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HydroNets: Leveraging River Network Structure and Deep Neural Networks for Hydrologic Modeling

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Accurate and scalable hydrologic models are essential building blocks of several important applications, from water resource management to timely flood warnings. In this work we present a novel family of hydrologic models, called HydroNets, that leverages river network connectivity structure within deep neural architectures. The injection of this connectivity structure prior knowledge allows for scalable and accurate hydrologic modeling.

Prior knowledge plays an important role in machine learning and AI. On one extreme of the prior knowledge spectrum there are expert systems, which exclusively rely on domain expertise encoded into a model. On the other extreme there are general purpose agnostic machine learning methods, which are exclusively data-driven, without intentional utilization of inductive bias for the problem at hand. In the context of hydrologic modeling, conceptual models such as the Sacramento Soil Moisture Accounting Model (SAC-SMA) are closer to expert systems. Such models require explicit functional modeling of water volume flow in terms of their input variables and model parameters (e.g., precipitation, hydraulic conductivity, etc.) which could be calibrated using data. Instances of agnostic methods for stream flow hydrologic modelling, which for the most part do not utilize problem specific bias, have recently been presented by Kratzert et al. (2018, 2019) and by Shalev et al. (2019). These works showed that general purpose deep recurrent neural networks, such as long short-term models (LSTMs), can achieve state-of-the-art hydrologic forecasts at scale with less information.

One of the fundamental reasons for the success of deep neural architectures in most application domains is the incorporation of prior knowledge into the architecture itself. This is, for example, the case in machine vision where convolutional layers and max pooling manifest essential invariances of visual perception. In this work we present HydroNets, a family of neural network models for hydrologic forecasting. HydroNets leverage the inherent (graph-theoretic) tree structure of river water flow, existing in any multi-site hydrologic basin. The network architecture itself reflects river network connectivity and catchment structures such that each sub-basin is

represented as a tree node, and edges represent water flow from sub-basins to their containing basin. HydroNets are constructed such that all nodes utilize a shared global model component, as well as site-specific sub-models for local modulations. HydroNets thus combine two signals: site specific rainfall-runoff and upstream network dynamics, which can lead to improved predictions at longer horizons. Moreover, the proposed architecture, with its shared global model, tend to reduce sample complexity, increase scalability, and allows for transferability to sub-basins that suffer from scarce historical data. We present several simulation results over multiple basins in both India and the USA that convincingly support the proposed model and its advantages.