In [27]:

```
import pandas as pd
import numpy as np

import seaborn as sns
from matplotlib import pyplot as plt
from sklearn.metrics import plot_confusion_matrix,classification_report
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.naive_bayes import MultinomialNB as MB
from sklearn.naive_bayes import GaussianNB as GB
```

Import new dataset

In [2]:

```
data_train = pd.read_csv("SalaryData_Train.csv")
data_test = pd.read_csv("SalaryData_Test.csv")
data_train.head()
```

Out[2]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	s
0	39	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Ma
1	50	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Ma
2	38	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Ma
3	53	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Ma
4	28	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Fema

In [3]:

```
data_train.info() #no null values
```

```
<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
```

In [4]:

```
data_train.describe() #capital gain and capital loss are not good predictors
```

Out[4]:

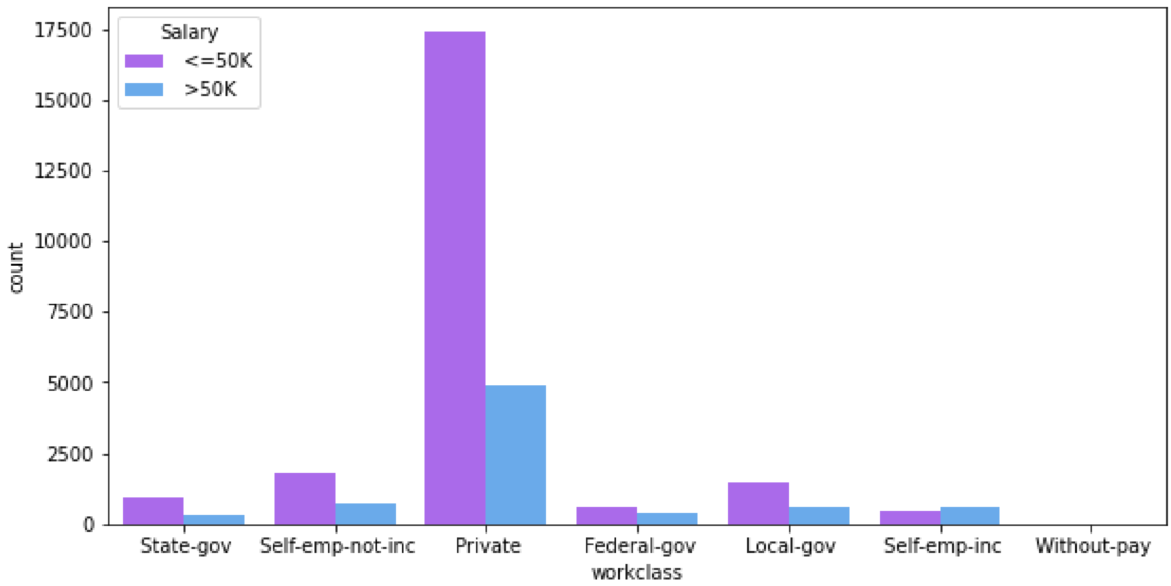
	age	educationno	capitalgain	capitalloss	hoursperweek
count	30161.000000	30161.000000	30161.000000	30161.000000	30161.000000
mean	38.438115	10.121316	1092.044064	88.302311	40.931269
std	13.134830	2.550037	7406.466611	404.121321	11.980182
min	17.000000	1.000000	0.000000	0.000000	1.000000
25%	28.000000	9.000000	0.000000	0.000000	40.000000
50%	37.000000	10.000000	0.000000	0.000000	40.000000
75%	47.000000	13.000000	0.000000	0.000000	45.000000
max	90.000000	16.000000	99999.000000	4356.000000	99.000000

In [5]:

```python
dims = (10,5)
fig, ax = plt.subplots(figsize=dims)
sns.countplot(ax = ax, data=data_train,x='workclass',hue='Salary',palette='cool_r')
```

Out[5]:

<AxesSubplot:xlabel='workclass', ylabel='count'>

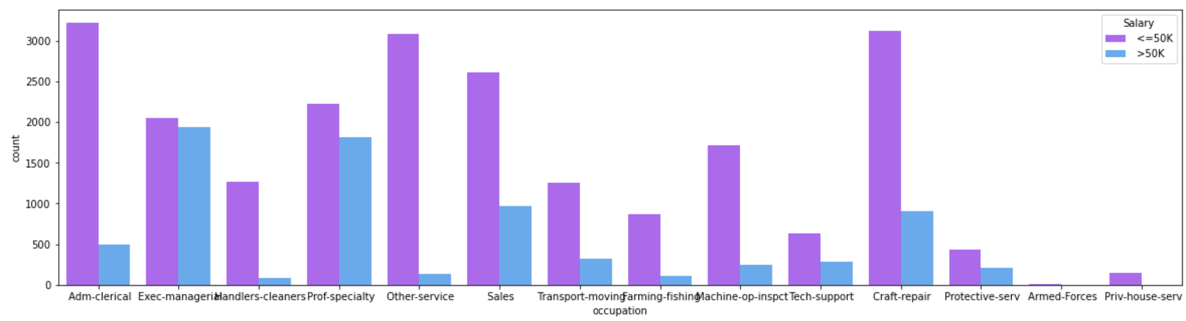


In [6]:

```python
dims = (20,5)
fig, ax = plt.subplots(figsize=dims)
sns.countplot(data=data_train,x='occupation',hue='Salary',palette='cool_r')
```

