# Adaptive Estimation of Nonlinear Response Functions in V1 with Gaussian Processes

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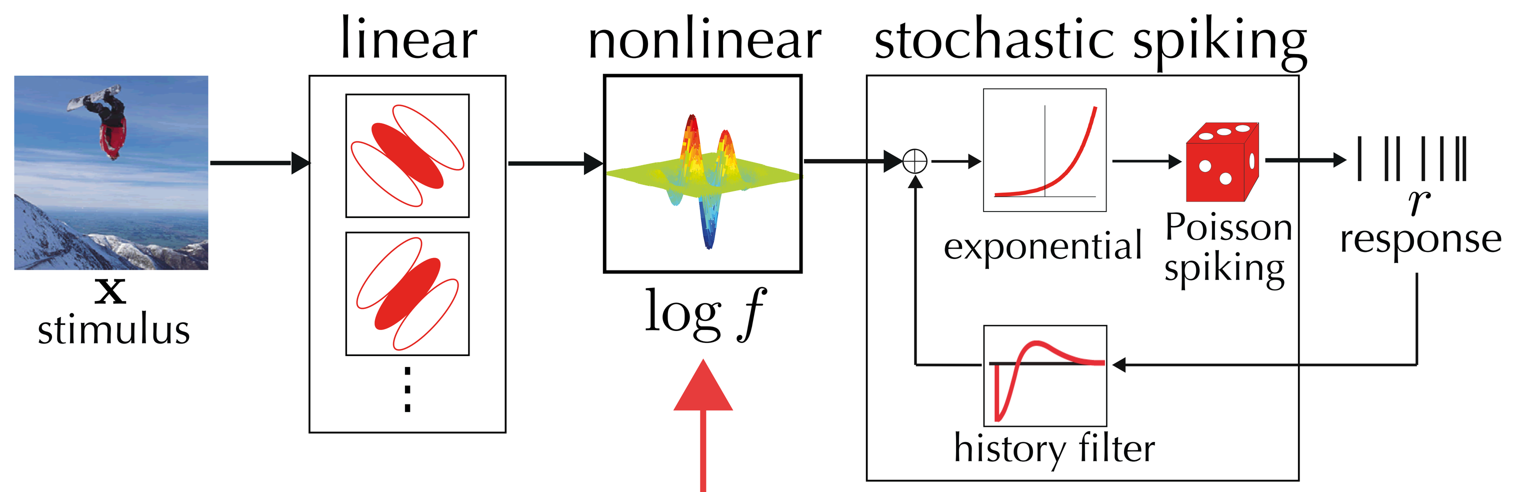
COSYNE 2012
#III-11

## 1. Neural characterization problem




Question: how to efficiently learn neural response nonlinearities in closed-loop experiments?

## 2. logGP-Poisson encoding model

**generative model**

hyper-parameters $\theta$ — flat hyper-prior on $\theta = \{\mu, \rho, \tau\}$ (mean, variance, correlation scale)

nonlinearity $f$ — log-Gaussian process prior

$$f|\theta \sim \ln\mathcal{N}(\mu\ , K)$$

$$k(\mathbf{x}_i, \mathbf{x}_j) = \rho \exp\left(-\frac{||\mathbf{x}_i - \mathbf{x}_j||^2}{(2\tau)}\right)$$

$\mathbf{x}$ stimulus → $r$ response — likelihood

$$r|\mathbf{x} \sim \text{Poiss}(f(\mathbf{x}))$$

MAP inference: $\mathbf{f}_{map} = \arg\max_{\mathbf{f}} \log p(\mathbf{f}|\mathbf{r}, \mathbf{X}, \theta)$

**setting hyperparameters**

- Set $\theta$ by maxizing marginal likelihood (Laplace approximation):

$$p(\mathbf{r}|\theta) = \int p(\mathbf{r}|\mathbf{f})p(\mathbf{f}|\theta)d\mathbf{f} \approx \frac{p(\mathbf{r}|X, \mathbf{f}) \ln\mathcal{N}(\mu\ ,\ )}{\ln\mathcal{N}(\mathbf{f}_{map}, \Lambda)}$$

Poisson likeli. log-normal approx. log-normal posterior } iterate!

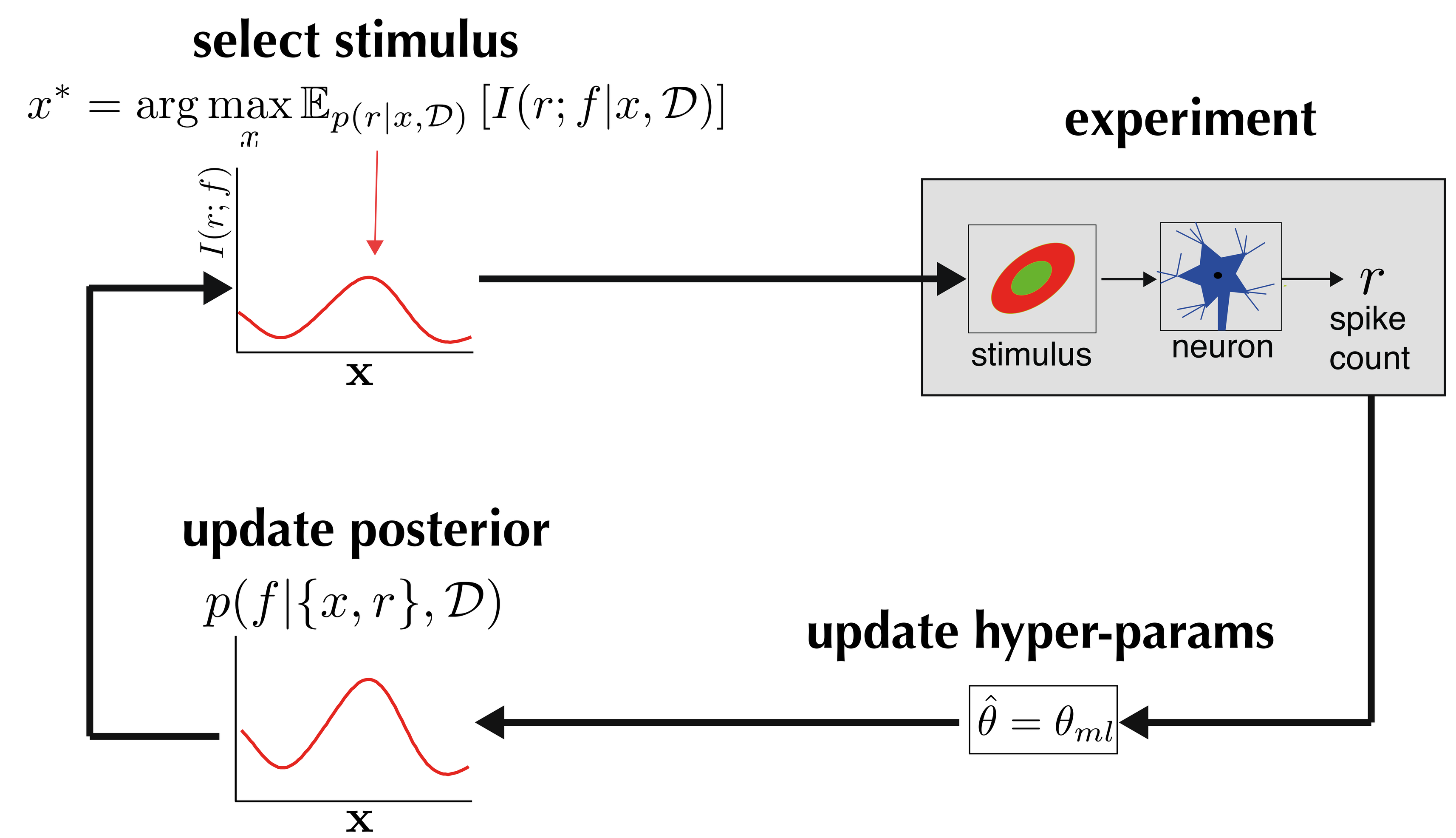
- Numerical update of posterior & evidence for each $\theta$ : expensive!

numerical update: $\hat{\theta} \rightarrow \ln\mathcal{N}(\mathbf{f}_{map}, \Lambda)$ posterior → evidence optimization: $\mathbf{f}_{map} = \Lambda(H\mathbf{m} + K^{-1}\mu_f)$

$\mathcal{N}(\mathbf{m}, H^{-1})$ likelihood    where $\Lambda = (H + K^{-1})^{-1}$

## 3. Adaptive stimulus selection

- select stimulus $\mathbf{x}$ that maximizes expected information gain on each trial




- maximizing information = minimizing posterior uncertianty

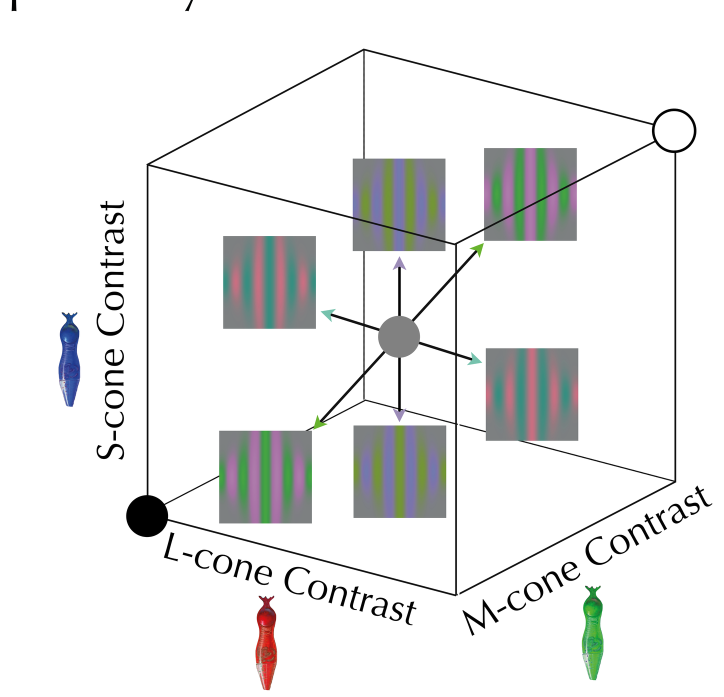
$$\arg\max_x \mathbb{E}_{p(r|x,\mathcal{D})}[I(r; f|x, \mathcal{D})] = \arg\min_x \mathbb{E}_{p(r|x,\mathcal{D})}[H(f|\mathcal{D}, \{x, r\})]$$

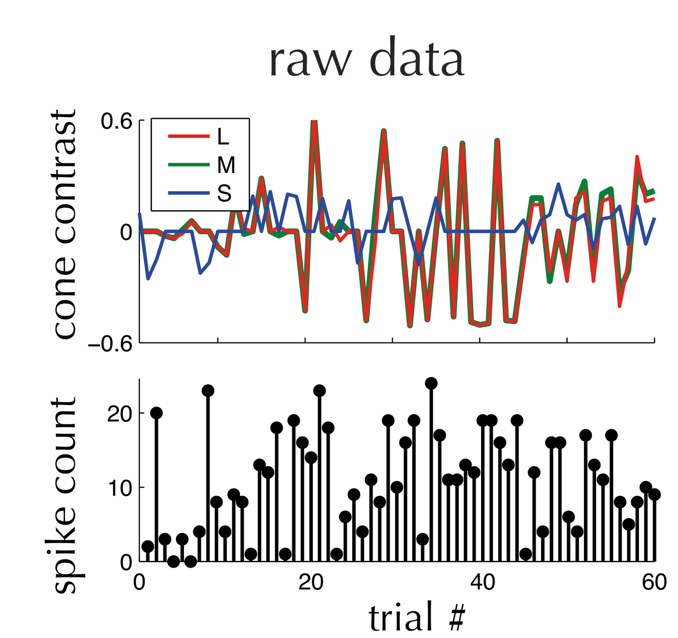
- reduction in entropy = $\mathbf{f}_{map}(x)\sigma_p^2(x)e^{\frac{\sigma_p^2(x)}{2}}$

posterior variance of $\log f$

## 4. Experimental setup

- color-tuned neurons in macaque V1
- spectrally-modulated Gabor stimuli

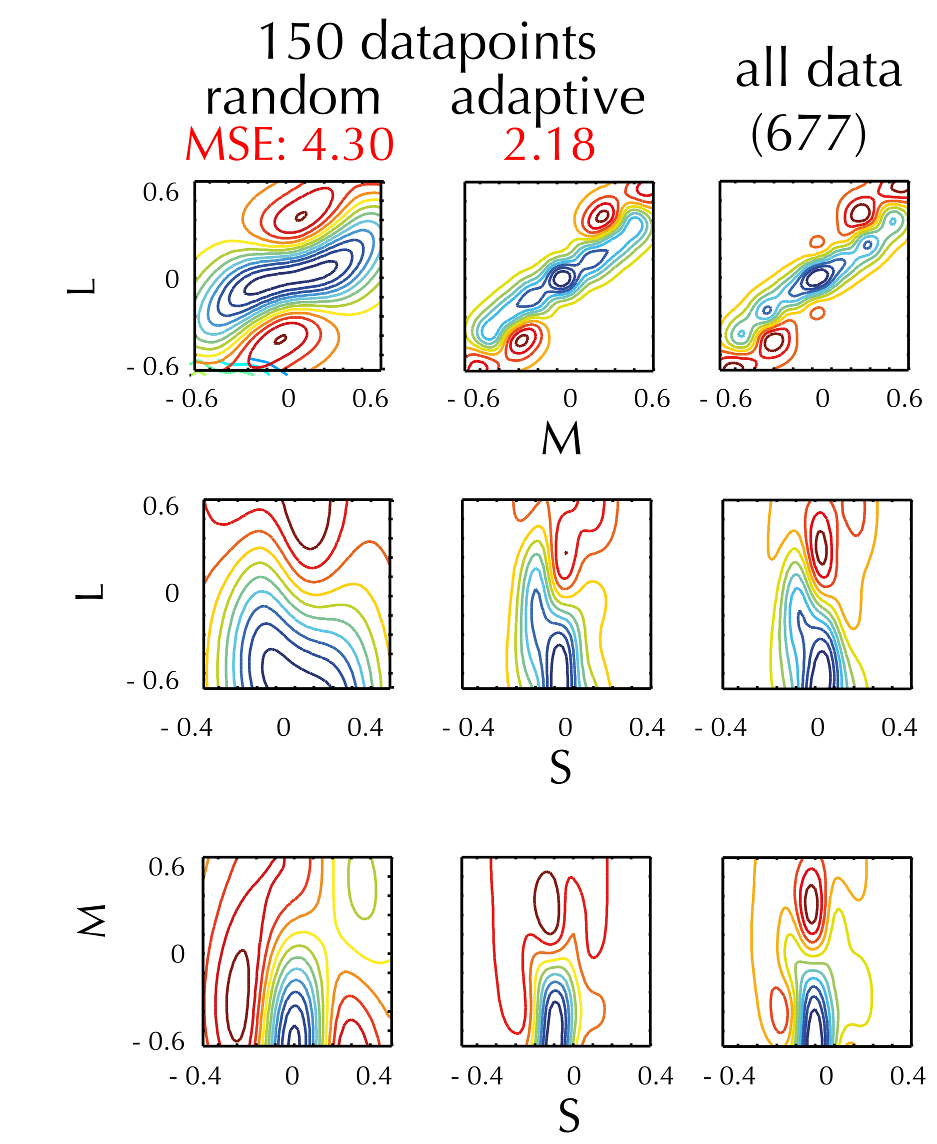


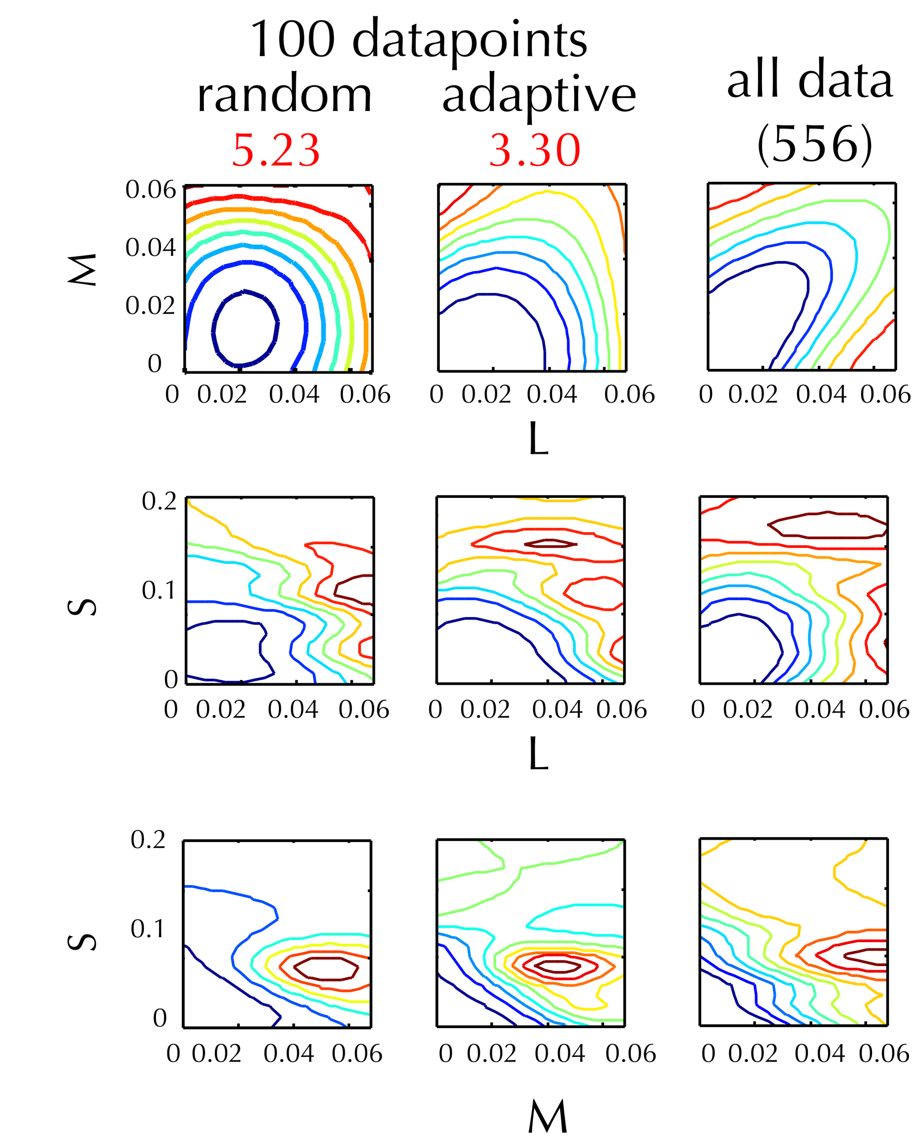

## 5. Results

- 2D slices of 3D nonliearity

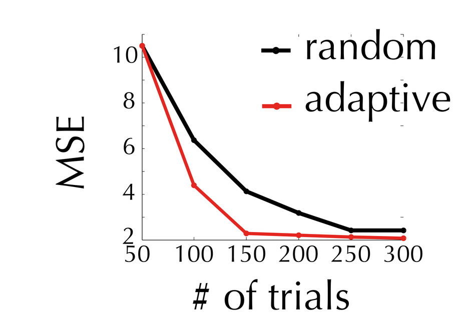
**Cell1 :**



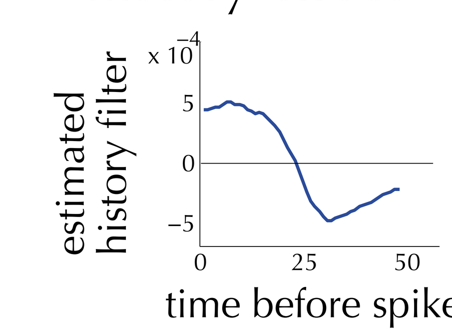

**Cell2 :**



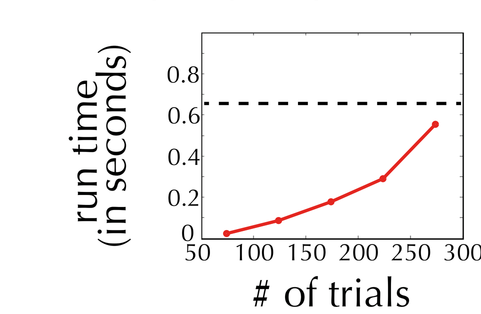

- MSE




- history effect




- run time




## 6. Conclusions

- flexible logGP-Poisson model for neural nonlinearities
- optimal design based on mutual information
- rapid learning of nonlinearities in closed-loop experiments

## Acknowledgements:

Support was provided by the Center for Perceptual Systems (MP), the Sloan Fellowship (JWP), and the McKnight Foundation and NIH Grant EY018849 (GDH).