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A New Modeling Framework for Multiscale Neural Activity Underlying Behavior

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I. Introduction

- The ability to record simultaneous multiscale brain activity introduces the new challenge of modeling discrete/continuous modalities jointly.
- Model-based multiscale decoders can lead to more accurate BMI's.
- We build a **multiscale model** for ECoG/LFP and spiking activity as follows:

Two Simultaneous Observations

$$x_t = \mathbf{A}x_{t-1} + \mathbf{B}u_t + w_t \;\; ; \;\; COV(w_t) = \mathbf{Q}$$

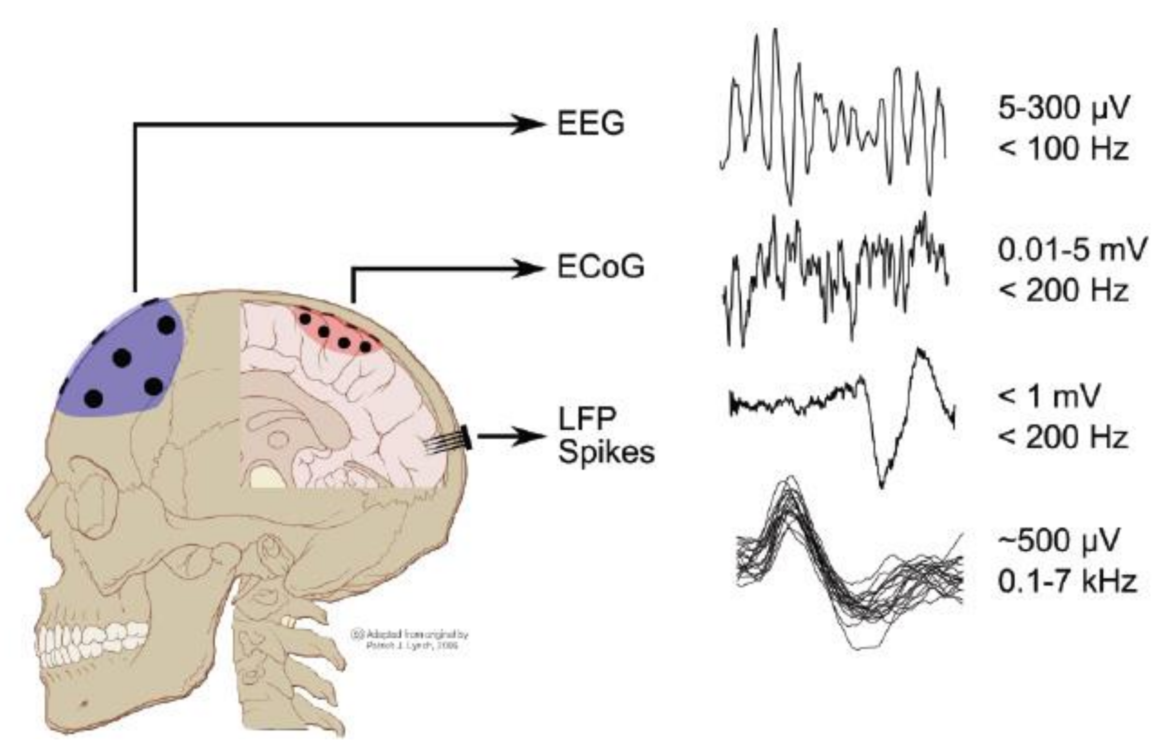
$$y_t = \mathbf{C}x_t + \mathbf{D}u_t + v_t \;\; ; \;\; COV(v_t) = \mathbf{R}$$

$$P(N_t|x_t) = \prod_C (\lambda_c(t|x_t, H_t^c).\Delta)^{N_t^c}.e^{-(\lambda_c(t|x_t,H_t^c).\Delta}$$

