Lifelong Learning for Closed-Loop Soil Moisture Control

Jack Foster

School of Computer Science, University of Lincoln, UK

Abstract

As the agricultural industry comes under increasing strains due to population growth, climate change, and geo-political strife, there is a need to increase crop yield to ensure food security in the coming years. As crop yield is intrinsically tied to soil-moisture, this work proposes a lifelong learning-based precipitation prediction model, paired with a bespoke sensor-based weather station, to facilitate the optimisation of soil-moisture. The project concludes with a novel extension of the elastic weight consolidation algorithm through application of a variational autoencoder to estimate an intractable likelihood term.

Introduction

The global food-supply chain is expected to be under increasing strain over the next decades due to pressure from problems such as population growth and climate change (1). It is therefore necessary to increase the yield of existing farming infrastructure to ensure the increase in demand can be met. This project leverages an LSTM network to predict precipitation in the next 24 hours from readings of the current temperature, humidity, dew point and barometric pressure; obtained via a bespoke sensor system. The predictions are used to inform watering regimens, to optimise the moisture content of the soil and thus optimise the yield for a set of planted radishes. Soil-moisture sensor readings are used alongside the lifelong learning paradigm elastic weight consolidation (2) to create a closed-loop control system that optimises the LSTM network even after it has been deployed. Finally, a novel extension of the EWC algorithm is contributed, using a variational autoencoder to estimate the intractable likelihood term.

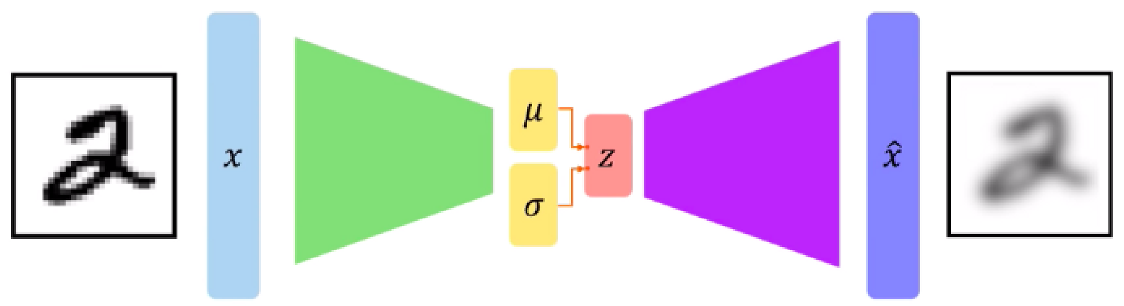


Figure: Generic VAE architecture

Aim and Objectives

This project aims to answer 5 research questions:

- Can a neural network model accurately predict future precipitation?
- Is the future soil-moisture state pertinent to optimising soil-moisture levels?
- Does lifelong learning alleviate issues around regional perturbations in atmospheric data?
- Does the closed-loop control of soil-moisture data improve the soil-moisture levels of a crop bed?
- Can the EWC algorithm be improved with subset likelihood estimation with a variational autoencoder?

Methodology

The following artefacts were built:

- An LSTM precipitation prediction network
- An elastic weight consolidation system to enable lifelong learning from sensor readings
- A bespoke, sensor-based hardware weather station with WiFi server functionality
- A VAE-based EWC algorithm. The VAE uses variational Bayes' to estimate the intractable likelihood term $p(\theta|a)$, or the likelihood of a parameter set given the data a model trained on. Traditionally in EWC, a Laplace approximation is implemented via the Fisher information matrix to estimate the term on a per-weight basis. Instead, here a VAE is used to estimate the parameter on an $n-$dimensional vector of parameters.

Experimental Setup

The following experiments were conducted:

- Precipitation classification and EWC performance evaluation on MeteoNet dataset.
- Real-world deployment of weather station, prediction model and EWC feedback system. 4 Pots of radishes were planted. One watered by a human agent, one based solely on sensor readings, one with sensors and an LSTM, and finally using sensors and an LSTM with EWC.
- Comparison of EWC and VAE-EWC on Perumtated MNIST dataset

Results

Results showed that a time-series LSTM with readings from the last 7 days lead to a classification accuracy of 72.35%. Results also showed that using EWC led to statistically significant improvements in LSTM precipitation prediction accuracy when transferred from one region to another. While the real-world deployment did not yield statistically significant results, the LSTM-based system reached up to 50% more yield than non-LSTM systems (16g to 24g). The EWC-based LSTM also outperformed non-LSTM methods (20g), but was worse than the base LSTM due to a high learning rate causes oscillations early in training. The EWC model outperformed the base LSTM in the final week of obvservation, once learning had stabilised.

The VAE version of EWC performed overall worse, however there is evidence to suggest that it may be better suited to problems where there are a large number of tasks. Furthermore, the experiment was only exploratory, and there is a wide range of future works that may improve the VAE approach. The initial results were promising, and the VAE system was still better than not using a lifelong learning strategy.

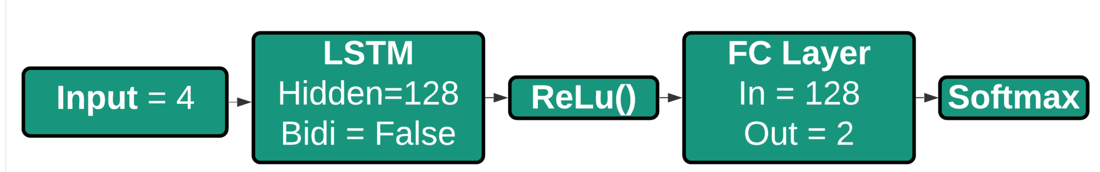
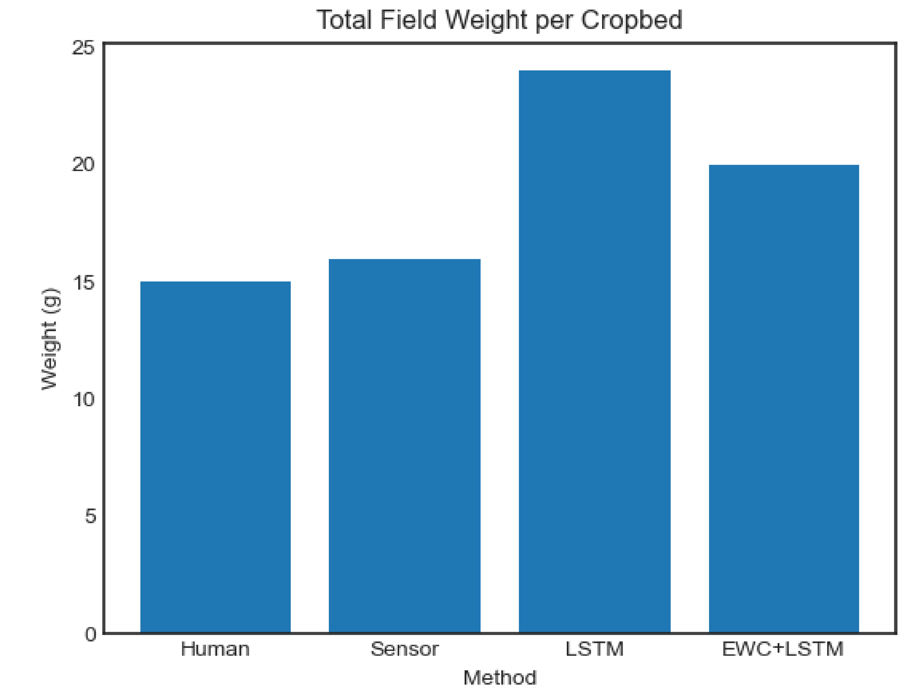


Figure: Final Precipitation Prediction Model



References

[1] Susan Ambler-Edwards, Katherine Sarah Bailey, Alexandra Kiff, Tim Lang, Robert Lee, Terry Keith Marsden, David Wyn Simons, and Hardin Tibbs, "Food futures: rethinking uk strategy. a chatham house report," 2009.

[2] James Kirkpatrick, Razvan Pascanu, Neil Rabinowitz, Joel Veness, Guillaume Desjardins, Andrei A Rusu, Kieran Milan, John Quan, Tiago Ramalho, Agnieszka Grabska-Barwinska, et al., "Overcoming catastrophic forgetting in neural networks," *Proceedings of the national academy of sciences*, vol. 114, no. 13, pp. 3521–3526, 2017.

Acknowledgements

Thank you to my project supervisor, Prof Simon Parsons, for his contributions and support. Thanks to the EPSRC AgriFoRwArDs CDT for their support and funding. And finally, thanks to George Sheppard and Abbey Bowen for their advice and support.