TIME SERIES MODELLING OF COVID CASES AND HOSPITALISATIONS

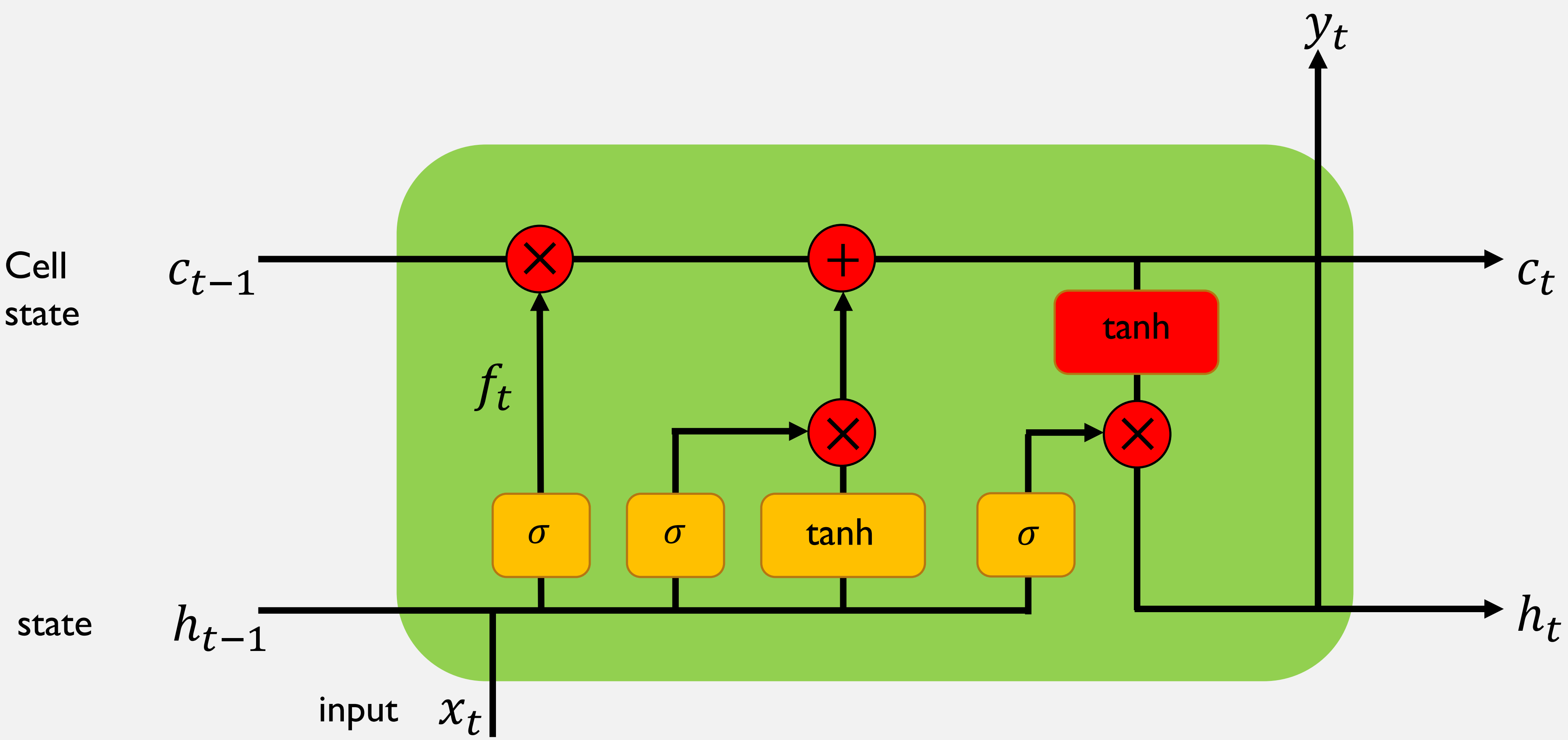
LONG SHORT TERM MEMORY (LSTM) NETWORKS

Information is added or removed through gates

Gates optionally let information through for example via a sigmoid neural net layer and pointwise multiplication.

LONG SHORT TERM MEMORY (LSTM) NETWORKS

1- Forget   2- Store   3- Update   4-Output



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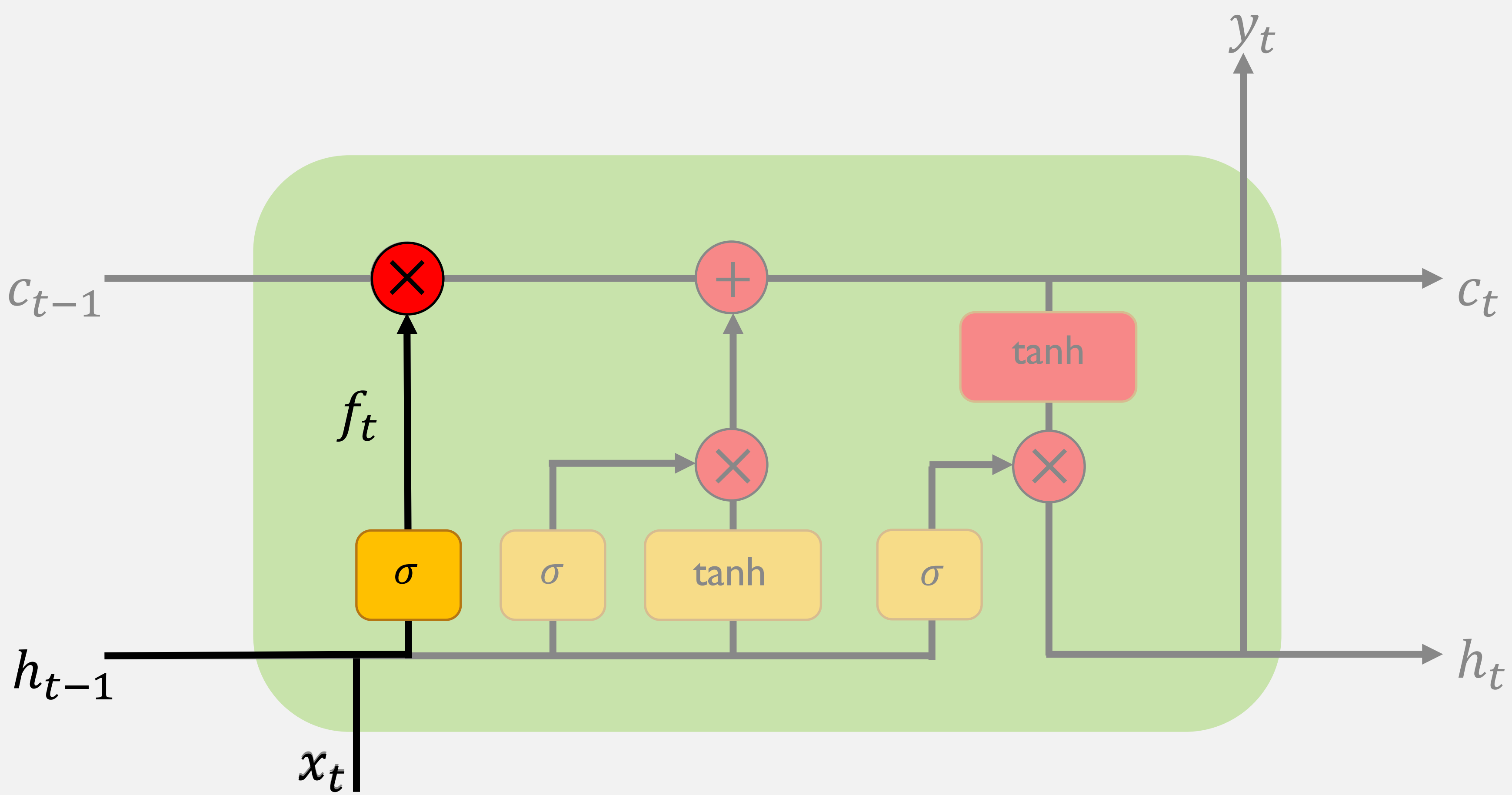

LONG SHORT TERM MEMORY (LSTM) NETWORKS

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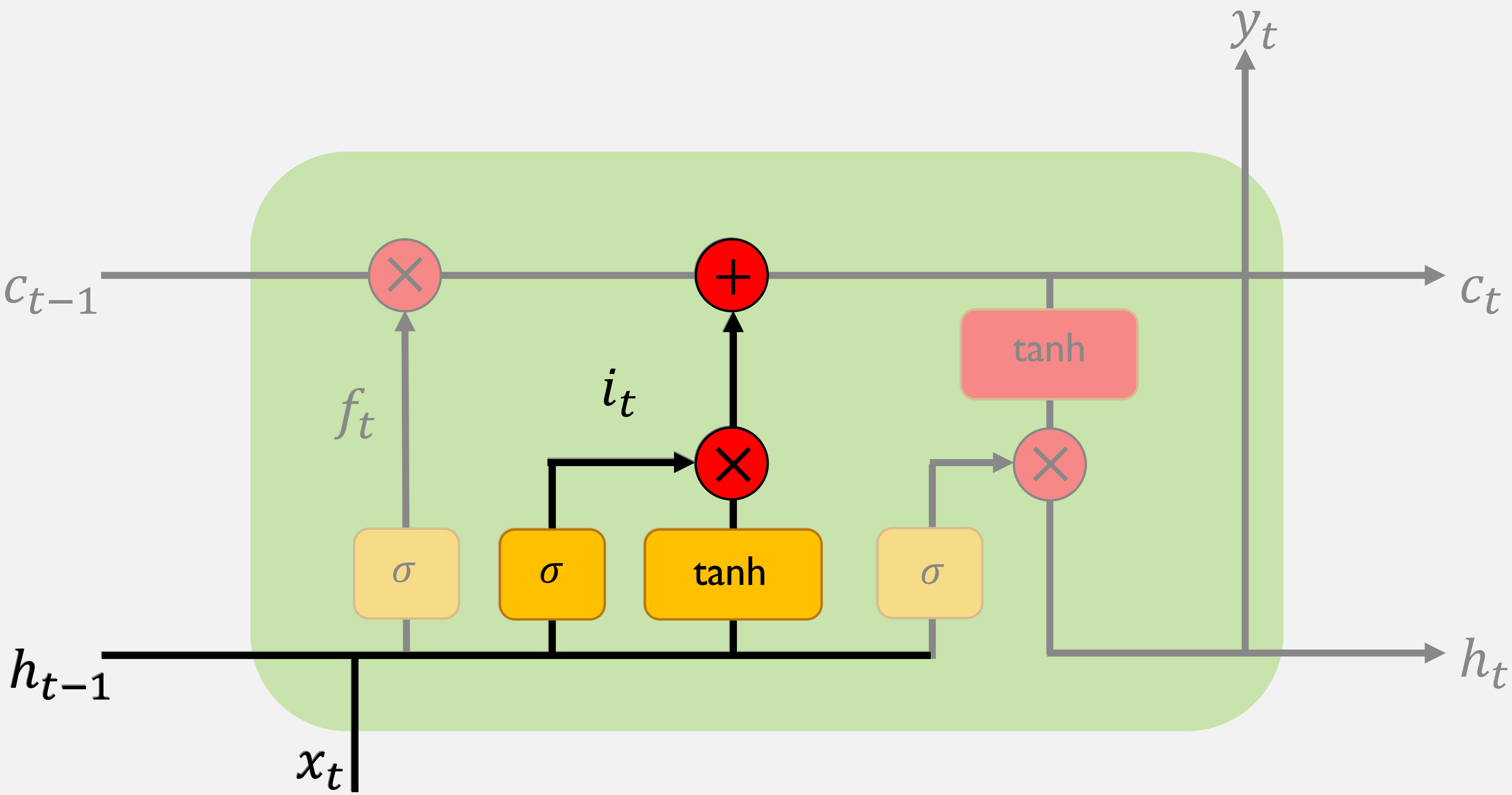

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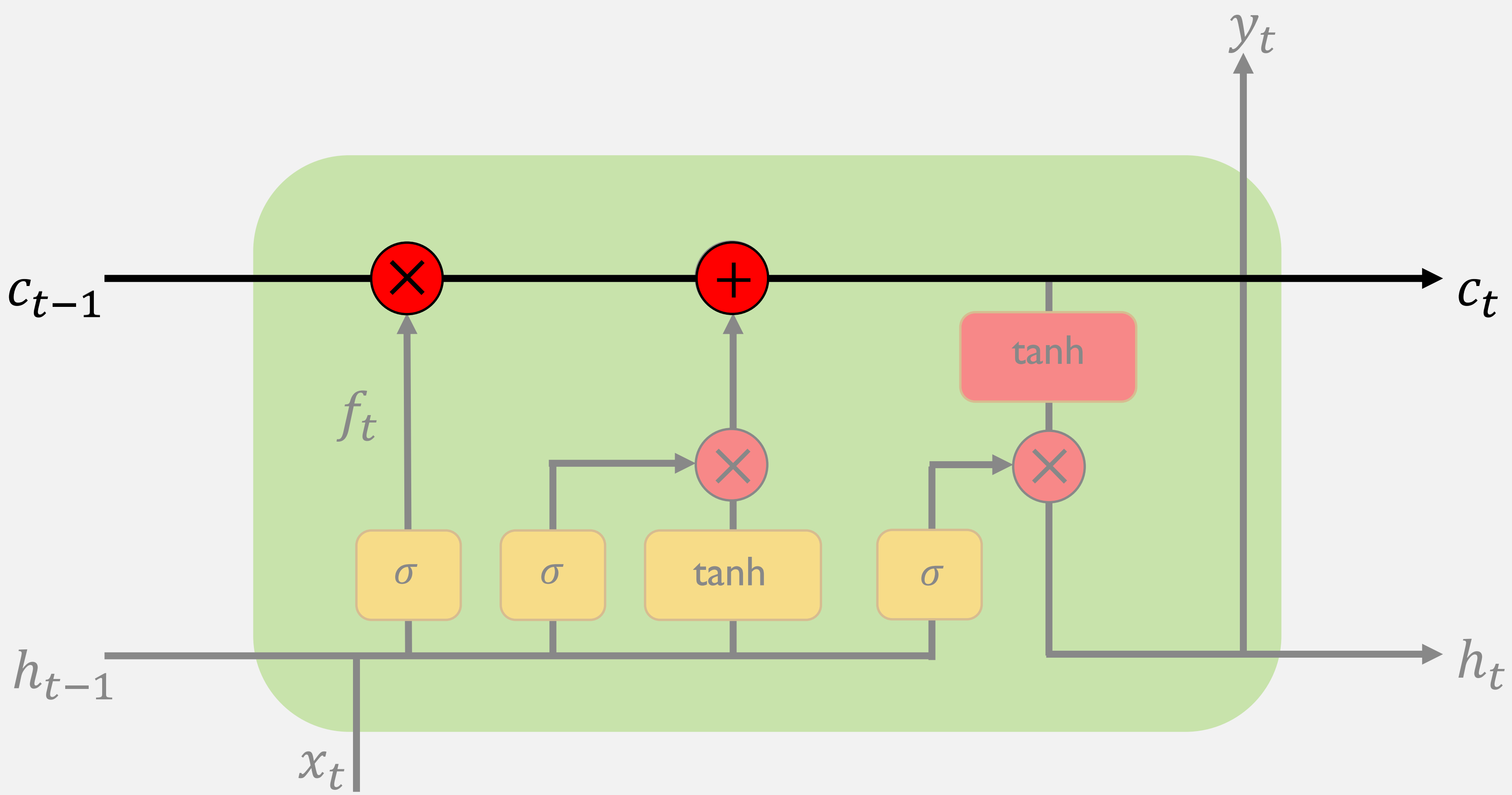

LONG SHORT TERM MEMORY (LSTM) NETWORKS

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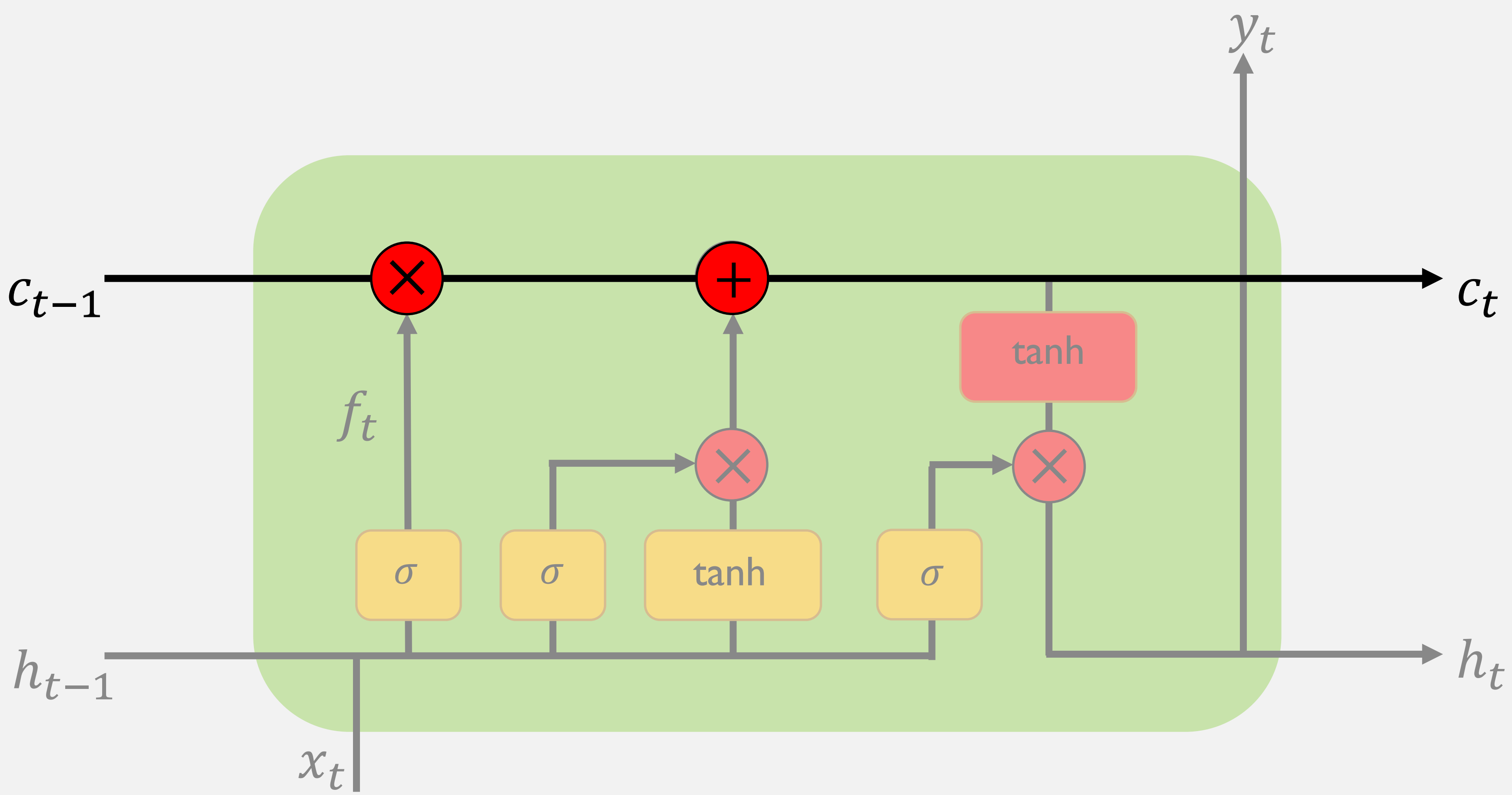

LONG SHORT TERM MEMORY (LSTM) NETWORKS

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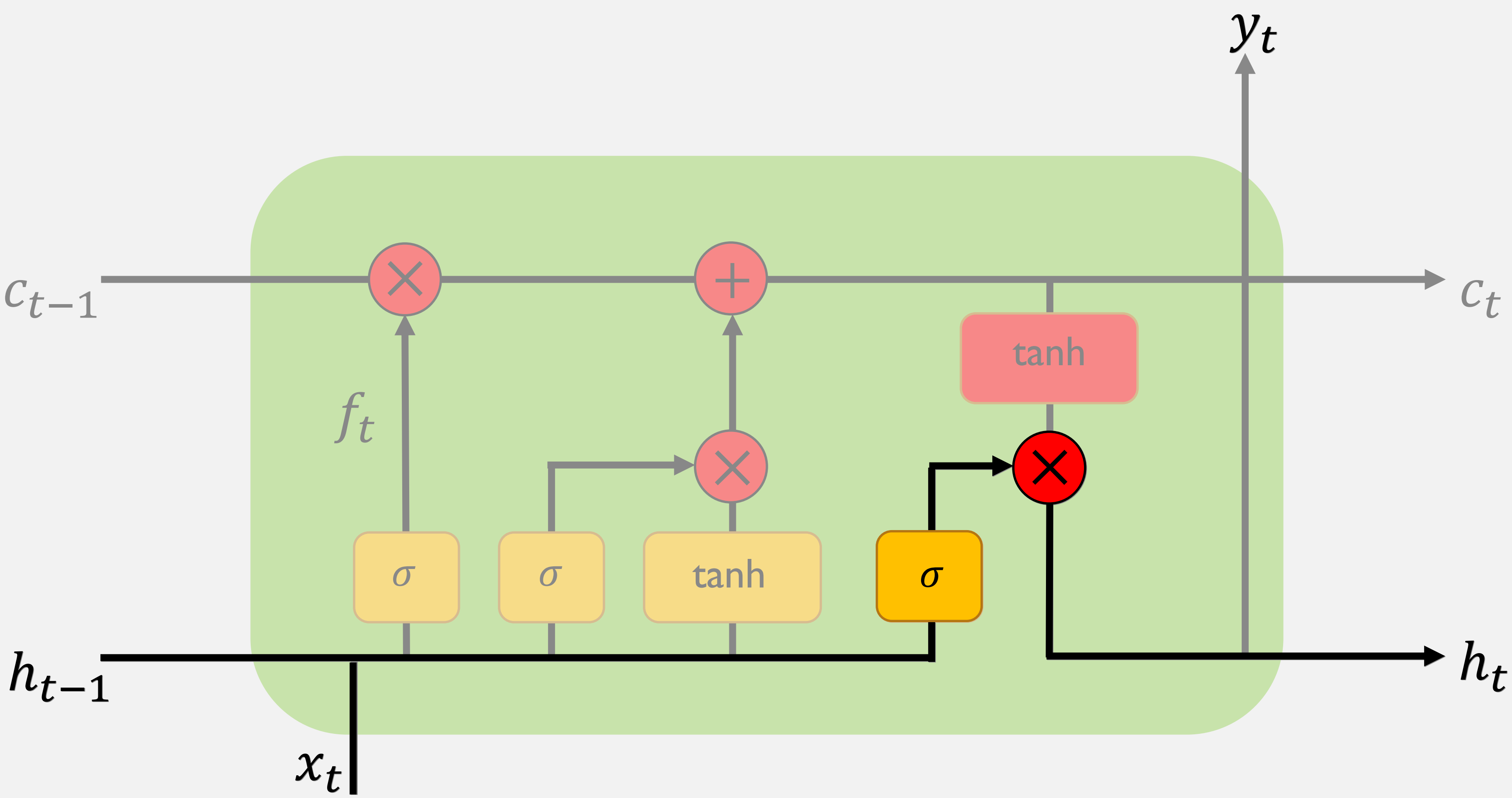


LONG SHORT TERM MEMORY (LSTM) NETWORKS

Key concepts

1- Maintain a separate cell state from what is outputted
2- Use gates to contro linformation flow.
- forget gatees get rid of irrelevant information
- store information from current input
- selectively update cell state

Ouput gate returns a filtered version of the cell state.

3- There is backpropagation through time with uninterrupted gradient flow

LSTM DATA

- Total transaction counts in Oxford street (time series)
- Total international arrivals in the UK (from UK nationals and non-UK nationals)
- Total number of new Covid-19 positive tests (per date of test) in greater London
- Day of the week
- Total Number of new Covid-19 hospitalisations in greater London per date

From 19/03/2020
To 31/01/2021
n= 289

LSTM PREPROCESSING

- Min-max scaling between 0 and 1
- Transformation of time series to supervised data (generating a shift of one day before as the predictors).
- Prediction lag = 1 day (it would be interesting to see if we can use several days prediction lag).

LSTM MODEL 1: CASES

```
[40]: # design network
model = Sequential()
model.add(LSTM(100,#number of neurons (100 works qquite well!)
               input_shape=(train_X.shape[1], train_X.shape[2])))
model.add(Dense(units=1, activation='linear')) #here we can also set the activation = 'relu'
model.compile(loss='mae', optimizer='adam')
```

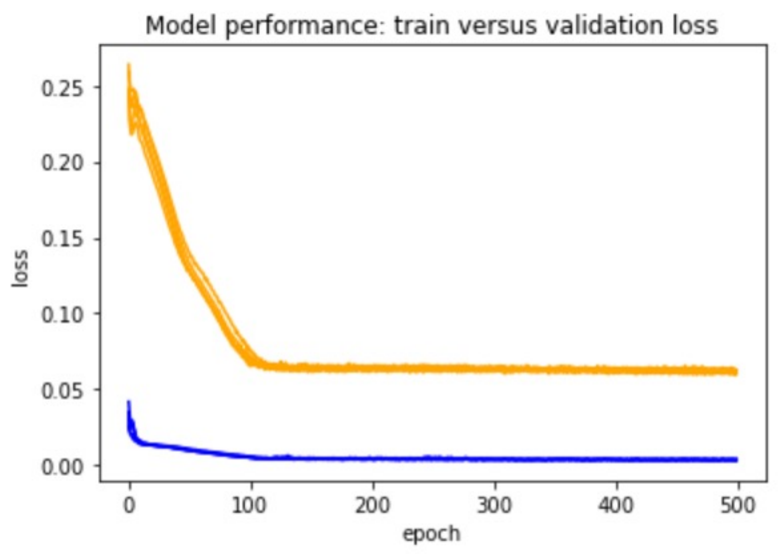
```
[ ]: history = model.fit(
    train_X, train_y,
    epochs=500,#300 works well!
    batch_size=72,
    validation_data=(test_X, test_y),
    verbose=2,
    shuffle=False
)
```

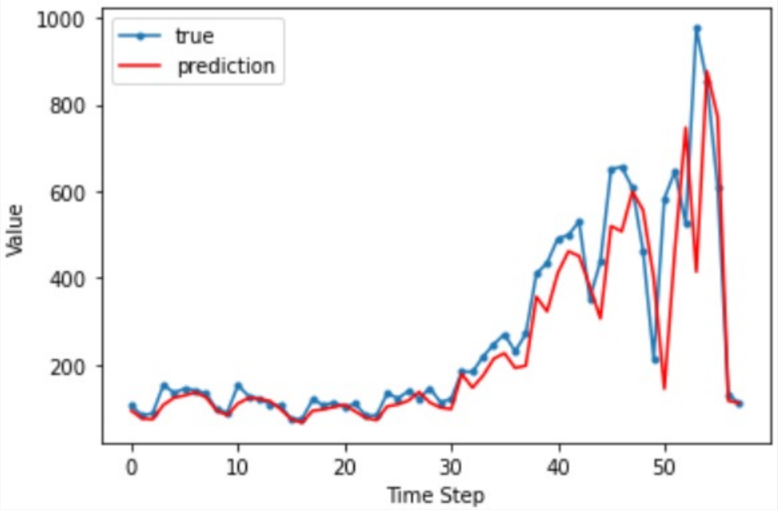
LSTM MODEL II: HOSPITALISATIONS

```
[141]: # design network
model = Sequential()
model.add(LSTM(300,#number of neurons (100 works qquite well!)
               input_shape=(train_X.shape[1], train_X.shape[2])))
model.add(Dense(units=1, activation = 'linear')) #here we can also set the activation = 'rel
model.compile(loss='mae', optimizer='adam')
```

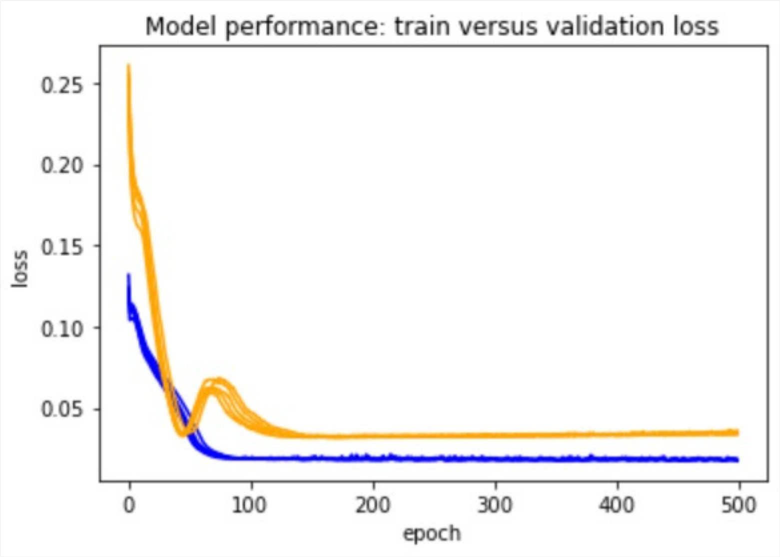
```
[ ]: history = model.fit(
    train_X, train_y,
    epochs=300,#500 works well
    batch_size=72,
    validation_data=(test_X, test_y),
    verbose=2,
    shuffle=False
)
```

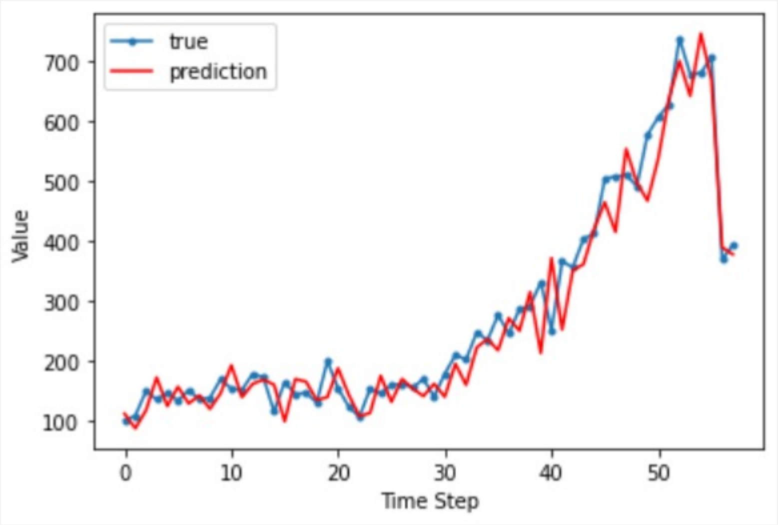
LSTM RESULTS: CASES MODEL





LSTM RESULTS: HOSPITALISATIONS MODEL





NEXT STEPS LSTM MODELS

VERY EMPIRICAL !

- Try a longer lag, not one day but 5 or 7 or maybe even 14.
- Include the number of vaccinations as predictors
- Include the lockdown status in the predictors
- Include holiday status in the predictor….
- Include weather conditions as predictors => yes! Use openWeather… average temp, cloudedness, rainfall.
- Try making the predictor time-series stationary
- Try predicting several days in the future.
- **Try doing feature importance, maybe even SHAP!**
- **Try doing feature extraction! (look it up!)**

NEXT STEPS OVERALL

- Try recurrent Neural Networks (also convolutional?)
- Try transformer models
- Try 'simple' linear timeseries models !
- Use the Clairvoyance pipeline : https://www.vanderschaar-lab.com/clairvoyance-alpha-the-first-unified-end-to-end-automl-pipeline-for-time-series-data/

⇒ Try clairvoyance, counterfactual recurrent network (CRN) https://iclr.cc/virtual_2020/poster_BJg866NFvB.html

⇒ Try the clairvoyance INVASE for interpretability: https://www.vanderschaar-lab.com/from-black-boxes-to-white-boxes/

⇒ Search what counterfactual actually means.

⇒ Download the software from here: https://bitbucket.org/mvdschaar/mlforhealthlabpub/src/02edab3b2b6d635470fa80184bbfd03b8bf8082d/app/clairvoyance, here is an eplanation on how to use it: https://bitbucket.org/mvdschaar/mlforhealthlabpub/raw/02edab3b2b6d635470fa80184bbfd03b8bf8082d/app/clairvoyance/paper/alpha_final.pdf

Try contacting Mihaela van der Schaar?

ADVICE FROM MARC & GIANLUCA

- Run models on influenza data (for 2019) and on a non-communicable disease like a typ of cancer.
- Try Prophet (from Facebook)
- Try a MARCOV SEIR model on Pystan (need to read more about that!)
- **Try and understand LSTM model you have !!!! Translate it to the diagram!**
- **Look at the three waves separately !**
- Run the same LSTM model by removing the transactions and only with transactions
- Try SVR!

VECTOR AUTOREGRESSION WITH MOVING AVERAGE : VARIMA

Aim : use two time series to predict one of them.

Granger causality test: test if a time series is can be predicted with itself and another time series.

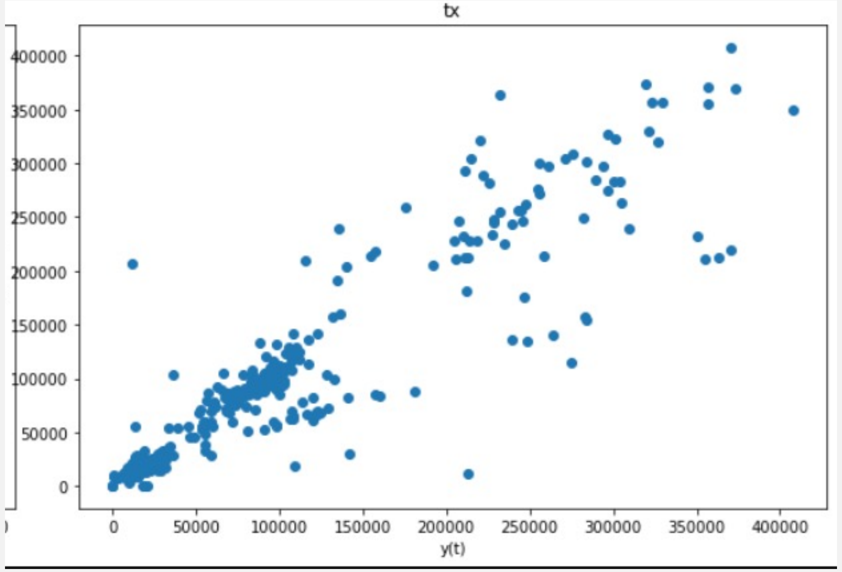
VARIMA DATA

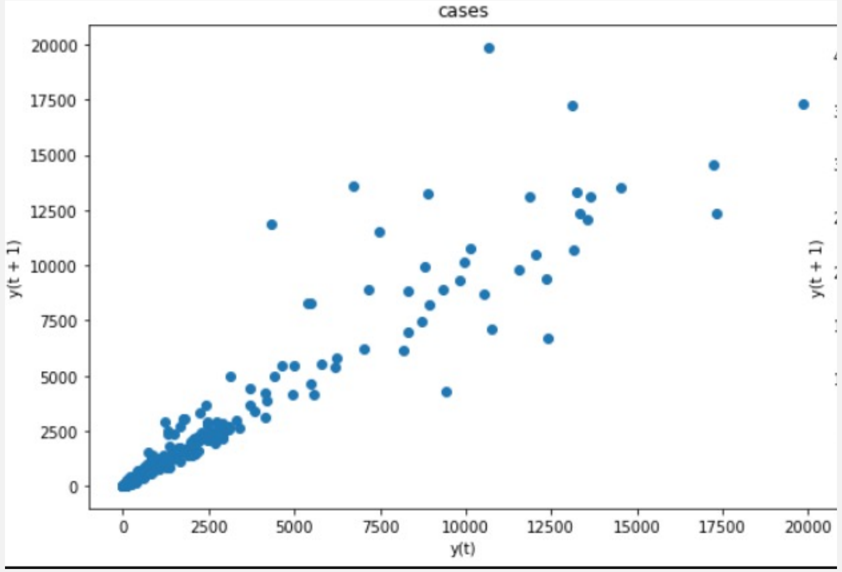
- Daily transaction counts in Oxford Street
- Daily new COVID-19 cases in Greater London or
- Daily new COVID-19 hospitalisations in Greater London
- Train – test split : 80%-20%

From 12/02/2020
To 26/02/2021
n= 354

VARIMA MODEL 1: FOR CASES PREPROCESSING

- Differencing (with lag of 1 day) to make transaction time-series stationary
- Log transformation and differencing (with lag of 1 day) to make the case time series stationary.





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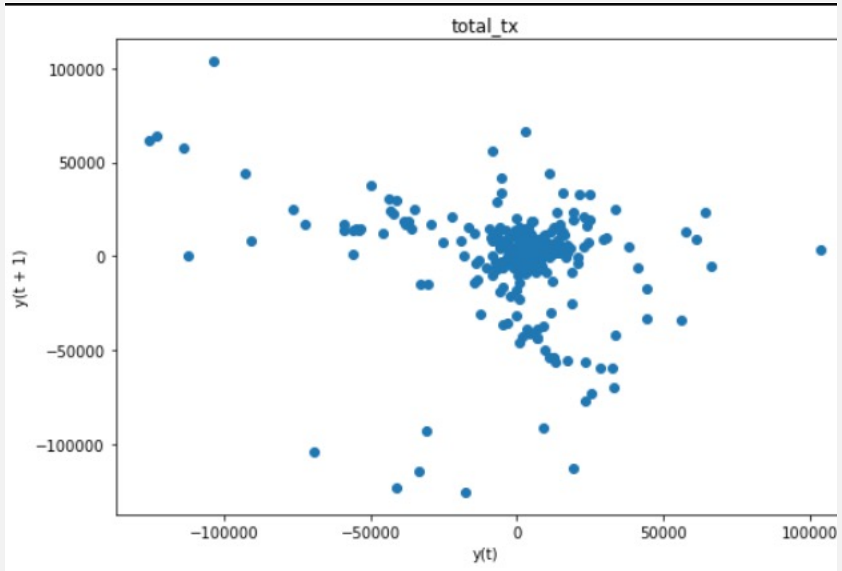
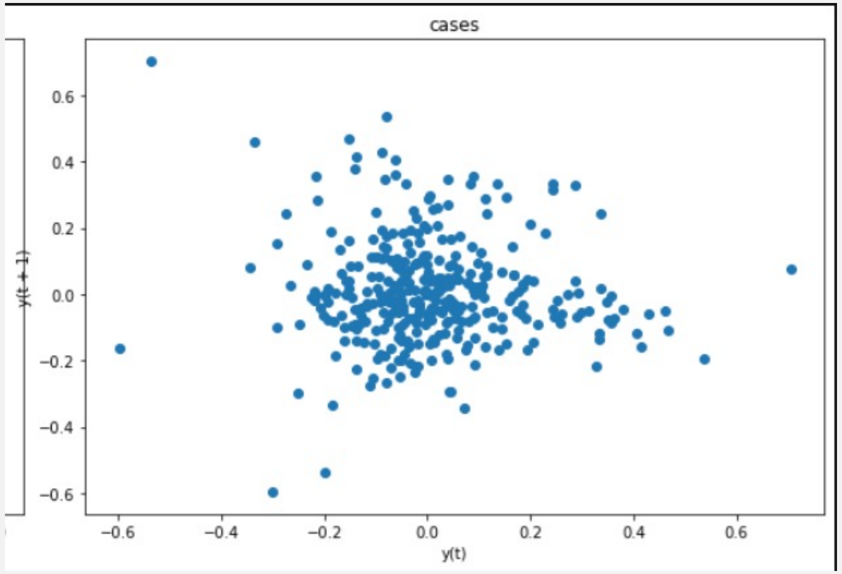




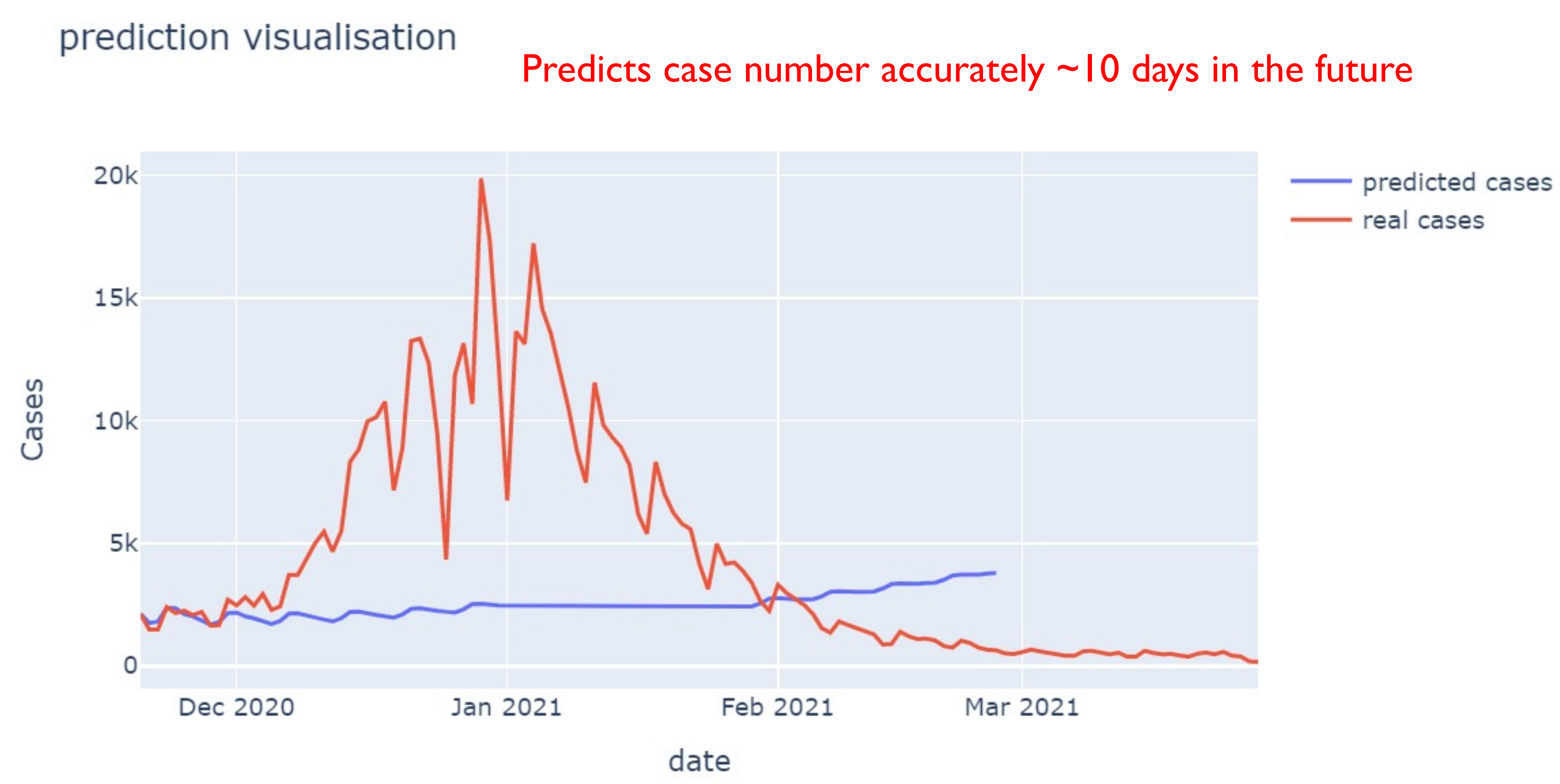
$\Rightarrow$ AD Fuller test: we can reject H0 of time series being non-stationary.
$\Rightarrow$ KPSS test: we cannot reject the null hypothesis that the series is stationary.

VARIMA MODEL 1: FOR CASES

- We chose a lag of 11 days, since that presented the lowest AIC for a VAR model on the raw data.
- We tested for serial correlation of the residuals with the Durbin-Watson test and found no significant serial correlation.
- We tested for cointegration of the time series with the augmented Engle-Granger two-step cointegration test and found that the transactions and case time-series were cointegrated.
- We tested for Granger causality, H0 = x does **not** ‘cause’ y in both directions and we found that in both cases we could reject the null hypothesis. So we found **Granger causality of transactions on cases and of cases on transactions.**

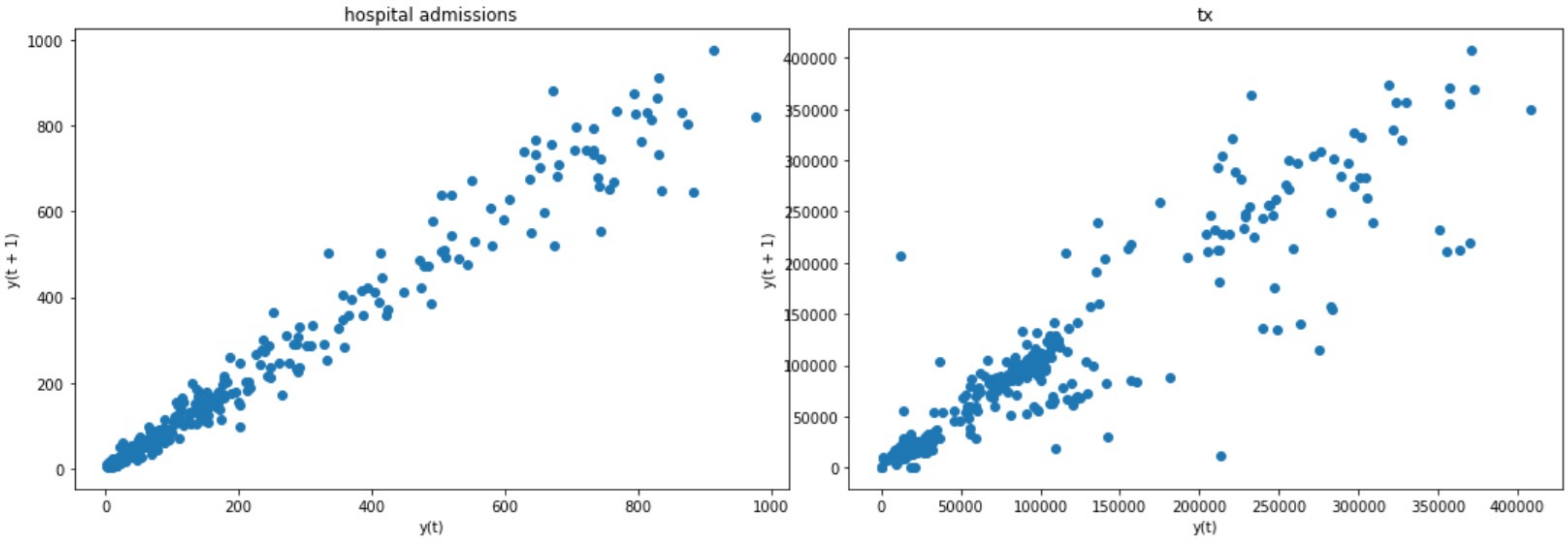
VARIMA MODEL 1: RESULTS

Predicts case number accurately ~10 days in the future



VARIMA MODEL 2: FOR HOSPITALISATIONS PREPROCESSING

- Differencing (with lag of 1 day) to make transaction time-series stationary
- Log transformation and differencing (with lag of 1 day) to make the hospitalisation time series stationary.



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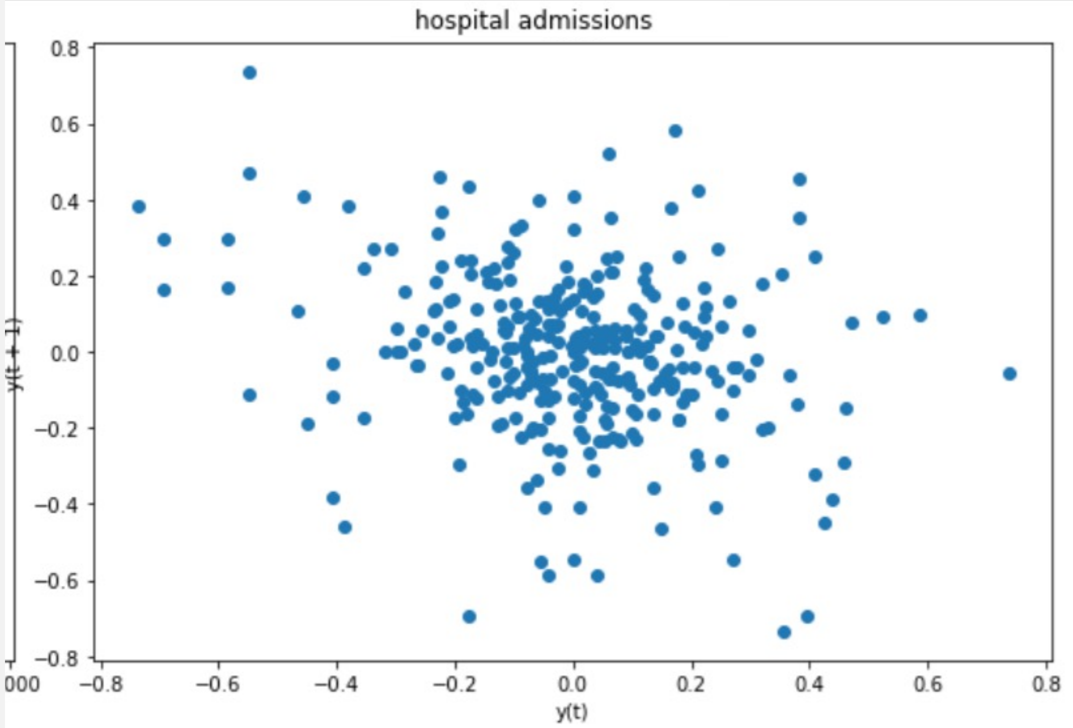

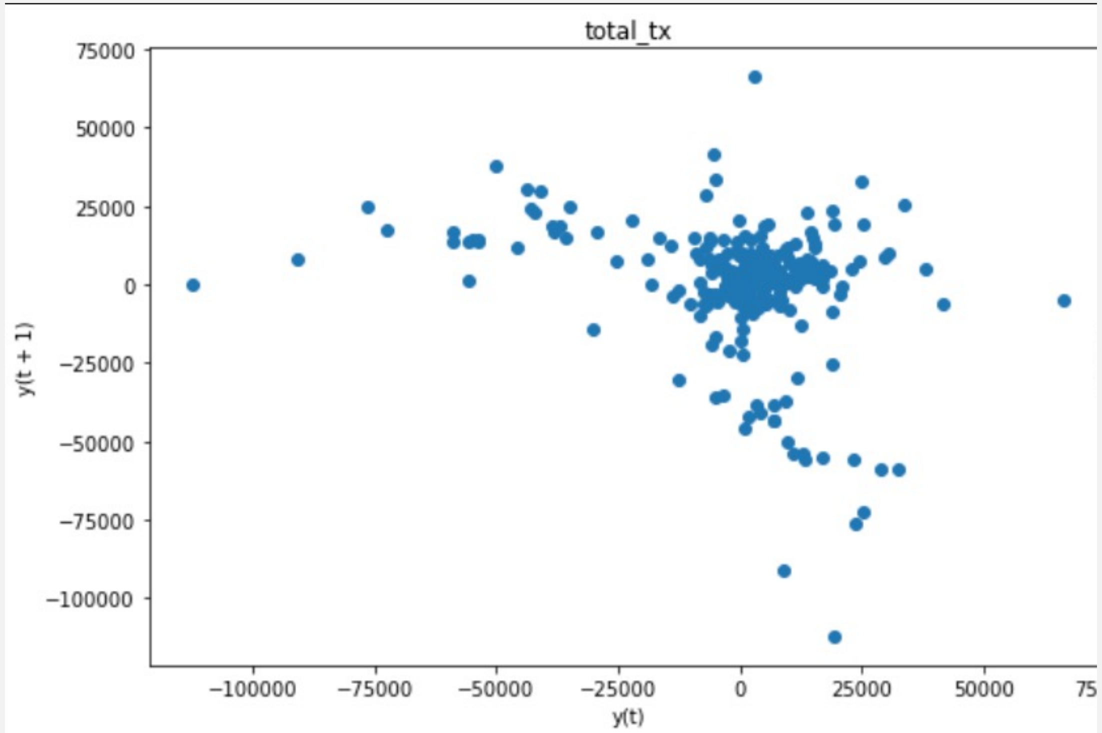

⇒ AD Fuller test: we can reject H0 of time series being non-stationary.

⇒ KPSS test: we cannot reject the null hypothesis that the series is stationary.

VARIMA MODEL 2: FOR HOSPITALISATIONS

- We chose a lag of 11 days, since that presented the lowest AIC for a VAR model on the raw data.
- We tested for serial correlation of the residuals with the Durbin-Watson test and found no significant serial correlation.
- We tested for cointegration of the time series with the augmented Engle-Granger two-step cointegration test and found that the transactions and hospital admission time-series were cointegrated.
- We tested for Granger causality, H0 = x does **not** 'cause' y in both directions and we found that in both cases we could reject the null hypothesis. So we found **Granger causality of transactions on hospital admissions and of hospital admissions on transactions.**

VARIMA MODEL 2: HOSPITALISATIONS RESULTS