In [2]:

```
# Importig Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.preprocessing import StandardScaler

from sklearn import svm
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report


from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.model_selection import train_test_split, cross_val_score

# Loading data
train_data = pd.read_csv('SalaryData_Train(1).csv')
test_data = pd.read_csv('SalaryData_Test(1).csv')
```

In [3]:

```
#EDA & Data Preprocessing
train_data.shape
```

Out[3]:

```
(30161, 14)
```

In [4]:

```
test_data.shape
```

Out[4]:

```
(15060, 14)
```

In [5]:

```
train_data.head()
```

Out[5]:

	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 [6]:

```
test_data.head()
```

Out[6]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	sex
0	25	Private	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male
1	38	Private	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male
2	28	Local-gov	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male
3	44	Private	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male
4	34	Private	10th	6	Never-married	Other-service	Not-in-family	White	Male

In [7]:

```
# Checking for null values
train_data.isna().sum()
```

Out[7]:

```
age              0
workclass        0
education        0
educationno      0
maritalstatus    0
occupation       0
relationship     0
race             0
sex              0
capitalgain      0
capitalloss      0
hoursperweek     0
native           0
Salary           0
dtype: int64
```

In [8]:

```
test_data.isna().sum()
```

Out[8]:

```
age              0
workclass        0
education        0
educationno      0
maritalstatus    0
occupation       0
relationship     0
race             0
sex              0
capitalgain      0
capitalloss      0
hoursperweek     0
native           0
Salary           0
dtype: int64
```

In [9]:

```
train_data.dtypes
```

Out[9]:

```
age               int64
workclass        object
education        object
educationno       int64
maritalstatus    object
occupation       object
relationship     object
race             object
sex              object
capitalgain       int64
capitalloss       int64
hoursperweek      int64
native           object
Salary           object
dtype: object
```

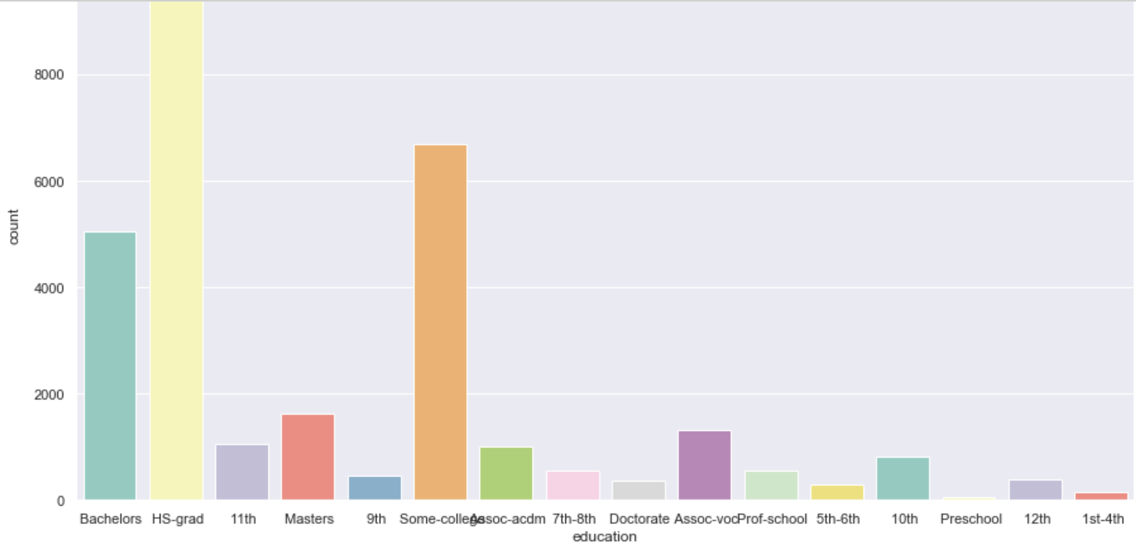
In [10]:

```
# frequency for categorical fields
category_col =['workclass', 'education','maritalstatus', 'occupation', 'relationship', 'rac
for c in category_col:
    print (c)
    print (train_data[c].value_counts())
    print('\n')
```

```
 1st-4th          151
 Preschool         45
Name: education, dtype: int64



maritalstatus
 Married-civ-spouse       14065
 Never-married             9725
 Divorced                  4214
 Separated                  939
 Widowed                    827
 Married-spouse-absent      370
 Married-AF-spouse           21
Name: maritalstatus, dtype: int64



occupation
 Prof-specialty       4038
 Craft-repair         4030
 Exec-managerial      3992
```

