investigate-a-dataset

September 17, 2020

1 Growth in Communication Technologies in different countries of the world from 2007-2016 and comparison with per capita income.

1.1 Table of Contents

The world has witnessed a tremendous progress in the field of communication technologies in recent years. Although the technology for tools such as the Internet, the mobile phone, home wireless networks, etc has been available for many years, the rate of diffusion for these technologies has seen significant changes in recent years. For this project, I have chosen to analyse the growth of some communication technologies in different countries throughout the world, based on their per capita income. The datasets have been chosen from Gapminder World. https://www.gapminder.org/data/

Gapminder has collected a lot of information about how people live their lives in different countries, tracked across the years, and on a number of different indicators. From the website, the datasets are obtained by choosing the following indicators:

Category: Infrastructure, Sub Category: Communication, Datasets:
1. Broadband Subscribers (total) 2. Cell Phones (total) 3. Internet Users(total)

Category: Economy, Sub Category: Incomes & Growth, Dataset:
4. Income per person (GDP/capita, PPP inflation-adjusted)

The data obtained is investigated and analysed in an attempt to find the answers to the following questions:

1. How do different countries in the world, based on their per capita income, compare in their use of the following communication technologies during the period 2007-2016: Broadband subscribers, Cell phones, Internet users. Is there any relation between the per capita income and the use of these communication technologies?

2. Is there any noticeable trend that can be observed in the use of these communication technologies over the years between 2007-2016?

```
In [1]: # The python libraries necessary for our analysis and visualisations are imported
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        %matplotlib inline
```

Data Wrangling

I will load in the data, check for cleanliness, and then trim and clean datasets for analysis in this section.

1.1.1 General Properties

```
In [2]: df_income=pd.read_csv('income_per_person_gdppercapita_ppp_inflation_adjusted.csv')
        df_broadband=pd.read_csv('broadband_subscribers.csv')
        df_cellphones=pd.read_csv('cell_phones_total.csv')
        df_internet=pd.read_csv('internet_users.csv')
```

The required datasets are loaded. There are 4 different datasets relating to distribution of GDP per person, and number of broadband subscribers, cellphones users and internet users for all countries in the world over the years.

I will check if all the four datasets have loaded properly and look at a brief preview of the data in each of the datasets.

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

Out[3]:

	country	1998	1999	2000	2001	2002	2003	2004	2005
0	Afghanistan	NaN	NaN	NaN	NaN	NaN	NaN	200.0	220.0
1	Albania	NaN	NaN	NaN	NaN	NaN	NaN	NaN	272.0
2	Algeria	NaN	NaN	NaN	NaN	NaN	18000.0	36000.0	135000.0
3	Andorra	NaN	NaN	NaN	NaN	1150.0	3600.0	6280.0	10300.0
4	Angola	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

	2006	2007	2008	2009	2010	2011	2012
0	500.0	500.0	500.0	1000.0	1500.0	NaN	1500.0
1	NaN	10000.0	64000.0	92000.0	106000.0	128000.0	160000.0
2	170000.0	287000.0	485000.0	818000.0	900000.0	981000.0	1150000.0
3	14600.0	18500.0	20700.0	22900.0	24500.0	25800.0	26900.0
4	7460.0	11700.0	15900.0	15000.0	15000.0	15800.0	20500.0

	2013	2014	2015	2016
0	1500.0	1500.0	7070.0	8800.0
1	183000.0	208000.0	243000.0	266000.0
2	1280000.0	1600000.0	2270000.0	2860000.0
3	27700.0	28800.0	30700.0	32500.0
4	22300.0	87800.0	154000.0	123000.0

```
In [4]: df_cellphones.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	...

	2007	2008	2009	2010	2011	2012
0	4670000.0	7900000.0	10500000.0	10200000.0	13800000.0	15300000.0
1	2320000.0	1860000.0	2460000.0	2690000.0	3100000.0	3500000.0
2	27600000.0	27000000.0	32700000.0	32800000.0	35600000.0	37500000.0
3	63500.0	64200.0	64500.0	65500.0	65000.0	63900.0
4	4960000.0	6770000.0	8110000.0	9400000.0	12100000.0	12800000.0

	2013	2014	2015	2016
0	16800000.0	18400000.0	19700000	21600000.0
1	3690000.0	3360000.0	3400000	3370000.0
2	39500000.0	43300000.0	43200000	47000000.0
3	63900.0	66200.0	71300	71100.0
4	13300000.0	14100000.0	13900000	13000000.0

[5 rows x 58 columns]

In [5]: `df_internet.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	...

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
0	1.90	1.84	3.55	4.0	5.0	5.45	5.9	7.0	8.26	10.6
1	15.00	23.90	41.20	45.0	49.0	54.70	57.2	60.1	63.30	66.4
2	9.45	10.20	11.20	12.5	14.9	18.20	22.5	29.5	38.20	42.9
3	70.90	70.00	78.50	81.0	81.0	86.40	94.0	95.9	96.90	97.9
4	1.70	1.90	2.30	2.8	3.1	6.50	8.9	10.2	12.40	13.0

[5 rows x 58 columns]

In [6]: `df_income.head()`

Out[6]:

	country	1800	1801	1802	1803	1804	1805	1806	1807	1808	...
0	Afghanistan	603	603	603	603	603	603	603	603	603	...
1	Albania	667	667	667	667	667	668	668	668	668	...
2	Algeria	715	716	717	718	719	720	721	722	723	...
3	Andorra	1200	1200	1200	1200	1210	1210	1210	1210	1220	...
4	Angola	618	620	623	626	628	631	634	637	640	...

	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
0	1530	1610	1660	1840	1810	1780	1750	1740	1800	1870
1	9530	9930	10200	10400	10500	10700	11000	11400	11900	12400
2	12600	12900	13000	13200	13300	13500	13700	14000	13800	13700
3	41700	39000	42000	41900	43700	44900	46600	48200	49800	51500
4	5910	5900	5910	6000	6190	6260	6230	6030	5940	5850

[5 rows x 220 columns]

Before starting with analysis I will make data suitable for analysis by performing required cleaning steps. For that, I will perform the following actions:

1) Check that the structure and format of the dataframes are correct.
2) Filter out the data from the datasets that is not required for analysis:
    a) Check that the country names are consistent across the datasets, that is, if there are any country names that do not appear in all of the datasets, might be decided to remove them as necessary.
    b) Remove the data relating to the years that are not relevant for analysis.
3) Make sure that the data is in a format suitable for analysis, for example, data required for numerical analysis must be in a numeric (integer/float) format.

```
In [7]: #check the format and shape of the dataframes
        df_income.shape

Out[7]: (193, 220)

In [8]: df_broadband.shape

Out[8]: (192, 20)

In [9]: df_cellphones.shape

Out[9]: (194, 58)

In [10]: df_internet.shape

Out[10]: (194, 58)
```

From the above steps we find that the number of rows is not consistent for the four dataframes, which indicates that the country names are not consistent across them. We will therefore check and find out the list of countries which are not common to all the datasets, and remove them from our analysis purpose. We will then continue our analysis with the list of countries which appear in all the 4 datasets.

For this purpose, there is a function `get_different_rows`. This function takes two dataframes as input parameters(source_df, new_df) and returns the rows from the new_df that differ from the source_df.

I will apply this function to the country columns in all the 4 dataframes, and obtain the list of countries which do not appear in all the dataframes. We then modify our existing dataframes by removing this list of countries, and proceed with further analysis from thereon.

```
In [11]: # define the function to compare two dataframes
         def get_different_rows(source_df, new_df):
             """Returns just the rows from the new dataframe that differ from the source datafra
             merged_df = source_df.merge(new_df, indicator=True, how='outer')
             changed_rows_df = merged_df[merged_df['_merge'] == 'right_only']
             return changed_rows_df.drop('_merge', axis=1)

In [12]: #compare the df_income and df_broadband dataframes
         get_different_rows(df_income[['country']],df_broadband[['country']])

Out[12]:            country
         193  Liechtenstein

In [13]: #compare the df_income and df_cellphones dataframes
         get_different_rows(df_income[['country']],df_cellphones[['country']])

Out[13]:            country
         193  Liechtenstein

In [14]: #compare the df_income and df_internet dataframes
         get_different_rows(df_income[['country']],df_internet[['country']])

Out[14]:            country
         193  Liechtenstein

In [15]: #compare the df_broadband and df_internet dataframes
         get_different_rows(df_broadband[['country']],df_internet[['country']])

Out[15]:           country
         192   North Korea
         193  Sierra Leone

In [16]: #compare the df_broadband and df_cellphones dataframes
         get_different_rows(df_broadband[['country']],df_cellphones[['country']])

Out[16]:           country
         192   North Korea
         193  Sierra Leone
```

Thus we have obtained 'Liechtenstein','North Korea','Sierra Leone' as the list of countries for which we do not have data in all the datasets. We therefore decide to drop the rows coresponding to any of these countries from all our datasets and we get the modified dataframes excluding these countries.

```
In [17]: df_income = df_income.loc[~df_income['country'].isin(['Liechtenstein','North Korea','Si

In [18]: df_broadband = df_broadband.loc[~df_broadband['country'].isin(['Liechtenstein','North K

In [19]: df_cellphones = df_cellphones.loc[~df_cellphones['country'].isin(['Liechtenstein','Nort
```

```
In [20]: df_internet = df_internet.loc[~df_internet['country'].isin(['Liechtenstein','North Kore
```

We then verify if the number of rows is now consistent across all the datasets.

```
In [21]: df_income.shape

Out[21]: (191, 220)

In [22]: df_broadband.shape

Out[22]: (191, 20)

In [23]: df_cellphones.shape

Out[23]: (191, 58)

In [24]: df_internet.shape

Out[24]: (191, 58)
```

The number of rows(country names) is now consistent in all the dataframes.Then I will focus on the columns. For the purpose of analysis, I require data for the years 2007-2016, the other years are not much relevant for this project. I therefore clean datasets further by retaining data for the years 2007-2016, and removing the data corresponding to all other years from all the datasets.

I will start with the income dataset.

I first filter out the year columns for all years except 2007-2016 and check the properties of this dataset.

```
In [25]: df_income = df_income.filter(['country','2007', '2008','2009','2010', '2011','2012','20
         df_income.head()

Out[25]:        country   2007   2008   2009   2010   2011   2012   2013   2014   2015  \
         0  Afghanistan   1290   1300   1530   1610   1660   1840   1810   1780   1750
         1      Albania   8450   9150   9530   9930  10200  10400  10500  10700  11000
         2      Algeria  12600  12700  12600  12900  13000  13200  13300  13500  13700
         3      Andorra  43400  41400  41700  39000  42000  41900  43700  44900  46600
         4       Angola   5440   5980   5910   5900   5910   6000   6190   6260   6230

             2016
         0   1740
         1  11400
         2  14000
         3  48200
         4   6030
```

I will need two new columns to this dataset for analysis purpose - 'AverageIncome' and 'IncomeCategory'.

The 'AverageIncome' column contains the mean value of the income for each country for the years 2007-2016, that is, it is the average value of the data for other columns in that row.

```
In [26]: df_income['AverageIncome'] = df_income.mean(axis=1)

In [27]: df_income.describe()

Out[27]:                 2007           2008           2009           2010  \
         count     191.000000     191.000000     191.000000     191.000000
         mean    16940.801047   17040.282723   16332.188482   16602.811518
         std     20086.189436   19711.604292   18536.692201   18803.759034
         min       575.000000     591.000000     588.000000     609.000000
         25%      3120.000000    3245.000000    3245.000000    3330.000000
         50%      9280.000000    9720.000000    9580.000000    9930.000000
         75%     23050.000000   23800.000000   22100.000000   22050.000000
         max    119000.000000  120000.000000  117000.000000  125000.000000

                         2011           2012           2013           2014  \
         count     191.000000     191.000000     191.000000     191.000000
         mean    16865.492147   17028.340314   17172.701571   17374.486911
         std     19133.233951   18975.905485   18899.225043   18942.196328
         min       614.000000     616.000000     598.000000     602.000000
         25%      3405.000000    3485.000000    3575.000000    3645.000000
         50%     10100.000000   10400.000000   10600.000000   10900.000000
         75%     22700.000000   23100.000000   23400.000000   24100.000000
         max    129000.000000  125000.000000  123000.000000  121000.000000

                         2015           2016  AverageIncome
         count     191.000000     191.000000     191.000000
         mean    17601.204188   17781.345550   17073.965445
         std     19150.911489   19190.675015   19075.733188
         min       623.000000     625.000000     617.700000
         25%      3410.000000    3455.000000    3372.000000
         50%     11100.000000   11400.000000   10224.000000
         75%     24450.000000   24500.000000   22950.000000
         max    120000.000000  118000.000000  121700.000000
```

From the above table I see that the minimum per capita Average Income value is 617 dollars, and the maximum is 121700 dollars. The different statistical parameters can also be observed.

The countries are then divided into 5 categories based on their Average per capita Incomes. The 'IncomeCategory' column denotes the category to which this country has been assigned based on its Average Income value. For the purposes of this project, I have chosen to divide the countries into the following 5 categories:

Group5: Countries with per capita average income between $ 500 -5000
Group4: Countries with per capita average income between $ 5000-10000
Group3: Countries with per capita average income between $ 10000-30000
Group2: Countries with per capita average income between $ 30000-50000
Group1: Countries with per capita average income between $ 50000-125000

```
In [28]: df_income['IncomeCategory'] = pd.cut(df_income['AverageIncome'],
                                              bins=[500,5000,10000,30000,50000,125000], include_
                                              labels=['Group5', 'Group4', 'Group3', 'Group2','Gr
```

In [29]:
```
df_income.head(10)
```

Out[29]:

	country	2007	2008	2009	2010	2011	2012	2013
0	Afghanistan	1290	1300	1530	1610	1660	1840	1810
1	Albania	8450	9150	9530	9930	10200	10400	10500
2	Algeria	12600	12700	12600	12900	13000	13200	13300
3	Andorra	43400	41400	41700	39000	42000	41900	43700
4	Angola	5440	5980	5910	5900	5910	6000	6190
5	Antigua and Barbuda	24200	24000	20800	19100	18600	19100	18900
6	Argentina	17900	18400	17200	18700	19600	19200	19500
7	Armenia	7010	7560	6530	6700	7020	7510	7730
8	Australia	40700	41300	41200	41400	41800	42600	42900
9	Austria	43700	44300	42500	43200	44200	44400	44200

	2014	2015	2016	AverageIncome	IncomeCategory
0	1780	1750	1740	1631.0	Group5
1	10700	11000	11400	10126.0	Group3
2	13500	13700	14000	13150.0	Group3
3	44900	46600	48200	43280.0	Group2
4	6260	6230	6030	5985.0	Group4
5	19500	20100	20800	20510.0	Group3
6	18800	19100	18500	18690.0	Group3
7	7970	8180	8170	7438.0	Group4
8	43400	43800	44400	42350.0	Group2
9	44100	44100	44100	43880.0	Group2

In [30]:
```
# set the country name as the index of the dataframe
df_income.set_index('country',inplace=True)
```

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

Out[31]:

country	2007	2008	2009	2010	2011	2012	2013	2014	2015
Afghanistan	1290	1300	1530	1610	1660	1840	1810	1780	1750
Albania	8450	9150	9530	9930	10200	10400	10500	10700	11000
Algeria	12600	12700	12600	12900	13000	13200	13300	13500	13700
Andorra	43400	41400	41700	39000	42000	41900	43700	44900	46600
Angola	5440	5980	5910	5900	5910	6000	6190	6260	6230

country	2016	AverageIncome	IncomeCategory
Afghanistan	1740	1631.0	Group5
Albania	11400	10126.0	Group3
Algeria	14000	13150.0	Group3
Andorra	48200	43280.0	Group2
Angola	6030	5985.0	Group4

In [32]:
```
df_income.shape
```

Out[32]: (191, 12)

I now apply a similar procedure to the other three datasets (df_broadband, df_cellphones and df_internet). For each of them, I remove the year columns except from 2007-2016, and reset the country column as index for each.

I will also add the Income Category column from the income dataset to the other three datasets for ease of analysis.

In [33]:
```
# Broadband dataset is modified according to procedure mentioned
df_broadband = df_broadband.filter(['country','2007', '2008','2009','2010', '2011','201
df_broadband.set_index('country',inplace=True)
df_broadband['IncomeCategory'] = df_income['IncomeCategory']
df_broadband.head()
```

Out[33]:

country	2007	2008	2009	2010	2011	2012
Afghanistan	500.0	500.0	1000.0	1500.0	NaN	1500.0
Albania	10000.0	64000.0	92000.0	106000.0	128000.0	160000.0
Algeria	287000.0	485000.0	818000.0	900000.0	981000.0	1150000.0
Andorra	18500.0	20700.0	22900.0	24500.0	25800.0	26900.0
Angola	11700.0	15900.0	15000.0	15000.0	15800.0	20500.0

country	2013	2014	2015	2016	IncomeCategory
Afghanistan	1500.0	1500.0	7070.0	8800.0	Group5
Albania	183000.0	208000.0	243000.0	266000.0	Group3
Algeria	1280000.0	1600000.0	2270000.0	2860000.0	Group3
Andorra	27700.0	28800.0	30700.0	32500.0	Group2
Angola	22300.0	87800.0	154000.0	123000.0	Group4

In [34]:
```
# Cellphones dataset is modified according to procedure mentioned
df_cellphones = df_cellphones.filter(['country','2007', '2008','2009','2010', '2011','2
df_cellphones.set_index('country',inplace=True)
df_cellphones['IncomeCategory'] = df_income['IncomeCategory']
df_cellphones.head()
```

Out[34]:

country	2007	2008	2009	2010	2011
Afghanistan	4670000.0	7900000.0	10500000.0	10200000.0	13800000.0
Albania	2320000.0	1860000.0	2460000.0	2690000.0	3100000.0
Algeria	27600000.0	27000000.0	32700000.0	32800000.0	35600000.0
Andorra	63500.0	64200.0	64500.0	65500.0	65000.0
Angola	4960000.0	6770000.0	8110000.0	9400000.0	12100000.0

country	2012	2013	2014	2015	2016
Afghanistan	15300000.0	16800000.0	18400000.0	19700000	21600000.0
Albania	3500000.0	3690000.0	3360000.0	3400000	3370000.0
Algeria	37500000.0	39500000.0	43300000.0	43200000	47000000.0

```
Andorra          63900.0     63900.0     66200.0     71300     71100.0
Angola        12800000.0  13300000.0  14100000.0  13900000  13000000.0

              IncomeCategory
country
Afghanistan         Group5
Albania             Group3
Algeria             Group3
Andorra             Group2
Angola              Group4
```

In [35]:
```
# Internet dataset is modified according to procedure mentioned
df_internet = df_internet.filter(['country','2007', '2008','2009','2010', '2011','2012'
df_internet.set_index('country',inplace=True)
df_internet['IncomeCategory'] = df_income['IncomeCategory']
df_internet.head()
```

Out[35]:
```
              2007   2008   2009  2010  2011   2012  2013  2014   2015  2016  \
country
Afghanistan   1.90   1.84   3.55   4.0   5.0   5.45   5.9   7.0   8.26  10.6
Albania      15.00  23.90  41.20  45.0  49.0  54.70  57.2  60.1  63.30  66.4
Algeria       9.45  10.20  11.20  12.5  14.9  18.20  22.5  29.5  38.20  42.9
Andorra      70.90  70.00  78.50  81.0  81.0  86.40  94.0  95.9  96.90  97.9
Angola        1.70   1.90   2.30   2.8   3.1   6.50   8.9  10.2  12.40  13.0

              IncomeCategory
country
Afghanistan         Group5
Albania             Group3
Algeria             Group3
Andorra             Group2
Angola              Group4
```

1.1.2 Data Cleaning

In this section, I will check the properties of the broadband, cellphones and internet datasets, and find out if there are any data issues that need to be addressed.

In [36]:
```
df_broadband.shape
```

Out[36]:
```
(191, 11)
```

In [37]:
```
df_broadband.head()
```

Out[37]:
```
                  2007      2008      2009      2010      2011       2012  \
country
Afghanistan      500.0     500.0    1000.0    1500.0       NaN     1500.0
Albania        10000.0   64000.0   92000.0  106000.0  128000.0   160000.0
Algeria       287000.0  485000.0  818000.0  900000.0  981000.0  1150000.0
```

```
Andorra       18500.0   20700.0   22900.0   24500.0   25800.0    26900.0
Angola        11700.0   15900.0   15000.0   15000.0   15800.0    20500.0

                  2013       2014       2015       2016 IncomeCategory
country
Afghanistan     1500.0     1500.0     7070.0     8800.0         Group5
Albania       183000.0   208000.0   243000.0   266000.0         Group3
Algeria      1280000.0  1600000.0  2270000.0  2860000.0         Group3
Andorra        27700.0    28800.0    30700.0    32500.0         Group2
Angola         22300.0    87800.0   154000.0   123000.0         Group4
```

```
In [38]: df_broadband.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 191 entries, Afghanistan to Zimbabwe
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   2007            170 non-null    float64
 1   2008            177 non-null    float64
 2   2009            178 non-null    float64
 3   2010            184 non-null    float64
 4   2011            179 non-null    float64
 5   2012            185 non-null    float64
 6   2013            187 non-null    float64
 7   2014            186 non-null    float64
 8   2015            188 non-null    float64
 9   2016            186 non-null    float64
 10  IncomeCategory  191 non-null    category
dtypes: category(1), float64(10)
memory usage: 16.8+ KB
```

Here I can see that in the broadband dataset, there are 191 rows and 10 columns. However, from `Non-Null Count` values I can understand all the columns corresponding to the years 2007-2016 contain some missing values. For every missing value in the dataset, I replace the missing value by the mean of that row which contains the missing value. For example, when we were checking `df_broadband.head()` in the first row, I can see that for country Afghanistan, the data for the year 2011 is missing. So I replace this missing value by the mean of other values for Afghanistan for the years 2007-2016. In this way, all the missing values in the dataset is replaced by the mean value of that row corresponding to that country.

```
In [39]: #replace null values by mean
         df_broadband=df_broadband.T.fillna(df_broadband.mean(axis=1)).T
```

We now check the properties of the dataset again to see if the missing values have been replaced correctly, and all the required data are in numeric format.

```
In [40]: df_broadband.head()
```

```
Out[40]:                2007    2008    2009    2010     2011      2012      2013  \
         country
         Afghanistan     500     500    1000    1500  2652.22      1500      1500
         Albania       10000   64000   92000  106000   128000    160000    183000
         Algeria      287000  485000  818000  900000   981000  1.15e+06  1.28e+06
         Andorra       18500   20700   22900   24500    25800     26900     27700
         Angola        11700   15900   15000   15000    15800     20500     22300

                         2014      2015      2016 IncomeCategory
         country
         Afghanistan     1500      7070      8800         Group5
         Albania       208000    243000    266000         Group3
         Algeria      1.6e+06  2.27e+06  2.86e+06         Group3
         Andorra        28800     30700     32500         Group2
         Angola         87800    154000    123000         Group4
```

```
In [41]: df_broadband.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 191 entries, Afghanistan to Zimbabwe
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   2007            191 non-null    object
 1   2008            191 non-null    object
 2   2009            191 non-null    object
 3   2010            191 non-null    object
 4   2011            191 non-null    object
 5   2012            191 non-null    object
 6   2013            191 non-null    object
 7   2014            191 non-null    object
 8   2015            191 non-null    object
 9   2016            191 non-null    object
 10  IncomeCategory  191 non-null    object
dtypes: object(11)
memory usage: 22.9+ KB
```

Thus the missing values in the df_broadband dataframe have been correctly replaced by the mean values of each row. However the data is in string format which is not suitable for numerical analysis purpose as scikit-learn or most machine learning estimators are not able to take stings as input. This needs to be converted to a numeric format which is done below.

```
In [42]: df_broadband[["2007", "2008","2009", "2010","2011", "2012","2013", "2014","2015", "2016
             "2007", "2008","2009", "2010","2011", "2012","2013", "2014","2015", "2016"]].apply(
```

```
In [43]: df_broadband.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 191 entries, Afghanistan to Zimbabwe
```

```
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   2007            191 non-null    float64
 1   2008            191 non-null    float64
 2   2009            191 non-null    float64
 3   2010            191 non-null    float64
 4   2011            191 non-null    float64
 5   2012            191 non-null    float64
 6   2013            191 non-null    float64
 7   2014            191 non-null    float64
 8   2015            191 non-null    float64
 9   2016            191 non-null    float64
 10  IncomeCategory  191 non-null    object
dtypes: float64(10), object(1)
memory usage: 22.9+ KB
```

```
In [44]: df_broadband.head()
```

Out[44]:

country	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	IncomeCategory
Afghanistan	500.0	500.0	1000.0	1500.0	2652.222222	1500.0	1500.0	1500.0	7070.0	8800.0	Group5
Albania	10000.0	64000.0	92000.0	106000.0	128000.000000	160000.0	183000.0	208000.0	243000.0	266000.0	Group3
Algeria	287000.0	485000.0	818000.0	900000.0	981000.000000	1150000.0	1280000.0	1600000.0	2270000.0	2860000.0	Group3
Andorra	18500.0	20700.0	22900.0	24500.0	25800.000000	26900.0	27700.0	28800.0	30700.0	32500.0	Group2
Angola	11700.0	15900.0	15000.0	15000.0	15800.000000	20500.0	22300.0	87800.0	154000.0	123000.0	Group4

Hence the missing values have been correctly replaced and the broadband dataset is clean for further analysis.

I now apply a similar procedure to the other two datasets. - The datasets are cleaned by replacing the missing values by the mean value for each row corresponding to that country. - Any non-numeric/string values are converted to numeric values.

```
In [45]: # Checking the properties of the Cell Phones dataset.
         df_cellphones.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 191 entries, Afghanistan to Zimbabwe
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype
```

```
---  ------          --------------  -----
 0   2007            188 non-null    float64
 1   2008            186 non-null    float64
 2   2009            187 non-null    float64
 3   2010            190 non-null    float64
 4   2011            189 non-null    float64
 5   2012            190 non-null    float64
 6   2013            189 non-null    float64
 7   2014            189 non-null    float64
 8   2015            191 non-null    int64
 9   2016            189 non-null    float64
 10  IncomeCategory  191 non-null    category
dtypes: category(1), float64(9), int64(1)
memory usage: 16.8+ KB
```

```
In [46]: # replace missing values by mean
         df_cellphones=df_cellphones.T.fillna(df_cellphones.mean(axis=1)).T

In [47]: df_cellphones.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 191 entries, Afghanistan to Zimbabwe
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   2007            191 non-null    object
 1   2008            191 non-null    object
 2   2009            191 non-null    object
 3   2010            191 non-null    object
 4   2011            191 non-null    object
 5   2012            191 non-null    object
 6   2013            191 non-null    object
 7   2014            191 non-null    object
 8   2015            191 non-null    object
 9   2016            191 non-null    object
 10  IncomeCategory  191 non-null    object
dtypes: object(11)
memory usage: 22.9+ KB
```

```
In [48]: #convert string values to numeric data
         df_cellphones[["2007","2008","2009","2010","2011","2012","2013","2014","2015","2016"]]

In [49]: df_cellphones.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 191 entries, Afghanistan to Zimbabwe
Data columns (total 11 columns):
```

```
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   2007            191 non-null    float64
 1   2008            191 non-null    float64
 2   2009            191 non-null    float64
 3   2010            191 non-null    float64
 4   2011            191 non-null    float64
 5   2012            191 non-null    float64
 6   2013            191 non-null    float64
 7   2014            191 non-null    float64
 8   2015            191 non-null    int64
 9   2016            191 non-null    float64
 10  IncomeCategory  191 non-null    object
dtypes: float64(9), int64(1), object(1)
memory usage: 22.9+ KB
```

```
In [50]: df_cellphones.head()
```

Out[50]:

country	2007	2008	2009	2010	2011
Afghanistan	4670000.0	7900000.0	10500000.0	10200000.0	13800000.0
Albania	2320000.0	1860000.0	2460000.0	2690000.0	3100000.0
Algeria	27600000.0	27000000.0	32700000.0	32800000.0	35600000.0
Andorra	63500.0	64200.0	64500.0	65500.0	65000.0
Angola	4960000.0	6770000.0	8110000.0	9400000.0	12100000.0

country	2012	2013	2014	2015	2016
Afghanistan	15300000.0	16800000.0	18400000.0	19700000	21600000.0
Albania	3500000.0	3690000.0	3360000.0	3400000	3370000.0
Algeria	37500000.0	39500000.0	43300000.0	43200000	47000000.0
Andorra	63900.0	63900.0	66200.0	71300	71100.0
Angola	12800000.0	13300000.0	14100000.0	13900000	13000000.0

country	IncomeCategory
Afghanistan	Group5
Albania	Group3
Algeria	Group3
Andorra	Group2
Angola	Group4

Thus I have checked that the Cellphones data has been made ready for analysis.
I now repeat the process for the Internet Users data.

```
In [51]: df_internet.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 191 entries, Afghanistan to Zimbabwe
```

```
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   2007            188 non-null    float64
 1   2008            187 non-null    float64
 2   2009            186 non-null    float64
 3   2010            186 non-null    float64
 4   2011            189 non-null    float64
 5   2012            186 non-null    float64
 6   2013            188 non-null    float64
 7   2014            188 non-null    float64
 8   2015            188 non-null    float64
 9   2016            188 non-null    float64
 10  IncomeCategory  191 non-null    category
dtypes: category(1), float64(10)
memory usage: 16.8+ KB
```

```
In [52]: # replace missing values by mean
         df_internet=df_internet.T.fillna(df_internet.mean(axis=1)).T

In [53]: #convert data to numeric format
         df_internet[["2007", "2008","2009", "2010","2011", "2012","2013", "2014","2015", "2016"

In [54]: df_internet.info()

<class 'pandas.core.frame.DataFrame'>
Index: 191 entries, Afghanistan to Zimbabwe
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   2007            190 non-null    float64
 1   2008            190 non-null    float64
 2   2009            190 non-null    float64
 3   2010            190 non-null    float64
 4   2011            190 non-null    float64
 5   2012            190 non-null    float64
 6   2013            190 non-null    float64
 7   2014            190 non-null    float64
 8   2015            190 non-null    float64
 9   2016            190 non-null    float64
 10  IncomeCategory  191 non-null    object
dtypes: float64(10), object(1)
memory usage: 22.9+ KB
```

Exploratory Data Analysis

In this section we will explore the data and try to find answers to reaearch questions.

Research Question 1 : How do different countries in the world, based on their per capita income, compare in their use of the following communication technologies (broadband subscribers, cell phones and internet users) in the last decade (2007-2016)? Is there any relation between the per capita income and the use of communication technologies?

Now that I have cleaned the data for processing, I will proceed to replace the country name in each of the datasets by the corresponding Income Category to which it belongs. This is done for ease of calculation, as my analysis is related to the analysis of communication trends based on the categories of Income Groups, rather than specific countries individually.

I first substitute the country names by the Income Category for the broadband dataset, and then find the mean values of broadband numbers for each of the Groups for the years 2007-2016.

```
In [55]: df_broadband.set_index('IncomeCategory',inplace=True)

In [56]: df_broadband.head(10)
```

Out[56]:

IncomeCategory	2007	2008	2009	2010	2011
Group5	5.000000e+02	500.0	1000.0	1500.0	2.652222e+03
Group3	1.000000e+04	64000.0	92000.0	106000.0	1.280000e+05
Group3	2.870000e+05	485000.0	818000.0	900000.0	9.810000e+05
Group2	1.850000e+04	20700.0	22900.0	24500.0	2.580000e+04
Group4	1.170000e+04	15900.0	15000.0	15000.0	1.580000e+04
Group3	2.270000e+03	4990.0	16000.0	7120.0	6.000000e+03
Group3	2.600000e+06	3110000.0	3510000.0	4030000.0	4.570000e+06
Group4	3.900000e+03	13800.0	39900.0	93600.0	1.610000e+05
Group2	6.006667e+06	5320000.0	5220000.0	5510000.0	5.550000e+06
Group2	1.620000e+06	1730000.0	1880000.0	2050000.0	2.100000e+06

IncomeCategory	2012	2013	2014	2015	2016
Group5	1500.0	1500.0	1500.0	7070.0	8800.0
Group3	160000.0	183000.0	208000.0	243000.0	266000.0
Group3	1150000.0	1280000.0	1600000.0	2270000.0	2860000.0
Group2	26900.0	27700.0	28800.0	30700.0	32500.0
Group4	20500.0	22300.0	87800.0	154000.0	123000.0
Group3	13100.0	15600.0	10800.0	10000.0	9260.0
Group3	5150000.0	6250000.0	6520000.0	6860000.0	7230000.0
Group4	212000.0	243000.0	273000.0	286000.0	299000.0
Group2	5740000.0	5980000.0	6540000.0	6830000.0	7370000.0
Group2	2130000.0	2230000.0	2360000.0	2460000.0	2520000.0

```
In [57]: df_broadband_groups=df_broadband.groupby('IncomeCategory').mean()

In [58]: df_broadband_groups
```

Out[58]:

IncomeCategory	2007	2008	2009	2010

```
Group1          7.712160e+06  8.318690e+06  8.670940e+06  9.165250e+06
Group2          5.278484e+06  5.756228e+06  6.179022e+06  6.533831e+06
Group3          1.877983e+06  2.439118e+06  3.043659e+06  3.644198e+06
Group4          1.289667e+05  2.068083e+05  2.998894e+05  4.092667e+05
Group5          8.096504e+04  1.347447e+05  2.043398e+05  2.742467e+05

                         2011          2012          2013          2014  \
IncomeCategory
Group1          9.586810e+06  1.003931e+07  1.043635e+07  1.063081e+07
Group2          6.849246e+06  7.078117e+06  7.324872e+06  7.590835e+06
Group3          4.393354e+06  4.937034e+06  5.387800e+06  5.750347e+06
Group4          4.509092e+05  5.285834e+05  6.093182e+05  6.776852e+05
Group5          3.281533e+05  3.837077e+05  4.169794e+05  4.946096e+05

                         2015          2016
IncomeCategory
Group1          1.110308e+07  1.152827e+07
Group2          7.875682e+06  8.121353e+06
Group3          7.202681e+06  8.107711e+06
Group4          8.635482e+05  1.001986e+06
Group5          5.871907e+05  7.121449e+05
```

We apply a similar process as above to the cellphones and internet datasets. We first substitute the country names by the Income Category for each dataset, and then find the mean values of cellphones/internet numbers for each of the Groups 1-5 for the years 2007-2016.

```
In [59]: df_internet.set_index('IncomeCategory',inplace=True)

In [60]: df_internet_groups=df_internet.groupby('IncomeCategory').mean()

In [61]: df_internet_groups
```

```
Out[61]:                      2007       2008       2009       2010       2011  \
         IncomeCategory
         Group1          62.980000  65.760000  68.770000  73.700000  75.850000
         Group2          59.559286  63.222143  66.493929  69.113393  72.460714
         Group3          28.162000  32.018833  35.995259  40.138333  43.793333
         Group4          11.168966  13.658621  16.772759  20.851724  24.055172
         Group5           4.477135   5.449881   6.460833   7.815825   9.206706

                              2012       2013       2014       2015       2016
         IncomeCategory
         Group1          79.050000  83.150000  85.220000  86.070000  89.020000
         Group2          74.991964  77.556250  79.145536  80.459821  82.320536
         Group3          48.090222  51.578333  55.161667  58.751667  61.685000
         Group4          26.993448  30.279310  33.352069  37.404138  40.304138
         Group5          10.832738  12.734286  15.527778  18.411746  20.806032
```

```
In [62]: df_cellphones.set_index('IncomeCategory',inplace=True)
```

```
In [63]: df_cellphones_groups=df_cellphones.groupby('IncomeCategory').mean()

In [64]: df_cellphones_groups
```

Out[64]:

IncomeCategory	2007	2008	2009	2010	\
Group1	2.796614e+07	2.949380e+07	3.119760e+07	3.258754e+07	
Group2	2.402014e+07	2.527934e+07	2.611444e+07	2.642936e+07	
Group3	2.460290e+07	2.867172e+07	3.215142e+07	3.545298e+07	
Group4	1.271248e+07	1.656713e+07	1.923416e+07	2.273001e+07	
Group5	8.066883e+06	1.201062e+07	1.633859e+07	2.156401e+07	

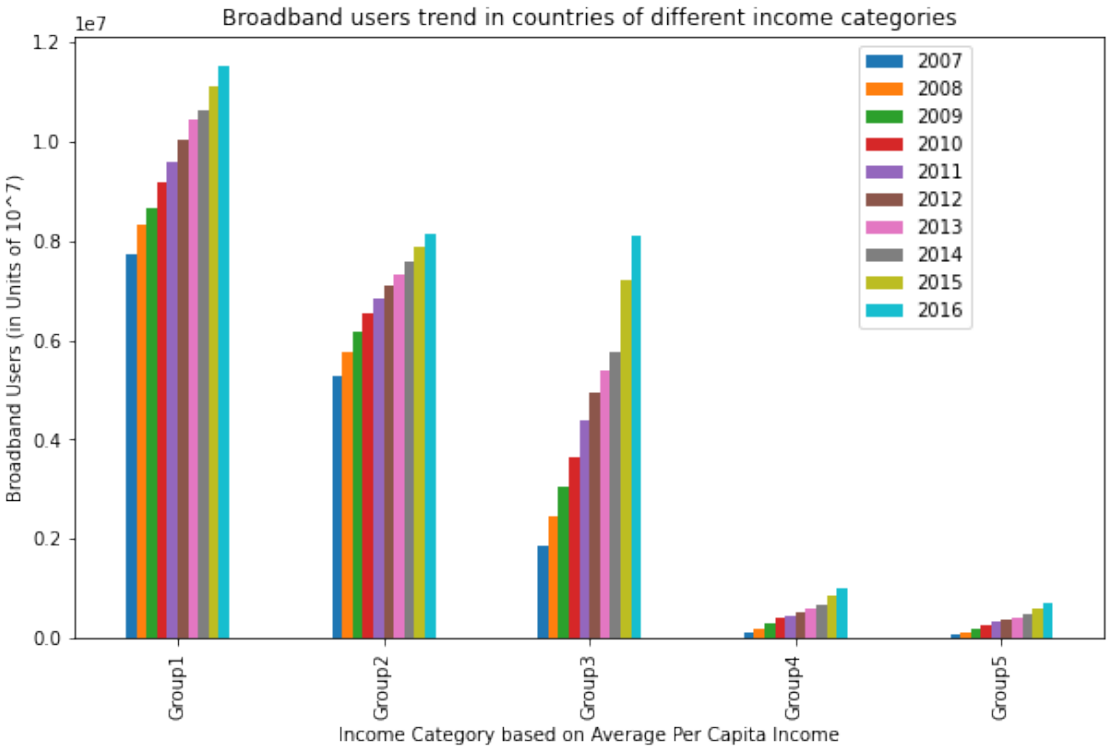
IncomeCategory	2011	2012	2013	2014	\
Group1	3.407898e+07	3.522342e+07	3.632425e+07	4.100377e+07	
Group2	2.747520e+07	2.805518e+07	2.861731e+07	2.896489e+07	
Group3	3.864451e+07	4.179604e+07	4.517381e+07	4.661710e+07	
Group4	2.574550e+07	2.870434e+07	3.081737e+07	3.188913e+07	
Group5	2.575668e+07	2.672580e+07	2.841492e+07	3.100323e+07	

IncomeCategory	2015	2016
Group1	4.359340e+07	4.516503e+07
Group2	2.924032e+07	2.986492e+07
Group3	4.677156e+07	4.810103e+07
Group4	3.298998e+07	3.442544e+07
Group5	3.260727e+07	3.528996e+07

I will now proceed with the visualisation of data using the tables obtained above.

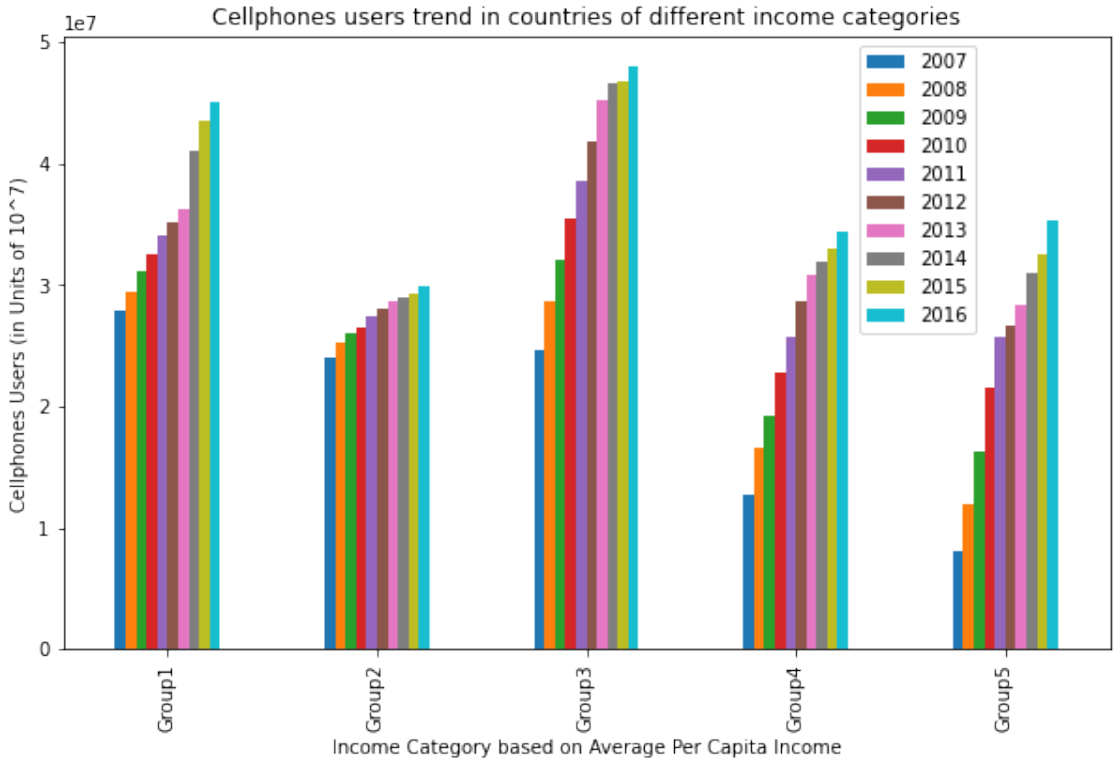
Plot number 1 showing the comparison between the number of broadband users for each group of countries, for years 2007-2016.

```
In [65]: df_broadband_groups.plot(kind='bar',figsize=(10,6));
         plt.title('Broadband users trend in countries of different income categories');
         plt.xlabel('Income Category based on Average Per Capita Income')
         plt.ylabel('Broadband Users (in Units of 10^7)');
         plt.legend(bbox_to_anchor=(0.88,1.0005),loc="best");
```



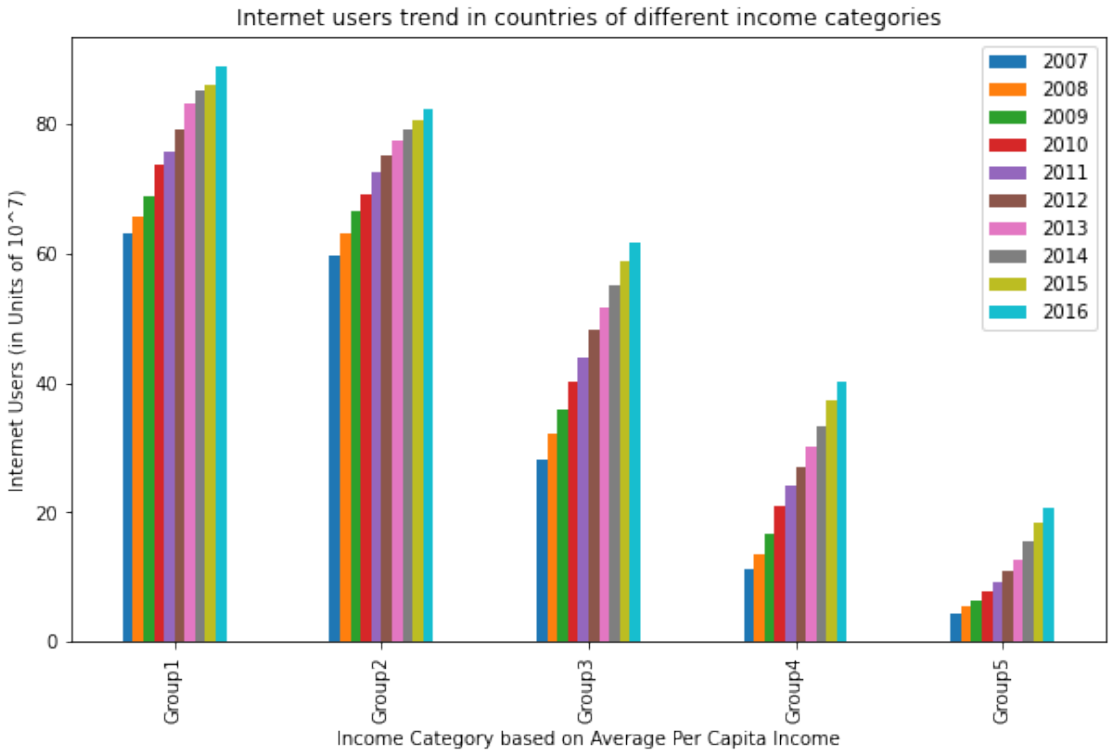
Plot number 2 showing the comparison between the number of cellphones users for each group of countries, for years 2007-2016.

```
In [66]: df_cellphones_groups.plot(kind='bar',figsize=(10,6));
         plt.title('Cellphones users trend in countries of different income categories');
         plt.xlabel('Income Category based on Average Per Capita Income')
         plt.ylabel('Cellphones Users (in Units of 10^7)');
         plt.legend(bbox_to_anchor=(0.88,1.0005),loc="best");
```



Plot number 3 showing the comparison between the number of internet users for each group of countries, for years 2007-2016.

```
In [67]: df_internet_groups.plot(kind='bar',figsize=(10,6));
         plt.title('Internet users trend in countries of different income categories');
         plt.xlabel('Income Category based on Average Per Capita Income');
         plt.ylabel('Internet Users (in Units of 10^7)');
```



Results: From the above analysis and plots, we can conclude that:

1. In terms of broadband use, Group 1 countries (countries with the highest per capita average income) has always ranked the highest. The number of broadband users decreases as the per capita average income decreases, and Group 5 countries (countries with the lowest per capita average income) has the least number of broadband users for all years. The number of broadband users in Group 1 countries is significantly (approximately 20 times) higher than Group 5 countries. The trend shows a decreasing trend of broadband users from higher income countries to lower income countries.

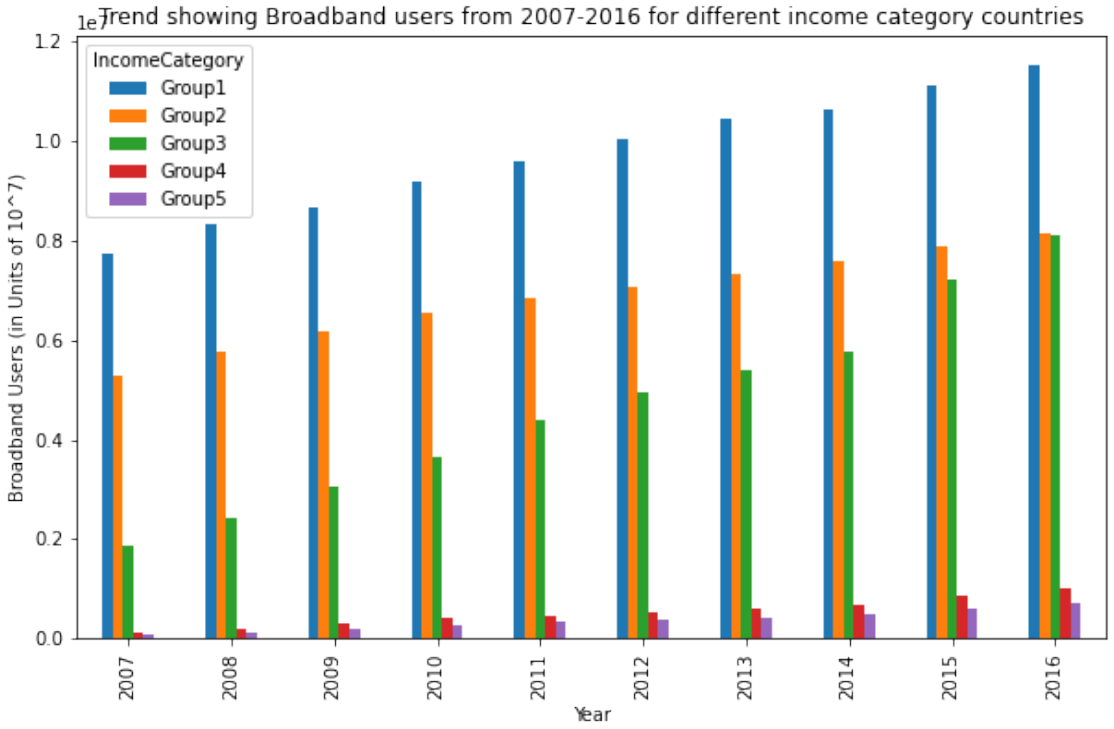
2. In terms of cellphones use, we observe less significant differences than broadband use. Here, Group 3 countries are observed to have the most number of users, followed by Group 1 countries, although the difference margin is smaller. Thus medium income countries (average per capita income 10000-30000) have recorded highest number of cell phone users. This is followed by Group 2, Group 4, and Group 5 countries, and we can observe that the difference in number of cellphone users has reduced, with Group 4 and 5 exceeding Group 2 for the last two years.

3. Internet user trends follow a similar trend to broadband use. Group 1 countries with the highest per capita income have highest number of users, and the number of users falls with the country's per capita income. Group 5 countries with the lowest per capita income have recorded lowest number of users. The difference is appreciable.

Research Question 2: Is there any noticeable trend that can be observed in the use of these communication technologies over the years between 2007-2016?

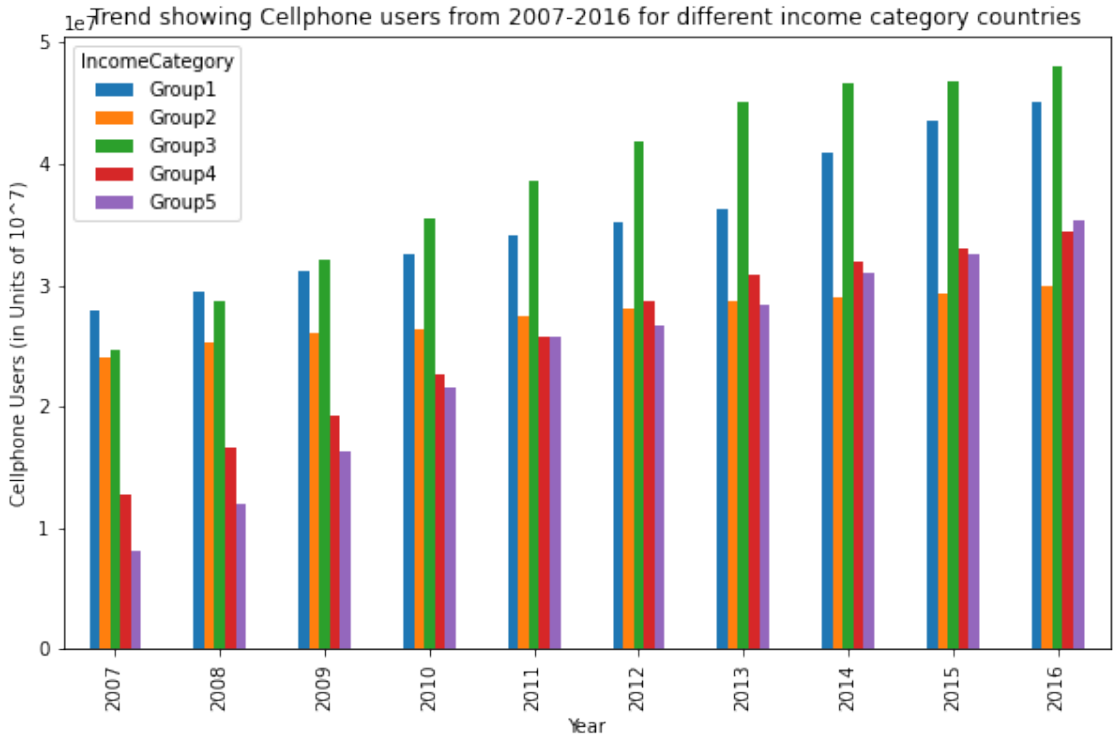
Plot number 4 showing the relative growth between the number of broadband users for years 2007-2016.

```
In [68]: df_broadband_groups.T.plot(kind='bar',figsize=(10,6));
         plt.title('Trend showing Broadband users from 2007-2016 for different income category c
         plt.xlabel('Year');
         plt.ylabel('Broadband Users (in Units of 10^7)');
```



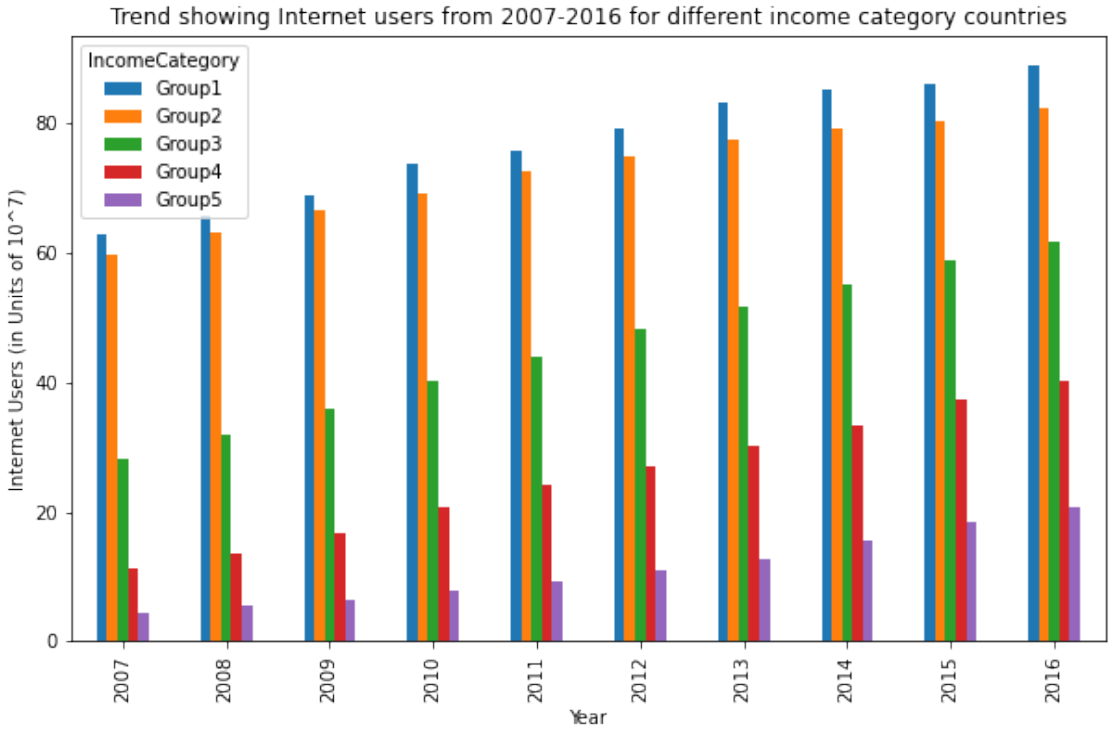
Plot number 5 showing the relative growth between the number of cellphone users for years 2007-2016.

```
In [69]: df_cellphones_groups.T.plot(kind='bar',figsize=(10,6));
         plt.title('Trend showing Cellphone users from 2007-2016 for different income category c
         plt.xlabel('Year');
         plt.ylabel('Cellphone Users (in Units of 10^7)');
```



Plot number 6 showing the relative growth between the number of internet users for years 2007-2016.

```
In [70]: df_internet_groups.T.plot(kind='bar',figsize=(10,6));
         plt.title('Trend showing Internet users from 2007-2016 for different income category co
         plt.xlabel('Year');
         plt.ylabel('Internet Users (in Units of 10^7)');
```



Results: From the above analysis and Plots 4,5 and 6 we can observe that the number of broadband, cellphones and internet users has maintained an increasing trend every year from 2007-2016. This is consistent for countries in all income groups and for all communication means, but the trend is more pronounced in the earlier years of the decade compared to the later years.

1.1.3 Conclusions

Thus in this project we have gained some insights on the growing use of communication technologies throughout the world, and seen how it compares with the country's GDP. However, we should keep in mind that the findings are not exhaustive, we have not considered other factors like population density, political situation, geographical constraints, etc. Thus a change in a country's per capita income may not necessarily impact the use of communication technologies, or vice versa.

1.1.4 Supplementary Analysis

Additionally, from earlier analysis in the Data Wrangling section, I have presented below the segmentation of the countries into different income categories for this project, along with the number of countries in each Group and their names.

Countries categorised according to their averge per capita income as follows:

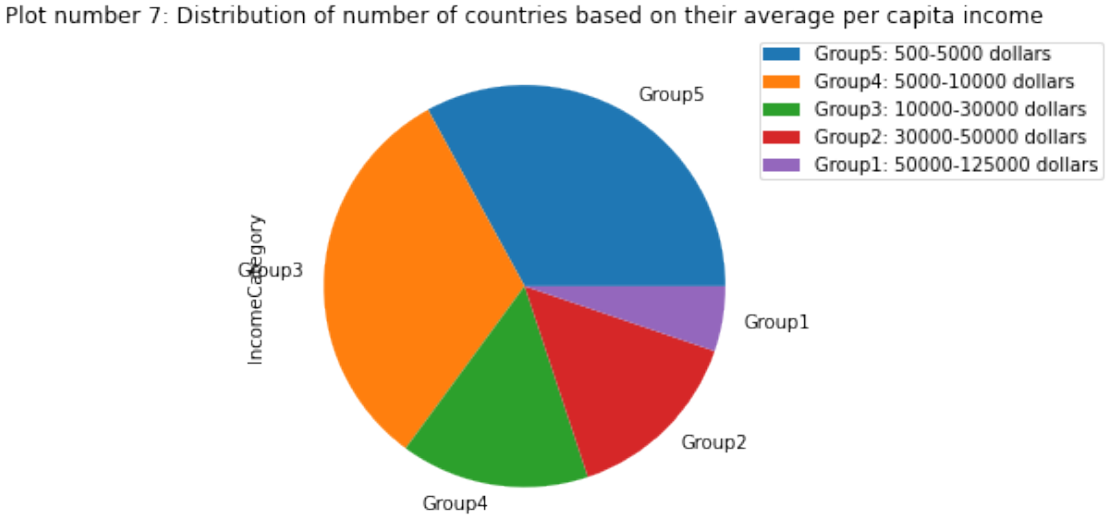
```
In [71]: df_income_categories=df_income['IncomeCategory'].value_counts()
         df_income_categories
```

```
Out[71]: Group5    63
         Group3    61
         Group4    29
         Group2    28
         Group1    10
         Name: IncomeCategory, dtype: int64

In [72]: df_income_categories.plot(kind='pie',figsize=(5,5));

         plt.title('Plot number 7: Distribution of number of countries based on their average pe
         pieLabels = ['Group5: 500-5000 dollars',
                      'Group4: 5000-10000 dollars',
                      'Group3: 10000-30000 dollars',
                      'Group2: 30000-50000 dollars',
                      'Group1: 50000-125000 dollars']

         plt.legend(pieLabels,borderpad=.2,bbox_to_anchor=(0.95,1.005),loc="best");
```



We also obtain a list of countries in each category:

```
In [73]: df_income=df_income.reset_index()

In [74]: for x in range(1,6):
             print("\n The Group {} countries are : \n{}"
                   .format(x, df_income['country'][df_income['IncomeCategory'] == "Group{}".form

 The Group 1 countries are :
['Brunei', 'Kuwait', 'Luxembourg', 'Monaco', 'Norway', 'Qatar', 'Singapore', 'Switzerland', 'Uni
```

```
 The Group 2 countries are :
['Andorra', 'Australia', 'Austria', 'Bahrain', 'Belgium', 'Canada', 'Cyprus', 'Denmark', 'Equato

 The Group 3 countries are :
['Albania', 'Algeria', 'Antigua and Barbuda', 'Argentina', 'Azerbaijan', 'Bahamas', 'Barbados',

 The Group 4 countries are :
['Angola', 'Armenia', 'Belize', 'Bhutan', 'Bolivia', 'Cape Verde', 'Congo, Rep.', 'Ecuador', 'Eg

 The Group 5 countries are :
['Afghanistan', 'Bangladesh', 'Benin', 'Burkina Faso', 'Burundi', 'Cambodia', 'Cameroon', 'Centr
```