Out[6]:

<AxesSubplot:xlabel='occupation', ylabel='count'>



In [7]:

```
data_train.Salary.value_counts() #Data is highly biased
```

Out[7]:

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

In [8]:

```
data_test.Salary.value_counts() #Data is highly biased
```

Out[8]:

```
 <=50K    11360
 >50K      3700
Name: Salary, dtype: int64
```

In [9]:

```
data_train.occupation.value_counts()
```

Out[9]:

```
 Prof-specialty       4038
 Craft-repair         4030
 Exec-managerial      3992
 Adm-clerical         3721
 Sales                3584
 Other-service        3212
 Machine-op-inspct    1965
 Transport-moving     1572
 Handlers-cleaners    1350
 Farming-fishing       989
 Tech-support          912
 Protective-serv       644
 Priv-house-serv       143
 Armed-Forces            9
Name: occupation, dtype: int64
```

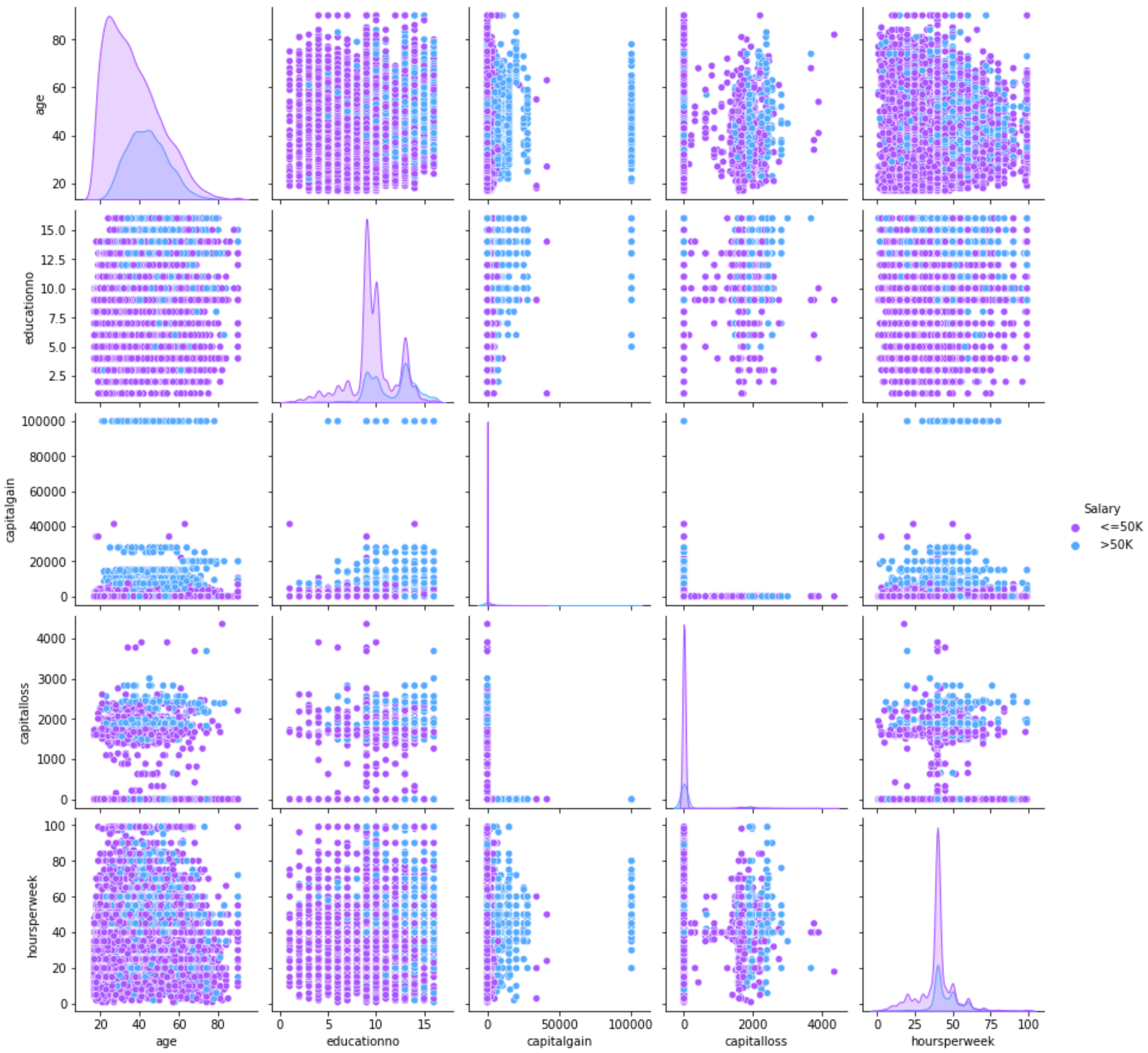
Visualisation EDA

In [10]:

```
sns.pairplot(data_train,hue='Salary',palette='cool_r')
```

Out[10]:

```
<seaborn.axisgrid.PairGrid at 0x1886941e6d0>
```



Feature Engineering

All the features in the dataset are relevant and can be used for model training. There a number of categorical values onto which label encoding can be performed. capital gain and capital loss add lots of variability in the data and hence removing them would be a good move.

In [13]:

```
labels = ['workclass', 'education', 'maritalstatus', 'occupation', 'relationship', 'race',
dftrain = data_train.copy()
dftest = data_test.copy()
label_encoder = preprocessing.LabelEncoder()