In [11]:

```
# countplot for all categorical columns
import seaborn as sns
sns.set(rc={'figure.figsize':(15,8)})
cat_col = ['workclass', 'education','maritalstatus', 'occupation', 'relationship', 'race',
for col in cat_col:
    plt.figure() #this creates a new figure on which your plot will appear
    sns.countplot(x = col, data = train_data, palette = 'Set3');
```



In [12]:

```
# printing unique values from each categoricla columns

print('workclass',train_data.workclass.unique())
print('education',train_data.education.unique())
print('maritalstatus',train_data['maritalstatus'].unique())
print('occupation',train_data.occupation.unique())
print('relationship',train_data.relationship.unique())
print('race',train_data.race.unique())
print('sex',train_data.sex.unique())
print('native',train_data['native'].unique())
print('Salary',train_data.Salary.unique())
```

```
workclass [' State-gov' ' Self-emp-not-inc' ' Private' ' Federal-gov' ' Loca
l-gov'
 ' Self-emp-inc' ' Without-pay']
education [' Bachelors' ' HS-grad' ' 11th' ' Masters' ' 9th' ' Some-college'
 ' Assoc-acdm' ' 7th-8th' ' Doctorate' ' Assoc-voc' ' Prof-school'
 ' 5th-6th' ' 10th' ' Preschool' ' 12th' ' 1st-4th']
maritalstatus [' Never-married' ' Married-civ-spouse' ' Divorced'
 ' Married-spouse-absent' ' Separated' ' Married-AF-spouse' ' Widowed']
occupation [' Adm-clerical' ' Exec-managerial' ' Handlers-cleaners' ' Prof-s
pecialty'
 ' Other-service' ' Sales' ' Transport-moving' ' Farming-fishing'
 ' Machine-op-inspct' ' Tech-support' ' Craft-repair' ' Protective-serv'
 ' Armed-Forces' ' Priv-house-serv']
relationship [' Not-in-family' ' Husband' ' Wife' ' Own-child' ' Unmarried'
 ' Other-relative']
race [' White' ' Black' ' Asian-Pac-Islander' ' Amer-Indian-Eskimo' ' Othe
r']
sex [' Male' ' Female']
native [' United-States' ' Cuba' ' Jamaica' ' India' ' Mexico' ' Puerto-Ric
o'
 ' Honduras' ' England' ' Canada' ' Germany' ' Iran' ' Philippines'
 ' Poland' ' Columbia' ' Cambodia' ' Thailand' ' Ecuador' ' Laos'
 ' Taiwan' ' Haiti' ' Portugal' ' Dominican-Republic' ' El-Salvador'
 ' France' ' Guatemala' ' Italy' ' China' ' South' ' Japan' ' Yugoslavia'
 ' Peru' ' Outlying-US(Guam-USVI-etc)' ' Scotland' ' Trinadad&Tobago'
 ' Greece' ' Nicaragua' ' Vietnam' ' Hong' ' Ireland' ' Hungary']
Salary [' <=50K' ' >50K']
```

In [13]:

```
train_data[['Salary', 'age']].groupby(['Salary'], as_index=False).mean().sort_values(by='ag
```

Out[13]:

	Salary	age
1	>50K	43.959110
0	<=50K	36.608264

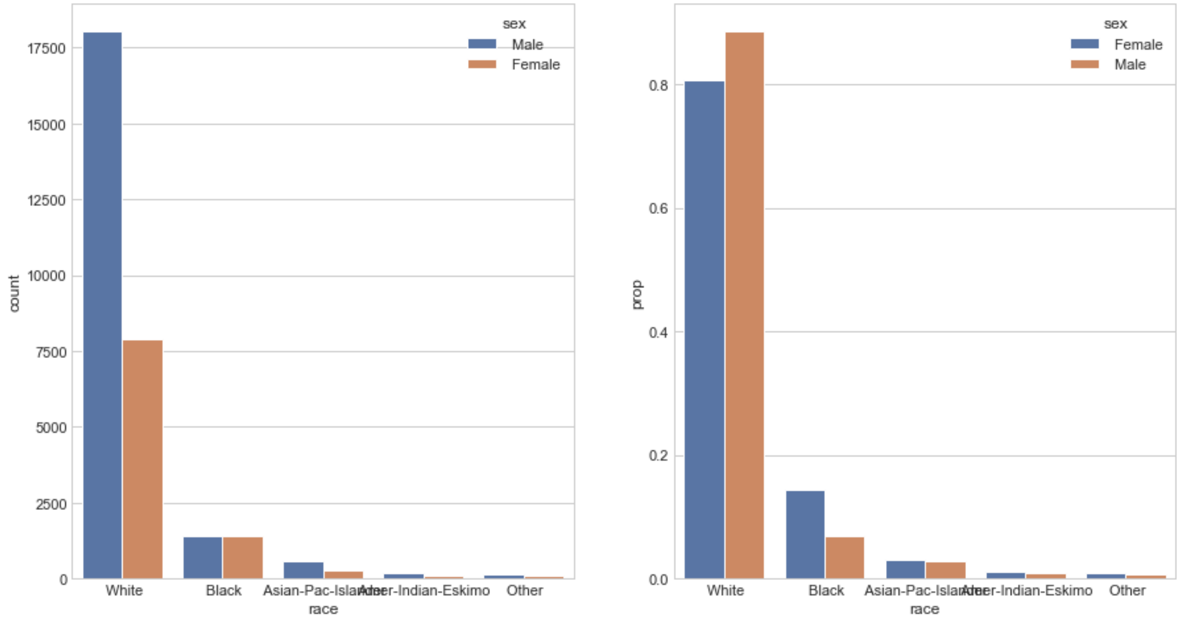
In [14]:

```
plt.style.use('seaborn-whitegrid')
x, y, hue = "race", "prop", "sex"
#hue_order = ["Male", "Female"]
plt.figure(figsize=(20,5))
f, axes = plt.subplots(1, 2)
sns.countplot(x=x, hue=hue, data=train_data, ax=axes[0])

prop_df = (train_data[x]
           .groupby(train_data[hue])
           .value_counts(normalize=True)
           .rename(y)
           .reset_index())

sns.barplot(x=x, y=y, hue=hue, data=prop_df, ax=axes[1])
```

Out[14]:

```
<AxesSubplot:xlabel='race', ylabel='prop'>
```

```
<Figure size 1440x360 with 0 Axes>
```



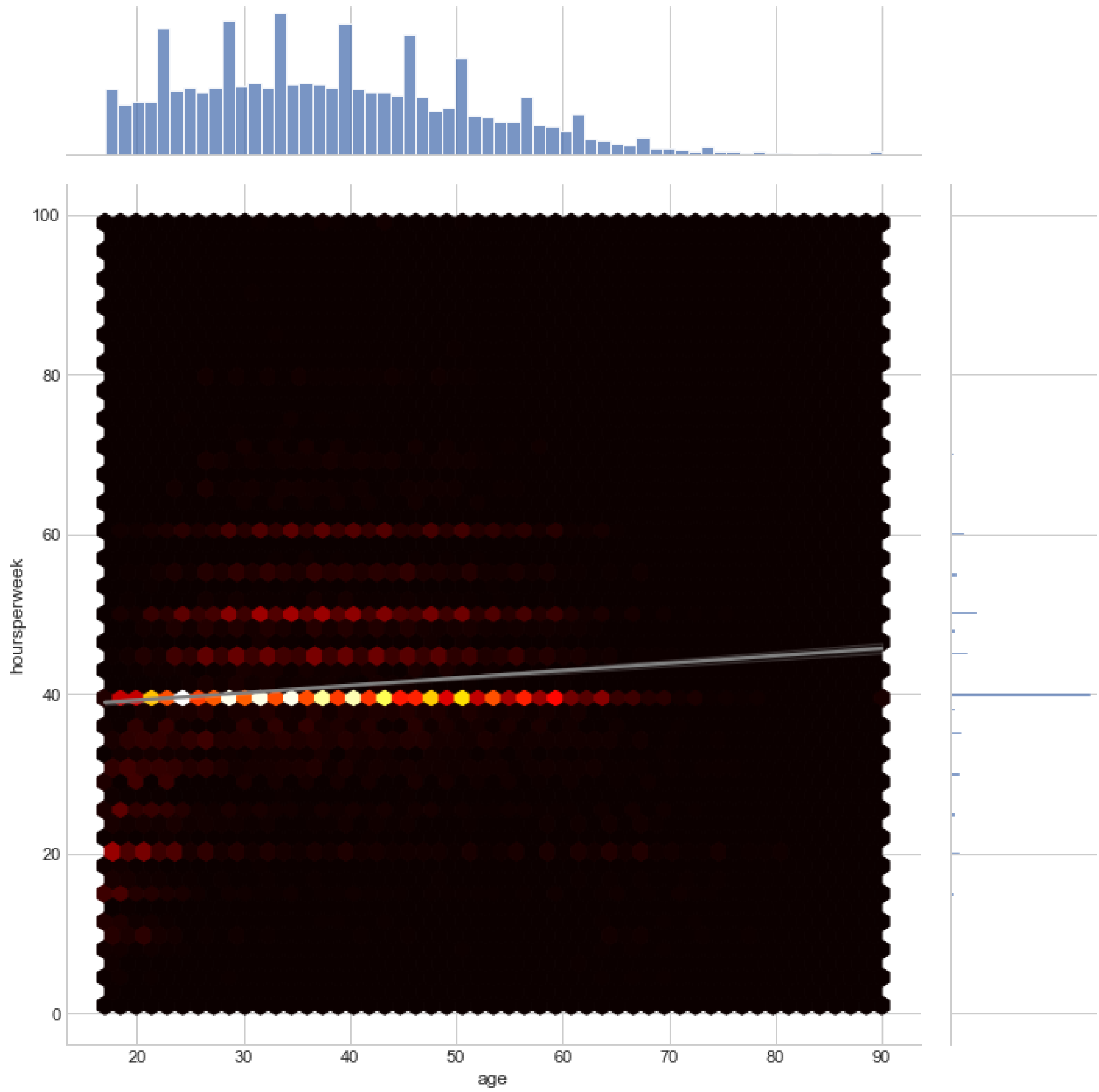
In [15]:

```
g = sns.jointplot(x = 'age',
              y = 'hoursperweek',
              data = train_data,
              kind = 'hex',
              cmap= 'hot',
              size=10)

#http://stackoverflow.com/questions/33288830/how-to-plot-regression-line-on-hexbins-with-se
sns.regplot(train_data.age, train_data['hoursperweek'], ax=g.ax_joint, scatter=False, color
```

```
C:\Users\sowmya sandeep\anaconda3\lib\site-packages\seaborn\axisgrid.py:218
2: UserWarning: The `size` parameter has been renamed to `height`; please up
date your code.
  warnings.warn(msg, UserWarning)
C:\Users\sowmya sandeep\anaconda3\lib\site-packages\seaborn\_decorators.py:3
6: FutureWarning: Pass the following variables as keyword args: x, y. From v
ersion 0.12, the only valid positional argument will be `data`, and passing
other arguments without an explicit keyword will result in an error or misin
terpretation.
  warnings.warn(
```

