## The Well Being of Women

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### Reason Topic was Selected

As women, we care about women's well-being and strive to figure out what aspects of life most impact if women live long and happy lives.

### Sources of data

#### 3 Main Sources

- 1. LivWell (Kaggle)
- Latitude/Longitude (Kaggle)
- 3. GDP (world bank data)

#### Livwell (Kaggle)

- a. LivWell is a global longitudinal database
- **b.** Provides a range of key indicators related to:
  - i. Women's socioeconomic status, health and well-being,
  - . Women's access to basic services, and demographic outcomes.
- C. https://www.kaggle.com/datasets/konradb/wellbeing-of-women-in-52-countries?resource=download

#### 2. Latitude and Longitude (Kaggle)

- **a.** Latitude and Longitude for Every Country and State
- **b.** Provides the GPS coordinates for every world country and every USA state
- C. <a href="https://www.kaggle.com/datasets/paultimothymooney/latitude-and-longitude-for-every-country-and-state?select=world-country-and-usa-states-latitude-and-longitude-values.csv">https://www.kaggle.com/datasets/paultimothymooney/latitude-and-longitude-for-every-country-and-state?select=world-country-and-usa-states-latitude-and-longitude-values.csv</a>

#### 3. GDP (World Bank Data)

- a. World Bank national accounts data, and OECD National Accounts data files
- https://data.worldbank.org/indicator/NY.GDP.MKTP.CD

### Questions the team hopes to answer with data

Is there a relationship between country demographics and aspects of life indicators (domestic violence rate, marriage age, years of education, and fertility rate) that impact women's overall well-being?

Does GDP relate to these aspects of life?

## Data Exploration and Analysis



# Data Exploration

#### Data Cleaning:

- Pandas will be used to clean the data and perform an exploratory analysis.
- Further analysis will be completed using Python
  - Image below shows the main stats from the LivWell data

11vewell_etl_df = 11vewell_etl_df.loc[livewell_etl_df['year']>= 2000    12vewell_etl_df.describe()									
count         5967.000000         5967.000000         5967.000000         5967.000000         5967.000000           mean         2007.827216         1.243674         1.23557         1.239853         1.150581         1.063693         0.969010           std         4.755202         0.576403         0.48798         0.463376         0.411243         0.381618         0.374867           min         2000.00000         0.000000         0.000000         0.000000         0.000000         0.000000           25%         2004.00000         0.876000         0.92000         0.935167         0.877321         0.808000         0.718000           50%         2008.000000         1.226667         1.18200         1.184000         1.104000         1.020000         0.920000           75%         2012.000000         1.557750         1.46775         1.457321         1.360000         4.016000         4.756000           max         2019.000000         7.924000         6.15400         6.020000         4.656000         4.016000         4.756000	19]:								
mean         2007.827216         1.243674         1.23557         1.239853         1.150581         1.063693         0.969010           std         4.755202         0.576403         0.48798         0.463376         0.411243         0.381618         0.374867           min         2000.00000         0.00000         0.00000         0.00000         0.00000         0.00000         0.00000         0.00000         0.00000         0.00000         0.718000           50%         2008.00000          1.226667         1.18200         1.184000         1.104000         1.020000         0.920000           75%         2012.000000         1.557750         1.46775         1.457321         1.360000         4.016000         4.756000           max         2019.000000         7.924000         6.15400         6.020000         4.656000         4.016000         4.756000			year	DM_age_15.19_p_se	DM_age_20.24_p_se	DM_age_25.29_p_se	DM_age_30.34_p_se	DM_age_35.39_p_se	DM_age_40.44_p_se
std         4.755202         0.576403         0.48798         0.463376         0.411243         0.381618         0.374867           min         2000.00000         0.000000         0.000000         0.000000         0.000000         0.000000           25%         2004.00000         0.876000         0.92000         0.935167         0.877321         0.808000         0.718000           50%         2008.000000         1.226667         1.18200         1.184000         1.104000         1.020000         0.920000           75%         2012.000000         1.557750         1.46775         1.457321         1.360000         4.016000         4.016000         4.756000           max         2019.000000         7.924000         6.15400         6.020000         4.656000         4.016000         4.756000		count	5967.000000	5967.000000	5967.00000	5967.000000	5967.000000	5967.000000	5967.000000
min         2000.000000         0.000000         0.000000         0.000000         0.000000         0.000000           25%         2004.00000         0.876000         0.92000         0.935167         0.877321         0.808000         0.718000           50%         2008.000000         1.226667         1.18200         1.184000         1.104000         1.020000         0.920000           75%         2012.000000         1.557750         1.46775         1.457321         1.360000         1.262678         1.141833           max         2019.000000         7.924000         6.15400         6.020000         4.656000         4.016000         4.756000		mean	2007.827216	1.243674	1.23557	1.239853	1.150581	1.063693	0.969010
25%         2004.000000         0.876000         0.92000         0.935167         0.877321         0.808000         0.718000           50%         2008.000000         1.226667         1.18200         1.184000         1.104000         1.020000         0.920000           75%         2012.000000         1.557750         1.46775         1.457321         1.360000         1.262678         1.141833           max         2019.00000         7.924000         6.15400         6.020000         4.656000         4.016000         4.756000		std	4.755202	0.576403	0.48798	0.463376	0.411243	0.381618	0.374867
50%         2008.00000         1.226667         1.18200         1.184000         1.104000         1.020000         0.920000           75%         2012.000000         1.557750         1.46775         1.457321         1.360000         1.262678         1.141833           max         2019.00000         7.924000         6.15400         6.020000         4.656000         4.016000         4.756000		min	2000.000000	0.000000	0.00000	0.000000	0.000000	0.000000	0.000000
<b>75%</b> 2012.000000 1.557750 1.46775 1.457321 1.360000 1.262678 1.141833 max 2019.000000 7.924000 6.15400 6.020000 4.656000 4.016000 4.756000		25%	2004.000000	0.876000	0.92000	0.935167	0.877321	0.808000	0.718000
max 2019.000000 7.924000 6.15400 6.020000 4.656000 4.016000 4.756000		50%	2008.000000	1.226667	1.18200	1.184000	1.104000	1.020000	0.920000
		75%	2012.000000	1.557750	1.46775	1.457321	1.360000	1.262678	1.141833
8 rows × 38 columns		max	2019.000000	7.924000	6.15400	6.020000	4.656000	4.016000	4.756000
		8 rows	× 38 columns						

## Data Exploration

### **Database Storage:**

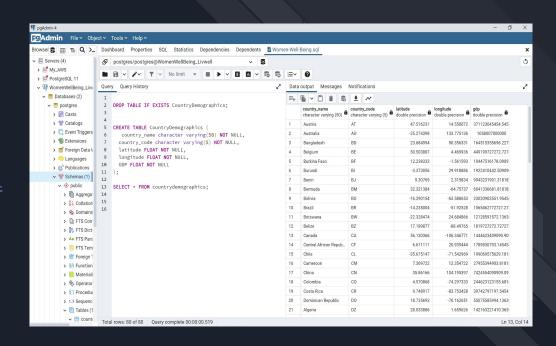
- AWS RDS is the database setup
- Integration of Postgres sql to display the ETL process for country demographics.
- Created S3 buckets and uploaded data
- Rearranged columns
- Dropped null values into another dataframe
- Uploaded cleaned dataframe into database table in PostgresSQL for further analysis

## Data Exploration

#### Database Storage:

Screenshot of database updations

- Links:
  - PostgresSQL
    - https://qithub.com/Betsy-Kalkwarf/Women-Well-Being/blob/main/Women-Well-Being.sql
  - CountryETL.ipynb
    - https://github.com/Betsy-Kalkwarf/Women-Well-Being/blob/main/CountryETL.ipynb



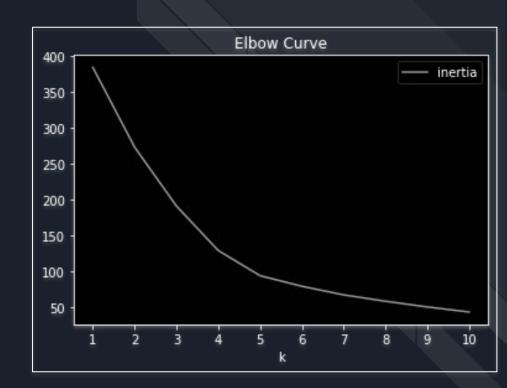
### **Machine Learning:**

- Training and Test set up is Unsupervised
  - Chosen due to source not having any predictions
  - Wanted to cluster indicators chosen based on the country
- SciKit Learn is the machine learning library we'll be using to create a classifier.
  - Jupyter notebooks:
    - ML\_indicators.ipynb
    - CountryETL.ipynb

### **Machine Learning:**

- Data was retrieved from database
- Set up ML model
- Scaled, fit and transformed the data
- Applied PCA for reduction
- Checked the Elbow Curve to decide the best K-value for clustering

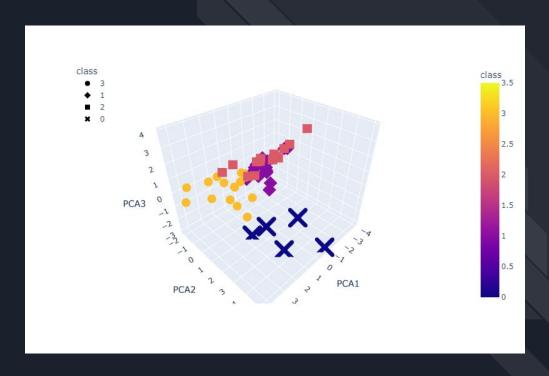
Edit the elbow curve pic to show which data we chose



#### **Machine Learning:**

• 3D scatter plot created to check clusters

- Links
  - o Code:
    - https://github.com/Betsy-Kalkwarf/Women-W ell-Being/blob/main/ML\_Indicators.ipvnb
  - o Picture:
    - https://github.com/Betsy-Kalkwarf/Women-Well-Being/blob/main/Resources/PCA-Cluster.png



#### Dashboard:

The dashboard is hosted on **Tableau**.

## Conclusion:

Answer to question 1

Answer to Question 2

