NB_Adult_Sal_classification

January 17, 2022

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
```

0.0.1 Problem statement

0.0.2 Prepare a classification model using Naive Bayes for salary data

Data Description:

```
age -- age of a person
workclass   -- A work class is a grouping of work
education   -- Education of an individuals
maritalstatus -- Marital status of an individulas
occupation   -- occupation of an individuals
relationship --
race --  Race of an Individual
sex --  Gender of an Individual
capitalgain --  profit received from the sale of an investment
capitalloss -- A decrease in the value of a capital asset
hoursperweek -- number of hours work per week
native -- Native of an individual
Salary -- salary of an individual
```

[2]:
```python
rawData = pd.read_csv('SalaryData_Train.csv',skipinitialspace=True)
rawData.head()
```

[2]:
```
   age         workclass  education  educationno       maritalstatus  \
0   39         State-gov  Bachelors           13       Never-married
1   50  Self-emp-not-inc  Bachelors           13  Married-civ-spouse
2   38           Private    HS-grad            9            Divorced
3   53           Private       11th            7  Married-civ-spouse
4   28           Private  Bachelors           13  Married-civ-spouse

          occupation   relationship   race     sex  capitalgain  capitalloss  \
0       Adm-clerical  Not-in-family  White    Male         2174            0
1    Exec-managerial        Husband  White    Male            0            0
```

```
2  Handlers-cleaners  Not-in-family  White    Male            0             0
3  Handlers-cleaners        Husband  Black    Male            0             0
4     Prof-specialty           Wife  Black  Female            0             0

   hoursperweek         native Salary
0            40  United-States  <=50K
1            13  United-States  <=50K
2            40  United-States  <=50K
3            40  United-States  <=50K
4            40           Cuba  <=50K
```

1 # First hand Intution of the Data

The first hand interpretatino of the problem statement is that there are 12 Attributes of a pe

Irregularities in DATA DESCRIPTION & ACTUAL DATA

While the discription says 12 columns but the actual data has 13 columns. Further the data des

1.1 *My intution is that

    'educationno' is no of years of education and
    'relationship' is the role of the individual with respect to his family.

So that makes Salary Column/Feature as our y variable. In other words 'Salary' Feature is our dependent variable/predicted variable/fitted variable and rest of features are independent variables/predictors.

2 # EDA

2.0.1 What is the shape of the dataset ???

There are 30161 rows and 14 columns in the dataset (13 are predictors and 1 is predicted)

2.0.2 What are the Datatypes of each columns in the dataset ???

There are two datatypes in the dataset, namely, int64 and object. int64 clearly tells that the

However, the object datatypes may incluede string data with special characters in it. We need

2.0.3 Are there any 'object' Datatypes in the dataset ???

Yes, there are 9 columns mraked as object datatype. It is not a problem as long as it is a str

2.0.4 Are there any Missing Values in the dataset ???

Luckily, there are no missing values in the data set.

[3]:
```
rawData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30161 entries, 0 to 30160
Data columns (total 14 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   age            30161 non-null  int64
 1   workclass      30161 non-null  object
 2   education      30161 non-null  object
 3   educationno    30161 non-null  int64
 4   maritalstatus  30161 non-null  object
 5   occupation     30161 non-null  object
 6   relationship   30161 non-null  object
 7   race           30161 non-null  object
 8   sex            30161 non-null  object
 9   capitalgain    30161 non-null  int64
 10  capitalloss    30161 non-null  int64
 11  hoursperweek   30161 non-null  int64
 12  native         30161 non-null  object
 13  Salary         30161 non-null  object
dtypes: int64(5), object(9)
memory usage: 3.2+ MB
```

[4]:
```
object_columns = []
numeric_columns = []
for i in rawData.columns:
    if rawData[i].dtypes == object:
        object_columns.append(i)
    else:
        numeric_columns.append(i)
print(f'no of object columns in the dataset are␣
 ↪{len(object_columns)}\n',object_columns,end='\n\n')
print(f'no of object columns in the dataset are␣
 ↪{len(numeric_columns)}\n',numeric_columns,end='\n\n')
```

```
no of object columns in the dataset are 9
 ['workclass', 'education', 'maritalstatus', 'occupation', 'relationship',
'race', 'sex', 'native', 'Salary']

no of object columns in the dataset are 5
 ['age', 'educationno', 'capitalgain', 'capitalloss', 'hoursperweek']
```

***

2.0.5 Whether the columns contain the values that, they should represent or is something messy ???

luckily for us there are no unwanted data in the categorical values. All the string values in the dataset make sense. However, some of the features have high cardinality, which need to be analised, they are not invalid though.

As fas as the numerical data goes right now what we can say is that they all contain valid data and if there are outliers in the data set if subject to further analysis.

3 ## Data DICTIONARY:

```
age (numerical)             -- age of a person

workclass (Categorical)     -- A work class is a grouping of work              --  7 Classes
                               Class                      Count
                               -----                      -----
                               Private                   22285
                               Self-emp-not-inc           2499
                               Local-gov                  2067
                               State-gov                  1279
                               Self-emp-inc               1074
                               Federal-gov                 943
                               Without-pay                  14

education (Categorical)     -- Education of an individuals                      -- 16 Classes

educationno (numerical)     -- No of years in education

maritalstatus (Categorical) -- Marital status of an individulas                 --  7 Classes
                               Class                              Count
                               -----                              -----
                               Married-civ-spouse                 14065   (married a civilian spo
                               Never-married                       9725
                               Divorced                            4214
                               Separated                            939
                               Widowed                              827
                               Married-spouse-absent                370
                               Married-AF-spouse                     21   (married a Armed forces

occupation  (Categorical)  -- occupation of an individuals                      -- 14 Classes

relationship (Categorical) -- Relationship or Role in the family                --  6 Classes
                               Class                      Count
                               -----                      -----
                               Husband                    12463
                               Not-in-family               7726
                               Own-child                   4466
                               Unmarried                   3212
                               Wife                        1406
                               Other-relative               888
```

```
race (Categorical)           --  Race of an Individual                               --  5 Classes
                                  Class                Count
                                  -----                ------
                                  White                25932
                                  Black                 2817
                                  Asian-Pac-Islander     895
                                  Amer-Indian-Eskimo     286
                                  Other                  231

sex (Categorical)            --  Gender of an Individual                             --  2 Classes
                                 Class        Count
                                 -----        -----
                                  Male        20380
                                  Female       9781

capitalgain   --  profit received from the sale of an investment
capitalloss   -- A decrease in the value of a capital asset
hoursperweek  -- number of hours work per week
native                      -- Native of an individual                               -- 40 Classes

Salary (Categorical)        -- salary of an individual                               --  2 Classes
                                  Class    Count
                                  -----    -----
                                  <=50K    22653
                                  >50K      7508
```

[5]:
```python
for x in object_columns:
    i = rawData.columns.get_loc(x)
    print(f'\033[7m({i}) \033[0m\033[1mThe unique values in {x} are {rawData[x].
 ↪nunique()}\033[0m',end='\n\n')
    if rawData[x].nunique() < 10:
        print(pd.DataFrame(rawData[x].value_counts()),end='\n\n')
    else:
        print(f'\033[4mThe first Five unique values and their count out of␣
 ↪{rawData[x].nunique()} unique values\033[0m',end='\n\n')
        print(pd.DataFrame(rawData[x].value_counts())[:5],end='\n\n')
```

(1) The unique values in workclass are 7

```
                  workclass
Private               22285
Self-emp-not-inc       2499
Local-gov              2067
State-gov              1279
Self-emp-inc           1074
Federal-gov             943
Without-pay              14
```

(2) The unique values in education are 16

The first Five unique values and their count out of 16 unique values

	education
HS-grad	9840
Some-college	6677
Bachelors	5044
Masters	1627
Assoc-voc	1307

(4) The unique values in maritalstatus are 7

	maritalstatus
Married-civ-spouse	14065
Never-married	9725
Divorced	4214
Separated	939
Widowed	827
Married-spouse-absent	370
Married-AF-spouse	21

(5) The unique values in occupation are 14

The first Five unique values and their count out of 14 unique values

	occupation
Prof-specialty	4038
Craft-repair	4030
Exec-managerial	3992
Adm-clerical	3721
Sales	3584

(6) The unique values in relationship are 6

	relationship
Husband	12463
Not-in-family	7726
Own-child	4466
Unmarried	3212
Wife	1406
Other-relative	888

(7) The unique values in race are 5

	race
White	25932

```
Black                  2817
Asian-Pac-Islander      895
Amer-Indian-Eskimo      286
Other                   231
```

(8) The unique values in sex are 2

```
          sex
Male    20380
Female   9781
```

(12) The unique values in native are 40

The first Five unique values and their count out of 40 unique values

```
               native
United-States   27504
Mexico            610
Philippines       188
Germany           128
Puerto-Rico       109
```

(13) The unique values in Salary are 2

```
       Salary
<=50K   22653
>50K     7508
```

4 Univatiate analysis

4.1 Understanding the y Variable

```
There are two categories i.e.
    1)  less than or equal to 50 Thousand Salary (<=50K)
    2)  Greater than 50 Thousand Salary (>50K)
```

The Dataset is dominated by one class. The dominating Class is the one with less than or equal to 50 thousand. The raito of class data is 3:1. So the dominating class is 3 times bigger than non dominating class. (I think I will do resampling from the data)

[6]:
```python
rawData.Salary.value_counts()
```

[6]:
```
<=50K    22653
>50K      7508
Name: Salary, dtype: int64
```

[7]:
```
print('\033[1mThe ratio of class <=50K : class >50K is', np.round((22653/
↪(22653+7508)),2),':',np.round((7508/(22653+7508)),2))
```

```
The ratio of class <=50K : class >50K is 0.75 : 0.25
```

5 Understanding "X" —VS— "y" (Independent VS Dependent)

5.1 Categorical features

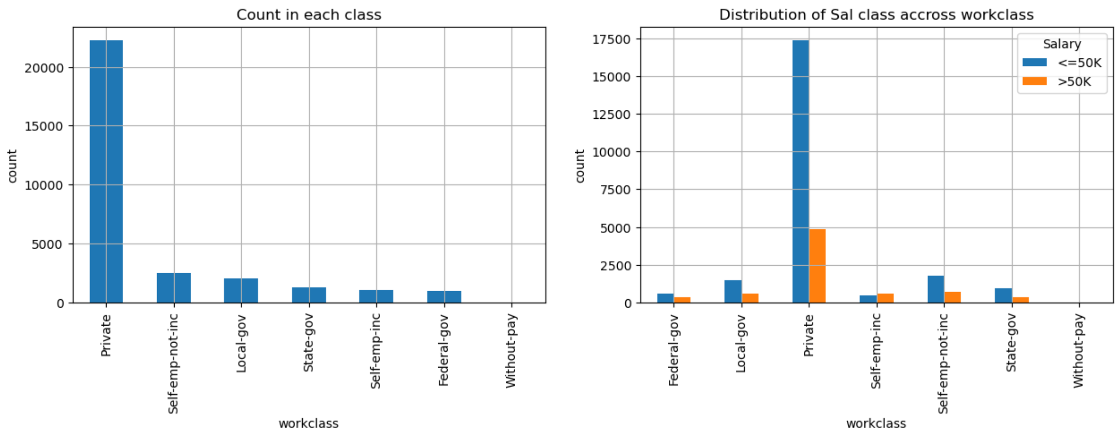
5.2 Work Class VS Salary

