## DS5100

2020 Tokyo Olympics
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## Project Scenario

- Brief Introduction About the data set
- Olympics
- https://olympics.com/en/olympic-games/tokyo-2020/medals
- GDP
https://www.worldometers.info/gdp/gdp-by-country/
- Kaggle Integration
- https://www.kaggle.com/arjunprasadsarkhel/2021-olympics-in-tokyo?select=Teams.xlsx


## Dataset Introduction

- Pandas Dataframe to csv
https://github.com/hyunsukr/DS5100-Final/tree/main/data
- Dimension
- Tokyo Olympics: $74 \times 14$
- Historical Olympics: $1315 \times 9$
- Data was webscrapped and engineered to produce a final dataframe with the information below.

|  | Name | Gold | Silver | Bronze | Total | Country | GDP | GDP abbreviated | GDP growth | Population | GDP per capita | NOC | Discipline | Continents |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 0 | USA United States of America | 39 | 41 | 33 | 113 | United States | \$19,485,394,000,000.00 | \$19.485 trillion | 2.27\% | 325,084,756 | \$59,939.00 | United States of America | 47 | North America |
| 1 | CHN People's Republic of China | 38 | 32 | 18 | 88 | China | \$12,237,700,479,375.00 | \$12.238 trillion | 6.90\% | 1,421,021,791 | \$8,612.00 | People's Republic of China | 33 | Asia |
| 2 | JPN Japan | 27 | 14 | 17 | 58 | Japan | \$4,872,415,104,315.00 | \$4.872 trillion | 1.71\% | 127,502,725 | \$38,214.00 | Japan | 48 | Asia |
| 3 | GBR Great Britain | 22 | 21 | 22 | 65 | United Kingdom | \$2,637,866,340,434.00 | \$2.638 trillion | 1.79\% | 66,727,461 | \$39,532.00 | Great Britain | 28 | Europe |
| 4 | ROC ROC | 20 | 28 | 23 | 71 | Russia | \$1,578,417,211,937.00 | \$1.578 trillion | 1.55\% | 145,530,082 | \$10,846.00 | ROC | 34 | Asia |
| 5 | AUS Australia | 17 | 7 | 22 | 46 | Australia | \$1,323,421,072,479.00 | \$1.323 trillion | 1.96\% | 24,584,620 | \$53,831.00 | Australia | 35 | Australia |
| 6 | NED Netherlands | 10 | 12 | 14 | 36 | Netherlands | \$830,572,618,850.00 | \$831 billion | 3.16\% | 17,021,347 | \$48,796.00 | Netherlands | 27 | Europe |
| 7 | FRA France | 10 | 12 | 11 | 33 | France | \$2,582,501,307,216.00 | \$2.583 trillion | 1.82\% | 64,842,509 | \$39,827.00 | France | 33 | Europe |

## Dataset Web Scraping

- Class called Web_Scrapper
- Three data sets were webscrapped Olympics
GDP
Only gives 2020 (recent GDP) GDP Historical Data
ass Web_Scrapper():
def _init_(self, baselink="https://olympics.com/tokyo-2020/0lympic-games/en/results/all-sports/", history = \{\}):
self.baselink = baselink
(ith open('src/resources/history.json') as json_file:
history = json.load(json_file)
self.history = history
def scrape_gdp_history(self, years):
\#\# Not Tested Yet
time_series = pd.DataFrame()
pbar.start()
for i in pbar(range(0, len(years))):
if int(years[i]) > 1949:
df = self.scrape_gdp_economy(years[i])
time_series = time_series.append(df)
return time_series
def scrape_gdp_economy(self, year):
URL = 'https://countryeconomy.com/gdppyear=' + year
$r=$ requests.get(URL) \#http requests tot ehs specified url and save it in $k$
soup $=$ BeautifulSoup (r.content, 'htmL5lib')
tables = soup.find_all('table', \{'id': 'tbA'\})
tables_percap = soup.find_all('table', \{'id':'tbPC'\})
tempList = []
for table in tables:
for child in table.children:
for td in child:
for $t r$ in $t d$ :
templist.append(tr.get_text())
second_templist $=$ []
for table in tables_percap:
for child in table.children:
for td in child:
second templist, append(tr. get_text())
empList $=$ tempList [5:len(tempList)-1]
econd templist $=$ second tempList [6:len(second templist) -11


## Data Processing - Interaction

- Interaction with user
- Progress bar to show \% data pull
- Give feedback to user how much the data pull is complete.

- DS5100-Final - python src/main.py - $105 \times 32$
(venv) MacBook-Pro:DS5100-Final maxryoo\$ python src/main.py
Kicking off Data Pipeline
Collecting Historical Olympic Data



## Data Processing - Data Engineering

"United States of America" : "United States" "People's Republic of China" : "China",
"Japan" : "Japan",
"Great Britain" : "United Kingdom", "ROC" : "Russia",
"Australia" : "Australia",
"Netherlands": "Netherlands",

- Joined datasets based on country name
- Some country names were different
- Had to map countries names through a
json (dictionary) through data cleaning
- Added geographical location for the data
- Continents each country is located
- Utilized a third party package
- pycountry-convert

```
class Cleaner():
    def _init_(self):
        # Opening JSON Mapping file
        with open('src/resources/mapping.json') as json_file:
        mapping = json.load(json_file)
    with open('src/resources/mapping_continents.json') as json_file:
        cont_map = json.load(json_file)
    self.continent_maps = cont_map
    self.country_maps = mapping
    def join_gdp(self, gdp, olympic, join_cols=['Country']):
        temp_olympic = olympic.copy()
        temp_olympic["Country"] = temp_olympic["Name"].str[4:].map(self.country_maps
        joined = pd.merge(temp_olympic, gdp, how='left', on=join_cols)
        return joined
    def join_aggregate_teams(self, teams, olympic):
        teams = teams.groupby("NOC")["Discipline"].count().reset_index()
        emp = olympic.copy()
    temp ['tempName'] = temp["Name"].str [4:]
    oined = pd.merge(temp, teams, how='inner', left_on='tempName', right_on='NOC')
    joined = joined.drop(colun
    return joined
```


## Testing

- Pytest to test the code / coverage
- Data engineering functions and data quality testing
- All methods relating to data
- Code coverage of $100 \%$ except main



## Exploratory Data Analysis

Countries Competing


Africa: 12.16\%


Total Medals Won

## World Statistics



## Conclusions:

- US has highest GDP and number of medals won
- China second for both
- Relationship not as strong for rest of world
- Russia, Australia, \& Great Britain have high medal counts but lower GDPs compared to US and China


## Medal Count versus GDP



Medals Won versus GDP Per Capita: . 2975


Medals Won versus GDP: 0.8362

Conclusion: The relationship between GDP and medals won is much stronger than the relationship between GDP per capita and medals won.

## Model Building

- Multiple Linear Regression
- $\quad R^{\wedge} 2=0.8479990568528668$
- Mean Squared Error = 109.1391895919251
- $\quad$ Root Mean Squared Error $=10.446970354697342$
- Possible Next Steps
- Multicollinearity
- Linear Regression assumption checking
- GDP and Population had a beta of 0, which may raise eyebrows

Feature Coefficient

| $\mathbf{7}$ | Continents_Europe | 6.200415 |
| :--- | ---: | ---: |
| $\mathbf{8}$ | Continents_North America | 4.484664 |
| $\mathbf{5}$ | Continents_Asia | 3.548857 |
| $\mathbf{6}$ | Continents_Australia | 2.443772 |
| $\mathbf{4}$ | Discipline | 0.784625 |
| $\mathbf{0}$ | GDP | 0.000000 |
| $\mathbf{2}$ | Population | 0.000000 |
| $\mathbf{9}$ | Continents_South America | -6.659379 |
| $\mathbf{1}$ | GDP growth | -0.138194 |
| $\mathbf{3}$ | GDP per capita | -0.000042 |

## Time Series Analysis



125 Total Number of Gold Medals aquired by nations of North America 125
100

 Total Number of Bronze Medals aquired by nations of Europe

 Total Number of Silver Medals aquired by nations of North America


Total Number of Bronze Medals aquired by nations of North America

## Conclusion / Next Steps

- Code in github is available with virtual environments
- Making the github repo a package repo will make it so that we can deploy the package. Setup.py
- Dive deeper in the Multiple Linear Regression model such as multicollinearity etc.

