This project was completed by

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Project Description

This project aims to study marital age in different countries. It does so by studying the relationship between marital age for females and different economic and social factors. The aim of this project is to see if the average age of when females get married in a country has an effect on or affected by other important socioeconomic variables like GDP, female unemployment, and female education. The data we have was obtained from the World Bank's website: https://data.worldbank.org/. The data is specific for the year 2011 as it is the most recent year with sufficient data. We use graphs and maps to present the results of thi data as well as some statistical measurement. Our data suggests a positive correlation between marital age and GDP and Female students, but a negative correlation between marital age and unemployed females. However, it also shows a weak correlation so the results are not reliable. Throughout this project, there will be some comentaries to further elaborate results and explain the process.

```
import pandas as pd
import requests
import numpy as np
import matplotlib.pyplot as plt
import requests, io
import zipfile as zf
import shutil
import os
```

```
url1 = "https://raw.githubusercontent.com/ovp203/My_first_repository_/master/SMAM_data_20
url2 = "https://raw.githubusercontent.com/ovp203/My_first_repository_/master/GDP_data_201
url3 = "https://raw.githubusercontent.com/ovp203/My_first_repository_/master/unemployment_
url5 = "https://raw.githubusercontent.com/ovp203/My_first_repository_/master/education_da
url6 = "https://raw.githubusercontent.com/ovp203/My_first_repository_/master/population_d

GDPdata = pd.read_csv(url2)
SMAMdata = pd.read_csv(url1)
unemployment_data = pd.read_csv(url3)
EDUCATIONdata = pd.read_csv(url5)
popdata = pd.read_csv(url6)
```

After importing the data, we started cleaning it by removing the unwanted variables to make it easier to read

```
SMAMdata.drop(["ISO code"], axis=1, inplace = True)
SMAMdata.drop(["YearStart"], axis=1, inplace = True)
SMAMdata.drop(["YearEnd"], axis=1, inplace = True)
SMAMdata.drop(["Sex"], axis=1, inplace = True)
SMAMdata.drop(["DataProcess"], axis=1, inplace = True)
SMAMdata.drop(["DataCatalog ShortName"], axis=1, inplace = True)
SMAMdata.drop(["DataCatalog ID"], axis=1, inplace = True)
SMAMdata.drop(["DataCatalog LongName"], axis=1, inplace = True)
SMAMdata.drop(["Data Source"], axis=1, inplace = True)
SMAMdata.drop(["Note on Data"], axis=1, inplace = True)
SMAMdata.drop(["Note on Country and Population"], axis=1, inplace = True)


GDPdata.drop(["Country Code"], axis=1, inplace = True)
GDPdata.drop(["Indicator Name"], axis=1, inplace = True)
GDPdata.drop(["Indicator Code"], axis=1, inplace = True)


unemployment_data.drop(["Series"], axis=1, inplace = True)
unemployment_data.drop(["Country Code"], axis=1, inplace = True)
unemployment_data.drop(["VarName"], axis=1, inplace = True)


EDUCATIONdata.drop(["Country Code"], axis=1, inplace = True)
EDUCATIONdata.drop(["Indicator Code"], axis=1, inplace = True)
EDUCATIONdata.drop(["Indicator Name"], axis=1, inplace = True)
```

We then rename the variables to make it clearer: 1) Marital Age is the average age of a female when she first gets married in every country. 2) GDP is the GDP of the country 3) Unemployed females is the percentage of females who are unemployed from the total females in the labor force. 4) Population is the population of each country. 5) Female students is the percentage of students in secondary education that are females

```
SMAMdata.rename(columns = {"DataValue": "Marital Age", "Country or area": "Country Name"
GDPdata.rename(columns = {"2011": "GDP"}, inplace = True)
unemployment_data.rename(columns = {"Value": "Unemployed Females"}, inplace = True)
popdata.rename(columns = {"2011": "Population"}, inplace = True)
EDUCATIONdata.rename(columns = {"2011": "Female Students"}, inplace = True)
```

Following, we merge all data sets together to get one big data set.

```
combo = pd.merge(SMAMdata,GDPdata,
                 on='Country Name',
                 how='left',
                 indicator=True)

combo3 = pd.merge(combo2, unemployment_data,
                 on= 'Country Name',
                 how = 'left')
combo3 = pd.merge(combo3, popdata,
                 on= 'Country Name',
                 how = 'left')
DataSet = pd.merge(combo3,EDUCATIONdata,
                  on= 'Country Name',
                  how= 'left')


DataSet.drop(["_merge"], axis=1, inplace = True)
```

Here we are making sure that all variables are floats so that we can round them to the nearest 1 decimal place

```
DataSet.dtypes
```

```
Country Name            object
Marital Age            float64
GDP                    float64
LFPR                   float64
Unemployed Females     float64
Population             float64
Female Students        float64
dtype: object
```

Just viewing the data set to make sure we are good and proceed

```
DataSet.head()
```

	Country Name	Marital Age	GDP	LFPR	Unemployed Females	Population	Female Students
0	Albania	25.1	1.289087e+10	36.070000	13.750000	2.905195	47.347382
1	Armenia	24.6	1.014211e+10	31.430000	19.610001	2.875581	47.848419
2	Australia	29.9	1.390557e+12	67.470001	5.300000	22.340024	NaN
3	Austria	27.1	4.311203e+11	54.810001	4.580000	8.391643	47.758678
4	Bangladesh	18.6	1.286379e+11	NaN	NaN	153.911916	52.526081

We are rounding all the variables to 1 decimal place.

```
desred_decimals = 1
DataSet['Female Students'] = DataSet['Female Students'].apply(lambda x: round(x,desred_de
DataSet['Unemployed Females'] = DataSet['Unemployed Females'].apply(lambda x: round(x,des

DataSet['Marital Age'] = DataSet['Marital Age'].apply(lambda x: round(x,desred_decimals))
DataSet['GDP'] = DataSet['GDP'].apply(lambda x: round(x,desred_decimals))
```

```
DataSet.head()
```

	Country Name	Marital Age	GDP	LFPR	Unemployed Females	Population	Female Students
0	Albania	25.1	1.289087e+10	36.070000	13.8	2.905195	47.3
1	Armenia	24.6	1.014211e+10	31.430000	19.6	2.875581	47.8
2	Australia	29.9	1.390557e+12	67.470001	5.3	22.340024	NaN
3	Austria	27.1	4.311203e+11	54.810001	4.6	8.391643	47.8
4	Bangladesh	18.6	1.286379e+11	NaN	NaN	153.911916	52.5

We then sort the values to be in ascending order of marital age to be able to plot the graph

```
DataSet = DataSet.sort_values(["Marital Age"], ascending=True, axis=0)
```

```
DataSet.corr()
```

...

	Marital Age	GDP	LFPR	Unemployed Females	Population	Female Students
Marital Age	1.000000	0.160481	0.273015	-0.116044	-0.257301	0.032460
GDP	0.160481	1.000000	0.269742	-0.125114	0.340039	-0.142043
LFPR	0.273015	0.269742	1.000000	-0.585635	-0.009165	-0.123991
Unemployed Females	-0.116044	-0.125114	-0.585635	1.000000	0.258407	0.056181
Population	-0.257301	0.340039	-0.009165	0.258407	1.000000	-0.194367

The above table shows the correlation between all variables. It is clear that marital age has a positive corelation with GDP and Female Students, as in the higher % of female students, the higher the age females get married. The higher the GDP, the higher the age of females when they get married.

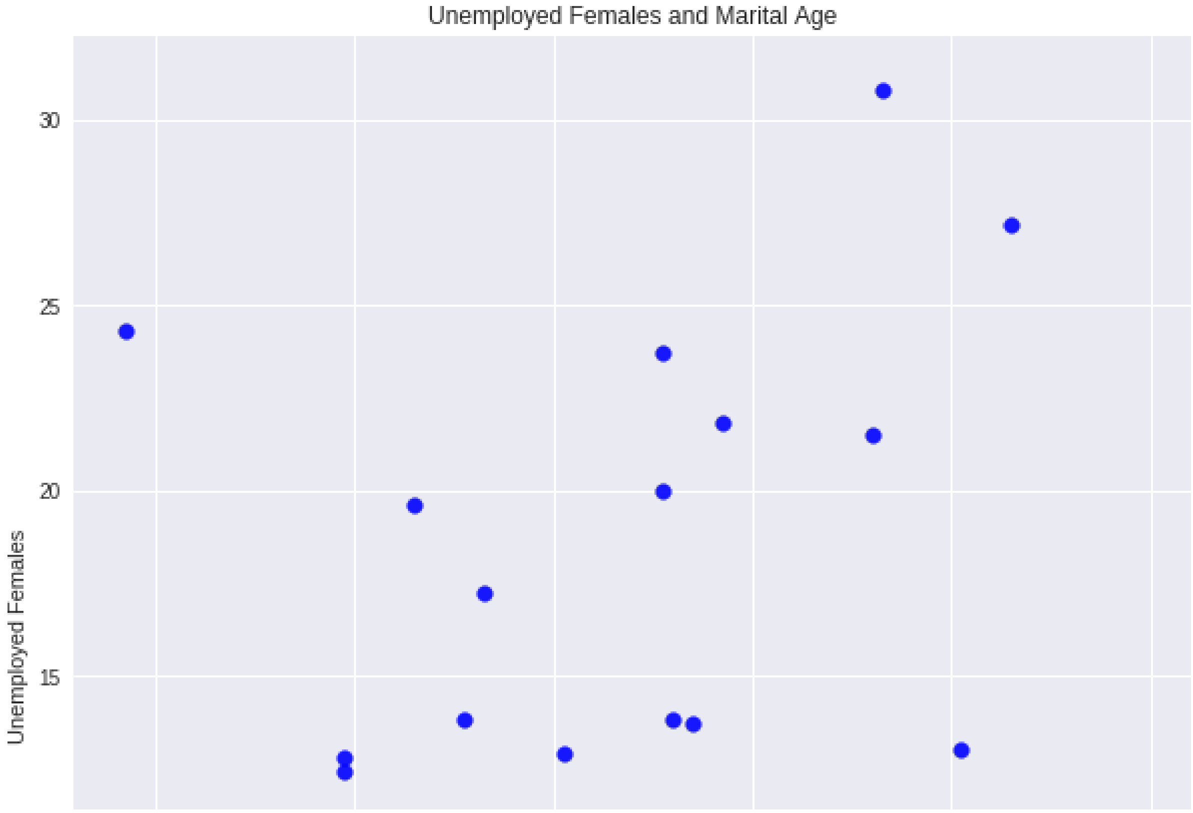
The results also show that there is a negative correlation between the age when females get married and the % of unemployed females. This shows that the more unemployed females, the earlier females get married.

This is a graph showing the relationship between unemployed females and marital age.

There is a really weak correlation between the variables. However, it is interesting to observe that some of the outliers have a high unemployment rate and, at the same time, high marital age.

```
DataSet.plot.scatter(x="Marital Age",
                y="Unemployed Females",
                alpha=0.9,
                title='Unemployed Females and Marital Age',
                s=60,
                figsize=(10, 11),
                color = "blue")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fdc9ff5ecd0>
```

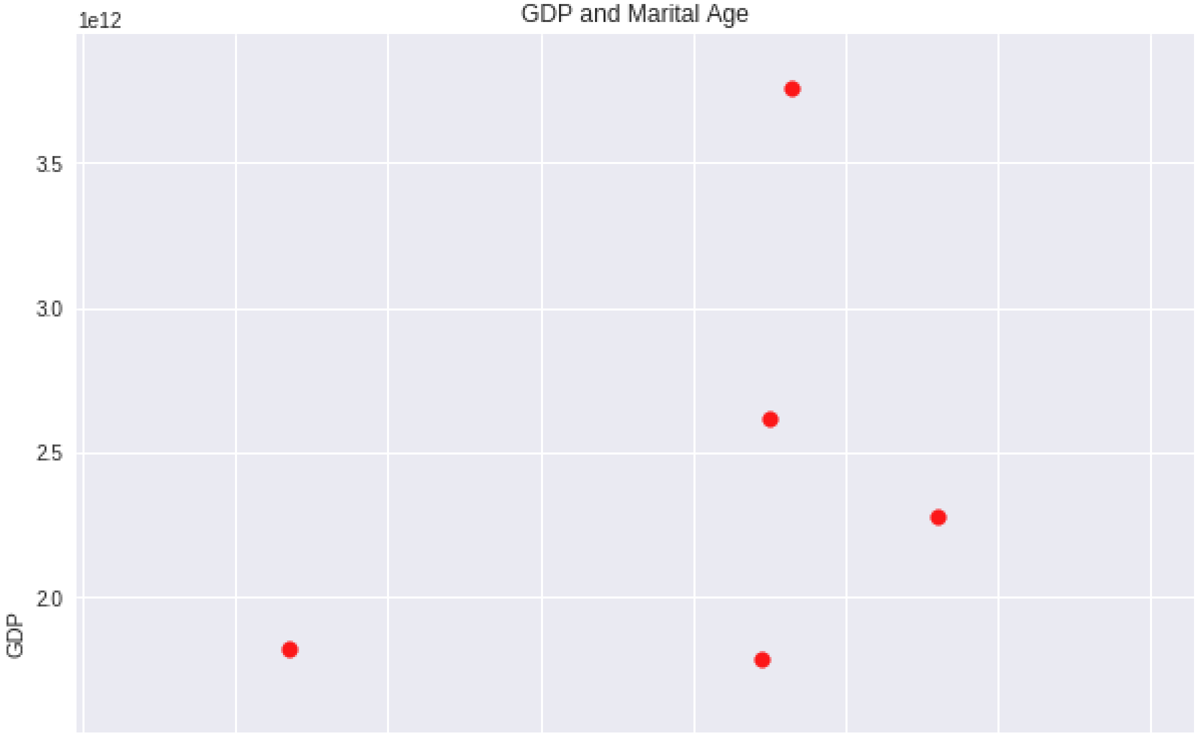


This is a graph between GDP and Marital Age.

The relationship seems no be not very significant, however, there is a slight trend of some countries that have higher GDP to have a higher marital age.

```
DataSet.plot.scatter(x="Marital Age",
                y="GDP",
                alpha=0.9,
                title='GDP and Marital Age',
                s=60,
                figsize=(10, 11),
                color = "red")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fdc9ff51f90>
```



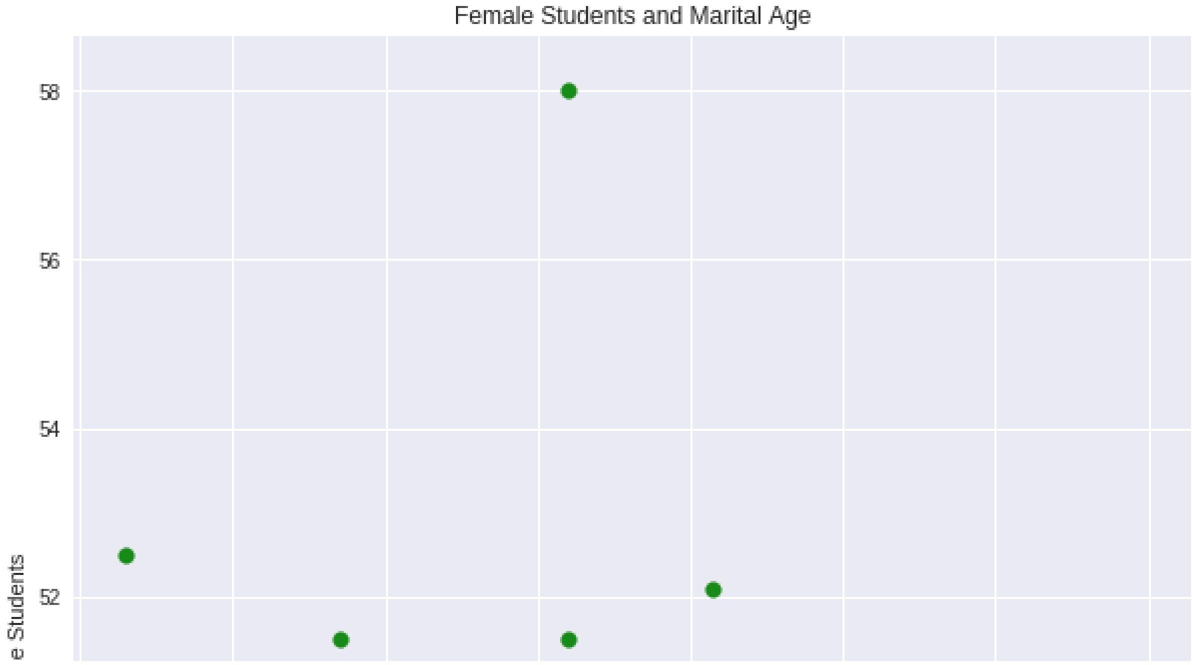
This is a graph between Marital Age and Female students

The relationship between variable is rather weak overall, however, we can observe that in countries that have the lowest education rates the marital age is very low.

```
DataSet.plot.scatter(x="Marital Age",
                y="Female Students",
                alpha=0.9,
                title='Female Students and Marital Age',
                s=60,
                figsize=(10, 11),
                color = "green")
```

...

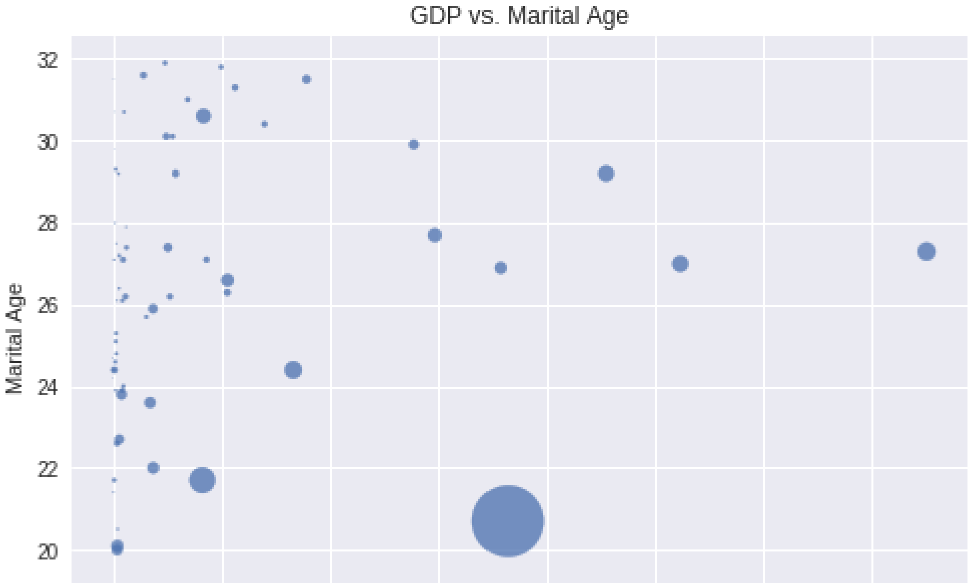
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fdcacecbd50>
```



Now we will demonstrate the relationship of GDP to the marital age on a plot given the size of the countries

We are setting the GDP as our x-axis and the marital age as y-axis. The size of the bubble correlate with the size of the countries, which gives us the idea about where the larger and smaller countries stand in relationship to the outliers.

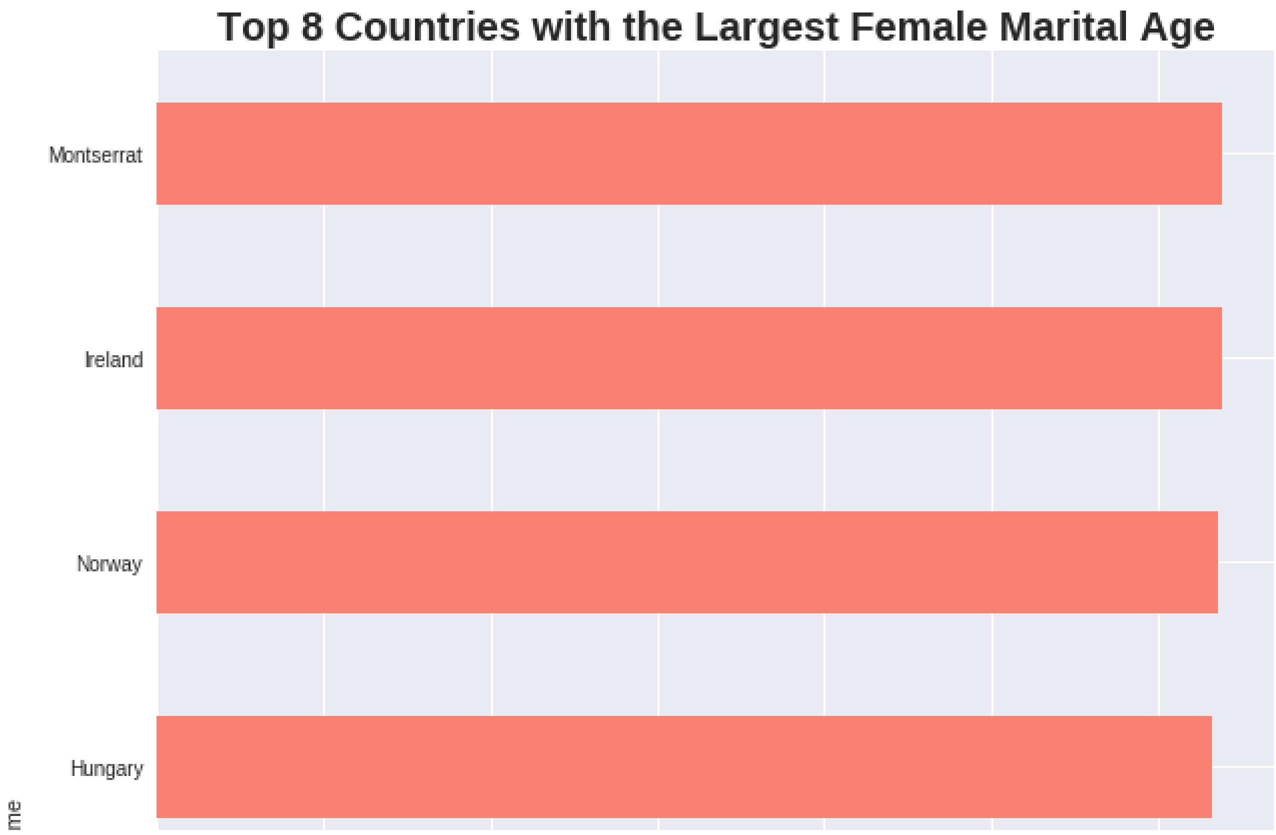
```
fig, ax = plt.subplots()

ax.scatter((DataSet["GDP"]), (DataSet["Marital Age"]),
            s=DataSet['Population'],
            alpha= 0.76)


ax.set_title("GDP vs. Marital Age")
ax.set_ylabel("Marital Age")
ax.set_xlabel("GDP")
xlabel_list = np.exp(range (5, 20))
xlabel_list = np.round(xlabel_list, -2)


ax.set_xticklabels(xlabel_list)

ax.spines["right"].set_visible(False)
ax.spines["top"].set_visible(False)

plt.savefig("hc.png", bbox_inches="tight", dpi = 600)

plt.show()
```



This is a bar chart of the top 8 countries with highest female marital age.

Montserrat is the highest with 31.9 as the average age, followed by Ireland and Norway.

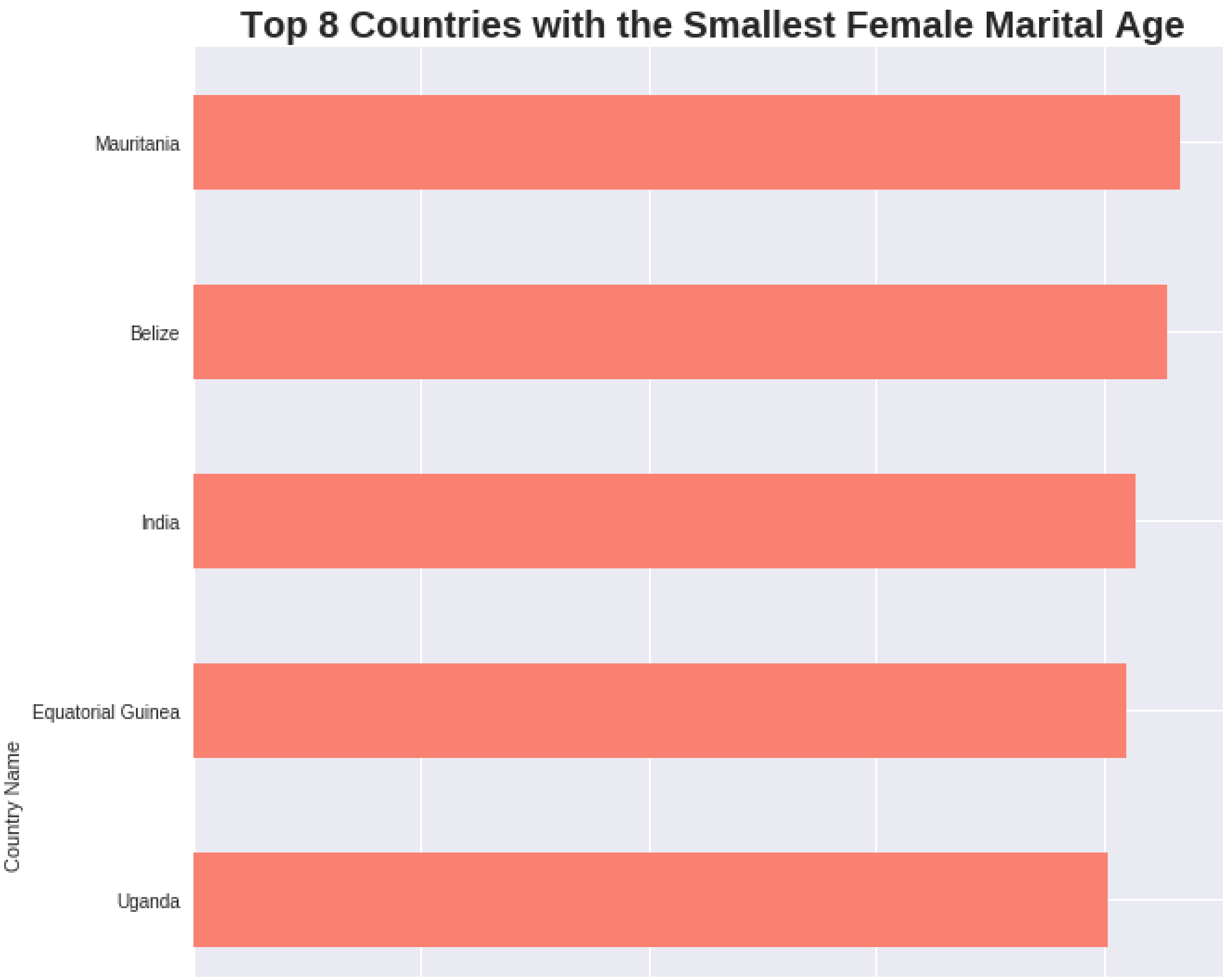
```
DataSet = DataSet.set_index("Country Name")
dsnew = DataSet.sort_values("Marital Age")
dsnew = DataSet["Marital Age"].tail(8)
dsnew.plot(kind="barh", figsize=(10, 15), color= "salmon")
plt.title("Top 8 Countries with the Largest Female Marital Age", fontsize=20,fontweight='
plt.show()
```



This bar chart shows the top 8 countries witht the lowest female marital age.

Bangladesh is country whose average female gets married the earliest with an average marital age of 18.6, followed by Mozambique and Nepal.

```
dsnew = DataSet.sort_values("Marital Age")
dsnew = DataSet["Marital Age"].head(8)
dsnew.plot(kind="barh", figsize=(10, 15), color= "salmon")
plt.title("Top 8 Countries with the Smallest Female Marital Age", fontsize=20,fontweight=
plt.show()
```



Mapping

In order to demonstrate on a map how the marital age varies not only across countries, but across regions of the world as well, we created a map. The lowest marital age correlates with the lightest color and the highest marital age with the darker accordingly. Due to the limited availability of the data for marital age, unfortunately, we are not able to abserve the colors for every country of the world. However, we can observe the general trends: in Australia, Greenland and most of the countries of Northern Europe the marital age is higher than average, while in countries with data for Africa, Asia and the Middle East it is lower.

```
!pip install geopandas
```

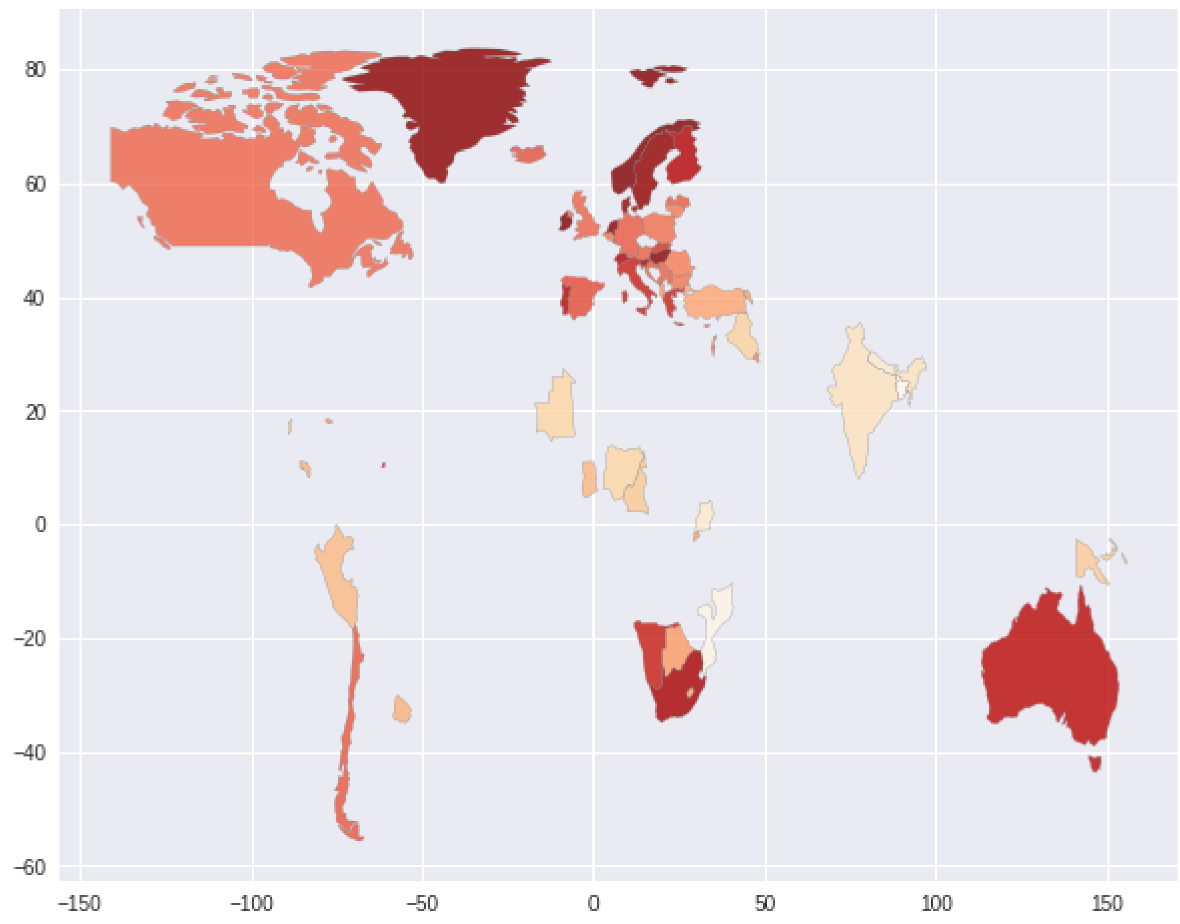
```
Requirement already satisfied: geopandas in /usr/local/lib/python2.7/dist-packa
Requirement already satisfied: descartes in /usr/local/lib/python2.7/dist-packa
Requirement already satisfied: shapely in /usr/local/lib/python2.7/dist-package
Requirement already satisfied: fiona in /usr/local/lib/python2.7/dist-packages
Requirement already satisfied: pandas in /usr/local/lib/python2.7/dist-packages
Requirement already satisfied: pyproj in /usr/local/lib/python2.7/dist-packages
Requirement already satisfied: matplotlib in /usr/local/lib/python2.7/dist-pack
Requirement already satisfied: six>=1.7 in /usr/local/lib/python2.7/dist-packag
Requirement already satisfied: click-plugins in /usr/local/lib/python2.7/dist-p
Requirement already satisfied: enum34 in /usr/local/lib/python2.7/dist-packages
Requirement already satisfied: cligj>=0.4 in /usr/local/lib/python2.7/dist-pack
Requirement already satisfied: munch in /usr/local/lib/python2.7/dist-packages
```

```
world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))
world.rename(columns = {"name": "Country Name"}, inplace = True)
```

```
NEW = pd.merge(world, DataSet, on='Country Name')
```

```
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr
```

```
fig, ax = plt.subplots(figsize = (10,8))

NEW.plot(ax = ax, edgecolor='tab:grey',
            column='Marital Age',
            cmap='OrRd',
            alpha = 0.8)
plt.show()
```



Conclusion

In conclusion, after running all these codes and getting the correlation, it seems that marital age is more culturally related and based by regions than dependent on other socioeconomic factors. Of course you may be able to link a correlation but as mentioned before it is a weak correlation.