investigate-a-dataset

November 16, 2017

1 Project: Investigating Gapminder Data

1.1 Table of Contents

Introduction

Over time, countries develop in terms of productivity often measured in GDP. As GDP rises, there is often an acompanying change in workforce composition and median age. This investigation aims to investigate metrics from four datasets from the gapminder website in order to analyze what the general trends are.

In order to help group the dataset by continents/regions and sub-regions, a CSV file containing this information was also downloaded. The corresponding github page can be found here.

The directing questions for this investigation is as follows:

1. As a country develops, how does the composition of its workforce change?
2. Which countries are progressing the fastest?
3. What can countries expect as their GDP rises?
4. How does the age of a country change over time?

Datasets analyzed:

- Gross Domestic Product per capita in constant USD (value from the year 2000)
  - Adjusted for inflation
  - Not adjusted for differences in cost of living between countries
- Agriculture workers (% total labor force)
- Industry workers (% total labor force)
- Service workers (% total labor force)

The parameters used will be as follows:

- Independent variable:
  - Time
- Dependent variables:
  - GDP
  - % employment in Agriculture, Service and Industrial sectors

Github respository can be found here.

In [1]:
```
# Import libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import ttest_ind

%matplotlib inline
```

Defining Functions

In [2]:
```
def df_T_properly(df):
    """
    Transposes the dataframe, sets the column titles to the first row in the
    transposed dataframe before removing the first row and returning the pro-
    perly transposed.

    Used in: calculate_nan_density_country(df_list)
    """

    # Transpose dataframe
    df2 = df.transpose()

    # Rename columns
    df2.columns = df2.iloc[0]

    # Reset columns
    df3 = df2.reindex(df2.index.drop('Country'))

    return df3
```

In [3]:
```
def plot_nan_density_year(df, df_name, x_label = "Year"):
    """
    Calculates the density of non-NaN values inside of a dataframe for each
    row (i.e. year) and creates a plot with specified title showing this change.
    """
```

```
        # Calculate density per row
        year = []
        density = []
        for i in range(df.shape[1]):
            if i == 0: continue
            year.append(int(df.columns[i]))
            density.append(df.iloc[:, i].count()/len(df.iloc[:, i]))

        # Plot Results
        plt.plot(year, density)
        plt.xlabel(x_label)
        plt.ylabel("Non-NaN Density")
        plt.title("Non-NaN values for {}".format(df_name))
        axes = plt.gca()
        axes.set_ylim([0, 1])
        plt.show()
```

```
In [4]: def basic_plot(x_series, y_series, x_label = "x", y_label="y",
                       y_ticks=False, plt_title = "plot"):
        """
        Creates a basic plot from two series, used for creating quick and dirty
        plots.

        For changing the xticks, input an integer for reduced_xticks. This only
        works if x_series can be converted to an integer

        You can also adjust the yticks by adding a tuple in the form of
        (start, finish)
        """

        # Change years to int
        x_series = x_series.astype(int)

        # Create plot
        plt.plot(x_series, y_series, c='red')
        plt.xlabel(x_label)
        if y_ticks: plt.yticks(y_ticks)
        plt.ylabel(y_label)
        plt.title(plt_title)
        plt.show
```

```
In [5]: def calculate_nan_density_country(df_list):
        """
        Looks at a list of dataframes and calculates the NaN density for each
        country and returns that information inside of a datafame.

        Section of code will try to find the largest intersection of countries
        shared by all dataframes.
```

```
    This is so that the data can be grouped-by filtered and merged with other dfs
    later which will help gain into more insight into which columns that need to
    be dropped or transformed in some way.

    Dependencies:
        country_check(check_country, df)
        common_countries(smallest_list)
        df_T_properly(df)
    """

    # Initialize values
    n_countries = {}
    smallest = 1e400

    # Find dataframes with lowest number of nonNaN rows
    for df in df_list:

        # Create relevant entry in dictionary
        if not eval(df).shape[0] in n_countries.keys(): n_countries[eval(df).shape[0]]=
        else: n_countries[eval(df).shape[0]].append(df)

        # Keep track of smallest value
        if eval(df).shape[0] < smallest:
            smallest = eval(df).shape[0]

    # Check smallest number of countries is unique
    if len(n_countries[smallest]) > 1:

        # Rename list
        smallest_list = n_countries[smallest]

        # Find unique columns
        check_country = common_countries(smallest_list)

    else: check_country =  list(eval(n_countries[smallest][0])['Country'])

    # Check that all check_country appear in ccode
    check_country2 = country_check(check_country, df_ccode)
    check_country3 = country_check(check_country2, df_GDP)
    check_country4 = country_check(check_country3, df_age)

    # Create dictionary which will be converted to dataframe
    dict_to_df = {}

    # Fill dictionary with relevant values
    for country in check_country4:
```

```
            # Init. row list
            row_list = []

            for df in df_list:
                # Calculate length

                df_row_length = eval(df)[eval(df)['Country']==country].iloc[0, 1:].notnull

                # Calculate non-NaN values
                df_row_nonNaN = eval(df)[eval(df)['Country']==country].iloc[0, 1:].notnull

                # Append to List
                row_list.append(df_row_nonNaN/df_row_length)

            # Insert values into dictionary
            dict_to_df[country] = row_list

        # Convert dictionary to dataframe and transpose
        return_df = pd.DataFrame(dict_to_df)
        return_df.insert(loc = 0, column = 'Country', value = df_list)
        return_df = df_T_properly(return_df)

        return return_df
```

```
In [6]: def common_countries(smallest_list):
        """
        Checks a list of strings that can be evaluated to dataframes and returns
        countries which are not found in all dataframes.

        Used in: calculate_nan_density_country(df_list)
        """

        # Init. list
        ignore_country = []
        check_country= []

        # Check columns
        for i in range(len(smallest_list)):

            # Init j value to compare with later dfs
            j = i

            # Check larger dfs
            while j < len(smallest_list):

                # Find unique columns
                set_diff = set(eval(smallest_list[i])['Country']).difference(
                           set(eval(smallest_list[j])['Country']))
```

```
                    # Add new unique columns to list
                    for k in set_diff:
                        if k not in ignore_country: ignore_country.append(k)

                    # Increment j for next loop
                    j+=1

            # find check_columns
            for df in smallest_list:
                good_columns = list(set(eval(df).Country).difference(set(ignore_country)))
                for col in good_columns:
                    if col not in check_country: check_country.append(col)

            return check_country
```

In [7]:
```
def country_check(check_country, df):
    """
    Makes sure that each country can be found in df.

    Used in: calculate_nan_density_country(df_list)
    """

    # Init. list
    check_country2 = []

    # Check columns
    for country in check_country:
        try:
            if country in list(df['name']): check_country2.append(country)
        except KeyError:
            if country in list(df['Country']): check_country2.append(country)

    return check_country2
```

In [8]:
```
def imputation_average(df):
    """
    Takes dataframe and imputes missing values for each column by using the
    mean of the column. Dataframe is then returned with all column names and
    indexesintact.
    """

    # Iterate over columns
    for i in range(df.shape[0]):

        # Calculate column mean
        row_mean = df.iloc[i, 1:].mean()
```

```
            # Fill NaN values
            df.iloc[i]=df.iloc[i].fillna(row_mean)

        return df
```

