Gapminder World (Building a mchine learning model to pedict life expectancy)

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Introduction

> Gapminder has collected a lot of information about how people live heir lives in different countries, racked across the years, and on a umber of different indicators. For this project I selected child mortality, income, life expectancy, and population indicators.
>
> I am going to clean and merge these indicators into one DataFrame then build a mahine learning model to predict life expectancy.

Data Wrangling

Asessing and cleaning Data

In [1]:

```
# Importing packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import datetime as dt
sns.set_style('darkgrid')

# Loading data and printing out a few lines.
df1 = pd.read_csv('child_mortality_0_5_year_olds_dying_per_1000_born.csv')
df2 = pd.read_csv('income_per_person_gdppercapita_ppp_inflation_adjusted (1).csv')
df3 = pd.read_csv('life_expectancy_years (1).csv')
df4 = pd.read_csv('population_total.csv')
```

In [2]:

```
# Transposing year rows and renaming the value columns
data_files = [df1, df2, df3, df4]
names = ['child_mortality','income','life_expectancy','population']
i = 0
names = ['child_mortality','income','life_expectancy','population']
for df in data_files:
    df = df.melt(['country'], var_name='year')
    df = df.rename(columns = {'value': names[i]}, inplace = False)
    data_files[i] = df
    i += 1
df1, df2, df3, df4 = data_files
```

In [3]:

```
df1.head() # Checking
```

Out[3]:

	country	year	child_mortality
0	Afghanistan	1800	469.0
1	Albania	1800	375.0
2	Algeria	1800	460.0
3	Andorra	1800	NaN
4	Angola	1800	486.0

In [4]:

```
# Merging data files in one data file
dfm1= pd.merge(df1,df2,on=['year', 'country'], how= 'left')
dfm2 = pd.merge(dfm1,df3,on=['year', 'country'], how= 'left')
df = pd.merge(dfm2,df4,on=['year', 'country'], how= 'left')
```

In [5]:

```
df.head() #checking
```

Out[5]:

	country	year	child_mortality	income	life_expectancy	population
0	Afghanistan	1800	469.0	603.0	28.2	3280000
1	Albania	1800	375.0	667.0	35.4	400000
2	Algeria	1800	460.0	715.0	28.8	2500000
3	Andorra	1800	NaN	1200.0	NaN	2650
4	Angola	1800	486.0	618.0	27.0	1570000

In [6]:

```
# Getting the dataset information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 58695 entries, 0 to 58694
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   country          58695 non-null  object
 1   year             58695 non-null  object
 2   child_mortality  57045 non-null  float64
 3   income           46513 non-null  float64
 4   life_expectancy  55528 non-null  float64
 5   population       58695 non-null  int64
dtypes: float64(3), int64(1), object(2)
memory usage: 3.1+ MB
```

Data has 58695 rows and 4 columns, child mortality represnets dead childs below age 5 per 1.000 births so it should be converted into intg.

In [7]:

```
# Checking for null values and duplicates
df.isnull().sum()
```

Out[7]:

```
country                0
year                   0
child_mortality     1650
income             12182
life_expectancy     3167
population             0
dtype: int64
```

Data has alot of null values that shouldn't be dropped because number of countries will be decreased from 195 to 187! It is better to fill nun values with zeros.

In [8]:

```
# Dealing with null values
df = df.fillna(df.mean())
```

In [9]:

```
# Checking
df.isnull().sum()
```

Out[9]:

```
country            0
year               0
child_mortality    0
income             0
life_expectancy    0
population         0
dtype: int64
```

In [10]:

```
# Changing the type of the child mortality column data into intg
df.child_mortality=df.child_mortality.astype(int)
```

In [11]:

```
# Checking
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 58695 entries, 0 to 58694
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   country          58695 non-null  object
 1   year             58695 non-null  object
 2   child_mortality  58695 non-null  int32
 3   income           58695 non-null  float64
 4   life_expectancy  58695 non-null  float64
 5   population       58695 non-null  int64
dtypes: float64(2), int32(1), int64(1), object(2)
memory usage: 2.9+ MB
```

In [12]:

```
# Checking for duplicate rows
df.duplicated().sum()
```

Out[12]: 0

It is clear that data has no toataly duplicate rows

In [13]:

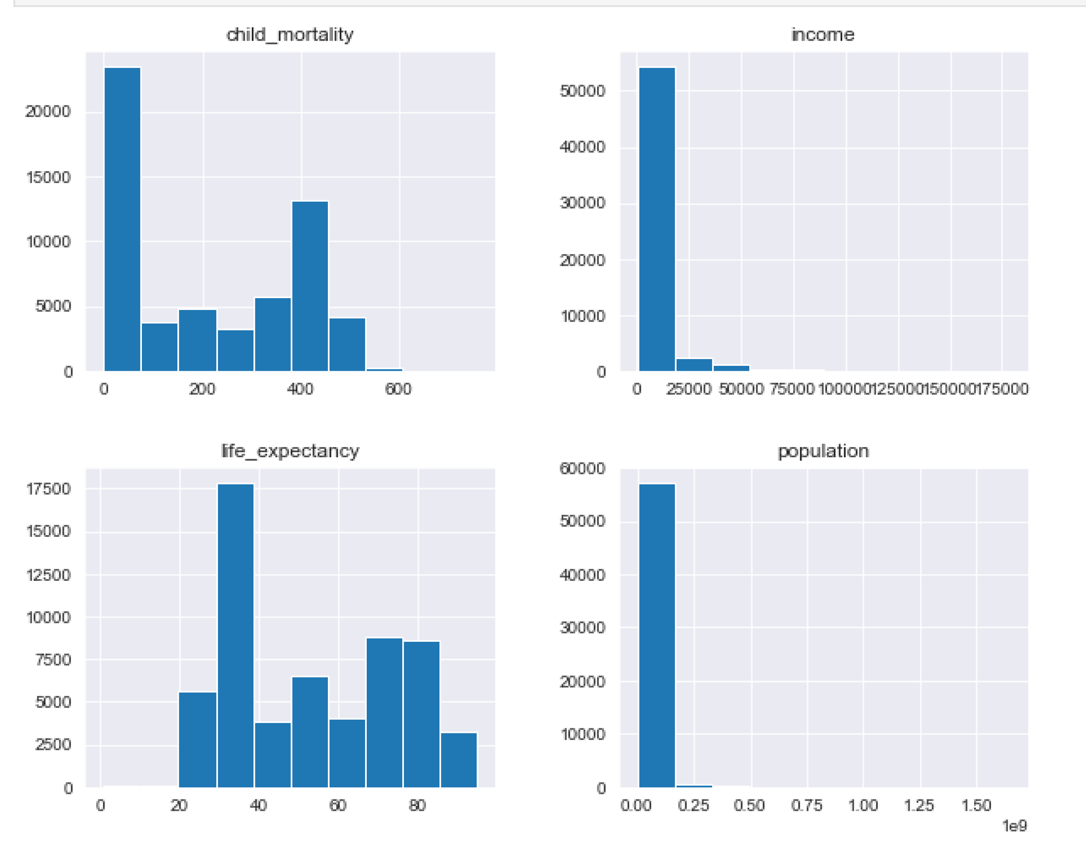
```
# Getting some statistical info
df.describe()
```

Out[13]:

	child_mortality	income	life_expectancy	population
count	58695.000000	58695.000000	58695.000000	5.869500e+04
mean	209.415436	6428.630340	53.036046	2.328525e+07
std	182.800302	11886.813967	21.074137	1.007173e+08
min	0.000000	245.000000	1.010000	6.450000e+02
25%	17.000000	1050.000000	32.600000	4.220000e+05
50%	200.000000	2730.000000	53.036046	2.610000e+06
75%	400.500000	6428.630340	73.500000	1.080000e+07
max	756.000000	179000.000000	94.800000	1.650000e+09

In [14]:

```
# Visulizing data
df.hist(figsize= (10,8));
```



There is no outliers

In [15]:

```
# Correlation
df.corr()
```

Out[15]:

	child_mortality	income	life_expectancy	population
child_mortality	1.000000	-0.436589	-0.942181	-0.149972
income	-0.436589	1.000000	0.434868	0.037429
life_expectancy	-0.942181	0.434868	1.000000	0.167494
population	-0.149972	0.037429	0.167494	1.000000

It seems that there is a correlation between income/life expectancy and child mortality (inverse relation).

Building a machine learning model to predict life expectancy

In [16]:

```
# define features and target
y = df['life_expectancy']
X = df[['child_mortality', 'income', 'population']]

# Import Regressors
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet
from sklearn.ensemble import RandomForestRegressor

#import pipline
from sklearn.pipeline import make_pipeline

# Import mean_squared_error as MSE
from sklearn.metrics import mean_squared_error as MSE

# Import train_test_split
from sklearn.model_selection import train_test_split
# Split data into 80% train and 20% test
X_train, X_test, y_train, y_test= train_test_split(X, y,
test_size=0.2,
random_state=3)
```

In [17]:

```
# Instantiate regressors
dt = DecisionTreeRegressor()
reg = LinearRegression()
ridge = Ridge()
lasso = Lasso()
elastic = ElasticNet()
rf = RandomForestRegressor()

Regressors = [('Linear Regression', reg),
('Decision Tree', dt),
('Ridge', ridge),
('Lasso', lasso),
('Elastic',elastic),
('Random Forest',rf)]
```

In [20]:

```
for reg_name, reg in Regressors:
    #fit reg to the training set
    reg.fit(X_train, y_train)
    # Predict the labels of the test set
    y_pred = reg.predict(X_test)
    # Evaluate the test-set RMSE of reg on the test set
    print('{:s} : {:.3f}'.format(reg_name, MSE(y_test, y_pred)**.5))
```

```
Linear Regression : 6.922
Decision Tree : 3.408
Ridge : 6.922
Lasso : 6.922
Elastic : 6.922
Random Forest : 2.497
```

Building a tuned Decision Tree model to predict life expectancy

In [23]:

```
from sklearn.model_selection import RandomizedSearchCV
param_dist = {"max_depth": [3, None],
              "max_features": np.arange(1, 3),
              "min_samples_leaf": np.arange(1, 9)}

# Instantiate a Decision Tree classifier: tree
tree = DecisionTreeRegressor(random_state= 3)
# Instantiate the RandomizedSearchCV object: tree_cv
tree_cv = RandomizedSearchCV(tree, param_dist, cv=5)

# Instantiate the pipline
pl = make_pipeline(tree_cv)
# Fit 'pl' to the training-set
pl.fit(X_train, y_train)
# Predict test-set labels
y_pred = pl.predict(X_test)
# Compute test-set RMSE
rmse_pl = MSE(y_test, y_pred)**.5
print(rmse_pl)
```

```
3.1038738979845633
```

Building a VotingRegressor model to predict life expectancy

In [22]:

```
#import the voting regressor
from sklearn.ensemble import VotingRegressor
vc = VotingRegressor(estimators=Regressors)

#instantiate a pipeline
pl = make_pipeline(vc)

# Fit 'pl' to the training-set
pl.fit(X_train, y_train)
# Predict test-set labels
y_pred = pl.predict(X_test)
# Compute test-set RMSE
rmse_pl = MSE(y_test, y_pred)**.5
print(rmse_pl)
```

```
4.969262401479132
```

Building a RandomForestRegressor model to predict life expectancy

In [27]:

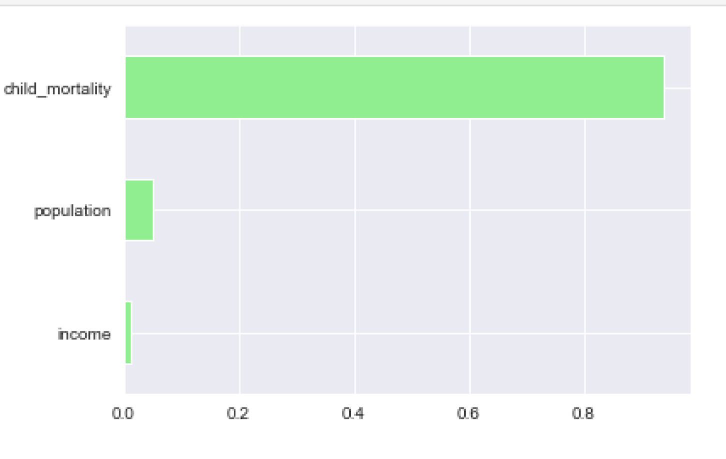
```
# Instantiate a random forests regressor 'rf'
rf = RandomForestRegressor(random_state= 3)

# Instantiate a pipeline
pl = make_pipeline(rf)
# Fit 'pl' to the training-set
pl.fit(X_train, y_train)
# Predict test-set labels
y_pred = pl.predict(X_test)
# Compute test-set RMSE
rmse_pl = MSE(y_test, y_pred)**.5
print(rmse_pl)
```

```
2.5078964685897756
```

In [131…

```
# Create a pd.Series of features importances
importances_rf = pd.Series(rf.feature_importances_, index = X.columns)
# Sort importances_rf
sorted_importances_rf = importances_rf.sort_values()
# Make a horizontal bar plot
sorted_importances_rf.plot(kind='barh', color='lightgreen'); plt.show()
```



Building a BaggingRegressor model to predict life expectancy

In [72]:

```
# Imort the BaggingRegressor
from sklearn.ensemble import BaggingRegressor
# Instantiate a Regrssion-tree 'dt'
dt = DecisionTreeRegressor(max_depth=4, min_samples_leaf=0.16, random_state=3)
# Instantiate a BaggingRegressor 'br'
br = BaggingRegressor(base_estimator=dt, n_estimators=300, n_jobs=-1)

# Instantiate a pipeline
pl = make_pipeline(br)

# Fit 'pl' to the training-set
pl.fit(X_train, y_train)
# Predict test-set labels
y_pred = pl.predict(X_test)
# Compute test-set RMSE
rmse_pl = MSE(y_test, y_pred)**.5
print(rmse_pl)
```

AdaBoost and GradientBoosting Regressors

In [128…

```
from sklearn.ensemble import  AdaBoostRegressor
dt = DecisionTreeRegressor(max_depth=1, random_state=3)
adb_reg = AdaBoostRegressor(base_estimator=dt, n_estimators=100)

pl = make_pipeline(adb_reg)

# Fit 'pl' to the training-set
pl.fit(X_train, y_train)
# Predict test-set labels
y_pred = pl.predict(X_test)
# Compute test-set RMSE
rmse_pl = MSE(y_test, y_pred)**.5
print(rmse_pl)
```

```
9.045225987049681
```

In [129…

```
from sklearn.ensemble import  GradientBoostingRegressor
gbr = GradientBoostingRegressor(n_estimators=300, max_depth=1, random_state=3)

pl = make_pipeline(gbr)

# Fit 'pl' to the training-set
pl.fit(X_train, y_train)
# Predict test-set labels
y_pred = pl.predict(X_test)
# Compute test-set RMSE
rmse_pl = MSE(y_test, y_pred)**.5
print(rmse_pl)
```

```
4.61178115456449
```

Conclusions

After training more than a regression model, random forest had the lowest rmse, and child_mortality is the feature that has the mose effect on life expectancy. It is recommended use that model in predictions.