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CHAPTER

Statistical Machine-Learning Methods to Model Brain Plasticity

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Abstract

This chapter discusses statistical machine-learning (ML) approaches to model brain plasticity, which involves complex changes in the brain due to natural or induced causes. The chapter highlights various advantages that ML models have compared with traditional models of brain plasticity. Since brain plasticity can be analyzed at various levels of granularity, this chapter discusses several approaches to model brain plasticity, starting with some examples of the most traditionally studied, that is, the plasticity of the visual and motor control systems and synaptic plasticity for memory throughout the mammalian neocortex. Then brain plasticity models are discussed in various contexts and scales, including the main aspects to be considered in multiscale plasticity modeling, with specific information about models at the neuron level, the cortical column, and plasticity changes as a result of natural development. Following this, the chapter discusses modeling of plasticity's effect on higher-level cognitive functions, specifically those related to behavior, cognition, learning, decision making, intelligence, and memory. Plasticity when it results from trauma or brain damage is then reviewed. The chapter concludes by reviewing open research questions and future research directions for machine-learning modeling of brain plasticity.

Keywords: [brain plasticity](#), [statistical machine-learning](#), [brain development](#), [brain damage](#), [Hebbian and homeostatic plasticity](#), [visual control](#), [motor control](#)

Subject: [Cognition and Behavioural Neuroscience](#), [Neuroscience](#)

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Introduction

Brain plasticity refers to permanent structural and functional changes in the brain due to neural reorganization resulting from natural development or in response to some stimuli. Although modeling various aspects of brain function and properties, including plasticity, using machine learning has a long tradition, the modeling of specific components of brain plasticity remains an ongoing challenge due to its multifaceted complexity, which includes aspects of structure (Mateos-Aparicio & Rodriguez Moreno, 2019), function (Grafman, 2000), development (Raznahan et al., 2011), and artificial direct (Boutet et al., 2021) and indirect stimulation (Witney, 2018). Thus, accurately modeling brain plasticity in its different facets and scales remains challenging. Improving our models is paramount to understanding the processes affecting the healthy brain and the changes and adaptations the brain experiences in the presence of ailments, including brain injuries and neurodegenerative processes, such as Parkinson's disease, Alzheimer's, stroke, and many others. The importance of this modeling task is critical because creating a baseline of plasticity under normal conditions is needed to understand other processes, as some aspects of plasticity are still not fully understood and plasticity is not necessarily effective and could be maladaptive—that is, it can lead to a decrease in cognitive, motor, and sensory performance. Furthermore, one of the biggest methodological challenges when breaking down a complex problem, such as brain plasticity, is to identify statistical regularities among the elements of the system. Statistical machine learning (ML) provides one set of tools for discovering statistical regularities of how the neuron and neuron circuits are structured and operate, which in the end could help us understand how plasticity—changes in the neuron structure as well as in the neural connections and pathways—works. These regularities can inform the development of psychological theories or scientific questions to clarify the mechanisms that may be responsible for plasticity in its different levels of granularity. ML models could facilitate this task because of several of their characteristics, including automated feature extraction, nonlinear modeling capabilities, flexibility, and so on. Recent work has shown that ML has the potential to address issues in modeling population-based statistical analysis problems in neuroscience (see Zhu et al., 2023): large-scale observational study design, detecting changes in brain structure and function recorded during neuroimaging experiments, estimation methods and statistical theory for the analysis of populations of complex objects, data imputation, data integration, dimensionality reduction, genetic analysis, causality research, and predictive modeling. In this chapter, we present a list of relevant ML methods for brain plasticity that could serve as a reference for neuroscientists interested in data-driven ML models for identifying data patterns to solve neuroplasticity research questions. It could also serve as a reference for ML practitioners interested in current and open problems in brain plasticity.

Advantages of machine learning models.

Machine learning has made remarkable advancements over the past few decades. Its ability to transform our lives is increasingly apparent in many areas, from everyday activities to complex scientific endeavors. In terms of the neuroscience of brain plasticity, the advantages of ML compared with traditional approaches include but are not limited to modeling superiority due to relatively mild theory agnosticism and scalability, data-driven flexibility, nonlinear representability, ease of integrating data via multimodal fusion, and powerful adaptability and flexibility.

First, in most scenarios, ML outperforms traditional statistical methods by managing vast and continuous data streams and uncovering complex patterns (Bowe et al., 2023; Schmidgall & Hays, 2023). More complex models, which are common in ML to capture nonlinearity, may be crucial for understanding the dynamic nature of brain plasticity. In contrast, traditional statistical methods like linear regression, and certain CCA and ANOVA models could struggle with nonlinear relationships (Cortes-Briones et al., 2022; Henkes et al., 2024; Pagan et al., 2016); and large-scale data in neuroplasticity research (Mukamel et al., 2009). Second, deep learning models, such as convolutional neural networks (CNNs), are vital for studying neuroplasticity because they can

automatically extract features from raw data (Schmidgall & Hays, 2023). CNN models reveal significant patterns, such as the correlation between image memorability and inferior temporal cortex responses (Jaegle et al., 2019), while traditional methods require labor-intensive and sometimes biased (due to overrestrictive linear assumptions) manual feature selection. Third, neural networks and reinforcement learning algorithms are essential for capturing nonlinear relationships in data (e.g., recurrent neural networks (RNNs), stochastic processes [Rebesco et al., 2010; Yoon et al., 2022], and reward-based learning [Wang et al., 2018]), crucial for understanding brain plasticity. Nonlinear models like three-factor learning rules (Schmidgall & Hays, 2023) and spike-timing-dependent plasticity (STDP) in spiking neural networks (SNNs) (Song & Abbott, 2001) provide detailed insights into synaptic plasticity dynamics, which traditional models either cannot adequately represent or cannot efficiently represent (Henkes et al., 2024) (the latter is an advantage SNNs hold even over traditional NNs). Fourth, machine learning enables comprehensive analysis by integrating diverse data types, a critical capability for neuroplasticity research. Combining neural activity, structural imaging (Zhu et al., 2023), and behavioral data (Shine et al., 2019; Talukdar et al., 2019) offers a more complete understanding of brain function and plasticity, with hierarchical Bayesian frameworks (Lee & Mumford, 2003), support vector machines (Dormal et al., 2016; Talukdar et al., 2019), manifold flows (Shidara et al., 1993) and reinforcement learning models (Zhang & Yu, 2013) effectively merging multiple information sources or interactive environments. Finally, the flexibility of machine learning models makes them ideal for studying brain plasticity's complex and evolving nature. These models are used for various applications, such as modeling synaptic changes (Montague & Sejnowski, 1994; Schmidgall & Hays, 2023; Song & Abbott, 2001), predicting cognitive outcomes (Lee & Mumford, 2003; Wang et al., 2018), and simulating neural plasticity of decision-making with reinforcement learning (Callaway et al., 2022; Dayan & Daw, 2008; Leider & Griffiths, 2017) and hierarchical model-based control (Botvinick & Weinstein, 2014), whereas traditional methods often require modifications to address different research questions or datasets.

Modeling challenges.

