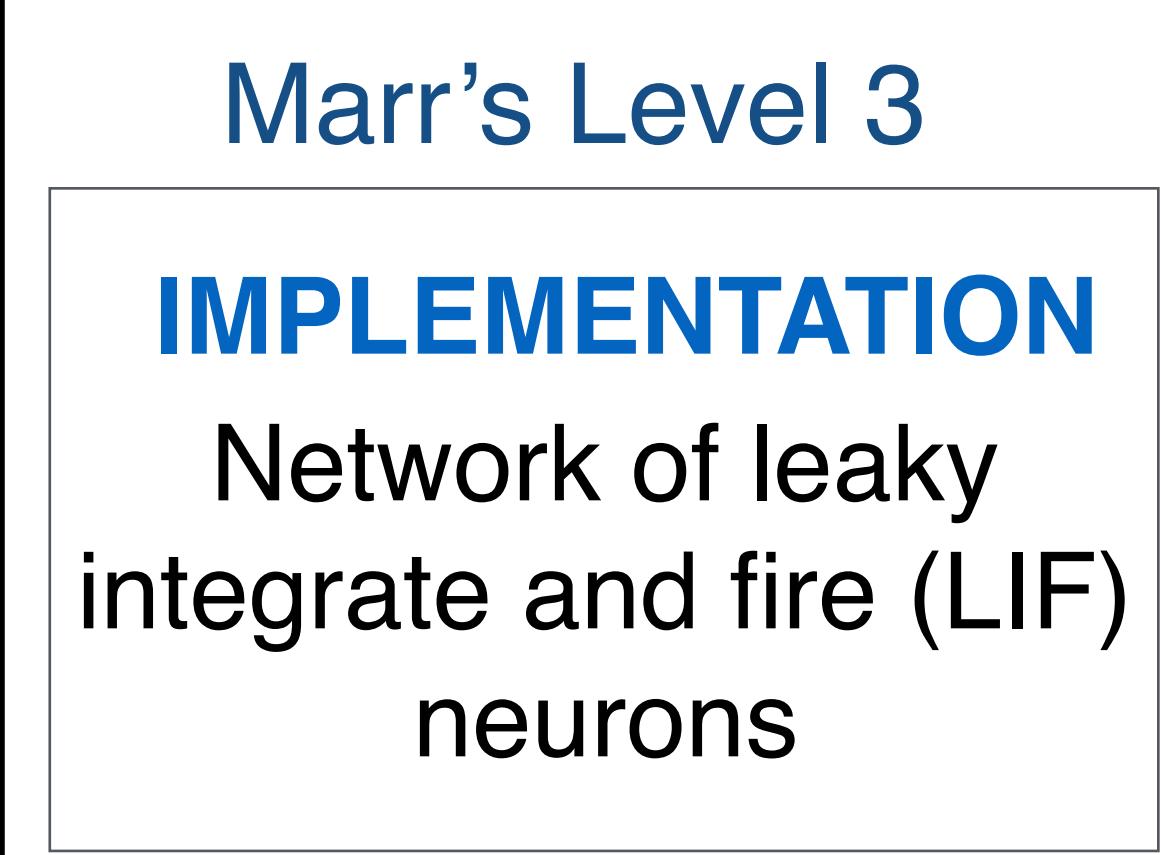
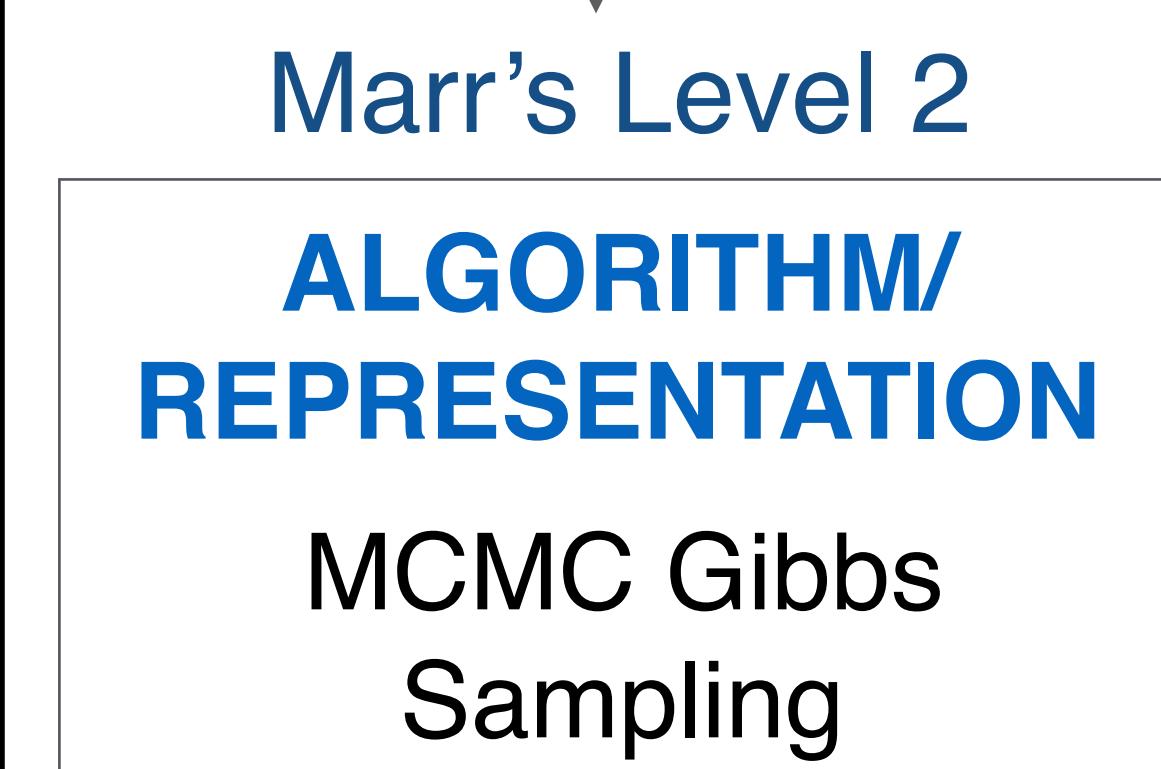


