Final project: Predict whether income exceeds $50K/yr.

Data Set Information:

Extraction was done by Barry Becker from the 1994 Census database. A set of reasonably clean records was extracted using the following conditions: ((AAGE>16) && (AGI>100) && (AFNLWGT>1)&& (HRSWK>0))

Prediction task is to determine whether a person makes over 50K a year.

Attribute Information:

Listing of attributes:

- earn: >50K, <=50K (**Target atribute**)
- age: continuous.
- workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov State-gov, Without-pay, Never-worked.
- fnlwgt: continuous.
- 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.
- education-num: continuous.
- marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.
- 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.
- relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.
- race: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.
- sex: Female, Male.
- capital-gain: continuous.
- capital-loss: continuous.
- hours-per-week: continuous.
- 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.

```
#Import main libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

We will use **adult.data** from UCI ML repository: https://archive.ics.uci.edu/ml/datasets/Census+Income

```
#Load DataSet
df_adult = pd.read_csv("/content/adult.data",sep=',',header=None)
```

1.Exploratory data analysis

```
#DataFrame visualization
df_adult.head()
```

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	Married-civ-	Handlers-	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	United-	[illegible]

```
#Dataframe size:
print('Size DF: ',df_adult.shape)
```

```
Size DF:  (32561, 15)
```

OBS:

- There are not header for each feature (column). So, it will be necesary to rename each column.

```
#Set headers for each feature (reference website):
col_names = ["age","workclass","fnlwgt","education","education-num","marital-status",
           "occupation","relationship","race","sex","capital-gain","capital-loss","hours-per-week","native-country","earn"]
df_adult.columns = col_names
```

```
#Verify Changes:
df_adult.head()
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	h
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	

```
#Check data Type
df_adult.dtypes
```

```
age                int64
workclass         object
fnlwgt             int64
education         object
education-num      int64
marital-status    object
occupation        object
relationship      object
race              object
sex               object
capital-gain       int64
capital-loss       int64
hours-per-week     int64
native-country    object
earn              object
dtype: object
```

OBS:

- There are 6 numeric variables and 9 categorical variable.
- Target variable is "earn".

```
# Let us explore more about "earn" variable:
df_adult['earn'].value_counts()
```

```
 <=50K    24720
 >50K      7841
Name: earn, dtype: int64
```

OBS:

- Consider that target variable is not balanced in DataSet.

```
#Check for missing Values:
df_adult.isnull().sum()
```

```
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
earn              0
dtype: int64
```

2.Correlation and Outliers

Let us briefly analyze the correlation between variables and the presence of any outliers.