```
workclass (Categorical)         -- A work class is a grouping of work              --  7 Classes
                             Class                  Count
                             -----                  -----
                             Private               22285
                             Self-emp-not-inc       2499
                             Local-gov              2067
                             State-gov              1279
                             Self-emp-inc           1074
                             Federal-gov             943
                             Without-pay              14
```

As we can see `'Private'` class dominates that workclass feature with about 73% of times in the dataset. However, distribution of sal class accross workclass show no uniformity. While, mejority of people in `'self-emp-inc'` class earn greater than 50K salary, and people from `'governmant'` classes tend to do better in earning more than 50K, while people from `'Private'` class tend to show that more than 75% of people earn less than 50K Salary

So, possibly we can `think of clubing all the Govt sector workclasses in to a single class to make it more representative.`

[8]:
```
fig,ax = plt.subplots(1,2,figsize=(15,4))
rawData.workclass.value_counts().
↪plot(ax=ax[0],kind='bar',grid=True,title='Count in each class',
                                      xlabel='workclass',ylabel='count')
pd.crosstab(rawData.workclass, rawData.Salary).plot(ax=ax[1],kind='bar',
                                                    grid=True, ylabel='count',
                                                    title='Distribution of Sal␣
↪class accross workclass')
# sns.countplot(x='workclass',hue='Salary',data=rawData, ax=ax[0])
# sns.catplot(x='workclass',hue='Salary',kind='count',data=rawData,ax=ax[1])
# plt.draw()
# ax[0].set_xticklabels(ax[0].get_xticklabels(),rotation=45,ha='right')
plt.show()
```



5.3 education vs salary

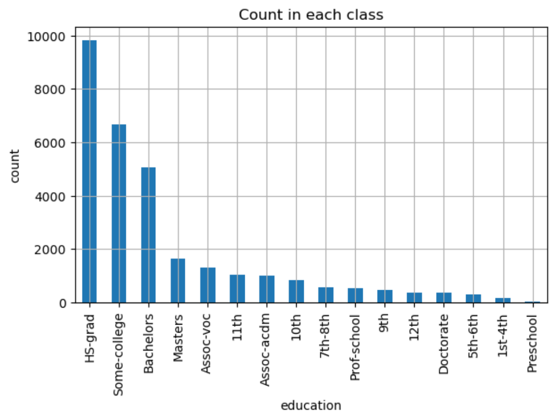
```
education (Categorical)        -- Education of an individuals
-- 16 Classes
```

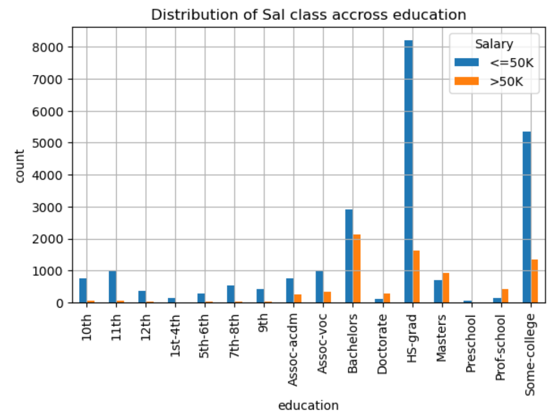
|class|count|||class|count| |—-|—-|||—-|—-| |HS-grad|9840|||7th-8th|557| |Some-college| 6677|||Prof-school| 542| |Bachelors| 5044|||9th| 455| |Masters| 1627|||12th| 377| |Assoc-voc| 1307|||Doctorate| 375| |11th| 1048|||5th-6th| 288| |Assoc-acdm| 1008|||1st-4th| 151| |10th| 820|||Preschool| 45|

Education feature is plagued with high cardinality and only few classes dominate the feature. `HS-grad, Some college,bachelors` together they account for about 72% of the values and rest of 13 classes represent only 28% of the data. Large classes tend to dominate the algorithm and influence the prediction. let us try to balance the data that are similar and can be grouped. We can work to club smaller classes to make a larger class to make it more representative. one such idea we can think of clubbing all the classes ranging from `1st to 12th`. However, we need to figure out how to treat prof-school, preschool, doctorate, etc.

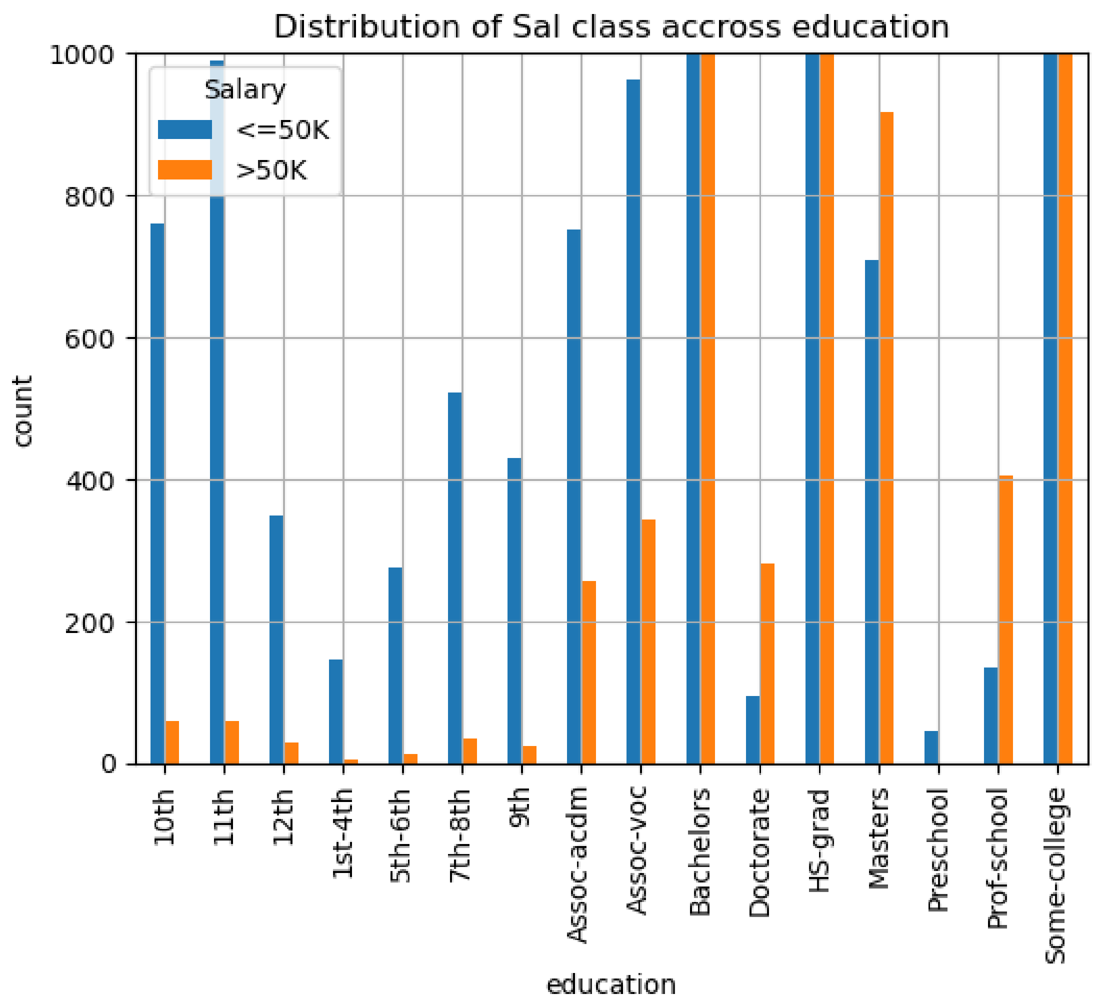
Another thing we notice is that the higher the education the better the salaries. in our case only higher education classes have good representation in greater than 50K salary. `So we can say that education has a strong influence on the your salary, in our case your chance of earning greater than 50k salary increases with education.`

[9]:
```
fig,ax = plt.subplots(1,2,figsize=(15,4))
rawData.education.value_counts().
 ↪plot(ax=ax[0],kind='bar',grid=True,title='Count in each class',
                                xlabel='education',ylabel='count')
pd.crosstab(rawData.education, rawData.Salary).plot(ax=ax[1],kind='bar',
                                                  grid=True, ylabel='count',
                                                  title='Distribution of Sal␣
 ↪class accross education')
plt.show()
```





[10]:
```
pd.crosstab(rawData.education, rawData.Salary).plot(kind='bar',
                                                    grid=True, ylabel='count',
                                                    title='Distribution of Sal␣
 ↪class accross education',ylim=(0,1000))
plt.show()
```



5.4 maritalstatus Vs Salary

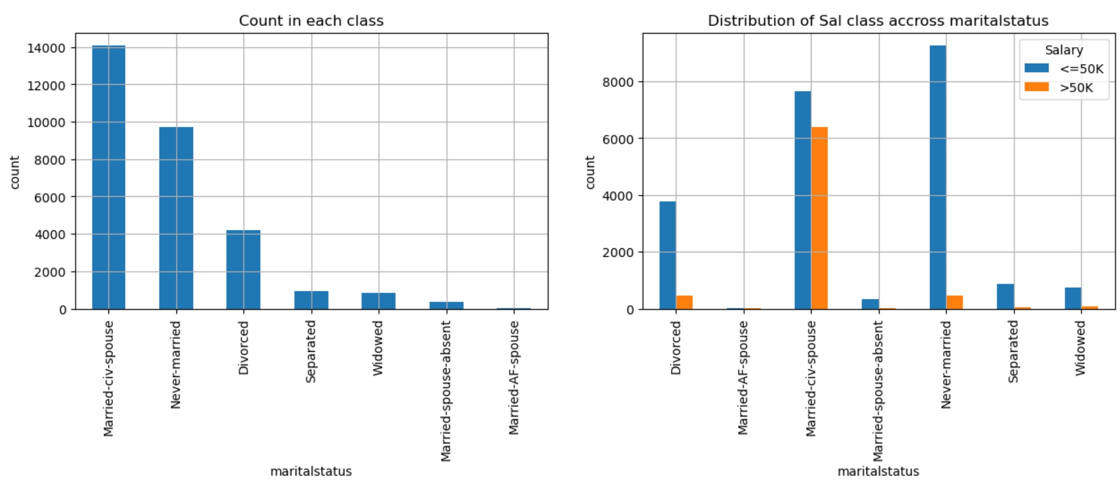
maritalstatus (Categorical) – Marital status of an individulas – `7 Classes`

Class	Count
Married-civ-spouse	14065
Never-married	9725
Divorced	4214
Separated	939
Widowed	827
Married-spouse-absent	370
Married-AF-spouse	21

As we can note that three classes namely `Married-civ-spouse, Never-married, Divorced` account for about 92% of the data. we can actually club the data in such a way that they represent three classes, namely `married, never married, and (divorced or separated or spouse absent)`.

The only inference we can draw is that married-civ-spouse class has the highest above 50K salary. but this could be the people in class never married are young and they starting their career and pople in all other categories are retired. Hence, we can not confidently say any thing about marrital status and salary class.

[11]:
```
fig,ax = plt.subplots(1,2,figsize=(15,4))
rawData.maritalstatus.value_counts().
 ↪plot(ax=ax[0],kind='bar',grid=True,title='Count in each class',
                                    xlabel='maritalstatus',ylabel='count')
pd.crosstab(rawData.maritalstatus, rawData.Salary).plot(ax=ax[1],kind='bar',
                                                  grid=True, ylabel='count',
                                                  title='Distribution of Sal␣
 ↪class accross maritalstatus')
plt.show()
```



[12]:
```
pd.crosstab(rawData.maritalstatus, rawData.Salary)
```

[12]:
```
Salary                 <=50K  >50K
maritalstatus
Divorced                3762   452
Married-AF-spouse         11    10
Married-civ-spouse      7666  6399
Married-spouse-absent    339    31
Never-married           9255   470
Separated                873    66
Widowed                  747    80
```

[13]:
```python
# rawData.groupby(['maritalstatus']).count()
pd.pivot_table(data=rawData,␣
↪values='age',columns=['maritalstatus'],index=['sex','education'])
```

[13]:
```
maritalstatus         Divorced  Married-AF-spouse  Married-civ-spouse  \
sex    education
Female 10th          44.898305                NaN           36.571429
       11th          41.916667                NaN           41.571429
       12th          40.562500                NaN           38.142857
       1st-4th       60.750000                NaN           42.666667
       5th-6th       51.777778                NaN           44.692308
       7th-8th       50.700000                NaN           43.900000
       9th           45.407407                NaN           44.050000
       Assoc-acdm    40.348485          35.000000           35.464789
       Assoc-voc     40.905405                NaN           36.562500
       Bachelors     43.711191          27.000000           38.014493
       Doctorate     49.100000                NaN           42.666667
       HS-grad       43.035955          30.857143           40.634096
       Masters       46.953333                NaN           42.710280
       Preschool           NaN                NaN           39.000000
       Prof-school   42.900000                NaN           39.730769
       Some-college  42.592593          28.000000           39.637931
Male   10th          42.404255                NaN           46.367893
       11th          40.617021                NaN           41.866221
       12th          40.550000                NaN           42.585859
       1st-4th       63.000000                NaN           46.985075
       5th-6th       52.777778                NaN           44.891473
       7th-8th       47.500000                NaN           50.137584
       9th           47.520000                NaN           44.658031
       Assoc-acdm    41.630769                NaN           41.370270
       Assoc-voc     39.552632          29.000000           41.210345
       Bachelors     44.571429          34.500000           42.834697
       Doctorate     50.500000                NaN           48.479167
       HS-grad       40.980000          31.800000           42.491198
       Masters       47.620253                NaN           44.997605
       Preschool     36.000000                NaN           46.642857
       Prof-school   44.303030                NaN           46.413889
       Some-college  41.809798          26.000000           42.131436

maritalstatus        Married-spouse-absent  Never-married  Separated  \
sex    education
Female 10th                      36.714286      22.894231  41.777778
       11th                      31.800000      21.578199  38.576923
       12th                      29.250000      22.794521  36.875000
       1st-4th                   33.666667      32.666667  49.000000
       5th-6th                   50.000000      34.960000  43.636364
       7th-8th                   45.500000      36.620690  45.333333
```

	9th	42.000000	31.829268	44.357143
	Assoc-acdm	46.166667	29.789474	41.062500
	Assoc-voc	34.400000	29.821429	42.481481
	Bachelors	41.862069	30.138955	40.857143
	Doctorate	43.000000	43.000000	39.750000
	HS-grad	39.683333	29.138962	38.979508
	Masters	45.888889	38.182266	41.916667
	Preschool	NaN	38.300000	48.000000
	Prof-school	NaN	36.114286	43.333333
	Some-college	35.111111	25.764372	38.301587
Male	10th	46.625000	25.317949	39.666667
	11th	33.727273	22.963333	33.588235
	12th	49.333333	23.348837	36.000000
	1st-4th	40.142857	30.000000	48.333333
	5th-6th	40.200000	28.789474	43.857143
	7th-8th	55.000000	32.943662	30.750000
	9th	34.000000	26.718750	43.461538
	Assoc-acdm	44.750000	29.202532	38.000000
	Assoc-voc	44.200000	30.222857	38.307692
	Bachelors	42.928571	30.974742	41.232558
	Doctorate	49.333333	39.181818	47.000000
	HS-grad	38.645833	28.375357	37.561538
	Masters	50.333333	37.530726	43.454545
	Preschool	42.333333	33.000000	NaN
	Prof-school	51.000000	36.320755	44.400000
	Some-college	40.200000	26.579189	38.773810

maritalstatus		Widowed
sex	education	
Female	10th	60.600000
	11th	54.655172
	12th	58.142857
	1st-4th	59.642857
	5th-6th	61.666667
	7th-8th	62.657895
	9th	62.857143
	Assoc-acdm	49.000000
	Assoc-voc	59.333333
	Bachelors	51.685185
	Doctorate	68.666667
	HS-grad	57.787456
	Masters	55.821429
	Preschool	66.000000
	Prof-school	64.333333
	Some-college	56.105263
Male	10th	53.222222
	11th	59.000000

```
12th            72.000000
1st-4th         69.500000
5th-6th         78.500000
7th-8th         64.111111
9th             52.666667
Assoc-acdm      36.500000
Assoc-voc       66.500000
Bachelors       60.000000
Doctorate       62.666667
HS-grad         60.189655
Masters         61.125000
Preschool       71.000000
Prof-school     42.500000
Some-college    61.388889
```

5.5 occupation Vs Salary

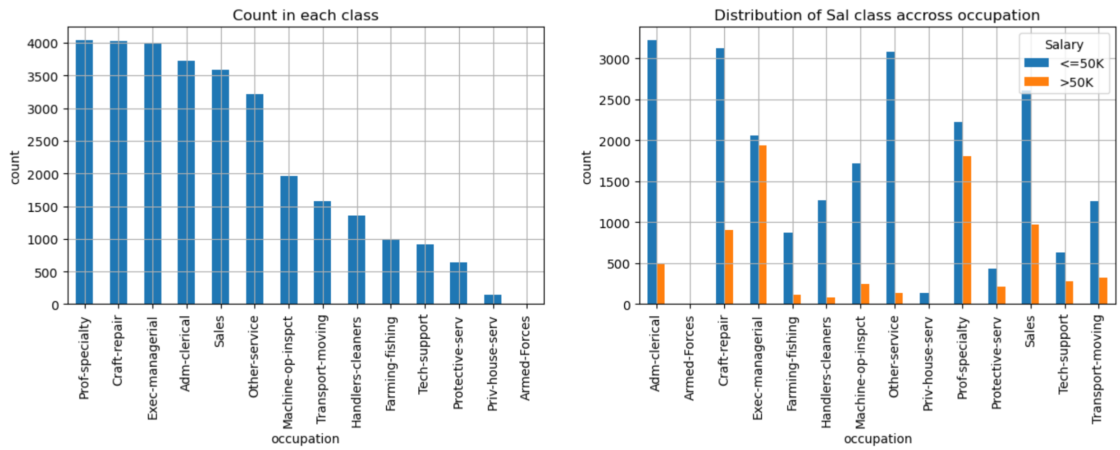
occupation (Categorical) – occupation of an individuals – 14 Classes

|Sl no|Class|Count||Sl no|Class|Count| |—–|—–|—–||—–|—–|—–| | 1)| Prof-specialty | 4038|| 8)| Transport-moving | 1572| | 2)| Craft-repair | 4030|| 9)| Handlers-cleaners| 1350| | 3)| Exec-managerial | 3992||10)| Farming-fishing | 989| | 4)| Adm-clerical | 3721||11)| Tech-support | 912| | 5)| Sales | 3584||12)| Protective-serv | 644| | 6)| Other-service | 3212||13)| Priv-house-serv | 143| | 7)| Machine-op-inspct| 1965||14)| Armed-Forces | 9| |||cont….|

As it can be noted that the classes of occupation are well distributed. there are some columns who have low representation. `Armed forces` accorss features has low representation, don't really know how to handle it. There are high chances of model going wrong in that calass.

However, it is very evident that your `occupation has high influence on your chances of earning salary greater than 50K`.

[14]:
```
fig,ax = plt.subplots(1,2,figsize=(15,4))
rawData.occupation.value_counts().
↪plot(ax=ax[0],kind='bar',grid=True,title='Count in each class',
                                      xlabel='occupation',ylabel='count')
pd.crosstab(rawData.occupation, rawData.Salary).plot(ax=ax[1],kind='bar',
                                                    grid=True, ylabel='count',
                                                    title='Distribution of Sal␣
↪class accross occupation')
plt.show()
```



5.6 relationship Vs Salary

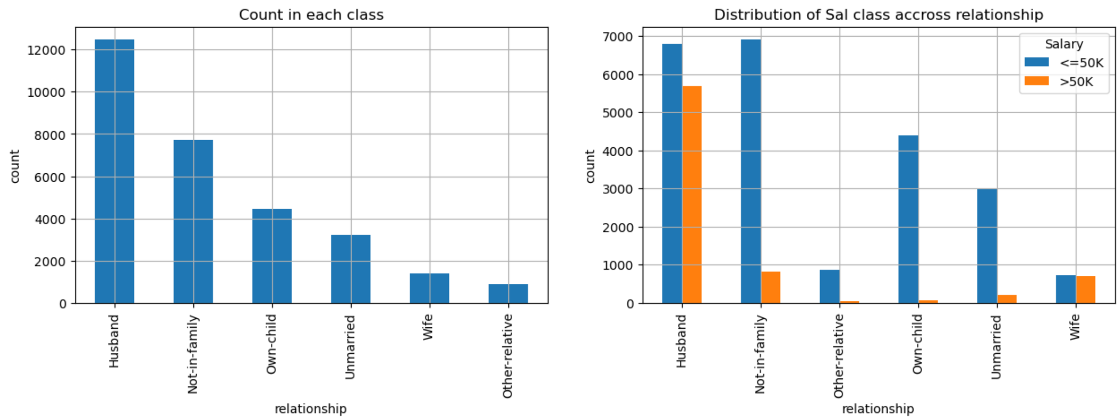
relationship (Categorical) – Relationship or Role in the family – 6 Classes

|Class||Count| |—–||—–| |Husband|12463| |Not-in-family|7726| |Own-child|4466| |Unmarried|3212| |Wife|1406| |Other-relative|888|

Relationship has a `vague` representation in the dataset. It tries to expalin the relationship of the invdividual with other members of the family, such as, `husband, not-in-family, own-child, wife or other-relative`. However `unmarried` is a status not a relationship. Any way we already have the `maritalstatus as an attribute`, so, we may not `need this feature`

`LET US DROP THIS FEATURE`

[15]:
```
fig,ax = plt.subplots(1,2,figsize=(15,4))
rawData.relationship.value_counts().
 ↪plot(ax=ax[0],kind='bar',grid=True,title='Count in each class',
                                     xlabel='relationship',ylabel='count')
pd.crosstab(rawData.relationship, rawData.Salary).plot(ax=ax[1],kind='bar',
                                                      grid=True, ylabel='count',
                                                      title='Distribution of Sal␣
 ↪class accross relationship')
plt.show()
```



5.7 Race Vs Salary

race (Categorical) – Race of an Individual – 5 Classes

|Class| |Count| |—–| |—–| |White| |25932| |Black| |2817| |Asian-Pac-Islander| |895| |Amer-Indian-Eskimo| |286| |Other| |231|

Race is completely dominated by one class i.e. `'White'` which is almost 90% of the weight of the data. We can group the rest of the classes in to one single group to increase their representation.

Looking at the data it cleary shows that your chances of the being in salary greater than 50K increases if you belong to the class `'white'`

[16]:
```
fig,ax = plt.subplots(1,2,figsize=(15,4))
rawData.race.value_counts().plot(ax=ax[0],kind='bar',grid=True,title='Count in␣
 ↪each class',
                                      xlabel='race',ylabel='count')
pd.crosstab(rawData.race, rawData.Salary).plot(ax=ax[1],kind='bar',
                                                     grid=True, ylabel='count',
                                                     title='Distribution of Sal␣
 ↪class accross race')
plt.show()
```

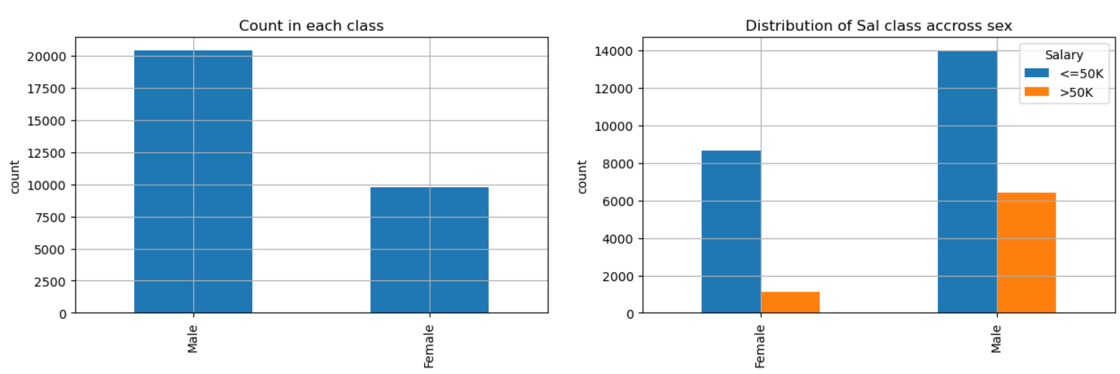
5.8 Sex Vs Salary

sex (Categorical) – Gender of an Individual – 2 Classes

|Class| |Count| |—–| |—–| |Male | |20380| |Female| |9781|

Sex is also dominated by the `Male` class, and also one can notice gender bias in salaries based on ses. it shows that if your are white male you have very high probabilty that your are earning more than 50K

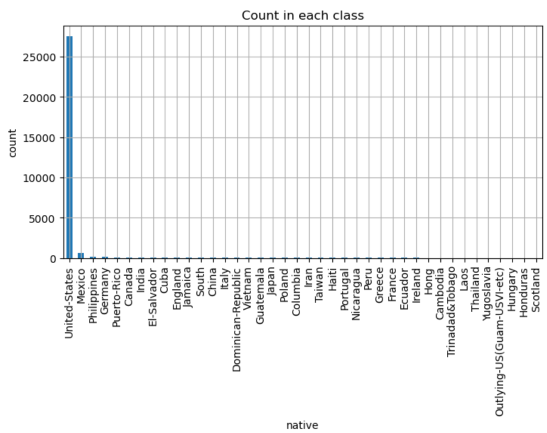
[17]:
```
fig,ax = plt.subplots(1,2,figsize=(15,4))
rawData.sex.value_counts().plot(ax=ax[0],kind='bar',grid=True,title='Count in␣
↪each class',
                                        xlabel='sex',ylabel='count')
pd.crosstab(rawData.sex, rawData.Salary).plot(ax=ax[1],kind='bar',
                                                    grid=True, ylabel='count',
                                                    title='Distribution of Sal␣
↪class accross sex')
plt.show()
```

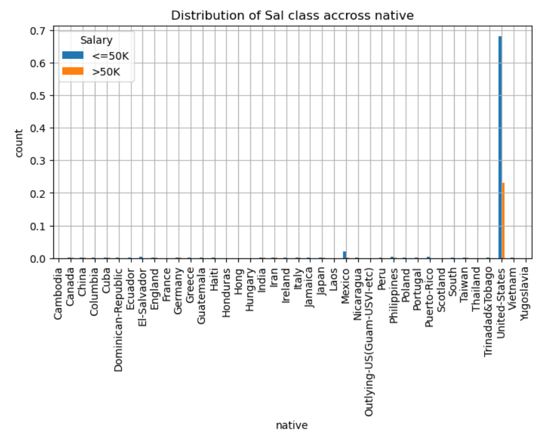


5.9 Native

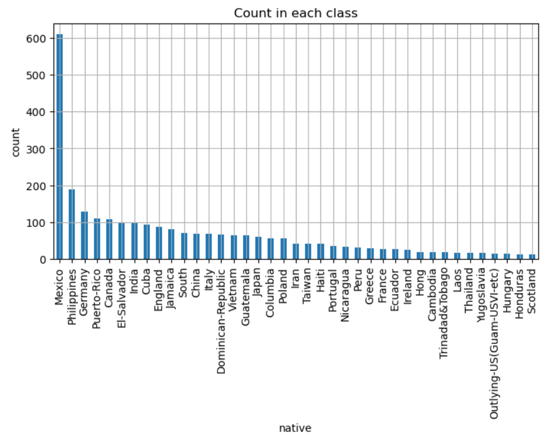
native – Native of an individual – 40 Classes

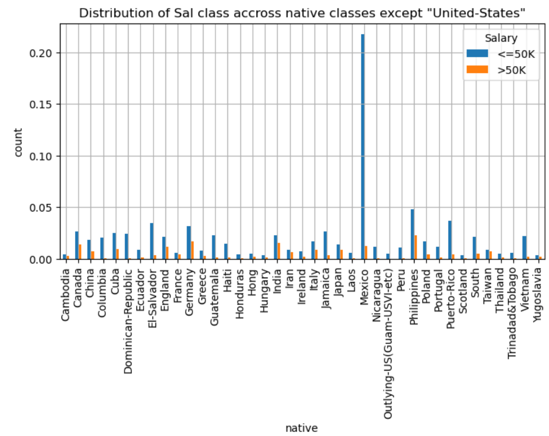
[18]:
```
fig,ax = plt.subplots(1,2,figsize=(18,4))
rawData.native.value_counts().plot(ax=ax[0],kind='bar',grid=True,title='Count␣
↪in each class',
                                                  xlabel='native',ylabel='count')
pd.crosstab(rawData.native, rawData.Salary,normalize=True).
↪plot(ax=ax[1],kind='bar',
                                                                   grid=True, ylabel='count',
                                                                   title='Distribution of Sal␣
↪class accross native')
plt.show()
```





[19]:
```
fig,ax = plt.subplots(1,2,figsize=(18,4))
rawData[rawData.native != 'United-States']['native'].value_counts().
↪plot(ax=ax[0],kind='bar',grid=True,
                                                                                         ␣
↪title='Count in each class',
                                                                                         ␣
↪xlabel='native',ylabel='count')
pd.crosstab(rawData[rawData.native != 'United-States']['native'],
            rawData.Salary,normalize=True).plot(ax=ax[1],kind='bar',
                                                        grid=True, ylabel='count',
                                                        title='Distribution of Sal class␣
↪accross native classes except "United-States"')
plt.show()
```





6 Understanding X / ind-variables —VS— y / Dep-variable

6.1 Numerical features

age (numerical) – age of a person - Age is not that useful feature as we have no of years of education ‘educationno’

educationno (numerical) – No of years in education - good feature which shows a strong relationship with salary

capitalgain – profit received from the sale of an investment - Sparse column but shows a good predictor as per PPSCORE.

capitalloss – A decrease in the value of a capital asset - not so good as capital gain.

hoursperweek – number of hours work per week — not an useful column however there is a strong relation with salary.

[20]:
```
# rawData.corr()
```

[21]:
```
%matplotlib inline
# sns.pairplot(rawData,hue='Salary')
```

6.2 Age Vs Salary

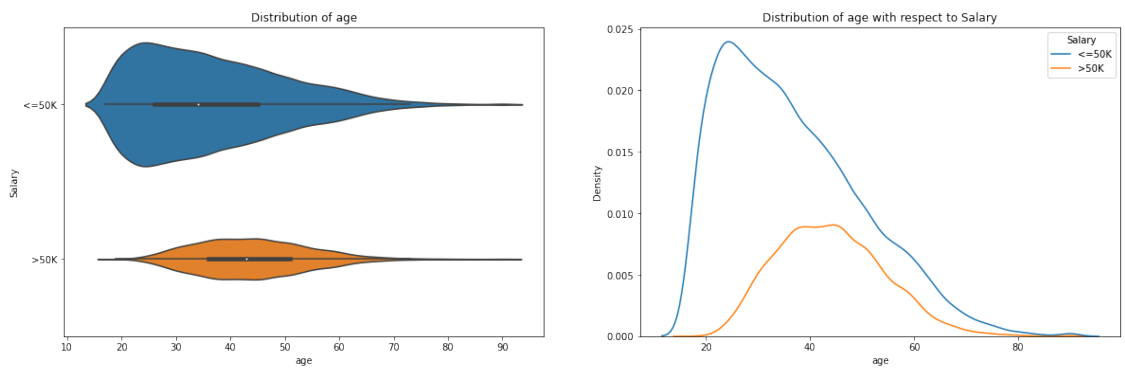
Age slightly right skewed in the data set. Age is no distinguisher of classes in salary. Person in the middle aged gorup are the working class and it is imparative that the salary greater than 50K will also be in that age bracket.

As we can see from the picture below the class of greater than 50K is lying in the center. which clearly not distinguishable.

However what we can note with the violin plot is that Age can be devided into three groups, i.e. less than 30 - your salary for sure will be less than 50K and between 30years to 60years, your chance of drawing salary greater than 50K increases, lastly above 60 where you chances of higher salaries is same as less than 50K.

Age feature must be compared with occupation, workclass, relationship and marital status.

[22]:
```
fig,ax = plt.subplots(1,2,figsize=(20,6))
# rawData.age.plot.hist(ax=ax[0],by='native',bins=35,title='Distribution of␣
↪Age')
# rawData.groupby('Salary')['age'].plot(ax=ax[1],title='Age vs␣
↪Salary',xlabel='Index',ylabel='Age')
# sns.kdeplot(x=rawData.age,ax=ax[0])
sns.violinplot(x=rawData.age,y=rawData.Salary,ax=ax[0],scale='count')
sns.kdeplot(x=rawData.age,hue=rawData.Salary,ax=ax[1])
ax[0].set_title('Distribution of age')
ax[1].set_title('Distribution of age with respect to Salary')
plt.show()
```



6.3 educationno Vs Salary

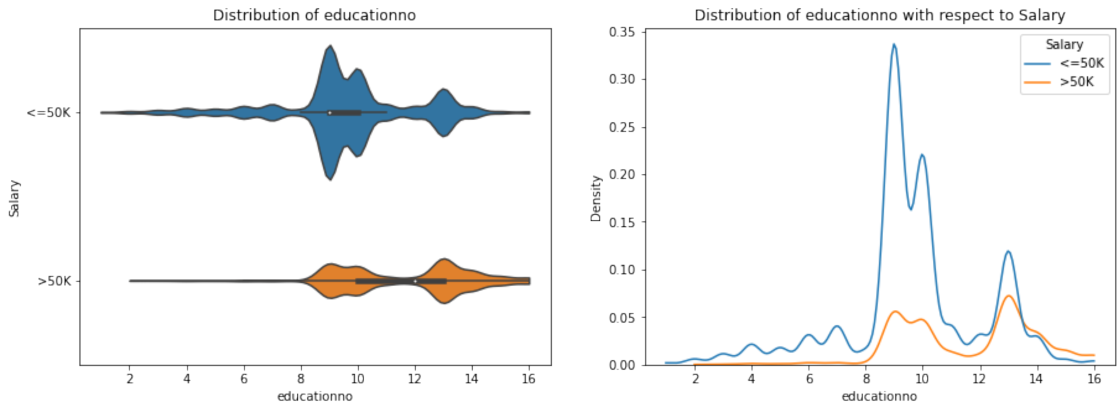
Educationno is a better distinguisher of Salary classes as we can note that as the number of years of education increases your chance of earning salary more than 50K increases.

the below violinplot clearly shows that there are two phases where we have high salaries. One class is that of highschool dropouts, who happen to start their own enterprises and the other class who compete their undergraduation and go on to complete graduation. The second category must be doing mangagerial or highly skilled job hence the salaries are better. we need to compare the education no feature with workclass and occupation.

This is good feature

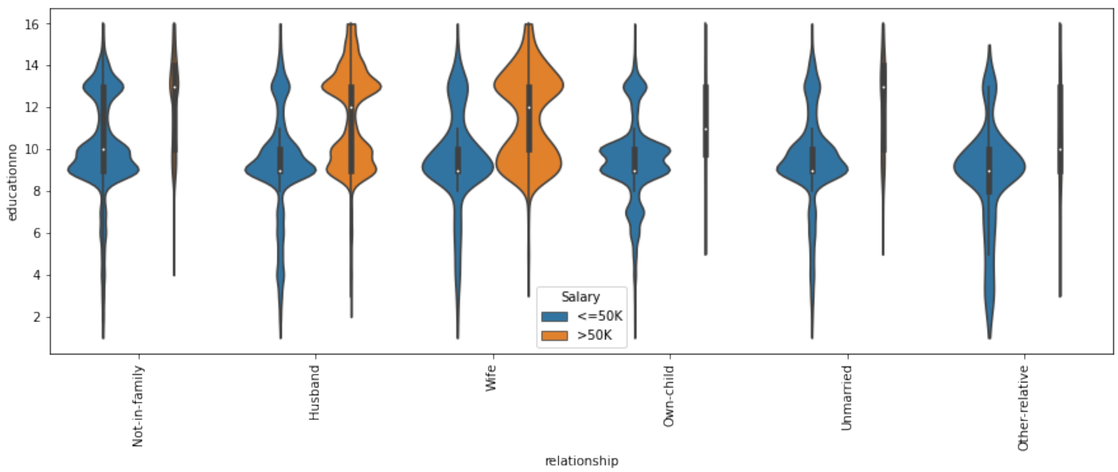
[23]:
```
fig,ax = plt.subplots(1,2,figsize=(15,5))
# rawData.educationno.plot.hist(ax=ax[0],bins=5,title='Distribution - no of␣
↪years education')
# rawData.groupby('Salary')['educationno'].plot(ax=ax[1],title='no of years␣
↪education vs Salary',xlabel='Index',ylabel='Age')
```

