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Transfer Learning as a Technique to Utilise Machine Learning for Predictions of ITER Plasma Behaviour

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The Culham Center for Fusion Energy (CCFE) is a UK-based research facility dedicated to the scientific development of mature technologies for the safe and efficient use of nuclear fusion energy, which is heavily involved in the development of the International Thermonuclear Experimental Reactor (ITER), a nuclear fusion energy megaproject in Provence, southern France.

The plasma inside a nuclear fusion reactor reaches enormous temperatures of up to 100 million Kelvin, which can make the interior of the reactor prone to unwanted turbulence. Such turbulence, when detected by measurement devices, takes the form of a *chaotic time series*. A time series is a sequence of measurements $(x_1, x_2, x_3, ...)$ which is strictly ordered in time. This means the number x_1 must have been measured before the number x_2, and so on. Time series are very important in science and engineering and appear in many relevant applications, such as climatology, economics and plasma physics. Some time series are especially irregular and hard-to-predict. Time series of this type are called *chaotic*. The reason why chaotic time series are hard to predict is that tiny changes in their present state can completely change their long-term behaviour. CCFE have a strong interest in methods to better understand and predict the onset and the short-term evolution of chaos in time series data in order to foresee and ultimately prevent turbulent behaviour in fusion reactors. Our aim is to explore the potential of modern artificial intelligence techniques to predict chaotic behaviour in time series data.

To predict the onset and the evolution of chaotic dynamics in time series measurements, we experiment with *multilayer perceptrons (MLPs)*, which represent an important type of computational artificial intelligence model that can automatically extract knowledge from data. MLPs are inspired by the biological nervous system and are thus often referred to as *artificial neural networks*. Artificial neural networks need to be trained on a given data set to learn from its features and are then used to make predictions on previously unseen data.

We conduct three different groups of numerical experiments:

1. we apply MLPs to predict the time of onset of chaos in a given time series,
2. we train MLPs to explicitly forecast the future values of a chaotic time series, and
3. we test whether our trained MLPs can transfer some of their learned predictive capabilities to new data sets with previously unseen dynamical rules. Across all of these experiments, we use two different types of MLPs: the standard type as well as a new, modified type called *rational MLP*.

Rational MLPs have recently been shown to be superior to standard MLPs in certain applications and we are interested in seeing if this superiority still holds for prediction tasks on chaotic data sets.

Engineering and Physical Sciences Research Council

For our first group of experiments (1), we simulate chaotic time series data using the *Lorenz system*, which is a classical mathematical model from meteorology, well-known for its chaotic behaviour. Time series from the Lorenz system start off being regular and then become chaotic after some time. We successfully train MLPs to take as their input nothing more than the starting value of a Lorenz system time series and give as their output an accurate time prediction for the onset of chaos in the respective input time series. We observe that rational neural networks learn faster and reach higher accuracies than their standard counterparts.

For our second group of experiments (2), we simulate chaotic time series data using a scaled version of the x-component of the Lorenz system whose values lie between 0 and 1. In addition, we use the *logistic map* as a source of data. For chaotic time series from the Lorenz system and the logistic map, we successfully train MLPs to take as input 3 consecutive time series values and give as output an estimate of the next 10 time series values. Our MLP forecasting errors for Lorenz system time series data compared to the error of a uniformly random guess are depicted in Figure 1. We see that both rational- and standard neural networks successfully learn to predict the near-term future of the system, although the predictions become less accurate as the number of time steps into the future (i.e. the prediction horizon) increases, as expected. Once again, we observe that rational MLPs clearly outperform standard MLPs.

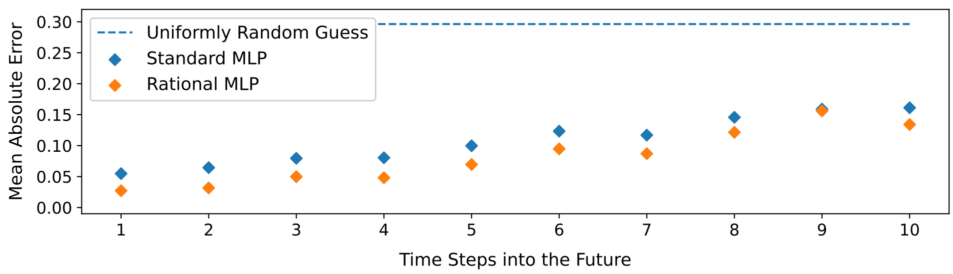

Figure 1 – MLP forecasting errors for Lorenz system time series compared to the forecasting error of a uniformly random guess. Note that the absolute error between an exact value x and an estimate $\hat{x}$ is defined as $|x-\hat{x}|$.

Finally, in our third group of experiments (3), we use the MLPs trained in (2) to forecast chaotic time series whose dynamics are governed by new rules to which the models were not exposed to during training. This is known as *transfer learning*. We observe that MLPs trained on the Lorenz system successfully predict oscillatory time series generated via the logistic map. We also find that MLPs trained on chaotic logistic map time series with a key parameter set to 4 can be used to predict logistic map time series for a much wider range of parameter values associated with chaotic behaviour.

Discussion, Conclusions and Future Impact

Three key conclusions which can be drawn from our novel computational investigations are: (*i*) the high suitability of MLPs for the accurate data-driven prediction of the temporal onset of chaos in time-series data, (*ii*) the clear superiority of rational MLPs over standard MLPs across a variety of prediction tasks associated with chaotic data sets, and (*iii*) the capabilities of MLPs trained for chaotic time series forecasting to transfer their learned predictive abilities to certain new systems with previously unseen dynamical rules. These scientific insights are of high relevance to CCFE in their quest for the development of data-driven methods for the analysis and prediction of chaotic time series data stemming from turbulence in nuclear fusion reactors.

Dr Debasmita Samaddar, Computational Plasma Physicist at CCFE, said:

> *Markus had to demonstrate exceptional tenacity, enthusiasm and technical capability to overcome all the challenges. His results demonstrate that neural networks can be efficiently used to predict onset of chaos in a dynamical system - a result crucial to the performance of a fusion reactor. He further compares and establishes the superiority of one method over another - thus leading to exciting results."*