Project: Investigate a Dataset (GDP Per Capita in Different Regions !)

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Introduction

Dataset: *gapminder*, For this project I chose 4 different indicators to work with:

1. Babies per woman (total Fertility rate).
2. Human Development index: which ranks countries by the level of human development based on health, education and living standards.
3. Internet Users: the percentage of internet users in the country in a specific year.
4. OWID education index: Education index based on average years of schooling.

Dependent Varaible: Income per person (GDP / capita, PPP$ inflation-adjusted)

- The data is adjusted for different countries and in international dollars

Definitions

- GDP (Gross Domestic Product): "market value of all the finished goods and services produced within a country's borders in a specific time period". src (https://www.investopedia.com/terms/g/gdp.asp)
- GDP / Capita: "a measure of a country's economic output that accounts for its number of people. It divides the country's gross domestic product by its total population" src (https://www.thebalance.com/gdp-per-capita-formula-u-s-compared-to-highest-and-lowest-3305848#:~:text=The%20gross%20domestic%20product%20per,product%20by%20its%20tc

*for the data sources and more info -> data (https://www.gapminder.org/data)

Questions

1. Which countries have developed the most (GDP / Capita) in the choosen time period (2000 - 2017)

2. What are the characteristics of these countries that has developed the most in the time period?

3. Do these countries have higher educational index or other index because they have a higher GDP/Capita or they have a higher GDP/Capita because they have a

higher educational index?

In [1]:
```
# importing modules
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

# setting matplotlib style
plt.style.use('seaborn-whitegrid')
```

In [2]:
```
# loading the data in the correct format
def read_csv(csv=None):
    # getting the dataset and transposing it
    df = pd.read_csv(f'data/{csv}', index_col=0, header=None).T
    # fixing the columns naming after transposing
    df.rename(columns={'country': 'year'}, inplace=True)
    # Making sure that the year column is in int format
    df['year'] = df['year'].astype(int)
    print(f"Starting Year: {df['year'].min()} | Ending Year: {df['year']
    return df
```

- The function loads the data and then transpose it to be in the right format where the year and countries are the columns and the data items are the rows.
- The function also prints the starting and ending of the indicator dataframe.
- The function also makes sure that the `year` feature is in the right format as `int`.

Data Wrangling

General Properties

GDP Per Capita Dataset

In [3]:
```
df_income = read_csv('income_per_person_gdppercapita_ppp_inflation_adjus
df_income.head()
```

```
Starting Year: 1800 | Ending Year: 2040
```

Out[3]:

	year	Afghanistan	Albania	Algeria	Andorra	Angola	Antigua and Barbuda	Argentina	Armenia	Austr
1	1800	603	667	715	1200	618	757	1640	514	
2	1801	603	667	716	1200	620	757	1640	514	
3	1802	603	667	717	1200	623	757	1650	514	
4	1803	603	667	718	1200	626	757	1650	514	
5	1804	603	667	719	1210	628	757	1660	514	

5 rows × 194 columns

In [4]:
```
df_income.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 241 entries, 1 to 241
Columns: 194 entries, year to Zimbabwe
dtypes: int64(194)
memory usage: 367.1 KB
```

The features are in the right format as `int` .

According to the [dataset description (https://www.gapminder.org/data/documentation/gd001/)](https://www.gapminder.org/data/documentation/gd001/): the dataset ends in 2018

So we will trim the dataset to only include data up till year 2018.

In [5]:
```
# the dataset ends at 2018
df_income = df_income[df_income['year'] <= 2018]
df_income.tail()
```

Out[5]:

	year	Afghanistan	Albania	Algeria	Andorra	Angola	Antigua and Barbuda	Argentina	Armenia	Austr
215	2014	1800	10700	13500	44900	6810	20800	18900	7950	43
216	2015	1770	11000	13800	46600	6650	21400	19200	8170	44
217	2016	1760	11400	13900	48200	6260	22400	18600	8160	44
218	2017	1760	11800	13900	49800	6050	22900	18900	8750	44
219	2018	1740	12300	13900	51500	5730	23800	18300	9180	45

5 rows × 194 columns

In [6]:
```
# missing values
df_income.isna().sum().sum()
```

Out[6]:
```
0
```

In [7]:
```
# number of duplicates
df_income.duplicated().sum()
```

Out[7]:
```
0
```

The dataset is clean and has no duplicates

OWID Education Index

In [8]:
```
df_owid = read_csv('owid_education_idx.csv')
df_owid.tail()
```

```
Starting Year: 1870 | Ending Year: 2017
```

Out[8]:

	year	Afghanistan	Albania	Algeria	Andorra	Angola	Antigua and Barbuda	Argentina	Armenia	Austr
144	2013	0.233	0.647	0.520	0.68	0.327	0.613	0.653	0.760	0.
145	2014	0.233	0.647	0.527	0.68	0.327	0.613	0.653	0.767	0.
146	2015	0.240	0.647	0.527	0.68	0.333	0.613	0.653	0.773	0.
147	2016	0.240	0.667	0.533	0.68	0.340	0.613	0.660	0.780	0.
148	2017	0.253	0.667	0.533	0.68	0.340	0.613	0.660	0.780	0.

5 rows × 188 columns

In [9]:
```
df_owid.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 148 entries, 1 to 148
Columns: 188 entries, year to Zimbabwe
dtypes: float64(187), int64(1)
memory usage: 218.5 KB
```

The features are in the right format as `float`, except for the year as `int`.

In [10]:
```
# total missing values per country
df_owid.isna().sum()
```

Out[10]:
```
0
year             0
Afghanistan     96
Albania         96
Algeria         96
Andorra        130
              ...
Venezuela       96
Vietnam        112
Yemen           96
Zambia          96
Zimbabwe        96
Length: 188, dtype: int64
```

In [11]:
```
# total missing values
df_owid.isna().sum().sum()
```

Out[11]:
```
20087
```

In [12]:
```
# number of duplicates
df_owid.duplicated().sum()
```

Out[12]:
```
0
```

The dataset seems to have **20087** missing values accross many countries. And has no duplicates.

The missing values will be delt after loading all the features.

Human Development Index

In [13]:
```
df_hid = read_csv('hdi_human_development_index.csv')
df_hid.tail()
```

```
Starting Year: 1990 | Ending Year: 2018
```

Out[13]:

	year	Afghanistan	Albania	Algeria	Andorra	Angola	Antigua and Barbuda	Argentina	Armenia	Austra
25	2014	0.488	0.787	0.749	0.853	0.557	0.767	0.825	0.746	0.9
26	2015	0.490	0.788	0.751	0.850	0.565	0.770	0.828	0.748	0.9
27	2016	0.491	0.788	0.755	0.854	0.570	0.772	0.828	0.751	0.9
28	2017	0.493	0.789	0.758	0.852	0.576	0.774	0.832	0.758	0.9
29	2018	0.496	0.791	0.759	0.857	0.574	0.776	0.830	0.760	0.9

5 rows × 189 columns

In [14]:
```
df_hid.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 29 entries, 1 to 29
Columns: 189 entries, year to Zimbabwe
dtypes: float64(188), int64(1)
memory usage: 43.0 KB
```

In [15]:
```
# missing values per country
df_hid.isna().sum()
```

Out[15]:
```
0
year           0
Afghanistan    0
Albania        0
Algeria        0
Andorra       10
              ..
Venezuela      0
Vietnam        0
Yemen          0
Zambia         0
Zimbabwe       0
Length: 189, dtype: int64
```

In [16]:
```
# total number of missing values
df_hid.isna().sum().sum()
```

Out[16]:
```
517
```

In [17]:
```
df_hid.duplicated().sum()
```

Out[17]:
```
0
```

The dataset seems to have **517** missing values accross the countries. And has no duplicates.

The missing values will be delt after loading all the features.

Internet Users

In [18]:
```
df_iu = read_csv('internet_users.csv')
df_iu.tail()
```

```
Starting Year: 1960 | Ending Year: 2019
```

Out[18]:

	year	Afghanistan	Albania	Algeria	Andorra	Angola	Antigua and Barbuda	Argentina	Armenia	Austra
56	2015	8.26	63.3	38.2	96.9	12.4	70.0	68.0	59.1	84
57	2016	NaN	66.4	42.9	97.9	13.0	73.0	71.0	64.3	86
58	2017	11.40	71.8	47.7	91.6	14.3	NaN	74.3	64.7	86
59	2018	NaN	NaN	49.0	NaN	NaN	NaN	NaN	68.2	N.
60	2019	NaN	69.6	NaN	NaN	NaN	NaN	NaN	NaN	N.

5 rows × 195 columns

In [19]:
```
df_iu.isna().sum()
```

Out[19]:
```
0
year            0
Afghanistan    43
Albania        35
Algeria        34
Andorra        38
               ..
Venezuela      33
Vietnam        35
Yemen          37
Zambia         34
Zimbabwe       35
Length: 195, dtype: int64
```

In [20]:
```
df_iu.isna().sum().sum()
```

Out[20]:
```
6744
```

In [21]:
```
df_iu.duplicated().sum()
```

Out[21]:
```
0
```

The dataset seems to have **6744** missing values accross the countries. And has no duplicates.

The missing values will be delt after loading all the features.

Babies per woman (Fertility Rate)

Babies per woman (Fertility Rate)

In [22]:
```
df_fertility = read_csv('children_per_woman_total_fertility.csv')
df_fertility.head()
```

```
Starting Year: 1800 | Ending Year: 2100
```

Out[22]:

	year	Afghanistan	Albania	Algeria	Angola	Antigua and Barbuda	Argentina	Armenia	Australia	Austri
1	1800	7.0	4.6	6.99	6.93	5.00	6.8	7.80	6.50	5.1
2	1801	7.0	4.6	6.99	6.93	5.00	6.8	7.80	6.48	5.1
3	1802	7.0	4.6	6.99	6.93	4.99	6.8	7.81	6.46	5.1
4	1803	7.0	4.6	6.99	6.93	4.99	6.8	7.81	6.44	5.1
5	1804	7.0	4.6	6.99	6.93	4.99	6.8	7.81	6.42	5.1

5 rows × 185 columns

In [23]:
```
df_fertility.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 301 entries, 1 to 301
Columns: 185 entries, year to Zimbabwe
dtypes: float64(184), int64(1)
memory usage: 437.4 KB
```

In [24]:
```
df_fertility.isna().sum()
```

Out[24]:
```
0
year           0
Afghanistan    0
Albania        0
Algeria        0
Angola         0
              ..
Venezuela      0
Vietnam        0
Yemen          0
Zambia         0
Zimbabwe       0
Length: 185, dtype: int64
```

In [25]:
```
df_fertility.isna().sum().sum()
```

Out[25]:
```
0
```

In [26]:
```
df_fertility.duplicated().sum()
```

Out[26]:
```
0
```

The features are in the right format as `float`, except for the `year as int`.

Making sure that we are working with the same data across all indicators

The datasets are quite different. Some datasets have more countries than others. Also some datasets has too many missing values for some time periods.

The goal

- Countries that are present in all of our indicators datasets (intersection)
- The time period with the least missing values

In [27]:
```
# getting the columns of all of the datasets
dfs_columns = [df_income.columns, df_iu.columns, df_hid.columns, df_owic
```

In [28]:
```
for c in dfs_columns:
    print(f'Number of countries = {len(c)-1}') # we subtract 1 as the ye
```

```
Number of countries = 193
Number of countries = 194
Number of countries = 188
Number of countries = 187
Number of countries = 184
```

As we can see the number of countries differe from one dataset to the other.

Getting the intersections between the countries

In this section we will get the countries that are present in all of the datasets we have.

We also didn't remove the `year` column as we know it's present in all of the datasets and we will need it later.

In [29]:
```
countries = dfs_columns[0]
intersections = 0
for c in dfs_columns[1:]:
    countries = np.intersect1d(countries, c)
    intersections += 1
    print(f'Number of countries after intersection {intersections}: {len
```

```
Number of countries after intersection 1: 194
Number of countries after intersection 2: 188
Number of countries after intersection 3: 186
Number of countries after intersection 4: 181
```

Getting the data for the common countries only

Now as we have a list of the common countries in all of our datasets we can use this list to update our datasets.

In [30]:
```
# update the rest of the datasets
df_income = df_income[countries]
df_iu = df_iu[countries]
df_hid = df_hid[countries]
df_owid = df_owid[countries]
df_fertility = df_fertility[countries]
```

In [31]:
```
dfs_columns = [df_income.columns, df_iu.columns, df_hid.columns, df_owid
for c in dfs_columns:
    print(f'Number of countries = {len(c)-1}')
```

```
Number of countries = 180
Number of countries = 180
Number of countries = 180
Number of countries = 180
Number of countries = 180
```

Now all of our datasets have the same set of countries

Choosing the time period with the lowest number of null values

as some of the datasets have a high number of null values, we will need to find the time period with the lowest number of nulls accorss all datasets.

some datasets have a high number of nulls specifically in the early years because of data collection reasons we will discuss it later on.

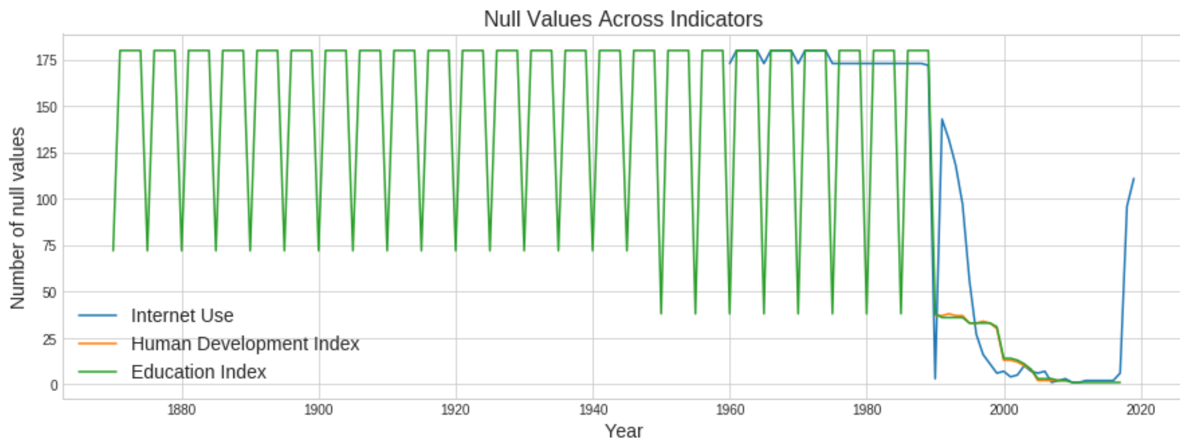
In [32]:
```
# counting the number of nulls in each year in a dataset
def null_per_year(df):
    nulls = {}
    for y in df['year']:
        n_nulls = df[df['year'] == y].isna().sum().sum()
        if n_nulls > 0:
            nulls[y] = n_nulls

    return pd.Series(nulls).to_frame('nulls')
```

In [33]:
```
# making a dictionary of the datasets for faster iterating
dfs = {'Income': df_income, 'Interent Use': df_iu, 'Human Development In
```

In [34]:
```
null_dfs = []
print('-'*5, 'Dataframes with nulls!', '-'*5)
for df in dfs:
    n_nulls = dfs[df].isna().sum().sum()
    if n_nulls > 0:
        print(f"Numer of Nulls in {df}: {n_nulls}")
        null_dfs.append(df)
```

```
----- Dataframes with nulls! -----
Numer of Nulls in Interent Use: 6153
Numer of Nulls in Human Development Index: 415
Numer of Nulls in Education Index: 19162
```

In [35]:
```
plt.figure(figsize=(15, 5))
for df in null_dfs:
    nulls = null_per_year(dfs[df])
    plt.plot(nulls)

plt.title('Null Values Across Indicators', fontsize=16)
plt.xlabel('Year', fontsize=14)
plt.ylabel('Number of null values', fontsize=14)
plt.legend(['Internet Use', 'Human Development Index', 'Education Index'
plt.show()
```

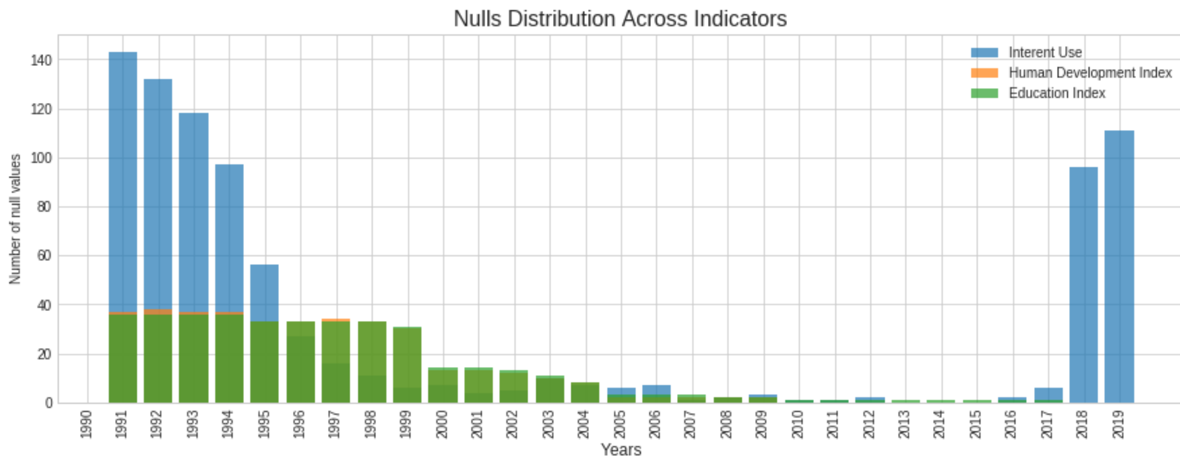


- the internet was available to the public in [1991 (https://thenextweb.com/insider/2011/08/06/20-years-ago-today-the-world-wide-web-opened-to-the-public/#:~:text=Today%20is%20a%20significant%20day,the%20project%20on%20the%20alt](https://thenextweb.com/insider/2011/08/06/20-years-ago-today-the-world-wide-web-opened-to-the-public/#:~:text=Today%20is%20a%20significant%20day,the%20project%20on%20the%20alt) so there's no data prior to this year in the internet use datasets and it also took the world some years until it was available to a descent amount of people.
- also the educational index data was not stable until the early **1990s**.

Nulls Distribution Across Indicators

- according to the above insights, we will plot the nulls distribution across years starting 1991 so we can clearly see the difference.
- and then descide on th time period we will choose

In [36]:
```
fig = plt.figure(figsize=(15, 5))
for df in null_dfs:
    nulls = null_per_year(dfs[df]).loc[1991:]
    plt.bar(nulls.index, nulls['nulls'], alpha=0.7)

plt.title('Nulls Distribution Across Indicators', fontsize=16)
plt.xlabel('Years', fontsize=12)
plt.ylabel('Number of null values')
plt.legend(null_dfs)
plt.xticks(np.arange(1990, 2020), rotation='vertical')
plt.show()
```



The time period with the lowest number of nulls will be from **2007-2016** but I choose the time period **2000-2017** as I can handle small number of missing data without affecting the results.

In [37]:
```
# updating the dataframes
df_income = df_income.query('2017 >= year >= 2000')
df_iu = df_iu.query('2017 >= year >= 2000')
df_hid = df_hid.query('2017 >= year >= 2000')
df_owid = df_owid.query('2017 >= year >= 2000')
df_fertility = df_fertility.query('2017 >= year >= 2000')
```

Here we are updating the dataframes to only include the time period **2000-2017**

In [38]:
```
df_income.tail()
```

Out[38]:

	Afghanistan	Albania	Algeria	Angola	Antigua and Barbuda	Argentina	Armenia	Australia	Austria	A:
214	1810	10500	13300	6730	20100	19600	7720	43200	44300	
215	1800	10700	13500	6810	20800	18900	7950	43700	44200	
216	1770	11000	13800	6650	21400	19200	8170	44100	44300	
217	1760	11400	13900	6260	22400	18600	8160	44600	44700	
218	1760	11800	13900	6050	22900	18900	8750	44900	45500	

5 rows × 181 columns

Making sure that we have the correct years -> the year column is at the end of the dataframe

In [39]:
```
# updating our dictionary to include the updated dataframes
dfs = {'Income': df_income, 'Interent Use': df_iu, 'Human Development In
```

In [40]:
```
for df in dfs:
    print(dfs[df].shape, 'Shape ', df)
```

```
(18, 181) Shape  Income
(18, 181) Shape  Interent Use
(18, 181) Shape  Human Development Index
(18, 181) Shape  Education Index
(18, 181) Shape  Fertility
```

- Now all the indicators have the same number of columns **181**: 180 country + the year column.
- All the indicators are across **18** years in the time period **2000-2017**

Filling Missing Values

- In this section we will examine the remaining missing values and handle them
    - Dropping countries with too many missing values
    - Interpolation

In [41]:
```
# number of missing values per indicator
for df in dfs:
    print(' number of missing values in ', df, ' :', dfs[df].isna().sum(
```

```
 number of missing values in  Income  : 0
 number of missing values in  Interent Use  : 64
 number of missing values in  Human Development Index  : 66
 number of missing values in  Education Index  : 81
 number of missing values in  Fertility  : 0
```

In [42]:
```
# the number of missing Education Index per country
df_owid.isna().sum()[df_owid.isna().sum()>0]
```

Out[42]:
```
0
Bhutan             5
Comoros            4
Eritrea            5
Grenada            2
Guinea-Bissau      5
Lebanon            5
Montenegro         3
Nigeria            3
Palestine          4
South Korea       18
South Sudan        8
Suriname           4
Turkmenistan      10
Vanuatu            5
dtype: int64
```

Here we find that **Turkmenistan and South Korea** have a high number of missing values.

We will add the countries with missing values in a set as we explore the other features and then drop these countries from our datasets.

In [43]:
```
# countries to drop set
drop_countries = {'Turkmenistan', 'South Korea'}
```

In [44]:
```
# the number of missing Internet users entries per country
df_iu.isna().sum()[df_iu.isna().sum()>0]
```

Out[44]:
```
0
Afghanistan                      2
Antigua and Barbuda              1
Australia                        3
Azerbaijan                       2
Bangladesh                       1
Belarus                          3
Belize                           2
Bhutan                           1
Ecuador                          1
Eritrea                          4
Guyana                           5
Iraq                             1
Ireland                          1
Liberia                          2
Libya                            1
Madagascar                       1
Mongolia                         4
Montenegro                       4
Myanmar                          1
Pakistan                         1
Rwanda                           1
Serbia                           4
Seychelles                       1
South Sudan                     13
St. Vincent and the Grenadines   1
Sudan                            3
dtype: int64
```

Here we find that **South Sudan** has a high number of missing values so we add to our drop set.

In [45]:
```
# adding South Sudan to the drop set
drop_countries.add('South Sudan')
```

In [46]:
```
# the number of missing Human Development Index entries per country
df_hid.isna().sum()[df_hid.isna().sum()>0]
```

Out[46]:
```
0
Antigua and Barbuda     5
Bhutan                  5
Eritrea                 5
Grenada                 2
Guinea-Bissau           5
Lebanon                 5
Montenegro              3
Nigeria                 3
Palestine               4
South Sudan            10
Suriname                4
Turkmenistan           10
Vanuatu                 5
dtype: int64
```

Here we find that **South Sudan and Turkmenistan** have a high number of missing values so we add to our drop set.

As we are using a **set** to store these names, it will **automatically ignore duplicates**.

In [47]:
```
# Adding the new countries to the drop list
drop_countries.add('South Sudan')
drop_countries.add('Turkmenistan')
```

In [48]:
```
# drop countries with very high missing values
drop_countries = list(drop_countries)
df_income.drop(drop_countries, axis=1, inplace=True)
df_iu.drop(drop_countries, axis=1, inplace=True)
df_hid.drop(drop_countries, axis=1, inplace=True)
df_owid.drop(drop_countries, axis=1, inplace=True)
df_fertility.drop(drop_countries, axis=1, inplace=True)
```

In [49]:
```
# updating our dictionary
dfs = {'Income': df_income, 'Interent Use': df_iu, 'Human Development Ir
```

In [50]:
```
for df in dfs:
    print(' number of missing values in ', df, ' :', dfs[df].isna().sum(
```

```
 number of missing values in  Income  : 0
 number of missing values in  Interent Use  : 51
 number of missing values in  Human Development Index  : 46
 number of missing values in  Education Index  : 45
 number of missing values in  Fertility  : 0
```

After removing the countries with high number of missing values our numbers changed as follows:

- Internet Use: 64 -> 51

- Human Development Index 66 -> 46
- Education Index -> 81 -> 45

We can now fill these missing values using pandas **interpolation**.

Filling Missing Values using Interpolation

- As our data seems to follow a trend as it increases or decrease overtime filling it the mean or median won't be the best choice
- So I will be filling the missing data using **Interpolation**
  - The `limit_direction` is set to `both` so the algorithm doesn't leave any empty values even if they are at the start or the end of the dataframe.

In [51]:
```
# filling missing values with interpolation
df_iu = df_iu.interpolate(method='linear', limit_direction='both')
df_hid = df_hid.interpolate(method='linear', limit_direction='both')
df_owid = df_owid.interpolate(method='linear', limit_direction='both')
```

In [52]:
```
# updating the dictionary
dfs = {'Income': df_income, 'Interent Use': df_iu, 'Human Development In
```

In [53]:
```
for df in dfs:
    print(' number of missing values in ', df, ' :', dfs[df].isna().sum(
```

```
 number of missing values in  Income  : 0
 number of missing values in  Interent Use  : 0
 number of missing values in  Human Development Index  : 0
 number of missing values in  Education Index  : 0
 number of missing values in  Fertility  : 0
```

Now we have no missing values in any of our dataframes and we are ready for the next step

Exploratory Data Analysis

1. Which countries have developed the most (GDP / Capita) in the choosen time period (2000 - 2017)

In [54]:
```
# getting the difference between the income the first and last years
df_countries_difference = pd.DataFrame(df_income.iloc[-1, :] - df_income
df_countries_difference.drop('year', axis=0, inplace=True) # dropping th
df_countries_difference.tail()
```

Out[54]:

	difference
0	
Venezuela	-100
Vietnam	3660
Yemen	-1600
Zambia	1590
Zimbabwe	-380

Now we have a dataframe of how much each country's GDP/Capita has changed from the first year in the time period to the last year.

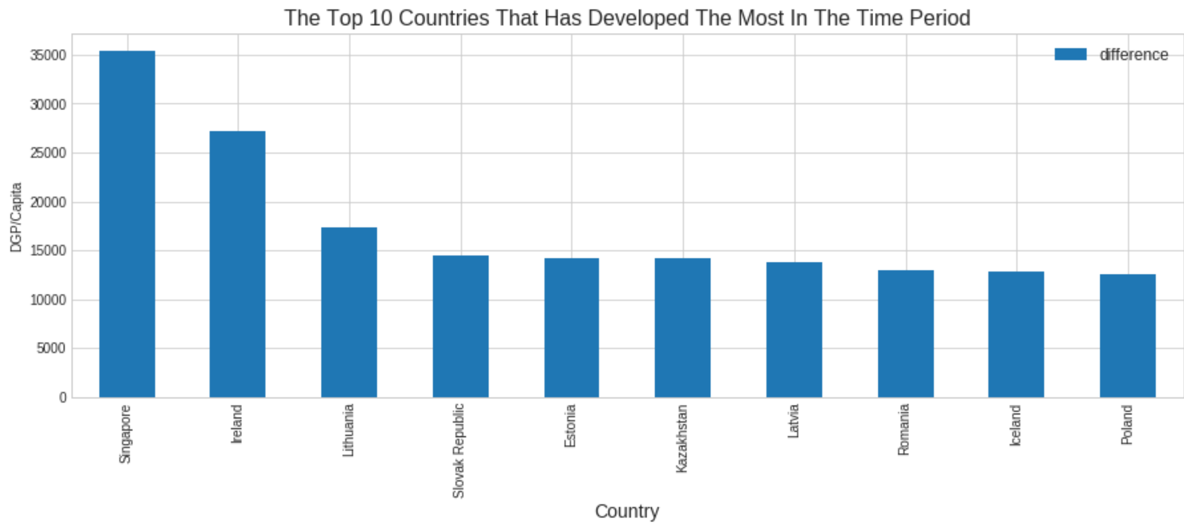
We can sort them and get the **top 10 countries that developed the most in the time period**.

In [55]:
```
most_advancing_10 = df_countries_difference.sort_values('difference', as
most_advancing_10
```

Out[55]:

	difference
0	
Singapore	35400
Ireland	27200
Lithuania	17400
Slovak Republic	14500
Estonia	14200
Kazakhstan	14150
Latvia	13800
Romania	13000
Iceland	12800
Poland	12600

In [56]:
```
# plotting the top 10 countries
most_advancing_10.plot(kind='bar', figsize=(15, 5))
plt.title('The Top 10 Countries That Has Developed The Most In The Time
plt.xlabel('Country', fontsize=14)
plt.ylabel('DGP/Capita')
plt.legend(fontsize=12)
plt.show()
```

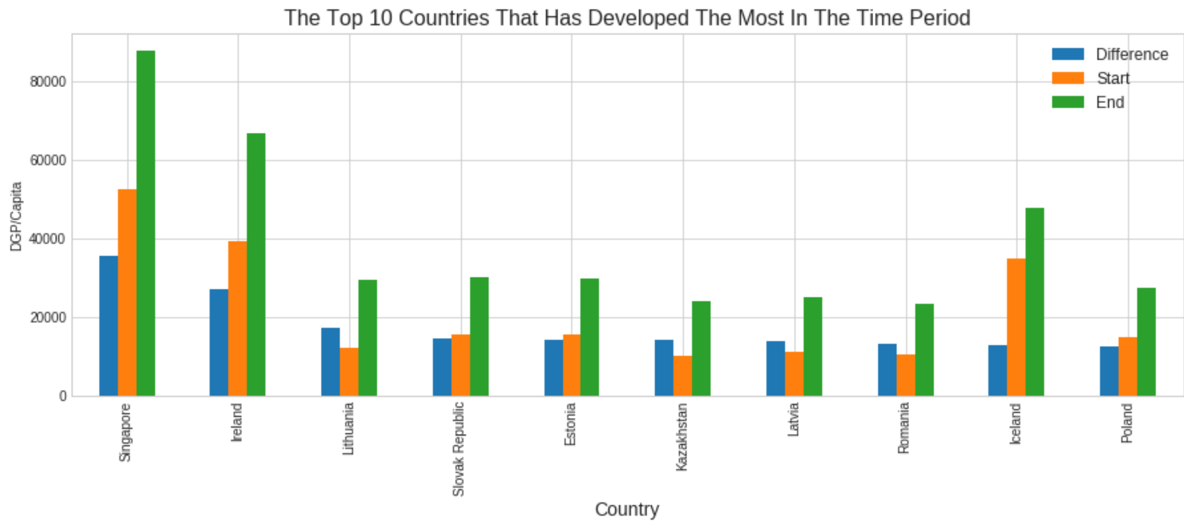


So these are the top 10 advancing countries in the time period. We can add more data like at what GDP/Capita these countries started and ended.

In [57]:
```
# adding the start and end GDP/Capita for each country
start = []
end = []
for country in most_advancing_10.index:
    start.append(df_income[country].iloc[0])
    end.append(df_income[country].iloc[-1])
```

In [58]:
```
most_advancing_10['start'] = start
most_advancing_10['end'] = end
```

In [59]:
```
# plotting the top 10 countries
most_advancing_10.plot(kind='bar', figsize=(15, 5))
plt.title('The Top 10 Countries That Has Developed The Most In The Time
plt.xlabel('Country', fontsize=14)
plt.ylabel('DGP/Capita')
plt.legend(['Difference', 'Start', 'End'], fontsize=12)
plt.show()
```

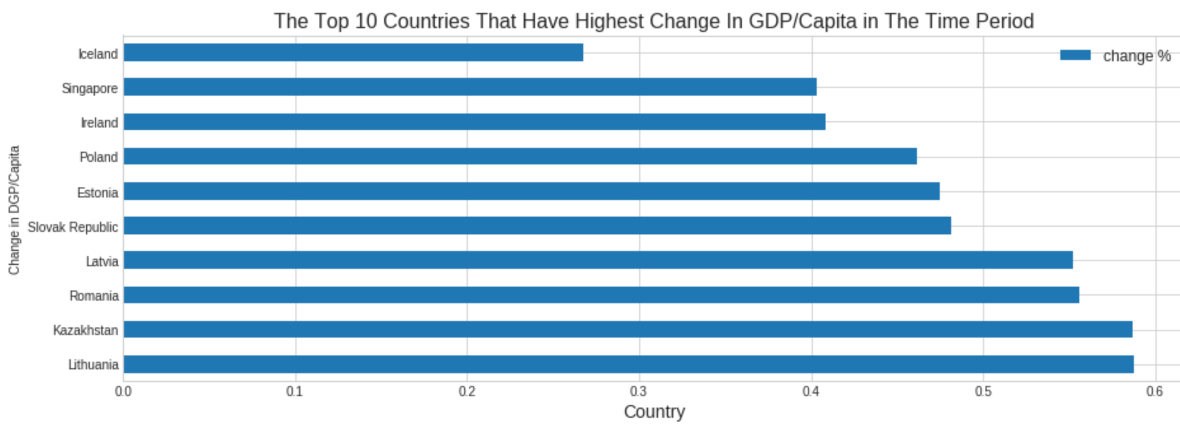


Here we can clearly see that some countries already started with a higher GDP/Capita like **Singapore and Ireland**. But they still manage to make a big change. Although some other countries had a small start they still made a big difference and outperformed countries like **Iceland** which had a higher start than countries like **Romania, Latvia, Kazakhstan, Estonia, Slovak Republic and Lithuania** but they made higher difference.

In [60]:
```
# calculating the change
most_advancing_10['change %'] = most_advancing_10['difference']/ most_ad
most_advancing_10['change %']
```

Out[60]:
```
0
Singapore         0.403189
Ireland           0.408408
Lithuania         0.587838
Slovak Republic   0.481728
Estonia           0.474916
Kazakhstan        0.587137
Latvia            0.552000
Romania           0.555556
Iceland           0.267782
Poland            0.461538
Name: change %, dtype: float64
```

In [61]:
```
# plotting the top 10 countries
most_advancing_10['change %'].sort_values(ascending=False).plot(kind='ba
plt.title('The Top 10 Countries That Have Highest Change In GDP/Capita i
plt.xlabel('Country', fontsize=14)
plt.ylabel('Change in DGP/Capita')
plt.legend(fontsize=12)
plt.show()
```



Here the change is more clear and we can see that although **Singapore** had the highest difference, it didn't have the highest change as it already started at a higher GDP/Capita.

We can also see the countries with the highest change are **Lithuania and Kazakhstan**.

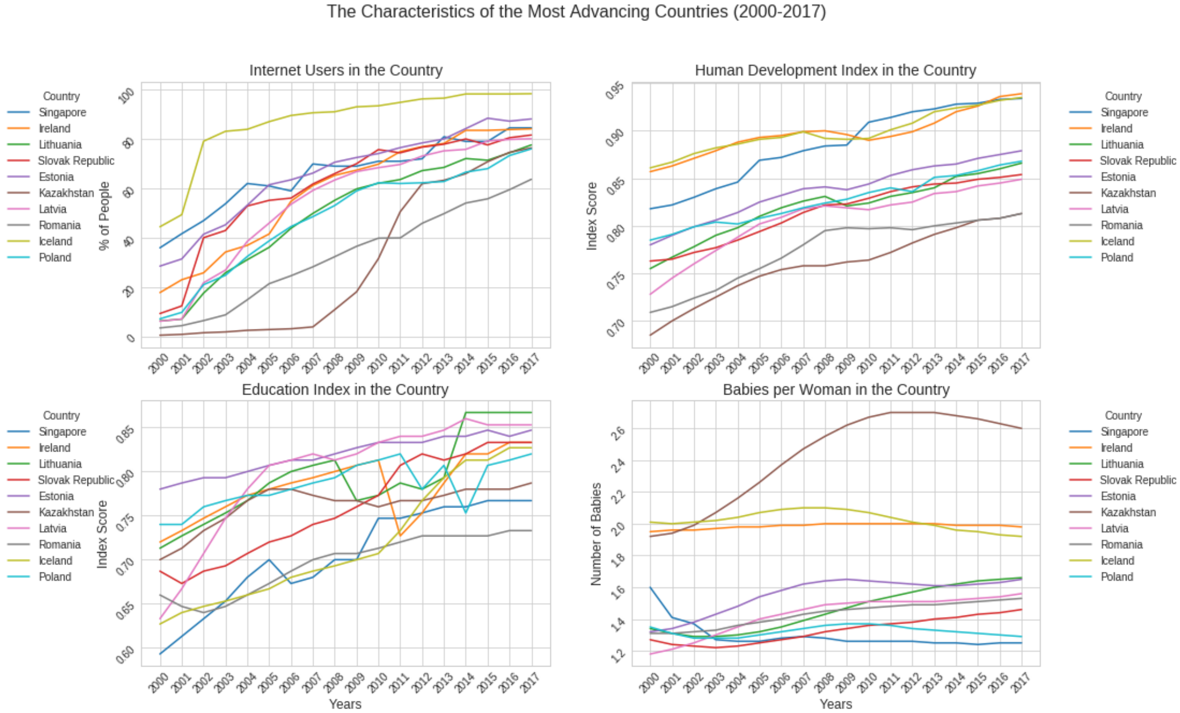
2. What are the characteristics of these countries that has developed the most in the time period?

In [62]:
```
def plot_features(df):

    # making the subplots
    fig, axs = plt.subplots(2, 2, figsize=(15, 10))

    fig.suptitle('The Characteristics of the Most Advancing Countries (2

    # Plotting Internet Use data
    for c in df.index:
        axs[0][0].plot(df_iu['year'], df_iu[c].values)

    axs[0][0].legend(df.index, title='Country', bbox_to_anchor=(-.35, 1)
    axs[0][0].set_title('Internet Users in the Country', fontsize=14)
    axs[0][0].set_ylabel('% of People', fontsize=12)
    axs[0][0].set_xticks(df_iu['year'].values)
    axs[0][0].tick_params(labelrotation=45)

    # Plotting Human Development Index data
    for c in df.index:
        axs[0][1].plot(df_hid['year'], df_hid[c].values)

    axs[0][1].legend(df.index, title='Country', bbox_to_anchor=(1.05, 1)
    axs[0][1].set_title('Human Development Index in the Country', fontsi
    axs[0][1].set_ylabel('Index Score', fontsize=12)
    axs[0][1].set_xticks(df_hid['year'].values)
    axs[0][1].tick_params(labelrotation=45)


    # Plotting the Education Index data
    for c in df.index:
        axs[1][0].plot(df_owid['year'], df_owid[c].values)

    axs[1][0].legend(df.index, title='Country', bbox_to_anchor=(-.35, 1)
    axs[1][0].set_title('Education Index in the Country', fontsize=14)
    axs[1][0].set_xlabel('Years', fontsize=12)
    axs[1][0].set_ylabel('Index Score', fontsize=12)
    axs[1][0].set_xticks(df_owid['year'].values)
    axs[1][0].tick_params(labelrotation=45)

    # Plotting the Fertility data
    for c in df.index:
        axs[1][1].plot(df_fertility['year'], df_fertility[c].values)

    axs[1][1].legend(df.index, title='Country', bbox_to_anchor=(1.05, 1)
    axs[1][1].set_title('Babies per Woman in the Country', fontsize=14)
    axs[1][1].set_xlabel('Years', fontsize=12)
    axs[1][1].set_ylabel('Number of Babies', fontsize=12)
    axs[1][1].set_xticks(df_fertility['year'].values)
    axs[1][1].tick_params(labelrotation=45)

    #fig.tight_layout()
    plt.show()
```

The function takes a dataframe where the index of the dataframe is the names of the countries and then makes a subplot of the 4 indicators we have (Internet Use, Human Development

Index, Education Index, Fertility rating) across the years.

In [63]:
```
plot_features(most_advancing_10)
```



In [64]:
```
most_advancing_10.sort_values('end')
```

Out[64]:

	difference	start	end	change %
0				
Romania	13000	10400	23400	0.555556
Kazakhstan	14150	9950	24100	0.587137
Latvia	13800	11200	25000	0.552000
Poland	12600	14700	27300	0.461538
Lithuania	17400	12200	29600	0.587838
Estonia	14200	15700	29900	0.474916
Slovak Republic	14500	15600	30100	0.481728
Iceland	12800	35000	47800	0.267782
Ireland	27200	39400	66600	0.408408
Singapore	35400	52400	87800	0.403189

According to the plots all these countries are very similar in the first 3 indicators:

- Over the years their scores increases in number of interent users, education and human development index.
- Although their ending points differes we can still see that they have good scores
  - we can see that the top 3 countries in Human Development are **Singapore, Ireland and Iceland**. This can easly be explained as they did have a higher starting and

ending GDP/Capita than other countries on the list.
    - We can also see that most of these countries have a really high percentage of their people using the internet.
    - And most of them also have a very high educational index
- For the Fertility indicator
    - We can see that most of the countries are below **1.6**
    - They are all below 2.0 except for **Kazakhstan** which is the country with the second to lowest ending GDP/Capita but we can't say that the fertility rate is the final indicator on country's development as **Romania** has a lowe Fertility rates but still has the lowest GDP/Capita.
    - **But we can say that most of the most advancing countries has a low fertility rate**.

- One more question we can ask now: does these countries have higher educational index or other index because they have a higher GDP/Capita or they have a higher GDP/Capita because they have a higher educational index?

3.Do these countries have higher educational index or other index because they have a higher GDP/Capita or they have a higher GDP/Capita because they have a higher educational index?

To answer this question we will have to answer the 2 questions within and then we will reach our conclusion. I will be answering these questions using the ending points (2017) in our data as it is the closest to our time and would be more accurate.

Does countries with higher education index have higher income?

In [65]:
```
# getting the countries with the highest education in 2017
df_owid[df_owid['year'] == 2017].sort_values(by=148, axis=1, ascending=F
```

Out[65]:

	year	Germany	Switzerland	United States	Canada	Lithuania	Israel	Australia	United Kingdom	Latvia
148	2017	0.94	0.893	0.893	0.887	0.867	0.867	0.86	0.86	0.853

1 rows × 178 columns

In [66]:
```
# the top 5 countries according to the educational index in 2017
highest_education = ['Germany', 'United States', 'Switzerland', 'Canada'
# getting only the data for these countries
highest_education_scores = df_owid[df_owid['year'] == 2017][highest_educ
```

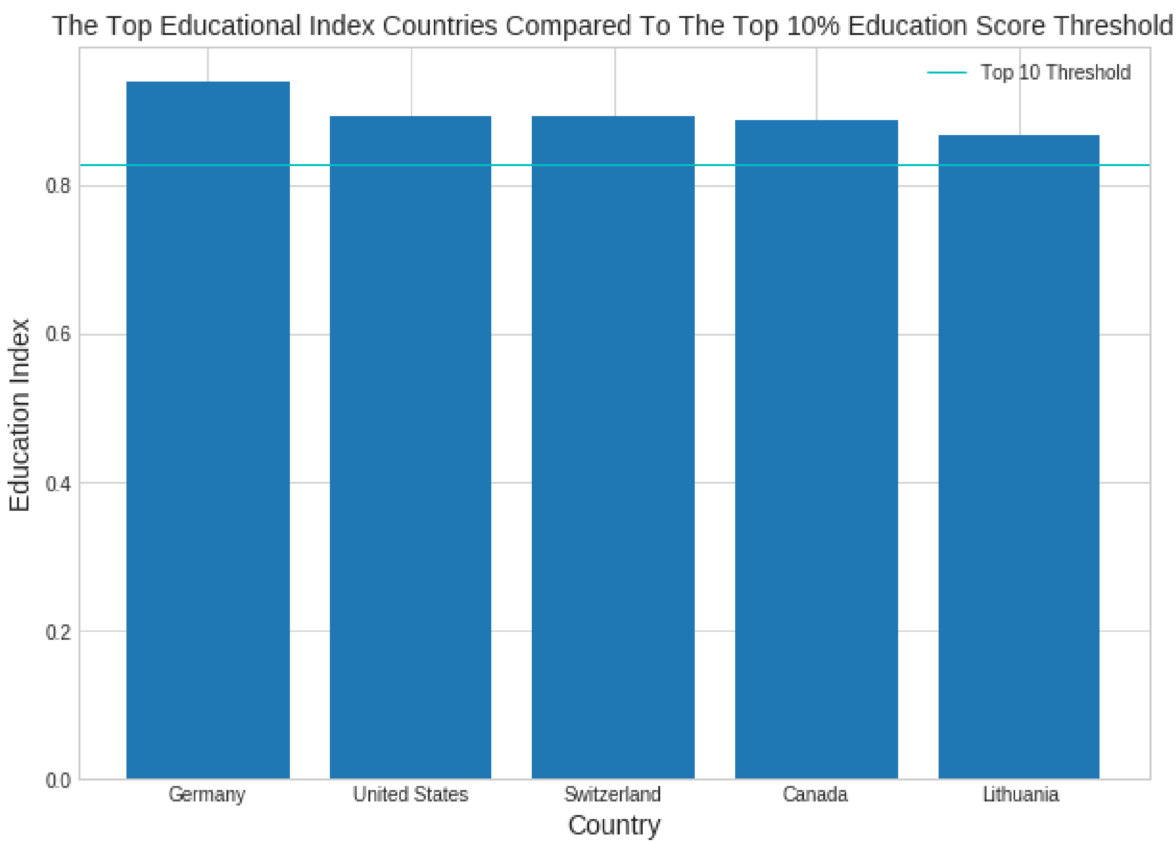
In [67]:
```
# getting the top 10% threshold in the eductional index
highest_education_scores['top 10'] = df_owid[df_owid['year'] == 2017].dı
highest_education_scores
```

Out[67]:

	Germany	United States	Switzerland	Canada	Lithuania	top 10
148	0.94	0.893	0.893	0.887	0.867	0.8294

Here we are comparing the countries educational scores to say if they are among the top 10% of the scores in 2017 or not.

In [68]:
```
plt.figure(figsize=(10, 7))
plt.bar(highest_education_scores.columns[:-1], highest_education_scores.
plt.axhline(y=highest_education_scores.iloc[0, -1],linewidth=1, color='c
plt.legend()
plt.title('The Top Educational Index Countries Compared To The Top 10% E
plt.xlabel('Country', fontsize=14)
plt.ylabel('Education Index', fontsize=14)
plt.show()
```

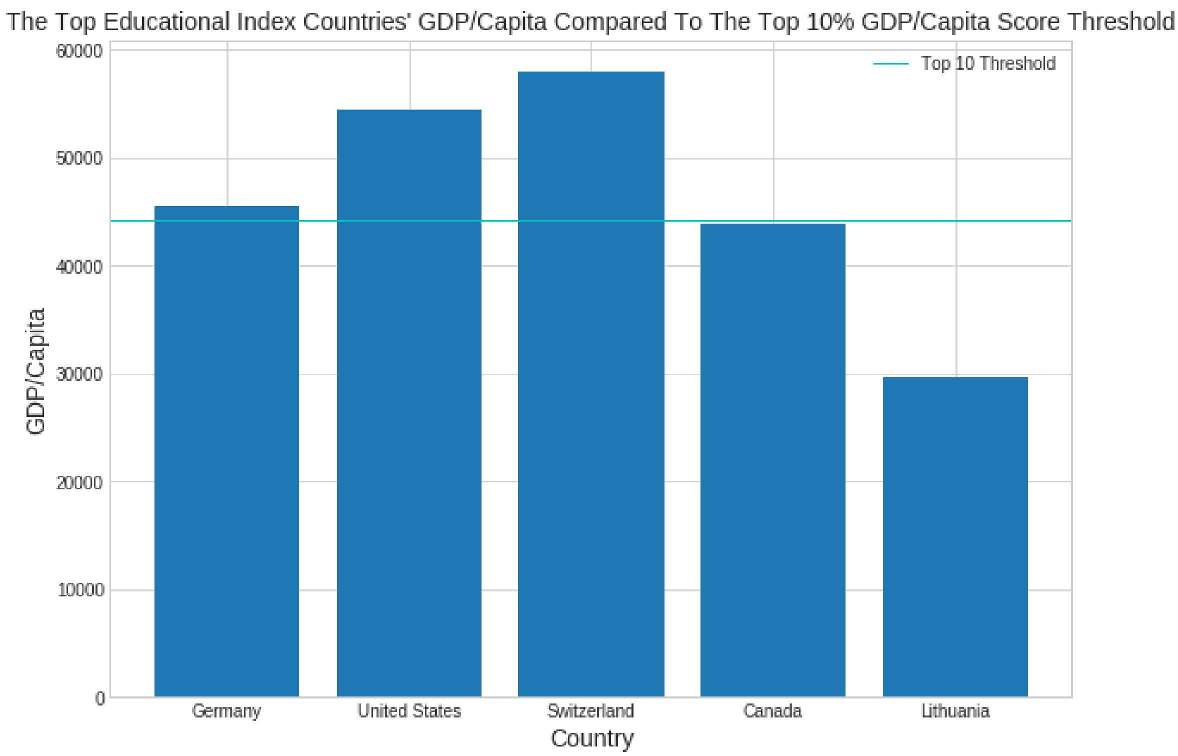


This shows the top 5 countries in educational score compared to the top 10 percent threshold. We will use it to compare results in the comming cells.

In [69]:
```
# now getting the GDP/Capita to of these countries
highest_education_income_scores = df_income[df_income['year'] == 2017][ŀ
```

In [70]:
```
# getting the top 10% income threshold
highest_education_income_scores['top 10'] = df_income[df_income['year']
```

In [71]:
```
plt.figure(figsize=(10, 7))
plt.bar(highest_education_income_scores.columns[:-1], highest_education_
plt.axhline(y=highest_education_income_scores.iloc[0, -1],linewidth=1, c
plt.legend()
plt.title("The Top Educational Index Countries' GDP/Capita Compared To T
plt.xlabel('Country', fontsize=14)
plt.ylabel('GDP/Capita', fontsize=14)
plt.show()
```



We can see that nearly all of the countries with the top educational scores have a really high GDP/Capita and they are among the top 10% except for Lithuania which still has a really high GDP/Capita but not in the top 10%.

now to the other question.

Does countries with higher income index have higher education index?

In [72]:
```
# getting the countries with the highest GDP/Capita in 2017
df_income[df_income['year'] == 2017].sort_values(by=218, axis=1, ascendi
```

Out[72]:

	Qatar	Luxembourg	Singapore	Brunei	United Arab Emirates	Ireland	Kuwait	Norway	Switzerland
218	113000	93100	87800	72500	66700	66600	66000	65000	58000

1 rows × 178 columns

In [73]:
```
# the top 5 countires according to the GDP/Capita in 2017
highest_income = ['Qatar', 'Luxembourg', 'Singapore', 'Brunei', 'United
# getting the scores for only these countries
highest_income_scores = df_income[df_income['year'] == 2017][highest_inc
highest_income_scores
```

Out[73]:

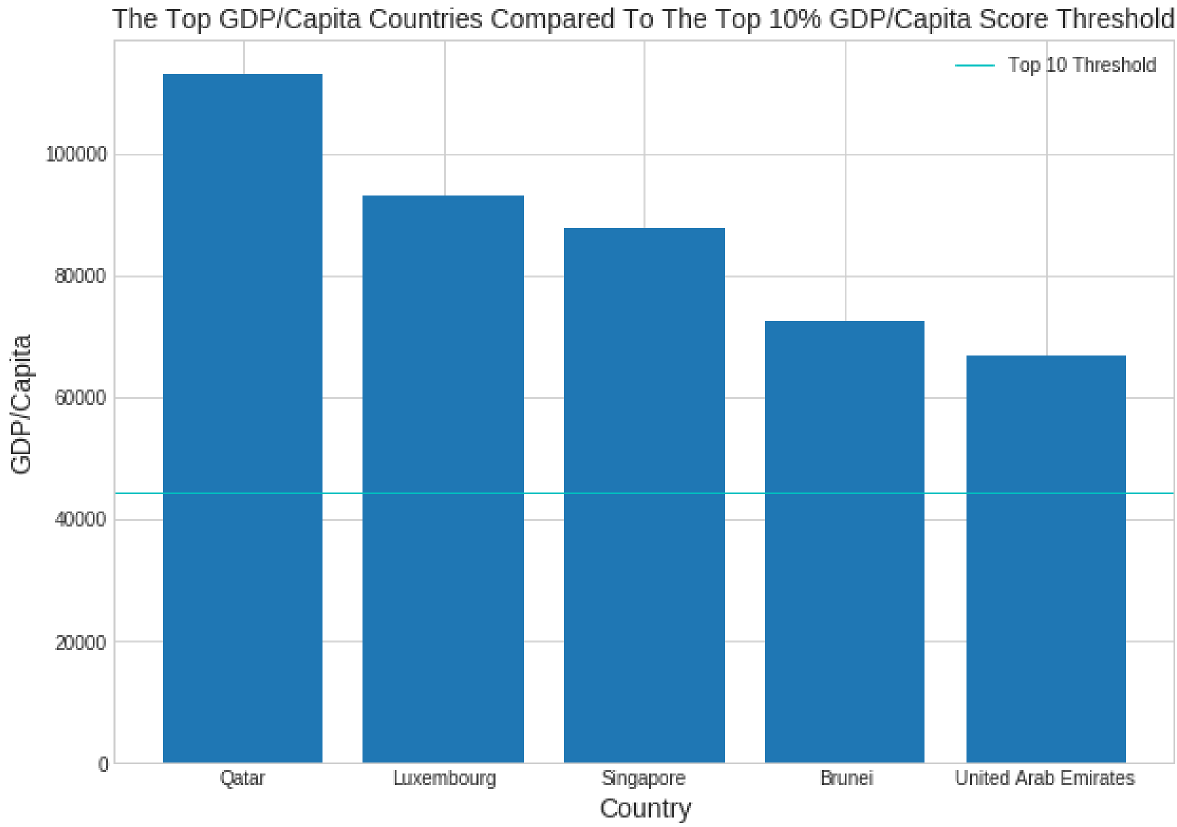
	Qatar	Luxembourg	Singapore	Brunei	United Arab Emirates
218	113000	93100	87800	72500	66700

In [74]:
```
# getting the top 10% threshold in the GDP/Capita
highest_income_scores['median'] = df_income[df_income['year'] == 2017].c
highest_education_scores
```

Out[74]:

	Germany	United States	Switzerland	Canada	Lithuania	top 10
148	0.94	0.893	0.893	0.887	0.867	0.8294

In [75]:
```
plt.figure(figsize=(10, 7))
plt.bar(highest_income_scores.columns[:-1], highest_income_scores.iloc[0
plt.axhline(y=highest_income_scores.iloc[0, -1],linewidth=1, color='c',
plt.legend()
plt.title('The Top GDP/Capita Countries Compared To The Top 10% GDP/Capi
plt.xlabel('Country', fontsize=14)
plt.ylabel('GDP/Capita', fontsize=14)
plt.show()
```



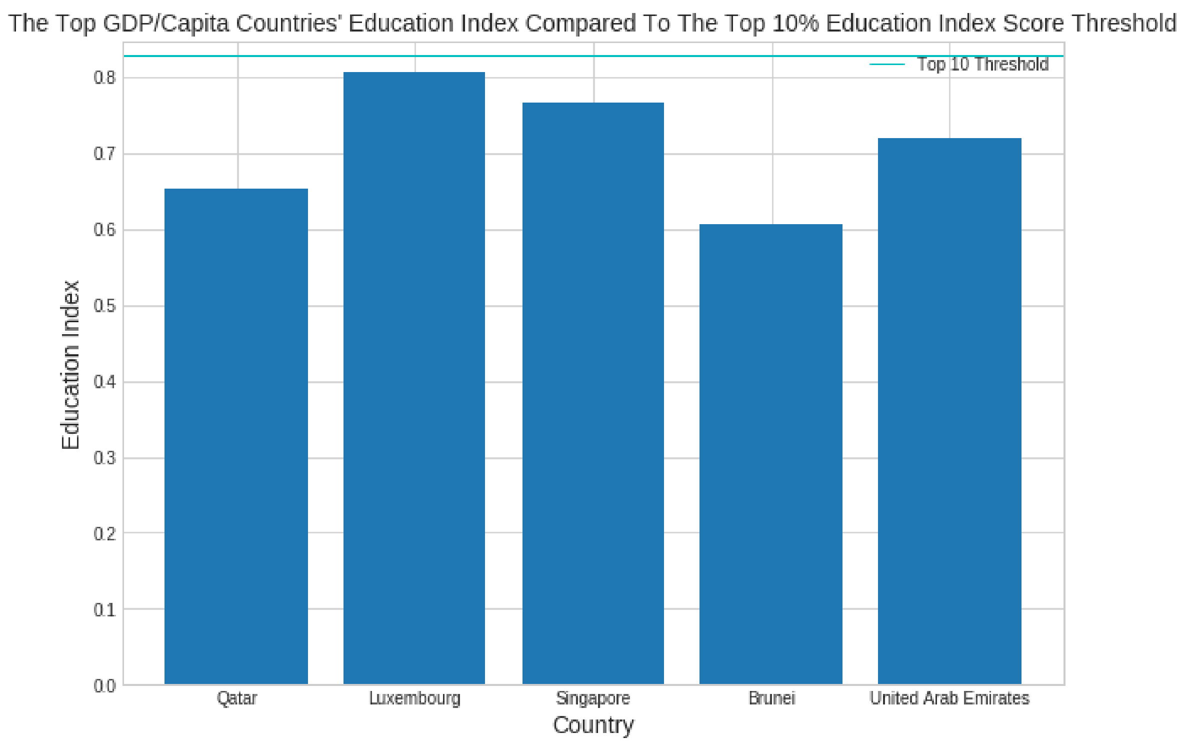
This shows the top 5 countries in GDP/Capita compared to the top 10 percent threshold. We will use it to compare results in the comming cells.

In [76]:
```
# now getting the education index for these countries
highest_income_edu_scores = df_owid[df_owid['year'] == 2017][highest_inc
# adding the top 10% education index threshold
highest_income_edu_scores['top 10'] = df_owid[df_owid['year'] == 2017].c
highest_income_edu_scores
```

Out[76]:

	Qatar	Luxembourg	Singapore	Brunei	United Arab Emirates	top 10
148	0.653	0.807	0.767	0.607	0.72	0.8294

In [77]:
```
plt.figure(figsize=(10, 7))
plt.bar(highest_income_edu_scores.columns[:-1], highest_income_edu_score
plt.axhline(y=highest_income_edu_scores.iloc[0, -1],linewidth=1, color='
plt.legend()
plt.title("The Top GDP/Capita Countries' Education Index Compared To The
plt.xlabel('Country', fontsize=14)
plt.ylabel('Education Index', fontsize=14)
plt.show()
```



Although these countries have the highest GDP/Capita, they still are not in the top 10% when it comes to the Education Index. But they still have a relatively high Education Index.

The answer to our question *Do these countries have higher educational index or other index because they have a higher GDP/Capita or they have a higher GDP/Capita because they have a higher educational index?*

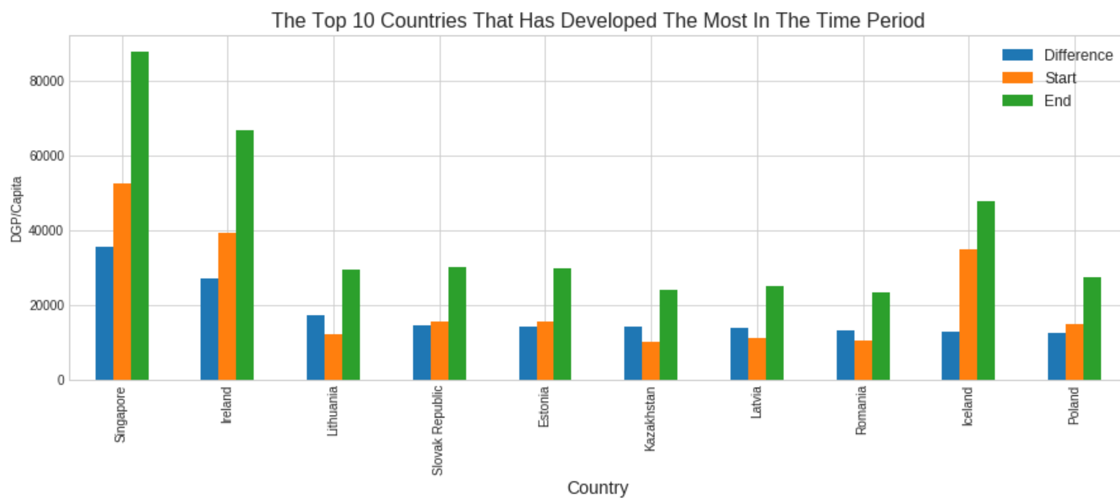
We can say that having a really high Education Index can guarantee you to have a really high GDP/Capita even among the top 10% But having the highest GDP/Capita can't guarantee you to have the highest Education Index top 10% but still can get you a relatively high score to be among the top countries.

Conclusions

Which countries has developed the most (GDP / Capita) in the choosen time period (2000 - 2017)?

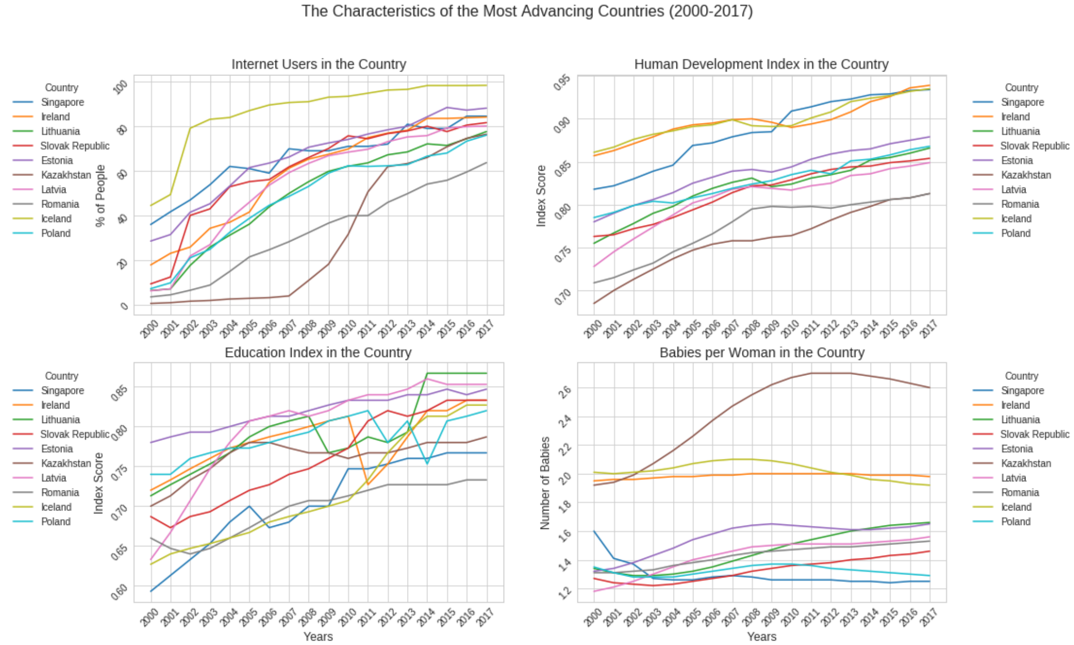
- Singapore, Ireland, Lithuania, Slovak Republic, Estonia,

```
Kazakhstan, Latvia, Romania, Iceland, Poland
```



What are the characteristics of these countries that has developed the most in the time period?

- Over the years in the time period:
  - Increasing Number of Internet Users.
  - Increasing Educational Index.
  - Increasing Human Development Index.
  - Lower Fertility rates below 2.0 and sometime below 1.6 except for Kazakhstan



Do these countries have higher educational index or other index because they have a higher GDP/Capita or they have a higher GDP/Capita because they have a higher educational index?

- Having a really high Education Index can guarantee you to have a really high GDP/Capita even among the top 10% But having the highest GDP/Capita can't guarantee you to have the highest Education Index top 10% but still can get you a relatively high score to be among the top countries.

Countries with the highest Education Index	Countries with the highest GDP/Capita