Modeling brain plasticity from data is extremely complex due to the various levels of resolution involved, ranging from changes in pathways among the brain's over 86 billion neurons and a similar number of neuroglial cells, to systematic changes in the connections within the brain's subsystems, regions, and components. First, at a smaller scale, Hebbian descriptions of synaptic plasticity are the most-modeled type of brain plasticity (Daw et al., 2006; Magee & Grienberger, 2020; Parisi et al., 2019). However, this process involves various mechanisms like homeostatic plasticity and the role of other brain cells, such as the Bergmann glia (Mukamel et al., 2009; Yoon et al., 2022), which are ongoing research efforts in neuroscience. Second, at a higher scale, traditional research on brain plasticity often focuses on specific systems, such as the visual system, which includes many modeling techniques, including automated untangling of object manifolds, and hierarchical Bayesian frameworks, discussed below.

Models of visual system plasticity have matured to the point of being informed by research on the developing brain (Zaadnoordijk et al., 2022) and brain reorganization due to visual impairment (Dormal et al., 2016), although many methodological questions remain unsolved—such as the best strategies for the development of system-level plasticity models that could be used, for instance, for next-generation retinal neuroprosthesis (Yu et al., 2020). Finally, higher-order cognitive functions and their neuroplasticity basis have been modeled using various supervised ML models, such as Bayesian techniques, neural networks, and reinforcement learning. Cognitive growth, for example, is modeled through metacognitive reinforcement learning (Krueger et al., 2017), at a cognitive level, but probabilistic approaches have also been used. For instance, Bayesian inference has been used for word and concept learning (Tenenbaum & Griffiths, 2001; Xu & Tenenbaum, 2007). A discussion of the Bayesian perspective of learning appears in Xu and Tenenbaum (2001). An important step in modeling brain plasticity is to identify brain regions of interest (ROIs) associated with or affected by neuroplasticity, acknowledging that both specialized and domain-general regions contribute to human cognition (Fedorenko et al., 2010). Most noticeably, integrating the mechanistic elements of plasticity at various levels of granularity

is still a challenging modeling problem. Due to these intricacies, ML models appear as valuable tools for modeling brain plasticity due to their automated pattern mining or their predictive capabilities.

In the next sections we discuss plasticity from the perspective of major (and widely studied) brain systems, scales, and cognitive functions. We also present some ML modeling insights associated with the healthy versus the impaired brain and conclude with a reference to open problems and a discussion of plasticity modeling with ML. Figure 1 illustrates these various levels of granularity where plasticity manifests in the brain, starting from synaptic and homeostatic plasticity (neuron) to physical and functional neural connectivity reconfiguration (circuits) that affect the brain systems. We argue that ML can provide an additional set of tools that could improve predictive performance from a neuropsychological perspective and better data integration and variable association discovery from a neuroscience perspective. This can be achieved by ML's properties, which help identify probabilistic and statistical regularities that are responsible for brain plasticity. Figure 2 summarizes the cognitive function and brain structure of the ML models discussed in this chapter. Examples of ML models for each of the four model types, as well as their context application, are detailed in Table 1.

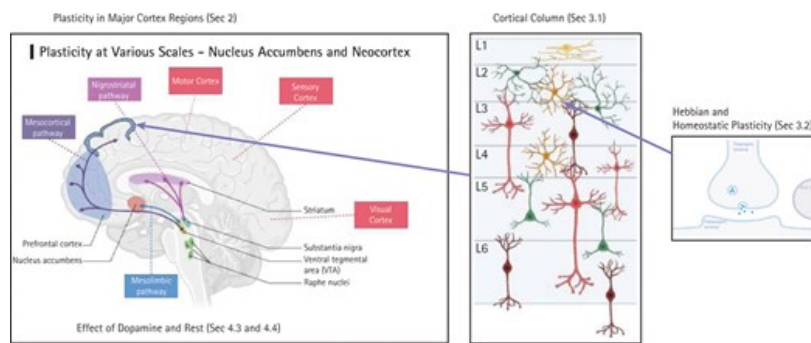


Figure 1 A topic linking other aspects of plasticity in this chapter is dopamine. The primary reward circuit of the brain involves dopaminergic projections from the ventral tegmental area (VTA) to the nucleus accumbens, releasing dopamine in response to rewards. The nucleus accumbens is innervated by glutamatergic neurons from the medial prefrontal cortex, amygdala, hippocampus, and other regions. The caudate and putamen nuclei of the striatum receive input from the substantia nigra zona compacta and the prefrontal cortex. In addition to affecting memory, other regions are directly affected by the dopaminergic systems, including sensory-motor, visual, and auditory systems, also studied in this chapter.

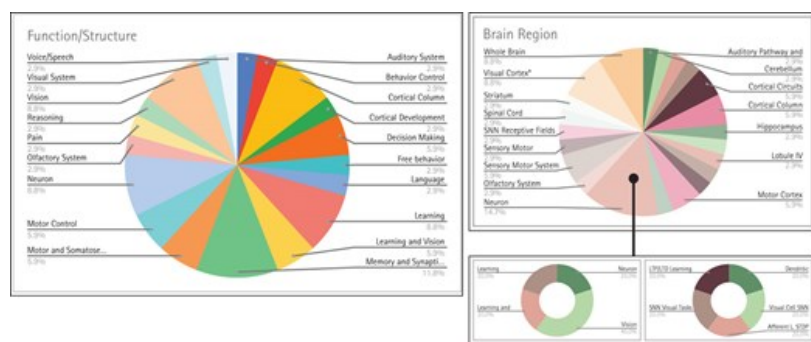


Figure 2 A snapshot of the reported literature on ML to model brain plasticity. Left: The proportion of studies addressing different cognitive functions. Top right: The most investigated brain regions and the percentage of studies reported in this document per the reported data or target region. Bottom right: A breakdown of the literature on neuron modeling by the cognitive function involved (left) and specific cell property/function (right).

Table 1: Selection of Models of neural plasticity and their domain of application

Work	Human Data	Function/Structure	Resolution	ML Method	D
Yoon et al., 2022	no (mice)	Pain and analgesic effect	1,3	Bidirectional RNN	Yes
Rebesco et al., 2010	no (rats)	Free behavior & stimulation	1,2	Bayesian point-process	yes
Mussa-Ivaldi & Solla, 2004	no (small animal)	Motor control	1-3	Atractor, Mixture of, and layered NN	yes
Gallego et al., 2020	no (monkeys)	Motor and somatosensory	1-3	PCA, CCA	no
Flint et al., 2016	no (monkeys)	motor and somatosensory	1-3	PCA, CCA, RNN, Wiener filters	no
Wolpert & Ghahramani, 2000	yes?	Motor planning & control	3	Bayesian, Kalman filters, other	no
Sutton et al., 2019	yes?	Visual system	1	NN: balanced excitatory/inhibitory nets	yes
Acharya et al., 2022	yes	–	1	NN: dendritic pl.	yes
Marblestone et al., 2016	synth	–	1	NN: dendritic pl.	yes
Diehl & Cook, 2015	yes	–	1	NN: dendritic pl. (various)	yes
Brunel et al., 2004	no	Synaptic storage	1	Probabilistic & information theoretical	yes
Potjans & Diesmann, 2014	no	Cortical column	1,2	NN + probabilistic	yes
Alexandre et al., 1991	no	Cortical column	1,2	NN with bio-inspired units	yes
Dean, 2005	no	Cortical column	1,2	Probabilistic graphical models	yes
Hessler et al., 1993	no (mammals)	Memory and synaptic p.	1,2,3	Probabilistic/difference equation	yes
Song et al., 2005	no (mammals)	Memory and synaptic p.	1,2,3	Probabilistic	yes
Varshney et al., 2006	no (mammals)	Memory and synaptic p.	1,2,3	Probabilistic, power law scaling, Lagrange multip.	yes
Braitenburg & Schüz, 2013	no (mammals)	Memory and synaptic p.	1,2,3	Probabilistic various (book)	yes
Schilling et al., 2023	yes	Auditory system	1,2	Bayesian, NN	no
Vukovic et al., 2021	yes	Language	3	SpaceNetClassifier, GraphNet	yes
Hiratani & Latham, 2020	mammals	Olfactory system	3	Bayesian inference and NN	yes
Raznahan et al., 2011	yes	–	3	Linear and mixed-effects	yes

Bermudez et al., 2009	yes	–	2,3	Pattern-mining: MACACC	no
Song & Abbott, 2001	yes	visual (not directly stated)	2	NN, SNN with Poisson process spikes	yes
Schmidgall & Hays, 2023	yes	Learning (& Vision)	1,2	Triplet-based STDP, DP-SNN, NM-SNN, CNN	yes
Benjamin et al., 2019	synth	Vision	1,2	NN with Hilbert-constrained SGD	no
Krishnan et al., 2017	yes	–	3	Sparse-reduced rank regression	yes
Schwartz et al., 2016	yes	–	3	Regularized Gompertz model	no
Xu & Tenenbaum, 2007	yes	Learning	3,4	Bayesian inference	yes
Thomson & Lebiere, 2013	yes	Learning	3	Constrained Bayesian inference	yes
Nessler et al., 2013	yes	Learning	1,2,3	STDP, Bayesian inf. with spike-based EM	yes
Habenschuss et al., 2012	yes	Learning & vision	3	Recurrent SNN, EM, & WTA architecture	yes
Cohen et al., 2007	yes	Behavior control	3	RL	yes
Lieder & Griffiths, 2017	yes	Reasoning	3,4	RL on metacognitive variables	no
Montague et al., 1996	yes/synth/no	Decision-making	1,2,3	RL (temporal differences), SNN	yes
O'Doherty et al., 2004	yes/no	Decision-making	1,2	RL & SNN	yes

Note: **Human data** indicates if the model was tested on human data or other species. **Resolution.** 1: Neuronal/cellular-level mechanisms, 2: Neuron circuit mechanisms, 3: Brain anatomic region mechanisms, 4: Systemic mechanisms (plasticity at the system level) and broader cognitive phenomena (e.g., learning, development, aging, brain disorders, etc.). **D:** Is the model used to either directly model brain plasticity itself or to simulate it, or not (e.g., it is used to model brain plasticity confounders, determinants, predictors, factors, or plasticity emergent phenomena).

Machine-Learning Models of Neuroplasticity

Brain plasticity has been extensively studied in sensory-motor control, the visual system, and the mammal neocortex memory system using techniques from machine learning and control theory. For instance, Wolpert and Ghahramani (2000) infer the motor commands from motor behavior. Both forward and inverse models are essential for understanding how the brain adapts to acquire skills and recover from damage (Kiper et al., 2016), with examples including eye movements (Shidara et al., 1993), limb control (Takahashi & Reinkensmeyer, 2003), and memory storage capacity (Varshney et al., 2006). Inverse problems in various sensory systems (visual [Acharya et al., 2022; Diehl & Cook, 2015; Marblestone et al., 2016; Sutton et al., 2019]), auditory ([Schilling et al., 2023; Vukovic et al., 2021]), olfactory [Hiratani & Latham, 2020], etc.) demonstrate the influence of plasticity in the cortical semantic network. Research on synaptic plasticity and neural networks emphasizes machine-learning techniques linking coding theory and optimization of synaptic weights in models such as perceptrons and Hopfield networks to describe memory storage capacity, providing insights into neuroplasticity and the development of computational tools from a neural basis. These models exploit data-driven inferential ML techniques and their adaptability to brain elements and functions, showcasing the data-driven flexibility needed to capture the complexity and dynamics of neurons and neural circuits.

Motor Control

Motor control is one of the areas of neuroplasticity modeling that showcases the strengths of ML (Figure 1). Scalability issues may arise in neuroplasticity modeling when accounting for circuit reconfiguration and not only for single-neuron plasticity or neuron-to-neuron interactions. For instance, Rebesco et al. (2010) apply the Bienenstock-Cooper-Munro approach of Izhikevich and Desai (2003), which incorporates spike-timing-dependent plasticity to infer functional connectivity from the characteristics of spike discharge recorded during spontaneous behavior. Rebesco et al. (2010) experiment with large networks, rather than relying solely on the strength of response to stimulation as other models do. Thus, modeling large-scale time-dependent neural interactions to identify the most likely interactions given the recorded spikes can benefit from ML, which also offers data-driven flexibility in identifying functional connectivity patterns in sensorimotor cortical neurons.

Motor control is modeled in Musasa-Ivaldi and Solla (2004) where the prediction of the current motor state is based on delayed sensory feedback and the history of motor commands. This nonlinear representability is achieved by three types of coordinate representations that sensory and motor systems use to generate and control movements, exploiting the intrinsic redundancy of the musculoskeletal system for adaptable and successful task completion despite variance in trajectory parameters. Additionally, muscle synergies activated through stimulation of specific loci along the spinal cord provide evidence for a vocabulary of motor primitives that can be combined, either simultaneously or sequentially, to generate a broad repertoire of complex movements. Among sensorimotor neural decoding, some models that describe neural plasticity resort to machine-learning models that represent neural activity as a dynamical system that could also facilitate nonlinear representability. For instance, Gallego et al. (2020) and Flint et al. (2016) use principal component analysis (PCA), Wiener filter (Glaser et al., 2020), canonical correlation analysis (CCA), and RNNs applied to neural decoding (Sussillo et al., 2015). It also uses other models as decoders, such as long short-term memory (LSTM) and XGBoost, which provide data-driven flexibility for pattern mining.

Bayesian models have been used to study neural plasticity and network structure of the underlying functional connectivity between the recorded neurons (Stevenson et al., 2008), using multi-electrode arrays specifically implanted to measure the plasticity of primary motor (M1) and premotor (PMd) cortices of a monkey, which showcases flexibility and automated parameter selection. However, there are some areas of research in neuroplasticity where ML's flexibility and adaptability can still be exploited. For instance, in Wei et al. (2014),

the authors examined the systemic aspect of plasticity, and applied more traditional ANOVA methods to show that generalization of movement-behavior learning was better for computer users when compared with a non-computer-user group of the study participants, while the speed and degree of learning remained unaltered. In general, plasticity is usually modeled with traditional statistical models for systemic, behavioral, or brain-wide plasticity phenomena, such as learning. For instance, in Albert et al. (2012), a regression model is used to represent saccadic adaptation as determined by a study of the eye movements of monkeys with lesions to the posterior cerebellar vermis that impair adaptation. This shows that oculomotor adaptation is well matched to the spectrum of timescales that affect normal, natural changes in the oculomotor plant as well as artificial experimental perturbations. Evidence of ML usefulness includes Dyer et al. (2017), which uses a probabilistic approach for data-driven modeling of statistics of movement of motor variables to neural activity, that facilitates multimodal fusion of these two data modalities.

