```
1 import numpy as np
```

- 5 import scipy.stats as stats
- 6 from scipy.stats.mstats import winsorize
- 7 from sklearn.decomposition import PCA
- 8 from sklearn.preprocessing import scale
- 9 import os
- 10 %matplotlib inline
- 1 df = pd.read_csv('/content/Life Expectancy Data.csv', header=0)

1 df.head()

	Country	Year	Status	Life expectancy	Adult Mortality	infant deaths	Alcohol	percentage expenditure			
0	Afghanistan	2015	Developing	65.0	263.0	62	0.01	71.279624	_		
1	Afghanistan	2014	Developing	59.9	271.0	64	0.01	73.523582			
2	Afghanistan	2013	Developing	59.9	268.0	66	0.01	73.219243			
3	Afghanistan	2012	Developing	59.5	272.0	69	0.01	78.184215			
4	Afghanistan	2011	Developing	59.2	275.0	71	0.01	7.097109			
5 rows × 22 columns											

```
1 orig_cols = list(df.columns)
```

1 df.columns

1 df.rename(columns={'thinness_1-19_years':'thinness_10-19_years'}, inplace=True)

1 df.describe().iloc[:, 1:]

	life_expectancy	adult_mortality	infant_deaths	alcohol	percentage_exper
count	2928.000000	2928.000000	2938.000000	2744.000000	2938.
mean	69.224932	164.796448	30.303948	4.602861	738.
std	9.523867	124.292079	117.926501	4.052413	1987.
min	36.300000	1.000000	0.000000	0.010000	0.
25%	63.100000	74.000000	0.000000	0.877500	4.
50%	72.100000	144.000000	3.000000	3.755000	64.
75%	75.700000	228.000000	22.000000	7.702500	441.
max	89.000000	723.000000	1800.000000	17.870000	19479

² import pandas as pd

³ import seaborn as sns

⁴ import matplotlib.pyplot as plt

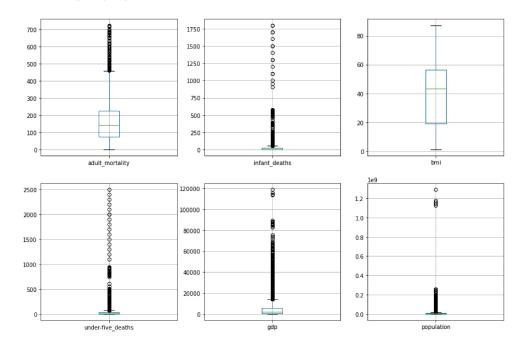
² new_cols = []

³ for col in orig_cols:

⁴ new_cols.append(col.strip().replace(' ', ' ').replace(' ', '_').lower())

⁵ df.columns = new_cols

```
plt.figure(figsize=(15,10))
for i, col in enumerate(['adult_mortality', 'infant_deaths', 'bmi', 'under-five_deaths', 'gdp', 'population'], start
plt.subplot(2, 3, i)
df.boxplot(col)
```



