, hspace=.2)
plt.show()
```


workclass
Private
State-gov
Federal-gov
Self-emp-not-inc
Self-emp-inc
Local-gov
Without-pay
Never-worked
education
HS-grad
Some-college
7th-8th
10th
Doctorate
Prof-school
Bachelors
Masters
11th
Assoc-acdm
Assoc-voc
1st-4th
5th-6th
12th
9th
Preschool
marital.status
Widowed
Divorced
Separated
Never-married
Married-civ-spouse
Married-spouse-absent
Married-AF-spouse
occupation
Prof-specialty
Exec-managerial
Machine-op-inspct
Other-service
Adm-clerical
Craft-repair
Transport-moving
Handlers-cleaners
Sales
Farming-fishing
Tech-support
Protective-serv
Armed-Forces
Priv-house-serv
relationship
Not-in-family
Unmarried
Own-child
Other-relative
Husband
Wife
race
White
Black
Asian-Pac-Islander
Other
Amer-Indian-Eskimo
sex
Female
Male
native.country
United-States
Mexico
Greece
Vietnam
China
Taiwan
India
Philippines
Trinadad&Tobago
Canada
South
Holand-Netherlands
Puerto-Rico
Poland
Iran
England
Germany
Italy
Japan
Hong
Honduras
Cuba
Ireland
Cambodia
Peru
Nicaragua
Dominican-Republic
Haiti
El-Salvador
Hungary
Columbia
Guatemala
Jamaica
Ecuador
France
Yugoslavia
Scotland
Portugal
Laos
Thailand
Outlying-US(Guam-USVI-etc)
income
<=50K
>50K
age
20 30 40 50 60 70 80 90
0.0 0.2 0.4 0.6 0.8 1.0

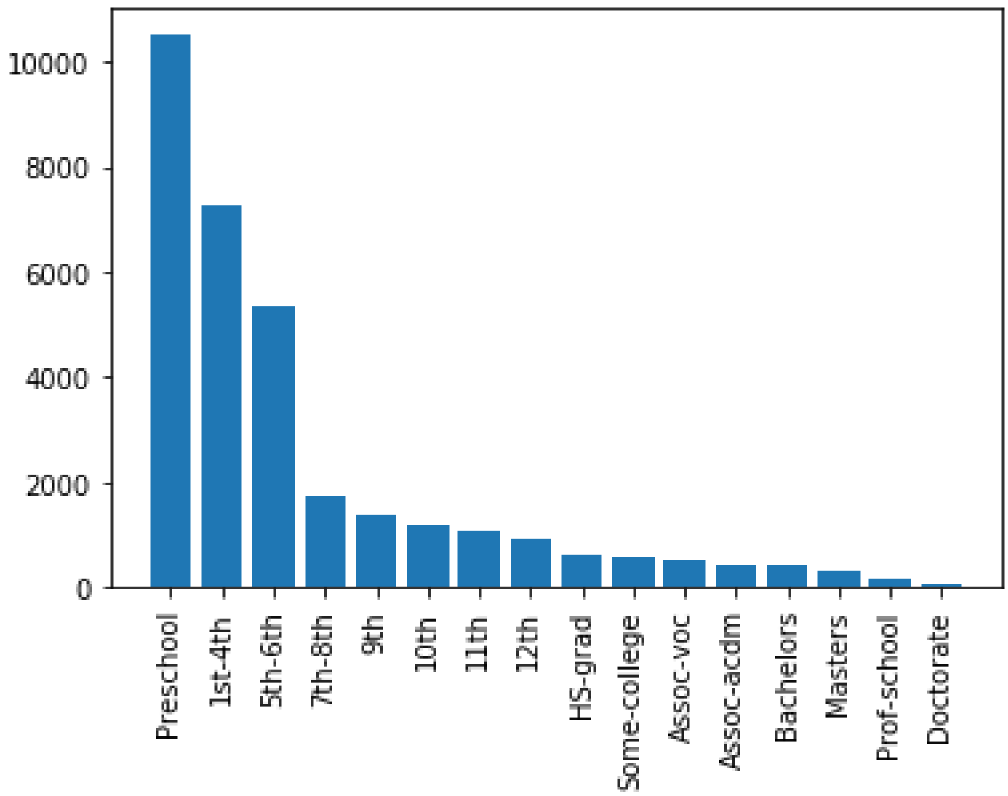
0.6.1 2.2.1 Exploring categorical data individually with respect to age

[12]:
```
def plot_chart(x_axis_val,y_axis_val):
    heights = y_axis_val
    bars = x_axis_val
    y_pos = range(len(bars))
    plt.bar(y_pos, heights)
    plt.xticks(y_pos, bars, rotation=90)
```

[13]:
```
education_df=pd.DataFrame(ds.groupby(['education.num', 'education'])['age'].
 ↪count())
education_df=education_df.sort_values(by=['age'],ascending=False)
plot_chart(ds.sort_values(by=['education.num'])['education'].
 ↪unique(),education_df['age'])
pd.DataFrame(education_df).reset_index().rename({'age': 'count'}, axis=1).
 ↪sort_values(by=['count'],ascending=False)
```

[13]:

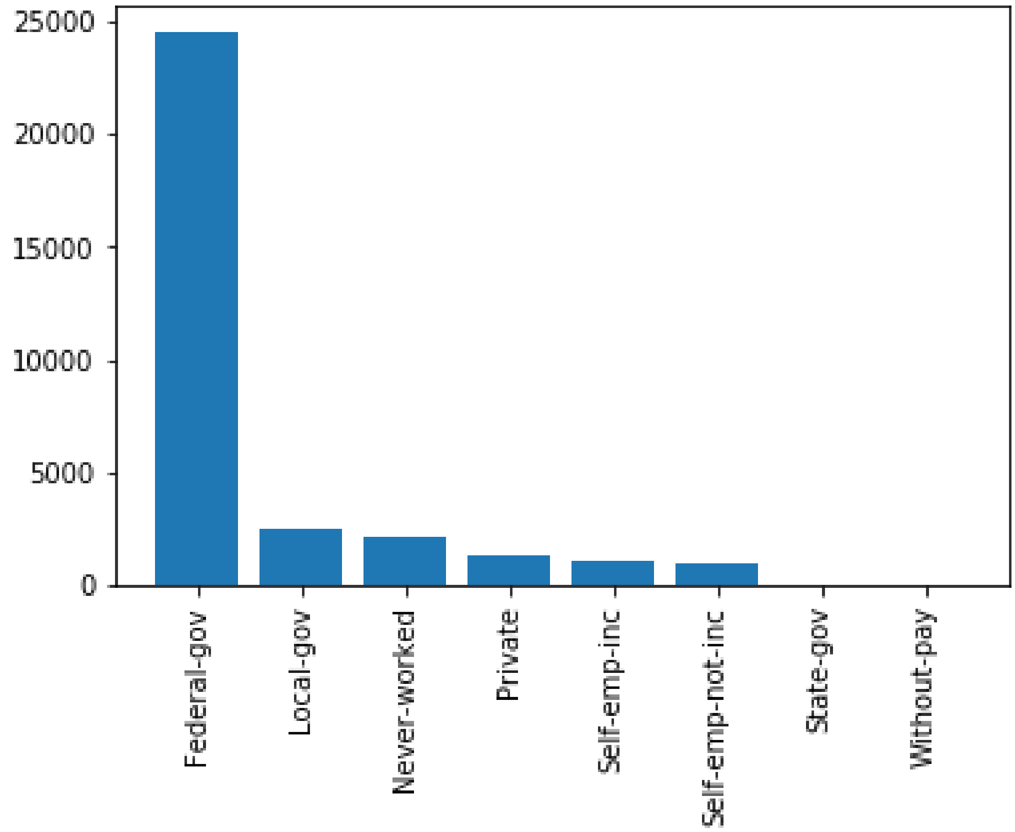
	education.num	education	count
0	9	HS-grad	10501
1	10	Some-college	7291
2	13	Bachelors	5355
3	14	Masters	1723
4	11	Assoc-voc	1382
5	7	11th	1175
6	12	Assoc-acdm	1067
7	6	10th	933
8	4	7th-8th	646
9	15	Prof-school	576
10	5	9th	514
11	8	12th	433
12	16	Doctorate	413
13	3	5th-6th	333
14	2	1st-4th	168
15	1	Preschool	51



[14]:
```
type_employer_df=pd.DataFrame(ds.groupby(['workclass'])['age'].count()).
↪reset_index().rename({'age': 'count'}, axis=1).
↪sort_values(by=['count'],ascending=False)
plot_chart(ds.sort_values(by=['workclass'])['workclass'].
↪unique(),type_employer_df['count'])
type_employer_df
```

[14]:

	workclass	count
3	Private	24532
5	Self-emp-not-inc	2541
1	Local-gov	2093
6	State-gov	1298
4	Self-emp-inc	1116
0	Federal-gov	960
7	Without-pay	14
2	Never-worked	7

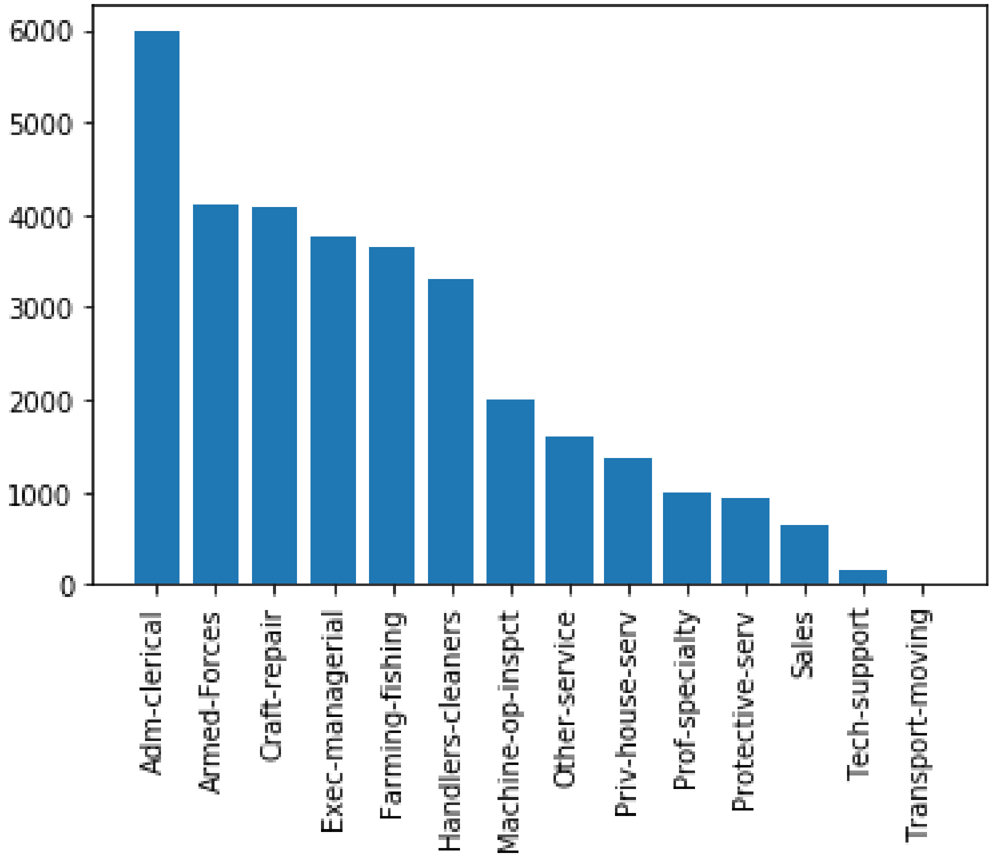


[15]:
```
occupation_df=pd.DataFrame(ds.groupby(['occupation'])['age'].count()).
↪reset_index().rename({'age': 'count'}, axis=1).
↪sort_values(by=['count'],ascending=False)
plot_chart(ds.sort_values(by=['occupation'])['occupation'].
↪unique(),occupation_df['count'])
occupation_df
```

[15]:

	occupation	count
9	Prof-specialty	5983
2	Craft-repair	4099
3	Exec-managerial	4066
0	Adm-clerical	3770
11	Sales	3650
7	Other-service	3295
6	Machine-op-inspct	2002
13	Transport-moving	1597
5	Handlers-cleaners	1370
4	Farming-fishing	994
12	Tech-support	928
10	Protective-serv	649

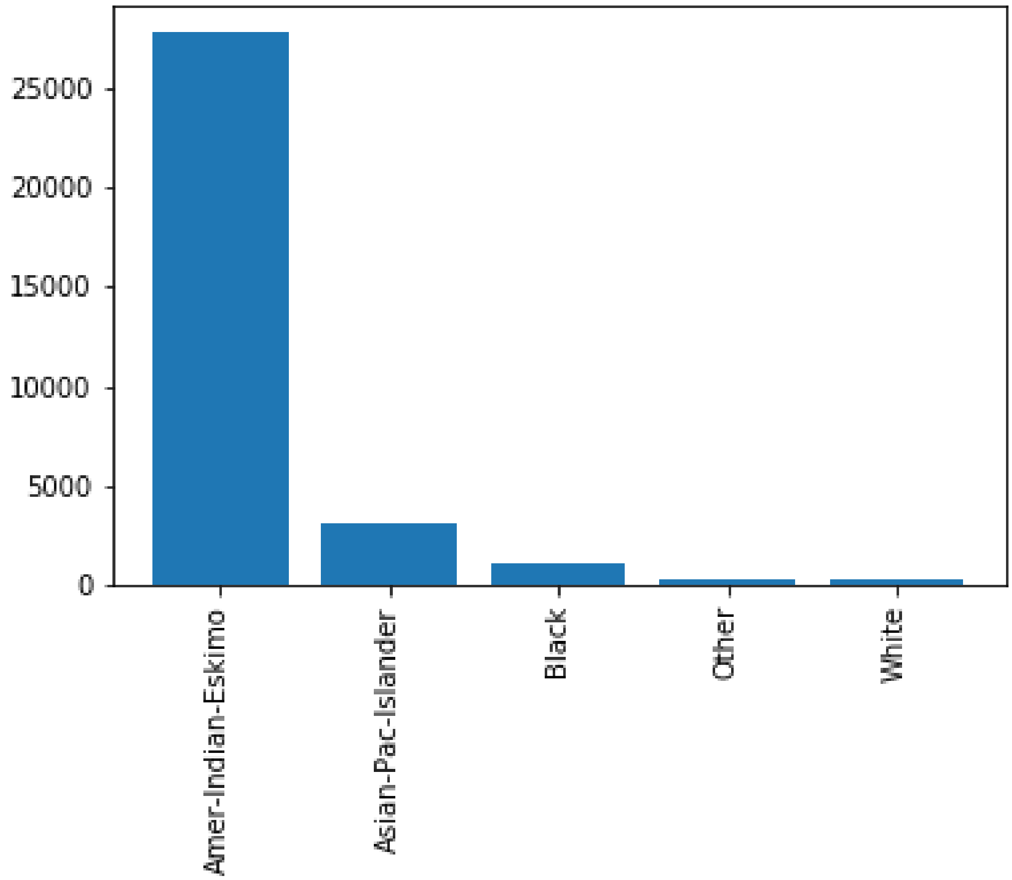
```
8     Priv-house-serv    149
1        Armed-Forces      9
```



[16]:
```
race_df=pd.DataFrame(ds.groupby(['race'])['age'].count()).reset_index().
↪rename({'age': 'count'}, axis=1).sort_values(by=['count'],ascending=False)
plot_chart(ds.sort_values(by=['race'])['race'].unique(),race_df['count'])
race_df
```

[16]:

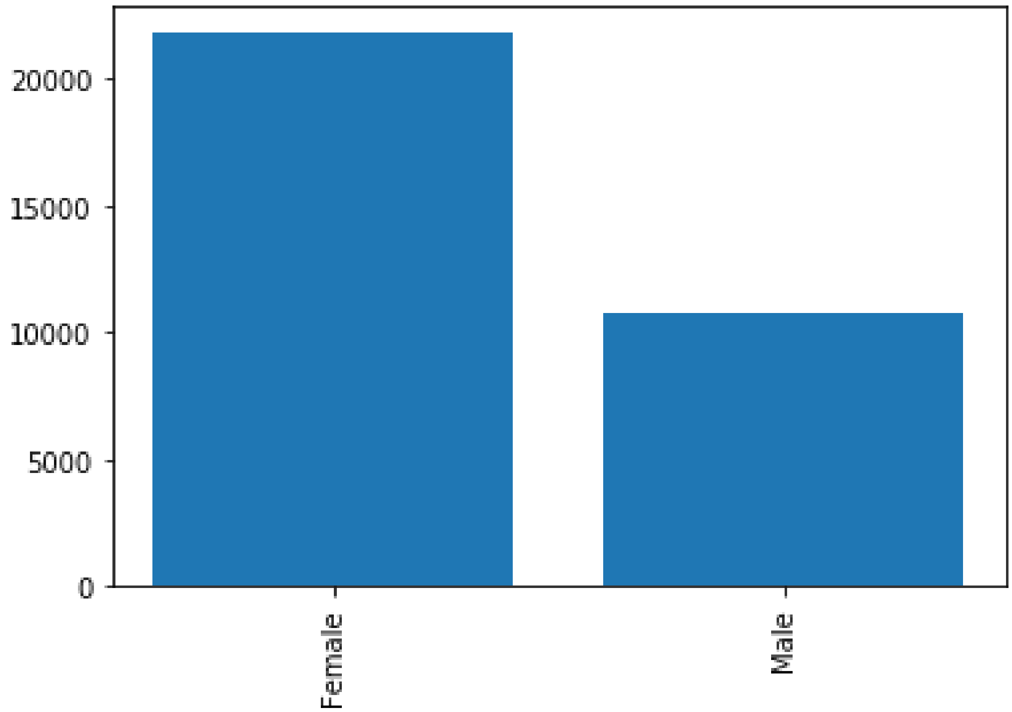
	race	count
4	White	27816
2	Black	3124
1	Asian-Pac-Islander	1039
0	Amer-Indian-Eskimo	311
3	Other	271



[17]:
```
sex_df=pd.DataFrame(ds.groupby(['sex'])['age'].count()).reset_index().
 ↪rename({'age': 'count'}, axis=1).sort_values(by=['count'],ascending=False)
plot_chart(ds.sort_values(by=['sex'])['sex'].unique(),sex_df['count'])
sex_df
```

[17]:

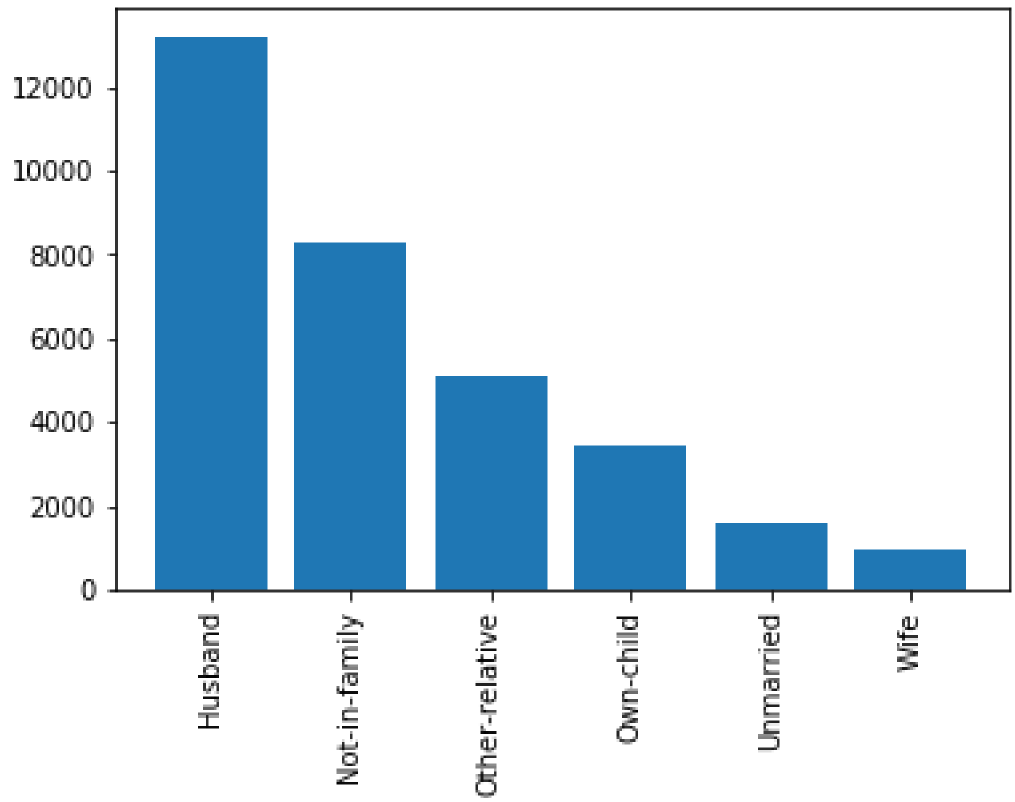
	sex	count
1	Male	21790
0	Female	10771



[18]:
```
relation_df=pd.DataFrame(ds.groupby(['relationship'])['age'].count()).
 ↪reset_index().rename({'age': 'count'}, axis=1).
 ↪sort_values(by=['count'],ascending=False)
plot_chart(ds.sort_values(by=['relationship'])['relationship'].
 ↪unique(),relation_df['count'])
relation_df
```

[18]:

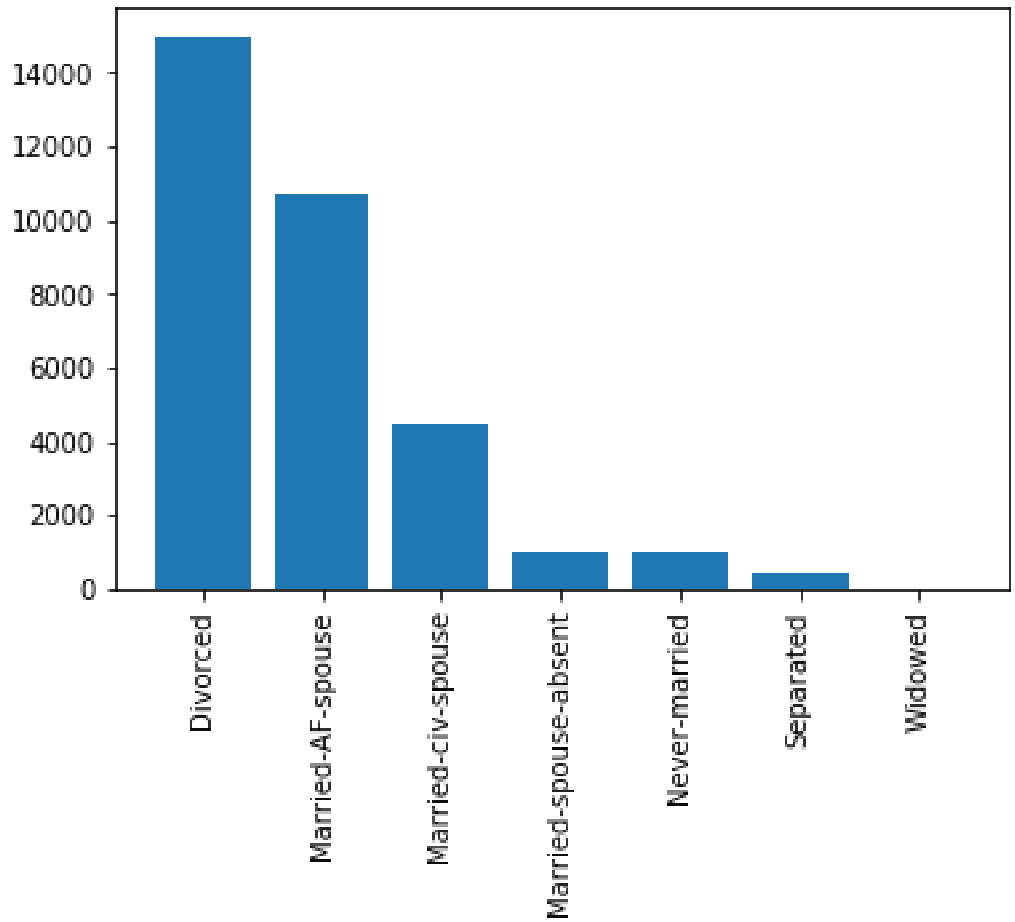
	relationship	count
0	Husband	13193
1	Not-in-family	8305
3	Own-child	5068
4	Unmarried	3446
5	Wife	1568
2	Other-relative	981



[19]:
```
marital_df=pd.DataFrame(ds.groupby(['marital.status'])['age'].count()).
↪reset_index().rename({'age': 'count'}, axis=1).
↪sort_values(by=['count'],ascending=False)
plot_chart(ds.sort_values(by=['marital.status'])['marital.status'].
↪unique(),marital_df['count'])
marital_df
```

[19]:

	marital.status	count
2	Married-civ-spouse	14976
4	Never-married	10683
0	Divorced	4443
5	Separated	1025
6	Widowed	993
3	Married-spouse-absent	418
1	Married-AF-spouse	23

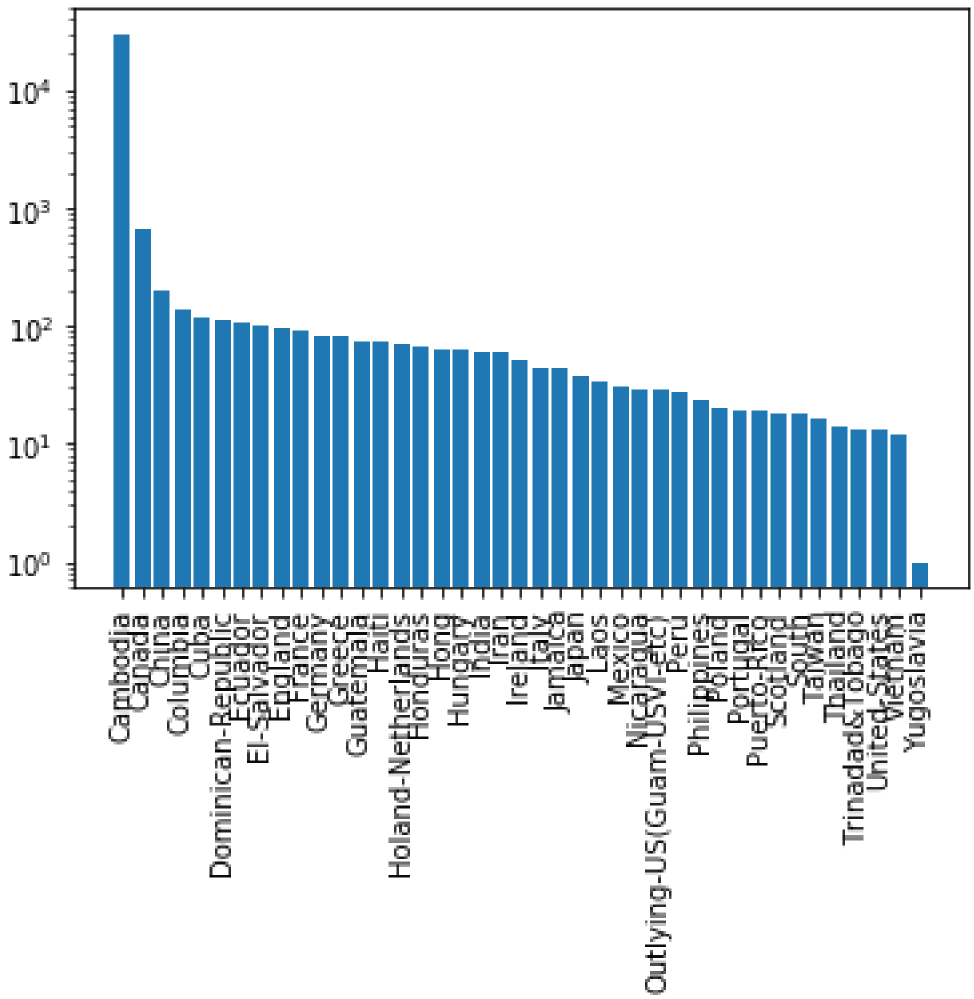


[20]:
```
country_df=pd.DataFrame(ds.groupby(['native.country'])['age'].count()).
↪reset_index().rename({'age': 'count'}, axis=1).
↪sort_values(by=['count'],ascending=False)
plot_chart(ds.sort_values(by=['native.country'])['native.country'].
↪unique(),country_df['count'])
plt.yscale('log')
country_df
```

[20]:

	native.country	count
38	United-States	29753
25	Mexico	643
29	Philippines	198
10	Germany	137
1	Canada	121
32	Puerto-Rico	114
7	El-Salvador	106
18	India	100

4	Cuba	95
8	England	90
22	Jamaica	81
34	South	80
2	China	75
21	Italy	73
5	Dominican-Republic	70
39	Vietnam	67
12	Guatemala	64
23	Japan	62
30	Poland	60
3	Columbia	59
35	Taiwan	51
13	Haiti	44
19	Iran	43
31	Portugal	37
26	Nicaragua	34
28	Peru	31
11	Greece	29
9	France	29
6	Ecuador	28
20	Ireland	24
16	Hong	20
37	Trinadad&Tobago	19
0	Cambodia	19
24	Laos	18
36	Thailand	18
40	Yugoslavia	16
27	Outlying-US(Guam-USVI-etc)	14
17	Hungary	13
15	Honduras	13
33	Scotland	12
14	Holand-Netherlands	1

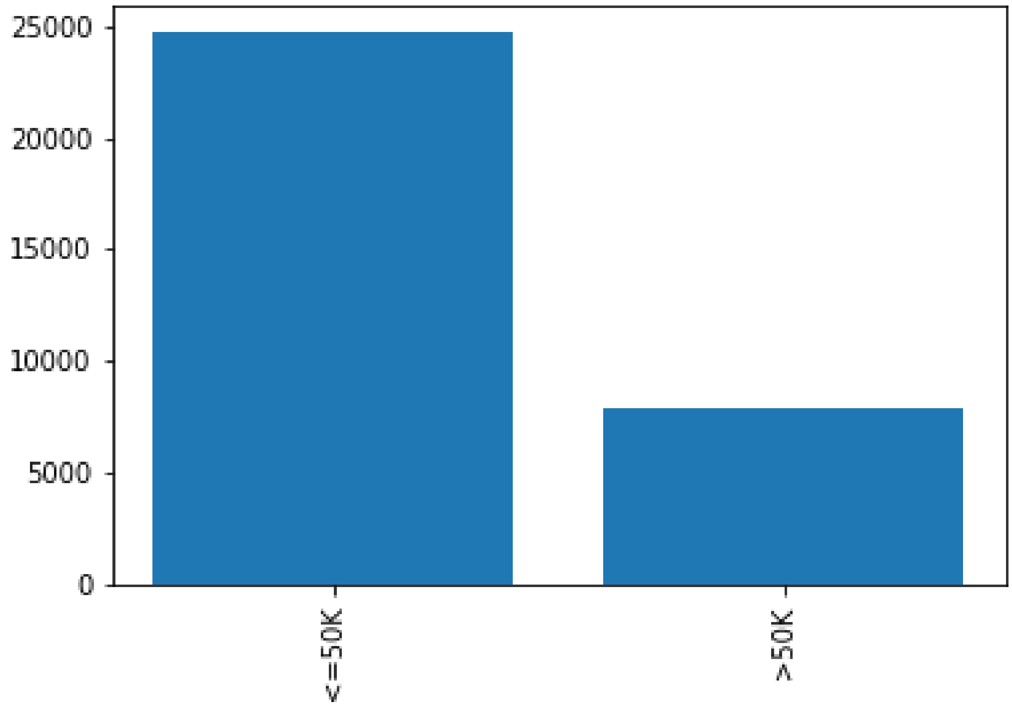


[21]:

```
income_df=pd.DataFrame(ds.groupby(['income'])['age'].count()).reset_index().
 ↪rename({'age': 'count'}, axis=1).sort_values(by=['count'],ascending=False)
plot_chart(ds.sort_values(by=['income'])['income'].unique(),income_df['count'])
income_df
```

[21]:

	income	count
0	<=50K	24720
1	>50K	7841



0.6.2 There are two types in target class: one is "50K" and the other is' $<=50K$ '. Below is the understanding

- The data is distribution with tags is unbalanced, and the proportion of '$<=50K$' tags is greater, which is 75%.
- Understood that the imbalance of label data distribution.
- It will be a binary task.

0.7 2.3 Encoding Categorical Values

[22]:
```
from sklearn import preprocessing
label_encoder=preprocessing.LabelEncoder()
max_val=0
rows=[]
for idx,col_val in enumerate(filtered):
    unq_cnt=ds[col_val].nunique()
    rows.append([col_val,unq_cnt])
    if max_val < unq_cnt:
        max_val=unq_cnt
df_temp = pd.DataFrame(rows, columns=["Feature", "Encoded Value"])
u=[i for i in range(max_val)]
encode_trans_inv=pd.DataFrame(data={"Encoded Value":np.array(u)})
ds_enc=ds.copy()
```

```
for idx,col_val in enumerate((df_temp.sort_values(by="Encoded␣
↪Value",ascending=False))['Feature']):
    ds_enc[col_val]=label_encoder.fit_transform(ds_enc[col_val])
    label_encoder_name_mapping = dict(zip(label_encoder.classes_, label_encoder.
↪transform(label_encoder.classes_)))
    encode_trans_inv[col_val]=pd.Series(np.
↪array(list(label_encoder_name_mapping.keys())))
print('Encoded Ouput table interpretation')
encode_trans_inv
```

```
Encoded Ouput table interpretation
```

[22]:

	Encoded Value	native.country	education	\
0	0	Cambodia	10th	
1	1	Canada	11th	
2	2	China	12th	
3	3	Columbia	1st-4th	
4	4	Cuba	5th-6th	
5	5	Dominican-Republic	7th-8th	
6	6	Ecuador	9th	
7	7	El-Salvador	Assoc-acdm	
8	8	England	Assoc-voc	
9	9	France	Bachelors	
10	10	Germany	Doctorate	
11	11	Greece	HS-grad	
12	12	Guatemala	Masters	
13	13	Haiti	Preschool	
14	14	Holand-Netherlands	Prof-school	
15	15	Honduras	Some-college	
16	16	Hong	NaN	
17	17	Hungary	NaN	
18	18	India	NaN	
19	19	Iran	NaN	
20	20	Ireland	NaN	
21	21	Italy	NaN	
22	22	Jamaica	NaN	
23	23	Japan	NaN	
24	24	Laos	NaN	
25	25	Mexico	NaN	
26	26	Nicaragua	NaN	
27	27	Outlying-US(Guam-USVI-etc)	NaN	
28	28	Peru	NaN	
29	29	Philippines	NaN	
30	30	Poland	NaN	
31	31	Portugal	NaN	
32	32	Puerto-Rico	NaN	
33	33	Scotland	NaN	

```
34            34                       South           NaN
35            35                      Taiwan           NaN
36            36                    Thailand           NaN
37            37             Trinadad&Tobago           NaN
38            38               United-States           NaN
39            39                     Vietnam           NaN
40            40                  Yugoslavia           NaN

           occupation          workclass         marital.status  \
0        Adm-clerical        Federal-gov               Divorced
1        Armed-Forces          Local-gov      Married-AF-spouse
2        Craft-repair       Never-worked     Married-civ-spouse
3     Exec-managerial            Private  Married-spouse-absent
4     Farming-fishing       Self-emp-inc          Never-married
5   Handlers-cleaners   Self-emp-not-inc              Separated
6   Machine-op-inspct          State-gov                Widowed
7       Other-service        Without-pay                    NaN
8     Priv-house-serv                NaN                    NaN
9      Prof-specialty                NaN                    NaN
10    Protective-serv                NaN                    NaN
11              Sales                NaN                    NaN
12       Tech-support                NaN                    NaN
13   Transport-moving                NaN                    NaN
14                NaN                NaN                    NaN
15                NaN                NaN                    NaN
16                NaN                NaN                    NaN
17                NaN                NaN                    NaN
18                NaN                NaN                    NaN
19                NaN                NaN                    NaN
20                NaN                NaN                    NaN
21                NaN                NaN                    NaN
22                NaN                NaN                    NaN
23                NaN                NaN                    NaN
24                NaN                NaN                    NaN
25                NaN                NaN                    NaN
26                NaN                NaN                    NaN
27                NaN                NaN                    NaN
28                NaN                NaN                    NaN
29                NaN                NaN                    NaN
30                NaN                NaN                    NaN
31                NaN                NaN                    NaN
32                NaN                NaN                    NaN
33                NaN                NaN                    NaN
34                NaN                NaN                    NaN
35                NaN                NaN                    NaN
36                NaN                NaN                    NaN
37                NaN                NaN                    NaN
```

38	NaN	NaN	NaN
39	NaN	NaN	NaN
40	NaN	NaN	NaN

	relationship	race	sex	income
0	Husband	Amer-Indian-Eskimo	Female	<=50K
1	Not-in-family	Asian-Pac-Islander	Male	>50K
2	Other-relative	Black	NaN	NaN
3	Own-child	Other	NaN	NaN
4	Unmarried	White	NaN	NaN
5	Wife	NaN	NaN	NaN
6	NaN	NaN	NaN	NaN
7	NaN	NaN	NaN	NaN
8	NaN	NaN	NaN	NaN
9	NaN	NaN	NaN	NaN
10	NaN	NaN	NaN	NaN
11	NaN	NaN	NaN	NaN
12	NaN	NaN	NaN	NaN
13	NaN	NaN	NaN	NaN
14	NaN	NaN	NaN	NaN
15	NaN	NaN	NaN	NaN
16	NaN	NaN	NaN	NaN
17	NaN	NaN	NaN	NaN
18	NaN	NaN	NaN	NaN
19	NaN	NaN	NaN	NaN
20	NaN	NaN	NaN	NaN
21	NaN	NaN	NaN	NaN
22	NaN	NaN	NaN	NaN
23	NaN	NaN	NaN	NaN
24	NaN	NaN	NaN	NaN
25	NaN	NaN	NaN	NaN
26	NaN	NaN	NaN	NaN
27	NaN	NaN	NaN	NaN
28	NaN	NaN	NaN	NaN
29	NaN	NaN	NaN	NaN
30	NaN	NaN	NaN	NaN
31	NaN	NaN	NaN	NaN
32	NaN	NaN	NaN	NaN
33	NaN	NaN	NaN	NaN
34	NaN	NaN	NaN	NaN
35	NaN	NaN	NaN	NaN
36	NaN	NaN	NaN	NaN
37	NaN	NaN	NaN	NaN
38	NaN	NaN	NaN	NaN
39	NaN	NaN	NaN	NaN
40	NaN	NaN	NaN	NaN

[23]:
```
ds_enc.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 int32
fnlwgt            32561 non-null int64
education         32561 non-null int32
education.num     32561 non-null int64
marital.status    32561 non-null int32
occupation        32561 non-null int32
relationship      32561 non-null int32
race              32561 non-null int32
sex               32561 non-null int32
capital.gain      32561 non-null int64
capital.loss      32561 non-null int64
hours.per.week    32561 non-null int64
native.country    32561 non-null int32
income            32561 non-null int32
dtypes: int32(9), int64(6)
memory usage: 2.6 MB
```

0.7.1 2.3.1 Percentage of Income Data

[24]:
```
from collections import Counter
target = ds.values[:,-1]
counter = Counter(target)
for k,v in counter.items():
    per = v / len(target) * 100
    print('Class=%s, Count=%d, Percentage=%.3f%%' % (k, v, per))
```

```
Class=<=50K, Count=24720, Percentage=75.919%
Class=>50K, Count=7841, Percentage=24.081%
```

[25]:
```
ds_enc.head()
```

[25]:
```
   age  workclass  fnlwgt  education  education.num  marital.status  \
0   90          3   77053         11              9               6
1   82          3  132870         11              9               6
2   66          3  186061         15             10               6
3   54          3  140359          5              4               0
4   41          3  264663         15             10               5

   occupation  relationship  race  sex  capital.gain  capital.loss  \
0           9             1     4    0             0          4356
1           3             1     4    0             0          4356
```

```
2          9            4     2    0             0          4356
3          6            4     4    0             0          3900
4          9            3     4    0             0          3900

   hours.per.week  native.country  income
0              40              38       0
1              18              38       0
2              40              38       0
3              40              38       0
4              40              38       0
```

0.7.2 2.4 Entire dataset corelation after encoding

[26]:
```python
corr =ds_enc.corr()
corr.style.background_gradient(cmap='coolwarm').set_precision(2)
```

[26]:
```
<pandas.io.formats.style.Styler at 0x1e8d1afe208>
```

Highly Correlated Values

- education-income: 0.34
- age-income: 0.24
- hours.per.week-income: 0.23
- sex-hours.per.week: 0.23
- sex-income: 0.22
- age-hours.per.week: 0.1

0.8 3. Extract X as all columns except the Income column and Y as Income column.

[27]:
```python
X = ds.iloc[:,:14]
Y = ds.iloc[:,-1:]
X.head()
```

[27]:
```
   age workclass  fnlwgt     education  education.num marital.status  \
0   90   Private   77053       HS-grad              9        Widowed
1   82   Private  132870       HS-grad              9        Widowed
2   66   Private  186061  Some-college             10        Widowed
3   54   Private  140359       7th-8th              4       Divorced
4   41   Private  264663  Some-college             10      Separated

          occupation   relationship   race     sex  capital.gain  \
0     Prof-specialty  Not-in-family  White  Female             0
1    Exec-managerial  Not-in-family  White  Female             0
2     Prof-specialty      Unmarried  Black  Female             0
3  Machine-op-inspct      Unmarried  White  Female             0
4     Prof-specialty      Own-child  White  Female             0
```

```
   capital.loss  hours.per.week native.country
0          4356              40  United-States
1          4356              18  United-States
2          4356              40  United-States
3          3900              40  United-States
4          3900              40  United-States
```

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

[28]:
```
  income
0  <=50K
1  <=50K
2  <=50K
3  <=50K
4  <=50K
```

[29]:
```
X = ds_enc.iloc[:,:14]
Y = ds_enc.iloc[:,-1:]
X.head()
```

[29]:
```
   age  workclass  fnlwgt  education  education.num  marital.status  \
0   90          3   77053         11              9               6
1   82          3  132870         11              9               6
2   66          3  186061         15             10               6
3   54          3  140359          5              4               0
4   41          3  264663         15             10               5

   occupation  relationship  race  sex  capital.gain  capital.loss  \
0           9             1     4    0             0          4356
1           3             1     4    0             0          4356
2           9             4     2    0             0          4356
3           6             4     4    0             0          3900
4           9             3     4    0             0          3900

   hours.per.week  native.country
0              40              38
1              18              38
2              40              38
3              40              38
4              40              38
```

[30]:
```
Y.head()
```

[30]:
```
   income
0       0
1       0
```

