SDG_Analysis

July 8, 2025

[1]:
```
import csv
import pandas as pd
import seaborn as sns
import numpy as np
import os
import plotly.express as px
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from matplotlib.pyplot import figure
import matplotlib.pyplot as plt
```

[2]:
```
from IPython.display import Image, display
```

1 Executive Summary

I analysed a dataset on sustainable development in all countries between the 1990s and 2020. The data analysis suggests that urban populations have risen consistently in the 1990s, however, when dividing the average between states, one finds significant deviations in off growth of urban populations between countries, which may have significantly skewed the total average. Moreover, we found a positive correlation between the number of flights and GDP growth, suggesting that an increase in flights is merely an externality of economic growth. The same thing cannot be necessarily stated about the relationship between the percentage of 'green' areas in a country and economic growth, as one can find that the largest economic growing economies have had positive forestation efforts, while other growing economies had negative forestation efforts.

More broadly, I checked the composition of the data itself, I cheched how much data was collected throughout the years and I tried to explain why we had positive or negative trends. Further, I checked which categories have the most collected data and which income group those those countries belong to.

2 Introduction

The Sustainable development goals dataset contains various data, collected over thirty years, about countries from all over the world. In an age where climate change presents a severe problem to our society, sustainable development is the answer. I chose to analyze this dataset because I think it is the most relevant topic and I am interested in the statistics behind our collective progress or failure. I am expecting to see some patterns behind the growth of energy consumption, gas emission, and other relevant data like traffic or GPP.

3 Data Cleaning

Firstly, I am going to check how many empty values I have in each column.

[3]:
```
data = pd.read_csv("SDGData.csv") #we are using pandas to to read CSV file␣
↪"SDGData.csv" and load it to dataframe caled "data
data.isna().sum() #we chech all columns with NaN values and we sum them
```

[3]:
```
Country Name            0
Country Code            0
Indicator Name          0
Indicator Code          0
1990                82491
1991                77866
1992                76175
1993                77041
1994                76595
1995                74313
1996                74866
1997                73487
1998                74118
1999                71668
2000                60801
2001                63642
2002                61648
2003                63279
2004                61514
2005                58098
2006                59457
2007                57546
2008                58751
2009                57802
2010                54163
2011                53820
2012                53390
2013                55608
2014                52788
2015                53103
2016                53346
2017                51517
2018                54078
2019                60308
2020                71630
Unnamed: 35        106488
dtype: int64
```

[4]:
```
data[data["1990"].isna()] #we deplayed our missing values
```

[4]:

```
       Country Name Country Code  \
0        Arab World          ARB
1        Arab World          ARB
2        Arab World          ARB
3        Arab World          ARB
4        Arab World          ARB
...             ...          ...
106482     Zimbabwe          ZWE
106483     Zimbabwe          ZWE
106485     Zimbabwe          ZWE
106486     Zimbabwe          ZWE
106487     Zimbabwe          ZWE

                                           Indicator Name     Indicator Code  \
0       Access to clean fuels and technologies for coo...     EG.CFT.ACCS.ZS
1                Access to electricity (% of population)     EG.ELC.ACCS.ZS
2       Access to electricity, rural (% of rural popul...  EG.ELC.ACCS.RU.ZS
3       Access to electricity, urban (% of urban popul...  EG.ELC.ACCS.UR.ZS
4       Account ownership at a financial institution o...     FX.OWN.TOTL.ZS
...                                                   ...                ...
106482  Wage and salaried workers, total (% of total e...     SL.EMP.WORK.ZS
106483  Water productivity, total (constant 2015 US$ G...  ER.GDP.FWTL.M3.KD
106485  Women making their own informed decisions rega...  SG.DMK.SRCR.FN.ZS
106486  Women who were first married by age 15 (% of w...  SP.M15.2024.FE.ZS
106487  Women who were first married by age 18 (% of w...  SP.M18.2024.FE.ZS

        1990       1991       1992       1993       1994       1995  ...  \
0        NaN        NaN        NaN        NaN        NaN        NaN  ...
1        NaN        NaN        NaN        NaN        NaN        NaN  ...
2        NaN        NaN  54.722944  56.807039  57.872605  57.447725  ...
3        NaN        NaN        NaN        NaN        NaN        NaN  ...
4        NaN        NaN        NaN        NaN        NaN        NaN  ...
...      ...        ...        ...        ...        ...        ...  ...
106482   NaN  36.110001  36.290001  35.459999  36.070000  36.590000  ...
106483   NaN        NaN   7.343931        NaN        NaN        NaN  ...
106485   NaN        NaN        NaN        NaN        NaN        NaN  ...
106486   NaN        NaN        NaN        NaN   6.400000        NaN  ...
106487   NaN        NaN        NaN        NaN  31.000000        NaN  ...

             2012       2013       2014       2015       2016       2017  \
0       85.644218  85.932567  86.232384  86.478597  86.722685  86.937933
1       87.039588  88.992620  88.015356  88.681886  89.195062  90.324659
2       75.377022  79.582622  77.666157  78.951592  79.791665  82.373066
3       96.980079  97.239057  96.856101  97.021313  97.261799  97.483658
4             NaN        NaN  30.470000        NaN        NaN  37.230000
...           ...        ...        ...        ...        ...        ...
106482  34.009998  33.770000  33.720001  33.369999  33.000000  32.810001
```

```
106483   5.428183        NaN        NaN        NaN        NaN   6.307054
106485        NaN        NaN        NaN  59.900000        NaN        NaN
106486        NaN        NaN        NaN   3.700000        NaN        NaN
106487        NaN        NaN  33.500000  32.400000        NaN        NaN

             2018       2019       2020  Unnamed: 35
0       87.040774  87.235539  87.307068          NaN
1       88.910749  89.999946  90.277735          NaN
2       82.970754  83.740500  81.660899          NaN
3       97.581237  98.278287  97.540397          NaN
4             NaN        NaN        NaN          NaN
...           ...        ...        ...          ...
106482  32.650002  31.250000        NaN          NaN
106483        NaN        NaN        NaN          NaN
106485        NaN        NaN        NaN          NaN
106486        NaN   5.418352        NaN          NaN
106487        NaN  33.658057        NaN          NaN

[82491 rows x 36 columns]
```

We are cleaning the code by deleting the rows with empty values.

[5]:
```python
delete = ["Unnamed: 35"]
data.drop(delete, inplace = True, axis =1) #we are droping the column with label␣
 ↪"unnamed 35"
deleteNull = data.dropna() #we created new dataframe called "deleteNull" by␣
 ↪dropping all rows with
                           #missing values (NaN) from the "data" dataframe using␣
 ↪the "dropna()" method.
display(deleteNull) #we displayed "deleteNull" dataframe
```

```
       Country Name Country Code  \
14       Arab World          ARB
15       Arab World          ARB
20       Arab World          ARB
21       Arab World          ARB
46       Arab World          ARB
...             ...          ...
106447     Zimbabwe          ZWE
106476     Zimbabwe          ZWE
106477     Zimbabwe          ZWE
106478     Zimbabwe          ZWE
106484     Zimbabwe          ZWE

                                           Indicator Name     Indicator Code  \
14      Adolescent fertility rate (births per 1,000 wo...        SP.ADO.TFRT
15      Adolescents out of school (% of lower secondar...  SE.SEC.UNER.LO.ZS
20                Air transport, freight (million ton-km)  IS.AIR.GOOD.MT.K1
```

```
21                  Air transport, passengers carried       IS.AIR.PSGR
46       Children out of school (% of primary school age)     SE.PRM.UNER.ZS
...                                                   ...               ...
106447           Total natural resources rents (% of GDP)  NY.GDP.TOTL.RT.ZS
106476                                   Urban population        SP.URB.TOTL
106477           Urban population (% of total population)  SP.URB.TOTL.IN.ZS
106478               Urban population growth (annual %)        SP.URB.GROW
106484  Women Business and the Law Index Score (scale ...        SG.LAW.INDX

                1990          1991          1992          1993          1994  \
14      7.113965e+01  6.906830e+01  6.733238e+01  6.534887e+01  6.337310e+01
15      3.455981e+01  3.384271e+01  3.407919e+01  3.280204e+01  3.399356e+01
20      1.753600e+03  1.562200e+03  1.970600e+03  2.225700e+03  2.637100e+03
21      3.148400e+07  2.883510e+07  3.387710e+07  3.401740e+07  3.596830e+07
46      2.702107e+01  2.639510e+01  2.897263e+01  2.851501e+01  2.631989e+01
...              ...           ...           ...           ...           ...
106447  4.212482e+00  9.664192e+00  1.081682e+01  8.724395e+00  9.487028e+00
106476  3.024147e+06  3.176318e+06  3.324547e+06  3.432105e+06  3.528870e+06
106477  2.898800e+01  2.973800e+01  3.049900e+01  3.094000e+01  3.133500e+01
106478  5.285272e+00  4.909360e+00  4.561076e+00  3.184035e+00  2.780393e+00
106484  5.500000e+01  5.500000e+01  5.750000e+01  5.750000e+01  6.687500e+01

                1995  ...          2011          2012          2013  \
14      6.123988e+01  ...  4.986697e+01  4.979107e+01  4.934536e+01
15      3.320302e+01  ...  2.033557e+01  1.906521e+01  2.160821e+01
20      2.924400e+03  ...  1.713693e+04  1.971176e+04  2.223401e+04
21      3.591820e+07  ...  1.358376e+08  1.520142e+08  1.662093e+08
46      2.714195e+01  ...  1.501091e+01  1.489191e+01  1.573564e+01
...              ...  ...           ...           ...           ...
106447  8.542652e+00  ...  7.870900e+00  5.933415e+00  5.018225e+00
106476  3.620850e+06  ...  4.257061e+06  4.306228e+06  4.359432e+06
106477  3.173200e+01  ...  3.301500e+01  3.283400e+01  3.265400e+01
106478  2.573110e+00  ...  9.896685e-01  1.148333e+00  1.227943e+00
106484  6.687500e+01  ...  8.687500e+01  8.687500e+01  8.687500e+01

                2014          2015          2016          2017          2018  \
14      4.885400e+01  4.827974e+01  4.750474e+01  4.668712e+01  4.600272e+01
15      2.043842e+01  1.949834e+01  1.865456e+01  1.845517e+01  1.722070e+01
20      2.469890e+04  2.591846e+04  2.786970e+04  3.034273e+04  3.186918e+04
21      1.816273e+08  1.959570e+08  2.143187e+08  2.234962e+08  2.326702e+08
46      1.596792e+01  1.574502e+01  1.555506e+01  1.496600e+01  1.403608e+01
...              ...           ...           ...           ...           ...
106447  5.532246e+00  4.568286e+00  4.468060e+00  6.038088e+00  6.085075e+00
106476  4.416224e+06  4.473872e+06  4.531238e+06  4.589452e+06  4.650597e+06
106477  3.250400e+01  3.238500e+01  3.229600e+01  3.223700e+01  3.220900e+01
106478  1.294326e+00  1.296922e+00  1.274094e+00  1.276544e+00  1.323497e+00
106484  8.687500e+01  8.687500e+01  8.687500e+01  8.687500e+01  8.687500e+01
```

```
                2019          2020
14      4.524537e+01  4.440661e+01
15      1.636922e+01  1.683747e+01
20      3.162185e+04  2.733222e+04
21      2.462847e+08  8.393290e+07
46      1.401778e+01  1.390687e+01
...              ...           ...
106447  3.098784e+00  1.184752e+01
106476  4.717307e+06  4.792105e+06
106477  3.221000e+01  3.224200e+01
106478  1.424249e+00  1.573169e+00
106484  8.687500e+01  8.687500e+01

[15415 rows x 35 columns]
```

Let's check again how many empty values we have now after data cleaning…

[6]:
```
deleteNull.isna().sum() #we chech all columns with NaN values and we sum them
```

[6]:
```
Country Name      0
Country Code      0
Indicator Name    0
Indicator Code    0
1990              0
1991              0
1992              0
1993              0
1994              0
1995              0
1996              0
1997              0
1998              0
1999              0
2000              0
2001              0
2002              0
2003              0
2004              0
2005              0
2006              0
2007              0
2008              0
2009              0
2010              0
2011              0
2012              0
2013              0
2014              0
```

```
2015                0
2016                0
2017                0
2018                0
2019                0
2020                0
dtype: int64
```

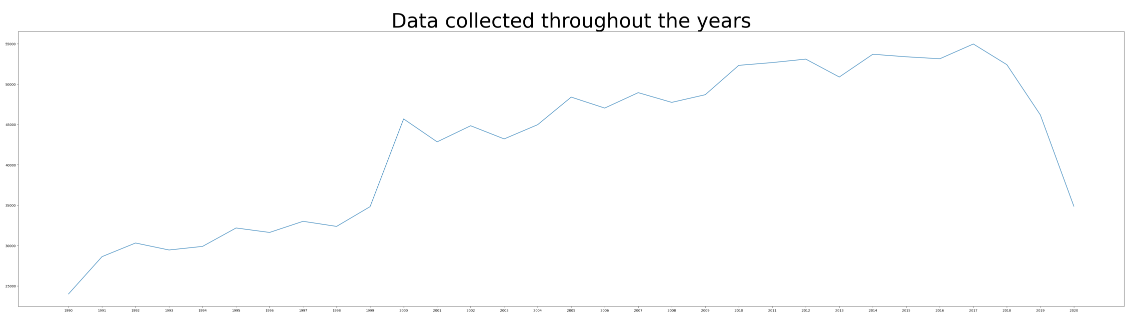
We can see that we have no more empty values, now we are going to find out what is our data set really about.

4 Exploratory Data Analysis

Let's try to show how much data was collected throughout the years

[7]:
```
plt.rcParams["figure.figsize"] = (60,15) #to spread out the years

plt.plot(data.count()[4:]) #we removed first 4 columns because those are our␣
↪categories and we are interested in the data
plt.title('Data collected throughout the years', fontsize = 60) #we put label
```

[7]:
```
Text(0.5, 1.0, 'Data collected throughout the years')
```



We can see that we were more and more diligent when collecting the data as years went exception being in the last couple of years. I think this was due to Covid-19 Virus.

Now I am going to check which categories have the most data. I did that by checking how many countries have the data in each category.

[8]:
```
table = deleteNull.groupby(["Indicator Name"]).count().sort_values("Country␣
↪Code") #we are grouping categories with country codes
df_new = table.iloc[:,0:1] #we want to show only "Indicator Name" and "Country"␣
↪columns
display(df_new) #we displayed table
```

```
                                                  Country Name
Indicator Name
```

```
Compulsory education, duration (years)                         1
Preprimary education, duration (years)                         1
Poverty headcount ratio at $1.90 a day (2011 PP...             1
Proportion of people living below 50 percent of...             1
Share of youth not in education, employment or ...             1
...                                                          ...
Primary education, duration (years)                          248
Forest area (sq. km)                                         249
Urban population growth (annual %)                           257
Urban population                                             258
Urban population (% of total population)                     259

[147 rows x 1 columns]
```

We can see those categories like "Preprimary education, duration (years)" or "Proportion of people living below 50 percent of median income (%)" have collected data from only one country each, while the category "Urban population" has collected information from 258 countries making it much more viable choice to find some global patterns.

Now, I wondered if the higher-income countries have more percentage of data collected compared to lower-income countries. For that, I checked our second dataset called "SDGCountry". I summed how many NaN datapoints I have and I divided it with the total number of datapoints for each 'Income Group'.

[9]:
```
data2 = pd.read_csv("SDGCountry.csv")  #we are using pandas to to read CSV file␣
 ↪""SDGCountry.csv"" and load it to dataframe caled "data2"
data2.drop(["Unnamed: 30"], inplace = True, axis =1) #we are droping the column␣
 ↪with label "unnamed 30"

income_group = data2['Income Group'].unique() #we created array of unique income␣
 ↪groups
table = [] #we created empty list to store our values
for i in income_group[:-1]: #for loop that iterates over each income group
    data = data2[data2['Income Group'] == i] #we created new dataset
    table.append((data.isna().sum().sum())/(data.count().sum()+data.isna().sum().
 ↪sum())) #we caluclate the ratio of missing data and all data
    print(i, ":", (data.isna().sum().sum())/(data.count().sum()+data.isna().
 ↪sum().sum())) #we print our results
```

```
High income : 0.305
Low income : 0.2369047619047619
Lower middle income : 0.2037037037037037
Upper middle income : 0.2111111111111111
```

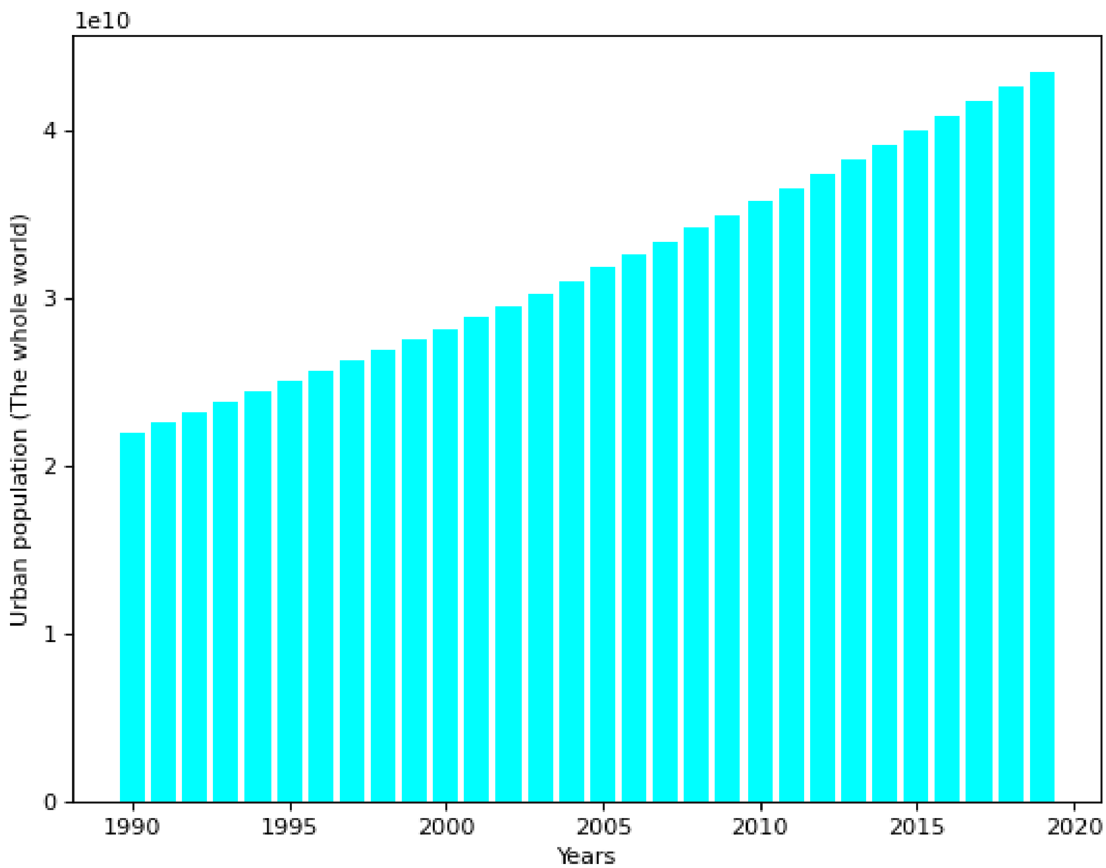
Right opposite to our premises, the high-income countries have the most missing values compared to the total amount of values they have. We can also see that countries that belong to the "Lower middle income" group have the least missing values.

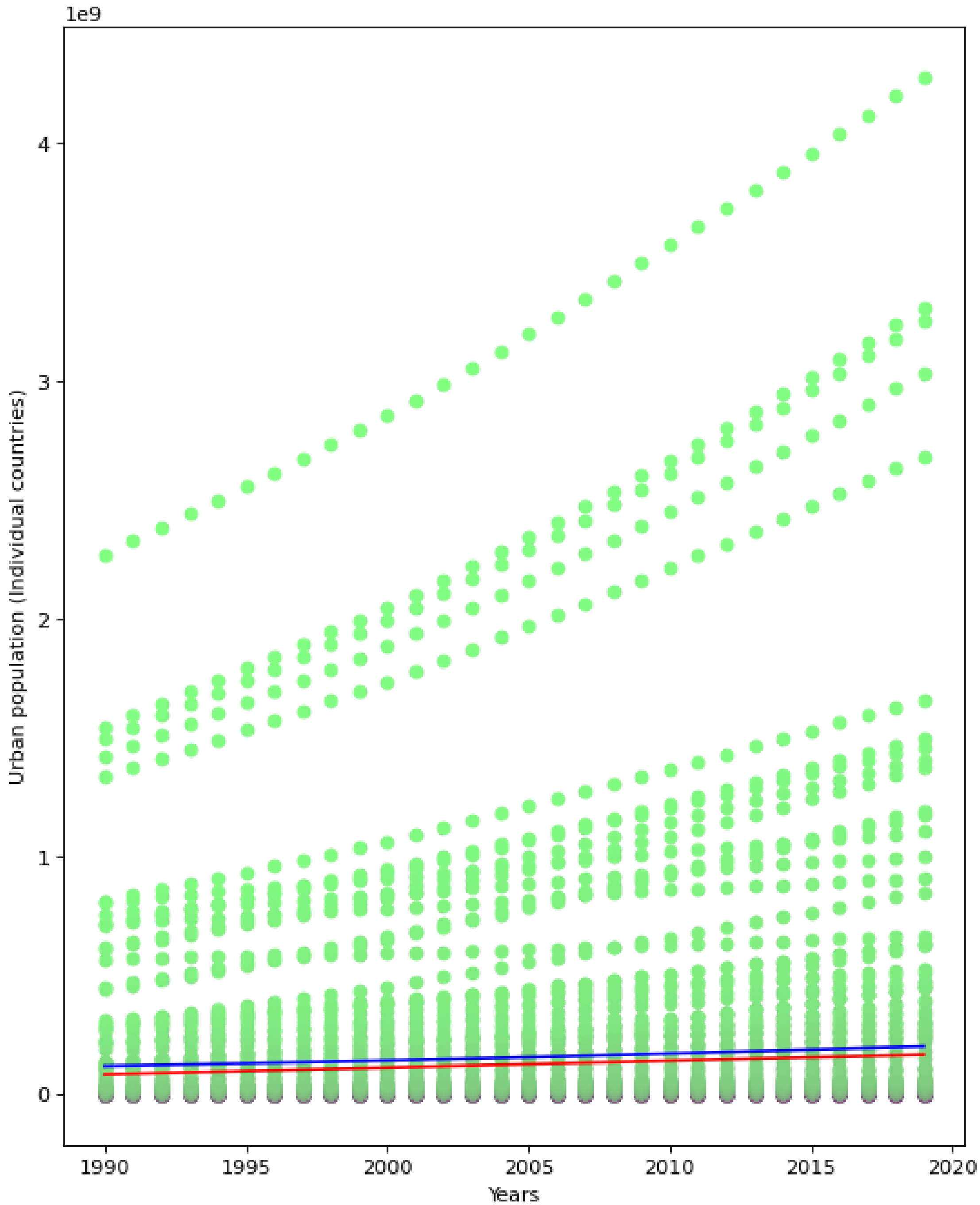
5 Descriptive Analytics

6 What was urban population growth from 1990 to 2020?

The first question asked was as follows; "what was urban population growth from 1990 to 2020?" this is a relevant point because, as an increase in urban populations suggests a higher concentration of individuals within high industry areas and economic zones of the state.

[10]:
```
pop = deleteNull[deleteNull["Indicator Code"] == "SP.URB.TOTL"] #we selected␣
↪only the rows where the
                                                                 #"Indicator␣
↪Code" column is equal to "SP.URB.TOTL"
figure(figsize=(8, 6), dpi=80) #size and the resolution of the figure

plt.bar(range(1990,2020),[sum(pop[str(year)]) for year in␣
↪range(1990,2020)],color="#00FFFF") #we generate plot bar
plt.xlabel("Years") #label on graph
plt.ylabel("Urban population (The whole world)") # label on graph
plt.show()

X = np.array(sum([[year for j in range(len(pop))]for year in range(1990,2020)],␣
↪[])).reshape((-1, 1))
y = np.array(sum([list(pop[str(year)])for year in range(1990,2020)],[]))
reg = LinearRegression().fit(X, y) #we created linear regression
y_pred = reg.predict(np.array(range(1990,2020)).reshape(-1, 1))
figure(figsize=(8, 10), dpi=80) #size and the resolution of the figure
plt.plot(range(1990,2020), y_pred,color="red") #plot
plt.xlabel("Years") #we added label "Years"
plt.ylabel("Urban population (Individual countries)") #label "Urban population"

ytemp = [sorted(list(pop[str(year)])) for year in range(1990,2020)] #create␣
↪temporaty list that contains sorted list of urban population values
for i in range(len(pop)):
    plt.scatter(range(1990,2020), [ytemp[year][i] for year in range(2020-1990)],␣
↪color = (0.5, i/len(pop), 0.5))
plt.plot(range(1990,2020),[sum(pop[str(year)])/len(pop)+10**7.5 for year in␣
↪range(1990,2020)],color="blue")
plt.show() #we displayed plot

print("Predicted number for average people in 2050 and 2100, respectively",reg.
↪predict(np.array([2050,2100]).reshape(-1,1)))
```


1e10
Urban population (The whole world)
0
1
2
3
4
1990
1995
2000
2005
2010
2015
2020
Years




```
Predicted number for average people in 2050 and 2100, respectively
[2.54829257e+08 3.98826961e+08]
```

