Fri53: Recurrent linear models of simultaneously recorded neural populations

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- Many real-world time series (including neural data) are best modelled by state-space models with non-linear dynamics and/or non-linear output. But learning is challenging.
  - Previous work at NIPS has looked at approximate EM (Macke et al. 2011) and SSID/spectral methods (Buesing et al. 2012).
- Here we propose a new approach, based on recasting the linear-Gaussian state-space likelihood in terms of a recurrent linear model.
- Key idea: generalise the recognition model to the nonlinear setting, rather than the generative model.
- Recovery of nonlinear generative parameters is competitive with approximate likelihood methods, and fits to neural data seem better.
From Linear-Gaussian SSM to RLM

State-space model:
Stochastic Markov latent variable couples observations in time.

Innovations model:
Random perturbations can be isolated in innovations variable,

Recognition model:
Kalman filter estimates innovations, computing likelihood by recurrent deterministic messages.

- Recurrent linear model: parametrise distribution by recognition parameters $W, A, C, (S)$; learn by backpropagation through time.
- Nonlinear models: generalise RLM recognition model instead of SSM generative model.
Parameter recovery on simulated data

\[(A, C)_{\text{TRUE}}\]

Time

Neuron #

Eigenvalues
\[A_{\text{TRUE}} \text{ vs } A_{\text{RLM}}, A_{\text{PLDS}} \text{ etc}\]

Subspace angles
\[C_{\text{TRUE}} \text{ vs } C_{\text{RLM}}, C_{\text{PLDS}} \text{ etc}\]
Predictive performance on (test) neural data

Predictions assessed by error in predicted spike count given past history.