Neural Models of Task Adaptation: A Tutorial on Spiking Networks for Executive Control

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Abstract—**Understanding cognitive flexibility and task-switching mechanisms in neural systems requires biologically plausible computational models. This tutorial presents a step-by-step approach to constructing a spiking neural network (SNN) that simulates task-switching dynamics within the cognitive control network. The model incorporates biologically realistic features, including lateral inhibition, adaptive synaptic weights through unsupervised Spike Timing-Dependent Plasticity (STDP), and precise neuronal parameterization within physiologically relevant ranges. The SNN is implemented using Leaky Integrate-and-Fire (LIF) neurons, which represent excitatory (glutamatergic) and inhibitory (GABAergic) populations. We utilize two real-world datasets as tasks, demonstrating how the network learns and dynamically switches between them. Experimental design follows cognitive psychology paradigms to analyze neural adaptation, synaptic weight modifications, and emergent behaviors such as Long-Term Potentiation (LTP), Long-Term Depression (LTD), and Task-Set Reconfiguration (TSR). Through a series of structured experiments, this tutorial illustrates how variations in task-switching intervals affect performance and multitasking efficiency. The results align with empirically observed neuronal responses, offering insights into the computational underpinnings of executive function. By following this tutorial, researchers can develop and extend biologically inspired SNN models for studying cognitive processes and neural adaptation.**

Index Terms—**Spiking Neural Network, neuroscience, cognitive modeling, STDP, unsupervised learning, cognitive science, pattern recognition, cognitive computing, Computational neuroscience**

I. INTRODUCTION

The ability to adapt and switch between tasks is a fundamental aspect of cognitive flexibility, shaping decision-making and behavioral efficiency in dynamic environments. Task-switching has been widely studied across disciplines such as psychology, cognitive neuroscience, and artificial intelligence [1], [2]. While humans often shift between tasks seamlessly, performance variations arise depending on prior experience, task familiarity, and cognitive load. Understanding these processes requires computational models that can capture the underlying neural mechanisms driving adaptive control and decision-making. Empirical studies have identified increased neural activity in the cognitive control network, particularly in the prefrontal cortex (PFC), when engaging in task-switching [3]–[5]. These findings have influenced cognitive modeling

frameworks, including Brain-Inspired Cognitive Architectures (BICA) [6], [7], which attempt to replicate executive function processes in artificial systems. However, many existing models focus on task-switching in highly controlled experimental conditions [3], relying on cue-based paradigms or human subject trials [8], limiting their applicability to real-world multitasking scenarios. This tutorial introduces a computational approach for simulating task-switching behavior using biologically plausible spiking neural networks (SNNs), a third-generation neural network model inspired by the brain's action potential dynamics [9]. Unlike traditional artificial neural networks, SNNs encode information through temporally precise spikes, mimicking the natural firing patterns of neurons. Our implementation employs the Leaky Integrate-and-Fire (LIF) neuron model, which efficiently captures neuronal excitability and inhibition within cortical circuits. Synaptic plasticity is governed by Spike Timing-Dependent Plasticity (STDP), an unsupervised learning rule that adjusts synaptic weights based on the relative timing of pre- and post-synaptic spikes [10].

II. RELATED WORK

Computational models inspired by cognitive neuroscience have advanced our ability to simulate task-switching mechanisms in biologically plausible frameworks. Foundational cognitive architectures such as SOAR [11], [12] and ACT-R [13] have contributed to our understanding of decision-making processes, influencing early models of cognitive flexibility. Empirical studies further established the prefrontal cortex (PFC) as a key region in task-switching, with experiments such as the Wisconsin Card Sorting Test (WCST) demonstrating its role in adaptive behavior [14]–[16]. Spiking Neural Networks (SNNs) have emerged as a biologically realistic approach to modeling neural dynamics, particularly due to their ability to replicate synaptic plasticity mechanisms such as Spike Timing-Dependent Plasticity (STDP) [10], [17]. Prior studies have successfully applied SNNs to pattern recognition and classification tasks [18] and have modeled sensory processing systems like the mammalian olfactory system [19]. These findings establish a computational foundation for implementing task-switching models with biologically grounded learning dynamics. Our work extends these studies by developing a two-

layered SNN model that processes real-world stimuli, rather than relying on traditional cue-based switching paradigms. Inspired by task-switching cost experiments [8], we investigate how switching intervals impact neural adaptation and performance, providing insights into how networks reconfigure in response to new tasks. By leveraging SNNs with STDP-based learning, we demonstrate how biologically plausible mechanisms can encode dynamic task transitions, supporting the study of cognitive flexibility in more realistic, data-driven contexts.

