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. 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

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

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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		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
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		8 rows	× 38 columns						

Data Exploration

Database Storage:

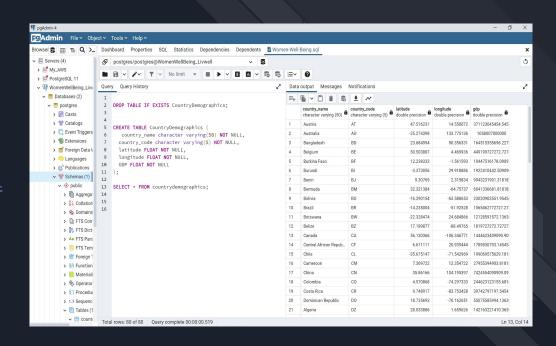
- AWS RDS is the database setup
- Integration of Postgres sql to display the ETL process for country demographics.
- Created S3 buckets and uploaded data
- Rearranged columns
- Dropped null values into another dataframe
- Uploaded cleaned dataframe into database table in PostgresSQL for further analysis

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



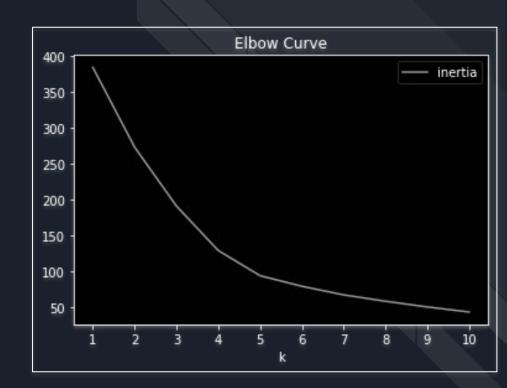
Machine Learning:

- 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

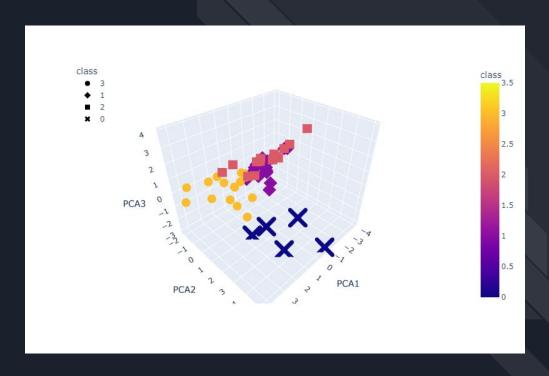
Edit the elbow curve pic to show which data we chose



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**.

Thanks!

Are there any questions?

