In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, GradientBo
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
%matplotlib inline
```

Labelling Data

In [2]:

```
train = pd.read_csv('adult_data.csv',names =["age","work_class","fnlwgt","education
                                             "education_num","marital-status","occu
                                             "relationship","race","sex","capital_g
                                             "hours_per_week","native_country","inc
)
```

In [3]:

```
test = pd.read_csv('adult_data.csv',names =["age","work_class","fnlwgt","education"
,"education_num","marital-status","occupation","relationship","race","sex","capital
)
```

In [4]:

```
train.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   work_class      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  income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

Data Pre-Processing

Checking for Null Values

In [5]:

```
train.isnull().sum()
```

Out[5]:

```
age               0
work_class        0
fnlwgt            0
education         0
education_num     0
marital-status    0
occupation        0
relationship      0
race              0
sex               0
capital_gain      0
capital_loss      0
hours_per_week    0
native_country    0
income            0
dtype: int64
```

In [6]:

```
print(train.shape)
```

(32561, 15)

In [7]:

```
train.head()
```

Out[7]:

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

In [8]:

```
train.describe()
```

Out[8]:

	age	fnlwgt	education_num	capital_gain	capital_loss	hours_per_wee
count	32561.000000	3.256100e+04	32561.000000	32561.000000	32561.000000	32561.00000
mean	38.581647	1.897784e+05	10.080679	1077.648844	87.303830	40.43745
std	13.640433	1.055500e+05	2.572720	7385.292085	402.960219	12.34742
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1.00000
25%	28.000000	1.178270e+05	9.000000	0.000000	0.000000	40.00000
50%	37.000000	1.783560e+05	10.000000	0.000000	0.000000	40.00000
75%	48.000000	2.370510e+05	12.000000	0.000000	0.000000	45.00000
max	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000	99.00000

Checking for Special Characters

In [9]:

```
col_names = train.columns
num_data = train.shape[0]
for c in col_names:
    num_data = train[c].isin([" ?"]).sum()
    print(num_data)
    if num_data > 0:
        print (c)
        print (num_data)
        print ("{0:.2f}%".format(float(num_data) / num_data * 100))
        print ("\n")
```

```
0
1836
work_class
1836
100.00%


0
0
0
0
1843
occupation
1843
100.00%


0
0
0
0
0
0
583
native_country
583
100.00%


0
```

Removing Special Characters

In [10]:

```
train = train[train["work_class"] != " ?"]
train = train[train["occupation"] != " ?"]
train = train[train["native_country"] != " ?"]

train.shape
```

Out[10]:

```
(30162, 15)
```

Exploratory Data Analysis

Features description

- Age : Age of a person
- work class : type of employement
- Education : Qualification of employee
- Education_num : ID of the education course
- Martial_status : weather the employee is married or not or any other status
- Occupation : class of employement
- Relationship : relationship with employee
- Race : race of employee
- sex : gender of employee
- capital_gain : gain
- capital_loss : loss
- hours_per_week : working hours of employee per week
- native_country : origin of employee
- income : income class of employee

Countplot of categories

In [11]:

```
#sns.distplot(data.education.value_counts())
#sns.jointplot(x="education_num", y="age", data=data, kind="kde");
category_col =['work_class', 'race', 'education','marital-status', 'occupation',
               'relationship', 'sex', 'native_country', 'income']


fig, axs = plt.subplots(nrows=3, ncols=3, figsize=(45,25))
#fig.tight_layout()
[sns.countplot(y=feature, hue='income', data=train, order=train[feature].value_coun
#[axs.flatten()[idx].set_title(feature) for idx, feature in enumerate(to_count)]
plt.plot()
```

Out[11]:

```
[]
```

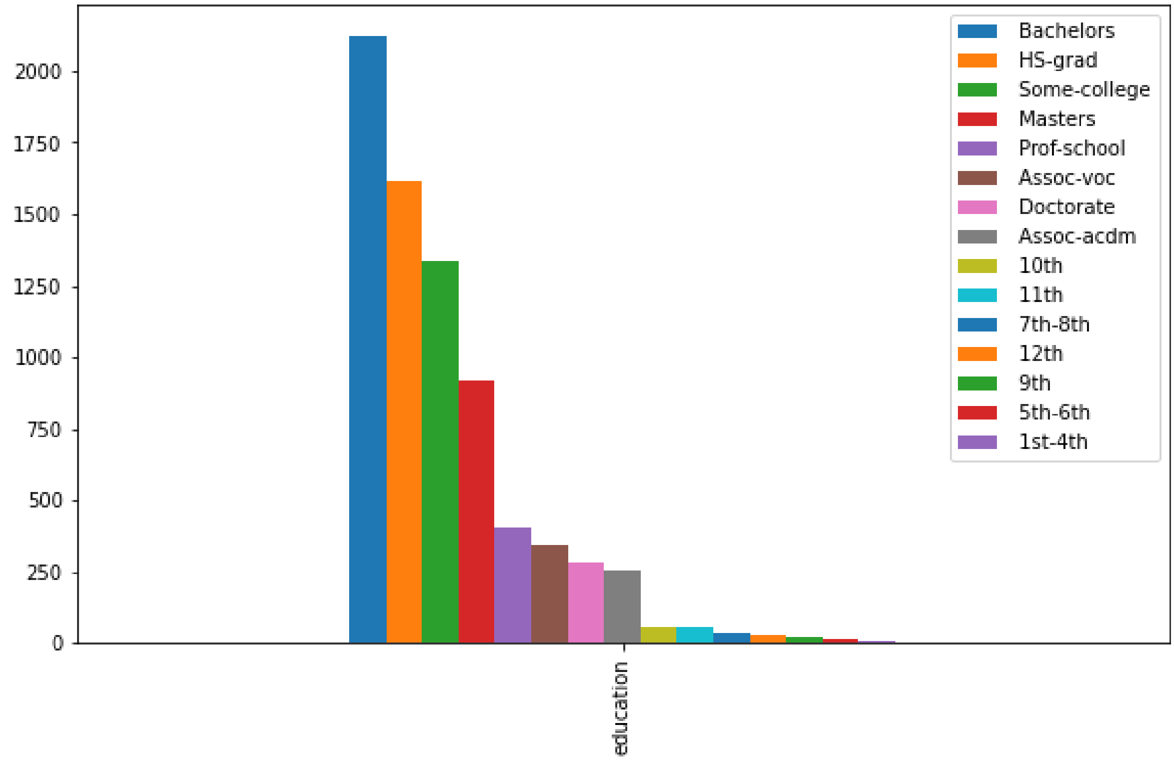
Income of the employee based on the qualification

In [12]:

```
c = train[train['income'] == ' >50K']['education'].value_counts()
df = pd.DataFrame([c])
df.plot(kind='bar',figsize=(10,6))
```

Out[12]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f32507ea2e8>
```



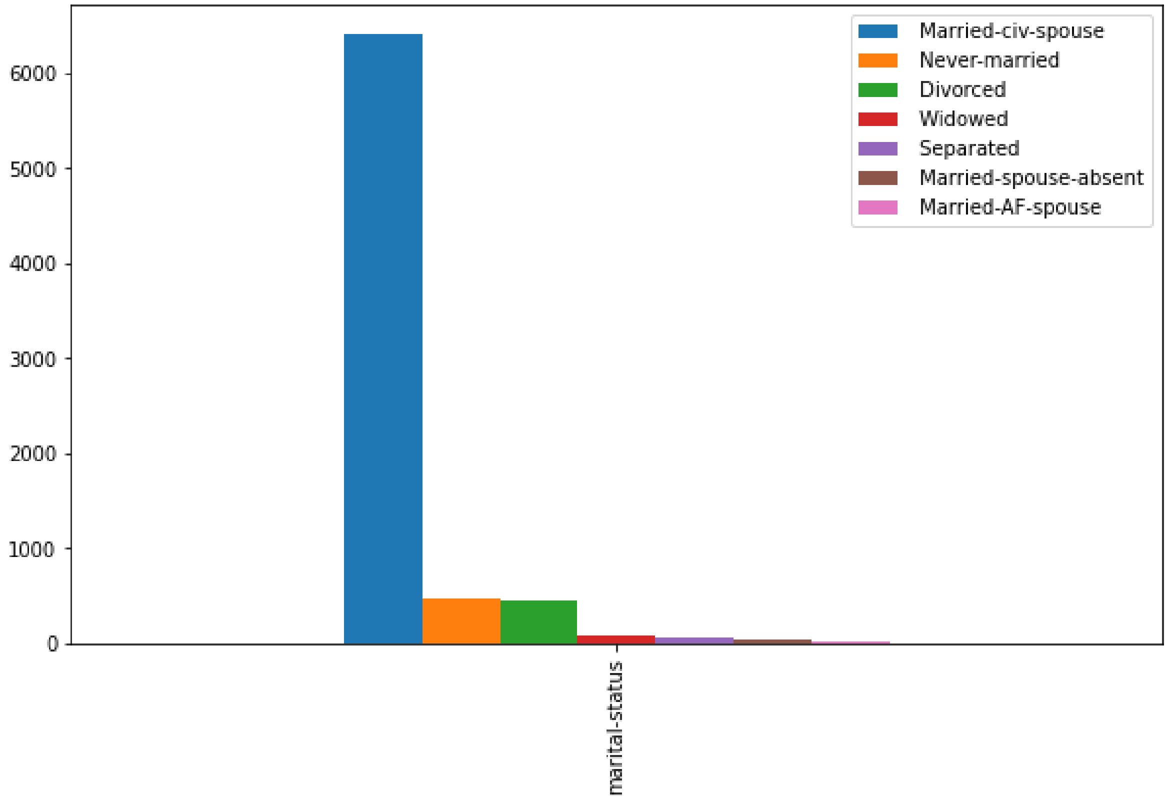
Income of the employee based on the marital status

In [13]:

```
c = train[train['income'] == ' >50K']['marital-status'].value_counts()
df = pd.DataFrame([c])
df.plot(kind='bar',figsize=(10,6))
```

Out[13]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f324f78db00>
```



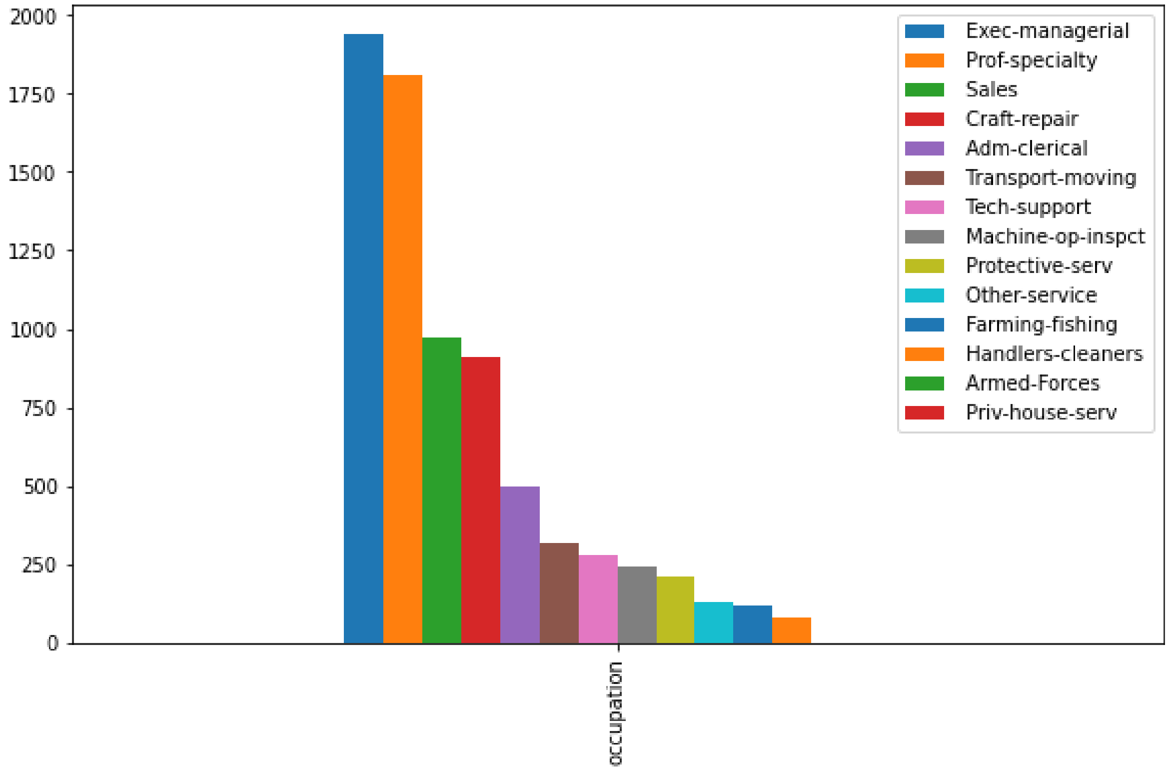
Income of the employee based on the occupation

In [14]:

```
c = train[train['income'] == ' >50K']['occupation'].value_counts()
df = pd.DataFrame([c])
df.plot(kind='bar',figsize=(10,6))
```

Out[14]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f324f70dc50>
```



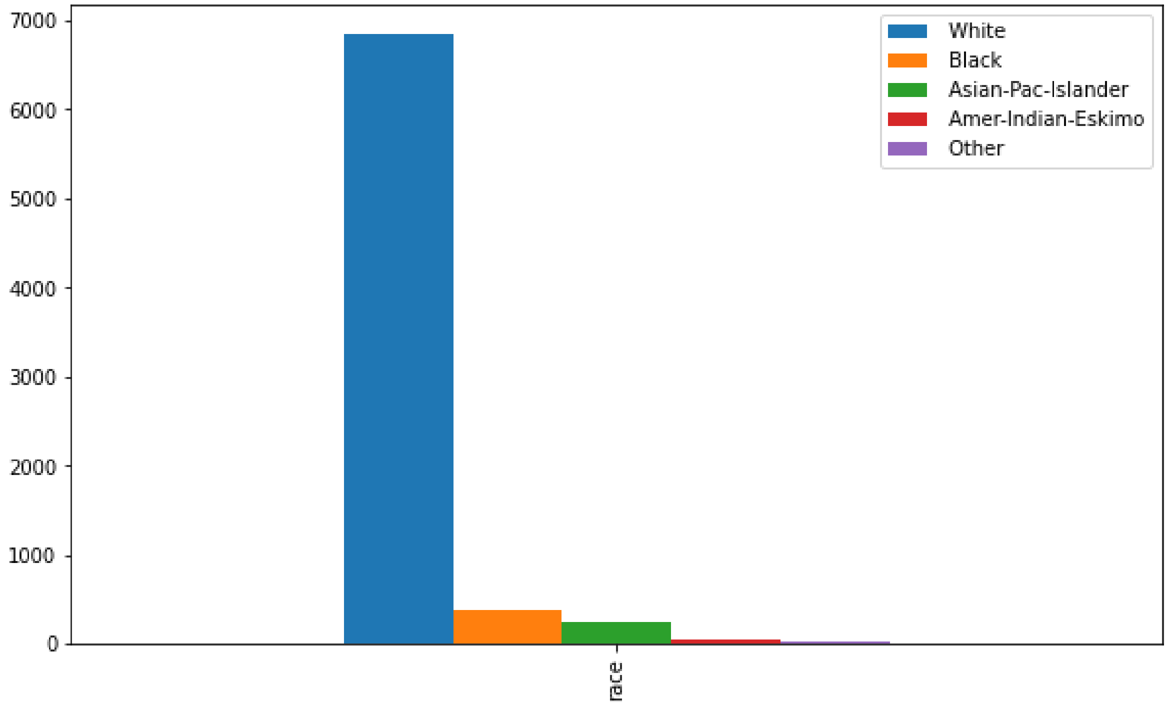
Income of the employee based on the race

In [15]:

```
c = train[train['income'] == ' >50K']['race'].value_counts()
df = pd.DataFrame([c])
df.plot(kind='bar',figsize=(10,6))
```

Out[15]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f324ea2ad30>
```



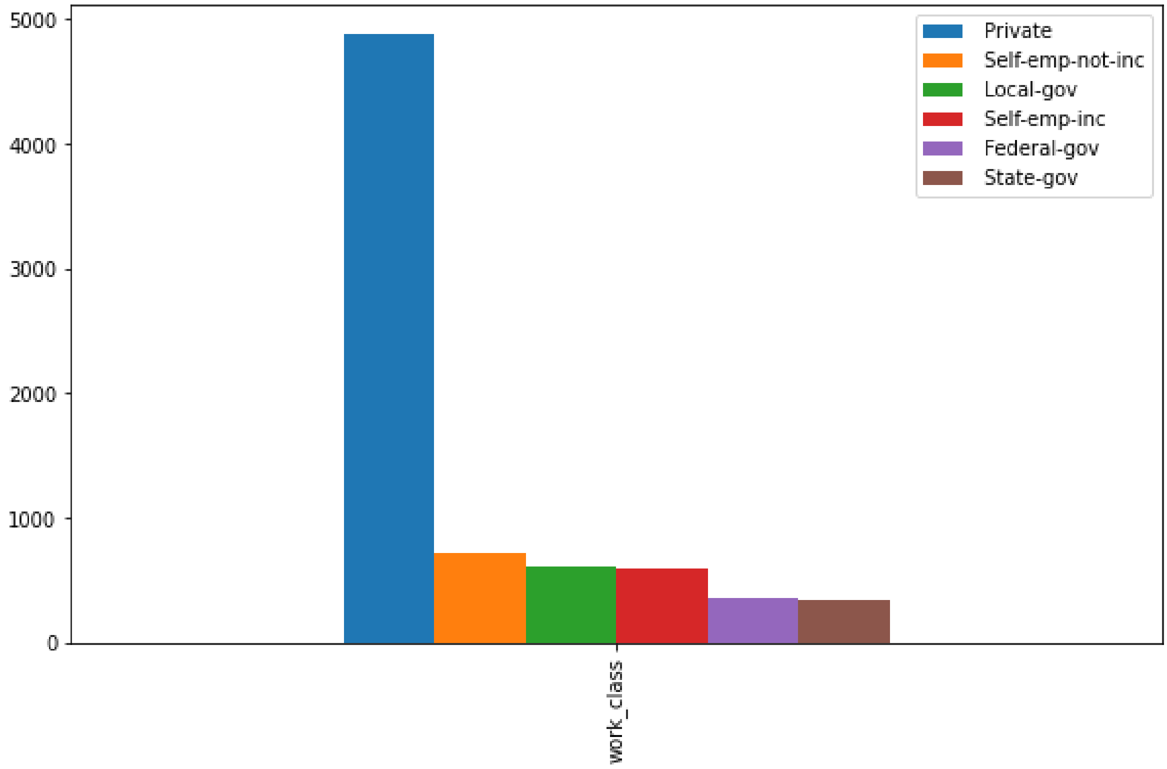
Income of the employee based on the work class

In [16]:

```
c = train[train['income'] == ' >50K']['work_class'].value_counts()
df = pd.DataFrame([c])
df.plot(kind='bar',figsize=(10,6))
```

Out[16]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f324f5b5b70>
```



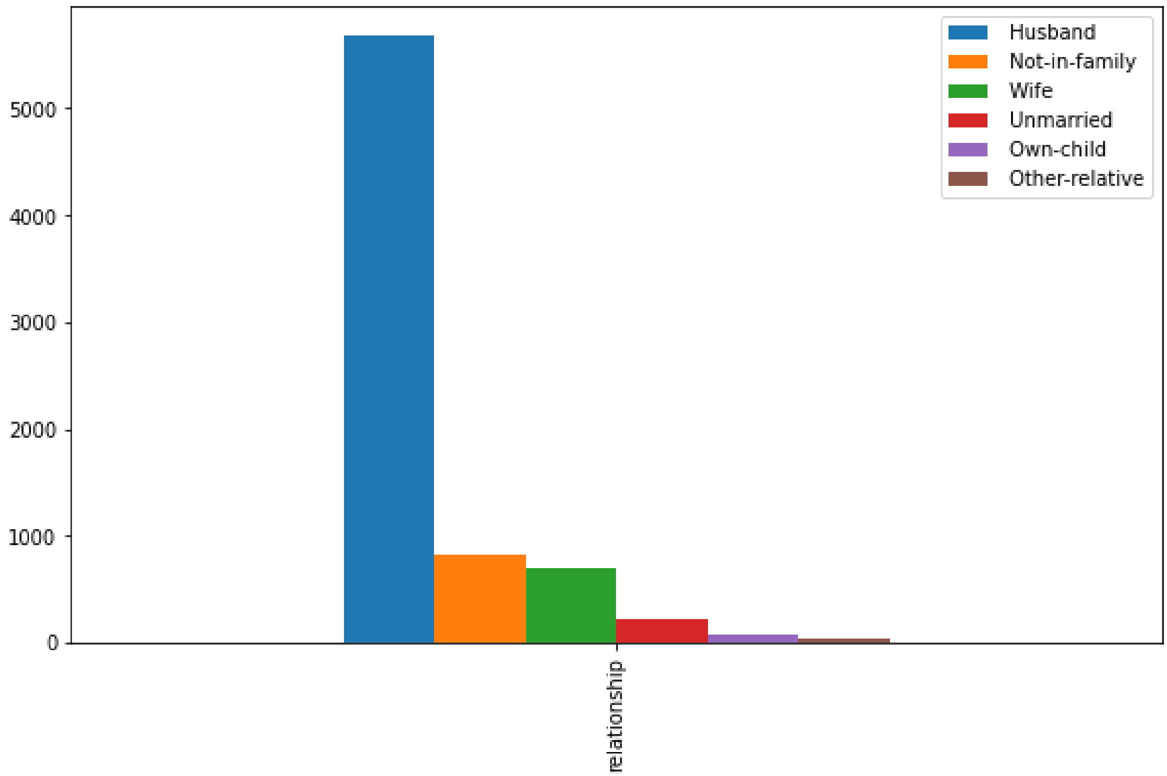
Income of the employee based on the relationship

In [17]:

```
c = train[train['income'] == ' >50K']['relationship'].value_counts()
df = pd.DataFrame([c])
df.plot(kind='bar',figsize=(10,6))
```

Out[17]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f324f52e748>
```



In [18]:

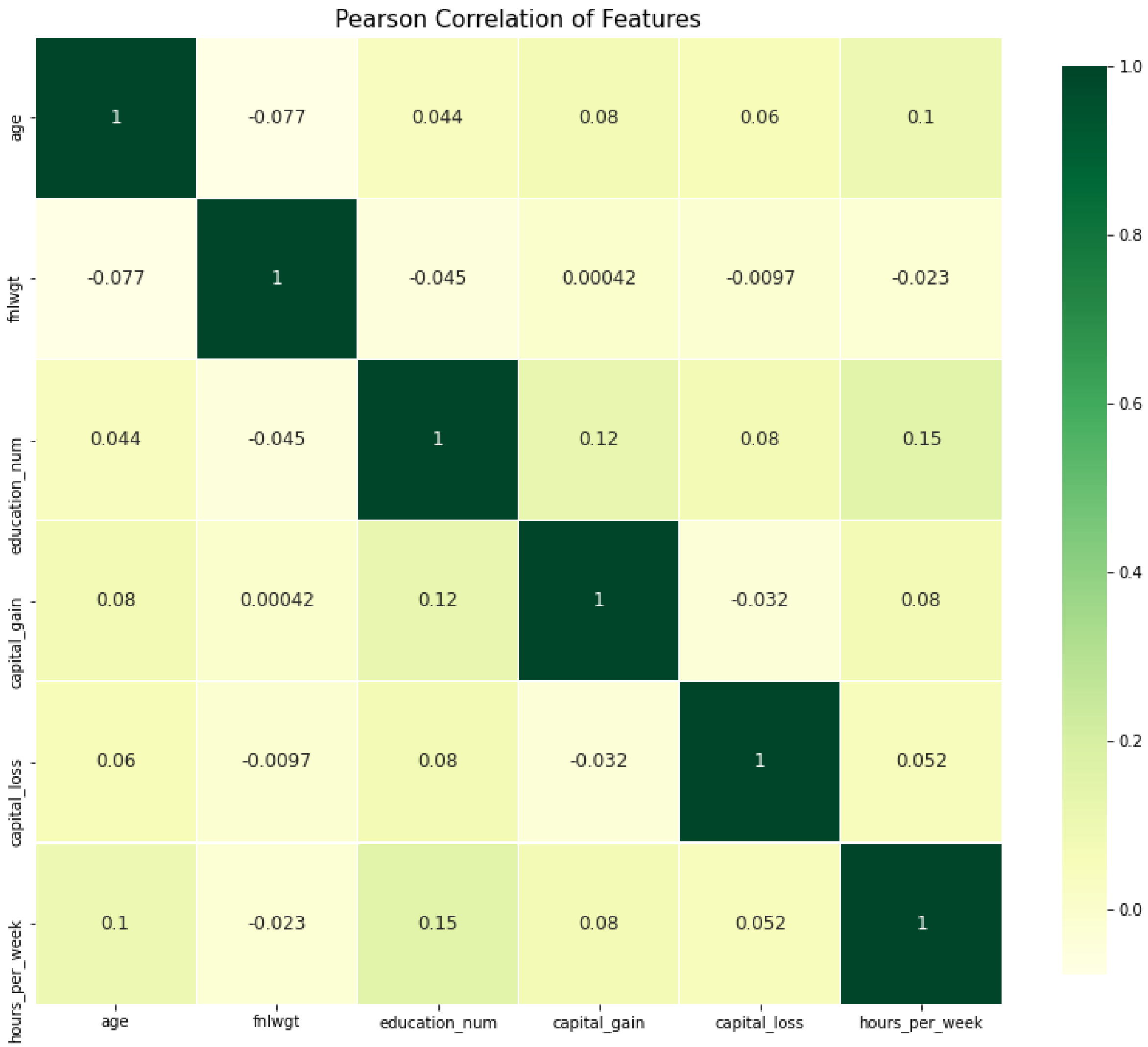
```
#correlation heatmap of dataset

#took this code sample from another kernel on this site
def correlation_heatmap(df):
    _ , ax = plt.subplots(figsize =(14, 12))
    colormap = sns.diverging_palette(220, 10, as_cmap = True)

    _ = sns.heatmap(
        df.corr(),
        cmap = "YlGn",
        square=True,
        cbar_kws={'shrink':.9 },
        ax=ax,
        annot=True,
        linewidths=0.1,vmax=1.0, linecolor='white',
        annot_kws={'fontsize':12 }
    )

    plt.title('Pearson Correlation of Features', y=1.05, size=15)

correlation_heatmap(train)
```



Label Encoding

In [19]:

```
enc=LabelEncoder()
train['race']=enc.fit_transform(train['race'])
train['sex']=enc.fit_transform(train['sex'])
train['relationship']=enc.fit_transform(train['relationship'])
train['occupation']=enc.fit_transform(train['occupation'])
train['marital-status']=enc.fit_transform(train['marital-status'])
train['native_country']=enc.fit_transform(train['native_country'])
train['income']=enc.fit_transform(train['income'])
train['work_class']=enc.fit_transform(train['work_class'])
```

Feature Selection

In [20]:

```
data = train.drop(['education', 'fnlwgt'], axis = 1)
```

In [21]:

```
data.head(10)
```

Out[21]:

	age	work_class	education_num	marital-status	occupation	relationship	race	sex	capital_gain
0	39	5	13	4	0	1	4	1	2174
1	50	4	13	2	3	0	4	1	0
2	38	2	9	0	5	1	4	1	0
3	53	2	7	2	5	0	2	1	0
4	28	2	13	2	9	5	2	0	0
5	37	2	14	2	3	5	4	0	0
6	49	2	5	3	7	1	2	0	0
7	52	4	9	2	3	0	4	1	0
8	31	2	14	4	9	1	4	0	14084
9	42	2	13	2	3	0	4	1	5178

In [22]:

```
result = data.income
data.drop('income', 1, inplace=True)
```

In [23]:

```
train_x , test_x , train_y , test_y = train_test_split( data , result , train_size
```

K-Nearest Neighbours

In [24]:

```
knn = KNeighborsClassifier(n_neighbors = 3)
knn.fit(train_x, train_y)
predicted_knn = knn.predict(test_x)
acc_knn = (accuracy_score(test_y, predicted_knn)) * 100
acc_knn

print("Accuracy: %s%%" % (100*accuracy_score(test_y, predicted_knn)))
print(confusion_matrix(test_y, predicted_knn))
print(classification_report(test_y, predicted_knn))
```

```
Accuracy: 83.53409216488011%
[[6101  685]
 [ 805 1458]]
              precision    recall  f1-score   support

           0       0.88      0.90      0.89      6786
           1       0.68      0.64      0.66      2263

    accuracy                           0.84      9049
   macro avg       0.78      0.77      0.78      9049
weighted avg       0.83      0.84      0.83      9049
```

Random Forest

In [25]:

```
rf = RandomForestClassifier(n_estimators=100)
rf.fit(train_x, train_y)
predicted_rf = rf.predict(test_x)
acc_rf = (accuracy_score(test_y, predicted_rf)) * 100
acc_rf

print("Accuracy: %s%%" % (100*accuracy_score(test_y, predicted_rf)))
print(confusion_matrix(test_y, predicted_rf))
print(classification_report(test_y, predicted_rf))
```

```
Accuracy: 84.86020554757432%
[[6223  563]
 [ 807 1456]]
              precision    recall  f1-score   support

           0       0.89      0.92      0.90      6786
           1       0.72      0.64      0.68      2263

    accuracy                           0.85      9049
   macro avg       0.80      0.78      0.79      9049
weighted avg       0.84      0.85      0.85      9049
```

Decision Tree

In [26]:

```
def train_using_entropy(X_train, X_test, y_train):

    # Decision tree with entropy
    clf_entropy = DecisionTreeClassifier(
            criterion = "entropy", random_state = 100,
            max_depth = 3, min_samples_leaf = 5)

    # Performing training
    clf_entropy.fit(X_train, y_train)
    return clf_entropy
```

In [27]:

```
# Function to perform training with giniIndex.
def train_using_gini(X_train, X_test, y_train):

    # Creating the classifier object
    clf_gini = DecisionTreeClassifier(criterion = "gini",
            random_state = 100,max_depth=3, min_samples_leaf=5)

    # Performing training
    clf_gini.fit(X_train, y_train)
    return clf_gini
```

In [28]:

```
# Function to make predictions
def prediction(X_test, clf_object):

    # Predicton on test with giniIndex
    y_pred = clf_object.predict(X_test)
    return y_pred
```

In [29]:

```
# Function to calculate accuracy
def cal_accuracy(y_test, y_pred):


    print ("Accuracy : ",
        accuracy_score(y_test,y_pred)*100)

    print(confusion_matrix(y_test, y_pred))

    print(classification_report(y_test, y_pred))

    return accuracy_score(y_test,y_pred)*100
```

