DYNAMIC BAYESIAN NETWORKS FOR
PROBABILISTIC TIME SERIES PREDICTION

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Standard approaches for climatological time series prediction (embedding techniques, neural networks, etc.) aim to fit the nonlinear dynamics underlying the time series using historical data to train the parameters. The method of analogs improves the efficiency of the above techniques by selecting a local set of training data based on the output (predictions) of numerical atmospheric models. However, when the output of the numerical model is an ensemble of predictions, the above methodology does not provide a convenient forecasting framework to infer a probabilistic prediction for the time series. Moreover, when dealing with multivariate spatially distributed time series (e.g., 550 meteorological stations over the Iberian peninsula) there is no efficient spatio-temporal prediction model which considers all the available information. In this work, we present dynamic Bayesian networks for spatio-temporal probabilistic rainfall time series prediction. The spatial and temporal dependencies among the different stations are encoded into a directed acyclic graph, which is learnt from the available data. This dependency graph allows deriving a probabilistic model consistent with all the available information. The resulting model is combined with numerical atmospheric predictions using a new state variable, which is added to the graph. Afterwards, any available information both from the future or past output of a numerical model and from the past precipitation outcomes at a set of stations, can be used as evidence for the model. Efficient inference mechanisms provide the conditional distributions of the desired variables at a desired future time. We show how standard analog techniques are a special case of the proposed methodology when no spatial dependencies are considered in the model.