Multi-Timescale LSTM for Rainfall–Runoff Forecasting

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Rainfall–runoff predictions are generally evaluated on reanalysis datasets such as the DayMet, Maurer, or NLDAS forcings in the CAMELS dataset. While useful for benchmarking, this does not fully reflect real-world applications. There, meteorological information is much coarser, and fine-grained predictions are at best available until the present. For any prediction of future discharge, we must rely on forecasts, which introduce an additional layer of uncertainty. Thus, the model inputs need to switch from past data to forecast data at some point, which raises several questions: How can we design models that support this transition? How can we design tests that evaluate the performance of the model? Aggravating the challenge, the past and future data products may include different variables or have different temporal resolutions.

We demonstrate how to seamlessly integrate past and future meteorological data in one deep learning model, using the recently proposed Multi-Timescale LSTM (MTS-LSTM, [1]). MTS-LSTMs are based on LSTMs but can generate rainfall–runoff predictions at multiple timescales more efficiently. One MTS-LSTM consists of several LSTMs that are organized in a branched structure. Each LSTM branch processes a part of the input time series at a certain temporal resolution. Then it passes its states to the next LSTM branch—thus sharing information across branches. We generalize this layout to handovers across data products (rather than just timescales) through an additional branch. This way, we can integrate past and future data in one prediction pipeline, yielding more accurate predictions.