for x in labels:
    dftrain[x] = label_encoder.fit_transform(dftrain[x])
    dftest[x] = label_encoder.fit_transform(dftest[x])
dftrain.head()
```

Out[13]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	sex
0	39	5	9	13	4	0	1	4	1
1	50	4	9	13	2	3	0	4	1
2	38	2	11	9	0	5	1	4	1
3	53	2	1	7	2	5	0	2	1
4	28	2	9	13	2	9	5	2	0

Train test split

we dont need to split since we have a seperate data set on which testing can be done

In [23]:

```
X_train = dftrain.iloc[:,:-1]
y_train = dftrain['Salary']
X_test = dftest.iloc[:,:-1]
y_test = dftest['Salary']
```

Naive Bayes Classifier

Default Parameters - MultinomialNB

In [25]:

```
model_mb = MB()
model_mb.fit(X_train,y_train)
```

Out[25]:

```
▾ MultinomialNB
MultinomialNB()
```

In [26]:

```
model_gb = GB()
model_gb.fit(X_train,y_train)
```

Out[26]:

```
▾ GaussianNB
GaussianNB()
```

Evaluation

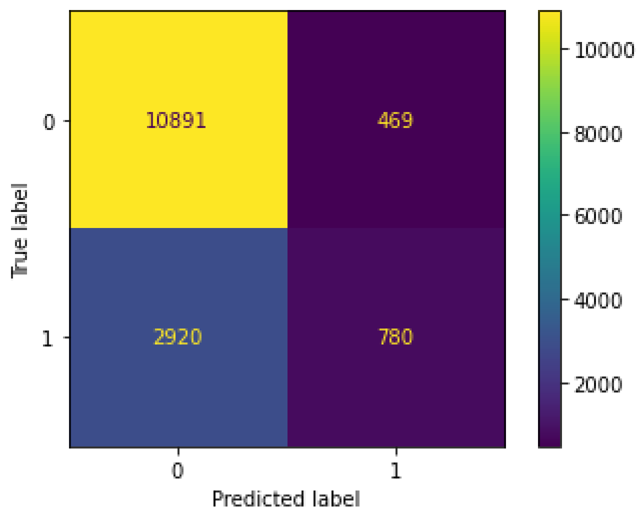
In [28]:

```
def report(model):
    preds = model.predict(X_test)
    print(classification_report(y_test,preds))
    plot_confusion_matrix(model,X_test,y_test)
#MultinomialNB Evaluation
print('MultinomialNB')
report(model_mb) #model has high inbuilt bias
```

```
MultinomialNB
              precision    recall  f1-score   support

           0       0.79      0.96      0.87     11360
           1       0.62      0.21      0.32      3700

    accuracy                           0.77     15060
   macro avg       0.71      0.58      0.59     15060
weighted avg       0.75      0.77      0.73     15060
```



