Investigate_a_Dataset

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1 Project: Gapminder World Data Analysis

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Introduction

Gapminder world contains diverse information about countries around the world In this research I am interested in studying the communication evolution during the duration 2000 to 2017, as the evolution leap in communication technologies at this particular time

I will use the datasets for the percent of fixed-line-phone and cell-phone, and internet users in all world countries. > **Communication** is chosen to be analyzed in this research will focus on the following points: - Study the **fixed line phones** usage during **2000 - 2017** - Study the **cell phones** usage during **2000 - 2017** - Study the **internet** usage during the duration **2000 - 2017** - Study the **relation** between the number of **fixed line** phones users and the number of the **cell phones** users during the interval **2000 - 2017**

```
In [1]: #import all neeeded libraries to perform analysis
        import numpy as np
        import pandas as pd
        import seaborn as sns
        import matplotlib.pyplot as plt
        import numpy as np
        % matplotlib inline
```

Data Wrangling - Read the datasets - Extract the needed dataset from the entire datasets, we need the data for the duration 2000 to 2017 - Handle the null values. (Delete the rows that have empty cells, as they are very limited, as the aom is to study the entire world behaviour not specific country) - Merge the fixed line subscribers dataframe with cell phones to study the relation between them

1.1.1 Read the datasets

```
In [2]: df_cell_phone = pd.read_csv("cell_phones_per_100_people.csv")
        df_fixed_line = pd.read_csv("fixed_line_subscribers_per_100_people.csv")
        df_net_users = pd.read_csv("internet_users.csv")
```

Let's view the first few rows of each dataset to get an overview of each dataset and to show if there are needed wrangling techniques will show up

```
In [3]: df_fixed_line.head()
```

```
Out[3]:       country    1960  1961  1962  1963  1964    1965  1966  1967  1968  \
        0  Afghanistan  0.0856   NaN   NaN   NaN   NaN  0.0934   NaN   NaN   NaN
        1      Albania  0.4180   NaN   NaN   NaN   NaN  0.7380   NaN   NaN   NaN
        2      Algeria     NaN   NaN   NaN   NaN   NaN  0.5790   NaN   NaN   NaN
        3      Andorra     NaN   NaN   NaN   NaN   NaN  2.7000   NaN   NaN   NaN
        4       Angola  0.1220   NaN   NaN   NaN   NaN  0.1730   NaN   NaN   NaN

            ...       2009    2010     2011    2012    2013    2014   2015    2016  \
        0   ...     0.0181   0.057   0.0449   0.289   0.297   0.305   0.32   0.323
        1   ...    12.2000  11.300  11.6000  10.700   9.680   8.140   7.84   8.610
        2   ...     7.2900   8.120   8.3400   8.800   8.210   7.960   8.22   8.400
        3   ...    44.9000  45.200  45.9000  46.500  47.800  48.300  49.80  50.100
        4   ...     1.3500   1.200   0.6580   0.830   0.826   1.070   1.02   1.060

             2017    2018
        0   0.327   0.344
        1   8.550   8.620
        2   9.910   9.950
        3  49.900  51.100
        4   0.540   0.558

        [5 rows x 60 columns]
```

There are many null values at the sixties as the landline was not spread at that time globally

```
In [4]: df_cell_phone.head()
```

```
Out[4]:       country  1960  1961  1962  1963  1964  1965  1966  1967  1968  ...  \
        0  Afghanistan   0.0   NaN   NaN   NaN   NaN   0.0   NaN   NaN   NaN  ...
        1      Albania   0.0   NaN   NaN   NaN   NaN   0.0   NaN   NaN   NaN  ...
        2      Algeria   0.0   NaN   NaN   NaN   NaN   0.0   NaN   NaN   NaN  ...
        3      Andorra   0.0   NaN   NaN   NaN   NaN   0.0   NaN   NaN   NaN  ...
        4       Angola   0.0   NaN   NaN   NaN   NaN   0.0   NaN   NaN   NaN  ...

           2009  2010   2011   2012   2013   2014   2015   2016   2017   2018
        0  37.0  35.0   45.8   49.2   52.1   55.2   57.3   61.1   65.9   59.1
        1  82.9  91.3  106.0  120.0  127.0  116.0  118.0  117.0  126.0   94.2
        2  92.6  91.1   97.1  100.0  104.0  111.0  109.0  116.0  111.0  112.0
        3  76.4  77.6   77.7   77.5   79.1   83.6   91.4   98.5  104.0  107.0
        4  36.0  40.3   49.8   50.9   51.1   52.2   49.8   45.1   44.7   43.1

        [5 rows x 60 columns]
```

Cellphones were created very recently which explains the null values for the sixties till ninties

```
In [5]: df_net_users.head()
```

```
Out[5]:        country  1960  1961  1962  1963  1964  1965  1966  1967  1968  ...   \
        0  Afghanistan   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN  ...
        1      Albania   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN  ...
        2      Algeria   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN  ...
        3      Andorra   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN  ...
        4       Angola   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN  ...

            2009  2010  2011   2012  2013  2014   2015  2016  2017  2018
        0   3.55   4.0   5.0   5.45   5.9   7.0   8.26  11.2  13.5   NaN
        1  41.20  45.0  49.0  54.70  57.2  60.1  63.30  66.4  71.8   NaN
        2  11.20  12.5  14.9  18.20  22.5  29.5  38.20  42.9  47.7  49.0
        3  78.50  81.0  81.0  86.40  94.0  95.9  96.90  97.9  91.6   NaN
        4   2.30   2.8   3.1   6.50   8.9  21.4  12.40  13.0  14.3   NaN

        [5 rows x 60 columns]
```

Internet was created very recently which explains the null values for the sixties till ninties

The heads of the three datasets showed that: * There are data for years other than the needed interval. These years data shall be removed, by removing their related columns * As the country shall be used as an index to refer to each country data in the selected interval, it shall be changed for all datasets to be the index * We need to view the NaNs after croping unneeded data, to decide how to deal with them * The values for the data is shown with the same format, we do not need to change thier format

1.1.2 Extract the needed dataset from the entire datasets, we need the data for the duration 2000 to 2017

- This duration has been chosen to study a very close duration interval in communication.
- And as the inventing of cellphones and Internet was availble only after ninties, we can afford more data without nulls in 2000's years as they spreaded perfectly in these years

In this step we will make the country the index of the dataframe to ease referring to the rows

```
In [6]: # For the three dataset we will remove all columns but the country and the columns range
        # Keep the country and the columns 2000 till 2017 for df_fixed_line dataset
        df_fixed_line =  pd.concat([df_fixed_line['country'] , df_fixed_line.loc[:, '2000':'2017
        # Make the country column the index of df_fixed_line dataset
        df_fixed_line = df_fixed_line.set_index('country')
        # Keep the country and the columns 2000 till 2017 for df_cell_phone dataset
        df_cell_phone =  pd.concat([df_cell_phone['country'] , df_cell_phone.loc[:, '2000':'2017
        # Make the country column the index of df_cell_phone dataset
        df_cell_phone = df_cell_phone.set_index('country')
        # Keep the country and the columns 2000 till 2017 for df_net_users dataset
        df_net_users =  pd.concat([df_net_users['country'] , df_net_users.loc[:, '2000':'2017']]
        # Make the country column the index of df_net_users dataset
        df_net_users = df_net_users.set_index('country')
```

1.1.3 Handle the null values. (Delete the rows that have empty cells, as they are very limited, as the aim is to study the entire world behaviour not specific country)

df_fixed_line dataset

```
In [7]: # Show the info of df_fixed_line to know if there are missing values in the chosen inter
        df_fixed_line.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 194 entries, Afghanistan to Zimbabwe
Data columns (total 18 columns):
2000    189 non-null float64
2001    189 non-null float64
2002    190 non-null float64
2003    190 non-null float64
2004    190 non-null float64
2005    189 non-null float64
2006    187 non-null float64
2007    189 non-null float64
2008    189 non-null float64
2009    191 non-null float64
2010    193 non-null float64
2011    192 non-null float64
2012    193 non-null float64
2013    192 non-null float64
2014    193 non-null float64
2015    192 non-null float64
2016    191 non-null float64
2017    189 non-null float64
dtypes: float64(18)
memory usage: 28.8+ KB
```

```
In [8]: # Show the rows that have NaNs
        df_fixed_line[df_fixed_line.isna().any(axis=1)]
```

Out[8]:

country	2000	2001	2002	2003	2004	2005
Afghanistan	0.140	0.134	0.146	0.155	NaN	NaN
Brunei	24.200	26.000	23.400	23.200	23.100	23.000
Central African Republic	0.260	0.240	0.237	0.245	0.253	0.248
Liberia	0.235	0.230	0.228	NaN	NaN	NaN
Marshall Islands	7.880	8.140	8.360	8.350	10.100	NaN
Montenegro	NaN	NaN	NaN	NaN	NaN	27.700
Nauru	17.400	18.100	17.800	18.000	18.200	18.300
Palau	NaN	NaN	35.300	37.200	39.000	40.300
Samoa	4.880	5.510	6.680	7.490	9.180	10.800
Saudi Arabia	14.300	15.200	15.700	15.600	16.000	16.100
Serbia	NaN	NaN	NaN	NaN	29.100	27.500

```
Somalia                    0.282   0.381   0.368   1.020   0.987   0.957
South Sudan                  NaN     NaN     NaN     NaN     NaN     NaN
Tajikistan                 3.520   3.590   3.700   3.750   4.100   4.130
Timor-Leste                  NaN     NaN     NaN   0.208   0.216   0.235
Vietnam                    3.180   3.780   4.820   5.350  12.200     NaN

                            2006     2007     2008     2009     2010     2011  \
country
Afghanistan                  NaN      NaN      NaN   0.0181   0.0570   0.0449
Brunei                    21.700  21.2000  21.3000  21.0000  20.6000  20.3000
Central African Republic     NaN      NaN      NaN   0.0821   0.0212   0.0184
Liberia                      NaN   0.0592   0.0554   0.0632   0.1490   0.2310
Marshall Islands             NaN      NaN      NaN      NaN      NaN      NaN
Montenegro                27.200  28.5000  28.0000  27.6000  27.3000  27.3000
Nauru                     18.300  18.3000  18.2000  19.1000   0.0000   0.0000
Palau                     37.500  39.0000  39.5000  39.0000  38.9000  39.0000
Samoa                        NaN      NaN      NaN      NaN   4.3000      NaN
Saudi Arabia              16.100  15.9000  15.8000  15.7000  15.2000  16.4000
Serbia                    29.700  32.9000  34.0000  34.4000  34.6000  33.8000
Somalia                    0.929   0.9030   0.8770   0.8530   0.8300   0.7270
South Sudan                  NaN      NaN      NaN      NaN   0.0252   0.0224
Tajikistan                   NaN   4.1400   3.9800   4.7200   4.8800   4.9400
Timor-Leste                0.246   0.2350   0.2500   0.2710   0.2660   0.2740
Vietnam                   10.100  13.1000  17.1000  20.0000  16.3000  11.4000

                            2012     2013     2014     2015     2016     2017
country
Afghanistan                0.28900   0.297   0.3050   0.3200   0.3230   0.3270
Brunei                    17.80000     NaN  17.5000  18.3000  17.7000  19.7000
Central African Republic   0.01860   0.018   0.0179   0.0419   0.0433   0.0458
Liberia                    0.33200   0.259   0.2300   0.2010   0.1740      NaN
Marshall Islands               NaN     NaN   4.1300      NaN      NaN      NaN
Montenegro                27.10000  27.000  26.3000  24.6000  23.6000  24.2000
Nauru                      0.00000   0.000   0.0000      NaN      NaN      NaN
Palau                     41.50000  41.300  40.4000  40.8000      NaN      NaN
Samoa                      4.37000   4.390   6.1300   5.9200   4.9800   4.3300
Saudi Arabia              16.50000  16.400      NaN  11.8000  13.1000  14.1000
Serbia                    33.30000  34.000  32.1000  31.2000  30.3000  29.6000
Somalia                    0.55100   0.490   0.4260   0.3700   0.3380      NaN
South Sudan                0.00148   0.000   0.0000   0.0000   0.0000   0.0000
Tajikistan                 4.99000   5.270   5.3400   5.4100   5.4000   5.3900
Timor-Leste                0.26500   0.260   0.3030   0.2270   0.2090   0.1920
Vietnam                   10.60000   7.410   7.3300   7.9000   5.9800   4.6400
```

The aim of this research is to study having fixed line phones around the world, as we will still have 91.7% of the world countries would be representative for all other countries

```
In [9]: #Remove rows with null values
        df_fixed_line.dropna(how='any', axis=0, inplace=True)
```

```
        #Ensure that the null values are removed
        df_fixed_line.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 178 entries, Albania to Zimbabwe
Data columns (total 18 columns):
2000    178 non-null float64
2001    178 non-null float64
2002    178 non-null float64
2003    178 non-null float64
2004    178 non-null float64
2005    178 non-null float64
2006    178 non-null float64
2007    178 non-null float64
2008    178 non-null float64
2009    178 non-null float64
2010    178 non-null float64
2011    178 non-null float64
2012    178 non-null float64
2013    178 non-null float64
2014    178 non-null float64
2015    178 non-null float64
2016    178 non-null float64
2017    178 non-null float64
dtypes: float64(18)
memory usage: 26.4+ KB
```

df_cell_phone dataset

```
In [10]: # Show the info of df_cell_phone to know if there are missing values in the chosen inte
         df_cell_phone.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 194 entries, Afghanistan to Zimbabwe
Data columns (total 18 columns):
2000    189 non-null float64
2001    189 non-null float64
2002    189 non-null float64
2003    190 non-null float64
2004    191 non-null float64
2005    191 non-null float64
2006    189 non-null float64
2007    191 non-null float64
2008    189 non-null float64
2009    190 non-null float64
2010    193 non-null float64
2011    192 non-null float64
```

```
2012    193 non-null float64
2013    192 non-null float64
2014    192 non-null float64
2015    194 non-null float64
2016    192 non-null float64
2017    193 non-null float64
dtypes: float64(18)
memory usage: 28.8+ KB
```

In [11]:
```
# Show the rows that have NaNs
df_cell_phone[df_cell_phone.isna().any(axis=1)]
```

Out[11]:

country	2000	2001	2002	2003	2004	2005	2006	\
Guinea	0.511	0.661	1.0600	1.27	1.74	2.07	NaN	
Marshall Islands	0.881	0.951	1.0500	1.12	1.18	1.19	NaN	
Micronesia, Fed. Sts.	0.000	0.000	0.0934	5.49	12.00	13.30	17.70	
Montenegro	NaN	NaN	NaN	NaN	78.60	88.10	104.00	
Nauru	11.600	14.700	NaN	NaN	NaN	NaN	NaN	
Palau	NaN	NaN	12.5000	19.80	19.80	30.60	42.70	
Samoa	1.430	1.430	1.5300	5.92	8.96	13.40	25.20	
Serbia	NaN	NaN	NaN	NaN	51.20	59.90	72.60	
Sierra Leone	0.260	0.566	1.3500	2.18	NaN	NaN	NaN	
South Sudan	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
Timor-Leste	NaN	NaN	NaN	2.12	2.65	3.32	4.83	
Tuvalu	0.000	0.000	0.0000	0.00	5.07	13.00	15.80	

country	2007	2008	2009	2010	2011	2012	2013	\
Guinea	21.00	28.2	35.00	39.2	46.6	52.4	68.3	
Marshall Islands	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
Micronesia, Fed. Sts.	26.30	26.6	26.70	26.7	26.7	29.9	29.6	
Montenegro	145.00	186.0	208.00	187.0	185.0	158.0	159.0	
Nauru	NaN	NaN	NaN	62.0	66.5	67.1	NaN	
Palau	55.80	62.4	69.70	80.8	87.0	97.2	102.0	
Samoa	47.20	NaN	NaN	48.4	NaN	53.0	52.4	
Serbia	92.90	106.0	110.00	110.0	114.0	102.0	103.0	
Sierra Leone	13.00	16.4	18.50	31.2	32.6	32.9	58.3	
South Sudan	NaN	NaN	NaN	15.8	18.3	22.7	27.6	
Timor-Leste	7.55	11.8	32.70	43.3	55.2	54.8	56.4	
Tuvalu	17.60	NaN	9.59	15.2	20.0	26.1	31.3	

country	2014	2015	2016	2017
Guinea	77.9	94.2	94.6	97.0
Marshall Islands	27.1	27.0	NaN	27.6
Micronesia, Fed. Sts.	NaN	20.7	21.2	20.7

```
Montenegro            162.0  161.0  166.0  166.0
Nauru                   NaN   90.5   94.5   94.6
Palau                 108.0  134.0    NaN    NaN
Samoa                  55.4   62.3   77.6   63.6
Serbia                105.0  103.0  103.0   97.6
Sierra Leone           67.8   78.9   85.7   88.5
South Sudan            27.2   27.1   24.9   25.6
Timor-Leste           117.0  115.0  122.0  125.0
Tuvalu                 34.6   59.5   67.7   70.4
```

- For some coutnries, they were parts of other countires before a specific date, as South Sudan.
- South Sudan was a part of Sudan till 2010.
- In this research our aim is to study the having cell phones around the world, as we will still have 93% of the world countries would be representative for all other countries

```
In [12]: #Remove rows with null values
         df_cell_phone.dropna(how='any', axis=0, inplace=True)
         #Ensure that the null values are removed
         df_cell_phone.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 182 entries, Afghanistan to Zimbabwe
Data columns (total 18 columns):
2000    182 non-null float64
2001    182 non-null float64
2002    182 non-null float64
2003    182 non-null float64
2004    182 non-null float64
2005    182 non-null float64
2006    182 non-null float64
2007    182 non-null float64
2008    182 non-null float64
2009    182 non-null float64
2010    182 non-null float64
2011    182 non-null float64
2012    182 non-null float64
2013    182 non-null float64
2014    182 non-null float64
2015    182 non-null float64
2016    182 non-null float64
2017    182 non-null float64
dtypes: float64(18)
memory usage: 27.0+ KB
```

df_net_users dataset

```
In [13]: # Show the info of df_net_users to know if there are missing values in the chosen inter
         df_net_users.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 194 entries, Afghanistan to Zimbabwe
Data columns (total 18 columns):
2000    184 non-null float64
2001    186 non-null float64
2002    187 non-null float64
2003    181 non-null float64
2004    184 non-null float64
2005    185 non-null float64
2006    184 non-null float64
2007    191 non-null float64
2008    190 non-null float64
2009    189 non-null float64
2010    189 non-null float64
2011    192 non-null float64
2012    189 non-null float64
2013    190 non-null float64
2014    190 non-null float64
2015    190 non-null float64
2016    190 non-null float64
2017    192 non-null float64
dtypes: float64(18)
memory usage: 28.8+ KB
```

```
In [14]: # Show more details about the rows that have NaNs
         df_net_users[df_net_users.isna().any(axis=1)]
```

Out[14]:

country	2000	2001	2002	2003	2004	2005	2006
Afghanistan	NaN	0.00472	0.00456	0.0879	0.1060	1.2200	2.110
Andorra	10.5000	NaN	11.30000	13.5000	26.8000	37.6000	48.900
Australia	46.8000	52.70000	NaN	NaN	NaN	63.0000	66.000
Azerbaijan	0.1480	0.30600	5.00000	NaN	NaN	8.0300	12.000
Belarus	1.8600	4.30000	8.95000	NaN	NaN	NaN	16.200
Belize	5.9600	NaN	5.68000	NaN	9.8000	17.0000	24.000
Eritrea	0.1370	0.15800	0.22700	NaN	NaN	NaN	NaN
Guyana	6.6100	13.20000	NaN	NaN	NaN	NaN	NaN
Iraq	NaN	0.10000	0.50000	0.6000	0.9000	0.9000	0.952
Liberia	0.0177	0.03380	0.03270	0.0319	0.0310	NaN	NaN
Libya	0.1870	0.36700	2.24000	2.8100	3.5300	3.9200	4.300
Mongolia	1.2600	1.65000	2.04000	NaN	NaN	NaN	NaN
Montenegro	NaN	NaN	NaN	NaN	25.4000	27.1000	28.900
Myanmar	NaN	0.00029	0.00043	0.0241	0.0243	0.0652	0.182
Nauru	NaN	2.99000	NaN	NaN	NaN	NaN	NaN
North Korea	0.0000	0.00000	0.00000	0.0000	0.0000	0.0000	0.000
Pakistan	NaN	1.32000	2.58000	5.0400	6.1600	6.3300	6.500
Palau	NaN	NaN	20.20000	21.6000	27.0000	NaN	NaN

Rwanda	0.0628	0.24100	0.29300	0.3570	0.4310	0.5560	NaN
San Marino	48.8000	50.30000	50.80000	50.0000	50.6000	50.3000	50.200
Serbia	NaN	NaN	NaN	NaN	23.5000	26.3000	27.200
Seychelles	7.4000	11.00000	14.30000	14.6000	24.3000	25.4000	35.000
Somalia	0.0200	0.07900	0.11600	0.3760	1.0500	1.0800	1.100
South Sudan	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Sudan	0.0258	0.14000	0.43900	0.5380	0.7920	1.2900	NaN
Timor-Leste	NaN	NaN	0.00000	NaN	NaN	0.0990	0.500
Tuvalu	5.2400	NaN	NaN	NaN	NaN	NaN	NaN

country	2007	2008	2009	2010	2011	2012	2013	2014	2015	\
Afghanistan	1.900	1.84	3.55	4.00	5.00	5.45	5.90	7.00	8.26	
Andorra	70.900	70.00	78.50	81.00	81.00	86.40	94.00	95.90	96.90	
Australia	69.500	71.70	74.30	76.00	79.50	79.00	83.50	84.00	84.60	
Azerbaijan	14.500	17.10	27.40	46.00	50.00	54.20	73.00	75.00	77.00	
Belarus	19.700	23.00	27.40	31.80	39.60	46.90	54.20	59.00	62.20	
Belize	24.600	26.30	27.20	28.20	30.70	31.00	33.60	38.70	41.60	
Eritrea	0.410	0.47	0.54	0.61	0.70	0.80	0.90	0.99	1.08	
Guyana	13.800	18.20	23.90	29.90	30.00	30.50	31.00	32.00	34.00	
Iraq	0.930	1.00	1.06	2.50	5.00	7.10	9.20	13.20	58.00	
Liberia	0.551	0.53	2.00	2.30	2.50	2.60	3.20	5.41	33.00	
Libya	4.720	9.00	10.80	14.00	14.00	NaN	16.50	17.80	19.00	
Mongolia	9.000	9.80	10.00	10.20	12.50	16.40	17.70	19.90	22.50	
Montenegro	30.800	32.90	35.10	37.50	35.60	56.80	60.30	61.00	68.10	
Myanmar	0.217	0.22	0.22	0.25	0.98	4.00	8.00	11.50	21.70	
Nauru	NaN	NaN	NaN	NaN	54.00	NaN	NaN	NaN	NaN	
North Korea	0.000	0.00	0.00	0.00	0.00	0.00	NaN	NaN	NaN	
Pakistan	6.800	7.00	7.50	8.00	9.00	9.96	10.90	12.00	14.00	
Palau	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
Rwanda	2.120	4.50	7.70	8.00	7.00	8.02	9.00	10.60	18.00	
San Marino	50.400	54.50	54.20	NaN	49.60	NaN	NaN	NaN	NaN	
Serbia	33.100	35.60	38.10	40.90	42.20	48.10	53.50	62.10	65.30	
Seychelles	38.400	40.40	NaN	41.00	43.20	47.10	50.40	51.30	54.30	
Somalia	1.120	1.14	1.16	NaN	1.25	1.38	1.50	1.63	1.76	
South Sudan	NaN	NaN	NaN	NaN	NaN	NaN	3.83	4.52	5.50	
Sudan	8.660	NaN	NaN	16.70	17.50	21.00	22.70	24.60	26.60	
Timor-Leste	1.000	1.50	2.00	3.00	4.00	7.00	11.00	17.50	23.00	
Tuvalu	10.000	15.00	20.00	25.00	30.00	35.00	37.00	39.20	42.70	

country	2016	2017
Afghanistan	11.20	13.50
Andorra	97.90	91.60
Australia	86.50	86.50
Azerbaijan	78.20	79.00
Belarus	71.10	74.40
Belize	44.60	47.10

```
Eritrea       1.18   1.31
Guyana       35.70  37.30
Iraq         21.20  49.40
Liberia       7.32   7.98
Libya        20.30  21.80
Mongolia     22.30  23.70
Montenegro   69.90  71.30
Myanmar      25.10  30.70
Nauru          NaN  57.00
North Korea    NaN    NaN
Pakistan     12.40  15.50
Palau          NaN    NaN
Rwanda       20.00  21.80
San Marino     NaN  60.20
Serbia       67.10  70.30
Seychelles   56.50  58.80
Somalia       1.88   2.00
South Sudan   6.68   7.98
Sudan        14.10  30.90
Timor-Leste  25.20  27.50
Tuvalu       46.00  49.30
```

It is noticed that North Korea row has zeros for the entire row, or NaN, as the internet is very restricted to the officials while the citizens are allowed to access only the local network

Will proceed in removing all the countries that have null values for the same mentioned reasons that our aim is to study intrent users globally

```
In [15]: #Remove rows with null values
         df_net_users.dropna(how='any', axis=0, inplace=True)
         #Ensure that the null values are removed
         df_net_users.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 167 entries, Albania to Zimbabwe
Data columns (total 18 columns):
2000    167 non-null float64
2001    167 non-null float64
2002    167 non-null float64
2003    167 non-null float64
2004    167 non-null float64
2005    167 non-null float64
2006    167 non-null float64
2007    167 non-null float64
2008    167 non-null float64
2009    167 non-null float64
2010    167 non-null float64
2011    167 non-null float64
2012    167 non-null float64
```

```
2013    167 non-null float64
2014    167 non-null float64
2015    167 non-null float64
2016    167 non-null float64
2017    167 non-null float64
dtypes: float64(18)
memory usage: 24.8+ KB
```

Exploratory Data Analysis

1.1.4 Research Question 1: The percentage of fixed line users globally

Let's view a simple description of `df_fixed_line` to have an overview of the fixed line phones around the world during the selected interval

```
In [16]: df_fixed_line.describe()
```

Out[16]:

	2000	2001	2002	2003	2004	2005
count	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000
mean	19.953920	20.130734	20.218831	20.138825	20.116184	19.945266
std	21.539404	21.289378	21.227481	20.818229	20.447487	19.951775
min	0.020800	0.020600	0.020000	0.018900	0.019800	0.019300
25%	2.157500	2.415000	2.550000	2.902500	2.870000	2.952500
50%	10.600000	11.000000	11.450000	12.000000	12.850000	13.500000
75%	32.225000	31.850000	31.925000	31.625000	31.675000	31.250000
max	93.200000	91.300000	103.000000	101.000000	101.000000	100.000000

	2006	2007	2008	2009	2010	2011
count	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000
mean	19.822456	19.779702	19.788347	20.003864	19.653938	19.500479
std	19.563460	19.166201	18.977029	19.768812	19.389480	19.241837
min	0.017100	0.005990	0.061800	0.067800	0.000000	0.000000
25%	3.077500	3.057500	3.055000	3.087500	3.027500	3.147500
50%	13.750000	14.350000	14.900000	15.050000	14.950000	15.150000
75%	30.425000	30.125000	29.250000	29.725000	28.975000	29.825000
max	100.000000	101.000000	100.000000	123.000000	120.000000	124.000000

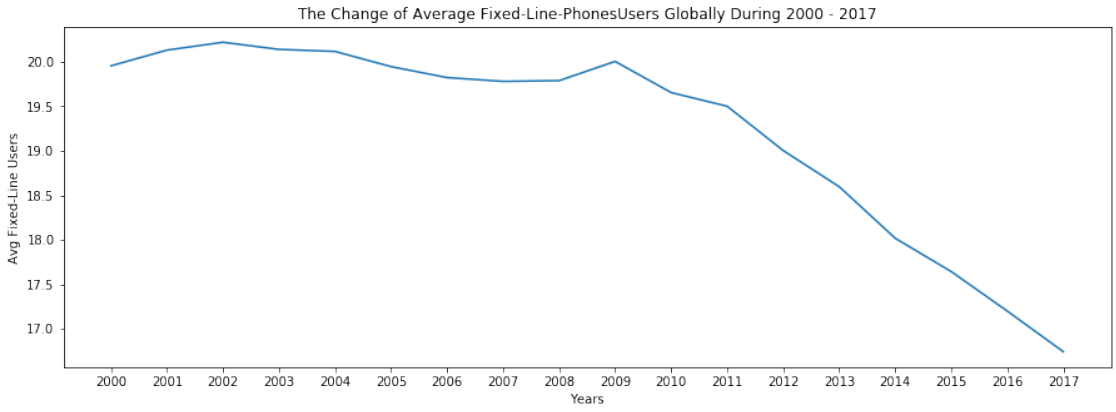
	2012	2013	2014	2015	2016	2017
count	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000
mean	19.003238	18.597315	18.018135	17.643936	17.200351	16.744628
std	18.855449	18.660616	18.600667	18.183759	17.564793	17.288308
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	3.385000	3.202500	2.840000	2.442500	2.305000	2.255000
50%	15.000000	13.250000	13.200000	13.700000	13.700000	13.350000
75%	29.175000	28.675000	25.875000	24.650000	24.375000	23.600000
max	125.000000	127.000000	136.000000	130.000000	122.000000	122.000000

Generally we can tell that the number of having fixed-line phones decreased during the interval 2000-2017, ploting the mean of all countries will give us a clearer overview

As we will plot the same plot for the three dataset, the following function is written to plot the related line and bar graphs for any of the datasets

```
In [17]: # Plot the line or bar chart with tailored ylabel and title based on the sent parameter
         # The default is to draw line charts as is used here more than bar charts
         def plot_chart(ylabel, this_title, plotting_data, bar_chart=False):
             plt.xlabel('Years')
             plt.ylabel(ylabel)
             plt.title('The Change of Average '+ this_title + ' During 2000 - 2017')
             # Define the needed number of ticks for the x axis, for the selected interval it is
             ind = np.arange(len(plotting_data.index))
             # Add the number of bins with their related labels (2000, 2001, 2002,..., 2017) to
             plt.xticks(ind, (plotting_data.index))
             if bar_chart:
                 plotting_data.plot.bar(color='#1f77b4');
             else:
                 plotting_data.plot(figsize = (15, 5));
```

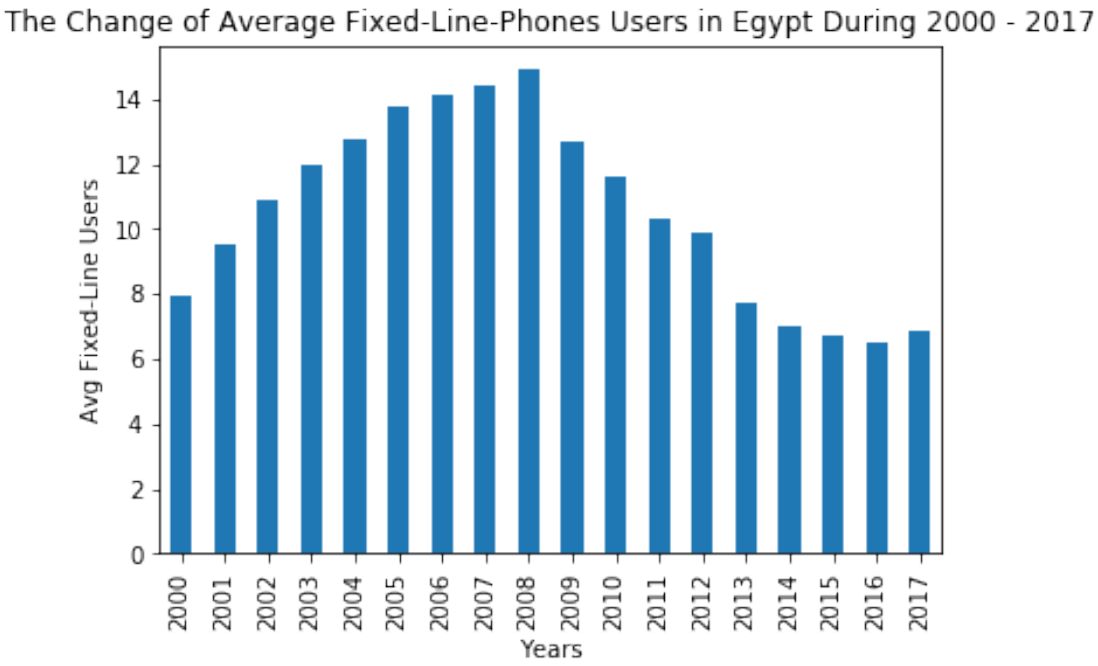
```
In [18]: plot_chart('Avg Fixed-Line Users', 'Fixed-Line-PhonesUsers Globally', df_fixed_line.mea
```



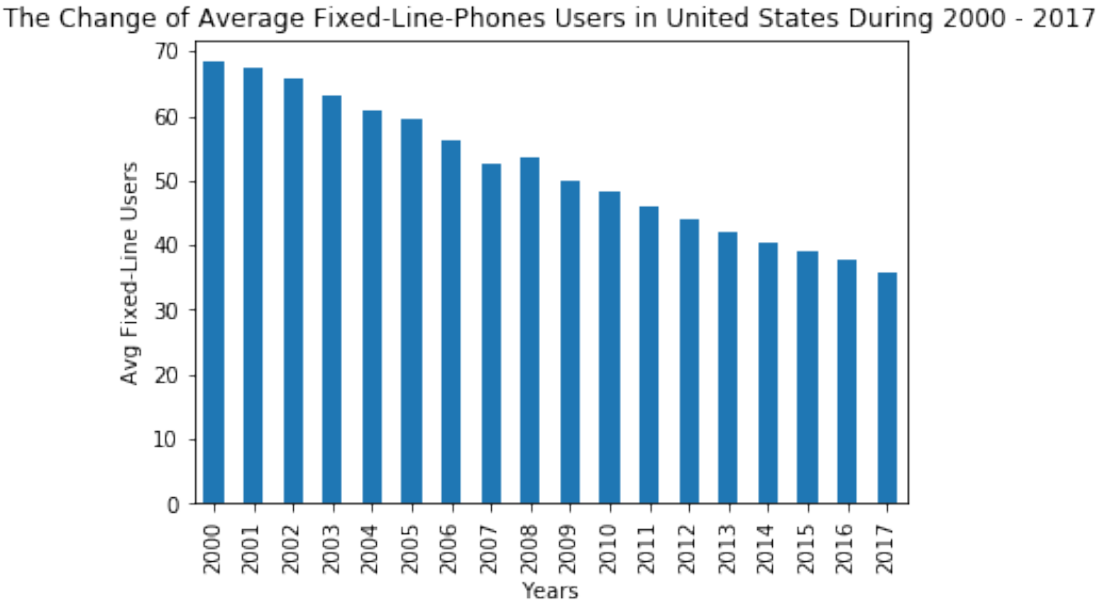
During the studied duration the usage of fixed-line phones decreased globally It can be noticed that linear decrease in fixed line holders happened after 2009

Let's check Egypt, United States and Canada countries change in the number of fixed-line-phone users:

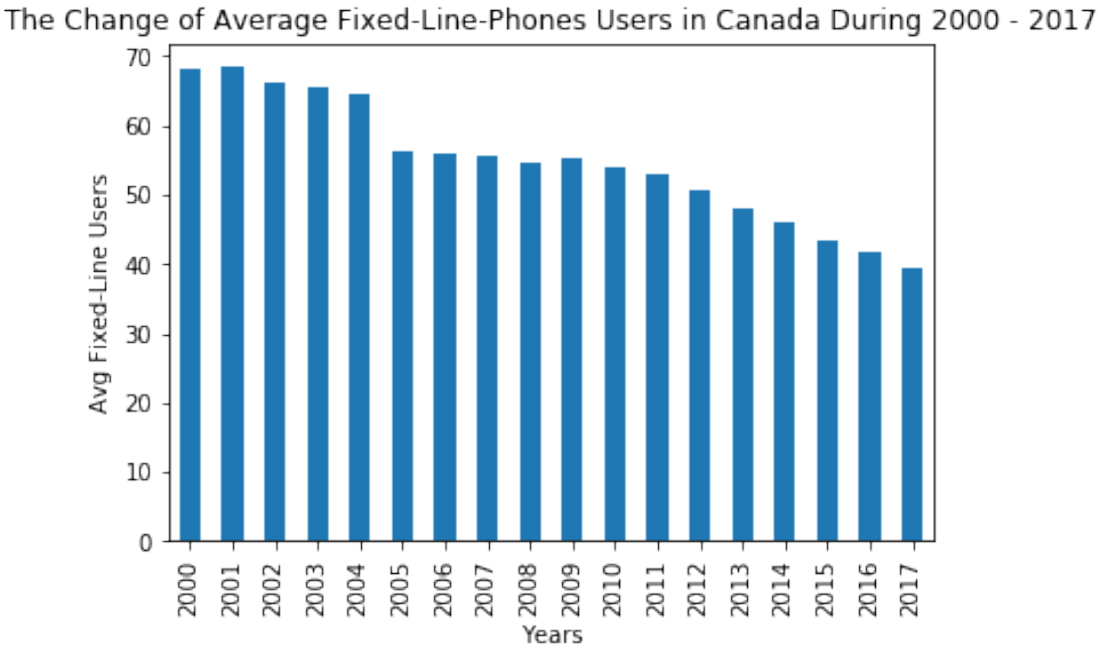
```
In [19]: plot_chart('Avg Fixed-Line Users', 'Fixed-Line-Phones Users in Egypt', df_fixed_line.lo
```



In [20]: plot_chart('Avg Fixed-Line Users', 'Fixed-Line-Phones Users in United States', df_fixed



In [21]: plot_chart('Avg Fixed-Line Users', 'Fixed-Line-Phones Users in Canada', df_fixed_line.l



- The above charts show similar behaviour, that they all have a decrease in fixed-line usage across the countries Egypt, United States and Canada
- However, each one of them decreased differently
- **Egypt**: got an increase in fixed-line usage during the duration 2000 to 2008, then the number of users decreased exponentially after 2008. And the number of users did not exceed 16%
- **United States**: Shows that 70% of its population were using the fixed lines. It was decreasing lineary reached to 40% in 2017
- **Canada**: The users of fixed-line in Canadas were approximatly 70%, and decreased suddenly to 55% in 2005. Remained in this percent till 2011 then it started decaying lineary, reached to 40% in 2017

1.1.5 Research Question 2: The percentage of cell phone users globally

Let's view a simple description of `df_cell_phone` to have an overview of the cell-phone usage around the world during the selected interval

```
In [22]: df_cell_phone.describe()
```

```
Out[22]:              2000        2001        2002        2003        2004        2005  \
         count  182.000000  182.000000  182.000000  182.000000  182.000000  182.000000
         mean    15.664243   20.605828   24.802069   30.202436   36.052478   43.768176
         std     22.136402   26.145133   28.679241   31.240410   33.337076   36.189680
         min      0.000000    0.000000    0.000000    0.000000    0.000000    0.000000
         25%      0.428750    0.920500    1.935000    3.387500    5.940000    8.892500
         50%      4.590000    8.080000   11.450000   18.300000   25.050000   36.350000
         75%     22.425000   30.950000   39.750000   54.625000   62.550000   74.375000
```

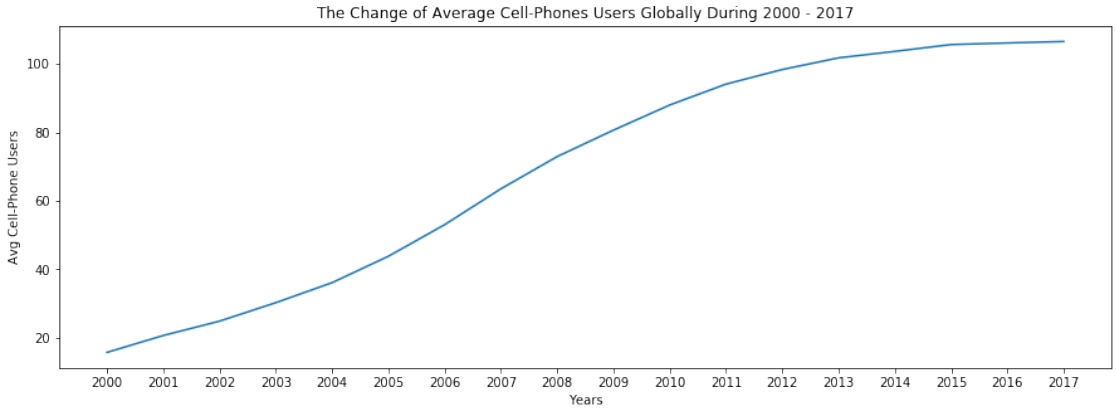
```
max     76.600000   92.900000  107.000000  120.000000  113.000000  130.000000

              2006        2007        2008        2009        2010        2011  \
count   182.000000  182.000000  182.000000  182.000000  182.000000  182.000000
mean     53.010527   63.500637   72.924044   80.650456   88.003297   94.108901
std      38.814358   40.862251   41.515976   41.078768   40.558092   39.563856
min       0.000000    0.000000    0.000000    0.284000    1.170000    2.440000
25%      17.225000   24.450000   34.100000   47.300000   58.200000   69.575000
50%      50.050000   62.900000   74.550000   87.050000   92.300000  100.350000
75%      82.750000   97.450000  105.750000  110.750000  116.000000  120.500000
max     153.000000  153.000000  160.000000  169.000000  191.000000  197.000000

              2012        2013        2014        2015        2016        2017
count   182.000000  182.000000  182.000000  182.000000  182.00000  182.000000
mean     98.375220  101.787967  103.680769  105.673077  106.13956  106.573077
std      38.839482   38.342983   36.875540   36.014940   36.24140   35.514782
min       6.850000    9.710000   11.200000   12.900000   14.20000   15.000000
25%      70.075000   73.725000   75.025000   80.275000   83.20000   85.450000
50%     106.000000  107.000000  107.000000  109.000000  110.00000  110.500000
75%     123.750000  125.750000  129.000000  130.000000  128.00000  129.000000
max     182.000000  182.000000  206.000000  200.000000  213.00000  209.000000
```

Q1 indicates that lower number of the users around the world reached to 85.45% in 2017, which shows the wide spread of phones around the world

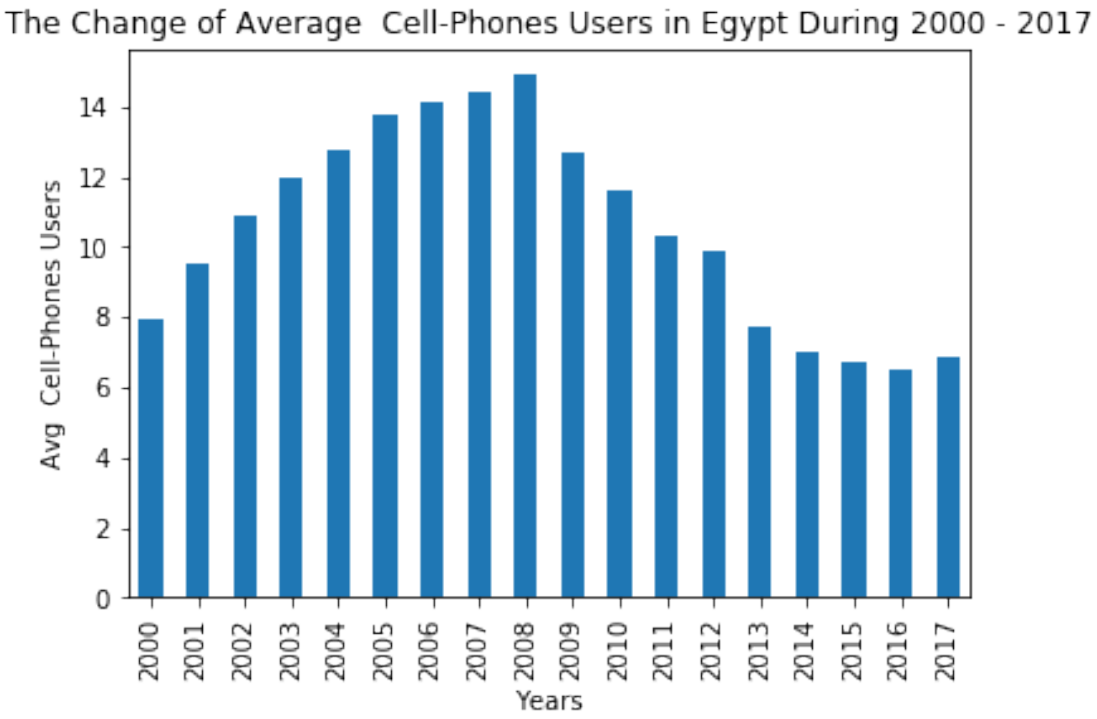
```
In [23]: plot_chart('Avg Cell-Phone Users', 'Cell-Phones Users Globally', df_cell_phone.mean())
```



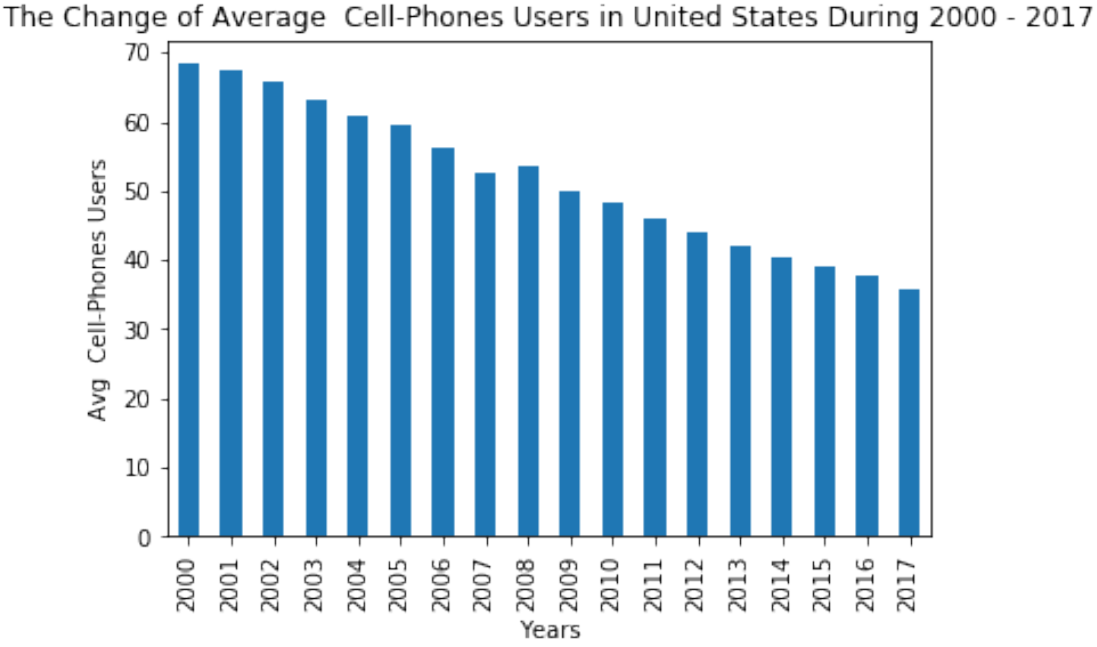
From this graph we can see that the percentage of having cell phones has increased from 15% to 110%, which indicates that all worlds' population have at least one cell phone, and some of them has two or more

Let's check Canada, United States and Egypt countries change in the number of cell-phone users:

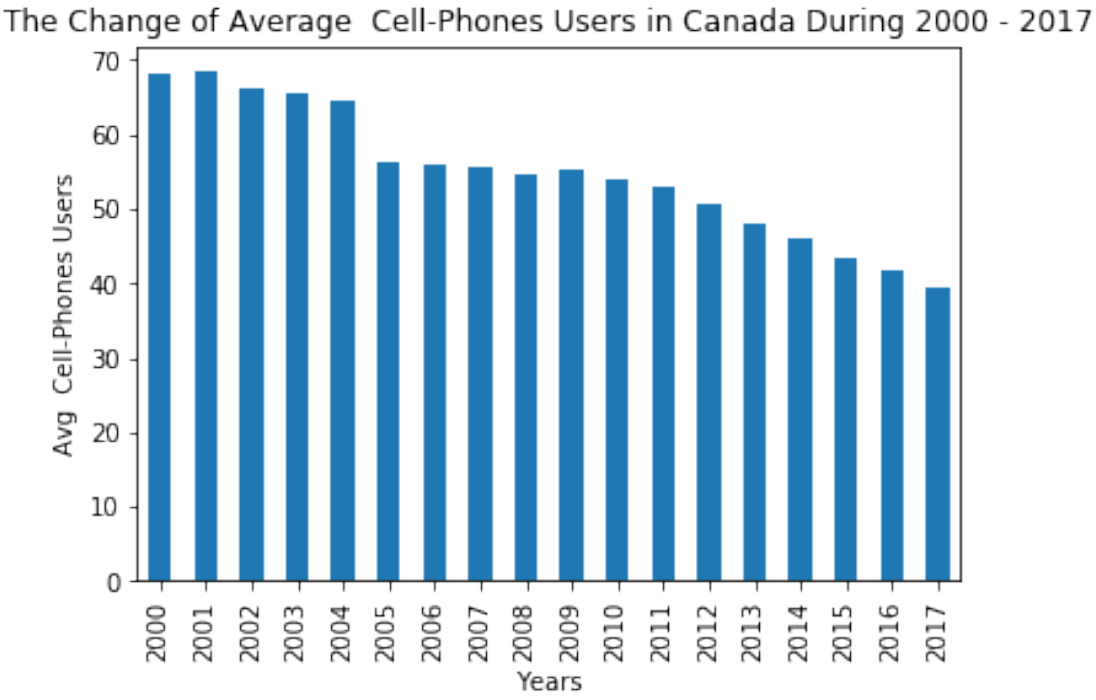
```
In [24]: plot_chart('Avg  Cell-Phones Users', ' Cell-Phones Users in Egypt', df_fixed_line.loc['
```




```
In [25]: plot_chart('Avg  Cell-Phones Users', ' Cell-Phones Users in United States', df_fixed_li
```



```
In [26]: plot_chart('Avg  Cell-Phones Users', ' Cell-Phones Users in Canada', df_fixed_line.loc[
```



Studying the change of Egypt, United States and Canada all show an impressive increase in the percentage of cell-phone users durig 2000 - 2017 - **Egypt**: The usage of cell-phones in Egypt increased exponentially from 2000 (approximatly 0 users) to 2012 (approximatly 113%). Then aprroximatly 10% of the users abonded their second device. After 2015 the percent started increasing lineary untill 2017 - **United States**: The usage of cell-phones in United states increased lineary from 2000 (approximatly 40% users) to 2013 (approximatly 100%). Then suddenly 10% of the users got their second device, and their percent increases lineary - **Canada**: The usage of cell-phones in Canada increased lineary from 2000 (approximatly 30% users) to 2013 (approximatly 80%). Then, the increase started to be slower, and remained with the same slow slope till 2017

1.1.6 Research Question 3: The percentage of Internet users globally

Let's view a simple description of `df_net_users` to have an overview of the Internet usage around the world during the selected interval

```
In [27]: df_net_users.describe()
```

```
Out[27]:              2000        2001        2002        2003        2004        2005  \
         count  167.000000  167.000000  167.000000  167.000000  167.000000  167.000000
         mean     8.012891   10.048140   13.366136   15.686285   18.044476   20.051964
         std     12.925621   15.119349   18.683297   20.472809   22.053525   23.217105
         min      0.005900    0.011500    0.055500    0.064600    0.077500    0.215000
         25%      0.401000    0.633000    1.080000    1.670000    2.250000    2.905000
```

50%	2.110000	2.850000	4.330000	6.200000	7.640000	9.740000
75%	7.505000	11.700000	18.050000	22.600000	27.350000	32.000000
max	52.000000	64.000000	79.100000	83.100000	83.900000	87.000000

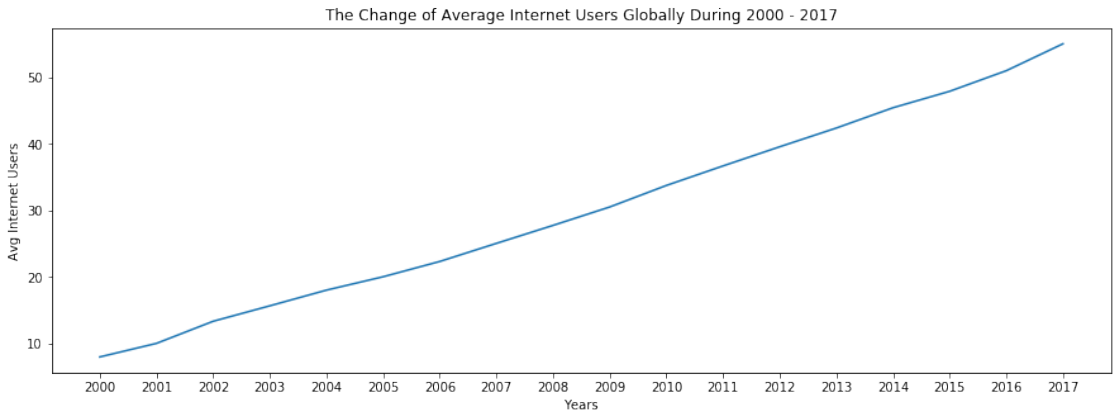
	2006	2007	2008	2009	2010	2011	\
count	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	
mean	22.348341	25.067180	27.767006	30.530000	33.763832	36.695569	
std	24.318869	25.428419	26.373101	27.069817	27.580774	27.993375	
min	0.228000	0.240000	0.250000	0.260000	0.580000	0.900000	
25%	3.650000	4.250000	5.675000	6.710000	8.185000	10.350000	
50%	12.300000	16.000000	20.800000	24.300000	28.300000	34.000000	
75%	35.150000	40.550000	44.250000	50.200000	53.500000	57.350000	
max	89.500000	90.600000	91.000000	93.000000	93.400000	94.800000	

	2012	2013	2014	2015	2016	2017
count	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000
mean	39.571677	42.385509	45.432754	47.901976	50.997186	55.034611
std	28.512657	28.759817	28.456613	28.288138	28.322489	27.738526
min	1.050000	1.150000	1.250000	2.480000	3.760000	2.660000
25%	12.750000	15.050000	18.850000	21.150000	24.600000	30.800000
50%	36.800000	41.000000	44.900000	48.900000	53.200000	59.100000
75%	62.100000	66.000000	69.050000	71.550000	76.000000	78.800000
max	96.200000	96.500000	98.200000	98.200000	98.200000	100.000000

The desciption shows that there is an increase in Interenet usage around the world. If we looked mainly on max, we can see that the maximum usage in 2000 reached to 50% of a country reached to 100% in 2017

Plotting the mean of Internet users will show clearer view about the Internet usage around the world

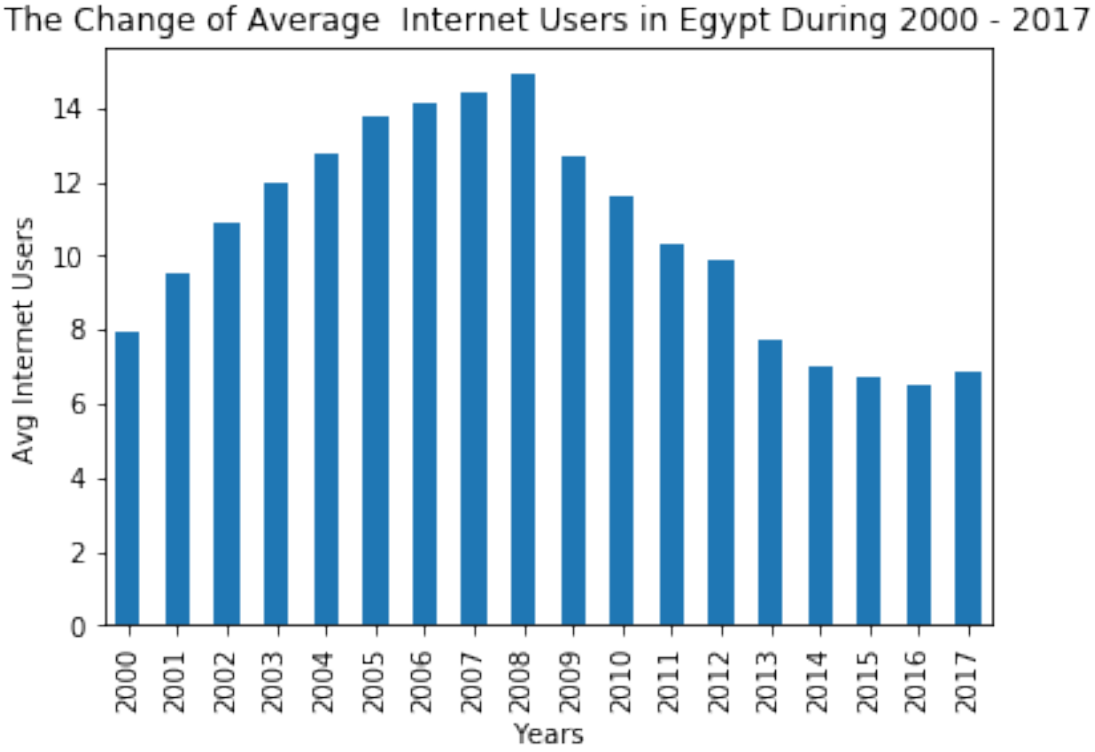
```
In [28]: plot_chart('Avg Internet Users', 'Internet Users Globally', df_net_users.mean())
```



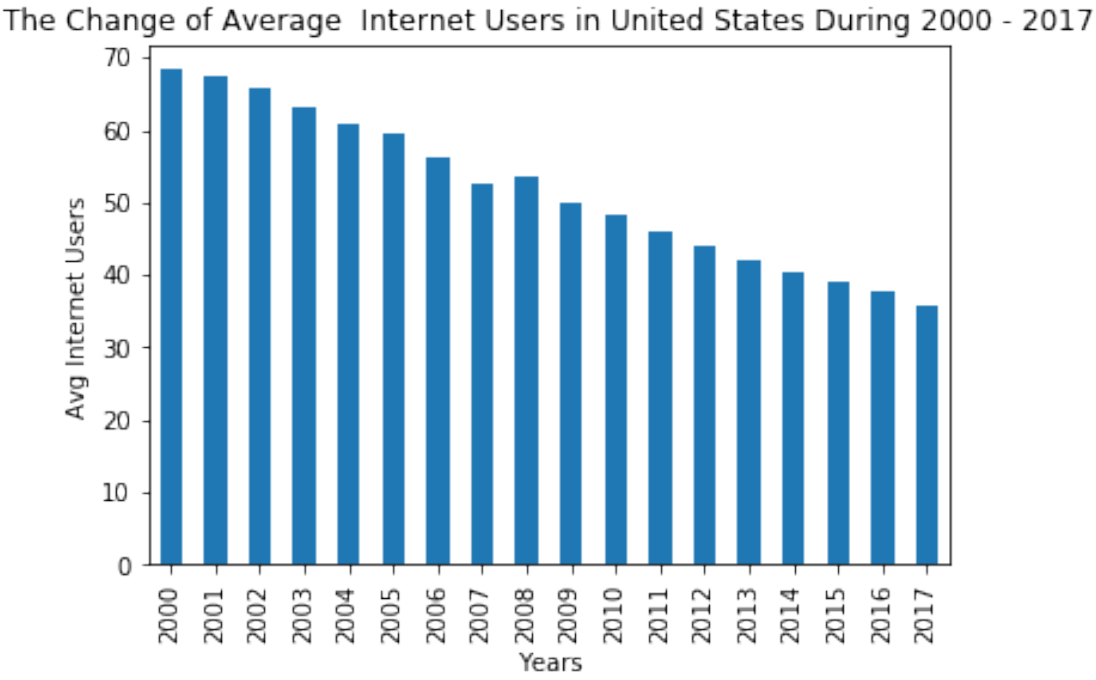
From this graph we can see that the percentage of using internet has increased from 8% to more than 50%, and the increase happened linearly

Let's check Egypt, United States and Canada countries change in the number of Internet users:

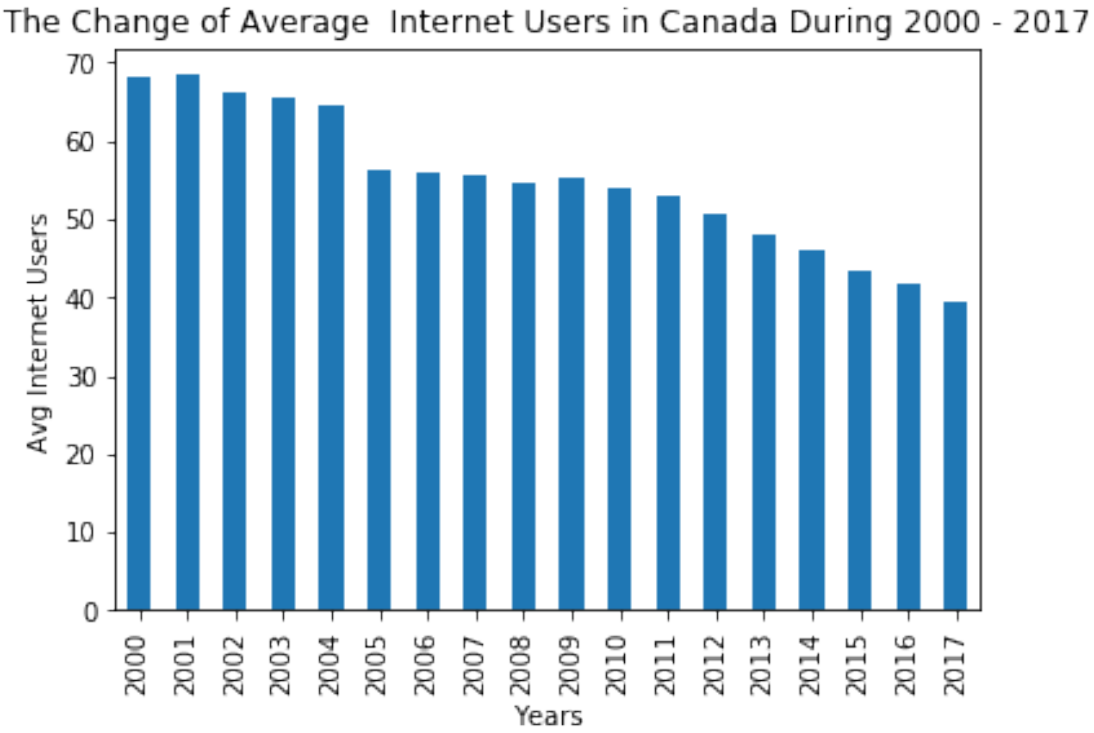
```
In [29]: plot_chart('Avg Internet Users', ' Internet Users in Egypt', df_fixed_line.loc['Egypt']
```




```
In [30]: plot_chart('Avg Internet Users', ' Internet Users in United States', df_fixed_line.loc[
```



```
In [31]: plot_chart('Avg Internet Users', ' Internet Users in Canada', df_fixed_line.loc['Canada
```

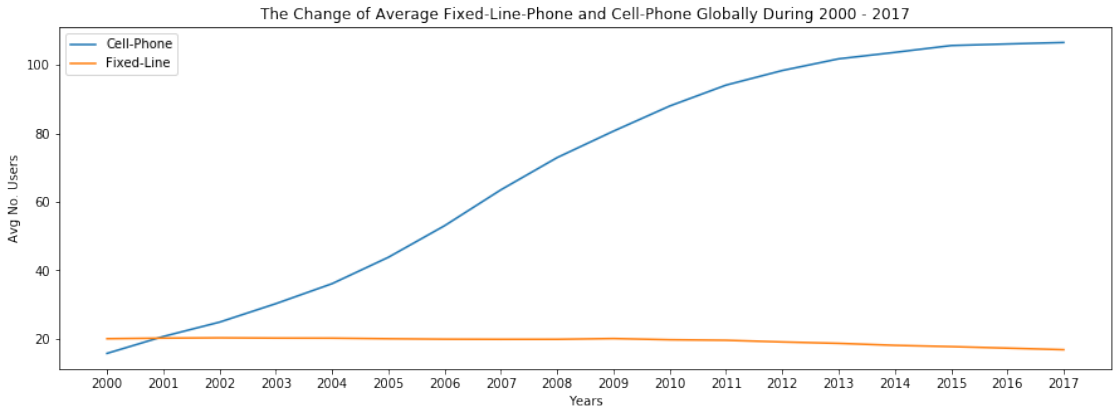


Studying the change of Egypt, United States and Canada all show an impressive increase in the percentage of internet users durig 2000 - 2017 - **Egypt**: The usage of internet in Egypt increased linearly from 2000 (approximatly 0 users) to 2004 (approximatly 4%). Then suddenly more 6% users started using Internet. Since 2004 the increase of Internet users in Egypt increased exponentially reached to 45% in 2017 - **United States**: The percent of Internet users was increasing exponentially since 2000 (40%) till 2007 (75%). The duration from 2007 to 2015 was having stable increase and decrease Internet users.After that the increase got back to exponential increase till 2017, reached to 87.3% - **Canada**: The behaviour of Internt users increase in Canada was the same linear increase during the interval 2000 - 2017

1.1.7 Research Question 4: Relation Between the number of cell phone users and the number of fixed lines users

We can see the relation between the two datasets by plotting the means of the the tow datasets on one chart as below:

```
In [32]: # Draw the mean of the df_cell_phone, then add df_fixed_line above it to see if there i
         plot_chart('Avg No. Users', 'Fixed-Line-Phone and Cell-Phone Globally', df_cell_phone.m
         df_fixed_line.mean().plot();
         plt.legend(['Cell-Phone','Fixed-Line']);
```



- From the graph it can be seen, that the usage of fixed-line phones was very limited by 2000, 20% of the entire world population were having fixed lines
- However cell-phones were used by 15% in 2000, and in 2017 each person has a phone or more. As the percent 110% indicates that 10% are having two cell-phones at least
- The decay in using fixed-line phones happened linery while the increase of cell-phones happened exponentially and affected the usage of fixed-line phones
- As indicated before in 2009 the fixed-line-phone users decreased rapidly, which was the time of smartphones invention

1.1.8 Limitations

There were very missing values about communication tools for the duration in 1990 - 2000, which was the real days of the rising of Interent and cell phones. If these data were available, the rise and fall of fixed-line phones would be clearer.

Also the start of using Internet will be very clear, and would help more investigating the countries of origin of Internet and cell phones as USA.

Conclusions

- Generally the number of fixed-line users decreased lineary during [2000-2017]
- The number of cell-phones increased exponentially during [2000 - 2017]
- Internet Users increased lineary during the duration [2000 - 2017]
- Amongst the studied communication tools, there is no spread any tool as cell-phones which reached to 100% in 2013 around the world
- There are some information for countries are important to be noticed as:
- North Korea that still could access global Internet
- And South Sudan that was part of another country during the studied duration [2000 - 2010]
- Fixed-line phones have a huge decrease in the number of users in 2009, as the cell-phones reached to 80% of population around the world during that year

```
In [66]: from subprocess import call
         call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```

```
Out[66]: 0
```

```
In [ ]:
```