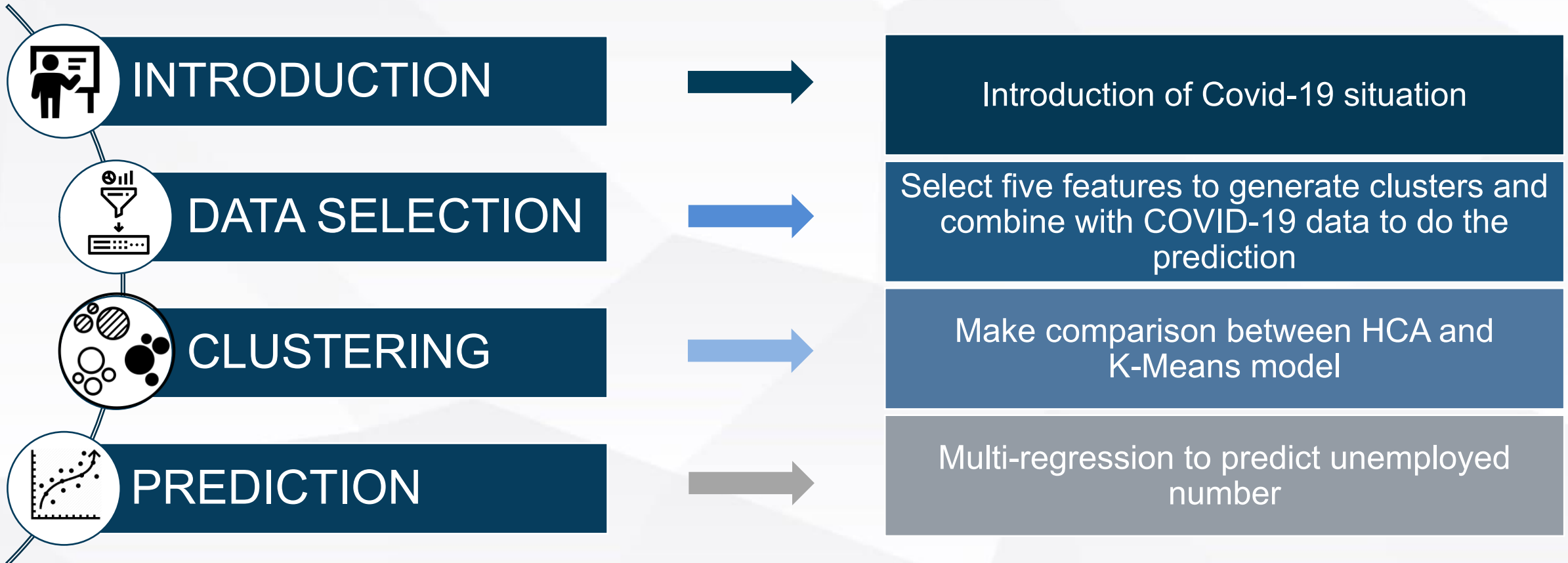


# Covid-19 Impact

Group 5

# CONTENTS

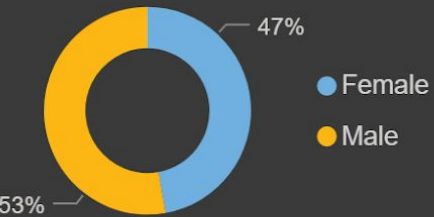


# Covid-19 Data Analysis

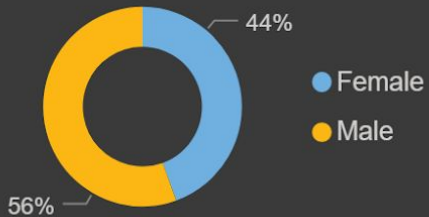
Data collected from US, China-Taiwan and Japan from November 2019 to May 2020

US Avg. Death Rate	Taiwan Avg. Death Rate	Japan Avg. Death Rate
5.20%	1.42%	2.59%

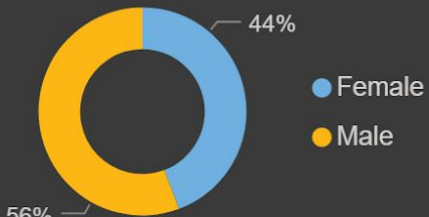
## Laborforce in US



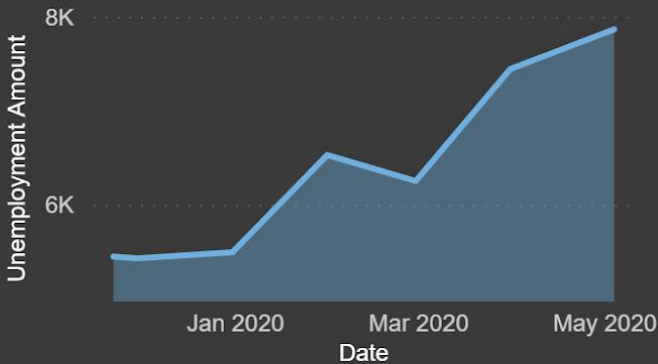
## Laborforce in Taiwan



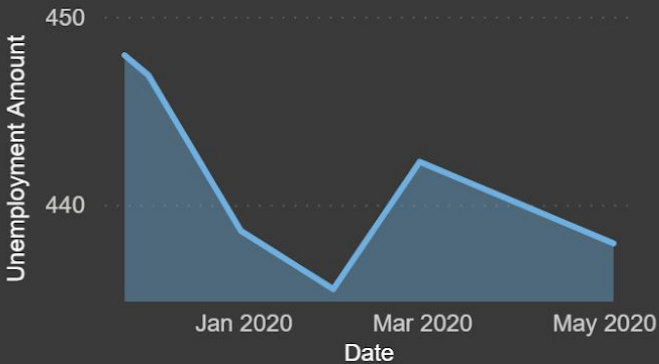
## Laborforce in Japan



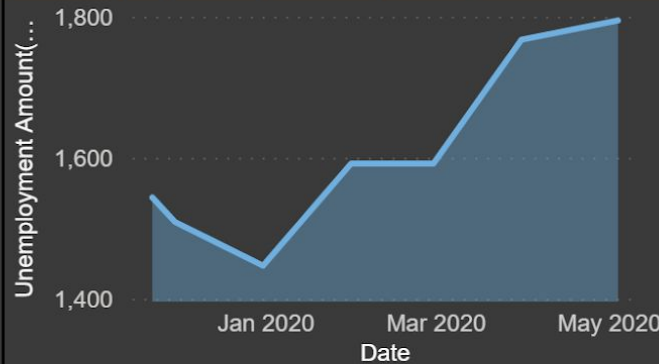
## Unemployment in US



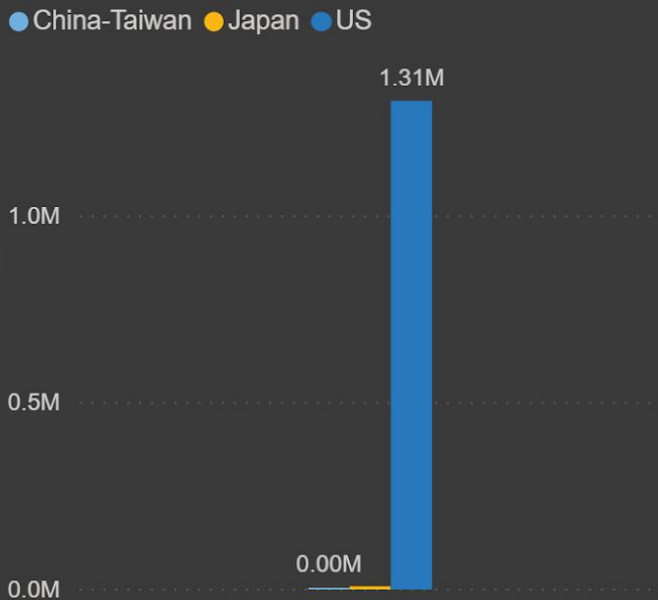
## Unemployment in Taiwan



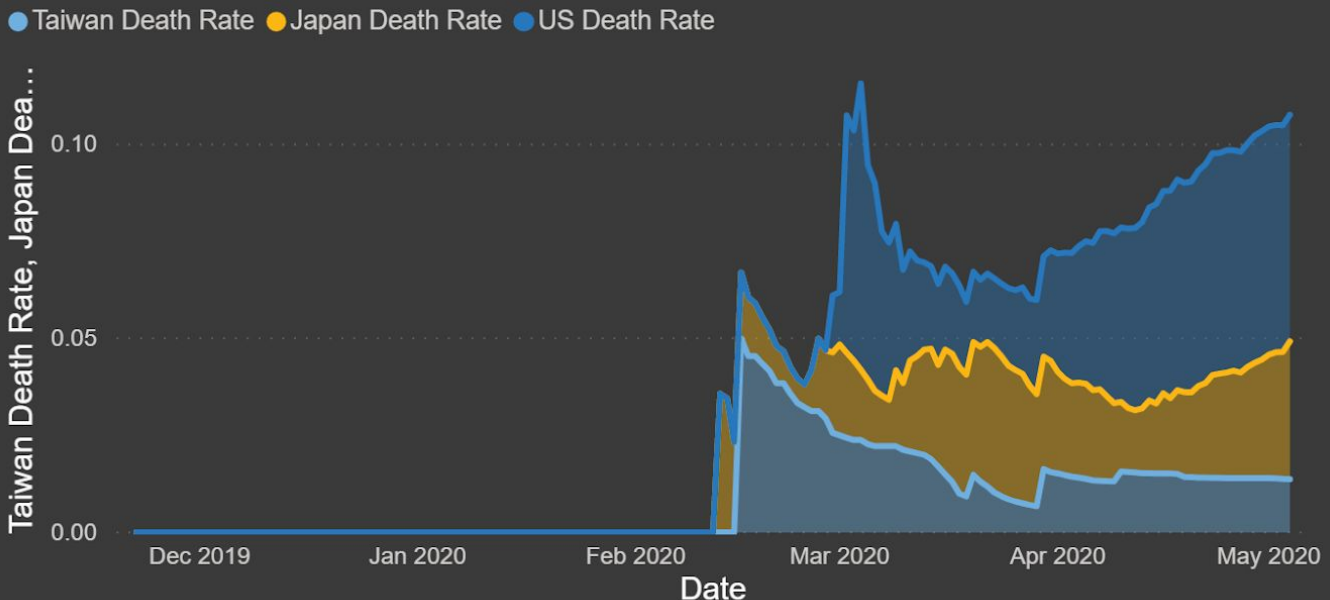
## Unemployment(1000s) in Japan



## Death number among three countries

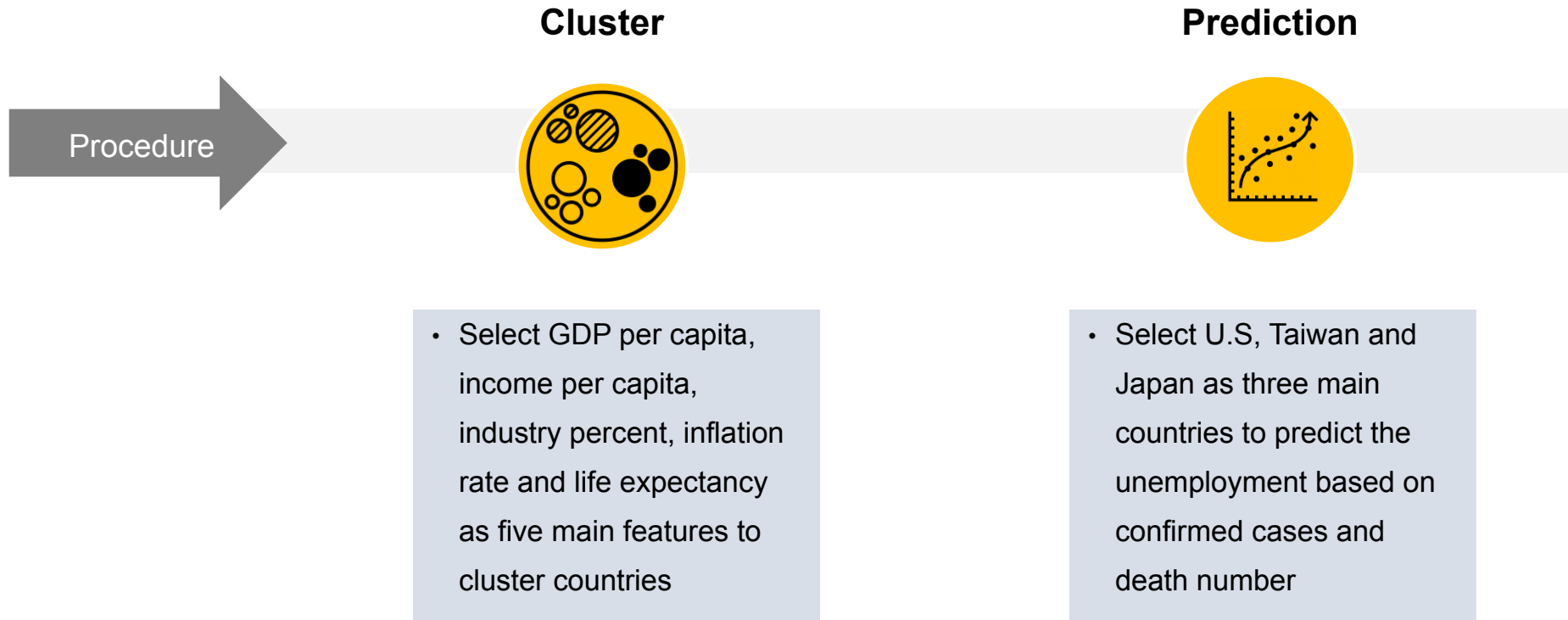


## Taiwan Death Rate, Japan Death Rate and US Death Rate by Date



# Data Selection

---



---

**Data Source:** John Hopkins <https://github.com/CSSEGISandData/COVID-19>  
International Labour Organization <https://ilostat ilo.org/>, <https://covid19.healthdata.org/united-states-of-america>  
MIT prediction model <https://www.covidanalytics.io/projections>  
Gapminder <https://www.gapminder.org/data/>

# Cluster – Data Preprocessing



gdp\_per\_ca  
pita\_yearly\_  
growth



income\_per  
\_person



industry\_pe  
rcent\_of\_g  
dp



inflation\_an  
nual\_perce  
nt



life\_expecta  
ncy\_years

## Merge Files

	country	gdp_per_cap	...	inflation	life_exp
0	Afghanistan	3.02	...	0.792	63.7
1	Albania	5.03	...	0.948	78.3
2	Algeria	2.63	...	7.560	77.9
3	Andorra	NaN	...	0.896	NaN
4	Angola	3.46	...	34.800	64.6
..	...	...	...	...	...
180	Venezuela	-0.56	...	NaN	75.2
181	Vietnam	4.90	...	3.400	74.6
182	Yemen	1.28	...	47.200	68.1
183	Zambia	2.89	...	9.330	63.7
184	Zimbabwe	2.87	...	28.000	61.7



## Replace Missing Value

	country	gdp_per_cap	income_per_cap	...	inflation	life_exp
	Afghanistan	3.020000	1740.0	...	0.792000	63.700000
	Albania	5.030000	12300.0	...	0.948000	78.300000
	Algeria	2.630000	13900.0	...	7.560000	77.900000
	Andorra	2.913517	51500.0	...	0.896000	72.996703
	Angola	3.460000	5730.0	...	34.800000	64.600000
	...	...	...	...	...	...
	Venezuela	-0.560000	12500.0	...	5.288489	75.200000
	Vietnam	4.900000	6610.0	...	3.400000	74.600000
	Yemen	1.280000	2360.0	...	47.200000	68.100000
	Zambia	2.890000	3740.0	...	9.330000	63.700000
	Zimbabwe	2.870000	2620.0	...	28.000000	61.700000

*# merge all columns into one dataset*

```
merged_inner1 = pd.merge(gdp_df, income_df, on='country')
merged_inner2 = pd.merge(merged_inner1, industry_percent_df, on='country')
merged_inner3 = pd.merge(merged_inner2, inflation_df, on='country')
merged_total = pd.merge(merged_inner3, life_exp_df, on='country')
```

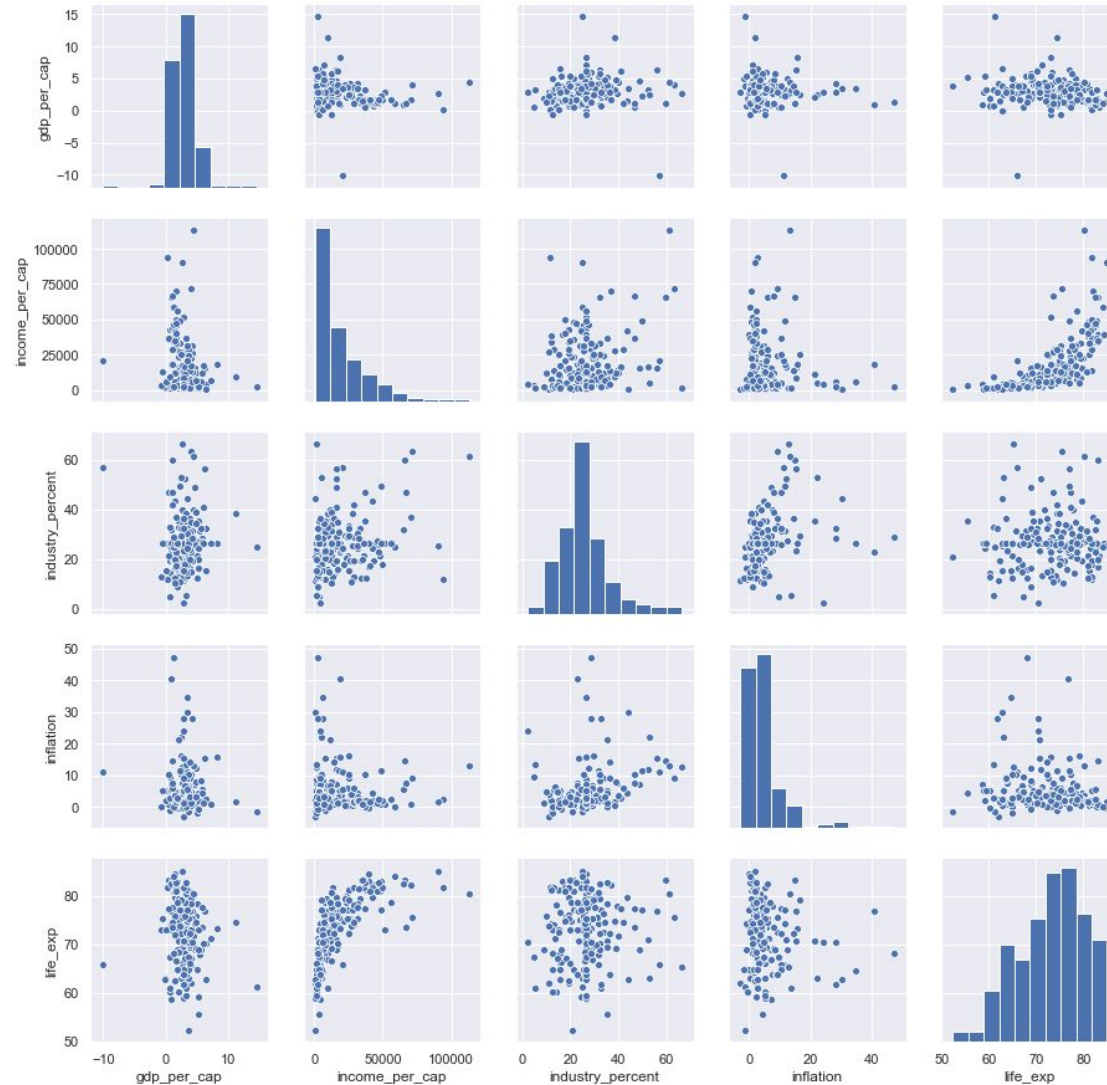
```
from sklearn.preprocessing import Imputer
```

*# replce nan value to mean*

```
imputer = Imputer(missing_values=np.nan, strategy='mean')
```



# Cluster – Pairplot



Show relationships  
between variables

# Cluster - Dimension Reduction

2D

```
n_clusters = 2, silhouette score 0.390532
n_clusters = 3, silhouette score 0.407605
n_clusters = 4, silhouette score 0.395579
n_clusters = 5, silhouette score 0.417256
n_clusters = 6, silhouette score 0.373466
n_clusters = 7, silhouette score 0.369369
n_clusters = 8, silhouette score 0.377828
```

3D

```
n_clusters = 2, silhouette score 0.324499
n_clusters = 3, silhouette score 0.311090
n_clusters = 4, silhouette score 0.330543
n_clusters = 5, silhouette score 0.314995
n_clusters = 6, silhouette score 0.346927
n_clusters = 7, silhouette score 0.342908
n_clusters = 8, silhouette score 0.362966
```

4D

```
n_clusters = 2, silhouette score 0.325129
n_clusters = 3, silhouette score 0.290669
n_clusters = 4, silhouette score 0.333702
n_clusters = 5, silhouette score 0.351264
n_clusters = 6, silhouette score 0.336181
n_clusters = 7, silhouette score 0.304214
n_clusters = 8, silhouette score 0.304703
```

After two, three and four dimensional comparison, we can see that the model performs best when  $n = 5$  and  $d = 2$

# Cluster - Model Comparison

---

HCA		K-Means	
n clusters	silhouette score	n clusters	silhouette score
2	0.324499	2	0.390532
3	0.311090	3	0.407605
4	0.330543	4	0.395579
5	0.314995	5	0.417256
6	0.346927	6	0.373466
7	0.342908	7	0.369369
8	0.362966	8	0.377828

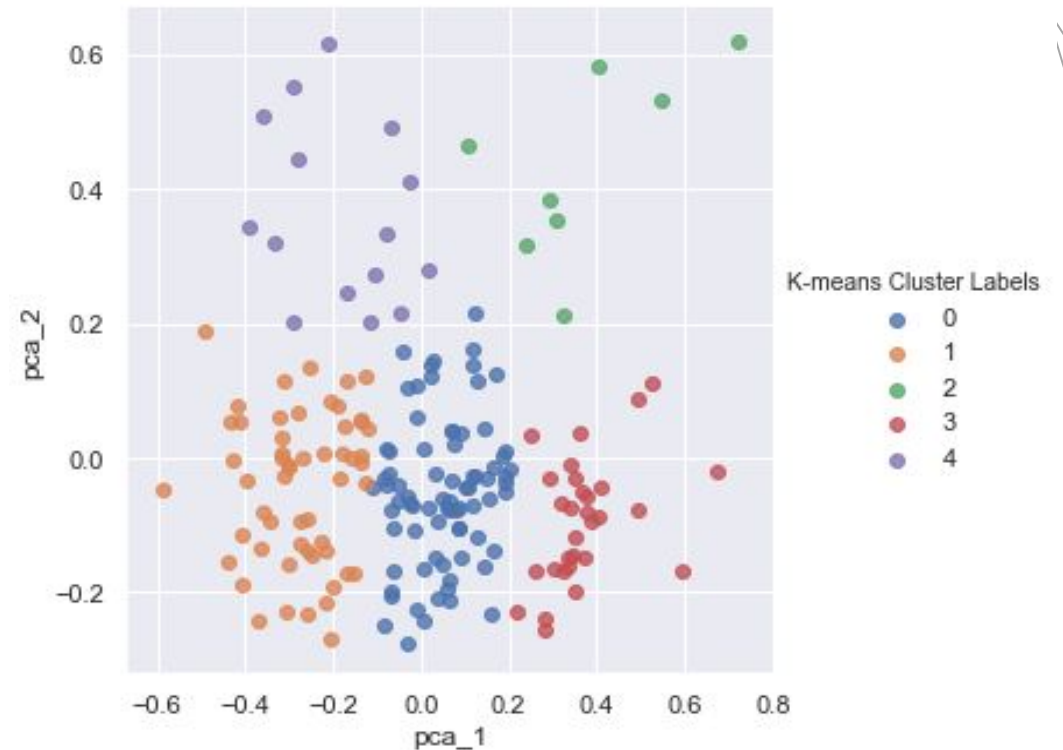
To determine the best k values, 2-8 clusters are tested, we can see from the table when model is K-Means and n = 5 the result is the best, thus I choose K-Means model and divide countries in 5 clusters



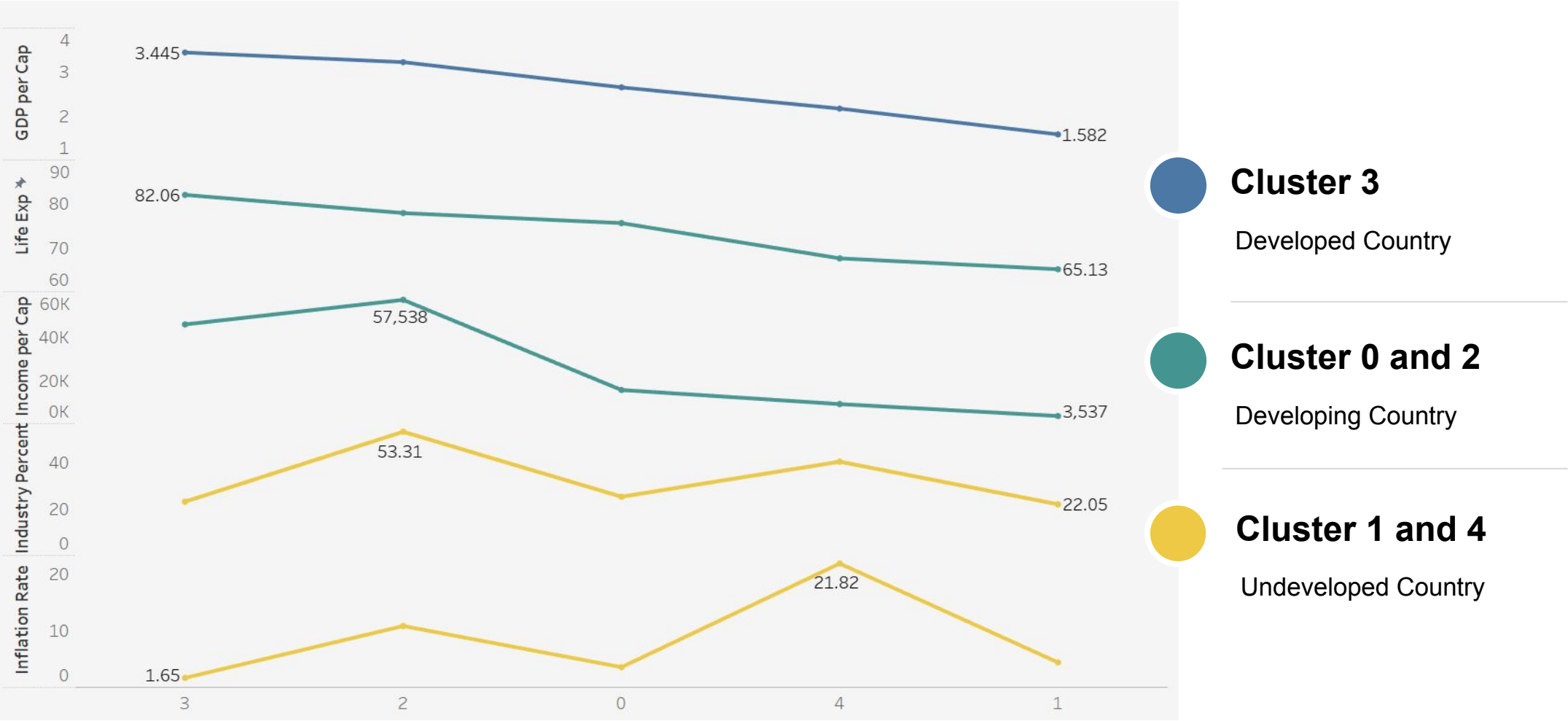
# Cluster – Result

```
# tol: stop when the distance between centers of two adjacent clusters is  
# less than 0.0001  
# max_iter: stop when iteration reach to 500  
clus_kmeans = KMeans(n_clusters=5, tol=0.0001, max_iter=500)  
# fit to input data  
kmeans =clus_kmeans.fit(X_pca)  
  
# get cluster assignments of input data and print first ten results  
df_country['K-means Cluster Labels'] = kmeans.labels_  
print(df_country[:10])  
  
# visualize the group of countries set with the cluster labels displayed  
X_pca_frame['K-means Cluster Labels'] = kmeans.labels_  
sns.lmplot(x='pca_1', y='pca_2',  
           hue="K-means Cluster Labels", data=X_pca_frame, fit_reg=False)  
  
# save the results in csv file  
df_country.to_csv(r'kmeans_cluster.csv', index = False)
```

- Above is the code snippet used to build cluster model
- Finally 5 clusters are established
- Scatter Plots to show cluster results



# Cluster – Result



# Prediction - Overview

## Random Forest

- Higher accuracy
- Better at handling missing values while maintaining accuracy
- Low bias due to Bagging & Ensembling

## Linear Regression

- Helpful to use if direct linear relationship between Covid cases & Unemployment exists

## Prediction - Liberties with the data

---

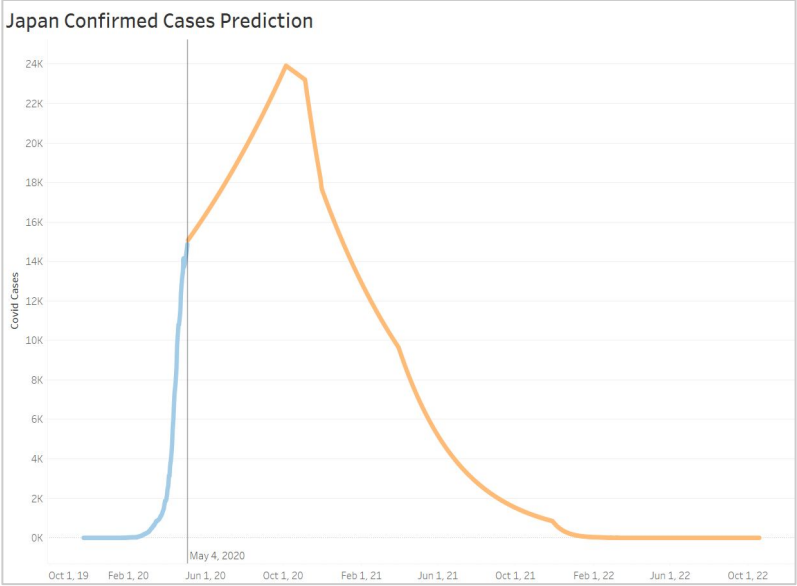
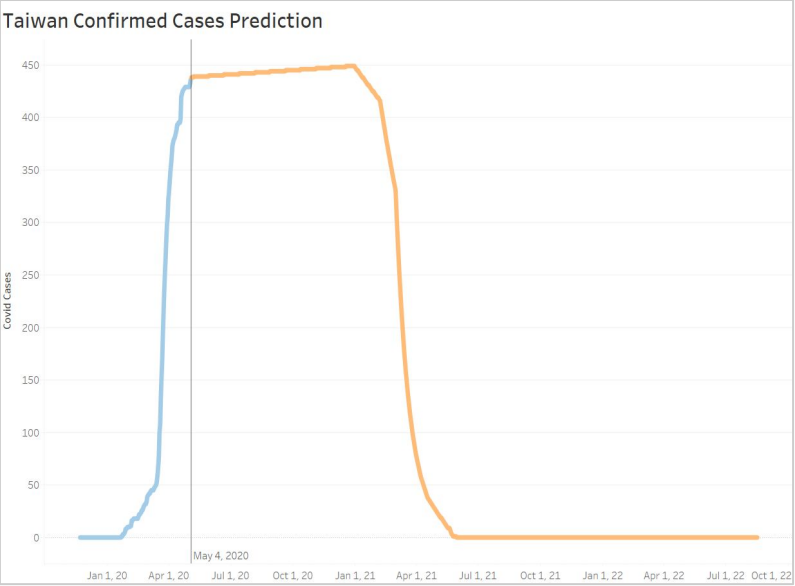
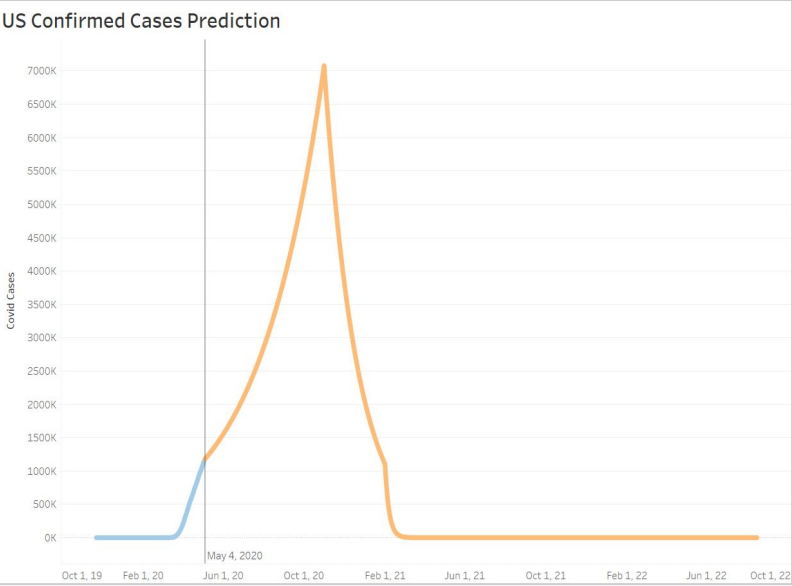
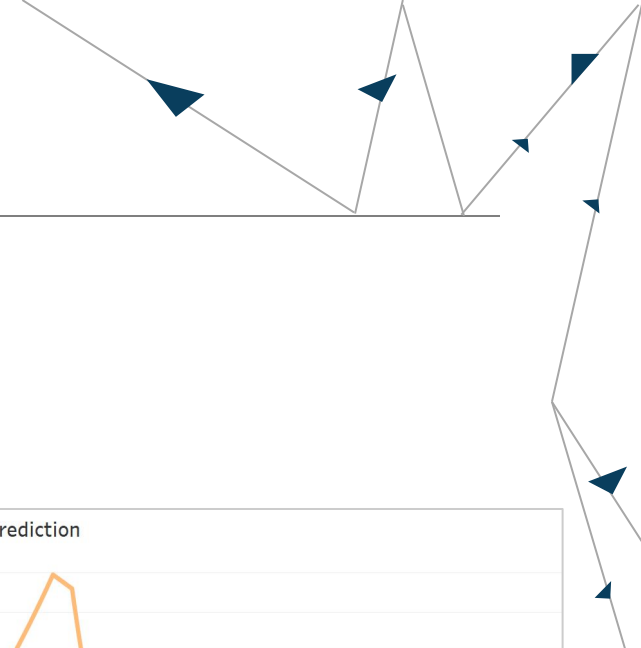
Covid cases in the future cannot be predicted with any real accuracy.

Too many variables to consider such as:

- Economic factors
- Political Factors
- Medical research progress
- Many more

Covid-19 case for each country were manually predicted based on information available and educated guesses

# Confirmed Cases Prediction



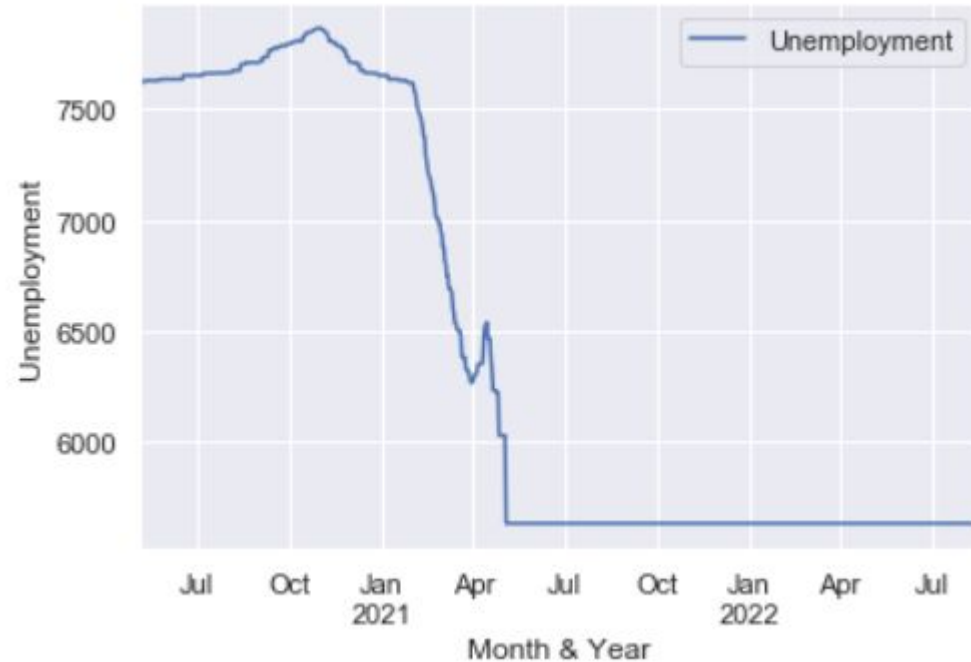


# Prediction - Results

---

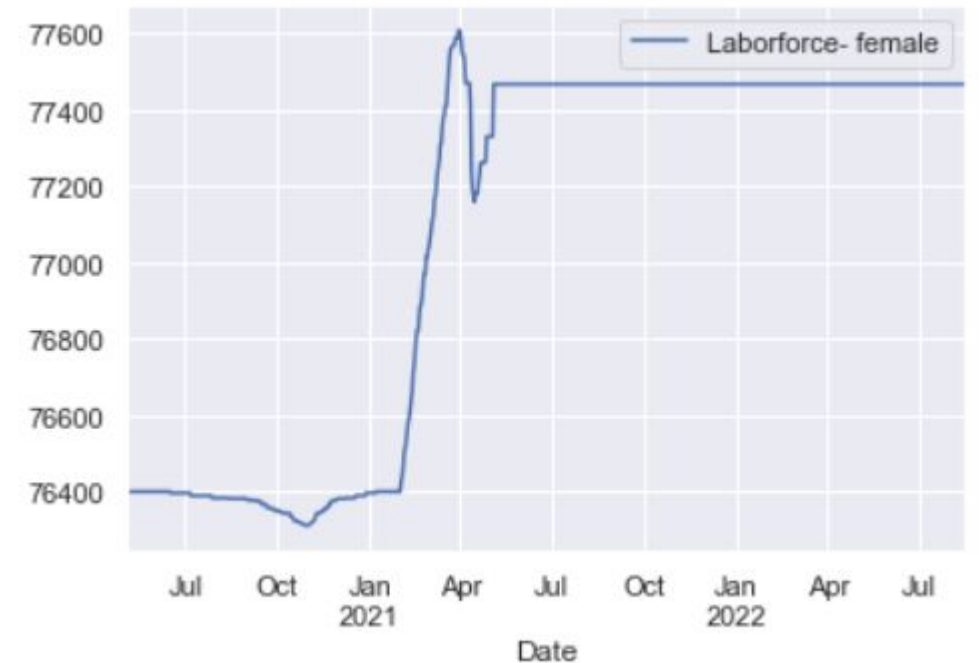
Model/Country	US	Japan	Taiwan
RF F1 Score	96%	87%	72%
Linear Regression R Squared	75%	22%	13%

# Unemployment Prediction, US



Random Forest F1 Score = 96%

Linear Regression R squared = 75%

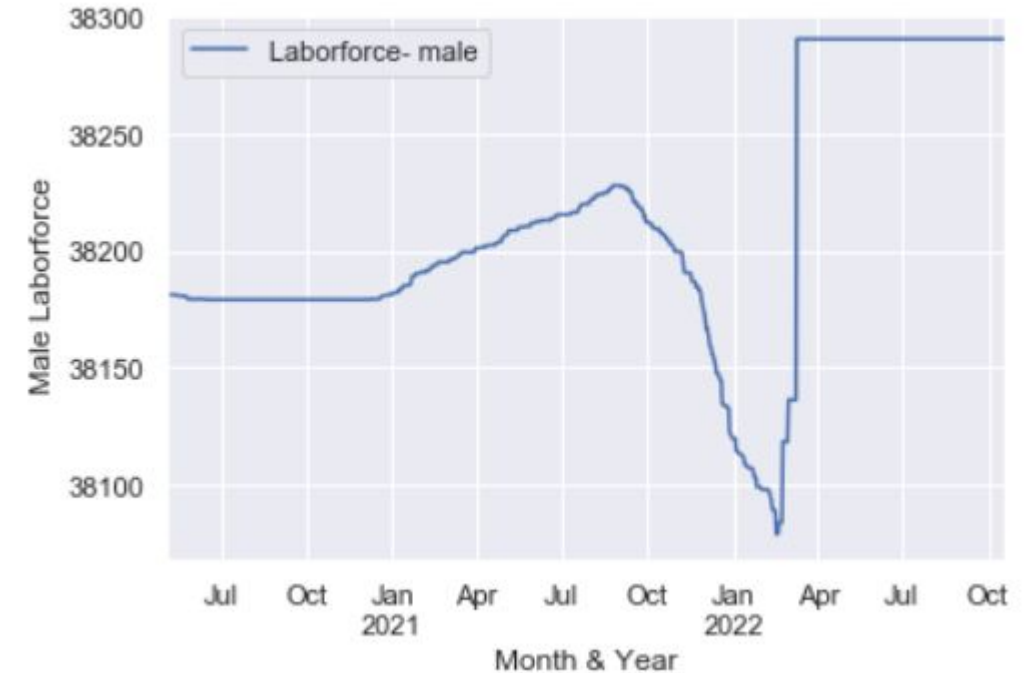


# Unemployment Prediction, Japan

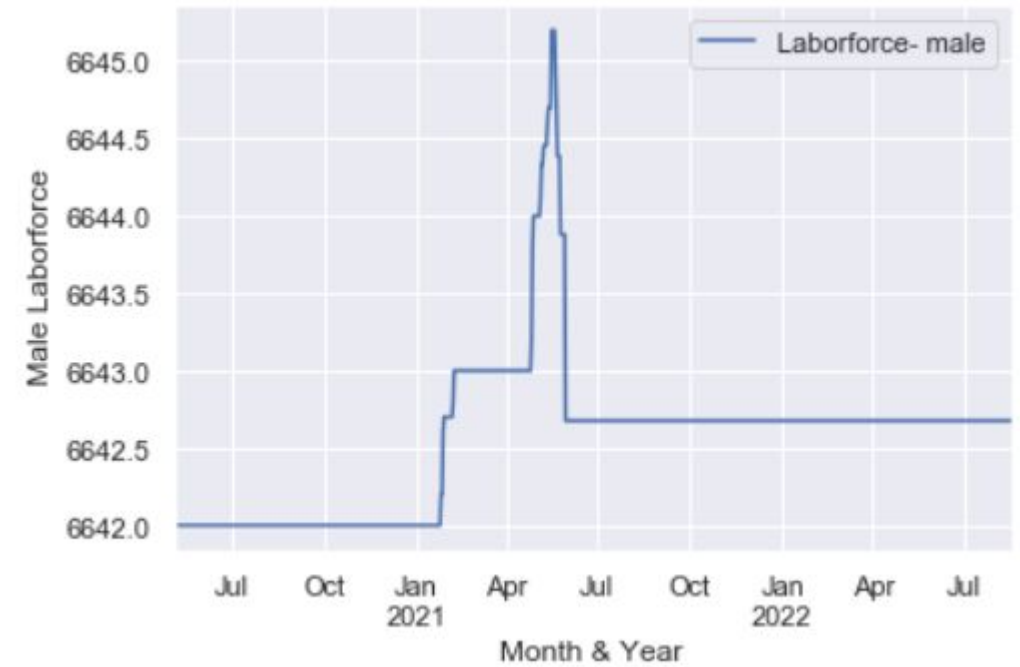
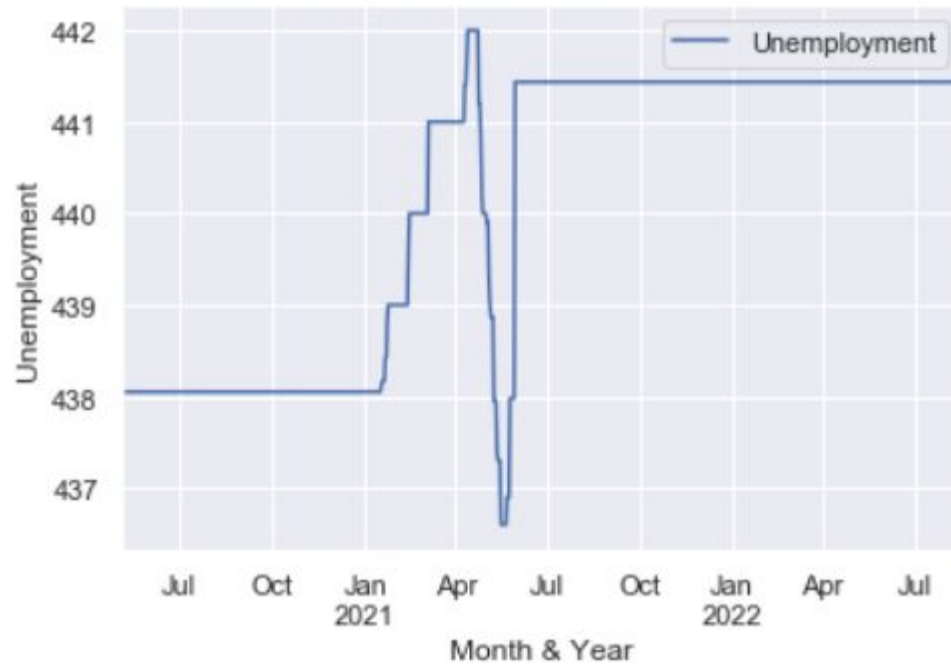


Random Forest F1 Score = 87%

Linear Regression R squared = 22%

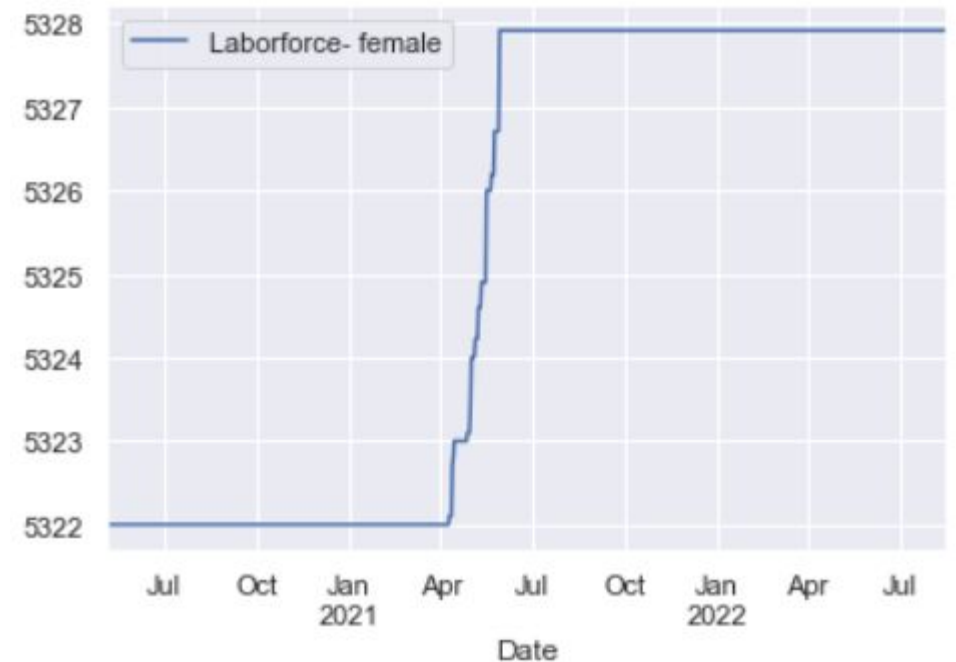


# Unemployment Prediction, Taiwan



Random Forest F1 Score = 72%

Linear Regression R squared = 13%



# THANKS

Group  
5

Menghe Dou Parashara, Praharsh Tianyu Wei Ahmed, Awadh Srivastava, Ullas