Data Wrangling

1.1.1 Viewing the Data

```
In [9]: # Import data
        df_GDP = pd.read_csv('data_csv/GDPpercapitaconstant2000US.csv')
        df_agric = pd.read_csv('data_csv/indicator_t agriculture employ.csv')
        df_indus = pd.read_csv('data_csv/indicator_t industry employ.csv')
        df_servi = pd.read_csv('data_csv/indicator_t service employ.csv')
        df_age = pd.read_csv('data_csv/indicator_median age.csv')
        df_ccode = pd.read_csv('data_csv/country_codes.csv')

In [10]: df_GDP.head()

Out[10]:                  Country         1960         1961        1962        1963  \
         0              Abkhazia          NaN          NaN         NaN         NaN
         1           Afghanistan          NaN          NaN         NaN         NaN
         2  Akrotiri and Dhekelia          NaN          NaN         NaN         NaN
         3               Albania          NaN          NaN         NaN         NaN
         4               Algeria  1280.384828  1085.414612  855.947986  1128.41578

                  1964         1965         1966         1967         1968  \
         0          NaN          NaN          NaN          NaN          NaN
         1          NaN          NaN          NaN          NaN          NaN
         2          NaN          NaN          NaN          NaN          NaN
         3          NaN          NaN          NaN          NaN          NaN
         4  1170.323896  1215.015783  1127.614288  1200.558225  1291.863983

               ...              2002         2003         2004         2005  \
         0     ...               NaN          NaN          NaN          NaN
         1     ...               NaN          NaN          NaN          NaN
         2     ...               NaN          NaN          NaN          NaN
         3     ...       1313.722725  1381.040832  1454.022854  1525.723589
         4     ...       1871.921986  1971.512803  2043.135713  2115.186028

                  2006         2007         2008         2009         2010  \
         0          NaN          NaN          NaN          NaN          NaN
         1          NaN          NaN          NaN          NaN          NaN
         2          NaN          NaN          NaN          NaN          NaN
         3  1594.495067  1681.613910  1804.419415  1857.352947  1915.424459
         4  2124.957754  2155.485231  2173.787903  2192.703976  2231.980246

                  2011
         0          NaN
```

```
1          NaN
2          NaN
3  1965.707230
4  2255.225482

[5 rows x 53 columns]
```

```
In [11]: df_agric.head()
```

```
Out[11]:                Country  1980  1981  1982  1983  1984  1985  1986  1987  1988  \
0               Algeria   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN
1        American Samoa   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN
2                Angola   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN
3              Anguilla   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN
4  Antigua and Barbuda   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN

   ...   1998  1999  2000  2001  2002  2003       2004  2005  2006  2007
0  ...    NaN   NaN   NaN  21.1   NaN  21.1  20.700001   NaN   NaN   NaN
1  ...    NaN   NaN   NaN   NaN   NaN   NaN        NaN   NaN   NaN   NaN
2  ...    NaN   NaN   NaN   NaN   NaN   NaN        NaN   NaN   NaN   NaN
3  ...    NaN   2.3   NaN   2.9   NaN   NaN        NaN   NaN   NaN   NaN
4  ...    NaN   NaN   NaN   2.6   NaN   NaN        NaN   NaN   NaN   NaN

[5 rows x 29 columns]
```

```
In [12]: df_indus.head()
```

```
Out[12]:                Country  1980  1981  1982  1983  1984  1985  1986  1987  1988  \
0               Algeria   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN
1        American Samoa   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN
2                Angola   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN
3              Anguilla   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN
4  Antigua and Barbuda   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN

   ...   1998  1999  2000       2001  2002  2003  2004  2005  2006  2007
0  ...    NaN   NaN   NaN  24.299999   NaN  24.0  26.0   NaN   NaN   NaN
1  ...    NaN   NaN   NaN        NaN   NaN   NaN   NaN   NaN   NaN   NaN
2  ...    NaN   NaN   NaN        NaN   NaN   NaN   NaN   NaN   NaN   NaN
3  ...    NaN  20.5   NaN  18.900000   NaN   NaN   NaN   NaN   NaN   NaN
4  ...    NaN   NaN   NaN  14.600000   NaN   NaN   NaN   NaN   NaN   NaN

[5 rows x 29 columns]
```

```
In [13]: df_servi.head()
```

```
Out[13]:                Country  1980  1981  1982  1983  1984  1985  1986  1987  1988  \
0               Algeria   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN
1        American Samoa   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN
2                Angola   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN
```

```
3             Anguilla   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN
4  Antigua and Barbuda   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN

   ...   1998  1999  2000       2001  2002       2003  2004  2005  2006  2007
0  ...    NaN   NaN   NaN  54.500000   NaN  54.799999  53.0   NaN   NaN   NaN
1  ...    NaN   NaN   NaN        NaN   NaN        NaN   NaN   NaN   NaN   NaN
2  ...    NaN   NaN   NaN        NaN   NaN        NaN   NaN   NaN   NaN   NaN
3  ...    NaN  67.5   NaN  76.699997   NaN        NaN   NaN   NaN   NaN   NaN
4  ...    NaN   NaN   NaN  74.599998   NaN        NaN   NaN   NaN   NaN   NaN

[5 rows x 29 columns]
```

```
In [14]: df_age.head()
```

```
Out[14]:     Median age    1950    1955    1960    1965    1970    1975    1980  \
0  Afghanistan  18.597  18.462  18.311  18.193  17.994  17.648  17.357
1       AFRICA  19.173  18.862  18.434  18.020  17.690  17.524  17.505
2      Albania  20.640  20.202  19.677  18.955  18.844  19.490  21.349
3      Algeria  19.927  19.307  18.170  16.742  15.808  16.165  16.910
4       Angola  19.401  18.882  18.244  17.481  16.987  16.828  16.652

     1985    1990   ...      2005    2010    2015    2020    2025    2030  \
0  17.091  16.845   ...    16.490  16.868  17.326  17.810  18.319  18.936
1  17.443  17.541   ...    19.058  19.676  20.401  21.233  22.245  23.381
2  22.505  23.815   ...    28.532  29.968  31.796  33.636  35.737  37.988
3  17.318  18.183   ...    24.015  26.247  28.311  30.333  32.300  34.187
4  16.449  16.198   ...    16.718  17.385  17.989  18.658  19.510  20.435

     2035    2040    2045    2050
0  19.775  20.918  22.196  23.522
1  24.593  25.851  27.153  28.492
2  40.292  42.258  43.702  44.268
3  35.547  36.877  38.145  39.416
4  21.623  22.891  24.197  25.561

[5 rows x 22 columns]
```

```
In [15]: df_ccode.head()
```

```
Out[15]:             name alpha-2 alpha-3  country-code     iso_3166-2   region  \
0     Afghanistan      AF     AFG             4  ISO 3166-2:AF     Asia
1   Åland Islands      AX     ALA           248  ISO 3166-2:AX   Europe
2         Albania      AL     ALB             8  ISO 3166-2:AL   Europe
3         Algeria      DZ     DZA            12  ISO 3166-2:DZ   Africa
4  American Samoa      AS     ASM            16  ISO 3166-2:AS  Oceania

        sub-region  region-code  sub-region-code
0    Southern Asia        142.0             34.0
1  Northern Europe        150.0            154.0
```

```
2  Southern Europe        150.0            39.0
3  Northern Africa          2.0            15.0
4        Polynesia          9.0            61.0
```

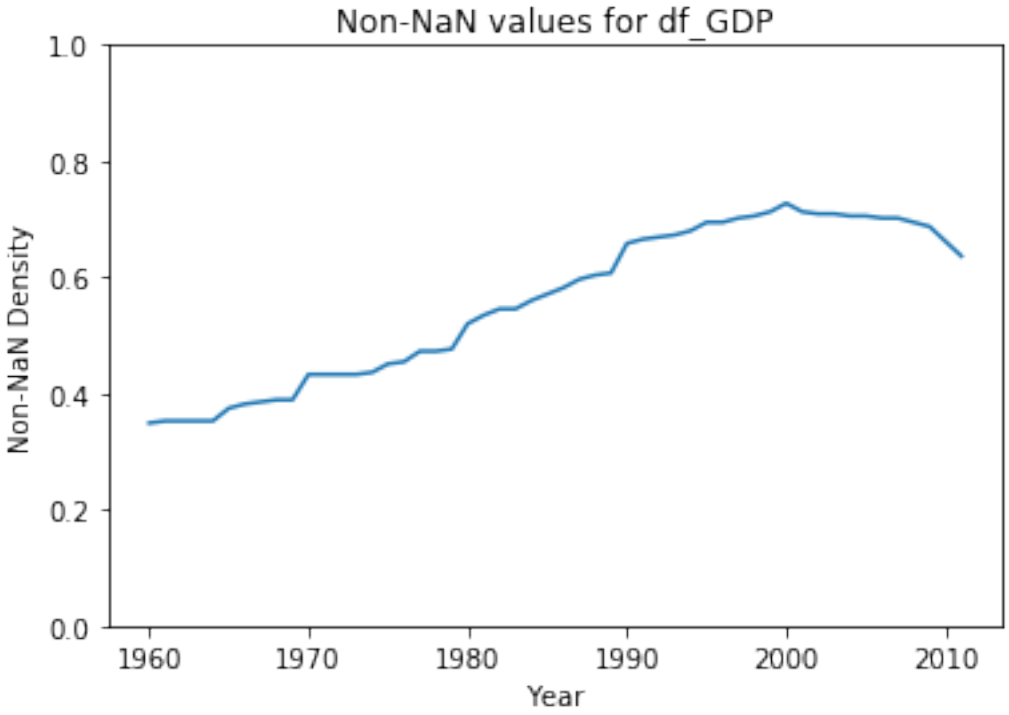
From the above "heads" of the dataframes, it is possible to see that a LOT of data is missing from these CSV files. This is likely because data tracking has only become easy within the last couple of decades, this is especially true for countries that are still developing.

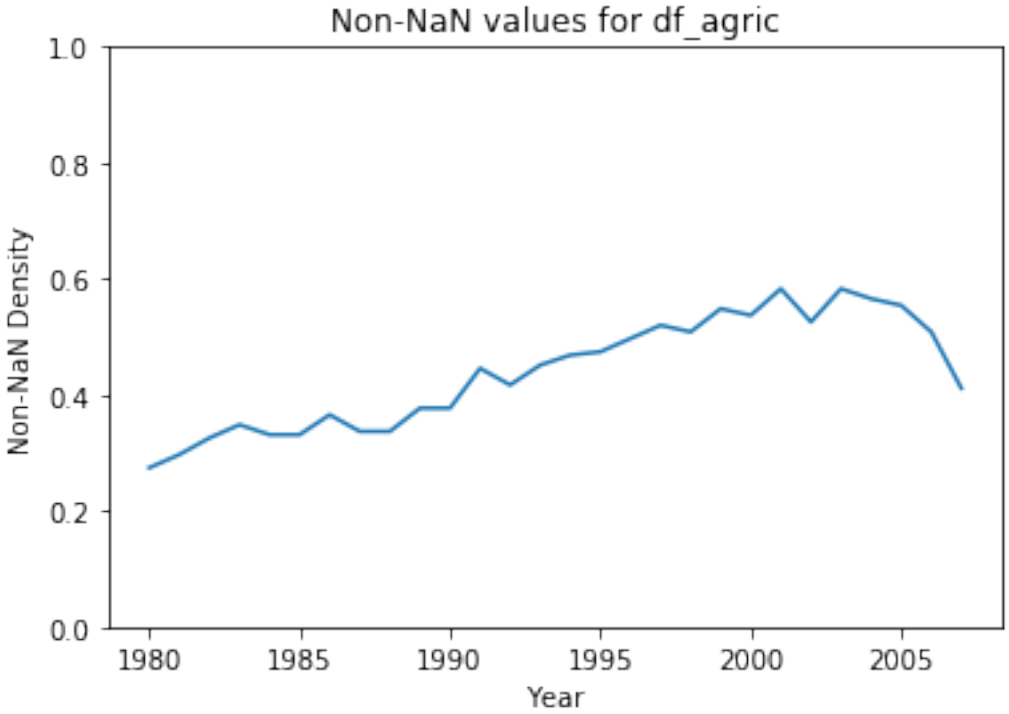
Hence, this creates an immediate bias in any analysis that will be done in this notebook where the information about more economically developed countries (MEDCs) will be more accurate and complete than less economically developed countries (LEDCs).

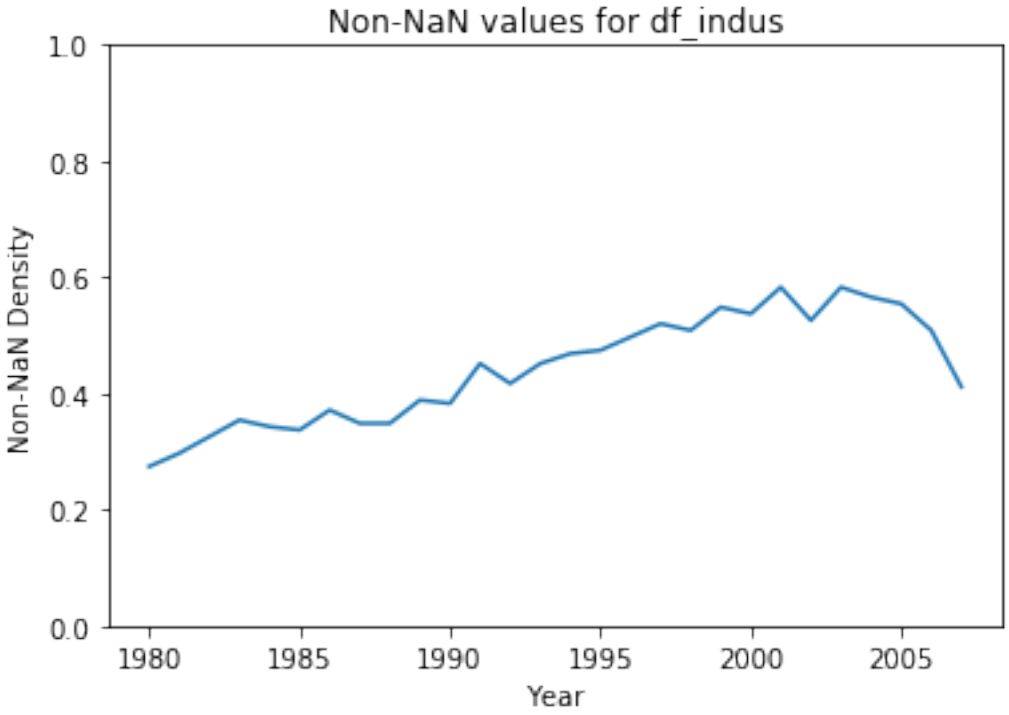
If there are only a couple of missing values then it is usually possible to impute an average and fill these spaces. However, there are many data series where more than 50% of the data is missing. I will find the rows (countries) which have more than 70% filled data and keep those rows. The rest of the rows will be dropped because they do not contain enough information to be of use. (At least, not in a way that produces anything non-artificial or low resolution.)

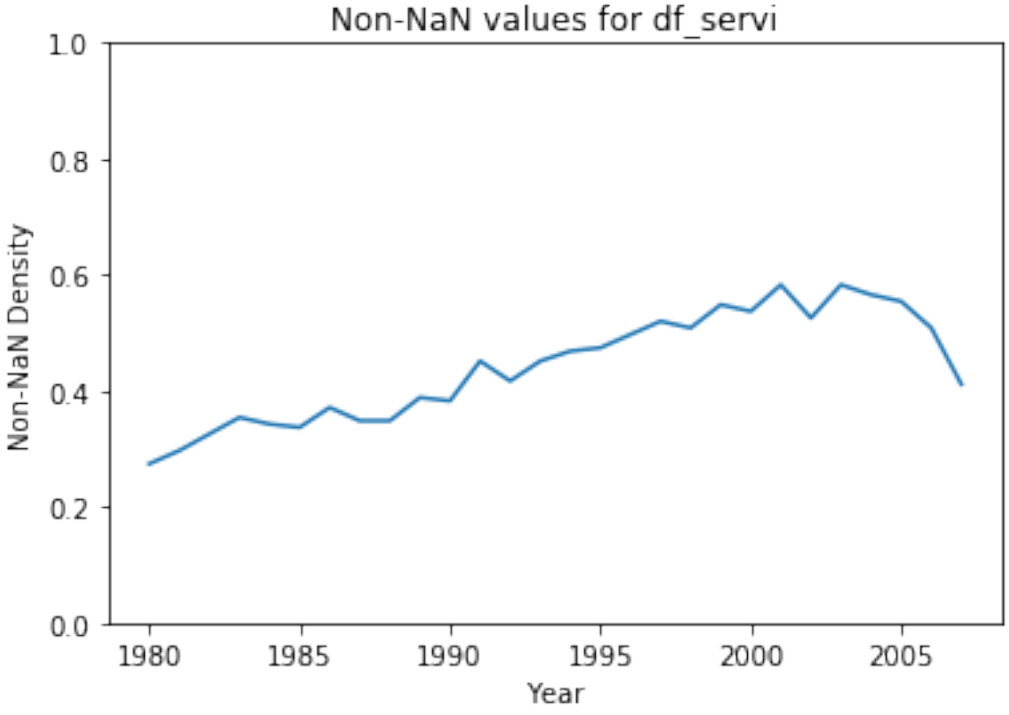
1.1.2 Finding countries with "more complete" data

```
In [16]: # Drop columns from df_ccode which will not be used
         df_ccode.drop(['alpha-2','alpha-3' ,'country-code', 'iso_3166-2', 'region-code',
                        'sub-region-code'], axis=1, inplace=True)

In [17]: # Rename bad label in df_age
         df_age.rename(columns={'Median age': 'Country'}, inplace=True)

In [18]: # Create dataframe list
         df_list = ["df_GDP", "df_agric", "df_indus", "df_servi", "df_age"]

In [19]: for df in df_list:
             if df == 'df_age': continue # Skip df_age, no NaN values
             plot_nan_density_year(eval(df), df)
```


Non-NaN values for df_GDP
Non-NaN Density
Year
1.0
0.8
0.6
0.4
0.2
0.0
1960
1970
1980
1990
2000
2010


Non-NaN values for df_agric
Non-NaN Density
Year
1.0
0.8
0.6
0.4
0.2
0.0
1980
1985
1990
1995
2000
2005


Non-NaN values for df_indus
Non-NaN Density
Year
1.0
0.8
0.6
0.4
0.2
0.0
1980
1985
1990
1995
2000
2005


Non-NaN values for df_servi
Non-NaN Density
Year
1.0
0.8
0.6
0.4
0.2
0.0
1980
1985
1990
1995
2000
2005

In these plots we can see how NaN density drops over time and suddenly spikes after the turn of the millenia, I am not exactly sure as to why this is but it's worth noting.

In [20]:
```
# Calculate Non-NaN density for each country
meta_df_NaN_Density = calculate_nan_density_country(df_list)

# Fix indexing issues
meta_df_NaN_Density.reset_index(inplace=True)
meta_df_NaN_Density.rename({'index': 'Country'}, axis=1, inplace=True)

meta_df_NaN_Density.head()
```

Out[20]:

Country	Country	df_GDP	df_agric	df_indus	df_servi	df_age
0	Algeria	1	0.107143	0.107143	0.107143	1
1	Angola	0.519231	0.0357143	0.0357143	0.0357143	1
2	Argentina	1	0.714286	0.714286	0.714286	1
3	Armenia	0.423077	0.214286	0.214286	0.214286	1
4	Aruba	0.326923	0.0714286	0.0714286	0.0714286	1

So now it is possible to see which countries have the most complete data. The threshold used for this analysis will be 70% non-NaN data but this threshold can be changed for furether experimentation if one wishes.

In [21]:
```
# Find countries with Non-NaN densities higher than 0.7
threshold = 0.70
mdND_70 = meta_df_NaN_Density[(meta_df_NaN_Density['df_GDP'] > threshold) &\
                              (meta_df_NaN_Density['df_agric'] > threshold) &\
                              (meta_df_NaN_Density['df_indus'] > threshold) &\
                              (meta_df_NaN_Density['df_servi'] > threshold) &\
                              (meta_df_NaN_Density['df_age'] > threshold)]

# Join with df_ccode to determine general locations of countries
df_ccode.rename({'name': 'Country'}, axis=1, inplace=True)
mdND_70 = df_ccode.merge(right = mdND_70, how='inner', on='Country')

# Define countries to investigate
country_list = list(mdND_70['Country'])

mdND_70.head()
```

Out[21]:

	Country	region	sub-region	df_GDP	df_agric	\
0	Argentina	Americas	South America	1	0.714286	
1	Australia	Oceania	Australia and New Zealand	1	1	
2	Austria	Europe	Western Europe	1	0.892857	
3	Barbados	Americas	Caribbean	0.961538	0.857143	
4	Belgium	Europe	Western Europe	1	0.785714	

	df_indus	df_servi	df_age
0	0.714286	0.714286	1

```
1         1         1      1
2  0.892857  0.892857      1
3  0.857143  0.857143      1
4  0.785714  0.785714      1
```

Now that we know which countries have complete data, we can aggregate this data so that we know what regions or sub-regions these countries come from.

```
In [22]: # Count rows by region
         mdND_70.groupby('region')['Country'].count()
```

```
Out[22]: region
         Africa       1
         Americas    10
         Asia        10
         Europe      15
         Oceania      1
         Name: Country, dtype: int64
```

```
In [23]: # Count rows by sub-region
         mdND_70.groupby('sub-region')['Country'].count()
```

```
Out[23]: sub-region
         Australia and New Zealand    1
         Caribbean                    3
         Central America              3
         Eastern Asia                 1
         Eastern Europe               1
         Northern Africa              1
         Northern America             1
         Northern Europe              5
         South America                3
         South-Eastern Asia           5
         Southern Asia                1
         Southern Europe              4
         Western Asia                 3
         Western Europe               5
         Name: Country, dtype: int64
```

As we can see, most of the data comes from The Americas, Europe and Asia. Data from Africa is relatively incomplete which makes it harder to do analysis on it without completely fabricating the data. This is a bias that will just need to be accepted for this analysis, to improve in this bias more complete data over Africa will need to be recorded in the future which will become easier as the contitnent's infrastructures develop.

1.1.3 Update Dataframes

```
In [24]: # Update dataframes in df_T_List to contain the relevant countries
         df_GDP = df_GDP[df_GDP['Country'].isin(country_list)]
```

```
df_agric = df_agric[df_agric['Country'].isin(country_list)]
df_indus = df_indus[df_indus['Country'].isin(country_list)]
df_servi = df_servi[df_servi['Country'].isin(country_list)]
df_age = df_age[df_age['Country'].isin(country_list)]
```

```
In [25]: # Impute NaN values - Once again, no need to do anything with df_age
         df_GDP = imputation_average(df_GDP)
         df_agric = imputation_average(df_agric)
         df_indus = imputation_average(df_indus)
         df_servi = imputation_average(df_servi)
```

```
In [26]: ## check column values are appropriate
         #df_GDP.info()
         #df_agric.info()
         #df_indus.info()
         #df_servi.info()
```

Since the columns all have floating point values, there is not much point looking at the dataframe info, but that might be fun to look at if you're interesed. For now I'll just leave this code as comments because I'd rather it didn't execute and waste space. I'm just noting this step so that you guys know that I didn't forget.

```
In [27]: # Change percentage range from 0-100 to 0-1
         df_agric.iloc[:, 1:] = df_agric.iloc[:, 1:].divide(other=100)
         df_indus.iloc[:, 1:] = df_indus.iloc[:, 1:].divide(other=100)
         df_servi.iloc[:, 1:] = df_servi.iloc[:, 1:].divide(other=100)
```

```
In [28]: # Merge region and sub-region into dataframes
         df_GDP = df_ccode.merge(right = df_GDP, how='inner', on='Country')
         df_agric = df_ccode.merge(right = df_agric, how='inner', on='Country')
         df_indus = df_ccode.merge(right = df_indus, how='inner', on='Country')
         df_servi= df_ccode.merge(right = df_servi, how='inner', on='Country')
         df_age = df_ccode.merge(right = df_age, how='inner', on='Country')
```

```
In [29]: df_GDP.head()
```

Out[29]:

	Country	region	sub-region	1960	1961	\
0	Argentina	Americas	South America	5251.876754	5448.303627	
1	Australia	Oceania	Australia and New Zealand	9407.685082	9451.546304	
2	Austria	Europe	Western Europe	7434.183717	7802.972546	
3	Barbados	Americas	Caribbean	3396.945712	3646.654780	
4	Belgium	Europe	Western Europe	7454.716536	7799.889081	

	1962	1963	1964	1965	1966	\
0	5316.578969	4956.216522	5375.463707	5855.611563	5733.311946	
1	9351.023272	9749.128563	10231.144465	10633.094400	10635.677912	
2	7960.707270	8237.060529	8683.454516	8927.460698	9365.306134	
3	3961.399895	3744.022688	3915.325593	4347.904449	4509.680501	
4	8173.818456	8465.979625	8969.632551	9205.035593	9431.614088	

```
        ...          2002          2003          2004          2005  \
0       ...   6428.393836   6933.155594   7492.249508   8107.975365
1       ...  22402.991019  22825.571022  23498.261991  23929.164397
2       ...  24375.113835  24466.706298  24945.047766  25370.465866
3       ...   8717.534639   8873.568078   9181.616033   9454.342464
4       ...  23008.449937  23097.212617  23750.459812  24033.783302

           2006          2007          2008          2009          2010  \
0   8717.176296   9388.688523   9935.834246   9933.229024  10749.319224
1  24295.081380  24765.548902  25190.720626  25007.697756  25190.839860
2  26171.690912  27036.487332  27305.923295  26183.997598  26642.993858
3   9757.443433   9783.984173   9781.356913   9243.587053   7297.016106
4  24512.413136  25034.666923  25082.374127  24190.594952  24550.396553

           2011
0  11601.630223
1  25306.824938
2  27266.403350
3   7297.016106
4  24733.626956

[5 rows x 55 columns]
```

```
In [30]: df_agric.head()
```

```
Out[30]:      Country    region                 sub-region      1980     1981     1982  \
0  Argentina  Americas              South America  0.006750  0.00675  0.00100
1  Australia   Oceania  Australia and New Zealand  0.065000  0.06500  0.06400
2    Austria    Europe             Western Europe  0.070680  0.07068  0.07068
3   Barbados  Americas                  Caribbean  0.061167  0.09400  0.08600
4    Belgium    Europe             Western Europe  0.031000  0.03100  0.03100

    1983   1984     1985     1986    ...      1998   1999   2000   2001  \
0  0.003  0.003  0.00675  0.00675    ...     0.008  0.007  0.007  0.008
1  0.066  0.062  0.06200  0.06000    ...     0.049  0.050  0.050  0.048
2  0.099  0.094  0.09000  0.08600    ...     0.066  0.062  0.059  0.057
3  0.080  0.091  0.08500  0.08200    ...     0.044  0.043  0.037  0.042
4  0.031  0.031  0.03100  0.03000    ...     0.023  0.020  0.018  0.016

    2002   2003   2004      2005      2006      2007
0  0.010  0.014  0.012  0.011000  0.008000  0.006750
1  0.045  0.039  0.038  0.036000  0.035000  0.034000
2  0.057  0.056  0.050  0.055000  0.055000  0.057000
3  0.040  0.046  0.033  0.061167  0.061167  0.061167
4  0.017  0.017  0.020  0.020000  0.020000  0.024409

[5 rows x 31 columns]
```

```
In [31]: df_indus.head()
```

Out[31]:

	Country	region	sub-region	1980	1981	1982	1983	1984	1985	1986	...	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
0	Argentina	Americas	South America	0.263100	0.26310	0.29300	0.292	0.309	0.2631	0.2631	...	0.248	0.236	0.227	0.219	0.202	0.217	0.230	0.235000	0.237000	0.263100
1	Australia	Oceania	Australia and New Zealand	0.310000	0.30500	0.29700	0.284	0.280	0.2710	0.2660	...	0.218	0.213	0.218	0.209	0.210	0.210	0.212	0.211000	0.212000	0.212000
2	Austria	Europe	Western Europe	0.330560	0.33056	0.33056	0.388	0.381	0.3810	0.3780	...	0.304	0.306	0.306	0.299	0.296	0.296	0.278	0.276000	0.282000	0.273000
3	Barbados	Americas	Caribbean	0.207542	0.21600	0.23600	0.234	0.228	0.2320	0.2220	...	0.209	0.214	0.204	0.196	0.187	0.176	0.173	0.207542	0.207542	0.207542
4	Belgium	Europe	Western Europe	0.343000	0.32800	0.31800	0.310	0.304	0.2980	0.2920	...	0.251	0.267	0.263	0.260	0.254	0.248	0.249	0.247000	0.247000	0.276455

