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How Google's Flood Forecasting Initiative Leverages Deep Learning Hydrologic Models

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One of the major natural disasters is flooding, which causes thousands of fatalities, affects the lives of hundreds of millions, and results in huge economic damages annually. Google's Flood Forecasting Initiative aims at providing high-resolution flood forecasts and timely warnings around the globe, while focusing first on developing countries where most of the fatalities occur. The high level structure of Google's flood forecasting framework follows the natural hydrologic-hydraulic coupling, where the hydrologic modeling predicts discharge (or other proxies for discharge) based on rainfall-runoff relationships, and the hydraulic model produces high resolution inundation maps based on those discharge predictions. Within this general partition, both the hydraulic and hydrologic modules benefit by the use of advanced machine learning techniques allowing for precision and global scale.

Classical conceptual hydrologic models such as the Sacramento Soil Moisture Accounting Model explicitly model the dynamics of water volumes based on explicit measurements and estimates of the variables (parameters) involved. These models are, however, inherently challenged by the lack of accurate estimates of model parameters and by inaccurate/incomplete description of the complex non-linear rules that govern the underlying dynamics. In contrast, machine learning models, driven by data alone, are potentially capable of describing complex functional dynamics without explicit modelling. Both the hydrologic and hydraulic models employed by Google rely on data-driven machine learning technologies to achieve superior and scalable performance. In this presentation we focus on describing one of the deep neural hydrologic models proposed by Google.

As was already shown in a recent work by Kratzert et al. (2018, 2019)[1], a deep neural model can achieve high performance hydrologic forecasts using deep recurrent models such as long short-term memory networks (LSTMs). Moreover, it was shown by Shalev et al. (2019)[2] that a single globally shared LSTM can achieve state-of-the-art performance by utilizing a data-driven learned embedding without the need for geographical-specific attributes. While the need for explicit rules in pure conceptual modeling is likely to impede the creation of scalable and accurate hydrologic

models, an agnostic approach that ignores reliable and available physical properties of water networks is also likely to be sub-optimal. HydroNet is one of Google’s hydrologic models that leverages the known water network structure as well as deep neural technology to create a scalable and reliable hydrologic model. HydroNet builds a globally shared model together with regional adaptation sub-models at each site by utilizing the tree structure of river flow network, and is shown to achieve state-of-the-art scalable hydrologic modeling in several large basins in India and the USA.

[1] Kratzert, Frederik, Daniel Klotz, Guy Shalev, Günter Klambauer, Sepp Hochreiter, and Grey Nearing. "Benchmarking a catchment-aware Long Short-Term Memory Network (LSTM) for large-scale hydrological modeling." arXiv preprint arXiv:1907.08456 (2019).

[2] Shalev, Guy, Ran El-Yaniv, Daniel Klotz, Frederik Kratzert, Asher Metzger, and Sella Nevo. "Accurate Hydrologic Modeling Using Less Information." arXiv preprint arXiv:1911.09427 (2019).