1 df.isna().sum()

```
country
                                      0
year
                                      0
                                      0
status
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
                                     19
polio
total_expenditure
                                    226
diphtheria
                                     19
hiv/aids
                                      0
gdp
                                    448
population
                                    652
thinness_10-19_years
                                     34
thinness_5-9_years
                                     34
                                    167
                                    163
```

```
income_composition_of_resources
    schooling
    dtype: int64
1 mort_5_percentile = np.percentile(df.adult_mortality.dropna(), 5)
2 df.adult_mortality = df.apply(lambda x: np.nan if x.adult_mortality < mort_5_percentile else x.adult_mortality, axis
3 df.infant_deaths = df.infant_deaths.replace(0, np.nan)
4 df.bmi = df.apply(lambda x: np.nan if (x.bmi < 10 or x.bmi > 50) else x.bmi, axis=1)
5 df['under-five_deaths'] = df['under-five_deaths'].replace(0, np.nan)
1
    def nulls_breakdown(df=df):
2
       df_cols = list(df.columns)
3
       cols_total_count = len(list(df.columns))
       cols count = 0
4
       for loc, col in enumerate(df cols):
5
```

```
null_count = df[col].isnull().sum()
6
7
            total_count = df[col].isnull().count()
            percent_null = round(null_count/total_count*100, 2)
8
9
            if null_count > 0:
                cols_count += 1
10
11
                 print('[iloc = {}] {} has {} null values: {}% null'.format(loc, col, null_count, percent_null))
12
         cols_percent_null = round(cols_count/cols_total_count*100, 2)
        print('Out of {} total columns, {} contain null values; {}% columns contain null values.'.format(cols_total_cour
13
 1 nulls_breakdown()
     [iloc = 3] life_expectancy has 10 null values: 0.34% null
     [iloc = 4] adult_mortality has 155 null values: 5.28% null
     [iloc = 5] infant_deaths has 848 null values: 28.86% null
     [iloc = 6] alcohol has 194 null values: 6.6% null
    [iloc = 8] hepatitis_b has 553 null values: 18.82% null
     [iloc = 10] bmi has 1456 null values: 49.56% null
     [iloc = 11] under-five_deaths has 785 null values: 26.72% null
     [iloc = 12] polio has 19 null values: 0.65% null
     [iloc = 13] total_expenditure has 226 null values: 7.69% null
     [iloc = 14] diphtheria has 19 null values: 0.65% null
     [iloc = 16] gdp has 448 null values: 15.25% null
    [iloc = 17] population has 652 null values: 22.19% null
    [iloc = 18] thinness_10-19_years has 34 null values: 1.16% null
     [iloc = 19] thinness_5-9_years has 34 null values: 1.16% null
     [iloc = 20] income_composition_of_resources has 167 null values: 5.68% null
    [iloc = 21] schooling has 163 null values: 5.55% null
    Out of 22 total columns, 16 contain null values; 72.73% columns contain null values.
 1 df.drop(columns='bmi', inplace=True)
 1 imputed data = []
 2 for year in list(df.year.unique()):
      year_data = df[df.year == year].copy()
 4
      for col in list(year_data.columns)[3:]:
 5
         year_data[col] = year_data[col].fillna(year_data[col].dropna().mean()).copy()
      imputed_data.append(year_data)
 7 df = pd.concat(imputed data).copy()
 1 nulls_breakdown(df)
    Out of 21 total columns, \emptyset contain null values; \emptyset.0\% columns contain null values.
1
    cont_vars = list(df.columns)[3:]
 2
    def outliers_visual(data):
 3
        plt.figure(figsize=(15, 40))
        i = 0
4
       for col in cont_vars:
 5
 6
           i += 1
           plt.subplot(9, 4, i)
7
8
           plt.boxplot(data[col])
           plt.title('{} boxplot'.format(col))
9
10
            i += 1
11
            plt.subplot(9, 4, i)
```

plt.hist(data[col])

plt.show()

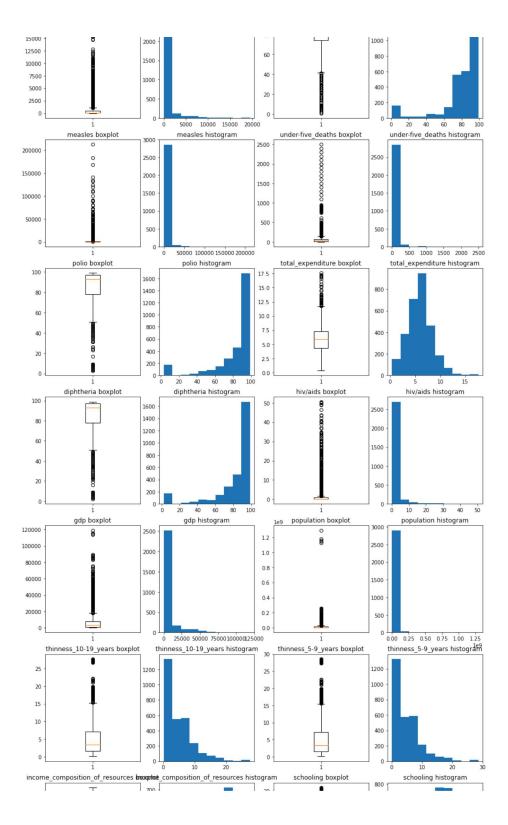
outliers_visual(df)

plt.title('{} histogram'.format(col))

13

14

15



```
1
   def outlier_count(col, data=df):
      print(15*'-' + col + 15*'-')
2
3
       q75, q25 = np.percentile(data[col], [75, 25])
4
       iqr = q75 - q25
5
       min_val = q25 - (iqr*1.5)
6
       max_val = q75 + (iqr*1.5)
       outlier_count = len(np.where((data[col] > max_val) | (data[col] < min_val))[0])</pre>
7
       outlier_percent = round(outlier_count/len(data[col])*100, 2)
9
       print('Number of outliers: {}'.format(outlier_count))
10
       print('Percent of data that is outlier: {}%'.format(outlier_percent))
1 for col in cont_vars:
2 outlier_count(col)
    -----life_expectancy-----
    Number of outliers: 17
    Percent of data that is outlier: 0.58%
    ----adult_mortality-----
    Number of outliers: 97
    Percent of data that is outlier: 3.3%
    -----infant_deaths-----
    Number of outliers: 135
    Percent of data that is outlier: 4.59%
    -----alcohol-----
    Number of outliers: 3
    Percent of data that is outlier: 0.1%
    -----percentage_expenditure-----
    Number of outliers: 389
```

```
-----hepatitis b-----
   Number of outliers: 222
   Percent of data that is outlier: 7.56%
   -----measles-----
   Number of outliers: 542
   Percent of data that is outlier: 18.45%
   -----under-five_deaths-----
   Number of outliers: 142
   Percent of data that is outlier: 4.83%
    -----polio-----
   Number of outliers: 279
   Percent of data that is outlier: 9.5%
    -----total expenditure-----
   Number of outliers: 51
   Percent of data that is outlier: 1.74%
    -----diphtheria------
   Number of outliers: 298
   Percent of data that is outlier: 10.14%
    -----hiv/aids-----
   Number of outliers: 542
   Percent of data that is outlier: 18.45%
   ----gdp-----
   Number of outliers: 300
   Percent of data that is outlier: 10.21%
    -----population-----
   Number of outliers: 203
   Percent of data that is outlier: 6.91%
   -----thinness_10-19_years-----
   Number of outliers: 100
   Percent of data that is outlier: 3.4%
    -----thinness_5-9_years-----
   Number of outliers: 99
   Percent of data that is outlier: 3.37%
    -----income_composition_of_resources-----
   Number of outliers: 130
   Percent of data that is outlier: 4.42%
    -----schooling-----
   Number of outliers: 77
   Percent of data that is outlier: 2.62%
  data=pd.get_dummies(df, columns=['country','status'])
   X = data.drop('life_expectancy', axis=1)
   y = data['life_expectancy']
  from sklearn.model_selection import train_test_split
  X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.2, random_state=42)
1 X_train.shape, X_test.shape, y_train.shape, y_test.shape
   ((2350, 213), (588, 213), (2350,), (588,))
1 from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
2 from sklearn.ensemble import GradientBoostingRegressor
3 gbr = GradientBoostingRegressor()
4 gbr.fit(X_train, y_train)
   gbr_pred = gbr.predict(X_test)
  print('R2 score is : {:.2f}'.format(r2_score(y_test, gbr_pred)))
   R2 score is : 0.94
1 Q1 = df.quantile(0.25)
2 \text{ Q3} = \text{df.quantile}(0.75)
3 IQR = Q3 - Q1
4 outliers = pd.DataFrame(((df < (Q1 - 1.5 * IQR)) | (df > (Q3 + 1.5 * IQR))).sum())
5 outliers1= outliers[:60]
6 outliers2 = outliers[60:120]
7 outliers3 = outliers[120:180]
8 outliers4 = outliers[180:]
9 outliers1,outliers2,outliers3,outliers4
    adult_mortality
                                   97
                                    3
    alcohol
    country
                                    0
```

Percent of data that is outlier: 13.24%

```
gdp
    hepatitis_b
                                      222
    hiv/aids
                                      542
    income_composition_of_resources
                                     130
    infant deaths
                                      135
    life_expectancy
                                       17
                                      542
    measles
    percentage_expenditure
                                      389
    polio
                                      279
    population
                                      203
    schooling
                                       77
    status
                                       0
    thinness 10-19 years
                                      100
    thinness_5-9_years
                                       99
    total_expenditure
                                       51
    under-five_deaths
                                      142
    vear
                                        0.
    Empty DataFrame
    Columns: [0]
    Index: [],
    Empty DataFrame
    Columns: [0]
    Index: [],
    Empty DataFrame
    Columns: [0]
    Index: [])
   from sklearn.ensemble import RandomForestRegressor
   rf = RandomForestRegressor()
   rf.fit(X_train, y_train)
   RandomForestRegressor()
  rf_pred=rf.predict(X_test)
   print('R2 score is : {:.2f}'.format(r2_score(y_test, rf_pred)))
   R2 score is : 0.96
1 rf.feature importances
   array([6.00791001e-03, 1.28939321e-01, 3.26100551e-03, 9.86419832e-03,
           5.02765740e-03, 2.17846056e-03, 7.98067254e-03, 6.42089596e-03,
          4.89367245e-03, 5.74286170e-03, 4.22662358e-03, 5.87124338e-01,
           3.07784093e-03, 2.91320046e-03, 6.43687308e-03, 1.05818258e-02,
           1.72407973e-01, 2.13619306e-02, 2.25015155e-06, 1.94925122e-05,
           1.76582409e-06, 4.78764533e-04, 1.36149705e-05, 4.69990003e-05,
           2.19254642e-06, 1.51342013e-06, 7.28547219e-06, 1.37030448e-04,
           5.21711505e-06, 2.56155271e-06, 2.18661046e-05, 5.43676652e-06,
           7.16938974e-06, 2.82880821e-05, 9.35300922e-05, 9.89013512e-05,
           3.29194530e-05, 1.20757384e-04, 1.45274223e-04, 4.69332958e-06,
          6.85465208e-06, 1.40357337e-06, 9.37322893e-06, 1.80101264e-05,
           7.79378542e-06, 9.19270371e-05, 4.13972522e-05, 3.72312543e-05,
          9.39730584e-06, 5.91096140e-05, 6.65797937e-06, 7.36905220e-05,
           3.05766430e-05, 2.08373939e-06, 2.52143787e-05, 9.24028761e-06,
           1.43492147e-18, 4.80110307e-04, 7.08832662e-06, 4.34145389e-04,
           2.04168651e-05, 5.59616892e-06, 1.68383345e-04, 2.55196993e-04,
           2.34534515e-05, 3.44684723e-05, 2.58300562e-06, 0.00000000e+00,
           7.12647185e-05, 1.07275610e-05, 1.58399623e-04, 8.42501978e-05,
           7.35638114e-05, 1.87815864e-04, 2.12012378e-04, 4.08420507e-05,
           3.33799867e-04, 6.90420075e-05, 1.42778259e-04, 5.24667186e-06,
           2.74377469e-06, 2.74956421e-06, 2.53721244e-05, 6.21561652e-05,
           3.00343468e-05, 2.21382298e-05, 8.69472732e-05, 2.26892792e-06,
           1.31222344e-05, 1.07447037e-04, 2.39480389e-04, 1.64019913e-04,
           1.72120129e-05, 9.10825738e-07, 8.54121708e-06, 2.42918648e-05,
          4.81062666e-06, 6.33302007e-05, 1.44279408e-05, 1.75157198e-06,
           1.20543728e-05, 3.25996824e-06, 1.98958731e-05, 8.65985084e-06,
           8.78540230e-05, 3.50413427e-05, 1.39538395e-04, 1.41644640e-06,
           3.62749982e-05, 4.73636724e-05, 3.75814896e-05, 7.24552178e-06,
          1.46118294e-06, 7.41727830e-06, 3.32103274e-05, 6.36193629e-05,
           4.10023964e-06, 1.39688291e-05, 1.91009576e-05, 5.75485476e-07,
          6.41810608e-05, 3.99226053e-05, 2.94688152e-06, 0.00000000e+00,
           3.93958080e-06, 2.59150607e-06, 5.55443301e-06, 1.16861507e-04,
           5.01828552e-07, 1.42957775e-04, 4.63998917e-05, 1.09486636e-05,
           4.93656253e-05, 8.80577268e-07, 7.57896529e-06, 7.38316333e-07,
```

298

diphtheria

```
1.26082593e-05, 7.63630990e-06, 2.82937959e-05, 2.18731901e-04,
3.94902420e-05, 3.59437103e-06, 1.78482387e-19, 1.47654975e-05,
6.60010794e-06, 6.54870987e-06, 1.45627528e-05, 4.22691166e-05,
1.35547549e-05, 1.26564771e-05, 1.79368171e-06, 1.96549877e-07,
5.33550636e-07, 3.39924949e-05, 1.12394257e-05, 3.74546811e-04,
2.09463981e-05, 3.74864091e-06, 5.32532023e-04, 1.07893947e-05,
9.33975745e-06, 1.15673893e-06, 1.09866624e-04, 6.44550514e-05,
2.66034948e-08, 2.95975598e-05, 2.48115142e-06, 3.42569285e-05,
1.74519262e-06, 1.40541613e-05, 6.56316642e-04, 4.64952056e-04,
3.48249275e-05, 1.20579807e-04, 3.62717167e-05, 1.44009772e-04,
5.29627115e-05, 1.03011141e-05, 1.55478372e-05, 1.52107677e-06,
2.71379234e-05, 1.65043524e-04, 9.32577536e-05, 3.94001195e-05,
1.13501360e-05, 7.18372903e-05, 2.97604536e-05, 8.39017182e-06,
4.42318053e-05, 5.28974766e-05, 2.12569497e-05, 3.61937618e-06,
4.17039876e-05, 1.61234657e-05, 1.60769035e-05, 1.18590244e-05,
0.00000000e+00, 1.46723315e-05, 1.90151200e-05, 7.54205765e-07,
5.98131260e-04, 3.54710815e-05, 2.58147327e-05, 1.63865386e-06,
1.12481484e-04, 2.67689062e-05, 1.80086731e-06, 7.17512818e-05,
3.97379600e-06, 2.33277718e-05, 7.61936216e-05, 8.05033281e-05,
9.31593893e-05])
```

```
1 import seaborn as sns
2 def plot_features(columns, importances, n=10):
3
      df = (pd.DataFrame({"features": columns,
                            "feature_importance": importances})
4
             .sort_values("feature_importance", ascending=False)
5
             .reset_index(drop=True))
6
      sns.barplot(x="feature_importance",
8
9
                   y="features",
10
                   data=df[:n],
                   orient="h")
11
```

1 plot_features(X_train.columns, rf.feature_importances_)

