In [1]:
```
# Import the required libraries for data preprocessing
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Data Preprocessing

- Load the data using the Pandas read function.
- print the dataset information
- Print the stastics about the data using describe function
- Visualize the correlation map to understand the correlation with the columns.
- Check for null values, and if the data contains any, remove them.
- Additionally, inspect for duplicate values and remove them if present.

In [2]:
```
# Load the data set and print the top 5 rows
data=pd.read_csv('C://Users//vinod//Downloads//salary.csv')
data.head()
```

Out[2]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female

In [3]:
```
# about the data set
data.info()
```

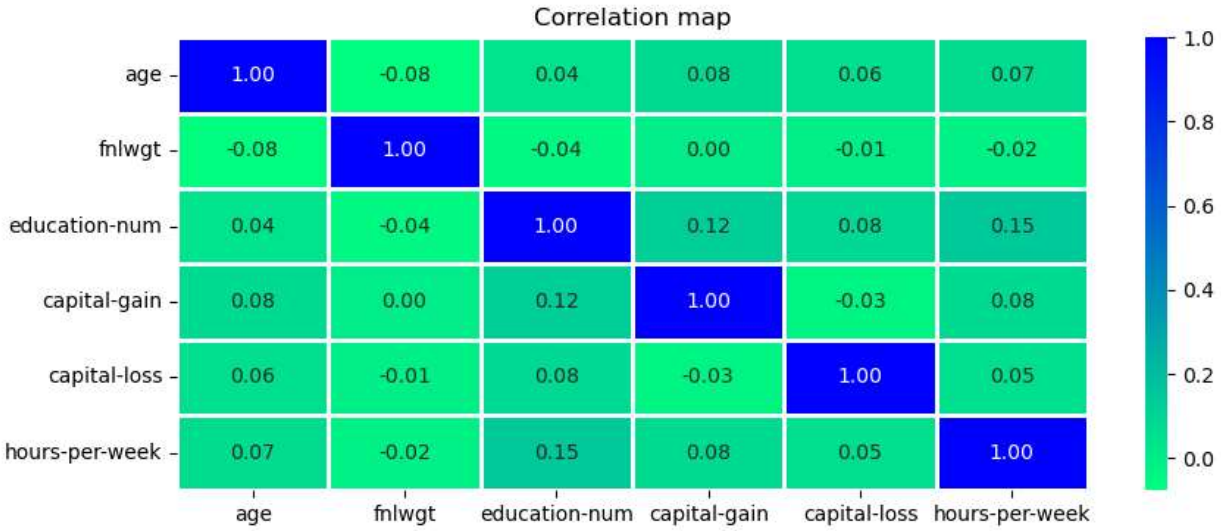
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32561 non-null  int64 
 1   workclass       32561 non-null  object
 2   fnlwgt          32561 non-null  int64 
 3   education       32561 non-null  object
 4   education-num   32561 non-null  int64 
 5   marital-status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital-gain    32561 non-null  int64 
 11  capital-loss    32561 non-null  int64 
 12  hours-per-week  32561 non-null  int64 
 13  native-country  32561 non-null  object
 14  salary          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

In [4]:
```
# Under standing  stastics in the data set
data.describe().style.background_gradient(cmap='tab20c')
```

Out[4]:

	age	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week
count	32561.000000	32561.000000	32561.000000	32561.000000	32561.000000	32561.000000
mean	38.581647	189778.366512	10.080679	1077.648844	87.303830	40.437456
std	13.640433	105549.977697	2.572720	7385.292085	402.960219	12.347429
min	17.000000	12285.000000	1.000000	0.000000	0.000000	1.000000
25%	28.000000	117827.000000	9.000000	0.000000	0.000000	40.000000
50%	37.000000	178356.000000	10.000000	0.000000	0.000000	40.000000
75%	48.000000	237051.000000	12.000000	0.000000	0.000000	45.000000
max	90.000000	1484705.000000	16.000000	99999.000000	4356.000000	99.000000

In [5]:
```
# Checking the correlation matirx
plt.figure(figsize=(10,4))
sns.heatmap(data.corr(),annot=True,cmap='winter_r',fmt='.2f',linewidths=1)
plt.title("Correlation map")
plt.show()
```



Data Cleaning Process

In [6]:
```
# Checking the null values in the data set
data.isna().sum()/len(data)*100
```

Out[6]:
```
age               0.0
workclass         0.0
fnlwgt            0.0
education         0.0
education-num     0.0
marital-status    0.0
occupation        0.0
relationship      0.0
race              0.0
sex               0.0
capital-gain      0.0
capital-loss      0.0
hours-per-week    0.0
native-country    0.0
salary            0.0
dtype: float64
```

In [7]:
```
#Checking the Percentage of the null values in the dataset
null_values=data.isna().sum()
total_shells=np.product(data.shape)
total_missing_values=null_values.sum()
percentage_missing_values=(total_missing_values/total_shells)*100
print(f'The data set contains {percentage_missing_values} of values')
```

```
The data set contains 0.0 of values
```

In [8]:
```
# Checking the duplicate values in the dataset
duplicate=data.duplicated().sum()
print(f'There is {duplicate} values in the data set we remove it')
```