```
2        0
3        0
4        0
```

[31]:
```
X.describe()
```

[31]:
```
                age     workclass        fnlwgt     education  education.num  \
count  32561.000000  32561.000000  3.256100e+04  32561.000000   32561.000000
mean      38.581647      3.094438  1.897784e+05     10.298210      10.080679
std       13.640433      1.107194  1.055500e+05      3.870264       2.572720
min       17.000000      0.000000  1.228500e+04      0.000000       1.000000
25%       28.000000      3.000000  1.178270e+05      9.000000       9.000000
50%       37.000000      3.000000  1.783560e+05     11.000000      10.000000
75%       48.000000      3.000000  2.370510e+05     12.000000      12.000000
max       90.000000      7.000000  1.484705e+06     15.000000      16.000000

       marital.status    occupation  relationship          race           sex  \
count    32561.000000  32561.000000  32561.000000  32561.000000  32561.000000
mean         2.611836      6.138755      1.446362      3.665858      0.669205
std          1.506222      3.972708      1.606771      0.848806      0.470506
min          0.000000      0.000000      0.000000      0.000000      0.000000
25%          2.000000      3.000000      0.000000      4.000000      0.000000
50%          2.000000      6.000000      1.000000      4.000000      1.000000
75%          4.000000      9.000000      3.000000      4.000000      1.000000
max          6.000000     13.000000      5.000000      4.000000      1.000000

       capital.gain  capital.loss  hours.per.week  native.country
count  32561.000000  32561.000000    32561.000000    32561.000000
mean    1077.648844     87.303830       40.437456       36.417155
std     7385.292085    402.960219       12.347429        6.056047
min        0.000000      0.000000        1.000000        0.000000
25%        0.000000      0.000000       40.000000       38.000000
50%        0.000000      0.000000       40.000000       38.000000
75%        0.000000      0.000000       45.000000       38.000000
max    99999.000000   4356.000000       99.000000       40.000000
```

[32]:
```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 14 columns):
age               32561 non-null int64
workclass         32561 non-null int32
fnlwgt            32561 non-null int64
education         32561 non-null int32
education.num     32561 non-null int64
marital.status    32561 non-null int32
```

```
occupation        32561 non-null int32
relationship      32561 non-null int32
race              32561 non-null int32
sex               32561 non-null int32
capital.gain      32561 non-null int64
capital.loss      32561 non-null int64
hours.per.week    32561 non-null int64
native.country    32561 non-null int32
dtypes: int32(8), int64(6)
memory usage: 2.5 MB
```

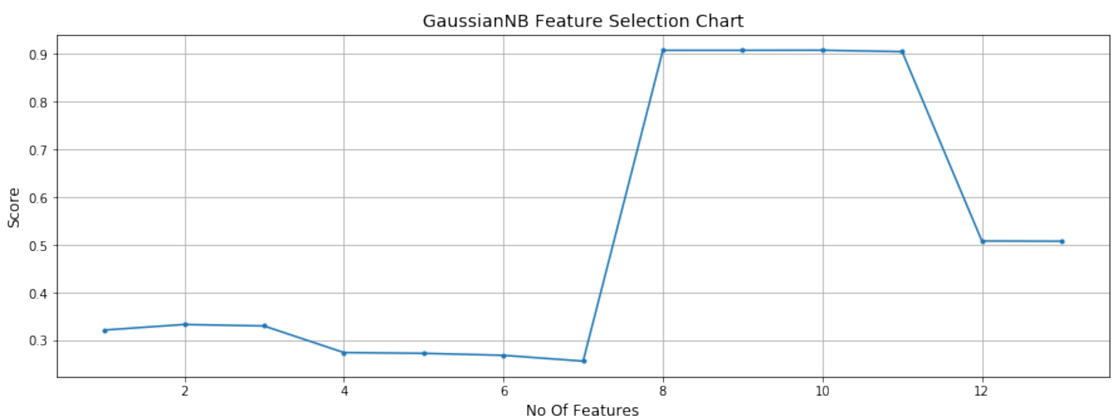
0.8.1 Finding important feature using correlation

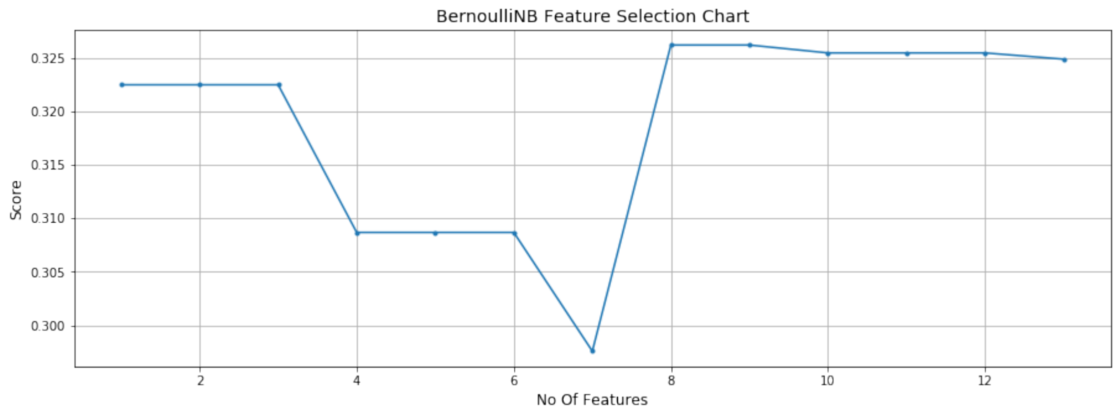
[33]:
```
col_names = ds_enc.columns
param=[]
correlation=[]
abs_corr=[]
for c in col_names:
    if c != "income":
        if len(ds_enc[c].unique()) <= 2:
            corr = spearmanr(ds_enc['income'],ds_enc[c])[0]
        else:
            corr = pointbiserialr(ds_enc['income'],ds_enc[c])[0]
        param.append(c)
        correlation.append(corr)
        abs_corr.append(abs(corr))
param_df=pd.DataFrame({'correlation':correlation,'parameter':param, 'abs_corr':
 ↪abs_corr})
param_df=param_df.sort_values(by=['abs_corr'], ascending=False)
param_df=param_df.set_index('parameter')
param_df
import warnings
warnings.filterwarnings('ignore')
```

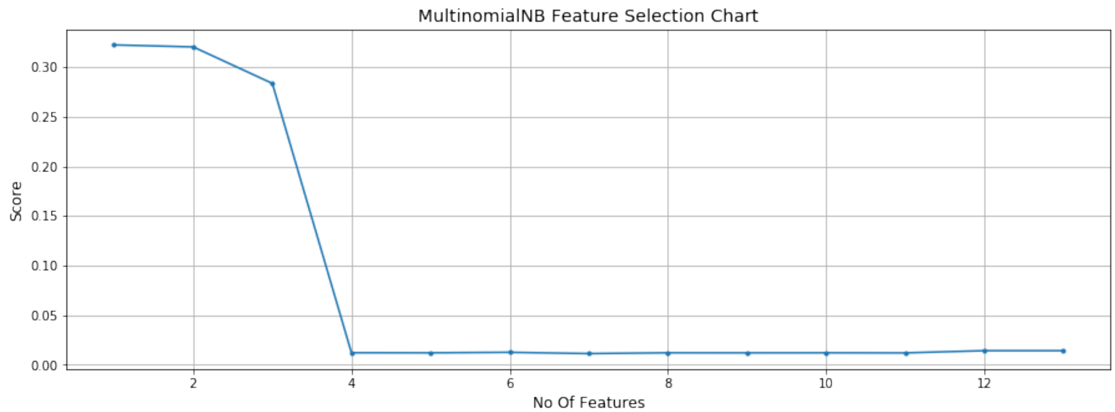
[34]:
```
for md in ['GaussianNB','BernoulliNB','MultinomialNB']:
    scoresCV = []
    scores = []
    for i in range(1,len(param_df)):
        new_df=ds_enc[param_df.index[0:i+1].values]
        X = new_df.ix[:,1::]
        y = new_df.ix[:,0]
        if md=='BernoulliNB':
            clf=BernoulliNB()
        if md=='MultinomialNB':
            clf= MultinomialNB()
        if md=='GaussianNB':
            clf=GaussianNB()
```

```
        scoreCV = cross_val_score(clf, X, y, cv= 10)
        scores.append(np.mean(scoreCV))

    plt.figure(figsize=(15,5))
    plt.plot(range(1,len(scores)+1),scores, '.-')
    plt.axis("tight")
    plt.title(md+' Feature Selection Chart', fontsize=14)
    plt.xlabel('No Of Features', fontsize=12)
    plt.ylabel('Score', fontsize=12)
    plt.grid();
    best_features=param_df.index[0:10].values
    print(md, ' Best features:\t',best_features)
```

```
GaussianNB  Best features:      ['education.num' 'relationship' 'age'
'hours.per.week' 'capital.gain'
 'sex' 'marital.status' 'capital.loss' 'education' 'race']
BernoulliNB  Best features:     ['education.num' 'relationship' 'age'
'hours.per.week' 'capital.gain'
 'sex' 'marital.status' 'capital.loss' 'education' 'race']
MultinomialNB  Best features:   ['education.num' 'relationship' 'age'
'hours.per.week' 'capital.gain'
 'sex' 'marital.status' 'capital.loss' 'education' 'race']
```







0.8.2 Top 10 Features

[35]:
```
best_features=param_df.index[0:10].values
print('Best features:\t',best_features)
```

```
Best features:   ['education.num' 'relationship' 'age' 'hours.per.week'
'capital.gain'
 'sex' 'marital.status' 'capital.loss' 'education' 'race']
```

0.9 4. Split the data into training set and testing set.

Split DataSet into training and testing - Split into features, training data

[36]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
def prepare_datafunc(dataSet, train_size=0.67):
    dataSet_features = dataSet.drop(['income'], axis=1)
    dataSet_response = dataSet['income']
```

```
    X_train, X_test, y_train, y_test =
↪train_test_split(dataSet_features,dataSet_response,train_size=0.
↪80,random_state=6,stratify=dataSet_response)
    return X_train, X_test, y_train, y_test
X_train, X_test, y_train, y_test = prepare_datafunc(ds_enc)
print('X Train Shape:',X_train.shape)
print('X Test Shape:',X_test.shape)
print('y Train Shape:',y_train.shape)
print('y Test Shape:',y_test.shape)
```

```
X Train Shape: (26048, 14)
X Test Shape: (6513, 14)
y Train Shape: (26048,)
y Test Shape: (6513,)
```

[37]:
```
pd.DataFrame(X_train).head()
```

[37]:
```
       age  workclass  fnlwgt  education  education.num  marital.status  \
25458   39          3   99452          9             13               2
26686   27          3  190525          8             11               4
7663    44          6  296326          9             13               4
9395    56          5  258752          9             13               2
9333    37          3  323155          3              2               2

       occupation  relationship  race  sex  capital.gain  capital.loss  \
25458           9             0     4    1             0             0
26686           6             4     4    1             0             0
7663            0             1     4    1             0             0
9395            3             0     4    1             0             0
9333            4             0     4    1             0             0

       hours.per.week  native.country
25458              50              38
26686              45              38
7663               40              38
9395               60              38
9333               85              25
```

0.10 5. Model the classifier using GaussianNB, BernoulliNB and MultinomialNB

[38]:
```
def get_score(model,X_test,y_test):
    return model.score(X_test,y_test)
```

0.11 5.1 MultinomialNB

[39]:
```
model = MultinomialNB()
model.fit(X_train, y_train)
naive_pre= model.predict(X_test)
MultinomialNBCnfMat=confusion_matrix(y_test,naive_pre)
print(classification_report(y_test,naive_pre))
MNB = accuracy_score(y_test, naive_pre)
print("The Accuracy for MultinomialNB is {}".format(MNB))
MultinomialNBScore = get_score(model,X_test,y_test)
```

```
              precision    recall  f1-score   support

           0       0.80      0.96      0.87      4945
           1       0.64      0.24      0.35      1568

    accuracy                           0.78      6513
   macro avg       0.72      0.60      0.61      6513
weighted avg       0.76      0.78      0.74      6513

The Accuracy for MultinomialNB is 0.7844311377245509
```

