COVID-19 Forecasting

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1 Introduction

We would like to predict the future confirmed and deaths results of the COVID-19. If forecasting can be done, we would be able to be prepared of what would happened, also it would be useful when a similar pandemic happens, we can use our experience to examine the data in such case.

2 Preprocessing

2.1 The Data

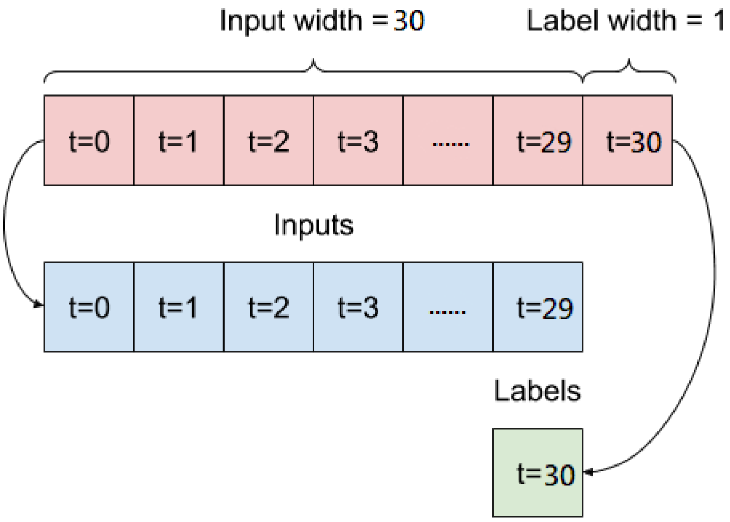
We will use the dataset from JHU CSSE COVID-19 Data which can be downloaded from https://github.com/CSSEGISandData/COVID-19. We will use the confirmed and deaths global datasets on their page. The files are csv files with format

Province/State	Country/Region	Lat	Long	1/22/20	1/23/20	1/24/20
NaN	Afghanistan	33.93911	67.709953	0	0	0
NaN	Albania	41.15330	20.168300	0	0	0
NaN	Algeria	28.03390	1.659600	0	0	0
NaN	Andorra	42.50630	1.521800	0	0	0
NaN	Angola	-11.20270	17.873900	0	0	0

here only the first few row and columns are listed. It consists the State, Region, the geographic location (latitude and longitude) and the confirmed/deaths each day starting from 2020/1/22. We collect the confirmed and deaths of each country into a array for later usage.

2.2 Data Windowing

We use the confirmed and death collected explained in previous section to train the model. We generate the training data by splitting the data in to windows, a example of a window can be given as following figure.



In this example, we split out dataset so that we wish to come up with a model that predict 1 day of confirmed/deaths given 30 days of confirmed/deaths datas. Later we will demonstrate different results with different data windowing.

2.3 Normalization

We normalize the given data by each window. Given an confirmed or deaths input window $\mathbf{x}$, which should be a array. If we use the windowing example as previous subsection, we get an array of 30 elements of confiremd/deaths people that day. We calculate the mean $\mu(\mathbf{x})$ and variance $\sigma(\mathbf{x})$, then the actual input data $\hat{\mathbf{x}}$ will be given by

$$\hat{\mathbf{x}}_i = \frac{\mathbf{x}_i - \mu(\mathbf{x})}{\sigma(\mathbf{x})} \quad \text{if } \sigma(\mathbf{x}) \neq 0,$$

and

$$\hat{\mathbf{x}}_i = \mathbf{x}_i - \mu(\mathbf{x}) \quad \text{if } \sigma(\mathbf{x}) = 0$$

for each i, where $\mathbf{x}_i$ and $\hat{\mathbf{x}}_i$ are elements of $\mathbf{x}$ and $\hat{\mathbf{x}}$ respectively.

For the output data $\mathbf{y}$, we will apply the mean and variance of the input window to get the actual output data $\hat{\mathbf{y}}$, that is

$$\hat{\mathbf{y}}_i = \frac{\mathbf{y}_i - \mu(\mathbf{x})}{\sigma(\mathbf{x})} \quad \text{if } \sigma(\mathbf{x}) \neq 0,$$

and

$$\hat{\mathbf{y}}_i = \mathbf{y}_i - \mu(\mathbf{x}) \quad \text{if } \sigma(\mathbf{x}) = 0$$

for each i, where $\mathbf{y}_i$ and $\hat{\mathbf{y}}_i$ are elements of $\mathbf{y}$ and $\hat{\mathbf{y}}$ respectively.

3 Models

The models will be implemented by using following libraries in Python: XGBoost, Scikit-learn, and TensorFlow.

3.1 XGBoost

First model we will try the infamous gradient boosting based library XGBoost. We omit the details here, but one can have a quick look at XGBoost's docs to have a quick look at XGBoost. Note that when predicting more days, since XGBoost only supports single output regression default, we will use scikit-learn's MultiOutputRegressor as a wrapper, which simply fits one regressor per target.

3.2 Linear Regression

We use standard linear regression model, which will be implemented by the scikit-learn library. We also use MultiOutputRegressor when predicting multiple days.

3.3 Dense Neural Network

We will use a simple dense neural network which is consists of two hidden layers with 64 neurons, while the layers are passed with activation function relu. The implementation will be using TensorFlow.

4 Results

The following results comparison of different models where the windowing and the training/testing set splitting are different, we will specify the details. Currently (2020/12/22), the time series data consists of 335 days of data. A score of each model will be calculated using the following rules. Let $\hat{Y} = \{\hat{\mathbf{y}}_i\}$ be the predicted values, and let $Y = \{\mathbf{y}_i\}$ be the corresponding true values, the predict score is defined as

$$\text{score} = 1 - \frac{\sum_i (\hat{\mathbf{y}}_i - \mathbf{y}_i)^2}{\sum_i (\mathbf{y}_i - \mu(Y))^2},$$

where $\mu(Y)$ is the mean of Y. This gives us a glance at how well the model is as 1 giving the best score, but one should not only look at this score to determine if a model's useful. In the following, we will also demonstrate the forecasting results of a given country, we will calculate the maximum error where both the dataset and the prediction has a value.

4.1 Multiple countries as training sets

First results comes where we use US, Spain, Belgium, China, France, Germany, United Kingdom, Italy data as training sets, but also keeping the last 150 days of data out of the windowing. All the other data window pairs will be collected as the testing set.

4.1.1 1 day prediction

Here we will predict 1 day by 30 days. We'll show the output of our program, which shows the training/testing score of each model and the maximum error and prediction figure of the model.

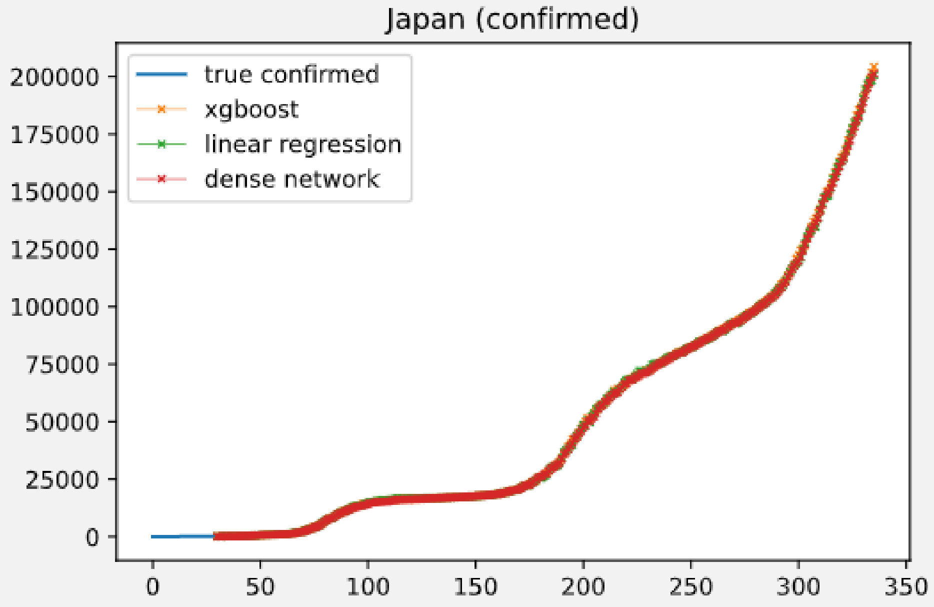
Data length: 335

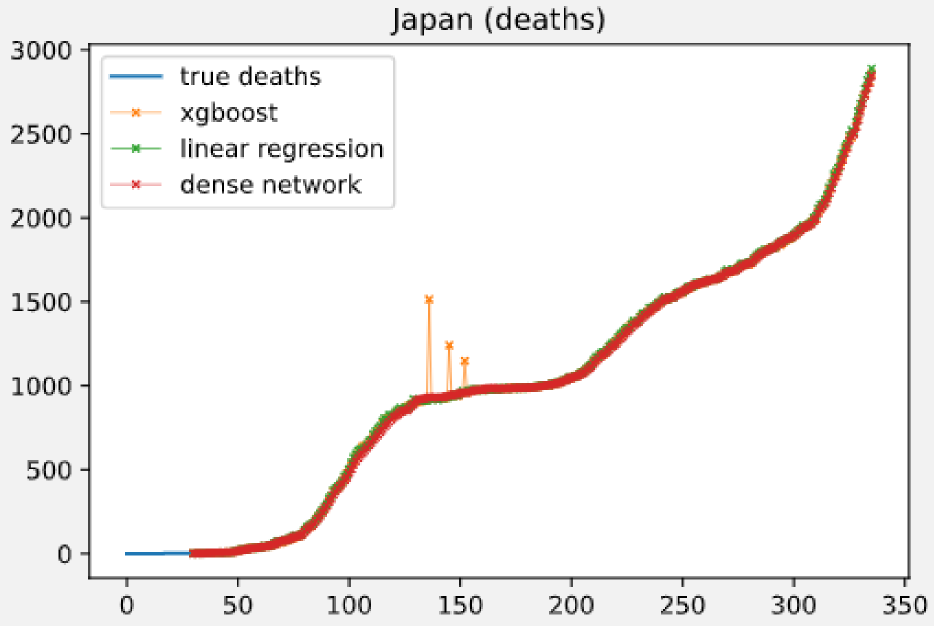
Training score	xgboost	linear regression	dense network
Confirmed	0.999968	0.813265	0.886461
Deaths	0.999985	0.566096	0.575712

Testing score	xgboost	linear regression	dense network
Confirmed	-0.788356	0.12582	0.31407
Deaths	0.0378059	0.163331	0.17573

Japan

Max error	xgboost	linear regression	dense network
Confirmed	1574.32	3076.88	3030.49
Deaths	599.835	41.3703	42.4389





We will omit other output of other countries. We see the dense network is giving the best score in testing, while XGBoost has the best score in training. In the output we given, XGBoost is giving the least maximum error in confirmed, but it gives the largest error in deaths.

4.1.2 10 days prediction

Here we'll show predictions of 10 days by inputting 30 days. To draw the figure of prediction, since there will be overlapping days of predictions, we simply skip 10 days to prevent overlapping and combine the figure.

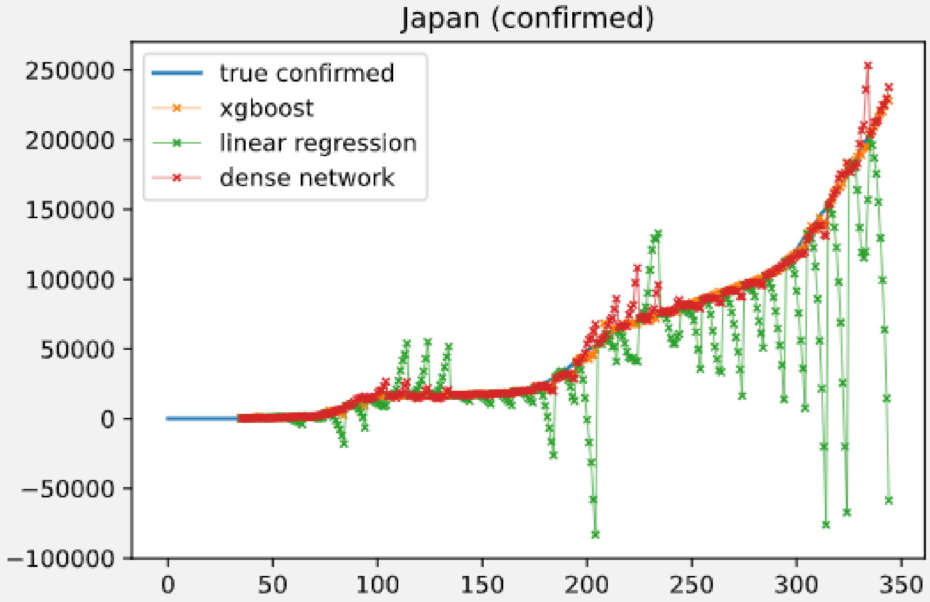
Data length: 335

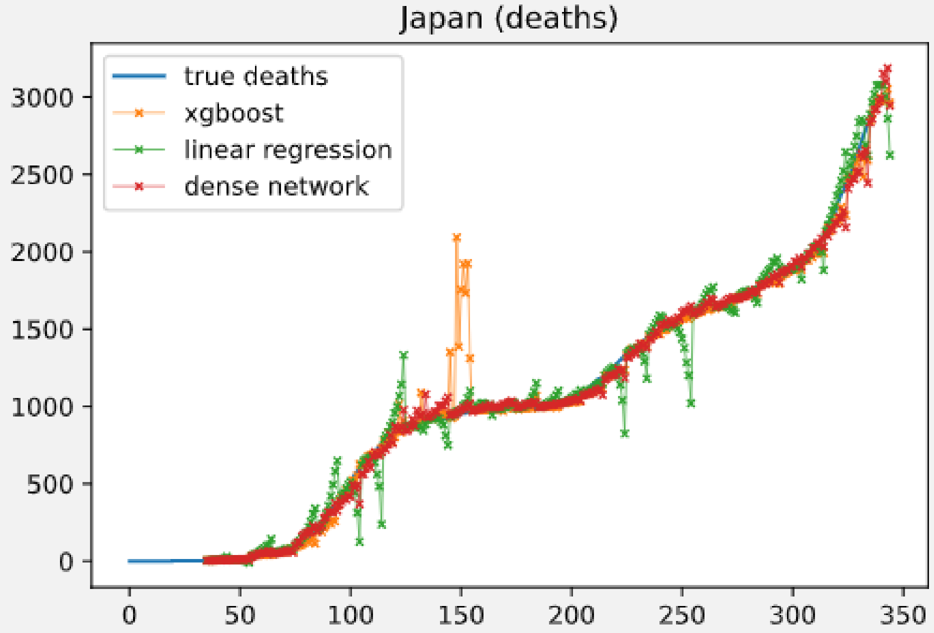
Training score	xgboost	linear regression	dense network
Confirmed	0.99999	0.527157	0.591767
Deaths	0.999992	0.595707	0.666162

Testing score	xgboost	linear regression	dense network
Confirmed	-41.751	-13.6738	-1.96249
Deaths	-0.522273	-1.43025	-0.457888

Japan

Max error	xgboost	linear regression	dense network
Confirmed	12425.2	242591	52186.7
Deaths	1158.32	571.676	389.853





In here linear regression definitely gives the worst results. In overall dense network has better score, but in some cases, as the Japan's confirmed we shown, XGBoost perform much better.

4.1.3 30 days prediction

Here we use 30 days to predict 30 days.

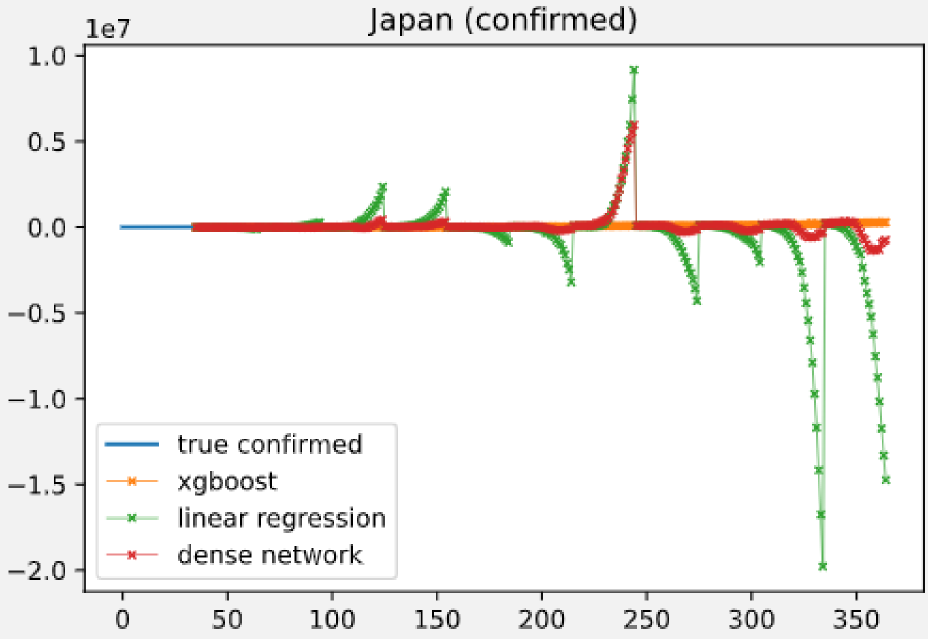
Data length: 335

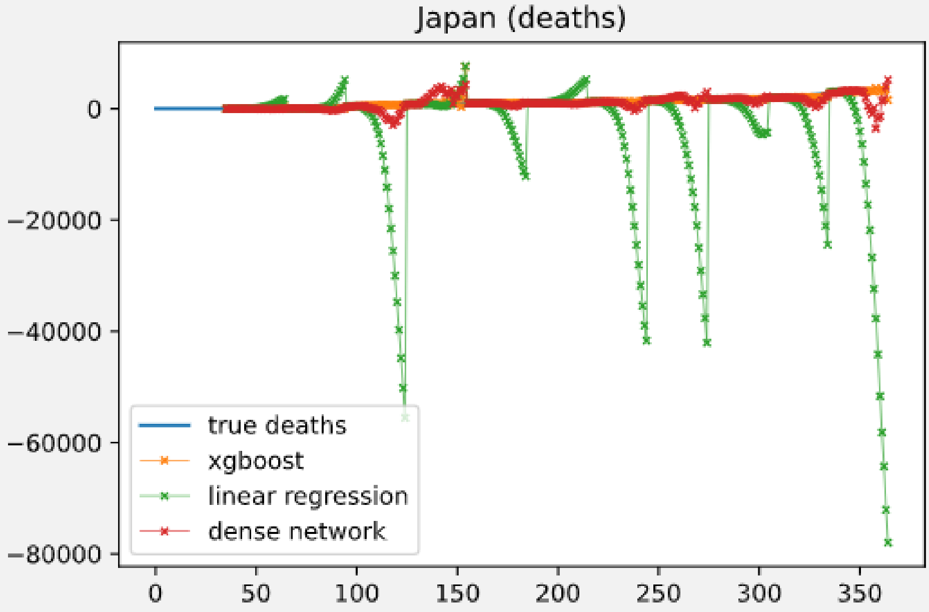
Training score	xgboost	linear regression	dense network
Confirmed	0.999997	0.467218	0.256903
Deaths	0.999997	0.490763	0.295669

Testing score	xgboost	linear regression	dense network
Confirmed	-21.9279	-11.9818	-1.95719
Deaths	-47.6586	-70.5059	-33.2122

Japan

Max error	xgboost	linear regression	dense network
Confirmed	52348	1.99932e+07	5.86749e+06
Deaths	6619.66	56423.7	3741.35





The results are similar to the 10 days one with linear regression being weaker.

4.2 Taiwan as training set

It is interesting to try Taiwan's dataset as the training set, since Taiwan has very few infected and deaths, so we may want to see in this case how the model performs. Interestingly, we notice that the multi-day prediction of deaths performs even better in this case.

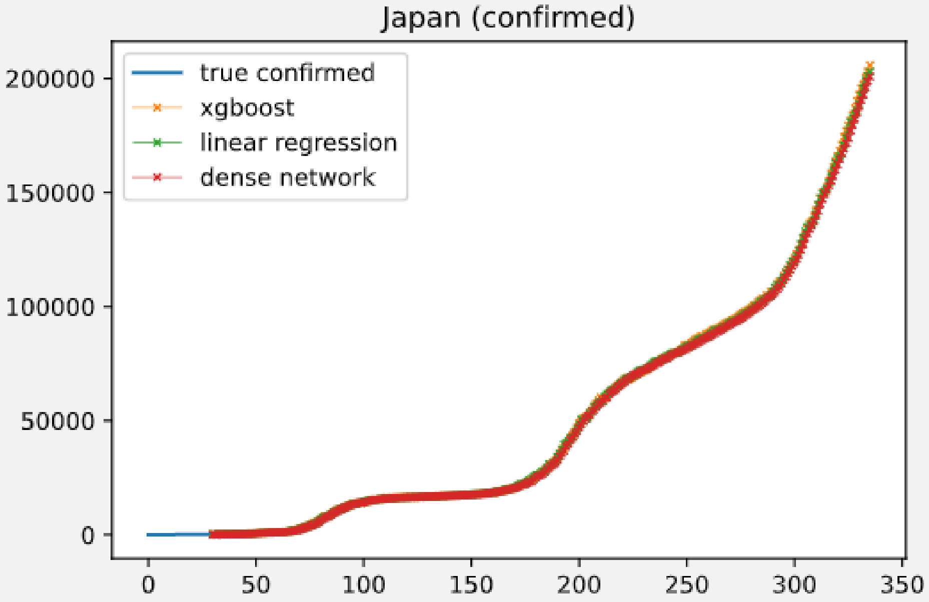
4.2.1 1 day prediction

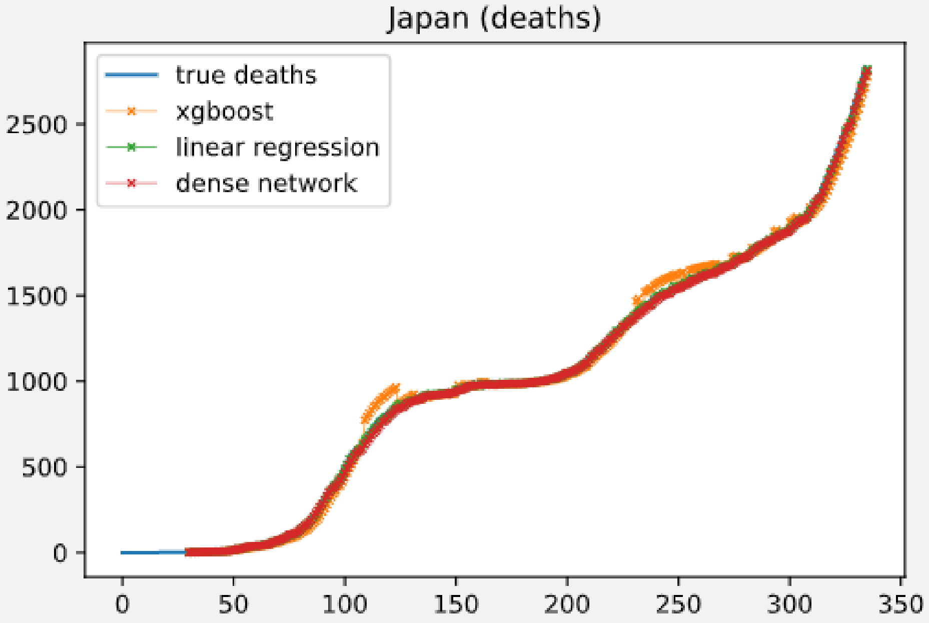
Data length: 335

Training score	xgboost	linear regression	dense network
Confirmed	0.999999	0.872291	0.766207
Deaths	1	0.862836	0.845123

Testing score	xgboost	linear regression	dense network
Confirmed	0.373952	0.359536	0.369799
Deaths	0.123399	0.0616844	0.169387

	Max error	xgboost	linear regression	dense network
Japan	Confirmed	2505.31	2187.56	4456.09
	Deaths	126.151	50.9315	63.4678





4.2.2 10 days prediciton

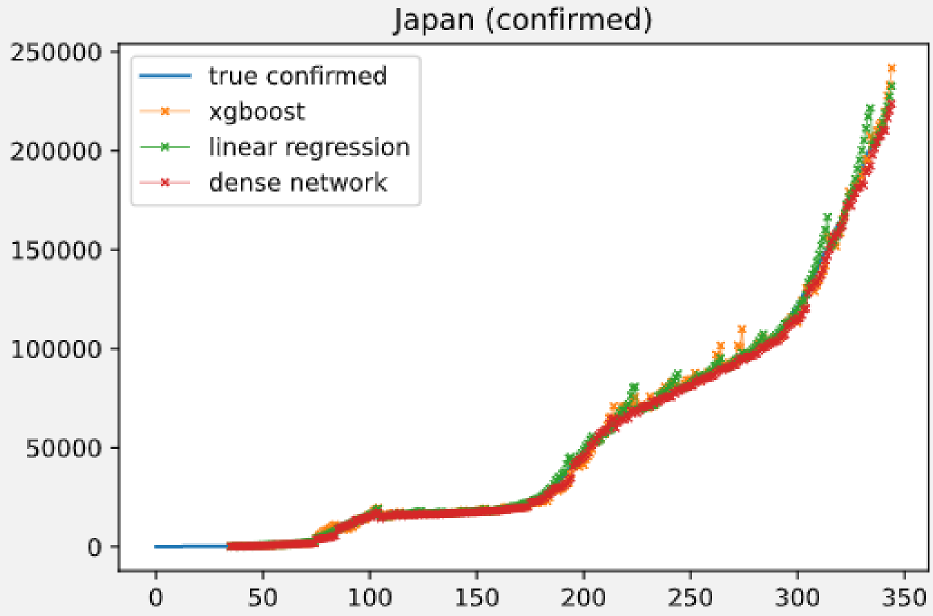
Data length: 335

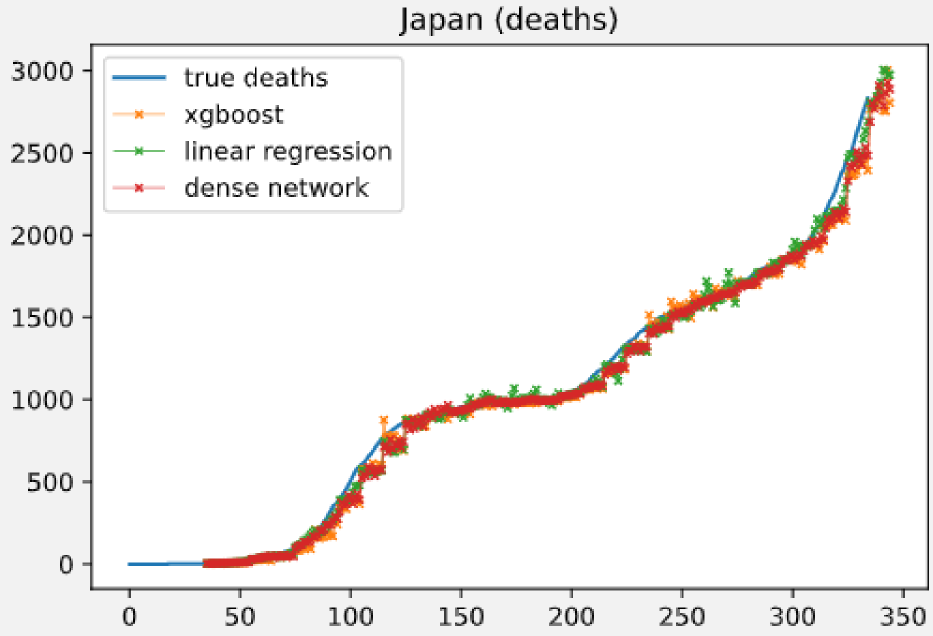
Training score	xgboost	linear regression	dense network
Confirmed	1	0.74128	0.38569
Deaths	1	0.750351	0.748695

Testing score	xgboost	linear regression	dense network
Confirmed	0.0715908	-0.126634	0.0118868
Deaths	0.029451	-3.15018	0.0911274

Japan

Max error	xgboost	linear regression	dense network
Confirmed	14870.1	20440.4	11261.9
Deaths	439.813	220.61	348.709





4.2.3 30 days prediction

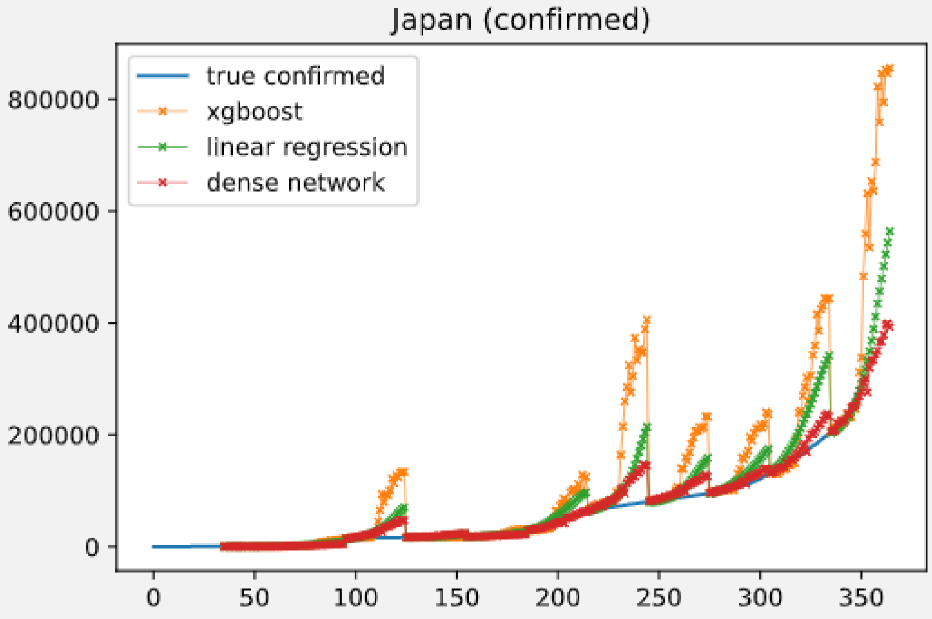
Data length: 335

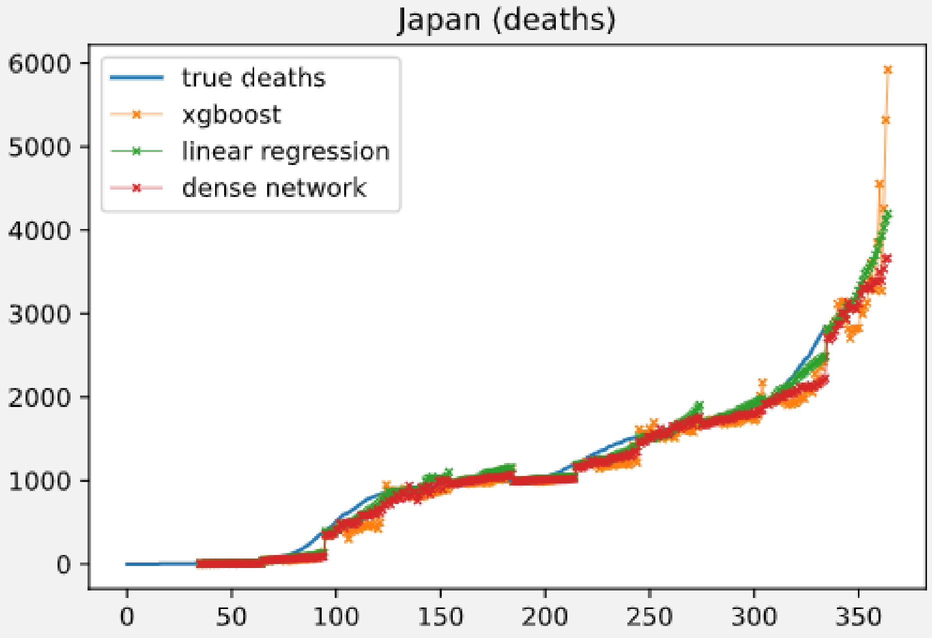
Training score	xgboost	linear regression	dense network
Confirmed	1	0.592588	0.244347
Deaths	1	0.731003	0.378217

Testing score	xgboost	linear regression	dense network
Confirmed	0.0247015	0.0661764	-0.00124943
Deaths	0.0231771	-0.0743319	0.000458915

Japan

Max error	xgboost	linear regression	dense network
Confirmed	326330	140927	68258
Deaths	530	343.506	608.476





5 The program

5.1 How to run

Here we demonstrate how to run our program in UNIX environment. A similar instruction can be found at https://github.com/twMisc/COVID-19-Forecasting-Python. Suppose one has python3, pip, git installed. First download the dataset and our program.

```
$ git clone https://github.com/CSSEGISandData/COVID-19/
$ git clone https://github.com/twMisc/COVID-19-Forecasting-Python
$ cd COVID-19-Forecasting-Python
```

Install the required packages in Python.

```
$ pip install xgboost numpy tensorflow scikit-learn tabulate matplotlib plotly pandas
```

Alternatively, install the requirements using requirements.txt if you encountered into some trouble.

```
$ pip install -r requirements.txt
```

Then modify the file `forecasting_setup.py` as required

```
observe_days = 30
predict_days = 1
keepdays = 150
training_countries = ['US','Spain']
```

- `observe_days`: input data length
- `predict_days`: output data length
- `keepdays`: the length of data to NOT use in training
- `training_countries`: the countries to be used in training, can be found in `country_list.txt`

Run `forecasting_run.py` in console to see the results if you want a quick glance.

```
$ python forecasting_run.py
```

5.2 Run in Visual Studio Code interactive window

To use this, you must have a Python environment where you have installed the Jupyter Package. You should also install the Python extension in VScode. Check out VScode's doc if you want to learn more.

Open `forecasting_run.py` in VScode, which also includes some explanation.

5.3 Run in Jupyter Notebook

If you have Jupyter Notebook or JupyterLab installed, you can use them as well.

Open `forecasting_run.ipynb` in JupyterLab or the classic Jupyter Notebook.

5.4 Run it in Python interpreter

You can also use the function yourself in your python console. After setting up `forecasting_setup.py`, in python, run something like

```
>>> from forecasting_multi import print_and_draw
>>> print_and_draw('Japan')
```

Replace Japan with any country in `country_list.txt`. Note that two html plot files `forecasting_confirmed.html` and `forecasting_deaths.html` generated by Plotly should also be available after running

```
print_and_draw(country_name).
```

where `country_name` is your input.

6 Conclusion

In our experiment, while linear regression may be useful if we want to predict only 1 day, the fails to predict well if more days are required. The XGBoost and dense neural network will be more useful in such case. In general we suggest using XGBoost or the dense network when predicting multiple days. The XGBoost model may still be improved since we do not have any correlation for the predict days, if we define some custom objective function the results may be improved.

Also, the testing results may vary depend on the training set chosen. If we choose the training countries more carefully, results may still be improved.