1. Neural characterization problem

- linear
- nonlinear
- stochastic spiking

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

2. logGP-Poisson encoding model

- generative model
  - hyperparameters
  - nonlinearity
- MAP inference: $f_{map} = \arg \max_f \log p(f|X, \theta)$

3. Adaptive stimulus selection

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

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

- maximizing information = minimizing posterior uncertainty

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

- reduction in entropy = $f_{map}(x) = \ln \text{variance of } \log f$

4. Experimental setup

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

- random adaptive
- 150 datapoints
- all data
- MSE: 4.30
- 5. Results

- 2D slices of 3D nonlinearity

- Cell1: 100 datapoints
- adaptive
- all data
- MSE: 5.23

- Cell2: random
- 150 datapoints
- all data
- MSE: 3.30

- reduction in entropy = $f_{map}(x) = \ln \text{variance of } \log f$

5. Conclusions

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

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