Data Analysis of The Growth of Global Obesity

10/05/2021 - Ward Ali Dib

Obesity is a condition that occurs when a person has excess weight or body fat that might affect their health. Obesity is a dangerous disease, affecting over a third of the world's population today. It is also associated with the leading causes of death in the United States and worldwide, including diabetes, heart disease, stroke, and some types of cancer. [1]

The obesity datasets in this report are from WHO [2] and contain data detailing the prevelance of obesity in each country for both men and women from 1975 up to 2016. As many studies link obesity to poverty and low quality of life, the GDP dataset from The World Bank [3] will be used to asses if those claims have some truth.

Reading and cleaning the datasets:

We will start by importing the libraries needed, then importing the dataset and checking for missing values. The missing values will then be removed before carrying out any statistical analysis.

In [1]:
```
# Import libraries needed.
import pandas as pd
import numpy as np
from numpy.polynomial.polynomial import polyfit
import matplotlib.pyplot as plt
import matplotlib.ticker as mtick
import plotly_express as px

# Assign plotting style.
plt.style.use('seaborn')
```

In [2]:
```
# Import all data files downloaded.

gdp = pd.read_csv('/Users/warda/Desktop/wrd/Uni/MSc/SEM 2/Data Handling/Assignment 2/Datasets/GDP.csv')
obesity = pd.read_csv('/Users/warda/Desktop/wrd/Uni/MSc/SEM 2/Data Handling/Assignment 2/Datasets/obesity.csv')
obesity_region = pd.read_csv('/Users/warda/Desktop/wrd/Uni/MSc/SEM 2/Data Handling/Assignment 2/Datasets/obesity-region.c
```

In [3]:
```
# Checking for missing values in the obesity dataset.

obesity.isna().any()
```

Out[3]:
```
Unnamed: 0     True
```

```
2016          False
2016.1        False
2016.2        False
2015          False
              ...
1976.1        False
1976.2        False
1975          False
1975.1        False
1975.2        False
Length: 127, dtype: bool
```

In [4]:

```python
# No missing values. However, upon inspecting the data manually, it does not look clean so we will clean.
# There are countries with no entries, so we will remove the rows with "No data" and proceed to clean the dataset.

missing_values = ["No data"]
obesity = pd.read_csv('/Users/warda/Desktop/wrd/Uni/MSc/SEM 2/Data Handling/Assignment 2/Datasets/obesity.csv',
                      header = [0,1], skiprows = [1,2], index_col = 0, na_values = missing_values)
obesity.isnull().values.any()

# Drop all rows with "No data" values.

obesity.dropna(axis = 0, inplace = True)

obesity.head()
```

Out[4]:

	2016			2015			2014			2013	...	1978	1977			197		
Country	Both sexes	Male	Female	Both sexes	Male	Female	Both sexes	Male	Female	Both sexes	...	Female	Both sexes	Male	Female	Both sexes	Male	Femal
Afghanistan	5.5 [3.4-8.1]	3.2 [1.3-6.4]	7.6 [4.3-12.4]	5.2 [3.3-7.7]	3.0 [1.3-6.0]	7.3 [4.1-11.8]	4.9 [3.1-7.3]	2.8 [1.2-5.6]	7.0 [4.0-11.3]	4.7 [2.9-6.9]	...	0.9 [0.3-2.2]	0.6 [0.2-1.2]	0.2 [0.0-0.7]	0.9 [0.3-2.1]	0.5 [0.2-1.1]	0.2 [0.0-0.7]	0. [0.2 2.0
Albania	21.7 [17.0-26.7]	21.6 [14.8-29.0]	21.8 [15.3-28.9]	21.1 [16.6-26.0]	20.9 [14.4-28.1]	21.3 [15.1-28.1]	20.5 [16.2-25.1]	20.2 [13.9-27.3]	20.8 [14.9-27.4]	19.9 [15.7-24.4]	...	9.1 [4.6-15.5]	6.8 [4.0-10.7]	4.8 [2.0-9.3]	8.9 [4.3-15.4]	6.7 [3.8-10.6]	4.6 [1.8-9.2]	8. [4.1 15.4
Algeria	27.4 [22.5-32.7]	19.9 [13.6-27.1]	34.9 [27.6-42.7]	26.7 [21.9-31.8]	19.2 [13.2-26.1]	34.2 [27.1-41.7]	26.0 [21.4-30.9]	18.5 [12.7-25.0]	33.6 [26.7-40.7]	25.3 [20.9-30.1]	...	11.8 [6.5-18.6]	7.4 [4.3-11.3]	3.1 [1.2-6.2]	11.4 [6.2-18.4]	7.2 [4.1-11.1]	2.9 [1.1-6.1]	11. [5.8 18.2
Andorra	25.6 [20.1-31.3]	25.9 [18.0-34.3]	25.3 [17.7-33.7]	25.4 [20.1-31.0]	25.5 [17.8-33.8]	25.2 [17.7-33.4]	25.2 [20.0-30.7]	25.2 [17.6-33.3]	25.1 [17.8-33.1]	25.0 [20.0-30.3]	...	17.5 [10.9-25.3]	14.0 [9.6-19.1]	10.7 [5.6-17.4]	16.9 [10.4-24.8]	13.5 [9.1-18.6]	10.2 [5.2-16.9]	16. [9.8 24.4

	2016			2015			2014			2013	...	1978			1977			197
Country	Both sexes	Male	Female	Both sexes	Male	Female	Both sexes	Male	Female	Both sexes	...	Female	Both sexes	Male	Female	Both sexes	Male	Femal
Angola	8.2 [5.1-12.2]	4.0 [1.6-7.9]	12.1 [6.8-19.0]	7.9 [4.9-11.7]	3.8 [1.5-7.3]	11.6 [6.5-18.2]	7.5 [4.7-11.2]	3.6 [1.4-6.9]	11.1 [6.2-17.5]	7.1 [4.4-10.6]	...	1.6 [0.5-3.7]	0.9 [0.3-2.0]	0.3 [0.0-0.9]	1.5 [0.4-3.6]	0.9 [0.3-2.0]	0.3 [0.0-0.9]	1. [0.4 3.5

5 rows × 126 columns

In [5]:
```python
# Now we clean the data and set the index to 'Country'.

obesity.columns.names = ['Year', 'Sex']
obesity.index.names = ['Country']
obesity.columns.names
obesity.index.names
```

Out[5]:
```
FrozenList(['Country'])
```

In [6]:
```python
obesity = obesity.stack(level=0)
obesity
```

Out[6]:

	Sex	Both sexes	Female	Male
Country	Year			
Afghanistan	1975	0.5 [0.2-1.1]	0.8 [0.2-2.0]	0.2 [0.0-0.6]
	1976	0.5 [0.2-1.1]	0.8 [0.2-2.0]	0.2 [0.0-0.7]
	1977	0.6 [0.2-1.2]	0.9 [0.3-2.1]	0.2 [0.0-0.7]
	1978	0.6 [0.2-1.3]	0.9 [0.3-2.2]	0.2 [0.1-0.7]
	1979	0.6 [0.3-1.3]	1.0 [0.3-2.3]	0.3 [0.1-0.8]
...	...	...	...	...
Zimbabwe	2012	14.3 [11.4-17.6]	23.5 [18.3-29.3]	4.0 [2.2-6.6]
	2013	14.6 [11.5-18.0]	23.9 [18.5-30.0]	4.2 [2.3-6.9]
	2014	14.9 [11.7-18.4]	24.4 [18.8-30.6]	4.4 [2.4-7.3]

Sex		Both sexes	Female	Male
Country	Year			
	2015	15.2 [11.9-18.8]	24.8 [18.9-31.3]	4.5 [2.4-7.6]
	2016	15.5 [12.0-19.2]	25.3 [19.1-32.0]	4.7 [2.5-8.0]

8022 rows × 3 columns

In [7]:
```
obesity = obesity.reset_index()
obesity
```

Out[7]:

