RESEARCH PAPER

Computational Modeling of Bayesian Inference Using Adaptive Spiking Neural Network in Biological Systems

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ABSTRACT

Background: Sampling-based theories suggest that the brain may perform probabilistic inference through neural activity. Previous models in the literature have shown that networks of leaky integrate-and-fire neurons can sample from discrete probability distributions. However, they often use simplified neuron models and represent each variable with a single neuron.

Methodology: In this work, we present a population-based implementation of discrete Bayesian inference using adaptive integrate-and-fire within the Neural Engineering Framework. Binary random variables are encoded by neural populations, and probabilistic inference is realized through recurrent population dynamics that approximate sampling from a target Boltzmann distribution. Spike frequency adaptation provides history-dependent behaviour, while keeping neuron dynamics deterministic.

Evaluation and Results: We evaluate the model on structured Bayesian inference task, including the Knill-Kersten problem, and on randomly generated Bayesian networks. The results show that adaptive integrate-and-fire neurons accurately reproduce target posterior distributions and support stable biologically plausible probabilistic inference.

Keywords: Adaptive leaky integrate-and-fire neurons, Bayesian inference, Neural engineering framework, Neural sampling, Spiking neural networks.

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1. Introduction

Perception requires the ability to infer hidden causes of sensory inputs under uncertainty. Sensory signals are often noisy, incomplete, and ambiguous, yet perceptual systems are able to generate stable and context-sensitive interpretations of the environment. Bayesian inference provides a formal description of these processes by defining probability distributions over latent variables conditioned on observed evidence. The neural implementation of such inference processes in networks of spiking neurons with biologically plausible dynamics remains an open challenge in computational neuroscience. Experimental studies indicate that neural activity reflects probabilistic representations rather than deterministic estimates. Variability in neural responses encodes uncertainty and contributes to behaviorally relevant computations[1,2]. Further, it has been shown that spontaneous and evoked cortical activity is consistent with sampling from internal probabilistic models of the environment[3,4,5]. These findings motivate computational frameworks in which probabilistic inference is represented by neural dynamics[6,7].

Earlier works proposed Bayesian inference in spiking neural systems using abstract or rate-based neuron models[8]. Sampling-based theories of neural computation provide one such framework where neural dynamics correspond to Markov chain Monte Carlo sampling from a target probability distribution. Buesing et al. showed that spiking neural networks can be interpreted as sampling from Boltzmann distributions over binary random variables (BRVs)[4]. Pecevski et al. extended this approach to general graphical models including Bayesian networks[9]. A fundamental step toward biological realism was achieved by Petrovici et al., who demonstrated that deterministic Leaky Integrate-and-Fire (LIF) neurons can exhibit effective stochastic sampling behavior when operating in a high conductance state[10]. Probst et al. provided the first theoretical framework showing that arbitrary probability distributions over BRVs can be implemented and sampled by network of spiking neurons, with single neuron dynamics forming the basic computational substrate[11]. Their framework includes explicit translation rules between probabilistic models and neural parameters and was validated on a structured

Bayesian inference task based on the Knill-Kersten illusion[12]. This task captures conditional dependencies between latent and observed variables and provides a mechanism for probabilistic inference in spiking neural networks. Despite these advances, the existing neural sampling model proposed by Probst et al. relies primarily on single LIF neurons. While this model captures basic spike generation and refractoriness, it omits intrinsic neuronal mechanisms that shape cortical dynamics. Spike-frequency adaptation is an important feature of cortical neurons and introduces history dependence in firing activity[10, 13, 14]. Recent theoretical studies indicate that intrinsic neuronal dynamics including adaptation affect variability structure and state space exploration in recurrent networks used for probabilistic inference[15, 16, 17, 18]. The role of adaptation within established neural sampling frameworks remains insufficiently characterized[7, 19].

In this work, we extend the neural sampling framework of Probst et al. by replacing LIF neurons with Adaptive Integrate-and-fire (ALIF) neurons[20]. The model is implemented within Neural Engineering Framework (NEF), enabling neural sampling with adaptive neuronal dynamics[21]. BRVs are represented by ensembles of ALIF neurons rather than individual LIF neurons, while the underlying inference task and target probability distributions remain unchanged. For clarity, we first illustrate the sampling framework at the level of individual ALIF neurons, which are representative of the dynamics exhibited within each population. We investigate probabilistic inference in discrete graphical models in networks with intrinsic neuronal adaptation. The Bayesian model of Knill–Kersten illusion is used as the inference task. All the models are implemented in Nengo, which provides a structured and reproducible environment for constructing and simulating spiking neural networks[22, 23]. This implementation enables a direct comparison between adaptive and non-adaptive neuron models under identical network conditions, isolating the functional influence of intrinsic adaption on neural sampling dynamics.

