METRO COLLEGE
OF TECHNOLOGY

Mini Project for Developing and Comparing Regression and Classification Machine Learning Models in Python Programming

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Submitted by:

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Course: Machine Learning and Big Data Analytics [DSA10]

Program: Data Science and Application - Advanced Diploma [6060]

Metro College of Technology

Date: 29 May, 2021

Source of the Dataset:

About this file
The Global Health Observatory (GHO) data repository under World Health Organization (WHO) keeps track of the health status as well as many other related factors for all countries The datasets are made available to public for the purpose of health data analysis. The dataset related to life expectancy, health factors for 193 countries has been collected from the same WHO data repository website and its corresponding economic data was collected from United Nation website. Among all categories of health-related factors only those critical factors were chosen which are more representative. It has been observed that in the past 15 years , there has been a huge development in health sector resulting in improvement of human mortality rates especially in the developing nations in comparison to the past 30 years. Therefore, in this project we have considered data from year 2000-2015 for 193 countries for further analysis. The individual data files have been merged together into a single dataset. On initial visual inspection of the data showed some missing values. As the datasets were from WHO, we found no evident errors. Missing data was handled in R software by using Missmap command. The result indicated that most of the missing data was for population, Hepatitis B and GDP. The missing data were from less known countries like Vanuatu, Tonga, Togo,Cabo Verde etc. Finding all data for these countries was difficult and hence, it was decided that we exclude these countries from the final model dataset. The final merged file(final dataset) consists of 22 Columns and 2938 rows which meant 20 predicting variables. All predicting variables was then divided into several broad categories:•Immunization related factors, Mortality factors, Economical factors and Social factors.
Source: https://www.kaggle.com

Regression Models

Let us import the required initial libraries.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import os
%matplotlib inline
```

Let us check the Current Working Directory.

In [2]:
```
os.getcwd()
```

Out[2]:
```
'C:\\Users\\ruzdomain\\Desktop\\MLBDA\\PROJECT'
```

Let us ensure that the Current Working Directory remains the one where we are working.

In [3]:
```
os.chdir(r'C:\Users\ruzdomain\Desktop\MLBDA\PROJECT')
```

In [4]:
```
os.getcwd()
```

Out[4]:
```
'C:\\Users\\ruzdomain\\Desktop\\MLBDA\\PROJECT'
```

Let us import the dataset by reading using panadas and explore the dataset.

In [5]:
```
df_reg = pd.read_csv('Life Expectancy Data.csv')
df_reg.head()
```

Out[5]:

	Country	Year	Status	Life expectancy	Adult Mortality	infant deaths	Alcohol	percentage expenditure	Hepatitis B	Measles	...	Polio	Total expenditure	Diphtheria	HIV/AIDS	GDP	Population	thinness 1-19 years	thinness 5-9 years
0	Afghanistan	2015	Developing	65.0	263.0	62	0.01	71.279624	65.0	1154	...	6.0	8.16	65.0	0.1	584.259210	33736494.0	17.2	17.3
1	Afghanistan	2014	Developing	59.9	271.0	64	0.01	73.523582	62.0	492	...	58.0	8.18	62.0	0.1	612.696514	327582.0	17.5	17.5
2	Afghanistan	2013	Developing	59.9	268.0	66	0.01	73.219243	64.0	430	...	62.0	8.13	64.0	0.1	631.744976	31731688.0	17.7	17.7
3	Afghanistan	2012	Developing	59.5	272.0	69	0.01	78.184215	67.0	2787	...	67.0	8.52	67.0	0.1	669.959000	3696958.0	17.9	18.0
4	Afghanistan	2011	Developing	59.2	275.0	71	0.01	7.097109	68.0	3013	...	68.0	7.87	68.0	0.1	63.537231	2978599.0	18.2	18.2

5 rows × 22 columns

In [6]:
```
df_reg.describe(include='all')
```

Out[6]:

	Country	Year	Status	Life expectancy	Adult Mortality	infant deaths	Alcohol	percentage expenditure	Hepatitis B	Measles	...	Polio	Total expenditure	Diphtheria	HIV/AIDS
count	2938	2938.000000	2938	2928.000000	2928.000000	2938.000000	2744.000000	2938.000000	2385.000000	2938.000000	...	2919.000000	2712.00000	2919.000000	2938.000000
unique	193	NaN	2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN
top	Hungary	NaN	Developing	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN
freq	16	NaN	2426	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN
mean	NaN	2007.518720	NaN	69.224932	164.796448	30.303948	4.602861	738.251295	80.940461	2419.592240	...	82.550188	5.93819	82.324084	1.742103
std	NaN	4.613841	NaN	9.523867	124.292079	117.926501	4.052413	1987.914858	25.070016	11467.272489	...	23.428046	2.49832	23.716912	5.077785
min	NaN	2000.000000	NaN	36.300000	1.000000	0.000000	0.010000	0.000000	1.000000	0.000000	...	3.000000	0.37000	2.000000	0.100000
25%	NaN	2004.000000	NaN	63.100000	74.000000	0.000000	0.877500	4.685343	77.000000	0.000000	...	78.000000	4.26000	78.000000	0.100000
50%	NaN	2008.000000	NaN	72.100000	144.000000	3.000000	3.755000	64.912906	92.000000	17.000000	...	93.000000	5.75500	93.000000	0.100000
75%	NaN	2012.000000	NaN	75.700000	228.000000	22.000000	7.702500	441.534144	97.000000	360.250000	...	97.000000	7.49250	97.000000	0.800000
max	NaN	2015.000000	NaN	89.000000	723.000000	1800.000000	17.870000	19479.911610	99.000000	212183.000000	...	99.000000	17.60000	99.000000	50.600000

11 rows × 22 columns

In [7]:
```
df_reg.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2938 entries, 0 to 2937
Data columns (total 22 columns):
 #   Column                           Non-Null Count  Dtype  
---  ------                           --------------  -----  
 0   Country                          2938 non-null   object 
 1   Year                             2938 non-null   int64  
 2   Status                           2938 non-null   object 
 3   Life expectancy                  2928 non-null   float64
 4   Adult Mortality                  2928 non-null   float64
 5   infant deaths                    2938 non-null   int64  
 6   Alcohol                          2744 non-null   float64
 7   percentage expenditure           2938 non-null   float64
 8   Hepatitis B                      2385 non-null   float64
 9   Measles                          2938 non-null   int64  
 10   BMI                             2904 non-null   float64
 11  under-five deaths                2938 non-null   int64  
 12  Polio                            2919 non-null   float64
 13  Total expenditure                2712 non-null   float64
 14  Diphtheria                       2919 non-null   float64
 15   HIV/AIDS                        2938 non-null   float64
 16  GDP                              2490 non-null   float64
 17  Population                       2286 non-null   float64
 18   thinness  1-19 years            2904 non-null   float64
 19   thinness 5-9 years             2904 non-null   float64
 20  Income composition of resources  2771 non-null   float64
 21  Schooling                        2775 non-null   float64
dtypes: float64(16), int64(4), object(2)
memory usage: 505.1+ KB
```

In [8]:
```
df_reg.shape
```

Out[8]:
```
(2938, 22)
```

In [9]:
```
df_reg.dtypes
```

Out[9]:
```
Country                           object
Year                               int64
Status                            object
Life expectancy                  float64
Adult Mortality                  float64
infant deaths                      int64
Alcohol                          float64
percentage expenditure           float64
Hepatitis B                      float64
Measles                            int64
 BMI                             float64
under-five deaths                  int64
Polio                            float64
Total expenditure                float64
Diphtheria                       float64
 HIV/AIDS                        float64
GDP                              float64
Population                       float64
 thinness  1-19 years            float64
 thinness 5-9 years              float64
Income composition of resources  float64
Schooling                        float64
dtype: object
```

Let us check the missing values per column and also in percentage.

In [10]:
```
df_reg.apply(lambda x: sum(x.isnull()))
```

Out[10]:
```
Country                             0
Year                                0
Status                              0
Life expectancy                    10
Adult Mortality                    10
infant deaths                       0
Alcohol                           194
percentage expenditure              0
Hepatitis B                       553
Measles                             0
 BMI                               34
under-five deaths                   0
Polio                              19
Total expenditure                 226
Diphtheria                         19
 HIV/AIDS                           0
GDP                               448
Population                        652
 thinness  1-19 years              34
 thinness 5-9 years                34
Income composition of resources    167
Schooling                         163
dtype: int64
```

In [11]:
```
def percentage_of_miss(df):
  df1=df[df.columns[df.isnull().sum()>=1]]
  total_miss = df1.isnull().sum().sort_values(ascending=False)
  percent_miss = (df1.isnull().sum()/df1.isnull().count()).sort_values(ascending=False)
  missing_data = pd.concat([total_miss, percent_miss], axis=1, keys=['Number of Missing', 'Percentage'])
  return(missing_data)
```

In [12]:
```
percentage_of_miss(df_reg)
```

Out[12]:

	Number of Missing	Percentage
Population	652	0.221920
Hepatitis B	553	0.188223
GDP	448	0.152485
Total expenditure	226	0.076923
Alcohol	194	0.066031
Income composition of resources	167	0.056841
Schooling	163	0.055480
thinness 5-9 years	34	0.011572
thinness 1-19 years	34	0.011572
BMI	34	0.011572
Diphtheria	19	0.006467
Polio	19	0.006467
Adult Mortality	10	0.003404
Life expectancy	10	0.003404

In [13]:
```
df_reg['Country'].value_counts()
```

Out[13]:
```
Hungary                16
Dominican Republic     16
Costa Rica             16
Congo                  16
Mongolia               16
                       ..
Saint Kitts and Nevis   1
Nauru                   1
Dominica                1
Niue                    1
San Marino              1
Name: Country, Length: 193, dtype: int64
```

In [14]:
```
df_reg['Status'].value_counts()
```

Out[14]:
```
Developing    2426
Developed      512
Name: Status, dtype: int64
```

Let us check duplicate rwos and missing values

In [16]:
```
dup_df_reg = df_reg[df_reg.duplicated()]
dup_df_reg
```

Out[16]:

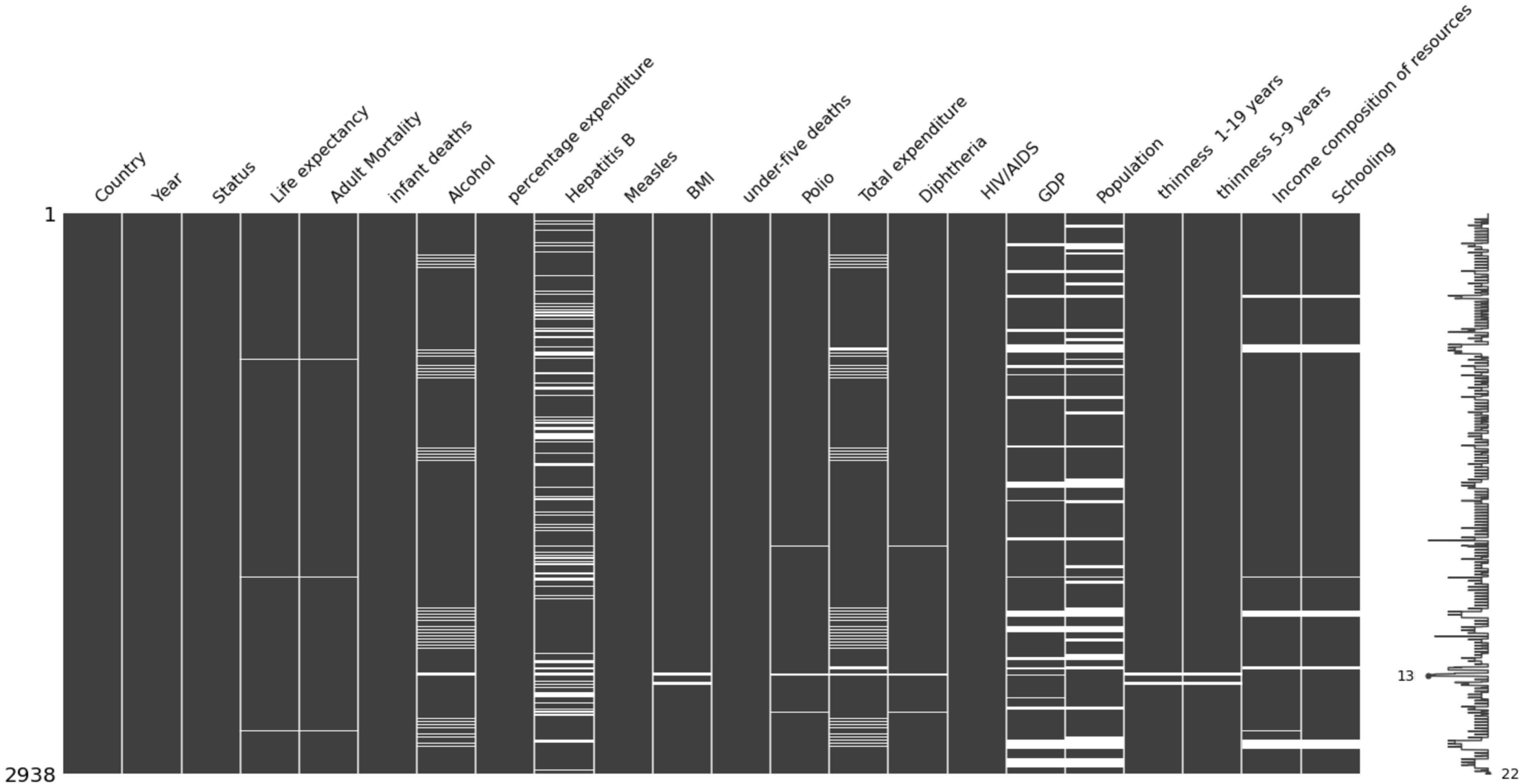
Country	Year	Status	Life expectancy	Adult Mortality	infant deaths	Alcohol	percentage expenditure	Hepatitis B	Measles	...	Polio	Total expenditure	Diphtheria	HIV/AIDS	GDP	Population	thinness 1-19 years	thinness 5-9 years	Income composition of resources	S

0 rows × 22 columns

In [17]:
```
import missingno as msno
```

In [18]:
```
msno.matrix(df_reg)
```

Out[18]: <AxesSubplot:>



Have a look at the correlation among all the columns numerical.

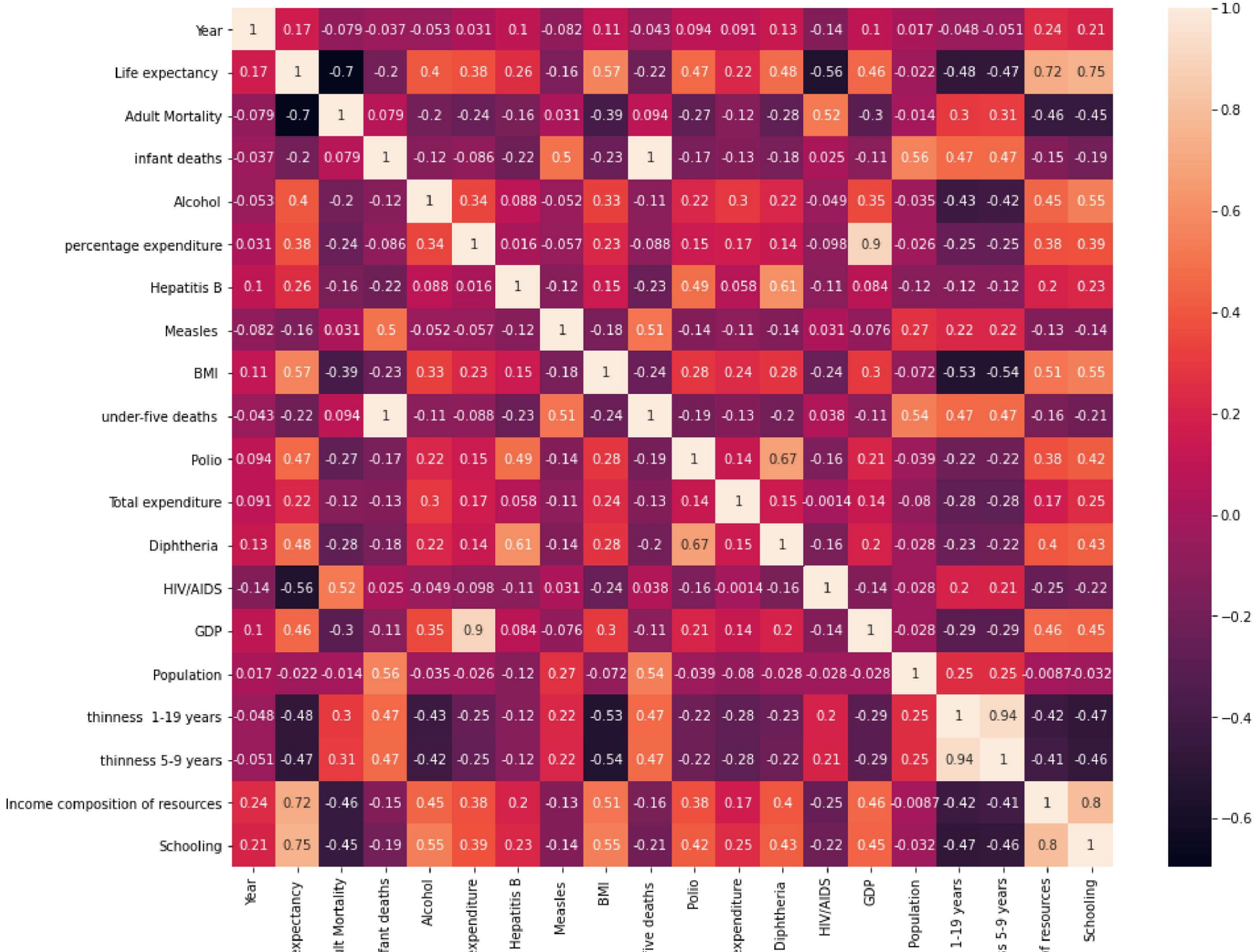
In [19]:
```
corr_df_reg=df_reg.corr()
corr_df_reg
```

Out[19]:

	Year	Life expectancy	Adult Mortality	infant deaths	Alcohol	percentage expenditure	Hepatitis B	Measles	BMI	under-five deaths	Polio	Total expenditure	Diphtheria	HIV/AIDS	GDP	Population	t
Year	1.000000	0.170033	-0.079052	-0.037415	-0.052990	0.031400	0.104333	-0.082493	0.108974	-0.042937	0.094158	0.090740	0.134337	-0.139741	0.101620	0.016969	-0
Life expectancy	0.170033	1.000000	-0.696359	-0.196557	0.404877	0.381864	0.256762	-0.157586	0.567694	-0.222529	0.465556	0.218086	0.479495	-0.556556	0.461455	-0.021538	-0
Adult Mortality	-0.079052	-0.696359	1.000000	0.078756	-0.195848	-0.242860	-0.162476	0.031176	-0.387017	0.094146	-0.274823	-0.115281	-0.275131	0.523821	-0.296049	-0.013647	0
infant deaths	-0.037415	-0.196557	0.078756	1.000000	-0.115638	-0.085612	-0.223566	0.501128	-0.227279	0.996629	-0.170689	-0.128616	-0.175171	0.025231	-0.108427	0.556801	0
Alcohol	-0.052990	0.404877	-0.195848	-0.115638	1.000000	0.341285	0.087549	-0.051827	0.330408	-0.112370	0.221734	0.296942	0.222020	-0.048845	0.354712	-0.035252	-0
percentage expenditure	0.031400	0.381864	-0.242860	-0.085612	0.341285	1.000000	0.016274	-0.056596	0.228700	-0.087852	0.147259	0.174420	0.143624	-0.097857	0.899373	-0.025662	-0
Hepatitis B	0.104333	0.256762	-0.162476	-0.223566	0.087549	0.016274	1.000000	-0.120529	0.150380	-0.233126	0.486171	0.058280	0.611495	-0.112675	0.083903	-0.123321	-0
Measles	-0.082493	-0.157586	0.031176	0.501128	-0.051827	-0.056596	-0.120529	1.000000	-0.175977	0.507809	-0.136166	-0.106241	-0.141882	0.030899	-0.076466	0.265966	0
BMI	0.108974	0.567694	-0.387017	-0.227279	0.330408	0.228700	0.150380	-0.175977	1.000000	-0.237669	0.284569	0.242503	0.283147	-0.243717	0.301557	-0.072301	-0
under-five deaths	-0.042937	-0.222529	0.094146	0.996629	-0.112370	-0.087852	-0.233126	0.507809	-0.237669	1.000000	-0.188720	-0.130148	-0.195668	0.038062	-0.112081	0.544423	0
Polio	0.094158	0.465556	-0.274823	-0.170689	0.221734	0.147259	0.486171	-0.136166	0.284569	-0.188720	1.000000	0.137330	0.673553	-0.159560	0.211976	-0.038540	-0
Total expenditure	0.090740	0.218086	-0.115281	-0.128616	0.296942	0.174420	0.058280	-0.106241	0.242503	-0.130148	0.137330	1.000000	0.152754	-0.001389	0.138364	-0.079662	-0
Diphtheria	0.134337	0.479495	-0.275131	-0.175171	0.222020	0.143624	0.611495	-0.141882	0.283147	-0.195668	0.673553	0.152754	1.000000	-0.164860	0.200666	-0.028444	-0
HIV/AIDS	-0.139741	-0.556556	0.523821	0.025231	-0.048845	-0.097857	-0.112675	0.030899	-0.243717	0.038062	-0.159560	-0.001389	-0.164860	1.000000	-0.136491	-0.027854	0
GDP	0.101620	0.461455	-0.296049	-0.108427	0.354712	0.899373	0.083903	-0.076466	0.301557	-0.112081	0.211976	0.138364	0.200666	-0.136491	1.000000	-0.028270	-0
Population	0.016969	-0.021538	-0.013647	0.556801	-0.035252	-0.025662	-0.123321	0.265966	-0.072301	0.544423	-0.038540	-0.079662	-0.028444	-0.027854	-0.028270	1.000000	0
thinness 1-19 years	-0.047876	-0.477183	0.302904	0.465711	-0.428795	-0.251369	-0.120429	0.224808	-0.532025	0.467789	-0.221823	-0.277101	-0.229518	0.204064	-0.285697	0.253944	1
thinness 5-9 years	-0.050929	-0.471584	0.308457	0.471350	-0.417414	-0.252905	-0.124960	0.221072	-0.538911	0.472263	-0.222592	-0.283774	-0.222743	0.207283	-0.290539	0.251403	0
Income composition of resources	0.243468	0.724776	-0.457626	-0.145139	0.450040	0.381952	0.199549	-0.129568	0.508774	-0.163305	0.381078	0.166682	0.401456	-0.249519	0.460341	-0.008735	-0
Schooling	0.209400	0.751975	-0.454612	-0.193720	0.547378	0.389687	0.231117	-0.137225	0.546961	-0.209373	0.417866	0.246384	0.425332	-0.220429	0.448273	-0.031668	-0

In [21]:
```
plt.figure(figsize=(15,12))
sns.heatmap(corr_df_reg,annot=True)
```

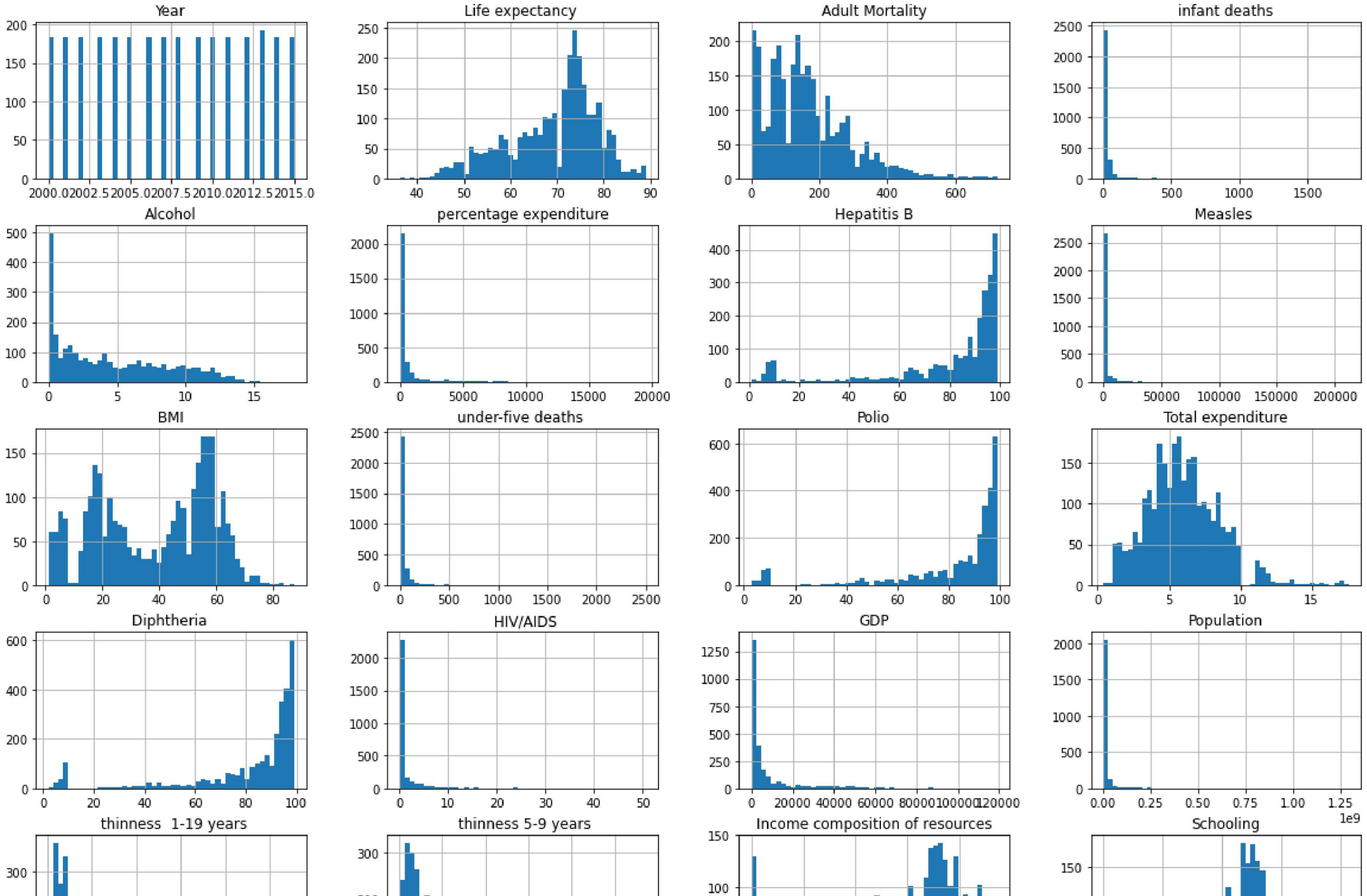
Out[21]: <AxesSubplot:>

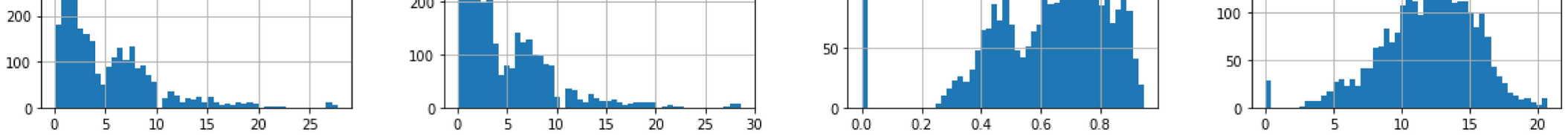


Life e
Adu
in
percentage e
under-
Total e
thinness
thinnes
Income composition o

Have a look visually at the numeric columns.

In [22]:
```
df_reg.hist(bins=50, figsize=(20,15))
plt.show()
```





We have miising vlaues in numeric columns only and hence let us replace those with the mean.

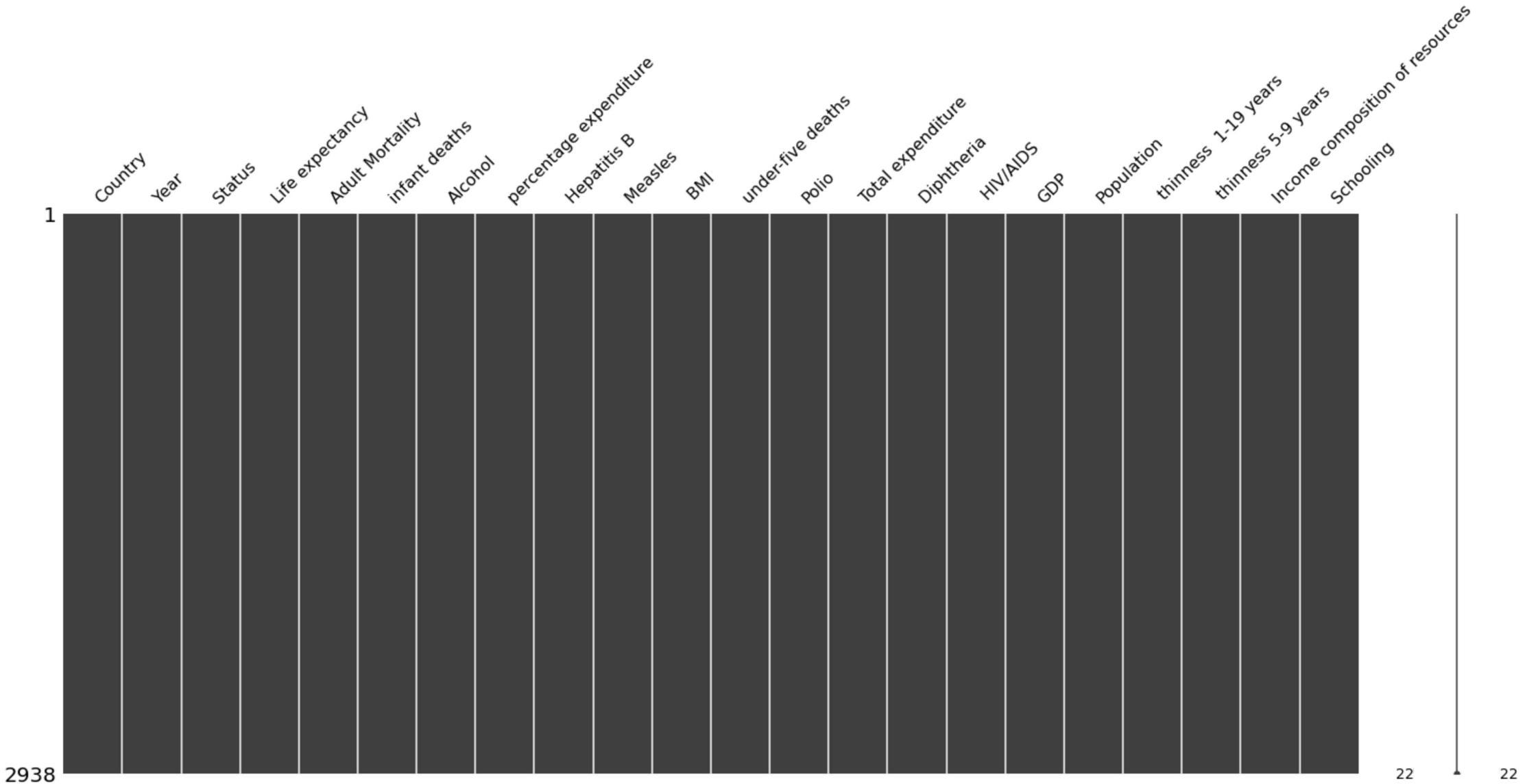
In [24]:
```
def imputer_mean(feature,data=df_reg):
    data[feature].fillna(data[feature].mean(),inplace=True)