```
sns.violinplot(x=rawData.educationno,y=rawData.
 ↪Salary,ax=ax[0],scale='count',cut=0)
sns.kdeplot(x=rawData.educationno,hue=rawData.Salary,ax=ax[1],cut=0)
ax[0].set_title('Distribution of educationno')
ax[1].set_title('Distribution of educationno with respect to Salary')
plt.show()
```



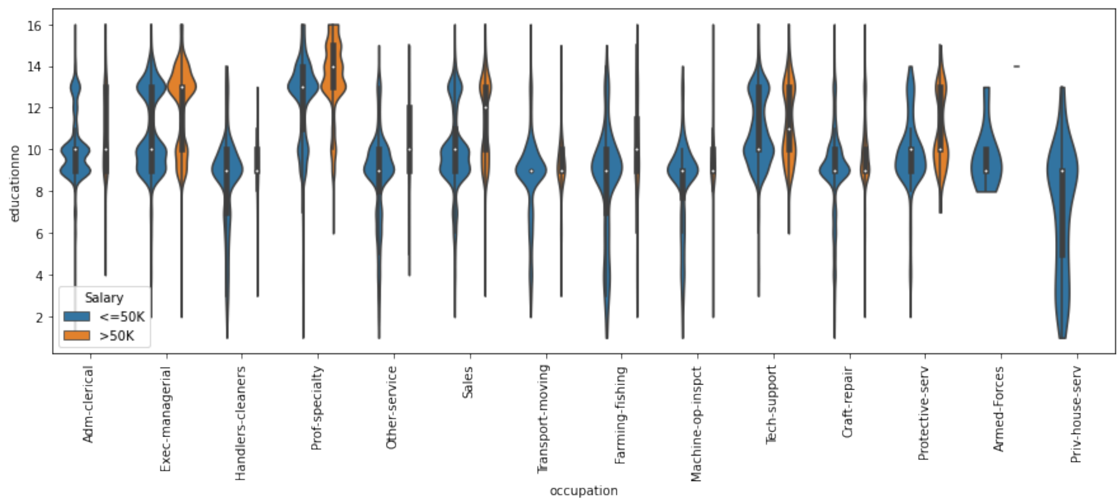
[24]:
```
plt.figure(figsize=(15,5))
sns.violinplot(x=rawData.relationship,y=rawData.educationno,hue=rawData.
 ↪Salary,scale='count',gridsize=100,cut=0)
plt.xticks(rotation=90)
plt.show
```

[24]: <function matplotlib.pyplot.show(close=None, block=None)>



[25]:
```
plt.figure(figsize=(15,5))
sns.violinplot(x=rawData.occupation,y=rawData.educationno,hue=rawData.
 ↪Salary,scale='count',split=False,cut=0)
plt.xticks(rotation=90)
plt.show
```

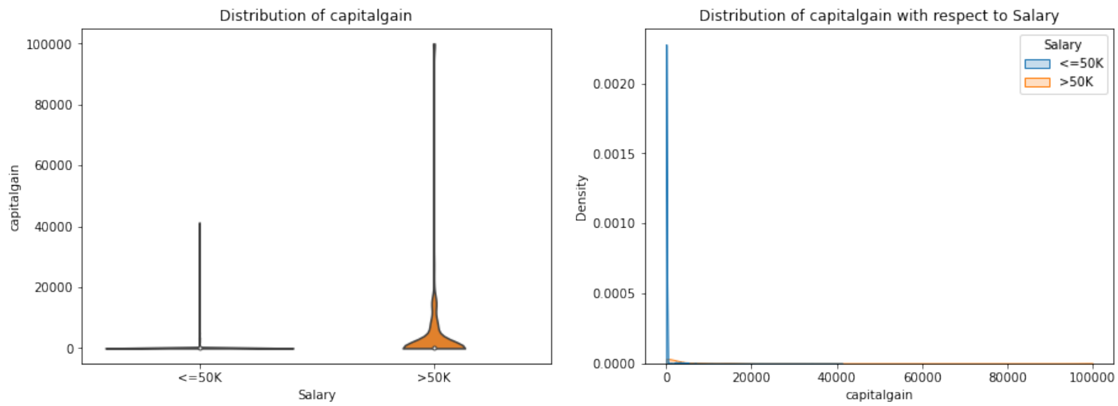
[25]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



6.4 capitalgain vs Salary

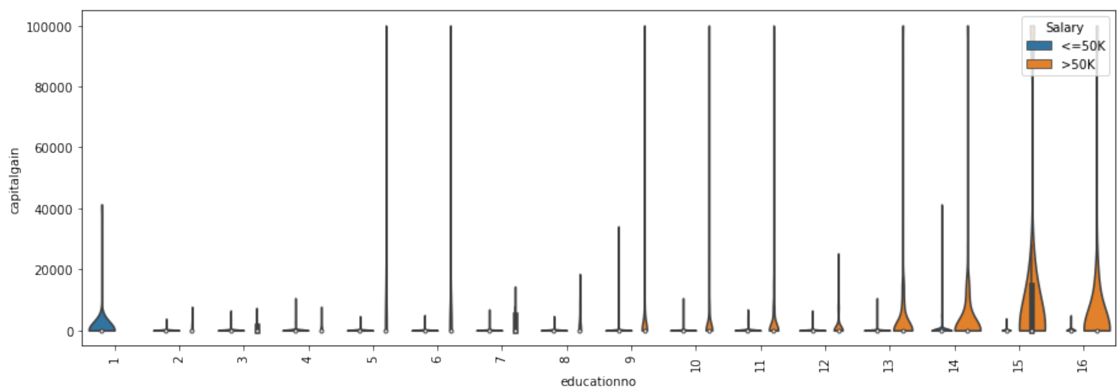
Capital gain has large number of 0 values, which might mean that the person has no capital gain or it might mean that there is no data available. only chance for someone to have capital gain or loss equal to zero is when he has no investment or he does not report his investment. hence the chances that the informatino is not available is very high. hence we can ignore this feature.

[26]:
```
fig,ax = plt.subplots(1,2,figsize=(15,5))
# rawData.capitalgain.plot.hist(ax=ax[0],bins=20,title='Distribution -␣
 ↪capitalgain')
# rawData.groupby('Salary')['capitalgain'].plot(ax=ax[1],title='capitalgain vs␣
 ↪Salary',xlabel='Index',ylabel='capitalgain')
sns.violinplot(y=rawData.capitalgain,x=rawData.
 ↪Salary,ax=ax[0],scale='count',ylim=(0,0.00001),cut=0)
sns.kdeplot(x=rawData.capitalgain,hue=rawData.Salary,ax=ax[1],fill=True,cut=0)
ax[0].set_title('Distribution of capitalgain')
ax[1].set_title('Distribution of capitalgain with respect to Salary')
# ax[1].set(ylim=(0,.00001))
plt.show()
```



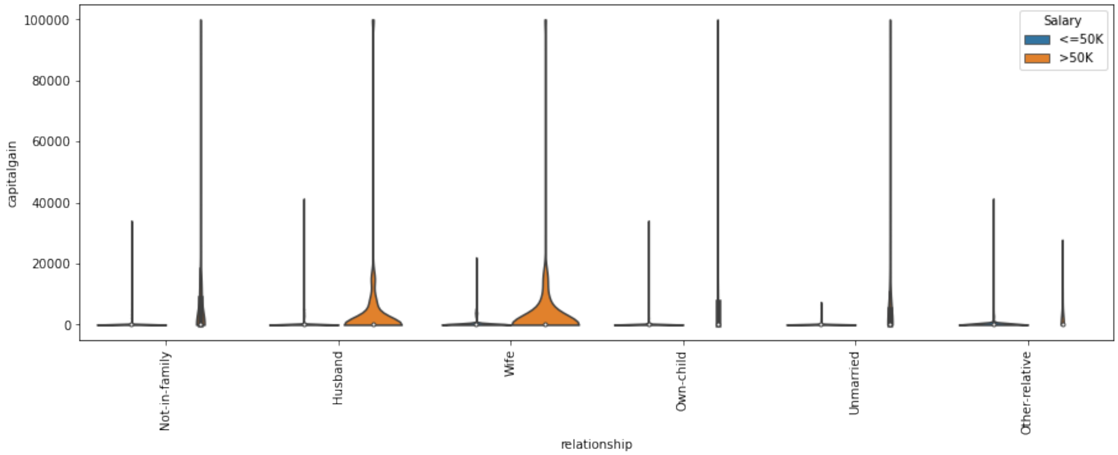
[27]:
```
plt.figure(figsize=(15,5))
sns.violinplot(x=rawData.educationno,y=rawData.capitalgain,hue=rawData.
↪Salary,scale='count',gridsize=100,cut=0)
plt.xticks(rotation=90)
plt.show
```

[27]: <function matplotlib.pyplot.show(close=None, block=None)>



[28]:
```
plt.figure(figsize=(15,5))
sns.violinplot(x=rawData.relationship,y=rawData.capitalgain,hue=rawData.
↪Salary,scale='count',gridsize=100,cut=0)
plt.xticks(rotation=90)
plt.show
```

[28]: <function matplotlib.pyplot.show(close=None, block=None)>



[29]:
```
rawData.groupby('Salary')['capitalgain'].sum()
```

[29]:
```
Salary
<=50K     3373041
>50K     29564100
Name: capitalgain, dtype: int64
```

[30]:
```
rawData[rawData.capitalgain > 0].groupby('Salary')['capitalgain'].count()
```

[30]:
```
Salary
<=50K     943
>50K     1595
Name: capitalgain, dtype: int64
```

6.5 capitalloss Vs Salary

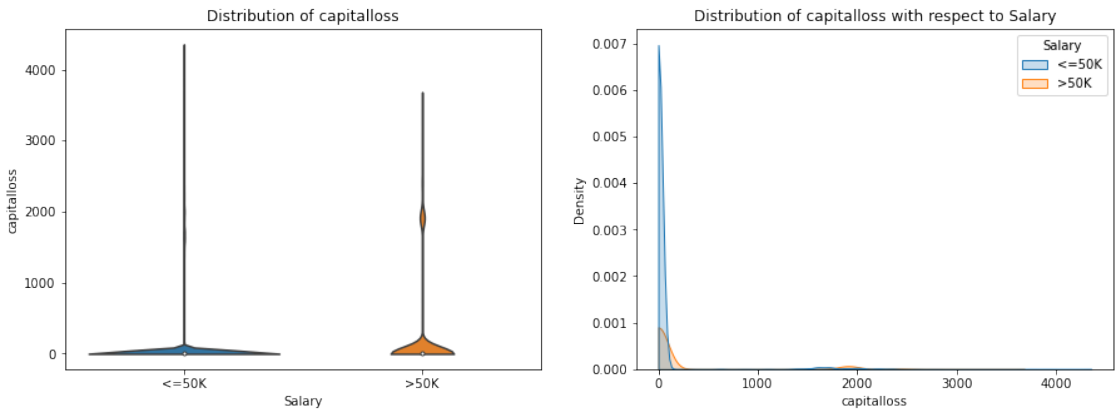
Capital loss has large number of 0 values, which might mean that the person has no capital capital or it might mean that there is no data available. only chance for someone to have capital gain or loss equal to zero is when he has no investment or he does not report his investment. hence the chances that the informatino is not available is very high.

However, when we see this feature along with relationship, educatinono we can see higher education capital loss shows greater chance of salary greater than 50K. possibly my understandin is that those who have investement, which shows in capital gain or loss, belong to the class of higher salary. even though the salary less than 50K category shows investments but its not as prevelent as it is in salary greater than 50K

further investigatino tell that capital gain and capital loss are completely independent of each other. Hence retaining this feature is good.

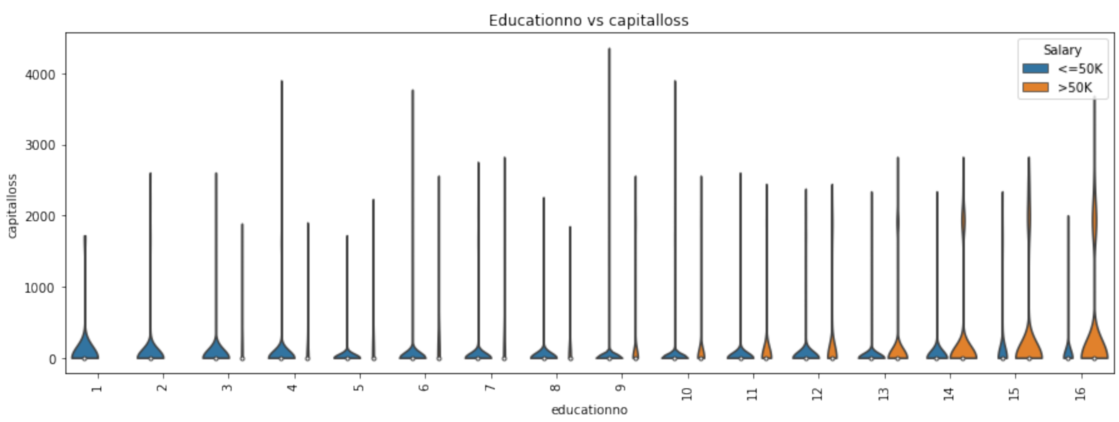
[31]:
```
fig,ax = plt.subplots(1,2,figsize=(15,5))
# rawData.capitalloss.plot.hist(ax=ax[0],bins=10,title='Distribution -␣
↪capitalloss')
```

```
# rawData.groupby('Salary')['capitalloss'].plot(ax=ax[1],title='capitalloss vs␣
↪Salary',xlabel='Index',ylabel='capitalloss')
sns.violinplot(y=rawData.capitalloss,x=rawData.
↪Salary,ax=ax[0],scale='count',ylim=(0,0.00001),cut=0)
sns.kdeplot(x=rawData.capitalloss,hue=rawData.Salary,ax=ax[1],fill=True,cut=0)
ax[0].set_title('Distribution of capitalloss')
ax[1].set_title('Distribution of capitalloss with respect to Salary')
plt.show()
```



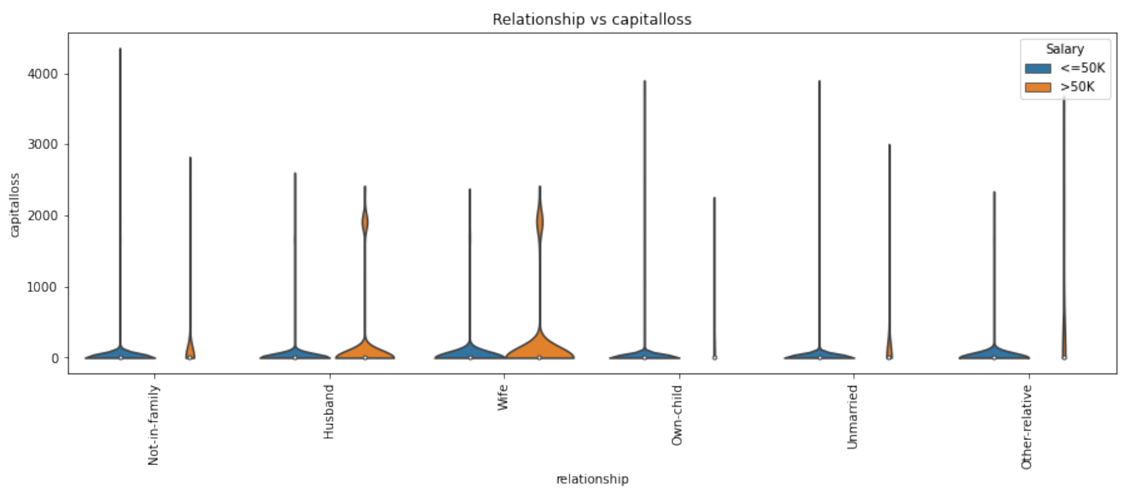
[32]:
```
plt.figure(figsize=(15,5))
sns.violinplot(x=rawData.educationno,y=rawData.capitalloss,hue=rawData.
↪Salary,scale='count',gridsize=100,cut=0)
plt.xticks(rotation=90)
plt.title('Educationno vs capitalloss')
plt.show
```

[32]: <function matplotlib.pyplot.show(close=None, block=None)>



[33]:
```
plt.figure(figsize=(15,5))
sns.violinplot(x=rawData.relationship,y=rawData.capitalloss,hue=rawData.
 ↪Salary,scale='count',gridsize=100,cut=0)
plt.xticks(rotation=90)
plt.title('Relationship vs capitalloss')
plt.show
```

[33]: <function matplotlib.pyplot.show(close=None, block=None)>



[34]:
```
print(rawData[rawData.capitalloss > 0].groupby('Salary')['capitalloss'].mean())
print(rawData[rawData.capitalloss > 0].groupby('Salary')['capitalloss'].count())
```

```
Salary
<=50K    1754.145138
>50K     1973.785617
Name: capitalloss, dtype: float64
Salary
<=50K    689
>50K     737
Name: capitalloss, dtype: int64
```

[35]:
```
rawData[(rawData.capitalgain > 0) & (rawData.capitalloss > 0)].shape
```

[35]: (0, 14)

[36]:
```
rawData[(rawData.capitalgain > 0) | (rawData.capitalloss > 0)].shape
```

[36]: (3964, 14)

6.6 hoursperweek vs Salary

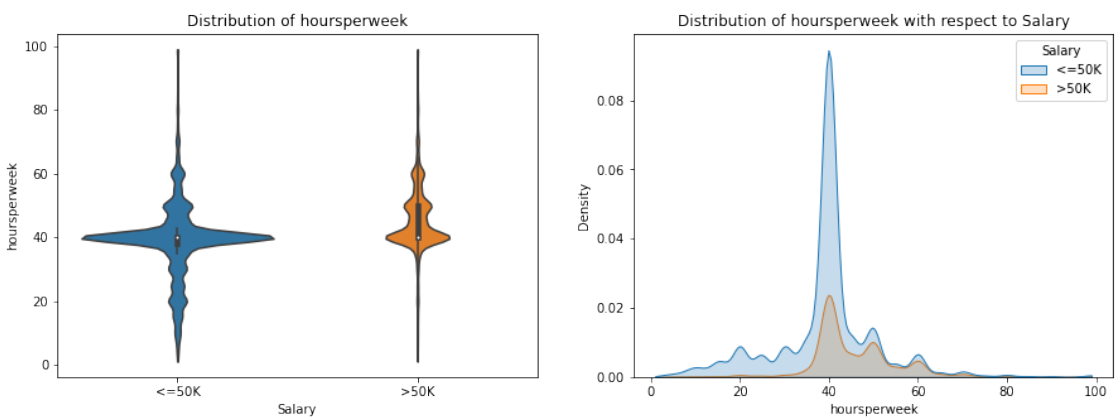
Mejority of the people work 40 hours per week, and possibly the people with salary more than 50K would have average hours per week more than 40 hours.

further down the line if we compare education and hoursperweek in relation with slary we can see that people with higher education and earning salary more than 50k tend to give more no of hours per week.

Also hoursper week and relationship distinguish the slary class, especialy if you are a husband and wife your chances of higher salary increases.

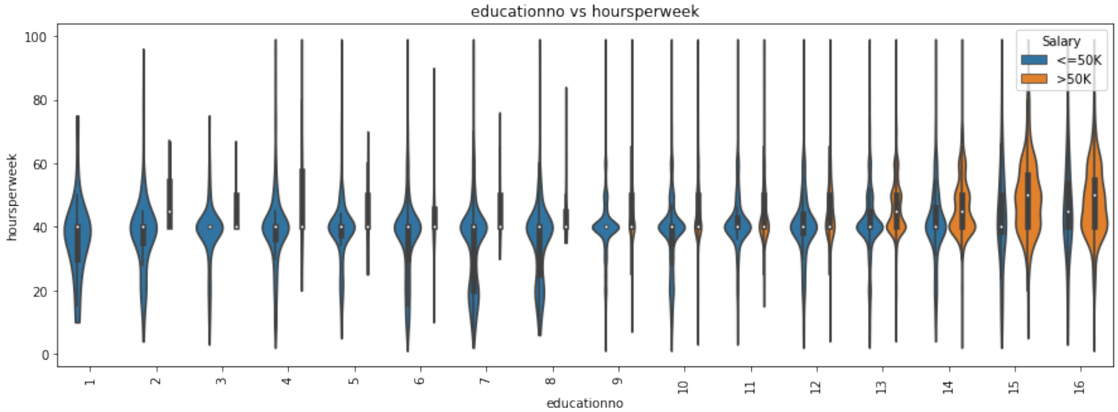
lastly, hoursperweek and occupation clearly show that there are high paid occupations, medium paid occupations and low paid occupations. we can regroup these into the three classes for our analysis.

[37]:
```
fig,ax = plt.subplots(1,2,figsize=(15,5))
# rawData.hoursperweek.plot.hist(ax=ax[0],bins=10,title='Distribution -␣
↪hoursperweek')
# rawData.groupby('Salary')['hoursperweek'].plot(ax=ax[1],title='hoursperweek␣
↪vs Salary',xlabel='Index',ylabel='hoursperweek')
sns.violinplot(y=rawData.hoursperweek,x=rawData.
↪Salary,ax=ax[0],scale='count',ylim=(0,0.00001),cut=0)
sns.kdeplot(x=rawData.hoursperweek,hue=rawData.Salary,ax=ax[1],fill=True,cut=0)
ax[0].set_title('Distribution of hoursperweek')
ax[1].set_title('Distribution of hoursperweek with respect to Salary')
plt.show()
```



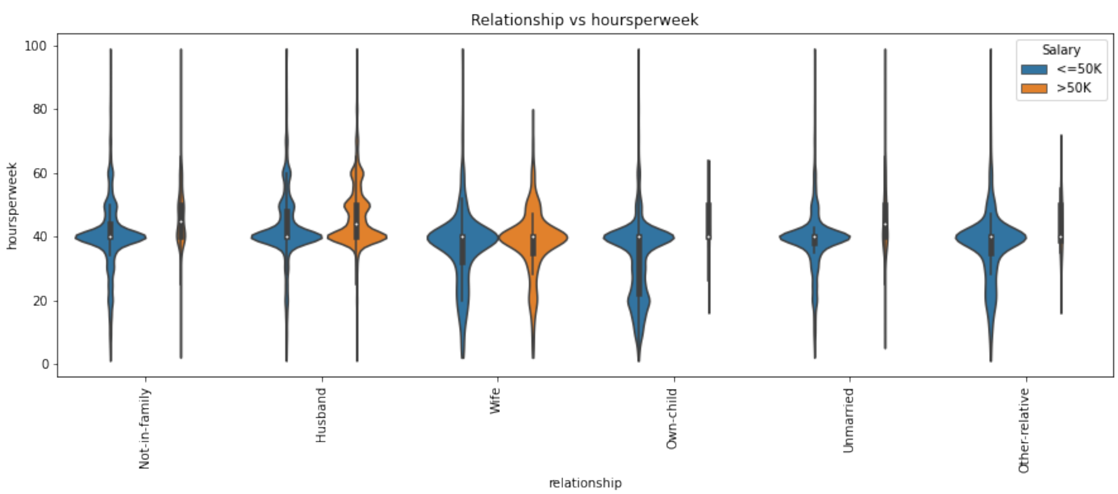
[38]:
```
plt.figure(figsize=(15,5))
sns.violinplot(x=rawData.educationno,y=rawData.hoursperweek,hue=rawData.
↪Salary,scale='count',gridsize=100,cut=0)
plt.xticks(rotation=90)
plt.title('educationno vs hoursperweek')
plt.show
```

[38]: <function matplotlib.pyplot.show(close=None, block=None)>



[39]:
```
plt.figure(figsize=(15,5))
sns.violinplot(x=rawData.relationship,y=rawData.hoursperweek,hue=rawData.
 ↪Salary,scale='count',scale_hue=True,cut=0)
plt.xticks(rotation=90)
plt.title('Relationship vs hoursperweek')
plt.show
```

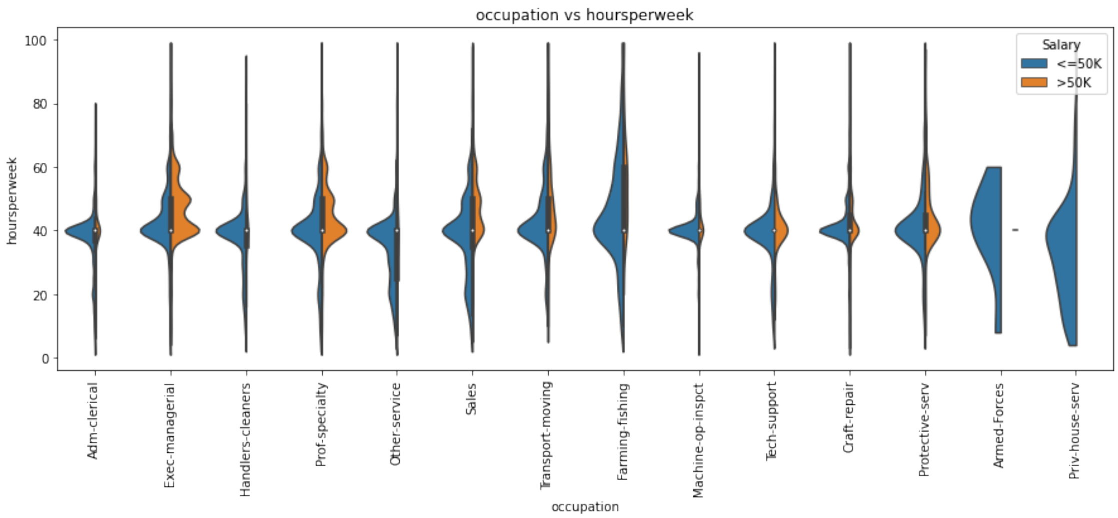
[39]: <function matplotlib.pyplot.show(close=None, block=None)>



[40]:
```
plt.figure(figsize=(15,5))
sns.violinplot(x=rawData.occupation,y=rawData.hoursperweek,hue=rawData.
 ↪Salary,scale='count',split=True,scale_hue=True,cut=0)
plt.xticks(rotation=90)
```

```
plt.title('occupation vs hoursperweek')
plt.show
```

[40]: <function matplotlib.pyplot.show(close=None, block=None)>



7 # DataPreprocessing

[41]:
```
encData = rawData.copy(deep=True)
```

Drop the reatures we don't want to use

```
matitalstatus : relationship is a better feature in relation salary than marital status
Education     : education and educatino no convey the same information. may be we will drop this
Native : native and race are more or less convey the same message hence we drop Native as it ha
```

[42]:
```
encData.shape
```

[42]: (30161, 14)

[43]:
```
encData.drop(['maritalstatus','education','native'],axis=1,inplace=True)
```

[44]:
```
encData.shape
```

[44]: (30161, 11)

7.0.1 Encoding the Y variable

```
'<=50' is coded as 0
'>50K' is coded as 1
```

[45]:
```
encData['Salary'] = encData.Salary.map({'<=50K' : 0, '>50K' : 1})
```

[46]:
```
encData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30161 entries, 0 to 30160
Data columns (total 11 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   age            30161 non-null  int64
 1   workclass      30161 non-null  object
 2   educationno    30161 non-null  int64
 3   occupation     30161 non-null  object
 4   relationship   30161 non-null  object
 5   race           30161 non-null  object
 6   sex            30161 non-null  object
 7   capitalgain    30161 non-null  int64
 8   capitalloss    30161 non-null  int64
 9   hoursperweek   30161 non-null  int64
 10  Salary         30161 non-null  int64
dtypes: int64(6), object(5)
memory usage: 2.5+ MB
```

7.1 Encloding workclass

class	Coded class
Private	Private
Self-emp-not-inc	Self-emp-not-inc
Local-gov	Gov
State-gov	Gov
Self-emp-inc	Self-emp-inc
Federal-gov	Gov
Without-pay	Without-pay

[47]:
```
encData['workclass'] = encData.workclass.map({'Private':
↪'Private','Self-emp-not-inc':'Self-emp-int-inc',
                                              'Local-gov':'Gov','State-gov':
↪'Gov','Self-emp-inc':'Self-emp-inc',
                                              'Federal-gov':'Gov','Without-pay':
↪'Without-pay'})
encData.head(2)
```

[47]:
```
   age          workclass  educationno       occupation   relationship   race  \
0   39                Gov           13     Adm-clerical  Not-in-family  White
1   50   Self-emp-int-inc           13  Exec-managerial        Husband  White
```

```
   sex  capitalgain  capitalloss  hoursperweek  Salary
0  Male         2174            0            40       0
1  Male            0            0            13       0
```

7.2 Encoding Occupation

class	class encoded
‘Adm-clerical’	Mediumpay
‘Exec-managerial’	Highpay
‘Handlers-cleaners’	Lowpay
‘Prof-specialty’	Highpay
‘Other-service’	Lowpay
‘Sales’	Mediumpay
‘Transport-moving’	Mediumpay
‘Farming-fishing’	Lowpay
‘Machine-op-inspct’	Mediumpay
‘Tech-support’	Mediumpay
‘Craft-repair’	Mediumpay
‘Protective-serv’	Mediumpay
‘Armed-Forces’	Lowpay
‘Priv-house-serv’	Lowpay

[48]:

```
encData['occupation'] = encData.occupation.map({'Adm-clerical':'Mediumpay',␣
↪'Exec-managerial':'Highpay', 'Handlers-cleaners':'Lowpay',
       'Prof-specialty':'Highpay', 'Other-service':'Lowpay', 'Sales':
↪'Mediumpay', 'Transport-moving':'Mediumpay',
       'Farming-fishing':'Lowpay', 'Machine-op-inspct':'Mediumpay',␣
↪'Tech-support':'Mediumpay',
       'Craft-repair':'Mediumpay', 'Protective-serv':'Mediumpay',␣
↪'Armed-Forces':'Lowpay',
       'Priv-house-serv':'Lowpay'})
encData.head(2)
```

[48]:

```
   age         workclass  educationno occupation   relationship   race   sex  \
0   39               Gov           13  Mediumpay  Not-in-family  White  Male
1   50  Self-emp-int-inc           13    Highpay        Husband  White  Male

   capitalgain  capitalloss  hoursperweek  Salary
0         2174            0            40       0
1            0            0            13       0
```

7.3 Encoding Relationship

class	Class Encoded
‘Not-in-family’	Other
‘Husband’	Husband
‘Wife’	Wife
‘Own-child’	Other
‘Unmarried’	Other
‘Other-relative’	Other

[49]:
```
encData['relationship'] = encData.relationship.map({'Not-in-family':'Other',␣
 ↪'Husband':'Husband', 'Wife':'Wife',
                                'Own-child':'Other', 'Unmarried':
 ↪'Other','Other-relative':'Other'})
encData.head(2)
```

[49]:
```
   age         workclass  educationno occupation relationship   race   sex  \
0   39               Gov           13  Mediumpay        Other  White  Male
1   50  Self-emp-int-inc           13    Highpay      Husband  White  Male

   capitalgain  capitalloss  hoursperweek  Salary
0         2174            0            40       0
1            0            0            13       0
```

7.4 Encoding Sex

Male = 1
Felmale = 0

[50]:
```
encData['sex'] = encData.sex.map({'Male':1,'Female':0})
encData.head(2)
```

[50]:
```
   age         workclass  educationno occupation relationship   race  sex  \
0   39               Gov           13  Mediumpay        Other  White    1
1   50  Self-emp-int-inc           13    Highpay      Husband  White    1

   capitalgain  capitalloss  hoursperweek  Salary
0         2174            0            40       0
1            0            0            13       0
```

7.5 Encoding Capitalgain

capitalgain <= 0 is retained as 0
capitalgain > 0 is coded as 1 indicating that the record has an occurance of capital gain inste

[51]:
```
encData.loc[encData['capitalgain'] > 0, 'capitalgain'] = 1
```

7.6 Encoding Capitalloss

capitalloss <= 0 is retained as 0
capitalloss > 0 is coded as 1 indicating that the record has an occurance of capital loss inste

[52]:
```
encData.loc[encData['capitalloss'] > 0, 'capitalloss'] = 1
```

[53]:
```
encData[(encData.capitalloss > 0) | (encData.capitalgain >0)]
```

[53]:
```
        age         workclass  educationno occupation relationship   race  sex  \
0        39               Gov           13  Mediumpay        Other  White    1
8        31           Private           14    Highpay        Other  White    0
9        42           Private           13    Highpay      Husband  White    1
22       43           Private            7  Mediumpay      Husband  White    1
30       45           Private           13    Highpay        Other  White    1
…     …                 …          …        …          …     …  …
30121    66               Gov            6  Mediumpay      Husband  White    1
30124    57               Gov            9  Mediumpay      Husband  White    1
30141    38           Private           13    Highpay        Other  Black    0
30148    65  Self-emp-int-inc           15    Highpay        Other  White    1
30160    52      Self-emp-inc            9    Highpay         Wife  White    0

       capitalgain  capitalloss  hoursperweek  Salary
0                1            0            40       0
8                1            0            50       1
9                1            0            40       1
22               0            1            40       0
30               0            1            40       0
…              …          …            …       …
30121            1            0            40       0
30124            1            0            40       1
30141            1            0            45       1
30148            1            0            60       0
30160            1            0            40       1

[3964 rows x 11 columns]
```

8 Applying Label encoder on Dataframe

[54]:
```
from sklearn.preprocessing import LabelEncoder
```

[55]:
```
lable = LabelEncoder()
```

[56]:
```
for i in encData.columns:
    if encData[i].dtypes == object:
        encData[i] = lable.fit_transform(encData[i])
```

[57]:
```
encData['Salary'] = encData['Salary'].astype('category') # marking Salary as a
↪Category column
```

[58]:
```
encData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30161 entries, 0 to 30160
Data columns (total 11 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   age            30161 non-null  int64
 1   workclass      30161 non-null  int32
 2   educationno    30161 non-null  int64
 3   occupation     30161 non-null  int32
 4   relationship   30161 non-null  int32
 5   race           30161 non-null  int32
 6   sex            30161 non-null  int64
 7   capitalgain    30161 non-null  int64
 8   capitalloss    30161 non-null  int64
 9   hoursperweek   30161 non-null  int64
 10  Salary         30161 non-null  category
dtypes: category(1), int32(4), int64(6)
memory usage: 1.9 MB
```

[59]:
```
encData
```

[59]:

	age	workclass	educationno	occupation	relationship	race	sex
0	39	0	13	2	1	4	1
1	50	3	13	0	0	4	1
2	38	1	9	1	1	4	1
3	53	1	7	1	0	2	1
4	28	1	13	0	2	2	0
…	…	…	…	…	…	…	…
30156	27	1	12	2	2	4	0
30157	40	1	9	2	0	4	1
30158	58	1	9	2	1	4	0
30159	22	1	9	2	1	4	1
30160	52	2	9	0	2	4	0

	capitalgain	capitalloss	hoursperweek	Salary
0	1	0	40	0
1	0	0	13	0
2	0	0	40	0
3	0	0	40	0
4	0	0	40	0
…	…	…	…	…
30156	0	0	38	0
30157	0	0	40	1

```
30158          0          0          40      0
30159          0          0          20      0
30160          1          0          40      1

[30161 rows x 11 columns]
```

9 Feature selection

We will use PPSCORE and DECISION TREE - FEATURE_IMPORTANCES to select our Features.

9.1 feature_importance_ using Decision Tree

feature importance on Full Dataset

[60]:
```python
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_val_score
```

[61]:
```python
X = encData.drop('Salary',axis=1)
y = encData.Salary
```

[62]:
```python
y
```

[62]:
```
0        0
1        0
2        0
3        0
4        0
        ..
30156    0
30157    1
30158    0
30159    0
30160    1
Name: Salary, Length: 30161, dtype: category
Categories (2, int64): [0, 1]
```

[63]:
```python
DT = DecisionTreeClassifier()
cross_val_score(DT,X,y,cv=10)
```

[63]:
```
array([0.79615512, 0.79708223, 0.78945623, 0.79111406, 0.80570292,
       0.78415119, 0.79608753, 0.80636605, 0.80736074, 0.7954244 ])
```

[64]:
```python
DT.fit(X,y)
DT.feature_importances_
```

[64]:
```
array([0.23106388, 0.06052974, 0.18515663, 0.04176161, 0.2429201 ,
       0.03052331, 0.00829095, 0.04262155, 0.01643108, 0.14070115])
```

[65]:
```
pd.DataFrame(zip(encData.drop('Salary',axis=1).columns, pd.Series(DT.
↪feature_importances_)),
             columns=['feature','score']).
↪sort_values(by='score',ascending=False)
```

[65]:

	feature	score
4	relationship	0.242920
0	age	0.231064
2	educationno	0.185157
9	hoursperweek	0.140701
1	workclass	0.060530
7	capitalgain	0.042622
3	occupation	0.041762
5	race	0.030523
8	capitalloss	0.016431
6	sex	0.008291

9.2 Selecting the Features based on decision tree

As per the input we are using only 5 columns for prediction

[66]:
```
newX = X.drop(['capitalgain','capitalloss','occupation','race','sex'],axis=1)
```

10 Splitting the data into Train and Test

```
X = Independent features
y = Dependent feature
```

[67]:
```
from sklearn.model_selection import train_test_split
```

[68]:
```
X_train,X_val,y_train,y_val = train_test_split(newX,y,test_size = .33,␣
↪shuffle=True,random_state=42)
```

[69]:
```
X_train.shape,X_val.shape,y_train.shape,y_val.shape
```

[69]: ((20207, 5), (9954, 5), (20207,), (9954,))

11 # Model Building - Naive Bayes

[70]:
```
from sklearn.naive_bayes import GaussianNB
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import␣
↪classification_report,plot_confusion_matrix,accuracy_score,confusion_matrix
```

[71]:
```
ignb = GaussianNB()
ignb.fit(X_train,y_train)
```

[71]: GaussianNB()

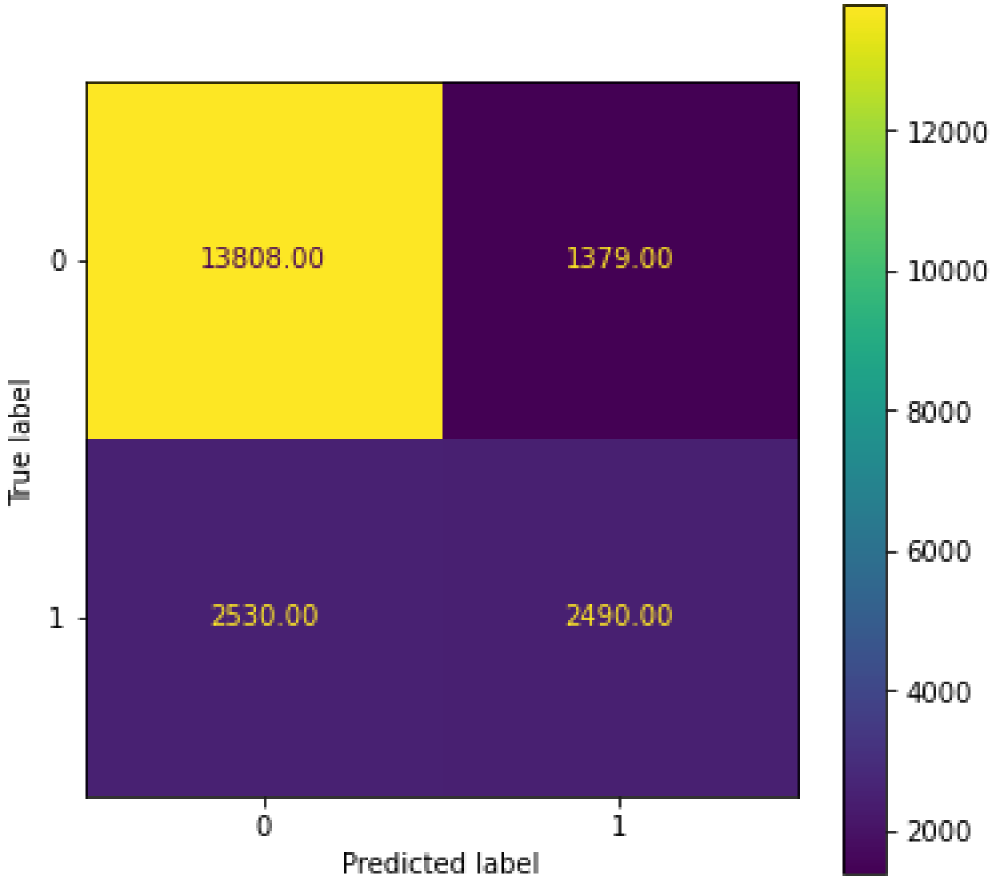
[72]:
```
pred_gnb = ignb.predict(X_train)
```

[73]:
```
ignb.score(X_train,y_train)
```

[73]: 0.8065521848864255

[74]:
```
fig,ax = plt.subplots(1,1,figsize=(6,6))
plot_confusion_matrix(ignb,
    X_train,
    y_train,
    labels=None,
    sample_weight=None,
    normalize=None,
    display_labels=None,
    include_values=True,
    xticks_rotation='horizontal',
    values_format='5.2f',
    cmap='viridis',
    ax=ax,)
```

[74]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1bde7619850>



12 Test on validation dataset

[75]:
```
y_pred = ignb.predict(X_val)
acc = accuracy_score(y_val, y_pred) * 100
print("Accuracy =", acc)
```

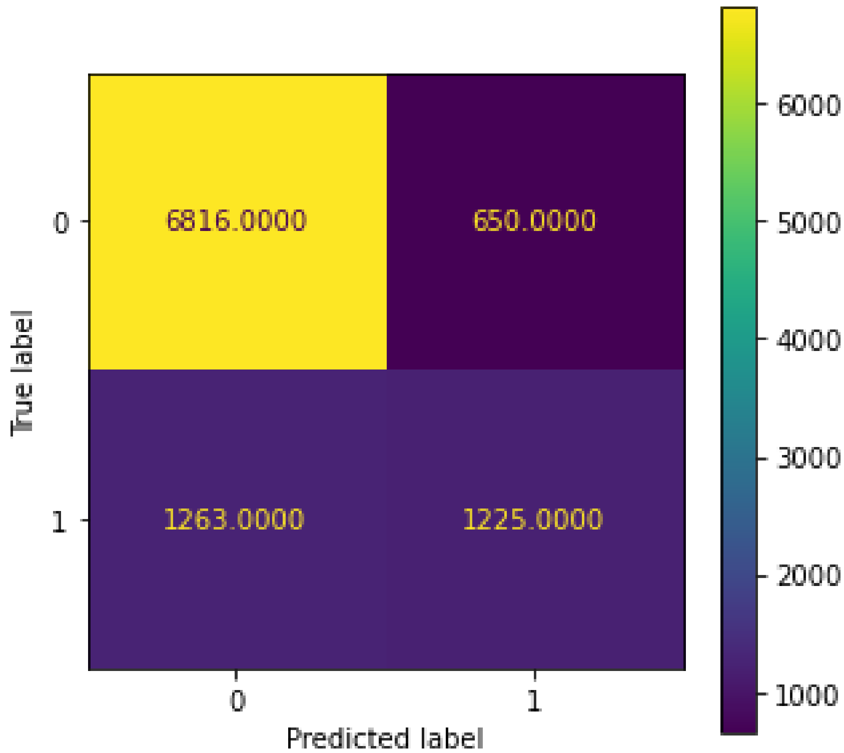
```
Accuracy = 80.78159533855737
```

[76]:
```
confusion_matrix(y_val, y_pred)
```

[76]:
```
array([[6816,  650],
       [1263, 1225]], dtype=int64)
```

[77]:
```
fig,ax = plt.subplots(1,1,figsize=(5,5))
plot_confusion_matrix(ignb,X_val,y_val,values_format = '.4f',ax=ax )
```

[77]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1bde7818e80>
```



12.1 *Conclusion - model building and validation*

WE are getting following scores for train and test

```
Crossval score - Train accuracy    = 80.65%
Validation accuracy - unknown data = 80.78%
```

As our train and test accuracy is same we can say the model is performing consistently.

13 # Testing on the Test dataset - Gaussian NB

13.1 Data processing on Test dataset

[78]:
```
Test_Data = pd.read_csv('SalaryData_Test.csv', skipinitialspace=True)
Test_Data[Test_Data.race == 'Black'].head()
```

[78]:

	age	workclass	education	educationno	maritalstatus	\
0	25	Private	11th	7	Never-married	
3	44	Private	Some-college	10	Married-civ-spouse	
17	34	Private	Some-college	10	Never-married	
22	23	Private	HS-grad	9	Separated	
25	46	State-gov	Some-college	10	Married-civ-spouse	

```
          occupation relationship   race     sex  capitalgain  capitalloss  \
0   Machine-op-inspct    Own-child  Black    Male            0            0
3   Machine-op-inspct      Husband  Black    Male         7688            0
17      Other-service    Own-child  Black  Female            0            0
22  Machine-op-inspct    Unmarried  Black    Male            0            0
25    Exec-managerial      Husband  Black    Male         7688            0

    hoursperweek         native Salary
0             40  United-States  <=50K
3             40  United-States   >50K
17            35  United-States  <=50K
22            54  United-States  <=50K
25            38  United-States   >50K
```

[79]:
```
Test_Data.drop(['maritalstatus','education','native'],axis=1,inplace=True)
```

[80]:
```
Test_Data.shape
```

[80]: (15060, 11)

13.1.1 Test Data - Encoding the Y variable

'<=50' is coded as 0
'>50K' is coded as 1

[81]:
```
Test_Data['Salary'] = Test_Data.Salary.map({'<=50K' : 0, '>50K' : 1})
Test_Data
```

[81]:
```
       age     workclass  educationno         occupation   relationship  \
0       25       Private            7  Machine-op-inspct      Own-child
1       38       Private            9    Farming-fishing        Husband
2       28     Local-gov           12    Protective-serv        Husband
3       44       Private           10  Machine-op-inspct        Husband
4       34       Private            6      Other-service  Not-in-family
…      …           …          …                …            …
15055   33       Private           13     Prof-specialty      Own-child
15056   39       Private           13     Prof-specialty  Not-in-family
15057   38       Private           13     Prof-specialty        Husband
15058   44       Private           13       Adm-clerical      Own-child
15059   35  Self-emp-inc           13    Exec-managerial        Husband

                    race   sex  capitalgain  capitalloss  hoursperweek  \
0                  Black  Male            0            0            40
1                  White  Male            0            0            50
2                  White  Male            0            0            40
3                  Black  Male         7688            0            40
4                  White  Male            0            0            30
…                    …     …          …            …            …
```

```
15055                White    Male           0             0            40
15056                White  Female           0             0            36
15057                White    Male           0             0            50
15058   Asian-Pac-Islander    Male        5455             0            40
15059                White    Male           0             0            60

       Salary
0           0
1           0
2           1
3           1
4           0
…         …
15055       0
15056       0
15057       0
15058       0
15059       1

[15060 rows x 11 columns]
```

[82]:

```
Test_Data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15060 entries, 0 to 15059
Data columns (total 11 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   age            15060 non-null  int64
 1   workclass      15060 non-null  object
 2   educationno    15060 non-null  int64
 3   occupation     15060 non-null  object
 4   relationship   15060 non-null  object
 5   race           15060 non-null  object
 6   sex            15060 non-null  object
 7   capitalgain    15060 non-null  int64
 8   capitalloss    15060 non-null  int64
 9   hoursperweek   15060 non-null  int64
 10  Salary         15060 non-null  int64
dtypes: int64(6), object(5)
memory usage: 1.3+ MB
```

13.2 Test Data - Enclcoding workclass

class	Coded class
Private	Private
Self-emp-not-inc	Self-emp-not-inc

class	Coded class
Local-gov	Gov
State-gov	Gov
Self-emp-inc	Self-emp-inc
Federal-gov	Gov
Without-pay	Without-pay

[83]:
```
Test_Data['workclass'] = Test_Data.workclass.map({'Private':
↪'Private','Self-emp-not-inc':'Self-emp-int-inc',
                                                 'Local-gov':'Gov','State-gov':
↪'Gov','Self-emp-inc':'Self-emp-inc',
                                                 'Federal-gov':'Gov','Without-pay':
↪'Without-pay'})
Test_Data.head(2)
```

[83]:
```
   age workclass  educationno         occupation relationship   race   sex  \
0   25   Private            7  Machine-op-inspct    Own-child  Black  Male
1   38   Private            9    Farming-fishing      Husband  White  Male

   capitalgain  capitalloss  hoursperweek  Salary
0            0            0            40       0
1            0            0            50       0
```

13.3 Test Data - Encoding Occupation

class	class encoded
'Adm-clerical'	Mediumpay
'Exec-managerial'	Highpay
'Handlers-cleaners'	Lowpay
'Prof-specialty'	Highpay
'Other-service'	Lowpay
'Sales'	Mediumpay
'Transport-moving'	Mediumpay
'Farming-fishing'	Lowpay
'Machine-op-inspct'	Mediumpay
'Tech-support'	Mediumpay
'Craft-repair'	Mediumpay
'Protective-serv'	Mediumpay
'Armed-Forces'	Lowpay
'Priv-house-serv'	Lowpay

[84]:
```python
Test_Data['occupation'] = Test_Data.occupation.map({'Adm-clerical':'Mediumpay',␣
↪'Exec-managerial':'Highpay', 'Handlers-cleaners':'Lowpay',
       'Prof-specialty':'Highpay', 'Other-service':'Lowpay', 'Sales':
↪'Mediumpay', 'Transport-moving':'Mediumpay',
       'Farming-fishing':'Lowpay', 'Machine-op-inspct':'Mediumpay',␣
↪'Tech-support':'Mediumpay',
       'Craft-repair':'Mediumpay', 'Protective-serv':'Mediumpay',␣
↪'Armed-Forces':'Lowpay',
       'Priv-house-serv':'Lowpay'})
Test_Data.head(2)
```

[84]:
```
   age workclass  educationno occupation relationship   race   sex  \
0   25   Private            7  Mediumpay    Own-child  Black  Male
1   38   Private            9     Lowpay      Husband  White  Male

   capitalgain  capitalloss  hoursperweek  Salary
0            0            0            40       0
1            0            0            50       0
```

13.4 Test Data - Encoding Relationship

class	Class Encoded
‘Not-in-family’	Other
‘Husband’	Husband
‘Wife’	Wife
‘Own-child’	Other
‘Unmarried’	Other
‘Other-relative’	Other

[85]:
```python
Test_Data['relationship'] = Test_Data.relationship.map({'Not-in-family':
↪'Other', 'Husband':'Husband', 'Wife':'Wife',
                                              'Own-child':'Other', 'Unmarried':
↪'Other','Other-relative':'Other'})
Test_Data.head(2)
```

[85]:
```
   age workclass  educationno occupation relationship   race   sex  \
0   25   Private            7  Mediumpay        Other  Black  Male
1   38   Private            9     Lowpay      Husband  White  Male

   capitalgain  capitalloss  hoursperweek  Salary
0            0            0            40       0
1            0            0            50       0
```

[86]:
```python
Test_Data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15060 entries, 0 to 15059
Data columns (total 11 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   age           15060 non-null  int64
```

```
 1   workclass     15060 non-null  object
 2   educationno   15060 non-null  int64
 3   occupation    15060 non-null  object
 4   relationship  15060 non-null  object
 5   race          15060 non-null  object
 6   sex           15060 non-null  object
 7   capitalgain   15060 non-null  int64
 8   capitalloss   15060 non-null  int64
 9   hoursperweek  15060 non-null  int64
 10  Salary        15060 non-null  int64
dtypes: int64(6), object(5)
memory usage: 1.3+ MB
```

13.5 Encoding Capitalgain

capitalgain <= 0 is retained as 0
capitalgain > 0 is coded as 1 indicating that the record has an occurance of capital gain inste

[87]:
```python
Test_Data.loc[Test_Data['capitalgain'] > 0, 'capitalgain'] = 1
```

13.6 Encoding Capitalloss

capitalloss <= 0 is retained as 0
capitalloss > 0 is coded as 1 indicating that the record has an occurance of capital loss inste

[88]:
```python
Test_Data.loc[Test_Data['capitalloss'] > 0, 'capitalloss'] = 1
```

[89]:
```python
Test_Data[(Test_Data.capitalloss > 0) | (Test_Data.capitalgain >0)]
```

[89]:
```
       age         workclass  educationno occupation relationship  \
3       44           Private           10  Mediumpay      Husband
5       63  Self-emp-int-inc           15    Highpay      Husband
8       65           Private            9  Mediumpay      Husband
11      48           Private            9  Mediumpay      Husband
20      45  Self-emp-int-inc            9  Mediumpay      Husband
…     …                 …         …          …          …
15033   60           Private           11    Highpay      Husband
15034   39           Private           13  Mediumpay        Other
15036   43               Gov           14    Highpay      Husband
15042   40           Private           15    Highpay      Husband
15058   44           Private           13  Mediumpay        Other

                     race    sex  capitalgain  capitalloss  hoursperweek  \
3                   Black   Male            1            0            40
5                   White   Male            1            0            32
8                   White   Male            1            0            40
11                  White   Male            1            0            48
20                  White   Male            1            0            90
```

```
...                    ...     ...          ...          ...           ...
15033                White    Male            1            0             40
15034                White  Female            0            1             40
15036                White    Male            0            1             50
15042                White    Male            1            0             55
15058   Asian-Pac-Islander    Male            1            0             40

       Salary
3           1
5           1
8           1
11          1
20          1
...       ...
15033       1
15034       0
15036       1
15042       1
15058       0

[1965 rows x 11 columns]
```

[90]:
```
Test_Data.shape
```

[90]:
```
(15060, 11)
```

[91]:
```
Test_Data.hoursperweek.value_counts()
```

[91]:
```
40    7107
50    1376
45     849
60     680
35     592
      ...
73       1
76       1
79       1
89       1
69       1
Name: hoursperweek, Length: 89, dtype: int64
```

14 Test Data - Applying Label encoder on Dataframe

[92]:
```
encTData = Test_Data.copy(deep=True)
# encTData = pd.get_dummies(Test_Data,drop_first=True)
for i in Test_Data.columns:
    if Test_Data[i].dtypes == object:
```

```
        encTData[i] = lable.fit_transform(encTData[i])
```

[93]:
```
encTData['Salary'] = encTData.Salary.astype('category')
```

[94]:
```
encTData.head(3)
```

[94]:
```
   age  workclass  educationno  occupation  relationship  race  sex  \
0   25          1            7           2             1     2    1
1   38          1            9           1             0     4    1
2   28          0           12           2             0     4    1

   capitalgain  capitalloss  hoursperweek Salary
0            0            0            40      0
1            0            0            50      0
2            0            0            40      1
```

[95]:
```
encTData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15060 entries, 0 to 15059
Data columns (total 11 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   age           15060 non-null  int64
 1   workclass     15060 non-null  int32
 2   educationno   15060 non-null  int64
 3   occupation    15060 non-null  int32
 4   relationship  15060 non-null  int32
 5   race          15060 non-null  int32
 6   sex           15060 non-null  int32
 7   capitalgain   15060 non-null  int64
 8   capitalloss   15060 non-null  int64
 9   hoursperweek  15060 non-null  int64
 10  Salary        15060 non-null  category
dtypes: category(1), int32(5), int64(5)
memory usage: 897.4 KB
```

[96]:
```
encTData.Salary.value_counts()
```

[96]:
```
0    11360
1     3700
Name: Salary, dtype: int64
```

[ ]:
```

```

[ ]:
```

```

[97]:
```
# Test_Data.
↪drop(['capitalgain','capitalloss','sex','race','occupation'],axis=1,inplace=True)
```

[98]:
```
Test_Data.shape
```

[98]:
```
(15060, 11)
```

15 Test Data - Splitting the Data in X,y

```
x = Independent features and
y = Dependent feature
```

[99]:
```
y_test = encTData.Salary.values
y_test
```

[99]:
```
[0, 0, 1, 1, 0, …, 0, 0, 0, 0, 1]
Length: 15060
Categories (2, int64): [0, 1]
```

[100]:
```
X_test = encTData.
↪drop(['Salary','capitalgain','capitalloss','sex','race','occupation'],axis=1)
print(type(X_test))
X_test.head()
```

```
<class 'pandas.core.frame.DataFrame'>
```

[100]:

	age	workclass	educationno	relationship	hoursperweek
0	25	1	7	1	40
1	38	1	9	0	50
2	28	0	12	0	40
3	44	1	10	0	40
4	34	1	6	1	30

15.1 Predicting on test dataset

[101]:
```
y_pred = ignb.predict(X_test)
acc = accuracy_score(y_test, y_pred) * 100
print("Accuracy =", acc)
```

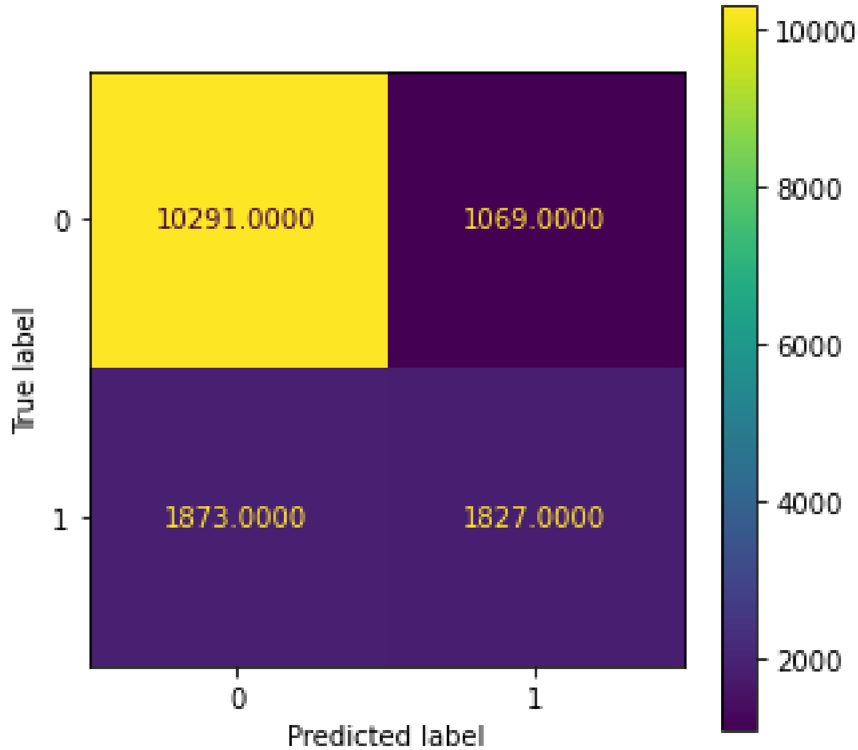
```
Accuracy = 80.46480743691899
```

[102]:
```
confusion_matrix(y_test, y_pred)
```

[102]:
```
array([[10291,  1069],
       [ 1873,  1827]], dtype=int64)
```

[103]:
```
fig,ax = plt.subplots(1,1,figsize=(5,5))
plot_confusion_matrix(ignb,X_test,y_test,values_format = '.4f',ax=ax )
```

[103]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1bde734aa30>



16 CONCLUSION - Gaussin Naive Bayes algo

THE MODEL ACCURACY ON VALIDATION AND TEST SETS ARE ALMOST EQUAL. THE VALIDATION ACCURACY STANDS AT 80.78% AND THE TEST ACCUARCY STANDS AT 80.46%, WHICH MEANS THAT THE MODEL IS CONSISTENTLY PERFORMING ON THE UNKNOWN DATASETS. HENCE, WE CAN PRESENT IT THE THE CLIENTS.

17 # MODEL BUILDING - Categorical Naive Bayes algorithm

Categorical NB is an alogorithm from sklearn library which is more suited to the datasets where more or all features are categorical in nature. Hence we shall try this on our data set. the two numerical columns, namely `'euducationno'` and `'hoursperweek'` are also descrete and can be treated as categorical columns.

[104]:
```
from sklearn.naive_bayes import CategoricalNB
```

[105]:
```
clf = CategoricalNB(alpha=.001)
```

[106]:
```
X = encData.drop('Salary',axis=1)
y = encData.Salary
```

[107]:
```
clf.fit(X,y)
```

[107]: CategoricalNB(alpha=0.001)

[108]:
```
clf.score(X,y)
```

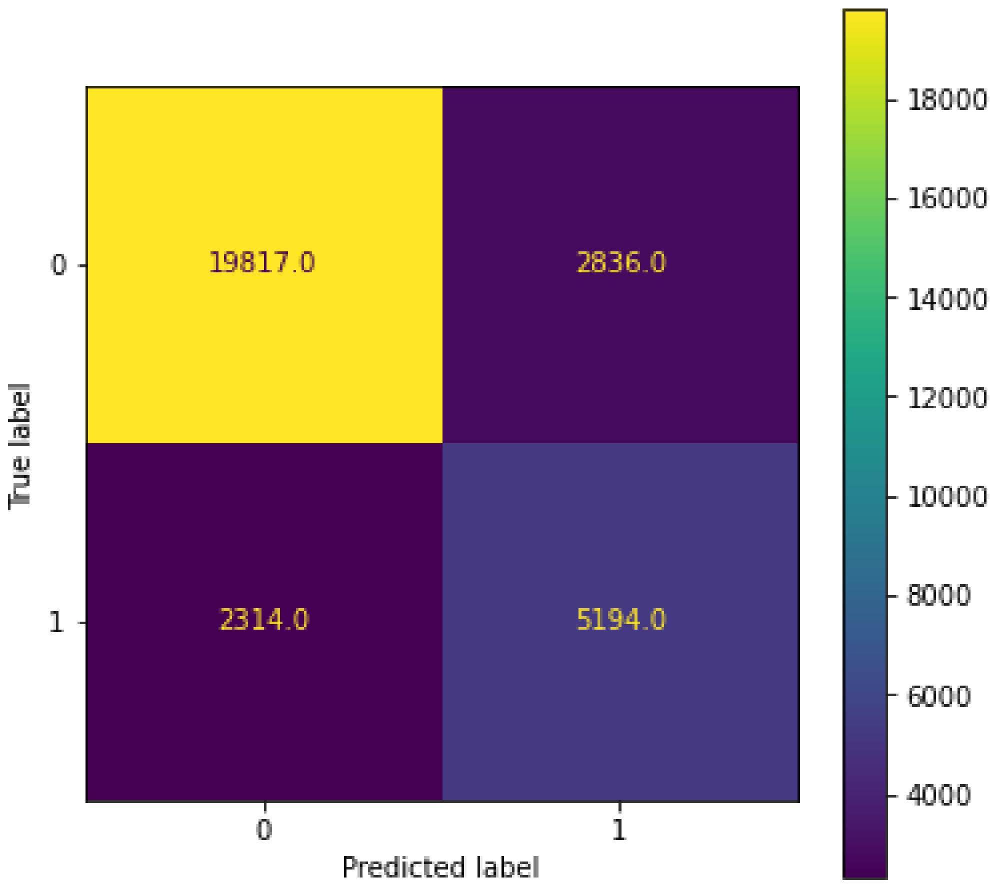
[108]: 0.8292496933125559

[109]:
```
confusion_matrix(y,clf.predict(X))
```

[109]:
```
array([[19817,  2836],
       [ 2314,  5194]], dtype=int64)
```

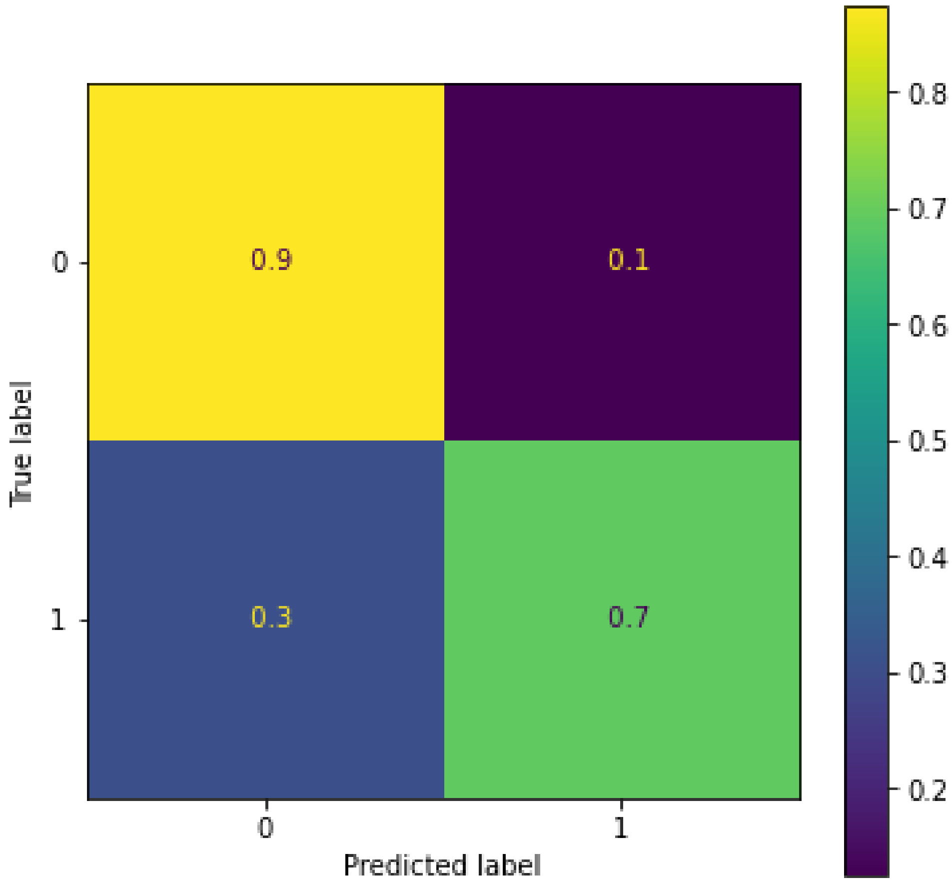
[110]:
```
fig,ax = plt.subplots(1,1,figsize=(6,6))
plot_confusion_matrix(clf,X,y,values_format='5.1f',ax=ax)
```

[110]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1bde745fd00>



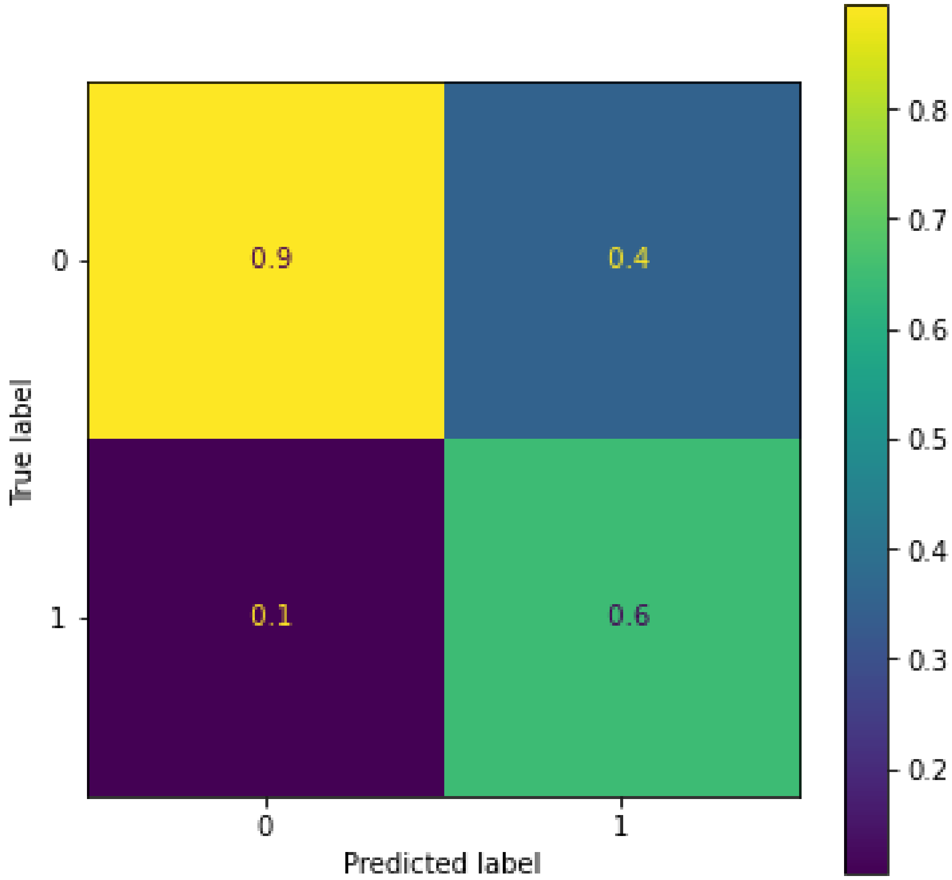
[111]:
```
fig,ax = plt.subplots(1,1,figsize=(6,6))
plot_confusion_matrix(clf,X,y,values_format='5.1f',ax=ax,normalize='true')
```

[111]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1bde742f490>



[112]:
```
fig,ax = plt.subplots(1,1,figsize=(6,6))
plot_confusion_matrix(clf,X,y,values_format='5.1f',ax=ax,normalize='pred')
```

[112]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1bde7e9ae20>



18 # Applying on the Test Data - Categorical NB

[113]:
```
encTData = Test_Data.copy(deep=True)
# encTData = pd.get_dummies(Test_Data,drop_first=True)
for i in Test_Data.columns:
    if Test_Data[i].dtypes == object:
        encTData[i] = lable.fit_transform(encTData[i])
```

[114]:
```
encTData['Salary'] = encTData.Salary.astype('category')
```

[115]:
```
encTData.head(3)
```

[115]:
```
   age  workclass  educationno  occupation  relationship  race  sex  \
0   25          1            7           2             1     2    1
1   38          1            9           1             0     4    1
2   28          0           12           2             0     4    1

   capitalgain  capitalloss  hoursperweek Salary
```

```
0              0              0             40       0
1              0              0             50       0
2              0              0             40       1
```

[116]:
```
Xt = encTData.drop('Salary',axis=1)
Xt.head()
```

[116]:
```
   age  workclass  educationno  occupation  relationship  race  sex  \
0   25          1            7           2             1     2    1
1   38          1            9           1             0     4    1
2   28          0           12           2             0     4    1
3   44          1           10           2             0     2    1
4   34          1            6           1             1     4    1

   capitalgain  capitalloss  hoursperweek
0            0            0            40
1            0            0            50
2            0            0            40
3            1            0            40
4            0            0            30
```

[117]:
```
yt = encTData.Salary
yt.head()
```

[117]:
```
0    0
1    0
2    1
3    1
4    0
Name: Salary, dtype: category
Categories (2, int64): [0, 1]
```

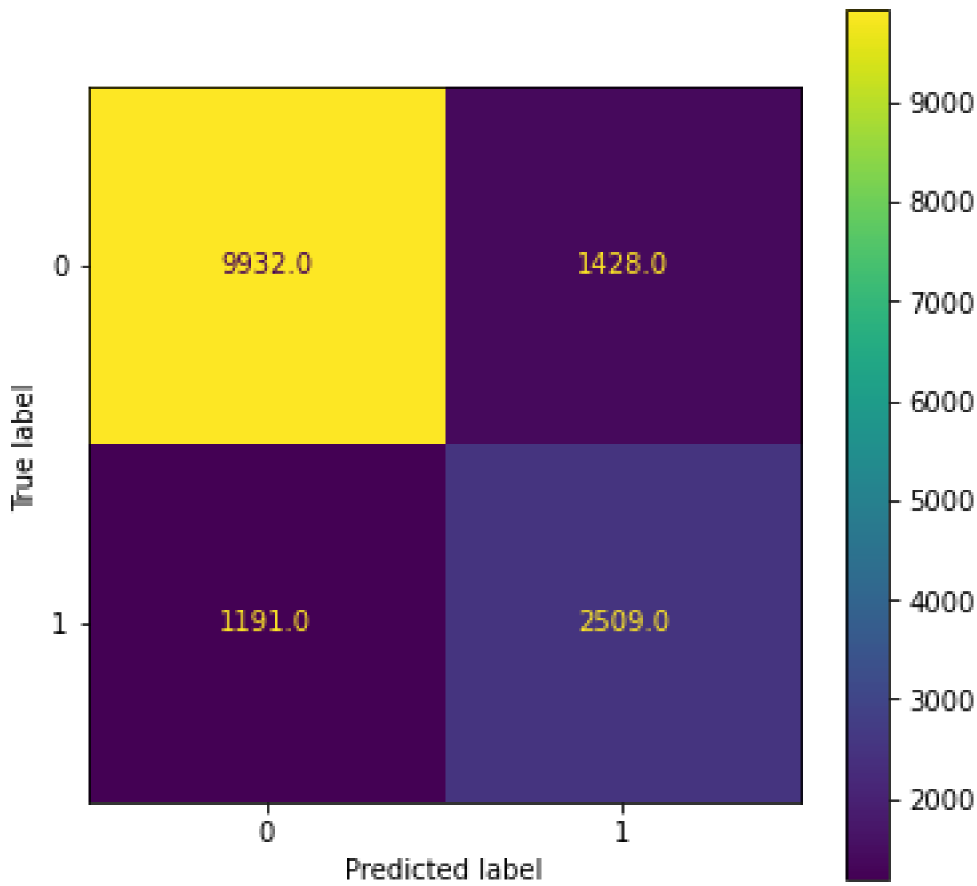
[118]:
```
clf.score(Xt,yt)
```

[118]:
```
0.8260956175298805
```

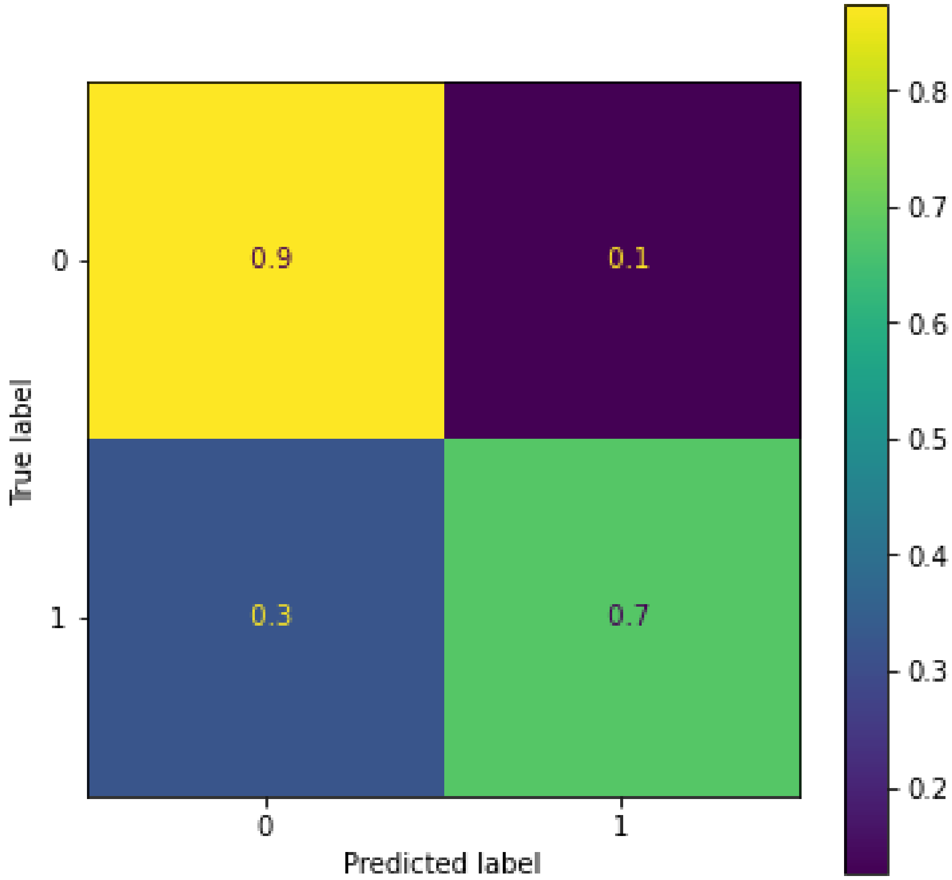
[119]:
```
confusion_matrix(yt,clf.predict(Xt))
```

[119]:
```
array([[9932, 1428],
       [1191, 2509]], dtype=int64)
```

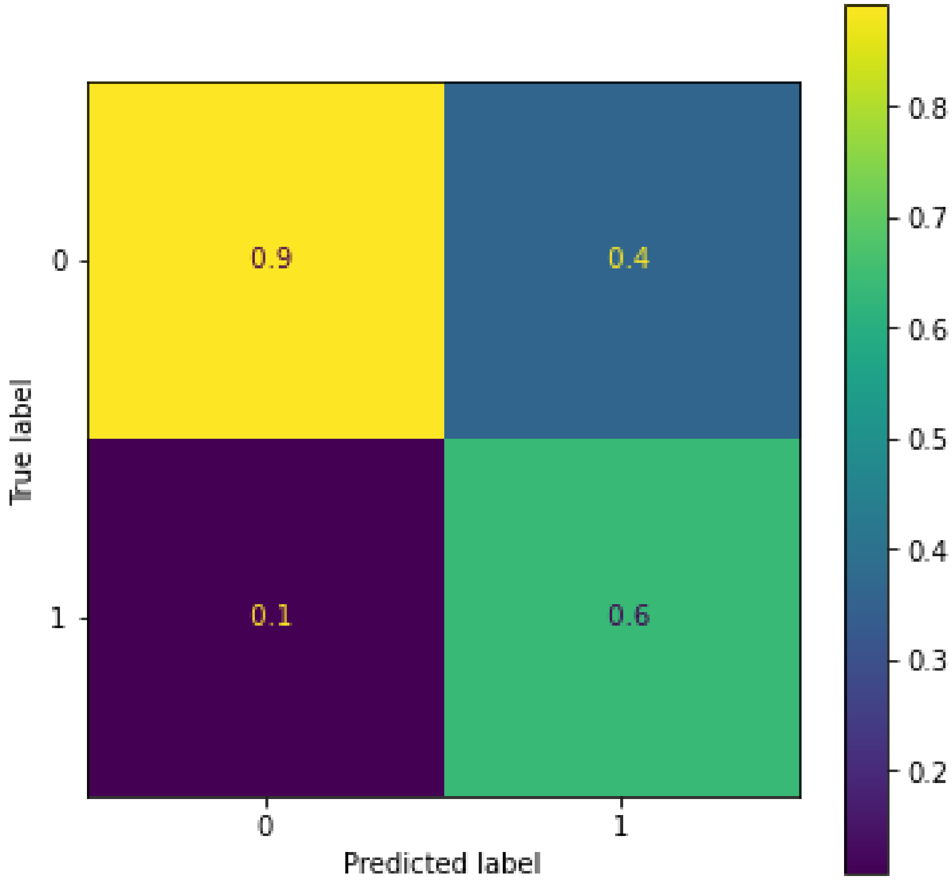
[120]:
```
fig,ax = plt.subplots(1,1,figsize=(6,6))
plot_confusion_matrix(clf,Xt,yt,values_format='5.1f',ax=ax)
plt.show()
```



[121]:
```
fig,ax = plt.subplots(1,1,figsize=(6,6))
plot_confusion_matrix(clf,Xt,yt,values_format='5.1f',ax=ax,normalize='true')
plt.show()
```



[122]:
```
fig,ax = plt.subplots(1,1,figsize=(6,6))
plot_confusion_matrix(clf,Xt,yt,values_format='5.1f',ax=ax,normalize='pred')
plt.show()
```



19 CONCLUSION - Categorical Naive Bayes algorithm

We can clearly see that overall Test accuracy has improved from 80.46% (Gaussian Naive Bayes) to 82.60% (CategoricalNB).

The Categorical NB is better suited for the dataset where most of the data is categorical in natures. Internally it trains to find relationship for each feature-class in X(predictors) with each class in Y(predicted).

[ ]: