In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix,classification_report
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

In [2]:

```
df=pd.read_csv("adult.csv",na_values='?')
```

In [3]:

```
df.head()
```

Out[3]:

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship
0	90	NaN	77053	HS-grad	9	Widowed	NaN	Not-in-family
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-family
2	66	NaN	186061	Some-college	10	Widowed	NaN	Unmarried
3	54	Private	140359	7th-8th	4	Divorced	Machine-op-inspct	Unmarried
4	41	Private	264663	Some-college	10	Separated	Prof-specialty	Own-child

In [4]:

```
df.shape
```

Out[4]:

```
(32561, 15)
```

In [5]:

```
df.isnull().sum()
```

Out[5]:

```
age                  0
workclass         1836
fnlwgt               0
education            0
education.num        0
marital.status       0
occupation        1843
relationship         0
race                 0
sex                  0
capital.gain         0
capital.loss         0
hours.per.week       0
native.country     583
income               0
dtype: int64
```

In [6]:

```
df.isin(['?']).sum()
```

Out[6]:

```
age               0
workclass         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 [7]:

```
df['workclass'].value_counts()
```

Out[7]:

```
Private             22696
Self-emp-not-inc     2541
Local-gov            2093
State-gov            1298
Self-emp-inc         1116
Federal-gov           960
Without-pay            14
Never-worked            7
Name: workclass, dtype: int64
```

In [8]:

```
df['occupation'].value_counts()
```

Out[8]:

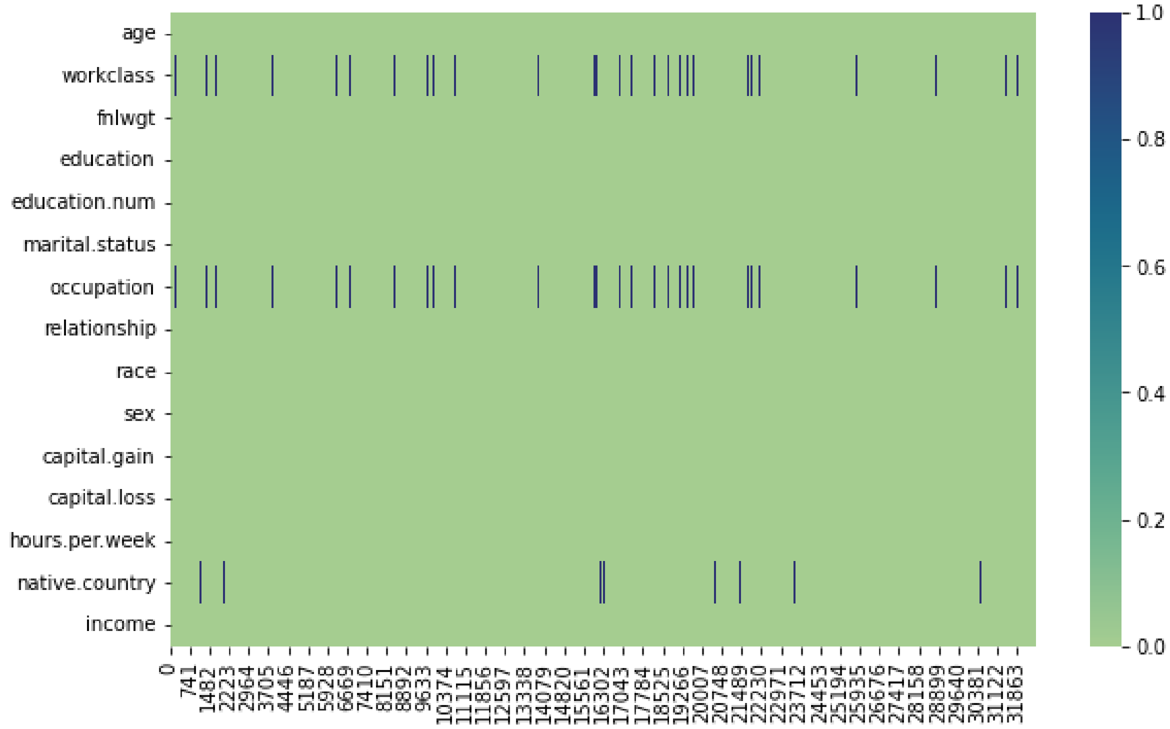
```
Prof-specialty       4140
Craft-repair         4099
Exec-managerial      4066
Adm-clerical         3770
Sales                3650
Other-service        3295
Machine-op-inspct    2002
Transport-moving     1597
Handlers-cleaners    1370
Farming-fishing       994
Tech-support          928
Protective-serv       649
Priv-house-serv       149
Armed-Forces            9
Name: occupation, dtype: int64
```

In [9]:

```
plt.figure(figsize=(10,6))
sns.heatmap(df.isna().transpose(),
            cmap="crest")
```

Out[9]:

<AxesSubplot:>



In [10]:

```
df.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       30725 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      30718 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  31978 non-null  object
 14  income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

In [11]:

```
df.columns
```

Out[11]:

```
Index(['age', 'workclass', 'fnlwgt', 'education', 'education.num',
       'marital.status', 'occupation', 'relationship', 'race', 'sex',
       'capital.gain', 'capital.loss', 'hours.per.week', 'native.country',
       'income'],
      dtype='object')
```

In [12]:

```
df.describe().T
```

Out[12]:

	count	mean	std	min	25%	50%	75%
age	32561.0	38.581647	13.640433	17.0	28.0	37.0	48.0
fnlwgt	32561.0	189778.366512	105549.977697	12285.0	117827.0	178356.0	237051.0
education.num	32561.0	10.080679	2.572720	1.0	9.0	10.0	12.0
capital.gain	32561.0	1077.648844	7385.292085	0.0	0.0	0.0	0.0
capital.loss	32561.0	87.303830	402.960219	0.0	0.0	0.0	0.0
hours.per.week	32561.0	40.437456	12.347429	1.0	40.0	40.0	45.0

In [13]:

```
numerical_feature=[i for i in df.columns if df[i].dtype!='O']
categorical_feature=[i for i in df.columns if df[i].dtype=='O']
```