features_miss= df_reg.columns[df_reg.isna().any()]
for feature in features_miss:
    imputer_mean(feature=feature)
```

In [25]:
```
df_reg.isnull().sum()
```

Out[25]:
```
Country                          0
Year                             0
Status                           0
Life expectancy                  0
Adult Mortality                  0
infant deaths                    0
Alcohol                          0
percentage expenditure           0
Hepatitis B                      0
Measles                          0
 BMI                             0
under-five deaths                0
Polio                            0
Total expenditure                0
Diphtheria                       0
 HIV/AIDS                        0
GDP                              0
Population                       0
 thinness  1-19 years            0
 thinness 5-9 years              0
Income composition of resources  0
Schooling                        0
dtype: int64
```

In [26]:
```
msno.matrix(df_reg)
```

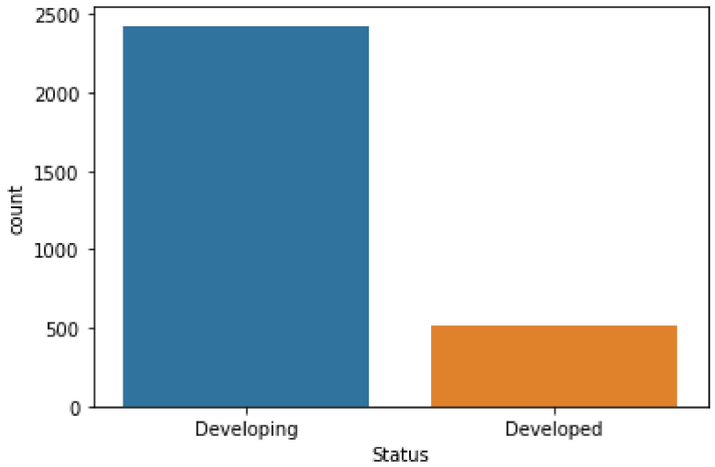
Out[26]: <AxesSubplot:>



Let us explore few aspects of the data before going ahead further.

In [27]:
```
sns.countplot(x='Status',data=df_reg)
```

Out[27]: <AxesSubplot:xlabel='Status', ylabel='count'>



In [28]:
```
df_status = df_reg.groupby('Status')
for sta,life in df_status:
    print(sta + ":" + str(life['Life expectancy '].mean()))
```

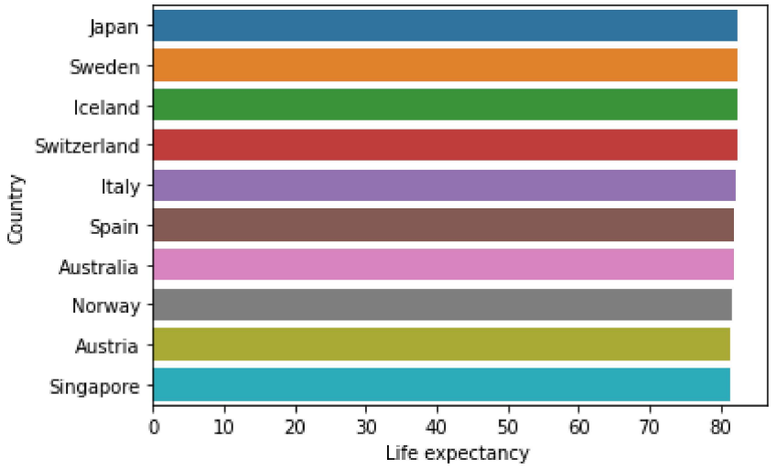
```
Developed:79.19785156249996
Developing:67.12017696493821
```

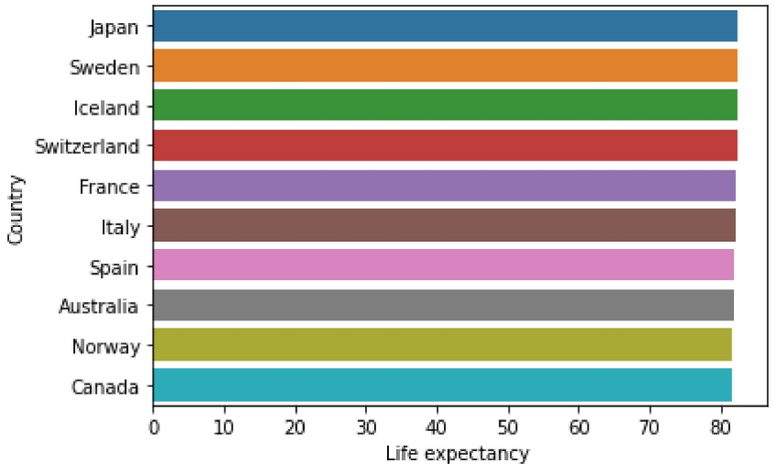
In [29]:
```
print('Top 10 developed countries with the longest life expectancy')
df_sta_ed = df_reg[df_reg.Status=='Developed'].groupby('Country')
print(df_sta_ed['Life expectancy '].mean().sort_values(ascending=False).head(10))
print('#'*50)
print('Top 10 countries with the longest life expectancy')
df_coun = df_reg.groupby('Country')
print(df_coun['Life expectancy '].mean().sort_values(ascending=False).head(10))
print('#'*50)
print('Top 10 countries with the shortest life expectancy')
print(df_coun['Life expectancy '].mean().sort_values(ascending=False).tail(10))
print('#'*50)
```

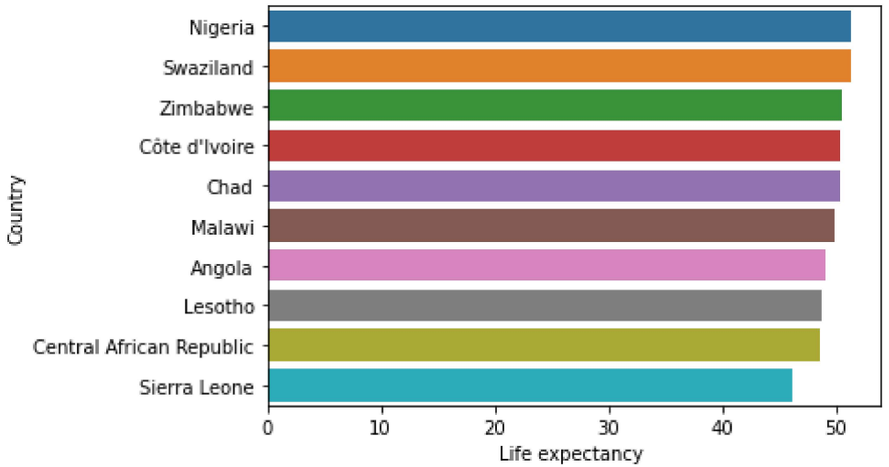
```
Top 10 developed countries with the longest life expectancy
Country
Japan          82.53750
Sweden         82.51875
Iceland        82.44375
Switzerland    82.33125
Italy          82.18750
Spain          82.06875
Australia      81.81250
Norway         81.79375
Austria        81.48125
Singapore      81.47500
Name: Life expectancy , dtype: float64
##################################################
Top 10 countries with the longest life expectancy
Country
Japan          82.53750
Sweden         82.51875
Iceland        82.44375
Switzerland    82.33125
France         82.21875
Italy          82.18750
Spain          82.06875
Australia      81.81250
Norway         81.79375
Canada         81.68750
Name: Life expectancy , dtype: float64
##################################################
Top 10 countries with the shortest life expectancy
Country
Nigeria                    51.35625
Swaziland                  51.32500
Zimbabwe                   50.48750
Côte d'Ivoire              50.38750
Chad                       50.38750
```

```
Malawi                       49.89375
Angola                       49.01875
Lesotho                      48.78125
Central African Republic     48.51250
Sierra Leone                 46.11250
Name: Life expectancy , dtype: float64
##################################################
```

In [30]:
```
df_ed = df_sta_ed['Life expectancy '].mean().sort_values(ascending=False).head(10)
dic = {'Country':df_ed.index,'Life expectancy ':df_ed.values}
df_ed = pd.DataFrame(dic)
df_long = df_coun['Life expectancy '].mean().sort_values(ascending=False).head(10)
dic = {'Country':df_long.index,'Life expectancy ':df_long.values}
df_long = pd.DataFrame(dic)
df_short = df_coun['Life expectancy '].mean().sort_values(ascending=False).tail(10)
dic = {'Country':df_short.index,'Life expectancy ':df_short.values}
df_short = pd.DataFrame(dic)
for df in [df_ed,df_long,df_short]:
    sns.barplot(x='Life expectancy ',y='Country',data=df)
    plt.show()
```







Let us seperate the lable and features.

In [31]:
```
y_base = df_reg['Life expectancy ']
X_base = df_reg.drop('Life expectancy ',axis=1)
X_base.head()
```

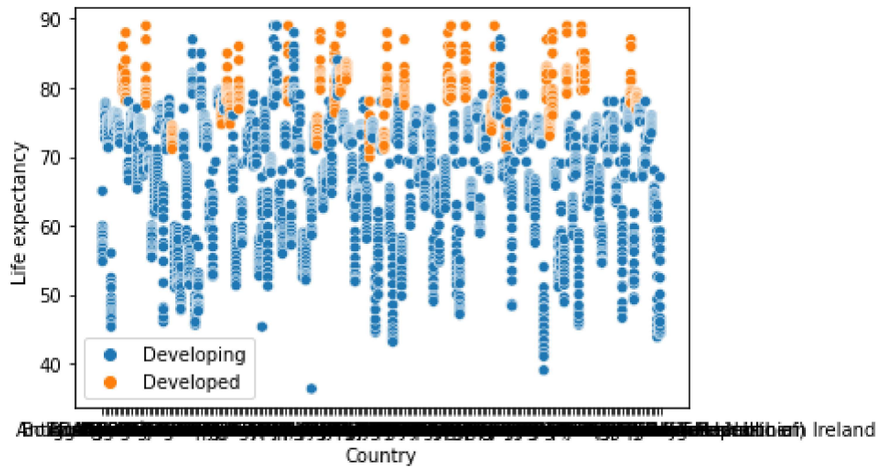
Out[31]:

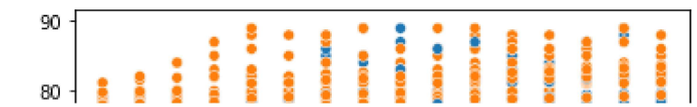
	Country	Year	Status	Adult Mortality	infant deaths	Alcohol	percentage expenditure	Hepatitis B	Measles	BMI	...	Polio	Total expenditure	Diphtheria	HIV/AIDS	GDP	Population	thinness 1-19 years	thinness 5-9 years	Inc compos resou
0	Afghanistan	2015	Developing	263.0	62	0.01	71.279624	65.0	1154	19.1	...	6.0	8.16	65.0	0.1	584.259210	33736494.0	17.2	17.3	
1	Afghanistan	2014	Developing	271.0	64	0.01	73.523582	62.0	492	18.6	...	58.0	8.18	62.0	0.1	612.696514	327582.0	17.5	17.5	
2	Afghanistan	2013	Developing	268.0	66	0.01	73.219243	64.0	430	18.1	...	62.0	8.13	64.0	0.1	631.744976	31731688.0	17.7	17.7	
3	Afghanistan	2012	Developing	272.0	69	0.01	78.184215	67.0	2787	17.6	...	67.0	8.52	67.0	0.1	669.959000	3696958.0	17.9	18.0	
4	Afghanistan	2011	Developing	275.0	71	0.01	7.097109	68.0	3013	17.2	...	68.0	7.87	68.0	0.1	63.537231	2978599.0	18.2	18.2	

5 rows × 21 columns

Let us explore the features with respect to label visually.

In [32]:
```
# X.columns
for features in X_base.columns:
    if features == 'Status':
        pass
    else:
        sns.scatterplot(x=X_base[features],y=y_base,hue=X_base['Status'])
        plt.legend()
        plt.show()
```





Perform lable encoding on Country and Year columns

In [33]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
X_base['Country'] = le.fit_transform(X_base['Country'])
X_base['Year'] = le.fit_transform(X_base['Year'])
# X.head(3)
# X.tail(3)
```

In [34]:
```
X_base.head()
```

Out[34]:

	Country	Year	Status	Adult Mortality	infant deaths	Alcohol	percentage expenditure	Hepatitis B	Measles	BMI	...	Polio	Total expenditure	Diphtheria	HIV/AIDS	GDP	Population	thinness 1-19 years	thinness 5-9 years	Incom compositio resource
0	0	15	Developing	263.0	62	0.01	71.279624	65.0	1154	19.1	...	6.0	8.16	65.0	0.1	584.259210	33736494.0	17.2	17.3	0.47
1	0	14	Developing	271.0	64	0.01	73.523582	62.0	492	18.6	...	58.0	8.18	62.0	0.1	612.696514	327582.0	17.5	17.5	0.47
2	0	13	Developing	268.0	66	0.01	73.219243	64.0	430	18.1	...	62.0	8.13	64.0	0.1	631.744976	31731688.0	17.7	17.7	0.47
3	0	12	Developing	272.0	69	0.01	78.184215	67.0	2787	17.6	...	67.0	8.52	67.0	0.1	669.959000	3696958.0	17.9	18.0	0.46
4	0	11	Developing	275.0	71	0.01	7.097109	68.0	3013	17.2	...	68.0	7.87	68.0	0.1	63.537231	2978599.0	18.2	18.2	0.45

5 rows × 21 columns

Convert the Status categorical feature using dummies

In [35]:
```
X_all = pd.get_dummies(X_base, ['Status'], drop_first=True)
```

In [36]:
```
X_all.head(10)
```

Out[36]:

	Country	Year	Adult Mortality	infant deaths	Alcohol	percentage expenditure	Hepatitis B	Measles	BMI	under-five deaths	...	Total expenditure	Diphtheria	HIV/AIDS	GDP	Population	thinness 1-19 years	thinness 5-9 years	Income composition of resources	Schooli
0	0	15	263.0	62	0.01	71.279624	65.0	1154	19.1	83	...	8.16	65.0	0.1	584.259210	33736494.0	17.2	17.3	0.479	1
1	0	14	271.0	64	0.01	73.523582	62.0	492	18.6	86	...	8.18	62.0	0.1	612.696514	327582.0	17.5	17.5	0.476	1
2	0	13	268.0	66	0.01	73.219243	64.0	430	18.1	89	...	8.13	64.0	0.1	631.744976	31731688.0	17.7	17.7	0.470	
3	0	12	272.0	69	0.01	78.184215	67.0	2787	17.6	93	...	8.52	67.0	0.1	669.959000	3696958.0	17.9	18.0	0.463	
4	0	11	275.0	71	0.01	7.097109	68.0	3013	17.2	97	...	7.87	68.0	0.1	63.537231	2978599.0	18.2	18.2	0.454	
5	0	10	279.0	74	0.01	79.679367	66.0	1989	16.7	102	...	9.20	66.0	0.1	553.328940	2883167.0	18.4	18.4	0.448	
6	0	9	281.0	77	0.01	56.762217	63.0	2861	16.2	106	...	9.42	63.0	0.1	445.893298	284331.0	18.6	18.7	0.434	
7	0	8	287.0	80	0.03	25.873925	64.0	1599	15.7	110	...	8.33	64.0	0.1	373.361116	2729431.0	18.8	18.9	0.433	
8	0	7	295.0	82	0.02	10.910156	63.0	1141	15.2	113	...	6.73	63.0	0.1	369.835796	26616792.0	19.0	19.1	0.415	
9	0	6	295.0	84	0.03	17.171518	64.0	1990	14.7	116	...	7.43	58.0	0.1	272.563770	2589345.0	19.2	19.3	0.405	

10 rows × 21 columns

In [37]:
```
X_all['Status_Developing'].value_counts()
```

Out[37]:
```
1    2426
0     512
Name: Status_Developing, dtype: int64
```

Let us apply standard scaler on the features.

In [38]:
```
from sklearn.preprocessing import StandardScaler
scs = StandardScaler()
X_alll = pd.DataFrame(scs.fit_transform(X_all))
```

In [39]:
```
X_alll.head()
```

Out[39]:

	0	1	2	3	4	5	6	7	8	9	...	11	12	13	14	15	16	17	18
0	-1.691042	1.621762	0.791586	0.268824	-1.172958	-0.335570	-0.705861	-0.110384	-0.964715	0.255359	...	0.925806	-0.732952	-0.323445	-0.525248	0.389975	2.813130	2.773279	-0.725401
1	-1.691042	1.404986	0.856072	0.285786	-1.172958	-0.334441	-0.838704	-0.168124	-0.989810	0.274060	...	0.934140	-0.859877	-0.323445	-0.523083	-0.230936	2.881408	2.817902	-0.740050
2	-1.691042	1.188210	0.831890	0.302749	-1.172958	-0.334594	-0.750142	-0.173531	-1.014905	0.292761	...	0.913306	-0.775260	-0.323445	-0.521632	0.352715	2.926927	2.862526	-0.769349
3	-1.691042	0.971434	0.864132	0.328193	-1.172958	-0.332096	-0.617299	0.032045	-1.040000	0.317696	...	1.075815	-0.648335	-0.323445	-0.518723	-0.168315	2.972446	2.929461	-0.803531
4	-1.691042	0.754658	0.888314	0.345155	-1.172958	-0.367862	-0.573018	0.051757	-1.060076	0.342631	...	0.804966	-0.606027	-0.323445	-0.564893	-0.181666	3.040724	2.974085	-0.847480

5 rows × 21 columns

In [40]:
```
y_base.head()
```

Out[40]:
```
0    65.0
1    59.9
2    59.9
3    59.5
4    59.2
Name: Life expectancy , dtype: float64
```

Let us use OLS to Check the regression results.

In [41]:
```
import statsmodels.api as sm
X2 = sm.add_constant(X_alll)
ols = sm.OLS(y_base,X2)
lr = ols.fit()
print(lr.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:       Life expectancy    R-squared:                       0.820
Model:                           OLS   Adj. R-squared:                  0.819
Method:                Least Squares   F-statistic:                     634.5
Date:               Fri, 28 May 2021   Prob (F-statistic):               0.00
Time:                       01:19:48   Log-Likelihood:                -8262.3
No. Observations:                2938   AIC:                         1.657e+04
Df Residuals:                    2916   BIC:                         1.670e+04
Df Model:                          21
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         69.2249      0.075    928.035      0.000      69.079      69.371
0              0.2555      0.076      3.361      0.001       0.106       0.405
1             -0.0428      0.080     -0.536      0.592      -0.200       0.114
2             -2.4625      0.099    -24.981      0.000      -2.656      -2.269
3             11.9566      0.994     12.034      0.000      10.008      13.905
4              0.2785      0.102      2.720      0.007       0.078       0.479
5              0.1991      0.168      1.183      0.237      -0.131       0.529
6             -0.3219      0.088     -3.646      0.000      -0.495      -0.149
7             -0.2234      0.088     -2.548      0.011      -0.395      -0.051
8              0.8684      0.098      8.847      0.000       0.676       1.061
9            -12.1661      0.991    -12.282      0.000     -14.108     -10.224
10             0.6520      0.104      6.257      0.000       0.448       0.856
11             0.1424      0.082      1.732      0.083      -0.019       0.304
12             0.9519      0.111      8.568      0.000       0.734       1.170
13            -2.4151      0.090    -26.900      0.000      -2.591      -2.239
14             0.4199      0.171      2.459      0.014       0.085       0.755
15             0.0104      0.091      0.115      0.909      -0.168       0.189
16            -0.3268      0.221     -1.478      0.140      -0.761       0.107
17            -0.0092      0.222     -0.042      0.967      -0.445       0.427
18             1.1824      0.131      9.019      0.000       0.925       1.439
19             2.1510      0.136     15.759      0.000       1.883       2.419
20            -0.5715      0.103     -5.565      0.000      -0.773      -0.370
==============================================================================
Omnibus:                      141.341   Durbin-Watson:                   0.703
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              427.781
Skew:                          -0.176   Prob(JB):                     1.28e-93
Kurtosis:                       4.836   Cond. No.                         45.6
```

```
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Let us using backward elimination to drop the feature giving p-value less than 0.05

In [42]:
```
while (lr.pvalues.max()>0.05):
    X2.drop(lr.pvalues.idxmax(),axis=1,inplace=True)
    ols = sm.OLS(y_base,X2)
    lr = ols.fit()
print(lr.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:       Life expectancy    R-squared:                       0.820
Model:                           OLS   Adj. R-squared:                  0.819
Method:                Least Squares   F-statistic:                     832.4
Date:               Fri, 28 May 2021   Prob (F-statistic):               0.00
Time:                       01:20:45   Log-Likelihood:                -8264.9
No. Observations:                2938   AIC:                         1.656e+04
Df Residuals:                    2921   BIC:                         1.667e+04
Df Model:                          16
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         69.2249      0.075    928.006      0.000      69.079      69.371
0              0.2577      0.076      3.404      0.001       0.109       0.406
2             -2.4723      0.098    -25.177      0.000      -2.665      -2.280
3             12.0236      0.976     12.323      0.000      10.110      13.937
4              0.3144      0.101      3.124      0.002       0.117       0.512
6             -0.3355      0.088     -3.819      0.000      -0.508      -0.163
7             -0.2286      0.087     -2.616      0.009      -0.400      -0.057
8              0.8770      0.097      9.048      0.000       0.687       1.067
9            -12.2259      0.981    -12.461      0.000     -14.150     -10.302
10             0.6503      0.104      6.248      0.000       0.446       0.854
12             0.9608      0.111      8.673      0.000       0.744       1.178
13            -2.3953      0.089    -26.927      0.000      -2.570      -2.221
14             0.5863      0.088      6.670      0.000       0.414       0.759
16            -0.3558      0.104     -3.405      0.001      -0.561      -0.151
18             1.1442      0.129      8.855      0.000       0.891       1.398
19             2.1578      0.136     15.887      0.000       1.891       2.424
20            -0.6119      0.101     -6.057      0.000      -0.810      -0.414
==============================================================================
Omnibus:                      134.011   Durbin-Watson:                   0.700
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              393.905
Skew:                          -0.167   Prob(JB):                     2.91e-86
Kurtosis:                       4.763   Cond. No.                         41.2
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In [43]:
```
X2.head()
```

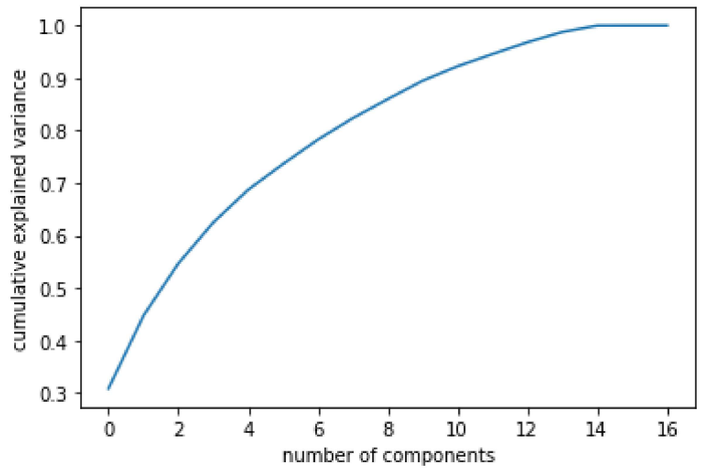
Out[43]:

	const	0	2	3	4	6	7	8	9	10	12	13	14	16	18	19	20
0	1.0	-1.691042	0.791586	0.268824	-1.172958	-0.705861	-0.110384	-0.964715	0.255359	-3.278638	-0.732952	-0.323445	-0.525248	2.813130	-0.725401	-0.579931	0.459399
1	1.0	-1.691042	0.856072	0.285786	-1.172958	-0.838704	-0.168124	-0.989810	0.274060	-1.051482	-0.859877	-0.323445	-0.523083	2.881408	-0.740050	-0.610570	0.459399
2	1.0	-1.691042	0.831890	0.302749	-1.172958	-0.750142	-0.173531	-1.014905	0.292761	-0.880163	-0.775260	-0.323445	-0.521632	2.926927	-0.769349	-0.641209	0.459399
3	1.0	-1.691042	0.864132	0.328193	-1.172958	-0.617299	0.032045	-1.040000	0.317696	-0.666013	-0.648335	-0.323445	-0.518723	2.972446	-0.803531	-0.671847	0.459399
4	1.0	-1.691042	0.888314	0.345155	-1.172958	-0.573018	0.051757	-1.060076	0.342631	-0.623183	-0.606027	-0.323445	-0.564893	3.040724	-0.847480	-0.763764	0.459399

Let us use PCA to check whether we can use drastically fewer number of principal componetnts or not.

In [44]:
```
from sklearn.decomposition import PCA
pca = PCA().fit(X2)
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance')
```

Out[44]:
```
Text(0, 0.5, 'cumulative explained variance')
```



But we see that we have to take 14 out of 16 to fully capture the gamut of variance and hence we did not go for using 14 by dropping only two.

Let us drop the const column as it is not part of the database.

In [45]:
```
X_fin=X2.drop('const',axis=1)
y_fin=y_base
X_fin.head()
```

Out[45]:

	0	2	3	4	6	7	8	9	10	12	13	14	16	18	19	20
0	-1.691042	0.791586	0.268824	-1.172958	-0.705861	-0.110384	-0.964715	0.255359	-3.278638	-0.732952	-0.323445	-0.525248	2.813130	-0.725401	-0.579931	0.459399
1	-1.691042	0.856072	0.285786	-1.172958	-0.838704	-0.168124	-0.989810	0.274060	-1.051482	-0.859877	-0.323445	-0.523083	2.881408	-0.740050	-0.610570	0.459399
2	-1.691042	0.831890	0.302749	-1.172958	-0.750142	-0.173531	-1.014905	0.292761	-0.880163	-0.775260	-0.323445	-0.521632	2.926927	-0.769349	-0.641209	0.459399
3	-1.691042	0.864132	0.328193	-1.172958	-0.617299	0.032045	-1.040000	0.317696	-0.666013	-0.648335	-0.323445	-0.518723	2.972446	-0.803531	-0.671847	0.459399
4	-1.691042	0.888314	0.345155	-1.172958	-0.573018	0.051757	-1.060076	0.342631	-0.623183	-0.606027	-0.323445	-0.564893	3.040724	-0.847480	-0.763764	0.459399

In [46]:
```
y_fin.head()
```

Out[46]:
```
0    65.0
1    59.9
2    59.9
3    59.5
4    59.2
Name: Life expectancy , dtype: float64
```

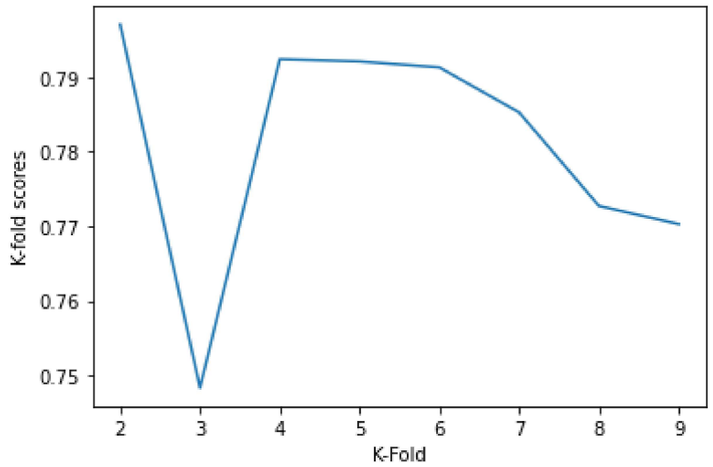
Let us import the required libraries for model development.

In [47]:
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score
cross_val_score(LinearRegression(),X_fin,y_fin,cv=5).mean()
```

Out[47]:
```
0.7920794860943001
```

Try to find the best value for k for from k-fold cross validation.

In [48]:
```
#Graph k-fold score for Linear Regression

l_scores = []
for i in range(2,10):
    l_scores.append(cross_val_score(LinearRegression(),X_fin,y_fin,cv=i).mean())



plt.plot(range(2,10),l_scores)
plt.xlabel('K-Fold')
plt.ylabel('K-fold scores')
plt.show()
```



From the above K=4 seems to be the optimum one.

Now, let us perform the test, train split from lable and features.

In [49]:
```
from sklearn.model_selection import train_test_split
X_train_lr,X_test_lr,y_train_lr,y_test_lr = train_test_split(X_fin,y_fin,
                                                    random_state=1,test_size=0.20)
```

Let us build the model.

In [50]:
```
# Let us build the model using using X_train and y_train and check the score using X_test and y_test
model_lr = LinearRegression()
model_lr.fit(X_train_lr,y_train_lr)
model_lr.score(X_test_lr,y_test_lr)
```

Out[50]:
```
0.7954100686387191
```

Let us now perform the evaluation of the model's performance.

In [51]:
```
y_pred_lr = model_lr.predict(X_test_lr)
from sklearn.metrics import r2_score,mean_squared_error
import math

print(f'R2 Score: {r2_score(y_test_lr,y_pred_lr)}')
print(f'Mean Squared Error, MSE: {mean_squared_error(y_test_lr,y_pred_lr)}')
print(f'RMSE: {math.sqrt(mean_squared_error(y_test_lr,y_pred_lr))}')
```

```
R2 Score: 0.7954100686387191
Mean Squared Error, MSE: 17.67405847480355
RMSE: 4.204052625122996
```

In [52]:
```
y_test_lr.head()
```

Out[52]:
```
1268    82.1
2719    58.4
2710    63.3
2028    67.9
351     47.8
Name: Life expectancy , dtype: float64
```

In [53]:
```
y_pred_lr[:5]
```

Out[53]:
```
array([79.30509709, 57.09871637, 65.13334181, 68.26389288, 40.5149948 ])
```

In [54]:
```
# Let us find the number of observations and number of features to be used in calculation for the adjusted R2
nl = len(X_test_lr)
kl = len(X_test_lr.iloc[0])
R2l = r2_score(y_test_lr,y_pred_lr)
R2l
```

Out[54]:
```
0.7954100686387191
```

In [55]:
```
Adj_R2l = 1 - ((nl-1)*(1- R2l)/(nl-kl-1))
print(f'The adjusted R2: {Adj_R2l}')
```

```
The adjusted R2: 0.7896772509473347
```

The performance of the model seems to be a goodish one from the value of value of R2 and Adjusted R2.

```
################################### K Nearest Neighbors  ##############################################
```

Let us import the requied libraries for the KNN model

In [56]:
```
#import the knn model
from sklearn.neighbors import KNeighborsRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import cross_val_score
import matplotlib.pyplot as plt
knn = KNeighborsRegressor()
```

Let us take the processed fetures and label from the linear regression pre-processing.

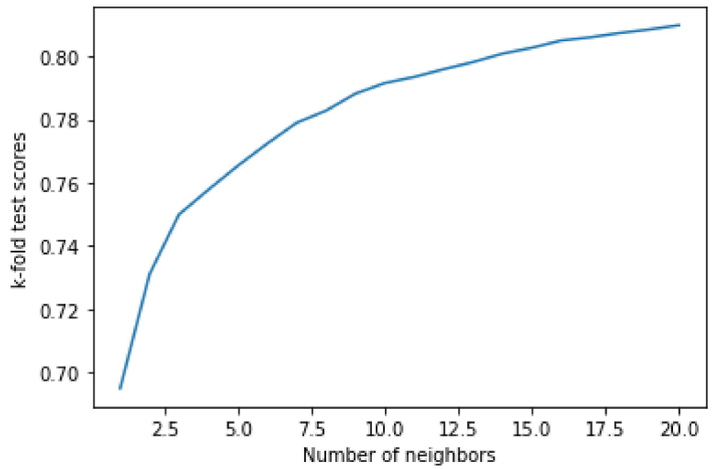
In [57]:
```
X_knn=X_fin
y_knn=y_fin
```

Performing scaling of the features using standard scaling

In [58]:
```
sc = StandardScaler()
X_knn = pd.DataFrame(sc.fit_transform(X_knn))
y_knn = pd.Series(y_knn)
```

In [59]:
```
#for no.of neighbors from 1 - 20, graph the k-fold scores

scores = []
for i in range(1,21,1):
    knn = KNeighborsRegressor(n_neighbors=i, weights='distance',p=2)
    scores.append(cross_val_score(knn,X_knn,y_knn,cv=5).mean())
```

In [60]:
```
import matplotlib.pyplot as plt
plt.plot(range(1,21,1),scores)
plt.xlabel('Number of neighbors')
plt.ylabel('k-fold test scores')
plt.show()
```



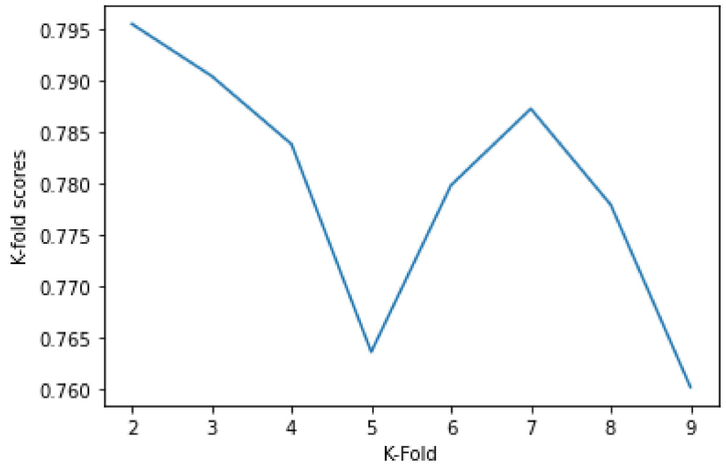
In [61]:
```
X_knn.shape
```

Out[61]: (2938, 16)

In [62]:
```
y_knn.shape
```

Out[62]: (2938,)

In [63]:
```
#Graph k-fold score for KNN

k_scores = []
for i in range(2,10):
    k_scores.append(cross_val_score(KNeighborsRegressor(),X_knn,y_knn,cv=i).mean())

plt.plot(range(2,10),k_scores)
plt.xlabel('K-Fold')
plt.ylabel('K-fold scores')
plt.show()
```



Here, k=7 seems to be the optimum one.

In [64]:
```
from sklearn.model_selection import train_test_split
X_train_k,X_test_k,y_train_k,y_test_k = train_test_split(X_knn,y_knn,
                                                         random_state=1)
```

In [65]:
```
# Let us build the model using using X_train and y_train and check the score using X_test and y_test
model_knn = KNeighborsRegressor()
model_knn.fit(X_train_k,y_train_k)
model_knn.score(X_test_k,y_test_k)
```

Out[65]: 0.8962654820785558

In [66]:
```
y_pred_k = model_knn.predict(X_test_k)
from sklearn.metrics import r2_score,mean_squared_error
import math

print(f'R2 Score: {r2_score(y_test_k,y_pred_k)}')
print(f'Mean Squared Error, MSE: {mean_squared_error(y_test_k,y_pred_k)}')
print(f'RMSE: {math.sqrt(mean_squared_error(y_test_k,y_pred_k))}')
```

```
R2 Score: 0.8962654820785558
Mean Squared Error, MSE: 8.838014022178921
RMSE: 2.9728797523914285
```

In [67]:
```
# Let us find the number of observations and number of features to be used in calculation for the adjusted R2
nk = len(X_test_k)
kk = len(X_test_k.iloc[0])
R2k = r2_score(y_test_k,y_pred_k)
R2k
```

Out[67]:
```
0.8962654820785558
```

In [68]:
```
Adj_R2k = 1 - ((nk-1)*(1- R2k)/(nk-kk-1))
print(f'The adjusted R2: {Adj_R2k}')
```

```
The adjusted R2: 0.8939538493672144
```

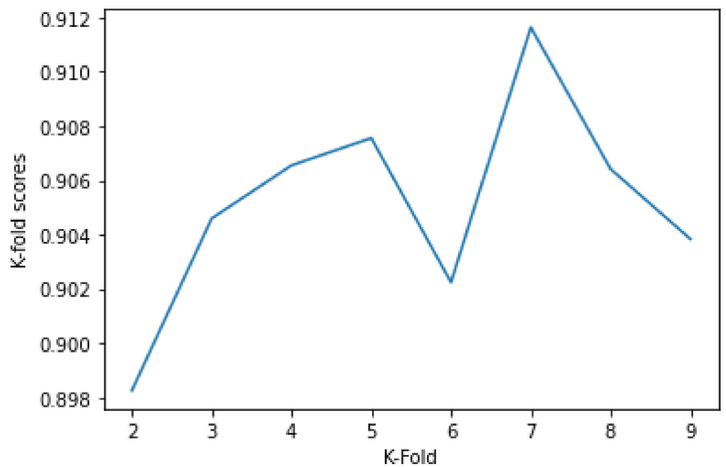
```
The performance of the model is much better as compared to the linear regression one.
```

```
########################################### Random Forest ##############################################
```

In [69]:
```
#import the Random Forest model
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score
import matplotlib.pyplot as plt
rfr = RandomForestRegressor()
```

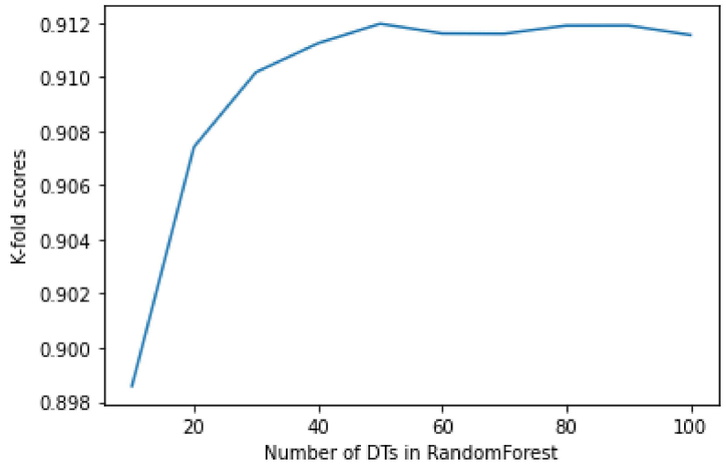
In [70]:
```
X_r=X_fin
y_r=y_fin
```

In [71]:
```
#Graph k-fold score for Random Forest

r_scores = []
for i in range(2,10):
    r_scores.append(cross_val_score(RandomForestRegressor(),X_r,y_r,cv=i).mean())



plt.plot(range(2,10),r_scores)
plt.xlabel('K-Fold')
plt.ylabel('K-fold scores')
plt.show()
```



In [72]:
```
#Graph k-fold score vs no. of estimators in Random Forest
rf_scores = []
for i in range(10,101,10):
    rf_scores.append(cross_val_score(RandomForestRegressor(n_estimators=i,random_state=9),
                                     X_r,y_r,cv=7).mean())
```

In [73]:
```
plt.plot(range(10,101,10),rf_scores)
plt.xlabel('Number of DTs in RandomForest')
plt.ylabel('K-fold scores')
plt.show()
```



Number of DT=50 seems to be optimum one.

Let us perform gridsearch parameter tuning.

In [74]:
```
params = {
            'n_estimators': [90, 100,110,120,130],
            'max_depth': [12,13,14,15]
        }
model_rfr = GridSearchCV(RandomForestRegressor(), params,cv=7)
model_rfr.fit(X_r,y_r)
```

Out[74]:
```
GridSearchCV(cv=7, estimator=RandomForestRegressor(),
             param_grid={'max_depth': [12, 13, 14, 15],
                         'n_estimators': [90, 100, 110, 120, 130]})
```

The best parameter found as given below:

In [75]:
```
model_rfr.best_params_
```

Out[75]:
```
{'max_depth': 13, 'n_estimators': 100}
```

In [76]:
```
model_rfr.best_score_
```

Out[76]:
```
0.9136803665596555
```

Let us now find the model with the best estimator from the parameter tuning.

In [77]:
```
best_model_rfr = model_rfr.best_estimator_
```

In [78]:
```
from sklearn.model_selection import train_test_split
X_train_rfr,X_test_rfr,y_train_rfr,y_test_rfr = train_test_split(X_r,y_r,
                                                random_state=5)
```

In [79]:
```
best_model_rfr.fit(X_train_rfr,y_train_rfr)
```

Out[79]:
```
RandomForestRegressor(max_depth=13)
```

In [80]:
```
best_model_rfr.score(X_test_rfr,y_test_rfr)
```

Out[80]:
```
0.9647003980751055
```

In [81]:
```
cross_val_score(RandomForestRegressor(n_estimators=120,max_depth=12),X_r,y_r,cv=7)
```

Out[81]:
```
array([0.91957785, 0.93719439, 0.88039985, 0.93699538, 0.92395707,
       0.87805821, 0.91235222])
```

In [82]:
```
y_pred_rfr = best_model_rfr.predict(X_test_rfr)
from sklearn.metrics import r2_score,mean_squared_error
import math

print(f'R2 Score: {r2_score(y_test_rfr,y_pred_rfr)}')
print(f'Mean Squared Error, MSE: {mean_squared_error(y_test_rfr,y_pred_rfr)}')
print(f'RMSE: {math.sqrt(mean_squared_error(y_test_rfr,y_pred_rfr))}')
```

```
R2 Score: 0.9647003980751055
Mean Squared Error, MSE: 3.2079059188199817
RMSE: 1.7910627903063538
```

In [83]:
```
# Let us find the number of observations and number of features to be used in calculation for the adjusted R2
nr = len(X_test_rfr)
kr = len(X_test_rfr.iloc[0])
R2r = r2_score(y_test_rfr,y_pred_rfr)
R2r
```

Out[83]:
```
0.9647003980751055
```

In [84]:
```
Adj_R2r = 1 - ((nr-1)*(1- R2r)/(nr-kr-1))
print(f'The adjusted R2: {Adj_R2r}')
```

```
The adjusted R2: 0.9639137774193975
```

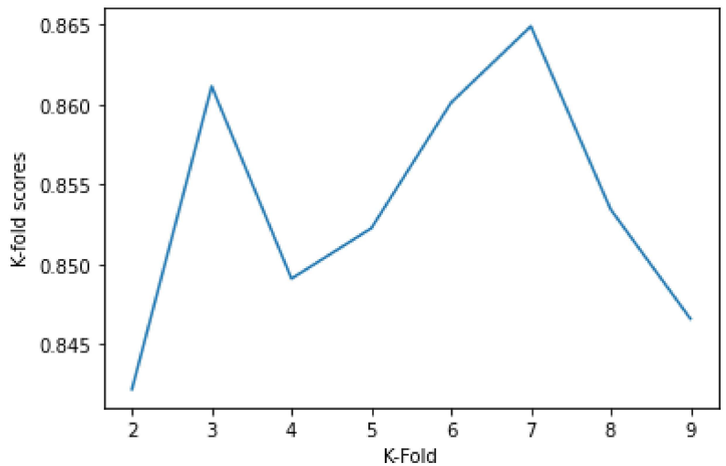
```
The performance of this model is very good as we find from the R2 and Adjusted R2
```

```
################################################ Adaboost ################################################
```

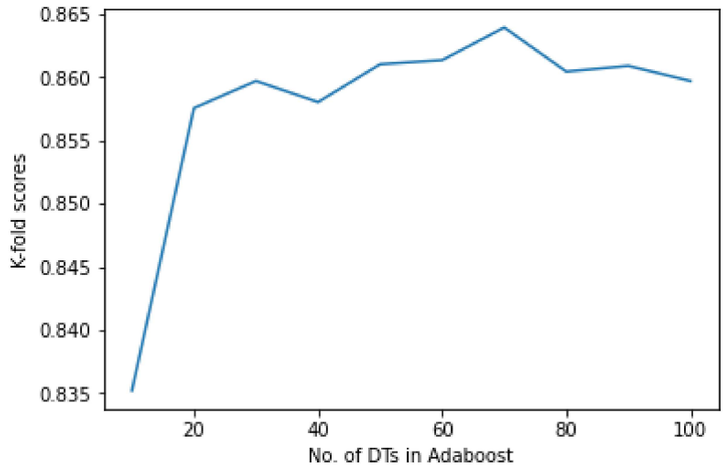
In [85]:
```
#import the adaboost model
from sklearn.ensemble import AdaBoostRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score
import matplotlib.pyplot as plt
adar = RandomForestRegressor()
```

In [86]:
```
X_a=X_fin
y_a=y_fin
```

In [87]:
```
#Graph k-fold score for AdaBoost

a_scores = []
for i in range(2,10):
    a_scores.append(cross_val_score(AdaBoostRegressor(),X_a,y_a,cv=i).mean())



plt.plot(range(2,10),a_scores)
plt.xlabel('K-Fold')
plt.ylabel('K-fold scores')
plt.show()
```



In [88]:
```
#Graph k-fold score vs no. of estimators in Adaboost which uses DT as base estimators
ada_scores = []
for i in range(10,101,10):
    ada_scores.append(cross_val_score(AdaBoostRegressor(n_estimators=i,random_state=0),
                                      X_a,y_a,cv=7).mean())
plt.plot(range(10,101,10),ada_scores)
plt.xlabel('No. of DTs in Adaboost')
plt.ylabel('K-fold scores')
plt.show()
```



In [89]:
```
from sklearn.tree import DecisionTreeRegressor
#including other params like max_depth, we will apply gridsearch to fine the best settings
params = {
            'n_estimators': [70,80,90,100],
            'base_estimator': [DecisionTreeRegressor(max_depth=9,random_state=0),
                               DecisionTreeRegressor(max_depth=10,random_state=0),
                               DecisionTreeRegressor(max_depth=11,random_state=0)]
        }
model_adar = GridSearchCV(AdaBoostRegressor(random_state=0), params,cv=7)
model_adar.fit(X_a,y_a)
```

Out[89]:
```
GridSearchCV(cv=7, estimator=AdaBoostRegressor(random_state=0),
             param_grid={'base_estimator': [DecisionTreeRegressor(max_depth=9,
                                                                  random_state=0),
                                            DecisionTreeRegressor(max_depth=10,
                                                                  random_state=0),
                                            DecisionTreeRegressor(max_depth=11,
                                                                  random_state=0)],
                         'n_estimators': [70, 80, 90, 100]})
```

In [90]:
```
model_adar.best_params_
```

Out[90]:
```
{'base_estimator': DecisionTreeRegressor(max_depth=10, random_state=0),
 'n_estimators': 80}
```

In [91]:
```
model_adar.best_score_
```

Out[91]:
```
0.9125502312572363
```

In [92]:
```
best_model_adar = model_adar.best_estimator_
```

In [93]:
```
from sklearn.model_selection import train_test_split
X_train_adar,X_test_adar,y_train_adar,y_test_adar = train_test_split(X_a,y_a,
                                                    random_state=0)
```

In [94]:
```
best_model_adar.fit(X_train_adar,y_train_adar)
```

Out[94]:
```
AdaBoostRegressor(base_estimator=DecisionTreeRegressor(max_depth=10,
                                                       random_state=0),
                  n_estimators=80, random_state=0)
```

In [95]:
```
best_model_adar.score(X_test_adar,y_test_adar)
```

Out[95]:
```
0.9623913309393325
```

In [96]:
```
y_pred_adar = best_model_adar.predict(X_test_adar)
from sklearn.metrics import r2_score,mean_squared_error
import math

print(f'R2 Score: {r2_score(y_test_adar,y_pred_adar)}')
print(f'Mean Squared Error, MSE: {mean_squared_error(y_test_adar,y_pred_adar)}')
print(f'RMSE: {math.sqrt(mean_squared_error(y_test_adar,y_pred_adar))}')
```

```
R2 Score: 0.9623913309393325
Mean Squared Error, MSE: 3.524677056861552
RMSE: 1.8774123300067973
```

In [97]:
```
# Let us find the number of observations and number of features to be used in calculation for the adjusted R2
na = len(X_test_adar)
ka = len(X_test_adar.iloc[0])
R2a = r2_score(y_test_adar,y_pred_adar)
R2a
```

Out[97]: 0.9623913309393325

In [98]:
```
Adj_R2a = 1 - ((na-1)*(1- R2a)/(na-ka-1))
print(f'The adjusted R2: {Adj_R2a}')
```

```
The adjusted R2: 0.9615532547485656
```

The performance of this model is also very good and similar to that of Random Forest Model

SVR

In [99]:
```
#import the SVR model
from sklearn.svm import SVR
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score
import matplotlib.pyplot as plt
svrr = SVR()
```

In [100]:
```
X_svr=X_fin
y_svr=y_fin
```

In [101]:
```
X_svr.head()
```

Out[101]:

	0	2	3	4	6	7	8	9	10	12	13	14	16	18	19	20
0	-1.691042	0.791586	0.268824	-1.172958	-0.705861	-0.110384	-0.964715	0.255359	-3.278638	-0.732952	-0.323445	-0.525248	2.813130	-0.725401	-0.579931	0.459399
1	-1.691042	0.856072	0.285786	-1.172958	-0.838704	-0.168124	-0.989810	0.274060	-1.051482	-0.859877	-0.323445	-0.523083	2.881408	-0.740050	-0.610570	0.459399
2	-1.691042	0.831890	0.302749	-1.172958	-0.750142	-0.173531	-1.014905	0.292761	-0.880163	-0.775260	-0.323445	-0.521632	2.926927	-0.769349	-0.641209	0.459399
3	-1.691042	0.864132	0.328193	-1.172958	-0.617299	0.032045	-1.040000	0.317696	-0.666013	-0.648335	-0.323445	-0.518723	2.972446	-0.803531	-0.671847	0.459399
4	-1.691042	0.888314	0.345155	-1.172958	-0.573018	0.051757	-1.060076	0.342631	-0.623183	-0.606027	-0.323445	-0.564893	3.040724	-0.847480	-0.763764	0.459399

In [102]:
```
y_svr.head()
```

Out[102]:
```
0    65.0
1    59.9
2    59.9
3    59.5
4    59.2
Name: Life expectancy , dtype: float64
```

In [103]:
```
sc = StandardScaler()
sc = StandardScaler()
X_svr = pd.DataFrame(sc.fit_transform(X_svr))
y_svr = pd.Series(y_svr)
```

In [104]:
```
X_svr.head()
```

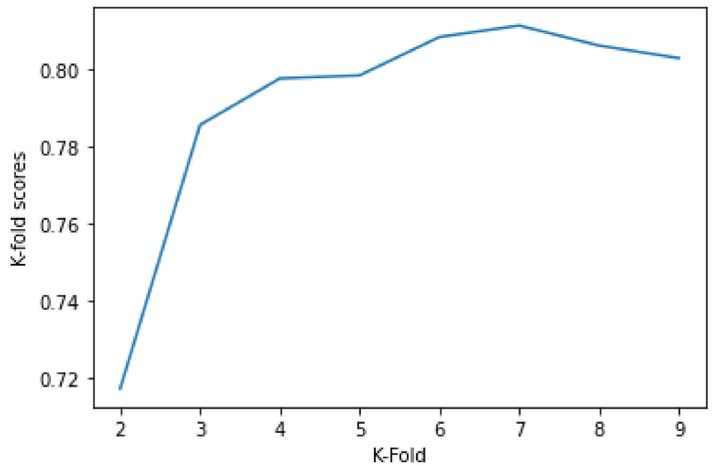
Out[104]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	-1.691042	0.791586	0.268824	-1.172958	-0.705861	-0.110384	-0.964715	0.255359	-3.278638	-0.732952	-0.323445	-0.525248	2.813130	-0.725401	-0.579931	0.459399
1	-1.691042	0.856072	0.285786	-1.172958	-0.838704	-0.168124	-0.989810	0.274060	-1.051482	-0.859877	-0.323445	-0.523083	2.881408	-0.740050	-0.610570	0.459399
2	-1.691042	0.831890	0.302749	-1.172958	-0.750142	-0.173531	-1.014905	0.292761	-0.880163	-0.775260	-0.323445	-0.521632	2.926927	-0.769349	-0.641209	0.459399
3	-1.691042	0.864132	0.328193	-1.172958	-0.617299	0.032045	-1.040000	0.317696	-0.666013	-0.648335	-0.323445	-0.518723	2.972446	-0.803531	-0.671847	0.459399
4	-1.691042	0.888314	0.345155	-1.172958	-0.573018	0.051757	-1.060076	0.342631	-0.623183	-0.606027	-0.323445	-0.564893	3.040724	-0.847480	-0.763764	0.459399

In [105]:
```
y_svr.head()
```

Out[105]:
```
0    65.0
1    59.9
2    59.9
3    59.5
4    59.2
Name: Life expectancy , dtype: float64
```

In [106]:
```
#Graph k-fold score for SVR

scores = []
for i in range(2,10):
    scores.append(cross_val_score(SVR(),X_svr,y_svr,cv=i).mean())

plt.plot(range(2,10),scores)
plt.xlabel('K-Fold')
plt.ylabel('K-fold scores')
plt.show()
```



In [107]:
```
from sklearn.model_selection import train_test_split, GridSearchCV
X_train_svr, X_test_svr, y_train_svr, y_test_svr = train_test_split(X_svr,y_svr,random_state=0)
```

In [108]:
```
params = {
            'kernel': ('linear', 'rbf'),
            'C': [1, 1.5, 2]
         }
grid_model_svr = GridSearchCV(SVR(gamma='scale',verbose=True),
                          params,cv=7)
grid_model_svr.fit(X_train_svr,y_train_svr)
```

```
[LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSV
M][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][Lib
SVM][LibSVM][LibSVM][LibSVM]
```

Out[108]:
```
GridSearchCV(cv=7, estimator=SVR(verbose=True),
             param_grid={'C': [1, 1.5, 2], 'kernel': ('linear', 'rbf')})
```

In [109]:
```
grid_model_svr.best_params_
```

Out[109]:
```
{'C': 2, 'kernel': 'rbf'}
```

In [110]:
```
grid_model_svr.best_score_
```

Out[110]:
```
0.8805991607340529
```

In [111]:
```
model_svr = grid_model_svr.best_estimator_
```

In [112]:
```
model_svr.fit(X_train_svr,y_train_svr)
```

```
[LibSVM]
```

Out[112]:
```
SVR(C=2, verbose=True)
```

In [113]:
```
model_svr.score(X_test_svr,y_test_svr)
```

Out[113]:
```
0.8853626474475291
```

In [114]:
```
y_pred_svr = model_svr.predict(X_test_svr)
from sklearn.metrics import r2_score,mean_squared_error
import math

print(f'R2 Score: {r2_score(y_test_svr,y_pred_svr)}')
print(f'Mean Squared Error, MSE: {mean_squared_error(y_test_svr,y_pred_svr)}')
print(f'RMSE: {math.sqrt(mean_squared_error(y_test_svr,y_pred_svr))}')
```

```
R2 Score: 0.8853626474475291
Mean Squared Error, MSE: 10.743790101937503
RMSE: 3.2777721247727856
```

In [115]:
```
# Let us find the number of observations and number of features to be used in calculation for the adjusted R2
ns = len(X_test_svr)
ks = len(X_test_svr.iloc[0])
R2s = r2_score(y_test_svr,y_pred_svr)
R2s
```

Out[115]:
```
0.8853626474475291
```

In [116]:
```
Adj_R2s = 1 - ((ns-1)*(1- R2s)/(ns-ks-1))
print(f'The adjusted R2: {Adj_R2s}')
```

```
The adjusted R2: 0.8828080546329894
```

The performance of this model is better than the linear regression one but did not give the best performance.

Regression Model Summary

Result	Linear Regression	KNN Regression	Random Forest Regression	AdaBoost Regression	SVR Regression
R2	0.7954	0.8963	0.9649	0.9631	0.8854
Adjusted R2	0.7897	0.8939	0.9642	0.9624	0.8828

- Based on the value of R2 and Adjusted R2 Random Forest and AdaBoost performed the best
- Linear Regression performed the worst of the models
- In-depth knowledge of tuning will help the model perform better

```
############################## Random Forest in pyspark in Anaconda Jupyter Notebook ##########################################
```

Regression Model with PySpark in Anaconda Jupyter Notebook on Local Machine

Let us use the preprocessed data from the sklearn models in local pyspark

In [ ]:
```
# For joining X and y and bring back to a .CSV file to be used in pyspark
result = pd.concat([X_all, y_base], axis=1, join='inner')
result.head(10)
result.to_csv('regression_pyspark.csv', index = False)
```

In [118]:
```
import findspark
findspark.init()
findspark.find()
```

Out[118]:
```
'C:\\spark-3.1.1-bin-hadoop2.7'
```

In [119]:
```
from pyspark.sql import SparkSession
import pyspark
```

In [120]:
```
spark= SparkSession.builder.appName("Random Forest Regression").getOrCreate()
```

In [121]:
```
spark
```

Out[121]:

SparkSession - in-memory

SparkContext

Spark UI (http://DinarTriOSEducation:4040)

Version

v3.1.1

Master

local[*]

AppName

Random Forest Regression

In [122]:
```
from pyspark.ml.feature import VectorAssembler
from pyspark.sql.types import *
from pyspark.sql.functions import *
from pyspark.ml.regression import *
from pyspark.ml.evaluation import *
from pyspark.ml.tuning import CrossValidator, ParamGridBuilder
```

In [123]:
```
df = spark.read.csv('regression_pyspark.csv',inferSchema=True, header=True)
```

In [124]:
```
df.limit(10).toPandas()
```

Out[124]:

	Country	Year	Adult Mortality	infant deaths	Alcohol	percentage expenditure	Hepatitis B	Measles	BMI	under-five deaths	...	Diphtheria	HIV/AIDS	GDP	Population	thinness 1-19 years	thinness 5-9 years	Income composition of resources	Schooling	Status_D
0	0	15	263.0	62	0.01	71.279624	65.0	1154	19.1	83	...	65.0	0.1	584.259210	33736494.0	17.2	17.3	0.479	10.1	
1	0	14	271.0	64	0.01	73.523582	62.0	492	18.6	86	...	62.0	0.1	612.696514	327582.0	17.5	17.5	0.476	10.0	
2	0	13	268.0	66	0.01	73.219243	64.0	430	18.1	89	...	64.0	0.1	631.744976	31731688.0	17.7	17.7	0.470	9.9	
3	0	12	272.0	69	0.01	78.184215	67.0	2787	17.6	93	...	67.0	0.1	669.959000	3696958.0	17.9	18.0	0.463	9.8	
4	0	11	275.0	71	0.01	7.097109	68.0	3013	17.2	97	...	68.0	0.1	63.537231	2978599.0	18.2	18.2	0.454	9.5	
5	0	10	279.0	74	0.01	79.679367	66.0	1989	16.7	102	...	66.0	0.1	553.328940	2883167.0	18.4	18.4	0.448	9.2	
6	0	9	281.0	77	0.01	56.762217	63.0	2861	16.2	106	...	63.0	0.1	445.893298	284331.0	18.6	18.7	0.434	8.9	
7	0	8	287.0	80	0.03	25.873925	64.0	1599	15.7	110	...	64.0	0.1	373.361116	2729431.0	18.8	18.9	0.433	8.7	
8	0	7	295.0	82	0.02	10.910156	63.0	1141	15.2	113	...	63.0	0.1	369.835796	26616792.0	19.0	19.1	0.415	8.4	
9	0	6	295.0	84	0.03	17.171518	64.0	1990	14.7	116	...	58.0	0.1	272.563770	2589345.0	19.2	19.3	0.405	8.1	

10 rows × 22 columns

In [125]:
```
df.printSchema()
```

```
root
 |-- Country: integer (nullable = true)
 |-- Year: integer (nullable = true)
 |-- Adult Mortality: double (nullable = true)
 |-- infant deaths: integer (nullable = true)
 |-- Alcohol: double (nullable = true)
 |-- percentage expenditure: double (nullable = true)
 |-- Hepatitis B: double (nullable = true)
 |-- Measles : integer (nullable = true)
 |--  BMI : double (nullable = true)
 |-- under-five deaths : integer (nullable = true)
 |-- Polio: double (nullable = true)
 |-- Total expenditure: double (nullable = true)
 |-- Diphtheria : double (nullable = true)
 |--  HIV/AIDS: double (nullable = true)
 |-- GDP: double (nullable = true)
 |-- Population: double (nullable = true)
 |--  thinness  1-19 years: double (nullable = true)
 |--  thinness 5-9 years: double (nullable = true)
 |-- Income composition of resources: double (nullable = true)
 |-- Schooling: double (nullable = true)
 |-- Status_Developing: integer (nullable = true)
 |-- Life expectancy : double (nullable = true)
```

In [126]:
```
print(df.count())
print(len(df.columns))
```

```
2938
22
```

In [127]:
```
df.columns
```

Out[127]:
```
['Country',
 'Year',
 'Adult Mortality',
 'infant deaths',
 'Alcohol',
 'percentage expenditure',
 'Hepatitis B',
 'Measles ',
 ' BMI ',
 'under-five deaths ',
 'Polio',
 'Total expenditure',
 'Diphtheria ',
 ' HIV/AIDS',
 'GDP',
 'Population',
 ' thinness  1-19 years',
 ' thinness 5-9 years',
 'Income composition of resources',
 'Schooling',
 'Status_Developing',
 'Life expectancy ']
```

In [128]:
```
input_columns = ['Country',
 'Year',
 'Adult Mortality',
 'infant deaths',
 'Alcohol',
 'percentage expenditure',
 'Hepatitis B',
 'Measles ',
 ' BMI ',
 'under-five deaths ',
 'Polio',
 'Total expenditure',
 'Diphtheria ',
 ' HIV/AIDS',
 'GDP',
 'Population',
 ' thinness  1-19 years',
 ' thinness 5-9 years',
 'Income composition of resources',
 'Schooling',
 'Status_Developing']
```

In [129]:
```
dependent_var = 'Life expectancy '
```

In [130]:
```
assembler = VectorAssembler(inputCols=input_columns, outputCol="features")
feature_vec=assembler.transform(df).select('features',dependent_var)
feature_vec.show(5)
```

```
+--------------------+----------------+
|            features|Life expectancy |
+--------------------+----------------+
|[0.0,15.0,263.0,6...|            65.0|
|[0.0,14.0,271.0,6...|            59.9|
|[0.0,13.0,268.0,6...|            59.9|
|[0.0,12.0,272.0,6...|            59.5|
|[0.0,11.0,275.0,7...|            59.2|
+--------------------+----------------+
only showing top 5 rows
```

In [131]:
```
# Split the data into train and test sets
train_data, test_data = feature_vec.randomSplit([.80,.20],seed=0)
```

In [132]:
```
from pyspark.ml.regression import RandomForestRegressor
r_model = RandomForestRegressor(labelCol=dependent_var, featuresCol="features",
                        maxDepth=15, minInfoGain=0.001, seed=0, numTrees=110)
rfModel = r_model.fit(train_data)

#Evaulation of the Model
predictions = rfModel.transform(test_data)

from pyspark.ml.evaluation import RegressionEvaluator
evaluator = RegressionEvaluator(labelCol=dependent_var,metricName='r2')
evaluator.evaluate(predictions)
```

Out[132]:
```
0.9628033866425842
```

In [133]:
```
evaluator_RMSE = RegressionEvaluator(labelCol=dependent_var,metricName='rmse')
evaluator_RMSE.evaluate(predictions)
```

Out[133]:
```
1.7772239064993989
```

In [134]:
```
evaluator_MSE = RegressionEvaluator(labelCol=dependent_var,metricName='mse')
evaluator_MSE.evaluate(predictions)
```

Out[134]:
```
3.1585248138329844
```

In [135]:
```
evaluator_MAE = RegressionEvaluator(labelCol=dependent_var,metricName='mae')
evaluator_MAE.evaluate(predictions)
```

Out[135]:
```
1.1046760378235159
```

In [136]:
```
#Grid Search
from pyspark.ml.tuning import ParamGridBuilder, CrossValidator
g_model = RandomForestRegressor(labelCol=dependent_var, featuresCol="features",
                        minInfoGain=0.001, seed=0)
paramGrid = (ParamGridBuilder()\
             .addGrid(g_model.maxDepth,[14,15,16])\
             .addGrid(g_model.numTrees,[100,110,120])\
             .build())

# Create 4-fold CrossValidator
cv = CrossValidator(estimator=g_model, estimatorParamMaps=paramGrid, evaluator=evaluator, numFolds=4)

cvModel = cv.fit(train_data)
```

In [137]:
```
#Get the best model
rf_bestModel = cvModel.bestModel
```

In [138]:
```
# Feature Importance
# Estimate of the importance of each feature
# Each feature's importance is the average of its importance across all trees
# In the ensemble the importance vector is normalized to sum up to 1.
print(" ")
print('\033[1m' + "Feature Importance"+ '\033[0m')
print("(Scores Up to 1)")
print("Lowest score signifies the least importance")
print(" ")
RF_FeatureImportance = rf_bestModel.featureImportances.toArray()
#Convert from numpy array to list
important_scores = []
for x in RF_FeatureImportance:
    important_scores.append(float(x))

# Then zip with input_columns list and create a df
result_is = spark.createDataFrame(zip(input_columns, important_scores), schema=['feature', 'score'])
print(result_is.orderBy(result_is["score"].desc()).show(truncate=False))

# Make predictions
# PySpark will automatically use the best model when we call fitmodel
predictions_fn = cvModel.transform(test_data)

# Then let us apply it

r2_rf_pys = evaluator.evaluate(predictions_fn)
print(r2_rf_pys)
```

Feature Importance
(Scores Up to 1)
Lowest score signifies the least importance

```
+------------------------------+--------------------+
|feature                       |score               |
+------------------------------+--------------------+
| HIV/AIDS                     |0.31072351545263877 |
|Adult Mortality               |0.19892861396192865 |
|Income composition of resources|0.16572465387890006 |
|Schooling                     |0.08072276350591182 |
| BMI                          |0.03859783444909763 |
|under-five deaths             |0.0291866077025837  |
|Diphtheria                    |0.025209013825530778|
|Polio                         |0.023700940148087057|
|infant deaths                 |0.02138439655182234 |
| thinness 5-9 years           |0.020566885767165647|
| thinness  1-19 years         |0.016925826918868316|
```

```
|Alcohol                        |0.010878319488922898|
|Year                           |0.010375815988753036|
|Status_Developing              |0.009361395062098113|
|Country                        |0.007592708264506554|
|Total expenditure              |0.006770998116881692|
|GDP                            |0.006737716095538603|
|percentage expenditure         |0.004887330857730387|
|Measles                        |0.00421273388375105 |
|Hepatitis B                    |0.003891945736207169|
+-------------------------------+--------------------+
only showing top 20 rows

None
0.9628680228132476
```

The performance of the the Regression model with PySpark is almost same to that of the sklearn

In [ ]:

Classification Models

Introduction:

In this project we will be working with the UCI/Kaggle adult dataset. We aim at predicting if people in the data set belong in a certain class by income, either making <=50k or >50k per year.

We will be performing EDA, Feature Engineering and Visualization while answering relevant questions that we need to ask ourselves in this journey to make the dataset ready for different classification models development and evaluation of the same.

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
import os
```

In [2]:
```
os.getcwd()
```

Out[2]:
```
'C:\\Users\\ruzdomain\\Desktop\\MLBDA\\NoteBooks_Data\\HTML_NOTEBOOK'
```

In [3]:
```
os.chdir(r'C:\Users\ruzdomain\Desktop\MLBDA\PROJECT')
```

In [4]:
```
os.getcwd()
```

Out[4]:
```
'C:\\Users\\ruzdomain\\Desktop\\MLBDA\\PROJECT'
```

In [5]:
```
df_class= pd.read_csv("adult_sal.csv", na_values  = '?')
df_class.head()
```

Out[5]:

	Unnamed: 0	age	type_employer	fnlwgt	education	education_num	marital	occupation	relationship	race	sex	capital_gain	capital_loss	hr_per_week	country	income
0	1	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	2	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	3	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3	4	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	5	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K

In [6]:
```
df_class.describe()
```

Out[6]:

	Unnamed: 0	age	fnlwgt	education_num	capital_gain	capital_loss	hr_per_week
count	32561.000000	32561.000000	3.256100e+04	32561.000000	32561.000000	32561.000000	32561.000000
mean	16281.000000	38.581647	1.897784e+05	10.080679	1077.648844	87.303830	40.437456
std	9399.695394	13.640433	1.055500e+05	2.572720	7385.292085	402.960219	12.347429
min	1.000000	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1.000000
25%	8141.000000	28.000000	1.178270e+05	9.000000	0.000000	0.000000	40.000000
50%	16281.000000	37.000000	1.783560e+05	10.000000	0.000000	0.000000	40.000000
75%	24421.000000	48.000000	2.370510e+05	12.000000	0.000000	0.000000	45.000000
max	32561.000000	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000	99.000000

Detail of the columns of the dataset

This is a table of the findings about all the variables:

Variable	Description
age	Age of the person
type_employer	Class of work
fnlwgt	Final weight of how much of the population it represents
education	Education level
education_num	Numeric education level
marital	Marital status of the person
occupation	Occupation of the person
relationship	Type of relationship
race	Race of the person
sex	Sex of the person
capital_gain	Capital gains obtained
capital_loss	Capital loss suffered
hr_per_week	Average number of hours working per week

country	Country of origin
income	Income level

In [7]:
```
df_class.drop("Unnamed: 0",axis=1, inplace=True)
```

In [8]:
```
df_class.describe(include='all')
```

Out[8]:

	age	type_employer	fnlwgt	education	education_num	marital	occupation	relationship	race	sex	capital_gain	capital_loss	hr_per_week	country	income
count	32561.000000	30725	3.256100e+04	32561	32561.000000	32561	30718	32561	32561	32561	32561.000000	32561.000000	32561.000000	31978	32561
unique	NaN	8	NaN	16	NaN	7	14	6	5	2	NaN	NaN	NaN	41	2
top	NaN	Private	NaN	HS-grad	NaN	Married-civ-spouse	Prof-specialty	Husband	White	Male	NaN	NaN	NaN	United-States	<=50K
freq	NaN	22696	NaN	10501	NaN	14976	4140	13193	27816	21790	NaN	NaN	NaN	29170	24720
mean	38.581647	NaN	1.897784e+05	NaN	10.080679	NaN	NaN	NaN	NaN	NaN	1077.648844	87.303830	40.437456	NaN	NaN
std	13.640433	NaN	1.055500e+05	NaN	2.572720	NaN	NaN	NaN	NaN	NaN	7385.292085	402.960219	12.347429	NaN	NaN
min	17.000000	NaN	1.228500e+04	NaN	1.000000	NaN	NaN	NaN	NaN	NaN	0.000000	0.000000	1.000000	NaN	NaN
25%	28.000000	NaN	1.178270e+05	NaN	9.000000	NaN	NaN	NaN	NaN	NaN	0.000000	0.000000	40.000000	NaN	NaN
50%	37.000000	NaN	1.783560e+05	NaN	10.000000	NaN	NaN	NaN	NaN	NaN	0.000000	0.000000	40.000000	NaN	NaN
75%	48.000000	NaN	2.370510e+05	NaN	12.000000	NaN	NaN	NaN	NaN	NaN	0.000000	0.000000	45.000000	NaN	NaN
max	90.000000	NaN	1.484705e+06	NaN	16.000000	NaN	NaN	NaN	NaN	NaN	99999.000000	4356.000000	99.000000	NaN	NaN

In [9]:
```
df_class.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   age            32561 non-null  int64 
 1   type_employer  30725 non-null  object
 2   fnlwgt         32561 non-null  int64 
 3   education      32561 non-null  object
 4   education_num  32561 non-null  int64 
 5   marital        32561 non-null  object
 6   occupation     30718 non-null  object
 7   relationship   32561 non-null  object
 8   race           32561 non-null  object
 9   sex            32561 non-null  object
 10  capital_gain   32561 non-null  int64 
 11  capital_loss   32561 non-null  int64 
 12  hr_per_week    32561 non-null  int64 
 13  country        31978 non-null  object
 14  income         32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

In [10]:
```
df_class.shape
```

Out[10]:
```
(32561, 15)
```

In [11]:
```
df_class.dtypes
```

Out[11]:
```
age              int64
type_employer    object
fnlwgt            int64
education        object
education_num     int64
marital          object
occupation       object
relationship     object
race             object
sex              object
capital_gain      int64
capital_loss      int64
hr_per_week       int64
country          object
income           object
dtype: object
```

In [12]:
```
missingrows = df_class.isna().sum()
```

In [13]:
```
missingrows
```

Out[13]:
```
age                 0
type_employer    1836
fnlwgt              0
education           0
education_num       0
marital             0
occupation       1843
relationship        0
race                0
sex                 0
capital_gain        0
capital_loss        0
hr_per_week         0
country           583
income              0
dtype: int64
```

In [14]:
```
def percentage_of_miss(df):
  df1=df[df.columns[df.isnull().sum()>=1]]
  total_miss = df1.isnull().sum().sort_values(ascending=False)
  percent_miss = (df1.isnull().sum()/df1.isnull().count()).sort_values(ascending=False)
  missing_data = pd.concat([total_miss, percent_miss], axis=1, keys=['Number of Missing', 'Percentage'])
  return(missing_data)
```

In [15]:
```
percentage_of_miss(df_class)
```

Out[15]:

	Number of Missing	Percentage
occupation	1843	0.056601
type_employer	1836	0.056386
country	583	0.017905

In [16]:
```
df_class = df_class.drop_duplicates()
```

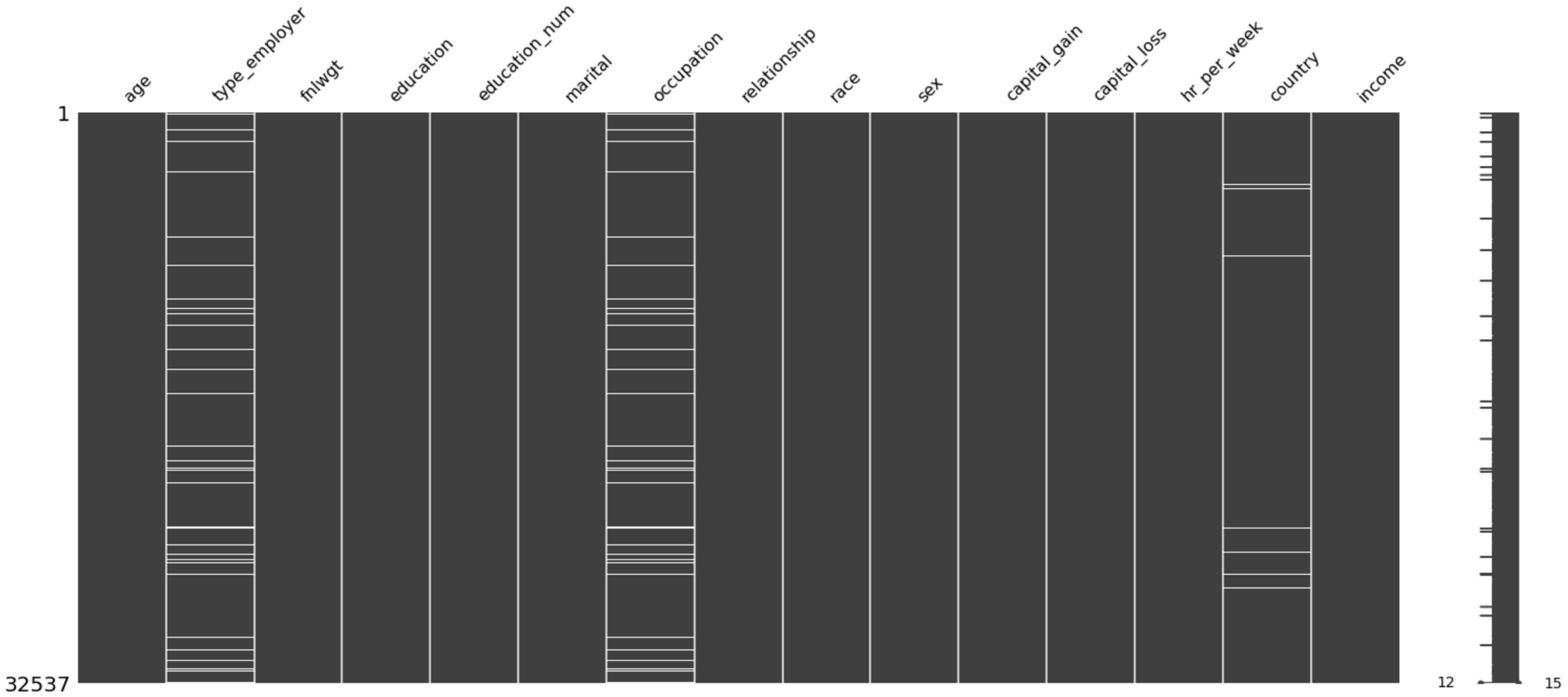
In [17]:
```
dup_df_class = df_class[df_class.duplicated()]
dup_df_class
```

Out[17]:

age	type_employer	fnlwgt	education	education_num	marital	occupation	relationship	race	sex	capital_gain	capital_loss	hr_per_week	country	income

In [18]:
```
import missingno as msno
msno.matrix(df_class)
```

Out[18]: <AxesSubplot:>



In [19]:
```
df_class.columns
```

Out[19]:
```
Index(['age', 'type_employer', 'fnlwgt', 'education', 'education_num',
       'marital', 'occupation', 'relationship', 'race', 'sex', 'capital_gain',
       'capital_loss', 'hr_per_week', 'country', 'income'],
      dtype='object')
```

```
# Exploratory Data Analysis
# Target variable: Segmentation (A,B,C,D) , Potential Predictors: All Others
```

```
# Univariate Analysis
```

In [20]:
```
df_class['country'].value_counts()
```

Out[20]:
```
United-States                 29153
Mexico                          639
Philippines                     198
Germany                         137
Canada                          121
Puerto-Rico                     114
El-Salvador                     106
India                           100
Cuba                             95
England                          90
Jamaica                          81
South                            80
China                            75
Italy                            73
Dominican-Republic               70
Vietnam                          67
Guatemala                        62
Japan                            62
Poland                           60
Columbia                         59
Taiwan                           51
Haiti                            44
Iran                             43
Portugal                         37
Nicaragua                        34
Peru                             31
Greece                           29
France                           29
Ecuador                          28
Ireland                          24
Hong                             20
Cambodia                         19
Trinadad&Tobago                  19
Laos                             18
Thailand                         18
Yugoslavia                       16
Outlying-US(Guam-USVI-etc)       14
Hungary                          13
Honduras                         13
Scotland                         12
Holand-Netherlands                1
Name: country, dtype: int64
```

In [21]:
```
df_class['occupation'].value_counts()
```

Out[21]:
```
Prof-specialty       4136
Craft-repair         4094
Exec-managerial      4065
Adm-clerical         3768
Sales                3650
Other-service        3291
Machine-op-inspct    2000
Transport-moving     1597
Handlers-cleaners    1369
Farming-fishing       992
Tech-support          927
Protective-serv       649
Priv-house-serv       147
Armed-Forces            9
Name: occupation, dtype: int64
```

In [22]:
```
df_class['type_employer'].value_counts()
```

Out[22]:
```
Private             22673
Self-emp-not-inc     2540
Local-gov            2093
State-gov            1298
Self-emp-inc         1116
Federal-gov           960
Without-pay            14
Never-worked            7
Name: type_employer, dtype: int64
```

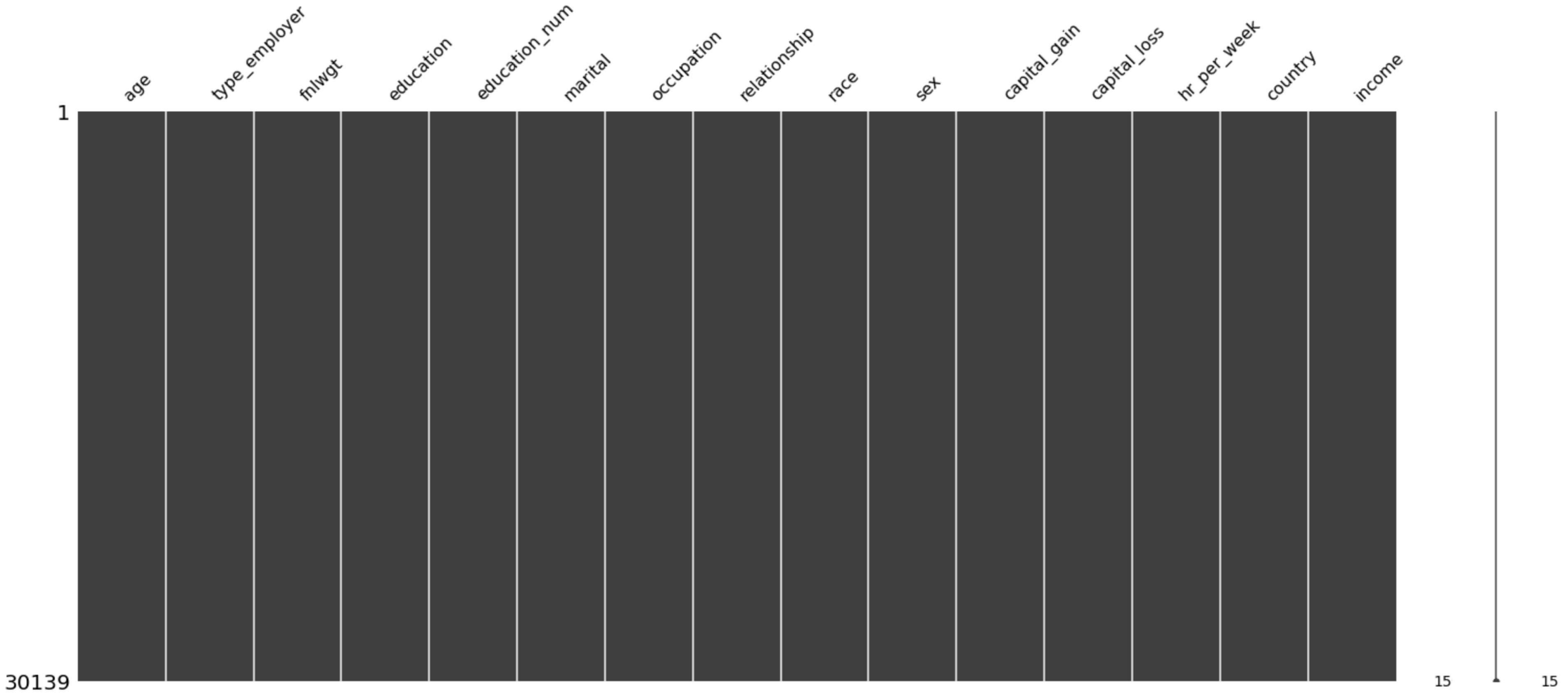
In [23]:
```
df_class['income'].value_counts()
```

Out[23]:
```
<=50K    24698
>50K      7839
Name: income, dtype: int64
```

In [24]:
```
df_class.dropna(axis=0, how='any',inplace=True)
```

In [25]:
```
msno.matrix(df_class)
```

Out[25]: <AxesSubplot:>



In [26]:
```
df_class.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30139 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   age            30139 non-null  int64 
 1   type_employer  30139 non-null  object
 2   fnlwgt         30139 non-null  int64 
 3   education      30139 non-null  object
 4   education_num  30139 non-null  int64 
 5   marital        30139 non-null  object
 6   occupation     30139 non-null  object
 7   relationship   30139 non-null  object
 8   race           30139 non-null  object
 9   sex            30139 non-null  object
 10  capital_gain   30139 non-null  int64 
 11  capital_loss   30139 non-null  int64 
 12  hr_per_week    30139 non-null  int64 
 13  country        30139 non-null  object
 14  income         30139 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

In [27]:
```
df_class['type_employer'].value_counts()
```

Out[27]:
```
Private             22264
Self-emp-not-inc     2498
Local-gov            2067
State-gov            1279
Self-emp-inc         1074
Federal-gov           943
Without-pay            14
Name: type_employer, dtype: int64
```

In [28]:
```
df_class.type_employer = df_class.type_employer.map(
                    {
                        'Local-gov': 'SL-gov',
                        'State-gov': 'SL-gov',
                        'Self-emp-inc': 'self-emp',
                        'Self-emp-not-inc': 'self-emp',
                        'Federal-gov': 'Federal-gov',
                        'Private': 'Private',
                        'Without-pay': 'Without-pay'

                    }
                    )
```

In [29]:
```
df_class['type_employer'].value_counts()
```

Out[29]:
```
Private        22264
self-emp        3572
SL-gov          3346
Federal-gov      943
Without-pay       14
Name: type_employer, dtype: int64
```

In [30]:
```
df_class['education'].value_counts()
```

Out[30]:
```
HS-grad         9834
Some-college    6669
Bachelors       5042
Masters         1626
Assoc-voc       1307
11th            1048
Assoc-acdm      1008
10th             820
7th-8th          556
Prof-school      542
9th              455
12th             377
Doctorate        375
5th-6th          287
1st-4th          149
Preschool         44
Name: education, dtype: int64
```

In [31]:
```
df_class['education_num'].value_counts()
```

Out[31]:
```
9     9834
10    6669
13    5042
14    1626
11    1307
7     1048
12    1008
6      820
4      556
15     542
5      455
8      377
16     375
3      287
2      149
1       44
Name: education_num, dtype: int64
```

In [32]:
```
df_class.head(10)
```

Out[32]:

	age	type_employer	fnlwgt	education	education_num	marital	occupation	relationship	race	sex	capital_gain	capital_loss	hr_per_week	country	income
0	39	SL-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	self-emp	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
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K
5	37	Private	284582	Masters	14	Married-civ-spouse	Exec-managerial	Wife	White	Female	0	0	40	United-States	<=50K
6	49	Private	160187	9th	5	Married-spouse-absent	Other-service	Not-in-family	Black	Female	0	0	16	Jamaica	<=50K
7	52	self-emp	209642	HS-grad	9	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	45	United-States	>50K
8	31	Private	45781	Masters	14	Never-married	Prof-specialty	Not-in-family	White	Female	14084	0	50	United-States	>50K
9	42	Private	159449	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	5178	0	40	United-States	>50K

In [33]:
```
df_class['marital'].value_counts()
```

Out[33]:
```
Married-civ-spouse       14059
Never-married             9711
Divorced                  4212
Separated                  939
Widowed                    827
Married-spouse-absent      370
Married-AF-spouse           21
Name: marital, dtype: int64
```

In [34]:
```
df_class.marital = df_class.marital.map(
                    {
                        'Separated': 'Not-Married',
                        'Divorced': 'Not-Married',
                        'Widowed': 'Not-Married',
                        'Never-married': 'Never-married',
                        'Married-civ-spouse': 'Married',
                        'Married-spouse-absent': 'Married',
                        'Married-AF-spouse': 'Married'

                    }
                    )
```

In [35]:
```
df_class['marital'].value_counts()
```

Out[35]:
```
Married          14450
Never-married     9711
Not-Married       5978
Name: marital, dtype: int64
```

In [36]:
```
df_class['country'].value_counts()
```

Out[36]:
```
United-States                 27487
Mexico                          606
Philippines                     188
Germany                         128
Puerto-Rico                     109
Canada                          107
El-Salvador                     100
India                           100
Cuba                             92
England                          86
Jamaica                          80
South                            71
China                            68
Italy                            68
Dominican-Republic               67
Vietnam                          64
Guatemala                        61
Japan                            59
Poland                           56
Columbia                         56
Taiwan                           42
Iran                             42
Haiti                            42
Portugal                         34
Nicaragua                        33
Peru                             30
Greece                           29
France                           27
Ecuador                          27
Ireland                          24
Hong                             19
Cambodia                         18
Trinadad&Tobago                  18
Laos                             17
Thailand                         17
Yugoslavia                       16
Outlying-US(Guam-USVI-etc)       14
Hungary                          13
Honduras                         12
Scotland                         11
Holand-Netherlands                1
Name: country, dtype: int64
```

In [37]:
```
LLL1 = ['China','Hong','India','Iran','Cambodia','Japan', 'Laos' , 'Philippines' ,'Vietnam' ,'Taiwan', 'Thailand']
DD1 = dict.fromkeys(LLL1, 'Asia')
LLL2 = ['Canada','United-States','Puerto-Rico']
DD2 = dict.fromkeys(LLL2, 'North.America')
LLL3 = ['England' ,'France', 'Germany' ,'Greece','Holand-Netherlands','Hungary','Ireland','Italy','Poland','Portugal','Scotland','Yugoslavia']
DD3 = dict.fromkeys(LLL3, 'Europe')
LLL4 = ['Columbia','Cuba','Dominican-Republic','Ecuador','El-Salvador','Guatemala','Haiti','Honduras','Mexico','Nicaragua','Outlying-US(Guam-USVI-etc)','Peru',
DD4 = dict.fromkeys(LLL4, 'Latin.and.South.America')
LLL5 = ['South']
DD5 = dict.fromkeys(LLL5, 'South')
DDD = {**DD1, **DD2, **DD3, **DD4, **DD5}
print(DDD)
```

```
{'China': 'Asia', 'Hong': 'Asia', 'India': 'Asia', 'Iran': 'Asia', 'Cambodia': 'Asia', 'Japan': 'Asia', 'Laos': 'Asia', 'Philippines': 'Asia', 'Vietnam': 'Asi
a', 'Taiwan': 'Asia', 'Thailand': 'Asia', 'Canada': 'North.America', 'United-States': 'North.America', 'Puerto-Rico': 'North.America', 'England': 'Europe', 'F
rance': 'Europe', 'Germany': 'Europe', 'Greece': 'Europe', 'Holand-Netherlands': 'Europe', 'Hungary': 'Europe', 'Ireland': 'Europe', 'Italy': 'Europe', 'Polan
d': 'Europe', 'Portugal': 'Europe', 'Scotland': 'Europe', 'Yugoslavia': 'Europe', 'Columbia': 'Latin.and.South.America', 'Cuba': 'Latin.and.South.America', 'D
ominican-Republic': 'Latin.and.South.America', 'Ecuador': 'Latin.and.South.America', 'El-Salvador': 'Latin.and.South.America', 'Guatemala': 'Latin.and.South.A
merica', 'Haiti': 'Latin.and.South.America', 'Honduras': 'Latin.and.South.America', 'Mexico': 'Latin.and.South.America', 'Nicaragua': 'Latin.and.South.Americ
a', 'Outlying-US(Guam-USVI-etc)': 'Latin.and.South.America', 'Peru': 'Latin.and.South.America', 'Jamaica': 'Latin.and.South.America', 'Trinadad&Tobago': 'Lati
n.and.South.America', 'South': 'South'}
```

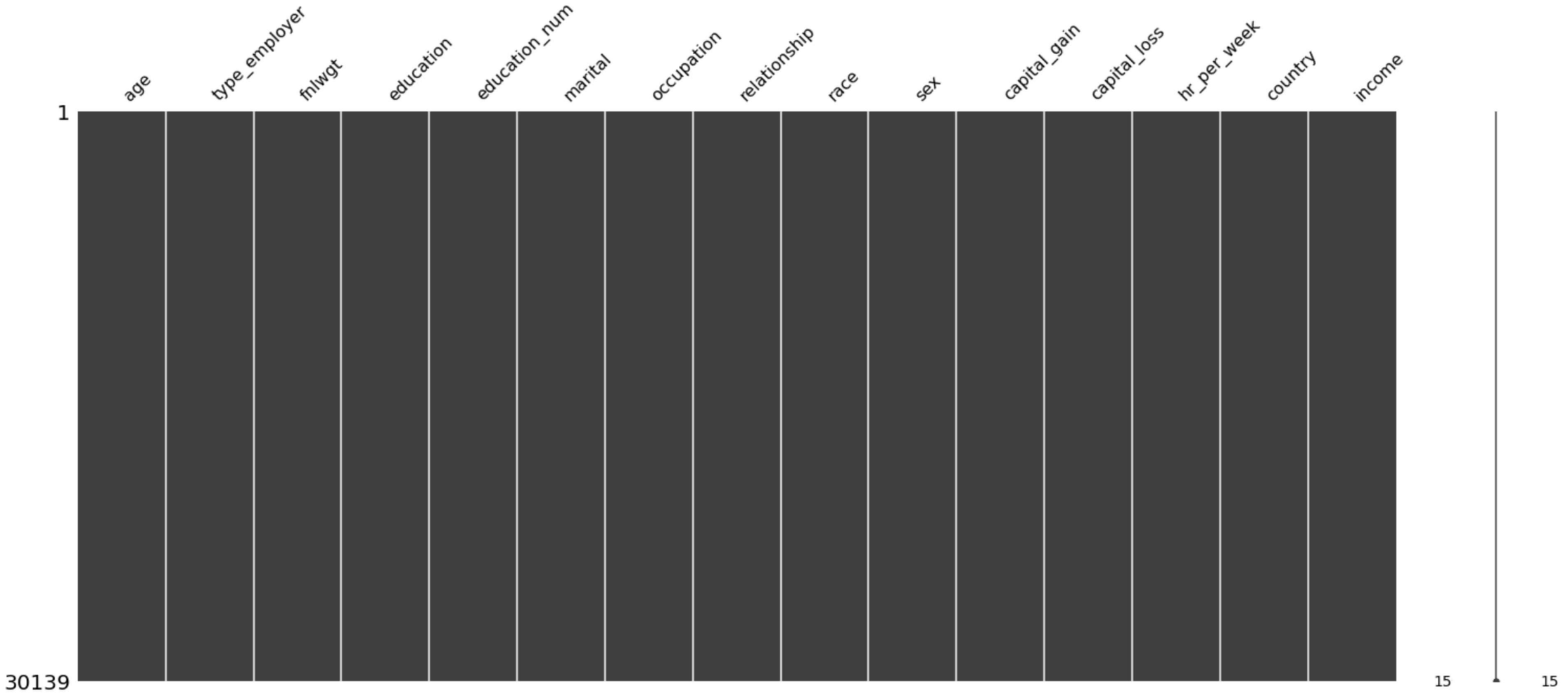
In [38]:
```
df_class['country'] = df_class['country'].map(DDD)
```

In [39]:
```
df_class['country'].value_counts()
```

Out[39]:
```
North.America             27703
Latin.and.South.America    1238
Asia                        634
Europe                      493
South                        71
Name: country, dtype: int64
```

In [40]:
```
msno.matrix(df_class)
```

Out[40]: <AxesSubplot:>

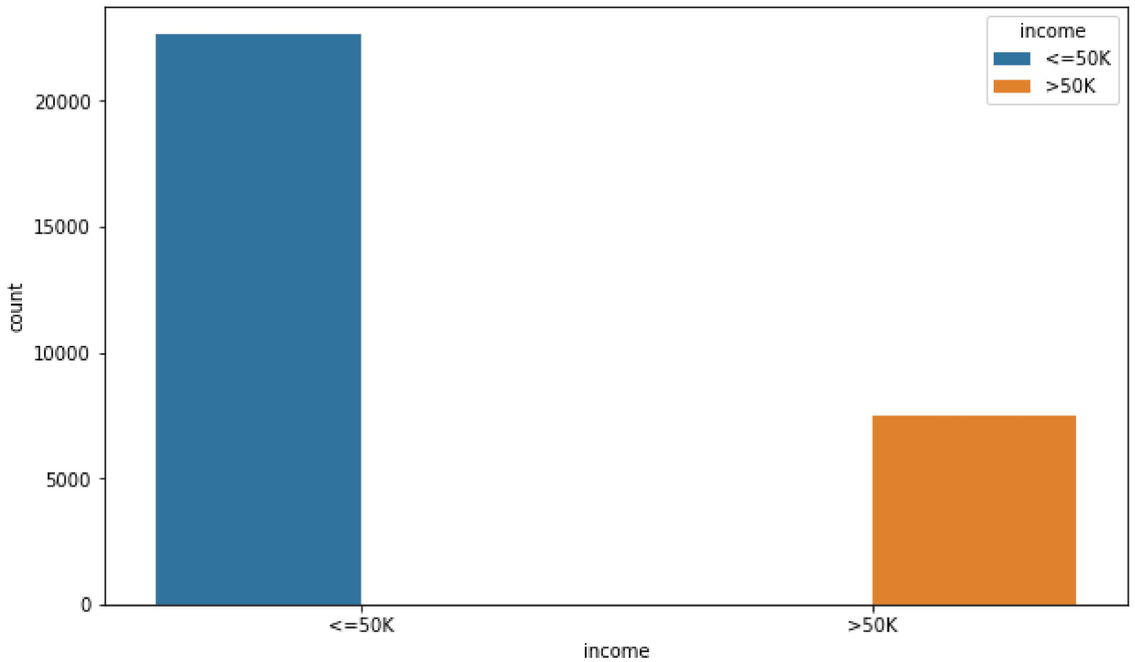


What is the distribution of target?

Our target here is income and since it is a categorical variable, in univaraite analysis for summarization we will find frequency and for visualization I would like to plot: pie chart or barchart.

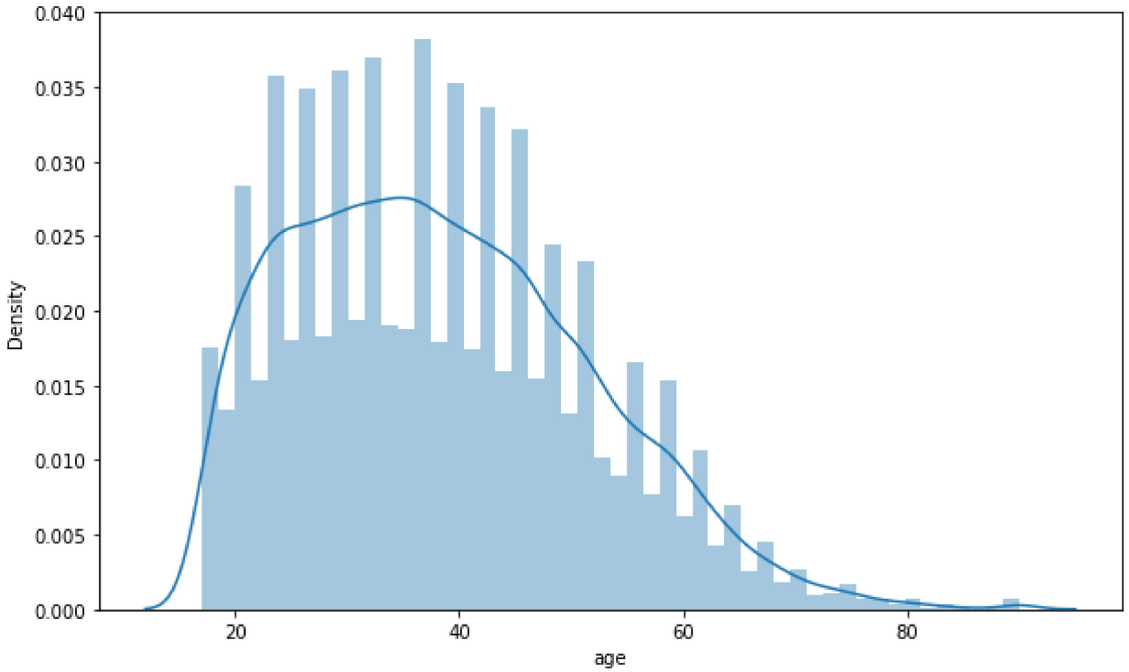
In [41]:
```
plt.rcParams['figure.figsize'] = (10, 6)
sns.countplot(df_class['income'],hue=df_class['income'])
```

Out[41]: <AxesSubplot:xlabel='income', ylabel='count'>



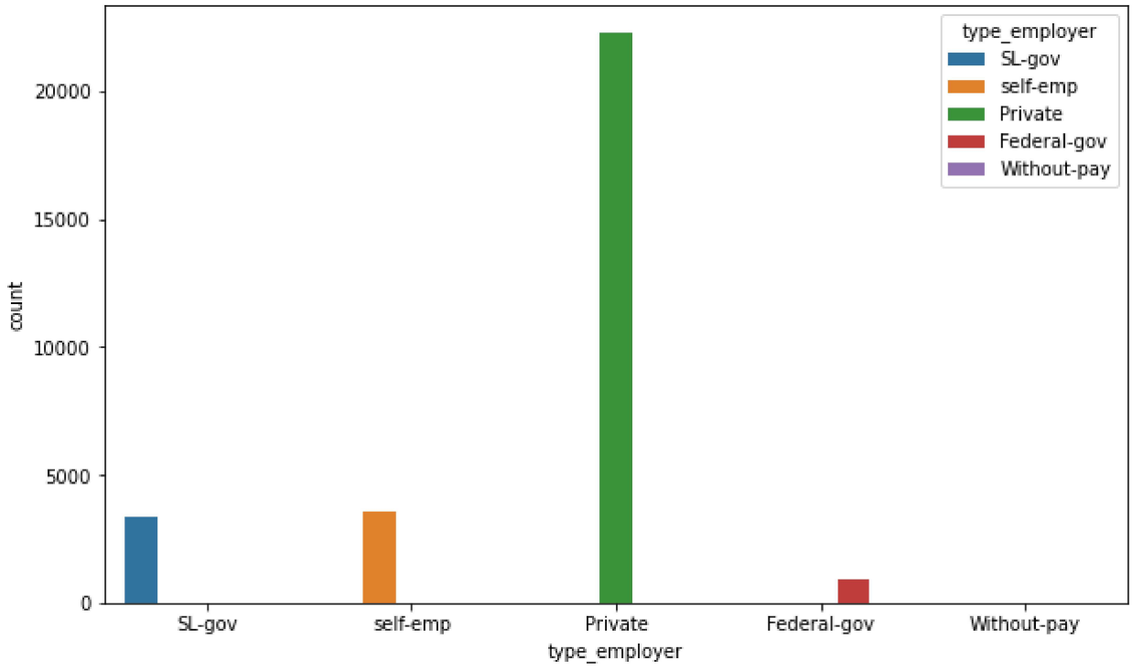
In [42]:
```
#Age
plt.rcParams['figure.figsize'] = (10, 6)
sns.distplot(df_class['age'])
```

Out[42]: <AxesSubplot:xlabel='age', ylabel='Density'>



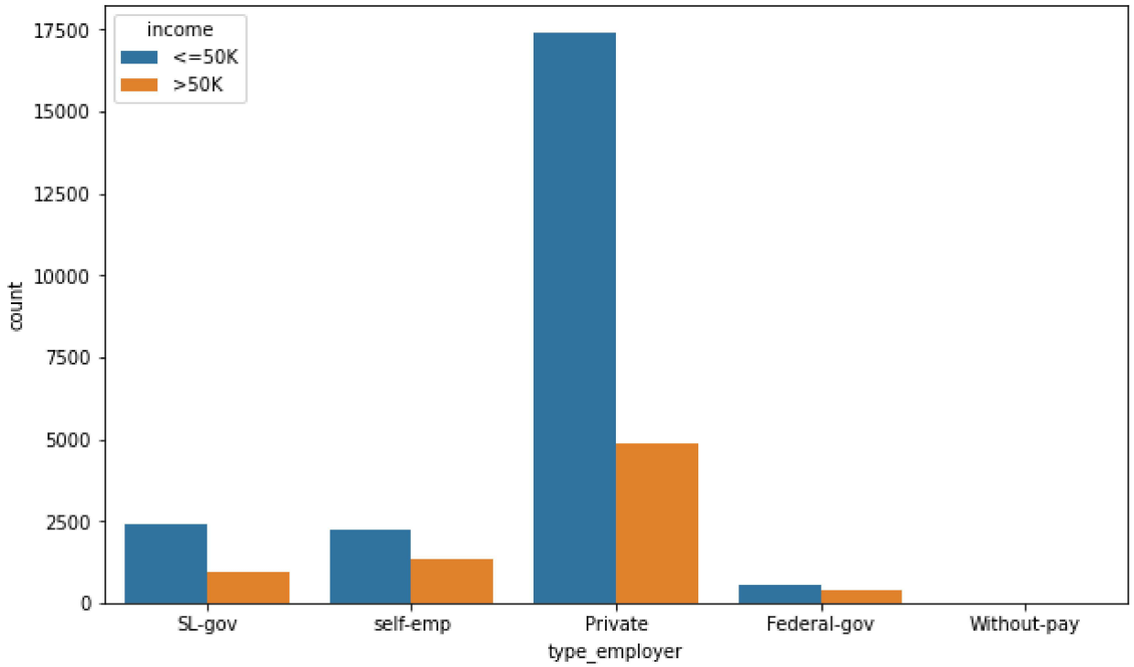
In [43]:
```
plt.rcParams['figure.figsize'] = (10, 6)
sns.countplot(df_class['type_employer'],hue=df_class['type_employer'])
```

Out[43]: <AxesSubplot:xlabel='type_employer', ylabel='count'>



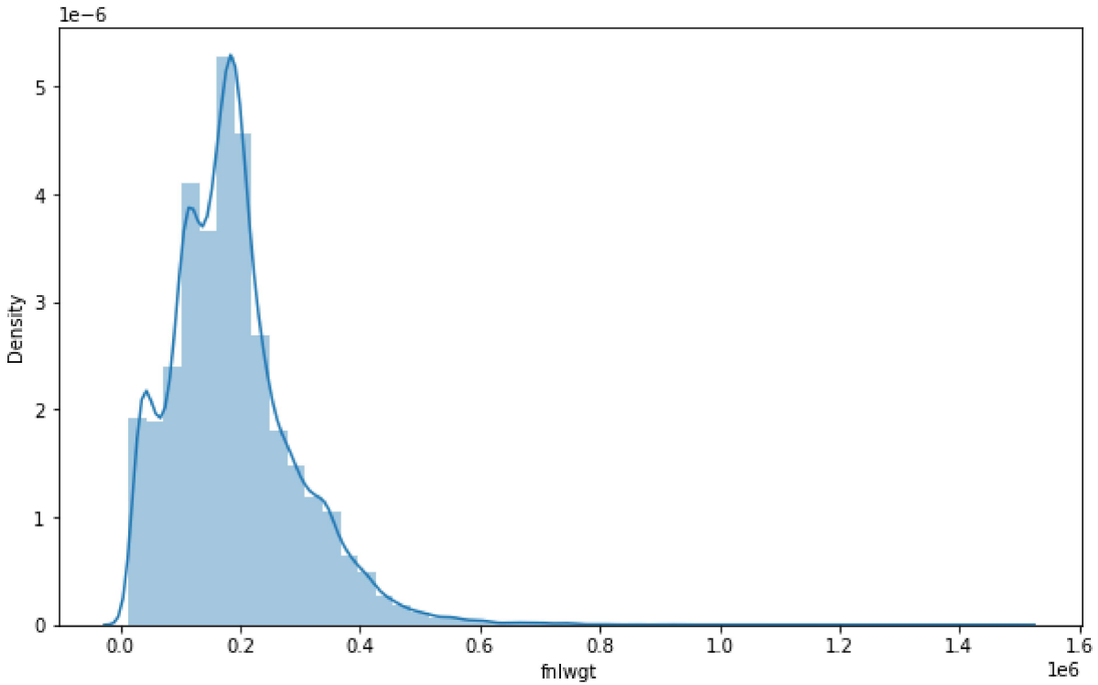
In [44]:
```
plt.rcParams['figure.figsize'] = (10, 6)
sns.countplot(df_class['type_employer'],hue=df_class['income'])
```

Out[44]:
```
<AxesSubplot:xlabel='type_employer', ylabel='count'>
```



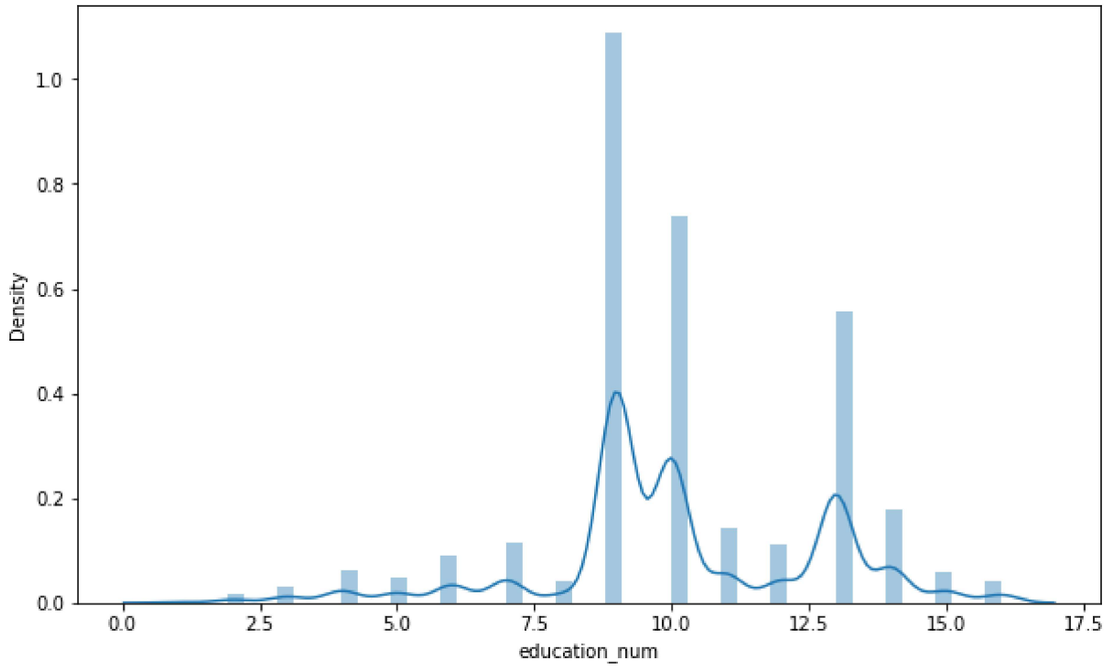
In [45]:
```
plt.rcParams['figure.figsize'] = (10, 6)
sns.distplot(df_class['fnlwgt'])
```

Out[45]:
```
<AxesSubplot:xlabel='fnlwgt', ylabel='Density'>
```



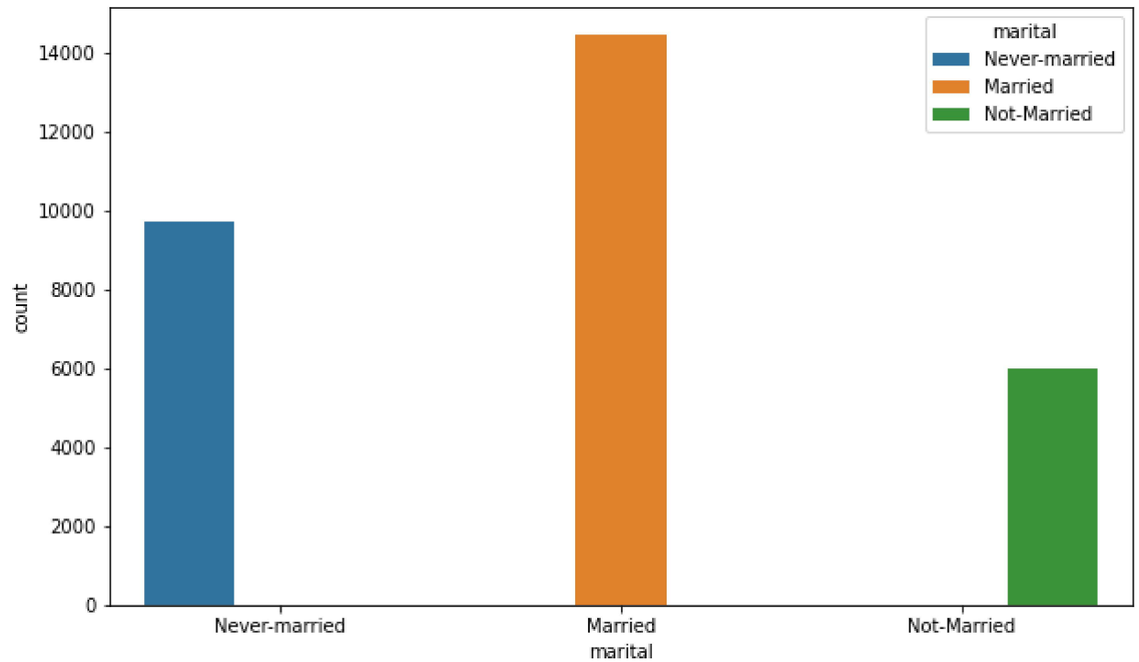
In [46]:
```
plt.rcParams['figure.figsize'] = (10, 6)
sns.distplot(df_class['education_num'])
```

Out[46]:
```
<AxesSubplot:xlabel='education_num', ylabel='Density'>
```



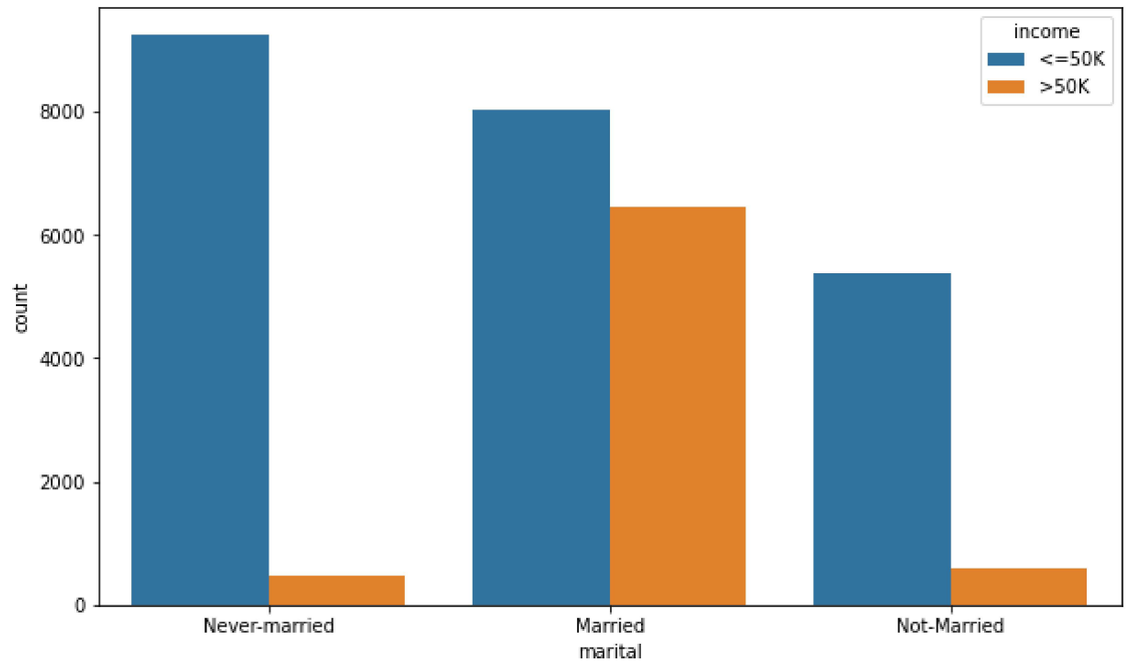
In [47]:
```
plt.rcParams['figure.figsize'] = (10, 6)
sns.countplot(df_class['marital'],hue=df_class['marital'])
```

Out[47]: <AxesSubplot:xlabel='marital', ylabel='count'>



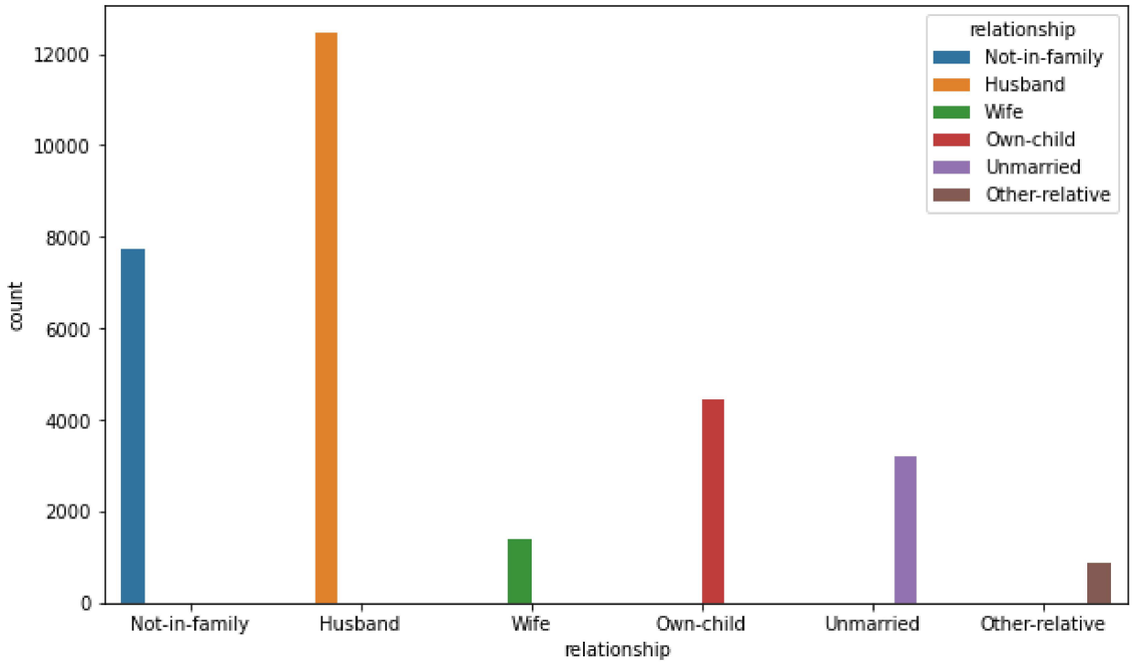
In [48]:
```
plt.rcParams['figure.figsize'] = (10, 6)
sns.countplot(df_class['marital'],hue=df_class['income'])
```

Out[48]:
```
<AxesSubplot:xlabel='marital', ylabel='count'>
```



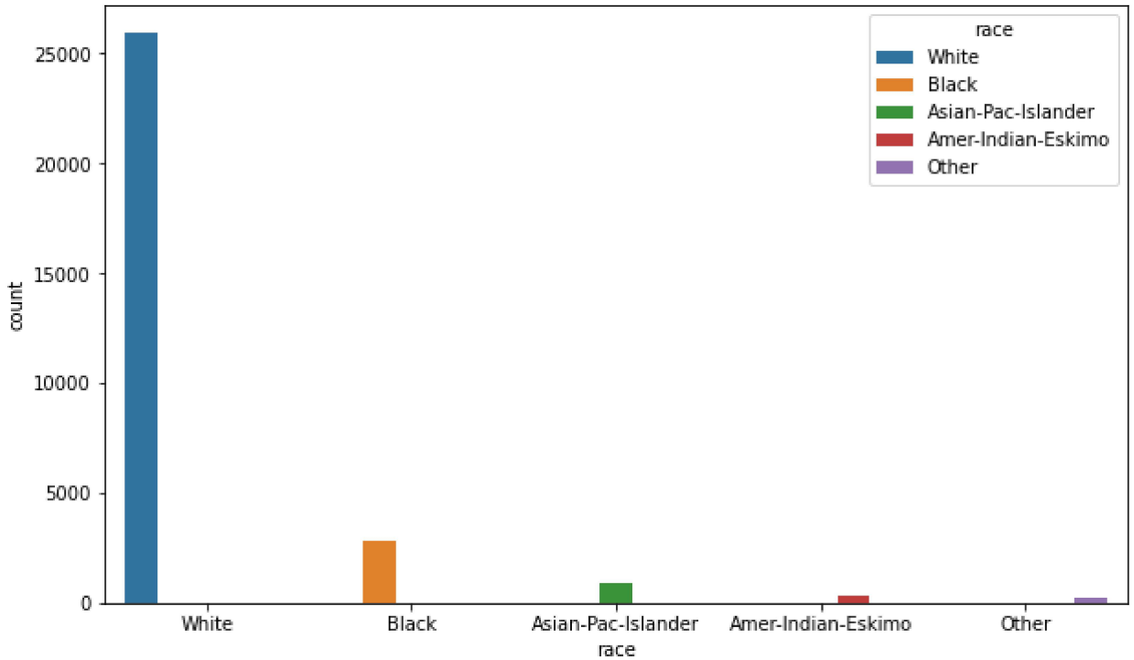
In [49]:
```
plt.rcParams['figure.figsize'] = (10, 6)
sns.countplot(df_class['relationship'],hue=df_class['relationship'])
```

Out[49]: <AxesSubplot:xlabel='relationship', ylabel='count'>



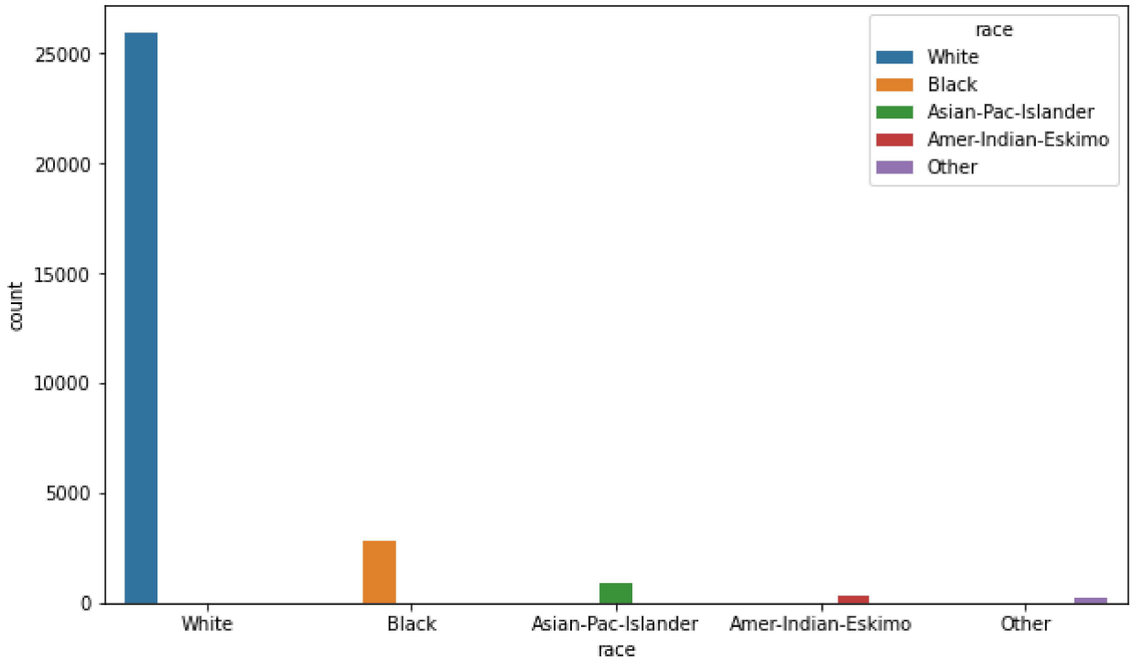
In [50]:
```
plt.rcParams['figure.figsize'] = (10, 6)
sns.countplot(df_class['race'],hue=df_class['race'])
```

Out[50]:
```
<AxesSubplot:xlabel='race', ylabel='count'>
```



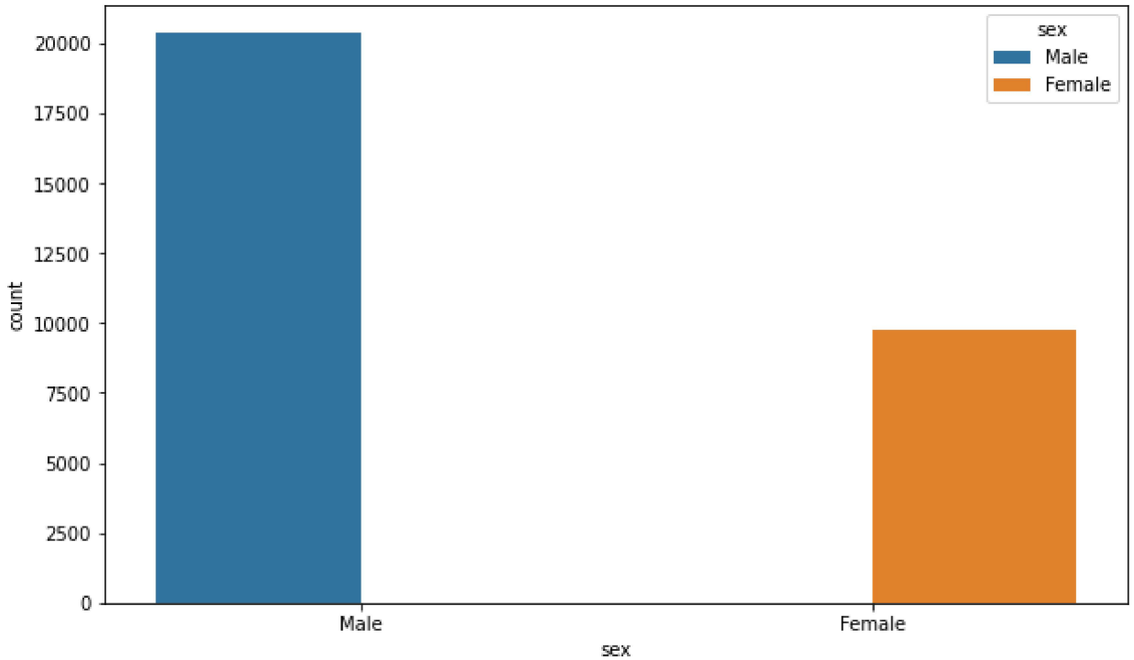
In [51]:
```
plt.rcParams['figure.figsize'] = (10, 6)
sns.countplot(df_class['race'],hue=df_class['race'])
```

Out[51]: <AxesSubplot:xlabel='race', ylabel='count'>



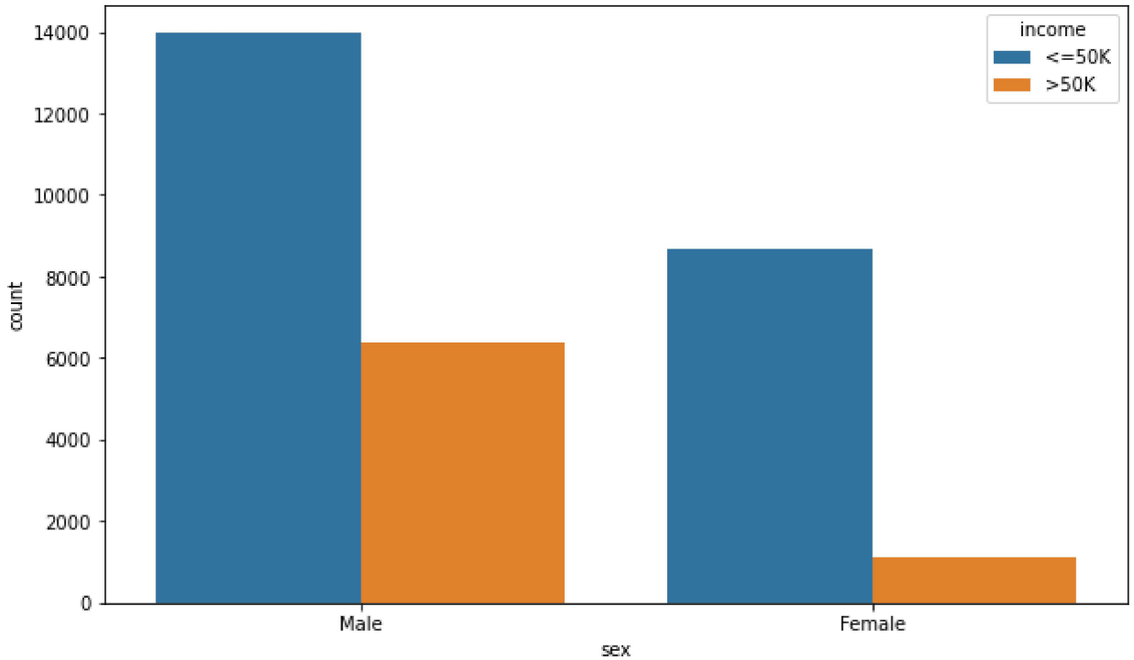
In [52]:
```
plt.rcParams['figure.figsize'] = (10, 6)
sns.countplot(df_class['sex'],hue=df_class['sex'])
```

Out[52]: <AxesSubplot:xlabel='sex', ylabel='count'>



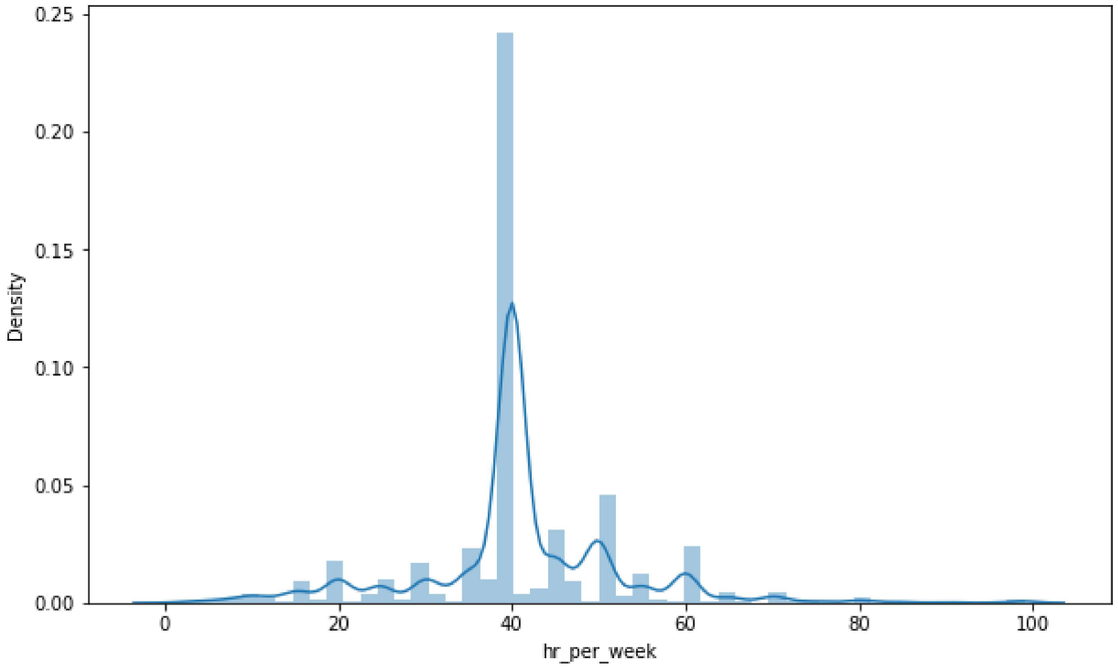
In [53]:
```
plt.rcParams['figure.figsize'] = (10, 6)
sns.countplot(df_class['sex'],hue=df_class['income'])
```

Out[53]:
```
<AxesSubplot:xlabel='sex', ylabel='count'>
```



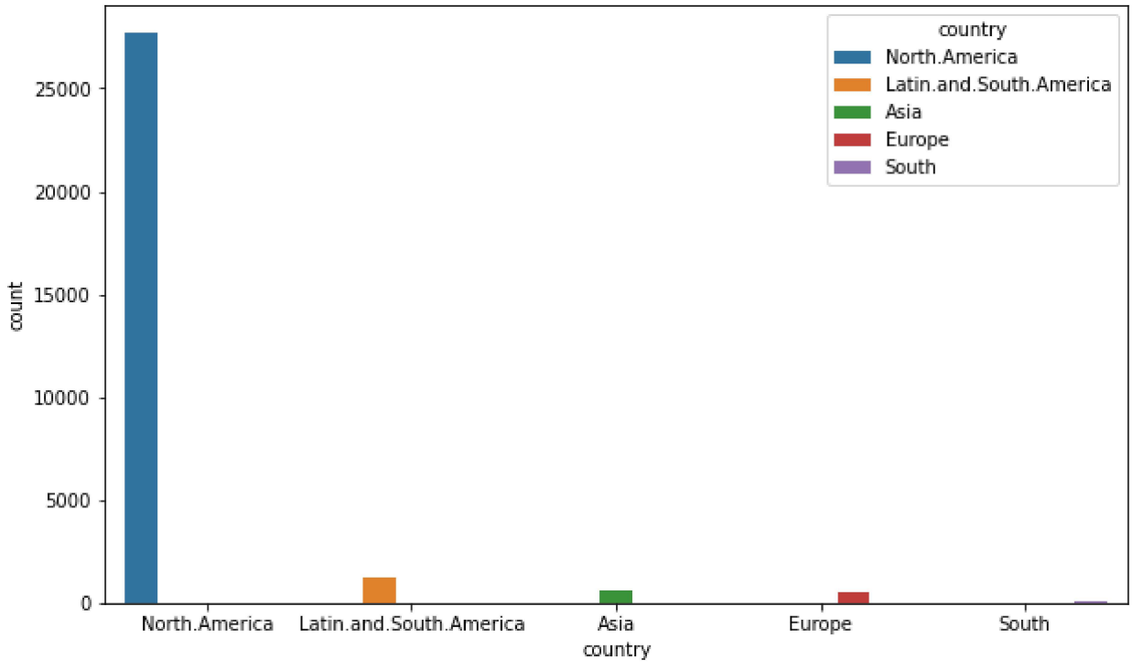
In [54]:
```
plt.rcParams['figure.figsize'] = (10, 6)
sns.distplot(df_class['hr_per_week'])
```

Out[54]:
```
<AxesSubplot:xlabel='hr_per_week', ylabel='Density'>
```



In [55]:
```
plt.rcParams['figure.figsize'] = (10, 6)
sns.countplot(df_class['country'],hue=df_class['country'])
```

Out[55]:
```
<AxesSubplot:xlabel='country', ylabel='count'>
```

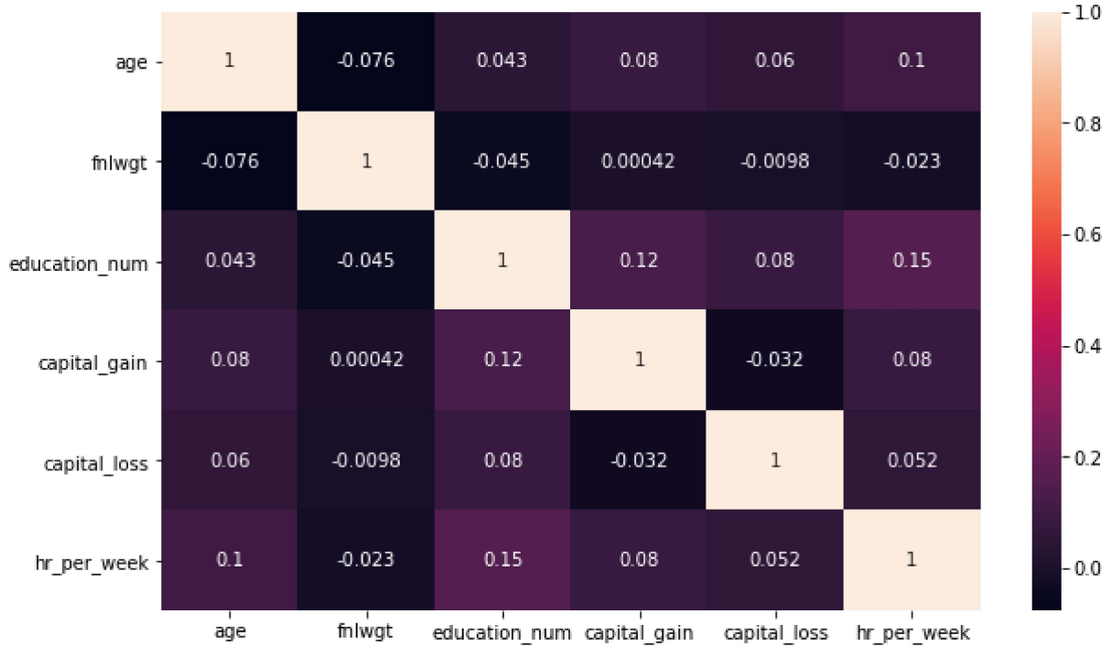



```
# A,B,C have higher Married people vs D has more Single people
```

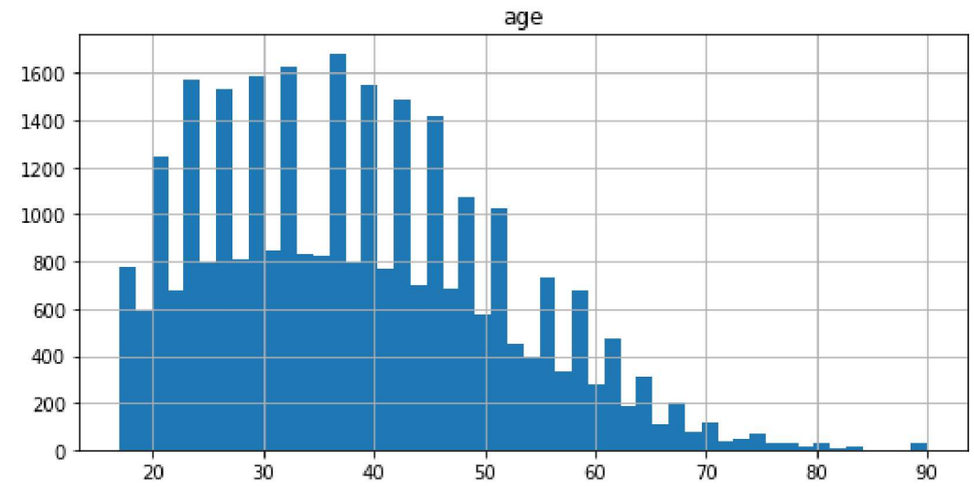
```
# Bivariate Analysis
```

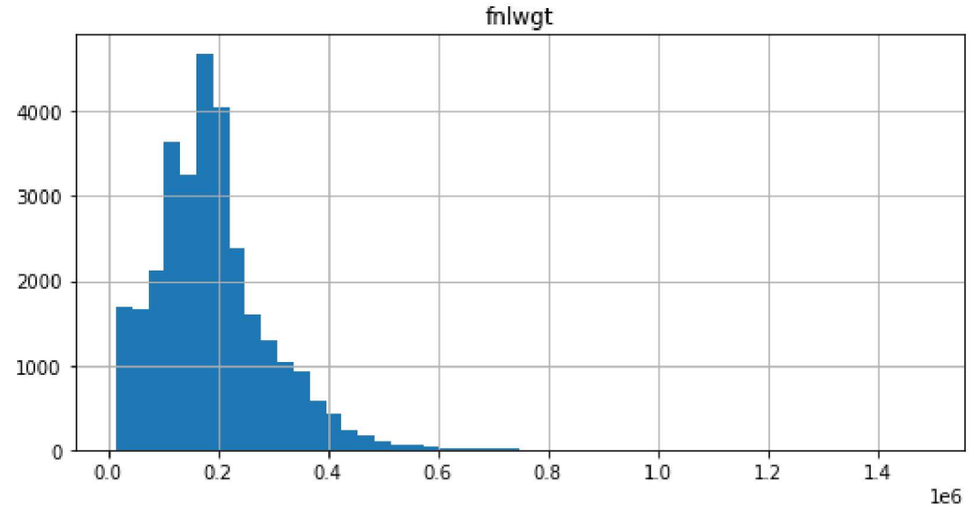
In [56]:
```
sns.heatmap(df_class.corr(),annot=True)
```

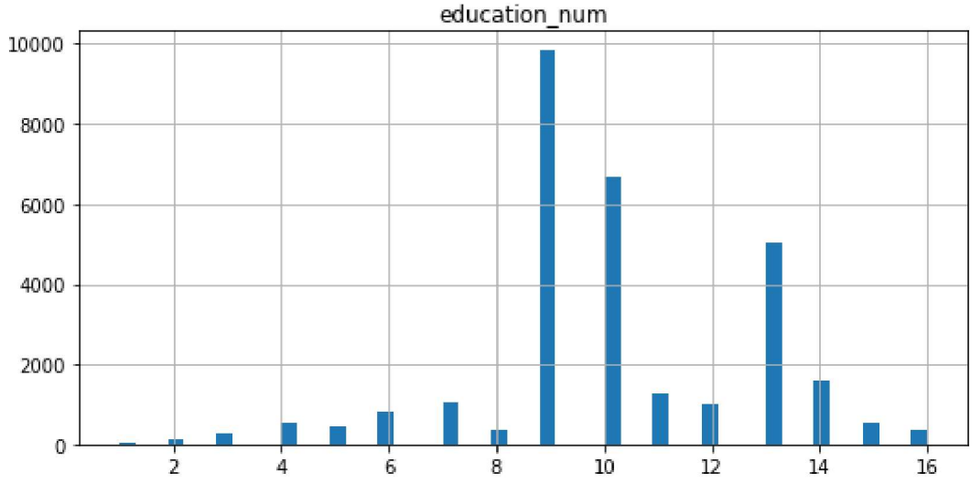
Out[56]: <AxesSubplot:>

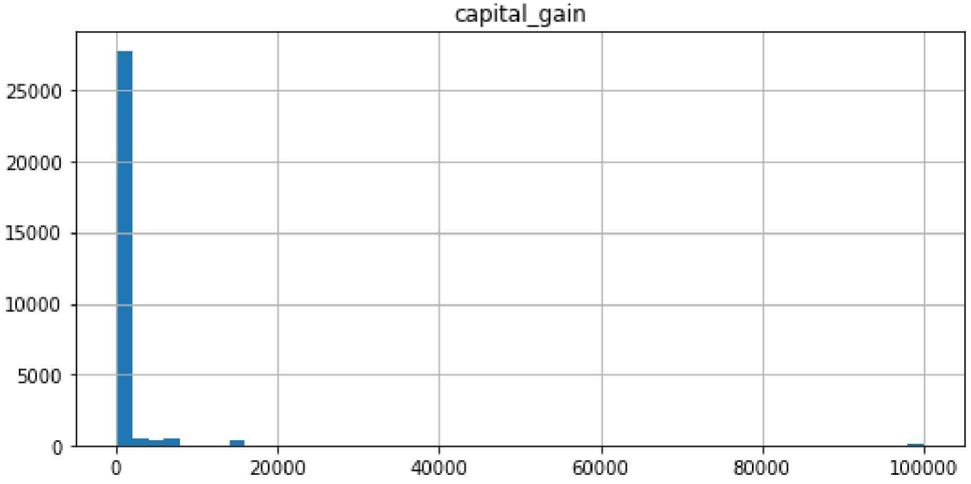


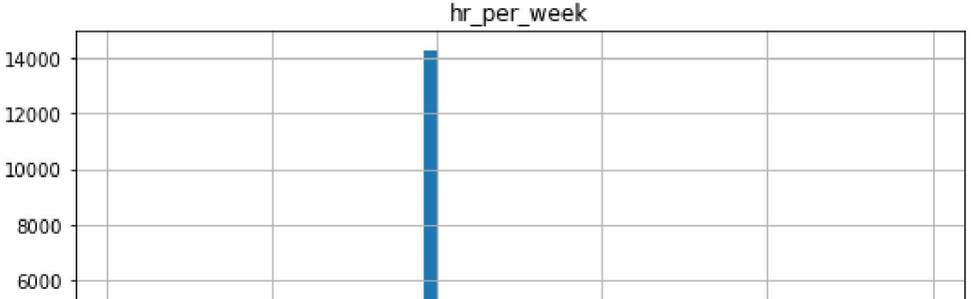
In [57]:
```
df_class.hist(bins=50, figsize=(20,15))
plt.show()
```

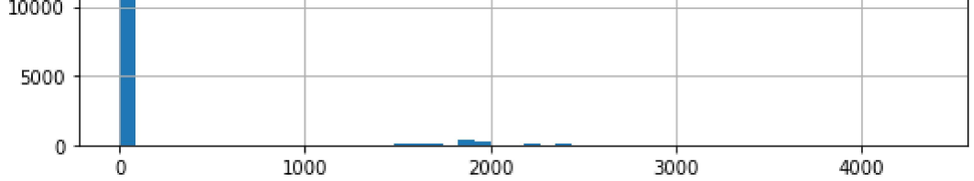


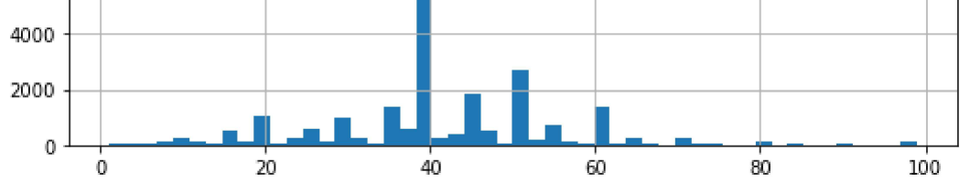












In [58]:
```
df_class.head(10)
```

Out[58]:

	age	type_employer	fnlwgt	education	education_num	marital	occupation	relationship	race	sex	capital_gain	capital_loss	hr_per_week	country	income
0	39	SL-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	North.America	<=50K
1	50	self-emp	83311	Bachelors	13	Married	Exec-managerial	Husband	White	Male	0	0	13	North.America	<=50K
2	38	Private	215646	HS-grad	9	Not-Married	Handlers-cleaners	Not-in-family	White	Male	0	0	40	North.America	<=50K
3	53	Private	234721	11th	7	Married	Handlers-cleaners	Husband	Black	Male	0	0	40	North.America	<=50K
4	28	Private	338409	Bachelors	13	Married	Prof-specialty	Wife	Black	Female	0	0	40	Latin.and.South.America	<=50K
5	37	Private	284582	Masters	14	Married	Exec-managerial	Wife	White	Female	0	0	40	North.America	<=50K
6	49	Private	160187	9th	5	Married	Other-service	Not-in-family	Black	Female	0	0	16	Latin.and.South.America	<=50K
7	52	self-emp	209642	HS-grad	9	Married	Exec-managerial	Husband	White	Male	0	0	45	North.America	>50K
8	31	Private	45781	Masters	14	Never-married	Prof-specialty	Not-in-family	White	Female	14084	0	50	North.America	>50K
9	42	Private	159449	Bachelors	13	Married	Exec-managerial	Husband	White	Male	5178	0	40	North.America	>50K

```
Let us drop education column since education and education_num seems to convey same information
```

In [59]:
```
df_class = df_class.drop(['education'],axis=1)
```

In [60]:
```
df_class.head(5)
```

Out[60]:

	age	type_employer	fnlwgt	education_num	marital	occupation	relationship	race	sex	capital_gain	capital_loss	hr_per_week	country	income
0	39	SL-gov	77516	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	North.America	<=50K
1	50	self-emp	83311	13	Married	Exec-managerial	Husband	White	Male	0	0	13	North.America	<=50K
2	38	Private	215646	9	Not-Married	Handlers-cleaners	Not-in-family	White	Male	0	0	40	North.America	<=50K
3	53	Private	234721	7	Married	Handlers-cleaners	Husband	Black	Male	0	0	40	North.America	<=50K
4	28	Private	338409	13	Married	Prof-specialty	Wife	Black	Female	0	0	40	Latin.and.South.America	<=50K

```
# Feature Engineering & Missing Value Treatment
```

In [61]:
```
df_class['occupation'].value_counts()
```

Out[61]:
```
Prof-specialty       4034
Craft-repair         4025
Exec-managerial      3991
Adm-clerical         3719
Sales                3584
Other-service        3209
Machine-op-inspct    1964
Transport-moving     1572
Handlers-cleaners    1349
Farming-fishing       987
Tech-support          911
Protective-serv       644
Priv-house-serv       141
Armed-Forces            9
Name: occupation, dtype: int64
```

In [62]:
```
df_class.type_employer = df_class.type_employer.map(
                    {
                        'Private': 0,
                        'self-emp': 1,
                        'SL-gov': 2,
                        'Federal-gov': 3,
                        'Without-pay': 4
                    }
                    )
```

In [63]:
```
df_class.marital = df_class.marital.map(
                    {
                        'Married': 0,
                        'Never-married': 1,
                        'Not-Married': 2
                    }
                    )
```

In [64]:
```
df_class = pd.get_dummies(df_class, columns=["occupation","relationship","country", "race"],drop_first=True)
```

In [77]:
```
df_class.head()
```

Out[77]:

	age	type_employer	fnlwgt	education_num	marital	race	sex	capital_gain	capital_loss	hr_per_week	...	occupation_Transport-moving	relationship_Not-in-family	relationship_Other-relative	relationship_Own-child
0	39	2	77516	13	1	White	Male	2174	0	40	...	0	1	0	0
1	50	1	83311	13	0	White	Male	0	0	13	...	0	0	0	0
2	38	0	215646	9	2	White	Male	0	0	40	...	0	1	0	0
3	53	0	234721	7	0	Black	Male	0	0	40	...	0	0	0	0
4	28	0	338409	13	0	Black	Female	0	0	40	...	0	0	0	0

5 rows × 33 columns

In [65]:
```
df_class['sex'].value_counts()
```

Out[65]:
```
Male      20366
Female     9773
Name: sex, dtype: int64
```

In [66]:
```
df_class.sex = df_class.sex.map(
                    {
                        'Female': 0,
                        'Male': 1
                    }
                    )
```

In [67]:
```
df_class.head()
```

Out[67]:

	age	type_employer	fnlwgt	education_num	marital	sex	capital_gain	capital_loss	hr_per_week	income	...	relationship_Unmarried	relationship_Wife	country_Europe	country_Latin.and.South
0	39	2	77516	13	1	1	2174	0	40	<=50K	...	0	0	0	
1	50	1	83311	13	0	1	0	0	13	<=50K	...	0	0	0	
2	38	0	215646	9	2	1	0	0	40	<=50K	...	0	0	0	
3	53	0	234721	7	0	1	0	0	40	<=50K	...	0	0	0	
4	28	0	338409	13	0	0	0	0	40	<=50K	...	0	1	0	

5 rows × 36 columns

In [68]:
```
df_class['income'].value_counts()
```

Out[68]:
```
<=50K    22633
>50K      7506
Name: income, dtype: int64
```

In [69]:
```
df_class.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30139 entries, 0 to 32560
Data columns (total 36 columns):
 #   Column                           Non-Null Count  Dtype
---  ------                           --------------  -----
 0   age                              30139 non-null  int64
 1   type_employer                    30139 non-null  int64
 2   fnlwgt                           30139 non-null  int64
 3   education_num                    30139 non-null  int64
 4   marital                          30139 non-null  int64
 5   sex                              30139 non-null  int64
 6   capital_gain                     30139 non-null  int64
 7   capital_loss                     30139 non-null  int64
 8   hr_per_week                      30139 non-null  int64
 9   income                           30139 non-null  object
 10  occupation_Armed-Forces          30139 non-null  uint8
 11  occupation_Craft-repair          30139 non-null  uint8
 12  occupation_Exec-managerial       30139 non-null  uint8
 13  occupation_Farming-fishing       30139 non-null  uint8
 14  occupation_Handlers-cleaners     30139 non-null  uint8
 15  occupation_Machine-op-inspct     30139 non-null  uint8
 16  occupation_Other-service         30139 non-null  uint8
 17  occupation_Priv-house-serv       30139 non-null  uint8
 18  occupation_Prof-specialty        30139 non-null  uint8
 19  occupation_Protective-serv       30139 non-null  uint8
 20  occupation_Sales                 30139 non-null  uint8
 21  occupation_Tech-support          30139 non-null  uint8
 22  occupation_Transport-moving      30139 non-null  uint8
 23  relationship_Not-in-family       30139 non-null  uint8
 24  relationship_Other-relative      30139 non-null  uint8
 25  relationship_Own-child           30139 non-null  uint8
 26  relationship_Unmarried           30139 non-null  uint8
 27  relationship_Wife                30139 non-null  uint8
 28  country_Europe                   30139 non-null  uint8
 29  country_Latin.and.South.America  30139 non-null  uint8
 30  country_North.America            30139 non-null  uint8
 31  country_South                    30139 non-null  uint8
 32  race_Asian-Pac-Islander          30139 non-null  uint8
 33  race_Black                       30139 non-null  uint8
 34  race_Other                       30139 non-null  uint8
 35  race_White                       30139 non-null  uint8
dtypes: int64(9), object(1), uint8(26)
memory usage: 4.5+ MB
```

In [70]:
```
df_class.income = df_class.income.map(
                    {
                        '<=50K': 0,
                        '>50K': 1
                    }
                    )
```

In [71]:
```
df_class.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30139 entries, 0 to 32560
Data columns (total 36 columns):
 #   Column                           Non-Null Count  Dtype
---  ------                           --------------  -----
 0   age                              30139 non-null  int64
 1   type_employer                    30139 non-null  int64
 2   fnlwgt                           30139 non-null  int64
 3   education_num                    30139 non-null  int64
 4   marital                          30139 non-null  int64
 5   sex                              30139 non-null  int64
 6   capital_gain                     30139 non-null  int64
 7   capital_loss                     30139 non-null  int64
 8   hr_per_week                      30139 non-null  int64
 9   income                           30139 non-null  int64
 10  occupation_Armed-Forces          30139 non-null  uint8
 11  occupation_Craft-repair          30139 non-null  uint8
 12  occupation_Exec-managerial       30139 non-null  uint8
 13  occupation_Farming-fishing       30139 non-null  uint8
 14  occupation_Handlers-cleaners     30139 non-null  uint8
 15  occupation_Machine-op-inspct     30139 non-null  uint8
 16  occupation_Other-service         30139 non-null  uint8
 17  occupation_Priv-house-serv       30139 non-null  uint8
 18  occupation_Prof-specialty        30139 non-null  uint8
 19  occupation_Protective-serv       30139 non-null  uint8
 20  occupation_Sales                 30139 non-null  uint8
 21  occupation_Tech-support          30139 non-null  uint8
 22  occupation_Transport-moving      30139 non-null  uint8
 23  relationship_Not-in-family       30139 non-null  uint8
 24  relationship_Other-relative      30139 non-null  uint8
 25  relationship_Own-child           30139 non-null  uint8
 26  relationship_Unmarried           30139 non-null  uint8
 27  relationship_Wife                30139 non-null  uint8
 28  country_Europe                   30139 non-null  uint8
 29  country_Latin.and.South.America  30139 non-null  uint8
 30  country_North.America            30139 non-null  uint8
 31  country_South                    30139 non-null  uint8
 32  race_Asian-Pac-Islander          30139 non-null  uint8
 33  race_Black                       30139 non-null  uint8
 34  race_Other                       30139 non-null  uint8
 35  race_White                       30139 non-null  uint8
dtypes: int64(10), uint8(26)
memory usage: 4.5 MB
```

In [74]:
```
df_class.dtypes
```

Out[74]:
```
age                                int64
type_employer                      int64
fnlwgt                             int64
education_num                      int64
marital                            int64
sex                                int64
capital_gain                       int64
capital_loss                       int64
hr_per_week                        int64
income                             int64
occupation_Armed-Forces            uint8
occupation_Craft-repair            uint8
occupation_Exec-managerial         uint8
occupation_Farming-fishing         uint8
occupation_Handlers-cleaners       uint8
occupation_Machine-op-inspct       uint8
occupation_Other-service           uint8
occupation_Priv-house-serv         uint8
occupation_Prof-specialty          uint8
occupation_Protective-serv         uint8
occupation_Sales                   uint8
occupation_Tech-support            uint8
occupation_Transport-moving        uint8
relationship_Not-in-family         uint8
relationship_Other-relative        uint8
relationship_Own-child             uint8
relationship_Unmarried             uint8
relationship_Wife                  uint8
country_Europe                     uint8
country_Latin.and.South.America    uint8
country_North.America              uint8
country_South                      uint8
race_Asian-Pac-Islander            uint8
race_Black                         uint8
race_Other                         uint8
race_White                         uint8
dtype: object
```

In [75]:
```
df_class.shape
```

Out[75]:
```
(30139, 36)
```

In [76]:
```
X_fin = df_class.drop(['income'],axis=1)
y_fin = df_class.income
```

In [77]:
```
X_fin.head()
```

Out[77]:

	age	type_employer	fnlwgt	education_num	marital	sex	capital_gain	capital_loss	hr_per_week	occupation_Armed-Forces	...	relationship_Unmarried	relationship_Wife	country_Europe	country_Lat
0	39	2	77516	13	1	1	2174	0	40	0	...	0	0	0	
1	50	1	83311	13	0	1	0	0	13	0	...	0	0	0	
2	38	0	215646	9	2	1	0	0	40	0	...	0	0	0	
3	53	0	234721	7	0	1	0	0	40	0	...	0	0	0	
4	28	0	338409	13	0	0	0	0	40	0	...	0	1	0	

5 rows × 35 columns

In [78]:
```
y_fin.head()
```

Out[78]:
```
0    0
1    0
2    0
3    0
4    0
Name: income, dtype: int64
```

In [79]:
```
from sklearn.preprocessing import MinMaxScaler
sc= MinMaxScaler()
X_fins = pd.DataFrame(sc.fit_transform(X_fin),columns = X_fin.columns)
X_fins.head()
```

Out[79]:

	age	type_employer	fnlwgt	education_num	marital	sex	capital_gain	capital_loss	hr_per_week	occupation_Armed-Forces	...	relationship_Unmarried	relationship_Wife	country_Europe	coun
0	0.301370	0.50	0.043338	0.800000	0.5	1.0	0.02174	0.0	0.397959	0.0	...	0.0	0.0	0.0	
1	0.452055	0.25	0.047277	0.800000	0.0	1.0	0.00000	0.0	0.122449	0.0	...	0.0	0.0	0.0	
2	0.287671	0.00	0.137244	0.533333	1.0	1.0	0.00000	0.0	0.397959	0.0	...	0.0	0.0	0.0	
3	0.493151	0.00	0.150212	0.400000	0.0	1.0	0.00000	0.0	0.397959	0.0	...	0.0	0.0	0.0	
4	0.150685	0.00	0.220703	0.800000	0.0	0.0	0.00000	0.0	0.397959	0.0	...	0.0	1.0	0.0	

5 rows × 35 columns

In [166]:
```
X_fins.shape
```

Out[166]:
```
(30139, 35)
```

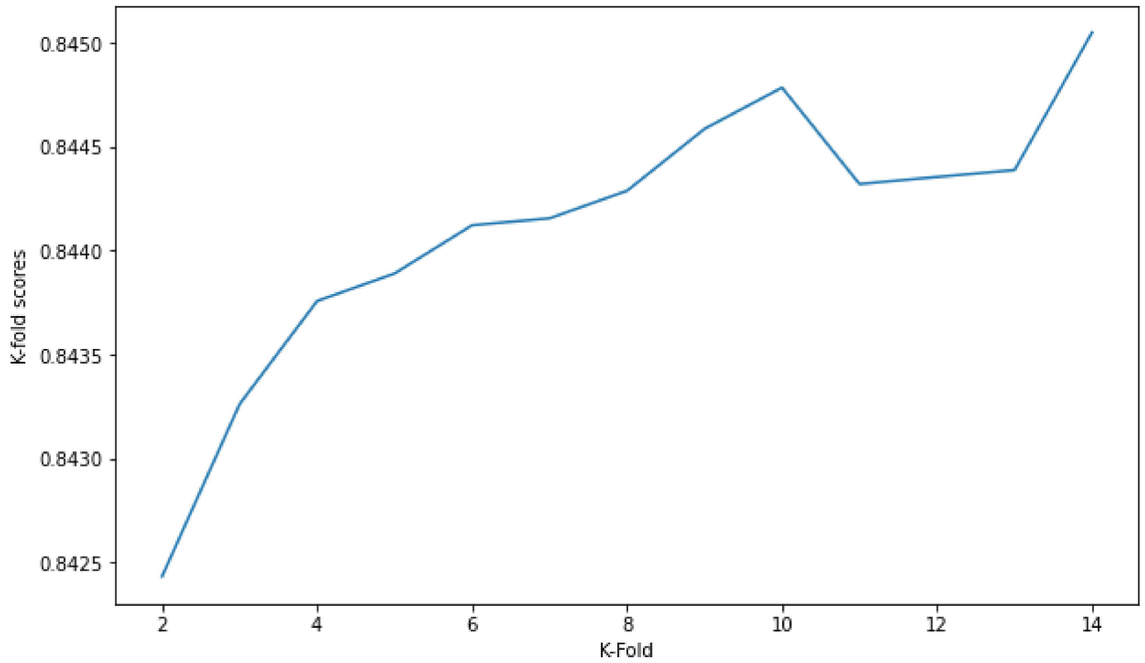
In [167]:
```
y_fin.shape
```

Out[167]:
```
(30139,)
```

In [89]:
```
#k-fold cross-validation score
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score
cross_val_score(LogisticRegression(max_iter=1000,tol=0.001),
                X_fins,y_fin,cv=10).mean()
```

Out[89]:
```
0.8447524782566852
```

In [86]:
```
#Graph k-fold score for Logistic Regression Classification

mlr_scores = []
for i in range(2,15):
    mlr_scores.append(cross_val_score(LogisticRegression(),X_fins,y_fin,cv=i).mean())



plt.plot(range(2,15),mlr_scores)
plt.xlabel('K-Fold')
plt.ylabel('K-fold scores')
plt.show()
```



In [87]:
```
from sklearn.model_selection import train_test_split
X_train_mlr, X_test_mlr, y_train_mlr, y_test_mlr = train_test_split(X_fins,
                                      y_fin,random_state=0,test_size=0.10)
```

In [88]:
```
from sklearn.metrics import classification_report, confusion_matrix
model_mlr = LogisticRegression()
model_mlr.fit(X_train_mlr,y_train_mlr)
y_pred_mlr = model_mlr.predict(X_test_mlr)
print(classification_report(y_test_mlr,y_pred_mlr))
```

```
              precision    recall  f1-score   support

           0       0.87      0.92      0.90      2248
           1       0.73      0.61      0.66       766

    accuracy                           0.84      3014
   macro avg       0.80      0.76      0.78      3014
weighted avg       0.84      0.84      0.84      3014
```

In [90]:
```
print(confusion_matrix(y_test_mlr,y_pred_mlr))
```

```
[[2077  171]
 [ 302  464]]
```

In [95]:
```
# Grid search cross validation
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
grid={"C":np.logspace(-3,3,7), "penalty":["l1","l2"]}# l1 lasso l2 ridge
logreg=LogisticRegression()
logreg_cv=GridSearchCV(logreg,grid,cv=10)
logreg_cv.fit(X_train_mlr,y_train_mlr)

print("tuned hpyerparameters :(best parameters) ",logreg_cv.best_params_)
print("accuracy :",logreg_cv.best_score_)
best_model_logreg = logreg_cv.best_estimator_
```

```
tuned hpyerparameters :(best parameters)  {'C': 100.0, 'penalty': 'l2'}
accuracy : 0.8471149915136016
```

In [96]:
```
best_model_logreg.fit(X_train_mlr,y_train_mlr)
y_pred_mlr_best = model_mlr.predict(X_test_mlr)
print(classification_report(y_test_mlr,y_pred_mlr_best))
```

```
              precision    recall  f1-score   support

           0       0.87      0.92      0.90      2248
           1       0.73      0.61      0.66       766

    accuracy                           0.84      3014
   macro avg       0.80      0.76      0.78      3014
weighted avg       0.84      0.84      0.84      3014
```

In [225]:
```
confusion_matrix(y_test_mlr,y_pred_mlr_best)
```

Out[225]:
```
array([[2077,  171],
       [ 302,  464]], dtype=int64)
```

```
################################### KNN ##############################################################
```

In [97]:
```
X_knnc = X_fins
X_knnc.head()
```

Out[97]:

	age	type_employer	fnlwgt	education_num	marital	sex	capital_gain	capital_loss	hr_per_week	occupation_Armed-Forces	...	relationship_Unmarried	relationship_Wife	country_Europe	coun
0	0.301370	0.50	0.043338	0.800000	0.5	1.0	0.02174	0.0	0.397959	0.0	...	0.0	0.0	0.0	
1	0.452055	0.25	0.047277	0.800000	0.0	1.0	0.00000	0.0	0.122449	0.0	...	0.0	0.0	0.0	
2	0.287671	0.00	0.137244	0.533333	1.0	1.0	0.00000	0.0	0.397959	0.0	...	0.0	0.0	0.0	
3	0.493151	0.00	0.150212	0.400000	0.0	1.0	0.00000	0.0	0.397959	0.0	...	0.0	0.0	0.0	
4	0.150685	0.00	0.220703	0.800000	0.0	0.0	0.00000	0.0	0.397959	0.0	...	0.0	1.0	0.0	

5 rows × 35 columns

In [98]:
```
y_knnc = y_fin
y_knnc.head()
```

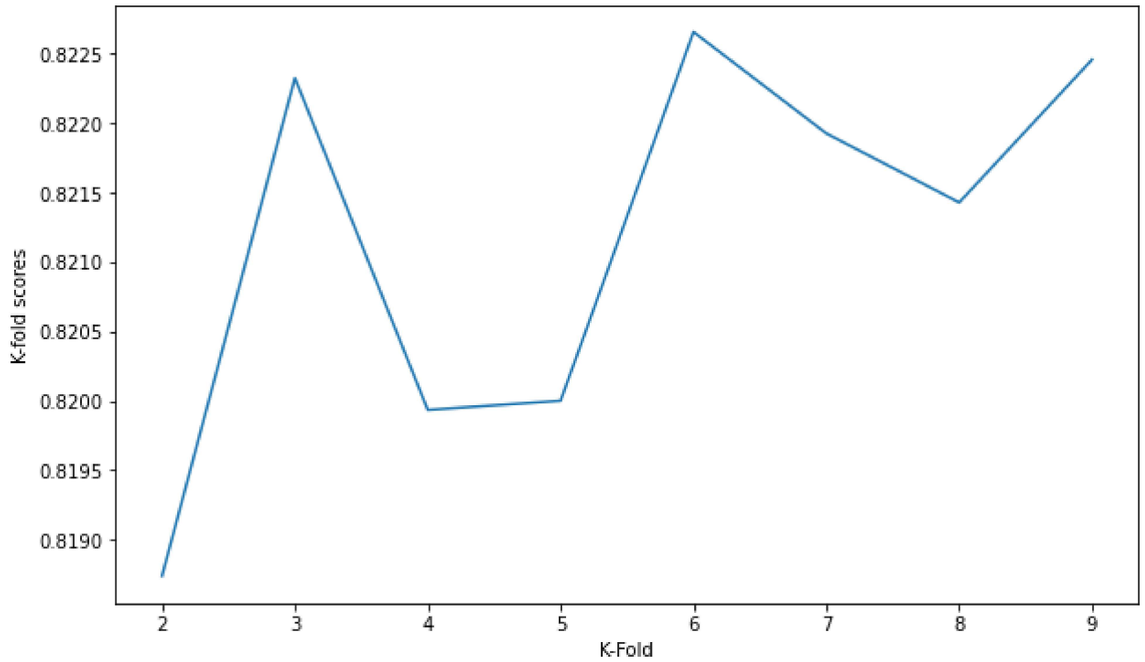
Out[98]:
```
0    0
1    0
2    0
3    0
4    0
Name: income, dtype: int64
```

In [99]:
```
#import the knn model
from sklearn.neighbors import KNeighborsClassifier
knnc = KNeighborsClassifier()
```

In [102]:
```
#see the cross_validated score for cv=4
from sklearn.model_selection import cross_val_score
cross_val_score(knnc,X_knnc,y_knnc,cv=6).mean()
```

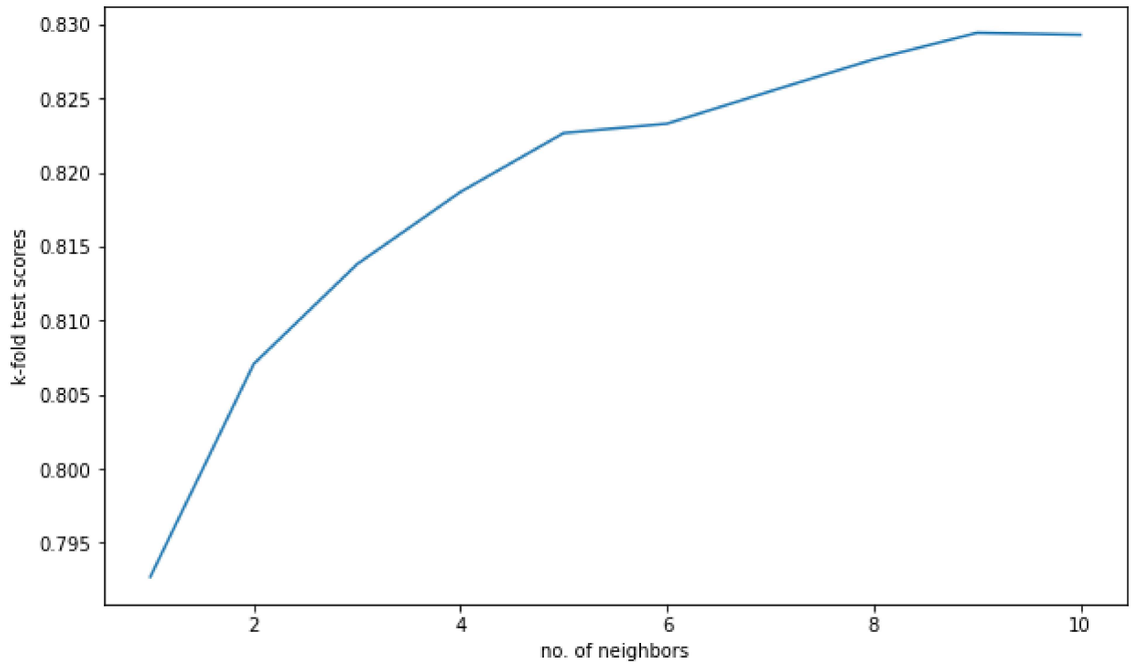
Out[102]:
```
0.8226553422198438
```

In [101]:
```
#Graph k-fold score for KNN

k_scores_mlr = []
for i in range(2,10):
    k_scores_mlr.append(cross_val_score(KNeighborsClassifier(),X_knnc,y_knnc,cv=i).mean())



plt.plot(range(2,10),k_scores_mlr)
plt.xlabel('K-Fold')
plt.ylabel('K-fold scores')
plt.show()
```



In [104]:
```
#for no.of neighbors from 1 - 10, graph the k-fold scores
scores_knnc = []
for i in range(1,11,1):
    knnc_p = KNeighborsClassifier(n_neighbors=i, weights='uniform')
    scores_knnc.append(cross_val_score(knnc_p,X_knnc,y_knnc,cv=6).mean())
```

In [105]:
```
import matplotlib.pyplot as plt
plt.plot(range(1,11,1),scores_knnc)
plt.xlabel('no. of neighbors')
plt.ylabel('k-fold test scores')
plt.show()
```



In [107]:
```
# Grid Search
from sklearn.model_selection import GridSearchCV
k_range = list(range(1, 16))
param_grid = dict(n_neighbors=k_range)
grid = GridSearchCV(knnc, param_grid, cv=6, scoring='accuracy')
grid.fit(X_knnc, y_knnc)
```

Out[107]:
```
GridSearchCV(cv=6, estimator=KNeighborsClassifier(),
             param_grid={'n_neighbors': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,
                                         13, 14, 15]},
             scoring='accuracy')
```

In [108]:
```
# view the complete results (list of named tuples)
grid.best_score_
```

Out[108]:
```
0.8311160910343206
```

In [109]:
```
from sklearn.model_selection import train_test_split
X_train_knnc, X_test_knnc, y_train_knnc, y_test_knnc = train_test_split(X_knnc,
                                        y_knnc,random_state=0,test_size=0.25)
```

In [110]:
```
from sklearn.metrics import classification_report, confusion_matrix
model_knnc = grid.best_estimator_
model_knnc.fit(X_train_knnc,y_train_knnc)
y_pred_knnc = model_knnc.predict(X_test_knnc)
print(classification_report(y_test_knnc,y_pred_knnc))
```

```
              precision    recall  f1-score   support

           0       0.87      0.91      0.89      5655
           1       0.68      0.60      0.64      1880

    accuracy                           0.83      7535
   macro avg       0.78      0.75      0.76      7535
weighted avg       0.82      0.83      0.83      7535
```

In [111]:
```
print(confusion_matrix(y_test_knnc,y_pred_knnc))
```

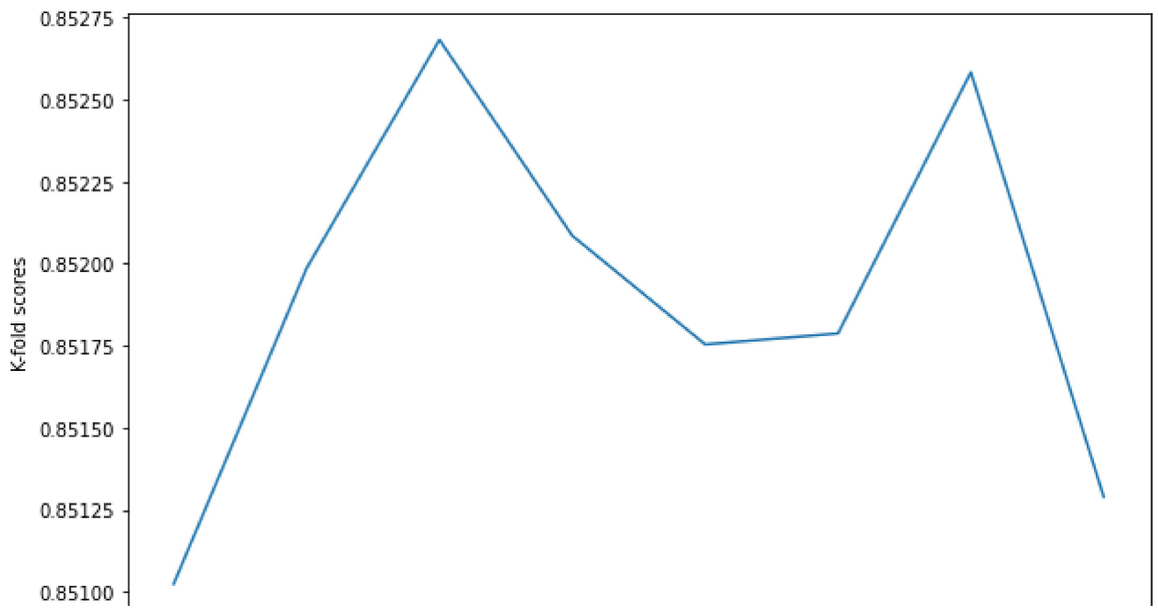
```
[[5140  515]
 [ 761 1119]]
```

```
################################### Random Forest Classifier ######################################
```

In [231]:
```
#import libraries
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.model_selection import cross_val_score
import matplotlib.pyplot as plt
```

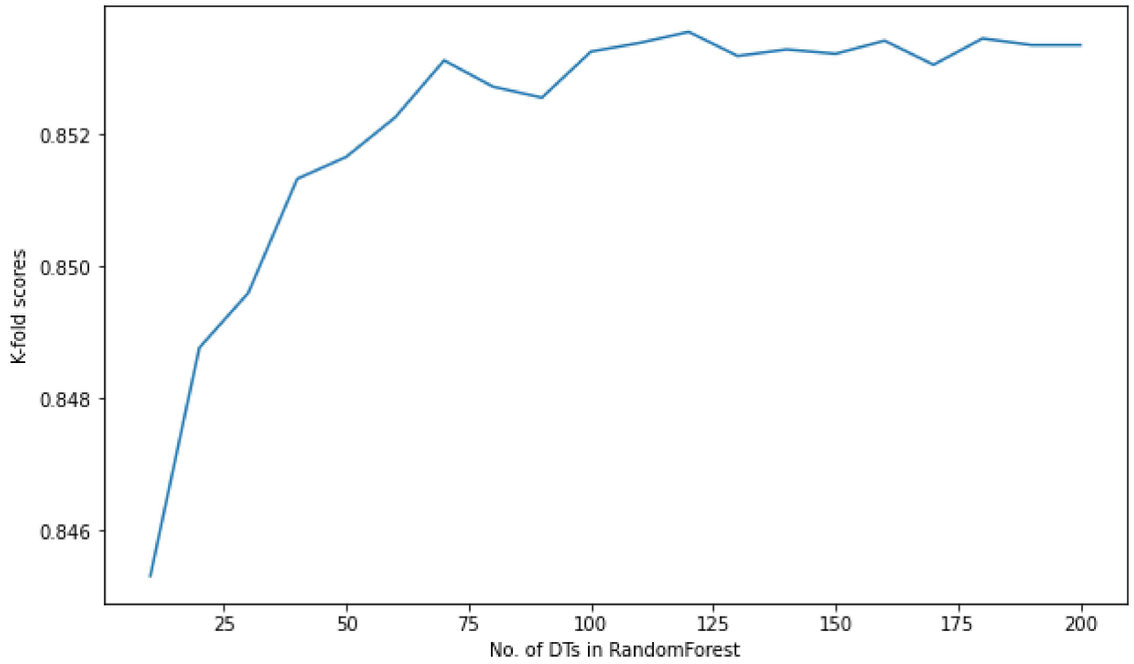
In [229]:
```
X_rfc = X_fins
y_rfc = y_fin
```

In [232]:
```
#Graph k-fold score for RF

k_scores_rfc = []
for i in range(2,10):
    k_scores_rfc.append(cross_val_score(RandomForestClassifier(),X_rfc,y_rfc,cv=i).mean())



plt.plot(range(2,10),k_scores_rfc)
plt.xlabel('K-Fold')
plt.ylabel('K-fold scores')
plt.show()
```



In [115]:
```
#Graph k-fold score vs no. of estimators in Random Forest
scores_rfc_es = []
for i in range(10,201,10):
    scores_rfc_es.append(cross_val_score(RandomForestClassifier(n_estimators=i,random_state=0),
                                         X_rfc,y_rfc,cv=10).mean())
```

In [116]:
```
plt.plot(range(10,201,10),scores_rfc_es)
plt.xlabel('No. of DTs in RandomForest')
plt.ylabel('K-fold scores')
plt.show()
```



In [117]:
```
#including other params like max_depth, we will apply gridsearch to fine the best settings for the RF
params_rfc = {
            'n_estimators': [70,80,90,100,110],
            'max_depth': [8,10,12,14,16]
        }
model_rfc = GridSearchCV(RandomForestClassifier(random_state=0), params_rfc,cv=10)
model_rfc.fit(X_rfc,y_rfc)
```

Out[117]:
```
GridSearchCV(cv=10, estimator=RandomForestClassifier(random_state=0),
             param_grid={'max_depth': [8, 10, 12, 14, 16],
                         'n_estimators': [70, 80, 90, 100, 110]})
```

In [118]:
```
model_rfc.best_params_
```

Out[118]:
```
{'max_depth': 16, 'n_estimators': 80}
```

In [119]:
```
model_rfc.best_score_
```

Out[119]:
```
0.8603137895485412
```

In [120]:
```
best_model_rfc = model_rfc.best_estimator_
```

In [121]:
```
X_train_rfc,X_test_rfc,y_train_rfc,y_test_rfc = train_test_split(X_rfc,y_rfc,random_state=0)
```

In [122]:
```
best_model_rfc.fit(X_train_rfc,y_train_rfc)
```

Out[122]:
```
RandomForestClassifier(max_depth=16, n_estimators=80, random_state=0)
```

In [123]:
```
y_pred_rfc = best_model_rfc.predict(X_test_rfc)
```

In [124]:
```
print(classification_report(y_test_rfc,y_pred_rfc))
```

```
              precision    recall  f1-score   support

           0       0.88      0.95      0.91      5655
           1       0.79      0.59      0.68      1880

    accuracy                           0.86      7535
   macro avg       0.83      0.77      0.79      7535
weighted avg       0.85      0.86      0.85      7535
```

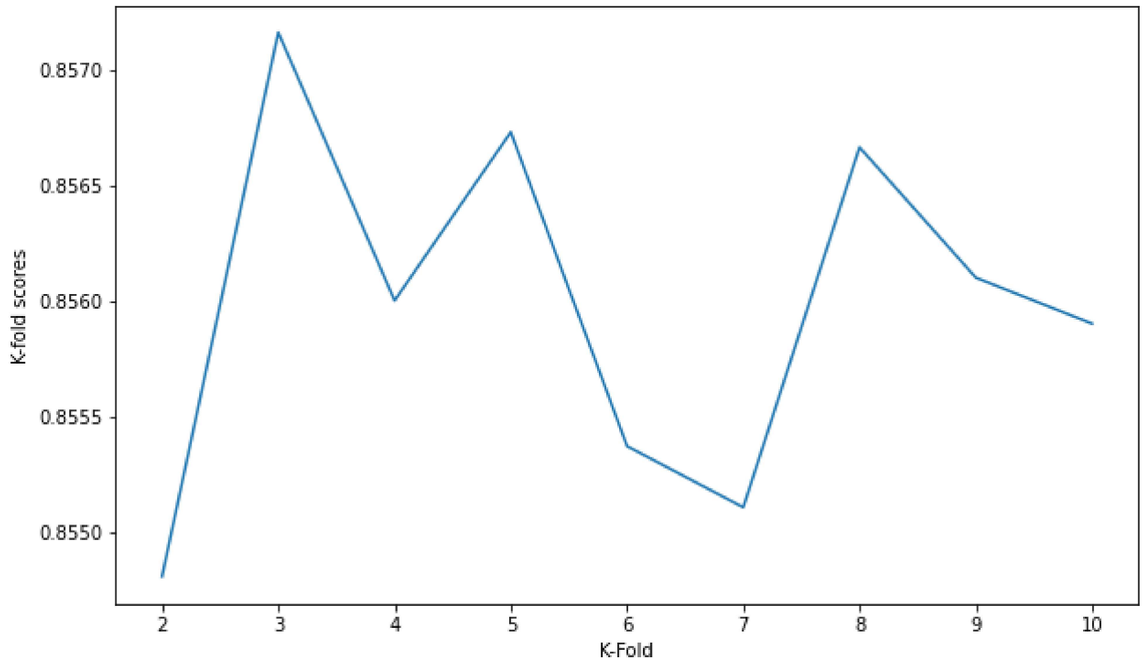
In [226]:
```
print(confusion_matrix(y_test_rfc,y_pred_rfc))
```

```
[[5357  298]
 [ 764 1116]]
```

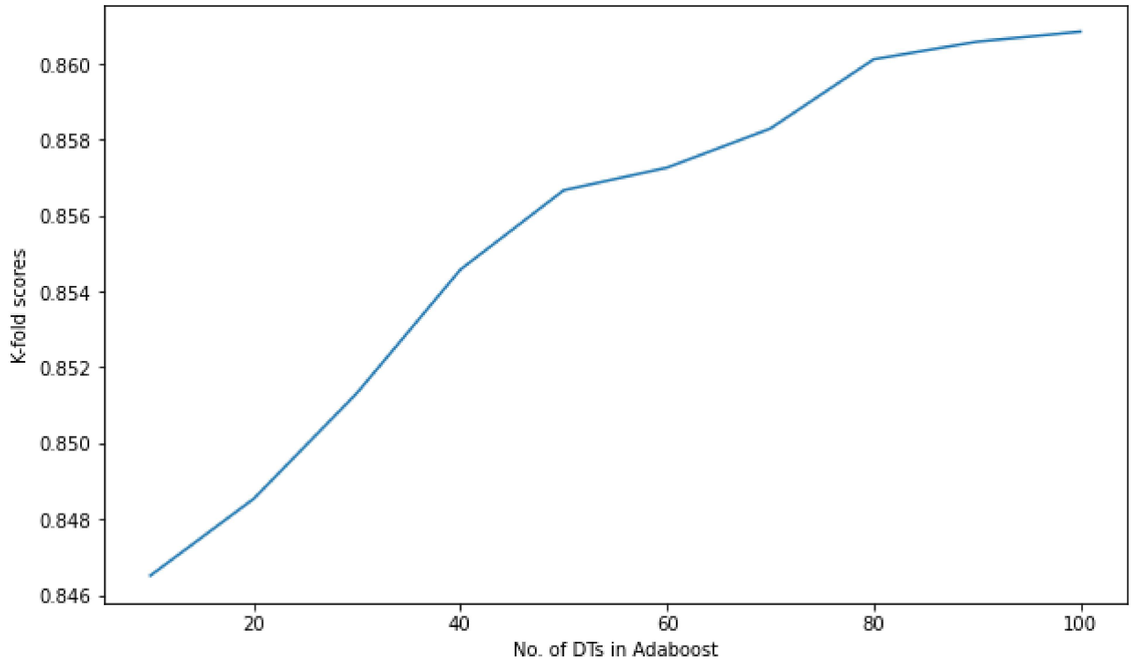
```
######################################## AdaBoost ##############################################################
```

In [125]:
```
X_adac = X_fins
y_adac = y_fin
```

In [127]:
```
#Graph k-fold score for AdaBoost
from sklearn.ensemble import AdaBoostClassifier
k_scores_adac = []
for i in range(2,11):
    k_scores_adac.append(cross_val_score(AdaBoostClassifier(),X_adac,y_adac,cv=i).mean())



plt.plot(range(2,11),k_scores_adac)
plt.xlabel('K-Fold')
plt.ylabel('K-fold scores')
plt.show()
```



In [128]:
```
from sklearn.ensemble import AdaBoostClassifier

#Graph k-fold score vs no. of estimators in Adaboost which uses DT as base estimators
scores_adac = []
for i in range(10,101,10):
    scores_adac.append(cross_val_score(AdaBoostClassifier(n_estimators=i,random_state=0),
                                       X_adac,y_adac,cv=8).mean())
plt.plot(range(10,101,10),scores_adac)
plt.xlabel('No. of DTs in Adaboost')
plt.ylabel('K-fold scores')
plt.show()
```



In [129]:
```
from sklearn.tree import DecisionTreeClassifier
#including other params like max_depth, we will apply gridsearch to fine the best settings
params = {
            'n_estimators': [70,80,90,100],
            'base_estimator': [DecisionTreeClassifier(max_depth=9,random_state=0),
                               DecisionTreeClassifier(max_depth=10,random_state=0),
                               DecisionTreeClassifier(max_depth=11,random_state=0)]
        }
model_adac = GridSearchCV(AdaBoostClassifier(random_state=0), params,cv=8)
model_adac.fit(X_adac,y_adac)
```

Out[129]:
```
GridSearchCV(cv=8, estimator=AdaBoostClassifier(random_state=0),
             param_grid={'base_estimator': [DecisionTreeClassifier(max_depth=9,
                                                                   random_state=0),
                                            DecisionTreeClassifier(max_depth=10,
                                                                   random_state=0),
                                            DecisionTreeClassifier(max_depth=11,
                                                                   random_state=0)],
                         'n_estimators': [70, 80, 90, 100]})
```

In [130]:
```
model_adac.best_params_
```

Out[130]:
```
{'base_estimator': DecisionTreeClassifier(max_depth=10, random_state=0),
 'n_estimators': 100}
```

In [131]:
```
model_adac.best_score_
```

Out[131]:
```
0.8267695734749814
```

In [132]:
```
best_model_adac = model_adac.best_estimator_
```

In [133]:
```
X_train_adac,X_test_adac,y_train_adac,y_test_adac = train_test_split(X_adac,y_adac,random_state=0)
```

In [134]:
```
best_model_adac.fit(X_train_adac,y_train_adac)
```

Out[134]:
```
AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=10,
                                                         random_state=0),
                   n_estimators=100, random_state=0)
```

In [135]:
```
y_pred_adac = best_model_adac.predict(X_test_adac)
```

In [136]:
```
print(classification_report(y_test_adac,y_pred_adac))
```

```
              precision    recall  f1-score   support

           0       0.87      0.89      0.88      5655
           1       0.66      0.61      0.63      1880

    accuracy                           0.82      7535
   macro avg       0.77      0.75      0.76      7535
weighted avg       0.82      0.82      0.82      7535
```

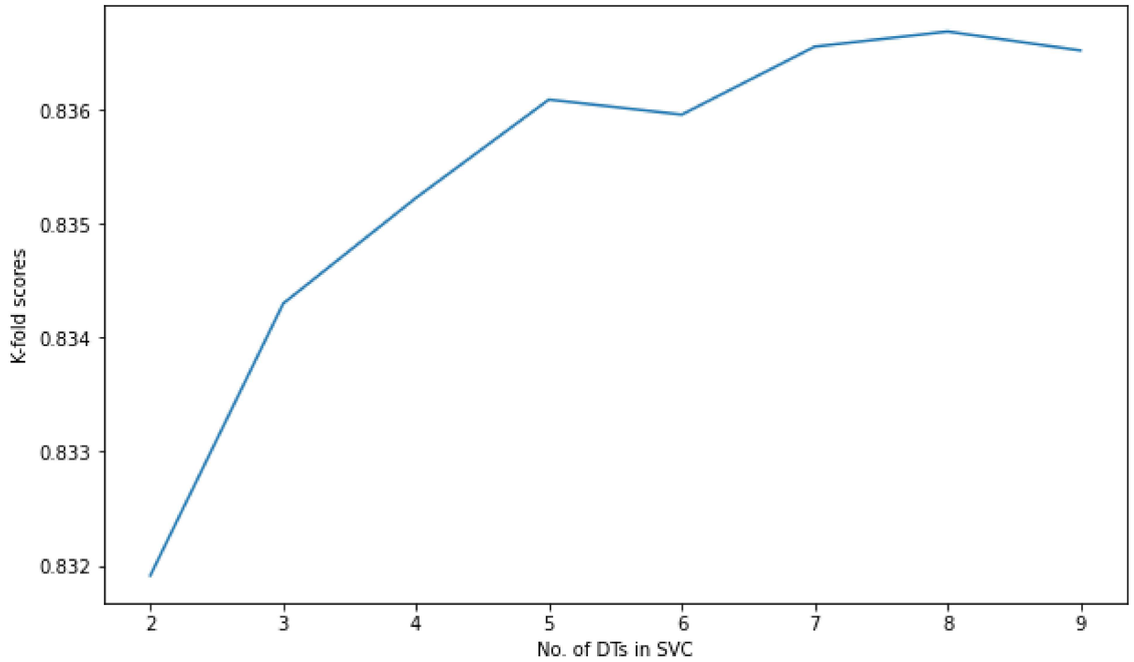
In [233]:
```
print(confusion_matrix(y_test_adac,y_pred_adac))
```

```
[[5058  597]
 [ 736 1144]]
```

```
########################################### SVM ###################################################################
```

In [137]:
```
X_svc = X_fins
y_svc = y_fin
```

In [138]:
```
from sklearn.svm import SVC
#Graph k-fold score vs no. of estimators in Adaboost which uses DT as base estimators
scores_svc = []
for i in range(2,10):
    scores_svc.append(cross_val_score(SVC(),
                                      X_svc,y_svc,cv=i).mean())
plt.plot(range(2,10),scores_svc)
plt.xlabel('No. of DTs in SVC')
plt.ylabel('K-fold scores')
plt.show()
```



In [140]:
```
from sklearn.model_selection import GridSearchCV
```

In [146]:
```
params_dictionary = {
                        'C' : [0.1, 1, 10],
                        'kernel': ['linear', 'rbf'],

                    }

model_svc = GridSearchCV(SVC(random_state=0, verbose=True),param_grid=params_dictionary,cv=8)
```

In [147]:
```
model_svc.fit(X_svc,y_svc)
```

```
[LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSV
M][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][Lib
SVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM]
```

Out[147]:
```
GridSearchCV(cv=8, estimator=SVC(random_state=0, verbose=True),
             param_grid={'C': [0.1, 1, 10], 'kernel': ['linear', 'rbf']})
```

In [148]:
```
model_svc.best_params_
```

Out[148]:
```
{'C': 10, 'kernel': 'rbf'}
```

In [149]:
```
model_svc.best_score_
```

Out[149]:
```
0.847871795771413
```

In [150]:
```
best_model_svm =model_svc.best_estimator_
```

In [151]:
```
from sklearn.model_selection import train_test_split
X_train_svm,X_test_svm,y_train_svm,y_test_svm = train_test_split(X_svc,y_svc,random_state=0)
```

In [152]:
```
best_model_svm.fit(X_train_svm,y_train_svm)
```

```
[LibSVM]
```

Out[152]:
```
SVC(C=10, random_state=0, verbose=True)
```

In [153]:
```
best_model_svm.score(X_test_svm,y_test_svm)
```

Out[153]:
```
0.8477770404777704
```

In [154]:
```
y_pred_svm = best_model_svm.predict(X_test_svm)
```

In [155]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test_svm,y_pred_svm))
```

```
              precision    recall  f1-score   support

           0       0.88      0.93      0.90      5655
           1       0.74      0.60      0.66      1880

    accuracy                           0.85      7535
   macro avg       0.81      0.77      0.78      7535
weighted avg       0.84      0.85      0.84      7535
```

In [234]:
```
print(confusion_matrix(y_test_svm,y_pred_svm))
```

```
[[5255  400]
 [ 747 1133]]
```

Classification Model Summary

Result	Logistic Regressio Classification	KNN Classification	Random Forest Classification	AdaBoost Classification	SVM Classification
F1-Accuracy	0.84	0.83	0.86	0.82	0.85
Precision-Macro	0.8	0.78	0.83	0.77	0.81
Precision-Weighted	0.84	0.82	0.85	0.82	0.84

- The result suggests that Random Forest Classification performed the best
- AdaBoost performed a bit low of the models
- Scores of all models were close

```
##################################### Random Forest Classification in pyspark ##############################################
```

Classification Model with PySpark in Anaconda Jupyter Notebook on Local Machine

In [170]:
```
# Preparing data for using in pyspark

# For joining X and y and bring back to a .CSV file to be used in pyspark
result = df_class
result.head(10)
```

Out[170]:

	age	type_employer	fnlwgt	education_num	marital	sex	capital_gain	capital_loss	hr_per_week	income	...	relationship_Unmarried	relationship_Wife	country_Europe	country_Latin.and.South
0	39	2	77516	13	1	1	2174	0	40	0	...	0	0	0	
1	50	1	83311	13	0	1	0	0	13	0	...	0	0	0	
2	38	0	215646	9	2	1	0	0	40	0	...	0	0	0	
3	53	0	234721	7	0	1	0	0	40	0	...	0	0	0	
4	28	0	338409	13	0	0	0	0	40	0	...	0	1	0	
5	37	0	284582	14	0	0	0	0	40	0	...	0	1	0	
6	49	0	160187	5	0	0	0	0	16	0	...	0	0	0	
7	52	1	209642	9	0	1	0	0	45	1	...	0	0	0	
8	31	0	45781	14	1	0	14084	0	50	1	...	0	0	0	
9	42	0	159449	13	0	1	5178	0	40	1	...	0	0	0	

10 rows × 36 columns

In [171]:
```
result.shape
```

Out[171]: (30139, 36)

In [172]:
```
result.to_csv('classification_pyspark.csv', index = False)
```

In [173]:
```
import findspark
findspark.init()
findspark.find()
```

Out[173]:
```
'C:\\spark-3.1.1-bin-hadoop2.7'
```

In [174]:
```
from pyspark.sql import SparkSession
import pyspark
```

In [175]:
```
spark= SparkSession.builder.appName("Random Forest Classification").getOrCreate()
```

In [176]:
```
spark
```

Out[176]:

SparkSession - in-memory

SparkContext

Spark UI (http://DinarTriOSEducation:4043)

Version

v3.1.1

Master

local[*]

AppName

Random Forest Classification

In [177]:
```
from pyspark.ml.feature import VectorAssembler
from pyspark.sql.types import *
from pyspark.sql.functions import *
from pyspark.ml.classification import *
from pyspark.ml.evaluation import *
from pyspark.ml.tuning import CrossValidator, ParamGridBuilder
```

In [178]:
```
df_spc = spark.read.csv('classification_pyspark.csv',inferSchema=True, header=True)
```

In [179]:
```
df_spc.limit(10).toPandas()
```

Out[179]:

	age	type_employer	fnlwgt	education_num	marital	sex	capital_gain	capital_loss	hr_per_week	income	...	relationship_Unmarried	relationship_Wife	country_Europe	country_Latin.and.South
0	39	2	77516	13	1	1	2174	0	40	0	...	0	0	0	
1	50	1	83311	13	0	1	0	0	13	0	...	0	0	0	
2	38	0	215646	9	2	1	0	0	40	0	...	0	0	0	
3	53	0	234721	7	0	1	0	0	40	0	...	0	0	0	
4	28	0	338409	13	0	0	0	0	40	0	...	0	1	0	
5	37	0	284582	14	0	0	0	0	40	0	...	0	1	0	
6	49	0	160187	5	0	0	0	0	16	0	...	0	0	0	
7	52	1	209642	9	0	1	0	0	45	1	...	0	0	0	
8	31	0	45781	14	1	0	14084	0	50	1	...	0	0	0	
9	42	0	159449	13	0	1	5178	0	40	1	...	0	0	0	

10 rows × 36 columns

In [180]:
```
df_spc.printSchema()
```

```
root
 |-- age: integer (nullable = true)
 |-- type_employer: integer (nullable = true)
 |-- fnlwgt: integer (nullable = true)
 |-- education_num: integer (nullable = true)
 |-- marital: integer (nullable = true)
 |-- sex: integer (nullable = true)
 |-- capital_gain: integer (nullable = true)
 |-- capital_loss: integer (nullable = true)
 |-- hr_per_week: integer (nullable = true)
 |-- income: integer (nullable = true)
 |-- occupation_Armed-Forces: integer (nullable = true)
 |-- occupation_Craft-repair: integer (nullable = true)
 |-- occupation_Exec-managerial: integer (nullable = true)
 |-- occupation_Farming-fishing: integer (nullable = true)
 |-- occupation_Handlers-cleaners: integer (nullable = true)
 |-- occupation_Machine-op-inspct: integer (nullable = true)
 |-- occupation_Other-service: integer (nullable = true)
 |-- occupation_Priv-house-serv: integer (nullable = true)
 |-- occupation_Prof-specialty: integer (nullable = true)
 |-- occupation_Protective-serv: integer (nullable = true)
 |-- occupation_Sales: integer (nullable = true)
 |-- occupation_Tech-support: integer (nullable = true)
 |-- occupation_Transport-moving: integer (nullable = true)
 |-- relationship_Not-in-family: integer (nullable = true)
 |-- relationship_Other-relative: integer (nullable = true)
 |-- relationship_Own-child: integer (nullable = true)
 |-- relationship_Unmarried: integer (nullable = true)
 |-- relationship_Wife: integer (nullable = true)
 |-- country_Europe: integer (nullable = true)
 |-- country_Latin.and.South.America: integer (nullable = true)
 |-- country_North.America: integer (nullable = true)
 |-- country_South: integer (nullable = true)
 |-- race_Asian-Pac-Islander: integer (nullable = true)
 |-- race_Black: integer (nullable = true)
 |-- race_Other: integer (nullable = true)
 |-- race_White: integer (nullable = true)
```

In [181]:
```
print(df_spc.count())
print(len(df_spc.columns))
```

```
30139
36
```

In [182]:
```
df_spc.columns
```

Out[182]:
```
['age',
 'type_employer',
 'fnlwgt',
 'education_num',
 'marital',
 'sex',
 'capital_gain',
 'capital_loss',
 'hr_per_week',
 'income',
 'occupation_Armed-Forces',
 'occupation_Craft-repair',
 'occupation_Exec-managerial',
 'occupation_Farming-fishing',
 'occupation_Handlers-cleaners',
 'occupation_Machine-op-inspct',
 'occupation_Other-service',
 'occupation_Priv-house-serv',
 'occupation_Prof-specialty',
 'occupation_Protective-serv',
 'occupation_Sales',
 'occupation_Tech-support',
 'occupation_Transport-moving',
 'relationship_Not-in-family',
 'relationship_Other-relative',
 'relationship_Own-child',
 'relationship_Unmarried',
 'relationship_Wife',
 'country_Europe',
 'country_Latin.and.South.America',
 'country_North.America',
 'country_South',
 'race_Asian-Pac-Islander',
 'race_Black',
 'race_Other',
 'race_White']
```

In [207]:
```
df_spark = df_spc.toDF('age','type_employer','fnlwgt','education_num','marital','sex','capital_gain', 'capital_loss', 'hr_per_week','label',
 'occupation_Armed_Forces', 'occupation_Craft_repair','occupation_Exec_managerial', 'occupation_Farming_fishing',
 'occupation_Handlers_cleaners', 'occupation_Machine_op_inspct', 'occupation_Other_service', 'occupation_Priv_house_serv',
 'occupation_Prof_specialty', 'occupation_Protective_serv', 'occupation_Sales', 'occupation_Tech_support',
 'occupation_Transport_moving', 'relationship_Not_in_family', 'relationship_Other_relative', 'relationship_Own_child',
 'relationship_Unmarried', 'relationship_Wife', 'country_Europe', 'country_Latin_and_South_America', 'country_North_America',
 'country_South', 'race_Asian_Pac_Islander', 'race_Black', 'race_Other', 'race_White')
```

In [208]:
```
df_spark.columns
```

Out[208]:
```
['age',
 'type_employer',
 'fnlwgt',
 'education_num',
 'marital',
 'sex',
 'capital_gain',
 'capital_loss',
 'hr_per_week',
 'label',
 'occupation_Armed_Forces',
 'occupation_Craft_repair',
 'occupation_Exec_managerial',
 'occupation_Farming_fishing',
 'occupation_Handlers_cleaners',
 'occupation_Machine_op_inspct',
 'occupation_Other_service',
 'occupation_Priv_house_serv',
 'occupation_Prof_specialty',
 'occupation_Protective_serv',
 'occupation_Sales',
 'occupation_Tech_support',
 'occupation_Transport_moving',
 'relationship_Not_in_family',
 'relationship_Other_relative',
 'relationship_Own_child',
 'relationship_Unmarried',
 'relationship_Wife',
 'country_Europe',
 'country_Latin_and_South_America',
 'country_North_America',
 'country_South',
 'race_Asian_Pac_Islander',
 'race_Black',
 'race_Other',
 'race_White']
```

In [209]:
```
input_columns = ['age',
 'type_employer',
 'fnlwgt',
 'education_num',
 'marital',
 'sex',
 'capital_gain',
 'capital_loss',
 'hr_per_week',
 'occupation_Armed_Forces',
 'occupation_Craft_repair',
 'occupation_Exec_managerial',
 'occupation_Farming_fishing',
 'occupation_Handlers_cleaners',
 'occupation_Machine_op_inspct',
 'occupation_Other_service',
 'occupation_Priv_house_serv',
 'occupation_Prof_specialty',
 'occupation_Protective_serv',
 'occupation_Sales',
 'occupation_Tech_support',
 'occupation_Transport_moving',
 'relationship_Not_in_family',
 'relationship_Other_relative',
 'relationship_Own_child',
 'relationship_Unmarried',
 'relationship_Wife',
 'country_Europe',
 'country_Latin_and_South_America',
 'country_North_America',
 'country_South',
 'race_Asian_Pac_Islander',
 'race_Black',
 'race_Other',
 'race_White' ]
```

In [210]:
```
dependent_var = 'label'
```

In [211]:
```
assembler = VectorAssembler(inputCols=input_columns, outputCol="features")
feature_vec=assembler.transform(df_spark).select('features',dependent_var)
feature_vec.show(5)
```

```
+--------------------+-----+
|            features|label|
+--------------------+-----+
|(35,[0,1,2,3,4,5,...|    0|
|(35,[0,1,2,3,5,8,...|    0|
|(35,[0,2,3,4,5,8,...|    0|
|(35,[0,2,3,5,8,13...|    0|
|(35,[0,2,3,8,17,2...|    0|
+--------------------+-----+
only showing top 5 rows
```

In [212]:
```
# Split the data into train and test sets
train_data, test_data = feature_vec.randomSplit([.80,.20],seed=0)
```

In [ ]:
```
```

In [213]:
```
# Let us add the parameters of choice
classifier_rfc = RandomForestClassifier()
paramGridRfc = (ParamGridBuilder() \
                .addGrid(classifier_rfc.maxDepth, [2, 5, 10]) \
                .build())

crossval_rfc = CrossValidator(estimator=classifier_rfc,
                              estimatorParamMaps=paramGridRfc,
                              evaluator=BinaryClassificationEvaluator(),
                              numFolds=2)
fitModel_rfc = crossval_rfc.fit(train_data)
bestModel_rfc = fitModel_rfc.bestModel
featureImportances = bestModel_rfc.featureImportances.toArray()
print("Feature Importances:\n ", featureImportances)
```

```
Feature Importances:
  [7.69336628e-02 8.39917794e-03 1.19365926e-02 1.81885692e-01
 2.50049744e-01 2.14331244e-02 1.61140535e-01 4.41334030e-02
 5.99494910e-02 0.00000000e+00 2.29683006e-03 2.77719634e-02
 2.50194588e-03 1.67385283e-03 1.40505112e-03 9.22067202e-03
 3.84047187e-05 1.20476613e-02 1.21550541e-03 1.82074208e-03
 2.08666555e-03 1.87715376e-03 3.42998641e-02 3.48814734e-03
 4.45704181e-02 1.11757483e-02 1.63918310e-02 1.23708213e-03
 8.55019194e-04 2.36010528e-03 6.13594221e-04 7.76931127e-04
 1.65417120e-03 3.75586822e-04 2.38363025e-03]
```

In [220]:
```
predictions = fitModel_rfc.transform(test_data)
predictions
```

Out[220]:
```
DataFrame[features: vector, label: int, rawPrediction: vector, probability: vector, prediction: double]
```

In [224]:
```
accuracy = BinaryClassificationEvaluator(metricName='areaUnderROC').evaluate(predictions)
print("\nAccuracy: ", accuracy)
```

```
Accuracy:  0.9022708533213222
```

As the AUC value in 0.9023 the project performed really good.

Regression and Classification Models with PySpark in Online Hadoop Environment

```
########################################Random Forest Regression ##############################################################
```

In [1]:
```
import os
import sys

os.environ["SPARK_HOME"] = "/usr/hdp/current/spark2-client"
os.environ["PYLIB"] = os.environ["SPARK_HOME"] + "/python/lib"
# In below two lines, use /usr/bin/python2.7 if you want to use Python 2
os.environ["PYSPARK_PYTHON"] = "/usr/local/anaconda/bin/python"
os.environ["PYSPARK_DRIVER_PYTHON"] = "/usr/local/anaconda/bin/python"
sys.path.insert(0, os.environ["PYLIB"] +"/py4j-0.10.4-src.zip")
sys.path.insert(0, os.environ["PYLIB"] +"/pyspark.zip")
```

In [2]:
```
from pyspark.sql import SparkSession
```

In [3]:
```
spark= SparkSession.builder.appName("Random Forest Regression and classification").getOrCreate()
spark
```

Out[3]:
```
<pyspark.sql.session.SparkSession at 0x7fa370061b70>
```

In [4]:
```
from pyspark.ml.feature import VectorAssembler
from pyspark.sql.types import *
from pyspark.sql.functions import *
from pyspark.ml.regression import *
from pyspark.ml.evaluation import *
from pyspark.ml.tuning import CrossValidator, ParamGridBuilder
```

In [5]:
```
df = spark.read.csv('Data/regression_pyspark.csv', inferSchema=True, header=True)
```

In [6]:
```
df.limit(10).toPandas()
```

Out[6]:

	Country	Year	Adult Mortality	infant deaths	Alcohol	percentage expenditure	Hepatitis B	Measles	BMI	under-five deaths	...	Diphtheria	HIV/AIDS	GDP	Population	thinness 1-19 years	thinness 5-9 years	Income composition of resources	Schooling	Status_D
0	0	15	263.0	62	0.01	71.279624	65.0	1154	19.1	83	...	65.0	0.1	584.259210	33736494.0	17.2	17.3	0.479	10.1	
1	0	14	271.0	64	0.01	73.523582	62.0	492	18.6	86	...	62.0	0.1	612.696514	327582.0	17.5	17.5	0.476	10.0	
2	0	13	268.0	66	0.01	73.219243	64.0	430	18.1	89	...	64.0	0.1	631.744976	31731688.0	17.7	17.7	0.470	9.9	
3	0	12	272.0	69	0.01	78.184215	67.0	2787	17.6	93	...	67.0	0.1	669.959000	3696958.0	17.9	18.0	0.463	9.8	
4	0	11	275.0	71	0.01	7.097109	68.0	3013	17.2	97	...	68.0	0.1	63.537231	2978599.0	18.2	18.2	0.454	9.5	
5	0	10	279.0	74	0.01	79.679367	66.0	1989	16.7	102	...	66.0	0.1	553.328940	2883167.0	18.4	18.4	0.448	9.2	
6	0	9	281.0	77	0.01	56.762217	63.0	2861	16.2	106	...	63.0	0.1	445.893298	284331.0	18.6	18.7	0.434	8.9	
7	0	8	287.0	80	0.03	25.873925	64.0	1599	15.7	110	...	64.0	0.1	373.361116	2729431.0	18.8	18.9	0.433	8.7	
8	0	7	295.0	82	0.02	10.910156	63.0	1141	15.2	113	...	63.0	0.1	369.835796	26616792.0	19.0	19.1	0.415	8.4	
9	0	6	295.0	84	0.03	17.171518	64.0	1990	14.7	116	...	58.0	0.1	272.563770	2589345.0	19.2	19.3	0.405	8.1	

10 rows × 22 columns

In [7]:
```
df.printSchema()
```

```
root
 |-- Country: integer (nullable = true)
 |-- Year: integer (nullable = true)
 |-- Adult Mortality: double (nullable = true)
 |-- infant deaths: integer (nullable = true)
 |-- Alcohol: double (nullable = true)
 |-- percentage expenditure: double (nullable = true)
 |-- Hepatitis B: double (nullable = true)
 |-- Measles : integer (nullable = true)
 |--  BMI : double (nullable = true)
 |-- under-five deaths : integer (nullable = true)
 |-- Polio: double (nullable = true)
 |-- Total expenditure: double (nullable = true)
 |-- Diphtheria : double (nullable = true)
 |--  HIV/AIDS: double (nullable = true)
 |-- GDP: double (nullable = true)
 |-- Population: double (nullable = true)
 |--  thinness  1-19 years: double (nullable = true)
 |--  thinness 5-9 years: double (nullable = true)
 |-- Income composition of resources: double (nullable = true)
 |-- Schooling: double (nullable = true)
 |-- Status_Developing: integer (nullable = true)
 |-- Life expectancy : double (nullable = true)
```

In [8]:
```
print(df.count())
print(len(df.columns))
```

```
2938
22
```

In [9]:
```
df.columns
```

Out[9]:
```
['Country',
 'Year',
 'Adult Mortality',
 'infant deaths',
 'Alcohol',
 'percentage expenditure',
 'Hepatitis B',
 'Measles ',
 ' BMI ',
 'under-five deaths ',
 'Polio',
 'Total expenditure',
 'Diphtheria ',
 ' HIV/AIDS',
 'GDP',
 'Population',
 ' thinness  1-19 years',
 ' thinness 5-9 years',
 'Income composition of resources',
 'Schooling',
 'Status_Developing',
 'Life expectancy ']
```

In [10]:
```
input_columns = ['Country',
 'Year',
 'Adult Mortality',
 'infant deaths',
 'Alcohol',
 'percentage expenditure',
 'Hepatitis B',
 'Measles ',
 ' BMI ',
 'under-five deaths ',
 'Polio',
 'Total expenditure',
 'Diphtheria ',
 ' HIV/AIDS',
 'GDP',
 'Population',
 ' thinness  1-19 years',
 ' thinness 5-9 years',
 'Income composition of resources',
 'Schooling',
 'Status_Developing']
```

In [11]:
```
dependent_var = 'Life expectancy '
```

In [12]:
```
assembler = VectorAssembler(inputCols=input_columns, outputCol="features")
feature_vec=assembler.transform(df).select('features',dependent_var)
feature_vec.show(5)
```

```
+--------------------+----------------+
|            features|Life expectancy |
+--------------------+----------------+
|[0.0,15.0,263.0,6...|            65.0|
|[0.0,14.0,271.0,6...|            59.9|
|[0.0,13.0,268.0,6...|            59.9|
|[0.0,12.0,272.0,6...|            59.5|
|[0.0,11.0,275.0,7...|            59.2|
+--------------------+----------------+
only showing top 5 rows
```

In [13]:
```
# Split the data into train and test sets
train_data, test_data = feature_vec.randomSplit([.80,.20],seed=0)
```

In [14]:
```
from pyspark.ml.regression import RandomForestRegressor
r_model = RandomForestRegressor(labelCol=dependent_var, featuresCol="features",
                        maxDepth=15, minInfoGain=0.001, seed=0, numTrees=110)
rfModel = r_model.fit(train_data)

#Evaulation of the Model
predictions = rfModel.transform(test_data)

from pyspark.ml.evaluation import RegressionEvaluator
evaluator = RegressionEvaluator(labelCol=dependent_var,metricName='r2')
evaluator.evaluate(predictions)
```

Out[14]:
```
0.9628827489068111
```

In [15]:
```
evaluator_RMSE = RegressionEvaluator(labelCol=dependent_var,metricName='rmse')
evaluator_RMSE.evaluate(predictions)
```

Out[15]:
```
1.9108899342203498
```

In [16]:
```
evaluator_MSE = RegressionEvaluator(labelCol=dependent_var,metricName='mse')
evaluator_MSE.evaluate(predictions)
```

Out[16]:
```
3.6515003407046525
```

In [17]:
```
evaluator_MAE = RegressionEvaluator(labelCol=dependent_var,metricName='mae')
evaluator_MAE.evaluate(predictions)
```

Out[17]:
```
1.1800372208612373
```

In [18]:
```
#Grid Search
from pyspark.ml.tuning import ParamGridBuilder, CrossValidator
g_model = RandomForestRegressor(labelCol=dependent_var, featuresCol="features",
                        minInfoGain=0.001, seed=0)
paramGrid = (ParamGridBuilder()\
             .addGrid(g_model.maxDepth,[14,15,16])\
             .addGrid(g_model.numTrees,[100,110,120])\
             .build())

# Create 4-fold CrossValidator
cv = CrossValidator(estimator=g_model, estimatorParamMaps=paramGrid, evaluator=evaluator, numFolds=4)

cvModel = cv.fit(train_data)
```

In [19]:
```
#Get the best model
rf_bestModel = cvModel.bestModel
```

In [20]:

```
# Feature Importance
# Estimate of the importance of each feature
# Each feature's importance is the average of its importance across all trees
# In the ensemble the importance vector is normalized to sum up to 1.
print(" ")
print('\033[1m' + "Feature Importance"+ '\033[0m')
print("(Scores Up to 1)")
print("Lowest score signifies the least importance")
print(" ")
RF_FeatureImportance = rf_bestModel.featureImportances.toArray()
#Convert from numpy array to list
important_scores = []
for x in RF_FeatureImportance:
    important_scores.append(float(x))

# Then zip with input_columns list and create a df
result_is = spark.createDataFrame(zip(input_columns, important_scores), schema=['feature', 'score'])
print(result_is.orderBy(result_is["score"].desc()).show(truncate=False))

# Make predictions
# PySpark will automatically use the best model when we call fitmodel
predictions_fn = cvModel.transform(test_data)

# Then let us apply it

r2_rf_pys = evaluator.evaluate(predictions_fn)
print(r2_rf_pys)
```

Feature Importance
(Scores Up to 1)
Lowest score signifies the least importance

```
+------------------------------+--------------------+
|feature                       |score               |
+------------------------------+--------------------+
| HIV/AIDS                     |0.2800681489734736  |
|Income composition of resources|0.2309916068868801  |
|Adult Mortality               |0.18060409546748368 |
|Schooling                     |0.07423916165506116 |
| BMI                          |0.053087054092978994|
|under-five deaths             |0.02477786961574394 |
| thinness 5-9 years           |0.02409517636340881 |
|Polio                         |0.019811351173397523|
|infant deaths                 |0.01950250606779067 |
| thinness  1-19 years         |0.015634094141502086|
|Diphtheria                    |0.010932942980514851|
```

```
|Status_Developing              |0.010286727902517214|
|Alcohol                        |0.009666914147932975|
|Year                           |0.009116300035461681|
|GDP                            |0.007527444761399395|
|Country                        |0.007388960152735073|
|Total expenditure              |0.006065317556911355|
|Measles                        |0.004861253800984754|
|percentage expenditure         |0.004213634770075251|
|Population                     |0.003904648510566814|
+-------------------------------+--------------------+
only showing top 20 rows

None
0.9631457106934475
```

The model with PySpark performed almost same as it performed on the local machine with sklearn.

Random Forest Classification

In [23]:
```
df_spc = spark.read.csv('Data/classification_pyspark.csv',inferSchema=True, header=True)
```

In [24]:
```
df_spc.limit(10).toPandas()
```

Out[24]:

	age	type_employer	fnlwgt	education_num	marital	sex	capital_gain	capital_loss	hr_per_week	income	...	relationship_Unmarried	relationship_Wife	country_Europe	country_Latin.and.South
0	39	2	77516	13	1	1	2174	0	40	0	...	0	0	0	
1	50	1	83311	13	0	1	0	0	13	0	...	0	0	0	
2	38	0	215646	9	2	1	0	0	40	0	...	0	0	0	
3	53	0	234721	7	0	1	0	0	40	0	...	0	0	0	
4	28	0	338409	13	0	0	0	0	40	0	...	0	1	0	
5	37	0	284582	14	0	0	0	0	40	0	...	0	1	0	
6	49	0	160187	5	0	0	0	0	16	0	...	0	0	0	
7	52	1	209642	9	0	1	0	0	45	1	...	0	0	0	
8	31	0	45781	14	1	0	14084	0	50	1	...	0	0	0	
9	42	0	159449	13	0	1	5178	0	40	1	...	0	0	0	

10 rows × 36 columns

In [25]:
```
df_spc.printSchema()
```

```
root
 |-- age: integer (nullable = true)
 |-- type_employer: integer (nullable = true)
 |-- fnlwgt: integer (nullable = true)
 |-- education_num: integer (nullable = true)
 |-- marital: integer (nullable = true)
 |-- sex: integer (nullable = true)
 |-- capital_gain: integer (nullable = true)
 |-- capital_loss: integer (nullable = true)
 |-- hr_per_week: integer (nullable = true)
 |-- income: integer (nullable = true)
 |-- occupation_Armed-Forces: integer (nullable = true)
 |-- occupation_Craft-repair: integer (nullable = true)
 |-- occupation_Exec-managerial: integer (nullable = true)
 |-- occupation_Farming-fishing: integer (nullable = true)
 |-- occupation_Handlers-cleaners: integer (nullable = true)
 |-- occupation_Machine-op-inspct: integer (nullable = true)
 |-- occupation_Other-service: integer (nullable = true)
 |-- occupation_Priv-house-serv: integer (nullable = true)
 |-- occupation_Prof-specialty: integer (nullable = true)
 |-- occupation_Protective-serv: integer (nullable = true)
 |-- occupation_Sales: integer (nullable = true)
 |-- occupation_Tech-support: integer (nullable = true)
 |-- occupation_Transport-moving: integer (nullable = true)
 |-- relationship_Not-in-family: integer (nullable = true)
 |-- relationship_Other-relative: integer (nullable = true)
 |-- relationship_Own-child: integer (nullable = true)
 |-- relationship_Unmarried: integer (nullable = true)
 |-- relationship_Wife: integer (nullable = true)
 |-- country_Europe: integer (nullable = true)
 |-- country_Latin.and.South.America: integer (nullable = true)
 |-- country_North.America: integer (nullable = true)
 |-- country_South: integer (nullable = true)
 |-- race_Asian-Pac-Islander: integer (nullable = true)
 |-- race_Black: integer (nullable = true)
 |-- race_Other: integer (nullable = true)
 |-- race_White: integer (nullable = true)
```

In [26]:
```
print(df_spc.count())
print(len(df_spc.columns))
```

```
30139
36
```

In [27]:
```
df_spc.columns
```

Out[27]:
```
['age',
 'type_employer',
 'fnlwgt',
 'education_num',
 'marital',
 'sex',
 'capital_gain',
 'capital_loss',
 'hr_per_week',
 'income',
 'occupation_Armed-Forces',
 'occupation_Craft-repair',
 'occupation_Exec-managerial',
 'occupation_Farming-fishing',
 'occupation_Handlers-cleaners',
 'occupation_Machine-op-inspct',
 'occupation_Other-service',
 'occupation_Priv-house-serv',
 'occupation_Prof-specialty',
 'occupation_Protective-serv',
 'occupation_Sales',
 'occupation_Tech-support',
 'occupation_Transport-moving',
 'relationship_Not-in-family',
 'relationship_Other-relative',
 'relationship_Own-child',
 'relationship_Unmarried',
 'relationship_Wife',
 'country_Europe',
 'country_Latin.and.South.America',
 'country_North.America',
 'country_South',
 'race_Asian-Pac-Islander',
 'race_Black',
 'race_Other',
 'race_White']
```

In [29]:

```
df_spark = df_spc.toDF('age','type_employer','fnlwgt','education_num','marital','sex','capital_gain', 'capital_loss', 'hr_per_week','label',
 'occupation_Armed_Forces', 'occupation_Craft_repair','occupation_Exec_managerial', 'occupation_Farming_fishing',
 'occupation_Handlers_cleaners', 'occupation_Machine_op_inspct', 'occupation_Other_service', 'occupation_Priv_house_serv',
 'occupation_Prof_specialty', 'occupation_Protective_serv', 'occupation_Sales', 'occupation_Tech_support',
 'occupation_Transport_moving', 'relationship_Not_in_family', 'relationship_Other_relative', 'relationship_Own_child',
 'relationship_Unmarried', 'relationship_Wife', 'country_Europe', 'country_Latin_and_South_America', 'country_North_America',
 'country_South', 'race_Asian_Pac_Islander', 'race_Black', 'race_Other', 'race_White')
```

In [30]:
```
df_spark.columns
```

Out[30]:
```
['age',
 'type_employer',
 'fnlwgt',
 'education_num',
 'marital',
 'sex',
 'capital_gain',
 'capital_loss',
 'hr_per_week',
 'label',
 'occupation_Armed_Forces',
 'occupation_Craft_repair',
 'occupation_Exec_managerial',
 'occupation_Farming_fishing',
 'occupation_Handlers_cleaners',
 'occupation_Machine_op_inspct',
 'occupation_Other_service',
 'occupation_Priv_house_serv',
 'occupation_Prof_specialty',
 'occupation_Protective_serv',
 'occupation_Sales',
 'occupation_Tech_support',
 'occupation_Transport_moving',
 'relationship_Not_in_family',
 'relationship_Other_relative',
 'relationship_Own_child',
 'relationship_Unmarried',
 'relationship_Wife',
 'country_Europe',
 'country_Latin_and_South_America',
 'country_North_America',
 'country_South',
 'race_Asian_Pac_Islander',
 'race_Black',
 'race_Other',
 'race_White']
```

In [31]:
```
input_columns = ['age',
 'type_employer',
 'fnlwgt',
 'education_num',
 'marital',
 'sex',
 'capital_gain',
 'capital_loss',
 'hr_per_week',
 'occupation_Armed_Forces',
 'occupation_Craft_repair',
 'occupation_Exec_managerial',
 'occupation_Farming_fishing',
 'occupation_Handlers_cleaners',
 'occupation_Machine_op_inspct',
 'occupation_Other_service',
 'occupation_Priv_house_serv',
 'occupation_Prof_specialty',
 'occupation_Protective_serv',
 'occupation_Sales',
 'occupation_Tech_support',
 'occupation_Transport_moving',
 'relationship_Not_in_family',
 'relationship_Other_relative',
 'relationship_Own_child',
 'relationship_Unmarried',
 'relationship_Wife',
 'country_Europe',
 'country_Latin_and_South_America',
 'country_North_America',
 'country_South',
 'race_Asian_Pac_Islander',
 'race_Black',
 'race_Other',
 'race_White' ]
```

In [32]:
```
dependent_var = 'label'
```

In [33]:
```
assembler = VectorAssembler(inputCols=input_columns, outputCol="features")
feature_vec=assembler.transform(df_spark).select('features',dependent_var)
feature_vec.show(5)
```

```
+--------------------+-----+
|            features|label|
+--------------------+-----+
|(35,[0,1,2,3,4,5,...|    0|
|(35,[0,1,2,3,5,8,...|    0|
|(35,[0,2,3,4,5,8,...|    0|
|(35,[0,2,3,5,8,13...|    0|
|(35,[0,2,3,8,17,2...|    0|
+--------------------+-----+
only showing top 5 rows
```

In [34]:
```
# Split the data into train and test sets
train_data, test_data = feature_vec.randomSplit([.80,.20],seed=0)
```

In [36]:
```
from pyspark.ml.feature import VectorAssembler
from pyspark.sql.types import *
from pyspark.sql.functions import *
from pyspark.ml.classification import *
from pyspark.ml.evaluation import *
from pyspark.ml.tuning import CrossValidator, ParamGridBuilder
```

In [37]:
```
# Let us add the parameters of choice
classifier_rfc = RandomForestClassifier()
paramGridRfc = (ParamGridBuilder() \
                .addGrid(classifier_rfc.maxDepth, [2, 5, 10]) \
                .build())

crossval_rfc = CrossValidator(estimator=classifier_rfc,
                              estimatorParamMaps=paramGridRfc,
                              evaluator=BinaryClassificationEvaluator(),
                              numFolds=2)
fitModel_rfc = crossval_rfc.fit(train_data)
bestModel_rfc = fitModel_rfc.bestModel
featureImportances = bestModel_rfc.featureImportances.toArray()
print("Feature Importances:\n ", featureImportances)
```

```
Feature Importances:
  [9.54698706e-02 8.26704946e-03 1.47975686e-02 1.65025952e-01
 2.49676161e-01 3.39127290e-02 1.68305101e-01 3.12779128e-02
 4.58002345e-02 0.00000000e+00 3.53626696e-03 2.86009313e-02
 4.41023080e-03 1.90498974e-03 2.58025969e-03 7.08905908e-03
 4.29764649e-05 3.45027216e-02 8.66871681e-04 2.60298261e-03
 2.65635442e-03 1.08715046e-03 3.34108568e-02 2.50976947e-03
 1.04737949e-02 1.21018098e-02 2.40403443e-02 1.39509943e-03
 3.19505348e-03 2.64807688e-03 6.21728374e-04 1.57287344e-03
 2.71690873e-03 5.84221601e-04 2.31608921e-03]
```

In [38]:
```
predictions = fitModel_rfc.transform(test_data)
predictions
```

Out[38]:
```
DataFrame[features: vector, label: int, rawPrediction: vector, probability: vector, prediction: double]
```

In [39]:
```
accuracy = BinaryClassificationEvaluator(metricName='areaUnderROC').evaluate(predictions)
print("\nAccuracy: ", accuracy)
```

```
Accuracy:  0.9072500398099641
```

As AUC is 0.9073, we can say that the model performed pretty well.

Conclusion

- Random Forest was found to be the best of the models
- Trying GridSearch is compute resource intensive especially for SVM
- In-depth understanding of parameter tuning is felt
- For KNN regression it performed very poorly when the features were not scaled
- PySpark performed the same on Anaconda local installation