III. NEURON MODEL AND ARCHITECTURE

The neural architecture implemented in this study is designed to replicate biologically plausible task-switching dynamics. The network consists of two primary layers: an excitatory layer responsible for processing incoming stimuli and an inhibitory layer that regulates neuronal activity. This layered approach mirrors cortical interactions where excitatory neurons drive information processing while inhibitory neurons modulate signal flow to prevent excessive activation.

The model is built using the BRIAN2 simulator [20] in Python. To achieve realistic neuronal behavior, the dynamics of each neuron are governed by the leaky integrate-and-fire (LIF) model, a well-established computational framework for simulating spike-based neural activity [21]. This model provides an effective approximation of how neurons integrate synaptic inputs and generate action potentials.

A. Leaky Integrate-and-Fire Model

The LIF neuron is mathematically modeled based on the properties of an electrical circuit comprising a capacitor (C) in parallel with a resistor (R). The neuron receives input in the form of a synaptic current $I(t)$, which is distributed across the resistive and capacitive components:

$$I(t) = I_R + I_C \tag{1}$$

where I_R represents the resistive current and I_C the capacitive current. The capacitive current is given by:

$$I_C = C\frac{dV}{dt} \tag{2}$$

Substituting this into Equation (1) and applying Ohm's law ($I_R = \frac{V - V_{rest}}{R}$), we derive the membrane voltage equation:

$$\tau_m \frac{dV}{dt} = -(V - V_{rest}) + RI(t) \tag{3}$$

where $\tau_m = RC$ is the membrane time constant, V is the membrane potential, and V_{rest} is the resting potential. This equation determines how a neuron accumulates charge over time in response to synaptic inputs.

TABLE I: Spiking Neuron Model Parameters

Parameter	Value
Threshold voltage (V_{th})	-60 mV
Resting potential (V_{rest})	-70 mV
Refractory period	10 ms
Membrane time constant (τ_m)	750 ms

B. Spike Generation and Refractory Mechanism

Neurons emit spikes when their membrane potential exceeds a predefined threshold V_{th}. This event triggers an action potential, after which the neuron resets to its resting potential and enters a refractory period. This behavior can be formalized as:

$$V_i(t) = \begin{cases} V_{reset}, & \text{if } V_i(t) > V_{th} \\ V_i(t), & \text{otherwise} \end{cases} \tag{4}$$

where V_{reset} represents the potential immediately after a spike, ensuring the neuron is ready to integrate new inputs.

C. Encoding Input as Spike Trains

Unlike conventional artificial neural networks, which process continuous-valued inputs, spiking neural networks rely on discrete events known as spikes. In this implementation, input values are transformed into spike trains using rate-based encoding. The likelihood of a spike occurring follows a Poisson distribution:

$$P(spike|\lambda) = \lambda e^{-\lambda} \tag{5}$$

where λ is the mean firing rate proportional to the input magnitude. This stochastic encoding method captures biological variability, making the network robust to noise and irregular spike timing.

IV. SPIKING NEURAL NETWORK FRAMEWORK

The spiking neural network (SNN) developed in this work is designed to model task-switching behavior by mimicking cortical processing dynamics. The architecture consists of two primary components: an excitatory processing layer and an inhibitory regulation layer. These layers interact to facilitate information propagation while maintaining network stability through biological constraints.

In this computational framework, synaptic plasticity is modeled using the Spike-Timing Dependent Plasticity (STDP) learning rule, which dynamically adjusts synaptic weights based on neuronal firing patterns. The following sections provide a detailed breakdown of the excitatory and inhibitory layers, their connectivity, and the STDP learning mechanism.

A. Excitatory Neuron Layer

The excitatory layer is responsible for encoding and processing incoming information. Each neuron in this layer receives stimuli encoded as Poisson-distributed spike trains, ensuring that the frequency of spikes is proportional to input

TABLE II: STDP Model Parameters

Parameter	Value
τ_{pre}	20 ms
τ_{post}	25 ms
A_{pre}	0.001 mV
A_{post}	-0.0105 mV
w_{max}	0.005 mV

intensity. The number of neurons in this layer corresponds to the dimensionality of the input dataset, allowing for feature-wise representation of information.

Information is transmitted between neurons through synaptic connections [22]. Excitatory postsynaptic potentials (EP-SPs) are generated when spikes arrive at a neuron, contributing to action potential formation. This behavior parallels the role of glutamate, a major excitatory neurotransmitter [23], [24], in biological neural networks.