Out[15]:

```
<AxesSubplot:xlabel='age', ylabel='hoursperweek'>
```



In [16]:

```
#Feature encoding
from sklearn.preprocessing import LabelEncoder

train_data = train_data.apply(LabelEncoder().fit_transform)
train_data.head()
```

Out[16]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	sex
0	22	5	9	12	4	0	1	4	1
1	33	4	9	12	2	3	0	4	1
2	21	2	11	8	0	5	1	4	1
3	36	2	1	6	2	5	0	2	1
4	11	2	9	12	2	9	5	2	0

In [17]:

```
test_data = test_data.apply(LabelEncoder().fit_transform)
test_data.head()
```

Out[17]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	sex
0	8	2	1	6	4	6	3	2	1
1	21	2	11	8	2	4	0	4	1
2	11	1	7	11	2	10	0	4	1
3	27	2	15	9	2	6	0	2	1
4	17	2	0	5	4	7	1	4	1

In [19]:

```
#Test-Train-Split
drop_elements = ['education', 'native', 'Salary']

X = train_data.drop(drop_elements, axis=1)

y = train_data['Salary']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=42)
```

In [20]:

```
#Building SVM Model
from sklearn import metrics

svc = SVC()
svc.fit(X_train, y_train)
# make predictions
prediction = svc.predict(X_test)
# summarize the fit of the model
print(metrics.classification_report(y_test, prediction))
print(metrics.confusion_matrix(y_test, prediction))

print("Accuracy:",metrics.accuracy_score(y_test, prediction))
print("Precision:",metrics.precision_score(y_test, prediction))
print("Recall:",metrics.recall_score(y_test, prediction))
```

```
              precision    recall  f1-score   support

           0       0.80      0.99      0.89      7466
           1       0.86      0.28      0.42      2488

    accuracy                           0.81      9954
   macro avg       0.83      0.63      0.65      9954
weighted avg       0.82      0.81      0.77      9954

[[7355  111]
 [1789  699]]
Accuracy: 0.8091219610206952
Precision: 0.8629629629629629
Recall: 0.2809485530546624
```

In [21]:

```
#Testing it on new test data from SalaryData_Test(1).csv
drop_elements = ['education', 'native', 'Salary']
X_new = test_data.drop(drop_elements, axis=1)

y_new = test_data['Salary']

# make predictions
new_prediction = svc.predict(X_new)
# summarize the fit of the model
print(metrics.classification_report(y_new, new_prediction))
print(metrics.confusion_matrix(y_new, new_prediction))

print("Accuracy:",metrics.accuracy_score(y_new, new_prediction))
print("Precision:",metrics.precision_score(y_new, new_prediction))
print("Recall:",metrics.recall_score(y_new, new_prediction))
```

```
              precision    recall  f1-score   support

           0       0.80      0.99      0.89     11360
           1       0.87      0.26      0.40      3700

    accuracy                           0.81     15060
   macro avg       0.84      0.63      0.65     15060
weighted avg       0.82      0.81      0.77     15060

[[11216   144]
 [ 2727   973]]
Accuracy: 0.8093625498007968
Precision: 0.8710832587287377
Recall: 0.26297297297297295
```

In [22]:

```
#Building SVM model with Hyper Parameters kernel='rbf',gamma=15, C=1
model = SVC(kernel='rbf',gamma=15, C=1)

model.fit(X_train, y_train)
# make predictions
prediction = model.predict(X_test)
# summarize the fit of the model
print(metrics.classification_report(y_test, prediction))
print(metrics.confusion_matrix(y_test, prediction))

print("Accuracy:",metrics.accuracy_score(y_test, prediction))
print("Precision:",metrics.precision_score(y_test, prediction))
print("Recall:",metrics.recall_score(y_test, prediction))
```

```
              precision    recall  f1-score   support

           0       0.76      0.98      0.86      7466
           1       0.56      0.08      0.15      2488

    accuracy                           0.75      9954
   macro avg       0.66      0.53      0.50      9954
weighted avg       0.71      0.75      0.68      9954

[[7304  162]
 [2280  208]]
Accuracy: 0.754671488848704
Precision: 0.5621621621621622
Recall: 0.08360128617363344
```

In [23]:

```
#Testing above model on SalaryData_Test(1).csv
# make predictions
new_prediction = model.predict(X_new)
# summarize the fit of the model
print(metrics.classification_report(y_new, new_prediction))
print(metrics.confusion_matrix(y_new, new_prediction))

print("Accuracy:",metrics.accuracy_score(y_new, new_prediction))
print("Precision:",metrics.precision_score(y_new, new_prediction))
print("Recall:",metrics.recall_score(y_new, new_prediction))
```

```
              precision    recall  f1-score   support

           0       0.76      0.98      0.86     11360
           1       0.55      0.07      0.13      3700

    accuracy                           0.76     15060
   macro avg       0.66      0.53      0.49     15060
weighted avg       0.71      0.76      0.68     15060

[[11147   213]
 [ 3437   263]]
Accuracy: 0.7576361221779548
Precision: 0.5525210084033614
Recall: 0.07108108108108108
```

In [24]:

```
#Building SVM model with Hyper Parameters kernel='linear',gamma=0.22, C=0.1
model_2 = SVC(kernel='linear',gamma=0.22, C=1)

model_2.fit(X_train, y_train)
# make predictions
prediction = model.predict(X_test)
# summarize the fit of the model
print(metrics.classification_report(y_test, prediction))
print(metrics.confusion_matrix(y_test, prediction))

print("Accuracy:",metrics.accuracy_score(y_test, prediction))
print("Precision:",metrics.precision_score(y_test, prediction))
print("Recall:",metrics.recall_score(y_test, prediction))
```

```
              precision    recall  f1-score   support

           0       0.76      0.98      0.86      7466
           1       0.56      0.08      0.15      2488

    accuracy                           0.75      9954
   macro avg       0.66      0.53      0.50      9954
weighted avg       0.71      0.75      0.68      9954

[[7304  162]
 [2280  208]]
Accuracy: 0.754671488848704
Precision: 0.5621621621621622
Recall: 0.08360128617363344
```

In [25]:

```
#Testing above model on SalaryData_Test(1).csv
# make predictions
new_prediction = model_2.predict(X_new)
# summarize the fit of the model
print(metrics.classification_report(y_new, new_prediction))
print(metrics.confusion_matrix(y_new, new_prediction))

print("Accuracy:",metrics.accuracy_score(y_new, new_prediction))
print("Precision:",metrics.precision_score(y_new, new_prediction))
print("Recall:",metrics.recall_score(y_new, new_prediction))
```

```
              precision    recall  f1-score   support

           0       0.81      0.97      0.88     11360
           1       0.77      0.29      0.42      3700

    accuracy                           0.80     15060
   macro avg       0.79      0.63      0.65     15060
weighted avg       0.80      0.80      0.77     15060

[[11044   316]
 [ 2639  1061]]
Accuracy: 0.8037848605577689
Precision: 0.7705156136528686
Recall: 0.28675675675675677
```

In [ ]:

```

```