Vision, Plasticity, and Memorability

The plasticity of the visual systems (Figure 1) offers various modeling opportunities to take advantage of ML's domain-agnosticism, scalability, data-driven flexibility, nonlinear representation, multimodal integration, and adaptability. Adaptation-like response reduction, known as “repetition suppression,” occurs in high-level visual brain areas with stimulus repetition and is considered a candidate mechanism for signaling visual memory percepts (Fahy et al., 1993; Fritsche et al., 2020; Heit et al., 1990; Miller & Desimone, 1994; Riches et al., 1991; Solgi et al., 2013). This mechanism uses ML's scalability to represent neural changes across various stimuli and conditions. The work of DiCarlo et al. (2012) suggests that the architecture and plasticity of the ventral visual stream might solve object recognition in the brain's inferior temporal (IT) cortex. The architecture presented uses a complex set of computational models where the plasticity of the ventral visual stream is partitioned based on specific cortical areas grouped in layers. Several of these models, including Solgi et al. (2013), highlight the domain-agnostic capabilities of ML in neural plasticity—for instance, via transfer learning. More specifically, it shows the specificity and transfer of perceptual learning (PL) using neurons with both sensory and motor inputs, whereby the training process activates both descending (top-down) and ascending (bottom-up) off-task processes related to an untrained condition. Transfer learning is achieved because these two processes lead to the involvement of more neurons in both lower-level feature representation areas and higher-level concept representation areas for the untrained condition.

The spike timing of the ventral pathway follows a Poisson-like stochastic generation (Kara et al., 2000; McAdams & Maunsell, 1999), in a nonlinear representation. At least two types of algorithms that use a global scale of cortical areas perspective have been postulated. The first type involves the automated untangling of the object manifold, applied locally to each cortical processing layer, as seen in Einhäuser et al. (2005), which is applied locally to each cortical processing layer (Fukushima, 1980; Heeger et al., 1996; Reisenhuber & Poggio, 1999; Serre et al., 2007b). The second type involves hierarchical Bayesian frameworks (Lee & Mumford, 2003; Rust & Stocker, 2010) based on feedback connections between different cortical areas, which are critical to resolving object ambiguity. Bayesian models are suitable for multimodal fusion tasks (ease of sharing priors, likelihood, etc.).

Local visual models, which can be more mechanistic than global ones, represent specific cellular operations, such as V1 cells (and-like operations, orientation responses, etc.), providing the basis for biological object recognition (Serre et al., 2007a) and are the basis for linear-nonlinear (LN) encoding models (Carandini et al., 2005). These models use adaptability by representing the dynamic and context-dependent operations of the visual system. For a detailed list of possible mechanisms of manifold untangling, the reader is referred to DiCarlo et al. (2012), which also underscores the necessity of artificial neural network (ANN) simulations to understand pattern recognition in the brain. However, plasticity may have a limited role in other visual processing tasks. To study inferotemporal (IT) image memorability modulation (Jaegle et al., 2019) used convolutional neural network (CNN) models to categorize objects. These simulations showed that variation in

the capacity to remember images strongly correlated with the magnitude of the population response in the IT cortex. Thus, since memorability seems to emerge from static, feed-forward, and fixed networks, plasticity may have a more limited role. This, however, does not rule out the role of plasticity at the neural circuit level as a factor for memorability.

Another system-level effect of plasticity modeled with ML is the dynamical *target match* signal processing of the visual system that represents whether a target appears in a currently viewed scene. Dynamic target match in the perirhinal cortex (PRH) has been modeled with a polynomial model with bootstrap and LN models, where synaptic plasticity is accounted for (Pagan & Rust, 2014). Pagan et al. (2016) use Hebbian descriptions of synaptic plasticity with NL pooling to create a supervised learning model of the plasticity of the visual system, namely the neural quadratic discriminant analysis (nQDA), which represents the signal transformation between neural representations in two high-level brain areas. Various deep neural networks have also been used to model memorability, further demonstrating the adaptability and multimodal fusion/nonlinear modeling capabilities of these models (Rust & Mehrpour, 2020).

Synaptic Plasticity for Memory in the Mammalian Neocortex

Synaptic plasticity for memory throughout the mammalian neocortex has been extensively studied, and research on synaptic plasticity and neural networks highlights how optimizing synaptic weight distributions and applying coding theory in models like perceptrons and Hopfield networks can enhance memory storage capacity and accuracy (Braitenberg & Schüz, 2013; Hessler et al., 1993; Song et al., 2005; Varshney et al., 2006). This supports the use of ML for a better understanding of the neuron's properties and the characteristics of neural circuits architecture affected by neuroplasticity and for developing methodological frameworks. For instance, the work of Hessler et al. (1993) introduces a novel method to measure the probability of vesicle fusion at synapses, revealing two classes of synapses with differing probabilities that influence synaptic efficacy and potentially underlie activity-dependent plasticity. The work of Song et al. (2005) reveals that local cortical circuitry differs from a random network by exhibiting nonrandom features, such as clustered connections and a lognormal distribution of synaptic strengths, with stronger connections forming a structural backbone within the network. The work of Varshney et al. (2006) proposes a theoretical framework to explain three notable properties of synapses: their inherent noise, wide distribution of weights, and sparse connectivity, focusing on potential discrete variations in synaptic weights. Based on optimizing information-storage capacity under volume constraints, this framework aligns with experimental data and makes new predictions. Readers interested in the cortical network are referred to Braitenberg and Schüz (2013), which covers various theories of its function, its plasticity, and other quantitative neuroanatomical properties.

In addition to modeling various properties of synapses associated with memory, other models study the storage capacity of particular neural network models. For instance, Brunel et al. (2004) show that optimizing synaptic weight distribution for learning and reliability in a perceptron model results in a high percentage of silent synapses, a pattern that closely matches the synaptic distribution in cerebellar Purkinje cells, suggesting that these cells can store substantial information. The paper of Gardner (1987) calculates the maximum storage capacity of a network as a function of the magnetization level m , while the work of Newman (1988) derives the memory lower bound with n binary neurons and symmetric l th-order synaptic connections. Likewise, the work of McEliece et al. (1987) applies coding theory to determine the memory capacity of a Hopfield network with associative memory of length n . They found that the maximum number of storable memories scales as $n/(2 \log n)$ for most recoverable memories, and $n/(4 \log n)$ for guaranteed exact recovery, with further analysis extending to quantized memory capacity. The work of Xu et al. (2012) shows that different brain circuits use distinct spike-coding schemes, with isolated spikes providing precise but unreliable neurotransmission, and bursts offering reliable but imprecise transmission, affecting memory formation and recall in the hippocampus and prefrontal cortex differently. The hippocampus is also affected by the neural activity of the entorhinal cortex associated with memory and other functions such as spatial orientation, which has been

modeled with deep recurrent neural networks (DRNNs) and self-supervised learning (Schaeffer et al., 2024). Rolls and Treves (1997) present a compendium of various models for cortical networks and memory.

Plasticity and Statistical Models of the Brain

Modeling brain plasticity requires incorporating existing models of brain function at multiple scales, as they offer crucial insights into adaptive changes across various brain regions. Representing both brain structure and function is critical for capturing the full scope of plasticity effects. Machine-learning models, such as hierarchical model-based control (Botvinick & Weinstein, 2014), help simulate disruptions in plasticity, predict cognitive outcomes, and analyze brain dynamics. These models demonstrate flexibility and scalability across domains, using approaches like approximate inference with generative adversarial models (Gershman, 2019) and mesoscale connectomics analysis (Mitra, 2014), which can manage diverse data.

