Time-series Forecasting for Ground Deformation

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Aim: To study a possibility of machine learning to forecast seasonality of ground deformation in UK InSAR data

Problem statement

- Interferometric Synthetic Aperture Radar (InSAR) data can detect surface deformation.
- Deep machine learning can model seasonal InSAR signals of specific locations for time-series forecasting.

Background

Recurrent Neural Network (RNN) [1]

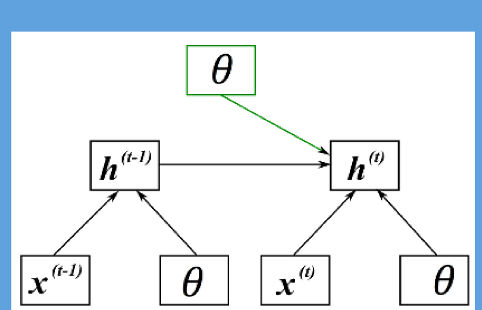
- Keep track of arbitrary long-term dependencies in the input sequences.
- Can scale to much longer sequences than classical networks.
- Designed to process sequences of variable lengths.
- Shared parameters with all previous output members.
- The learning selectively 'keeps' some part of the past and 'forgets' others.

Lossy summary of the past input up to t

Shared Parameters

Hidden states

Sequential data



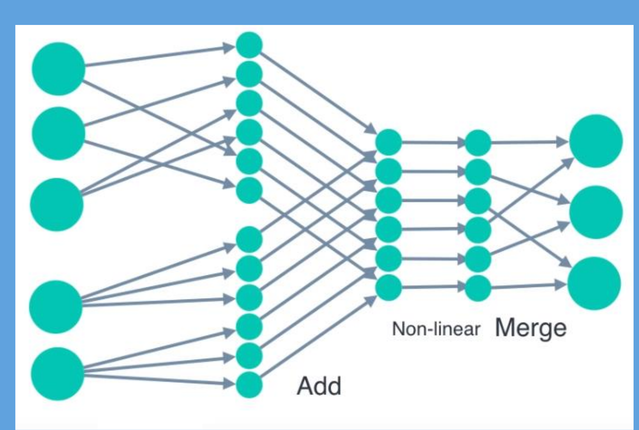
$$h^{(t)} = f(h^{(t-1)}, x^{(t)}; \theta)$$

Long-Short Term Memory (LSTM) [2]

- RNN that controls the ability to forget the past, enabling the LSTM to reset its own state.
- Has been commercially used in AI from predicting diseases to composing music:
  - Natural language text compression.
  - Unsegmented connected handwritting recognition.
  - Natural speech recognition.

A set of Inputs

Another set of Inputs

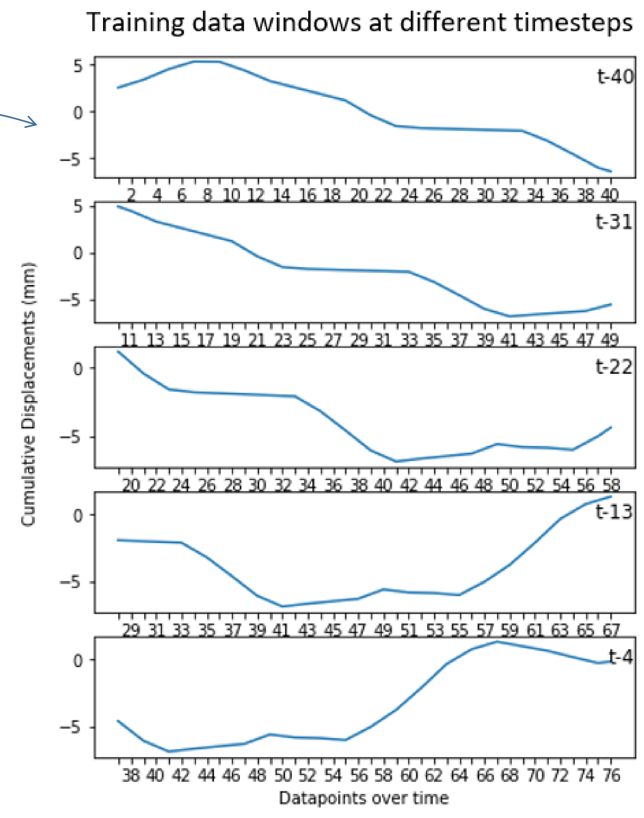


Method

Location 1 … **Location L**

Look backward: $t - N_x$ … $t - 1$

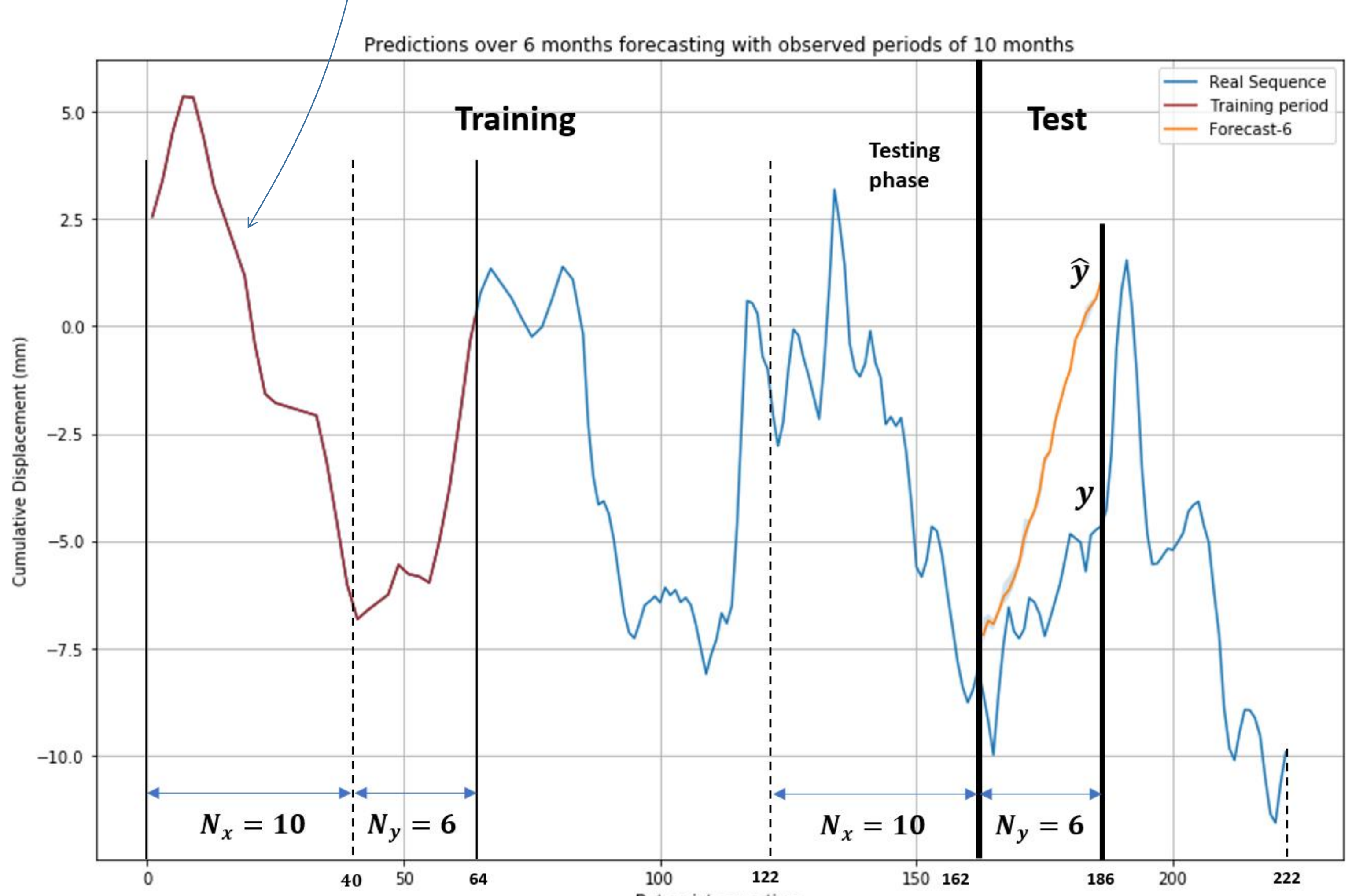
Look forward: t … $t + N_y$



Temporal sliding window

$d = 4 \rightarrow$ Number of datapoints for the period of (roughly) one month

$N_x \times d = 40$

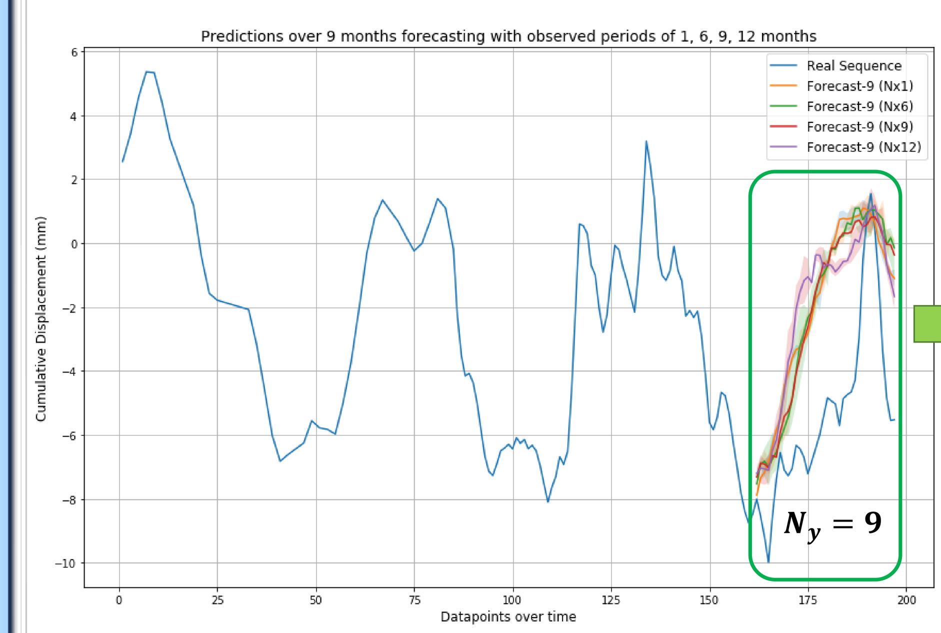


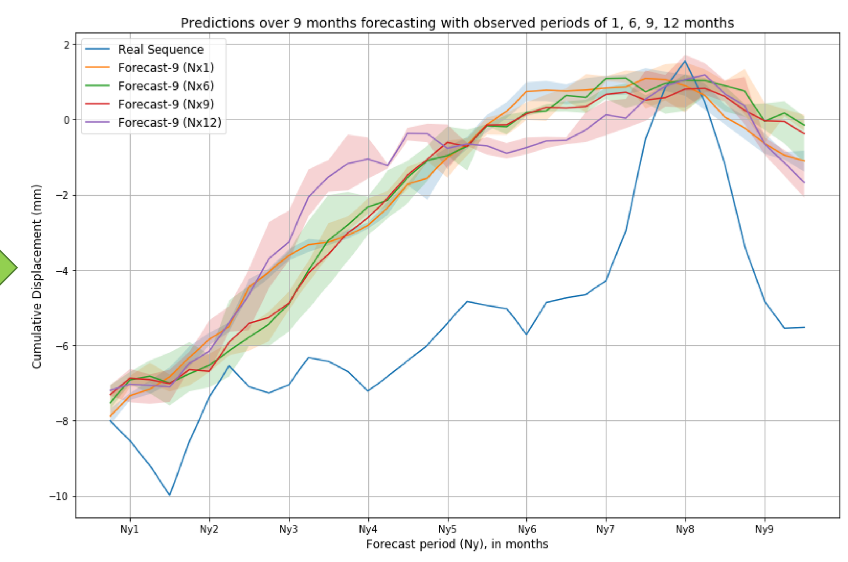
$$RMSE(\hat{y}) = \sqrt{MSE(\hat{y})} = \sqrt{E((\hat{y} - y)^2)}$$

Experiments & Results

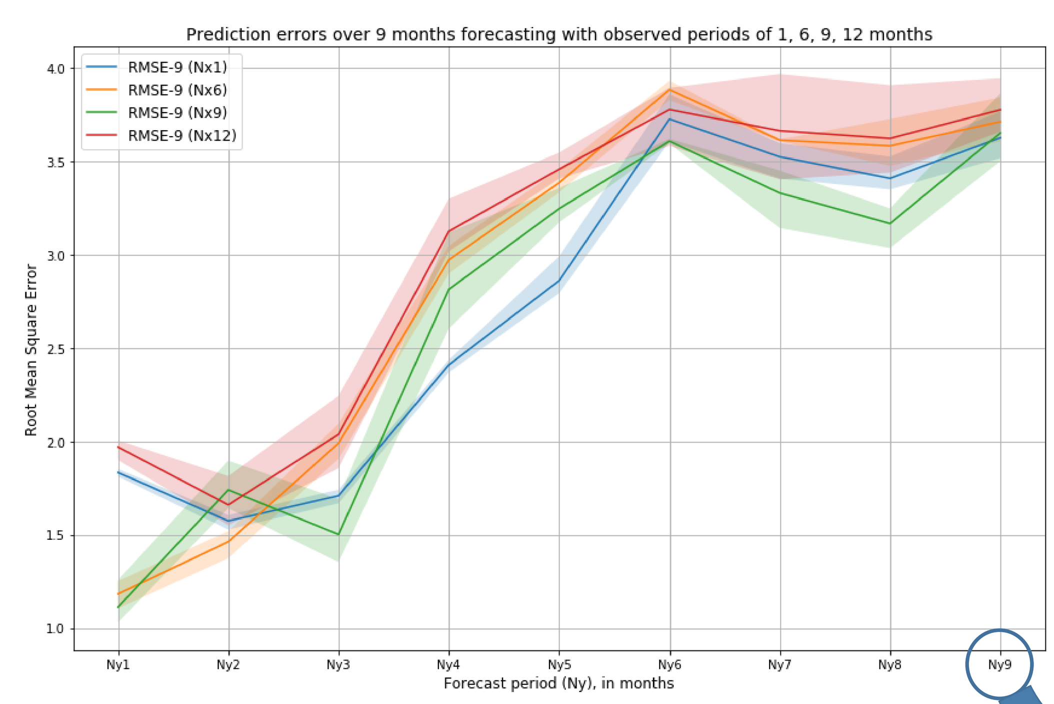
Prediction over time with models learned from different observed periods

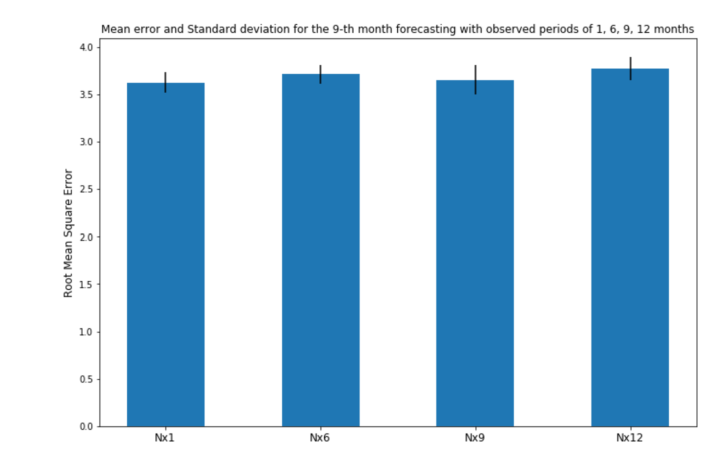
$N_x = \{1, 6, 9, 12\}$





Prediction errors over time with models learned from different observed periods





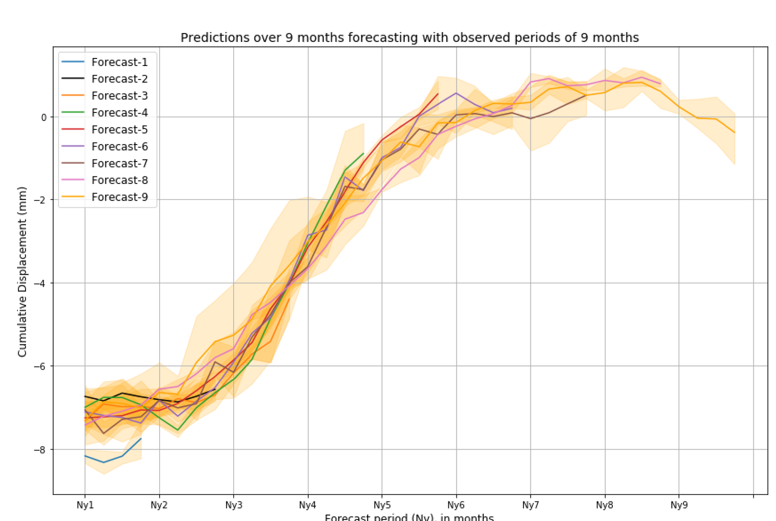
- For 9-month forecasts, varying size of $1 \leq N_x \leq 12$ is not very significant.
- For the 1st month forecast, $6 \leq N_x \leq 9$ provides lower error than $N_x \leq 1$, but $N_x \leq 12$ increases the error again.

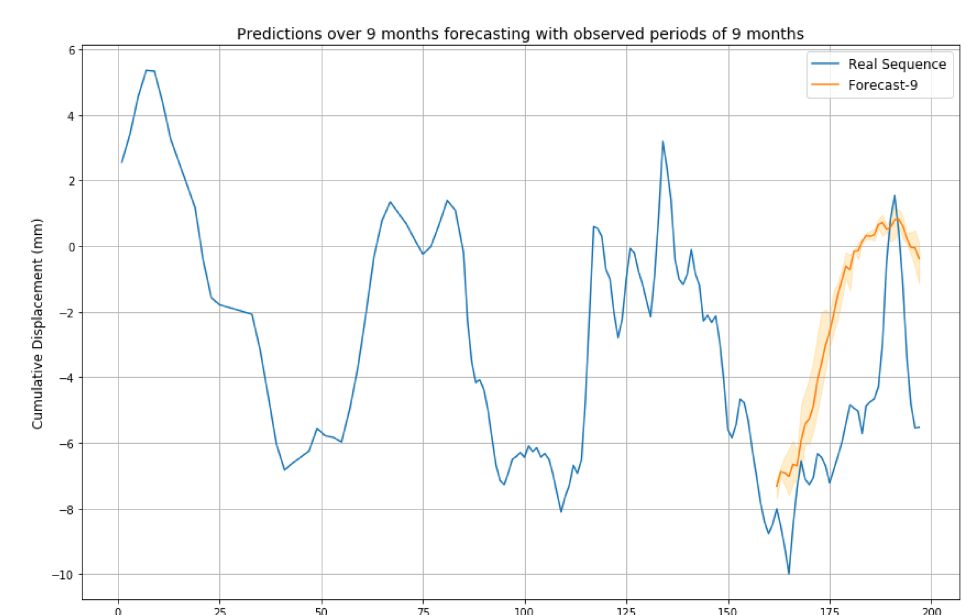
$N_x = 12$ provides the highest error when $N_y = 9$, in spite of $N_x > N_y$

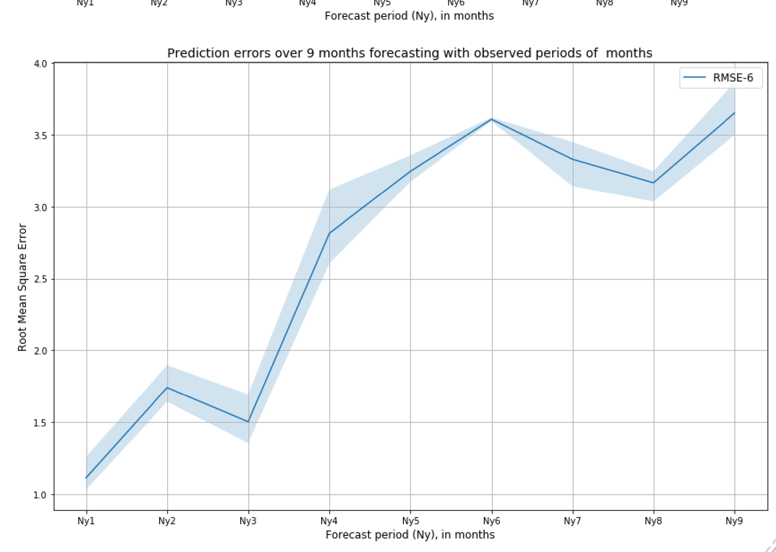
Predictions over time with models learned from a fixed observed period

$N_y = \{1, 2, \dots, 9\}$

$N_x = N_y = 9$







Next Steps

- Comparison to methods based on Seasonal Autoregressive Integrated Moving Averages (S-ARIMA).
- Consider other regression metrics depending on application.
- Transfer learning of LSTMs across multiple areas.
  - ❑ Velocity maps
  - ❑ Multiple locations
- Adaptation and comparison to geophysical models.

[1] Rumelhart, D. E., Hinton, G. E., and Williams, R. J. Learning representations by back-propagating errors. Nature, 323:533–, October 1986
[2] Hochreiter, S. and Schmidhuber, J. Long short-term memory. Neural Computation, 9(8):1735–1780, 1997. doi: 10.1162/neco.1997.9.8.1735.