# app

# October 7, 2019

#### 0.1 Overview

This homework asks you to visualize data from the Gapminder Foundation (https://www.gapminder.org). Download the full Gapminder dataset from the Open Numbers Github repository: https://github.com/open-numbers/ddf-gapminder-systema\_globalis

```
In [1]: import pandas as pd
    import matplotlib.pyplot as plt
    import seaborn as sns
    import numpy as np
    %matplotlib inline
```

# 0.2 Problem 1

In [3]: run\_1()

Take the Gapminder Test: http://forms.gapminder.org/s3/test-2018. What score did you receive? Did any of the answers surprise you? Choose a question from the test, re-state it, and answer it using visualization and summarization. Provide a figure and any relevant output with your answer.

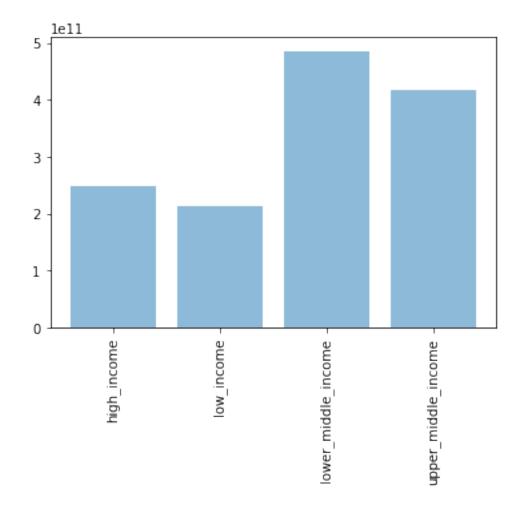
What score did you receive? - 23%

Did any of the answers surprise you? - Yes

Choose a question from the test, re-state it, and answer it using visualization and summarization. Provide a figure and any relevant output with your answer.

5. Where does the majority of the world population live?

```
income_groups population_total
0 high_income 249226583643
1 low_income 214102397309
2 lower_middle_income 485771893214
3 upper_middle_income 418248077494
```



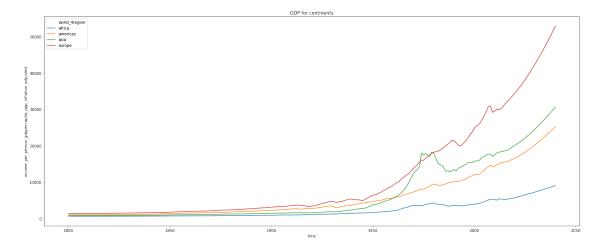
As observed from the above plot, the majority of the population lives in middle income countries.

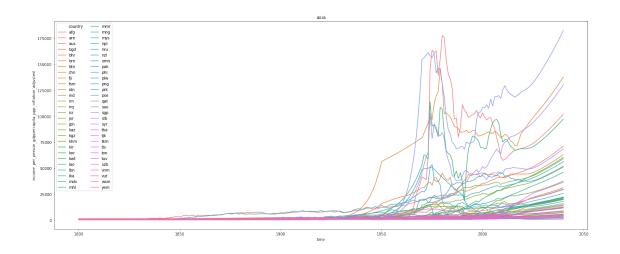
# 1 Problem 2

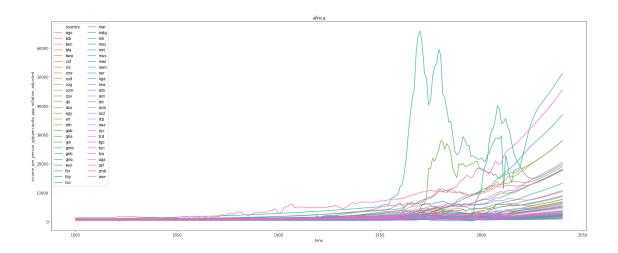
Visualize the distribution of income (GDP / capita) across countries and continents, and how the distribution of income changes over time. Interpret the visualization and what you notice. Are they any notable trends and/or deviations from that trend? What caveats apply to your conclusions?

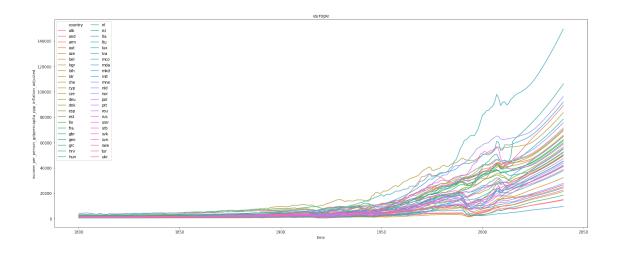
```
fig, ax = plt.subplots(figsize=(25,10))
            ax.title.set_text("GDP for continents")
            sns.lineplot(x="time", y="income_per_person_gdppercapita_ppp_inflation_adjusted", ]
            plt.legend(ncol=1, loc='upper left')
           plt.show()
In [5]: def gdp_for_countries(gdp_continent_df):
            continents = gdp_continent_df['world_4region'].unique()
            for i in range(len(continents)):
                df = gdp_continent_df[gdp_continent_df['world_4region'] == continents[i]]
                fig, ax = plt.subplots(figsize=(25,10))
                ax.title.set_text(continents[i])
                sns.lineplot(x="time", y="income_per_person_gdppercapita_ppp_inflation_adjuste
                plt.legend(ncol=2, loc='upper left')
                plt.show()
In [6]: def run_2():
            country_df = pd.read_csv('../input/ddf--gapminder--systema_globalis-master/ddf--en
            gdp_df = pd.read_csv('.../input/ddf--gapminder--systema_globalis-master/ddf--datapo
            gdp_continent_df = pd.merge(gdp_df, country_df[['country', 'world_4region']], left
            gdp_for_continents(gdp_continent_df)
            gdp_for_countries(gdp_continent_df)
```

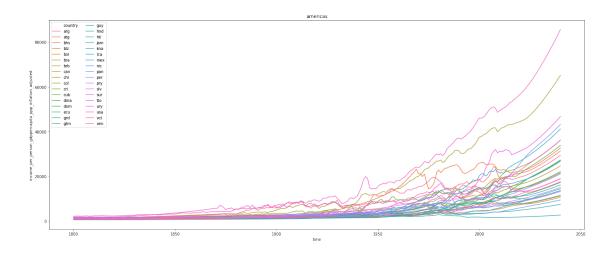
# In [7]: run\_2()











Around 1960, The gdp of asia has gone above that of the americas. The gdp of asia has also gone above that of europe on few occasions.

The gdp of all countries in europe and america seem to have steadily increased where as is asia nad africe, there seems to have a peak around 1970-1980's.

## 1.1 Problem 3

Use visualization to investigate the relationship between income (GDP / capita), life expectancy, and child mortality over time. How does each measure change over time within each continent? Interpret your visualizations, noting any trends and/or outliers.

```
In [11]: def run_3():
             country_df = pd.read_csv('../input/ddf--gapminder--systema_globalis-master/ddf--e
             gdp_df = pd.read_csv('../input/ddf--gapminder--systema_globalis-master/ddf--datap
             child_mortality_df = pd.read_csv('../input/ddf--gapminder--systema_globalis-master
             life_expectancy_df = pd.read_csv('../input/ddf--gapminder--systema_globalis-master
             result_df = pd merge(gdp_df, country_df[['country', 'world_4region']], left_on =
             result_df = pd.merge(result_df, child_mortality_df, on = ['geo', 'time'])
             result_df = pd.merge(result_df, life_expectancy_df, on = ['geo', 'time'])
             result_df.rename(columns={'child_mortality_0_5_year_olds_dying_per_1000_born':'ch
                                        'life_expectancy_years':'life_expectancy',
                                        'income_per_person_gdppercapita_ppp_inflation_adjusted
                              inplace=True)
             # Correlation over time between income (GDP / capita), life expectancy, and child
             grouped_time_df = result_df[['time', 'child_mortality', 'life_expectancy', 'gdp_p'
             sns.pairplot(grouped_time_df[['child_mortality', 'life_expectancy', 'gdp_per_capi'
             plt.suptitle('Correlation over time')
             fig, ax = plt.subplots(ncols=3, figsize=(25,10))
```

sns.lineplot(x="time", y='child\_mortality', data=grouped\_time\_df, ax=ax[0])
sns.lineplot(x="time", y='life\_expectancy', data=grouped\_time\_df, ax=ax[1])

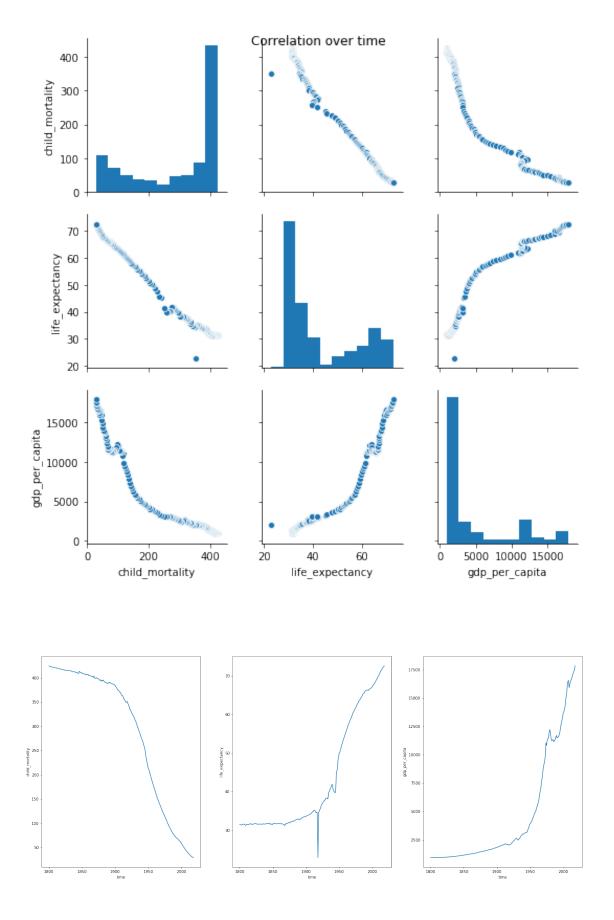
```
sns.lineplot(x="time", y='gdp_per_capita', data=grouped_time_df, ax=ax[2])
plt.show()

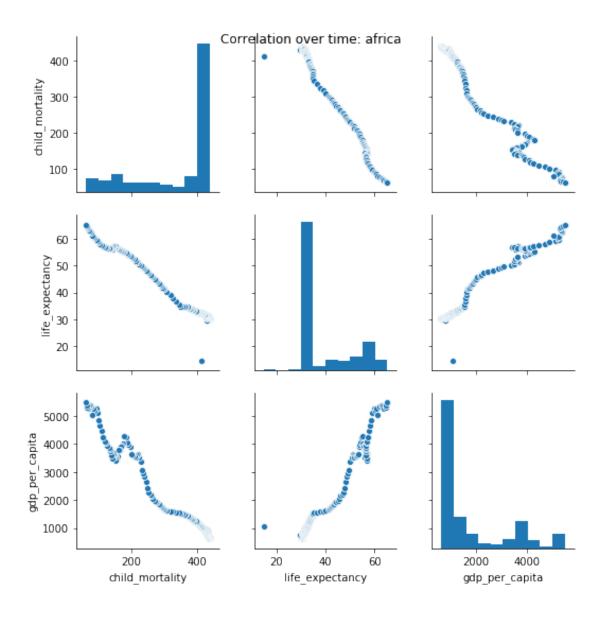
grouped_continent_time_df = result_df.groupby(['world_4region', 'time']).mean().re

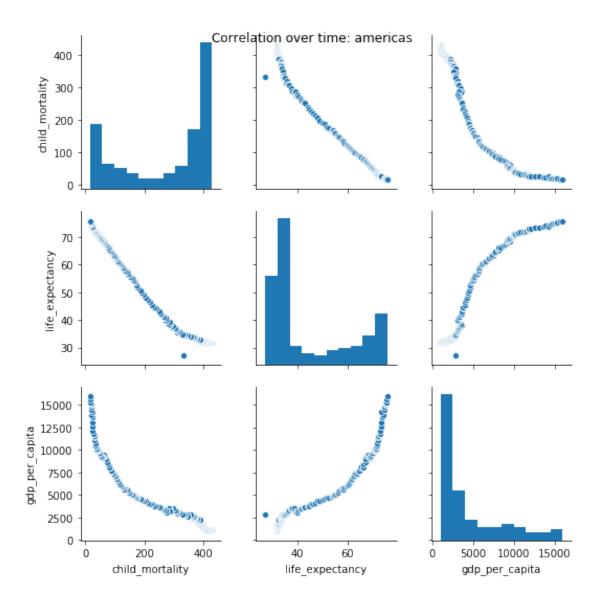
# Correlation over time between income (GDP / capita), life expectancy, and child
continents = grouped_continent_time_df['world_4region'].unique()
for i in range(len(continents)):
    df = grouped_continent_time_df[grouped_continent_time_df['world_4region'] == expectancy', 'gdp_per_capita']])
    plt.suptitle('Correlation over time: {}'.format(continents[i]))

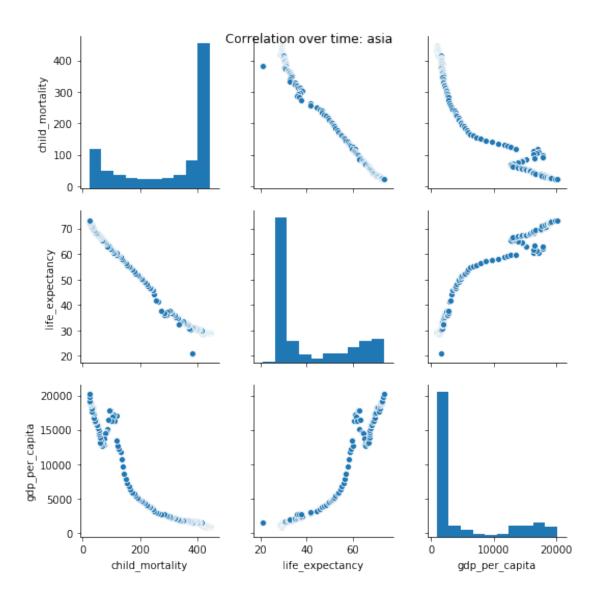
fig, ax = plt.subplots(ncols=3, figsize=(25,10))
sns.lineplot(x="time", y='child_mortality', hue='world_4region', data=grouped_continents_lineplot(x="time", y='life_expectancy', hue='world_4region', data=grouped_continents_lineplot(x="time", y='gdp_per_capita', hue='world_4region', data=grouped_continents_lineplot(x="time", y='gd
```

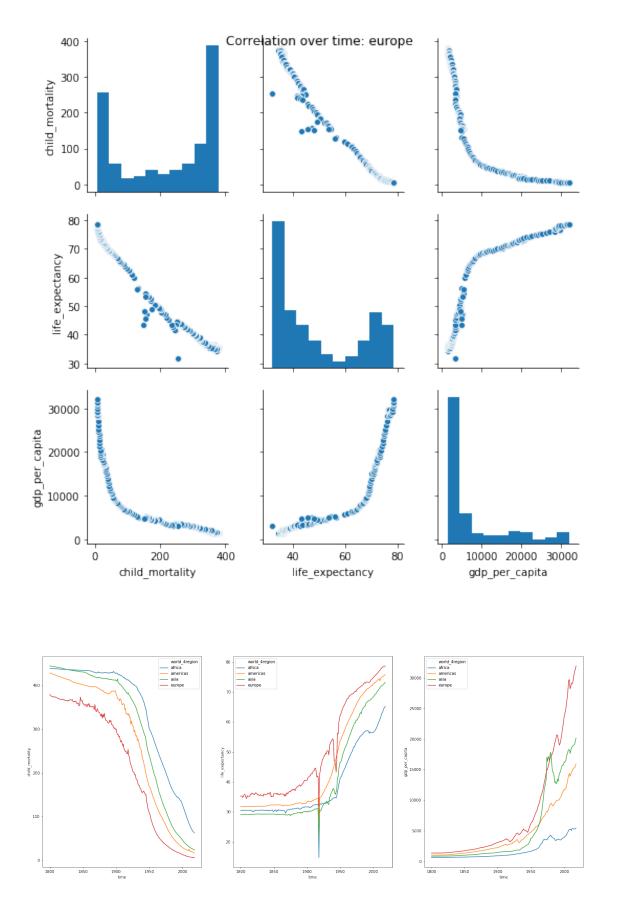
In [12]: run\_3()











Over the years, the child mortality has gone down where as the income and the life expectancy has gone up. However around the 1920's time frame, we can observe a sudden dip in the life expectancy.

In terms of correlation, child mortality seems to have score of -0.9 with both life expectancy and income, whereas life expectancy and income seems to be strongly positively correlated with each other.

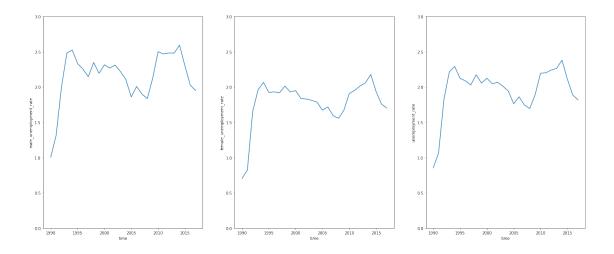
### 1.2 Problem 4

Choose two variables you have not investigated yet, and visualize their distributions, their relationship with each other, and how these change over time. Interpret your visualizations, noting any trends and/or outliers

Variables Chosen - long\_term\_unemployment\_rate, male\_long\_term\_unemployment\_rate, female\_long\_term\_unemployment\_rate

```
In [13]: def run_4():
                                 male_unemployed_df = pd.read_csv('../input/ddf--gapminder--systema_globalis-maste:
                                 female_unemployed_df = pd.read_csv('../input/ddf--gapminder--systema_globalis-mas
                                  country_df = pd.read_csv('../input/ddf--gapminder--systema_globalis-master/ddf--ex
                                 unemployed_df = pd.read_csv('../input/ddf--gapminder--systema_globalis-master/ddf
                                 result_df = pd.merge(male_unemployed_df, female_unemployed_df, on = ['geo', 'time
                                 result_df = pd.merge(result_df, unemployed_df, on = ['geo', 'time'])
                                 result_df = pd.merge(result_df, country_df[['country', 'world_4region', 'income_g'
                                 result_df.rename(columns={'male_long_term_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percent':'male_unemployment_rate_percen
                                                                                                      'long_term_unemployment_rate_percent':'unemployment_rate
                                                                                                         'female_long_term_unemployment_rate_percent':'female_u
                                                                              inplace=True)
                                 grouped_income_groups_time_df = result_df[['time', 'male_unemployment_rate', 'fem.
                                 fig, ax = plt.subplots(ncols=3, figsize=(25,10))
                                  sns.lineplot(x="time", y='male_unemployment_rate', data=grouped_income_groups_time
                                  ax[0].set_ylim([0,3])
                                  sns.lineplot(x="time", y='female_unemployment_rate', data=grouped_income_groups_t
                                  ax[1].set_ylim([0,3])
                                  sns.lineplot(x="time", y='unemployment_rate', data=grouped_income_groups_time_df,
                                 ax[2].set_ylim([0,3])
                                 plt.show()
```

In [14]: run\_4()



The unemployeent rate has increased over time compared to the initial years, however last few years the curve is on the downward path. Similar charactertistics are observed when you see in particular for male and female.

#### 1.3 Problem 5

Did you use static or interactive plots to answer the previous problems?

Explore the data using the interactive visualization tools at https://www.gapminder.org/tools, and watch the TED talk "The best stats you've ever seen" at https://www.youtube.com/watch?v=hVimVzgtD6w.

Discuss the advantages, disadvantages, and relative usefulness of using interactive/dynamic visualizations versus static visualizations.

I used static plots to answer the above questions.

Dynamic visualizations tend to keep the user more engaging and also a great tool for data exploration. It also enables to convey more information with a single dynamic plot.

However, dynamic visualizations relatively takes more time to code up compared to static ones. With new libraries like plotly, python has enabled python programmers to easily create a dynamic visualization and close the gap.