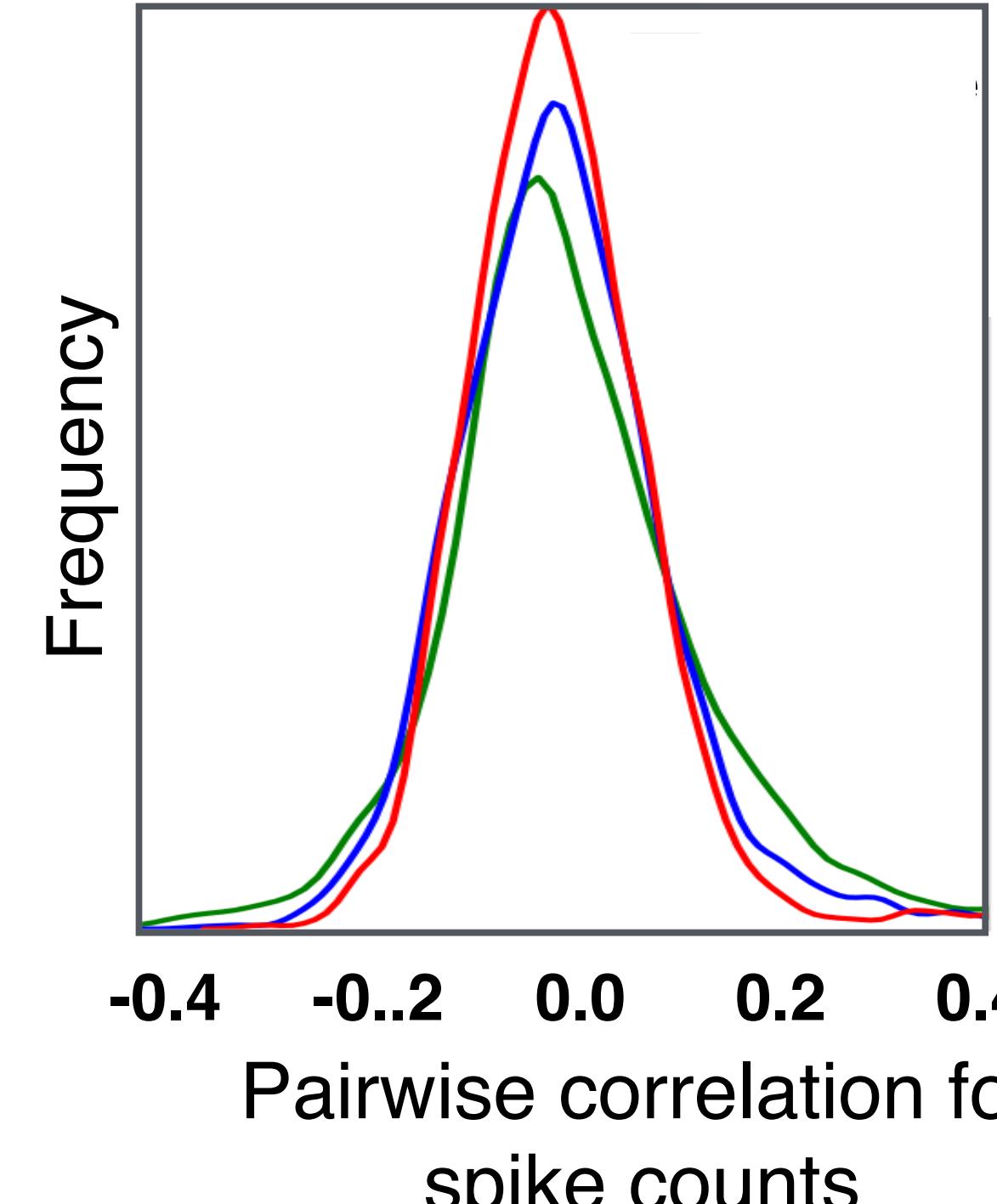
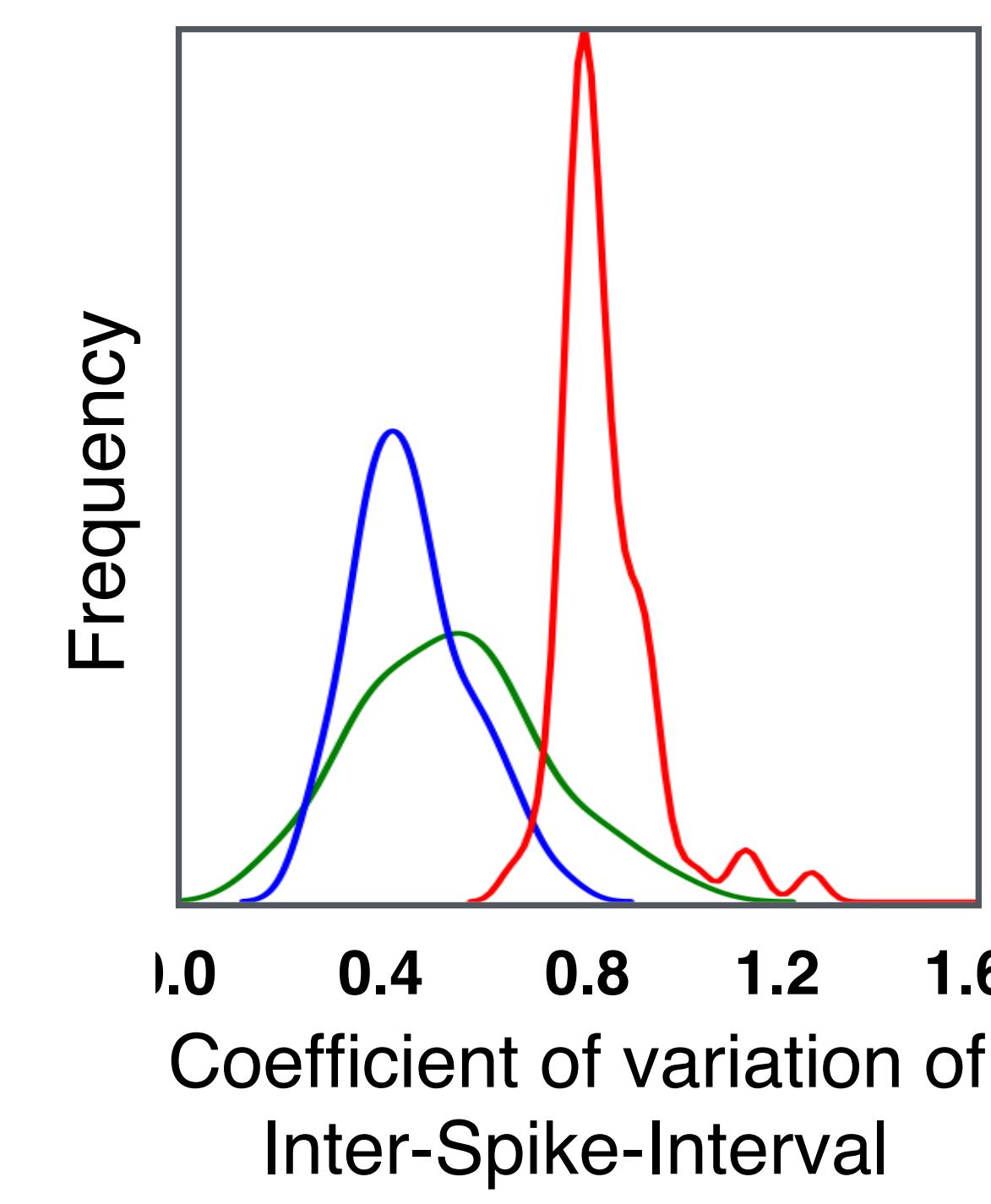
