













prominent in the case of the proposed models, compared to the conventional CRBM formulations. Finally, we also note the notable performance gains of all the considered energy-based models compared to the PYP-GP method, which relies on a much more computationally expensive Gaussian process model to perform sequential data modeling.

## Conclusions

In this paper, we proposed a method exploiting the merits of ESNs to enhance the sequential data modeling capabilities of CRBMs. Our approach consists in the utilization of an ESN reservoir to capture the temporal dynamics in the context of CRBMs instead of the linear autoregressive apparatus of existing approaches. This model formulation allows for extracting more complex temporal dynamics using less *trainable* model parameters.

Subsequently, we extended the so-obtained ES-CRBM model to obtain an implicit mixture of ES-CRBM experts, capable of better modeling multimodal sequential data, as well as performing classification of observed sequences, apart from data modeling and generation. Exact inference for our models was performed by means of an elegant alternating Gibbs sampling algorithm, while training was conducted by means of CD.

Our future goals focus on investigating the efficacy of our approach in a wide class of applications involving time-series data or data with temporal dynamics. Characteristic application areas include dynamic planning algorithms for multirobot swarms, automatic music improvisation and metacreation, and analysis and prediction of asset prices in financial markets using high-frequency measurements.

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