[5 rows x 31 columns]

```
In [32]: df_servi.head()
```

Out[32]:

	Country	region	sub-region	1980	1981	1982	1983	1984	1985	1986	...	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
0	Argentina	Americas	South America	0.708450	0.70845	0.59500	0.585	0.566	0.70845	0.70845	...	0.740	0.753	0.762	0.769	0.785	0.763	0.755	0.751000	0.752000	0.708450
1	Australia	Oceania	Australia and New Zealand	0.624000	0.62700	0.63700	0.648	0.655	0.66700	0.67400	...	0.733	0.737	0.733	0.742	0.745	0.750	0.748	0.750000	0.750000	0.751000
2	Austria	Europe	Western Europe	0.596280	0.59628	0.59628	0.512	0.522	0.52600	0.53200	...	0.629	0.631	0.634	0.643	0.645	0.647	0.670	0.667000	0.661000	0.668000
3	Barbados	Americas	Caribbean	0.660417	0.69100	0.67700	0.685	0.681	0.68300	0.69500	...	0.628	0.640	0.644	0.655	0.659	0.668	0.697	0.660417	0.660417	0.660417
4	Belgium	Europe	Western Europe	0.626000	0.64000	0.65100	0.659	0.665	0.67100	0.67800	...	0.679	0.708	0.714	0.719	0.726	0.732	0.728	0.726000	0.728000	0.685727

[5 rows x 31 columns]

```
In [33]: df_age.head()
```

Out[33]:

	Country	region	sub-region	1950	1955	1960	\
0	Argentina	Americas	South America	25.657	26.471	27.070	
1	Australia	Oceania	Australia and New Zealand	30.379	30.158	29.608	
2	Austria	Europe	Western Europe	35.696	35.201	35.524	
3	Barbados	Americas	Caribbean	24.558	24.271	22.320	
4	Belgium	Europe	Western Europe	35.526	34.713	35.246	

	1965	1970	1975	1980	...	2005	2010	2015	2020	\
0	27.398	27.593	27.663	27.377	...	29.120	30.439	31.615	32.837	
1	28.295	27.608	28.019	29.380	...	36.553	37.776	38.842	39.600	
2	34.972	33.892	33.818	34.671	...	39.953	41.768	43.495	44.785	
3	20.646	21.213	23.694	24.494	...	35.530	37.771	39.992	41.715	
4	34.752	34.580	34.037	34.210	...	40.232	41.301	42.380	43.175	

	2025	2030	2035	2040	2045	2050
0	34.147	35.551	36.931	38.163	39.271	40.386
1	40.432	41.213	41.925	42.440	42.728	42.937
2	45.604	46.579	47.460	48.196	48.655	48.543
3	43.497	45.284	46.885	48.059	48.657	48.614
4	43.742	44.231	44.628	44.925	44.879	44.684

[5 rows x 24 columns]

This marks the completion of the data wrangling section. Wiring about it now makes it look easy but this took me a couple days of solid work in order to do this, very good experience for the future.

Exploratory Data Analysis

Just as a refresher, here are the questions which I wanted to answer using this dataset:

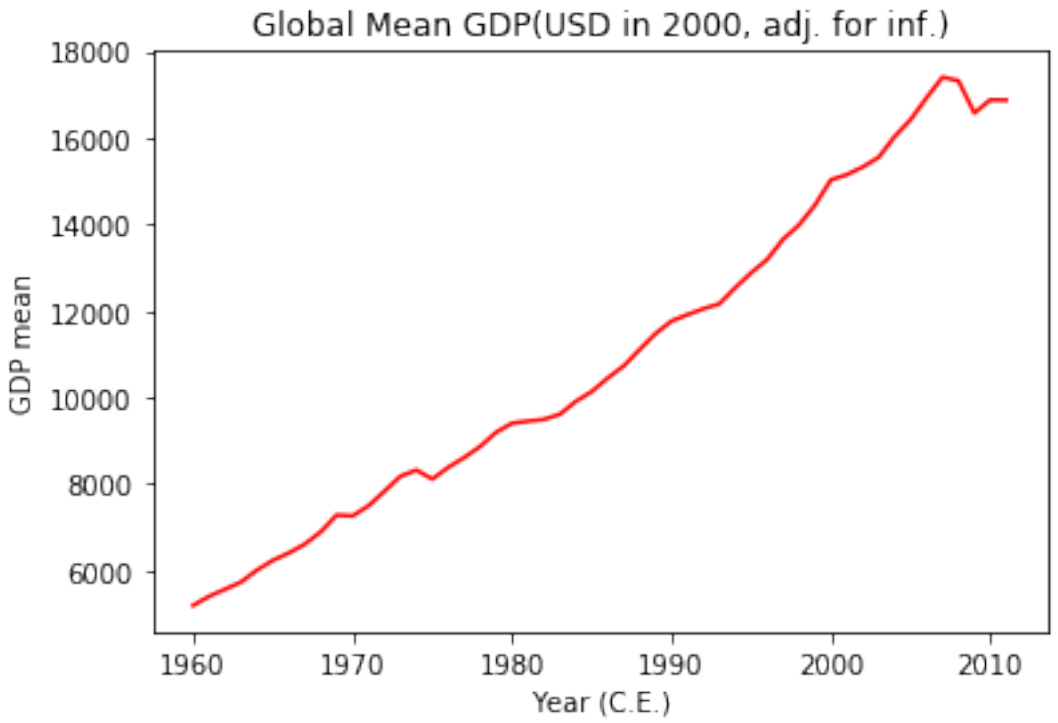
Directing questions: * As a country develops, how does the composition of its workforce change? * Which regions have progressed fastest in terms of GDP? * How does median age change with GDP?

Hence, * What can these countries expect as their GDP rises?

You can also view these questions in terms of region/sub-region

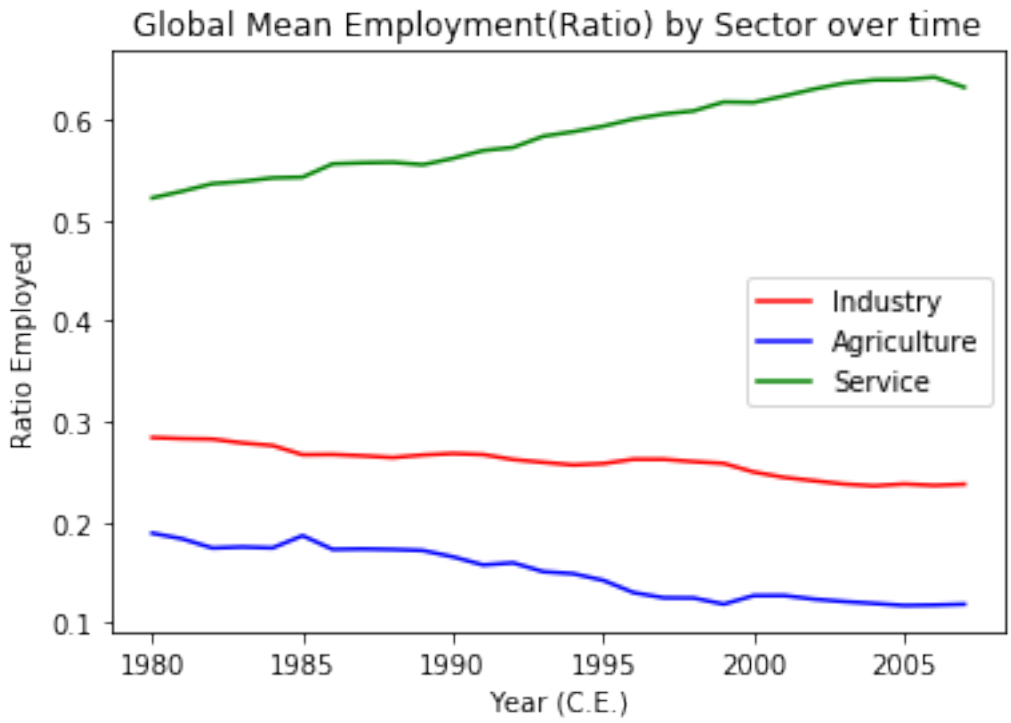
1.1.4 As a country develops, how does the composition of its workforce change?

```
In [34]: # Plot sample average GDP over time
         basic_plot(x_series=df_GDP.columns[3:],
                    y_series=df_GDP.mean(),
                    x_label= "Year (C.E.)",
                    y_label= 'GDP mean',
                    plt_title='Global Mean GDP(USD in 2000, adj. for inf.)')
```



I just wanted to quickly show that it is true that countries tend to rise in GDP over time. That down-tick in 2008 is the credit-crunch ofcourse.

```
In [35]: # Plot global average employment ratio over time
         plt.plot(df_indus.columns[3:].astype(int), df_indus.mean(),
                  c='red', label='Industry')
         plt.plot(df_agric.columns[3:].astype(int), df_agric.mean(),
                  c='blue', label='Agriculture')
         plt.plot(df_servi.columns[3:].astype(int), df_servi.mean(),
                   c='green', label='Service')
         plt.xlabel('Year (C.E.)')
         #plt.yticks((0, 0.25, 0.5, 0.75, 1))
         plt.ylabel('Ratio Employed')
         plt.title('Global Mean Employment(Ratio) by Sector over time')
         plt.legend()
         plt.show()
```



As we can see above, as a country develops there is a tendency for employment in service to increase and for employment in industry/agriculture to decrease. The time series of this data is too short to show what happened during the industrial revolution but if we were to look back that far we would likely find that most people were employed in agriculture and as technology made it possible to do greater work on the fields without as many workers, this changed as workers went into industry. Now, with the information revolution, we see an increasing amount of people going into the service industry as industrial jobs become automated.

This trend, where automation heavily effects what people do for a living is going to continue into the future. As to what that will mean for us we can't really see from this data because one would need more recent data where AI is playing a grater role in our soceity, during 2005 only the precurors of what comes in the next decade can be seen.

```
In [36]: # Calculating correlation coefficients
         corr_coeff_GDP_servi = np.corrcoef(x=df_GDP.mean()[20:-4], y=df_servi.mean())
         corr_coeff_agric_indus = np.corrcoef(x=df_agric.mean(), y=df_indus.mean())

In [37]: # Calculate correlation coefficient between GDP and service employment %
         corr_coeff_GDP_servi

Out[37]: array([[ 1.        ,  0.98120669],
                [ 0.98120669,  1.        ]])

In [38]: # Calculating correlation coefficients
         corr_coeff_agric_indus
```

```
Out[38]: array([[ 1.        ,  0.85837619],
                [ 0.85837619,  1.        ]])
```

We can see here how GDP and service employment and a 98.3% correlation with each other, the employment in agriculture and industry are also strongly correlated.

However, is this correlation causal? We can use a t-test to figure out whether this is the case.

```
In [39]: # Perform t-test on Service Employment ratio and GDP
         serv_ratio_series = df_GDP.mean()[20:-4]
         GDP_series = df_servi.mean()
         t_test_serv_GDP = ttest_ind(serv_ratio_series, GDP_series) # Imported from Sci-Py Sta

         t_test_serv_GDP
```

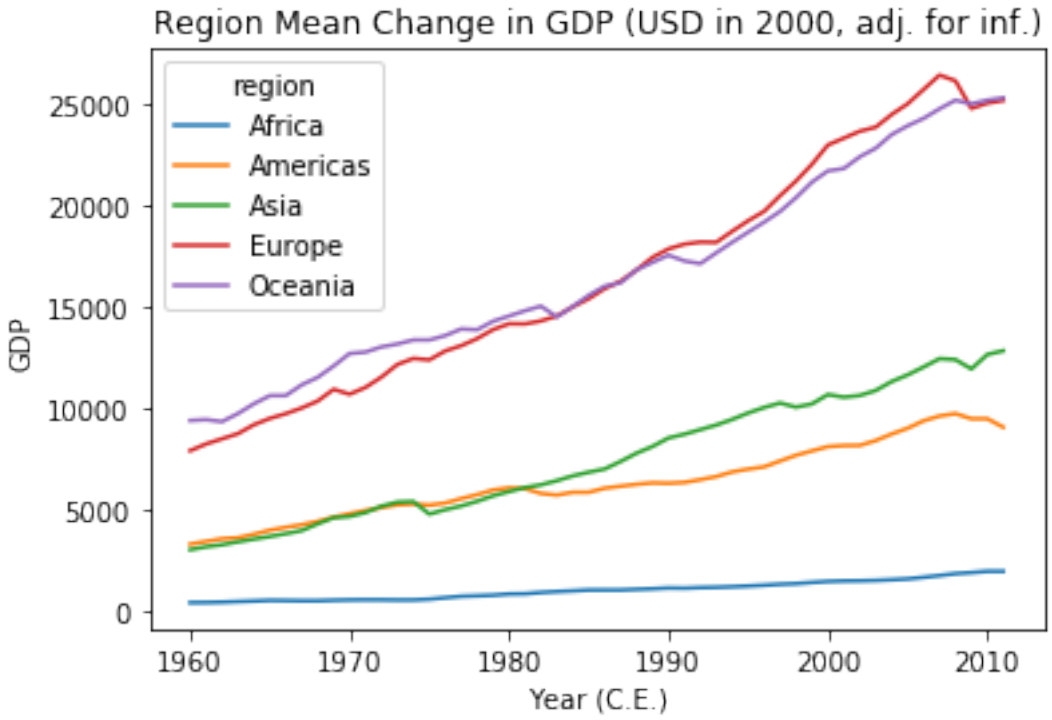
```
Out[39]: Ttest_indResult(statistic=27.152068970662953, pvalue=3.7059682395711783e-33)
```

The p-value of the t-test is almost 0 which shows that the strong correlation is unlikely to be a coincidence and that there is a sort of causal link here. Whether or not GDP causes a higher %employment in service industries or *vice. versa.* is not known but at least it's worth knowing that these two features are correlated in this way.

1.1.5 Which regions have progressed fastest in terms of GDP?

```
In [40]: # Grouping GDP by region
         ax = df_GDP.groupby('region').mean().T.plot(title='Region Mean Change in GDP (USD in 2
         ax.set_xlabel('Year (C.E.)')
         ax.set_ylabel('GDP')
```