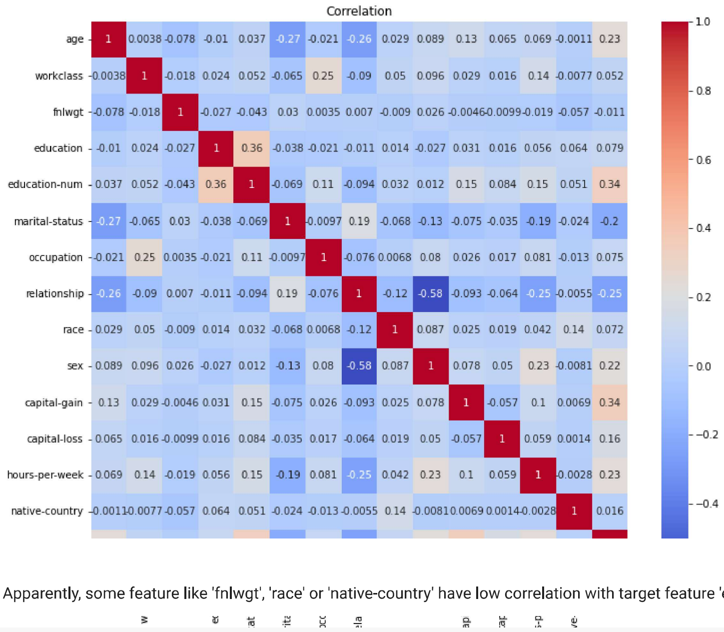
```
#Import Ordinal Encoder from scikit-learn
from sklearn.preprocessing import OrdinalEncoder
```

```
#Create a copy from original DataSet
df_adult_enc = df_adult.copy(deep=True)
```

```
oc = OrdinalEncoder()
df_adult_enc = pd.DataFrame(oc.fit_transform(df_adult_enc), columns =col_names)
df_adult_enc.head()
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hour pe we
0	22.0	7.0	2671.0	9.0	12.0	4.0	1.0	1.0	4.0	1.0	25.0	0.0	3!
1	33.0	6.0	2926.0	9.0	12.0	2.0	4.0	0.0	4.0	1.0	0.0	0.0	1:
2	21.0	4.0	14086.0	11.0	8.0	0.0	6.0	1.0	4.0	1.0	0.0	0.0	3!
3	36.0	4.0	15336.0	1.0	6.0	2.0	6.0	0.0	2.0	1.0	0.0	0.0	3!

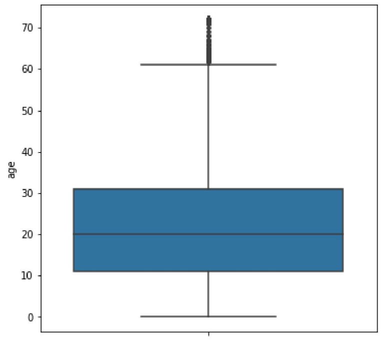
```
#Heatmap for correlation:
fig = plt.figure(figsize=(12,10))
sns.heatmap(df_adult_enc.corr(), annot=True,cmap='coolwarm')
plt.title('Correlation')
plt.show()
```

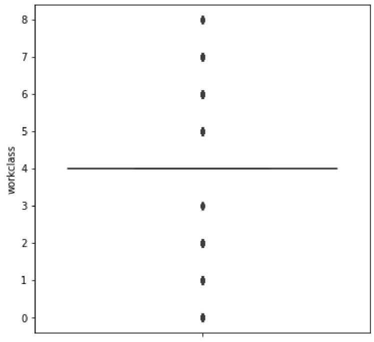


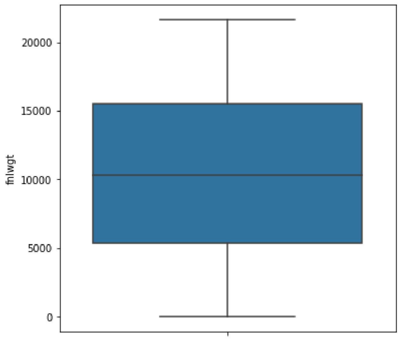
OBS:

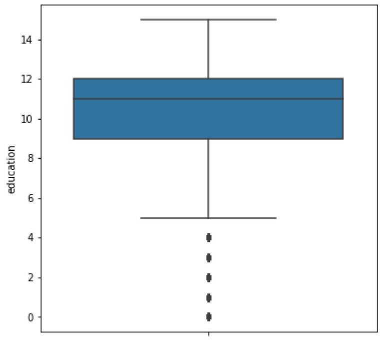
- Apparently, some feature like 'fnlwgt', 'race' or 'native-country' have low correlation with target feature 'earn'.

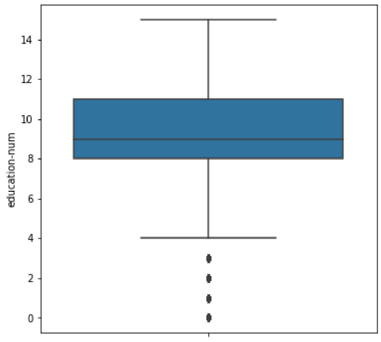
```
#let us check for outliers:
for i in col_names:
  plt.figure(figsize=(6,6))
  sns.boxplot(data=df_adult_enc, y=i)
  plt.show()
```

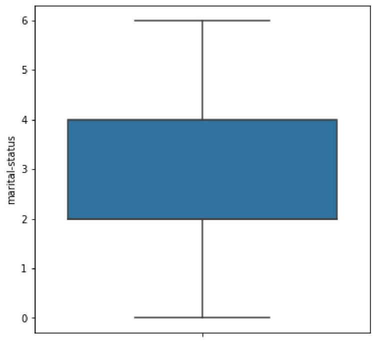

age
0
10
20
30
40
50
60
70

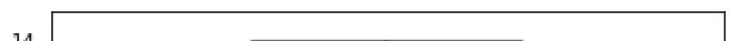

workclass
0
1
2
3
4
5
6
7
8

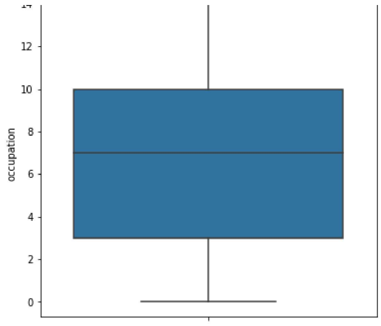

fnlwgt
0
5000
10000
15000
20000

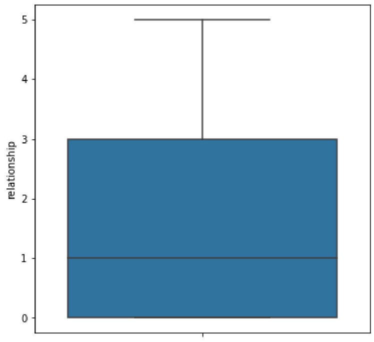

education
0
2
4
6
8
10
12
14

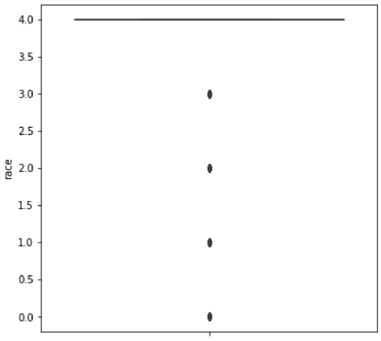

education-num
0
2
4
6
8
10
12
14

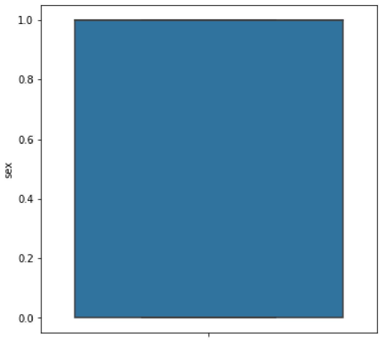

marital-status
0
1
2
3
4
5
6

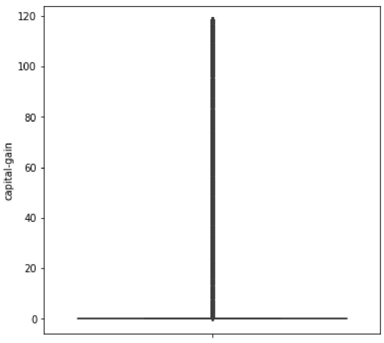


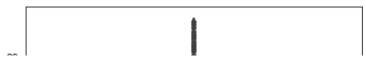












OBS:

- There are some outliers for 'age', 'education'and education-num'. We will continue with data processing.

3.Data Processing

```
#Separete Data Frame into 'x' variable and 'y' variable:
x = df_adult.drop(['earn'],axis=1)
y = df_adult['earn']
```

```
#Libraries to create the model:
from sklearn.model_selection import train_test_split
```

```
#30% for 'test' and 70% for 'train':
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.30, random_state=43)
```

```
#Check the size of train and test:
x_train.shape, x_test.shape
```

```
((22792, 14), (9769, 14))
```

```
y_train.shape, y_test.shape
```

```
((22792,), (9769,))
```

```
#Let us check the content of x_train:
x_train.head()
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital los
20717	24	Local-gov	32950	Bachelors	13	Never-married	Prof-specialty	Not-in-family	White	Male	0	
11366	37	State-gov	34996	HS-grad	9	Separated	Other-service	Unmarried	White	Female	0	
28940	46	Private	189498	Bachelors	13	Married-civ-	Prof-	Husband	White	Male	0	184

```
x_train.dtypes
```

```
age                int64
workclass         object
fnlwgt             int64
education         object
education-num      int64
marital-status    object
occupation        object
relationship      object
race              object
sex               object
capital-gain       int64
capital-loss       int64
hours-per-week     int64
native-country    object
dtype: object
```

OBS:

- we have numeric and categorical variables for 'X' (train and test). In order to continue with the algorithms, we will code the categorical variable.

4.Training model : Decision Tree

```
#if needed: !pip install category-encoders
!pip install category-encoders
```

```
#import category_encoders:
import category_encoders as ce

encoder = ce.OrdinalEncoder(cols=['workclass','education','marital-status','occupation','relationship','race','sex','native-country'])
x_train = encoder.fit_transform(x_train)
x_test = encoder.transform(x_test)
```

```
#Check transformation:
x_train.head()
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	h
20717	24	1	32950	1	13	1	1	1	1	1	0	0	
11366	37	2	34996	2	9	2	2	2	1	2	0	0	
28940	46	3	189498	1	13	3	1	3	1	1	0	1848	
28302	50	3	301583	2	9	1	3	1	1	1	0	0	

```
#Import Decision Tree
from sklearn.tree import DecisionTreeClassifier

#Create mode, depth=2 (x_train <5k)
tree = DecisionTreeClassifier(max_depth=2, random_state=43)
```

```
#Training:
tree.fit(x_train, y_train)
```

```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=2, random_state=43)
```

```
#Calculate predictions for Train and Test
y_train_pred_tree = tree.predict(x_train)
y_test_pred_tree = tree.predict(x_test)
```

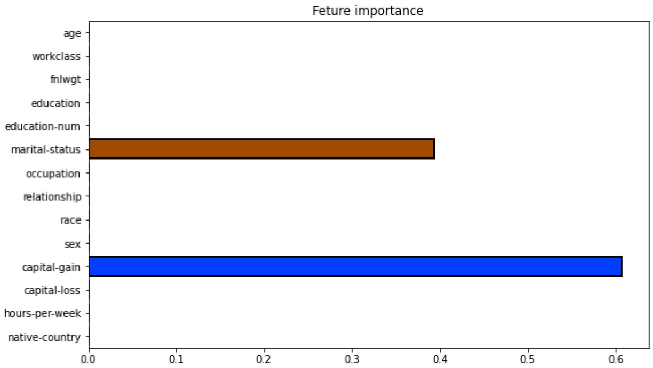
4.1.Evaluation model: Decision Tree

```
#Import metrics:
from sklearn.metrics import accuracy_score

#Accuracy for Train and test:
train_accuracy_tree = accuracy_score(y_train, y_train_pred_tree)
```

```
test_accuracy_tree = accuracy_score(y_test, y_test_pred_tree)

print('Train Accuracy:', train_accuracy_tree.round(4)*100,'%')
print('Test Accuracy:', test_accuracy_tree.round(4)*100,'%')
```

```
Train Accuracy: 80.12 %
Test Accuracy: 80.60000000000001 %
```

```
#More important features:
importances = tree.feature_importances_
columns = x.columns
plt.figure(figsize=(10,6))
sns.barplot(y=columns, x=importances, palette='bright', saturation=2.0, edgecolor='black',linewidth=2)
plt.title('Feture importance')
plt.show()
```



OBS:

- Using "Desicion Tree model", apparently features "marital-status" and "capital-gain" have more importace.
- Consider that accuracy for Train and test are too similar.
- Comparing "Feature Importances" and "Correlation" there are some feature like 'education' or 'sex' that should be compared.

5.Training model : Random Forest

```
#Import random forest
from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier(n_estimators = 10, random_state=43)
rf.fit(x_train, y_train)
```

```
RandomForestClassifier
RandomForestClassifier(n_estimators=10, random_state=43)
```

```
#Predictions for Random Forest:
y_train_pred_rf = rf.predict(x_train)
y_test_pred_rf = rf.predict(x_test)
```

5.1.Evaluation model: Random Forest

```
#Import metrics (if needed)
from sklearn.metrics import accuracy_score

#Accuracy for Train and Test:
train_accuracy_rf = accuracy_score(y_train, y_train_pred_rf)
test_accuracy_rf = accuracy_score(y_test, y_test_pred_rf)

print('Accuracy_train: ',train_accuracy_rf.round(4)*100)
print('Accuracy_test: ',test_accuracy_rf.round(4)*100)

#Important: we could reduce estimators numbers to avoid overfitting
```

```
Accuracy_train:  98.77
Accuracy_test:  85.16
```

OBS:

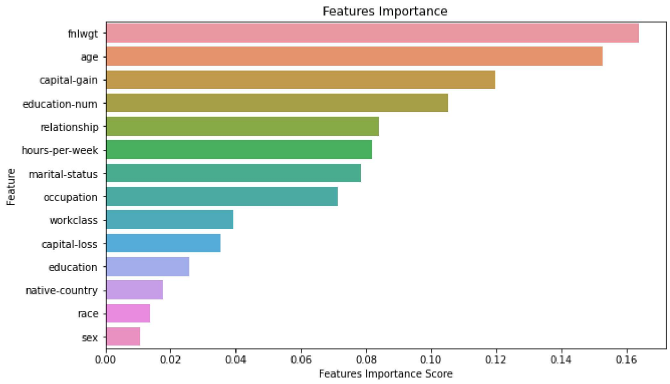
- "Accuracy_Test" improved using Random Forest, but "Accuracy_train" is almost overfitting.

```
# More Important Features:
features_scores = pd.Series(rf.feature_importances_,
                            index =x_train.columns).sort_values(ascending=False)
features_scores
```

```
fnlwgt            0.163847
age               0.152644
capital-gain      0.119785
education-num     0.105336
relationship      0.084091
hours-per-week    0.081711
marital-status    0.078482
occupation        0.071368
workclass         0.039424
capital-loss      0.035409
education         0.025792
native-country    0.017718
race              0.013689
sex               0.010705
dtype: float64
```

```
#BarPlot:
```

```
plt.figure(figsize=(10,6))
sns.barplot(x=features_scores, y=features_scores.index)
plt.xlabel('Features Importance Score')
plt.ylabel('Feature')
plt.title('Features Importance')
plt.show()
```



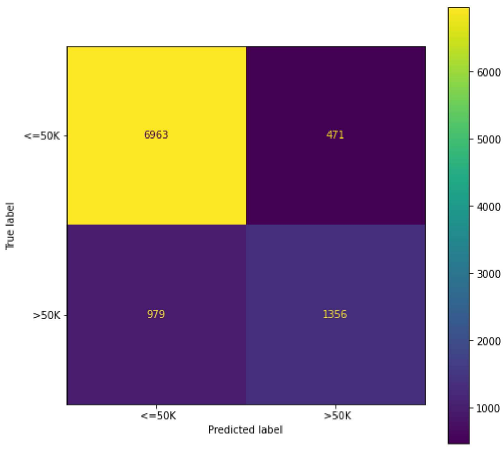
OBS:

- Using random forest algorithm, feature like 'fnlwgt' and 'age' become more relevant than 'capital-gain'.
- 'education-num', 'relationship', 'hours-per-week' become more relevant than 'marital-stauts'.

```
# Confusion Matrix for Ranfom Forest
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_test_pred_rf)
print('Matriz de confusion: \n\n',cm)
```

```
Matriz de confusion:

 [[6963  471]
 [ 979 1356]]
```

```
#Plot confusion matrix
from sklearn.metrics import ConfusionMatrixDisplay

cmp = ConfusionMatrixDisplay(cm, display_labels =rf.classes_)
fig, ax = plt.subplots(figsize=(8,8))
cmp.plot(ax=ax)
plt.show()
```




```
#Random Forest Metrics:
from sklearn.metrics import classification_report
print(classification_report(y_test, y_test_pred_rf))
```

```
              precision    recall  f1-score   support

       <=50K       0.88      0.94      0.91      7434
        >50K       0.74      0.58      0.65      2335

    accuracy                           0.85      9769
   macro avg       0.81      0.76      0.78      9769
weighted avg       0.84      0.85      0.84      9769
```

Final Observations:

- Using Radom Forest give us more precision than decision tree, but there are some considerations
    - Dataset is unbalanced (look at Confusion Matrix).
    - "Precision", "Recall", "f1-score" and "support" have better results for '<=50k' (because of unbalanced dataset)
- Comparing "Correlation" and "Randon Forest Feature importance" there are many similitude, except for feature "fnlwgt".It would be interesting to understand the relevance of this feature.