Seshu_Miriyala_Final_Project

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[1]:
```
'''This program analyzes the coffee consumption, production, export and imports␣
↪among various countries and answers some key questions'''

# importing the required libraries
# Need Numpy to perform the array operations
import numpy as np
# We use pandas to read the csv files and load them into data frames
import pandas as pd
# we use matplotlib for ploting graphs and charts
import matplotlib as mp
import matplotlib.pyplot as pp
```

1 Load the data

[2]:
```
# Loading coffee consumption data into data frame
# The data contains one column for the country name and one column each for the␣
↪years 1990 till 2018
# The units of measure are in thousands 60-Kg bags
consumption_data = pd.read_csv('inputs/domestic-consumption.csv',delimiter=',')
# Merging any duplicates
consumption_data = consumption_data.groupby("domestic_consumption",␣
↪as_index=True).sum()
# Checking the data after loadin into the data frame
consumption_data.head(5)
```

[2]:
```
                                    1990    1991    1992     1993    1994  \
domestic_consumption
Angola                              20.0    30.0    35.0    20.00    25.0
Benin                                0.0     0.0     0.0     0.00     0.0
Bolivia (Plurinational State of)    25.0    27.0    27.5    28.50    29.5
Brazil                            8200.0  8500.0  8900.0  9100.00  9300.0
Burundi                              2.0     1.6     1.7     1.91     2.0

                                    1995     1996     1997     1998     1999  \
domestic_consumption
Angola                              10.0     20.0     40.0     30.0     20.0
```

```
Benin                                 0.0      0.0      0.0      0.0      0.0
Bolivia (Plurinational State of)     30.5     31.5     32.5     33.0     34.0
Brazil                            10100.0  11000.0  11500.0  12200.0  12700.0
Burundi                               2.0      2.0      2.0      2.0      2.0

                                  …       2009     2010     2011     2012  \
domestic_consumption              …
Angola                            …     30.000     30.0     30.0     30.0
Benin                             …      0.000      0.0      0.0      0.0
Bolivia (Plurinational State of)  …     46.000     47.5     49.0     50.5
Brazil                            …  18390.000  19132.0  19720.0  20330.0
Burundi                           …      1.399      2.0      2.0      2.0

                                     2013     2014     2015     2016     2017  \
domestic_consumption
Angola                               30.0     30.0     30.0     30.0     30.0
Benin                                 0.0      0.0      0.0      0.0      0.0
Bolivia (Plurinational State of)     52.0     53.5     55.0     57.0     58.5
Brazil                            20085.0  20333.0  20508.0  21225.0  21997.0
Burundi                               2.0      2.0      2.0      2.0      2.0

                                     2018
domestic_consumption
Angola                               30.0
Benin                                 0.0
Bolivia (Plurinational State of)     60.0
Brazil                            22250.0
Burundi                               2.0

[5 rows x 29 columns]
```

[3]:
```python
# Loading the coffee production data into the data frames
# The data contains one column for the country name and one column each for the␣
↪years 1990 till 2018
# The units of measure are in thousands 60-Kg bags
production_data = pd.read_csv('inputs/total-production.csv', delimiter=',')
production_data = production_data.groupby("total_production", as_index=True).
↪sum()
# Checking the data after loading
production_data.head(5)
```

[3]:
```
                                        1990        1991        1992  \
total_production
Angola                               50.3450     79.3310     77.5200
Benin                                 0.0000      0.0000      1.8050
Bolivia (Plurinational State of)    122.7770    103.5360    120.2350
Brazil                            27285.6286  27293.4934  34603.3542
```

```
Burundi                             487.3930    667.1990    620.2380

                                        1993       1994        1995  \
total_production
Angola                               32.6080     76.802     62.1090
Benin                                 0.0500      0.000      0.0000
Bolivia (Plurinational State of)     50.8230    116.944    142.4850
Brazil                            28166.9786  28192.047  18060.2022
Burundi                             393.3540    664.143    433.9800

                                       1996       1997        1998  \
total_production
Angola                               70.925     64.330     85.3440
Benin                                 0.000      0.000      0.0000
Bolivia (Plurinational State of)    124.579    140.719    137.9850
Brazil                            29196.743  26148.004  36760.8533
Burundi                             400.969    249.785    491.9920

                                        1999  …        2009        2010  \
total_production                              …
Angola                               54.9390  …     13.4200     34.9700
Benin                                 0.0000  …      0.0000      0.0000
Bolivia (Plurinational State of)    157.7020  …    128.4751    117.2249
Brazil                            47577.8065  …  43976.8120  55428.4102
Burundi                             350.5500  …    111.6130    352.9776

                                        2011        2012        2013  \
total_production
Angola                               28.7150     32.7900     34.9350
Benin                                 0.0000      0.0000      0.0000
Bolivia (Plurinational State of)    131.8354    105.2812    119.9122
Brazil                            48591.8289  55418.0012  54688.9664
Burundi                             204.1328    405.9615    163.2177

                                        2014        2015        2016  \
total_production
Angola                               39.4050     40.5150     44.8300
Benin                                 0.0000      0.0000      0.0000
Bolivia (Plurinational State of)     99.8766     84.2191     77.9835
Brazil                            53304.7669  52870.5876  56788.1784
Burundi                             247.5500    274.1017    248.7933

                                        2017        2018
total_production
Angola                               35.0060     40.3874
Benin                                 0.0000      0.0000
Bolivia (Plurinational State of)     83.8112     82.5687
```

```
Brazil                           52739.8635  62924.8836
Burundi                            202.1079    178.4206

[5 rows x 29 columns]
```

[4]:

```python
# Laoding the prices paid to grower in each country into the data frame
# The data contains one column for the country name and one column each for the␣
 ↪years 1990 till 2018
# The units of measure are in USD/Kg
prices_paid_to_farmers = pd.read_csv('inputs/prices-paid-to-growers.csv',␣
 ↪delimiter=',')
prices_paid_to_farmers = prices_paid_to_farmers.
 ↪groupby("prices_paid_to_growers", as_index=True).mean()
# Displaying the first 5 rows for verification
prices_paid_to_farmers.head(5)
```

[4]:

```
                            1990      1991      1992      1993      1994  \
prices_paid_to_growers
Brazil                  0.984254  0.789049  0.803461  0.975950  2.207448
Colombia                1.534724  1.481790  1.204656  1.106477  1.898327
Dominican Republic      1.458168  1.382845  1.027841  1.172704  2.478234
El Salvador             1.116194  0.983322  0.682322  0.780397  2.191177
Ethiopia                1.348565  1.505322  1.351128  1.362442  2.418234

                            1995      1996      1997      1998      1999  …  \
prices_paid_to_growers                                                    …
Brazil                  2.351244  1.833606  2.464297  2.019828  1.445841  …
Colombia                2.199185  2.065245  2.939673  2.253433  1.906905  …
Dominican Republic      2.412000  1.935342  3.673587  2.102616  1.637609  …
El Salvador             2.218826  1.656073  2.762552  1.877384  1.256563  …
Ethiopia                2.539011  1.495287  2.010060  2.027901  1.449113  …

                            2009      2010      2011      2012      2013  \
prices_paid_to_growers
Brazil                  1.922988  2.298156  3.637459  2.833251  2.068699
Colombia                3.067442  3.985616  5.290868  3.679737  2.514539
Dominican Republic      2.340731  3.071276  4.217812  3.262839  3.112084
El Salvador             1.748205  2.425620  4.122256  2.651658  2.103276
Ethiopia                1.701150  1.886530  3.211088  2.269088  1.618110

                            2014      2015      2016      2017      2018
prices_paid_to_growers
Brazil                  2.382567  1.964829  2.214220  2.303390  1.746153
Colombia                3.525662  2.635854  2.727530  2.776185  2.505914
Dominican Republic      4.052172  3.775011  3.911395  3.826974  3.391053
El Salvador             2.582929  1.930439  1.976442  1.934159  1.645300
Ethiopia                1.837430  1.678360  1.927316  1.799278  1.560234
```

```
[5 rows x 29 columns]
```

[5]:
```python
# Loading the retail price of coffee in different countries
# The data contains one column for the country name and one column each for the␣
 ↪years 1990 till 2018
# The units of measure are in USD/Kg
coffee_retail_price = pd.read_csv('inputs/retail-prices.csv', delimiter=',')
coffee_retail_price = coffee_retail_price.groupby("retail_prices",␣
 ↪as_index=True).mean()
# Displaying the first 5 rows for verification
coffee_retail_price.head(5)
```

[5]:
```
                    1990       1991       1992       1993       1994  \
retail_prices
  Austria      10.816777  10.088300  11.015453  10.971302  10.110375
  Cyprus        6.247241   6.181015   6.335541   5.739514   7.019868
  Denmark       8.410596   8.101545   8.366446   7.682119   9.823400
  Finland       6.578366   6.004415   5.430464   4.282561   6.026490
  France        8.233996   7.571744   5.099338   4.481236   5.298013

                    1995       1996       1997       1998      1999  …  \
retail_prices                                                       …
  Austria      11.434879  11.964680   9.646799   8.763797  7.240618  …
  Cyprus        9.403974   9.116998   8.918322  10.176600  9.690949  …
  Denmark      12.295806  10.618102  10.949227  10.860927  8.675497  …
  Finland       8.763797   7.108168   7.726269   7.549669  5.739514  …
  France        8.145695   7.284768   6.092715   6.136865  5.629139  …

                    2009       2010       2011       2012       2013  \
retail_prices
  Austria      15.342163  14.768212  18.366446  18.498896  19.028698
  Cyprus       12.207506  11.501104  13.377483  14.039735  14.282561
  Denmark      11.677704  12.008830  15.275938  14.834437  14.039735
  Finland       7.748344   8.145695  11.832230  10.596026   9.470199
  France        8.366446   7.991170   9.116998   8.653422   8.653422

                    2014       2015       2016       2017       2018
retail_prices
  Austria      19.050773  16.423841  12.450331  13.730684  14.635762
  Cyprus       14.304636  11.699779  11.699779  12.141280  12.781457
  Denmark      14.194260  12.913907  10.905077  11.103753  11.699779
  Finland       9.514349   8.609272   8.101545   9.050773   9.359823
  France        8.322296   6.865342   7.196468   7.505519   8.123620

[5 rows x 29 columns]
```

[6]:
```python
# Loading the exports of coffee crop by different countries
# The data contains one column for the country name and one column each for the␣
↪years 1990 till 2018
# The units of measure are in thousands 60-Kg bags
coffee_exports = pd.read_csv('inputs/exports-crop-year.csv', delimiter=',')
coffee_exports = coffee_exports.groupby("exports_crop_year", as_index=True).
↪sum()
# Displaying the first 5 rows for verification
coffee_exports.head(5)
```

[6]:
```
                                    1990        1991        1992  \
exports_crop_year
Angola                           79.3450     74.3310     67.5200
Benin                             0.0000      0.0000      1.8050
Bolivia (Plurinational State of)  111.9770     82.9360    100.9350
Brazil                        17862.6286  21808.4934  16752.3542
Burundi                         412.3930    762.4910    671.6460

                                    1993       1994        1995  \
exports_crop_year
Angola                           27.6080     11.802     48.1090
Benin                             0.0500      0.000      0.0000
Bolivia (Plurinational State of)   36.5230     85.944    110.4850
Brazil                        18760.9786  15958.047  13760.2022
Burundi                         352.8700    580.127    464.0700

                                   1996       1997        1998  \
exports_crop_year
Angola                           50.925     54.330     55.3440
Benin                             0.000      0.000      0.0000
Bolivia (Plurinational State of)  105.079    109.219    100.9850
Brazil                        17259.743  15352.004  21084.8533
Burundi                         185.636    546.034    391.8500

                                    1999  …        2009        2010  \
exports_crop_year                         …
Angola                           39.9390  …      3.4200      4.9700
Benin                             0.0000  …      0.0000      0.0000
Bolivia (Plurinational State of)  122.7020  …     82.4751     69.7249
Brazil                        21185.8065  …  30254.8120  34054.4102
Burundi                         437.7990  …    172.9370    350.7196

                                    2011        2012        2013  \
exports_crop_year
Angola                            8.7150      7.7900      4.9350
Benin                             0.0000      0.0000      0.0000
Bolivia (Plurinational State of)   82.8354     54.7812     67.9122
```

```
Brazil                             32148.8289  29283.0012  32751.9664
Burundi                              202.1328    405.9615    159.2177

                                         2014        2015        2016  \
exports_crop_year
Angola                                 9.4050     10.5150     14.8300
Benin                                  0.0000      0.0000      0.0000
Bolivia (Plurinational State of)      46.3766     29.2191     20.9835
Brazil                             37781.7669  37472.5876  33491.1784
Burundi                              245.5500    274.1017    246.7933

                                         2017        2018
exports_crop_year
Angola                                 5.0060     10.3874
Benin                                  0.0000      0.0000
Bolivia (Plurinational State of)      25.3112     22.5687
Brazil                             30782.8635  37613.8836
Burundi                              195.1079    179.9206

[5 rows x 29 columns]
```

1.1 Cleaning the data

[7]:
```
consumption_data.isnull().sum().sum()
```

[7]: 0

[8]:
```
production_data.isnull().sum().sum()
```

[8]: 0

[9]:
```
prices_paid_to_farmers.isnull().sum().sum()
```

[9]: 0

[10]:
```
coffee_retail_price.isnull().sum().sum()
```

[10]: 0

[11]:
```
coffee_exports.isnull().sum().sum()
```

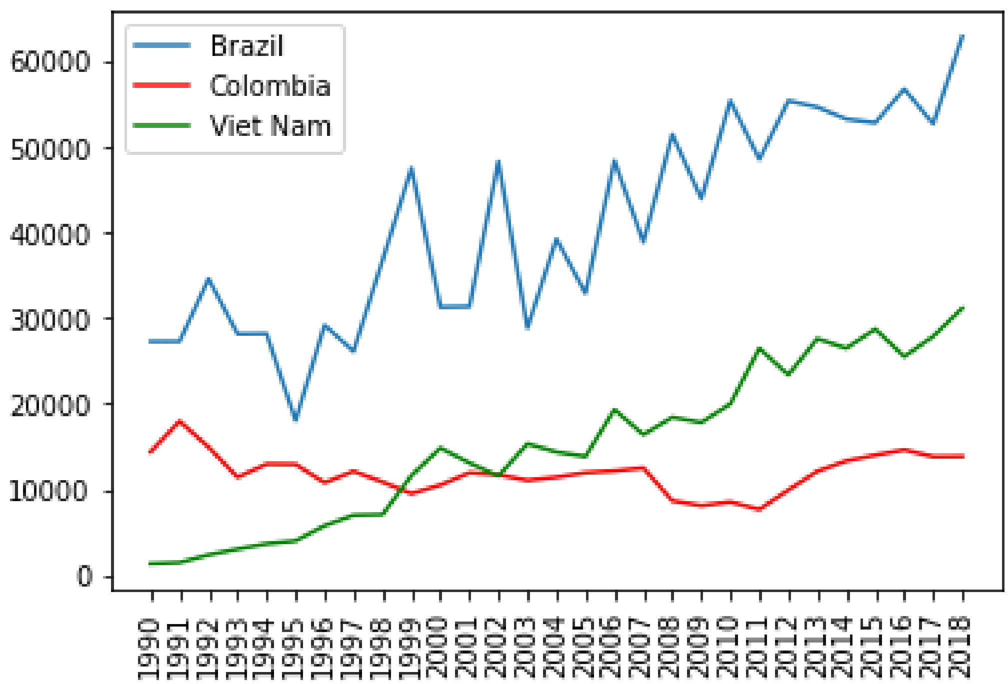
[11]: 0

1.2 Graph of brazil production data

In this section we try to graph the production of Brazil over the years

```
[12]: # Defining a function to draw line chart using matplotlib so that we can reuse␣
 ↪the code
def plotLineGraph(df, countriesList, colorList):
    x = np.arange(len(df.columns))
    for country in countriesList:
        t = np.array(df[df.index == country])[0]
        pp.plot(x, t, label=country, color=colorList[countriesList.
 ↪index(country)])
    pp.xticks(x,np.array(df.columns))
    pp.xticks(rotation=90)
    pp.legend()
    pp.show()

# Default colors used in the code
colorsList = list(['#1f77b4','red','green'])
```

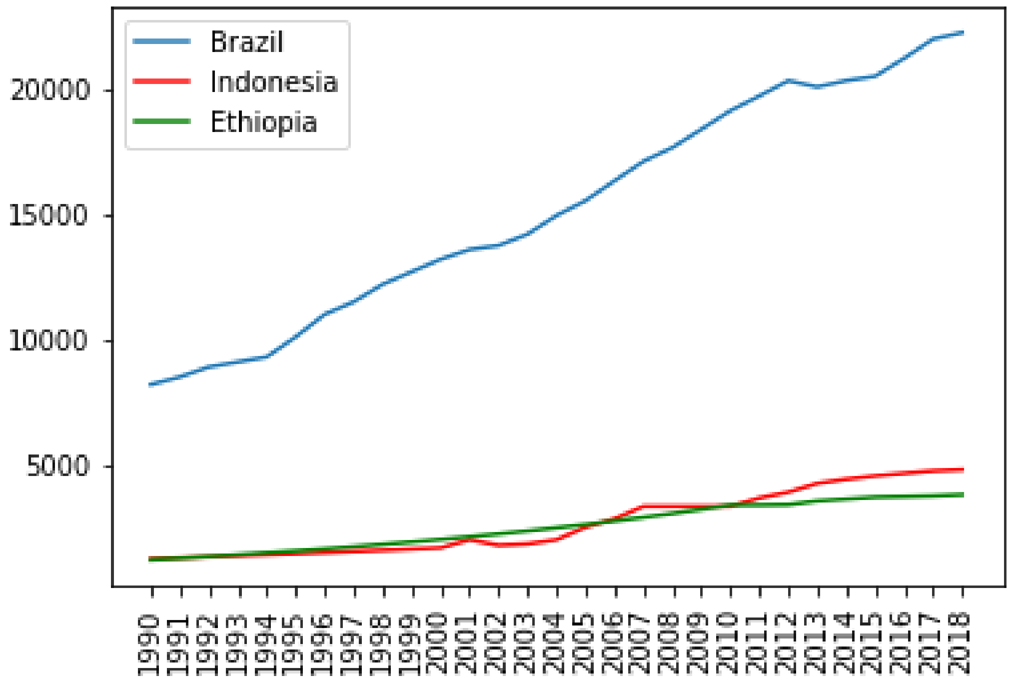
```
[13]: # Let us now see how are the production numbers for the coffee crop they grew␣
 ↪in Brazil, Columbia and Viet Nam
plotLineGraph(production_data, list(['Brazil', 'Colombia', 'Viet Nam']),␣
 ↪colorsList)
```



1.3 Graph of brazil consumption data

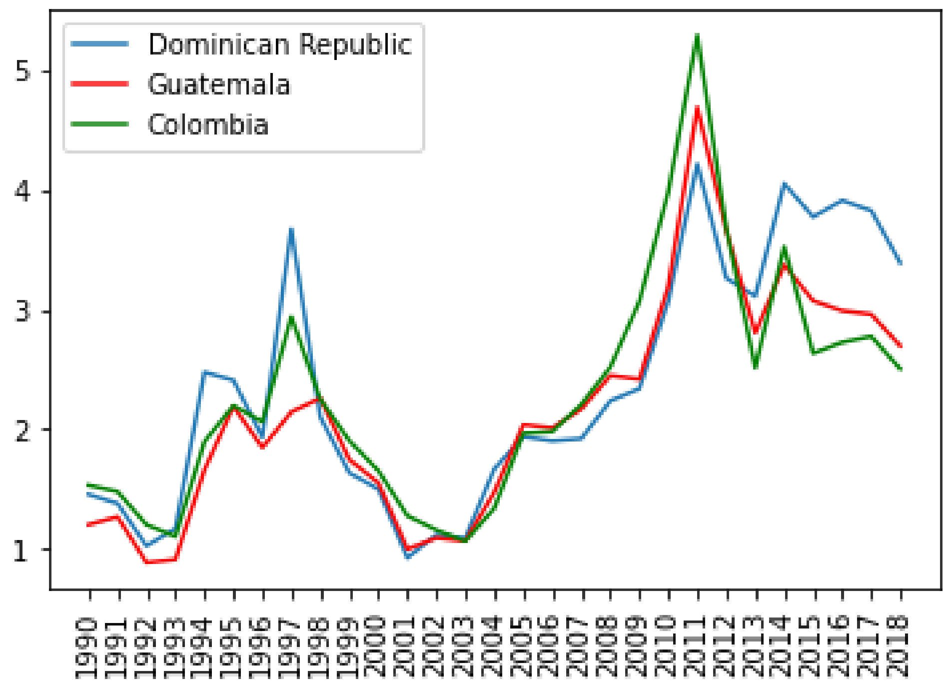
In this section we try to graph the consumption of Brazil over the years

[14]:
```
# Let us now see how are the production numbers for the coffee crop they grew␣
↪in Brazil, Columbia and Viet Nam
plotLineGraph(consumption_data, list(['Brazil', 'Indonesia', 'Ethiopia']),␣
↪colorsList)
```



As we can see, Consumption and production are high in Brazil than any other country

[15]:
```
# Let us now see how are the farmers paid for the coffee crop they grew in␣
↪Brazil, Columbia and India
plotLineGraph(prices_paid_to_farmers, list(['Dominican Republic', 'Guatemala',␣
↪'Colombia']), list(['#1f77b4','red','green']))
```



As we can see Prices of the top coffee expensive countries varies by time. In the recent years prices of coffee are trnding higher in Dominican Republic than other two countries

1.4 Taking average of last five years

In order to bertter analyze the data and to eliminate noise I have choosen to take average of last five years of data

[16]:
```
# Defining a function to compute Five Year Average
def computeFiveYearAvg(df):
    # We then sum up the values of the last five years and divide the sum by 5␣
 ↪to get the average
    df['Five_year_avg'] = (df['2014'] + df['2015'] + df['2016'] + df['2017'] +␣
 ↪df['2018'])/5

    # consumption_data.reset_index(inplace=True)
    # We then create a new data frame with the calculated values
    avg_df = pd.DataFrame(data={'Country': np.array(df.index),'Five_year_avg':␣
 ↪np.array(df.Five_year_avg)})
    avg_df.set_index('Country', inplace=True)

    return avg_df
```

[17]:
```
# Computing the Five Year avg for consumption data
avg_consumption_data = computeFiveYearAvg(consumption_data)
```

```
# Checking if the data frame is right
avg_consumption_data.head(5)
```

[17]:

```
                                  Five_year_avg
Country
Angola                                     30.0
Benin                                       0.0
Bolivia (Plurinational State of)           56.8
Brazil                                  21262.6
Burundi                                     2.0
```

[18]:

```
# Computing the Five Year avg for production data
avg_production_data = computeFiveYearAvg(production_data)
# Checking if the data frame is right
avg_production_data.head(5)
```

[18]:

```
                                  Five_year_avg
Country
Angola                                 40.02868
Benin                                   0.00000
Bolivia (Plurinational State of)       85.69182
Brazil                              55725.65600
Burundi                               230.19470
```

[19]:

```
# Computing the Five Year avg for Prices paid to farmers data
avg_prices_paid_to_farmers = computeFiveYearAvg(prices_paid_to_farmers)
# Checking if the data frame is right
avg_prices_paid_to_farmers.head(5)
```

[19]:

```
                    Five_year_avg
Country
Brazil                   2.122232
Colombia                 2.834229
Dominican Republic       3.791321
El Salvador              2.013854
Ethiopia                 1.760524
```

[20]:

```
# Computing the Five Year avg for Coffee retail price data
avg_coffee_retail_price = computeFiveYearAvg(coffee_retail_price)
# Checking if the data frame is right
avg_coffee_retail_price.head(5)
```

[20]:

```
            Five_year_avg
Country
   Austria      15.258278
   Cyprus       12.525386
   Denmark      12.163355
```

```
Finland        8.927152
France         7.602649
```

[21]:
```
# Computing the Five Year avg for coffee exports data
avg_coffee_exports = computeFiveYearAvg(coffee_exports)
# Checking if the data frame is right
avg_coffee_exports.head(5)
```

[21]:
```
                                  Five_year_avg
Country
Angola                                 10.02868
Benin                                   0.00000
Bolivia (Plurinational State of)       28.89182
Brazil                              35428.45600
Burundi                               228.29470
```

1.5 Which country consumes more coffee?

For this we need to sort the consumption data and get the coutry that consumes coffee most

[22]:
```
# Extracting the country which has highest coffee consumption
max_consumption_country = avg_consumption_data[avg_consumption_data.
 ↪Five_year_avg == np.max(avg_consumption_data.Five_year_avg)]
# Displaying the result
max_consumption_country
```

[22]:
```
         Five_year_avg
Country
Brazil         21262.6
```

1.6 Which countries have exccess coffee production or highest coffee deficit?

For this we need to take off the consumption numbers from the production for each country

[23]:
```
# Extracting the Five Year Avg coffee production and consumption data
avg_consumption_data = avg_consumption_data.rename(columns={'Five_year_avg':
 ↪'Five_year_avg_consumption'})
avg_production_data=avg_production_data.rename(columns={'Five_year_avg':
 ↪'Five_year_avg_production'})

# Merging the two datasets using the Country as the join column
production_consumption = pd.merge(avg_consumption_data,avg_production_data,␣
 ↪on='Country')
# Displaying the results of the join
production_consumption.head(5)
```

[23]:
```
                                    Five_year_avg_consumption  \
Country
Angola                                                   30.0
Benin                                                     0.0
Bolivia (Plurinational State of)                         56.8
Brazil                                                21262.6
Burundi                                                   2.0

                                    Five_year_avg_production
Country
Angola                                              40.02868
Benin                                                0.00000
Bolivia (Plurinational State of)                    85.69182
Brazil                                           55725.65600
Burundi                                            230.19470
```

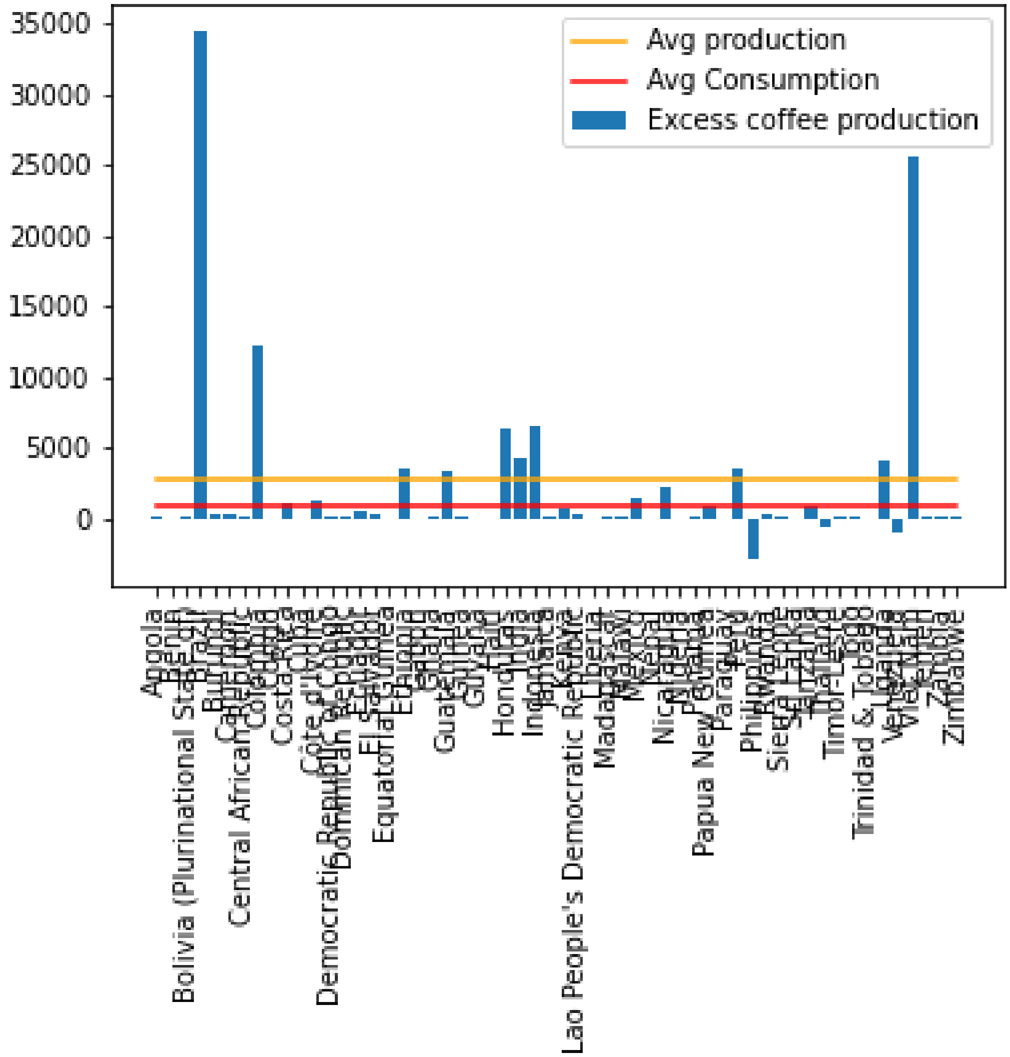
[24]:
```
# Subtracting the consumption values from production values for each country to␣
 ↪get the excess coffee the countries are producing
production_consumption['excess_production'] = production_consumption.
 ↪Five_year_avg_production - production_consumption.Five_year_avg_consumption

# Calculating the mean of production and consumption values across countries
production_consumption['mean_production'] = np.mean(production_consumption.
 ↪Five_year_avg_production)
production_consumption['mean_consumption'] = np.mean(production_consumption.
 ↪Five_year_avg_consumption)

# Filtering the countries which are deficit in coffee production
Excess_producing_countries = production_consumption[production_consumption.
 ↪excess_production > 0]

# Displaying the excess coffee production in tabular form
production_consumption.head(5)
```

[24]:
```
                                    Five_year_avg_consumption  \
Country
Angola                                                   30.0
Benin                                                     0.0
Bolivia (Plurinational State of)                         56.8
Brazil                                                21262.6
Burundi                                                   2.0

                                    Five_year_avg_production  excess_production  \
Country
Angola                                              40.02868           10.02868
Benin                                                0.00000            0.00000
Bolivia (Plurinational State of)                    85.69182           28.89182
```

```
Brazil                                                55725.65600        34463.05600
Burundi                                                 230.19470          228.19470

                                  mean_production  mean_consumption
Country
Angola                                2830.954115        867.873341
Benin                                 2830.954115        867.873341
Bolivia (Plurinational State of)      2830.954115        867.873341
Brazil                                2830.954115        867.873341
Burundi                               2830.954115        867.873341
```

[25]:

```
pp.bar(x=np.array(production_consumption.index), height=np.
 ↪array(production_consumption.excess_production), align='center',␣
 ↪label='Excess coffee production')
pp.xticks(rotation = 90)
pp.plot(np.array(production_consumption.index), production_consumption.
 ↪mean_production, color='orange', label="Avg production")
pp.plot(np.array(production_consumption.index), production_consumption.
 ↪mean_consumption, color='red', label="Avg Consumption")
pp.legend()
pp.show()
```



[26]:
```
# Extracting the country that has maxmimum coffee surplus production
max_surplus_country = production_consumption[production_consumption.
 ↪excess_production == np.max(production_consumption.excess_production)]

# Displaying the result
max_surplus_country
```

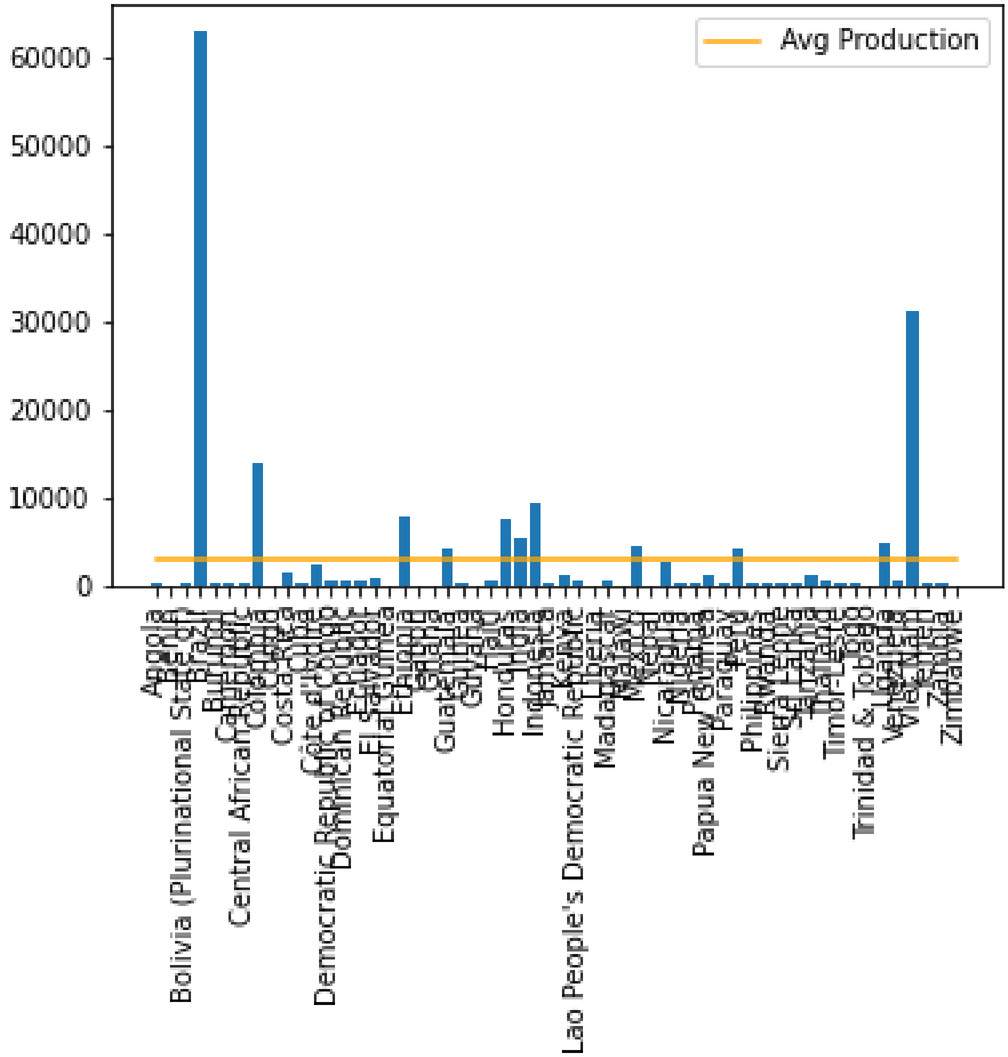
[26]:
```
         Five_year_avg_consumption  Five_year_avg_production  \
Country
Brazil                     21262.6                 55725.656

         excess_production  mean_production  mean_consumption
Country
Brazil           34463.056      2830.954115        867.873341
```

[27]:
```
# Extracting the country that has maximum coffe deficit
max_deficit_country = production_consumption[production_consumption.
↪excess_production == np.min(production_consumption.excess_production)]
# Displaying the results
max_deficit_country
```

[27]:
```
            Five_year_avg_consumption  Five_year_avg_production  \
Country
Philippines                    3062.0                 205.09132

            excess_production  mean_production  mean_consumption
Country
Philippines       -2856.90868      2830.954115        867.873341
```

1.7 Which country has best coffee production

[28]:
```
production_data['mean_production_2018'] = np.mean(production_data['2018'])
pp.bar(np.array(production_data.index), np.array(production_data['2018']))
pp.xticks(rotation=90)
pp.plot(np.array(production_data.index), np.array(production_data.
↪mean_production_2018), color='orange', label='Avg Production')
pp.legend()
pp.show()
```



[29]:
```python
# Extracting the country having the highest coffee production
max_production_country = production_data[production_data['2018'] == np.
 ↪max(production_data['2018'])]
# Displaying the results
max_production_country
```

[29]:
```
                          1990        1991        1992        1993        1994  \
total_production
Brazil              27285.6286  27293.4934  34603.3542  28166.9786  28192.047

                          1995       1996       1997        1998        1999  \
total_production
Brazil              18060.2022  29196.743  26148.004  36760.8533  47577.8065
```

```
                    …        2011        2012        2013        2014  \
total_production    …
Brazil              …  48591.8289  55418.0012  54688.9664  53304.7669

                          2015        2016        2017        2018  \
total_production
Brazil              52870.5876  56788.1784  52739.8635  62924.8836

                    Five_year_avg  mean_production_2018
total_production
Brazil                  55725.656           3052.441745

[1 rows x 31 columns]
```

[30]:
```
# Extracting the country which has minimum coffee production
min_production_country = production_data[production_data['2018'] == np.
 ↪min(production_data['2018'])]
# Displaying the results
min_production_country
```

[30]:
```
                    1990  1991   1992  1993  1994  1995  1996  1997  1998  1999  \
total_production
Benin                0.0   0.0  1.805  0.05   0.0   0.0   0.0   0.0   0.0   0.0

                    …  2011  2012  2013  2014  2015  2016  2017  2018  \
total_production    …
Benin               …   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0

                    Five_year_avg  mean_production_2018
total_production
Benin                         0.0           3052.441745

[1 rows x 31 columns]
```

It seems Brazil has the highest coffee production which is 62925 thousand 60Kg bags while Benin has not produced any coffee since 1990

1.8 How are farmers paid for the coffee they grow in each country

For this lets compare the crop price, retail price of coffee across countries

[31]:
```
# Extracting the prices paid to farmers in 2018 and using the logarthimic␣
 ↪function to reduce the gap
prices_paid = np.log(prices_paid_to_farmers[['2018']])
# Extracting the production values for 2018
coffee_production = np.log(production_data[['2018']])

# Renaming the column names to be clear during the merge operation
```

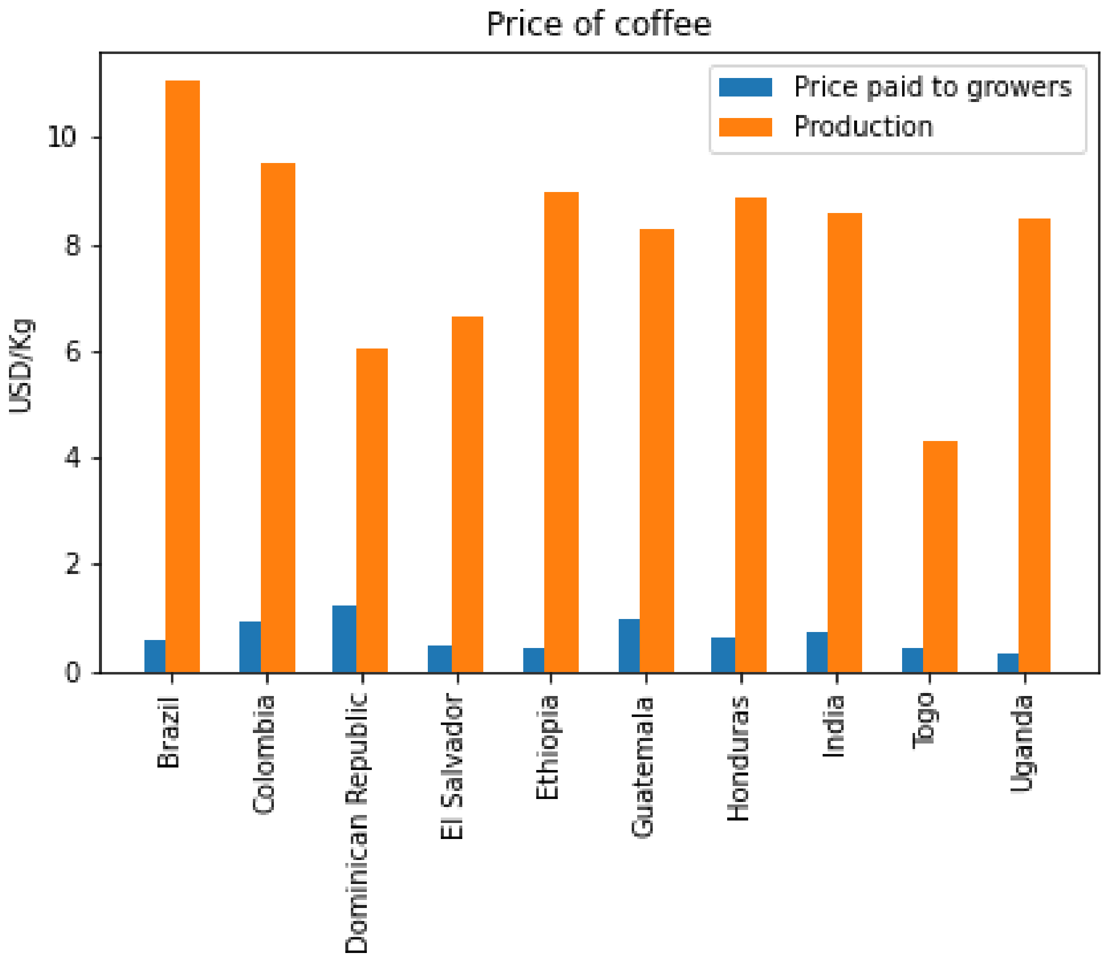
```python
prices_paid = prices_paid.rename(columns={'2018':'price_paid_to_growers_2018'})
coffee_production = coffee_production.rename(columns={'2018':'production_2018'})

#Joining th etwo datasets on Country
production_prices = prices_paid.join(coffee_production, how='inner')

# Displaying the result
production_prices.head(5)
```

[31]:

	price_paid_to_growers_2018	production_2018
Brazil	0.557415	11.049697
Colombia	0.918654	9.536615
Dominican Republic	1.221140	6.065899
El Salvador	0.497923	6.634532
Ethiopia	0.444836	8.958826

[32]:

```python
x = np.arange(len(production_prices.index))  # the label locations
width = 0.35  # the width of the bars

fig, ax = pp.subplots()
rects1 = ax.bar(x - width/3, production_prices.price_paid_to_growers_2018,␣
↪width, label='Price paid to growers')
rects2 = ax.bar(x + width/3, production_prices.production_2018, width,␣
↪label='Production')

# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('USD/Kg')
ax.set_title('Price of coffee')
ax.set_xticks(x)
ax.set_xticklabels(production_prices.index)
ax.legend()

fig.tight_layout()
pp.xticks(rotation=90)
pp.legend()
pp.show()
```



1.9 Which countries export most of the coffee?

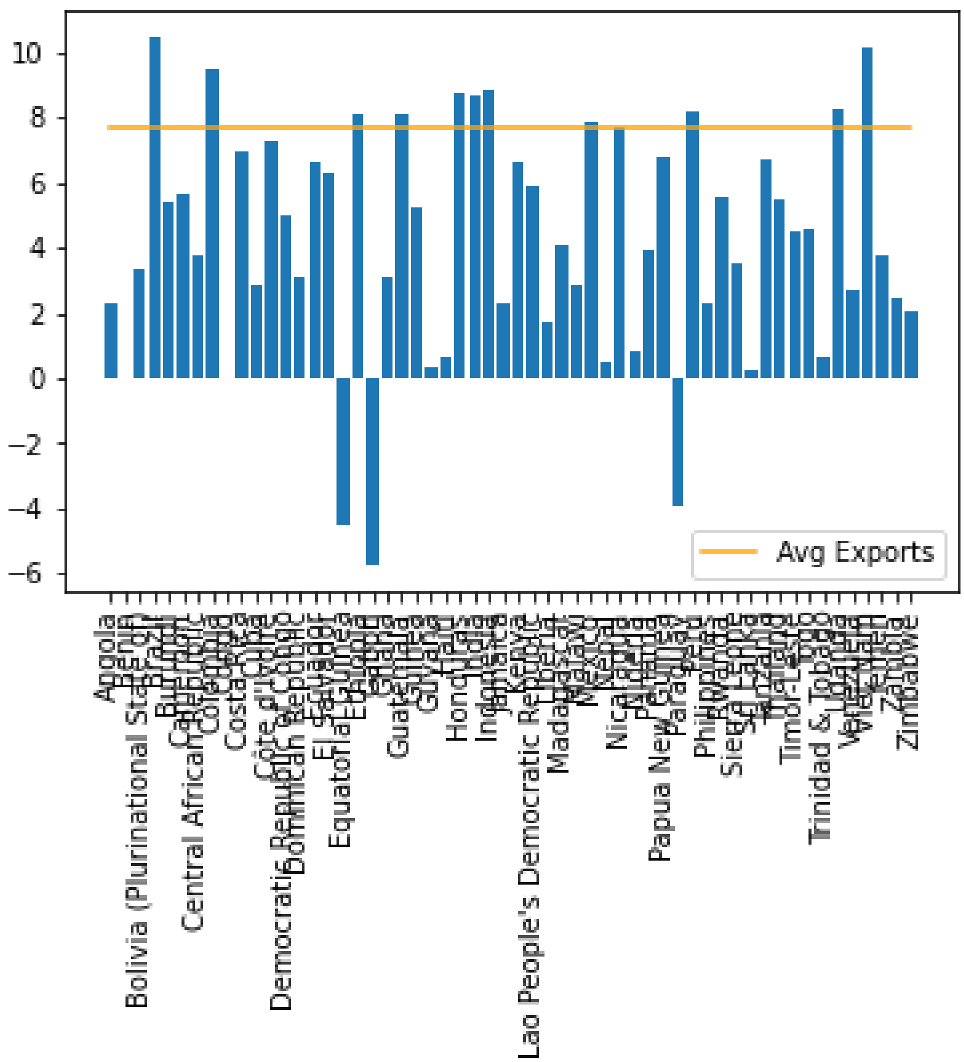
[33]:
```
avg_coffee_exports.head(5)
```

[33]:
```
                                    Five_year_avg
Country
Angola                                   10.02868
Benin                                     0.00000
Bolivia (Plurinational State of)         28.89182
Brazil                                35428.45600
Burundi                                 228.29470
```

[34]:
```
# Charting the Export values
avg_coffee_exports['mean_export_2018'] = np.mean(avg_coffee_exports.
 ↪Five_year_avg)
```

```
pp.bar(np.array(avg_coffee_exports.index), np.array(np.log(avg_coffee_exports.
 ↪Five_year_avg)))
pp.xticks(rotation=90)
pp.plot(np.array(avg_coffee_exports.index), np.array(np.log(avg_coffee_exports.
 ↪mean_export_2018)), color='orange', label='Avg Exports')
pp.legend()
pp.show()
```

```
/Users/seshumiriyala/opt/anaconda3/lib/python3.8/site-
packages/pandas/core/arraylike.py:358: RuntimeWarning: divide by zero
encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```



[35]:
```
# Extracting the maximum coffee exporting country
max_exporting_country = avg_coffee_exports[avg_coffee_exports['Five_year_avg']␣
 ↪== np.max(avg_coffee_exports['Five_year_avg'])]
# Displaying the results
max_exporting_country
```

[35]:
```
         Five_year_avg  mean_export_2018
Country
Brazil       35428.456       2136.673436
```

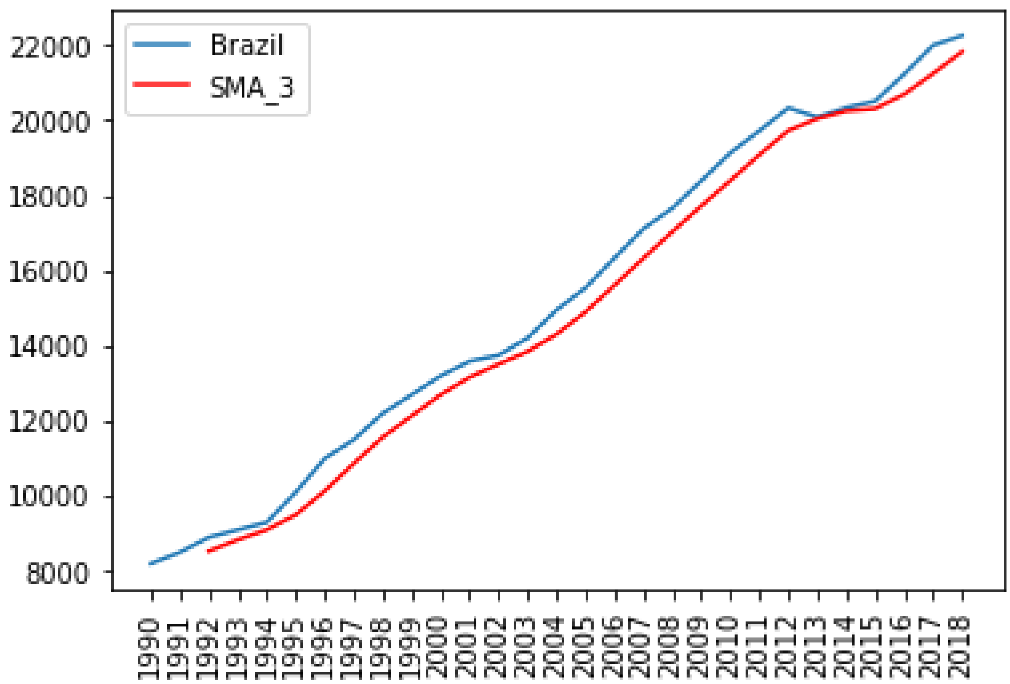
1.10 Forecasting the 2019 production and consumption for Brazil

[36]:
```
# Forecasting the production and consumption values using simple moving average
consumption_data_transposed = consumption_data.T
consumption_data_transposed['SMA_3'] = consumption_data_transposed.iloc[:,3].
 ↪rolling(window=3).mean()
consumption_data_transposed.head(5)
```

[36]:
```
domestic_consumption  Angola  Benin  Bolivia (Plurinational State of)  Brazil  \
1990                    20.0    0.0                              25.0  8200.0
1991                    30.0    0.0                              27.0  8500.0
1992                    35.0    0.0                              27.5  8900.0
1993                    20.0    0.0                              28.5  9100.0
1994                    25.0    0.0                              29.5  9300.0

domestic_consumption  Burundi  Cameroon  Central African Republic  Colombia  \
1990                     2.00    83.300                      28.0    1235.0
1991                     1.60    83.333                      28.0    1269.0
1992                     1.70    83.333                      28.0    1303.0
1993                     1.91   100.000                      25.0    1339.0
1994                     2.00   100.000                      15.0    1375.0

domestic_consumption  Congo  Costa Rica  …  Timor-Leste  Togo  \
1990                  3.000       375.0  …          0.0   1.0
1991                  2.667       375.0  …          0.0   1.0
1992                  2.667       375.0  …          0.0   1.0
1993                  3.000       375.0  …          0.0   1.0
1994                  3.000       375.0  …          0.0   1.0

domestic_consumption  Trinidad & Tobago  Uganda  Venezuela  Viet Nam  Yemen  \
1990                                8.0    70.0     782.39     150.0    0.0
1991                               11.5    75.0     815.48     230.0    0.0
1992                               10.0    75.0     849.97     250.0    0.0
1993                               10.0    75.0     885.93     267.0    0.0
1994                               14.0    80.0     923.40     267.0    0.0

domestic_consumption  Zambia  Zimbabwe        SMA_3
```

```
1990                    1.500     8.000          NaN
1991                    1.500     8.000          NaN
1992                    1.432     8.000  8533.333333
1993                    1.000     8.333  8833.333333
1994                    1.500     8.333  9100.000000

[5 rows x 57 columns]
```

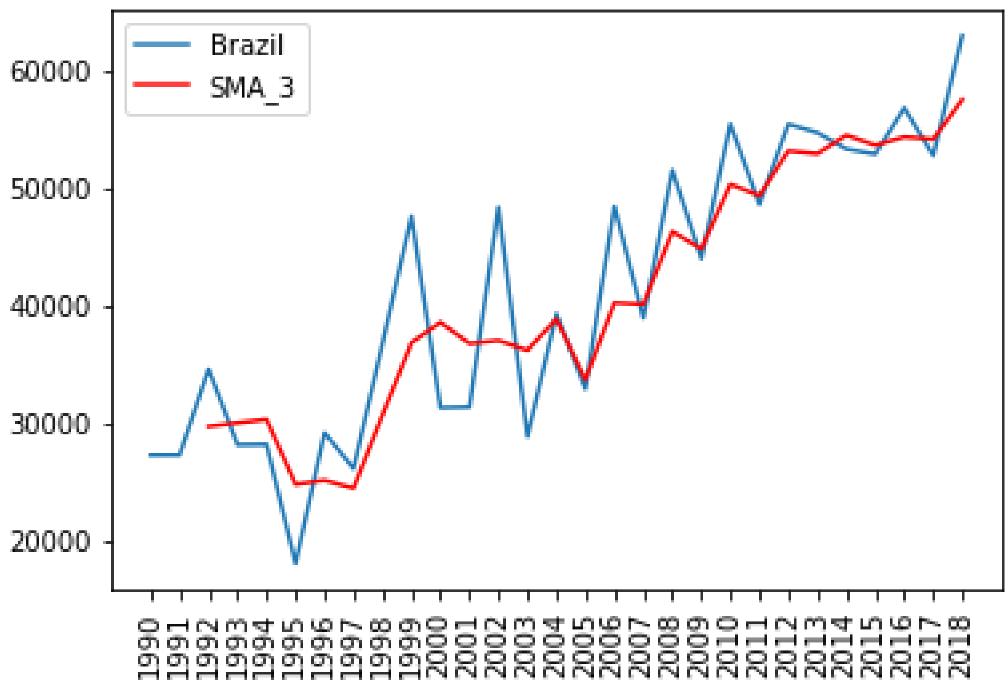
[37]:
```
# Let us now use the data to predict the coffee consumption for Brazil in 2019␣
↪and chart it
consumption_data_normal = consumption_data_transposed.T
del consumption_data_normal['Five_year_avg']
plotLineGraph(consumption_data_normal, list(['Brazil', 'SMA_3']),␣
↪list(['#1f77b4','red']))
```



[38]:
```
# Consumption values for Brazil in 2019 is
brazil_consumption_2019 = (consumption_data_normal[consumption_data_normal.
↪index == 'SMA_3']['2018'] + consumption_data_normal[consumption_data_normal.
↪index == 'SMA_3']['2017'] + consumption_data_normal[consumption_data_normal.
↪index == 'SMA_3']['2016'])/3
```

[39]:
```
# Let us now see how are the farmers paid for the coffee crop they grew in␣
↪Brazil, Columbia and India
# Forecating the production values using simple moving average
```

```
production_data_transposed = production_data.T
production_data_transposed['SMA_3'] = production_data_transposed.iloc[:,3].
 ↪rolling(window=3).mean()

production_data_normal = production_data_transposed.T

del production_data_normal['Five_year_avg']
del production_data_normal['mean_production_2018']
plotLineGraph(production_data_normal, list(['Brazil', 'SMA_3']),␣
 ↪list(['#1f77b4','red']))
```



[40]:
```
# Production values for Brazil in 2019 is

brazil_production_2019 = (production_data_normal[production_data_normal.index␣
 ↪== 'SMA_3']['2018'] + production_data_normal[production_data_normal.index ==␣
 ↪'SMA_3']['2017'] + production_data_normal[production_data_normal.index ==␣
 ↪'SMA_3']['2016'])/3
```

[41]:
```
print("Coffee production in Brazil for 2019 is", brazil_production_2019.
 ↪values[0], "(In thousand 60-kg bags)")
print("Coffee consumption in Brazil for 2019 is", brazil_consumption_2019.
 ↪values[0], "(In thousand 60-kg bags)")
```

```
Coffee production in Brazil for 2019 is 55312.78754444444 (In thousand 60-kg
bags)
```

```
Coffee consumption in Brazil for 2019 is 21252.0 (In thousand 60-kg bags)
```