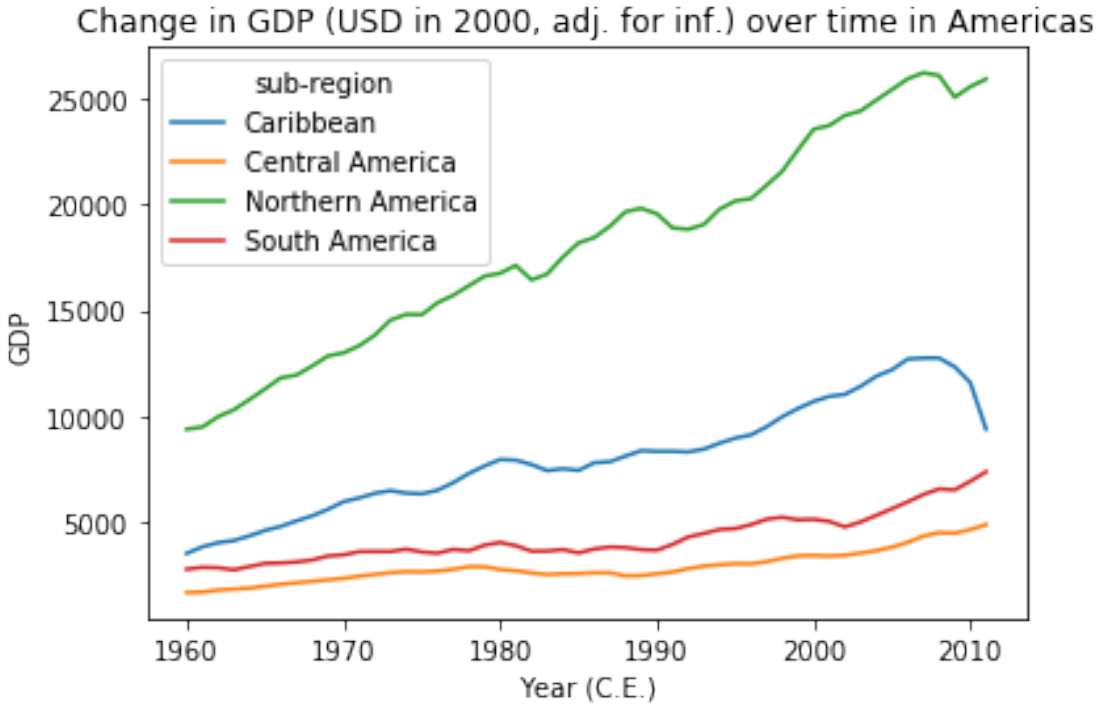
```
Out[40]: Text(0,0.5,'GDP')
```

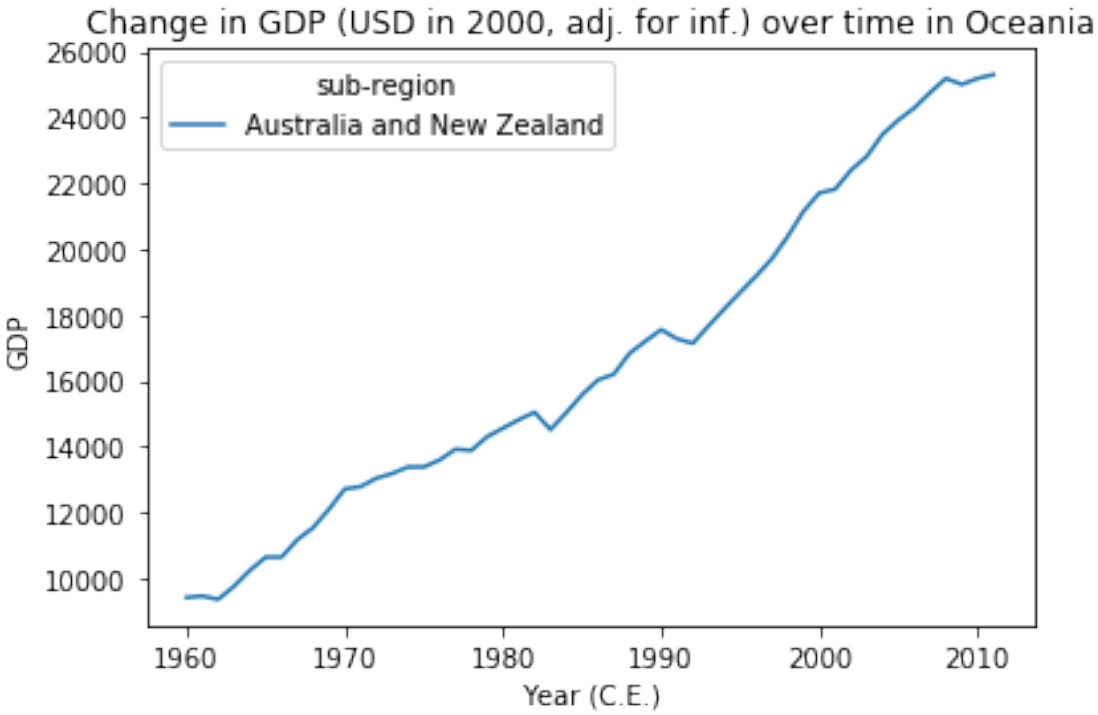


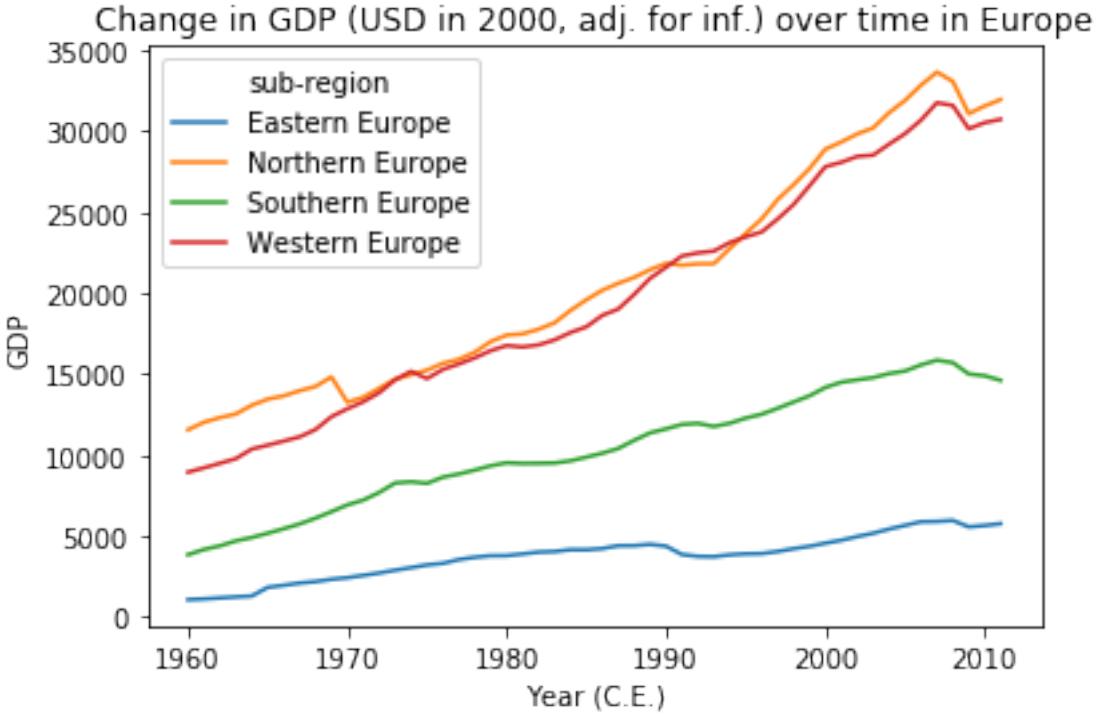
We can see here how certain continents have had an increase in productivity over time. It should be noted that Oceania and Africa represent the top GDP in their region instead of their average due to there being only one country being used for this analysis in both datasets.

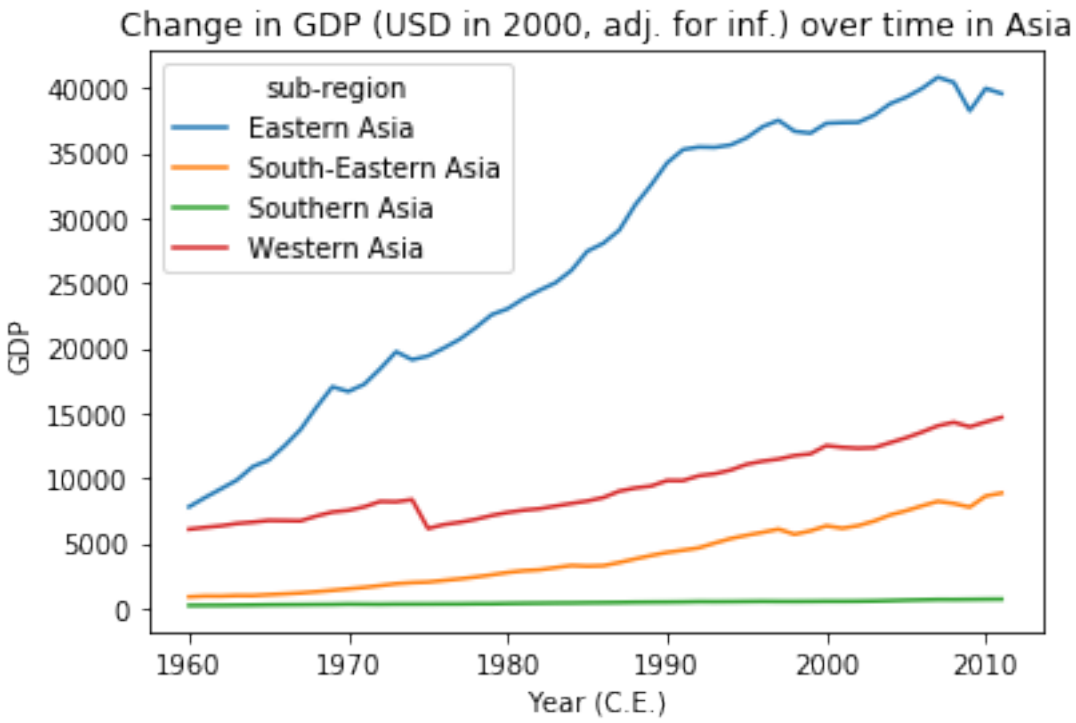
The americas also also skewed upward due to the presence of North America which has a much higher GDP than the rest of america as can be seen from the plots below where I broke things down by sub-region.

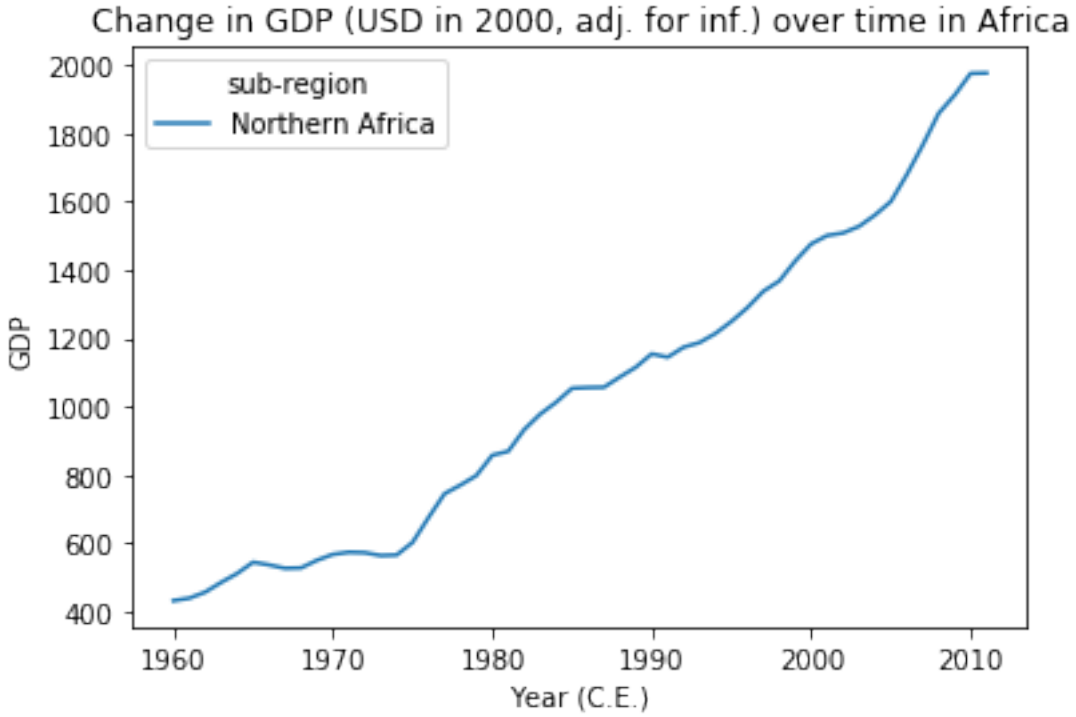
```
In [41]: # How about Countries within a region?
         for region in df_GDP['region'].unique():
             ax = df_GDP[df_GDP['region'] == region].groupby(
                     'sub-region').mean().T.plot(title='Change in GDP (USD in 2000, adj. for in
             ax.set_xlabel('Year (C.E.)')
             ax.set_ylabel('GDP')
```