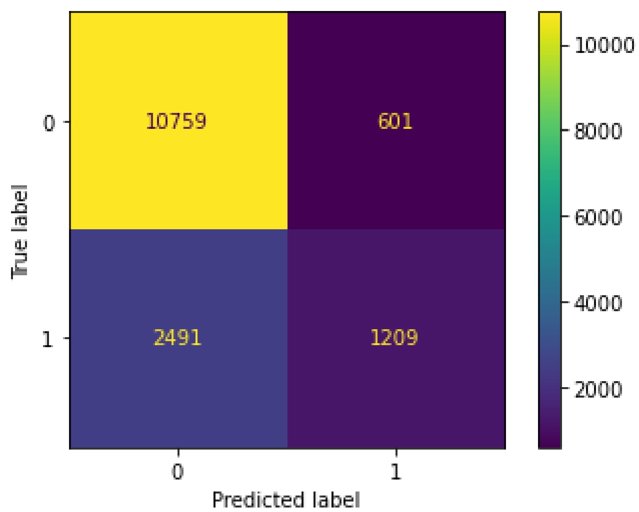
In [29]:

```
#GaussianNB Evaluation
print('GaussianNB')
report(model_gb) #model has high inbuilt bias but better results as compared to multinomial
```

```
GaussianNB
              precision    recall  f1-score   support

           0       0.81      0.95      0.87     11360
           1       0.67      0.33      0.44      3700

    accuracy                           0.79     15060
   macro avg       0.74      0.64      0.66     15060
weighted avg       0.78      0.79      0.77     15060
```



K-Fold validation

In [30]:

```
kfold = KFold(n_splits=10, random_state=100, shuffle=True)
results = cross_val_score(model_mb, X_train, y_train, cv=kfold)
print(results.mean())
```

```
0.7729185807392064
```

In [31]:

```
kfold = KFold(n_splits=10, random_state=100, shuffle=True)
results = cross_val_score(model_gb, X_train, y_train, cv=kfold)
print(results.mean())
```

```
0.7953978735881289
```

Bias Removal from training dataset

In [33]:

```
from imblearn.combine import SMOTETomek
from collections import Counter

#SMOTEK TECHNIQUE

#Define training dataset
X_train2 = dftrain.iloc[:,:-1]
y_train2 = dftrain['Salary']

#Count before
print(Counter(y_train2))

smt = SMOTETomek(sampling_strategy = 'auto')
X_train3, y_train3 = smt.fit_resample(X_train2, y_train2 )

#Count after
print(Counter(y_train3))
```

```
Counter({0: 22653, 1: 7508})
Counter({0: 22228, 1: 22228})
```

Building Final model

We will go for the gaussian model

In [34]:

```
model_fnl = GB()
model_fnl.fit(X_train3,y_train3)
```

Out[34]:

```
▾ GaussianNB
GaussianNB()
```

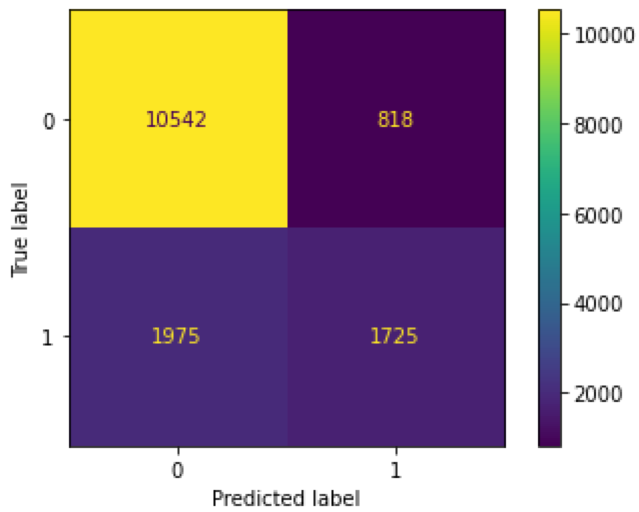
In [35]:

```
print('GaussianNB')
report(model_fnl) #Model performs much better after removing Bias from taining model.
```

```
GaussianNB
              precision    recall  f1-score   support

           0       0.84      0.93      0.88     11360
           1       0.68      0.47      0.55      3700

    accuracy                           0.81     15060
   macro avg       0.76      0.70      0.72     15060
weighted avg       0.80      0.81      0.80     15060
```



In [36]:

```
model_fnl.predict_proba(X_test)
```

Out[36]:

```
array([[9.99997686e-01, 2.31387714e-06],
       [7.03402085e-01, 2.96597915e-01],
       [8.32365821e-01, 1.67634179e-01],
       ...,
       [3.97512482e-01, 6.02487518e-01],
       [5.91029580e-05, 9.99940897e-01],
       [4.57356798e-01, 5.42643202e-01]])
```

Conclusion

We had tried out naive bayes classifier for our dataset. Both gaussian and multinomial methodologies were tried out where the former seemed a better option. Initial results were very poor as the input training dataset involved a lot of built-in bias. The testing dataset was also highly biased. The built in bias of the training model was removed using the Smotek technique. The final model had a descent accuracy which could be further improved if tested on an unbiased dataset

In [ ]:

```

```