Sex	Country	Year	Both sexes	Female	Male
0	Afghanistan	1975	0.5 [0.2-1.1]	0.8 [0.2-2.0]	0.2 [0.0-0.6]
1	Afghanistan	1976	0.5 [0.2-1.1]	0.8 [0.2-2.0]	0.2 [0.0-0.7]
2	Afghanistan	1977	0.6 [0.2-1.2]	0.9 [0.3-2.1]	0.2 [0.0-0.7]
3	Afghanistan	1978	0.6 [0.2-1.3]	0.9 [0.3-2.2]	0.2 [0.1-0.7]
4	Afghanistan	1979	0.6 [0.3-1.3]	1.0 [0.3-2.3]	0.3 [0.1-0.8]
...	...	...	...	...	...
8017	Zimbabwe	2012	14.3 [11.4-17.6]	23.5 [18.3-29.3]	4.0 [2.2-6.6]
8018	Zimbabwe	2013	14.6 [11.5-18.0]	23.9 [18.5-30.0]	4.2 [2.3-6.9]
8019	Zimbabwe	2014	14.9 [11.7-18.4]	24.4 [18.8-30.6]	4.4 [2.4-7.3]
8020	Zimbabwe	2015	15.2 [11.9-18.8]	24.8 [18.9-31.3]	4.5 [2.4-7.6]
8021	Zimbabwe	2016	15.5 [12.0-19.2]	25.3 [19.1-32.0]	4.7 [2.5-8.0]

8022 rows × 5 columns

In [8]:
```
# The numbers in the brackets represent the standardised age groups of the obese people.
# In this report, we are not interested in the age statistics so we will drop those entries from the dataset.

obesity['Standardised age estimate'] = obesity['Both sexes'].apply(lambda x:x.split()[1])
obesity['Both sexes'] = obesity['Both sexes'].apply(lambda x:x.split()[0])

obesity['Standardised age estimate'] = obesity['Male'].apply(lambda x:x.split()[1])
```

```python
obesity['Male'] = obesity['Male'].apply(lambda x:x.split()[0])

obesity['Standardised age estimate'] = obesity['Female'].apply(lambda x:x.split()[1])
obesity['Female'] = obesity['Female'].apply(lambda x:x.split()[0])

obesity.drop(['Standardised age estimate'], axis = 1, inplace = True)

obesity
```

Out[8]:

Sex	Country	Year	Both sexes	Female	Male
0	Afghanistan	1975	0.5	0.8	0.2
1	Afghanistan	1976	0.5	0.8	0.2
2	Afghanistan	1977	0.6	0.9	0.2
3	Afghanistan	1978	0.6	0.9	0.2
4	Afghanistan	1979	0.6	1.0	0.3
...	...	...	...	...	...
8017	Zimbabwe	2012	14.3	23.5	4.0
8018	Zimbabwe	2013	14.6	23.9	4.2
8019	Zimbabwe	2014	14.9	24.4	4.4
8020	Zimbabwe	2015	15.2	24.8	4.5
8021	Zimbabwe	2016	15.5	25.3	4.7

8022 rows × 5 columns

In [9]:

```python
# For the analysis, we need to pivot around 1 sex at a time. So we will melt the Obesity dataframe then split it.

obesity = obesity.melt(id_vars = ['Country', 'Year'], value_vars = ['Both sexes', 'Female', 'Male'],
                       value_name = 'Obesity %')
obesity
```

Out[9]:

	Country	Year	Sex	Obesity %
0	Afghanistan	1975	Both sexes	0.5
1	Afghanistan	1976	Both sexes	0.5

	Country	Year	Sex	Obesity %
2	Afghanistan	1977	Both sexes	0.6
3	Afghanistan	1978	Both sexes	0.6
4	Afghanistan	1979	Both sexes	0.6
...	...	...	...	...
24061	Zimbabwe	2012	Male	4.0
24062	Zimbabwe	2013	Male	4.2
24063	Zimbabwe	2014	Male	4.4
24064	Zimbabwe	2015	Male	4.5
24065	Zimbabwe	2016	Male	4.7

24066 rows × 4 columns

In [10]:

```
# Now we will generate seperate dataframes for each sex.

obesity_male = obesity.loc[obesity.Sex == 'Male', :].reset_index(drop = True)
obesity_male_pivot = obesity_male[['Country', 'Year', 'Obesity %']].pivot(index = 'Country',
                                                                          columns ='Year', values = 'Obesity %')

obesity_female = obesity.loc[obesity.Sex == 'Female', :].reset_index(drop = True)
obesity_female_pivot = obesity_female[['Country', 'Year', 'Obesity %']].pivot(index = 'Country',
                                                                              columns = 'Year', values = 'Obesity %')

obesity_both = obesity.loc[obesity.Sex == 'Both sexes', :].reset_index(drop = True)
obesity_both_pivot = obesity_both[['Country', 'Year', 'Obesity %']].pivot(index = 'Country',
                                                                          columns = 'Year', values = 'Obesity %')


obesity_both.head()
```

Out[10]:

	Country	Year	Sex	Obesity %
0	Afghanistan	1975	Both sexes	0.5
1	Afghanistan	1976	Both sexes	0.5
2	Afghanistan	1977	Both sexes	0.6
3	Afghanistan	1978	Both sexes	0.6

	Country	Year	Sex	Obesity %
4	Afghanistan	1979	Both sexes	0.6

Now that the obesity dataset is clean, we will clean proceed to cleaning and melting the two other datasets before performing any analysis.

In [11]:

```
gdp.head()
```

Out[11]:

	Country	Country Code	Indicator Name	Indicator Code	1960	1961	1962	1963	1964	1965	...	2011	
0	Aruba	ABW	GDP per capita (current US$)	NY.GDP.PCAP.CD	NaN	NaN	NaN	NaN	NaN	NaN	...	24985.993280	24713
1	Afghanistan	AFG	GDP per capita (current US$)	NY.GDP.PCAP.CD	59.773194	59.860874	58.458015	78.706388	82.095231	101.108305	...	591.162759	641
2	Angola	AGO	GDP per capita (current US$)	NY.GDP.PCAP.CD	NaN	NaN	NaN	NaN	NaN	NaN	...	4615.468028	5100
3	Albania	ALB	GDP per capita (current US$)	NY.GDP.PCAP.CD	NaN	NaN	NaN	NaN	NaN	NaN	...	4437.142885	4247
4	Andorra	AND	GDP per capita (current US$)	NY.GDP.PCAP.CD	NaN	NaN	NaN	NaN	NaN	NaN	...	43335.328860	38686

5 rows × 65 columns

In [12]:

```
# Melting the years.

# Transform
year_cols = [str(x) for x in list(range(1975, 2017))]
gdp_df = pd.melt(gdp, id_vars = ['Country', 'Country Code', 'Indicator Name', 'Indicator Code'], value_vars = year_cols)
```

```python
gdp_df.rename(columns = {'variable':'Year'}, inplace = True)
gdp_df.rename(columns = {'value':'GDP'}, inplace = True)
gdp_df.drop(['Indicator Code', 'Indicator Name', 'Country Code'], axis = 1, inplace = True)
gdp_df.sort_values(by=['Country', 'Year'])
gdp_df['Year'] = pd.to_numeric(gdp_df['Year'])
gdp_df = gdp_df[gdp_df['Year'] >= 1975]

gdp_df.head
```

Out[12]:

```
<bound method NDFrame.head of              Country  Year          GDP
0              Aruba  1975          NaN
1        Afghanistan  1975   186.510897
2             Angola  1975          NaN
3            Albania  1975          NaN
4            Andorra  1975  7169.101006
...              ...   ...          ...
11083         Kosovo  2016  3780.003689
11084    Yemen, Rep.  2016  1138.682995
11085   South Africa  2016  5272.918425
11086         Zambia  2016  1280.578447
11087       Zimbabwe  2016  1464.583529

[11088 rows x 3 columns]>
```

In [13]:

```python
gdp_df = gdp_df.sort_values(by = ['Country', 'Year'])
gdp_df
```

Out[13]:

	Country	Year	GDP
1	Afghanistan	1975	186.510897
265	Afghanistan	1976	197.445508
529	Afghanistan	1977	224.224797
793	Afghanistan	1978	247.354106
1057	Afghanistan	1979	275.738198
...	...	...	...
10031	Zimbabwe	2012	1304.969802
10295	Zimbabwe	2013	1430.000818
10559	Zimbabwe	2014	1434.899340
10823	Zimbabwe	2015	1445.071062

	Country	Year	GDP
11087	Zimbabwe	2016	1464.583529

11088 rows × 3 columns

In [14]:

```
# For later analysis, we will merge the GDP and Obesity dataframes.

inner_merged_total = pd.merge(obesity, gdp_df, on = ["Country"])
inner_merged_total.head()
inner_joined_total = obesity.join(
    gdp_df.set_index(["Country"]),
    lsuffix = "_x",
    rsuffix = "_y",
    on = ["Country"],
)
inner_joined_total
```

Out[14]:

	Country	Year_x	Sex	Obesity %	Year_y	GDP
0	Afghanistan	1975	Both sexes	0.5	1975.0	186.510897
0	Afghanistan	1975	Both sexes	0.5	1976.0	197.445508
0	Afghanistan	1975	Both sexes	0.5	1977.0	224.224797
0	Afghanistan	1975	Both sexes	0.5	1978.0	247.354106
0	Afghanistan	1975	Both sexes	0.5	1979.0	275.738198
...	...	...	...	...	...	...
24065	Zimbabwe	2016	Male	4.7	2012.0	1304.969802
24065	Zimbabwe	2016	Male	4.7	2013.0	1430.000818
24065	Zimbabwe	2016	Male	4.7	2014.0	1434.899340
24065	Zimbabwe	2016	Male	4.7	2015.0	1445.071062
24065	Zimbabwe	2016	Male	4.7	2016.0	1464.583529

860958 rows × 6 columns

In [15]:

```
inner_joined_total.set_index(['Country'], inplace = True)
```

```
inner_joined_total.sort_index(inplace = True)
inner_joined_total
```

Out[15]:

	Year_x	Sex	Obesity %	Year_y	GDP
Country					
Afghanistan	1975	Both sexes	0.5	1975.0	186.510897
Afghanistan	2003	Male	1.4	1981.0	264.111317
Afghanistan	2003	Male	1.4	1980.0	272.655286
Afghanistan	2003	Male	1.4	1979.0	275.738198
Afghanistan	2003	Male	1.4	1978.0	247.354106
...	...	...	...	...	...
Zimbabwe	2003	Both sexes	11.5	1980.0	901.499145
Zimbabwe	2003	Both sexes	11.5	1981.0	1043.746833
Zimbabwe	2003	Both sexes	11.5	1982.0	1073.063847
Zimbabwe	2002	Both sexes	11.2	2013.0	1430.000818
Zimbabwe	2016	Male	4.7	2016.0	1464.583529

860958 rows × 5 columns

In [16]:

```
# Now we will clean the 'Obesity per region' dataset.

obesity_region.head()
```

Out[16]:

	Unnamed: 0	2016	2016.1	2016.2	2015	2015.1	2015.2	2014	2014.1	2014.2	...	1978.2	1977
0	NaN	Prevalence of obesity among adults, BMI &Great...	Prevalence of obesity among adults, BMI &Great...	Prevalence of obesity among adults, BMI &Great...	Prevalence of obesity among adults, BMI &Great...	Prevalence of obesity among adults, BMI &Great...	Prevalence of obesity among adults, BMI &Great...	Prevalence of obesity among adults, BMI &Great...	Prevalence of obesity among adults, BMI &Great...	Prevalence of obesity among adults, BMI &Great...	...	Prevalence of obesity among adults, BMI &Great...	Prevalence of obesity among adults, BMI &Great...
1	NaN	18+ years	18+ years	18+ years	18+ years	18+ years	18+ years	18+ years	18+ years	18+ years	...	18+ years	18+ years

	Unnamed: 0	2016	2016.1	2016.2	2015	2015.1	2015.2	2014	2014.1	2014.2	...	1978.2	1977
2	WHO region	Both sexes	Male	Female	Both sexes	Male	Female	Both sexes	Male	Female	...	Female	Both sexes
3	Global	13.2 [12.5-13.9]	11.1 [10.2-12.2]	15.3 [14.2-16.4]	12.8 [12.2-13.5]	10.7 [9.9-11.7]	14.9 [13.9-15.9]	12.4 [11.8-13.0]	10.3 [9.6-11.2]	14.5 [13.6-15.4]	...	6.3 [5.3-7.4]	4.5 [3.9-5.2]
4	Africa	9.1 [8.2-10.0]	4.8 [3.9-5.9]	13.2 [11.8-14.8]	8.8 [8.0-9.6]	4.6 [3.8-5.6]	12.9 [11.5-14.3]	8.5 [7.7-9.3]	4.4 [3.6-5.3]	12.5 [11.2-13.8]	...	3.2 [2.2-4.4]	1.9 [1.3-2.5]

5 rows × 127 columns

In [17]:
```
obesity_region.isna().any()
```

Out[17]:
```
Unnamed: 0     True
2016          False
2016.1        False
2016.2        False
2015          False
              ...
1976.1        False
1976.2        False
1975          False
1975.1        False
1975.2        False
Length: 127, dtype: bool
```

In [18]:
```
missing_values = ["No data"]
obesity_region = pd.read_csv('/Users/warda/Desktop/wrd/Uni/MSc/SEM 2/Data Handling/Assignment 2/Datasets/obesity-region.c
                             header = [0,1], skiprows = [1,2], index_col = 0, na_values = missing_values)
obesity_region
```

Out[18]:

	2016			2015			2014			2013	...	1978			1977			1
WHO region	**Both sexes**	**Male**	**Female**	**Both sexes**	**Male**	**Female**	**Both sexes**	**Male**	**Female**	**Both sexes**	**...**	**Female**	**Both sexes**	**Male**	**Female**	**Both sexes**	**Male**	**Fen**
Global	13.2 [12.5-13.9]	11.1 [10.2-12.2]	15.3 [14.2-16.4]	12.8 [12.2-13.5]	10.7 [9.9-11.7]	14.9 [13.9-15.9]	12.4 [11.8-13.0]	10.3 [9.6-11.2]	14.5 [13.6-15.4]	12.1 [11.5-12.6]	...	6.3 [5.3-7.4]	4.5 [3.9-5.2]	2.9 [2.3-3.6]	6.2 [5.2-7.3]	4.4 [3.8-5.1]	2.8 [2.2-3.5]	[

	2016			2015			2014			2013	...	1978	1977			1		
WHO region	**Both sexes**	**Male**	**Female**	**Both sexes**	**Male**	**Female**	**Both sexes**	**Male**	**Female**	**Both sexes**	**...**	**Female**	**Both sexes**	**Male**	**Female**	**Both sexes**	**Male**	**Fen**
Africa	9.1 [8.2-10.0]	4.8 [3.9-5.9]	13.2 [11.8-14.8]	8.8 [8.0-9.6]	4.6 [3.8-5.6]	12.9 [11.5-14.3]	8.5 [7.7-9.3]	4.4 [3.6-5.3]	12.5 [11.2-13.8]	8.2 [7.5-8.9]	...	3.2 [2.2-4.4]	1.9 [1.3-2.5]	0.6 [0.3-1.1]	3.1 [2.1-4.4]	1.8 [1.2-2.5]	0.5 [0.3-1.0]	[
Americas	29.0 [27.1-31.0]	26.2 [23.4-29.1]	31.7 [28.8-34.4]	28.4 [26.6-30.3]	25.6 [23.0-28.3]	31.1 [28.5-33.7]	27.8 [26.1-29.6]	25.0 [22.6-27.5]	30.5 [28.1-32.9]	27.3 [25.7-28.8]	...	11.9 [9.6-14.5]	9.5 [8.0-11.2]	7.4 [5.5-9.6]	11.6 [9.2-14.2]	9.3 [7.7-11.0]	7.2 [5.2-9.4]	[1
South-East Asia	4.6 [3.8-5.5]	3.2 [2.4-4.3]	6.0 [4.8-7.5]	4.3 [3.6-5.1]	3.0 [2.3-4.0]	5.7 [4.6-7.0]	4.1 [3.5-4.8]	2.8 [2.2-3.7]	5.4 [4.4-6.6]	3.9 [3.3-4.5]	...	0.7 [0.4-1.1]	0.4 [0.2-0.6]	0.2 [0.1-0.4]	0.6 [0.3-1.1]	0.4 [0.2-0.6]	0.2 [0.1-0.4]	[
Europe	25.3 [23.6-27.0]	23.4 [21.1-25.6]	27.1 [24.7-29.5]	24.8 [23.2-26.3]	22.7 [20.6-24.8]	26.6 [24.4-28.9]	24.2 [22.8-25.7]	22.1 [20.2-24.1]	26.2 [24.1-28.3]	23.7 [22.4-25.1]	...	14.5 [11.8-17.6]	10.8 [9.1-12.7]	6.8 [5.3-8.7]	14.3 [11.4-17.4]	10.5 [8.8-12.5]	6.6 [5.0-8.5]	[1 1
Eastern Mediterranean	19.5 [17.8-21.2]	14.9 [12.7-17.2]	24.3 [21.8-26.9]	18.9 [17.4-20.5]	14.3 [12.3-16.4]	23.7 [21.3-26.1]	18.2 [16.8-19.7]	13.8 [11.9-15.6]	23.1 [20.9-25.3]	17.6 [16.3-19.0]	...	8.7 [6.1-11.9]	5.5 [4.1-7.2]	2.7 [1.6-4.2]	8.5 [5.8-11.7]	5.3 [3.8-7.1]	2.6 [1.5-4.1]	[1
Western Pacific	6.7 [5.5-8.1]	6.3 [4.6-8.4]	7.2 [5.5-9.3]	6.4 [5.3-7.6]	5.9 [4.4-7.7]	6.9 [5.3-8.7]	6.0 [5.0-7.1]	5.5 [4.2-7.1]	6.5 [5.2-8.2]	5.7 [4.8-6.7]	...	1.1 [0.8-1.6]	0.8 [0.6-1.0]	0.5 [0.3-0.7]	1.1 [0.7-1.6]	0.7 [0.5-1.0]	0.5 [0.3-0.7]	[

7 rows × 126 columns

In [19]:
```
obesity_region.isnull().values.any()
```

Out[19]:
```
False
```

In [20]:
```
obesity_region.dropna(axis = 0,inplace = True)
```

In [21]:
```
obesity_region
```

Out[21]:

	2016			2015			2014			2013	...	1978	1977			1		
WHO region	**Both sexes**	**Male**	**Female**	**Both sexes**	**Male**	**Female**	**Both sexes**	**Male**	**Female**	**Both sexes**	**...**	**Female**	**Both sexes**	**Male**	**Female**	**Both sexes**	**Male**	**Fen**

	2016			2015			2014			2013	...	1978	1977			1		
WHO region	Both sexes	Male	Female	Both sexes	Male	Female	Both sexes	Male	Female	Both sexes	...	Female	Both sexes	Male	Female	Both sexes	Male	Fen
Global	13.2 [12.5-13.9]	11.1 [10.2-12.2]	15.3 [14.2-16.4]	12.8 [12.2-13.5]	10.7 [9.9-11.7]	14.9 [13.9-15.9]	12.4 [11.8-13.0]	10.3 [9.6-11.2]	14.5 [13.6-15.4]	12.1 [11.5-12.6]	...	6.3 [5.3-7.4]	4.5 [3.9-5.2]	2.9 [2.3-3.6]	6.2 [5.2-7.3]	4.4 [3.8-5.1]	2.8 [2.2-3.5]	[
Africa	9.1 [8.2-10.0]	4.8 [3.9-5.9]	13.2 [11.8-14.8]	8.8 [8.0-9.6]	4.6 [3.8-5.6]	12.9 [11.5-14.3]	8.5 [7.7-9.3]	4.4 [3.6-5.3]	12.5 [11.2-13.8]	8.2 [7.5-8.9]	...	3.2 [2.2-4.4]	1.9 [1.3-2.5]	0.6 [0.3-1.1]	3.1 [2.1-4.4]	1.8 [1.2-2.5]	0.5 [0.3-1.0]	[
Americas	29.0 [27.1-31.0]	26.2 [23.4-29.1]	31.7 [28.8-34.4]	28.4 [26.6-30.3]	25.6 [23.0-28.3]	31.1 [28.5-33.7]	27.8 [26.1-29.6]	25.0 [22.6-27.5]	30.5 [28.1-32.9]	27.3 [25.7-28.8]	...	11.9 [9.6-14.5]	9.5 [8.0-11.2]	7.4 [5.5-9.6]	11.6 [9.2-14.2]	9.3 [7.7-11.0]	7.2 [5.2-9.4]	[1
South-East Asia	4.6 [3.8-5.5]	3.2 [2.4-4.3]	6.0 [4.8-7.5]	4.3 [3.6-5.1]	3.0 [2.3-4.0]	5.7 [4.6-7.0]	4.1 [3.5-4.8]	2.8 [2.2-3.7]	5.4 [4.4-6.6]	3.9 [3.3-4.5]	...	0.7 [0.4-1.1]	0.4 [0.2-0.6]	0.2 [0.1-0.4]	0.6 [0.3-1.1]	0.4 [0.2-0.6]	0.2 [0.1-0.4]	[
Europe	25.3 [23.6-27.0]	23.4 [21.1-25.6]	27.1 [24.7-29.5]	24.8 [23.2-26.3]	22.7 [20.6-24.8]	26.6 [24.4-28.9]	24.2 [22.8-25.7]	22.1 [20.2-24.1]	26.2 [24.1-28.3]	23.7 [22.4-25.1]	...	14.5 [11.8-17.6]	10.8 [9.1-12.7]	6.8 [5.3-8.7]	14.3 [11.4-17.4]	10.5 [8.8-12.5]	6.6 [5.0-8.5]	[1 1
Eastern Mediterranean	19.5 [17.8-21.2]	14.9 [12.7-17.2]	24.3 [21.8-26.9]	18.9 [17.4-20.5]	14.3 [12.3-16.4]	23.7 [21.3-26.1]	18.2 [16.8-19.7]	13.8 [11.9-15.6]	23.1 [20.9-25.3]	17.6 [16.3-19.0]	...	8.7 [6.1-11.9]	5.5 [4.1-7.2]	2.7 [1.6-4.2]	8.5 [5.8-11.7]	5.3 [3.8-7.1]	2.6 [1.5-4.1]	[1
Western Pacific	6.7 [5.5-8.1]	6.3 [4.6-8.4]	7.2 [5.5-9.3]	6.4 [5.3-7.6]	5.9 [4.4-7.7]	6.9 [5.3-8.7]	6.0 [5.0-7.1]	5.5 [4.2-7.1]	6.5 [5.2-8.2]	5.7 [4.8-6.7]	...	1.1 [0.8-1.6]	0.8 [0.6-1.0]	0.5 [0.3-0.7]	1.1 [0.7-1.6]	0.7 [0.5-1.0]	0.5 [0.3-0.7]	[

7 rows × 126 columns

In [22]:
```python
obesity_region.columns.names = ['Year', 'Sex']
obesity_region.index.names = ['WHO region']
obesity_region.columns.names
obesity_region.index.names
```

Out[22]:
```
FrozenList(['WHO region'])
```

In [23]:
```python
obesity_region = obesity_region.stack(level=0)
obesity_region = obesity_region.reset_index()
```

```
obesity_region
```

Out[23]:

Sex	WHO region	Year	Both sexes	Female	Male
0	Global	1975	4.3 [3.7-5.0]	5.9 [4.8-7.2]	2.7 [2.1-3.4]
1	Global	1976	4.4 [3.8-5.1]	6.1 [5.0-7.2]	2.8 [2.2-3.5]
2	Global	1977	4.5 [3.9-5.2]	6.2 [5.2-7.3]	2.9 [2.3-3.6]
3	Global	1978	4.6 [4.1-5.3]	6.3 [5.3-7.4]	3.0 [2.4-3.6]
4	Global	1979	4.8 [4.2-5.4]	6.4 [5.5-7.5]	3.1 [2.5-3.7]
...	...	...	...	...	...
289	Western Pacific	2012	5.3 [4.6-6.2]	5.9 [4.8-7.2]	4.8 [3.8-6.1]
290	Western Pacific	2013	5.7 [4.8-6.7]	6.2 [5.0-7.7]	5.1 [4.0-6.6]
291	Western Pacific	2014	6.0 [5.0-7.1]	6.5 [5.2-8.2]	5.5 [4.2-7.1]
292	Western Pacific	2015	6.4 [5.3-7.6]	6.9 [5.3-8.7]	5.9 [4.4-7.7]
293	Western Pacific	2016	6.7 [5.5-8.1]	7.2 [5.5-9.3]	6.3 [4.6-8.4]

294 rows × 5 columns

In [24]:

```python
# We will also get rid of the age column as with above.

obesity_region['Standardised age estimate'] = obesity_region['Both sexes'].apply(lambda x:x.split()[1])
obesity_region['Both sexes'] = obesity_region['Both sexes'].apply(lambda x:x.split()[0])

obesity_region['Standardised age estimate'] = obesity_region['Male'].apply(lambda x:x.split()[1])
obesity_region['Male'] = obesity_region['Male'].apply(lambda x:x.split()[0])

obesity_region['Standardised age estimate'] = obesity_region['Female'].apply(lambda x:x.split()[1])
obesity_region['Female'] = obesity_region['Female'].apply(lambda x:x.split()[0])
```

In [25]:

```python
obesity_region = obesity_region.sort_values(by=['WHO region', 'Year'])
obesity_region
```

Out[25]:

Sex	WHO region	Year	Both sexes	Female	Male	Standardised age estimate
42	Africa	1975	1.7	2.9	0.5	[1.9-4.2]
43	Africa	1976	1.8	3.0	0.5	[2.0-4.3]

Sex	WHO region	Year	Both sexes	Female	Male	Standardised age estimate
44	Africa	1977	1.9	3.1	0.6	[2.1-4.4]
45	Africa	1978	1.9	3.2	0.6	[2.2-4.4]
46	Africa	1979	2.0	3.3	0.6	[2.4-4.5]
...	...	...	...	...	...	...
289	Western Pacific	2012	5.3	5.9	4.8	[4.8-7.2]
290	Western Pacific	2013	5.7	6.2	5.1	[5.0-7.7]
291	Western Pacific	2014	6.0	6.5	5.5	[5.2-8.2]
292	Western Pacific	2015	6.4	6.9	5.9	[5.3-8.7]
293	Western Pacific	2016	6.7	7.2	6.3	[5.5-9.3]

294 rows × 6 columns

In [26]:
```
obesity_region.drop(['Standardised age estimate'], axis = 1, inplace = True)
obesity_region.reset_index(drop = True)
obesity_region
```

Out[26]:

Sex	WHO region	Year	Both sexes	Female	Male
42	Africa	1975	1.7	2.9	0.5
43	Africa	1976	1.8	3.0	0.5
44	Africa	1977	1.9	3.1	0.6
45	Africa	1978	1.9	3.2	0.6
46	Africa	1979	2.0	3.3	0.6
...	...	...	...	...	...
289	Western Pacific	2012	5.3	5.9	4.8
290	Western Pacific	2013	5.7	6.2	5.1
291	Western Pacific	2014	6.0	6.5	5.5
292	Western Pacific	2015	6.4	6.9	5.9

Sex	WHO region	Year	Both sexes	Female	Male
293	Western Pacific	2016	6.7	7.2	6.3

294 rows × 5 columns

In [27]:

```
# Melt regional obesity values.

obesity_region = obesity_region.melt(id_vars = ['WHO region', 'Year'],
                                     value_vars = ['Both sexes', 'Female', 'Male'],
                                     value_name = 'Obesity %')
obesity_region
```

Out[27]:

	WHO region	Year	Sex	Obesity %
0	Africa	1975	Both sexes	1.7
1	Africa	1976	Both sexes	1.8
2	Africa	1977	Both sexes	1.9
3	Africa	1978	Both sexes	1.9
4	Africa	1979	Both sexes	2.0
...	...	...	...	...
877	Western Pacific	2012	Male	4.8
878	Western Pacific	2013	Male	5.1
879	Western Pacific	2014	Male	5.5
880	Western Pacific	2015	Male	5.9
881	Western Pacific	2016	Male	6.3

882 rows × 4 columns

In [28]:

```
# For the analysis we will be looking at the obesity in regions overall, so we only need entries for both sexes.

obesity_region_both = obesity_region.loc[obesity_region.Sex == 'Both sexes', :].reset_index(drop = True)
obesity_region_both_pivot = obesity_region_both[['WHO region', 'Year',
                                                 'Obesity %']].pivot(index = 'WHO region',
                                                                     columns = 'Year',
```

```
                                                         values = 'Obesity %')
obesity_region_both
```

Out[28]:

	WHO region	Year	Sex	Obesity %
0	Africa	1975	Both sexes	1.7
1	Africa	1976	Both sexes	1.8
2	Africa	1977	Both sexes	1.9
3	Africa	1978	Both sexes	1.9
4	Africa	1979	Both sexes	2.0
...	...	...	...	...
289	Western Pacific	2012	Both sexes	5.3
290	Western Pacific	2013	Both sexes	5.7
291	Western Pacific	2014	Both sexes	6.0
292	Western Pacific	2015	Both sexes	6.4
293	Western Pacific	2016	Both sexes	6.7

294 rows × 4 columns

Analysis and discussion:

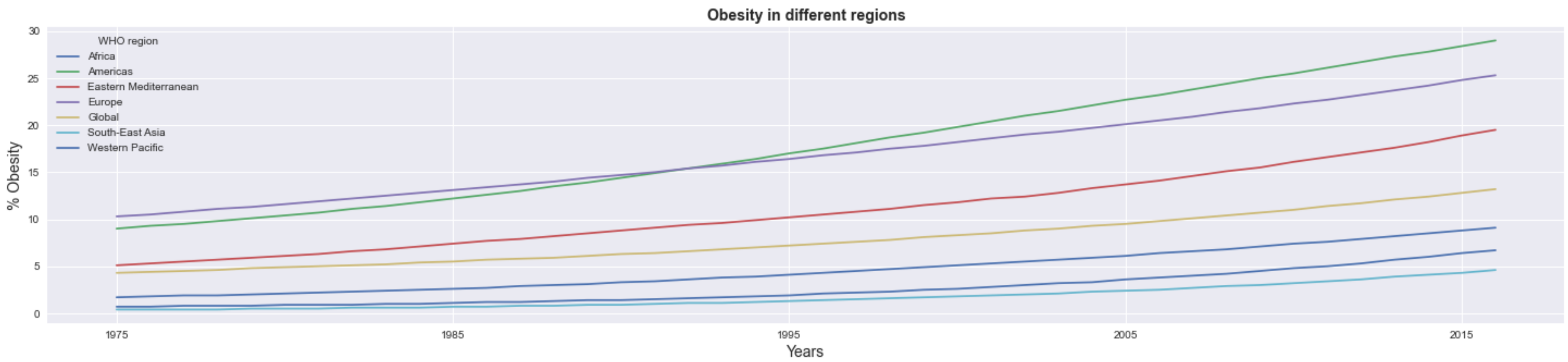
Now that the data is clean, we will take a look at the growth of obesity in populations over the years. We will isolate 20 countries that are on the two extreme ends of the spectrum; most obese, least obese, highest GDP, and lowest GDP. And after assessing the corelation, we will look at the differences between genders.