Change in GDP (USD in 2000, adj. for inf.) over time in Oceania
sub-region
Australia and New Zealand
GDP
Year (C.E.)
26000
24000
22000
20000
18000
16000
14000
12000
10000
1960
1970
1980
1990
2000
2010


Change in GDP (USD in 2000, adj. for inf.) over time in Europe
sub-region
Eastern Europe
Northern Europe
Southern Europe
Western Europe
GDP
Year (C.E.)
35000
30000
25000
20000
15000
10000
5000
0
1960
1970
1980
1990
2000
2010


Change in GDP (USD in 2000, adj. for inf.) over time in Asia
sub-region
Eastern Asia
South-Eastern Asia
Southern Asia
Western Asia
GDP
0
5000
10000
15000
20000
25000
30000
35000
40000
1960
1970
1980
1990
2000
2010
Year (C.E.)


Change in GDP (USD in 2000, adj. for inf.) over time in Africa
sub-region
Northern Africa
GDP
400
600
800
1000
1200
1400
1600
1800
2000
1960
1970
1980
1990
2000
2010
Year (C.E.)

How you display your data makes a large difference in how you interpret it. In the previous graph, it looked as if Africa had barely made any improvement on its productivity. However this is only because of it being compared to countries that have had an increased rate of productivity for quite some time now. (If you're indterested for why this is you can read the book by "Guns, Germs and Steel" by Jared Diamond)

When viewed on its own, Northern Africa had five-fold increase in productivity which is very promising. Furthermore, as the infrastructure develops, this rate of productivity increase will likely increase. It should still be noted that this is still one region of one of the largest continents on the planet and that regions with less economic development are missing from the data and so there is a bias which makes the situation look a little better than it is.

Interestingly, it is also possible to see how all have come level of inequality, where one sub-region has a higher GDP than the rest of the region. Perhaps this is due things like capital cities where most of the productivity that counts toward GDP is carried out?

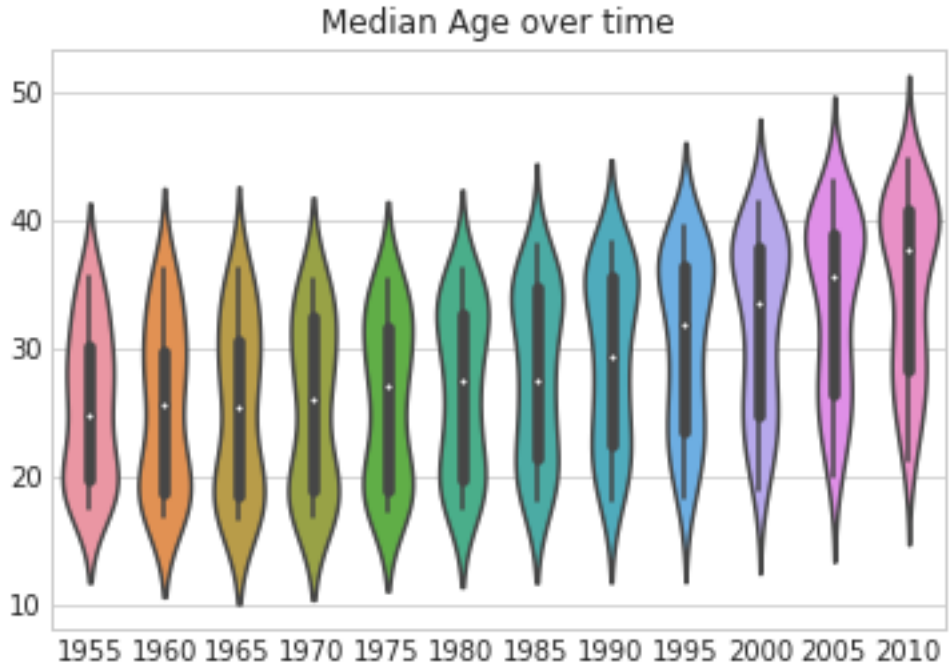
1.1.6 How does median age change with GDP?

So we have discovered that GDP and employment in the service industry are tightly linked and they are both proportional with time.

The decline in the agricultural and industrial industries are likely correlated with the growth of technology since the industrial revolution.

I also wanted to make a couple of quick graphs showing median age for my selection of countries. To do this I will create a violin plot which shows the median age for every half decade.

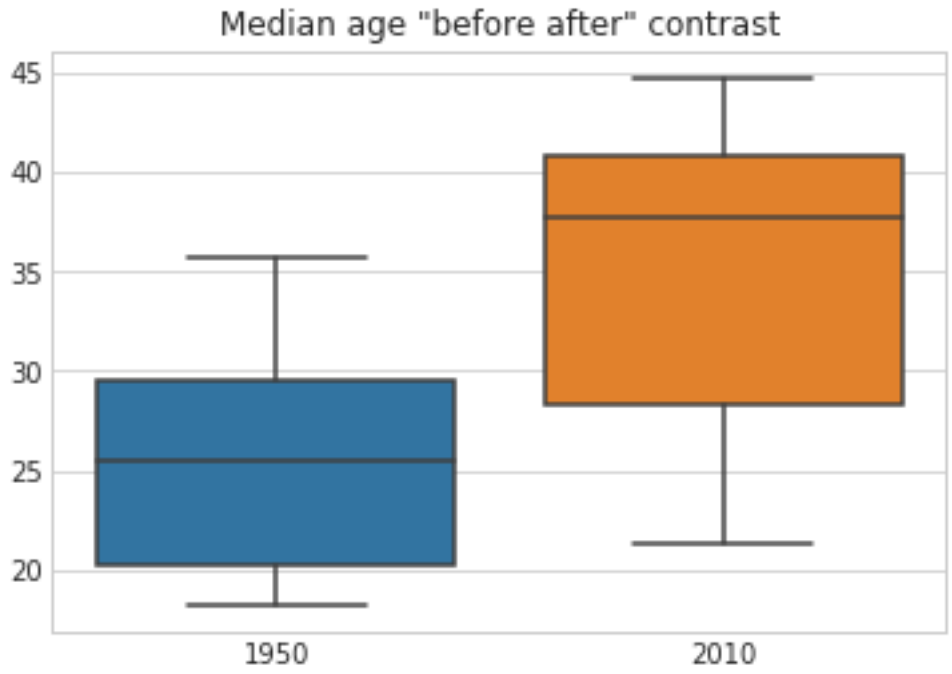
```
In [53]: # Seaborn set style
         sns.set_style('whitegrid')

         # Plot before and after world age distribution
         ax = sns.violinplot(data=df_age.iloc[:, 4:-8]).set_title('Median Age over time')
```



Here we can see that in 1995 the median age was roughly 25 across the globe, but with a split between the "rich" and "poor" countries. Over 60 years of this graph we can see how the median age is pulled upward signifying a much longer lifespan than before.

The before/after effects can be seen most starkly when thee instances are seen side by side. For the sake of vareity, I'll use a boxplot instead of a violin plot.

```
In [54]: # Create boxplot
         sns.boxplot(data=df_age[['1950', '2010']]).set_title('Median age "before after" contra
```



The world median has increased from roughly 25 years of age to 37 years of age. The median lifespan is so much higher that the top of the interquartile range (30) is now easily exceeded by 75% of the data in 2010.

Conclusions

- It was found that countries on average tend to rise in GDP. Although it is suspected that this is due to technological development, from this data alone it is not possible to say why. (This trend can also be seen when making discreete plots.)
  - However, as GDP rises, so does the percentage of people employed in the service sector, away from service and agriculture which have a correlation coefficient of 0.87.
  - This shows that as people leave the agriculture and industrial sectors, they'll tend to enter into the service sector.
- The correlation between the service sector and GDP is 0.98, which is very strong.

  - The probability that this is due to random chance is roughly 5e-33 (very low) which suggests that there is some sort of a causal link although directionality was not determined in this study.

- People are living much longer lives with the median age having risen substantially in the 60 years that the data shows.

It is important to keep in mind that this analysis has limitations due to GDP not being adjusted for differences in costs of living between countries. Missing data also means that this analysis is better suited for countries that are not experiencing extreme povery (which is most countries these days), many countries were dropped for having low data quality. This data is also over the course of roughly 20 years, which is too short a time scale to see how technology has impacted soceity over the course of time since the start of the industrial revolution which is where increased productivity and standards of living all started.

Naturally, the million-dollar question is "how will AI and qutomation" effect job sectors in the years to come? This question is difficult to answer because we're not sure what effects AI will have on our economy but answering it means a strategic advantage for whoever can make the right analysis.