Synaptic plasticity, governed by Hebbian and homeostatic mechanisms, underpins neural learning and adaptation. Models like spiking neural networks (SNNs) and spike-timing-dependent plasticity (STDP) explore the role of plasticity in coding, prediction, and brain network reconfigurations (Song & Abbott, 2001). Additionally, research highlights distinct plasticity mechanisms in dopamine neurons for movement and reward prediction, showing that plasticity affects both micro- and macro-level brain networks (Scott & Frank, 2023). Data integration and multimodal fusion across scales, including functional magnetic resonance (fMRI) data for modeling brain dynamics, strengthens our understanding of plasticity at different levels of brain function. Models like graph neural networks and relational learning are fundamental for representing the effects of plasticity on brain networks due to their nonlinear representability.

One promising method to link brain structure and function is through connectome-based approaches, which suggest that general intelligence is best predicted by global brain connectivity rather than localized neural representations (Anderson & Barbey, 2023). These approaches, alongside multimodal ML models like graph neural networks and relational learning, showcase adaptability, multimodal capabilities, and nonlinear representability for modeling the effects of plasticity on brain networks (Talukdar et al., 2023). Nonlinear dynamics in neural networks have also been studied using models like the cerebellum's three-layer feed-forward network (Shadmehr, 2020), shedding light on synaptic changes. Moreover, the integration of neural-level plasticity with metaplasticity furthers the understanding of adaptive mechanisms in the brain. Cortical information has effectively been used to model cognitive abilities in multivariate ML frameworks, while ML techniques like probabilistic graphical models (Na et al., 2021) and Bayesian models (Andersen et al., 2018) have successfully abstracted both brain structure and function. Biologically inspired neural models, influenced by cortical column research, show promise in applications ranging from intelligent video analytics to energy-efficient neural networks. Recent findings also indicate the importance of multiple brain networks in fluid intelligence (Wilcox & Barbey, 2023), supporting a broader perspective on how plasticity influences cognitive performance.

Plasticity at Different Scales of Resolution

At a microscale, plasticity is linked to rapid changes in the spatial distribution of synapses resulting from development, experience, and sleep-wake cycles. At this scale, neural network simulations show that *down-selection*, the process whereby some synapses' effectiveness is reduced or nullified (Hill et al., 2008; Nere et al., 2013; Olcese et al., 2010), leads to an increase in the signal-to-noise ratio of a sequence (of activations across [four] blocks of neurons) learned by the simulated network. Thus, the adaptability and nonlinearity of these models are necessary to capture down-selection that may be responsible for procedural and declarative memory consolidation.

A mesoscale connectomics analysis is critical for modeling brain plasticity because modeling plasticity requires differentiating stable functional and structural characteristics of the brain and distinguishing them from transient connections that arise from synaptic plasticity. However, such neuroscience analysis has only recently been proposed. Most of the modeling choices at the moment seem insufficient to deal with the large volumes of data and varying data types (matrix, networks, etc.) that also present challenges for previous domain knowledge encoding (Mitra, 2014), indicating the need for data-driven flexibility and scalability.

At a macro level, brain plasticity is evidenced by the reconfiguration of brain networks. However, the spatial scale (histological, functional, etc.) of plasticity is not the only difference between micro- and macro-level plasticity. While synaptic plasticity is a phenomenon exhibited at submillisecond timescales, changes in connectivity among brain regions could unfold over longer periods (days or even years) as a consequence of development or experience. At a micro level, an example of a neural network model is spike-timing-dependent plasticity (STDP) (Song & Abbott, 2001). At a macro level, the models used to represent changes in brain network organization can be diverse due to the specific aspects of plasticity that are represented (Zatorre et al., 2012). Brain plasticity can include changes in white or gray matter (diffusion imaging models [Avram et al., 2010; Barazany et al.; Wedeen et al., 2005] or changes in the connectivity of networks (small world phenomena [Bermudez et al., 2009; He et al., 2007; Raznahan et al., 2011]). In all three levels, adaptability, nonlinear representability, and scalability are necessary for modeling plasticity.

A case study: The cortical column.

Perhaps the most relevant example of a multi-scale neural plasticity modeling problem corresponds to the *cortical column* (Alexandre et al., 1991; Cain et al., 2016; Dean, 2005; Mikhailov & Karavay, 2024; Shen & Nair, 2023; Telynykh et al., 2021) (Figure 1). The columnar organization of the neocortex is a widely accepted model for cortical information processing, though its exact function remains an active area of research. The early modeling work of Alexandre et al. (1991) introduced a connectionist unit modeled after the cortical column, designed to simulate humanlike reasoning using simple and biologically plausible learning rules. Simulations demonstrated that multilayered networks composed of these units could perform pattern recognition tasks, such as speech and visual recognition, with performance comparable to the best networks at the time, while also enabling fast learning and recognition processes. Advancements in understanding the primate neocortex enabled the development of graphical models for associative recall, sequence prediction, and pattern completion, which can now be implemented using common computing clusters (Dean, 2005). These models offered insights into both neocortical functions and the tools that facilitated research on external neural structures for the creation of hybrid systems that integrate biological principles with modern ML techniques. Mikhailov and Karavay (2024) hypothesize a new function for the cortical column, supported by neurophysiological and computational evidence, which led to advances in evaluating memory capacity and developing efficient ML models for pattern recognition. Reverse-engineering the human brain has inspired the development of deep neural networks (DNNs), but these have diverged from biological plausibility and could lead to unsustainable demands on computing resources. Recent research suggests that cortical columns could be the key to creating brainlike, energy-efficient computing systems, and recent results indicate that this approach may be both feasible and promising (Shen & Nair, 2023).

The mammalian neocortex appears to be key to higher cognitive functions. The study of Cain et al. (2016) explores the computational properties of a cortical column model based on this structure. By using a population density model, Cain et al. (2016) shows a linear abstraction when excitatory and inhibitory neurons receive equal inputs. In this abstraction, multilayered input signals can be reduced to linear combinations, incorporating a subtractive operation that could function as an error signal. The video analytics system in Telynykh et al. (2021) models how living systems process information by simulating the formation and activation of detectors, analogous to cortical columns in the brain, for content-based image retrieval. This

biomorphic model visually demonstrates how specific stimuli, such as faces or numbers, are recognized, mirroring the way connections form and trigger in the brain's recognition columns.

Plasticity Modeling and Inference at the Neural Level

Synaptic Plasticity and Neural Adaptation

Synaptic plasticity, modulated through Hebbian and homeostatic plasticity, plays a critical role in the brain's ability to code and retain information, and reset neural states (Fox & Stryker, 2017). Various models have been proposed to explain the underlying mechanisms of synaptic plasticity. A couple of examples include a three-factor learning model using spiking neural networks (SNNs) (Schmidgall & Hays, 2023), and the input-output matching optimization (Benjamin et al., 2019).

The work of Rao and Sejnowski (2001) suggests that spike-timing-dependent plasticity in neocortical synapses can be interpreted as a form of temporal difference (TD) learning rule for prediction (Montague & Sejnowski, 1994; Sutton, 1998). Additionally, zero-lag synchronization of neuronal signals is believed to play a significant role across various neural systems, including spike-timing-dependent plasticity (Fornito et al., 2016; Varela et al., 2001). Nonetheless, the interplay of Hebbian and homeostatic plasticity remains an ongoing research effort.

Dopamine Neurons and Action-Related Signals

Recent studies suggest that dopamine (DA) neurons in the dorsomedial striatum (DMS) follow different plasticity rules, requiring an action-related signal rather than a prediction error signal. This suggests that plasticity in the dorsal striatum is influenced more by movement signals (action-related) than by prediction error, pointing to functional differences in how neural circuits adapt in this region (Figure 1). Specifically, midbrain DA neurons not only are involved in encoding reward prediction error (RPE) but also show movement-related signals, such as modulation by contralateral choices in mice. The analysis of DA signals on a trial-by-trial basis revealed that these signals are influenced by movement direction rather than RPE, suggesting a separation between the encoding of reward and movement, which may clarify various functions and dysfunctions of the DA system (Lee et al., 2019).

Mechanisms of Plasticity: A Unifying Framework

Research efforts at both the neuron and circuit levels have aimed to identify unifying mechanisms for plasticity. One proposed solution is based on gradients, which offer a consistent explanation for plasticity across these levels (Richards & Kording, 2023). A meta-learning algorithm has been developed to estimate gradients for underlying learning algorithms, modeling plasticity in complex synapses (Zucchet et al., 2022). This approach addresses the biological implausibility of backpropagation through data-driven multitask fusion using a dual-system architecture.

Integrating neural-level plasticity with higher-level plasticity, metaplasticity has been proposed for learning under uncertainty, allowing synaptic states to change without significantly altering efficacy. A modified Kalman filter has been used to model this, enabling the multiplicative evolution of the precision matrix (Piray & Daw, 2020).

Other unifying frameworks also account for the dynamics involved, such as principal components of brain hemodynamics from fMRI data, through domain-agnosticism (across various brain functions: motor, cognitive, language, memory) (Shine et al., 2019). Each time series of the principal components (tPC1) of the brain hemodynamics, partially captured with fMRI data (Shine et al., 2019), reflects an integration and

differentiation of cortical dynamics, capturing how the brain can perform the necessary neuromodulation for cognitive processes (Shine et al., 2019).

The Developing Brain

ML models of the developing brain emphasize domain-agnosticism, scalability, data-driven flexibility, and adaptability. The developing brain exhibits greater plasticity than the adult brain and is associated with a greater external exploration and internal representation (Gopnik, 2020). The developing brain experiences so-called critical and sensitive periods of plasticity (Hensch & Bilimoria, 2012). *Critical periods* refer to times when environmental input is crucial for properly developing particular brain circuits. If these circuits lack stimulation during this time, the related brain functions may be permanently affected. On the other hand, *sensitive periods* are less strict and represent times when environmental experiences exert significant influence on brain circuitry.

Current models of brain plasticity of the developing brain consider exploration-exploitation mechanisms and internal representations (Gopnik et al., 2017), and probabilistic (e.g., Bayesian) and ANN approaches (e.g., cortical plasticity in the developing brain was studied using an ANN, with the perceptron as a unit, to predict the activity in the primary visual cortex [Dumoulin Bridi et al., 2015]). However, ML could also predict cognitive outcomes, directly highlighting moments where optimality of outcomes can be expected from intervention during periods of optimal neuroplasticity—that is, critical and sensitive ones (Bowe et al., 2023). ML has been used to associate determinants to brain connectivity in even earlier stages, for example, in preterm infants via sparse-reduced rank regression (Krishnan et al., 2017), and to model the structure of fetal cortical expansion using constrained Gompertz models (Schwartz et al., 2016).

Plasticity, Intelligence, Memory, and Learning

While our focus has been on ML modeling of plasticity from a neuroscience perspective, plasticity also plays a significant role in higher-level cognitive processes. In this section, we explore a few of these processes, highlighting the benefits of ML in understanding them.

Small-world phenomena analysis indicates that anatomical networks of gray matter mirror functional organizational patterns (He et al., 2007), which can be influenced by developmental processes and external factors. For instance, brain networks are modified during development (Raznahan et al., 2011), and functional connectivity is sensitive to training (Bermudez et al., 2009). Recent models of biological learning use maplike structures (Tyulmankov et al., 2021) and network representations to study variations due to development and external stimuli. Associative-based mechanisms of biological learning rely on cortical plasticity, which affects the entire neocortex, which may also apply to processes like *statistical learning*, that is, the statistical structure inherent in auditory nonword speech stream (Conway, 2020). We highlight the role of ML models in understanding human behavior, cognition, and decision-making, especially through Bayesian reinforcement learning and Hebbian plasticity. Studies on speech processing plasticity demonstrate the complexities of modeling behavioral differences, while rest is shown to be crucial for memory consolidation and learning, with replay in place cells playing a significant role. Temporal difference (TD) learning is used to model dopaminergic neuron responses, illustrating the brain's use of both model-free and model-based methods in decision-making. Recent advancements in deep learning are reshaping theories of intelligence, proposing that meta-reinforcement learning and synaptic plasticity in neural networks could replicate biological learning processes.

Behavior, Cognition, Learning, Decision-making

Efforts have been made to formulate broader principles of neural plasticity that could explain human behavior and cognition using ML models. These resort to exploiting principles of neural adaptability transcending domains. For instance, Friston et al. (2021) use Hebbian plasticity to create a free energy optimization framework for neuronal computation and probabilistic world models. However, these efforts seem constrained due to the use of backpropagation and gradient descent for ANN estimation, as these approaches do not agree with our current understanding of plasticity and the development of biological neural circuits (Yildirim et al., 2020).

The most common approaches for modeling higher-cognitive aspects of plasticity include probabilistic (e.g., Bayesian causal learning) and reinforcement learning (RL) (Frankenhuis & Gopnik, 2023), which are well known for their data-driven flexibility. RL, in particular, has been used to model the plasticity of the brain in the context of emergent behaviors—for instance, phenotypic plasticity. This is a key distinction from the models we previously referenced, as some fall under cognitive science and not necessarily neuroscience. Traditional ML models such as Bayesian approaches (Habenschuss et al., 2012; Nessler et al., 2013; Thomson & Lebiere, 2013; Xu & Tenenbaum, 2001) and Gaussian processes (Meder et al., 2021) have been used to model the plasticity of learning. RL has been widely used for exploration-exploitation modeling problems at various neurological and behavioral resolution levels, which shows its versatility and scalability capabilities. Some RL examples include Zhang and Yu (2013), who use a Bayesian RL framework to model behavioral aspects of learning; Cohen et al. (2007), who use a doubly logistic model to represent the utility (cost and reward) in human decision-making; and Su and Cohen (2023), who model the firing mode of norepinephrine neurons in the locus coeruleus (a major neuromodulatory system involved in neural plasticity in the cortex) that simulates the RL process. These models suggest a strong dependence of the learning functions on the parameters rather than the learning task. A recent discussion on the locus coeruleus's role in learned behavior and plasticity is presented in Breton-Provencher et al. (2021).

The level of exploration is markedly larger at a young age, in terms of both internal representations and external information processing (Gopnik, 2020). Some earlier models, such as Wilson et al. (2014), use logistic regression to capture the set of spatial locations, rewards, and information about the choices in an experiment where the human solution to the explore-exploit problem was studied. It has long been believed that biological brains implement RL through the dopaminergic (DA) system (Cohen et al., 2007). Some RL methods have been used also to provide feedback to participants and enhance the plasticity of cognitive control. For instance, Markov decision process (MDP) has been used not only for modeling purposes but also for improving their planning strategies (Callaway et al., 2022). Lieder et al. (2018) model the adaptive control strategies involved in human learning using RL, more specifically MDPs.

The Effect of Speech and Plasticity on Behavior

Understanding plasticity in speech processing underscores the importance of multimodal fusion since multimodal data in the form of sequences of sound, neural behavior, and other variables need to be considered together by identifying the causal effects in the sequences. Thus, adaptability is also a critical characteristic of the models needed. Some of the challenges in speech processing plasticity illustrate the importance of understanding context constraints both for modeling plasticity and developing modern AI technologies. Cope et al. (2017) compared response profiles for otherwise identical sequences of speech tokens (nonsense words) and tone sweeps and used hierarchical cluster analysis to group patterns of speech-tokens using Spearman correlation. These patterns were studied for three groups of subjects: nonfluent variant primary progressive aphasia (nfvPPA), nonfluent aphasia due to stroke, and controls. While the model itself was not a generative one (simulation), but rather an unsupervised learning descriptive model, it provides valuable insights on the plasticity of speech processing, where nfvPPA performed somewhere between the other two groups and with no statistically significant difference compared to the other two groups. This shows that modeling these differences in plasticity is also challenging at the behavioral level (Cope et al., 2017).

Adaptive models are critically important in higher-level processes. Certain aspects of plasticity mechanisms seem to be emulated in higher-level cognitive processes. For instance, the rational meta-reasoning framework offers tools to explore how people select strategies or algorithms for cognitive tasks, including managing memory and deploying attention. Rational meta-reasoning models meta-reasoning (Griffiths et al., 2019) by incorporating the utility that would be acquired by executing a computation, and the cost as functions depending on the current state of the agent's belief. Models like rational meta-reasoning (Griffiths et al., 2019) elucidate decision-making strategies through computational lenses, integrating cognitive control signals within an adaptive framework. Specifically, rational meta-reasoning abstracts rationality in a similar manner as computing the value of computation (VOC), which is a function of the reward: the difference of the increase of the expected utility of executing a computation/signal to exert cognitive control minus the cost of the computation. However, this reward is not isolated and is the result of other cognitive control signals, and thus VOC is the sum of the current reward (for the current signal) plus the expected sum of meta-level rewards (Lieder et al., 2018). Thus, VOC measures the value of control resulting from a set of signals. However, with the rise of modern AI technologies, such as foundation models including large language models, a deeper understanding of the context and properties of natural plasticity becomes necessary. Three constraints associated with that context include time, computation, and communication constraints. Griffiths (2020) points out examples of ML models that comply with those constraints. Examples include rational meta-reasoning (Griffiths, 2020), model-agnostic meta-learning (Finn et al., 2017), and Bayesian inference (Grant et al., 2018), among others. In addition to identifying causal associations that explain the mechanisms of plasticity that affect higher-level cognitive processes, ML models could improve predictive performance from a neuropsychological perspective (Yarkoni & Westfall, 2017) and better data integration and variable association discovery from a neuroscience perspective (Vu et al., 2018).

Models integrating Markov decision processes (MDPs) and hidden Markov models (HMMs) (Jain et al., 2023) have been instrumental in inferring cognitive strategies, enhancing adaptability in planning and consolidation algorithms. The work of Lieder and Griffiths (2017) used a feed-forward neural network (FFNN) architecture that also incorporates Bayesian linear regression, Bayesian model selection, and linear predictive models (Sutton & Barto, 2018) applied to reinforcement learning problems for strategy selection. Cognitive plasticity required for learning the causal structure of the environment uses probabilistic models of cognition, where causal models specify the probability of observing a particular statistical pattern of evidence using Bayesian inference (Gopnik et al., 2017). A more detailed description of models of rationality in decision-making and historical notes appears in Lieder and Griffiths (2020).

Memory, Rest, and Plasticity

ML techniques used to model the interaction of rest, memory, and plasticity have been traditionally mostly probabilistic, in addition to neural simulations, because these provide data-driven flexibility, adaptability, and ease of data fusion for the associated signals. Rest plays an important role in brain plasticity as planning and consolidation occur (Ólafsdóttir et al., 2018) during rest, possibly aided by the distraction of sensory input (Wamsley, 2019). To represent the effect of rest in memory, a modeling choice is using the Bayes rule to compute probabilities of activities given neural activity to abstract *replay*, which is the process that place cells perform for recapitulating past trajectories (Ólafsdóttir et al., 2018). However, although replay seems to have an impact on memory plasticity and consolidation, the mechanism is still far from fully understood, and experimental and modeling challenges still exist. From a modeling perspective, McClelland et al. (1995) provided a measurable account of this possible relation between rest, learning, and memory. In this work, several neural network architectures and other related models are described (hippocampal synaptic plasticity during slow-wave sleep is a key element of the analysis). The consolidation process itself is captured with a parsimonious probabilistic model, where the probability of a correct neural response is a total probability function of the hippocampal system, the neocortical system, or random assignment. Details on the setup and parameters (including the consolidation) are presented in McClelland et al. (1995). The work of Agrawal et al. (2022) follows a similar idea and formulates the effect of fatigue on planning and consolidation (P&C) algorithmically within an RL framework, whereby fatigue works as a trigger of P&C. Although it is widely supported that the prefrontal cortex controls executive functions, discrete cortico-striatal networks control both goal-directed and automatic-habitual decision processes (Balleine et al., 2009). These processes are different and involve different forms of plasticity (Partridge et al., 2000; Smith et al., 2001), learning rules, and computations. A schema of the brain regions involved in these processes is shown in Figure 1.

Modeling the Effect of Dopamine on Plasticity

As in other neural modeling problems, the TD learning algorithm of reinforcement learning (Sutton & Barto, 2018) has been used (e.g., together with the actor-critic model) because the phasic burst of midbrain dopaminergic neurons fired during appetitive tasks can be well captured with TD prediction (Daw et al., 2006). Under the TD/actor-critic model, dopaminergic plasticity in the ventral striatum (and its afferents) has been associated with the critic, while dopaminergic plasticity in the dorsal striatum has been associated with the actor (Montague et al., 1996; O'Doherty et al., 2004). Dopaminergic neurons' functional coding has been modeled using regression (e.g., Engelhard et al., 2019).

Model-free and model-based TD learning approaches (Daw & Dayan, 2014) provide complementary insights into synaptic plasticity within striatal regions, highlighting the brain's adaptive strategies under uncertainty (Figure 1). While model-free RL models are useful to represent synaptic plasticity in certain scenarios as discussed earlier (ventral and dorsolateral striatum), the brain seems to use model-based methods for planning under uncertainty (Dayan & Daw, 2008). Suri and Schultz (2001) present another example of RL applied to neural activity: TD learning. Daw and Tobler (2014) offer a detailed introduction to dopamine response, plasticity, and RL modeling.