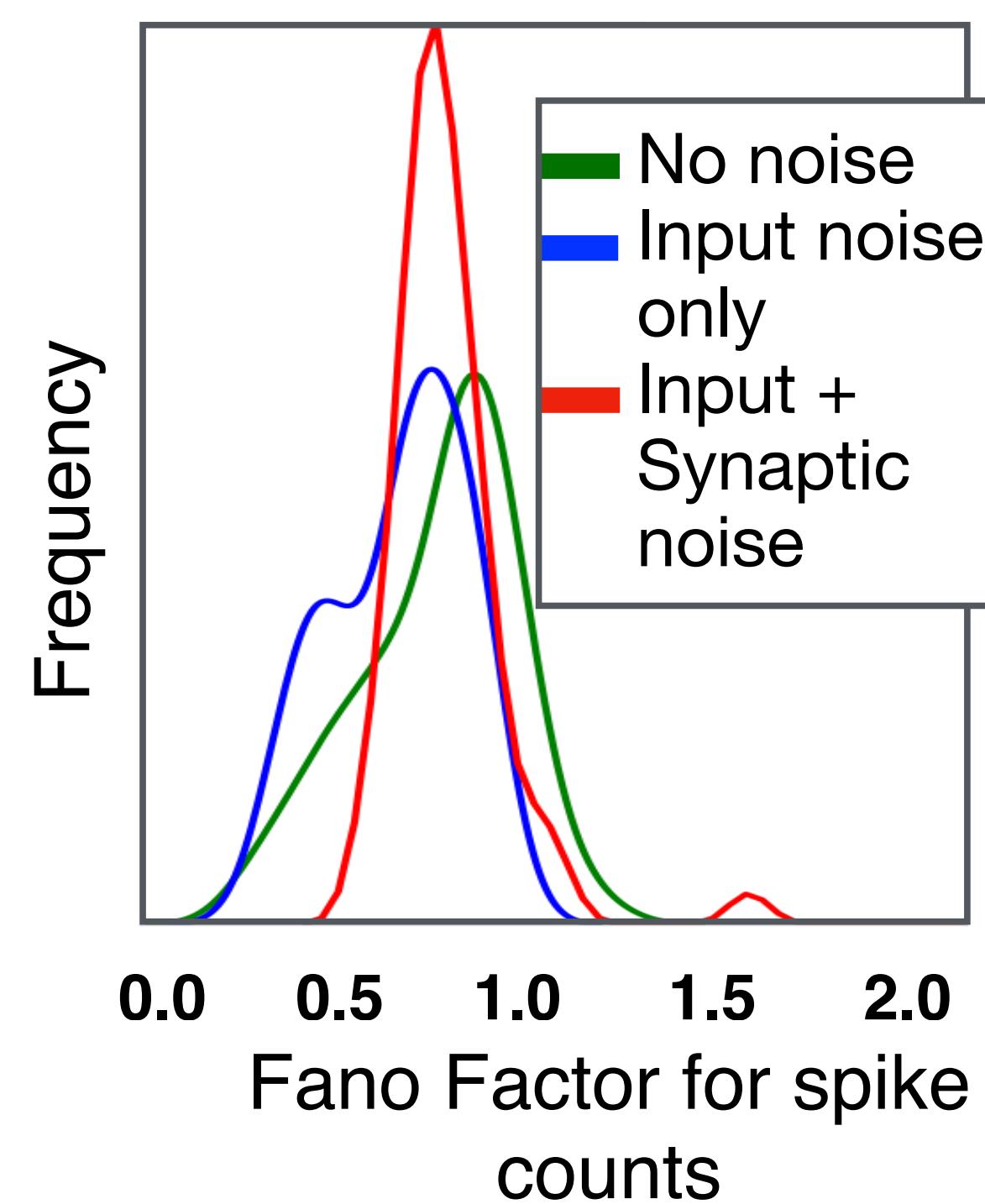
## Introduction

- Visual processing is often characterized as implementing **probabilistic inference**.<sup>[1]</sup>
- One candidate algorithm to do probabilistic inference, is '**neural sampling**'.<sup>[2,5,7]</sup>
- We derive a **spiking neural network model** using deterministic leaky integrate-and-fire (LIF) neurons and **stochastic synapses**<sup>[11]</sup> whose responses represent **binary samples** from the joint posterior in a linear model<sup>[9]</sup> of the retinal input.

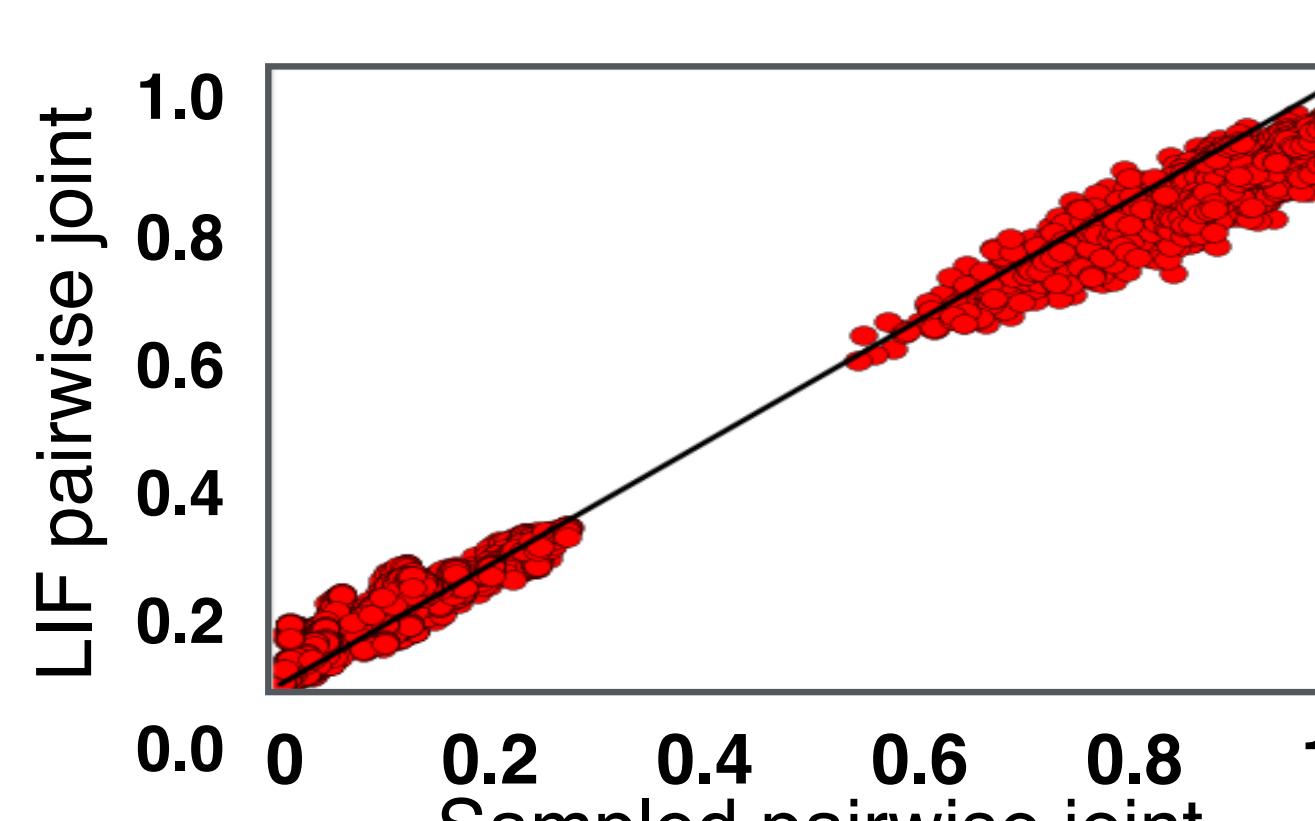
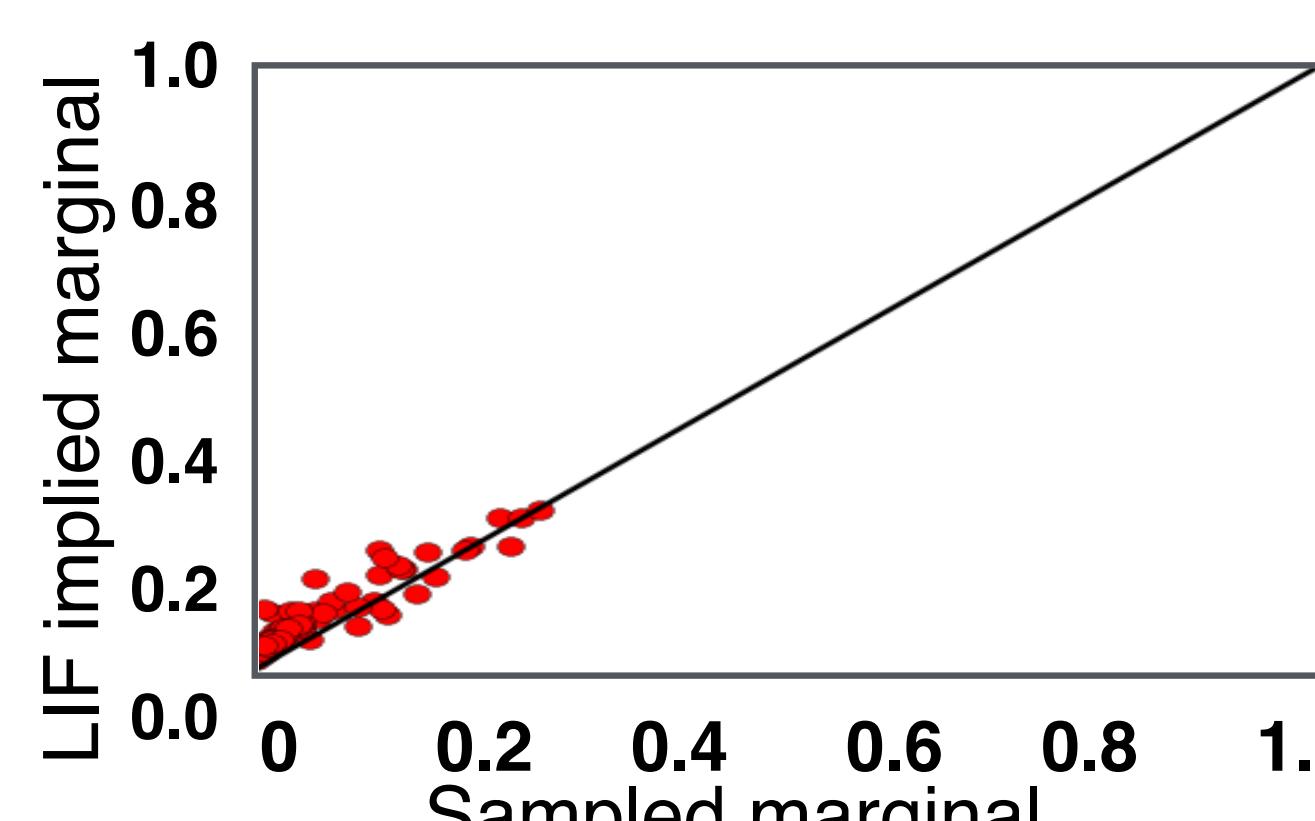
## Bridging Marr's three levels<sup>[10]</sup>



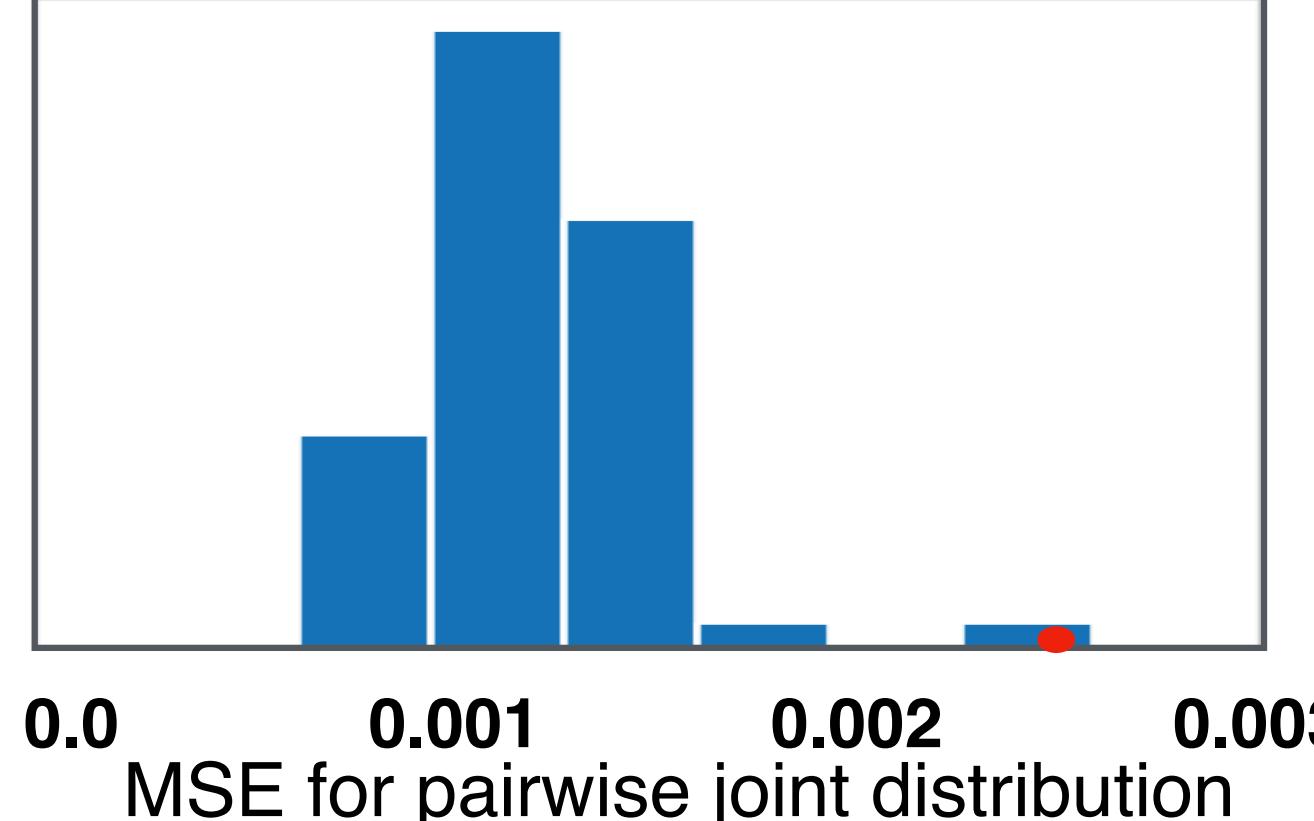
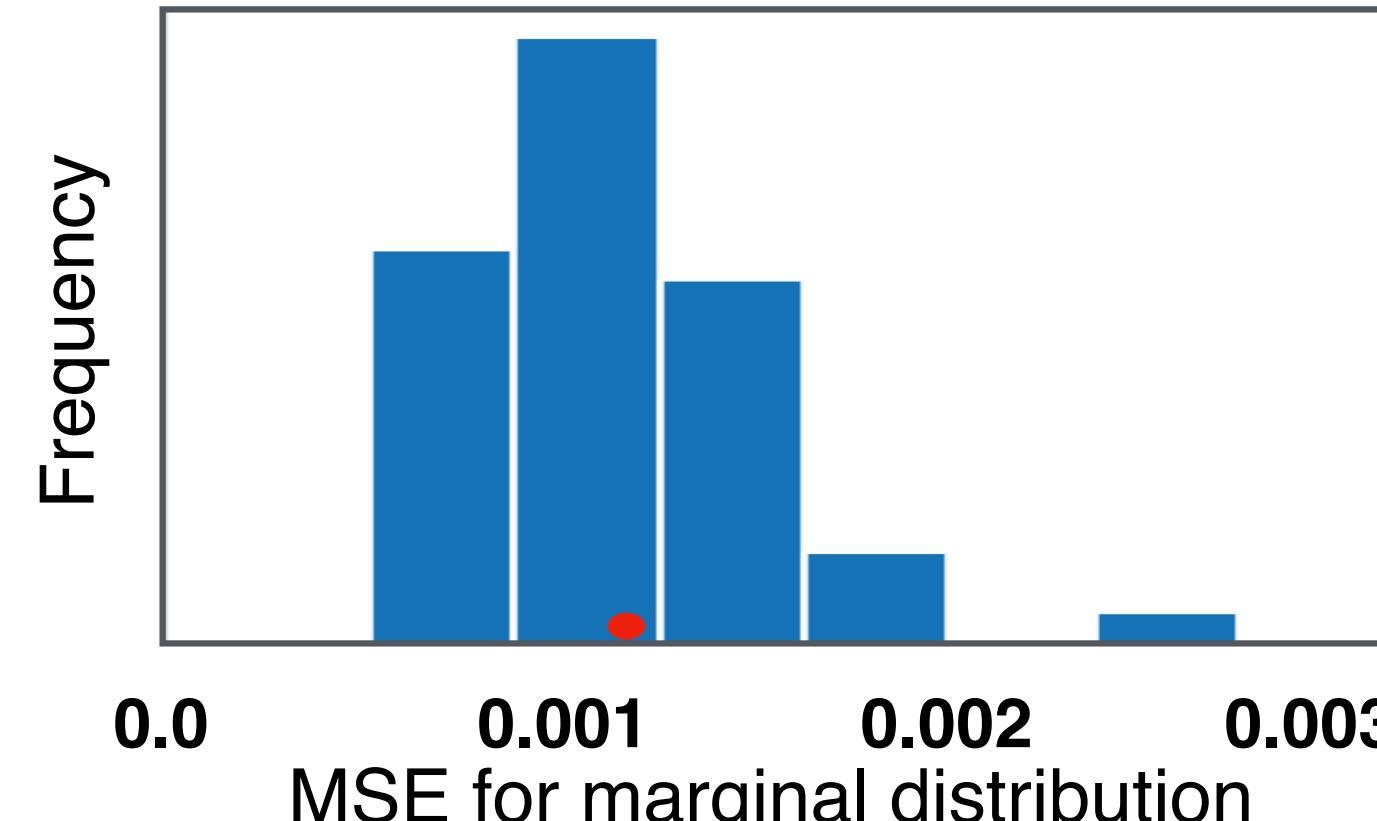
### Near Poisson variability in LIF network with Input + Synaptic noise



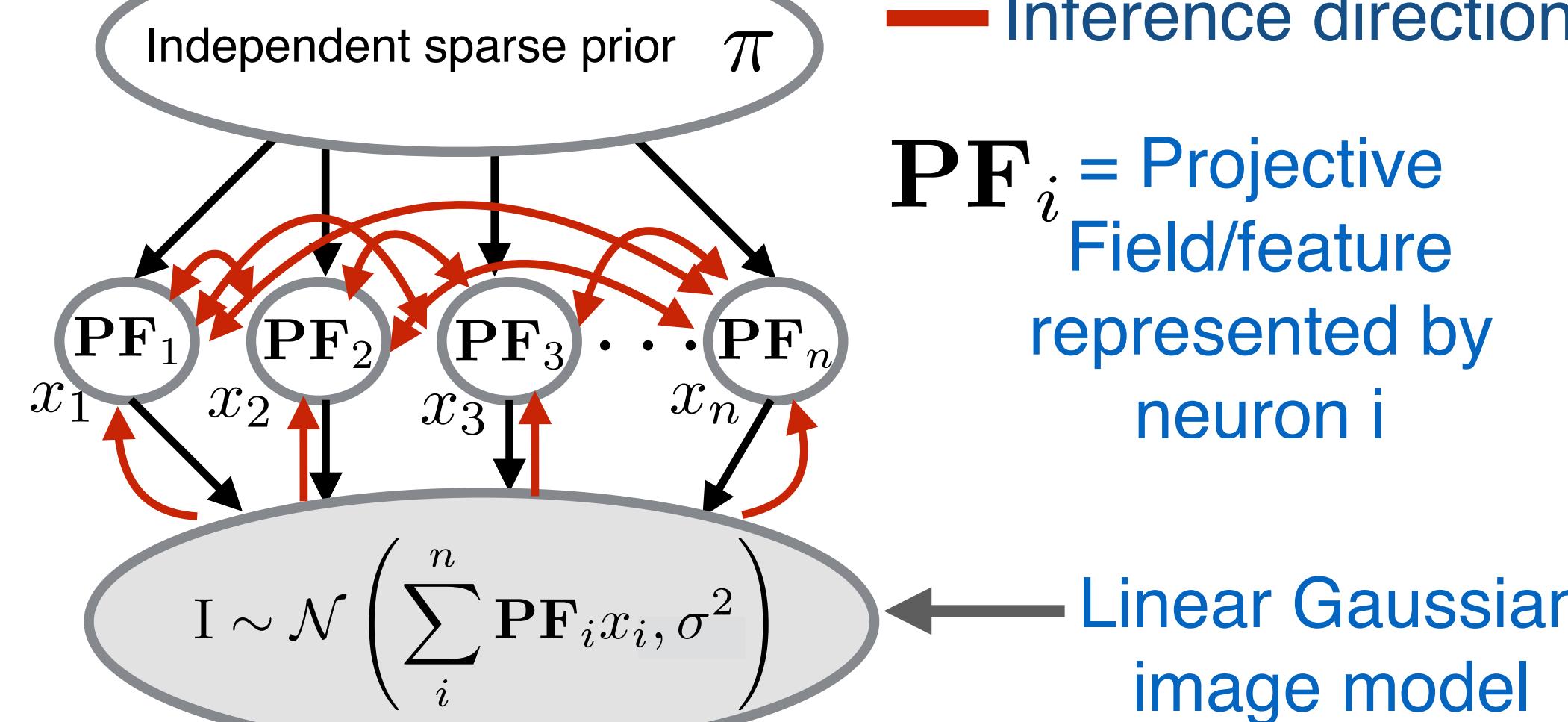
Good agreement between posterior implied by LIF network spikes and Gibbs samples for an example image



Mean Square Errors (MSE) across many images



— Generative model  
— Inference direction



Gibbs sampling for binary  $x$  with sparse prior:

$$p(x_k = 1|x_{-k}, I) \propto \exp\left(\frac{1}{\sigma^2} \|I - \mathbf{P}\mathbf{F}^T x\|^2\right) \times \prod_i^n \pi^{x_i} (1 - \pi^{1-x_i})$$

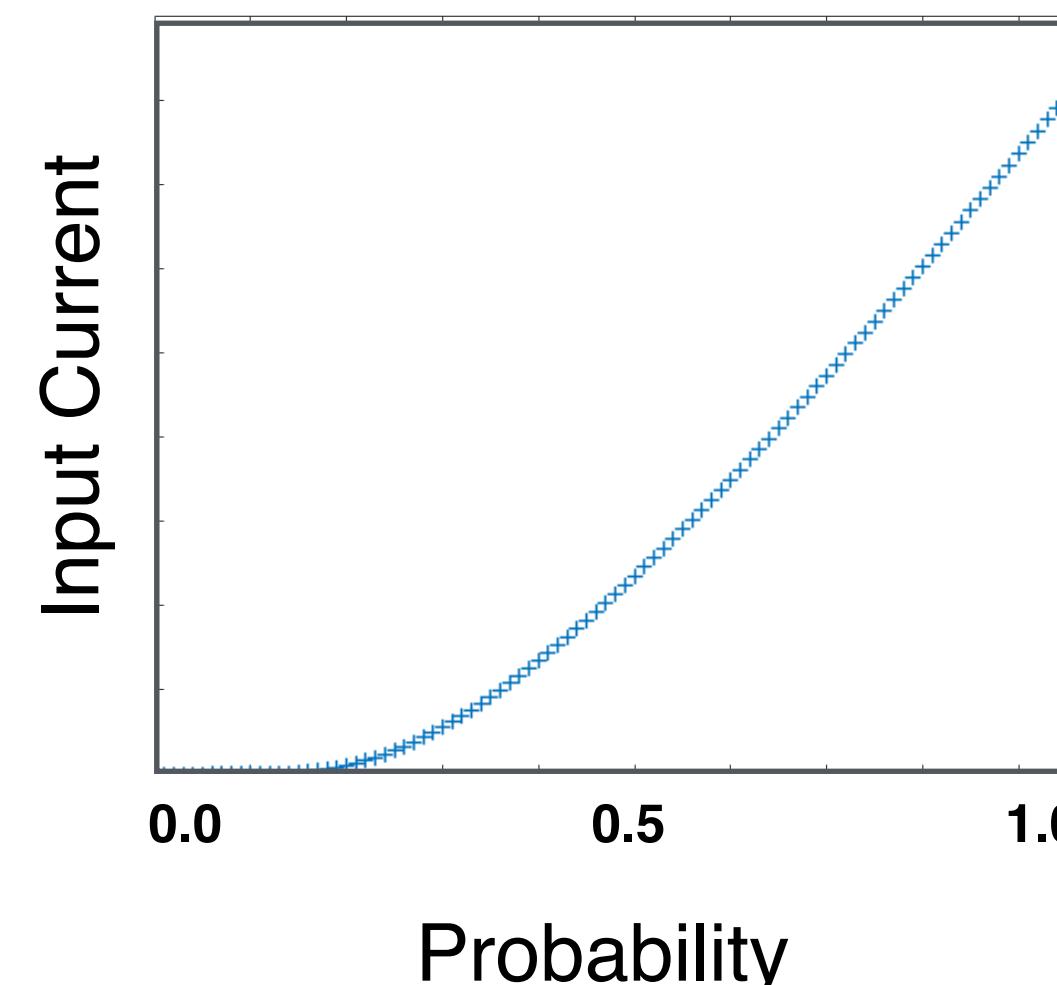
Binary samples of  $x$  can be interpreted as spikes

$x_1$	0 0 1 1 0	1 1 ...
$x_2$	1 0 0 0 0	1 ...
$x_3$	1 1 1 1 0	1 1 1 ...
:	:	:
$x_N$	0 0 1 1 1	1 1 1 ...

0 = no spike  
1 = spike

I Vs P in LIF neuron for fixed input:

$$p = \frac{1}{\Delta t} = \left[ \tau \ln \left( \frac{\text{I}_{\text{input current}}}{\text{I}_{\text{input current}} + (\text{V}_{\text{rest}} - \text{V}_{\text{threshold}})} \right) \right]^{-1}$$

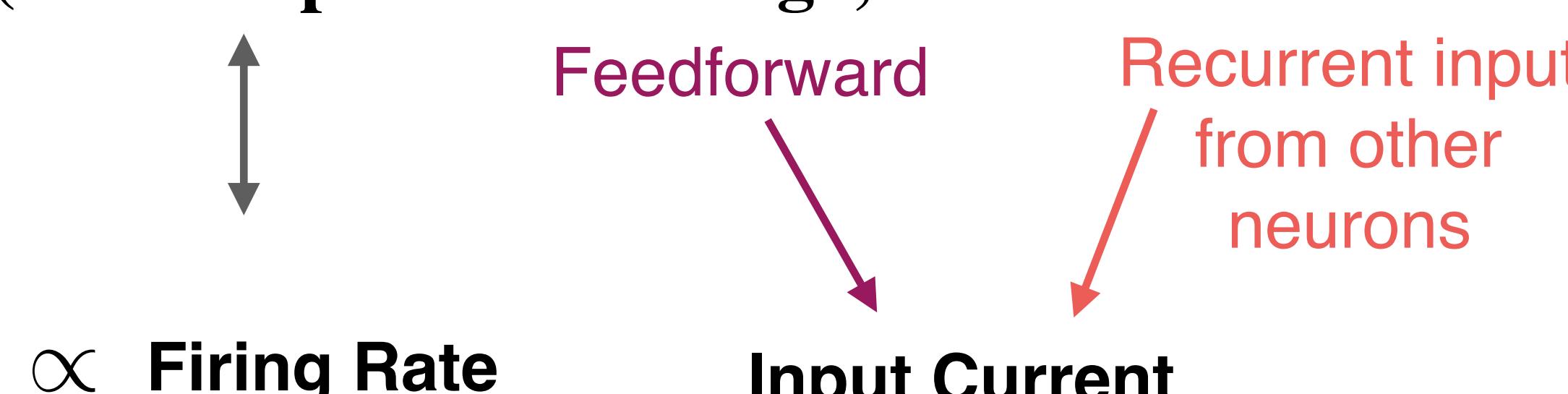


LIF equation(unitless):

$$\tau \frac{dV}{dt} = V - V_{\text{rest}} + \text{I}_{\text{input current}}$$

$$\text{I}_{\text{input current}} = \text{I}_{\text{recurrent}} + \text{I}_{\text{feedforward}}$$

p(neuron spikes now|Image, state of other neurons)



## Conclusion

Simulating the LIF network we find,

- agreement between posterior implied by LIF network spikes and Gibbs samples
- approximately contrast-invariant tuning curves
- near Poisson variability
- small noise correlations with mean of close to zero<sup>[6]</sup>
- negative causal influences between neurons of similar receptive fields<sup>[12]</sup>

Models	Hoyer and Hyvärinen, NIPS 2003	Buesing, Lars, et al., PLoS COMP BIO 2011 [4]	Bornschein, Jörg et al., PLoS COMP BIO 2013 [3]	Petrovici et al 2015 [8]	Gibbs Sampling in LIF neurons (Our Work)
V1 Model	✓		✓	✓	✓
MCMC Sampling	✓	✓		✓	✓
Binary Hidden States		✓	✓	✓	✓
Deterministic LIF neurons			✓	✓	✓

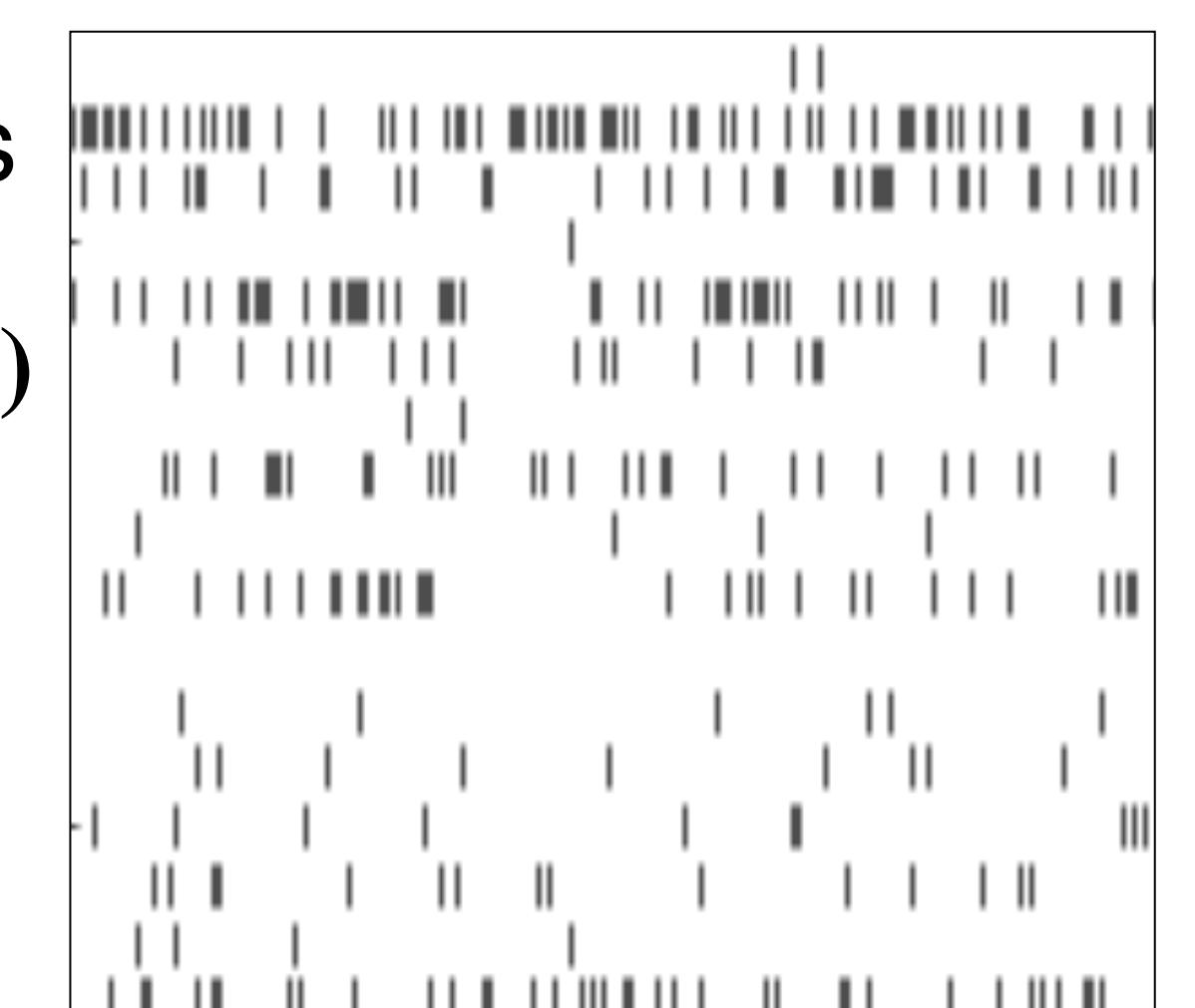
## References

- [1] Fiser, József, et al. (2010) [2] Hoyer, Patrik O., and Aapo Hyvärinen. NIPS. (2003) [3] Bornschein, Jörg et al PLoS CB 9,6 (2013) [4] Buesing, Lars, et al. PLoS CB (2011) [5] Orbán, Gergő, et al. Neuron (2016) [6] Ecker, Alexander S., et al. Science (2010) [7] Haefner, et al Neuron (2016) [8] Petrovici, Mihai A., et al. BMC neuroscience (2015) [9] Olshausen, and Field Vision research (1997) [10] David Marr, Vision (1982) [11] Aitchison, et al. arXiv preprint (2015) [12] Chettih et al Nature (2019)

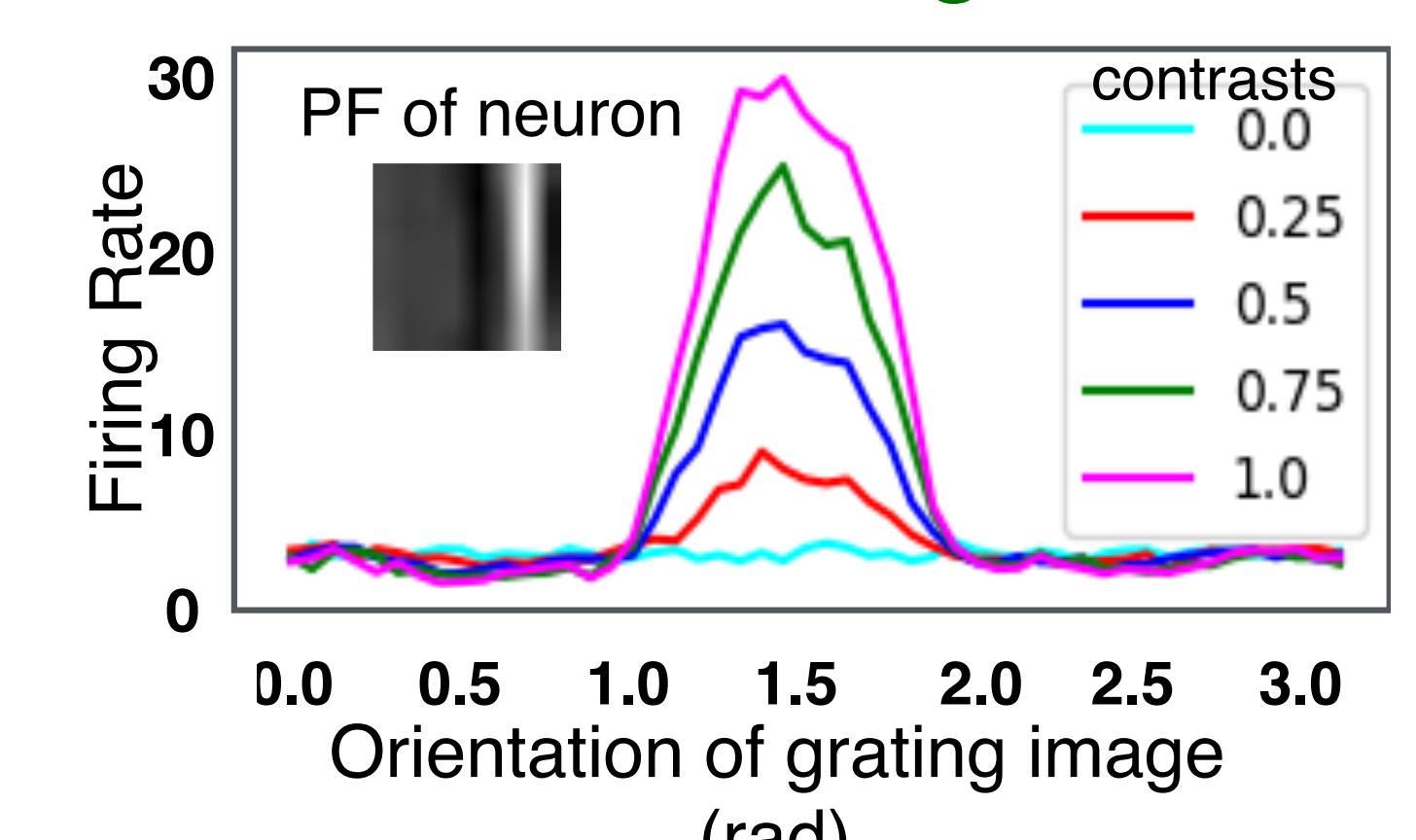
## Simulation details:

LIF  $\tau = 10\text{ms}$   
 $\text{V}_{\text{threshold}} = -55\text{mV}$   
 $\text{V}_{\text{rest}} = -70\text{mV}$   
Sampling time = 5ms

## Example spike raster



## Approximately contrast-invariant tuning curves



## Negative causal influence between neurons of similar RFs

