PREVENTING CATASTROPHIC FORGETTING USING PRIOR TRANSFER IN PHYSICS INFORMED BAYESIAN NEURAL NETWORKS

Problem statement

Hybrid modelling techniques have proven their worth in combining the robust characteristics of first principle modelling with the accuracy of data-driven modelling. However, it remains a challenge to update such methods while in production. This research investigated an approach where models could be constantly updated whilst retaining high performance on previously unseen operating conditions. On a simulation environment of a cam-follower system an improvement of 72% has been achieved compared to traditional methods.

Dealing with a varying model

In both physical and data-driven models, different challenges are posed when dealing with changes in your environment.

Physical modelling

Physical models often don’t have the flexibility to adapt to changes unless these changes are known by the operator. Expert knowledge is thus required to keep your model up to date. Many phenomena are difficult to account for such as degradation phenomena and damage.

Data-driven modelling

Models based on data can easily adapt to incoming data and be retrained/updated. The main challenge here is to not overfit on incoming noise. When multiple operating conditions are possible, one does not want the model to completely forget previous modelling states (i.e. catastrophic forgetting).

Hybrid modelling

Best of both worlds is attained when going to a hybrid model. Known changes by the expert can be accounted for in the physical equations, hence improving robustness concerning older operating conditions and thus reducing the phenomena of catastrophic forgetting. On the other hand, flexibility in adaptation is made possible by the data-driven component. The data-driven compensation however remains vulnerable to catastrophic forgetting.

Bayesian Neural Networks in Hybrid Models

- **Epistemic uncertainty**: Uncertainty exhibited by the model. Using a Bayesian neural network (BNN) a model with stochastic output samples is obtained. Using Monte Carlo sampling a mean and standard deviation on the predictions can be obtained.

\[ \sigma^2 = \frac{1}{N} \sum_{i=1}^{N} (y_i - \mu)^2 \]

- **Uncertainty based updates**: Using this uncertainty a weighted update can be performed. Unseen data will result in higher uncertainty in the model predictions and hence require a bigger model update. This translates to the BNN lost function as follows:

\[ \text{Loss} = \sum_{i=1}^{N} \log p(y_i|x) - \log p(y_i|x) | p(y_i|x) \]

Simulation results

- **Prior transfer**

  Initially no prior distribution of the weight is known. After training a trained posterior distribution is obtained. When we now update the model, the information captured in the trained posterior can be used as a starting point of the next model. Additionally, it can be used in the loss function as well to update the prior function, hence called Prior transfer.

- **BNN showing uncertainty on unseen data**

  Training data is depicted in blue whilst unseen data is shown in orange.

- **Using the updating methodology in a continual learning framework**

  An update can be performed on a fixed timescale. For big changes in operating conditions the model shows a high uncertainty and learns quickly. Over time the model achieved both more accurate and more certain predictions on the operational data.

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