```
There is 24 values in the data set we remove it
```

In [9]:
```
# Remove the duplicate values and store the data set as data variable
data=data.drop_duplicates()
after_remove_duplicates=data.duplicated().sum()
print(f'There is {after_remove_duplicates} values in the data set ')
```

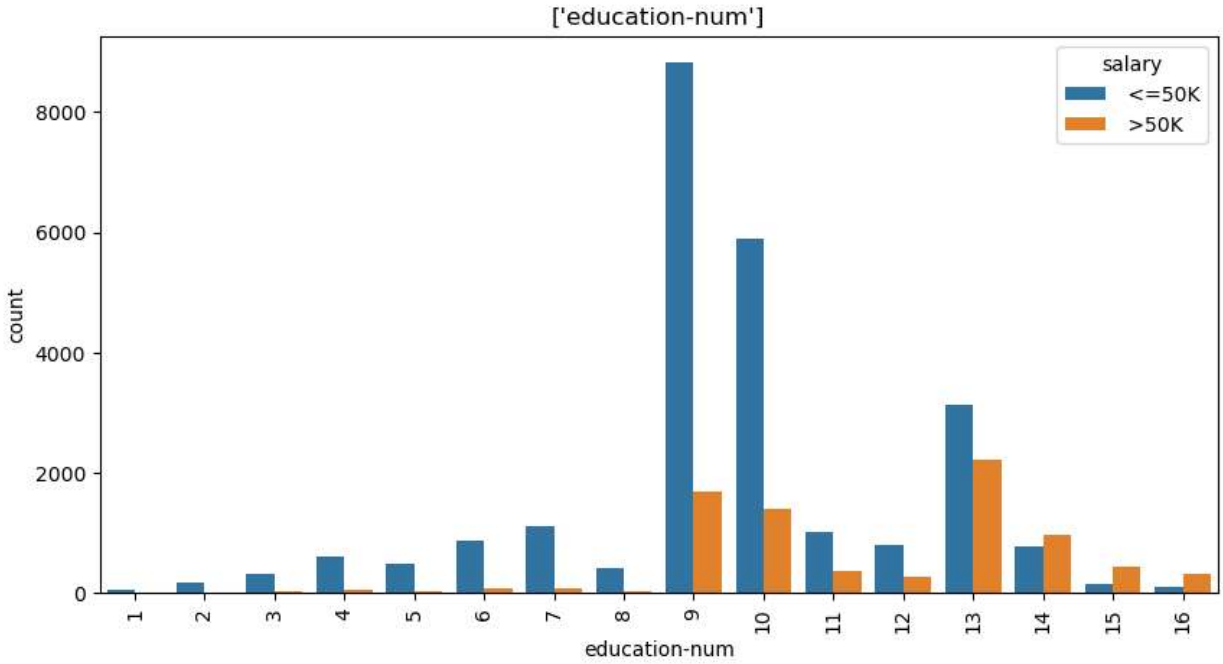
```
There is 0 values in the data set
```

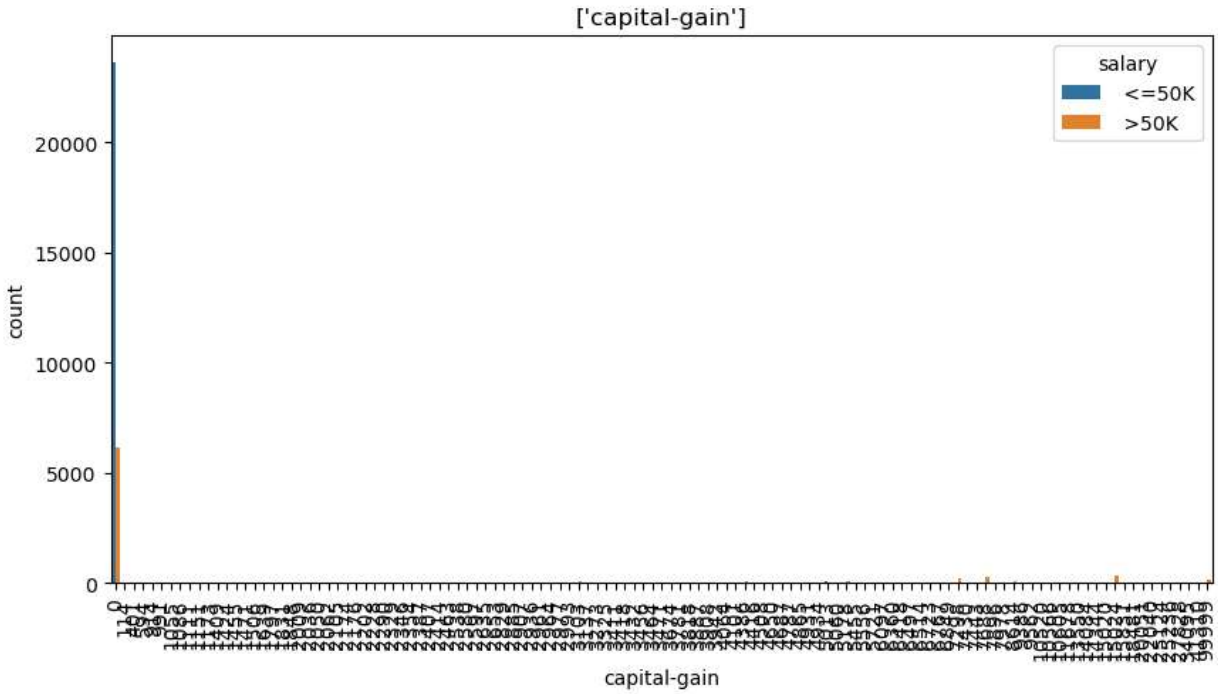
Explore Data Analysis Process

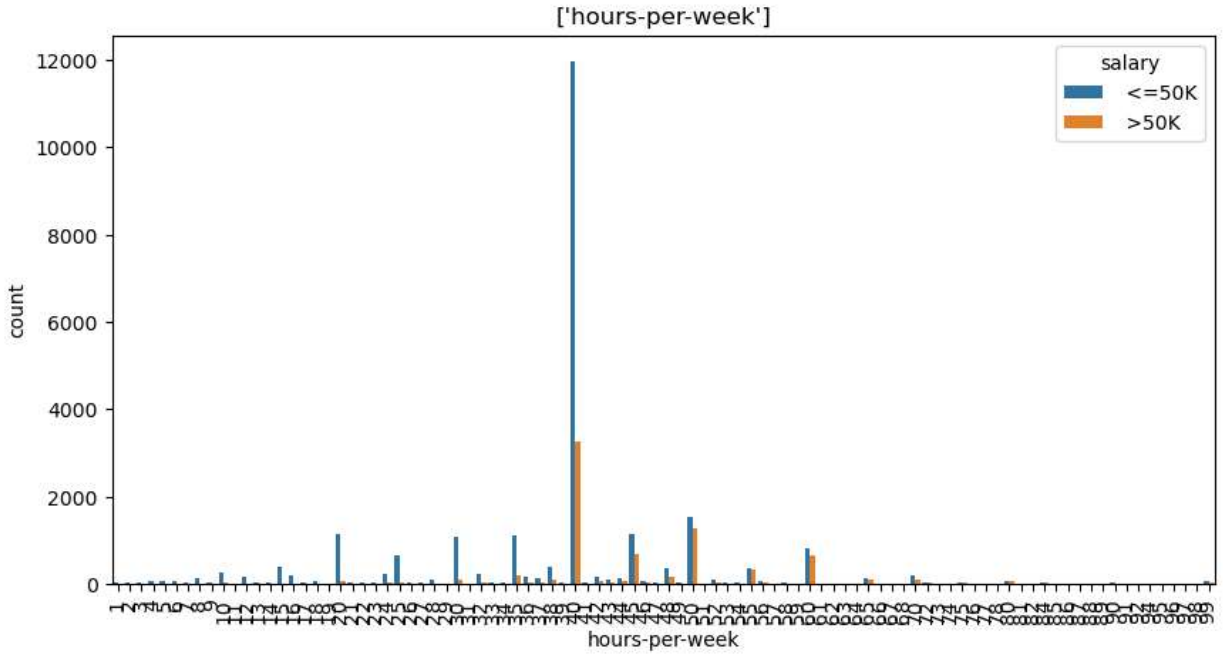
Question asked from the data:

- We use a for loop to print count plots for numerical columns to understand the most repeated values.
- We also visualize a histogram for the number of hours employees work.
- Additionally, we visualize the output percentages using a pie chart.
- Furthermore, we perform data cleaning by replacing unwanted names in the dataset with "Others".
- We create a pie chart to understand the distribution of output in numerical columns.
- We generate a separate dataset for the USA to analyze the most demanded education and jobs.
- We explore the education levels with the most hours worked in the USA.
- Using a for loop, we visualize selected numerical columns in the USA dataset using bar charts.
- Additionally, we utilize box plots with the dataset and hue values based on salary using a for loop.
- Furthermore, we create a pivot table for better data understanding.
- Lastly, we visualize the most demanded jobs with work hours ranging from less than 20 hours to 40 hours.

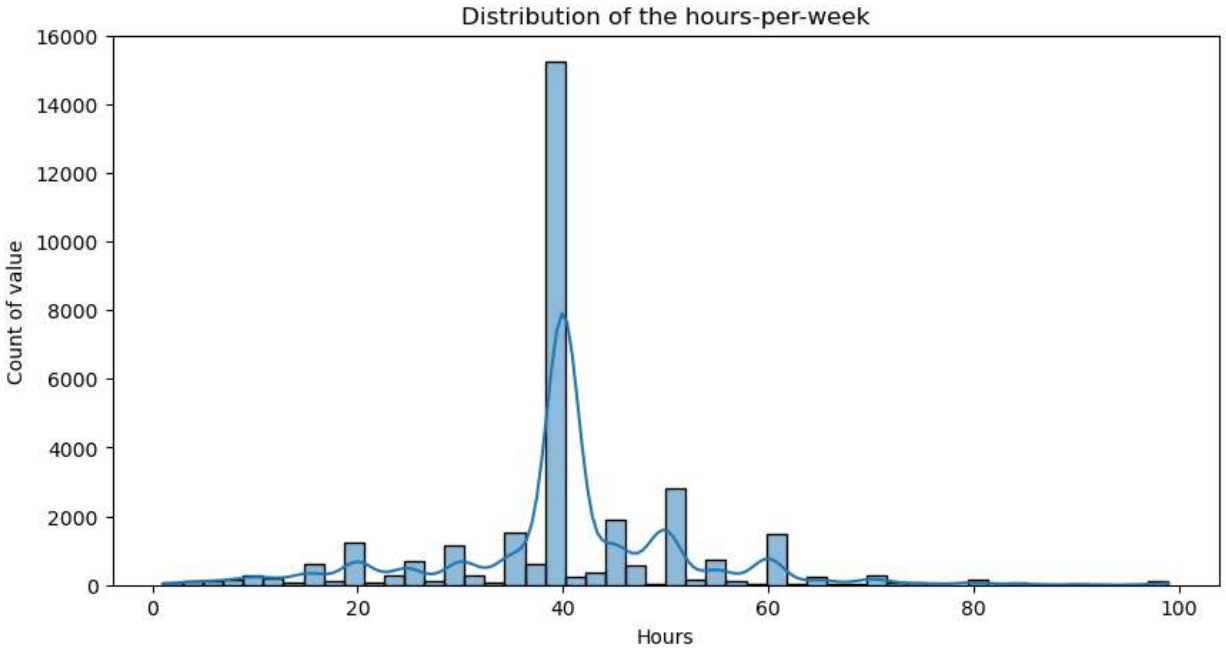
In [10]:
```
# create a count plot to visualize the some numerical columns in the data
numerical=['education-num','capital-gain','hours-per-week']
for i in numerical:
    plt.figure(figsize=(10,5))
    sns.countplot(data=data,x=i,hue='salary')
    plt.title([i])
    plt.xticks(rotation=90)
    plt.show()
```


['education-num']
salary
<=50K
>50K
count
education-num
0
2000
4000
6000
8000
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16

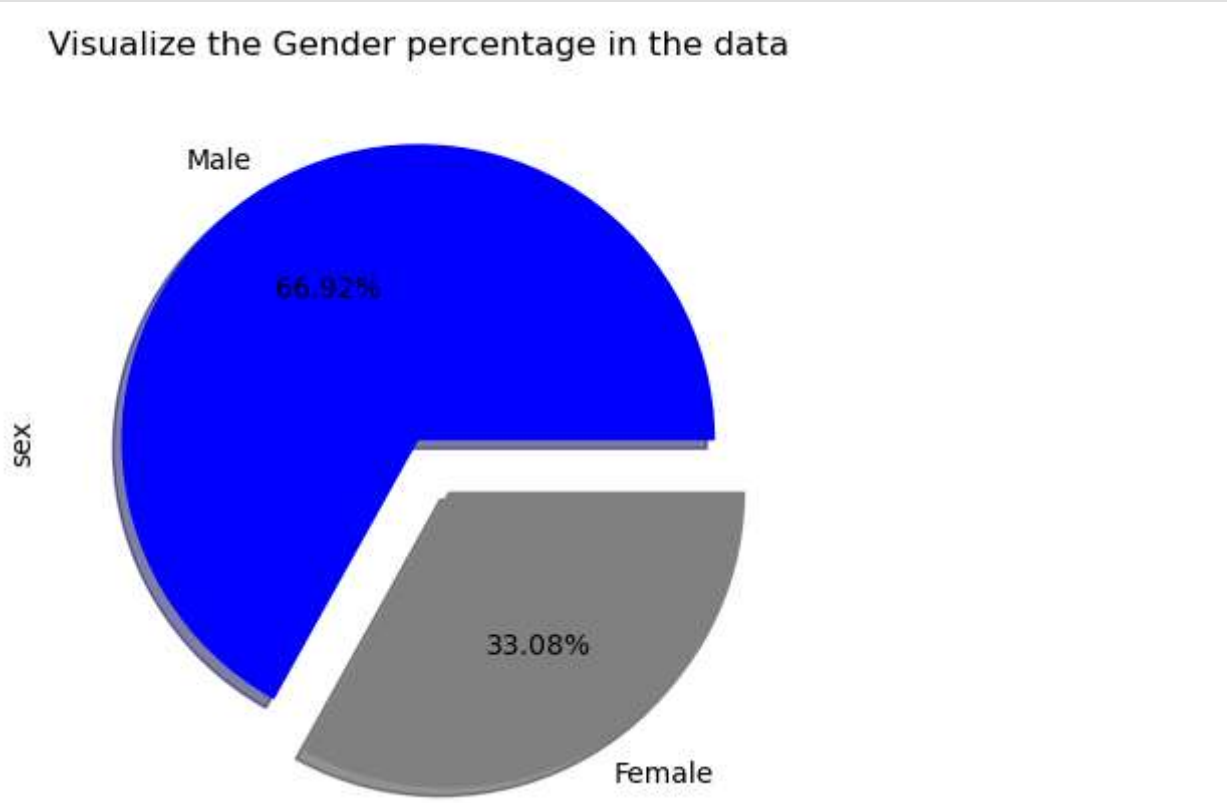

['capital-gain']
salary
<=50K
>50K
count
capital-gain
0
5000
10000
15000
20000



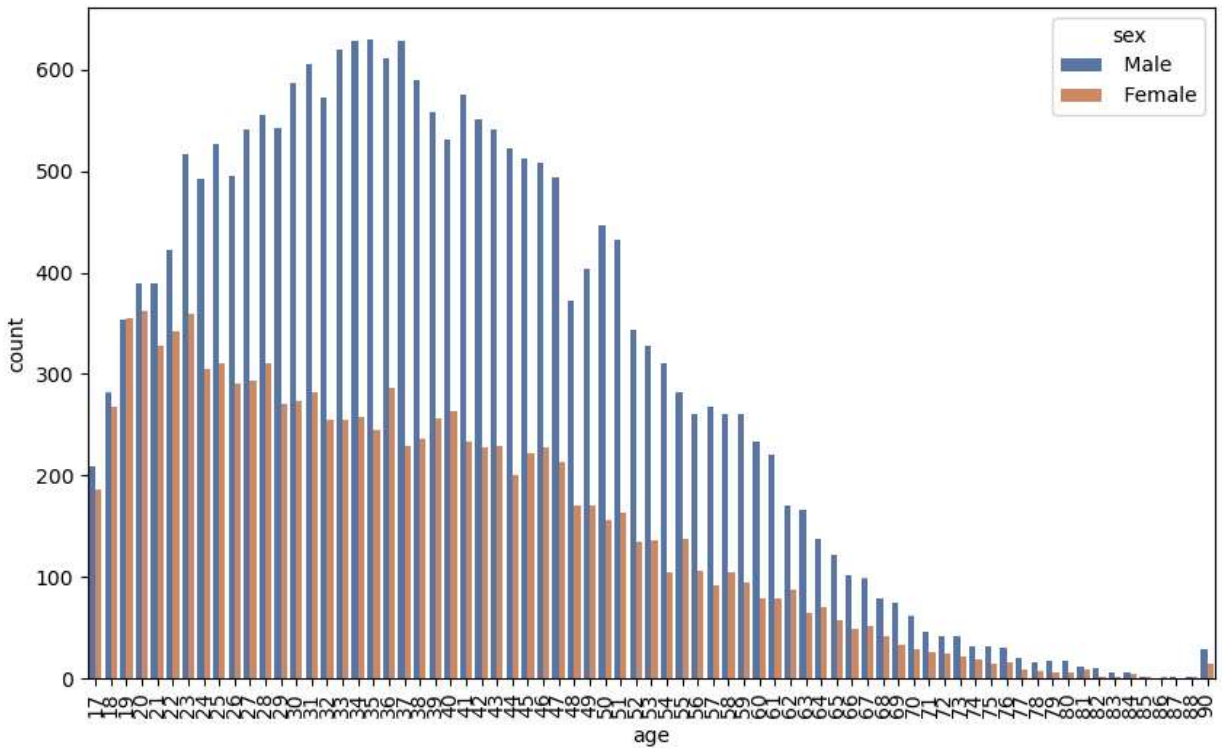
In [11]:
```
plt.figure(figsize=(10,5))
sns.histplot(data=data,x='hours-per-week',bins=50,kde=True)
plt.title("Distribution of the hours-per-week")
plt.xlabel("Hours")
plt.ylabel("Count of value")
plt.show()
```



In [12]:
```
# Let's find the percentage of the gender in the data set using the pie chat
data['sex'].value_counts().plot(kind='pie',
    explode=[0,0.2],
    labels=['Male','Female'],
    colors=['blue','gray'],
    autopct='%1.2f%%',
    shadow=True,
        )
plt.title("Visualize the Gender percentage in the data")
plt.show()
```

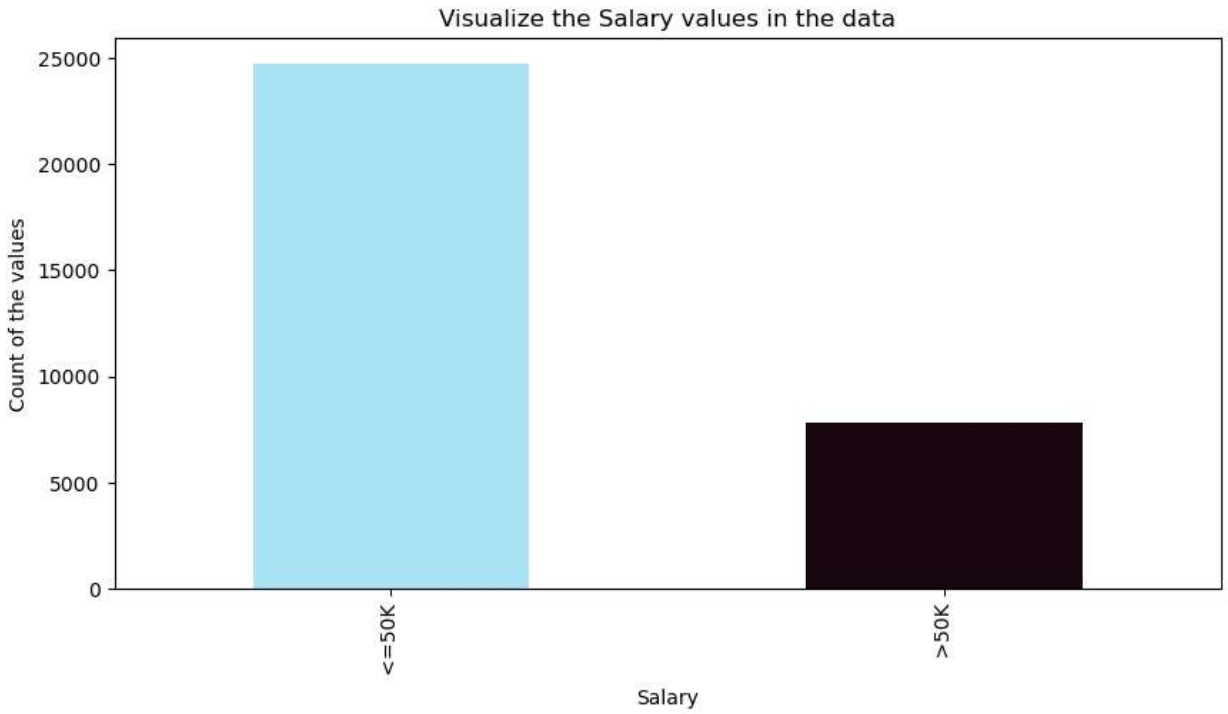


In [13]:
```
# Distibution of the age column with the gender
plt.figure(figsize=(10,6))
sns.countplot(data=data,x='age',hue='sex',palette='deep')
plt.xticks(rotation=90)
plt.show()
```



In [14]:
```
plt.figure(figsize=(10,5))
data['salary'].value_counts().sort_values(ascending=False).plot(kind='bar',
```

```
                                                                color=['#A9E2F3','#1907
plt.title("Visualize the Salary values in the data")
plt.xlabel("Salary")
plt.ylabel("Count of the values")
plt.show()
```

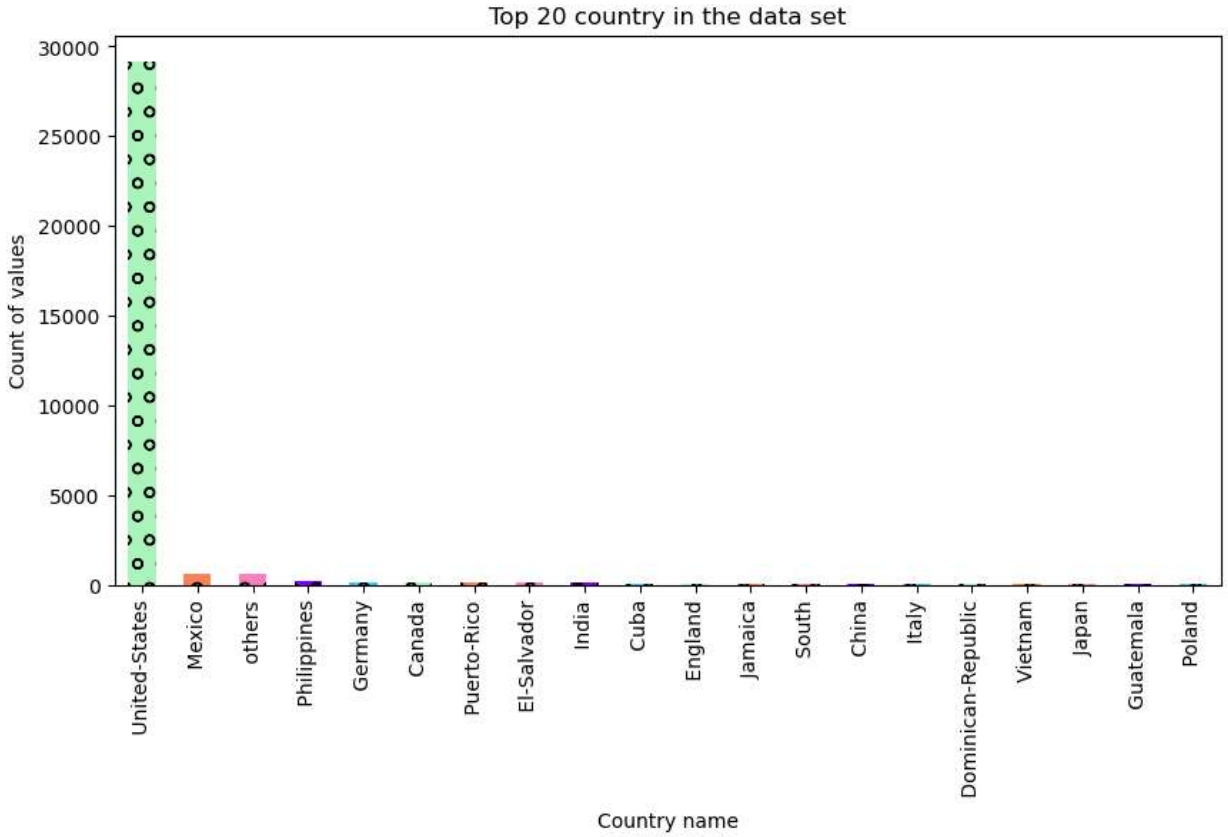


In [15]:
```
# The data contains the unwanted informatin we would like to remove and add new values
data['native-country'].value_counts().head(3)
```

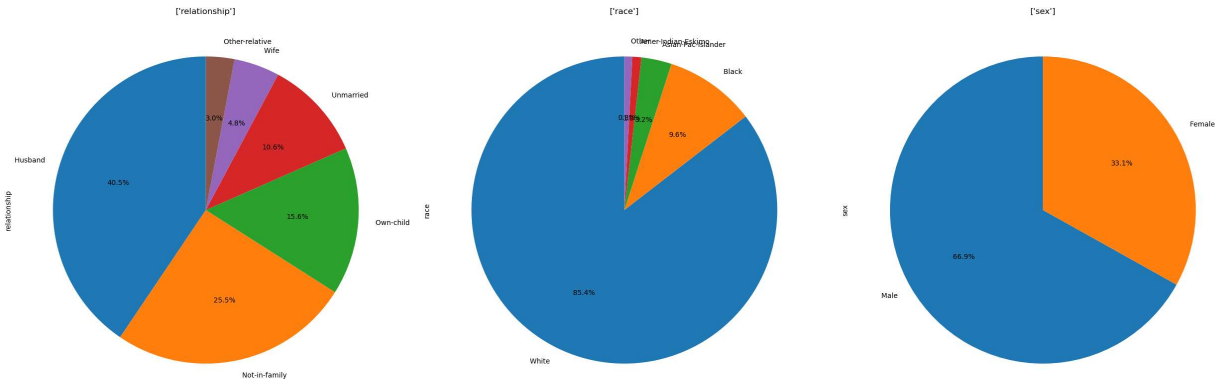
Out[15]:
```
 United-States    29153
 Mexico             639
 ?                  582
Name: native-country, dtype: int64
```

In [16]:
```
data['native-country']=data['native-country'].str.replace('?','others')
data['workclass']=data['workclass'].str.replace('?','others')
data['occupation']=data['occupation'].str.replace('?','others')
```

In [17]:
```
# Visualize the top 20 countrys in the dataset
data['native-country'].value_counts().nlargest(20)\
.plot(kind='bar',title="Top 20 country in the data set",hatch='o',figsize=(10,5),color
plt.xlabel("Country name")
plt.ylabel("Count of values")
plt.show()
```

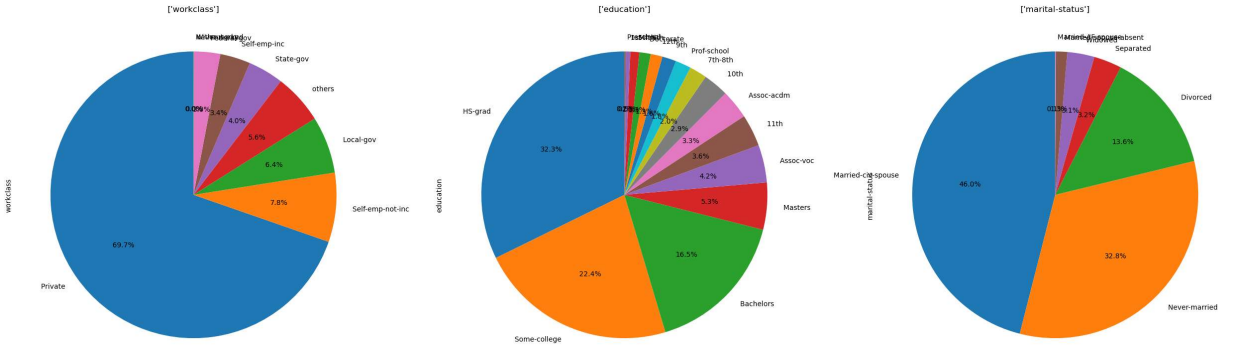


In [18]:
```
# Create a pie chart to understande the relationships, race,sex percentage with output
another_list=['relationship','race','sex']
num_of_columns=len(another_list)
plt.figure(figsize=(25,8))
for i, col in enumerate(another_list):
    plt.subplot(1,num_of_columns,i+1)
    data[col].value_counts().plot(kind='pie',autopct='%1.1f%%', startangle=90)
    plt.title([col])
plt.tight_layout()
plt.show()
```

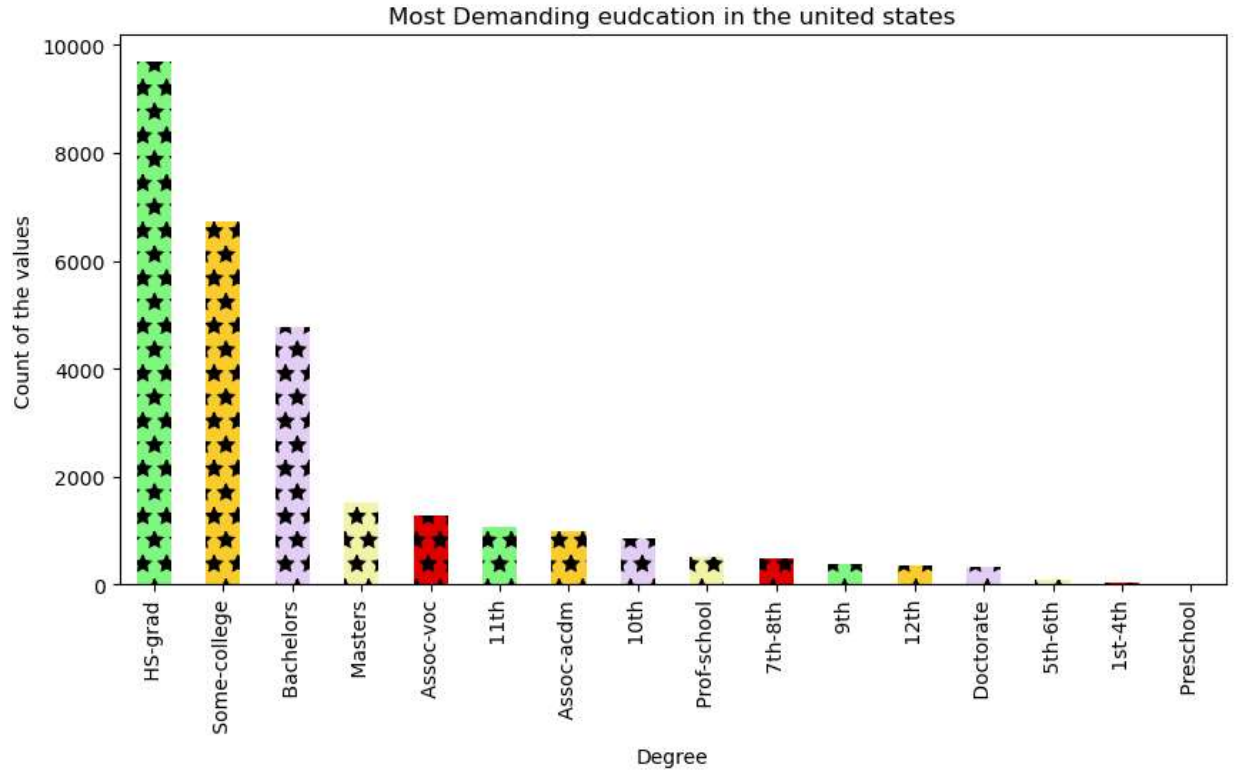


In [19]:
```
# Create a pie chart to understand the percentage of the workclass and education and m
work_place=['workclass','education','marital-status']
num_column=len(work_place)
plt.figure(figsize=(25,8))
for i,col in enumerate(work_place):
    plt.subplot(1,num_column,i+1)
    data[col].value_counts().plot(kind='pie',autopct='%1.1f%%', startangle=90)
    plt.title([col])
```

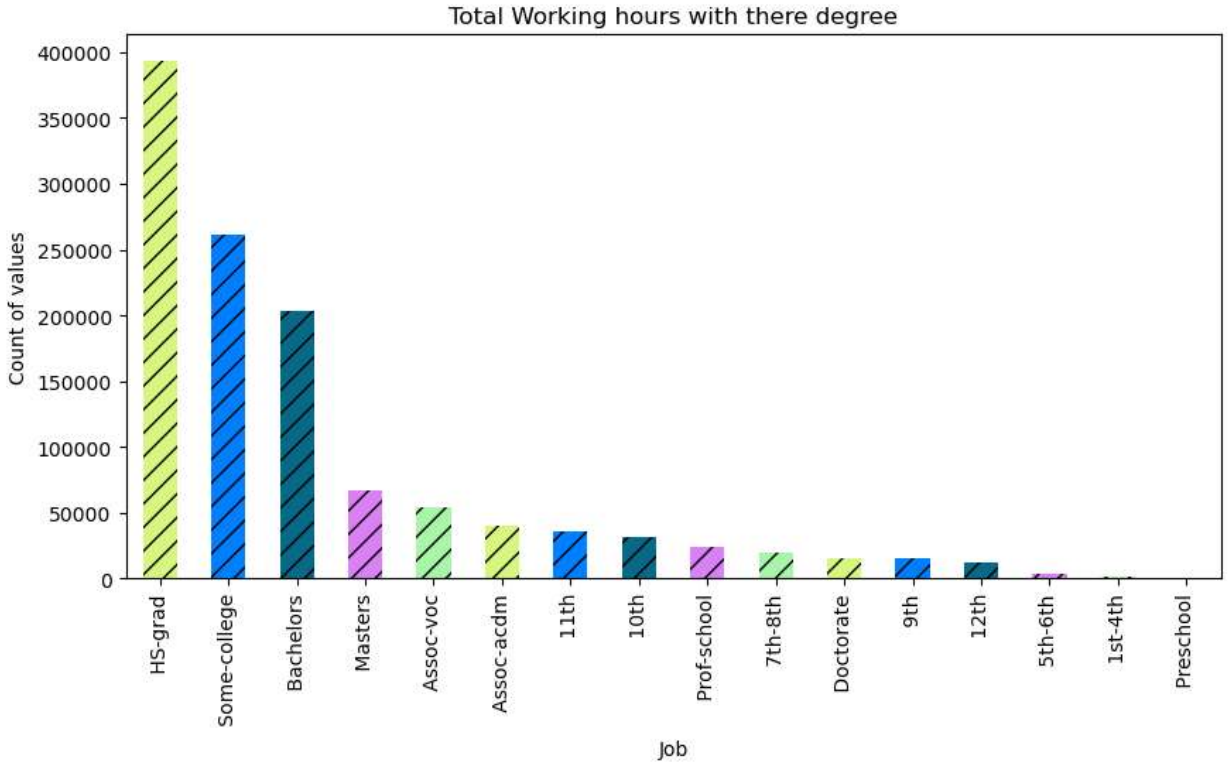
```
plt.tight_layout()
plt.show()
```



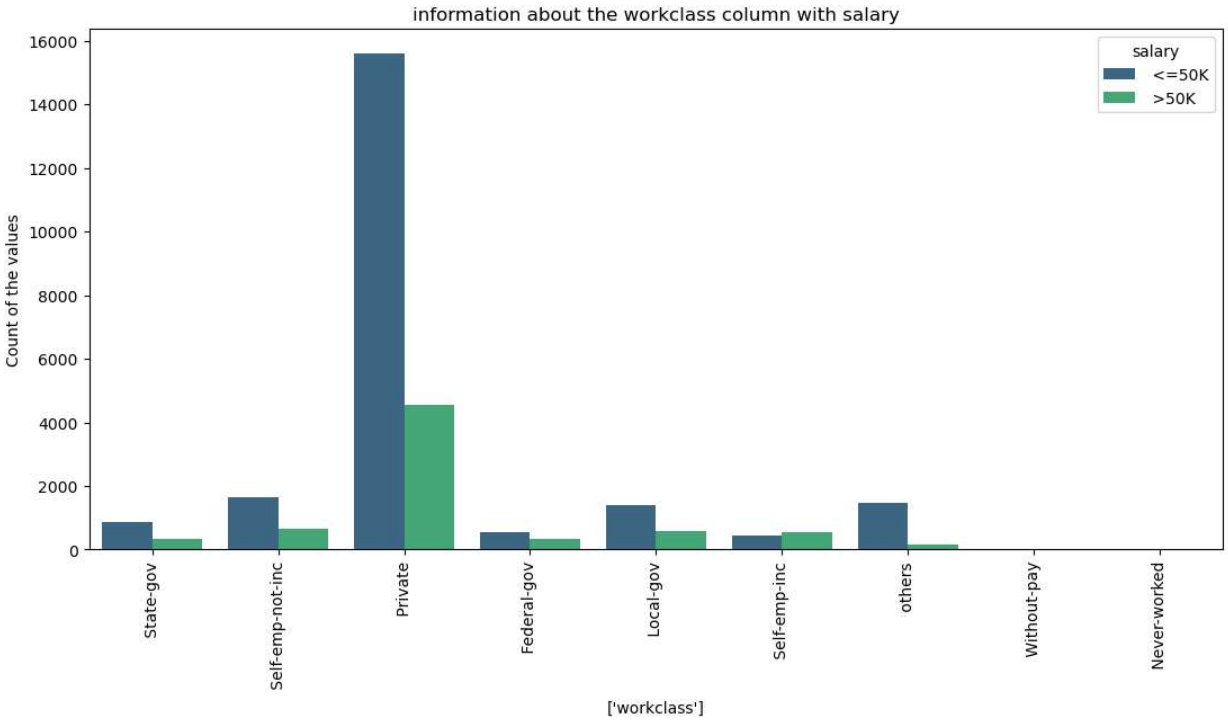
In [20]:
```
# Apply the different condition to the data to creat a seperate data frame for united
usa=data[data['native-country']==' United-States']
# Find the which education is most demanding in the unitedstates
usa['education'].value_counts().sort_values(ascending=False)\
.plot(kind='bar',figsize=(10,5),hatch='*',color=['#81F781','#FACC2E','#E3CEF6','#F2F5A
plt.title("Most Demanding eudcation in the united states")
plt.xlabel("Degree")
plt.ylabel("Count of the values")
plt.show()
```

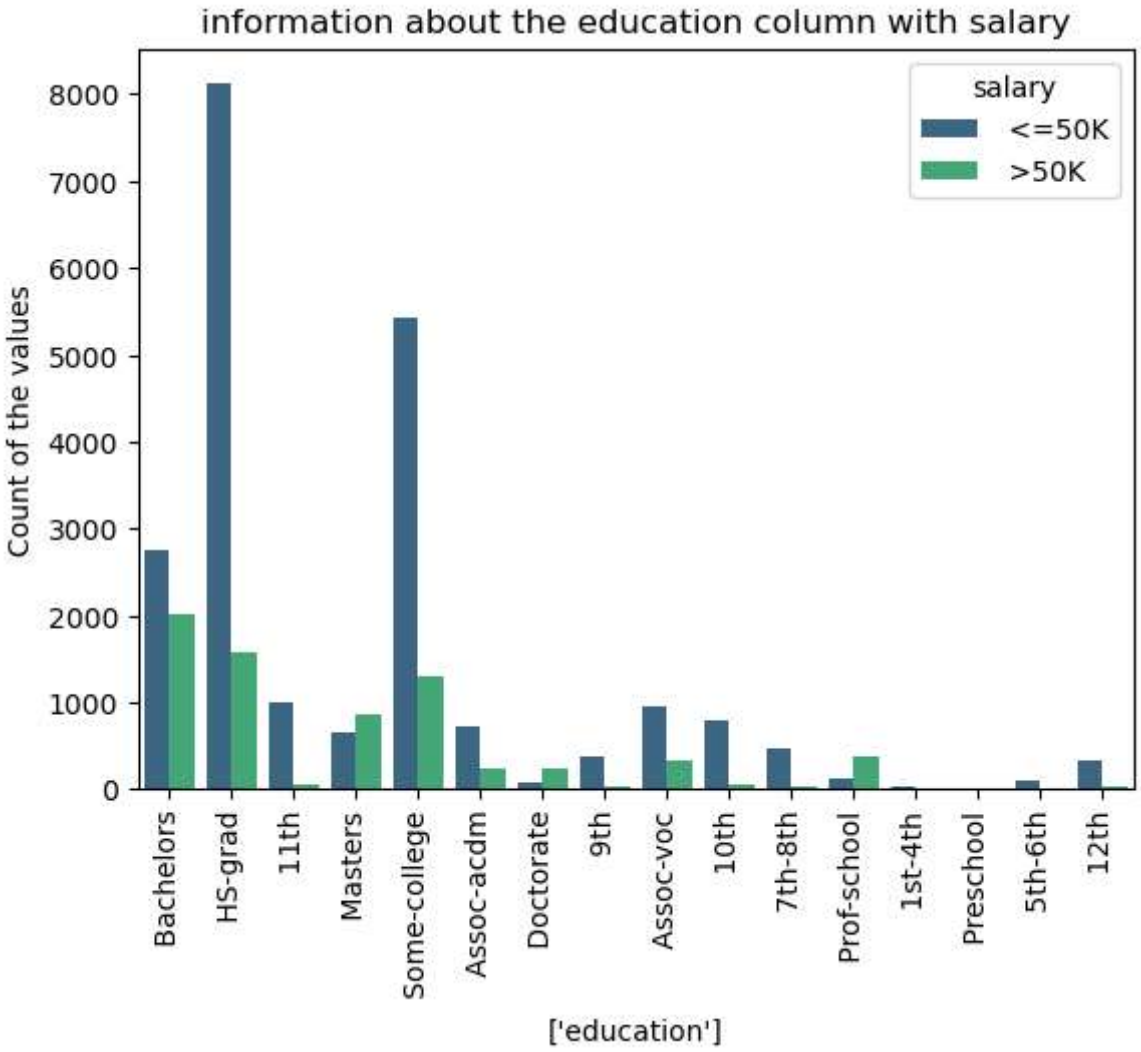


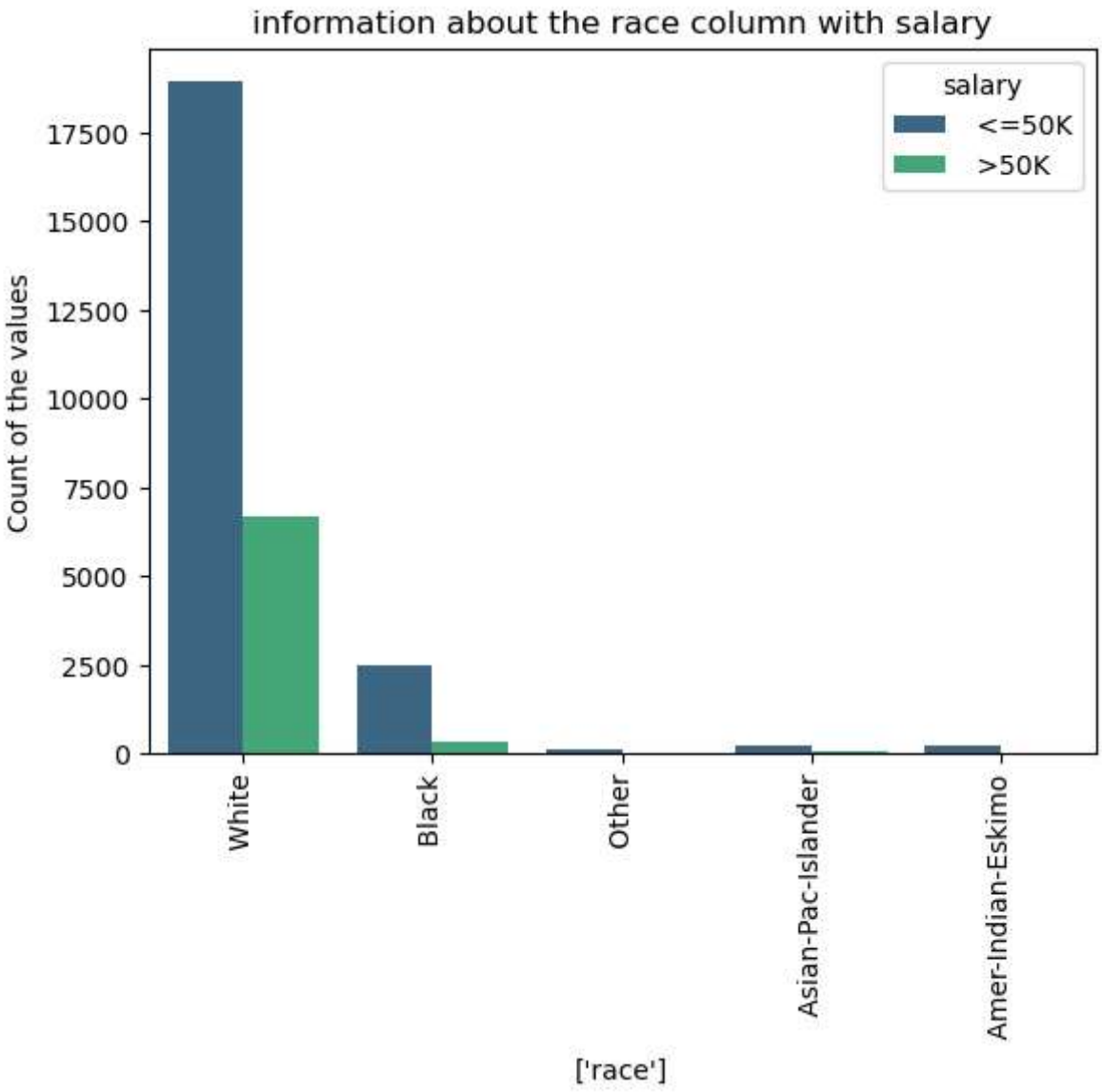
In [21]:
```
# Find the total working hours with there education using the bar chart
usa.groupby('education')['hours-per-week'].sum().sort_values(ascending=False)\
.plot(kind='bar',figsize=(10,5),hatch='//',color=['#D8F781','#0080FF','#086A87','#DA81
plt.title("Total Working hours with there degree")
plt.xlabel("Job")
plt.ylabel("Count of values")
plt.show()
```

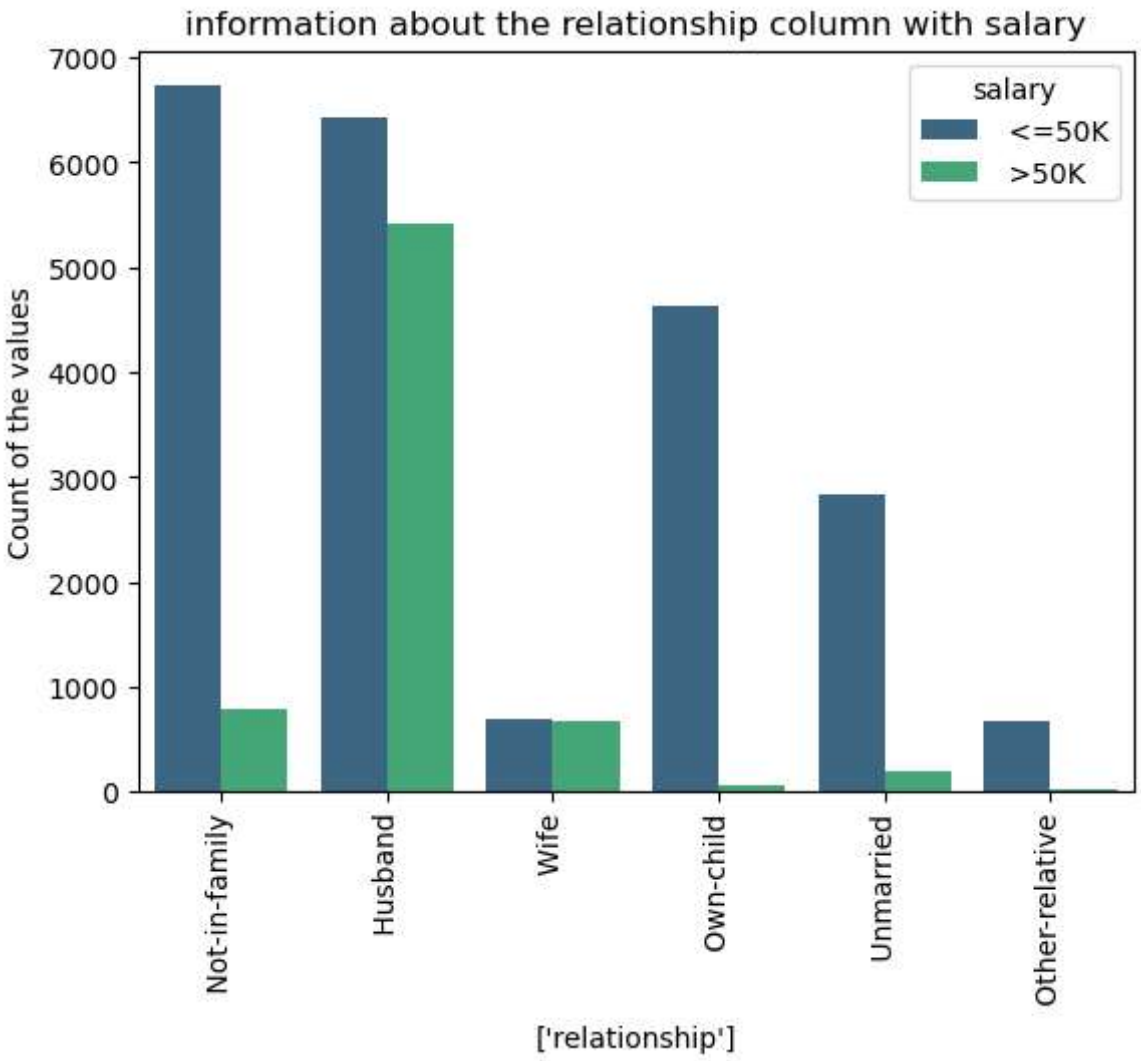


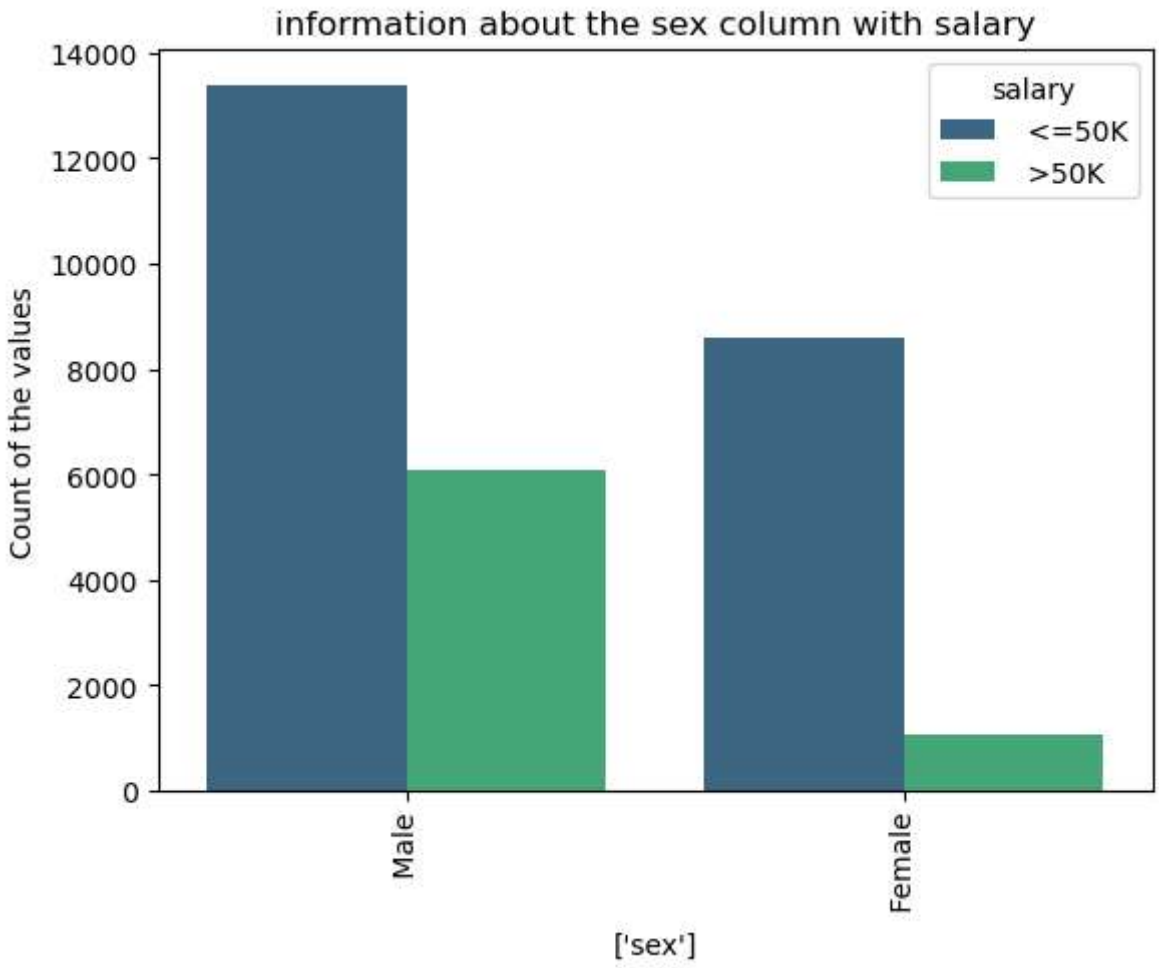
In [22]:
```
#Create a countplot to understanding the informaiton about the united states
plt.figure(figsize=(13,6))
for i in ['workclass','education','race','relationship','sex']:
    sns.countplot(data=usa,x=i,hue='salary',palette='viridis')
    plt.title(f'information about the {i} column with salary')
    plt.xlabel([i])
    plt.ylabel("Count of the values")
    plt.xticks(rotation=90)
    plt.show()
```



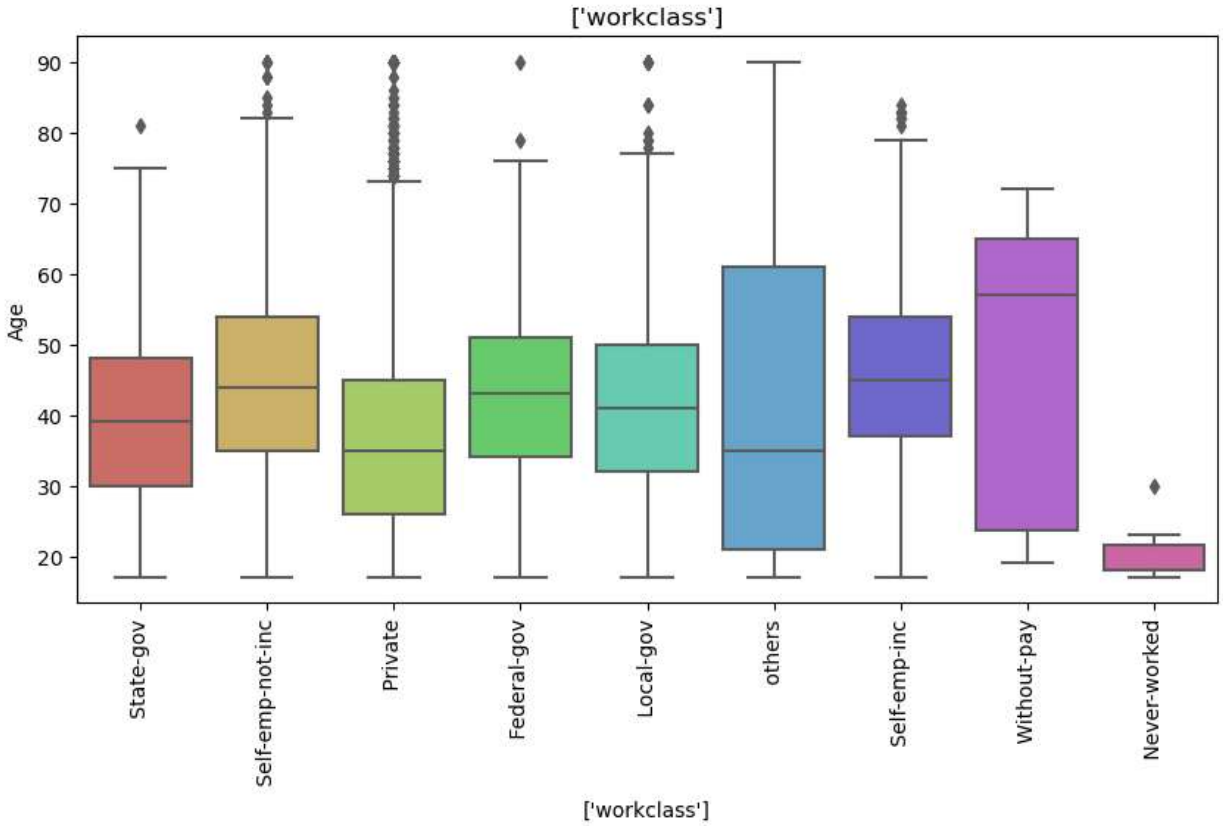

information about the education column with salary
salary
<=50K
>50K
Count of the values
8000
7000
6000
5000
4000
3000
2000
1000
0
Bachelors
HS-grad
11th
Masters
Some-college
Assoc-acdm
Doctorate
9th
Assoc-voc
10th
7th-8th
Prof-school
1st-4th
Preschool
5th-6th
12th
['education']

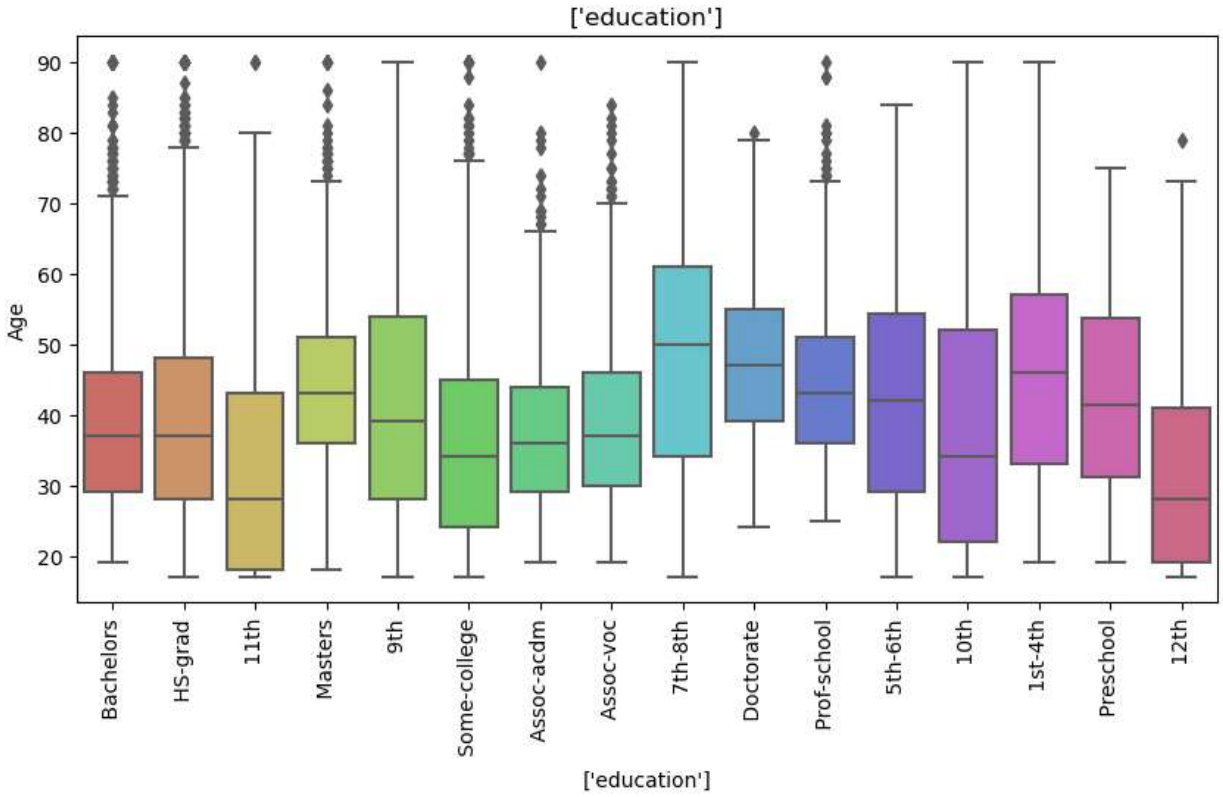

information about the race column with salary
salary
<=50K
>50K
Count of the values
17500
15000
12500
10000
7500
5000
2500
0
White
Black
Other
Asian-Pac-Islander
Amer-Indian-Eskimo
['race']

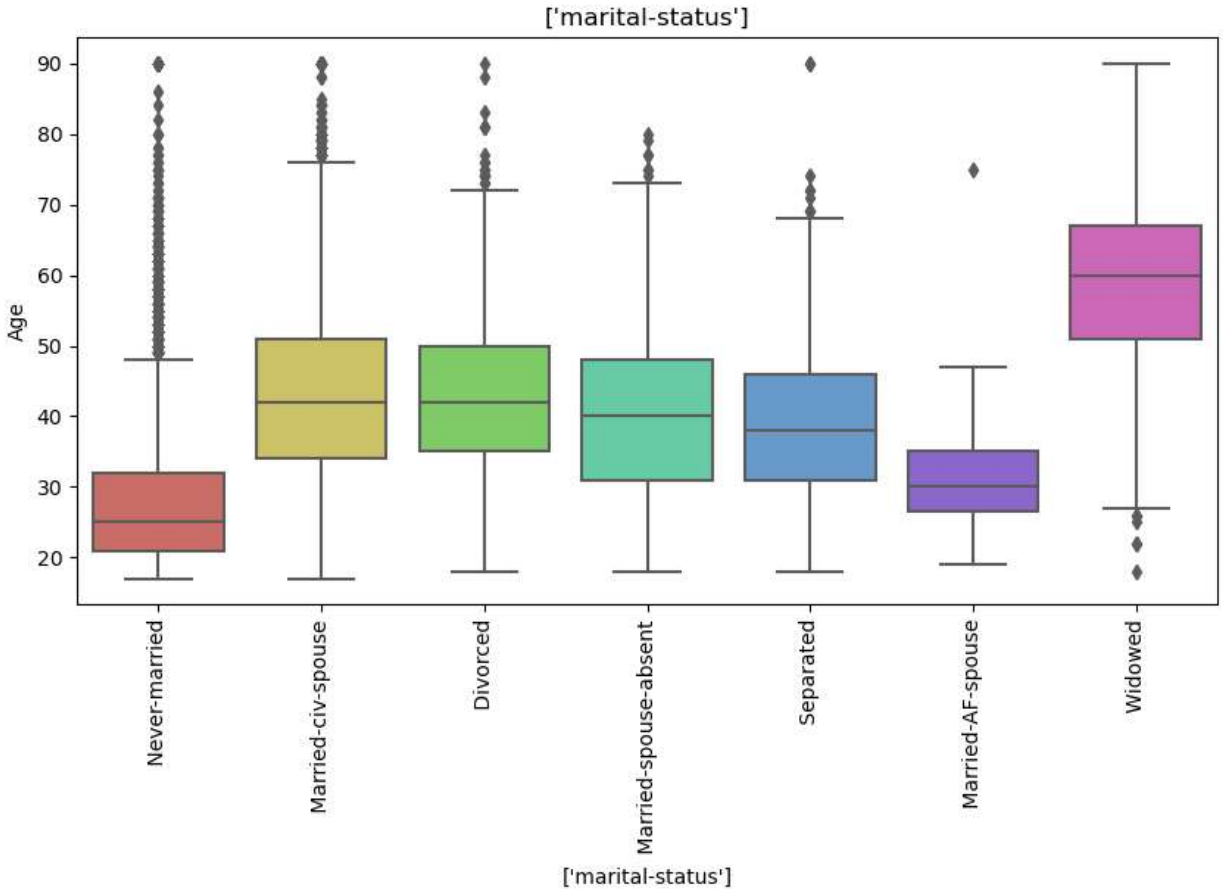

information about the relationship column with salary
salary
<=50K
>50K
Count of the values
7000
6000
5000
4000
3000
2000
1000
0
Not-in-family
Husband
Wife
Own-child
Unmarried
Other-relative
['relationship']

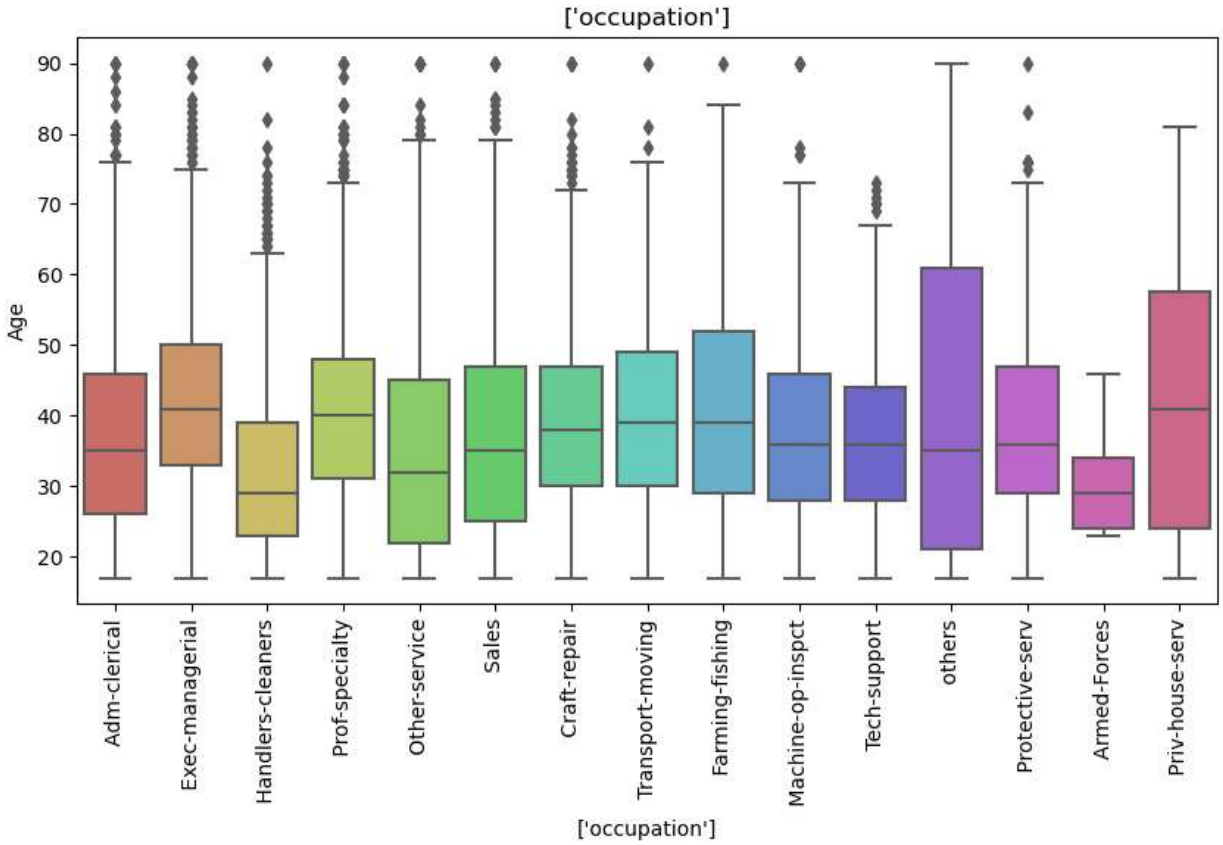


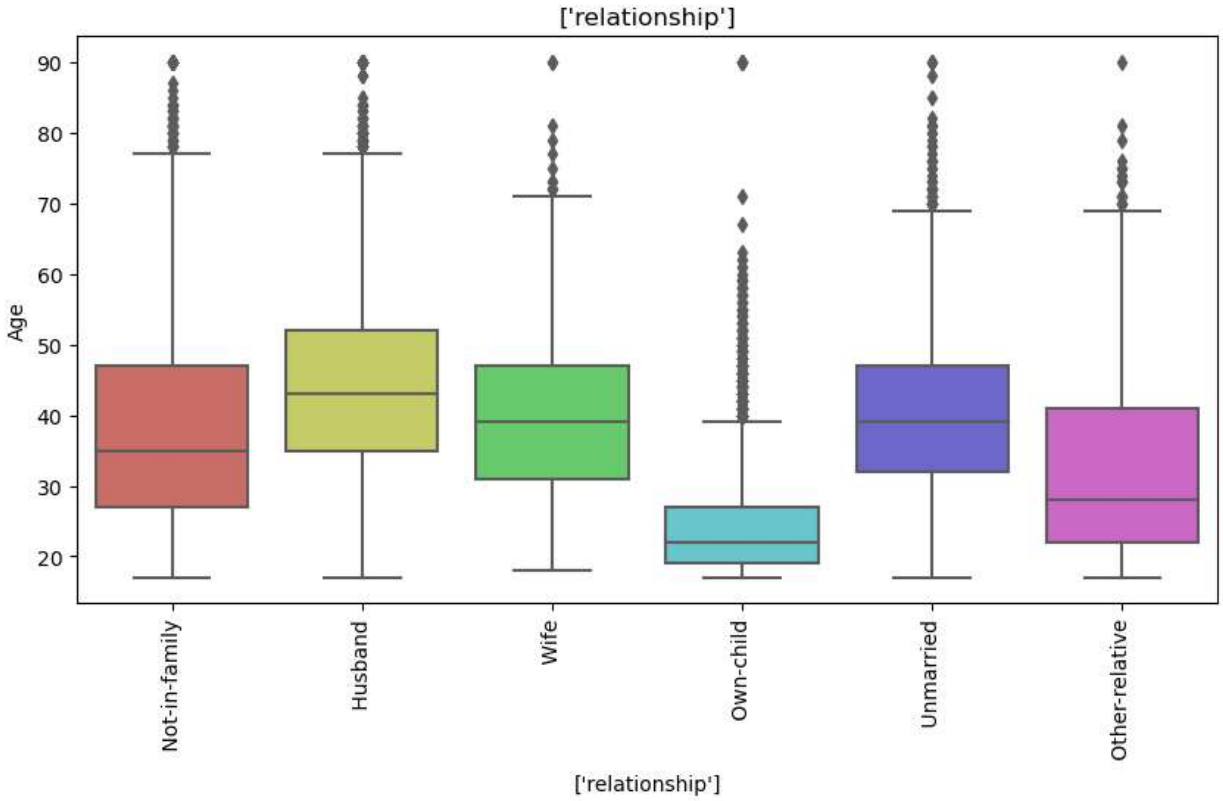
In [23]:
```
# Create a boxplot for numerical column with age
for i in ['workclass','education','marital-status','occupation','relationship','race']
    plt.figure(figsize=(10,5))
    sns.boxplot(data=data,x=data[i],y='age',palette='hls')
    plt.title([i])
    plt.xlabel([i])
    plt.xticks(rotation=90)
    plt.ylabel('Age')
    plt.show()
```

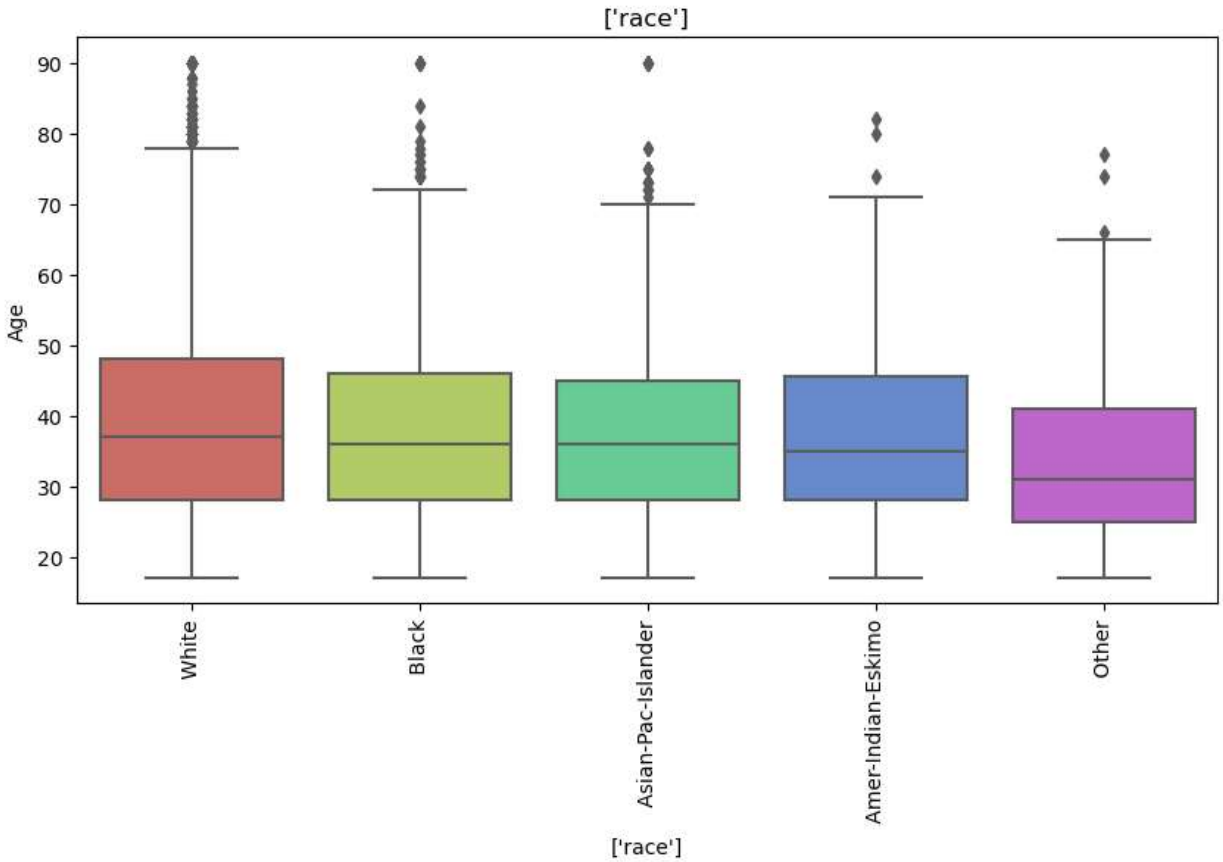

['workclass']
Age
90
80
70
60
50
40
30
20
State-gov
Self-emp-not-inc
Private
Federal-gov
Local-gov
others
Self-emp-inc
Without-pay
Never-worked
['workclass']


['education']
Age
90
80
70
60
50
40
30
20
Bachelors
HS-grad
11th
Masters
9th
Some-college
Assoc-acdm
Assoc-voc
7th-8th
Doctorate
Prof-school
5th-6th
10th
1st-4th
Preschool
12th
['education']


['marital-status']
Age
90
80
70
60
50
40
30
20
Never-married
Married-civ-spouse
Divorced
Married-spouse-absent
Separated
Married-AF-spouse
Widowed
['marital-status']

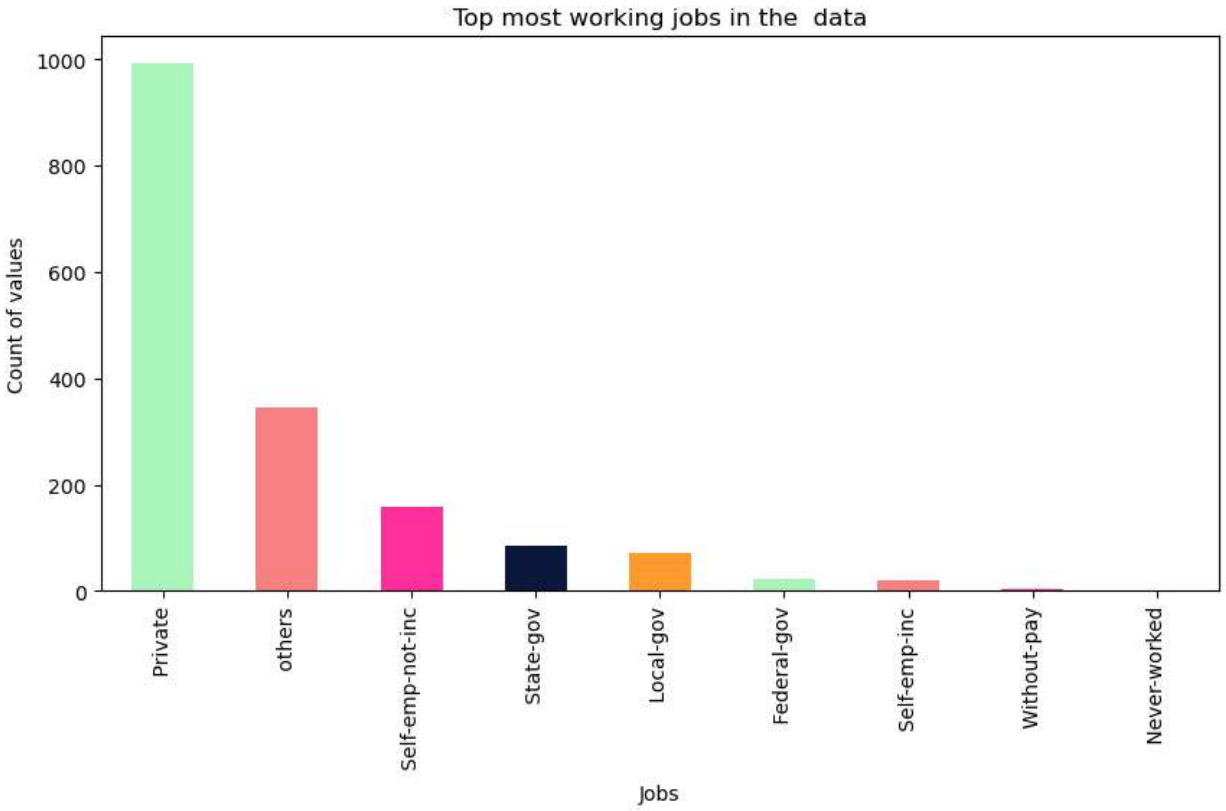

['occupation']
Age
90
80
70
60
50
40
30
20
Adm-clerical
Exec-managerial
Handlers-cleaners
Prof-specialty
Other-service
Sales
Craft-repair
Transport-moving
Farming-fishing
Machine-op-inspct
Tech-support
others
Protective-serv
Armed-Forces
Priv-house-serv
['occupation']





In [24]:
```
# Find the job between the range 20 to 40 hours with workclass
filterd_jobs=data[(data['hours-per-week']<20) & (data['hours-per-week']<=40)]
filterd_jobs['workclass'].value_counts().plot(kind='bar',figsize=(10,5),color=['#A9F5E
plt.title("Top most working jobs in the  data")
plt.xlabel("Jobs")
```

```
plt.ylabel("Count of values")
plt.show()
```



In [25]:
```
# using groupby condition find the some intresting facts
data.groupby('education')['salary'].value_counts()\
.unstack().style.background_gradient(cmap='gist_heat_r')
```

Out[25]:

salary	<=50K	>50K
education		
10th	871.000000	62.000000
11th	1115.000000	60.000000
12th	400.000000	33.000000
1st-4th	160.000000	6.000000
5th-6th	316.000000	16.000000
7th-8th	605.000000	40.000000
9th	487.000000	27.000000
Assoc-acdm	802.000000	265.000000
Assoc-voc	1021.000000	361.000000
Bachelors	3132.000000	2221.000000
Doctorate	107.000000	306.000000
HS-grad	8820.000000	1674.000000
Masters	763.000000	959.000000
Preschool	50.000000	nan
Prof-school	153.000000	423.000000
Some-college	5896.000000	1386.000000

In [26]:
```
# Create a pivot table
pivot_table=data.pivot_table(columns='workclass',index='education',values='hours-per-w
pivot_table.style.background_gradient(cmap='cividis_r')
```

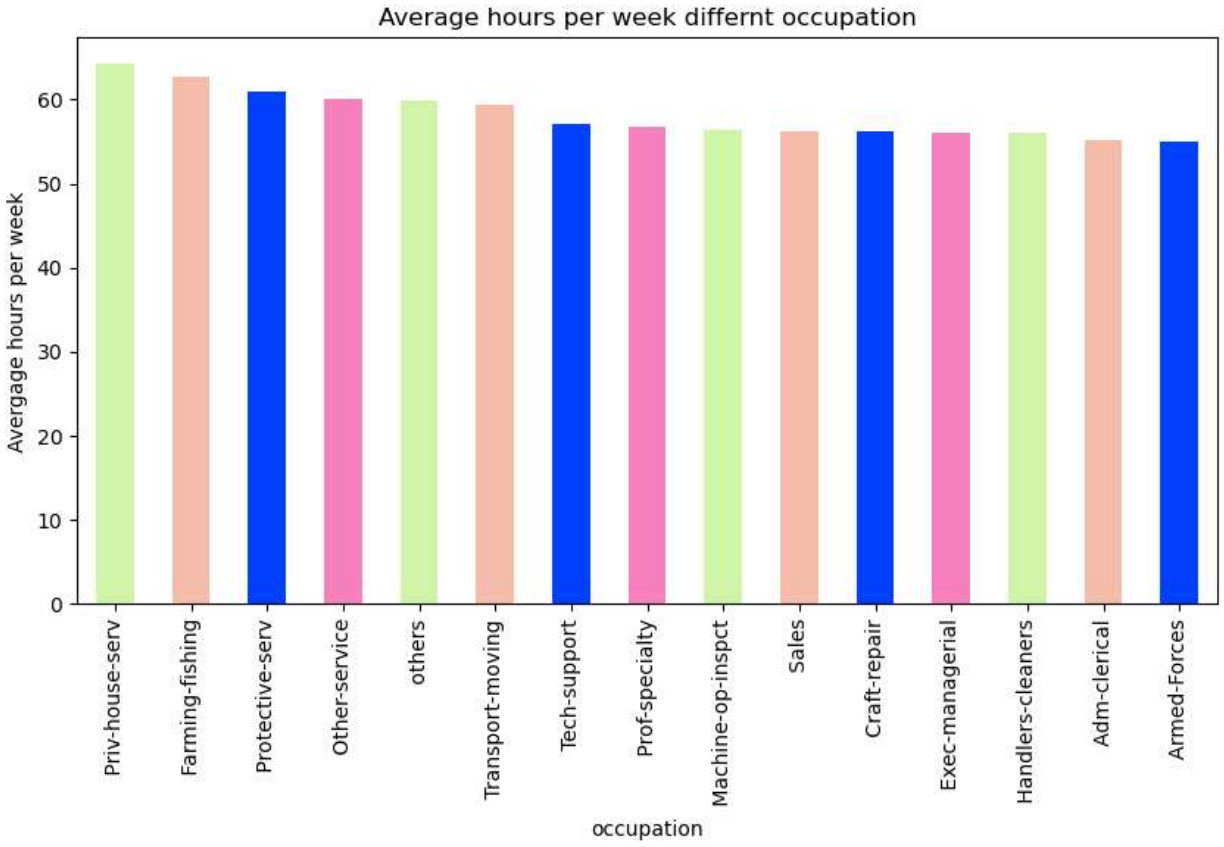
Out[26]:

workclass	Federal-gov	Local-gov	Never-worked	Private	Self-emp-inc	Self-emp-not-inc	Stat
education							
10th	253.000000	1185.000000	70.000000	25595.000000	729.000000	2915.000000	508.0
11th	247.000000	1100.000000	10.000000	31318.000000	550.000000	2429.000000	467.0
12th	175.000000	696.000000	nan	11702.000000	298.000000	851.000000	390.0
1st-4th	nan	132.000000	nan	5218.000000	80.000000	478.000000	20.0
5th-6th	40.000000	311.000000	nan	10449.000000	170.000000	686.000000	125.0
7th-8th	70.000000	1023.000000	35.000000	16882.000000	640.000000	4031.000000	318.0
9th	120.000000	853.000000	nan	14806.000000	469.000000	1417.000000	238.0
Assoc-acdm	2257.000000	3556.000000	nan	29795.000000	1677.000000	3139.000000	1511.0
Assoc-voc	1570.000000	3582.000000	nan	41432.000000	1898.000000	5067.000000	1890.0
Bachelors	9035.000000	20101.000000	nan	151538.000000	13487.000000	17627.000000	10717.0
Doctorate	803.000000	1177.000000	nan	8809.000000	1914.000000	2087.000000	4167.0
HS-grad	10580.000000	20067.000000	40.000000	314858.000000	13115.000000	39347.000000	10566.0
Masters	2858.000000	14989.000000	nan	39696.000000	4180.000000	5352.000000	6891.0
Preschool	nan	130.000000	nan	1495.000000	nan	nan	24.0
Prof-school	1447.000000	1316.000000	nan	12362.000000	4118.000000	6009.000000	1554.0
Some-college	10269.000000	15559.000000	44.000000	197110.000000	11156.000000	21401.000000	11277.0

In [27]:
```
# Some intresting questions asked from the data
print('The most demanding education is',data['education'].value_counts().idxmax())
print('\n the least demanding  education is',data['education'].value_counts().idxmin()
print('\n The highest working hours in the data is',data['hours-per-week'].value_count
print('\n The less working hours in the data is',data['hours-per-week'].value_counts()
print('\n Most dominate race is',data['race'].value_counts().idxmax())
print('\n Less dominate race is ',data['race'].value_counts().idxmin())
print('\n Most dominate occupation is',data['occupation'].value_counts().idxmax())
print('\n Less dominate race is',data['occupation'].value_counts().idxmin())
```

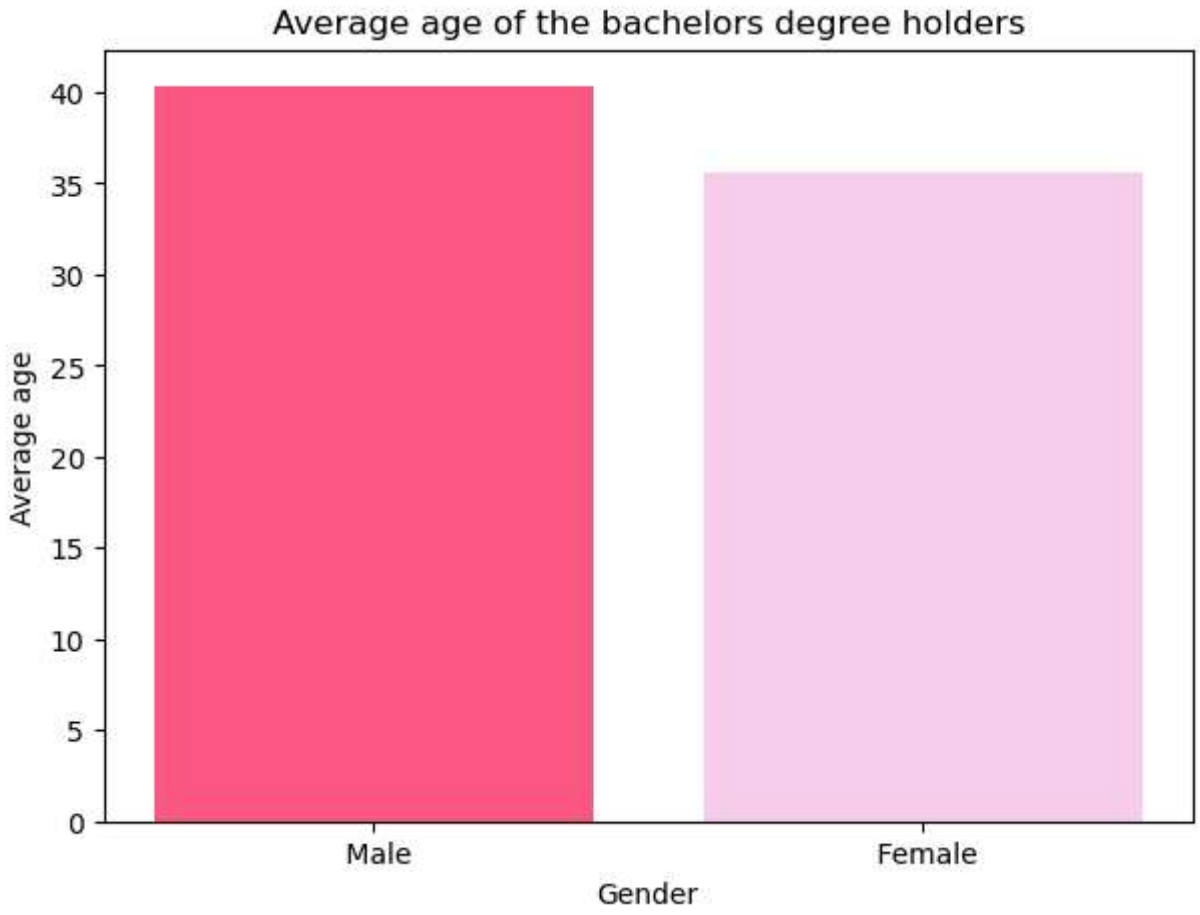
```
The most demanding education is  HS-grad

 the least demanding  education is  Preschool

 The highest working hours in the data is 40

 The less working hours in the data is 82

 Most dominate race is  White

 Less dominate race is   Other

 Most dominate occupation is  Prof-specialty

 Less dominate race is  Armed-Forces
```

In [28]:
```
# Find the average working hours with occupation where more then 50 hours
long_hours_jobs=data[(data['hours-per-week']>=50)]
long_hours_jobs.groupby('occupation')['hours-per-week'].mean().sort_values(ascending=F
.plot(kind='bar',figsize=(10,5),color=['#D0F5A9','#F5BCA9','#0040FF','#F781BE'])
plt.title("Average hours per week differnt occupation")
plt.xlabel("occupation")
plt.ylabel("Avergage hours per week")
plt.show()
```



In [29]:
```
# Find the average age of the bachelors degree holder
bachelors=data[(data['education']==' Bachelors')]
find_the_averge_age=bachelors.groupby('sex')['age'].mean().sort_values(ascending=False
plt.figure(figsize=(7,5))
plt.bar(find_the_averge_age.index,find_the_averge_age.values,color=['#FA5882','#F6CEEC
plt.title("Average age of the bachelors degree holders")
plt.xlabel('Gender')
```

```
plt.ylabel("Average age")
plt.show()
```



Observations:

- We observed that the majority of working hours per week fall within the 30 to 40 range.
- The pie chart illustrates a higher percentage of males in the dataset.
- The USA has the highest number of records in the dataset.
- A significant portion of employees earned a salary of less than 50k.
- Within the USA data, the most demanded degree is high school (hs-degree), which also corresponds to the highest working hours.
- The pie chart provides insights into various aspects of the output.
- Employees in the "private house service" sector work for more than 50 hours per week.
- Working hours for employees in private companies typically range between 20 to 40 hours.

Machine Learning Modeling

In [30]:
```
# Install the all Required libraries for the machine Learning Modeling
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder,StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
```

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from xgboost import XGBClassifier
from catboost import CatBoostClassifier
```

In [31]:
```
# Convert the all categories columns into numerical columns using the label encoding
for col in data.select_dtypes(include='object'):
    labelencoder=LabelEncoder()
    labelencoder.fit(data[col].unique())
    data[col]=labelencoder.transform(data[col])
```

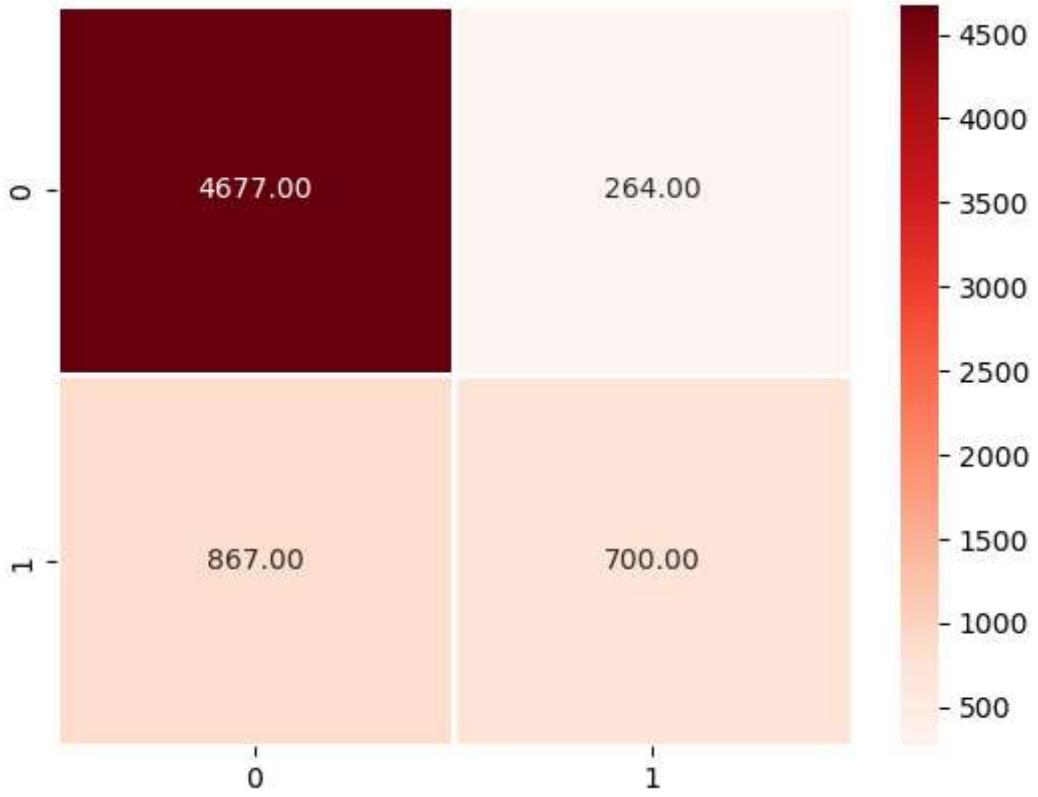
In [32]:
```
# Split the data into independent and dependent variable
X=data.drop(['salary'],axis=1)
y=data['salary']
# Normalization the data using the Standard Scaler
standard=StandardScaler()
X=standard.fit_transform(X)
# Split the data into train and test data
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.20,random_state=220)
```

In [33]:
```
# Create a function for machine learning modeling
def machine_learning_model(model,X_train,X_test,y_train,y_test):
    '''
    In the function we write about the code for machine learning model
    Firstly we fit the train data to the model
    and predict the values with test data and store the values with variable
    and then print the accuracy score along with classification and confusion matrix

    '''
    print(f'The {model} ')
    model.fit(X_train,y_train)
    y_pred=model.predict(X_test)
    model_score=accuracy_score(y_test,y_pred)
    print(f'\nThe accuracy score of the {model} is {model_score*100 :.2f}')
    print(f'\n {classification_report(y_test,y_pred)}')
    print(f'\n{confusion_matrix(y_test,y_pred)}')
    matrix=confusion_matrix(y_test,y_pred)
    sns.heatmap(matrix,annot=True,cmap='Reds',fmt='.2f',linewidths=1)
    plt.show()
    print('-'*30)
```

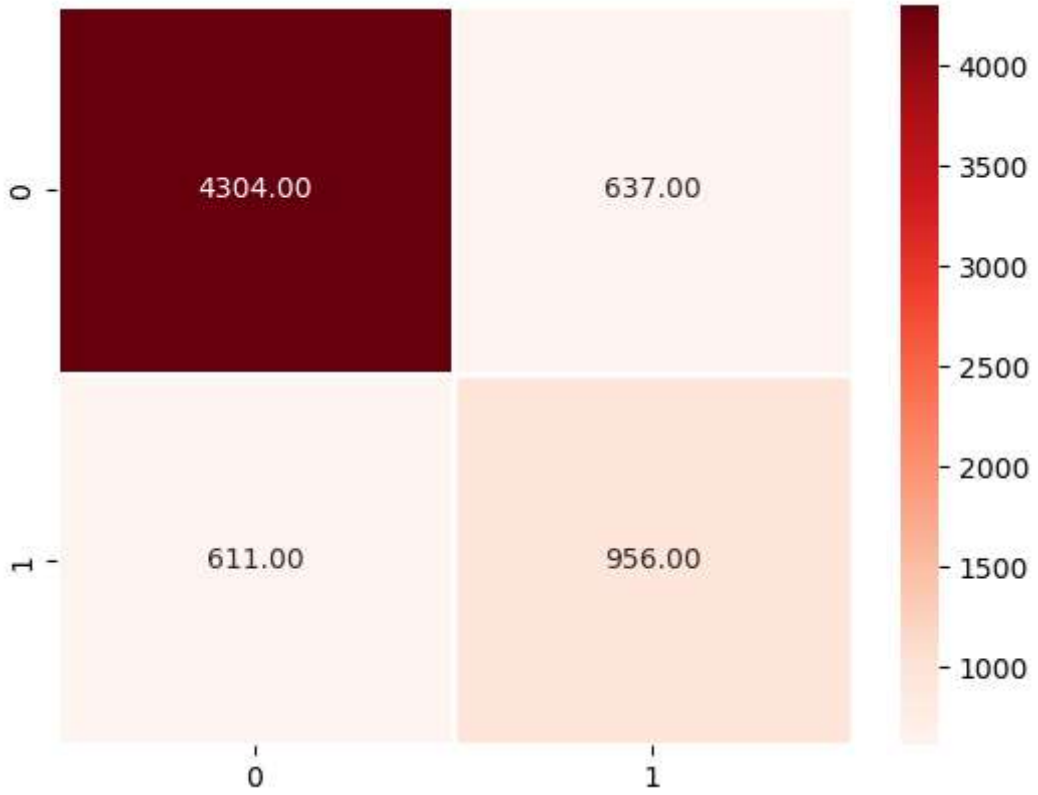
In [34]:
```
models={
    'logistic':LogisticRegression(penalty='l2'),
    'decison':DecisionTreeClassifier(criterion='gini',splitter='best',),
    'Random':RandomForestClassifier(n_estimators=50,criterion='gini'),
    'Knn':KNeighborsClassifier(),
    'xgb':XGBClassifier(),
    'catboost':CatBoostClassifier(iterations=1)
}
```

In [35]:
```
for i in range(len(models)):
    model_names=list(models.values())[i]
    names=list(models.keys())[i]
# And apply the machine learning function to the models
    machine_learning_model(model_names,X_train,X_test,y_train,y_test)
```

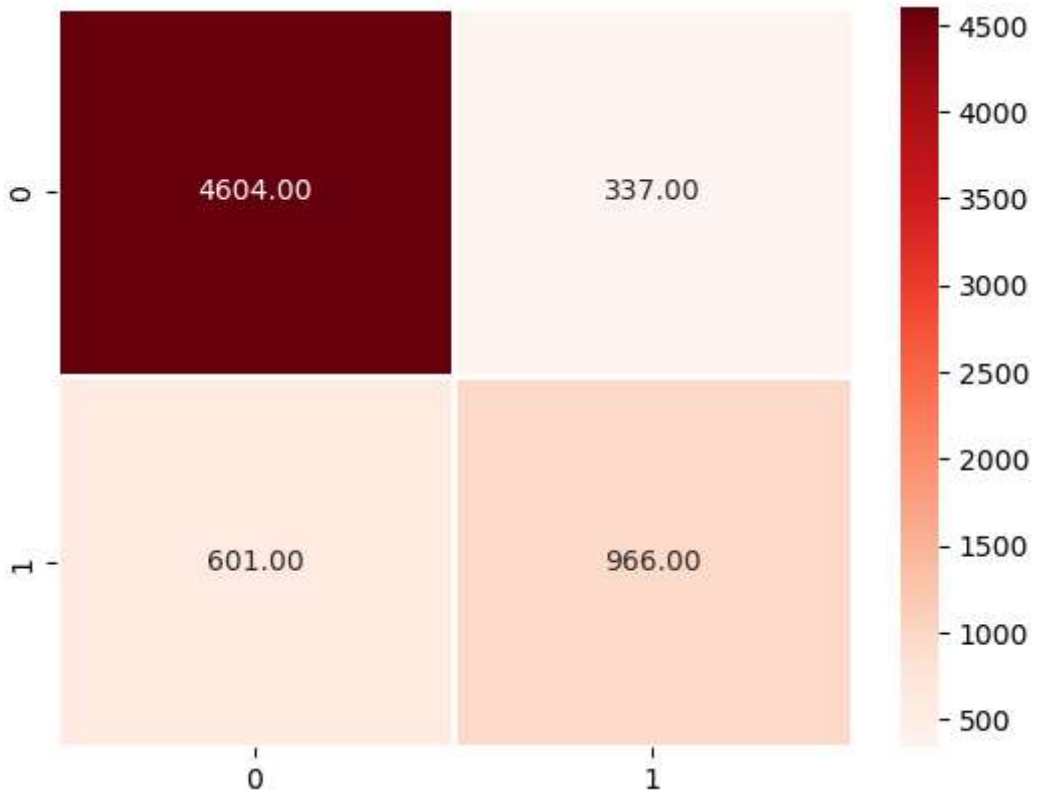
```
The LogisticRegression()

The accuracy score of the LogisticRegression() is 82.62

              precision    recall  f1-score   support

           0       0.84      0.95      0.89      4941
           1       0.73      0.45      0.55      1567

    accuracy                           0.83      6508
   macro avg       0.78      0.70      0.72      6508
weighted avg       0.82      0.83      0.81      6508


[[4677  264]
 [ 867  700]]
```



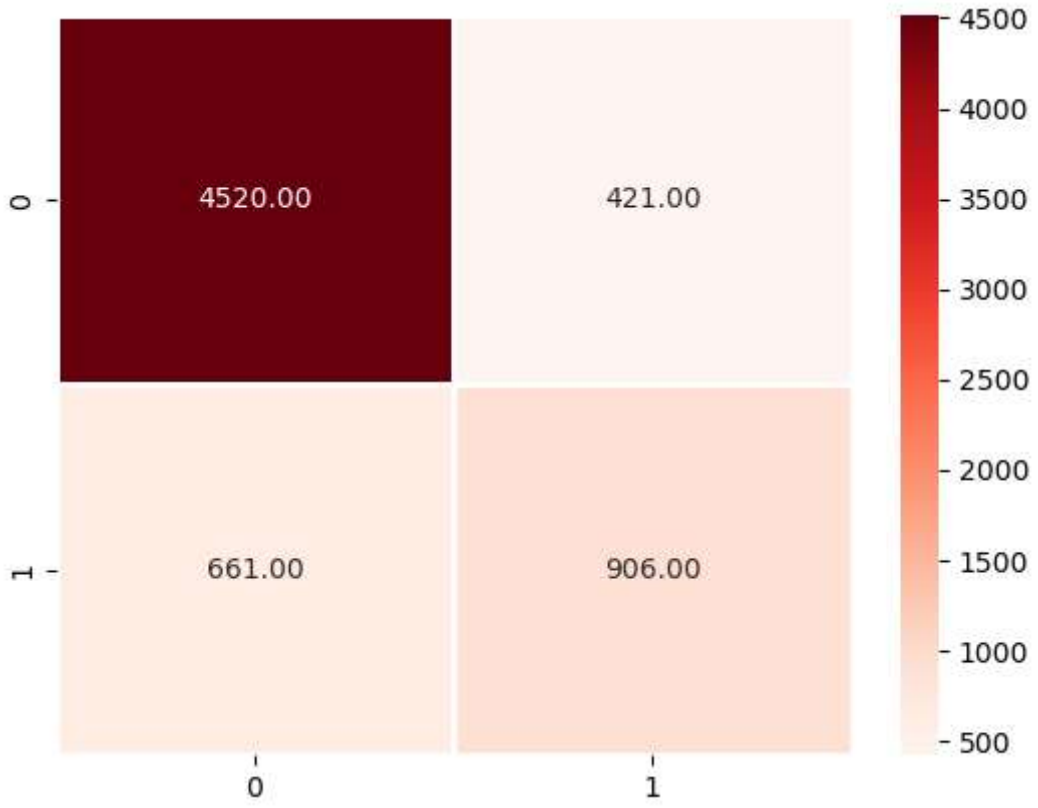

```
------------------------------
The DecisionTreeClassifier()

The accuracy score of the DecisionTreeClassifier() is 80.82

              precision    recall  f1-score   support

           0       0.88      0.87      0.87      4941
           1       0.60      0.61      0.61      1567

    accuracy                           0.81      6508
   macro avg       0.74      0.74      0.74      6508
weighted avg       0.81      0.81      0.81      6508


[[4304  637]
 [ 611  956]]
```



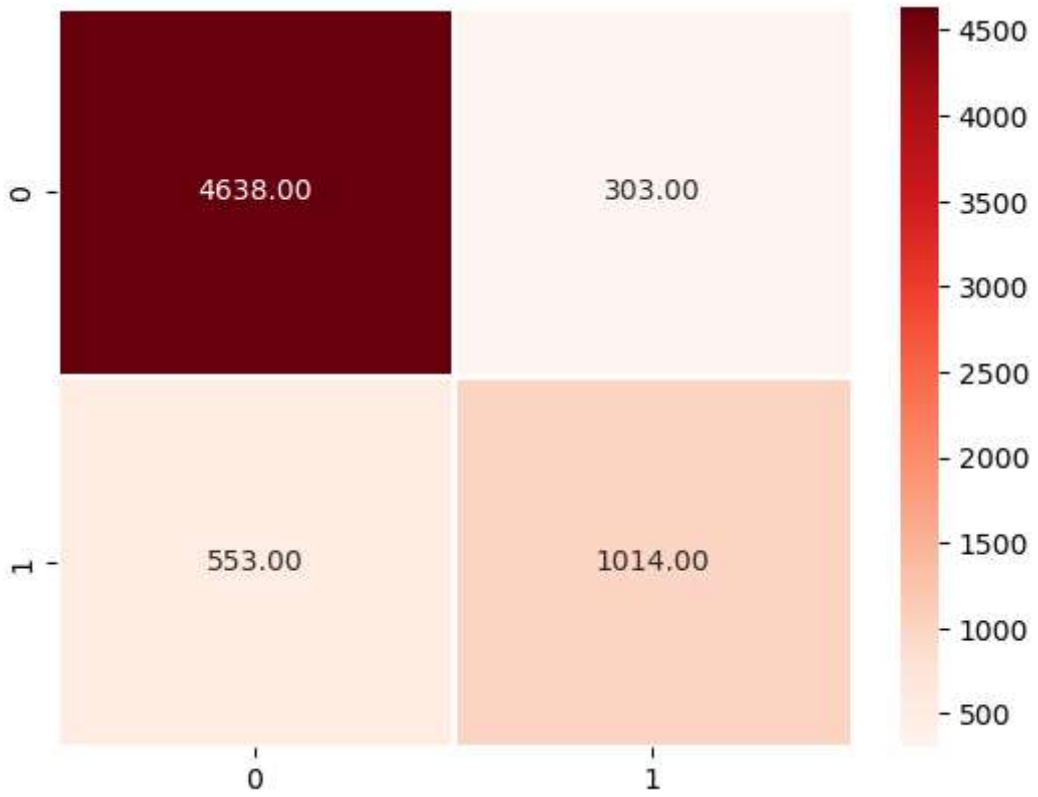

```
------------------------------
The RandomForestClassifier(n_estimators=50)

The accuracy score of the RandomForestClassifier(n_estimators=50) is 85.59

              precision    recall  f1-score   support

           0       0.88      0.93      0.91      4941
           1       0.74      0.62      0.67      1567

    accuracy                           0.86      6508
   macro avg       0.81      0.77      0.79      6508
weighted avg       0.85      0.86      0.85      6508


[[4604  337]
 [ 601  966]]
```



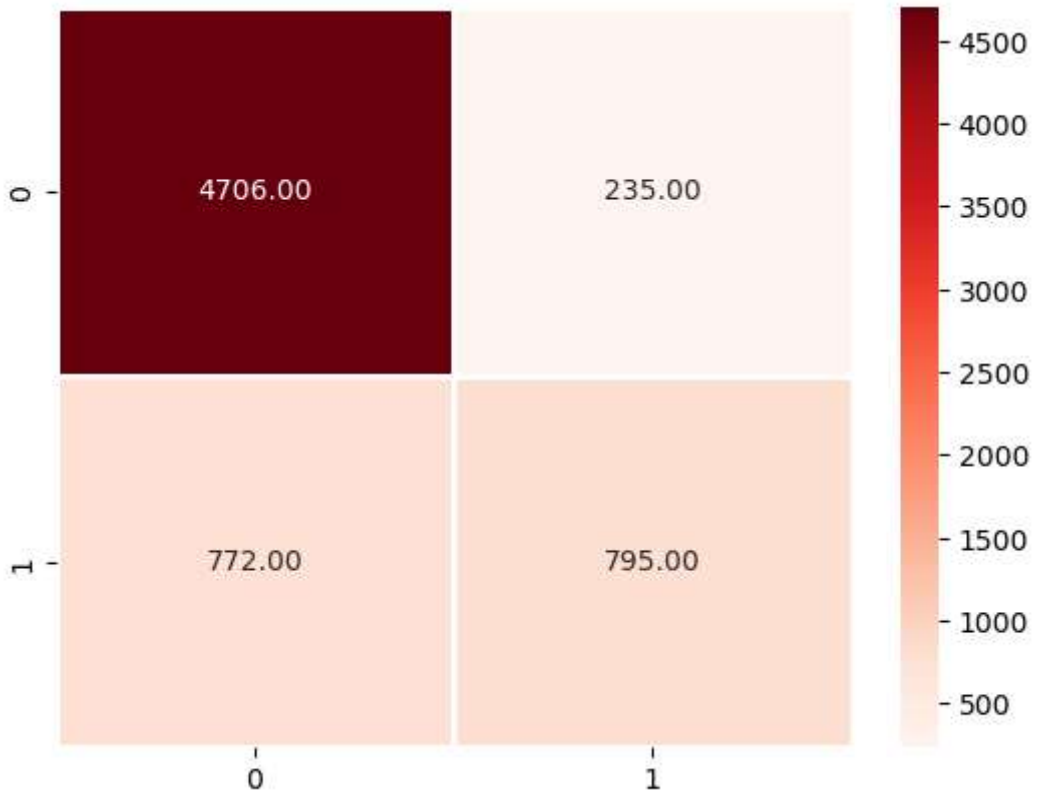

```
------------------------------
The KNeighborsClassifier()

The accuracy score of the KNeighborsClassifier() is 83.37

              precision    recall  f1-score   support

           0       0.87      0.91      0.89      4941
           1       0.68      0.58      0.63      1567

    accuracy                           0.83      6508
   macro avg       0.78      0.75      0.76      6508
weighted avg       0.83      0.83      0.83      6508


[[4520  421]
 [ 661  906]]
```


4520.00
421.00
661.00
906.00
0
1
0
1
4500
4000
3500
3000
2500
2000
1500
1000
500

```
------------------------------
The XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, ...)

The accuracy score of the XGBClassifier(base_score=None, booster=None, callbacks=Non
e,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, ...) is 86.85

              precision    recall  f1-score   support

           0       0.89      0.94      0.92      4941
           1       0.77      0.65      0.70      1567

    accuracy                           0.87      6508
   macro avg       0.83      0.79      0.81      6508
weighted avg       0.86      0.87      0.86      6508


[[4638  303]
 [ 553 1014]]
```

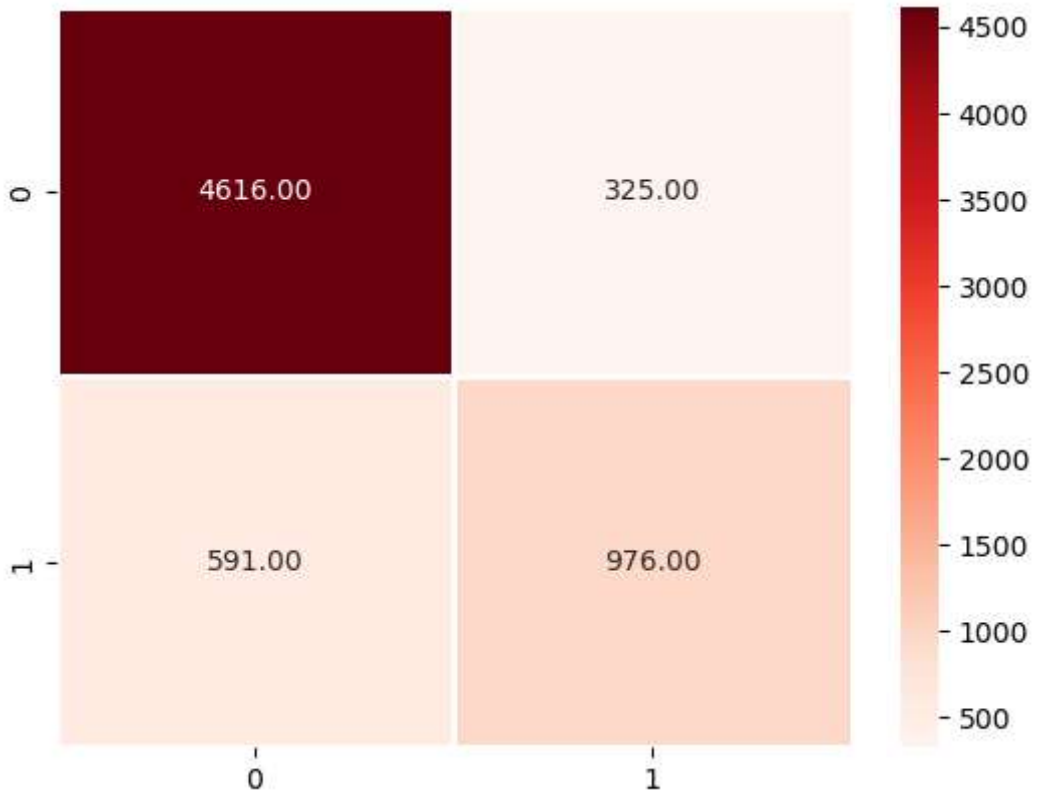



```
------------------------------
The <catboost.core.CatBoostClassifier object at 0x000001D5832C2E90>
Learning rate set to 0.5
0:      learn: 0.4868985        total: 165ms    remaining: 0us

The accuracy score of the <catboost.core.CatBoostClassifier object at 0x000001D5832C2
E90> is 84.53

              precision    recall  f1-score   support

           0       0.86      0.95      0.90      4941
           1       0.77      0.51      0.61      1567

    accuracy                           0.85      6508
   macro avg       0.82      0.73      0.76      6508
weighted avg       0.84      0.85      0.83      6508


[[4706  235]
 [ 772  795]]
```



In [36]:
```
Random=RandomForestClassifier()
machine_learning_model(Random,X_train,X_test,y_train,y_test)
```

```
The RandomForestClassifier()

The accuracy score of the RandomForestClassifier() is 85.93

              precision    recall  f1-score   support

           0       0.89      0.93      0.91      4941
           1       0.75      0.62      0.68      1567

    accuracy                           0.86      6508
   macro avg       0.82      0.78      0.80      6508
weighted avg       0.85      0.86      0.85      6508


[[4616  325]
 [ 591  976]]
```



In [37]:
```
# Let's dump the model
import pickle
# Let's dump the mode
pickle.dump(Random,open('RandomForest.pkl','wb'))
```

In [ ]:
```

```