[40]:
```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

0.12 5.2 GaussianNB

[41]:
```
model = GaussianNB()
model.fit(X_train, y_train)
naive_pre= model.predict(X_test)
GaussianNBCnfMat=confusion_matrix(y_test,naive_pre)
print(classification_report(y_test,naive_pre))
GNB = accuracy_score(y_test, naive_pre)
print("The Accuracy for GaussianNB is {}".format(GNB))
GaussianNBScore = get_score(model,X_test,y_test)
```

```
              precision    recall  f1-score   support

           0       0.82      0.95      0.88      4945
           1       0.68      0.34      0.46      1568

    accuracy                           0.80      6513
   macro avg       0.75      0.65      0.67      6513
weighted avg       0.79      0.80      0.78      6513

The Accuracy for GaussianNB is 0.8036235221863964
```

0.13 5.3 BernoulliNB

[42]:
```
model = BernoulliNB()
model.fit(X_train, y_train)
naive_pre= model.predict(X_test)
BernoulliNBCnfMat=confusion_matrix(y_test,naive_pre)
print(classification_report(y_test,naive_pre))
BNB = accuracy_score(y_test, naive_pre)
print("The Accuracy for BernoulliNB is {}".format(BNB))
BernoulliNBScore = get_score(model,X_test,y_test)
```

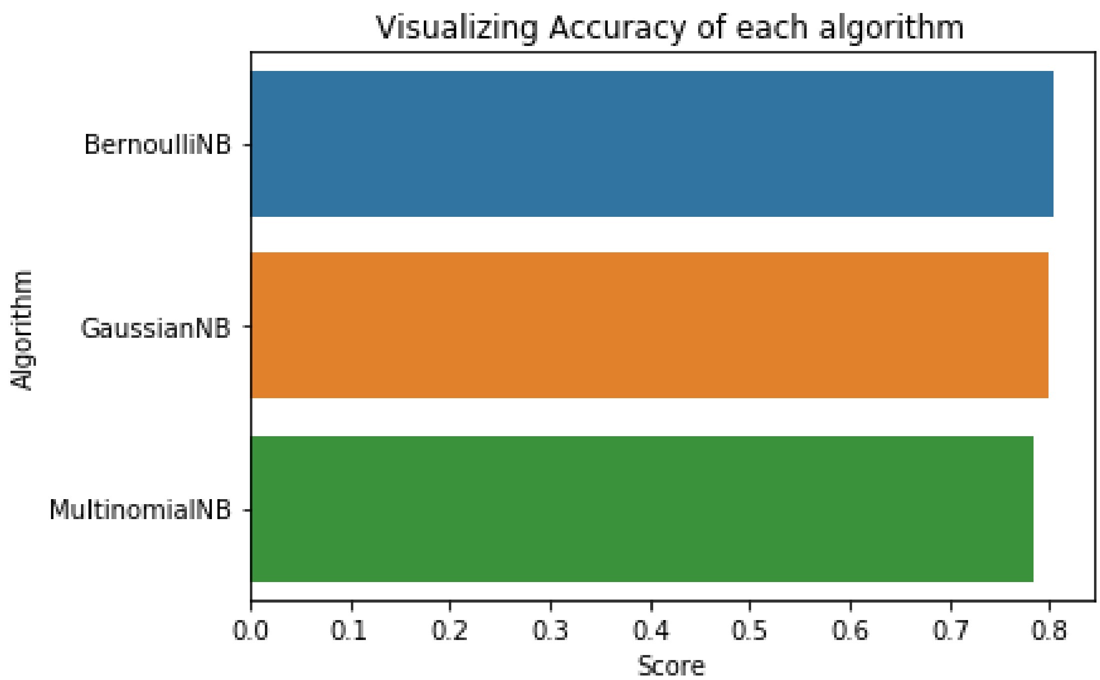
```
              precision    recall  f1-score   support

           0       0.87      0.86      0.87      4945
           1       0.58      0.59      0.59      1568

    accuracy                           0.80      6513
   macro avg       0.72      0.73      0.73      6513
weighted avg       0.80      0.80      0.80      6513

The Accuracy for BernoulliNB is 0.7985567326884692
```

0.14 6. Compute the accuracy and confusion matrix for each models.

0.14.1 Comparing the Performance of each algorithm

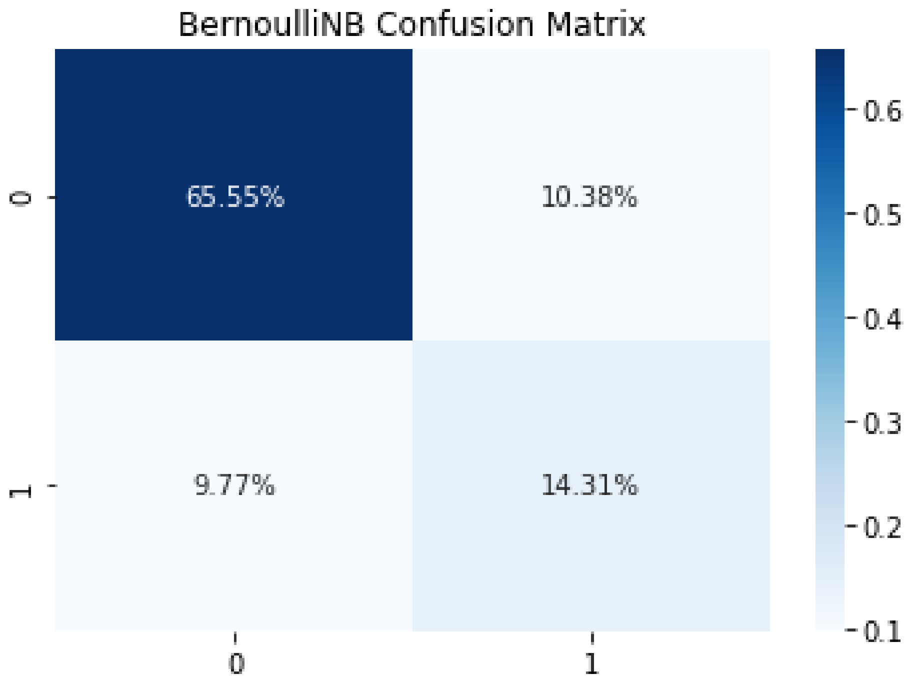
[43]:
```
import seaborn as sns
names = ['BernoulliNB', 'GaussianNB', 'MultinomialNB']
Algorithm = [GNB,BNB,MNB]
best = max(Algorithm)
for i in range(3):
    if best == Algorithm[i]:
        print(f'Best algorithm is {names[i]}, with BernoulliNBScore :␣
↪{Algorithm[i]}')
        sns.barplot(x=Algorithm, y=names)
plt.xlabel('Score')
plt.ylabel('Algorithm')
plt.title("Visualizing Accuracy of each algorithm")
plt.show()
```

```
Best algorithm is BernoulliNB, with BernoulliNBScore : 0.8036235221863964
```



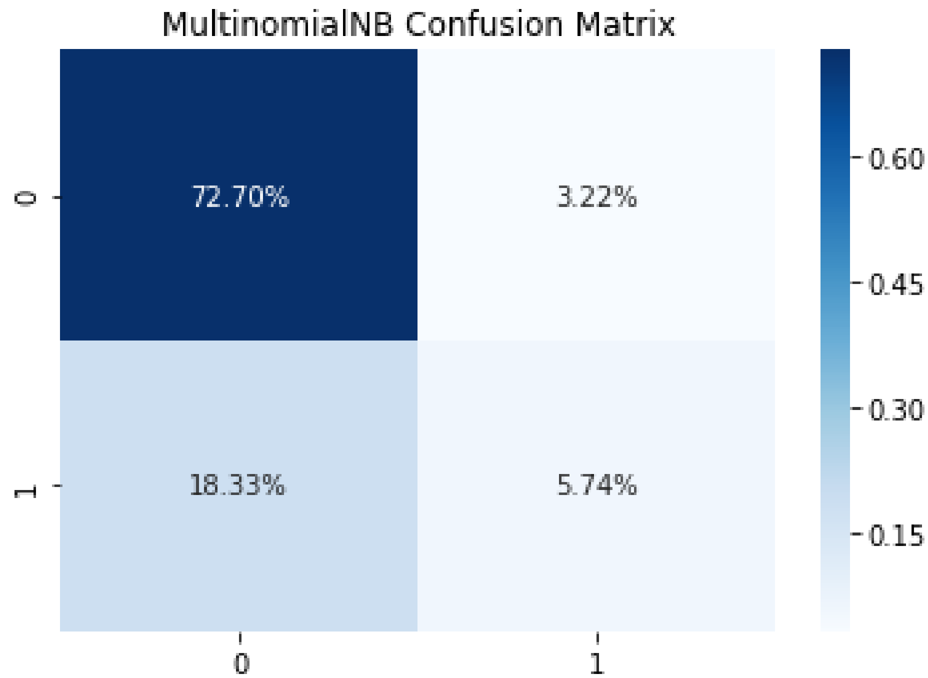
[44]:
```
ax = plt.axes()
sns.heatmap(BernoulliNBCnfMat/np.sum(BernoulliNBCnfMat), annot=True, fmt='.2%',␣
↪cmap='Blues', ax = ax)
ax.set_title('BernoulliNB Confusion Matrix')
```

[44]:
```
Text(0.5, 1.0, 'BernoulliNB Confusion Matrix')
```



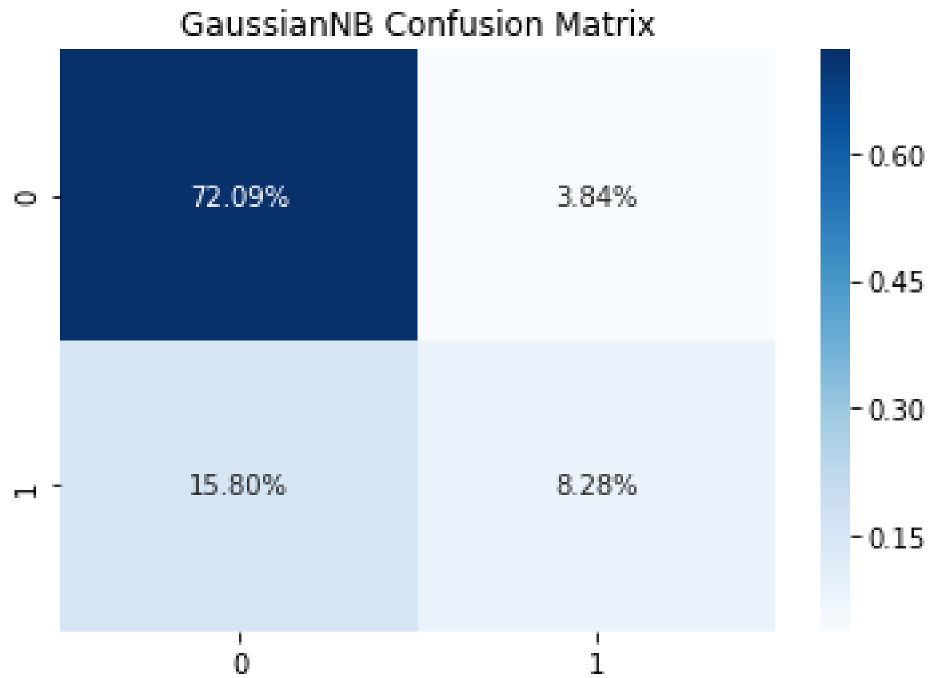
[45]:
```
ax = plt.axes()
sns.heatmap(MultinomialNBCnfMat/np.sum(MultinomialNBCnfMat), annot=True, fmt='.
 ↪2%', cmap='Blues', ax = ax)
ax.set_title('MultinomialNB Confusion Matrix')
```

[45]: Text(0.5, 1.0, 'MultinomialNB Confusion Matrix')



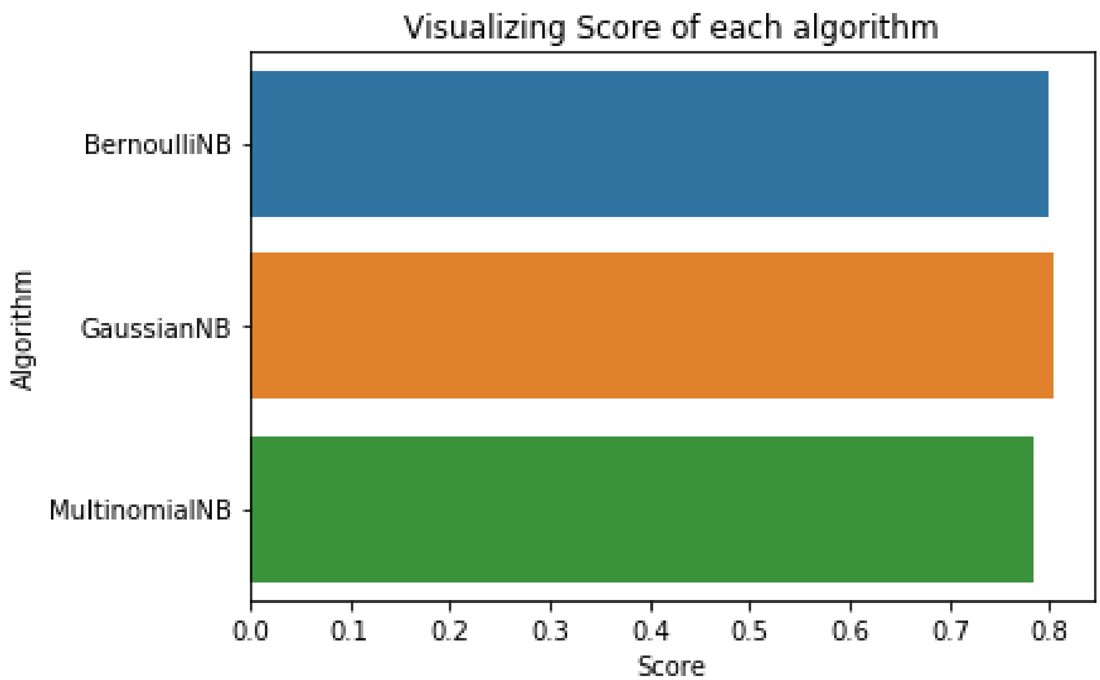
[46]:
```
ax = plt.axes()
sns.heatmap(GaussianNBCnfMat/np.sum(GaussianNBCnfMat), annot=True, fmt='.2%',␣
↪cmap='Blues', ax = ax)
ax.set_title('GaussianNB Confusion Matrix')
```

[46]: Text(0.5, 1.0, 'GaussianNB Confusion Matrix')



[47]:
```python
import seaborn as sns
names = ['BernoulliNB', 'GaussianNB', 'MultinomialNB']
Algorithm = [BernoulliNBScore,GaussianNBScore,MultinomialNBScore]
best = max(Algorithm)
for i in range(3):
    if best == Algorithm[i]:
        print(f'Best algorithm is {names[i]}, with score : {Algorithm[i]}')
        sns.barplot(x=Algorithm, y=names)
plt.xlabel('Score')
plt.ylabel('Algorithm')
plt.title("Visualizing Score of each algorithm")
plt.show()
```

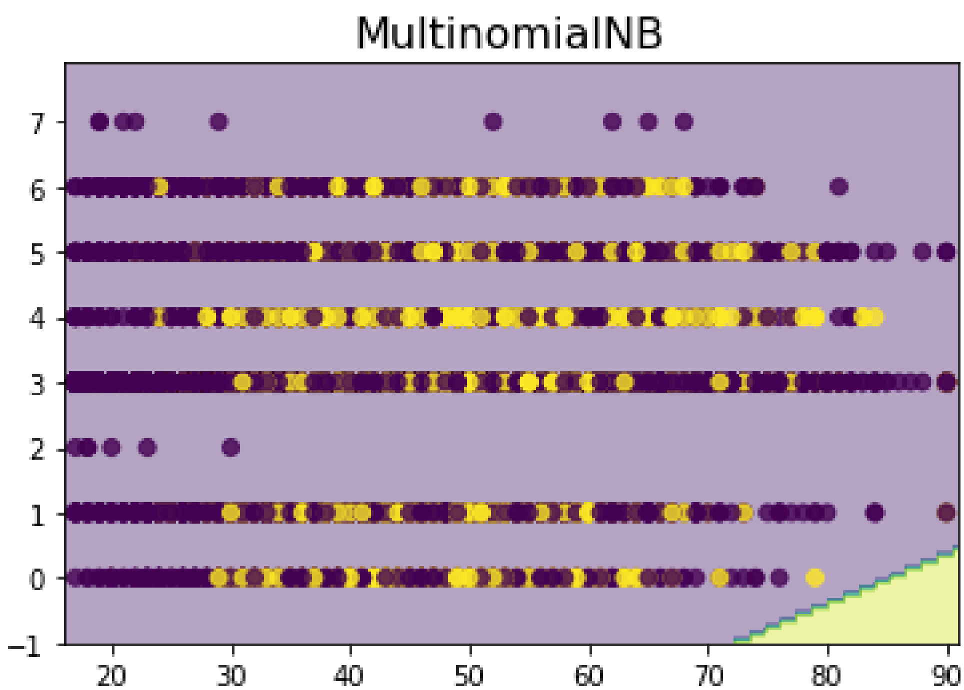
```
Best algorithm is GaussianNB, with score : 0.8036235221863964
```

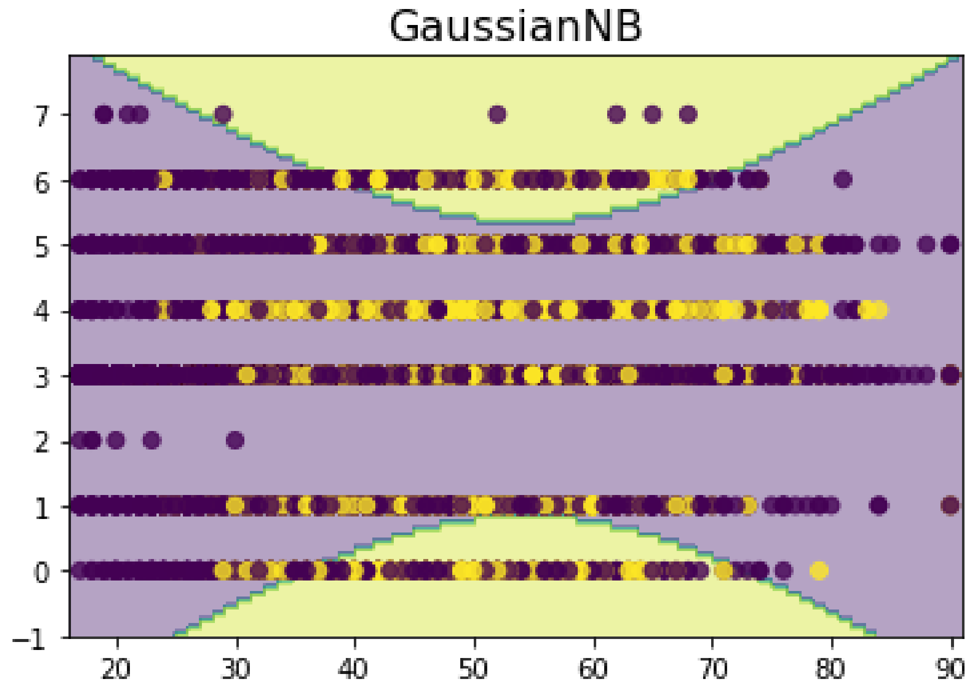


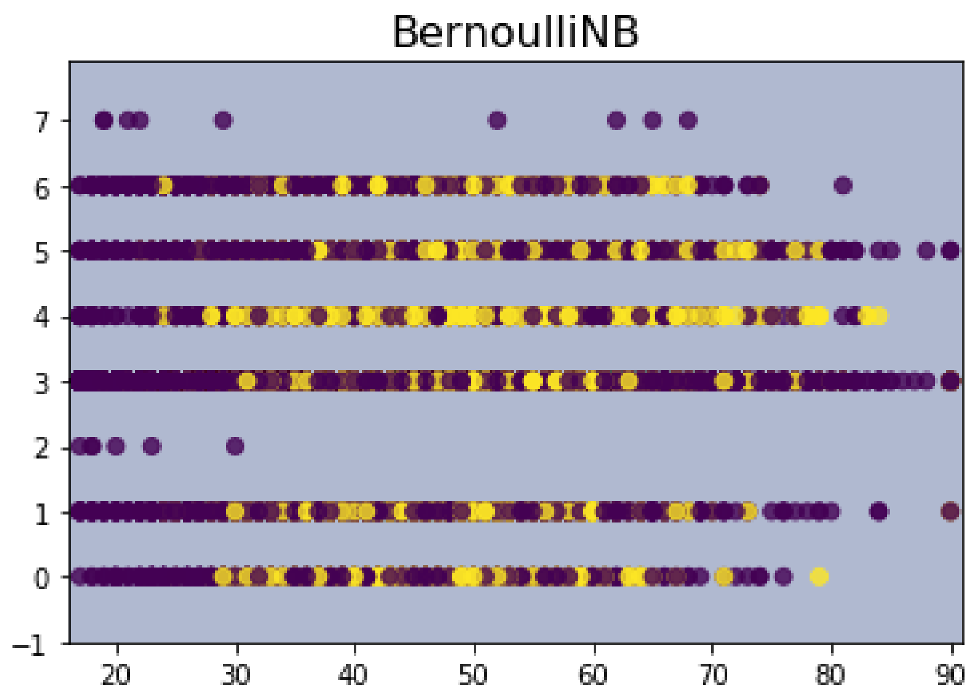
0.15 7. Plot the decision boundary, visualize training and test results of all the models

[48]:
```
def plot_decision_boundaries(X, y, model_class, **model_params):
    reduced_data = X.iloc[:, :2]
    model = model_class(**model_params)
    model.fit(reduced_data, y)
    h = .02
    x_min, x_max = reduced_data.iloc[:, 0].min() - 1, reduced_data.iloc[:, 0].
 ↪max() + 1
    y_min, y_max = reduced_data.iloc[:, 1].min() - 1, reduced_data.iloc[:, 1].
 ↪max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
    Z = model.predict(np.c_[xx.ravel(), yy.ravel()])
    x_min, x_max = X.iloc[:, 0].min() - 1, X.iloc[:, 0].max() + 1
    y_min, y_max = X.iloc[:, 1].min() - 1, X.iloc[:, 1].max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),np.arange(y_min, y_max, 0.
 ↪1))
    Z = model.predict(np.c_[xx.ravel(), yy.ravel()]).reshape(xx.shape)
    plt.contourf(xx, yy, Z, alpha=0.4)
    plt.scatter(X.iloc[:, 0], X.iloc[:, 1], c=y, alpha=0.8)
    return plt
```

[49]:
```
dataSet_features = ds_enc.drop(['income'], axis=1)
dataSet_response = ds_enc['income']
X_train, X_test, y_train, y_test =␣
 ↪train_test_split(dataSet_features,dataSet_response,train_size=0.
 ↪80,random_state=6,stratify=dataSet_response)
plt.figure()
plt.title('MultinomialNB',fontsize=16)
plot_decision_boundaries(X_train, y_train,MultinomialNB)
plt.show()

plt.figure()
plt.title('GaussianNB',fontsize=16)
plot_decision_boundaries(X_train, y_train,GaussianNB)
plt.show()

plt.figure()
plt.title('BernoulliNB',fontsize=16)
plot_decision_boundaries(X_train, y_train,BernoulliNB)
plt.show()
```



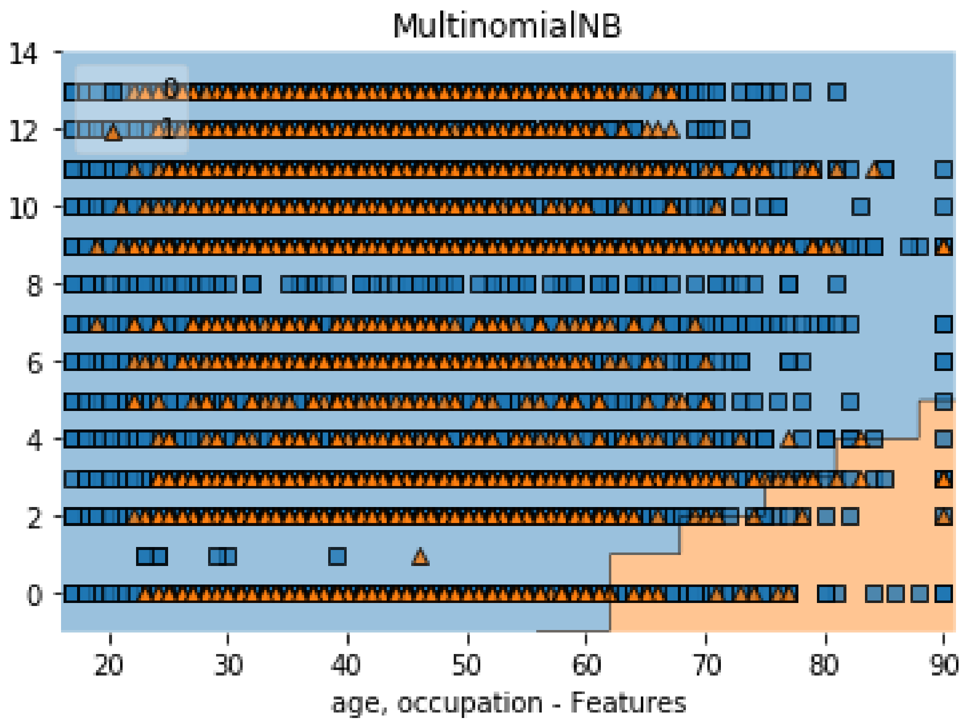

GaussianNB
7
6
5
4
3
2
1
0
−1
20
30
40
50
60
70
80
90


BernoulliNB
7
6
5
4
3
2
1
0
−1
20
30
40
50
60
70
80
90

0.15.1 7.1 Decision Boundary using mlxtend

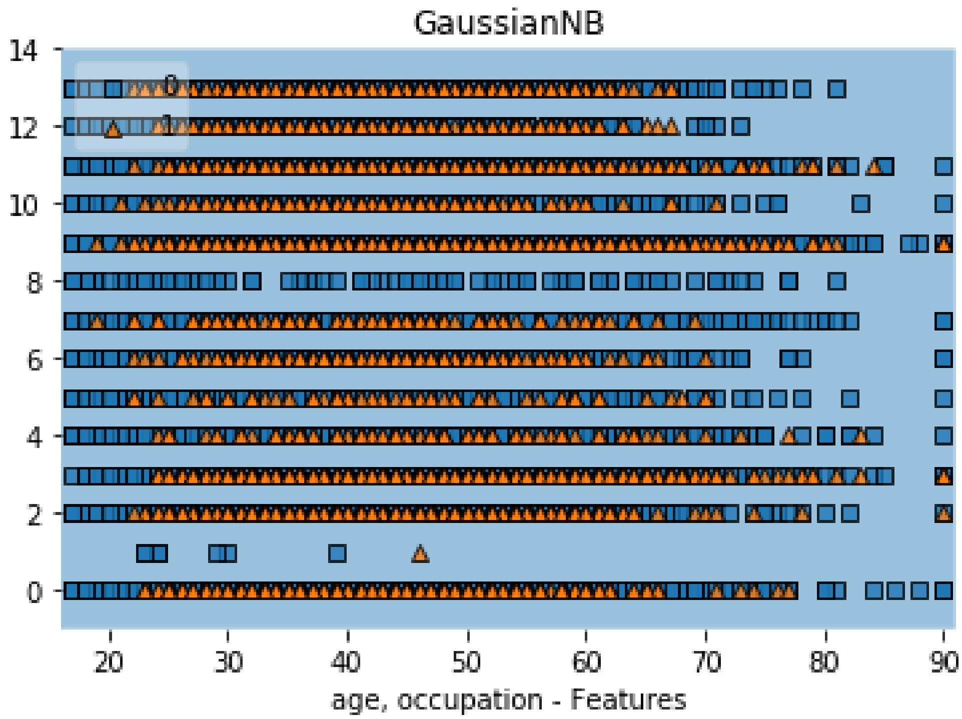
To Draw Decision Boundary below are the points considered, region of a problem space in which the output label of a classifier is ambiguous. - To draw decision boundary we have to consider 2 features & 1 output class

[50]:
```
X_train_sample=X_train[['age','occupation']].values
y_train_sample=y_train
logModel=MultinomialNB()
logModel.fit(X_train_sample,np.array(y_train_sample))
plot_decision_regions(X_train_sample,np.array(y_train_sample), clf=logModel,␣
↪legend=2)
plt.xlabel('age, occupation - Features')
plt.title('MultinomialNB')
plt.show()
```

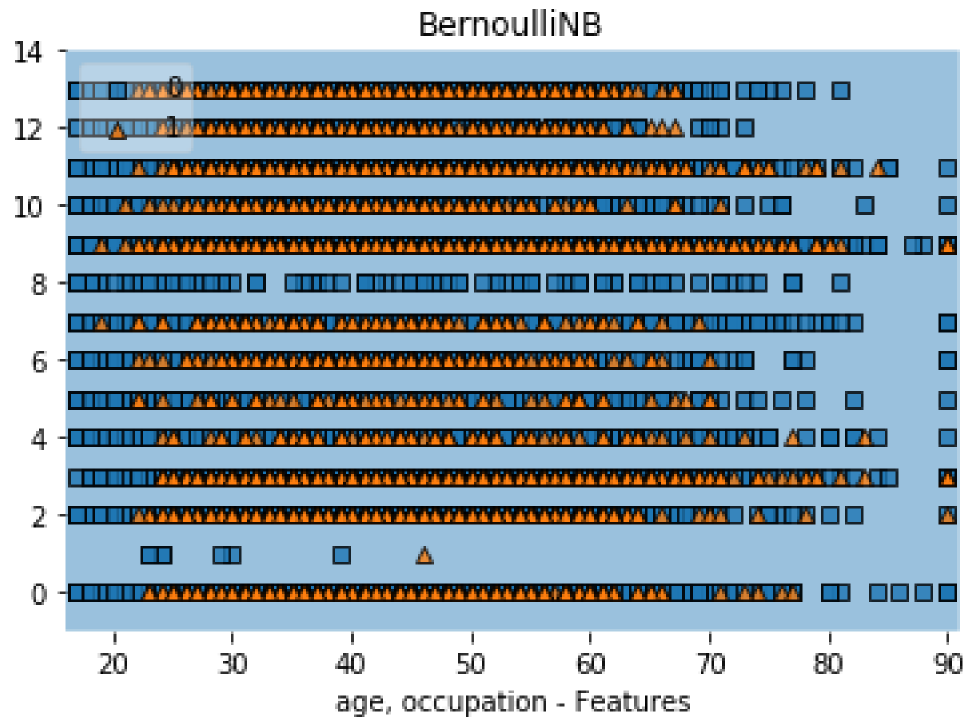


[51]:
```
X_train_sample=X_train[['age','occupation']].values
y_train_sample=y_train
logModel=GaussianNB()
logModel.fit(X_train_sample,np.array(y_train_sample))
plot_decision_regions(X_train_sample,np.array(y_train_sample), clf=logModel,␣
↪legend=2)
plt.xlabel('age, occupation - Features')
plt.title('GaussianNB')
```

```
plt.show()
```



[52]:
```
X_train_sample=X_train[['age','occupation']].values
y_train_sample=y_train
logModel=BernoulliNB()
logModel.fit(X_train_sample,np.array(y_train_sample))
plot_decision_regions(X_train_sample,np.array(y_train_sample), clf=logModel,␣
↪legend=2)
plt.xlabel('age, occupation - Features')
plt.title('BernoulliNB')
plt.show()
```



0.16 8. Create an output .csv file consisting actual Test set values of Y (column name: Actual) and Predictions of Y(column name: Predicted).

[53]:
```
out_ds=(X_test.join(y_test)).copy()
out_ds.head()
```

[53]:
```
       age  workclass  fnlwgt  education  education.num  marital.status  \
30767   43          3   87284         15             10               4
11068   37          1  174924         15             10               0
20582   21          3  383603          0              6               4
23127   42          3  197522         15             10               5
28292   61          3   79827         11              9               2

       occupation  relationship  race  sex  capital.gain  capital.loss  \
30767           5             1     4    1             0             0
11068          10             4     4    1             0             0
20582           7             1     4    0             0             0
23127           6             4     2    0             0             0
28292           3             0     4    1             0             0

       hours.per.week  native.country  income
30767              40              38       0
11068              48              10       0
```

20582	35	38	0
23127	40	38	0
28292	50	38	0

[54]:

```
out_ds.to_csv(os.path.join(cwd,'output.csv'),index=False)
```