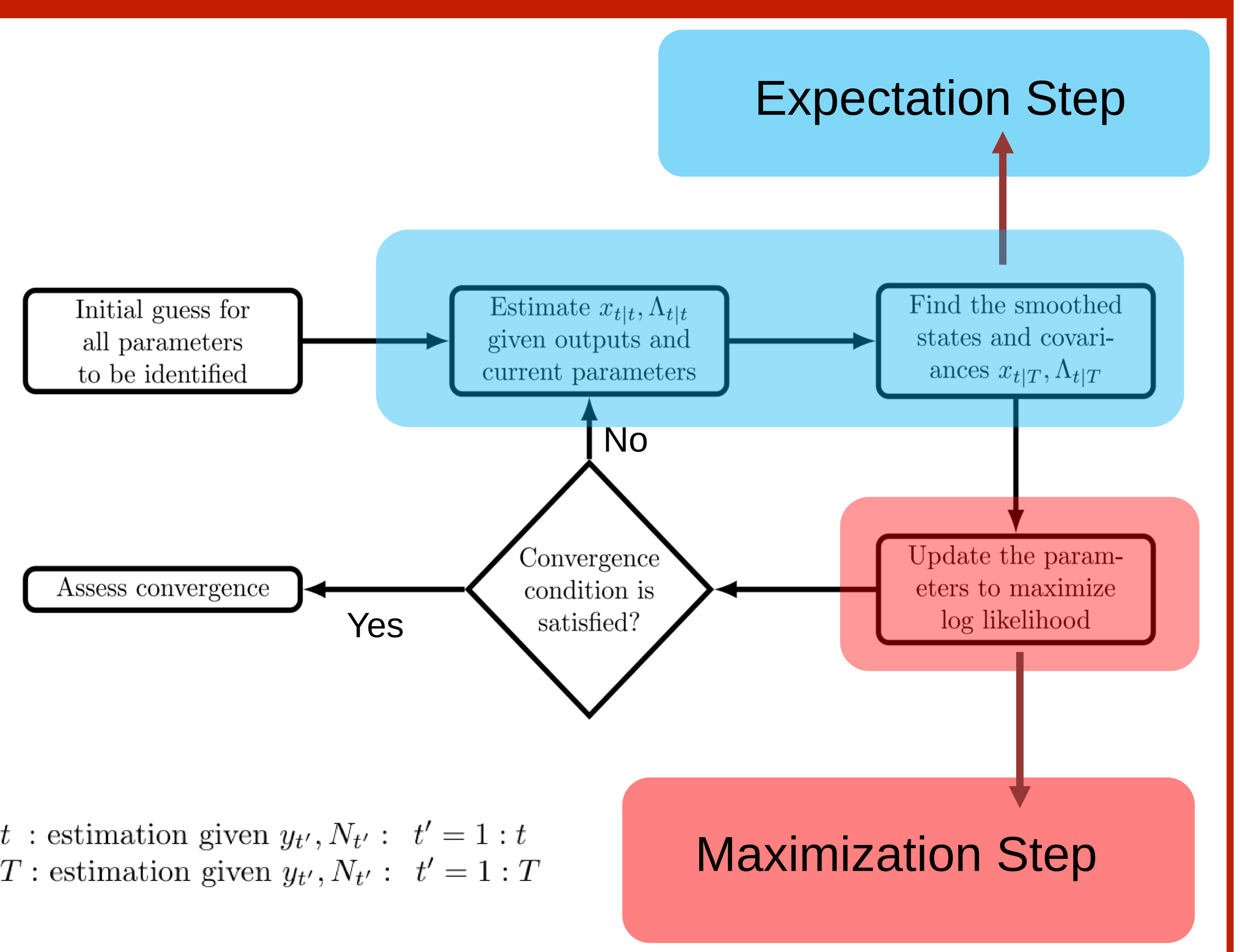
$$\lambda_c = e^{\beta_c + \boldsymbol{\alpha_c}^T.x}$$

Multiscale Model

- EM has been used to learn linear Gaussian dynamical models [Ghahramani et al., 1999] or to learn 1-dimensional point process models [Smith et al. 2003].
- We develop a new multiscale **EM algorithm** to identify multiscale model parameters.
- The parameters to be estimated are **A, B, Q, C,D, R,** $\boldsymbol{\beta_c}, \boldsymbol{\alpha_c}$ for c=1:N



II. Architecture



References:

Shanechi et al., PLoS Comp. Bio., 2016;
Hsieh & Shanechi, IEEE EMBC, Orlando, FL, 2016;
Smith et al., Neural Computation, 2003;
Ghahramani et al., Technical Report, 1999;

III. EM Algorithm

The goal is to find the equations for the expectation and maximization step for multiscale data

1. We write the **multiscale log likelihood** function:

$$\begin{aligned} L = & -\tfrac{1}{2}[x_1 - \Pi_1]^T \mathbf{V_1}^{-1}[x_1 - \Pi_1] - \tfrac{1}{2}\log|\mathbf{V_1}| \\ & - \sum_{t=2}^{T}([x_t - \mathbf{A}x_{t-1} - \mathbf{B}u_t]^T \mathbf{Q}^{-1}[x_t - \mathbf{A}x_{t-1} - \mathbf{B}u_t]) - \tfrac{T-1}{2}\log|\mathbf{Q}| \\ & - \sum_{t'=2}^{T'}([y_{t'} - \mathbf{C}x_{t'} - \mathbf{D}u_{t'}]^T \mathbf{R}^{-1}[y_{t'} - \mathbf{C}x_{t'} - \mathbf{D}u_{t'}]) - \tfrac{T'-1}{2}\log|\mathbf{R}| \\ & + \sum_{t=1}^{T}(\sum_{c=1}^{N}(N_t^c(\log\Delta + \beta_c + \boldsymbol{\alpha_c}^T.x_t) - \Delta.e^{\beta_c + \boldsymbol{\alpha_c}^T.x})) \end{aligned}$$

2. Expectation Step

$$x_{t|t-1} = \mathbf{A}x_{t-1|t-1} + \mathbf{B}u_t$$

$$\Lambda_{t|t-1} = \mathbf{A}\Lambda_{t-1|t-1}\mathbf{A}^T + \mathbf{Q}$$

$$\Lambda_{t|t}^{-1} = \Lambda_{t|t-1}^{-1} + \mathbf{C}^T R^{-1}\mathbf{C} + \left[\sum_{c=1}^{C} \boldsymbol{\alpha}_c \boldsymbol{\alpha}_c^T \lambda(t|x_t;\boldsymbol{\phi}_c)\Delta\right]_{x_{t|t-1}}$$

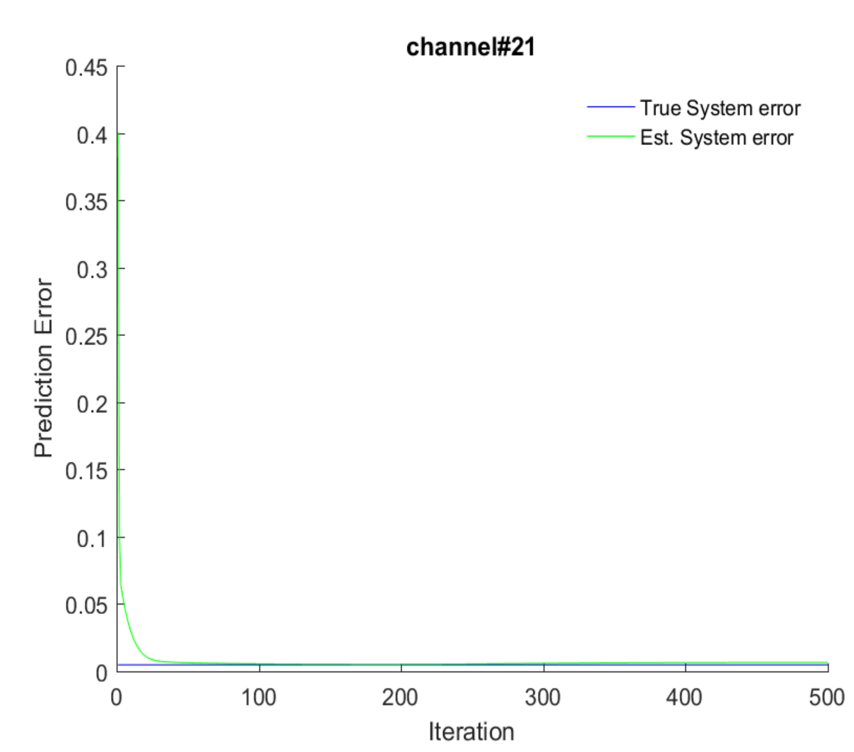
$$x_{t|t} = x_{t|t-1} + \Lambda_{t|t} \times \left[\mathbf{C}^T R^{-1}[Y_t - \mathbf{C}x_t - \mathbf{D}u_t] + \sum_{c=1}^{C} \boldsymbol{\alpha}_c [N_t^c - \lambda(t|x_t;\boldsymbol{\phi}_c)\Delta]\right]_{x_{t|t-1}}$$

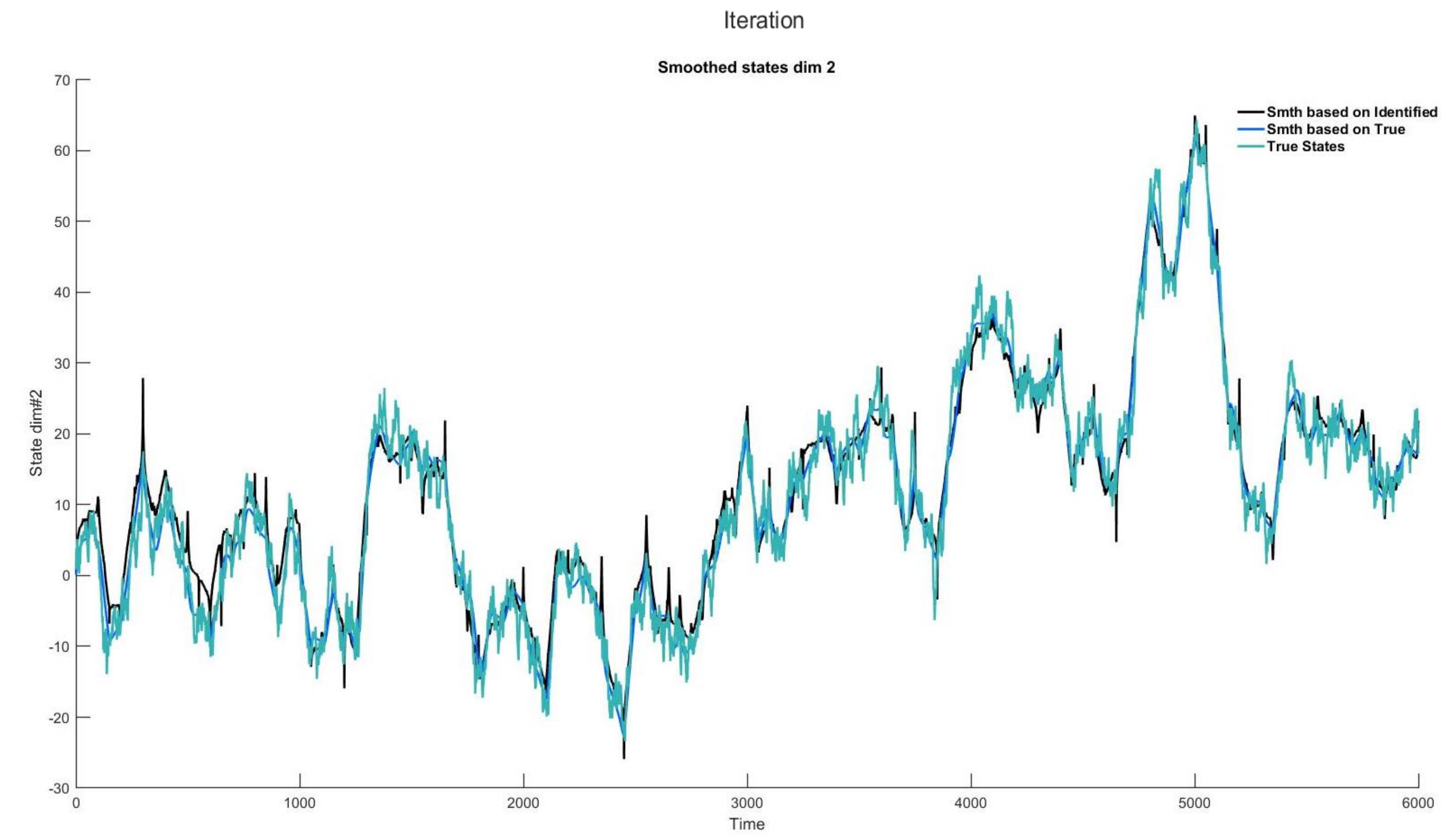
3. Maximization Step

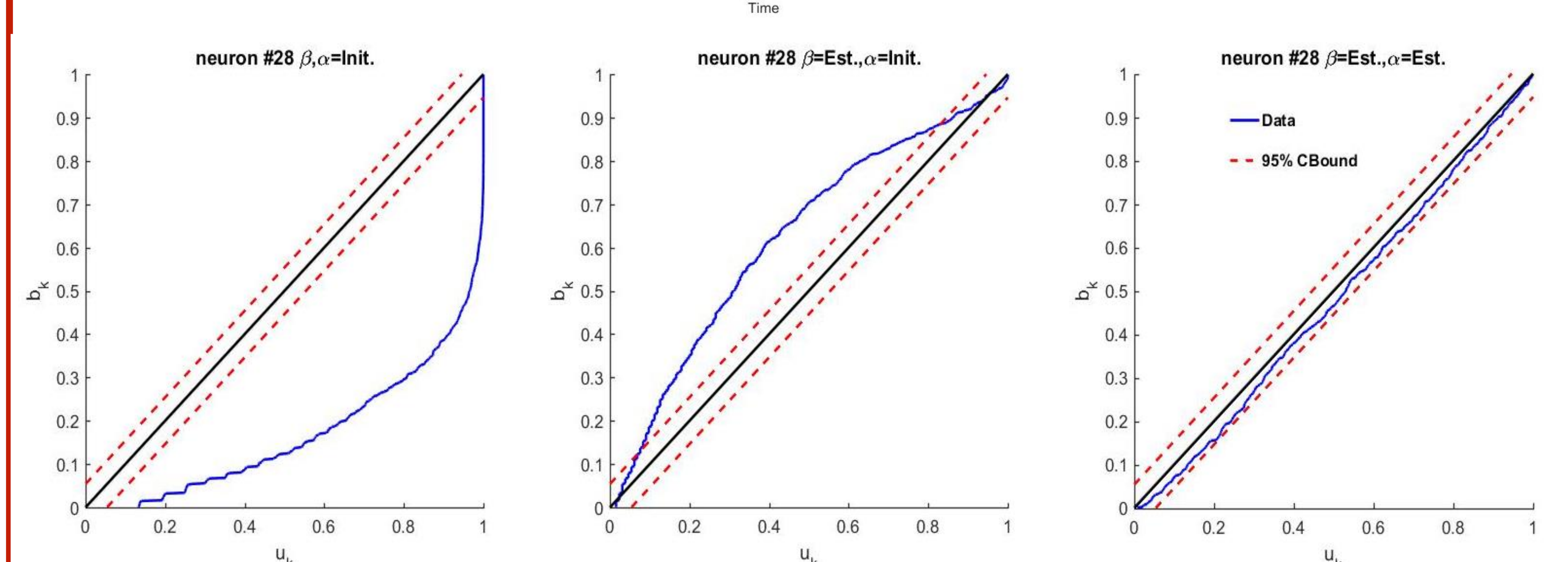
$$\frac{\partial L}{\partial \mathbf{A}} = 0 \;\; \frac{\partial L}{\partial \mathbf{B}} = 0 \;\; \frac{\partial L}{\partial \mathbf{Q}} = 0 \;\; \frac{\partial L}{\partial \mathbf{C}} = 0 \; \frac{\partial L}{\partial \mathbf{D}} = 0 \;\; \frac{\partial L}{\partial \mathbf{R}} = 0 \;\; \frac{\partial L}{\partial \boldsymbol{\alpha_c}} = 0 \;\; \frac{\partial L}{\partial \beta_c} = 0 \;\; \forall \;\; c = 1:N$$

IV. Results

- Goodness of fit assessment:
  - One-step(or multiple-step) ahead prediction error for continuous ECoG/LFP observations
  - KS plot for spiking observations
  - Open-Loop decoding







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