Covid-19 Pandemic Prediction

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Dataset introduction

Covid-19 Pandemic Prediction

- 2019 年 12 月 31 日，世衛組織收到關於中國湖北省武漢市多起肺炎病例的警報。
- 該病毒與任何其他已知病毒都不相符

  → 這引起了人們的關注，因為當病毒是新病毒時，我們不知道它會對人們造成什麼影響。
- 透過分析過去這段時間的疫情資料，可以為我們提供更多對於新冠病毒的瞭解，掌握目前趨勢，甚至進行本國疫情之預測
- 資料來自：
  https://www.kaggle.com/sudalairajkumar/novel-corona-virus-2019-dataset

Dataset

- 資料來源：約翰霍普金斯大學（Johns Hopkins） Github repository (as csv files)
- 306429 筆資料, 8 個 columns:
  - Sno - Serial number
  - ObservationDate - Date of the observation in MM/DD/YYYY
  - Province/State - Province or state of the observation (Could be empty when missing)
  - Country/Region - Country of observation
  - Last Update - Time in UTC at which the row is updated for the given province or country.
  - Confirmed - **Cumulative number** of confirmed cases till that date
  - Deaths - **Cumulative number** of of deaths till that date
  - Recovered - **Cumulative number** of recovered cases till that date

Data Preprocessing & Visualization

資料預處理

1. Standardizing the date-time column
   ➔ column “ObservationDate” to date time

```
[ ]   df['ObservationDate'] = pd.to_datetime(df['ObservationDate'])
```

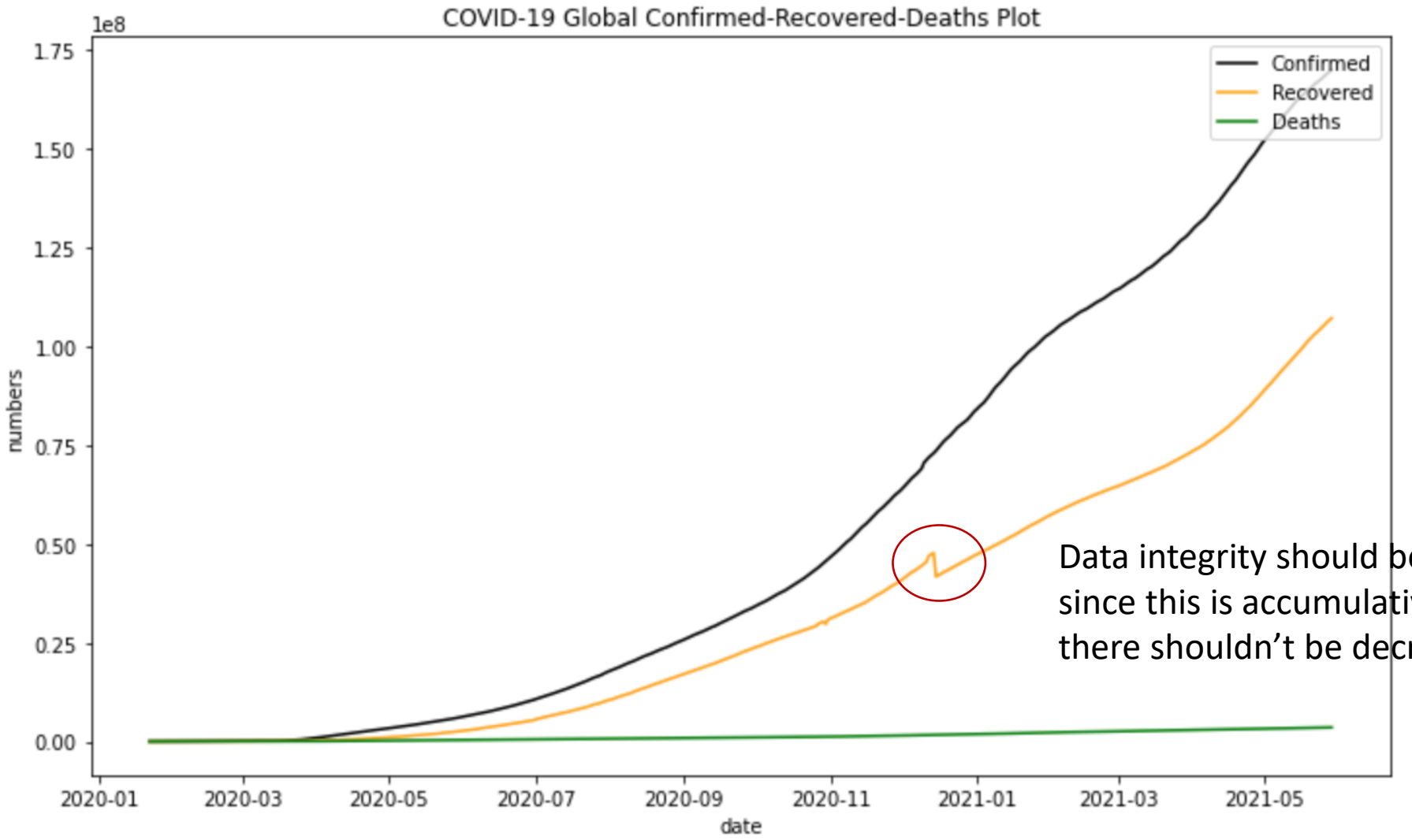
2. Group by Observation Date & sum up all the case count through the countries

```
preprocessed_df = df.groupby(df['ObservationDate'].dt.date)['Confirmed','Deaths','Recovered'].agg(['sum']) #算總和
```

   ➔ after grouping: 306429 rows × 8 columns → 494 rows × 3 columns

3. Data Visualization

COVID-19 Pandemic Global Trend Plot



Data integrity should be suspected since this is accumulative number, there shouldn't be decreasing

Model Training & Prediction

Part 2: COVID-19 台灣疫情預測

- We choose Taiwan as the country to do the prediction

```
[ ]  x = df[df['Country/Region']=='Taiwan'] #選要做分析的國家
```

