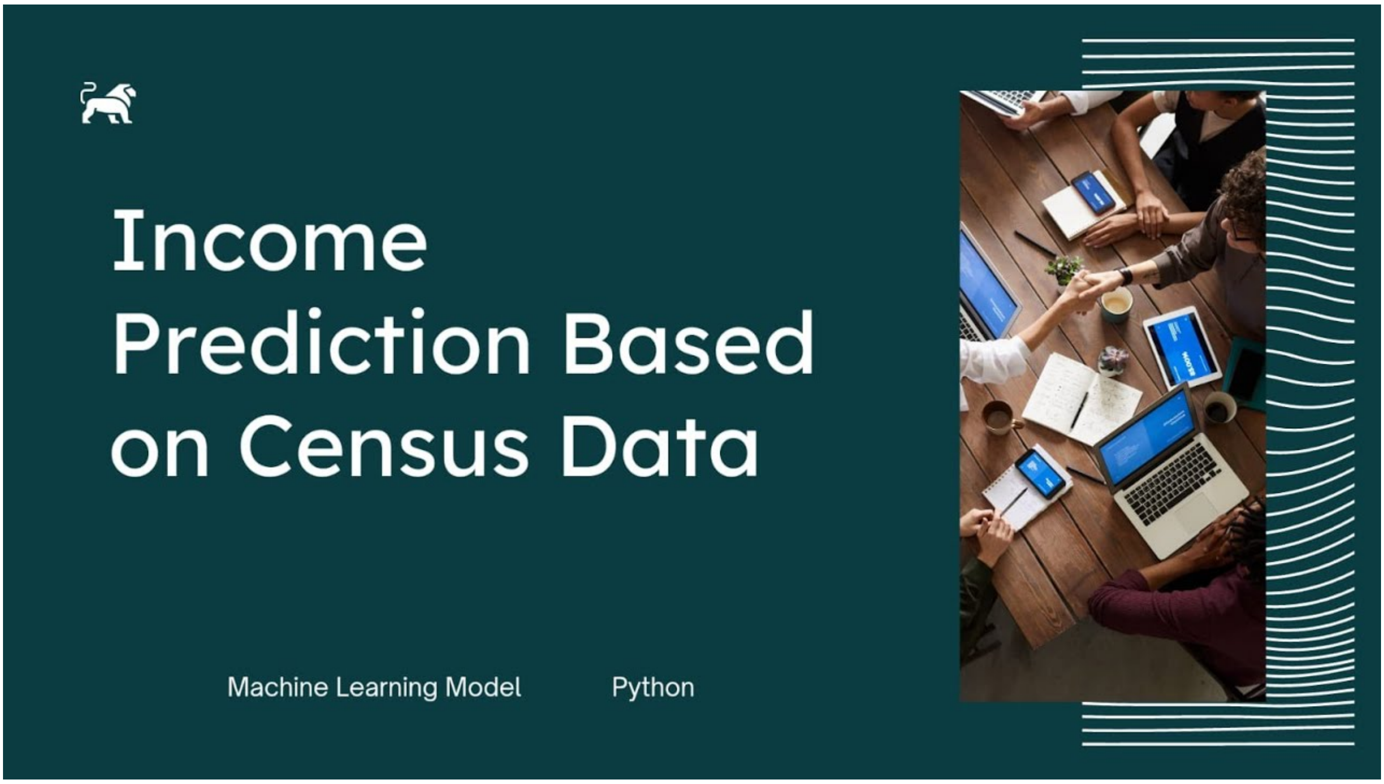
# Classification Model on Census Income dataset

Submitted by:- Ambarish Singh




## Problem Statement

- Predict Whether income of individual exceeds $50K/year or not based on attributes given

## Task Performed:-

1. Data Ingestion
2. Handle the null values
3. Replace column_name
4. Seperate categorical and Numerical Features
5. Univariate Analysis
6. Bivariate Analysis
7. Handle the outliers
8. Seperate Dependent and Independent features
9. Label encoding of categorical features

10. Test Accuracy using :
    - Decision Tree Classifier
    - Hyper-parameter tunning on Decision Tree
    - Random Forest Classifier
    - Hyper-parameter tunning on Random Forest Classifier
    - Bagging Classifier using SVC
    - Random Forest Classifier
    - Voting Classifier using Logistic Regression , Random forest classifier, GuassianNB
    - Extra Tree Classifier
    - Hyper-parameter tunning on Extra Tree Classifier
11. Make final report showing accuracy of all models
12. Store the best model in pickle file

# Attribute Information

1. age: continuous.
2. workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.
3. fnlwgt: continuous.
4. education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st 4th, 10th, Doctorate, 5th-6th, Preschool.
5. education-num: continuous.
6. marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.
7. occupation: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.
8. relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.
9. race: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.
10. sex: Female, Male.
11. capital-gain: continuous.
12. capital-loss: continuous.
13. hours-per-week: continuous.
14. native-country: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.

# Description:-

As the problem of inequality of income has become very prominent over the years, governments of different countries have been trying to address the problem so as to improve the economic stability of a nation.

In this study, Machine Learning Classification techniques is used in order to predict whether a person's yearly income falls in the income category of either greater than 50K Dollars or less then equal to 50K Dollars category based on a certain set of attributes. An analysis of this kind helps to figure out which individual attributes are necessary in improving an individual's income so that focus can be put on those specific factors so as to level up the income of individuals.

In [1]:

```
## Comment
## Observations
```

# Import required libraries

In [2]:

```
## Data Analysing
import pandas as pd
import numpy as np

## Graphical analysis
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from warnings import filterwarnings
filterwarnings('ignore')

## for model building
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.ensemble import BaggingClassifier
from sklearn.datasets import make_classification
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier,VotingClassifier
```

# Data Ingestion

In [3]:

```python
## Loading Dataset
df= pd.read_csv(r"adult.csv")
df
```

Out[3]:

| | age | workclass | fnlwgt | education | education.num | marital.status | oc |
|---|---|---|---|---|---|---|---|
| **0** | 90 | ? | 77053 | HS-grad | 9 | Widowed | |
| **1** | 82 | Private | 132870 | HS-grad | 9 | Widowed | n |
| **2** | 66 | ? | 186061 | Some-college | 10 | Widowed | |
| **3** | 54 | Private | 140359 | 7th-8th | 4 | Divorced | |
| **4** | 41 | Private | 264663 | Some-college | 10 | Separated | |
| **...** | ... | ... | ... | ... | ... | ... | |
| **32556** | 22 | Private | 310152 | Some-college | 10 | Never-married | F |
| **32557** | 27 | Private | 257302 | Assoc-acdm | 12 | Married-civ-spouse | |
| **32558** | 40 | Private | 154374 | HS-grad | 9 | Married-civ-spouse | |
| **32559** | 58 | Private | 151910 | HS-grad | 9 | Widowed | |
| **32560** | 22 | Private | 201490 | HS-grad | 9 | Never-married | |

32561 rows × 15 columns

In [5]:

```python
## Checking Shapes of a Dataset
df.shape
```

Out[5]:

```
(32561, 15)
```

## Check how many class in income feature

In [6]:

```
## Checking unique value in 'income' feature.
df['income'].unique()
```

Out[6]:

```
array(['<=50K', '>50K'], dtype=object)
```

## Convert classes in income feature to 0 and 1

In [7]:

```
## Converting Classes of Income Feature to 0 and 1.
df['income'] = df['income'].map({"<=50K": 0,">50K":1})
```

In [8]:

```
## Again Checking the unique Value of 'Income' Feature.
df['income'].unique()
```

Out[8]:

```
array([0, 1], dtype=int64)
```

## Check special symbols in data

In [9]:

```
## Checking if any special symbols are present in a dataset or not.
df[df['workclass'] == "?"][:5]
```

Out[9]:

| | age | workclass | fnlwgt | education | education.num | marital.status | occu |
|---|---|---|---|---|---|---|---|
| **0** | 90 | ? | 77053 | HS-grad | 9 | Widowed | |
| **2** | 66 | ? | 186061 | Some-college | 10 | Widowed | |
| **14** | 51 | ? | 172175 | Doctorate | 16 | Never-married | |
| **24** | 61 | ? | 135285 | HS-grad | 9 | Married-civ-spouse | |
| **44** | 71 | ? | 100820 | HS-grad | 9 | Married-civ-spouse | |

# Replace special symbol with np.nan

In [10]:

```
## Replacing Special Symbol with np.nan
df.replace("?",np.NAN,inplace = True)
```

# Checking the null values

In [11]:

```
## Checking total null value present in a dataset
df.isnull().sum()
```

Out[11]:

```
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
```

# Note

- If the feature is categorical feature then we have to use `bfill`
- `bfill` replaces NaN with forward & backward values

In [12]:

```
# replacing NaN with forward & backward values
df['workclass'] = df['workclass'].fillna(method = 'bfill')
df['occupation'] = df['occupation'].fillna(method = 'bfill')
df['native.country'] = df['native.country'].fillna(method = 'pad')
```

# Checking the null values again

In [13]:

```
## Again Checking total null value present in a dataset or not.
df.isnull().sum()
```

Out[13]:

```
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
```

# Observation

- Now, here is No Null Value present

# Replace columns names

In [14]:

```
## Replacing Column name for better understanding.
df.rename(columns= {
    'education.num' : "education_num",
    "marital.status" : "marital_status",
    "capital.gain" : "capital_gain",
    "capital.loss" : "capital_loss",
    "hours.per.week" : "hours_per_week",
    "native.country" : "native_country"
},inplace= True)

```

In [15]:

```
## Checking All Columns name present in a dataset.
df.columns
```

Out[15]:

```
Index(['age', 'workclass', 'fnlwgt', 'education', 'education_
num',
       'marital_status', 'occupation', 'relationship', 'rac
e', 'sex',
       'capital_gain', 'capital_loss', 'hours_per_week', 'nat
ive_country',
       'income'],
      dtype='object')
```

# Seperate categorical and numerical features

In [16]:

```
## Seperate categorical and numerical features from a dataset.
categorical_fea = [col for col in df.columns if df[col].dtype == object
numerical_fea = [col for col in df.columns if df[col].dtype != object]
```

In [17]:

```
## Checking all Categorical Features present in a dataset
categorical_fea
```

Out[17]:

```
['workclass',
 'education',
 'marital_status',
 'occupation',
 'relationship',
 'race',
 'sex',
 'native_country']
```

In [18]:

```
## ## Checking all Numerical Features present in a dataset
numerical_fea
```

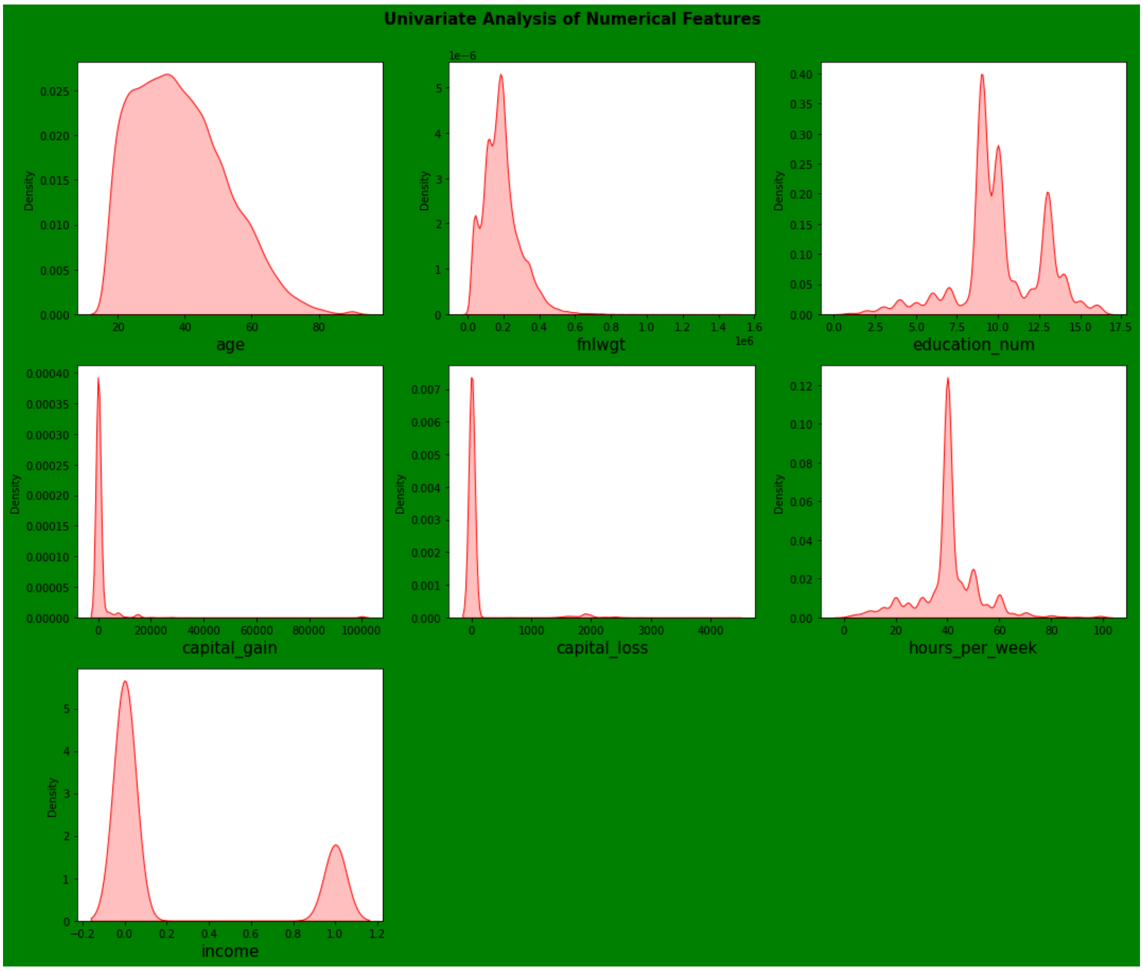
Out[18]:

```
['age',
 'fnlwgt',
 'education_num',
 'capital_gain',
 'capital_loss',
 'hours_per_week',
 'income']
```

# Univariate Analysis

In [19]:

```
## Ploting Univariate Analysis of Numerical Features:-
plt.figure(figsize=(15,20), facecolor='green')
plt.suptitle('Univariate Analysis of Numerical Features',fontweight = "
for i in range(0, len(numerical_fea)):
    plt.subplot(5, 3, i+1)
    sns.kdeplot(x=df[numerical_fea[i]],shade = True, color='r',data=df)
    plt.xlabel(numerical_fea[i],fontsize = 15)
    plt.tight_layout()
```



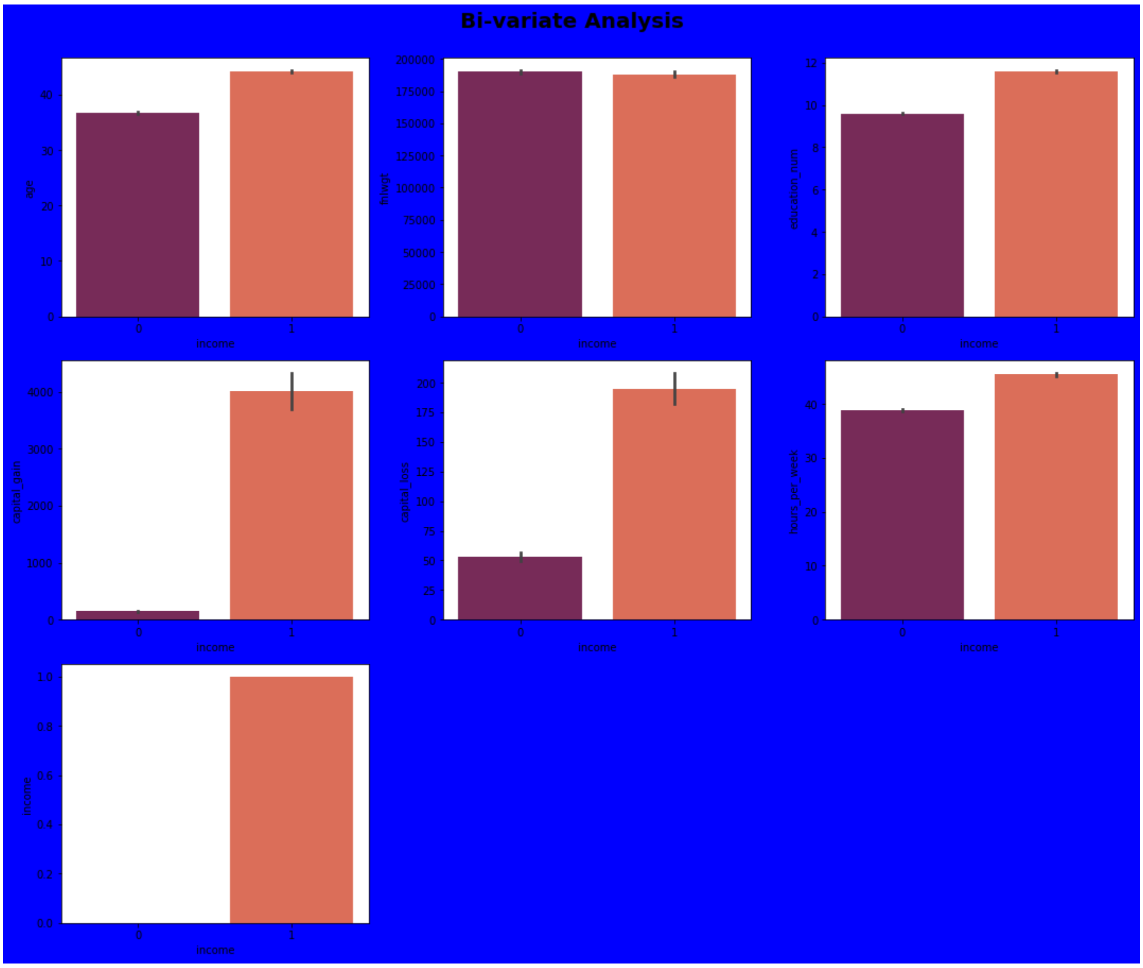

# Observations

- Age is aprroximately normally distributed.
- Final weight,capital loss & capital gain are heavily right skewed.

# Bivariate Analysis

In [20]:

```
## Ploting Bi-variate Analysis w.r.t Target column as 'income'

plt.figure(figsize=(15,20), facecolor='blue')
plt.suptitle('Bi-variate Analysis', fontsize=20, fontweight='bold', alp
for i in range(0, len(numerical_fea)):
    plt.subplot(5, 3, i+1)
    sns.barplot(y=numerical_fea [i], x='income', data = df,palette ="ro
    plt.tight_layout()
```

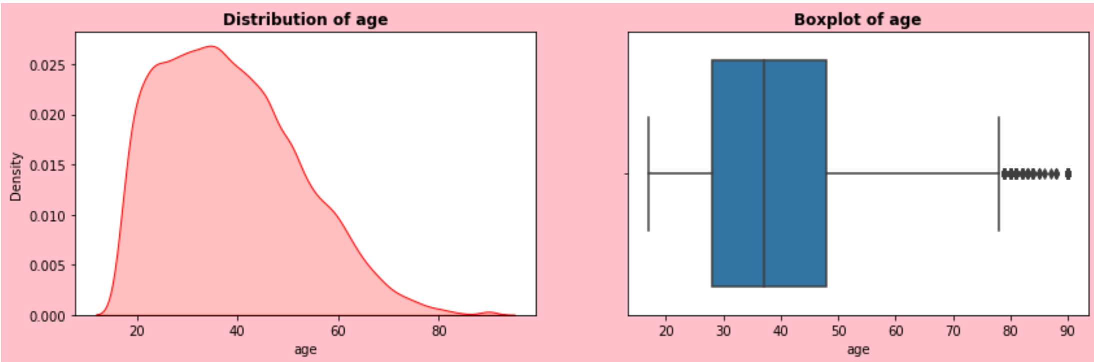


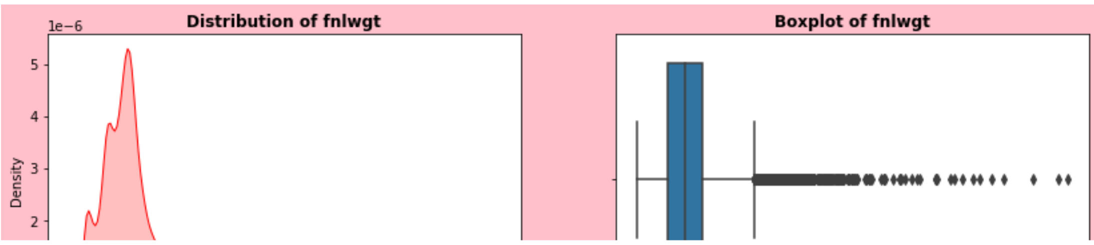

## Check distribution and outliers together

- Plot 2 Graphs Together

In [21]:

```python
## Ploting two graphs for checking Distribution and Outlier Togrther.
for fea in numerical_fea:
    plt.figure(figsize = (14,4), facecolor='pink')
    plt.subplot(121)
    sns.kdeplot(x=df[fea],shade = True, color='r',data=df)
    plt.title("Distribution of {}".format(fea),fontweight = 'bold' )

    plt.subplot(122)
    sns.boxplot(x= fea,data = df[numerical_fea])
    plt.title("Boxplot of {}".format(fea),fontweight = 'bold' )
    plt.show()
```

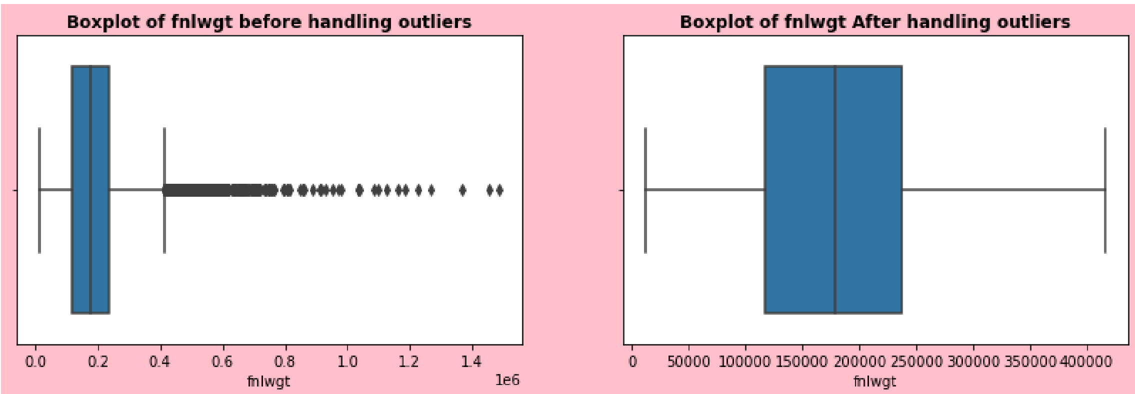


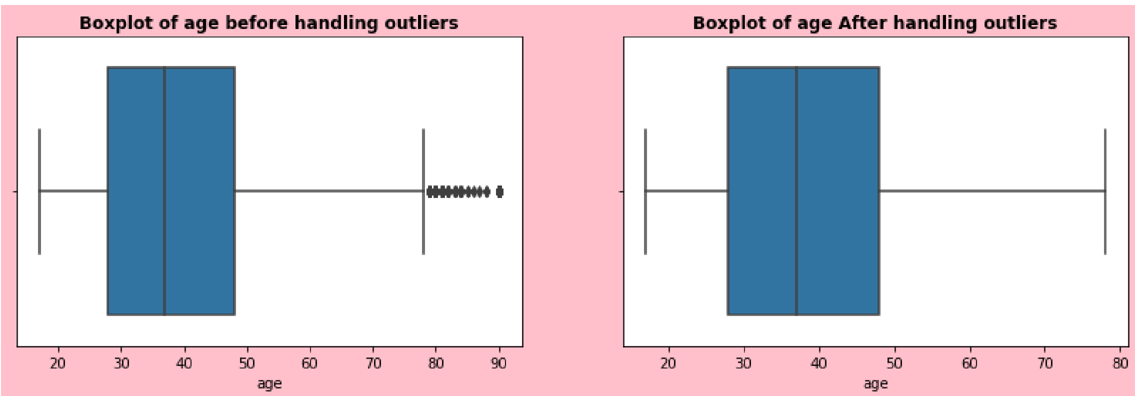



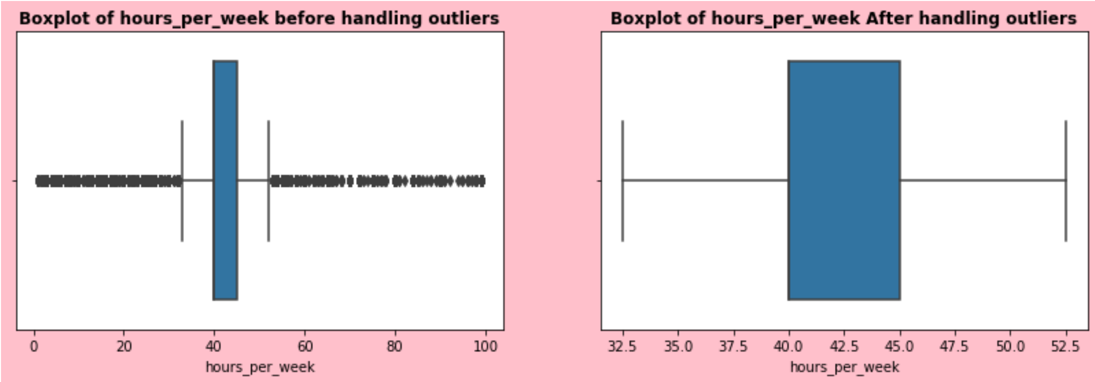

# Handling the outliers

In [22]:

```
## Handling the outliers

df1 = df.copy()
feature_to_use = ["fnlwgt",'age','hours_per_week']

for i in range(len(feature_to_use)):
    IQR = df1[feature_to_use[i]].quantile(0.75) - df1[feature_to_use[i]
    Lower_Limit = df1[feature_to_use[i]].quantile(0.25) - (1.5*IQR)
    UPPER_LIMIT = df1[feature_to_use[i]].quantile(0.75) + (1.5*IQR)
    df1[feature_to_use[i]]= np.where(df1[feature_to_use[i]]>UPPER_LIMIT
                                np.where(df1[feature_to_use[i]]<Lower_L


for fea in feature_to_use:
    plt.figure(figsize = (14,4), facecolor='pink')
    plt.subplot(121)
    sns.boxplot(x = fea, data = df)
    plt.title("Boxplot of {} before handling outliers".format(fea),font

    plt.subplot(122)
    sns.boxplot(x = fea, data = df1)
    plt.title("Boxplot of {} After handling outliers".format(fea),fontw
    plt.show()
```






# Seperate independent and dependent Feature

In [23]:

```python
## Creating Independent and Dependent Feature from dataset
x = df1.drop('income', axis = 1)
y = df1['income']
```

In [24]:

```python
## Checking top 5 Rows of a dataset
x.head()
```

Out[24]:

| | age | workclass | fnlwgt | education | education_num | marital_status | occ |
|---|---|---|---|---|---|---|---|
| **0** | 78.0 | Private | 77053.0 | HS-grad | 9 | Widowed | ma |
| **1** | 78.0 | Private | 132870.0 | HS-grad | 9 | Widowed | ma |
| **2** | 66.0 | Private | 186061.0 | Some-college | 10 | Widowed | |
| **3** | 54.0 | Private | 140359.0 | 7th-8th | 4 | Divorced | |
| **4** | 41.0 | Private | 264663.0 | Some-college | 10 | Separated | |

In [25]:

```
## Checking all Target_y value from dataset
y
```

Out[25]:

```
0        0
1        0
2        0
3        0
4        0
        ..
32556    0
32557    0
32558    1
32559    0
32560    0
Name: income, Length: 32561, dtype: int64
```

In [26]:

```
## Checking shapes of both x and y value.
x.shape , y.shape
```

Out[26]:

```
((32561, 14), (32561,))
```

# Label encoding on the categorical features

- If the data of feature is continous or discrete (numbers) then we dont have to do anything and we can directly standardize and train the model
- But when the data is categorical (string) then we have to perform encoding, it means convert it to 0 or 1, then only we can train the model

In [27]:

```
## Importing LabelEncoder
from sklearn.preprocessing import LabelEncoder
labelencoder_x = LabelEncoder()
```

In [28]:

```
## Fitting label Encoding in all categorical Feature.
x[categorical_fea] = x[categorical_fea].apply(LabelEncoder().fit_transf
```

In [29]:

```
## cheking top 5 rows of dataset.
x.head()
```

Out[29]:

| | age | workclass | fnlwgt | education | education_num | marital_status | occ |
|---|---|---|---|---|---|---|---|
| **0** | 78.0 | 3 | 77053.0 | 11 | 9 | 6 | |
| **1** | 78.0 | 3 | 132870.0 | 11 | 9 | 6 | |
| **2** | 66.0 | 3 | 186061.0 | 15 | 10 | 6 | |
| **3** | 54.0 | 3 | 140359.0 | 5 | 4 | 0 | |
| **4** | 41.0 | 3 | 264663.0 | 15 | 10 | 5 | |

In [30]:

```
## Checking top 5 rows of dataset.
y .head()
```

Out[30]:

```
0    0
1    0
2    0
3    0
4    0
Name: income, dtype: int64
```

# Train-Test Split

In [31]:

```
## Importing Train_test_Split and GridSearchCV library
from sklearn.model_selection import train_test_split,GridSearchCV
x_train , x_test , y_train , y_test = train_test_split(x,y,test_size=0.
```

In [32]:

```
## Checking both shapes of x and y training dataset
x_train.shape,y_train.shape
```

Out[32]:

```
((21815, 14), (21815,))
```

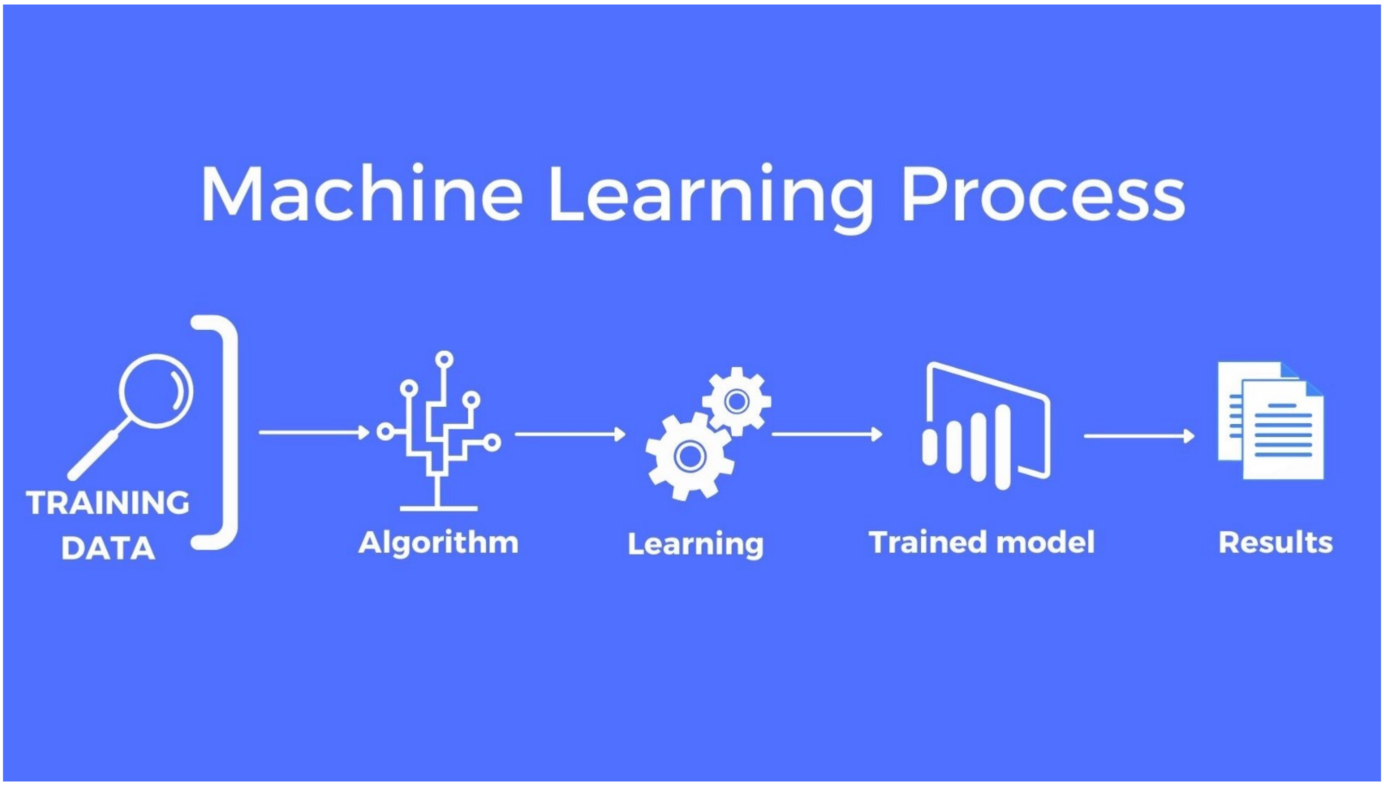
In [33]:

```
## Checking both shapes of x and y training dataset
x_test.shape,y_test.shape
```

Out[33]:

```
((10746, 14), (10746,))
```

# MODEL Building




## Decision Tree

In [34]:

```
report = []
```

In [35]:

```
## Importing Decision_Tree_Classifier
from sklearn.tree import DecisionTreeClassifier
model = DecisionTreeClassifier()
```

In [36]:

```
## fitting of Decision TRee Classifier model for Training dataset
model.fit(x_train,y_train)
```

Out[36]:

```
▾ DecisionTreeClassifier

DecisionTreeClassifier()
```

In [37]:

```
## checking Model score for Decision_TRee_Classifier model for Testing
model.score(x_test,y_test)
```

Out[37]:

```
0.811930020472734
```

In [38]:

```
## Model_Prediction for decision_tree_classifier.
dt_pred = model.predict(x_test)
```

In [41]:

```
## Importing accuracy_score library
from sklearn.metrics import accuracy_score
d_acc = accuracy_score(y_test,dt_pred)
report.append(['Decision Tree',d_acc])
d_acc
```

Out[41]:

```
0.811930020472734
```

# Hyperparameter Tunning of decision Tree with GridSearchCV

In [42]:

```
## Selecting Hyperparameter Tuninng for gridSearchCV
grid_param = {
    'criterion':['gini','entropy'],
    'max_depth': range(2,32,1),
    'min_samples_leaf': range(1,10,1),
    'min_samples_split': range(2,10,1),
    'splitter':['best','random']
}
```

In [43]:

```
dt_grid=GridSearchCV(estimator=model, param_grid= grid_param, cv = 3, n
```

In [45]:

```
## Fitting decision_tree_classifier Model in training dataset
dt_grid.fit(x_train,y_train)
```

Out[45]:

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

In [46]:

```
## choosing best Hyperparameter Tuining for Decision_Tree_Classifier.
dt_grid.best_params_
```

Out[46]:

```
{'criterion': 'gini',
 'max_depth': 8,
 'min_samples_leaf': 9,
 'min_samples_split': 8,
 'splitter': 'best'}
```

In [47]:

```
## Applyinng best Hyperparameter for Decision_tree_Classifier
dt_best_para = DecisionTreeClassifier(criterion = "entropy",
                                      max_depth= 8 ,
                                      min_samples_leaf= 3,
                                      min_samples_split= 2 ,
                                      splitter= "best")
```

In [48]:

```
## Fitting best Hyperparameter for Decision_tree_Classifier
dt_best_para.fit(x_train,y_train)
```

Out[48]:

```
DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', max_depth=8, min
_samples_leaf=3)
```

In [49]:

```
## Prediction
dt_best_para_pred2 = dt_best_para.predict(x_test)
```

In [50]:

```
print("Accuracy Before Hyper-parameter tunning:",accuracy_score(y_test,
print("Accuracy after Hyper-parameter tunning:",accuracy_score(y_test,d
```

```
Accuracy Before Hyper-parameter tunning: 0.811930020472734
Accuracy after Hyper-parameter tunning: 0.8535268937278988
```

In [51]:

```
hd_acc = accuracy_score(y_test,dt_best_para_pred2)
report.append(['Decision Tree Hyperparameter tunned',hd_acc])
```

## Random Forest Classifier

In [52]:

```
## Importing RandomForestClassifier model
from sklearn.ensemble import RandomForestClassifier
rf_model = RandomForestClassifier()
```

In [53]:

```
## Fitting RandomForestClassifier model in training dataset
rf_model.fit(x_train,y_train)
```

Out[53]:

```
▾ RandomForestClassifier
RandomForestClassifier()
```

In [54]:

```
## Prediction
y_pred_rf = rf_model.predict(x_test)
```

In [55]:

```
# Before Hyper-parameter tunning
rf_acc = accuracy_score(y_test,y_pred_rf)
report.append(['Random Forest',rf_acc])
accuracy_score(y_test,y_pred_rf)
```

Out[55]:

```
0.8566908617159873
```

## Hyperparameter Tunning of Random Forest Classifier with RandomizedSearchCV

In [56]:

```
Ran_param = {
    "max_depth" : [5,8,15,None,10],
    'max_features' : [3,'auto'],
    'min_samples_split' : [2,8,15,20],
    'n_estimators' : [50,100,200,500]
}
```

In [57]:

```
from sklearn.model_selection import RandomizedSearchCV
random = RandomizedSearchCV(estimator = RandomForestClassifier(),
                   param_distributions = Ran_param,
                   n_iter= 100,
                   cv = 3,
                   verbose = 2,
                   n_jobs=-1)
```

In [58]:

```
random.fit(x_train,y_train)
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fit
s
```

Out[58]:

```
▸ RandomizedSearchCV
▸ estimator: RandomForestClassifier
    ▸ RandomForestClassifier
```

In [60]:

```
random.best_params_,random.best_estimator_
```

Out[60]:

```
({'n_estimators': 500,
  'min_samples_split': 8,
  'max_features': 3,
  'max_depth': 15},
 RandomForestClassifier(max_depth=15, max_features=3, min_sam
ples_split=8,
                        n_estimators=500))
```

In [61]:

```
random.best_params =  RandomForestClassifier(max_depth= None, max_featu
                        n_estimators=50)
```

In [62]:

```
random.best_params.fit(x_train,y_train)
```

Out[62]:

```
▾                    RandomForestClassifier
RandomForestClassifier(max_features=3, min_samples_split=15,
n_estimators=50)
```

In [63]:

```
y_pred_rf_bestpara = random.best_params.predict(x_test)
```

In [64]:

```
print("Accuracy Before Hyper-parameter tunning:",accuracy_score(y_test,
print("Accuracy after Hyper-parameter tunning:",accuracy_score(y_test,d
```

```
Accuracy Before Hyper-parameter tunning: 0.811930020472734
Accuracy after Hyper-parameter tunning: 0.8535268937278988
```

In [95]:

```
hd_acc = accuracy_score(y_test,y_pred_rf_bestpara)
report.append(['Random Forest Hypertunned',hd_acc])
accuracy_score(y_test,y_pred_rf_bestpara)
```

Out[95]:

```
0.8606923506420994
```

# Bagging Classifier using SVC

In [66]:

```
from sklearn.svm import SVC
from sklearn.ensemble import BaggingClassifier
from sklearn.datasets import make_classification

model_bag_svc = BaggingClassifier(base_estimator=SVC(), n_estimators =
```

In [67]:

```
model_bag_svc.fit(x_train,y_train)
```

Out[67]:

```
▸ BaggingClassifier
▸ base_estimator: SVC
      ▸ SVC
```

In [88]:

```
y_pred_bag = model_bag_svc.predict(x_test)
```

In [89]:

```
bg_acc = accuracy_score(y_test, y_pred_bag)
report.append(['Bagging Classifier using SVC',bg_acc])
accuracy_score(y_test, y_pred_bag)
```

Out[89]:

```
0.7949934859482598
```

## Voting Classifier

In [72]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier, VotingClassifier

clf1 = LogisticRegression(multi_class= 'multinomial',random_state=1)
clf2 =RandomForestClassifier(n_estimators= 50, random_state=1)
clf3 = GaussianNB()

eclf1 = VotingClassifier(estimators= [('lr',clf1),('rf',clf2),('gnb',cl
```

In [73]:

```
eclf1.fit(x_train,y_train)
```

Out[73]:

```
VotingClassifier
lr                    rf                          gnb
LogisticRegression    RandomForestClassifier      GaussianNB
```

In [74]:

```
y_pred_votting = eclf1.predict(x_test)
```

In [75]:

```
vc_acc = accuracy_score(y_test,y_pred_votting)
report.append(['Voting Classifier',vc_acc])
accuracy_score(y_test,y_pred_votting)
```

Out[75]:

0.8106272101246975

## Extra Tree Classifier

In [76]:

```
from sklearn.ensemble import ExtraTreesClassifier
et_model = ExtraTreesClassifier()
```

In [77]:

```
et_model.fit(x_train,y_train)
```

Out[77]:

```
ExtraTreesClassifier
ExtraTreesClassifier()
```

In [78]:

```
y_pred_et = et_model.predict(x_test)
```

In [79]:

```
et_acc = accuracy_score(y_test,y_pred_et)
report.append(['Extra Trees Classifier', et_acc])
accuracy_score(y_test,y_pred_et)
```

Out[79]:

```
0.8417085427135679
```

# Hyperparameter tunning of ET_model by RandomSearchCV

In [80]:

```
Ran_param = {
    "max_depth" : [5,8,15,None,10],
    'max_features' : [3,'auto'],
    'min_samples_split' : [2,8,15,20],
    'n_estimators' : [50,100,200,500]
}
```

In [81]:

```
from sklearn.model_selection import RandomizedSearchCV
random = RandomizedSearchCV(estimator = et_model,
                   param_distributions = Ran_param,
                   n_iter= 100,
                   cv = 3,
                   verbose = 2,
                   n_jobs=-1)
```

In [82]:

```
random.fit(x_train,y_train)
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fit
s
```

Out[82]:

```
▸ RandomizedSearchCV
▸ estimator: ExtraTreesClassifier
    ▸ ExtraTreesClassifier
```

In [83]:

```
random.best_params_,random.best_estimator_
```

Out[83]:

```
({'n_estimators': 500,
  'min_samples_split': 15,
  'max_features': 3,
  'max_depth': None},
 ExtraTreesClassifier(max_features=3, min_samples_split=15, n
_estimators=500))
```

In [84]:

```
et_best_para =  ExtraTreesClassifier(max_depth= None, max_features= 3 ,
                        n_estimators=500)
```

In [85]:

```
et_best_para.fit(x_train,y_train)
```

Out[85]:

```
▾ ExtraTreesClassifier
ExtraTreesClassifier(max_features=3, min_samples_split=15, n
_estimators=500)
```

In [86]:

```
y_pred_et = et_best_para.predict(x_test)
```

In [87]:

```
et_acc_ht = accuracy_score(y_test,y_pred_et)
report.append(['Extra Tress Classifier Hypertuned', et_acc_ht])
accuracy_score(y_test,y_pred_et)
```

Out[87]:

```
0.8563186301879769
```

In [96]:

```
report
```

Out[96]:

```
[['Decision Tree', 0.811930020472734],
 ['Decision Tree', 0.811930020472734],
 ['Decision Tree Hyperparameter tunned', 0.8535268937278988],
 ['Random Forest', 0.8566908617159873],
 ['Random Forest Hypertunned', 0.8535268937278988],
 ['Voting Classifier', 0.8106272101246975],
 ['Extra Trees Classifier', 0.8417085427135679],
 ['Extra Tress Classifier Hypertuned', 0.8563186301879769],
 ['Bagging Classifier using SVC', 0.7949934859482598],
 ['Random Forest Hypertunned', 0.8606923506420994]]
```

In [97]:

```
i_report = pd.DataFrame(report, columns = ['Classifier','Accuracy'])
```

In [98]:

```
i_report.sort_values(by = "Accuracy",ascending = False)
```

Out[98]:

| | Classifier | Accuracy |
|---|---|---|
| **9** | Random Forest Hypertunned | 0.860692 |
| **3** | Random Forest | 0.856691 |
| **7** | Extra Tress Classifier Hypertuned | 0.856319 |
| **2** | Decision Tree Hyperparameter tunned | 0.853527 |
| **4** | Random Forest Hypertunned | 0.853527 |
| **6** | Extra Trees Classifier | 0.841709 |
| **0** | Decision Tree | 0.811930 |
| **1** | Decision Tree | 0.811930 |
| **5** | Voting Classifier | 0.810627 |
| **8** | Bagging Classifier using SVC | 0.794993 |

# Summary

- Random Forest Hypertunned gives the best accuracy

# Store the Best model (Random Forest Hypertunned) in a pickle file

In [101]:

```
import pickle
pickle.dump(y_pred_rf_bestpara, open('randomforest_hupertuned.sav','wb'
```

# THANK YOU

In [ ]:

```

```