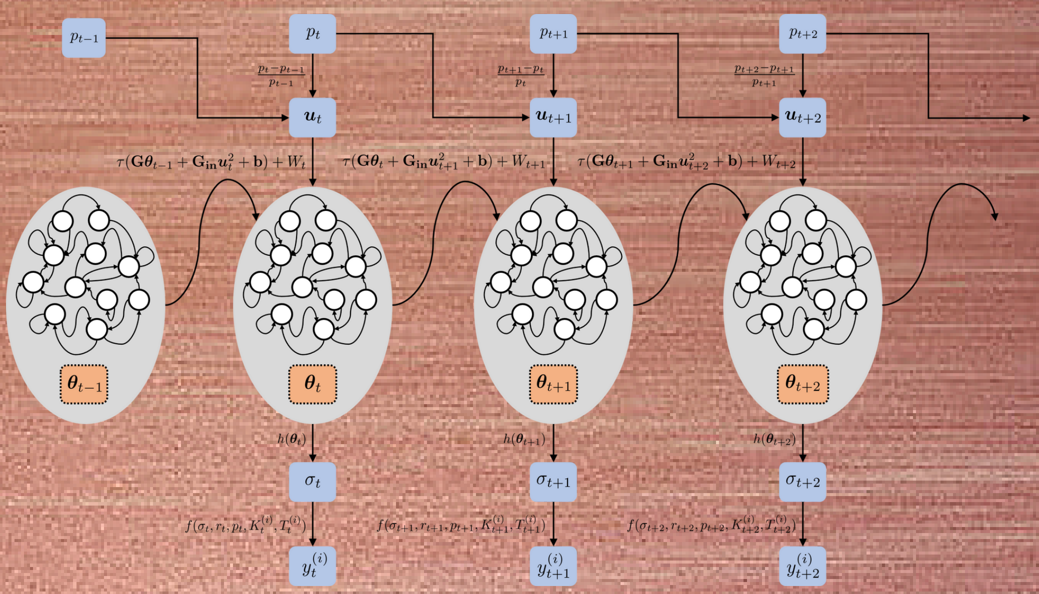
Inference and forecast problems of the nonlinear dynamical system have arisen in a variety of contexts. Reservoir computing and deep sequential models, on the one hand, have demonstrated efficient, robust, and superior performance in modeling simple and chaotic dynamical systems. However, their innate deterministic feature has partially detracted their robustness to noisy system, and their inability to offer uncertainty measurement has also been an insufficiency of the framework. On the other hand, the traditional state-space model framework is robust to noise. It also carries measured uncertainty, forming a just-right complement to the reservoir computing and deep sequential model framework.


**Ziyang Ding**

Senior Thesis


# At the Intersection of Deep Sequential and State-space Model Framework


**We propose the unscented reservoir smoother (URS), a model that unifies both deep sequential and state-space models to achieve both frameworks' superiorities. This is being achieved by merging the Unscented Kalman Filter with Reservoir computing approaches, with parameter training method developed upon forward-backward algorithm and generalized EM algorithm. Evaluated in the option pricing setting on top of noisy datasets, URS strikes highly competitive forecasting accuracy, especially those of longer-term, and uncertainty measurement. Further extensions and implications on URS are also discussed to generalize a full integration of both frameworks.**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