1. Global obesity growth.

In [29]:

```
# Now, we will compare the obesity in different regions over time.

obesity_region_both = obesity_region_both.groupby(['Year','WHO region'])['Obesity %'].sum().unstack(-1)

obesity_region_both = obesity_region_both.astype(float)

obesity_region_both.plot(kind ='line',figsize = (25, 5))
```

```
plt.title('Obesity in different regions', weight = 'bold', size = 14)
plt.ylabel('% Obesity', size = 14)
plt.xlabel('Years', size = 14)
plt.show()
```



2. Are obesity and poverty really linked?

In [30]:
```
obesity.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 24066 entries, 0 to 24065
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Country    24066 non-null  object
 1   Year       24066 non-null  object
 2   Sex        24066 non-null  object
 3   Obesity %  24066 non-null  object
dtypes: object(4)
memory usage: 752.2+ KB
```

In [31]:
```
# The data type for average obesity percentage is an object.
# Thus we will change the data type into numeric in order to do further analysis.

obesity['Obesity %'] = pd.to_numeric(obesity['Obesity %'],downcast = 'float')
```

In [32]:
```
# Let's find out the top 20 most obese countries, and append the results into a list.

high_obesity_countries = obesity.groupby('Country').mean().sort_values(by = 'Obesity %',
                                                                        ascending = False)['Obesity %'][:20]

countries_high = high_obesity_countries.index.tolist()
```

```python
values_high = high_obesity_countries.values.tolist()
high_obesity_countries
```

Out[32]:

```
Country
Nauru               53.093651
Palau               42.130951
Cook Islands        41.853176
Marshall Islands    40.512699
Tuvalu              35.123810
Niue                34.349998
Tonga               33.753174
Samoa               33.666668
Micronesia          31.968254
Kiribati            31.257936
Kuwait              29.295238
Qatar               26.287302
Saudi Arabia        23.864286
Jordan              23.599207
U.A.E               23.120634
U.S.A               22.896826
Bahrain             22.221428
Lebanon             21.991270
Libya               21.857937
Malta               21.683334
Name: Obesity %, dtype: float32
```

In [33]:

```python
# Let's find out the top 20 most obese countries, and append the results into a list.

low_obesity_countries = obesity.groupby('Country').mean().sort_values(by = 'Obesity %',
                                                                       ascending = True)['Obesity %'][:20].sort_values(asc
countries_low = low_obesity_countries.index.tolist()
values_low = low_obesity_countries.values.tolist()
low_obesity_countries
```

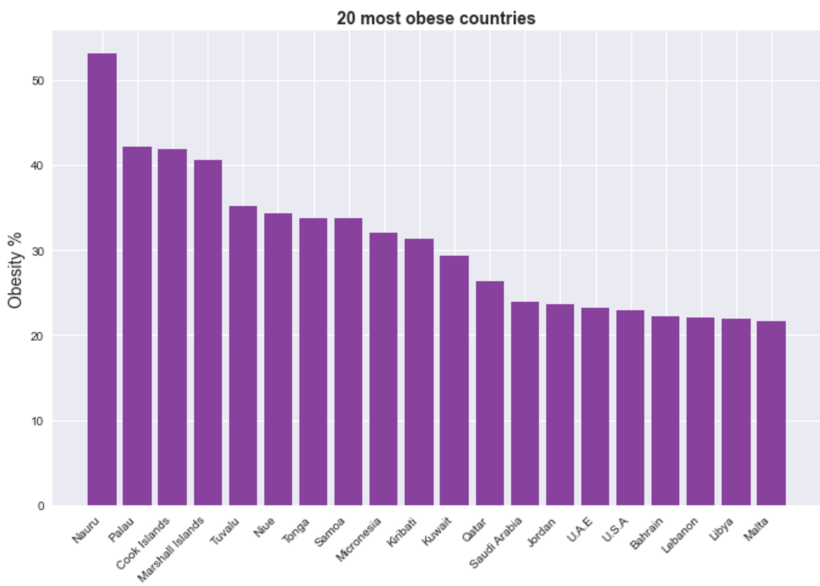
Out[33]:

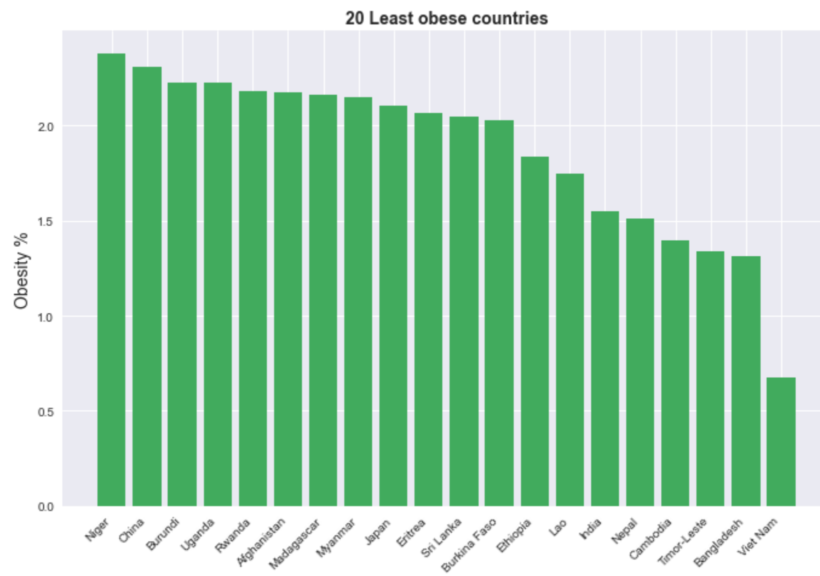
```
Country
Niger           2.378572
China           2.310318
Burundi         2.224603
Uganda          2.222222
Rwanda          2.177778
Afghanistan     2.175397
Madagascar      2.158730
Myanmar         2.146032
Japan           2.102381
Eritrea         2.068254
Sri Lanka       2.049206
Burkina Faso    2.028571
Ethiopia        1.833333
```

```
Lao             1.749206
India           1.551587
Nepal           1.509524
Cambodia        1.396032
Timor-Leste     1.340476
Bangladesh      1.312698
Viet Nam        0.676190
Name: Obesity %, dtype: float32
```

In [34]:

```python
# We will plot bar graps representing these lists above.


fig, ((ax1), (ax2)) = plt.subplots(figsize = (25, 8), nrows = 1, ncols = 2)
ax1.bar(x = countries_high, height = values_high, color = '#88419d')
ax1.set_title('20 most obese countries', weight = 'bold', size = 14)
ax1.set_ylabel('Obesity %', size = 14)

ax2.bar(x = countries_low, height = values_low, color = '#41ab5d')
ax2.set_title('20 Least obese countries', weight = 'bold', size = 14)
ax2.set_ylabel('Obesity %', size = 14)

fig.autofmt_xdate(rotation = 45)

plt.show()
```





In [35]:

```python
# For analysis we will convert GDP to numeric as well.
```

```python
gdp_df['GDP'] = pd.to_numeric(gdp_df['GDP'],downcast = 'float')
```

In [36]:

```python
# Highest 20 GDP countries.

countries_high_gdp = gdp_df.groupby('Country').mean().sort_values(by = 'GDP', ascending = False)['GDP'][:20]
high_gdp = countries_high_gdp.index.tolist()
values_gdp_high = countries_high_gdp.values.tolist()
countries_high_gdp
```

Out[36]:

```
Country
Monaco                       95846.226562
Cayman Islands               77501.640625
Liechtenstein                75509.445312
San Marino                   53783.199219
Luxembourg                   53303.914062
Channel Islands              51427.191406
Bermuda                      50121.117188
Isle of Man                  47850.941406
Norway                       43420.902344
Switzerland                  43267.558594
Faroe Islands                41393.910156
Virgin Islands (U.S.)        37195.597656
Qatar                        35330.542969
Denmark                      33184.062500
United Arab Emirates         33019.691406
Sweden                       32062.482422
United States                31144.863281
Iceland                      30967.693359
North America                30625.791016
Sint Maarten (Dutch part)    30222.626953
Name: GDP, dtype: float32
```

In [37]:

```python
# Lowest 20 GDP countries.

countries_low_gdp = gdp_df.groupby('Country').mean().sort_values(by = 'GDP',
                                                                  ascending = True)['GDP'][:20].sort_values(ascending = Fa
low_gdp = countries_low_gdp.index.tolist()
values_gdp_low = countries_low_gdp.values.tolist()
countries_low_gdp
```

Out[37]:

```
Country
Chad                        407.054443
Mozambique                  397.120483
Togo                        388.870453
Mali                        385.454742
Madagascar                  382.784393
Burkina Faso                371.460175
```

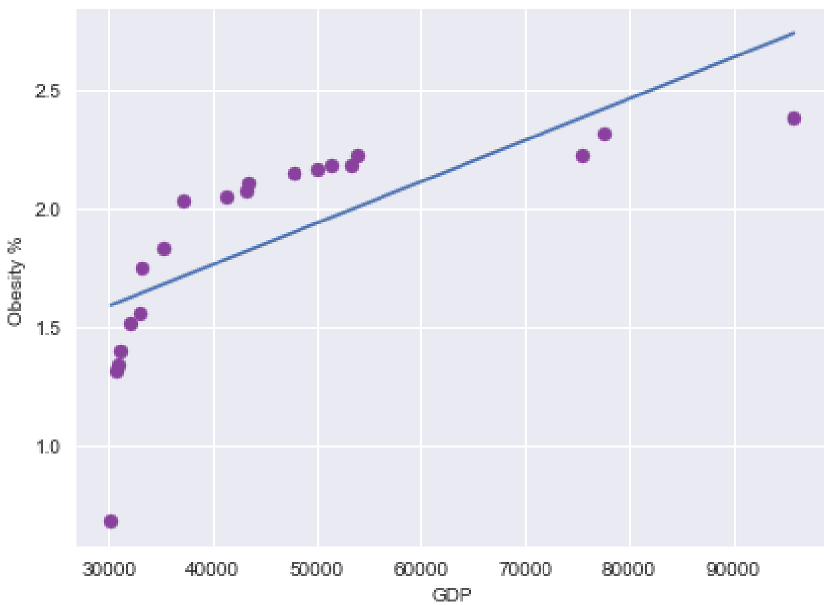
```
Afghanistan                 365.126007
Eritrea                     364.542328
Uganda                      362.363617
Central African Republic    361.817383
Rwanda                      353.993469
Niger                       331.960693
Guinea-Bissau               320.725616
Congo, Dem. Rep.            318.943787
Sierra Leone                297.747162
Nepal                       296.209473
Ethiopia                    256.673340
Malawi                      239.697357
Burundi                     191.724960
Somalia                     129.815674
Name: GDP, dtype: float32
```

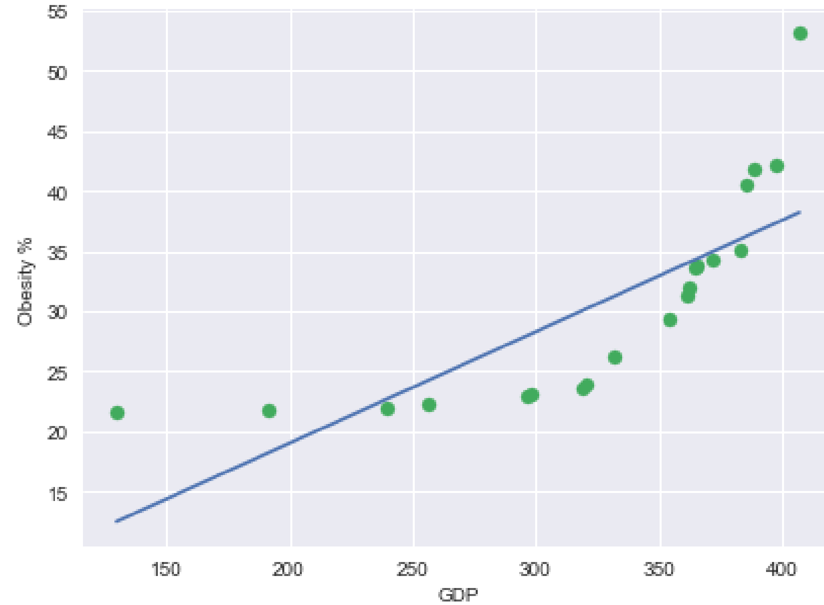
In [38]:

```
# Assigning these lists into numpy arrays in order to do a scatter plot.

# Most 20:
x1_array = np.array(values_gdp_high)
y1_array = np.array(values_low)

# least 20:

x2_array = np.array(values_gdp_low)
y2_array = np.array(values_high)
```

In [39]:

```
# 2 scatter plots of top GDP vs. obese


fig, ((ax11), (ax22)) = plt.subplots(figsize = (15, 5), nrows = 1, ncols = 2)
ax11.scatter(x1_array, y1_array, color = '#88419d')
ax11.plot(np.unique(x1_array), np.poly1d(np.polyfit(x1_array, y1_array, 1))(np.unique(x1_array)))
ax11.set_xlabel('GDP', size = 10)
ax11.set_ylabel('Obesity %', size = 10)

ax22.scatter(x2_array, y2_array, color = '#41ab5d')
ax22.plot(np.unique(x2_array), np.poly1d(np.polyfit(x2_array, y2_array, 1))(np.unique(x2_array)))
ax22.set_xlabel('GDP', size = 10)
ax22.set_ylabel('Obesity %', size = 10)


plt.show()
```





From the graphs above we see a positive correlation between low GDP and increased obesity rates. While countries with higher GDP tend to have less obesity among the overall population. However, there are some anomalies, like the Unites States and Qatar being on both the lists of "High GDP" and "Top 20 Obese Countries".

This would require further analysis of specific areas within these countries - are most the obese people in poorer regions with lower quality of life? Or is it an even split?

In the case of the United States, a study conducted in 2010 showed that counties with poverty rates of >35% had obesity rates 145% greater than wealthy counties. [4]

3. Is one gender more prone to obesity than the other?

In [40]:

```
# Now we will compare obesity percentages per gender globally.

obesity_region_male = obesity_region.loc[obesity_region.Sex == 'Male', :].reset_index(drop = True)
obesity_region_male_pivot = obesity_region_male[['WHO region',
                                                 'Year', 'Obesity %']].pivot(index = 'WHO region',
                                                                            columns = 'Year', values = 'Obesity %')
obesity_region_male['Obesity %'] = pd.to_numeric(obesity_region_male['Obesity %'], downcast = 'float')

obesity_region_female = obesity_region.loc[obesity_region.Sex == 'Female', :].reset_index(drop = True)
obesity_region_female_pivot = obesity_region_female[['WHO region',
                                                     'Year', 'Obesity %']].pivot(index = 'WHO region',
```

```python
                                                    columns = 'Year', values = 'Obesity %')
obesity_region_female['Obesity %'] = pd.to_numeric(obesity_region_female['Obesity %'], downcast = 'float')
```

In [41]:

```python
# Concating the new gendered dataframes into one:

obesity_region_gendered = obesity_region_male.merge(obesity_region_female, how = "outer")
obesity_region_gendered
```

Out[41]:

	WHO region	Year	Sex	Obesity %
0	Africa	1975	Male	0.5
1	Africa	1976	Male	0.5
2	Africa	1977	Male	0.6
3	Africa	1978	Male	0.6
4	Africa	1979	Male	0.6
...	...	...	...	...
583	Western Pacific	2012	Female	5.9
584	Western Pacific	2013	Female	6.2
585	Western Pacific	2014	Female	6.5
586	Western Pacific	2015	Female	6.9
587	Western Pacific	2016	Female	7.2

588 rows × 4 columns

In [42]:

```python
# We are interested in the gendered columns so we will group the dataframe by sex.

obesity_region_gendered = obesity_region_gendered.groupby(['Year','Sex'])['Obesity %'].sum().unstack(-1)
obesity_region_gendered.head()
```

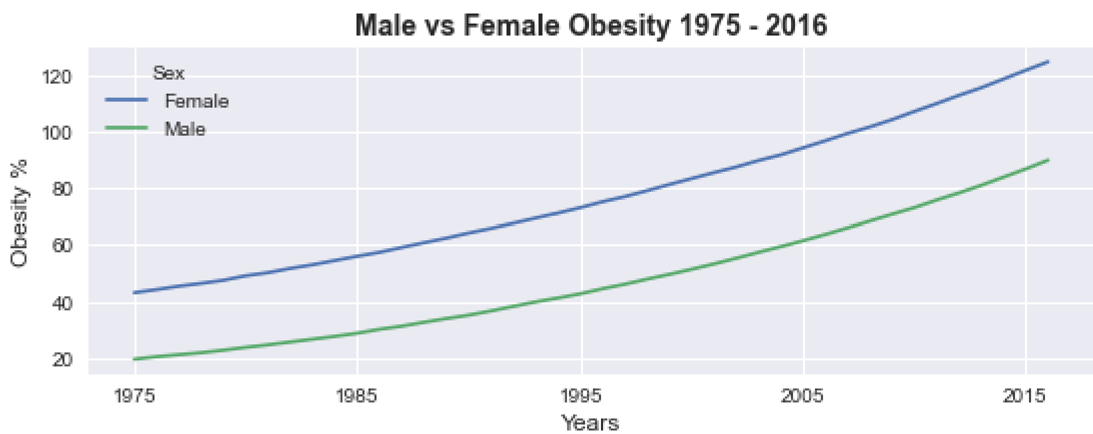
Out[42]:

Sex	Female	Male
Year		
1975	43.1	19.5
1976	44.2	20.4

Sex	Female	Male
Year		
1977	45.4	21.1
1978	46.4	21.8
1979	47.5	22.7

In [43]:

```
# Plotting this gendered data.

obesity_region_gendered.plot(kind = 'line', figsize=(9, 3))
plt.title('Male vs Female Obesity 1975 - 2016', weight = 'bold', size = 14)
plt.ylabel('Obesity %', size = 12)
plt.xlabel('Years', size = 12)
plt.show()
```

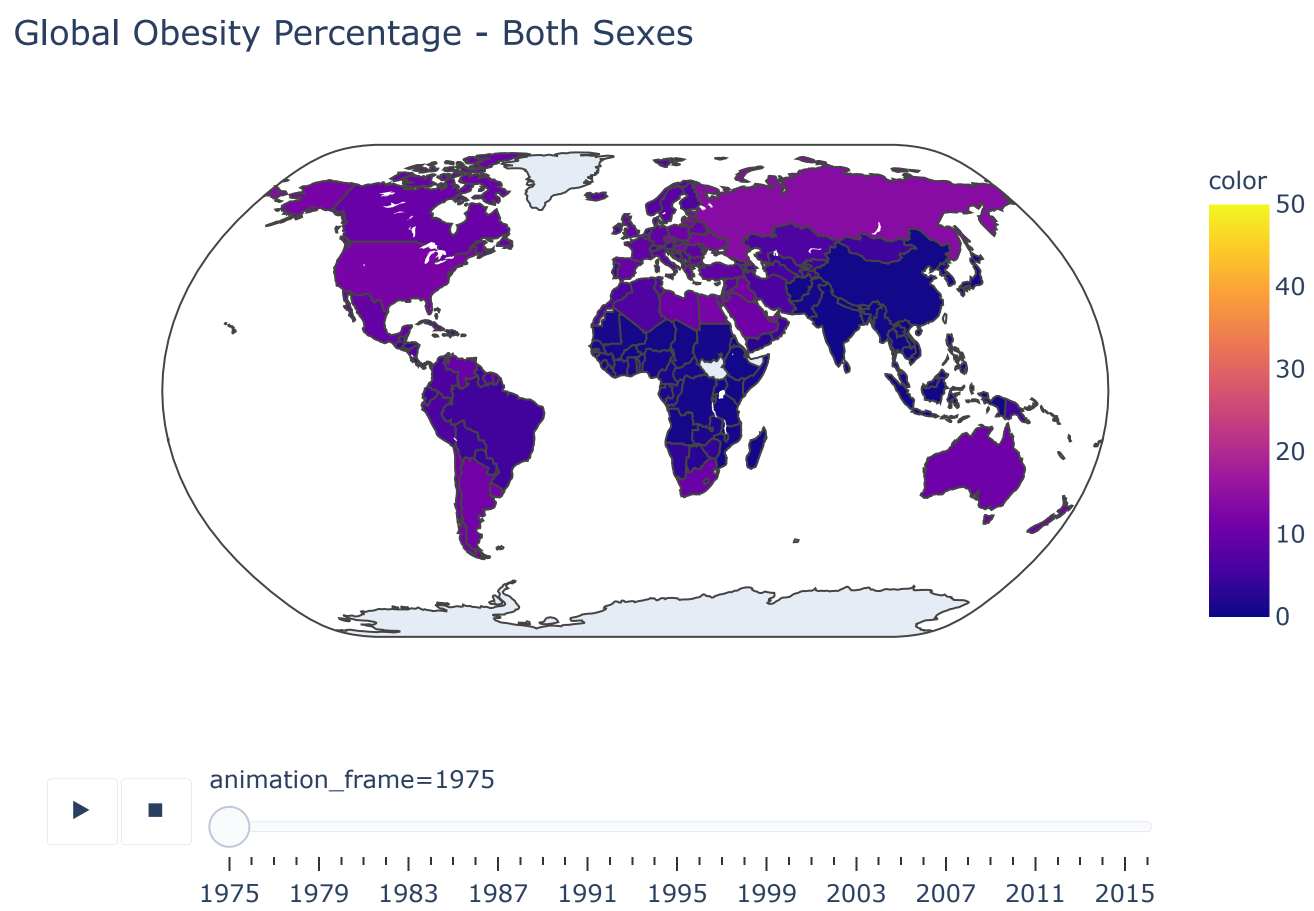


While both genders are prone to obesity, women seem to have higher rates of obesity than men. This could be due to many contributing factors that only affect women. PCOS, a condition that affects hormones and causes weight gain, only affects women. The risk of thyroid disease, which also causes weight gain, is about 10 times higher for women than for men. [5]

In [44]:

```
# Global heat map of obesity for both sexes.

px.choropleth(
    locations = obesity_both['Country'].astype(str),
    color = obesity_both['Obesity %'].astype(float),
    hover_name = obesity_both['Country'].astype(str),
    animation_frame = obesity_both['Year'].astype(int),
    color_continuous_scale = px.colors.sequential.Plasma,
```

```
    range_color = [0,50],
    locationmode = 'country names',
    height = 500,
    width = 700,
    title = 'Global Obesity Percentage - Both Sexes',
    projection = 'natural earth'
)
```



Conclusion:

From the data, we saw that gender and socio-economic status can both be factors resulting in obesity. There are various prevention strategies recommended by the WHO, and those include; a universal or public health approach directed at all members of a community; a selective approach directed at high-risk individuals and groups; and a targeted approach directed at individuals with weight-related problems and those at high risk of diseases associated with overweight and obesity. [6]

Prevention is key to treating obesity, and individuals with different needs than other need to be taken into account in order to achieve a healthier society as a whole.

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