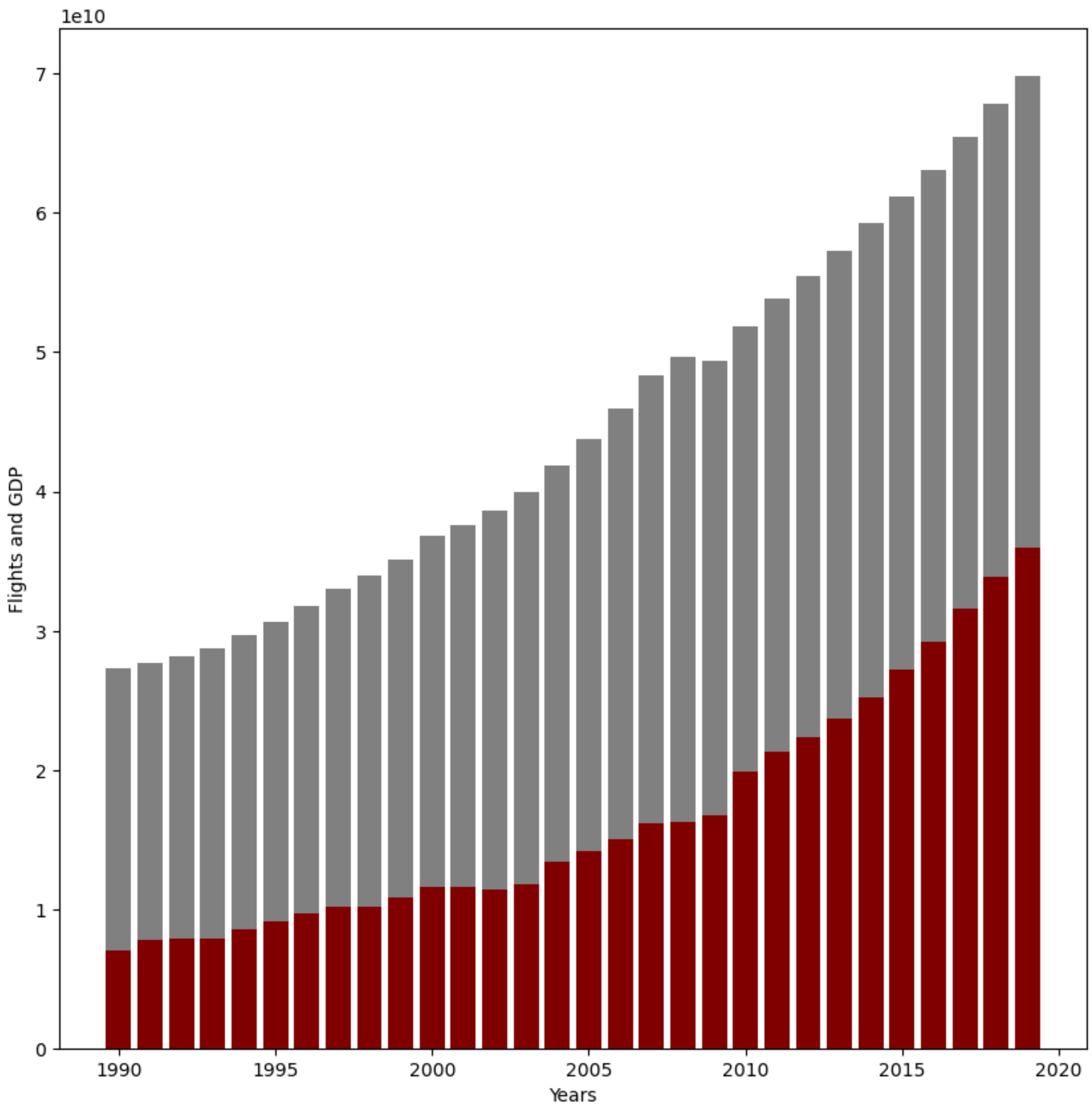
In reference to the first graph, one can see that urban population growth is linear in the last 30 years, with a steady growth of 666 million individuals per year. However, it must be recognized that different states have different rates of urban population growth which is highlighted in the second graph. It underscored that different states have significantly different urban population growth rates, where the world averages can be skewed by some states such as China and India. The red line represents a model which it attempts to predict the aggregate urban growth in the future, between all states using data from the 1990s to 2020.

By using a linear regression model, and assuming axioms in relation to other data points, the model was so accurate, that the blue line which represents the actual average of urban growth of states is overlapping with our prediction line (the red line). For visibility's sake, the blue line has to be scaled up by (10**7.5). From the linear regression model, we can thus approximate the world average urban population growth in 2050 and in 2100, and that is (2.54829257e+08 3.98826961e+08) respectively.

7 How is the growth of GDP correlated to the number of flights?

The second question asked was as follows; "how is the growth of GDP correlated to the number of flights?" this is an incredibly significant data point because while economic growth is paramount and is something that must always be thrived for, it can however have negative externalities, mostly manifesting itself with regressive changes to the climate. Airplanes are one of the most pollutant ways of transportation.

[11]:
```
flight = deleteNull[deleteNull["Indicator Code"] == "IS.AIR.PSGR"] #we selected␣
↪rows with "Indicator Code" columns called "IS.AIR.PSGR"
gdp = deleteNull[deleteNull["Indicator Code"] == "NY.GDP.MKTP.KD"] #we selected␣
↪rows with "Indicator Code" columns called "NY.GDP.MKTP.KD"
plt.figure(figsize=(10,10)) #we create 10x10 inch plot
plt.bar(range(1990,2020),[sum(gdp[str(year)])/(10**4) for year in␣
↪range(1990,2020)],color=(0.5,0.5,0.5))
    #we ploted sum of GDP (1990-2019)
plt.bar(range(1990,2020),[sum(flight[str(year)]) for year in␣
↪range(1990,2020)],color="maroon")
    #we ploted sum of air passenger traffic (1990-2019)
plt.xlabel("Years") #we added label "Years"
plt.ylabel("Flights and GDP") #we added label "Flights and GDP"
plt.show() #we displayed the plot
```

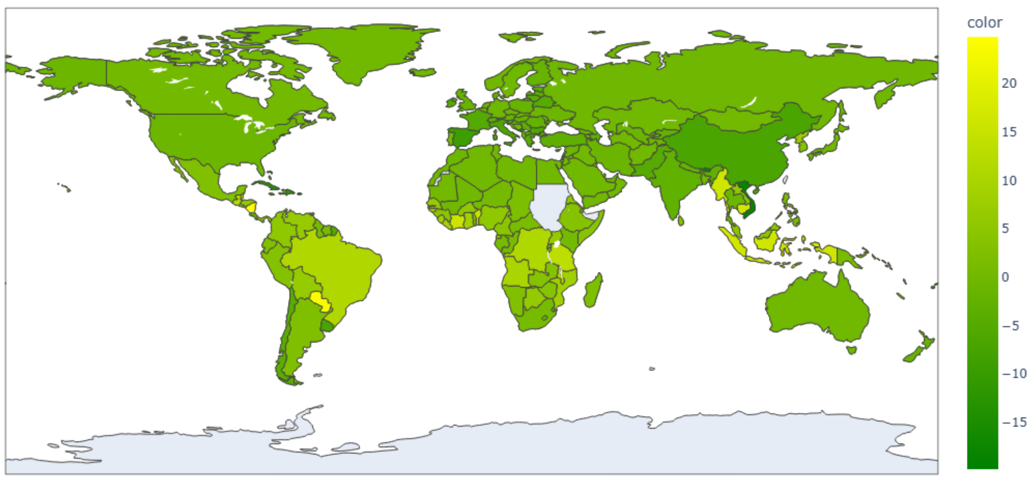


In reference to the third graph, there is a positive correlation between the number of flights and increases in GDP growth. An interesting observation was made on the graph that the rate of increase in the number of flights flattened correlated to the 2008 financial crisis, only further proving the positive correlation between the number of flights had, and economic growth. Where the number of flights started to increase again as soon as the economy started to recover in 2010

8 What is the change in 'green' areas in countries between 1990 and 2020?

The third question asked was as follows; "what is the change in 'green' areas in countries between 1990 and 2020?". This is relevant because, one would assume that in the context of economic growth, and industrialization, one would see a significant decrease in the number of 'green' areas, where green areas are defined as the % of the state land as forests.

[12]:
```
forest1 = deleteNull[deleteNull["Indicator Code"] == "AG.LND.FRST.ZS"]
fig = px.choropleth(forest1, locations="Country Code",
                    color=forest1["1990"]-forest1["2020"],
                    hover_name="Country Name",
                    color_continuous_scale=["green", "Yellow"],
                    width=1000,
                    height=600)


# Display interactive version in notebook
fig.show()
```



The relevance of forests can not be undermined, not only do they have the positive externality of making the world a little less bleak, but they are also the best natural CO2 suppressor. One can assume that the largest economic powers would have the largest deficit in such areas, but as highlighted in the map. Countries like China, which have experienced the largest rates of economic growth in the past 30 years (the time period within our data set), had negative deforestation rates of 6.66727%. In other words, the ‘green’ space actually increased. This is a fascinating point because economic development and growth can be achieved without excessive deforestation. Especially when one considers that African states had the opposite reaction where an increase in economic activity lead to higher rates of deforestation. One can attribute this to incompetent policy-making, using India and China as references (developing states with positive reforestation rates) however this only suggests that China and India are entering secondary and tertiary sectors of economies’ rather than primary sector ones like Africa.

9 Suggestions

The main problem with this data set was having multiple null values which resulted in losing many entries after the data clearing.

One of the ways of dealing with this problem would be through the use of trained artificial intelligence by machine learning. The AI will get trained on our unimpacted (not deleted/whole) data and then further be trained on existing data with the agenda of restoring the missing values. With our new stronger data we will be able to do more modeling and analysis which we previously could not.

Further, we could use our trained AI to approximate future data. With future data, we could be more aware of incoming problems and challenges and adjust ourselves accordingly. Furthermore, the key to having a rich and neat data set comes down to diligent and precise measuring and data collection. Newly collected data on top of our previously collected data will further enrich the overall data our IA is using to create its weights and that way even our previous data will become more precise.

Furthermore, we could use outsource the data from the other correlated and trustworthy data sets to make our pool of information that much bigger and more pottent to predictions.

To conclude, we live in world of information where we use data daily to analyze information, create models, make predictions, and come to conclusions about the world around us. More data enriches our capabilities to predict the seasonalities and trends in the data. Ergo it is key to obtain as much data as we can and some ways of generating more data are machine learning AI, outsourcing the data, and being more precise when measuring.

Bibliography List all sources you have utilised in the making of this report here. https://www.w3schools.com/colors/colors_hex.asp https://stackoverflow.com/questions/51161620/linear-regression-python https://stackoverflow.com/questions/7095441/defining-a-color-in-python https://stackoverflow.com/questions/43934864/using-matlab-in-python https://stackoverflow.com/questions/1514553/how-do-i-declare-an-array-in-python https://www.w3schools.com/python/numpy/default.asp https://www.w3schools.com/python/pandas/default.asp https://www.db.com/what-next/digital-disruption/better-than-humans/how-artificial-intelligence-is-changing-banking/index