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One-day-ahead streamflow forecasting via super-ensembles of several neural network architectures based on the Multi-Level Diversity Model

Darwin Brochero, Islem Hajji, Jasson Pina, Queralt Plana, Jean-Daniel Sylvain, Jenna Vergeynst, and Francois Anctil

Université Laval, Chaire de recherche EDS en prévisions et actions hydrologiques, Department of Civil and Water Engineering, QUÉBEC, Canada (darwin.brochero.1@ulaval.ca)

Theories about generalization error with ensembles are mainly based on the diversity concept, which promotes resorting to many members of different properties to support mutually agreeable decisions. Kuncheva (2004) proposed the Multi Level Diversity Model (MLDM) to promote diversity in model ensembles, combining different data subsets, input subsets, models, parameters, and including a combiner level in order to optimize the final ensemble.

This work tests the hypothesis about the minimisation of the generalization error with ensembles of Neural Network (NN) structures. We used the MLDM to evaluate two different scenarios: (i) ensembles from a same NN architecture, and (ii) a super-ensemble built by a combination of sub-ensembles of many NN architectures. The time series used correspond to the 12 basins of the MOdel Parameter Estimation eXperiment (MOPEX) project that were used by Duan et al. (2006) and Vos (2013) as benchmark.

Six architectures are evaluated: FeedForward NN (FFNN) trained with the Levenberg Marquardt algorithm (Hagan et al., 1996), FFNN trained with SCE (Duan et al., 1993), Recurrent NN trained with a complex method (Weins et al., 2008), Dynamic NARX NN (Leontaritis and Billings, 1985), Echo State Network (ESN), and leak integrator neuron (L-ESN) (Lukosevicius and Jaeger, 2009). Each architecture performs separately an Input Variable Selection (IVS) according to a forward stepwise selection (Anctil et al., 2009) using mean square error as objective function. Post-processing by Predictor Stepwise Selection (PSS) of the super-ensemble has been done following the method proposed by Brochero et al. (2011).

IVS results showed that the lagged stream flow, lagged precipitation, and Standardized Precipitation Index (SPI) (McKee et al., 1993) were the most relevant variables. They were respectively selected as one of the firsts three selected variables in 66, 45, and 28 of the 72 scenarios. A relationship between aridity index (Arora, 2002) and NN performance showed that wet basins are more easily modelled than dry basins.

Nash-Sutcliffe (NS) Efficiency criterion was used to evaluate the performance of the models. Test results showed that in 9 of the 12 basins, the mean sub-ensembles performance was better than the one presented by Vos (2013). Furthermore, in 55 of 72 cases (6 NN structures x 12 basins) the mean sub-ensemble performance was better than the best individual performance, and in 10 basins the performance of the mean super-ensemble was better than the best individual super-ensemble member. As well, it was identified that members of ESN and L-ESN sub-ensembles have very similar and good performance values.

Regarding the mean super-ensemble performance, we obtained an average gain in performance of 17%, and found that PSS preserves sub-ensemble members from different NN structures, indicating the pertinence of diversity in the super-ensemble. Moreover, it was demonstrated that around 100 predictors from the different structures are enough to optimize the super-ensemble. Although sub-ensembles of FFNN-SCE showed unstable performances, FFNN-SCE members were picked-up several times in the final predictor selection.

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