Inference by binary sampling as a model for V1 spiking responses

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Introduction

- Visual processing is often characterized as implementing **probabilistic inference**.
- We distinguish between **explicit** and **implicit** inference:
  - **explicit:** neurons compute the posterior over variables in an internal model of the world.
  - **implicit:** probabilistically "decoding" a distribution over other variables that aren't explicitly inferred
- One candidate algorithm to do explicit probabilistic inference, is '**neural sampling**' .
  - neural responses represent **samples from the posterior probability distribution over latent variables** in the brain's internal model of the world.
- A second debate concerns whether neural responses represent **samples of latent variables** (sampling with explicit representation) or **parameters of their distributions** (log probabilities for exponential families)**.**
- We propose that V1 spikes represent **binary samples** from a linear model of the image.

Marr's Level 1

Computational

Probabilistic Inference

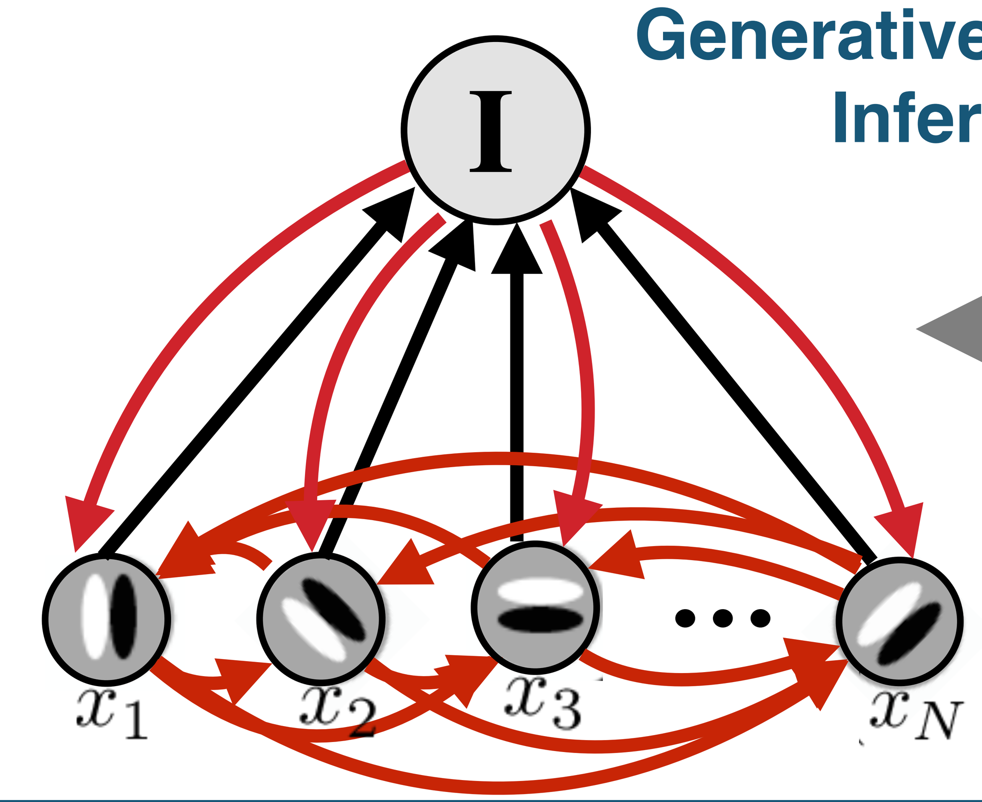
Linear Image Model equation:

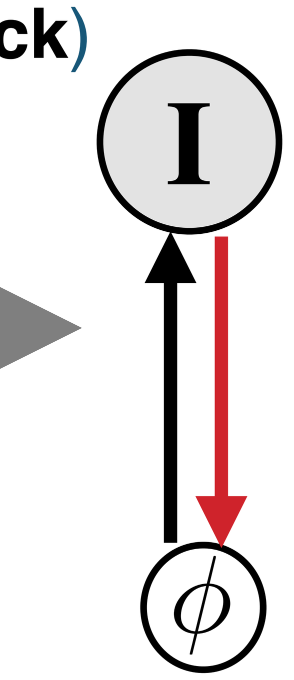
$$\mathbf{p}(\mathbf{I}|\tilde{\mathbf{x}}) = \mathcal{N}\left(\sum_{\mathbf{i}} \mathbf{PF_i x_i}, 1\right)$$

$\mathbf{PF_i} \rightarrow$ **Projective Field of** $\mathbf{i^{th}}$ **neuron**

1. Linear Gaussian Model
2. **Explicit Code**
3. Binary Sampling
4. Direct Probability

Generative Network (black)
Inference (red)





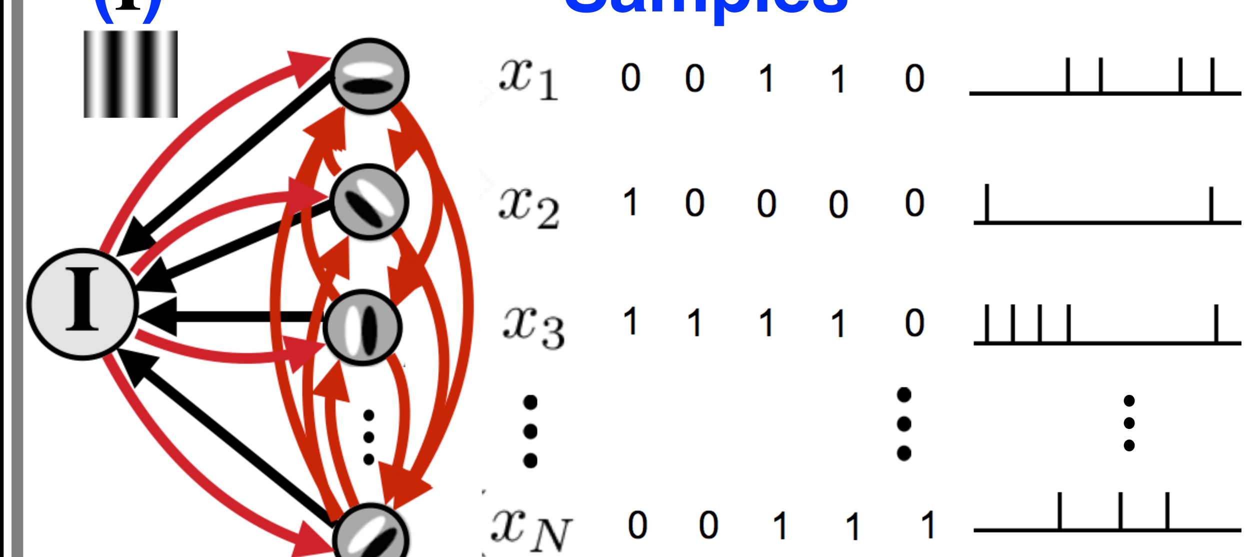
ϕ = orientation

1. Orientation
2. **Implicit Code**
3. Parametric Code
4. Log Probability

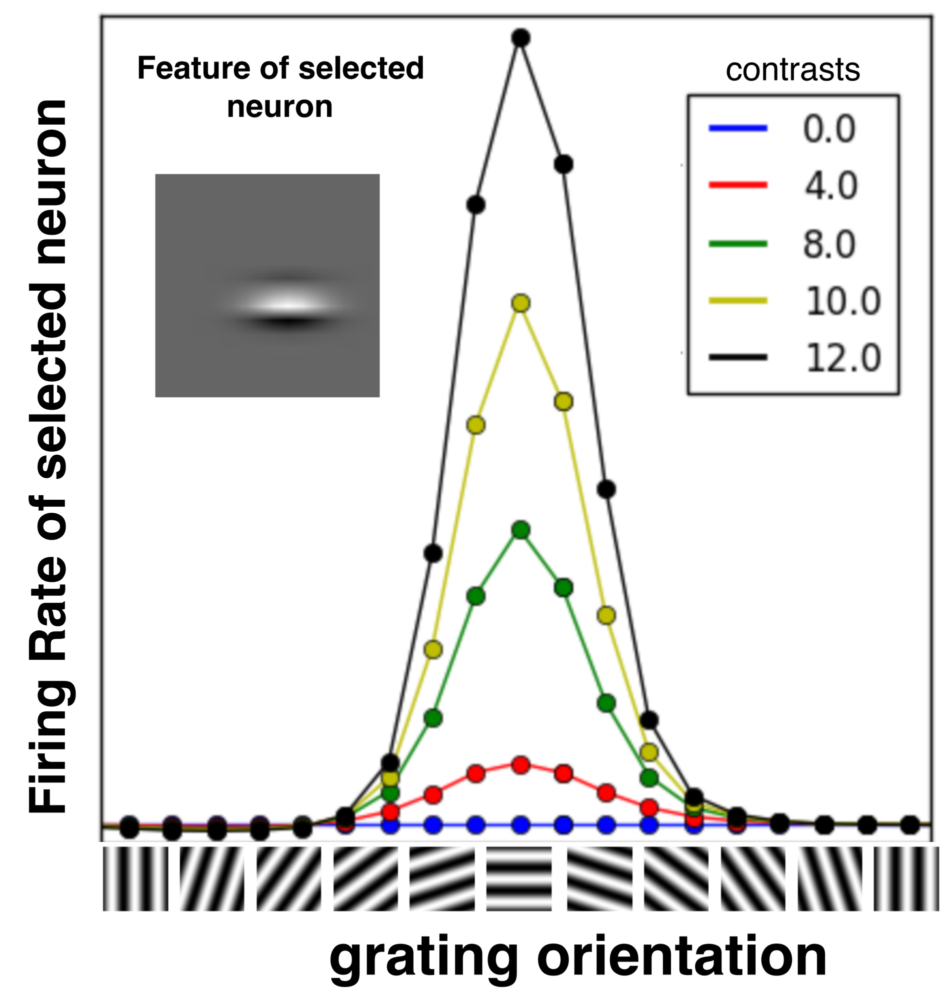
Marr's Level 2

Algorithm/Representation

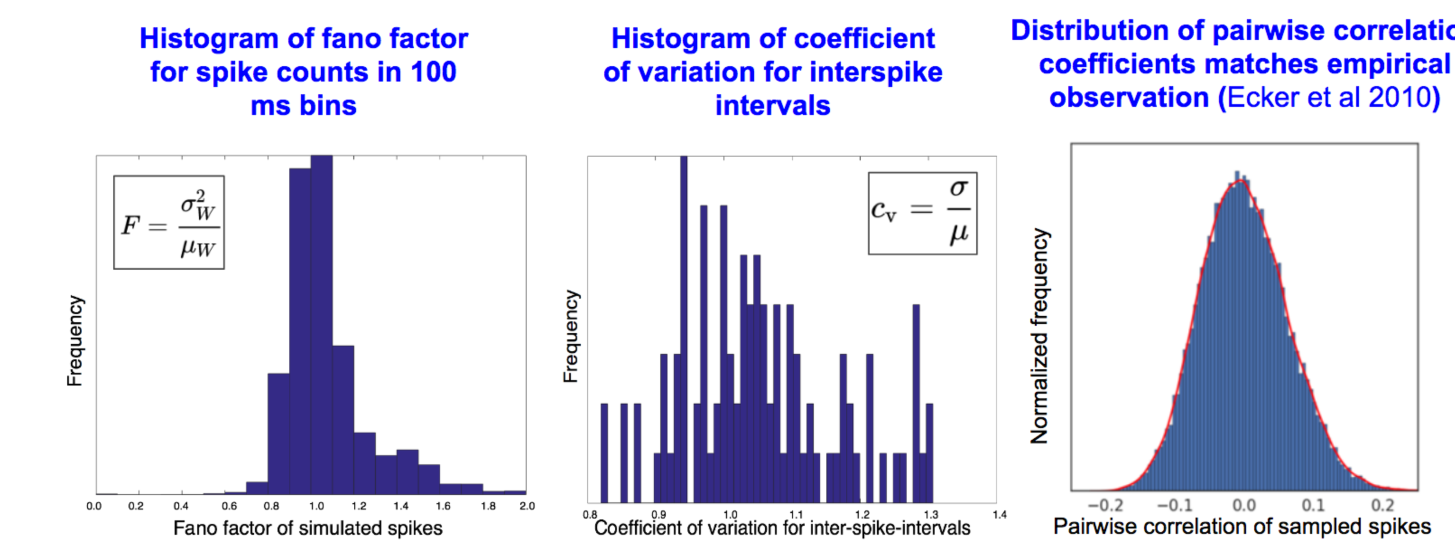
Binary Sampling



Orientation tuning curves scale with the contrast of grating



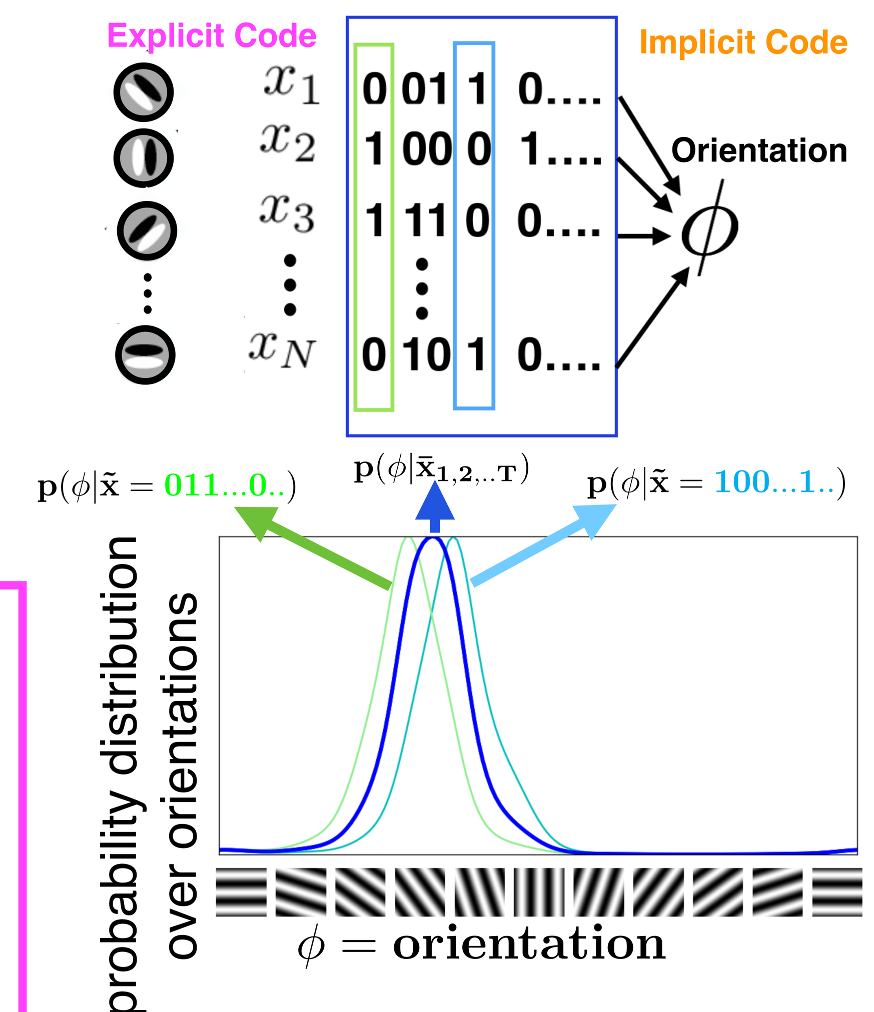
Simulated response statistics match empirical observations



Implicit decoder gives a distribution over orientations of an implicit model, given a set of binary sample vectors over features of an explicit model.

So sampling in binary hidden state of an explicit model is like sampling in parameter space of an implicit model.

Connecting Implicit and Explicit Code



Marr's Level 3

Implementation

Leaky Integration and Fire Network

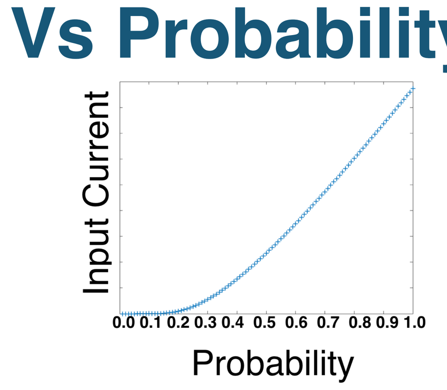
Connecting **Sampling** and **LIF**:

$$\mathbf{p(spike\ now|I, other\ recent\ updates)}$$

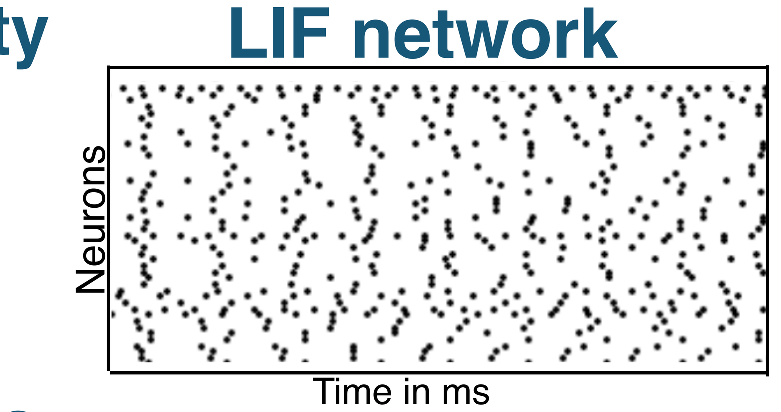
feedforward — recurrent input from other neurons

$\propto$ Firing Rate Input Current

Input Current Vs Probability

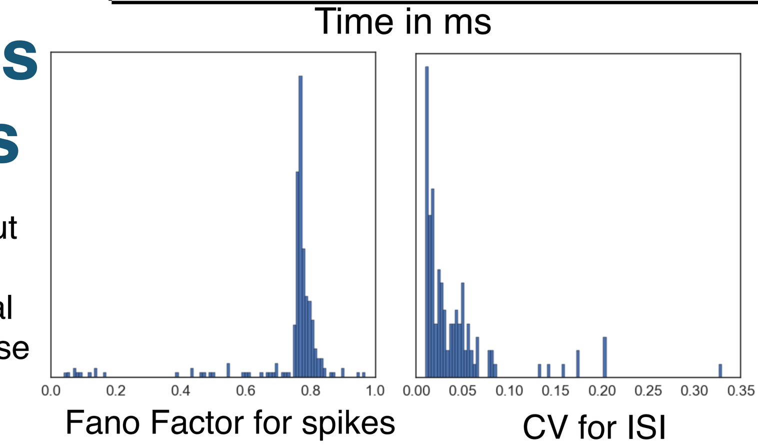


Simulated spikes in LIF network

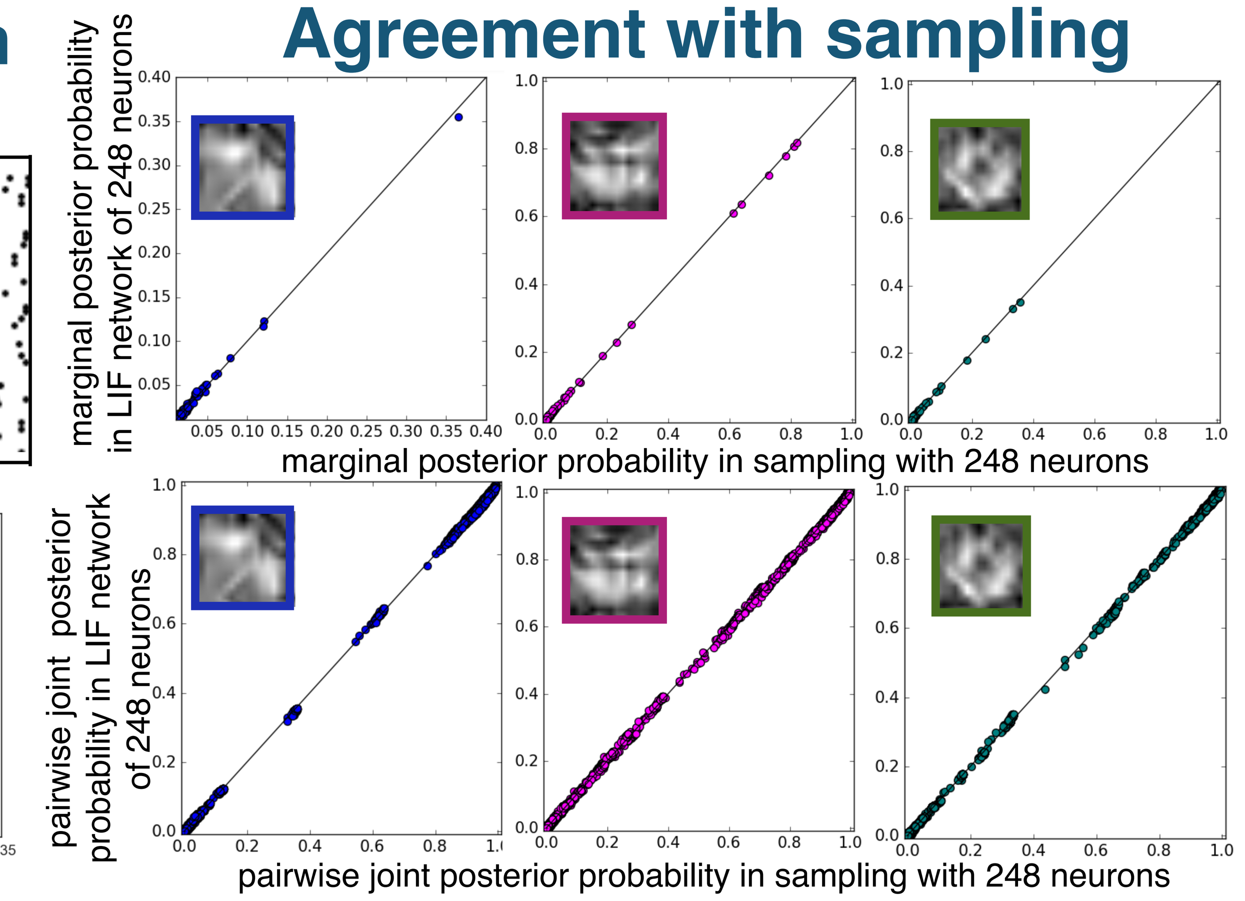


LIF Spikes Statistics

More regular but hierarchy and external/internal noise will increase irregularity



Agreement with sampling



Conclusions

- The spike rate in sampling code is proportional to the marginal posterior probability over the variable represented by the neuron
- Spike rates in our model can be interpreted as parameters of an exponential family (linear PPC)
- Firing rates are proportional to probability over Gabor features (explicit) but log probability over orientation (implicit)
- Neural responses in this model show contrast-invariant tuning.
- LIF network can implement sampling in binary linear-Gaussian image model