EMBEDDING PHYSICS-DRIVEN UNCERTAINTY IN NEURAL NETWORKS WITH ANCHORED ENSEMBLES

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ABSTRACT

The conjuncton of data mining and physics-based modeling holds great potential to help design, monitor and optimize civil infrastructure systems. Deep neural networks (NNs) are particularly attractive as they can handle a variety of data types relevant to civil engineering applications with specialized architectures – recurrent NNs can model time-dependent behaviors and dynamical systems, convolutional NNs have been leveraged to analyze materials microstructure image data, and graph NNs can embed topology information to study grid infrastructure systems. Embedding these data-driven algorithms with efficient and accurate uncertainty quantification is critical to deal with data inadequacies that characterize many engineering datasets (scarcity, imbalance, noisiness) and improve trustworthiness for use in high-consequence engineering decision-making. However, the over-parameterization of NNs, which grants them their flexibility and high accuracy, hinders their integration within a robust Bayesian inference framework. Anchored ensembling presents an interesting alternative that perfoms well in practice and allows consideration of a Bayesian prior. This talk will present recent advances in ensembling methods that integrate physics-driven prior knowledge, and promote ensemble diversity to mitigate the posterior uncertainty collapse encountered in vanilla ensembles. We will illustrate these enhancements for both regression and classification tasks relevant to civil engineering applications.