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Graph Neural Networks for Reservoir Level Forecasting and Draught Identification

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The management of water resource systems is a longstanding and inherently complex problem, balancing an increasing number of interests to meet short- and long-term objectives sustainably. The difficulty of analyzing large-scale, multi-reservoir water systems is compounded by the scale and interpretation of the historic data. Therefore, to assist in the decision-making processes for water allocation we propose the use of machine learning, specifically deep learning to uncover and interpret relationships in high-dimensional data that can enable more accurate forecasting.

We explore the problem of reservoir level prediction as a pilot study, comparing traditional machine learning approaches to our proposal of spatial-temporal graph neural networks that embed the topological nature of the water system. The graph convolutional neural network explicitly captures spatial interaction among segments of river within the system. The construction of the graph is as follows: nodes represent the reservoir and river monitoring stations; edges define the characteristics of the river sections connecting these stations (i.e. distance, flow, etc.); multiple states of the aforementioned graph, each at different measurement intervals. We then train the network to predict the water level of a node (reservoir measurement station) from previous time intervals. The proposed network is trained on historic data of the EBRO basin, Spain, from 1981 to 2018, specifically utilizing river and reservoir gauging station flow rate and fill level respectively, with the addition of characteristics defining each component of the water system.

We validate our approaches over a 4-year period, making predictions across various time frames, showing the robustness to various circumstances, and meeting necessary objective requirements ranging from daily to monthly forecasting. As an extension, we also investigate the use of our predictions to allow for drought identification, demonstrating just one of many use-cases where machine learning can uncover vital information that can lead to better management and planning decisions.