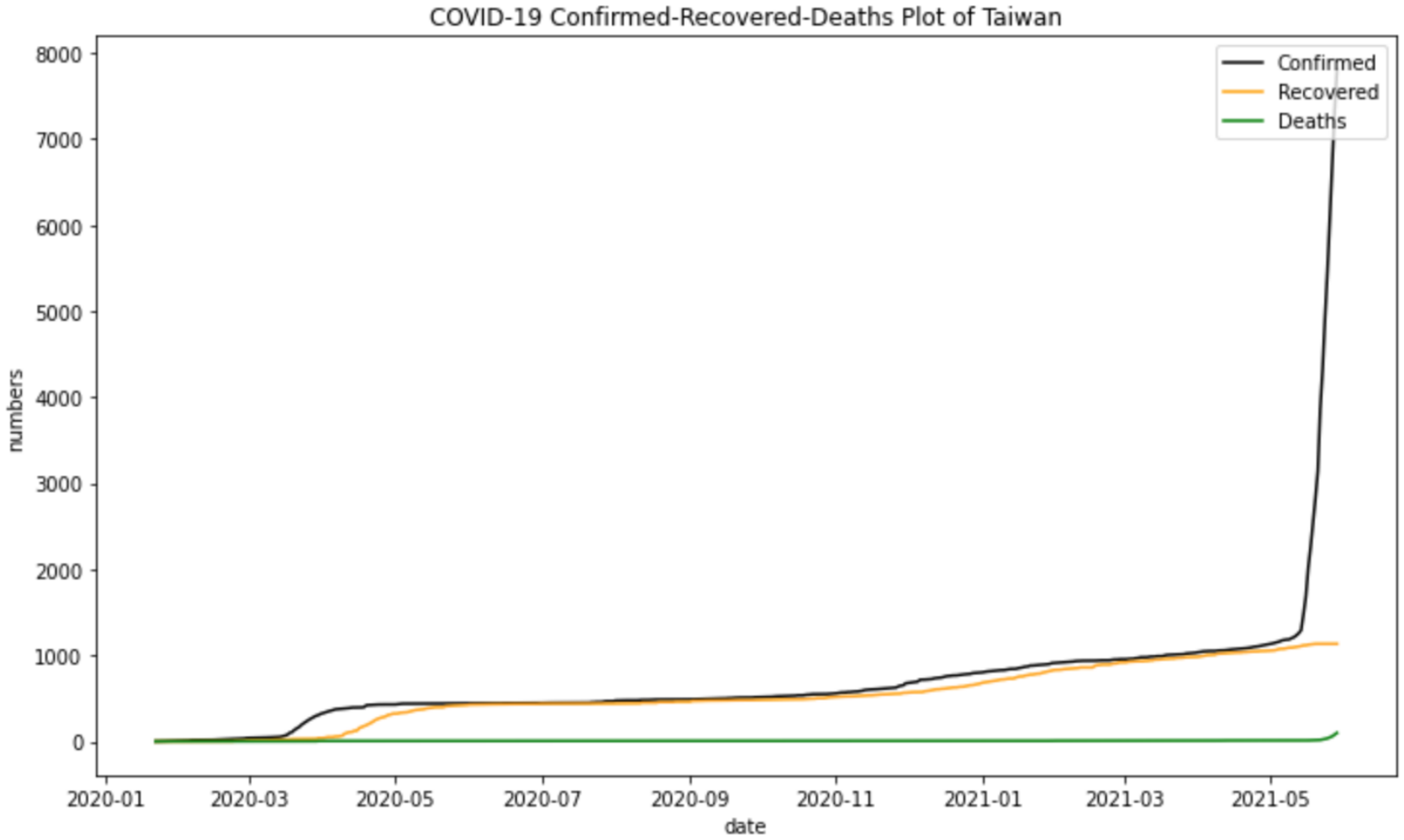
- Do the preprocessing as while dealing with the global data:
  - Standardizing the date-time
  - Group by & sum up
  - Data visualization

```
[ ]  preprocessed_x
```

ObservationDate	Confirmed sum	Deaths sum	Recovered sum
2020-01-22	1.0	0.0	0.0
2020-01-23	1.0	0.0	0.0
2020-01-24	3.0	0.0	0.0
2020-01-25	3.0	0.0	0.0
2020-01-26	4.0	0.0	0.0
...	...	...	...
2021-05-25	5456.0	35.0	1133.0
2021-05-26	6091.0	46.0	1133.0
2021-05-27	6761.0	59.0	1133.0
2021-05-28	7315.0	78.0	1133.0
2021-05-29	7806.0	99.0	1133.0

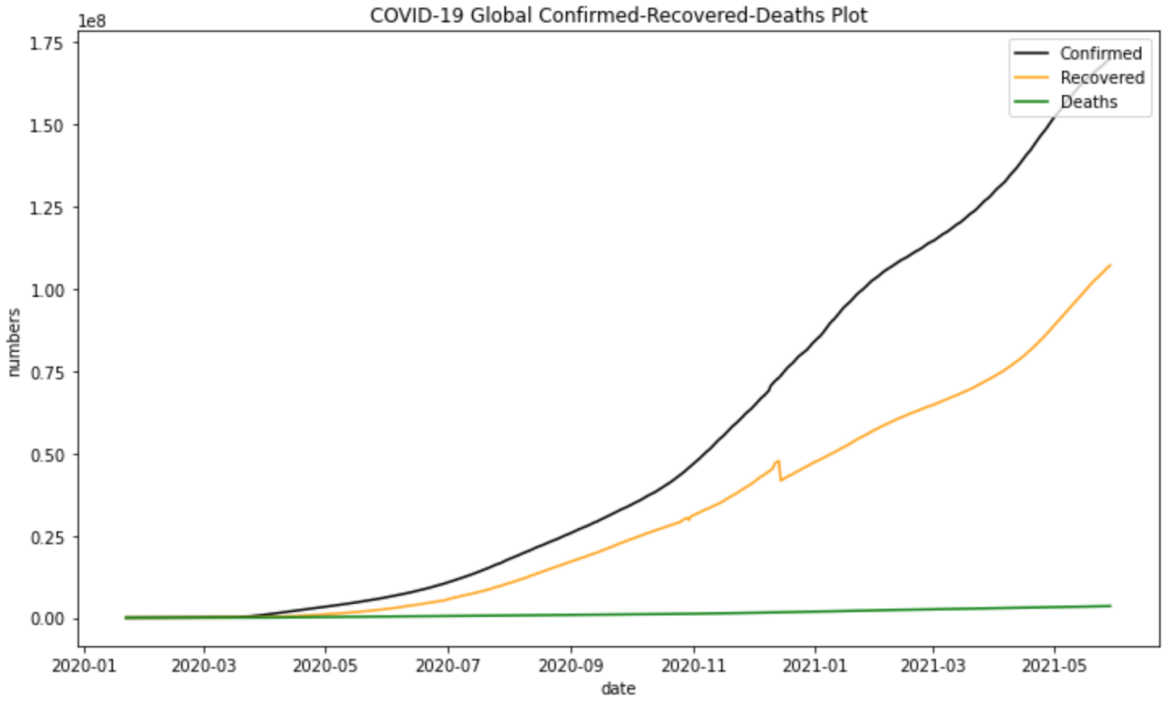
494 rows × 3 columns

COVID-19 台灣趨勢累計圖

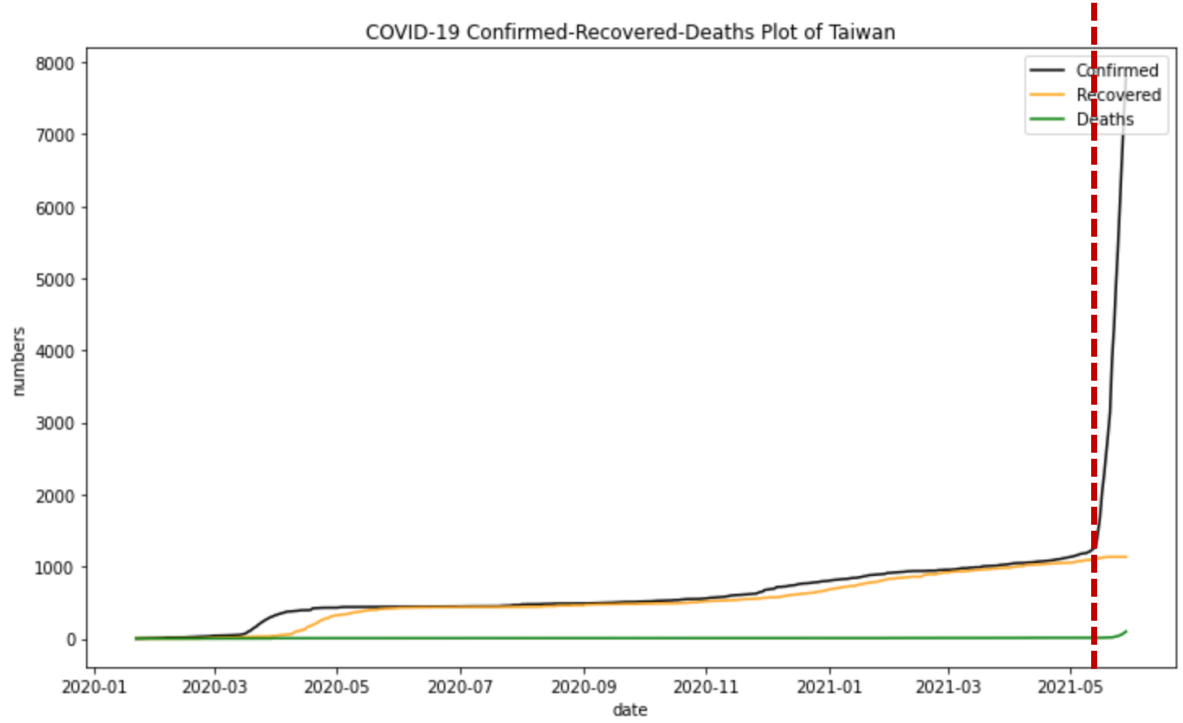


COVID-19 全球趨勢與台灣趨勢之比較

*** note: the order of magnitude is different in 2 plots

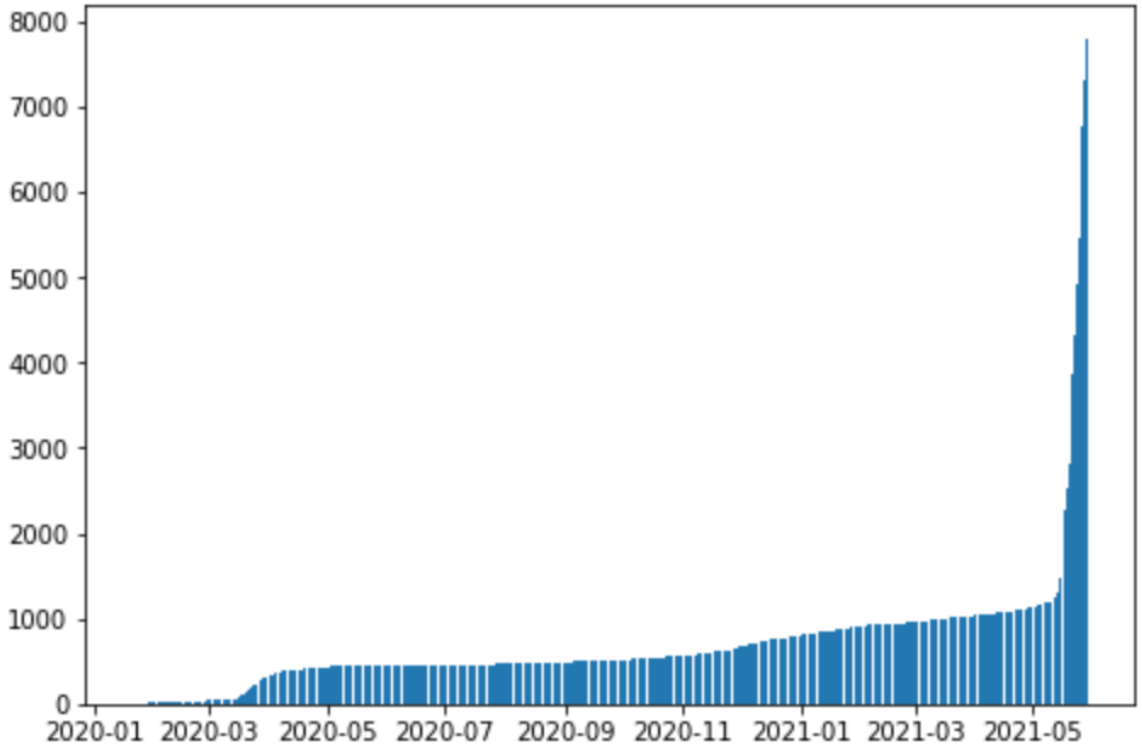


Outbreak in Mid-May

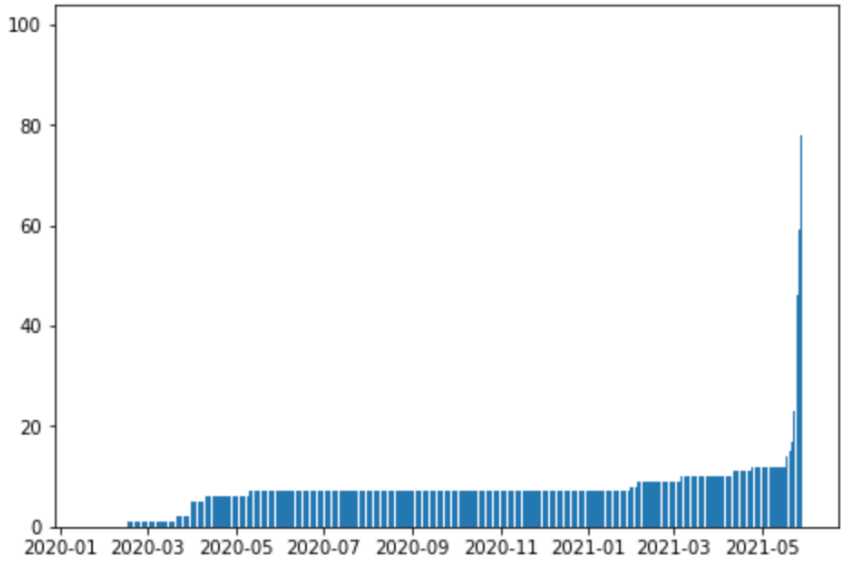


台灣案件數統計圖

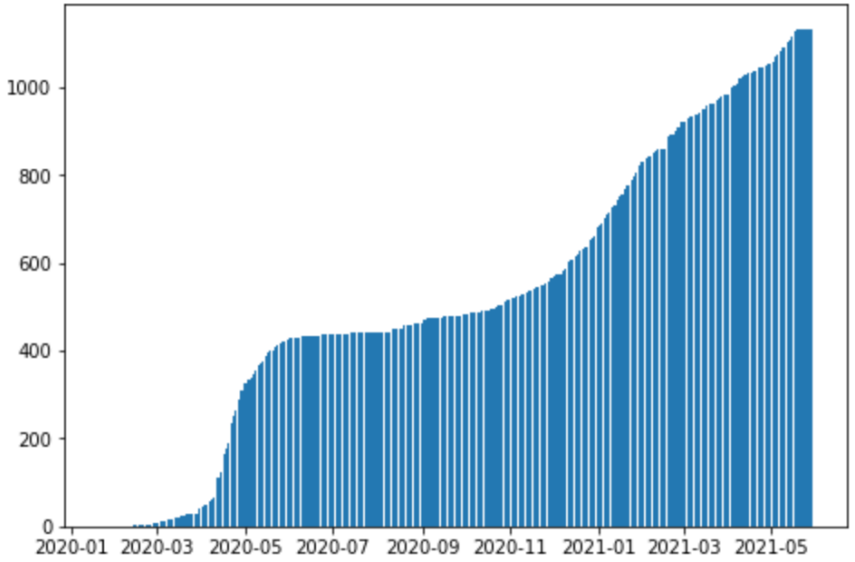
- 台灣確診數累計圖



- 台灣死亡數累計圖



- 台灣復原數累計圖

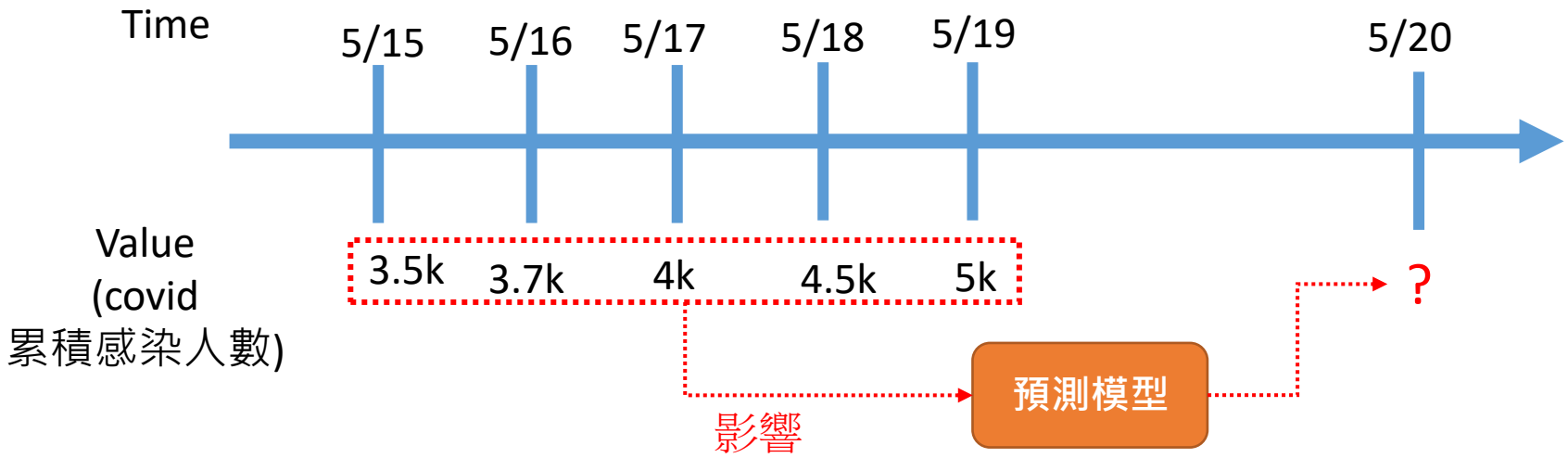


LSTM

以預測covid每日確診累積人數為例

使用LSTM的動機

- 欲處理的資料**具有時序上**的關係
  - 例如, 當我們打算預測5/20的累積感染人數時，5/20之前的感染人數(5/19,18...) 其實應該是會對5/20的預測有所影響的。



對比: 使用CNN or MLP 處理非時序性資料

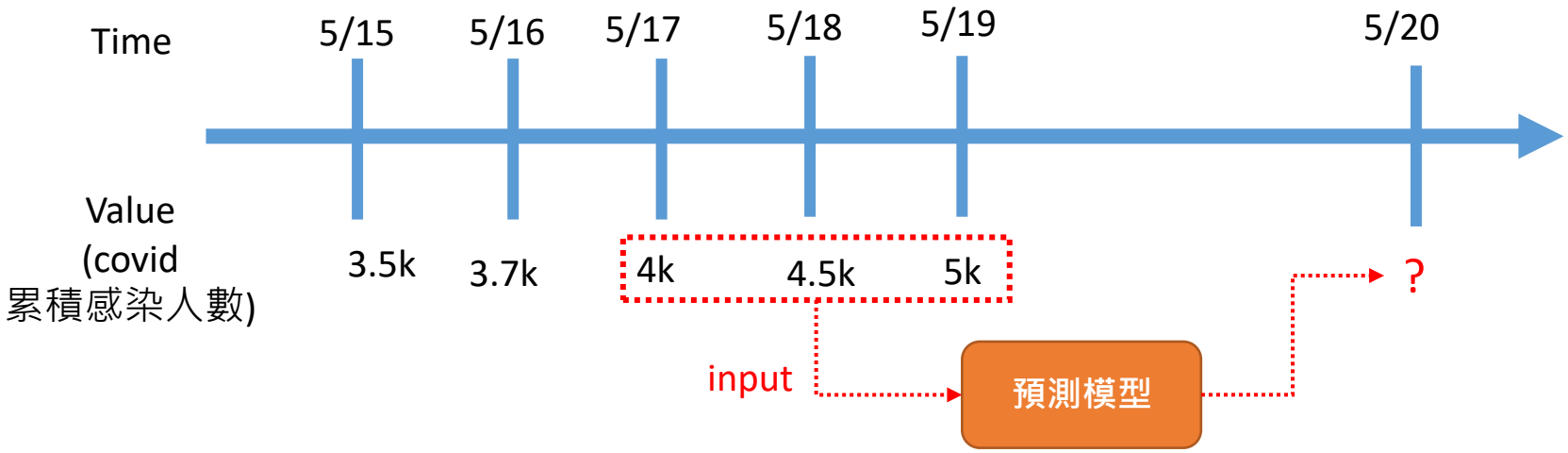
- **Task1 年收入預測**
  - 50000筆資料, 每筆資料代表了一個人的資訊
  - 每筆訓練資料內容為: 性別、出生地、人種、職業、年齡…