B. Spike-Timing Dependent Plasticity (STDP)

Synaptic plasticity plays a crucial role in learning and memory formation in biological systems. In this network, STDP is employed as an unsupervised learning mechanism, regulating synaptic strength based on the temporal relationship between pre- and post-synaptic spikes [25]. The STDP mechanism follows Hebbian principles, adjusting weights when correlated spiking activity is observed [26].

Each synapse is assigned an initial weight within the range $0 \leq w \leq w_{max}$. The weight function governing synaptic modification is defined as:

$$W(\Delta t) = \begin{cases} A_{pre}e^{-\Delta t/\tau_{pre}}, & \text{if } \Delta t > 0 \\ A_{post}e^{\Delta t/\tau_{post}}, & \text{if } \Delta t < 0 \end{cases} \qquad (6)$$

where $\Delta t = \tau_{post} - \tau_{pre}$ represents the difference in spike timing between pre- and post-synaptic neurons. The synaptic traces are updated as follows:

$$\begin{aligned} a_{pre} &\to a_{pre} + A_{pre} \\ w &\to w + a_{post} \end{aligned} \qquad (7)$$

For post-synaptic activity:

$$\begin{aligned} a_{post} &\to a_{post} + A_{post} \\ w &\to w + a_{pre} \end{aligned} \qquad (8)$$

These equations illustrate that if a pre-synaptic spike precedes a post-synaptic spike ($\tau_{pre} < \tau_{post}$), the synapse is reinforced. Conversely, if the post-synaptic spike occurs first ($\tau_{post} < \tau_{pre}$), the synapse weakens. Random, uncorrelated spikes lead to weight adjustments approaching zero, preventing spurious associations.

C. Inhibitory Neuron Layer

The inhibitory layer consists of neurons that regulate excitatory activity, ensuring controlled and selective activation. Each inhibitory neuron is associated with an excitatory counterpart, forming a one-to-one connection. Whenever an excitatory neuron spikes, its paired inhibitory neuron responds by suppressing activity in adjacent neurons. This mechanism is crucial for stabilizing network dynamics and preventing runaway excitation.

In addition to direct inhibition, inhibitory neurons provide lateral inhibition, a competitive mechanism that suppresses the activity of neighboring excitatory neurons. This is achieved by establishing connections to all excitatory neurons except the one responsible for triggering the inhibitory response. Such inhibitory feedback facilitates Winner-Take-All (WTA) competition, where only the most strongly activated neurons remain active [27].

The inhibitory neurons release gamma-aminobutyric acid (GABA), a neurotransmitter that reduces membrane potential, making neurons less likely to reach the spiking threshold. This regulation prevents overlapping pattern associations and ensures distinct task representations.

D. Network Dynamics and Learning Mechanism

By combining excitatory processing with inhibitory regulation, the network achieves efficient task-switching capabilities. Learning occurs through iterative exposure to input patterns, where STDP adjusts synaptic weights to strengthen relevant connections. Inhibition further refines the selection process, enhancing the network's ability to adapt dynamically.

Overall, this architecture provides a **biologically plausible framework** for studying how neural systems encode and adapt to changing tasks. The integration of spike-based encoding, plastic synaptic modifications, and competitive inhibition ensures that the network exhibits key properties observed in cognitive neuroscience.

V. EXPERIMENTAL FRAMEWORK

The objective of this experiment is to investigate how a spiking neural network (SNN) adapts to dynamic task-switching scenarios. The network is exposed to sequentially presented input patterns representing distinct cognitive tasks, requiring adaptation of synaptic weights based on the switching context. The experiment is structured to analyze neural plasticity, learning retention, and the impact of temporal task-switching intervals.

A. Task Switching Paradigm

The experiment consists of two alternating cognitive tasks, denoted as $\mathcal{T}_1$ and $\mathcal{T}_2$, each associated with distinct input distributions. These tasks are encoded as spatiotemporal spike trains, with patterns drawn from a generative process that ensures variability across trials. The transition between tasks is triggered probabilistically, with a switching probability P_s that defines the likelihood of shifting from $\mathcal{T}_1$ to $\mathcal{T}_2$ or vice versa.

Let the sequence of presented tasks be represented as a stochastic process:

$$S(t) = \begin{cases} \mathcal{T}_1, & \text{if } U(t) \leq P_s \\ \mathcal{T}_2, & \text{otherwise} \end{cases} \qquad (9)$$

where $U(t)$ is a uniformly distributed random variable in the range $[0, 1]$. This ensures that task switching occurs at unpredictable intervals, preventing the network from relying on periodic transitions.

B. Neural Encoding and Synaptic Adaptation

Each input stimulus is encoded as a spike train $\mathbf{x}(t)$, where the firing rate of each neuron is modulated by the stimulus intensity. The network consists of an excitatory layer responsible for processing incoming information and an inhibitory layer that regulates activity to prevent overfitting to any specific task.

Synaptic weights w_{ij} evolve according to a spike-timing-dependent plasticity (STDP) rule, where weight adjustments depend on the relative timing of pre- and post-synaptic spikes:

$$\Delta w_{ij} = \begin{cases} A_+ e^{-\Delta t/\tau_+}, & \Delta t > 0 \\ A_- e^{\Delta t/\tau_-}, & \Delta t < 0 \end{cases} \qquad (10)$$

where $\Delta t = t_{\text{post}} - t_{\text{pre}}$ is the spike timing difference, and (A_+, τ_+) and (A_-, τ_-) define the potentiation and depression parameters, respectively.

C. Task Switch Evaluation Metrics

The network is evaluated based on its ability to retain learned patterns across task switches. The following criteria are used to assess adaptation:

- **Synaptic Retention:** The stability of previously learned weights when switching between tasks.
- **Transition Efficiency:** The number of trials required for the network to adjust to a new task after a switch.
- **Task Separation Index (TSI):** A measure of distinct neural representations for $\mathcal{T}_1$ and $\mathcal{T}_2$:

$$TSI = \frac{||\mathbf{w}_{\mathcal{T}_1} - \mathbf{w}_{\mathcal{T}_2}||}{||\mathbf{w}_{\mathcal{T}_1}|| + ||\mathbf{w}_{\mathcal{T}_2}||} \qquad (11)$$

where $\mathbf{w}_{\mathcal{T}_1}$ and $\mathbf{w}_{\mathcal{T}_2}$ are the mean synaptic weight vectors for each task.

- **Reaction Latency:** The response time required for neurons to adapt after a task switch.

D. Experimental Protocol

The simulation runs for a total duration of T_{exp}, during which task switches are induced at randomized intervals. To analyze the effect of switching frequency, four conditions are considered:

1) Frequent task switching with short transition gaps.
2) Frequent task switching with long transition gaps.
3) Infrequent task switching with short transition gaps.
4) Infrequent task switching with long transition gaps.

Each trial consists of presenting a task stimulus for a fixed duration τ_{task}, after which the switching probability P_s determines whether a transition occurs.

E. Neural Dynamics and Learning Analysis

To validate the network's response to task switching, we examine the evolution of synaptic weights over time. The cumulative weight adjustment is defined as:

$$W_{\text{total}}(t) = \sum_{i,j} |w_{ij}(t) - w_{ij}(t_0)| \qquad (12)$$

where $w_{ij}(t_0)$ represents the initial synaptic weights. A higher $W_{\text{total}}(t)$ indicates stronger adaptation to changing tasks.

Additionally, neuronal firing rates are monitored before and after a switch event. The adaptation time is measured as:

$$\tau_{\text{adapt}} = \arg\min_t \left(\frac{d}{dt} R_{\text{neuron}}(t) \right)_{\text{switch}} \qquad (13)$$

where $R_{\text{neuron}}(t)$ is the population firing rate.

F. Observations and Expected Outcomes

The experiment is designed to analyze how the network dynamically reconfigures its synaptic structure to accommodate new tasks. The following trends are anticipated:

- Task switches with shorter transition gaps lead to more pronounced weight instability.
- Longer transition durations allow for better task consolidation and reduced interference.
- The TSI metric should indicate higher task separation when transition gaps are sufficiently long.
- Networks with stronger inhibitory regulation adapt more efficiently to switches.

The results of this experiment contribute to understanding the computational underpinnings of task-switching mechanisms in biologically plausible networks.

VI. RESULTS

The experimental framework evaluates how the spiking neural network (SNN) adapts to dynamic task-switching conditions by analyzing synaptic weight evolution, firing rate variations, and transition efficiency. The primary objective is to examine how learning representations are modified upon task transitions and how network stability is maintained across varying switching intervals.

A. Task-Switching Adaptation

The network undergoes sequential exposure to two alternating tasks, $\mathcal{T}_1$ and $\mathcal{T}_2$, over multiple trials. At each switch, the synaptic weights w_{ij} undergo modifications based on the sequence of pre- and post-synaptic spike timings. The weight evolution function is defined as:

$$W_{\text{avg}}(t) = \frac{1}{N} \sum_{i,j} |w_{ij}(t) - w_{ij}(0)| \qquad (14)$$

where N is the number of active synapses, and $W_{\text{avg}}(t)$ quantifies cumulative synaptic adaptation over time. A sharp decrease in $W_{\text{avg}}(t)$ upon task switching indicates a significant shift in neural representations.

B. Synaptic Plasticity and Learning Retention

To assess whether task switches disrupt memory consolidation, we define the retention coefficient ρ, which measures how much prior learning is retained after a switch:

$$\rho = \frac{||\mathbf{w}_{\mathcal{T}_{\text{prev}}} - \mathbf{w}_{\mathcal{T}_{\text{new}}}||}{||\mathbf{w}_{\mathcal{T}_{\text{prev}}}||} \quad (15)$$

where $\mathbf{w}_{\mathcal{T}_{\text{prev}}}$ and $\mathbf{w}_{\mathcal{T}_{\text{new}}}$ are the weight distributions before and after switching. Higher values of ρ indicate greater deviation from previous representations, signifying stronger interference between tasks.

C. Effect of Switching Interval on Neural Dynamics

The impact of task-switching frequency is analyzed by varying the switching interval τ_s. The adaptation time τ_{adapt} required for network stabilization post-switch is measured as:

$$\tau_{\text{adapt}} = \arg\min_t \left(\frac{d}{dt} R_{\text{neuron}}(t) \right)_{\text{switch}} \quad (16)$$

where $R_{\text{neuron}}(t)$ represents the global firing rate of excitatory neurons. Longer τ_s values lead to smoother adaptation, as observed in cognitive task-switching studies [8], [28].

D. Behavior Under Repeated Switching

Frequent switching introduces instability in synaptic learning due to continual interference. The weight variance across trials is given by:

$$\sigma_w^2 = \frac{1}{N} \sum_{i,j} (w_{ij} - W_{\text{avg}})^2 \quad (17)$$

where higher σ_w^2 values indicate increased weight fluctuations, leading to transient memory retention. Experimental results show that rapid task alternations lead to greater instability in synaptic strength, whereas longer stabilization periods facilitate learning consolidation.

E. Inhibitory Influence on Adaptation

The inhibitory neuron population plays a crucial role in stabilizing task-switching dynamics. To quantify inhibition strength, the inhibitory impact function I_{eff} is defined as:

$$I_{\text{eff}} = \frac{1}{M} \sum_i \int_{t_0}^{t_1} G_i(t) dt \quad (18)$$

where $G_i(t)$ represents the conductance level of inhibitory neurons, and M is the total number of inhibitory units. Higher I_{eff} values correspond to improved suppression of interference, leading to better adaptation.

F. Key Observations

The results provide insights into how task-switching affects neural plasticity:

- Shorter switching intervals lead to increased weight instability and reduced retention.
- Longer transition gaps improve adaptation efficiency by allowing sufficient synaptic restructuring.
- Networks with higher inhibitory strength exhibit greater stability in task alternation.
- Synaptic weight distributions show progressive convergence, confirming that the network learns persistent representations across tasks.

These findings align with established cognitive theories of task-set reconfiguration and neural adaptation [5], [29].

VII. CONCLUSION AND FUTURE WORK

This study presents a computational framework for modeling task-switching behavior using spiking neural networks. The results demonstrate how synaptic plasticity, inhibitory regulation, and switching intervals influence learning retention and adaptation dynamics. The findings align with known biological mechanisms of cognitive flexibility, particularly in relation to synaptic potentiation and depression.

The key contributions of this work are as follows:

- Development of a biologically plausible SNN model that exhibits task-switching behavior.
- Analysis of the interplay between synaptic adaptation, inhibitory control, and task retention.
- Quantification of weight evolution and adaptation time as indicators of switching efficiency.
- Validation of the network's ability to learn distinct representations across alternating tasks.

Future research directions include:

- Extending the model to incorporate more complex task hierarchies and memory-dependent transitions.
- Investigating the impact of neuromodulatory influences, such as dopamine, on task-switching efficiency.
- Exploring alternative neuron models beyond the leaky integrate-and-fire framework for enhanced biological realism.
- Implementing reinforcement learning mechanisms to allow adaptive task selection based on prior experience.

This study provides a foundation for further exploration of computational models of executive function, contributing to the broader understanding of how the brain optimally adapts to dynamically changing environments.

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