Binary classification machine learning model

1. Load Required Libraries

```
import pandas as pd
import numpy as np
```

2. Load Data set

```
data = pd.read_csv("adult.csv")

data.head()
```

```
   age  workclass  fnlwgt     education  educational-num      marital-
status  \
0   25    Private  226802          11th                7        Never-
married
1   38    Private   89814       HS-grad                9  Married-civ-
spouse
2   28  Local-gov  336951    Assoc-acdm               12  Married-civ-
spouse
3   44    Private  160323  Some-college               10  Married-civ-
spouse
4   18          ?  103497  Some-college               10        Never-
married

          occupation relationship   race  gender  capital-gain
capital-loss  \
0  Machine-op-inspct    Own-child  Black    Male             0
0
1    Farming-fishing      Husband  White    Male             0
0
2    Protective-serv      Husband  White    Male             0
0
3  Machine-op-inspct      Husband  Black    Male          7688
0
4                  ?    Own-child  White  Female             0
0

   hours-per-week native-country income
0              40  United-States  <=50K
1              50  United-States  <=50K
2              40  United-States   >50K
```

```
3              40  United-States   >50K
4              30  United-States  <=50K
```

3. Some details about dataset

Null values

```
data.isnull().sum()
```

```
age                  0
workclass            0
fnlwgt               0
education            0
educational-num      0
marital-status       0
occupation           0
relationship         0
race                 0
gender               0
capital-gain         0
capital-loss         0
hours-per-week       0
native-country       0
income               0
dtype: int64
```

- No missing values in Adult dataset

Data types

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48842 entries, 0 to 48841
Data columns (total 15 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   age              48842 non-null  int64
 1   workclass        48842 non-null  object
 2   fnlwgt           48842 non-null  int64
 3   education        48842 non-null  object
 4   educational-num  48842 non-null  int64
 5   marital-status   48842 non-null  object
 6   occupation       48842 non-null  object
 7   relationship     48842 non-null  object
 8   race             48842 non-null  object
 9   gender           48842 non-null  object
 10  capital-gain     48842 non-null  int64
```

```
 11  capital-loss     48842 non-null  int64
 12  hours-per-week   48842 non-null  int64
 13  native-country   48842 non-null  object
 14  income           48842 non-null  object
dtypes: int64(6), object(9)
memory usage: 5.6+ MB
```

- There are two datatypes which are included such as "int64","object"

Some statistical values

```
data.describe()

                age        fnlwgt  educational-num  capital-gain  \
count  48842.000000  4.884200e+04     48842.000000  48842.000000
mean      38.643585  1.896641e+05        10.078089   1079.067626
std       13.710510  1.056040e+05         2.570973   7452.019058
min       17.000000  1.228500e+04         1.000000      0.000000
25%       28.000000  1.175505e+05         9.000000      0.000000
50%       37.000000  1.781445e+05        10.000000      0.000000
75%       48.000000  2.376420e+05        12.000000      0.000000
max       90.000000  1.490400e+06        16.000000  99999.000000

       capital-loss  hours-per-week
count  48842.000000    48842.000000
mean      87.502314       40.422382
std      403.004552       12.391444
min        0.000000        1.000000
25%        0.000000       40.000000
50%        0.000000       40.000000
75%        0.000000       45.000000
max     4356.000000       99.000000
```

Dimenstion

```
data.shape

(48842, 15)
```

- Number of records : 48842
- Number of variables : 15

Column names

```
data.columns

Index(['age', 'workclass', 'fnlwgt', 'education', 'educational-num',
       'marital-status', 'occupation', 'relationship', 'race',
'gender',
       'capital-gain', 'capital-loss', 'hours-per-week', 'native-
```

```
country',
       'income'],
      dtype='object')
```

Categorical data counts

```
categorical_variable = []
for i in data.columns:
    if data[i].dtype == "object":
        categorical_variable.append(i)
    else:
        pass

print(categorical_variable)
```

```
['workclass', 'education', 'marital-status', 'occupation',
'relationship', 'race', 'gender', 'native-country', 'income']
```

```
for i in categorical_variable:
    print(data[i].value_counts(),"\n\n")
```

```
workclass
Private             33906
Self-emp-not-inc     3862
Local-gov            3136
?                    2799
State-gov            1981
Self-emp-inc         1695
Federal-gov          1432
Without-pay            21
Never-worked           10
Name: count, dtype: int64


education
HS-grad         15784
Some-college    10878
Bachelors        8025
Masters          2657
Assoc-voc        2061
11th             1812
Assoc-acdm       1601
10th             1389
7th-8th           955
Prof-school       834
9th               756
12th              657
Doctorate         594
5th-6th           509
1st-4th           247
```

```
Preschool             83
Name: count, dtype: int64


marital-status
Married-civ-spouse       22379
Never-married            16117
Divorced                  6633
Separated                 1530
Widowed                   1518
Married-spouse-absent      628
Married-AF-spouse           37
Name: count, dtype: int64


occupation
Prof-specialty       6172
Craft-repair         6112
Exec-managerial      6086
Adm-clerical         5611
Sales                5504
Other-service        4923
Machine-op-inspct    3022
?                    2809
Transport-moving     2355
Handlers-cleaners    2072
Farming-fishing      1490
Tech-support         1446
Protective-serv       983
Priv-house-serv       242
Armed-Forces           15
Name: count, dtype: int64


relationship
Husband           19716
Not-in-family     12583
Own-child          7581
Unmarried          5125
Wife               2331
Other-relative     1506
Name: count, dtype: int64


race
White                 41762
Black                  4685
Asian-Pac-Islander     1519
Amer-Indian-Eskimo      470
Other                   406
```

```
Name: count, dtype: int64


gender
Male      32650
Female    16192
Name: count, dtype: int64


native-country
United-States                 43832
Mexico                          951
?                               857
Philippines                     295
Germany                         206
Puerto-Rico                     184
Canada                          182
El-Salvador                     155
India                           151
Cuba                            138
England                         127
China                           122
South                           115
Jamaica                         106
Italy                           105
Dominican-Republic              103
Japan                            92
Guatemala                        88
Poland                           87
Vietnam                          86
Columbia                         85
Haiti                            75
Portugal                         67
Taiwan                           65
Iran                             59
Greece                           49
Nicaragua                        49
Peru                             46
Ecuador                          45
France                           38
Ireland                          37
Hong                             30
Thailand                         30
Cambodia                         28
Trinadad&Tobago                  27
Laos                             23
Yugoslavia                       23
Outlying-US(Guam-USVI-etc)       23
Scotland                         21
Honduras                         20
```

```
Hungary                                 19
Holand-Netherlands                       1
Name: count, dtype: int64


income
<=50K    37155
>50K     11687
Name: count, dtype: int64
```

4. Data pre-processing

Dropping columns

```
data.drop(columns="education",axis=1,inplace=True)
```

One-Hot-encoding

```
encoded_variable = ["workclass","marital-
status","occupation","relationship","race","native-country"]

new_data = pd.get_dummies(data, columns=encoded_variable,
dtype="int64")

new_data.head(2)

   age  fnlwgt  educational-num gender  capital-gain  capital-loss  \
0   25  226802                7   Male             0             0
1   38   89814                9   Male             0             0

   hours-per-week income  workclass_?  workclass_Federal-gov  ...  \
0              40  <=50K            0                      0  ...
1              50  <=50K            0                      0  ...

   native-country_Portugal  native-country_Puerto-Rico  \
0                        0                           0
1                        0                           0

   native-country_Scotland  native-country_South  native-
country_Taiwan  \
0                        0                     0
0
1                        0                     0
0

   native-country_Thailand  native-country_Trinadad&Tobago  \
0                        0                               0
```

```
1                        0                              0

   native-country_United-States  native-country_Vietnam  \
0                             1                       0
1                             1                       0

   native-country_Yugoslavia
0                          0
1                          0

[2 rows x 92 columns]
```

```
new_data["income"].value_counts()
```

```
income
<=50K    37155
>50K     11687
Name: count, dtype: int64
```

```
new_data["gender"].value_counts()
```

```
gender
Male      32650
Female    16192
Name: count, dtype: int64
```

```
new_data["income"] = new_data["income"].apply(lambda x : 0 if x ==
"<=50K" else 1)
new_data["gender"] = new_data["gender"].apply(lambda x : 1 if x ==
"Male" else 0)
```

```
new_data.head(4)
```

```
   age  fnlwgt  educational-num  gender  capital-gain  capital-loss  \
0   25  226802                7       1             0             0
1   38   89814                9       1             0             0
2   28  336951               12       1             0             0
3   44  160323               10       1          7688             0

   hours-per-week  income  workclass_?  workclass_Federal-gov  ...  \
0              40       0            0                      0  ...
1              50       0            0                      0  ...
2              40       1            0                      0  ...
3              40       1            0                      0  ...

   native-country_Portugal  native-country_Puerto-Rico  \
0                        0                           0
1                        0                           0
2                        0                           0
3                        0                           0
```

```
   native-country_Scotland  native-country_South  native-
country_Taiwan  \
0                        0                     0
0
1                        0                     0
0
2                        0                     0
0
3                        0                     0
0

   native-country_Thailand  native-country_Trinadad&Tobago  \
0                        0                               0
1                        0                               0
2                        0                               0
3                        0                               0

   native-country_United-States  native-country_Vietnam  \
0                             1                       0
1                             1                       0
2                             1                       0
3                             1                       0

   native-country_Yugoslavia
0                          0
1                          0
2                          0
3                          0

[4 rows x 92 columns]
```

- There are no categorical feature columns

Count of all feature column in new data set

```
column_names = new_data.columns.to_list()
len(column_names)

92
```

- There are large number of column. Now we check what are the most important columns related to income column.
- For that, we draw correlation between variables

correlation

```
new_data.corr()

                                     age    fnlwgt  educational-num
gender  \
```

```
age                                1.000000 -0.076628         0.030940
0.088120
fnlwgt                            -0.076628  1.000000        -0.038761
0.027739
educational-num                    0.030940 -0.038761         1.000000
0.009328
gender                             0.088120  0.027739         0.009328
1.000000
capital-gain                       0.077229 -0.003706         0.125146
0.047094
...                                     ...       ...              ...
...
native-country_Thailand           -0.001766 -0.001512         0.007283 -
0.007117
native-country_Trinadad&Tobago     0.001056  0.004153        -0.010201 -
0.009342
native-country_United-States       0.011888 -0.070645         0.104210 -
0.011167
native-country_Vietnam            -0.012337 -0.007479        -0.007544 -
0.001545
native-country_Yugoslavia          0.002905  0.004699        -0.005798
0.005262

                                capital-gain  capital-loss  hours-per-
week  \
age                                 0.077229      0.056944
0.071558
fnlwgt                             -0.003706     -0.004366        -
0.013519
educational-num                     0.125146      0.080972
0.143689
gender                              0.047094      0.045480
0.228560
capital-gain                        1.000000     -0.031441
0.082157
...                                      ...           ...
...
native-country_Thailand            -0.002781     -0.002338
0.008558
native-country_Trinadad&Tobago     -0.003039      0.004028        -
0.002911
native-country_United-States        0.004191      0.009449
0.004390
native-country_Vietnam             -0.002673     -0.000118        -
0.008289
native-country_Yugoslavia          -0.000474     -0.004713        -
0.000359

                                  income  workclass_?
```

```
workclass_Federal-gov  \
age                              0.230369     0.026931
0.049867
fnlwgt                          -0.006339    -0.005625                -
0.009996
educational-num                  0.332613    -0.079304
0.058072
gender                           0.214628    -0.064010
0.005861
capital-gain                     0.223013    -0.019062                -
0.003633
...                                   ...          ...
...
native-country_Thailand         -0.004219    -0.002557                -
0.004309
native-country_Trinadad&Tobago -0.009107    -0.002051
0.001076
native-country_United-States     0.032551     0.005258
0.013956
native-country_Vietnam          -0.015542    -0.004052                -
0.001509
native-country_Yugoslavia        0.005522    -0.005352                -
0.003772

                                ...  native-country_Portugal  \
age                             ...                 0.007016
fnlwgt                          ...                -0.013577
educational-num                 ...                -0.047816
gender                          ...                 0.009649
capital-gain                    ...                -0.004355
...                             ...                      ...
native-country_Thailand         ...                -0.000919
native-country_Trinadad&Tobago  ...                -0.000872
native-country_United-States    ...                -0.109626
native-country_Vietnam          ...                -0.001557
native-country_Yugoslavia       ...                -0.000804

                                native-country_Puerto-Rico  \
age                                               0.005474
fnlwgt                                            0.008708
educational-num                                  -0.041776
gender                                           -0.009940
capital-gain                                     -0.006137
...                                                    ...
native-country_Thailand                          -0.001525
native-country_Trinadad&Tobago                   -0.001446
native-country_United-States                     -0.181890
native-country_Vietnam                           -0.002583
native-country_Yugoslavia                        -0.001335
```

```
                                     native-country_Scotland  native-
country_South  \
age                                                 0.012281                -
0.001942
fnlwgt                                             -0.006523                -
0.010342
educational-num                                     0.000907
0.012984
gender                                             -0.002178                -
0.005272
capital-gain                                       -0.002317
0.003906
...                                                      ...
...
native-country_Thailand                            -0.000514                -
0.001204
native-country_Trinadad&Tobago                     -0.000488                -
0.001143
native-country_United-States                       -0.061346                -
0.143695
native-country_Vietnam                             -0.000871                -
0.002040
native-country_Yugoslavia                          -0.000450                -
0.001054

                                     native-country_Taiwan  \
age                                              -0.011872
fnlwgt                                           -0.001733
educational-num                                   0.045420
gender                                            0.003041
capital-gain                                      0.004260
...                                                    ...
native-country_Thailand                          -0.000905
native-country_Trinadad&Tobago                   -0.000859
native-country_United-States                     -0.107976
native-country_Vietnam                           -0.001533
native-country_Yugoslavia                        -0.000792

                                     native-country_Thailand  \
age                                                -0.001766
fnlwgt                                             -0.001512
educational-num                                     0.007283
gender                                             -0.007117
capital-gain                                       -0.002781
...                                                      ...
native-country_Thailand                             1.000000
native-country_Trinadad&Tobago                     -0.000583
native-country_United-States                       -0.073329
native-country_Vietnam                             -0.001041
```

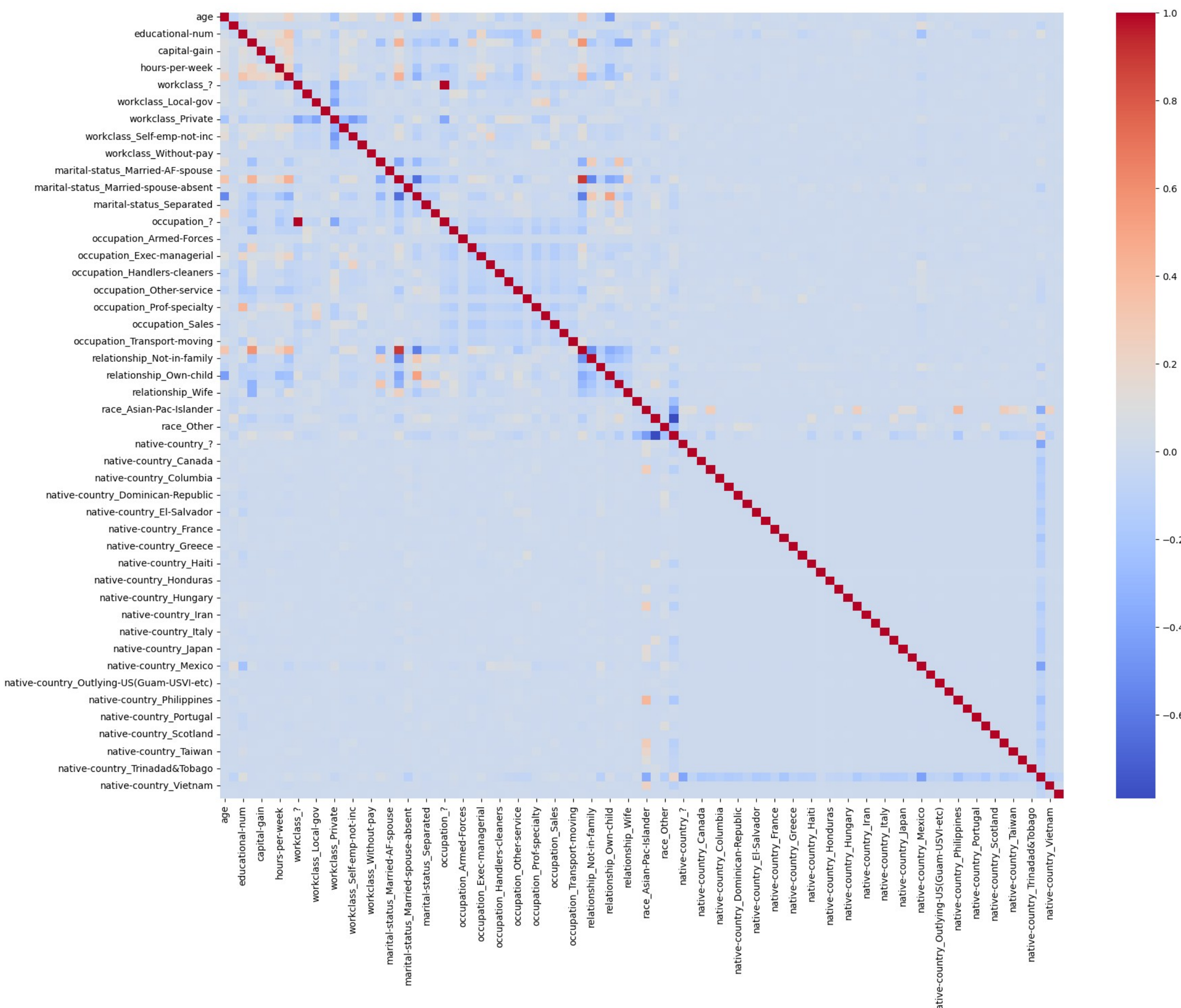
```
native-country_Yugoslavia                            -0.000538

                                native-country_Trinadad&Tobago  \
age                                                   0.001056
fnlwgt                                                0.004153
educational-num                                      -0.010201
gender                                               -0.009342
capital-gain                                         -0.003039
...                                                        ...
native-country_Thailand                              -0.000583
native-country_Trinadad&Tobago                        1.000000
native-country_United-States                         -0.069564
native-country_Vietnam                               -0.000988
native-country_Yugoslavia                            -0.000510

                                native-country_United-States  \
age                                                 0.011888
fnlwgt                                             -0.070645
educational-num                                     0.104210
gender                                             -0.011167
capital-gain                                        0.004191
...                                                      ...
native-country_Thailand                            -0.073329
native-country_Trinadad&Tobago                     -0.069564
native-country_United-States                        1.000000
native-country_Vietnam                             -0.124226
native-country_Yugoslavia                          -0.064202

                                native-country_Vietnam  \
age                                          -0.012337
fnlwgt                                       -0.007479
educational-num                              -0.007544
gender                                       -0.001545
capital-gain                                 -0.002673
...                                                ...
native-country_Thailand                      -0.001041
native-country_Trinadad&Tobago               -0.000988
native-country_United-States                 -0.124226
native-country_Vietnam                        1.000000
native-country_Yugoslavia                    -0.000912

                                native-country_Yugoslavia
age                                             0.002905
fnlwgt                                          0.004699
educational-num                                -0.005798
gender                                          0.005262
capital-gain                                   -0.000474
...                                                  ...
native-country_Thailand                        -0.000538
native-country_Trinadad&Tobago                 -0.000510
```

```
native-country_United-States                             -0.064202
native-country_Vietnam                                   -0.000912
native-country_Yugoslavia                                 1.000000

[92 rows x 92 columns]
```

Correlation plot

```python
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(20,15))
sns.heatmap(new_data.corr(), annot=False , cmap="coolwarm")
```

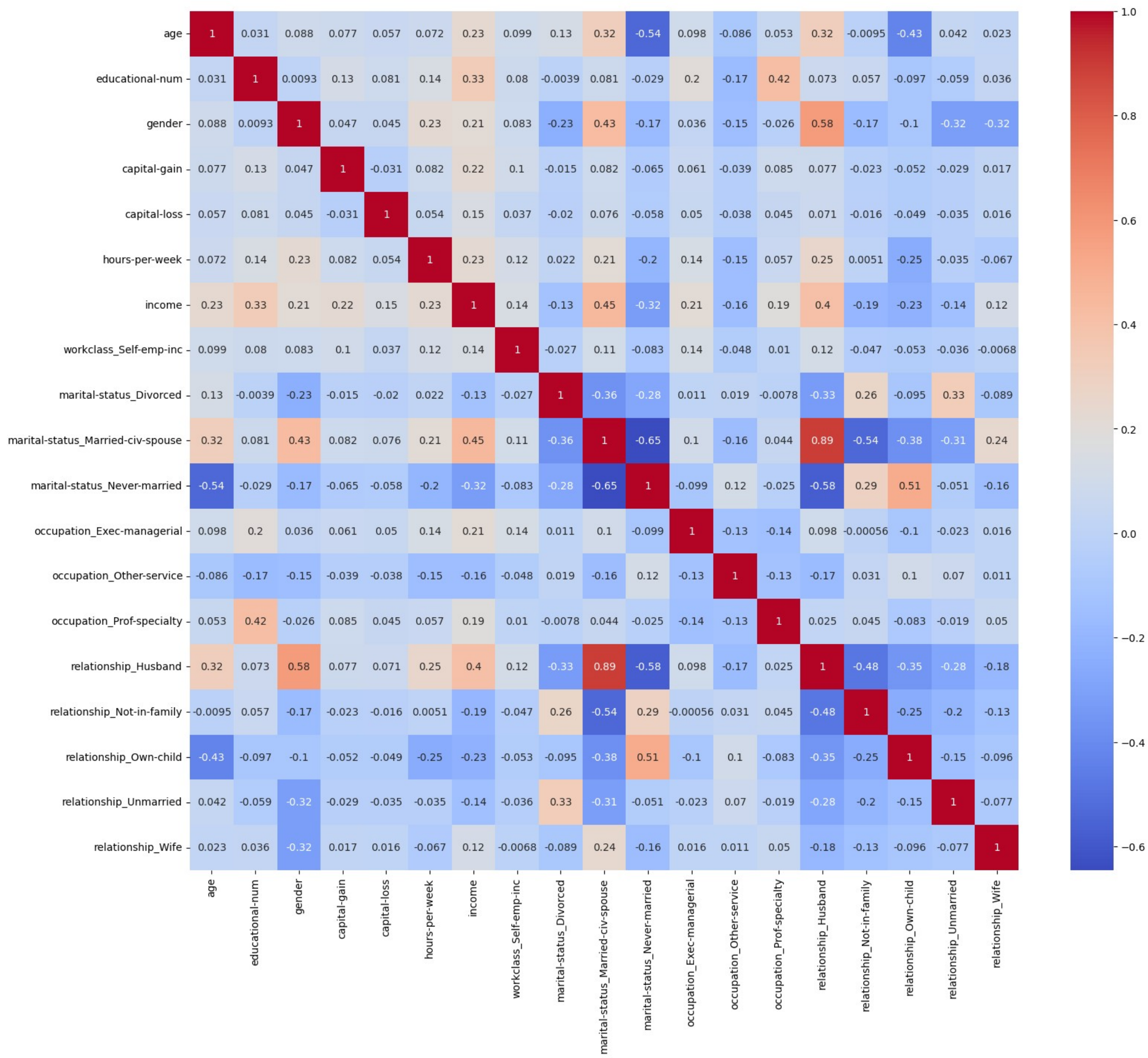
```
<Axes: >
```



- Due to presense of many column, we cann't get direct information about column.
- Let's try to get column which are important and which are not important

```
correlation = new_data.corr()["income"].abs()
correlation.sort_values(inplace=True)

correlation

native-country_Cuba                        0.000885
native-country_Hong                        0.001591
native-country_Holand-Netherlands          0.002538
native-country_Hungary                     0.003538
native-country_Ireland                     0.003744
                                             ...
marital-status_Never-married               0.318782
educational-num                            0.332613
relationship_Husband                       0.403791
marital-status_Married-civ-spouse          0.445853
income                                     1.000000
Name: income, Length: 92, dtype: float64

number_of_dropped_column = int(0.8 * len(new_data.columns))

drop_colun = correlation.iloc[:number_of_dropped_column].index

reduced_newdata = new_data.drop(columns=drop_colun, axis=1)

reduced_newdata.head(4)

   age  educational-num  gender  capital-gain  capital-loss  hours-
per-week  \
0   25                7       1             0             0
40
1   38                9       1             0             0
50
2   28               12       1             0             0
40
3   44               10       1          7688             0
40

   income  workclass_Self-emp-inc  marital-status_Divorced  \
0       0                       0                        0
1       0                       0                        0
2       1                       0                        0
3       1                       0                        0

   marital-status_Married-civ-spouse  marital-status_Never-married  \
0                                  0                             1
1                                  1                             0
2                                  1                             0
3                                  1                             0

   occupation_Exec-managerial  occupation_Other-service  \
0                           0                         0
```

```
1                                   0                                0
2                                   0                                0
3                                   0                                0

   occupation_Prof-specialty  relationship_Husband  \
0                          0                     0
1                          0                     1
2                          0                     1
3                          0                     1

   relationship_Not-in-family  relationship_Own-child
relationship_Unmarried  \
0                           0                       1
0
1                           0                       0
0
2                           0                       0
0
3                           0                       0
0

   relationship_Wife
0                  0
1                  0
2                  0
3                  0

plt.figure(figsize=(18,15))
sns.heatmap(reduced_newdata.corr(), annot=True, cmap="coolwarm")
plt.show()
```




```
new_correaltion = reduced_newdata.corr()["income"].abs()
new_correaltion = new_correaltion.sort_values()
new_correaltion
```

```
relationship_Wife                      0.120484
marital-status_Divorced                0.128335
workclass_Self-emp-inc                 0.139596
relationship_Unmarried                 0.143642
capital-loss                           0.147554
occupation_Other-service               0.155254
occupation_Prof-specialty              0.188793
relationship_Not-in-family             0.190372
occupation_Exec-managerial             0.210938
gender                                 0.214628
capital-gain                           0.223013
```

```
relationship_Own-child                     0.225691
hours-per-week                             0.227687
age                                        0.230369
marital-status_Never-married               0.318782
educational-num                            0.332613
relationship_Husband                       0.403791
marital-status_Married-civ-spouse          0.445853
income                                     1.000000
Name: income, dtype: float64
```

Machine Learning model

```python
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
```

Train test split

```python
train_data , test_data = train_test_split(reduced_newdata,
test_size=0.2)

train_data
```

```
       age  educational-num  gender  capital-gain  capital-loss  \
36148   32                9       1             0             0
29428   25               11       1             0             0
38293   28               10       1             0             0
30901   56               12       0             0             0
32247   24                9       0             0             0
...    ...              ...     ...           ...           ...
16218   34                9       1             0             0
43251   17                8       0             0             0
20477   76                5       1             0             0
23886   56                9       1             0             0
48377   25               11       1             0             0

       hours-per-week  income  workclass_Self-emp-inc  \
36148              40       0                       0
29428              41       0                       0
38293              50       0                       0
30901              40       0                       0
32247              50       1                       0
...               ...     ...                     ...
16218              50       1                       1
43251              16       0                       0
20477              40       0                       1
23886              45       0                       0
48377              40       0                       0
```

```
       marital-status_Divorced  marital-status_Married-civ-spouse  \
36148                        0                                  1
29428                        0                                  1
38293                        0                                  0
30901                        0                                  1
32247                        0                                  0
...                        ...                                ...
16218                        1                                  0
43251                        0                                  0
20477                        0                                  1
23886                        0                                  1
48377                        0                                  0

       marital-status_Never-married  occupation_Exec-managerial  \
36148                             0                           0
29428                             0                           0
38293                             1                           1
30901                             0                           0
32247                             0                           0
...                             ...                         ...
16218                             0                           0
43251                             1                           0
20477                             0                           0
23886                             0                           0
48377                             1                           0

       occupation_Other-service  occupation_Prof-specialty  \
36148                         0                          0
29428                         0                          0
38293                         0                          0
30901                         0                          0
32247                         1                          0
...                         ...                        ...
16218                         0                          0
43251                         1                          0
20477                         0                          1
23886                         0                          0
48377                         0                          0

       relationship_Husband  relationship_Not-in-family  \
36148                     1                           0
29428                     1                           0
38293                     0                           1
30901                     0                           0
32247                     0                           0
...                     ...                         ...
16218                     0                           0
43251                     0                           0
20477                     1                           0
23886                     1                           0
```

```
48377                          0                              0

       relationship_Own-child  relationship_Unmarried  
relationship_Wife
36148                       0                       0  
0
29428                       0                       0  
0
38293                       0                       0  
0
30901                       0                       0  
1
32247                       0                       1  
0
...                       ...                     ...                 .
..
16218                       0                       1  
0
43251                       1                       0  
0
20477                       0                       0  
0
23886                       0                       0  
0
48377                       1                       0  
0

[39073 rows x 19 columns]
```

test_data

```
       age  educational-num  gender  capital-gain  capital-loss  \
24616   56               10       0             0             0   
27714   26                9       1             0             0   
26767   20               10       0             0             0   
8169    58                9       1             0             0   
28331   54               13       0             0          1408   
...    ...              ...     ...           ...           ...   
48424   33                9       1             0             0   
38158   28               10       0             0             0   
23681   49                9       0             0             0   
29970   40                9       0          6849             0   
34021   44               12       1             0             0   

       hours-per-week  income  workclass_Self-emp-inc  \
24616              35       0                       0   
27714              40       0                       0   
26767              35       0                       0   
8169               20       0                       0   
28331              38       0                       0   
```

```
...                ...     ...                     ...
48424               45       0                       0
38158               40       0                       0
23681               35       0                       0
29970               38       0                       0
34021               40       0                       0

       marital-status_Divorced  marital-status_Married-civ-spouse  \
24616                        1                                  0
27714                        0                                  0
26767                        0                                  0
8169                         1                                  0
28331                        1                                  0
...                        ...                                ...
48424                        0                                  0
38158                        1                                  0
23681                        1                                  0
29970                        0                                  0
34021                        0                                  1

       marital-status_Never-married  occupation_Exec-managerial  \
24616                             0                           0
27714                             0                           0
26767                             1                           0
8169                              0                           0
28331                             0                           0
...                             ...                         ...
48424                             1                           0
38158                             0                           1
23681                             0                           0
29970                             1                           0
34021                             0                           0

       occupation_Other-service  occupation_Prof-specialty  \
24616                         0                          0
27714                         1                          0
26767                         0                          0
8169                          0                          0
28331                         0                          0
...                         ...                        ...
48424                         0                          0
38158                         0                          0
23681                         1                          0
29970                         0                          0
34021                         0                          1

       relationship_Husband  relationship_Not-in-family  \
24616                     0                           1
27714                     0                           1
26767                     0                           1
```

```
8169                          0                              0
28331                         0                              1
...                         ...                            ...
48424                         0                              1
38158                         0                              1
23681                         0                              0
29970                         0                              1
34021                         1                              0

       relationship_Own-child  relationship_Unmarried  
relationship_Wife  
24616                         0                       0  
0  
27714                         0                       0  
0  
26767                         0                       0  
0  
8169                          0                       1  
0  
28331                         0                       0  
0  
...                         ...                     ...                  .
..  
48424                         0                       0  
0  
38158                         0                       0  
0  
23681                         0                       1  
0  
29970                         0                       0  
0  
34021                         0                       0  
0  

[9769 rows x 19 columns]
```

```
x_train = train_data.drop(columns="income",axis=1)
y_train = train_data["income"]

x_test = test_data.drop(columns="income",axis=1)
y_test = test_data["income"]

forest = RandomForestClassifier()

forest.fit(x_train,y_train)
```

```
RandomForestClassifier()
```

```
forest.score(x_test,y_test)
```

```
0.8475790766711024
```

Feture importance of a model

```
forest.feature_importances_
```

```
array([0.22950308, 0.14649769, 0.00920759, 0.14119897, 0.0457812 ,
       0.13522563, 0.0079273 , 0.00546746, 0.11196443, 0.02370047,
       0.02287855, 0.00766976, 0.02072187, 0.06142157, 0.01017915,
       0.00859723, 0.0035046 , 0.00855345])
```

```
forest.feature_names_in_
```

```
array(['age', 'educational-num', 'gender', 'capital-gain', 'capital-
loss',
       'hours-per-week', 'workclass_Self-emp-inc',
       'marital-status_Divorced', 'marital-status_Married-civ-spouse',
       'marital-status_Never-married', 'occupation_Exec-managerial',
       'occupation_Other-service', 'occupation_Prof-specialty',
       'relationship_Husband', 'relationship_Not-in-family',
       'relationship_Own-child', 'relationship_Unmarried',
       'relationship_Wife'], dtype=object)
```

```
importances = dict(zip(forest.feature_names_in_ ,
forest.feature_importances_))
importances
```

```
{'age': 0.22950307649777954,
 'educational-num': 0.14649769438078195,
 'gender': 0.009207589777198549,
 'capital-gain': 0.14119897145958865,
 'capital-loss': 0.045781198579602556,
 'hours-per-week': 0.1352256316103745,
 'workclass_Self-emp-inc': 0.007927295195377196,
 'marital-status_Divorced': 0.005467462406718399,
 'marital-status_Married-civ-spouse': 0.11196443142218167,
 'marital-status_Never-married': 0.023700469987331437,
 'occupation_Exec-managerial': 0.022878553058078715,
 'occupation_Other-service': 0.007669756626209825,
 'occupation_Prof-specialty': 0.020721869111199172,
 'relationship_Husband': 0.06142156792379857 6,
 'relationship_Not-in-family': 0.010179152720353246,
 'relationship_Own-child': 0.008597228978533995,
 'relationship_Unmarried': 0.003504600445189981,
 'relationship_Wife': 0.008553449819702038}
```

```
importances_sorted = {k: v for k,v in sorted(importances.items(), key=
lambda x : x[1], reverse=True)}
importances_sorted
```

```
{'age': 0.22950307649777954,
 'educational-num': 0.14649769438078195,
 'capital-gain': 0.14119897145958865,
```

```
 'hours-per-week': 0.1352256316103745,
 'marital-status_Married-civ-spouse': 0.11196443142218167,
 'relationship_Husband': 0.061421567923798576,
 'capital-loss': 0.045781198579602556,
 'marital-status_Never-married': 0.023700469987331437,
 'occupation_Exec-managerial': 0.022878553058078715,
 'occupation_Prof-specialty': 0.020721869111199172,
 'relationship_Not-in-family': 0.010179152720353246,
 'gender': 0.009207589777198549,
 'relationship_Own-child': 0.008597228978533995,
 'relationship_Wife': 0.008553449819702038,
 'workclass_Self-emp-inc': 0.007927295195377196,
 'occupation_Other-service': 0.007669756626209825,
 'marital-status_Divorced': 0.005467462406718399,
 'relationship_Unmarried': 0.003504600445189981}
```

Hyper-parameter tuning

Grid search algorithm

```
from sklearn.model_selection  import GridSearchCV

param_grid = {
    'n_estimators': [100,200],
    'max_depth': [10,15],
    'min_samples_split': [2,4]
}

grid_serach = GridSearchCV(estimator = RandomForestClassifier() ,
                           param_grid= param_grid ,
                            verbose = 10 )

grid_serach.fit(x_train,y_train)
```

```
Fitting 5 folds for each of 8 candidates, totalling 40 fits
[CV 1/5; 1/8] START max_depth=10, min_samples_split=2,
n_estimators=100.........
[CV 1/5; 1/8] END max_depth=10, min_samples_split=2,
n_estimators=100;, score=0.857 total time=   1.0s
[CV 2/5; 1/8] START max_depth=10, min_samples_split=2,
n_estimators=100.........
[CV 2/5; 1/8] END max_depth=10, min_samples_split=2,
n_estimators=100;, score=0.862 total time=   1.0s
[CV 3/5; 1/8] START max_depth=10, min_samples_split=2,
n_estimators=100.........
[CV 3/5; 1/8] END max_depth=10, min_samples_split=2,
n_estimators=100;, score=0.862 total time=   1.1s
[CV 4/5; 1/8] START max_depth=10, min_samples_split=2,
n_estimators=100.........
[CV 4/5; 1/8] END max_depth=10, min_samples_split=2,
```

```
n_estimators=100;, score=0.857 total time=   1.0s
[CV 5/5; 1/8] START max_depth=10, min_samples_split=2,
n_estimators=100.........
[CV 5/5; 1/8] END max_depth=10, min_samples_split=2,
n_estimators=100;, score=0.863 total time=   1.7s
[CV 1/5; 2/8] START max_depth=10, min_samples_split=2,
n_estimators=200.........
[CV 1/5; 2/8] END max_depth=10, min_samples_split=2,
n_estimators=200;, score=0.858 total time=   2.6s
[CV 2/5; 2/8] START max_depth=10, min_samples_split=2,
n_estimators=200.........
[CV 2/5; 2/8] END max_depth=10, min_samples_split=2,
n_estimators=200;, score=0.862 total time=   2.0s
[CV 3/5; 2/8] START max_depth=10, min_samples_split=2,
n_estimators=200.........
[CV 3/5; 2/8] END max_depth=10, min_samples_split=2,
n_estimators=200;, score=0.863 total time=   2.4s
[CV 4/5; 2/8] START max_depth=10, min_samples_split=2,
n_estimators=200.........
[CV 4/5; 2/8] END max_depth=10, min_samples_split=2,
n_estimators=200;, score=0.858 total time=   2.6s
[CV 5/5; 2/8] START max_depth=10, min_samples_split=2,
n_estimators=200.........
[CV 5/5; 2/8] END max_depth=10, min_samples_split=2,
n_estimators=200;, score=0.863 total time=   2.7s
[CV 1/5; 3/8] START max_depth=10, min_samples_split=4,
n_estimators=100.........
[CV 1/5; 3/8] END max_depth=10, min_samples_split=4,
n_estimators=100;, score=0.857 total time=   1.2s
[CV 2/5; 3/8] START max_depth=10, min_samples_split=4,
n_estimators=100.........
[CV 2/5; 3/8] END max_depth=10, min_samples_split=4,
n_estimators=100;, score=0.862 total time=   1.2s
[CV 3/5; 3/8] START max_depth=10, min_samples_split=4,
n_estimators=100.........
[CV 3/5; 3/8] END max_depth=10, min_samples_split=4,
n_estimators=100;, score=0.863 total time=   1.2s
[CV 4/5; 3/8] START max_depth=10, min_samples_split=4,
n_estimators=100.........
[CV 4/5; 3/8] END max_depth=10, min_samples_split=4,
n_estimators=100;, score=0.859 total time=   1.2s
[CV 5/5; 3/8] START max_depth=10, min_samples_split=4,
n_estimators=100.........
[CV 5/5; 3/8] END max_depth=10, min_samples_split=4,
n_estimators=100;, score=0.863 total time=   1.3s
[CV 1/5; 4/8] START max_depth=10, min_samples_split=4,
n_estimators=200.........
[CV 1/5; 4/8] END max_depth=10, min_samples_split=4,
n_estimators=200;, score=0.858 total time=   2.5s
```

```
[CV 2/5; 4/8] START max_depth=10, min_samples_split=4,
n_estimators=200.........
[CV 2/5; 4/8] END max_depth=10, min_samples_split=4,
n_estimators=200;, score=0.861 total time=   2.5s
[CV 3/5; 4/8] START max_depth=10, min_samples_split=4,
n_estimators=200.........
[CV 3/5; 4/8] END max_depth=10, min_samples_split=4,
n_estimators=200;, score=0.864 total time=   2.7s
[CV 4/5; 4/8] START max_depth=10, min_samples_split=4,
n_estimators=200.........
[CV 4/5; 4/8] END max_depth=10, min_samples_split=4,
n_estimators=200;, score=0.859 total time=   2.4s
[CV 5/5; 4/8] START max_depth=10, min_samples_split=4,
n_estimators=200.........
[CV 5/5; 4/8] END max_depth=10, min_samples_split=4,
n_estimators=200;, score=0.864 total time=   2.7s
[CV 1/5; 5/8] START max_depth=15, min_samples_split=2,
n_estimators=100.........
[CV 1/5; 5/8] END max_depth=15, min_samples_split=2,
n_estimators=100;, score=0.860 total time=   1.6s
[CV 2/5; 5/8] START max_depth=15, min_samples_split=2,
n_estimators=100.........
[CV 2/5; 5/8] END max_depth=15, min_samples_split=2,
n_estimators=100;, score=0.862 total time=   1.6s
[CV 3/5; 5/8] START max_depth=15, min_samples_split=2,
n_estimators=100.........
[CV 3/5; 5/8] END max_depth=15, min_samples_split=2,
n_estimators=100;, score=0.864 total time=   1.8s
[CV 4/5; 5/8] START max_depth=15, min_samples_split=2,
n_estimators=100.........
[CV 4/5; 5/8] END max_depth=15, min_samples_split=2,
n_estimators=100;, score=0.858 total time=   2.2s
[CV 5/5; 5/8] START max_depth=15, min_samples_split=2,
n_estimators=100.........
[CV 5/5; 5/8] END max_depth=15, min_samples_split=2,
n_estimators=100;, score=0.864 total time=   2.5s
[CV 1/5; 6/8] START max_depth=15, min_samples_split=2,
n_estimators=200.........
[CV 1/5; 6/8] END max_depth=15, min_samples_split=2,
n_estimators=200;, score=0.862 total time=   5.4s
[CV 2/5; 6/8] START max_depth=15, min_samples_split=2,
n_estimators=200.........
[CV 2/5; 6/8] END max_depth=15, min_samples_split=2,
n_estimators=200;, score=0.862 total time=   3.2s
[CV 3/5; 6/8] START max_depth=15, min_samples_split=2,
n_estimators=200.........
[CV 3/5; 6/8] END max_depth=15, min_samples_split=2,
n_estimators=200;, score=0.864 total time=   3.0s
[CV 4/5; 6/8] START max_depth=15, min_samples_split=2,
```

```
n_estimators=200.........
[CV 4/5; 6/8] END max_depth=15, min_samples_split=2,
n_estimators=200;, score=0.858 total time=  11.7s
[CV 5/5; 6/8] START max_depth=15, min_samples_split=2,
n_estimators=200.........
[CV 5/5; 6/8] END max_depth=15, min_samples_split=2,
n_estimators=200;, score=0.866 total time=  16.7s
[CV 1/5; 7/8] START max_depth=15, min_samples_split=4,
n_estimators=100.........
[CV 1/5; 7/8] END max_depth=15, min_samples_split=4,
n_estimators=100;, score=0.861 total time=  12.8s
[CV 2/5; 7/8] START max_depth=15, min_samples_split=4,
n_estimators=100.........
[CV 2/5; 7/8] END max_depth=15, min_samples_split=4,
n_estimators=100;, score=0.861 total time=  17.2s
[CV 3/5; 7/8] START max_depth=15, min_samples_split=4,
n_estimators=100.........
[CV 3/5; 7/8] END max_depth=15, min_samples_split=4,
n_estimators=100;, score=0.863 total time=  22.6s
[CV 4/5; 7/8] START max_depth=15, min_samples_split=4,
n_estimators=100.........
[CV 4/5; 7/8] END max_depth=15, min_samples_split=4,
n_estimators=100;, score=0.858 total time=  22.0s
[CV 5/5; 7/8] START max_depth=15, min_samples_split=4,
n_estimators=100.........
[CV 5/5; 7/8] END max_depth=15, min_samples_split=4,
n_estimators=100;, score=0.864 total time=  20.2s
[CV 1/5; 8/8] START max_depth=15, min_samples_split=4,
n_estimators=200.........
[CV 1/5; 8/8] END max_depth=15, min_samples_split=4,
n_estimators=200;, score=0.861 total time=  52.6s
[CV 2/5; 8/8] START max_depth=15, min_samples_split=4,
n_estimators=200.........
[CV 2/5; 8/8] END max_depth=15, min_samples_split=4,
n_estimators=200;, score=0.863 total time=  42.1s
[CV 3/5; 8/8] START max_depth=15, min_samples_split=4,
n_estimators=200.........
[CV 3/5; 8/8] END max_depth=15, min_samples_split=4,
n_estimators=200;, score=0.865 total time=  41.9s
[CV 4/5; 8/8] START max_depth=15, min_samples_split=4,
n_estimators=200.........
[CV 4/5; 8/8] END max_depth=15, min_samples_split=4,
n_estimators=200;, score=0.859 total time=  39.7s
[CV 5/5; 8/8] START max_depth=15, min_samples_split=4,
n_estimators=200.........
[CV 5/5; 8/8] END max_depth=15, min_samples_split=4,
n_estimators=200;, score=0.866 total time=  36.4s

GridSearchCV(estimator=RandomForestClassifier(),
             param_grid={'max_depth': [10, 15], 'min_samples_split':
```

```
[2, 4],
                              'n_estimators': [100, 200]},
                verbose=10)
```

```
grid_serach.best_estimator_
```

```
RandomForestClassifier(max_depth=15, n_estimators=200)
```

```
forest = grid_serach.best_estimator_
```

```
forest.score(x_test,y_test)
```

```
0.8668236257549391
```

Feature importance

```
importance_2 = dict(zip(forest.feature_names_in_ ,
forest.feature_importances_))
```

```
importance_2_sorted = {k: v for k,v in sorted(importance_2.items() ,
key=lambda x : x[1], reverse=True)}
importance_2_sorted
```

```
{'capital-gain': 0.18844012369435825,
 'educational-num': 0.16368275005647895,
 'marital-status_Married-civ-spouse': 0.14593589493134992,
 'age': 0.10570393485521487,
 'relationship_Husband': 0.09998184983239732,
 'hours-per-week': 0.07445650761285139,
 'capital-loss': 0.05784183855570713,
 'marital-status_Never-married': 0.03340370919101083,
 'occupation_Exec-managerial': 0.02943417134275418 5,
 'occupation_Prof-specialty': 0.025017507244201032,
 'relationship_Wife': 0.016178924723374698,
 'gender': 0.012843329675338794,
 'relationship_Not-in-family': 0.01181184160383598,
 'occupation_Other-service': 0.009084914064736703,
 'relationship_Own-child': 0.008281374418932166,
 'workclass_Self-emp-inc': 0.007397869285820766,
 'marital-status_Divorced': 0.006498580979929942,
 'relationship_Unmarried': 0.0040048779317072665}
```