In [30]:

```
clf_entropy = train_using_entropy(train_x, test_x, train_y)
clf_gini = train_using_gini(train_x, test_x, train_y)
print("Results Using Gini Index:\n")
y_pred_gini = prediction(test_x, clf_gini)
acc_dt_gini = cal_accuracy(test_y, y_pred_gini)
print("Results Using Entropy:\n")
y_pred_entropy = prediction(test_x, clf_entropy)
acc_dt_entropy = cal_accuracy(test_y, y_pred_entropy)
```

```
Results Using Gini Index:

Accuracy :  83.84351862084209
[[6486  300]
 [1162 1101]]
              precision    recall  f1-score   support

           0       0.85      0.96      0.90      6786
           1       0.79      0.49      0.60      2263

    accuracy                           0.84      9049
   macro avg       0.82      0.72      0.75      9049
weighted avg       0.83      0.84      0.82      9049

Results Using Entropy:

Accuracy :  83.84351862084209
[[6486  300]
 [1162 1101]]
              precision    recall  f1-score   support

           0       0.85      0.96      0.90      6786
           1       0.79      0.49      0.60      2263

    accuracy                           0.84      9049
   macro avg       0.82      0.72      0.75      9049
weighted avg       0.83      0.84      0.82      9049
```

Support vector machine

In [31]:

```
svc = SVC()
svc.fit(train_x, train_y)
predicted_svc = svc.predict(test_x)
acc_svc = (accuracy_score(test_y, predicted_svc)) * 100
acc_svc

print("Accuracy: %s%%" % (100*accuracy_score(test_y, predicted_svc)))
print(confusion_matrix(test_y, predicted_svc))
print(classification_report(test_y, predicted_svc))
```

```
Accuracy: 79.76571996905736%
[[6580  206]
 [1625  638]]
              precision    recall  f1-score   support

           0       0.80      0.97      0.88      6786
           1       0.76      0.28      0.41      2263

    accuracy                           0.80      9049
   macro avg       0.78      0.63      0.64      9049
weighted avg       0.79      0.80      0.76      9049
```

Gradient Boosting

In [32]:

```
gbc = GradientBoostingClassifier()
gbc.fit(train_x, train_y)
predicted_gbc = gbc.predict(test_x)
acc_gbc = (accuracy_score(test_y, predicted_gbc)) * 100
acc_gbc

print("Accuracy: %s%%" % (100*accuracy_score(test_y, predicted_gbc)))
print(confusion_matrix(test_y, predicted_gbc))
print(classification_report(test_y, predicted_gbc))
```

```
Accuracy: 86.16421704055696%
[[6398  388]
 [ 864 1399]]
              precision    recall  f1-score   support

           0       0.88      0.94      0.91      6786
           1       0.78      0.62      0.69      2263

    accuracy                           0.86      9049
   macro avg       0.83      0.78      0.80      9049
weighted avg       0.86      0.86      0.86      9049
```

Ada Boosting

In [33]:

```
abc = AdaBoostClassifier()
abc.fit(train_x, train_y)
predicted_abc = abc.predict(test_x)
acc_abc = (accuracy_score(test_y, predicted_abc)) * 100
acc_abc

print("Accuracy: %s%%" % (100*accuracy_score(test_y, predicted_abc)))
print(confusion_matrix(test_y, predicted_abc))
print(classification_report(test_y, predicted_abc))
```

```
Accuracy: 85.47905845949829%
[[6324  462]
 [ 852 1411]]
              precision    recall  f1-score   support

           0       0.88      0.93      0.91      6786
           1       0.75      0.62      0.68      2263

    accuracy                           0.85      9049
   macro avg       0.82      0.78      0.79      9049
weighted avg       0.85      0.85      0.85      9049
```

Model Evaluation and Accuracy

In [34]:

```
models = pd.DataFrame({
'Model': ['Support Vector Machines', 'Random Forest','Decision Tree using Gini','De
],
'Score': [acc_svc, acc_rf, acc_dt_gini, acc_dt_entropy, acc_knn, acc_gbc,acc_abc]})
models.sort_values(by='Score', ascending=False)
```

Out[34]:

	Model	Score
5	Gradient Boosting	86.164217
6	Ada Boost	85.479058
1	Random Forest	84.860206
2	Decision Tree using Gini	83.843519
3	Decision Tree using Entropy	83.843519
4	K-Nearest Neighbours	83.534092
0	Support Vector Machines	79.765720

In [ ]: