Information theory and neural coding

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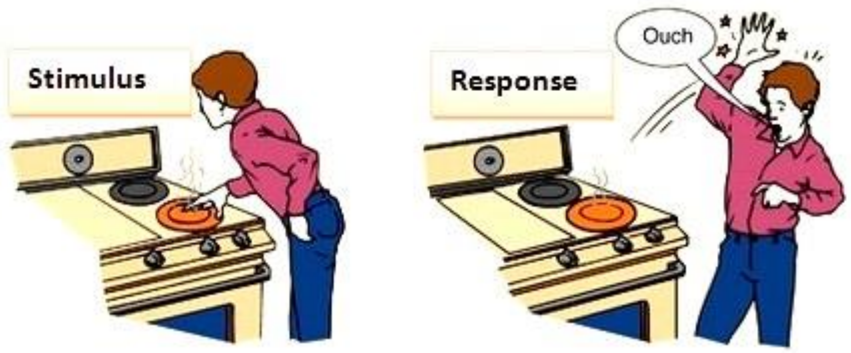
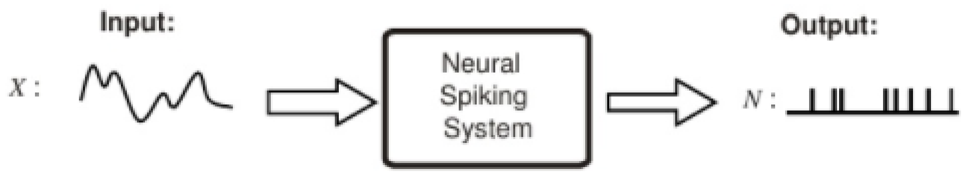
Introduction

What is stimulus and response?



What is neural coding?



What is a neural spike train?

“**Spike trains** are the time-series electrical signals recorded from individual neurons in the brain.”

Information theory and neural coding

Alexander Borst and Frédéric E. Theunissen

GENERAL CONCEPTS

Probability that the neural response takes the value $r_i = p(r_i)$ Probability that the stimulus condition takes the value $s_j = p(s_j)$ Probability that the response is r_i given the stimulus is $s_j = p(r_i \| s_j)$
Information about stimulus condition s_x $$I(R, sx) = \Sigma p(r_i \| s_x) \, log_2 \frac{p(r_i \| s_x)}{p(r_i)}$$
Average information obtained from all stimulus conditions $$I(R, S) = \sum\sum p(s_j) p(r_i \| s_j) log_2 \frac{p(r_i \| s_j)}{p(r_i)}$$

DYNAMIC STIMULI – Methods of estimation

Method of estimation	Driving Principle	Assumptions
Direct	Separate R into deterministic and a random component by repeating S many time $I(S,R) \rightarrow I(R,R_{det})$	The temporal resolution is small enough.
Upper Bound	Same as Direct method.	$R_{det} = R_{avg}$ $N = R - R_{avg}$ $I(R,R_{det}) \rightarrow I(R,R_{avg})$ It assumes that if Noise(N) is Gaussian then $I(S,R) = \int_0^k \log(1 + SNR(f))df$
Lower bound	Find best S_{est} from R. $I(S,R) \rightarrow I(S,S_{est})$	S is Gaussian. $N = S - S_{est}$.
Absolute lower	Same as lower bound. Find smallest $I(S',S_{est})$ that would give the same error as $(S - S_{est})$.	S is Gaussian.

Entropy and information in neural spike trains: Progress on the sampling problem

Ilya Nemenman, William Bialek and Rob de Ruyter van Steveninck

MODELS

Maximum likelihood entropy

$$S_{ML} = -\sum (f_i \log(f_i))$$

where,

f_i= frequency of occurrence of i^{th} possibility = n_i/N

n_i = number of time ith possibility occurred

N = sample size

Bayesian model

$$(S^{NSB})^m = \int d\mathbf{p} \left(-\sum_{i=1}^{K} p_i \log_2 p_i \right)^m P(\mathbf{p}|\mathbf{n}).$$

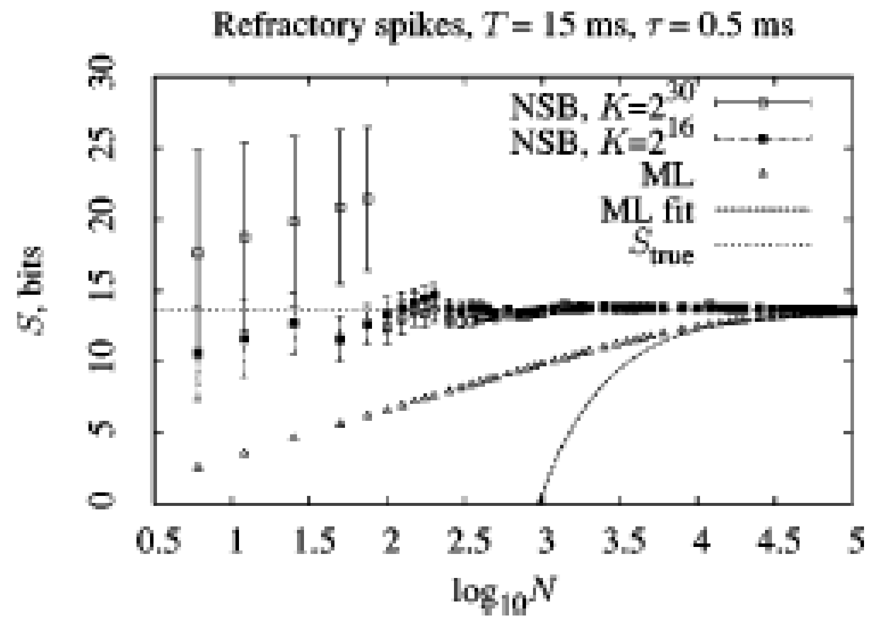
where,

$$P(\mathbf{p}|\mathbf{n}) = P(\mathbf{n}|\mathbf{p}) \mathcal{P}_{NSB}(\mathbf{p}) \cdot \frac{1}{P(\mathbf{n})},$$

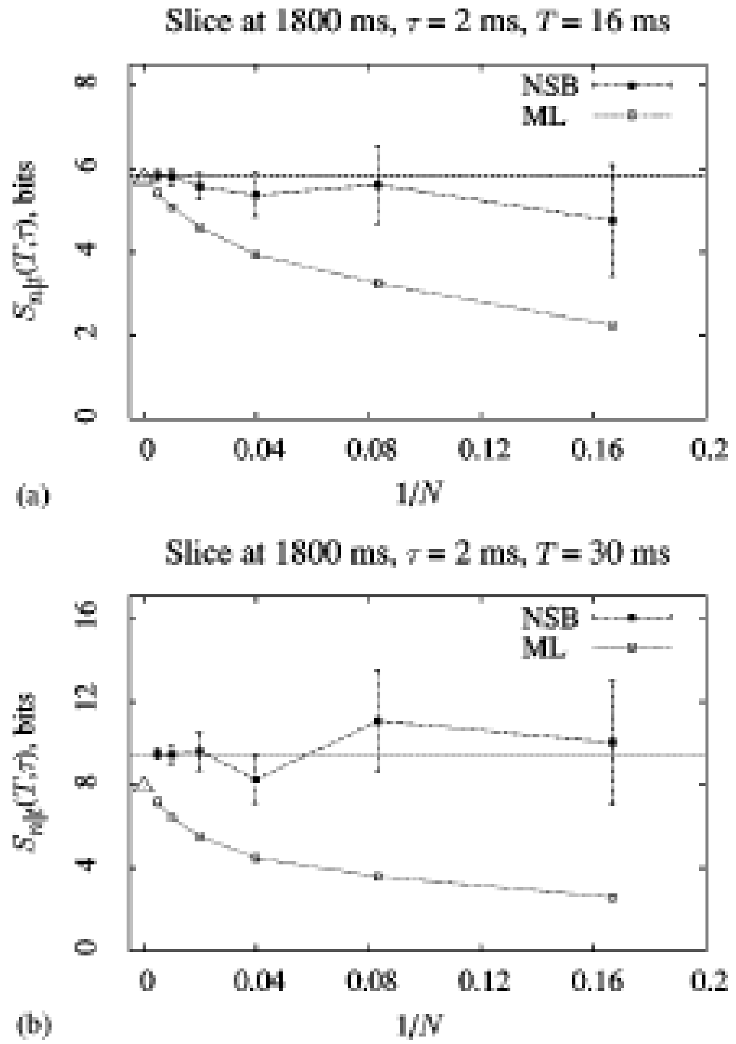
$$P(\mathbf{n}) = \int d\mathbf{p}\, P(\mathbf{n}|\mathbf{p}) \mathcal{P}_{NSB}(\mathbf{p}).$$

RESULTS

Synthetic data



Real Data



Mechanisms of Information Filtering in Neural Systems

Benjamin Lindner

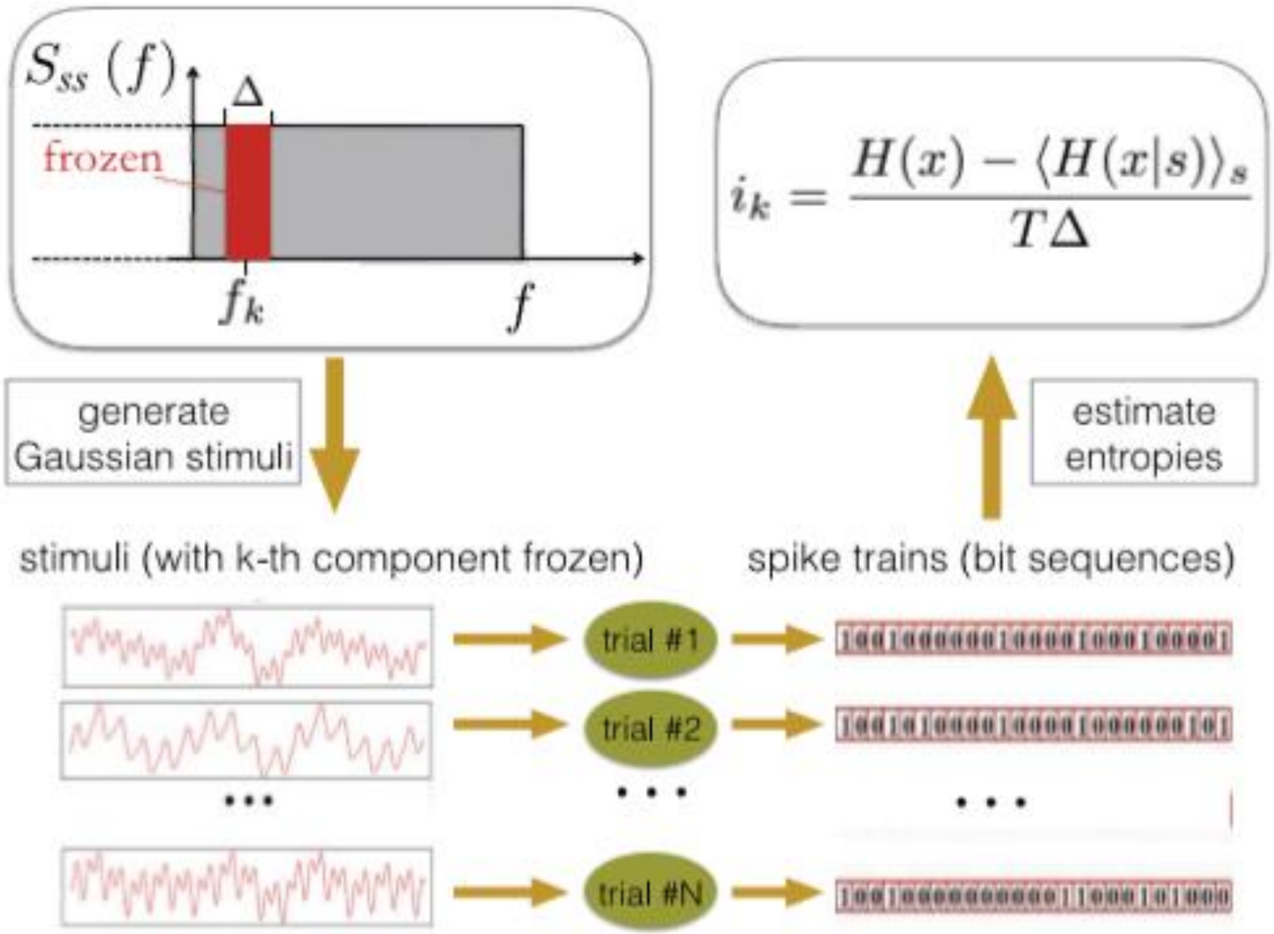
Stimulus-response coherence

$$C(f) = \frac{|S_{sx}(f)|^2}{S_{xx}(f)S_{ss}(f)},$$

$$R_{LB} = -\int_0^{\infty} df \log_2[1 - C(f)],$$

Response-response coherence

$$C_{x_1,x_2} = \frac{\langle S_{x_1,x_2}\rangle_s}{\sqrt{\langle S_{x_1,x_1}\rangle_s \langle S_{x_2,x_2}\rangle_s}}$$



Thank you