2. Materials and Methods

2.1. Bayesian Inference Task

The task is based on a non-trivial probabilistic inference problem inspired by Knill-Kersten visual illusion. Objects with nearly identical shading patterns can be perceived differently depending on their underlying shape. This demonstrates that visual perception requires inferring hidden causes of sensory input rather than relying on sensory signals alone. The mathematical formulation of the task is defined by using four BRVs, shown in equation (1).

$$Z = (Z_1, Z_2, Z_3, Z_4) \in \{0,1\} \tag{1}$$

The variables Z_1 and Z_2 represent hidden causes of the visual scene. The variable Z_1 denotes relative surface reflectance, where $Z_1 = 1$ indicates a change in reflectance across the surface and $Z_1 = 0$ indicates uniform reflectance as shown in Figure 1.

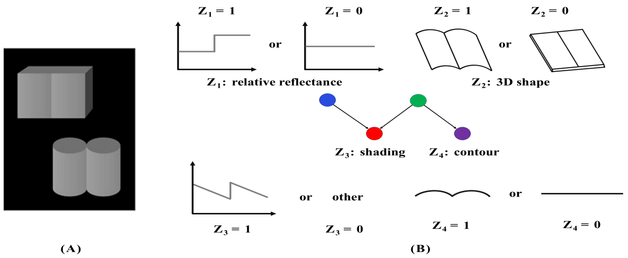

Figure 1. Illustration of the Bayesian inference task based on the Knill-Kersten illusion adapted from Probst et al.[11]. (A) An ambiguous visual stimulus composed of simple geometric shapes, where shading and contours can support multiple interpretations of the scene. (B) Corresponding graphical model with binary random variables, each can take values 0 or 1, and inference consists of estimating the latent variables given the observed shading and contour cues

The variable Z_2 denotes three-dimensional shape, where $Z_2 = 1$ corresponds to a curved shape, and $Z_2 = 0$ corresponds to a flat shape. These variables are latent and cannot be directly observed. The variables Z_3 and Z_4 represents observed sensory evidence. The variable Z_3 encodes shading information extracted from the image, while Z_4 encodes contour information that provides cues about object shape. During inference, Z_3 and Z_4 are treated as observed variables whose values are fixed.

The statistical dependencies between variables are defined by a Bayesian network. Reflectance Z_1 and shape Z_2 jointly influence shading Z_3, while shape Z_2 alone influence contour Z_4. This structure captures the ambiguity of the task, i.e. the same shading pattern can be explained either by a curved object with uniform reflectance or by a flat object with a reflectance change. As a result, shading alone does not uniquely determine the hidden causes. The joint probability distribution over all variables is defined by equation (2).

$$p(Z_1, Z_2, Z_3, Z_4) = p(Z_1)p(Z_2)p(Z_3|Z_1, Z_2)p(Z_4|Z_2) \tag{2}$$

Here, $p(Z_1)$ and $p(Z_2)$ represent prior beliefs over reflectance and shape, while the conditional distributions describe how shading and contour are generated from these hidden causes. Inference in the task consists of computing the posterior distribution over the hidden variables given the observed evidence, shown in equation (3).

$$p(Z_1, Z_2|Z_3, Z_4) = \frac{p(Z_1, Z_2, Z_3, Z_4)}{\sum_{Z_1,Z_2} p(Z_1, Z_2, Z_3, Z_4)} \quad (3)$$

Because multiple configurations of (Z_1, Z_2) can explain the same observed shading and contour, and the posterior distribution is generally multimodal. Information from contour Z_4 biases the interpretation of shading Z_3 by increasing the probability of shape-based explanations and suppressing alternatives reflectance- based explanations, or vice-versa. This interaction gives rise to explaining- away effects characteristic of this perceptual illusion.

2.2. Neural Sampling Framework Based on Boltzmann Distribution

Probabilistic inference for the above discussed task is commonly implemented using a neural sampling framework in which each binary random variable is represented by a single LIF neuron. Network dynamics are defined such that the collective spiking activity generates samples from a well-defined probability distribution over discrete state. Each variable $Z_i \in \{0,1\}$ is associated with one LIF neuron. The state $Z_i = 1$ is defined by the neuron in its refractory period following a spike, while $Z_i = 0$ corresponds to the neuron being outside the refractory period. This binary interpretation maps neuronal spike timing of the state of the corresponding random variable. The target distribution over the joint state vector Z is chosen to be a Boltzmann distribution, as given in equation (4).

$$p(Z) = \frac{1}{\mathcal{Z}} exp\left(\frac{1}{2} Z^T W Z + b^T Z\right) \quad (4)$$

Where, W is a symmetric weight matrix with zero diagonal, b is a vector of biases, and $\mathcal{Z}$ is the normalization constant. This distribution encodes the statistical dependencies specified by the Bayesian network. Each LIF neuron receives synaptic input from other neurons according to the weights W_{ij}, as well as constant background input that places the neuron in a high-conductance state. In this regime, the effective membrane time constant of neuron is short and spike generation becomes irregular and sensitive to synaptic input. Under these conditions, the probability that neuron i emits a spike approximates a logistic activation function, given the states of all other neurons. As a result, the conditional probability of the corresponding variable satisfies the following equation (5).

$$p(Z_i) = (1|Z_i)\sigma\left(1 + exp\left(-\sum_j W_{ij} Z_j - b_i\right)\right)^{-1} \quad (5)$$

Where $\sigma(\cdot)$ denotes the logistic function. This conditional distribution matches that of the Boltzmann model in equation (4). Consequently, asynchronous updates of neuronal states implement a Markov chain whose stationary distribution is the target distribution $p(Z)$.

2.3. The Proposed NEF-based Neural Sampling Framework with ALIF Model

The Bayesian inference task and neural sampling framework are implemented using ensembles of ALIF neurons within the Neural Engineering Framework (NEF). The inference task, target distribution, and neural sampling framework remain unchanged in the proposed NEF-based model. The network architecture shown in Figure 2, reflects the underlying Bayesian inference model and enables inference through neural population dynamics.

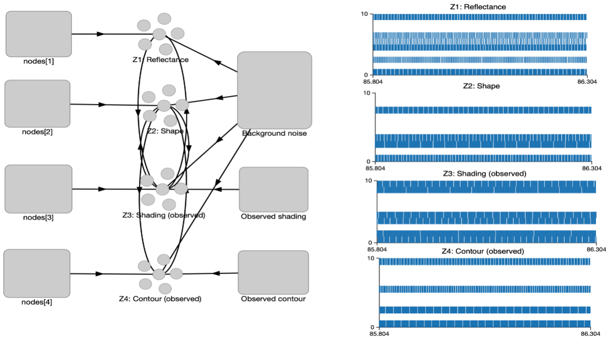

Figure 2. Neural implementation of the Knill–Kersten Bayesian inference model using spiking neuron populations. Left panel: Network architecture realizing the four BRVs of the inference task using ALIF neurons (schematically shown as five circles). The latent variables Z_1 (Reflectance) and Z_2 (Shape) interact recurrently with the observed variables Z_3 (Shading) and Z_4(Contour). Directed connections represents couplings implementing pairwise interactions specified by Boltzmann distribution. Constant external inputs clamp the observed-variable populations, representing fixed sensory evidence. Bias input blocks labelled nodes [1–4] provide constant drives corresponding to prior and likelihood terms of the probabilistic model. A shared background noise input delivers irregular activity to all populations, supporting stochastic spiking dynamics. Right panel: Raster plots of representative neurons from each population during convergence. Each row corresponds to individual neurons, and each vertical tick denotes a spike. The observed populations (Z_3, Z_4) exhibit sustained activity due to clamping, while, the latent populations (Z_1, Z_2) display stochastic spiking dynamics driven by recurrent interactions and background noise

The network represents a joint probability distribution over four BRVs and produce samples from the corresponding posterior distribution through recurrent population dynamics. The present implementation follows the neural sampling framework introduced for single LIF neuron representations and extends it by replacing with population of ALIF neurons. The joint probability distribution over BRVs is written in Boltzmann distribution as shown in equation (6).

$$p(Z) \propto exp\left(\frac{1}{2}Z^{T}WZ + b^{T}Z\right) \tag{6}$$

Within the NEF, each neural population represents the state of the corresponding BRV through its collective spiking activity. The population representation is defined by the mean activation, as expressed in equation (7).

$$x_i(t) \approx E[Z_i] = p(Z_i = 1) \tag{7}$$

The decoded population activity is given by equation (8).

$$\hat{x}_i(t) = \sum_{k=1}^{N_i} d_k^{(i)}\, a_k^{(i)}(t) \tag{8}$$

Where $a_k^{(i)}(t)$ denotes the spike train of neuron k in population i and $d_k^{(i)}$ are linear decoders obtained through NEF optimization. The neuronal dynamics that capture these properties are modeled using ALIF neurons. Each neuron obeys the following membrane voltage $V(t)$ and adaptation current $A(t)$ dynamics, as defined in equation (9-10).

$$\tau_m \frac{dV(t)}{dt} = -V(t) + I(t) - A(t) \tag{9}$$

$$\tau_A \frac{dA(t)}{dt} = -A(t) \tag{10}$$

Where $A(t)$ represents the spike frequency adaptation based on recent spiking history and τ_A is the adaptation time constant. Whenever $V(t)$ crosses the threshold θ, neuron emits a spike, where β controls the spike-triggered increase in adaptation, shown in equation (11).

$$If\ V(t) \geq \theta, \quad then \left\{ \begin{array}{c} V(t) \rightarrow V_{reset} \\ A(t) \rightarrow A(t) + \beta \end{array} \right. \tag{11}$$

This adaptation introduces slow negative feedback, yielding history-dependent firing dynamics. in NEF representation principle, neuronal activity is generated through a non-linear response function $G[\cdot]$, as given in equation (12).

$$a_k(t) = G[I_k(t)] = G\left[\alpha_i \sum_j W_{ij}\, \hat{x}_i(t) + b_i + I_i^{obs}(t)\right] \tag{12}$$

The total input current to population i is therefore given by equation (13).

$$I_i(t) = \sum_j W_{ij}\, \hat{x}_i(t) + b_i + I_i^{obs}(t) \tag{13}$$

Where, $I_i^{obs}(t)$ is a constant external input current applied only to the observed variables. The synaptic connections between populations j and i are constructed as given in equation (14).

$$W_{syn}^{(ij)} = \alpha\, e^{(i)} W_{ij} d^{(j)} \tag{14}$$

Where $e^{(i)}$ and $d^{(j)}$ denote the encoders and decoders respectively, and α is a global gain factor. Observed variables are implemented by clamping the corresponding population using constant external input, while latent variables populations evolve freely as shown in equation (15).

$$I_i^{obs}(t) = const, \quad i \in \{3,4\} \tag{15}$$

The resulting recurrent population dynamics defines a Markov process over network states as shown in equation (16), whose stationary distribution approximates the target posterior distribution $p(Z_1, Z_2 | Z_3, Z_4)$.

$$\lim_{T\to\infty} \frac{1}{T} \int_0^T \hat{x}_i(t) \approx p(Z_i = 1 | Z_3, Z_4) \tag{16}$$

Overall, this NEF-based implementation realizes the existing neural sampling Bayesian framework using ALIF neurons. This formulation provides the foundation for the results presented in the following section.

3. Results and Discussion

The results focus on whether the spiking dynamics reproduce the target probability distributions and whether inference behaviour emerges from deterministic population dynamics. while the proposed implementation represents BRVs at the population level, the sampling mechanism is illustrated using single ALIF neuron activity for clarity and interpretability. These single-neuron traces represent the dynamics exhibited by neurons within a population, since all neurons encode the same variable, receive similar inputs, and follow comparable spiking dynamics. Population-level sampling behaviour therefore emerges from the collective activity of ALIF neurons.

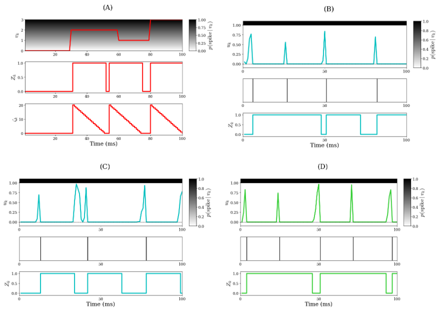

Figure 3. Sampling ALIF neuron dynamics under different temporal activation states

Figure 3 summarizes the sampling dynamics of a single neuron under different temporal states of its activation and spiking probability. Figure 3(A) shows the temporal progress of the variables related to a single sampling neuron. The x-axis represents time in milliseconds. The top panel depicts the instantaneous spiking probability $p(\text{spikes}|v_k)$ as a function of effective membrane potential $V(t)$, presented both as a grayscale background and a red trace representing the effects over time. The middle panel shows the binary state variable $Z_k \in \{0,1\}$ where changes to $Z_k = 1$ correspond to spike events. The bottom panel shows the refractory variable ς_k , which is reset to a fixed value after each spike and then declines linearly to zero. This illustrates that changes in the neuron's internal state modulate spiking probability, while spikes induce discrete state transitions and refractoriness structures the sampling dynamics. Figure 3(B) illustrates the stochastic spiking response of a sampling neuron driven by a time varying input. Despite the deterministic neuronal dynamics, probabilistic spiking arises due to background-driven fluctuations. It gives rise to discrete state transitions over time and linking continuous activation dynamics to binary sampling behaviour. Figure 3(C) depicts the time evolution of probabilistic spiking and the resulting state dynamics under a variable input. Fluctuations in the spiking probability led to irregular spike timing and corresponding state transitions, while preserving the binary interpretation of the neural activity. Figure 3(D) shows the sampling dynamics of a neuron under sharply peaked activation events. Brief but strong activation pulses reliably induce isolated spikes and corresponding state transitions, consistent with the sampling framework. In the population-based representation, each BRV is encoded by an ensemble of neurons exhibiting similar dynamics, such that the population activity reflects the same state transitions.

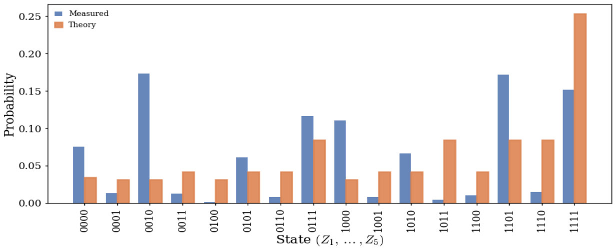

Figure 4. Measured state probabilities obtained from neural population activity compared with the target distribution over all binary random variables

Figure 4 compares the sampled distribution obtained from the neural network with corresponding target distribution. The x-axis represents all possible binary states of the system, shown as discrete configurations of the variables. The y-axis represents the probability assigned to each state. Blue bars indicate the measured probabilities estimated from neural activity over time, while orange bars show the theoretical probabilities computed from the target distribution. The close agreement between sampled and target probabilities demonstrates that ALIF neuron populations accurately reproduce the intended probabilistic structure. These results confirm that discrete Bayesian inference can be implemented using population dynamics of adaptive spiking neurons without relying on intrinsically stochastic neural mechanisms. Replacing single-neuron representations with ALIF neuron populations preserves correct posterior sampling, while introducing biologically relevant history-dependent dynamics through spike-frequency adaptation.

Figure 5 evaluates the generalization of the proposed ALIF-based neural sampling framework to randomly generated Bayesian networks, following the existing methodology proposed by Probst.et.al. Figure 5(A) analyzes the distribution of conditional probabilities sampled from symmetric Dirichlet distributions for different values of the concentration parameter η. Figure 5(B) shows median normalized Kullback-Leibler (KL) divergence between sampled and target distribution as a function of η, demonstrating stable sampling performance of the ALIF network across increasing inference difficulty.

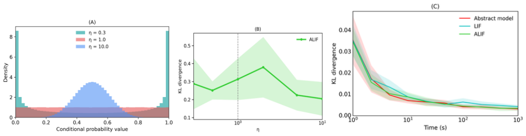

Figure 5. Sampling performance of ALIF-based neural populations on random Bayesian networks

Figure 5(C) illustrates temporal convergence of the normalized KL divergence, comparing the abstract model, LIF neurons, and the proposed ALIF-based implementation. The ALIF network converges reliably toward the target distribution, exhibiting convergence behavior comparable to the original LIF-based and abstract sampling models. This demonstrate that incorporating intrinsic neuronal adaptation preserves the correctness of neural sampling while providing a more biologically plausible population-based implementation.

4. Conclusion and Future Work

This study establishes a link between sampling-based probabilistic inference and population-level dynamics in adaptive spiking neural networks. By implementing discrete Bayesian inference using ALIF neuron ensembles within the NEF, we show that structured probabilistic computations can be embedded in deterministic, biologically plausible neural architectures. The proposed formulation demonstrates that intrinsic neuronal properties, such as spike-frequency adaptation, can be integrated into neural sampling models without compromising inference accuracy and stability. Although, this work provides a bridge between cognitive and neural computations, it is limited to simplified neuronal dynamic, restricted population sizes, and a specific inference task. Beyond the specific inference tasks studied here, the framework provides a flexible and scalable foundation for future models of probabilistic computations in the brain. The population-level formulation is naturally compatible with extensions to learning mechanisms, representations, and more complex cognitive tasks. As such, this work contributes an important step toward unifying probabilistic theories of cognition with mechanistic models of spiking neural networks. Overall, the proposed framework motivates and provides a pathway for studying probabilistic inference in biologically plausible neural systems.

Simulation Details

All experiments are performed using simulation tool Nengo, an open-source python library for building and simulating large-scale brain models, details of which can be assess through https://www.nengo.ai/getting-started/.

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