In [14]:

```
numerical_feature
```

Out[14]:

```
['age',
 'fnlwgt',
 'education.num',
 'capital.gain',
 'capital.loss',
 'hours.per.week']
```

In [15]:

```
categorical_feature
```

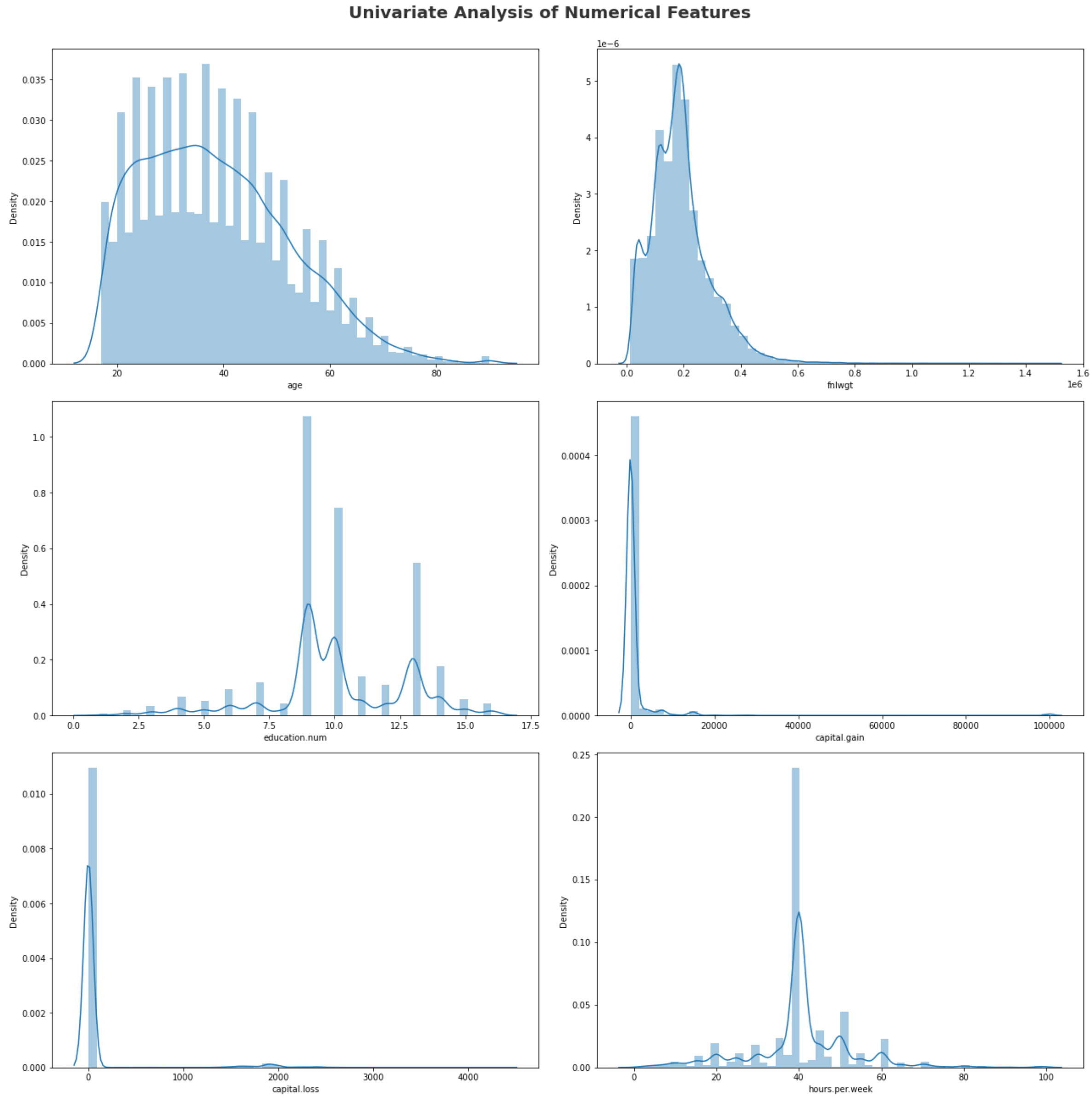
Out[15]:

```
['workclass',
 'education',
 'marital.status',
 'occupation',
 'relationship',
 'race',
 'sex',
 'native.country',
 'income']
```

Univariate analysis

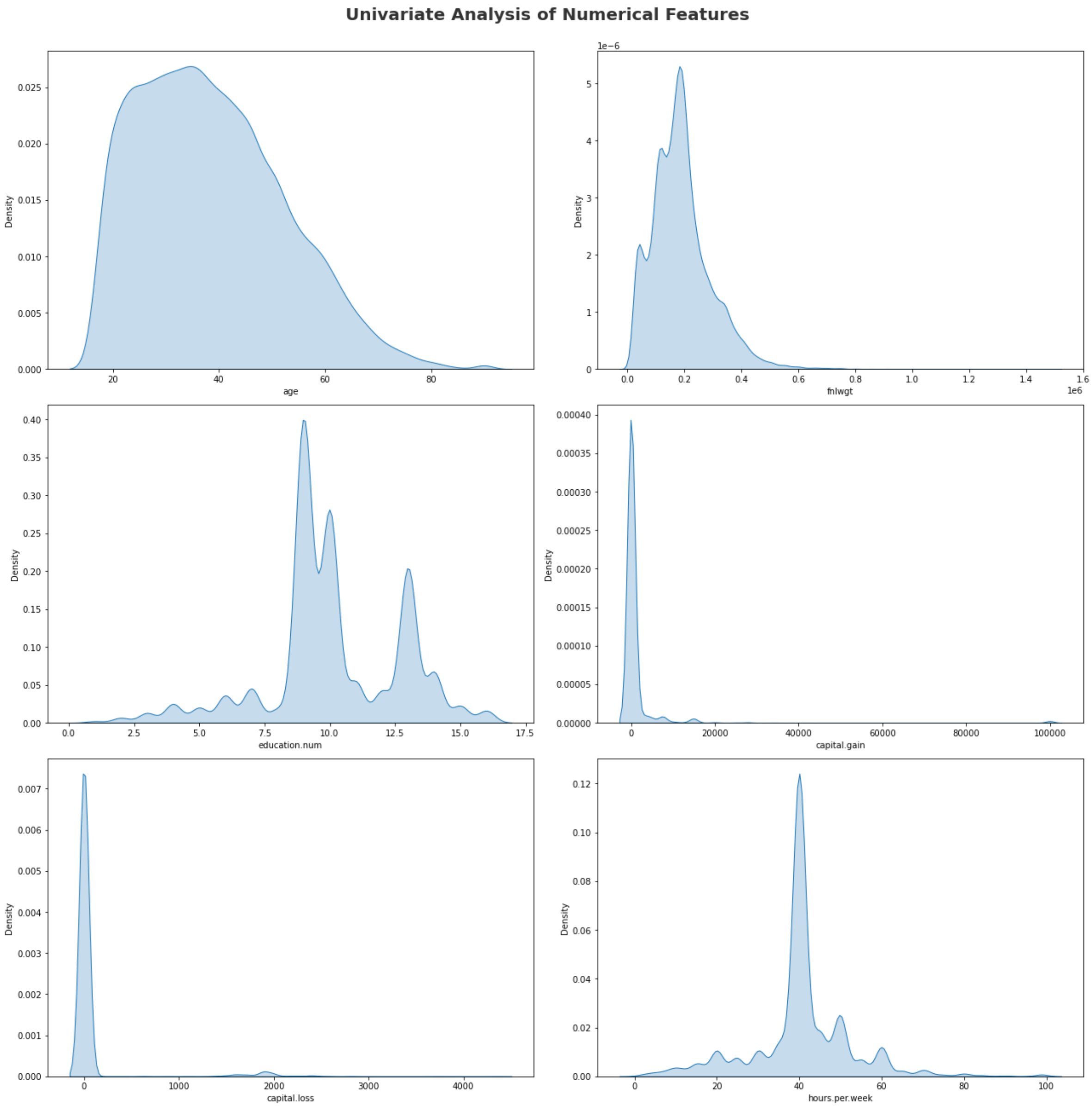
In [16]:

```
plt.figure(figsize=(18,18))
plt.suptitle('Univariate Analysis of Numerical Features', fontsize=20, fontweight='bold', a

for i in range(0, len(numerical_feature)):
    plt.subplot(3, 2, i+1)
    sns.distplot(df[numerical_feature[i]],label='income')
    plt.xlabel(numerical_feature[i])
    plt.tight_layout()
```



In [17]:

```
plt.figure(figsize=(18,18))
plt.suptitle('Univariate Analysis of Numerical Features', fontsize=20, fontweight='bold', a

for i in range(0, len(numerical_feature)):
    plt.subplot(3, 2, i+1)
    sns.kdeplot(x=df[numerical_feature[i]],shade=True,data=df)
    plt.xlabel(numerical_feature[i])
    plt.tight_layout()
```



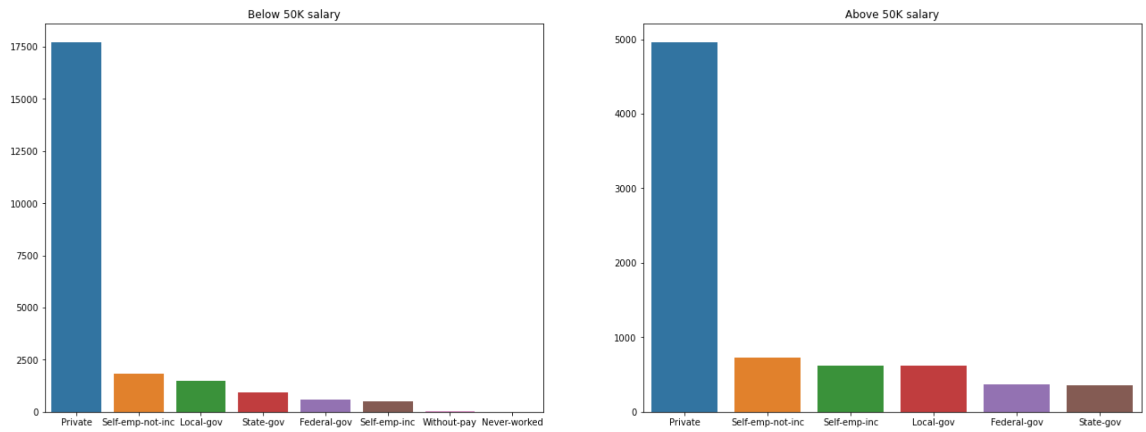
In [18]:

```
def cate_feature(df,categorical_feature):
    plt.figure(figsize=(22,8))
    a=df[df['income']=='<=50K'][categorical_feature].value_counts() # Below 50k salary
    b=df[df['income']=='>50K'][categorical_feature].value_counts() # Above 50k salary
    plt.subplot(1,2,1)
    plt.title('Below 50K salary')
    sns.barplot(a.index,a.values)
    plt.subplot(1,2,2)
    plt.title('Above 50K salary')
    sns.barplot(b.index,b.values)
    plt.show()
```

In [19]:

```
for i in categorical_feature:
    print(i,':\n')
    cate_feature(df,i)
```

```
workclass :
```




```
education :
```

Below 50K salary Above 50K salary

In [20]:

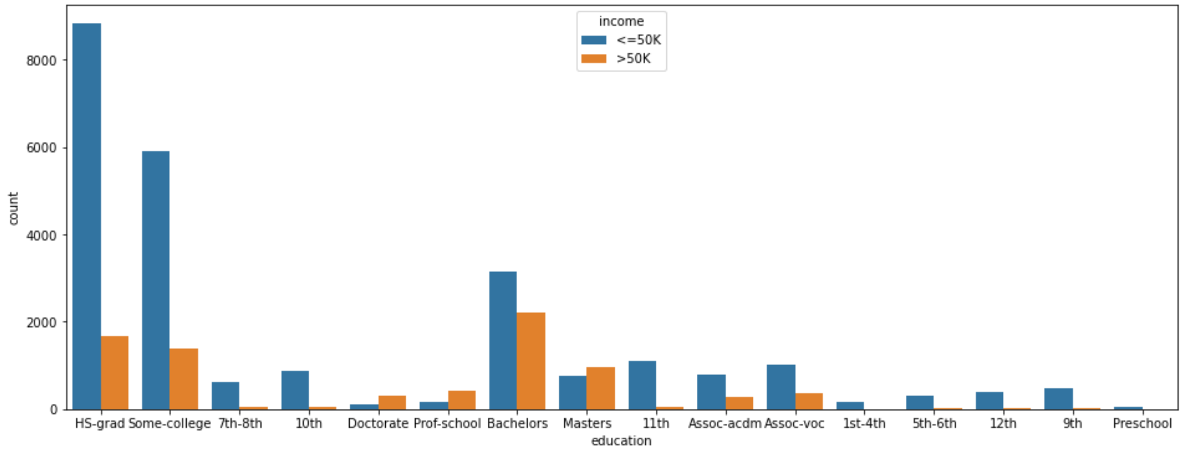
```
plt.figure(figsize=(18,18))
plt.suptitle('Univariate Analysis of Categorical Features', fontsize=20, fontweight='bold',

for i in range(0, len(categorical_feature)):
    plt.subplot(5, 2, i+1)
    sns.countplot(x=df[categorical_feature[i]],data=df)
    plt.xlabel(categorical_feature[i])
    plt.tight_layout()
```

In [21]:

```
plt.figure(figsize=(16,6))
sns.countplot(x="education",hue="income",data=df)
```

Out[21]:

```
<AxesSubplot:xlabel='education', ylabel='count'>
```

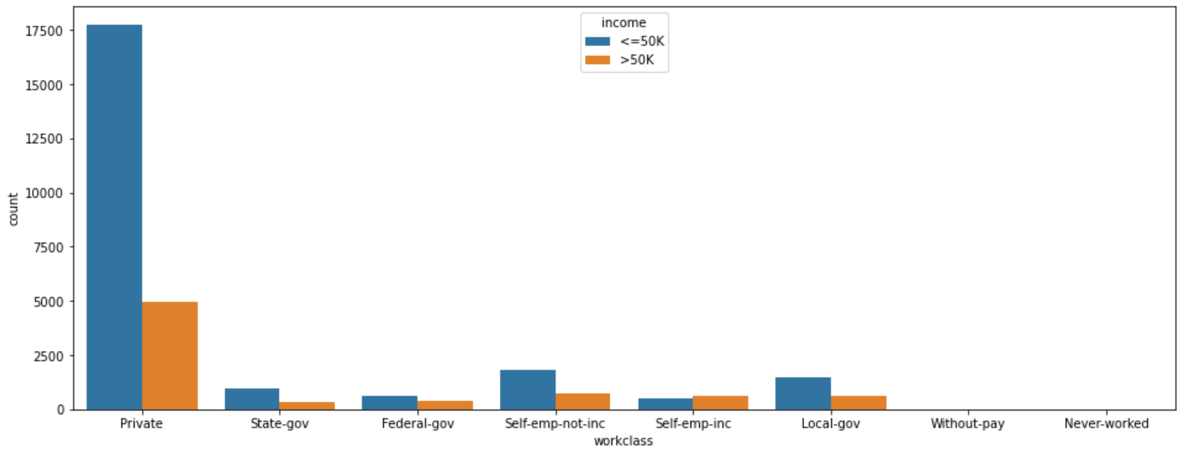


In [22]:

```
plt.figure(figsize=(16,6))
sns.countplot(x="workclass",hue="income",data=df)
```

Out[22]:

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

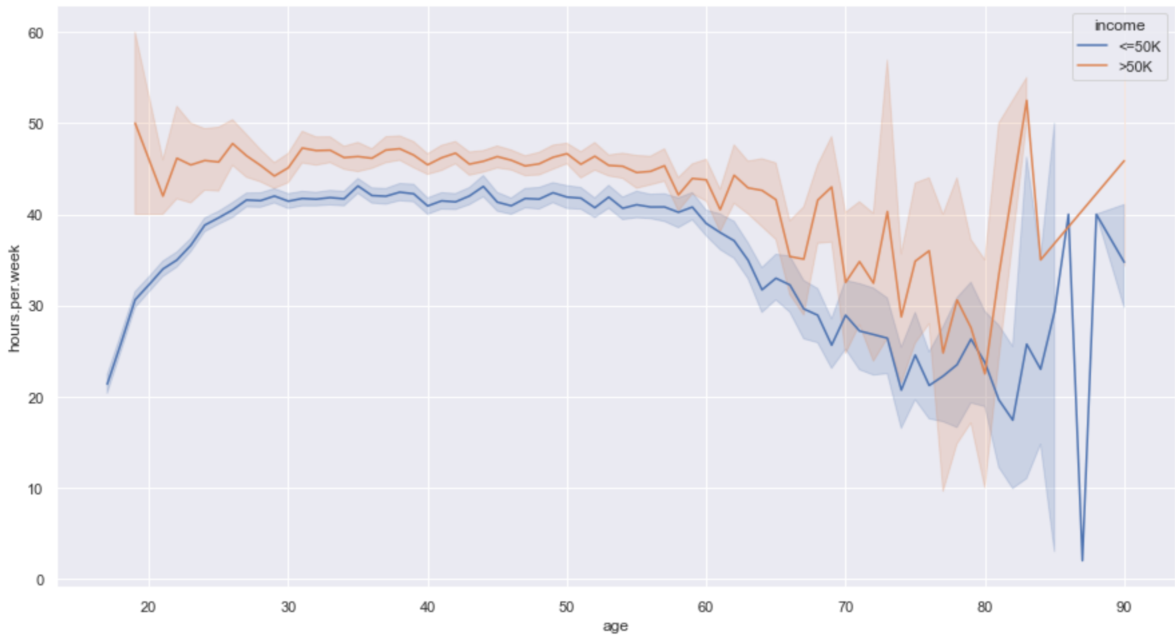


In [23]:

```
plt.figure(figsize=(15,8))
sns.set_theme(style="darkgrid")
sns.lineplot(x='age', y='hours.per.week',
             hue="income",
             data=df)
```

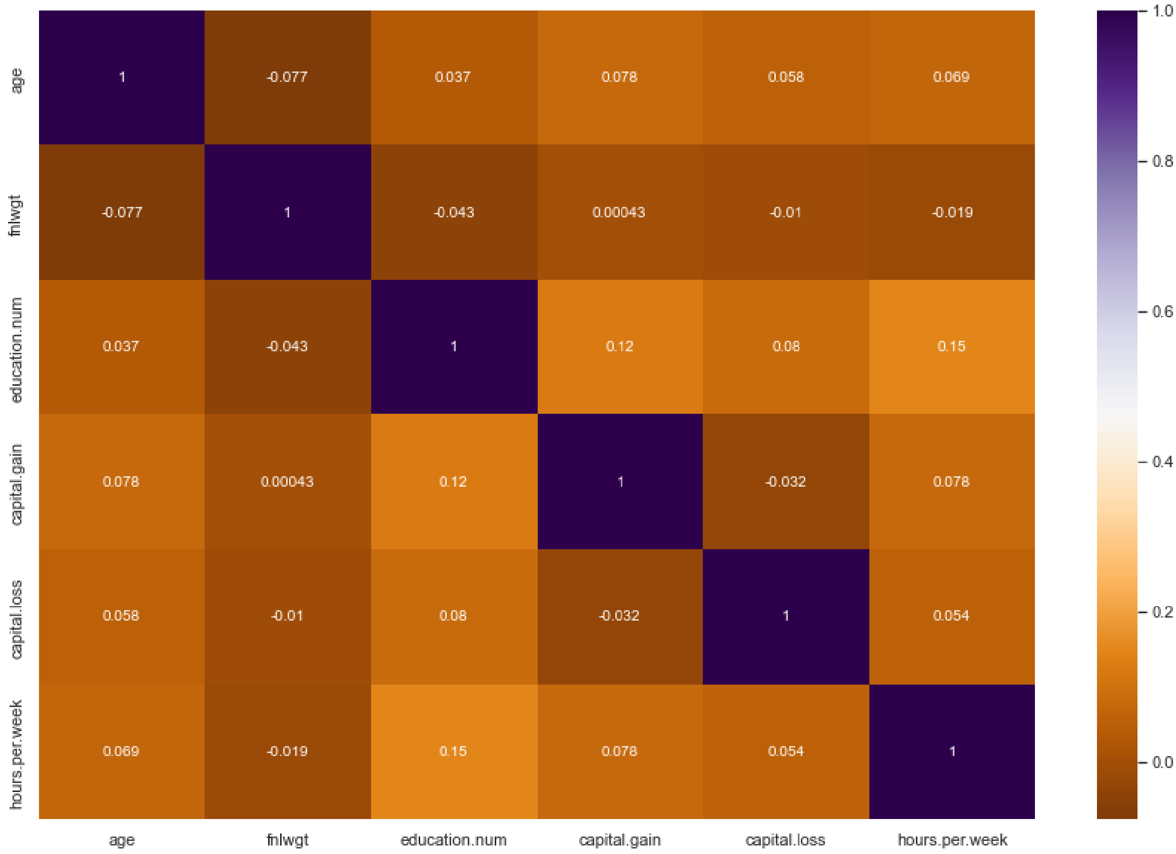
Out[23]:

```
<AxesSubplot:xlabel='age', ylabel='hours.per.week'>
```



In [24]:

```
plt.figure(figsize=(15, 10))
sns.heatmap(df.corr(), annot=True, cmap="PuOr", annot_kws={"size": 10})
plt.show()
```



Feature Engineering

In [25]:

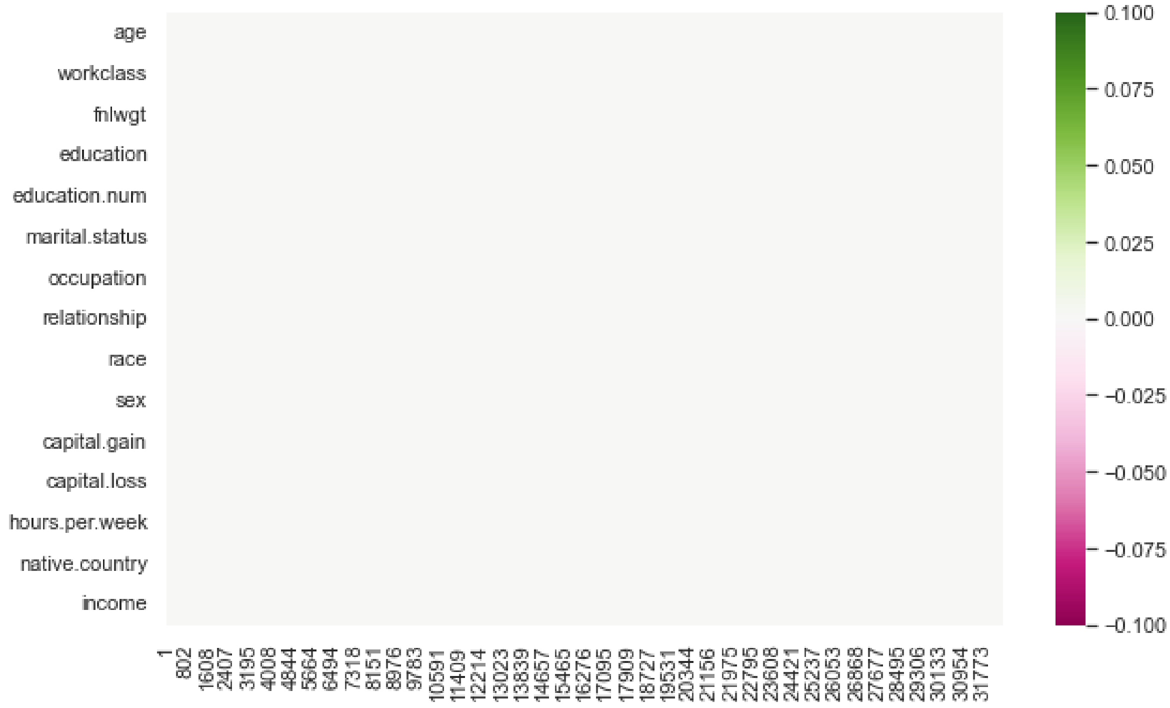
```
df=df.dropna(axis=0)
```

In [26]:

```
plt.figure(figsize=(10,6))
sns.heatmap(df.isna().transpose(),
           cmap="PiYG")
```

Out[26]:

```
<AxesSubplot:>
```



Label Encoding for Categorical feature

In [27]:

```
from sklearn.preprocessing import LabelEncoder
```

In [28]:

```
le=LabelEncoder()
```

In [29]:

```
for i in categorical_feature :
    df[i] = le.fit_transform(df[i])
```

In [30]:

```
df=df.drop(['marital.status','relationship','capital.gain','capital.loss',],axis=1)
```

In [31]:

```
df.head()
```

Out[31]:

	age	workclass	fnlwgt	education	education.num	occupation	race	sex	hours.per.week
1	82	2	132870	11	9	3	4	0	18
3	54	2	140359	5	4	6	4	0	40
4	41	2	264663	15	10	9	4	0	40
5	34	2	216864	11	9	7	4	0	45
6	38	2	150601	0	6	0	4	1	40

In [32]:

```
X=df.drop(['income'],axis=1)
y=df['income']
```

In [33]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=100)
```

In [34]:

```
X_train.shape
```

Out[34]:

```
(20208, 10)
```

In [35]:

```
y_train.shape
```

Out[35]:

```
(20208,)
```

In [36]:

```
X_test.shape
```

Out[36]:

```
(9954, 10)
```

In [37]:

```
y_test.shape
```

Out[37]:

```
(9954,)
```

In [38]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier,VotingClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import ExtraTreesClassifier
```

Decision Tree Classifier

In [39]:

```
dc=DecisionTreeClassifier()
```

In [40]:

```
dc.fit(X_train,y_train)
```

Out[40]:

```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

In [41]:

```
dc.score(X_train,y_train)
```

Out[41]:

```
0.9998020585906572
```

In [42]:

```
dc_pred=dc.predict(X_test)
```

In [43]:

```
from sklearn.metrics import accuracy_score,classification_report,confusion_matrix
from sklearn.model_selection import cross_val_score
```

In [44]:

```
accuracy_score(y_test,dc_pred)
```

Out[44]:

```
0.7458308217801889
```

In [45]:

```
print(classification_report(y_test,dc_pred))
```

```
              precision    recall  f1-score   support

           0       0.83      0.83      0.83      7458
           1       0.49      0.50      0.50      2496

    accuracy                           0.75      9954
   macro avg       0.66      0.66      0.66      9954
weighted avg       0.75      0.75      0.75      9954
```

In [46]:

```
grid_param_dc = {
    'criterion': ['gini', 'entropy'],
    'max_depth' : range(2,10,1),
    'min_samples_leaf' : range(1,8,1),
    'min_samples_split': range(2,8,1),
    'splitter' : ['best', 'random']

}
```

In [47]:

```
from sklearn.model_selection import GridSearchCV
grid_search_dc=GridSearchCV(estimator=dc,param_grid=grid_param_dc,cv=3,verbose=1)
```

In [48]:

```
grid_search_dc.fit(X_train,y_train)
```

```
Fitting 3 folds for each of 1344 candidates, totalling 4032 fits
```

Out[48]:

```
▸ GridSearchCV
▸ estimator: DecisionTreeClassifier
    ▸ DecisionTreeClassifier
```

In [49]:

```
grid_search_dc.best_params_
```

Out[49]:

```
{'criterion': 'entropy',
 'max_depth': 8,
 'min_samples_leaf': 7,
 'min_samples_split': 3,
 'splitter': 'random'}
```

In [50]:

```
dc_model_with_best_parm=DecisionTreeClassifier(criterion='gini',
 max_depth= 5,
 min_samples_leaf=6,
 min_samples_split= 2,
 splitter= 'best')
```

In [51]:

```
dc_model_with_best_parm.fit(X_train,y_train)
```

Out[51]:

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(max_depth=5, min_samples_leaf=6)
```

In [52]:

```
pred_dc_model_with_best_parm=dc_model_with_best_parm.predict(X_test)
```

In [53]:

```
print(accuracy_score(y_test,pred_dc_model_with_best_parm))
```

```
0.7976692786819369
```

In [54]:

```
print(classification_report(y_test,pred_dc_model_with_best_parm))
```

```
              precision    recall  f1-score   support

           0       0.82      0.94      0.87      7458
           1       0.67      0.38      0.49      2496

    accuracy                           0.80      9954
   macro avg       0.74      0.66      0.68      9954
weighted avg       0.78      0.80      0.78      9954
```

In [55]:

```
print(confusion_matrix(y_test,pred_dc_model_with_best_parm))
```

```
[[6980  478]
 [1536  960]]
```

RandomForestClassifier

In [56]:

```
rf= RandomForestClassifier()
```

In [57]:

```
rf.fit(X_train,y_train)
```

Out[57]:

```
▾ RandomForestClassifier
RandomForestClassifier()
```

In [58]:

```
rf.score(X_train,y_train)
```

Out[58]:

```
0.9997525732383215
```

In [59]:

```
rf_pred=rf.predict(X_test)
```

In [60]:

```
print(accuracy_score(y_test,rf_pred))
```

```
0.7958609604179224
```

In [61]:

```
rf_grid_param = {
    "n_estimators" : [90,100,110,120],
    'criterion': ['gini', 'entropy'],
    'max_depth' : range(2,20,1),
    'min_samples_leaf' : range(1,10,1),
    'min_samples_split': range(2,10,1),
    'max_features' : ['auto','log2']
}
```

In [62]:

```
from tpot import TPOTClassifier
```

In [63]:

```
rf_tpot_classifier = TPOTClassifier(generations= 5, population_size= 28, offspring_size= 14
                                 verbosity= 2, early_stop= 12,
                                 config_dict={'sklearn.ensemble.RandomForestClassifier': rf
                                 cv = 5, scoring = 'accuracy')
```

In [64]:

```
rf_tpot_classifier.fit(X_train,y_train)
```

```
Generation 1 - Current best internal CV score: 0.8133910201238885

Generation 2 - Current best internal CV score: 0.8133910201238885

Generation 3 - Current best internal CV score: 0.8134405985359614

Generation 4 - Current best internal CV score: 0.8138856042731719

Generation 5 - Current best internal CV score: 0.8138856042731719

Best pipeline: RandomForestClassifier(RandomForestClassifier(input_matrix, c
riterion=gini, max_depth=7, max_features=auto, min_samples_leaf=6, min_sampl
es_split=4, n_estimators=90), criterion=gini, max_depth=6, max_features=aut
o, min_samples_leaf=6, min_samples_split=5, n_estimators=110)
```

Out[64]:

```
TPOTClassifier
TPOTClassifier(config_dict={'sklearn.ensemble.RandomForestClassifier':
{'criterion': ['gini',

'entropy'],

'max_depth': range(2, 20),

'max_features': ['auto',

'log2'],
```

In [65]:

```
rf_accuracy = rf_tpot_classifier.score(X_test, y_test)
print(rf_accuracy)
```

```
0.8089210367691381
```

In [66]:

```
rf_g_pred=rf_tpot_classifier.predict(X_test)
```

In [67]:

```
print(accuracy_score(y_test,rf_g_pred))
```

```
0.8089210367691381
```

In [68]:

```
#grid_search_rf=GridSearchCV(estimator=rf,param_grid=rf_grid_param,cv=3,verbose=1)
```

In [69]:

```
#grid_search_rf.fit(X_train,y_train)
```

SVC

In [70]:

```
sv=SVC()
```

In [71]:

```
sv.fit(X_train,y_train)
```

Out[71]:

```
▾ SVC
SVC()
```

In [72]:

```
sv.score(X_train,y_train)
```

Out[72]:

```
0.7519794140934284
```

In [73]:

```
sv_pred=sv.predict(X_test)
```

In [74]:

```
print(accuracy_score(y_test,sv_pred))
```

```
0.7492465340566606
```

In [75]:

```
sv_grid_param = {
    "C" : [0.1,1,2,5,10,100],
    'kernel': ['linear', 'poly', 'rbf', 'sigmoid', 'precomputed'],
    'gamma':['scale', 'auto']
}
```

In [76]:

```
#grid_search_svm=GridSearchCV(estimator=sv,param_grid=sv_grid_param,cv=3,verbose=1)
```

In [77]:

```
#grid_search_svm.fit(X_train,y_train)
```

In [78]:

```
#from sklearn.model_selection import RandomizedSearchCV
```

In [79]:

```
#sv_randomcv=RandomizedSearchCV(estimator=sv,param_distributions=sv_grid_param ,n_iter=100,
                              #random_state=100,n_jobs=-1)
```

In [80]:

```
#sv_randomcv.fit(X_train,y_train)
```

In [81]:

```
#sv_tpot_classifier = TPOTClassifier(generations= 5, population_size= 28, offspring_size= 1
                                  #verbosity= 2, early_stop= 12,
                                  #config_dict={'sklearn.svm.SVC': sv_grid_param},
                                  #cv = 5, scoring = 'accuracy')
```

In [82]:

```
#sv_tpot_classifier.fit(X_train,y_train)
```

BaggingClassifier

In [83]:

```
bg=BaggingClassifier(n_estimators=10, random_state=0)
```

In [84]:

```
bg.fit(X_train,y_train)
```

Out[84]:

```
▾        BaggingClassifier
BaggingClassifier(random_state=0)
```

In [85]:

```
bg.score(X_train,y_train)
```

Out[85]:

```
0.9825811559778306
```

In [86]:

```
bg_pred=bg.predict(X_test)
```

In [87]:

```
print(accuracy_score(y_test,bg_pred))
```

```
0.7858147478400643
```

In [88]:

```
bg_grid_param = {
    "n_estimators" : [10,20,30,50,100],
    'max_samples': range(1,10,1),
    'oob_score':[True,False]
}
```

In [89]:

```
grid_search_bg=GridSearchCV(estimator=bg,param_grid=bg_grid_param,cv=3,verbose=1)
```

In [90]:

```
grid_search_bg.fit(X_train,y_train)
```

```
Fitting 3 folds for each of 90 candidates, totalling 270 fits
```

Out[90]:

```
▸ GridSearchCV
▸ estimator: BaggingClassifier
  ▸ BaggingClassifier
```

In [91]:

```
grid_search_bg.best_params_
```

Out[91]:

```
{'max_samples': 6, 'n_estimators': 10, 'oob_score': True}
```

In [92]:

```
bg_with_best_parm=BaggingClassifier(n_estimators=10,max_samples=6 ,oob_score=True)
```

In [93]:

```
bg_with_best_parm.fit(X_train,y_train)
```

Out[93]:

```
▾ BaggingClassifier
BaggingClassifier(max_samples=6, oob_score=True)
```

In [94]:

```
bg_with_best_parm_pred=bg_with_best_parm.predict(X_test)
```

In [95]:

```
print(accuracy_score(y_test,bg_with_best_parm_pred))
```

```
0.7427164958810528
```

ExtraTreesClassifier

In [96]:

```
et=ExtraTreesClassifier()
```

In [97]:

```
et.fit(X_train,y_train)
```

Out[97]:

```
▾ ExtraTreesClassifier
ExtraTreesClassifier()
```

In [98]:

```
et_pred=et.predict(X_test)
```

In [99]:

```
print(accuracy_score(y_test,et_pred))
```

```
0.7878239903556359
```

In [100]:

```
grid_param_et = {
    'n_estimators':range(100,200,20),
    'criterion': ['gini','entropy','log_loss'],
    'max_depth' : range(2,10,1),
    'min_samples_leaf' : range(1,8,1),
    'min_samples_split': range(2,8,1),
    'max_features' : ['sqrt', 'log2']

}
```

In [101]:

```
#grid_search_et=GridSearchCV(estimator=et,param_grid=grid_param_et,cv=3,verbose=1)
```

In [102]:

```
#grid_search_et.fit(X_train,y_train)
```

In [103]:

```
et_tpot_classifier = TPOTClassifier(generations= 5, population_size= 28, offspring_size= 14
                                    verbosity= 2, early_stop= 12,
                                    config_dict={'sklearn.ensemble.ExtraTreesClassifier': grid
                                    cv = 5, scoring = 'accuracy')
```

In [104]:

```
et_tpot_classifier.fit(X_train,y_train)
```

```
Generation 1 - Current best internal CV score: 0.80616601653928

Generation 2 - Current best internal CV score: 0.8115597534964779

Generation 3 - Current best internal CV score: 0.8115597534964779

Generation 4 - Current best internal CV score: 0.8115597534964779

Generation 5 - Current best internal CV score: 0.8132422114200303

Best pipeline: ExtraTreesClassifier(ExtraTreesClassifier(ExtraTreesClassifie
r(CombineDFs(input_matrix, input_matrix), criterion=gini, max_depth=7, max_f
eatures=log2, min_samples_leaf=2, min_samples_split=6, n_estimators=100), cr
iterion=gini, max_depth=6, max_features=sqrt, min_samples_leaf=6, min_sample
s_split=3, n_estimators=140), criterion=entropy, max_depth=9, max_features=s
qrt, min_samples_leaf=2, min_samples_split=5, n_estimators=140)
```

Out[104]:

```
▾                               TPOTClassifier
iterion': ['gini',

'entropy',

'log_loss'],
                                                                    'ma
x_depth': range(2, 10),
                                                                    'ma
x_features': ['sqrt',

'log2'],
```

In [105]:

```
et_accuracy = et_tpot_classifier.score(X_test, y_test)
print(et_accuracy)
```

```
0.8086196503918023
```

In [106]:

```
et_g_pred=et_tpot_classifier.predict(X_test)
```

In [107]:

```
print(accuracy_score(y_test,et_g_pred))
```

0.8086196503918023

AdaBoostClassifier

In [108]:

```
from sklearn.ensemble import AdaBoostClassifier
```

In [109]:

```
ad=AdaBoostClassifier()
```

In [110]:

```
ad.fit(X_train,y_train)
```

Out[110]:

```
▾ AdaBoostClassifier
AdaBoostClassifier()
```

In [111]:

```
ad.score(X_train,y_train)
```

Out[111]:

0.8135886777513855

In [112]:

```
ad_pred=ad.predict(X_test)
```

In [113]:

```
print(accuracy_score(y_test,ad_pred))
```

0.8089210367691381

In [114]:

```
grid_param_ad = {
    'n_estimators':range(50,100,10),
    'learning_rate':[0.01,1.0,2.0,5.0,10.0,100.0],
    'algorithm':['SAMME','SAMME.R']

}
```

In [115]:

```
grid_search_ad=GridSearchCV(estimator=ad,param_grid=grid_param_ad,cv=3,verbose=1)
```

In [116]:

```
grid_search_ad.fit(X_train,y_train)
```

```
Fitting 3 folds for each of 60 candidates, totalling 180 fits
```

Out[116]:

```
▸ GridSearchCV
▸ estimator: AdaBoostClassifier
    ▸ AdaBoostClassifier
```

In [117]:

```
grid_search_ad.best_params_
```

Out[117]:

```
{'algorithm': 'SAMME.R', 'learning_rate': 1.0, 'n_estimators': 90}
```

In [118]:

```
grid_search_ad_with_best_parm = AdaBoostClassifier(n_estimators =90,algorithm='SAMME.R', le
```

In [119]:

```
grid_search_ad_with_best_parm.fit(X_train,y_train)
```

Out[119]:

```
▾ AdaBoostClassifier
AdaBoostClassifier(n_estimators=90)
```

In [120]:

```
grid_search_ad_with_best_parm_pred = grid_search_ad_with_best_parm.predict(X_test)
```

In [121]:

```
print(accuracy_score(y_test,grid_search_ad_with_best_parm_pred))
```

```
0.8081173397629093
```

VotingClassifier

In [122]:

```
#vt=VotingClassifier(estimators=[('DT',dc), ('RF',rf), ('SVM', sv),('ADABOOST',ad)],voting=
```

In [125]:

```
#vt.fit(X_train,y_train)
from sklearn.linear_model import LogisticRegression
```

In [126]:

```
estimaors=[
    ('RFC',RandomForestClassifier()),
    ('Lr',LogisticRegression()),
    ('ETC',ExtraTreesClassifier(criterion='gini',max_depth=10,min_samples_leaf=2,min_sample
    ('BGC',BaggingClassifier(base_estimator=LogisticRegression()))
]
```

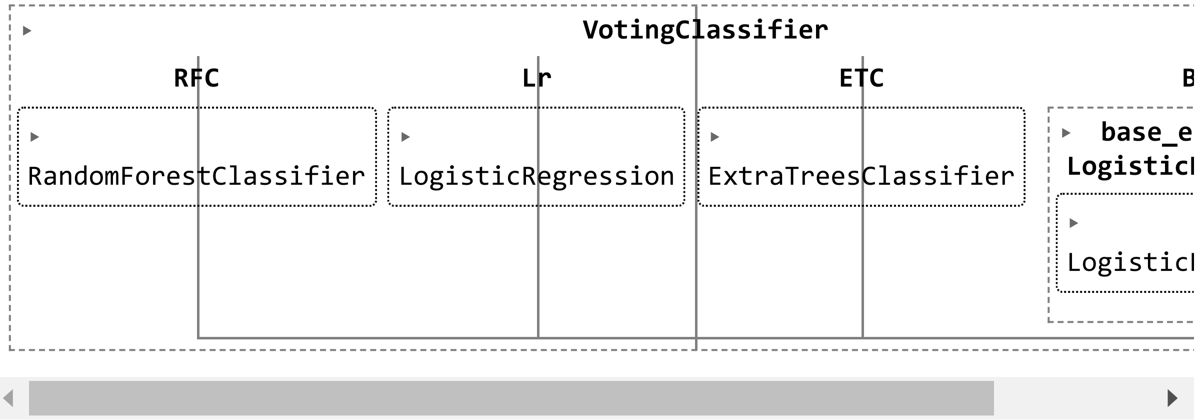
In [131]:

```
vt = VotingClassifier(estimators=estimaors,voting='hard')
```

In [132]:

```
vt.fit(X_train,y_train)
```

Out[132]:



In [133]:

```
vt.score(X_train,y_train)
```

Out[133]:

```
0.7519794140934284
```

In [134]:

```
vt_pred = vt.predict(X_test)
```

In [135]:

```
print(accuracy_score(y_test,vt_pred))
```

```
0.7492465340566606
```

In [ ]: