EGU2020-8853
https://doi.org/10.5194/egusphere-egu2020-8853
EGU General Assembly 2020

Learning from mistakes: Online updating for deep learning models.

Daniel Klotz[1], Frederik Kratzert[1], Alden K. Sampson[2], Günter Klambauer[1], Sepp Hochreiter[1], and Grey Nearing[3]
[1]LIT AI Lab and Institute for Machine Learning, Johannes Kepler University, Linz, Austria (klotz@ml.jku.at)
[2]Upstream Tech, NatelEnergy Inc., Alameda, CA, USA
[3]Department of Geological Sciences, University of Alabama, Tuscaloosa, AL, USA

Accurate streamflow forecasts are important for many operational purposes, like hydropower operation or flood risk management. It is obvious that for data-driven models best prediction performance would be obtained if recent streamflow observations were used as an additional model input. Therefore, there exists a certain imperative which demands to use forecasting models that use discharge signals whenever available.

Forecasting models are, however, not well suited when continuous measurement of discharge can not be guaranteed or for applications in ungauged settings. Regarding the former, missing data can have long lasting repercussions on data-driven models if large data-windows are used for the input. Regarding the latter, data-driven forecast models are not applicable at all. Additionally, we would like to point out that data-driven simulation models need to represent the underlying hydrological processes more closely since the setup explicitly reflects the rainfall-runoff relationship. To conclude, in many contexts, it is more appropriate to use process or simulation models, which do not use discharge as input.

Despite the above mentioned difficulties of forecasting models it would nevertheless be beneficial to integrate, whenever available, past runoff information in simulation models in order to improve their accuracy. To this end, multiple potential approaches and strategies are available. In the context of conceptual or physically based rainfall-runoff models, recent runoff information is usually exploited by data assimilation/updating approaches (e.g. input-, state-, parameter- or output-updating). In this contribution we concentrate on input-updating approaches, since it allows to adjust the system for a forecasting period even if no explicit process can be attached to the system states.

We propose and examine different input-updating techniques for DL-based runoff models that can be used as baselines for future studies on data-assimilation tasks and which can be used with

arbitrary differentiable model. To test the proposed approaches, we perform a series of experiments on a large set of basins throughout the continental United States. The results show that even simple updating techniques can strongly improve the forecasting accuracy.