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Large-scale river network modeling using Graph Neural Networks

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In the recent past, several studies have demonstrated the ability of deep learning (DL) models, especially based on Long Short-Term Memory (LSTM) networks, for rainfall-runoff modeling. However, almost all of these studies were limited to (multiple) individual catchments or small river networks, consisting of only a few connected catchments.

In this study, we investigate large-scale, spatially distributed rainfall-runoff modeling using DL models. Our setup consists of two independent model components: One model for the runoff-generation process and one for the routing. The former is an LSTM-based model that predicts the discharge contribution of each sub-catchment in a river network. The latter is a Graph Neural Network (GNN) that routes the water along the river network network in hierarchical order. The first part is set up to simulate unimpaired runoff for every sub-catchment. Then, the GNN routes the water through the river network, incorporating human influences such as river regulations through hydropower plants. The main focus is to investigate different model architectures for the GNN that are able to learn the routing task, as well as potentially accounting for human influence. We consider models based on 1D-convolution, attention modules, as well as state-aware time series models.

The decoupled approach with individual models for sub-catchment discharge prediction and routing has several benefits: a) We have an intermediate output of per-basin discharge contributions that we can inspect. b) We can leverage observed streamflow when available. That is, we can optionally substitute the discharge simulations of the first model with observed discharge, to make use of as much observed information as possible. c) We can train the model very efficiently. d) We can simulate any intermediate node in the river network, without requiring discharge observations.

For the experiments, we use a new large-sample dataset called LamaH (**La**rge-sa**m**ple D**a**ta for **H** ydrology in Central Europe) that covers all of Austria and the foreign upstream areas of the Danube. We consider the entire Danube catchment upstream of Bratislava, a highly diverse region, including large parts of the Alps, that covers a total area of more than 130000km2. Within that area, LamaH contains hourly and daily discharge observations for more than 600 gauge stations. Thus, we investigate DL-based routing models not only for daily discharge, but also for

hourly discharge.

Our first results are promising, both daily and hourly discharge simulation. For example, the fully DL-based distributed models capture the dynamics as well as the timing of the devastating 2002 Danube flood. Building upon our work on learning universal, regional, and local hydrological behaviors with machine learning, we try to make the GNN-based routing as universal as possible, striving towards a globally applicable, spatially distributed, fully learned hydrological model.