  - 訓練label: 0 = 年收入小於$50k, label:1 =年收入大於$50k
  - 任務目標是:
    - 給定一筆個人資訊 (性別、出生地、人種、職業、年齡), 預測其年收入大於or小於$50k
  - Model: MLP
- 對於這種任務而言，資料與資料之間就不具時序性。模型預測過程中，上一筆資料的預測結果並不會影響到這一筆資料的預測結果
  - 上一個人是否年收入> $50k 並不影響現在這個人的預測結果

對比: 使用CNN or MLP 處理非時序性資料

- Task2 影像分類
  - 20000筆動物影像資料
  - 訓練label 為影像所屬的動物類別
  - 任務目標是:
    - 給定一張影像，進行所屬動物類別的判斷
  - Model: CNN
- 對於這種任務而言，資料與資料之間就不具時序性。模型預測過程中，上一張影像的判斷結果並不會影響到這一張影像的判斷結果

Look back

- 前述提到了資料具有時序性，LSTM如何讓前幾筆資料能夠對現在這筆資料的預測產生影響?
- 首先從LSTM 中**look back**的概念開始:
  - Look back: 意即對於預測這筆資料，你打算往前看多少筆資料?
  - Ex: Look back = 3, 代表對於預測5/20 感染人數，我打算往前看3筆資料來幫助我進行這一次的預測。



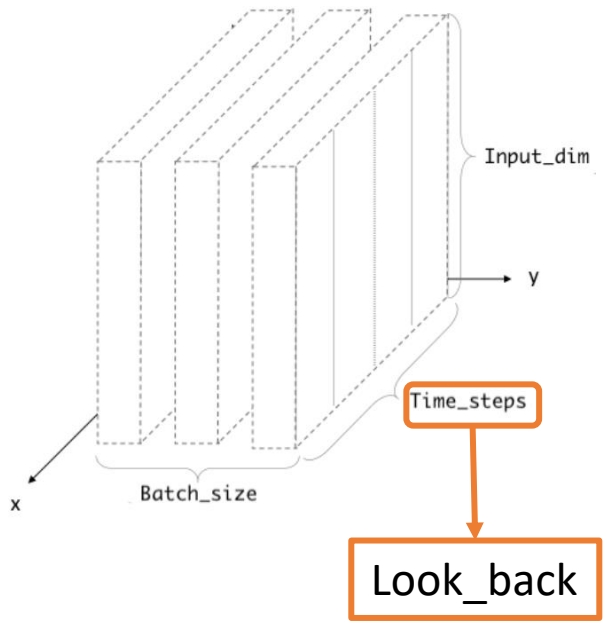
Look back

- 承接LSTM中look back (ex, look_back = 3)的想法，我們可以把資料進行預處理
- 將每三筆 (look_back size) 資料包起來當作一筆模型的訓練資料。

各日累積確診數

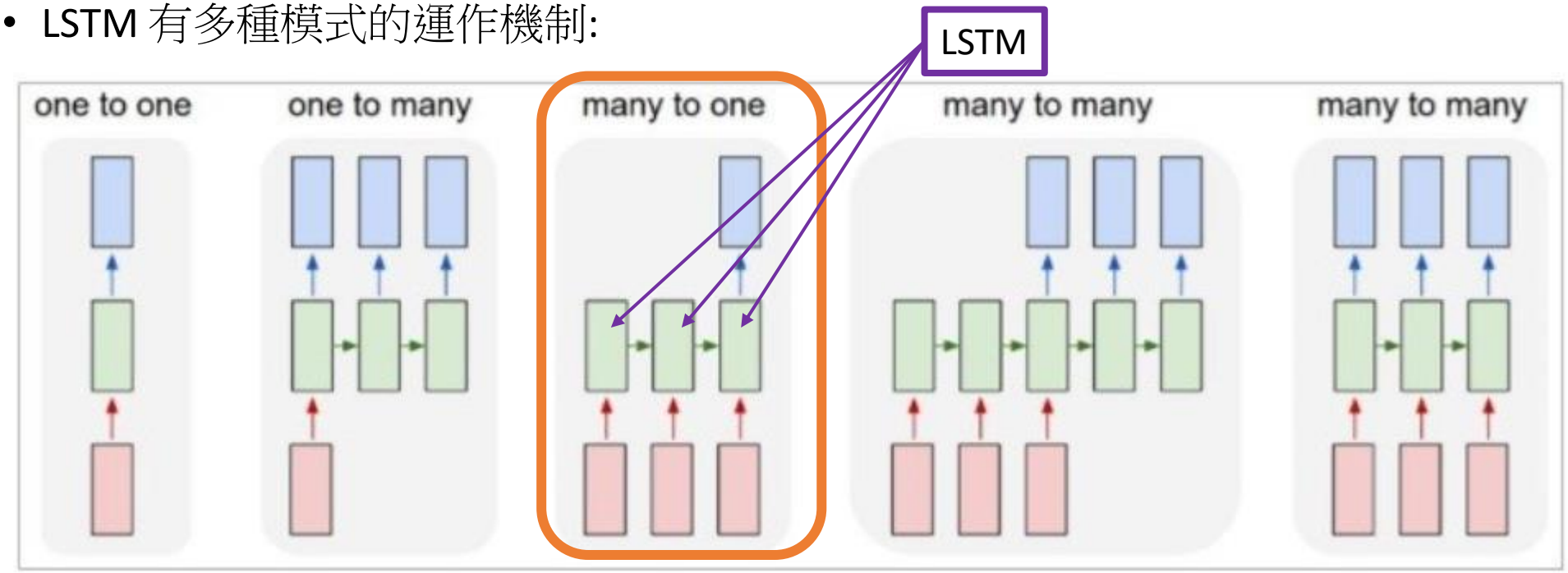
```
array([  1.,   1.,   3.,   3.,   4.,   5.,   8.,   8.,   9.,  10.,  10.,
        10.,  10.,  11.,  11.,  16.,  16.,  17.,  18.,  18.,  18.,  18.,
        18.,  18.,  18.,  20.,  22.,  22.,  23.,  24.,  26.,  26.,  28.,
        30.,  31.,  32.,  32.,  34.,  39.,  40.,  41.,  42.,  42.,  44.,
        45.,  45.,  45.,  45.,  47.,  48.,  49.,  50.,  53.,  59.,  67.,
        77.,  100.,  108.,  135.,  153.,  169.,  195.,  215.,  235.,  252.,  267.,
       283.,  298.,  306.,  322.,  329.,  339.,  348.,  355.,  363.,  373.,  376.,
       379.,  380.,  382.,  385.,  388.,  393.,  393.,  395.,  395.,  395.,  398.,
       420.,  422.,  425.,  426.,  427.,  428.,  429.,  429.,  429.,  429.,  429.,
       429.,  429.,  432.,  436.,  438.,  438.,  439.,  440.,  440.,  440.,  440.,
       440.,  440.,  440.,  440.,  440.,  440.,  440.,  440.,  440.,  440.,  440.,
       441.,  441.,  441.,  441.,  441.,  441.,  441.,  442.,  442.,  442.,  443.,
       443.,  443.,  443.,  443.,  443.,  443.,  443.,  443.,  443.,  443.,  443.,
       443.,  443.,  445.,  445.,  445.,  446.,  446.,  446.,  446.,  446.,  446.,
       446.,  447.,  447.,  447.,  447.,  447.,  447.,  447.,  448.,  449.,  449.,
       449.,  449.,  449.,  449.,  449.,  449.,  451.,  451.,  451.,  451.,  451.,
       451.,  451.,  451.,  451.,  451.,  451.,  455.,  455.,  458.,  458.,  458.,
       462.,  467.,  467.,  467.,  467.,  474.,  475.,  474.,  476.,  476.,  477.,
       477.,  479.,  477.,  477.,  480.,  481.,  481.,  481.,  482.,  484.,  485.,
       486.,  486.,  486.,  487.,  487.,  487.,  487.,  487.,  487.,  487.,  487.,
       488.,  488.,  488.,  488.,  489.,  489.,  490.,  492.,  493.,  494.,  495.,
       495.,  496.,  498.,  498.,  498.,  499.,  499.,  500.,  503.,  503.,  506.,
       507.,  509.,  509.,  509.,  509.,  510.,  510.,  510.,  513.,  513.,  514.,
       515.,  517.,  517.,  517.,  518.,  521.,  523.,  524.,  527.,  527.,  527.,
       529.,  530.,  530.,  531.,  535.,  535.,  535.,  540.,  543.,  544.,  548.,
       548.,  550.,  550.,  550.,  550.,  550.,  553.,  554.,  555.,  558.,  563.,
       567.,  568.,  569.,  573.,  573.,  577.,  578.,  580.,  584.,  589.,  597.,
       600.,  602.,  603.])
```

```
array([[  1.,   1.,   3.],  [ 18.,  18.,  18.],
       [  1.,   3.,   3.],  [ 18.,  18.,  18.],
       [  3.,   3.,   4.],  [ 18.,  18.,  20.],
       [  3.,   4.,   5.],  [ 18.,  20.,  22.],
       [  4.,   5.,   8.],  [ 20.,  22.,  22.],
       [  5.,   8.,   8.],  [ 22.,  22.,  23.],
       [  8.,   8.,   9.],  [ 22.,  23.,  24.],
       [  8.,   9.,  10.],  [ 23.,  24.,  26.],
       [  9.,  10.,  10.],  [ 24.,  26.,  26.],
       [ 10.,  10.,  10.],  [ 26.,  26.,  28.],
       [ 10.,  10.,  10.],  [ 26.,  28.,  30.],
       [ 10.,  10.,  11.],  [ 28.,  30.,  31.],
       [ 10.,  11.,  11.],  [ 30.,  31.,  32.],
       [ 11.,  11.,  16.],  [ 31.,  32.,  32.],
       [ 11.,  16.,  16.],  [ 32.,  32.,  34.],
       [ 16.,  16.,  17.],  [ 32.,  34.,  39.],
       [ 16.,  17.,  18.],  [ 34.,  39.,  40.],
       [ 17.,  18.,  18.],  [ 39.,  40.,  41.],
       [ 18.,  18.,  18.],  [ 40.,  41.,  42.],
       [ 18.,  18.,  18.],  [ 41.,  42.,  42.],
       [ 18.,  18.,  18.],  [ 42.,  42.,  44.],
       [ 18.,  18.,  20.],  [ 42.,  44.,  45.],
       [ 18.,  20.,  22.],
       [ 20.,  22.,  22.],
```



LSTM 架構

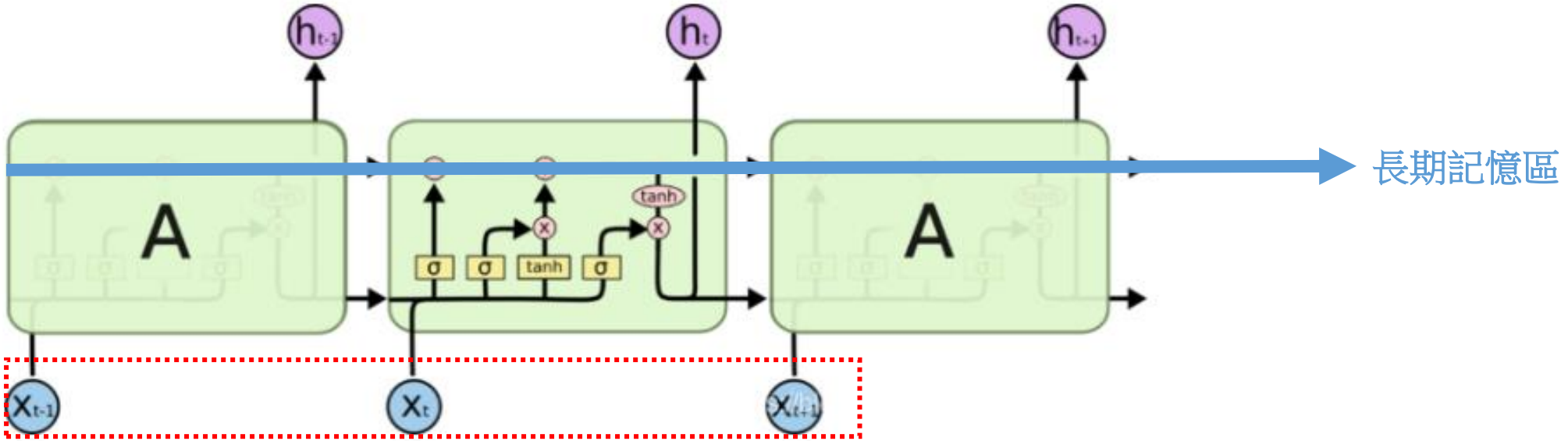
- 根據look back概念處理完訓練資料後，我們就可以來看 LSTM 的運作機制
- LSTM 有多種模式的運作機制:



- 端看訓練資料以及label的維度來決定，以預測covid累積確診人數為例，訓練資料3維(look back = 3) 而預測維度一維(某單日累積確診數)，LSTM 是採取上述 **Many-to-one**的模式。

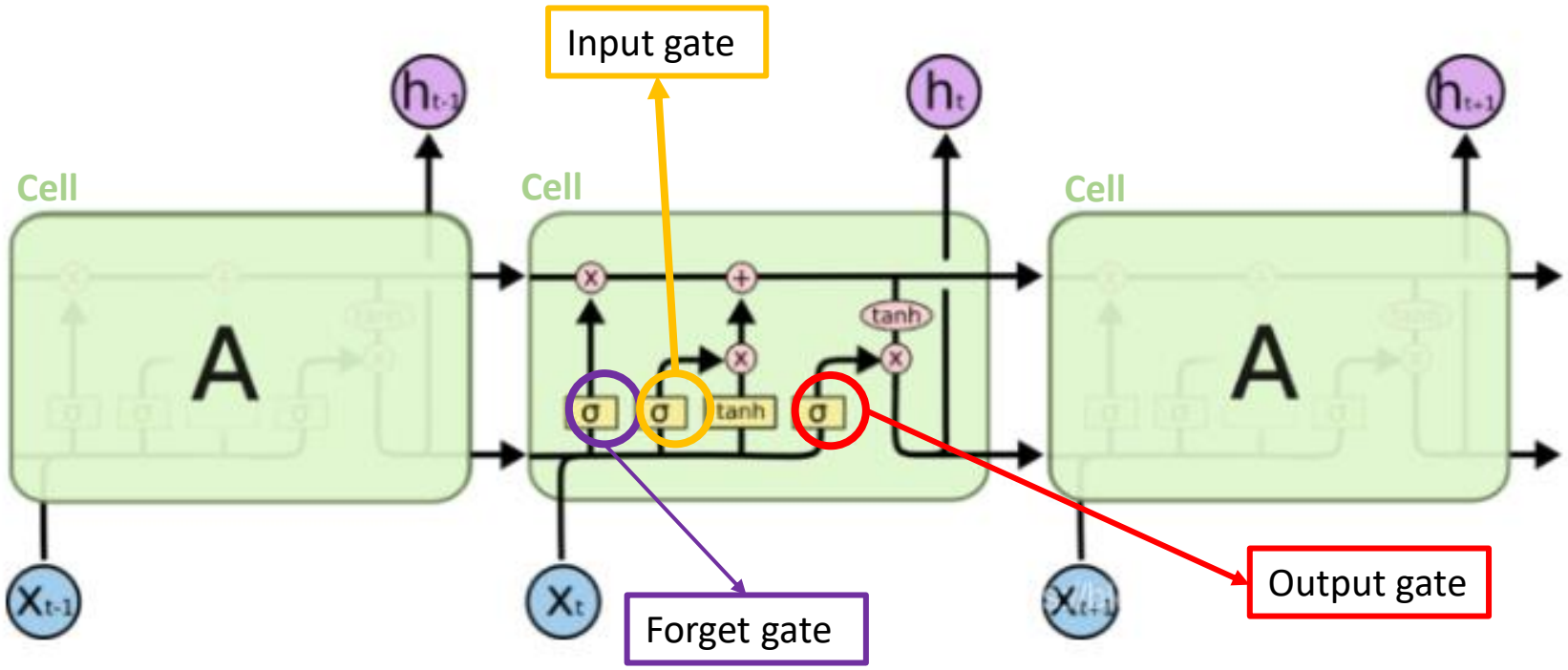
LSTM 架構

- LSTM 如何建立不同資料間的關係以及彼此之間怎麼傳遞訊息
- 長期記憶區就像是個輸送帶一樣，訊息在上面進行輸入、修改、傳送的動作，以此來達到不同資料之間訊息的交流以及保存。



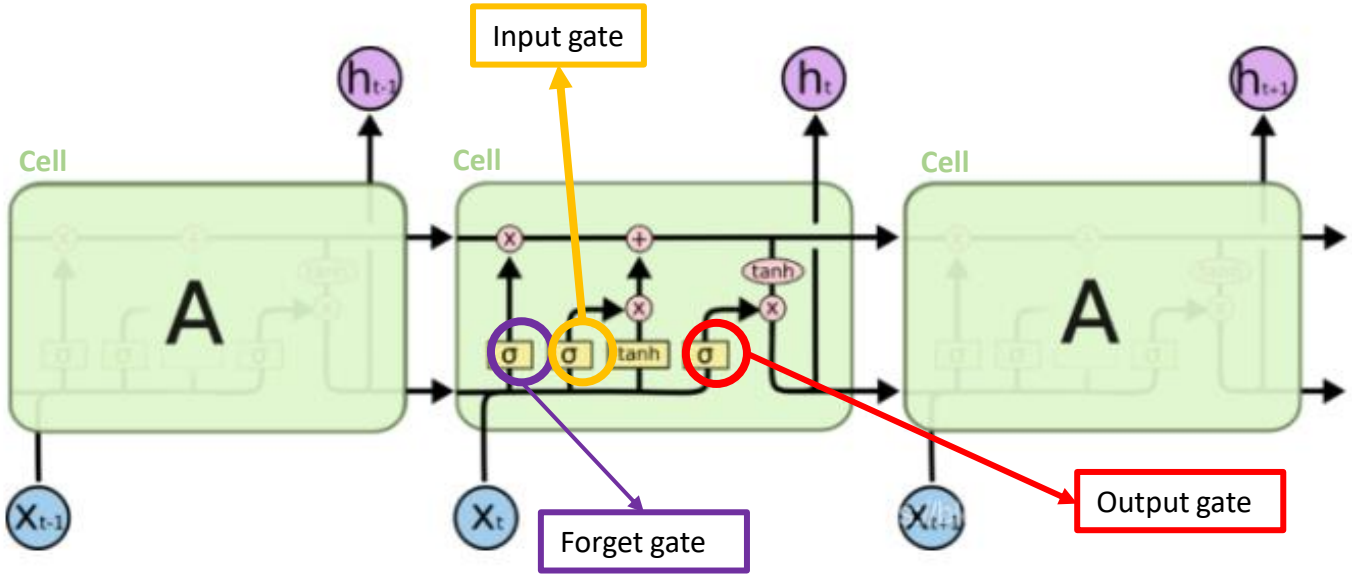
LSTM 架構

- 利用三個gate, 決定來自過去的訊息要保留多少、遺忘多少、如何使用過去訊息來與當下訊息進行計算
- **Forget gate**, **Input gate**, **Output gate**



LSTM 架構

- 三個gate
  - Forget gate : 累積至此的資訊，要忘記多少後再送入長期記憶區?
  - Input gate: 累積至此的資訊要使用多少來進行一個**cell**的計算後，再送入長期記憶區?
  - Output gate:累積至此的資訊要留多少進入下一個**cell**?



LSTM 架構

- 藉由上述 LSTM的設計架構，我們就能讓look back 範圍內的資料能夠充分的交流，最後再以彙整的資訊進行最後的output。
- LSTM最後output 出來的feature 會再當作後續 MLP 的input，直到最後輸出一維的預測累積感染人數。

```
model = Sequential()
# look_back = 3
model.add(LSTM(20, input_shape=(look_back, 1), activation='relu'))
model.add(Dense(64, activation='relu'))
model.add(Dense(8, activation='relu'))
model.add(Dense(1))
#model.compile(loss='mean_squared_error', optimizer='adam')
model.compile(loss='MSE', optimizer='adam')
history = model.fit(trainX, trainY, epochs=100, batch_size=8)
```

實驗結果

- 對於預測累積確診、康復、死亡人數，我們都各自建立的model，並從486筆資料中切出296筆作為訓練資料，190筆為驗證資料

```
model = Sequential()
# look_back = 3
model.add(LSTM(20, input_shape=(look_back, 1), activation='relu'))
model.add(Dense(64, activation='relu'))
model.add(Dense(8, activation='relu'))
model.add(Dense(1))
#model.compile(loss='mean_squared_error', optimizer='adam')
model.compile(loss='MSE', optimizer='adam')
history = model.fit(trainX, trainY, epochs=100,
```

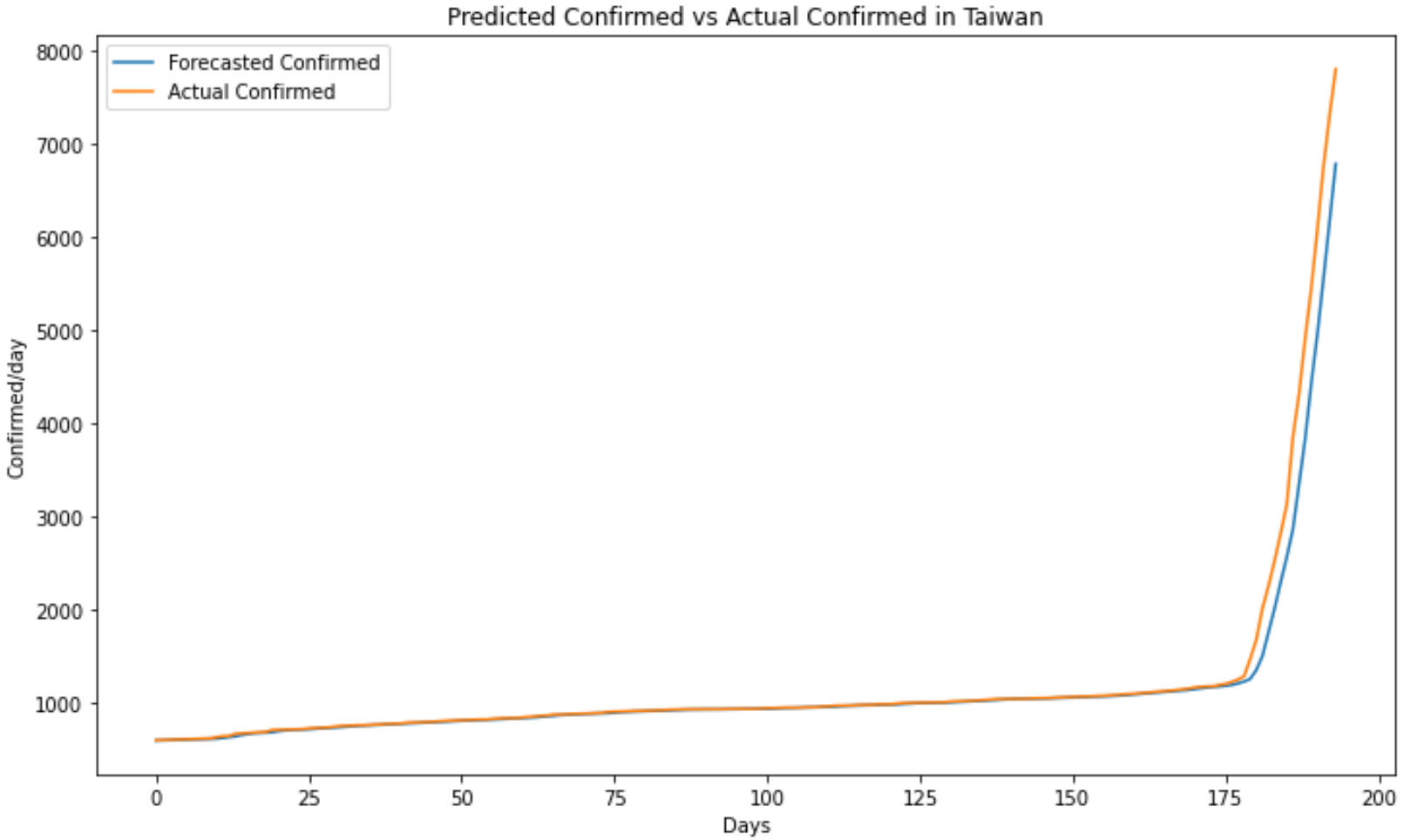
```
[ ] # split into train and test sets
    train_size = 300
    test_size = len(y_confirmed) - train_size
    trainX,testX = X[0:train_size],X[train_size:]
    trainY, testY = y_confirmed[0:train_size], y_confirmed[train_size:]
```

```
[ ] look_back = 3
    trainX, trainY = create_dataset(trainY, look_back)
    testX, testY = create_dataset(testY, look_back)
```

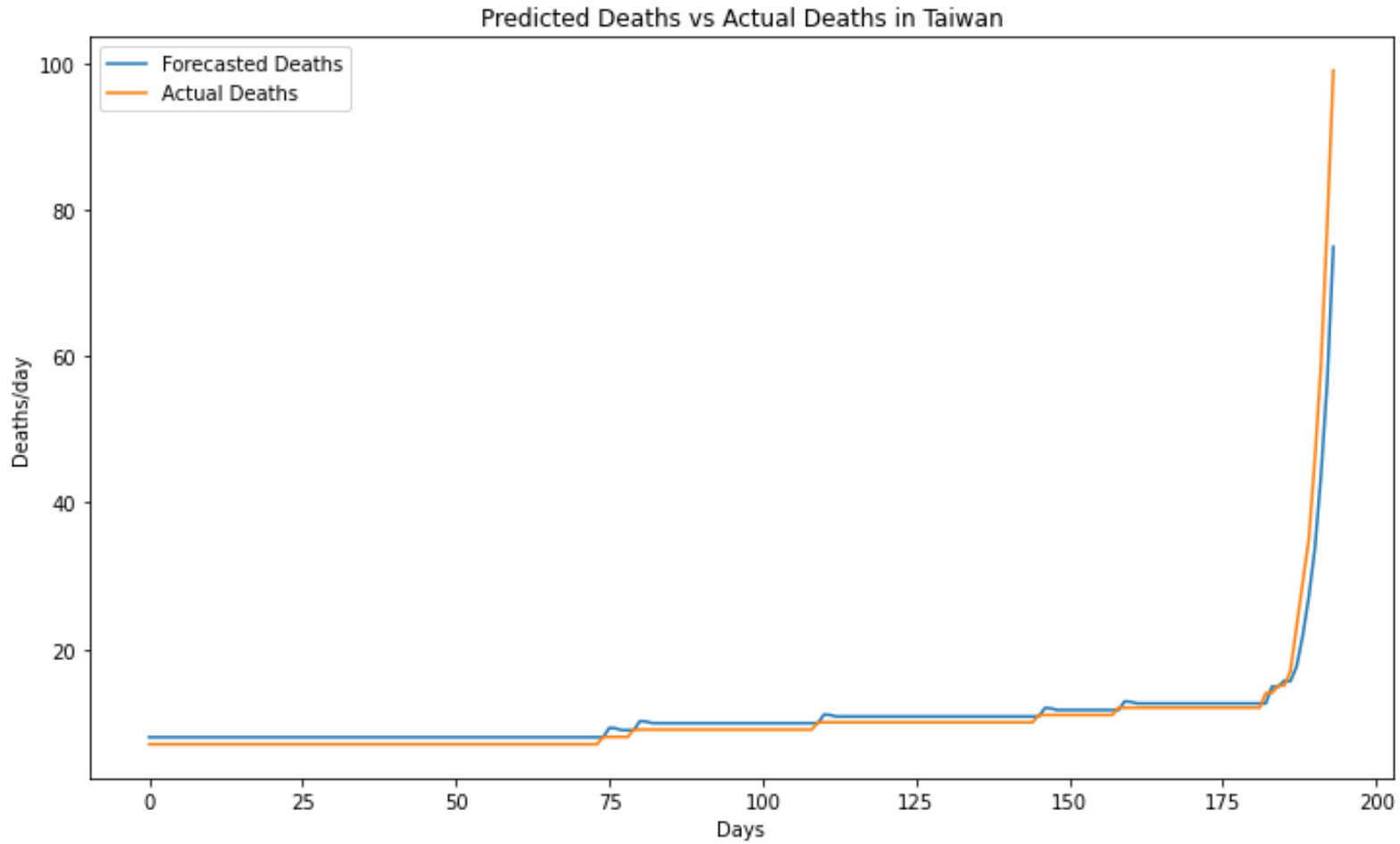
```
[ ] print(trainX.shape,trainY.shape,testX.shape, testY.shape)

    (296, 3) (296,) (190, 3) (190,)
```

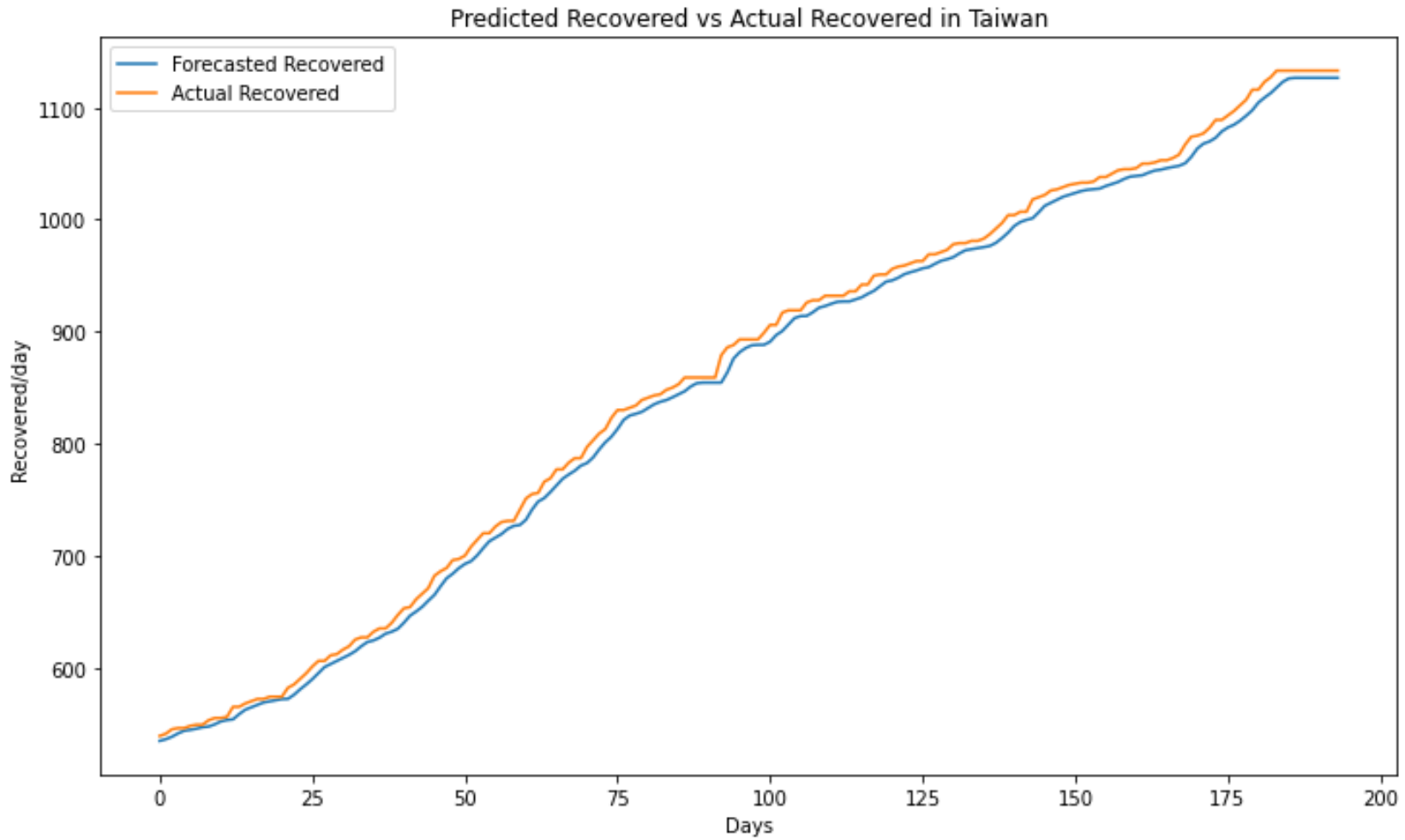
實驗結果


Predicted Confirmed vs Actual Confirmed in Taiwan
Forecasted Confirmed
Actual Confirmed
Confirmed/day
Days
8000
7000
6000
5000
4000
3000
2000
1000
0
25
50
75
100
125
150
175
200

實驗結果


Predicted Deaths vs Actual Deaths in Taiwan
Forecasted Deaths
Actual Deaths
Deaths/day
Days
100
80
60
40
20
0
25
50
75
100
125
150
175
200

實驗結果


Predicted Recovered vs Actual Recovered in Taiwan
Forecasted Recovered
Actual Recovered
Recovered/day
1100
1000
900
800
700
600
0
25
50
75
100
125
150
175
200
Days

實驗結果

- 上述實驗結果顯示，利用LSTM + MLP 的模型架構，能夠很好的擬合於訓練資料並且預測出合理的未來趨勢