Exploring Bayesian deep learning for weather forecasting with the Lorenz 84 system

Yang Liu, Dr. J. (Jisk) J. Attema, Prof. dr. W. (Wilco) Hazeleger

y.liu@esciencecenter.nl https://github.com/geek-yang/DLACs

Introduction

Recent developments in deep learning have led to many new neural networks potentially applicable to weather forecasting. However, these techniques are always based on deterministic neural networks (NN) and therefore prone to over-confident forecasts. This brings Bayesian deep learning (BDL) into our scope. In this study, we use Bayesian Long-Short Term Memory neural networks (BayesLSTM) to forecast output from the Lorenz 84 system with seasonal forcing, so as to examine if BDL is useful for weather forecast.

About Blue Action

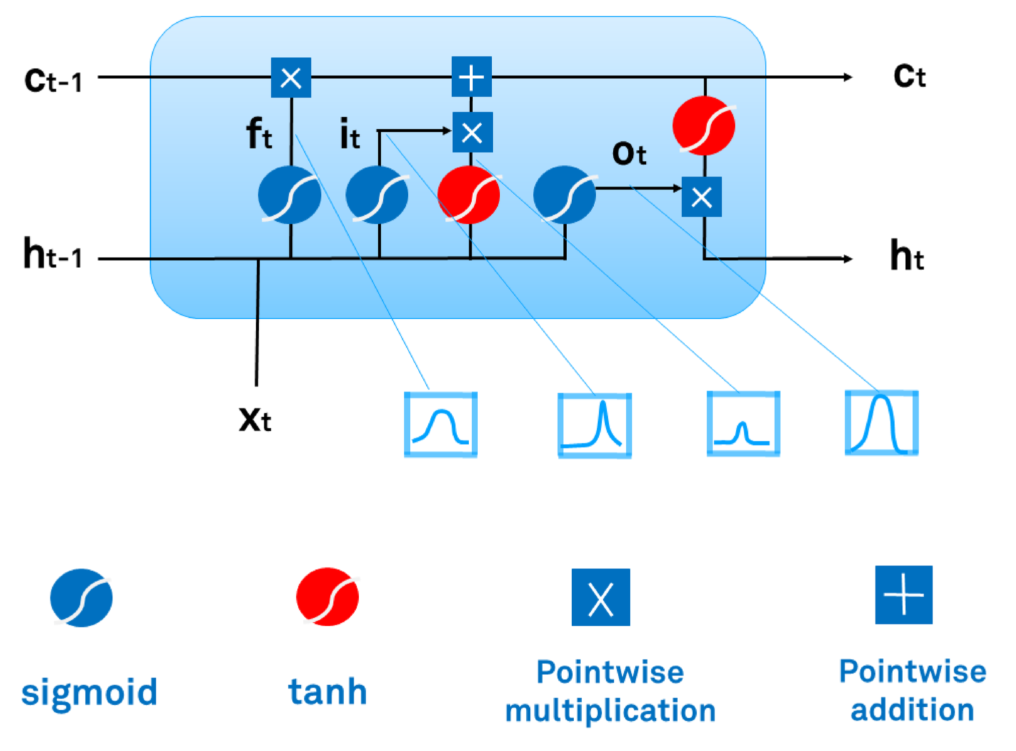
“Blue Action: Arctic Impact on Weather and Climate”, in short Blue Action, is a research and innovation action started from December 1st, 2016. It is funded by EU Horizon 2020 Work Programme.

Objectives

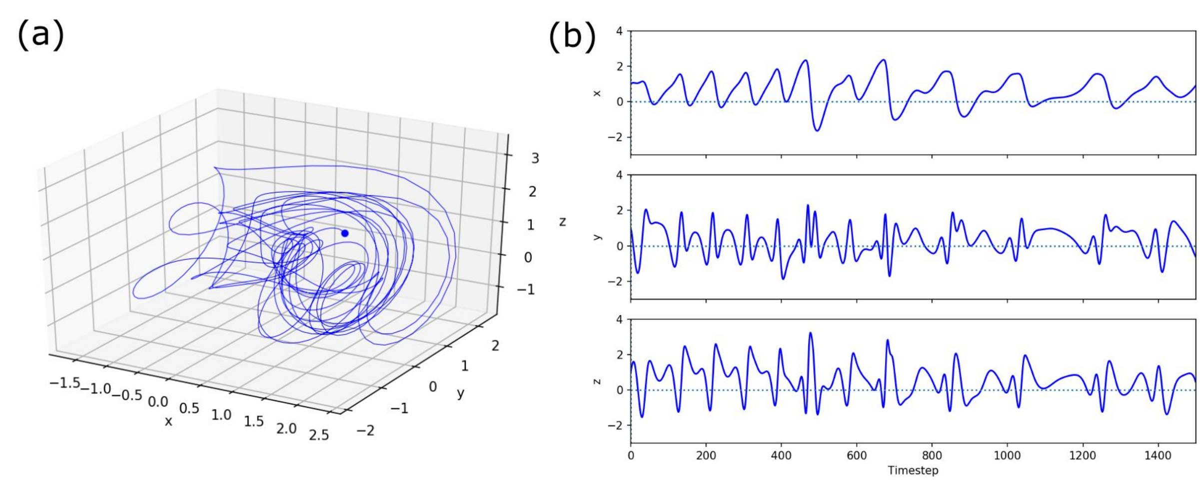
- Investigate the characteristics of BDL via the chaotic nature of Lorenz 84 model with seasonal forcing.
- Identify the types of uncertainty that represented by BDL both mathematically and numerically (forecast perturbed Lorenz model).
- Examine if BDL is useful for weather forecast.

Uncertainty

Methodology

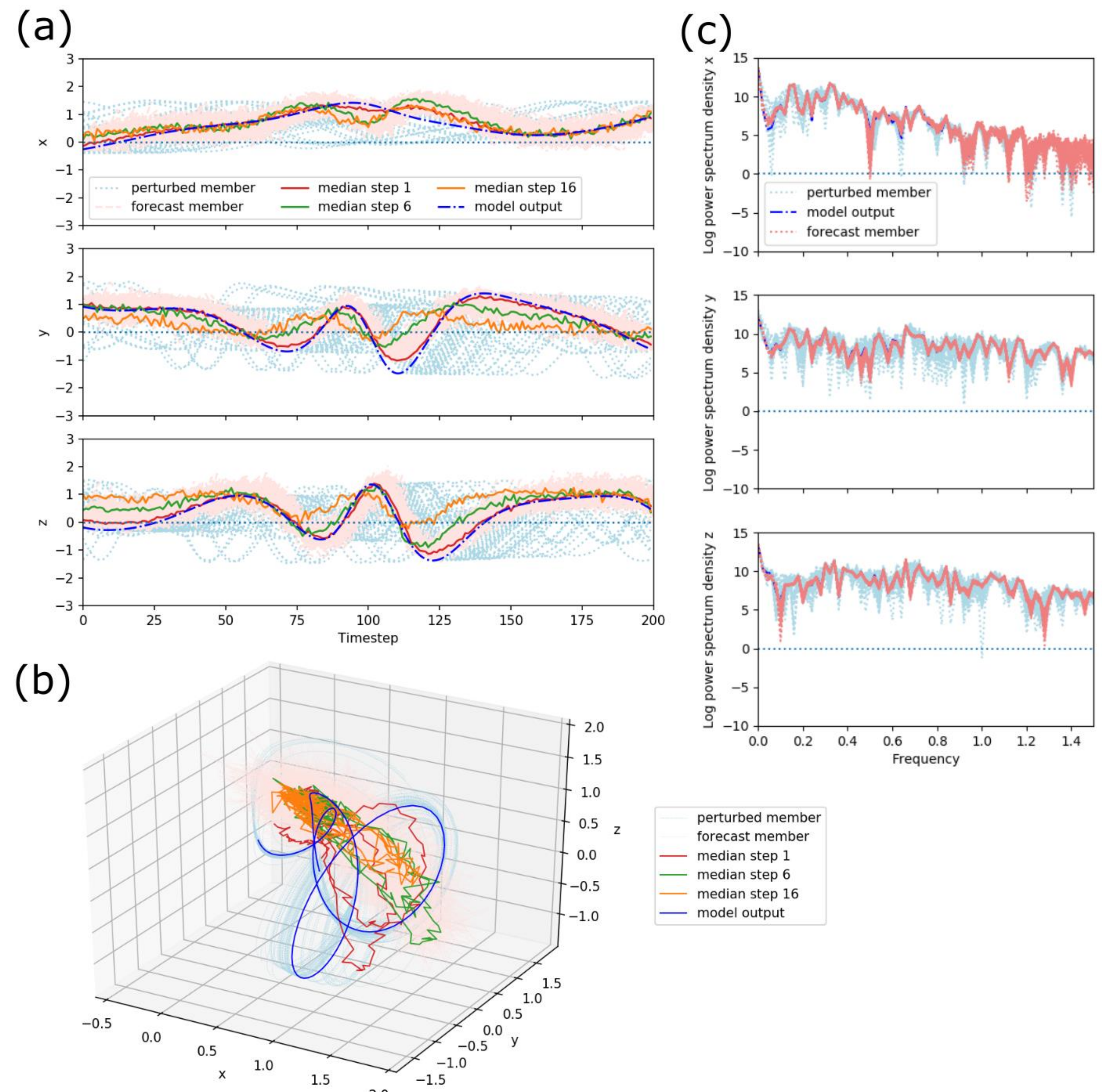


- Turn LSTM into BayesLSTM by replacing fixed weights with distributions through BDL.
- Train BayesLSTM by a variational inference scheme, namely the Bayes by Backprop approach. We approximate the posterior with a Gaussian distribution.
- Back-propagation (BP) is enabled by translating the global uncertainty in the weights into a form of local uncertainty via the local reparameterization trick.
- Perturb initial conditions (x) and model formulation (a) of Lorenz 84 model and forecast it with BayesLSTM.



Results

- Experiments with perturbed Lorenz model shows that BayesLSTM can produce similar results in the temporal space, the spectral space, and the Euclidean space, and therefore is able to represent the uncertainties in both the initial conditions and model formulation (not shown).
- Although the spread of BayesLSTM forecasts cannot cover the spread of Lorenz ensemble due to the strong sensitivity of Lorenz 84 model with seasonal forcing to the perturbation, the BayesLSTM forecasts are physically consistent with the model output and the ensemble saturates around the target sequences.



[Figure] Comparison of (a) timeseries of each variable and (b) trajectory and (c) logarithmic power spectrum of each variable between BayesLSTM ensemble forecasts and Lorenz 84 model output with perturbed initial conditions. The ensemble members from perturbed Lorenz model (perturbed member), the Lorenz model output without perturbation (model output), the ensemble members from BayesLSTM forecast (forecast member), and the ensemble median of BayesLSTM forecast at lead time step 1, 6, and 16 (median step 1, 6, and 16), are included in this Figure. The initial condition x is perturbed by 0.01%.

Conclusion

- Forecasts with BayesLSTM can stay close to the attractor of the Lorenz 84 system in the temporal space, the spectral space, and the Euclidean space, depending on lead time.
- Bayesian deep neural networks are able to address uncertainties in the initial conditions and model parameters and they are useful for weather forecasting.

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