Intelligence

Advances in deep learning theories focus on domain-agnostic and even universal humanlike principles of intelligence (Botvinick et al., 2017), reshaping traditional perspectives in neuroscience. For instance, Wang et al. (2018) suggest that meta-reinforcement learning can model learning in biological brains where recurrent networks on the prefrontal cortex implement the core of learning, which is trained by dopamine-driven synaptic plasticity (Botvinick et al., 2019). Payeur et al. (2021) propose to use synaptic plasticity paired with the neural circuitry dynamics (short-term synaptic dynamics, apical dendrite regeneration) as explanatory variables of learning, contrasting with traditional models that focus on pre- and postsynaptic activity to capture synaptic changes as a key physiological mechanism for learning. Here synaptic activity is regulated by high-frequency bursts of spikes where pyramidal neurons higher in the hierarchical circuit coordinate the plasticity of lower-level connections. In this work, a deep network model was used to learn the classification tasks. As discussed in Ascoli et al. (2014), simulations of neurons with accurate membrane biophysics, and molecular dynamics within individual synapses, could provide the foundation for modeling network plasticity and learning. General and fluid intelligence have both been modeled with ML methods linking brain network properties with cognitive ability (Anderson & Barbey, 2023; Wilcox & Barbey, 2023).

Brain Damage and Regeneration

Adaptive plasticity in the brain includes compensation, neural reserve, and degeneracy, which support functional recovery and reorganization by increasing activity in unaffected areas to counteract dysfunction. Conversely, maladaptive plasticity in schizophrenia impairs brain network modularity, disrupting cognitive functions. Advanced research uses ML tools, such as symbolic transfer entropy and generative adversarial models, to differentiate patients from healthy individuals based on network connectivity patterns. Understanding these neural disruptions and applying sophisticated neuroimaging methods are essential for creating effective treatments for cognitive impairments linked to psychiatric disorders and postsepsis conditions. ML is crucial to analyze and represent these neuroplasticity phenomena due to its flexibility, nonlinearity, and adaptation.

Adaptive Plasticity

Adaptive plasticity is the brain's capacity for compensation and reorganization to maintain correct function. This involves compensation, neural reserve, and degeneracy. *Compensation* is the reorganization of unaffected neural components whose activity is increased to compensate for the dysfunction of the affected elements. This process is facilitated by neural and cognitive plasticity. *Reserve* is the tissue within a system that can support brain function when needed. *Degeneracy* is the ability of alternative neural components to take on the functions of a damaged system. Adaptive plasticity involves complex network function adaptations (Scott & Frank, 2023), and metaplasticity mechanisms that affect both the intrinsic excitability of a neuron (Farashahi et al., 2017; Sehgal et al., 2013), and system level of the human cortex (Müller-Dahlhaus & Ziemann, 2015). The cerebellum, for instance, calibrates motor control parameters using error-based learning (Kiper et al., 2016). Metaplasticity of the neuron has been modeled to represent neuronal excitability (Sehgal et al., 2013) and incorporate adaptability through uncertainty-aware reward functions (Farashahi et al., 2017).

Studies on repetitive transcranial magnetic stimulation (rTMS) to enhance conventional rehabilitation highlight the potential in improving aphasia and visuospatial neglect after stroke. The interaction between brain hemispheres, especially regarding the primary motor cortex, is crucial in motor recovery, and techniques stimulating peripheral or central nervous systems are investigated to aid in overcoming motor deficits, which highlights the role of computational models to test hypotheses in these areas.

Most research focuses on understanding cellular mechanisms, developing techniques to enhance exercise-induced plasticity, and biomedical engineering for functional recovery. Neurotransmitter systems and pharmacological treatments like amphetamines, cholinergic agents, and selective serotonin reuptake inhibitors (SSRIs) have shown promise in aiding rehabilitation, but their direct impact on motor skill learning remains unclear. Maintaining brain plasticity across all ages is vital, with environmental changes influencing cortical reorganization. Neuroplasticity is essential in stroke rehabilitation, with various therapies enhancing motor recovery through brain reorganization. For instance, dopamine replacement therapy in humans has been shown to alleviate learning impairment for Parkinson's disease patients in cognitive RL tasks (Frank et al., 2004).

Maladaptive Plasticity

Maladaptive or aberrant plasticity may cause *dedifferentiation*, a process whereby reduced modularity of functional brain networks can affect specialized processes, for instance, in patients with schizophrenia (Winterer & Weinberger, 2004). Thus, much research attempts to exploit patterns related to network connectivity to identify schizophrenia and other psychiatric disorders. For instance, (Durstewitz et al., 2021) use ML methods to differentiate patients with schizophrenia from healthy controls using information theoretical representation using data-driven flexibility in brain dynamics. Masychev et al. (2021) use symbolic transfer entropy (STE) effective connectivity, and linearly constrained minimum variance (LCMV) for brain-source localization (BSL) for electroencephalography (EEG) data. Generative adversarial methods have been proposed to model plasticity and brain adaptation (Cortes-Briones et al., 2022).

Research on the functional brain networks of patient groups reveals reduced modularity, suggesting a less organized network structure (Alexander-Bloch et al., 2010). The dispersed and integrated activity in this cohort is attributed to abnormal plasticity, irregularities in neurodevelopmental circuitry, and alterations in modulatory effects linked to key catecholamines such as dopamine. These factors may affect nonlinear representability in fine-tuning and the signal-to-noise ratio during the processing of neural information (Winterer & Weinberger, 2004).

Modeling the glial role in neuroplasticity, which may be important to better understand cognitive impairment, has been explored less than the neuronal counterpart. Postsepsis cognitive impairment seems to arise from oxidative stress and neuroinflammation. Elevated levels of reactive oxygen species (ROS) cause cellular damage, which can be exacerbated with continuous microglial activation. These lead to problems like blood-brain-barrier dysfunction, synaptic loss, and neuronal cell death (Simpson & Oliver, 2020). All of these phenomena contribute to cognitive impairment (Roberson et al., 2023; Wu et al., 2015). Rehabilitation therapy plays a crucial role in promoting neuroplasticity by aiding in the creation of new neural pathways. Various non-invasive neuroimaging techniques like fMRI, magnetoencephalography (MEG), TMS, EEG, and positron emission tomography (PET) are used to understand brain connectivity changes during motor tasks and rehabilitation, offering insights into neural reorganization poststroke. Finally, various therapeutics and rehabilitation technologies for neuroplasticity-related illnesses have been studied using ML tools, including brain-computer interfaces (Chiou et al., 2024) and deep-brain stimulation (Alagapan et al., 2023).

Open Questions and Future Directions

Methodological Open Problems

Despite remarkable advancements, modeling plasticity is still an ongoing effort. Specifically, areas that can benefit from methodological and experimental insights include scale integration of plasticity, learning mechanisms, incorporation of cognitive functions, validation and benchmarking, and applications to real-world systems and model personalization.

Scale integration.

Modeling plasticity at different scales, from synaptic changes to large-scale brain network reconfigurations, remains a complex task, and integration with neuroanatomical domain knowledge remains a challenging task (Mitra, 2014). While many efforts have been made (Piray & Daw, 2020; Richards & Kording, 2023; Zucchet et al., 2022), integrating insights across these scales for a comprehensive understanding is an ongoing challenge.

Dynamic connectivity.

Capturing the dynamic nature of neural connectivity and understanding how it evolves in response to experiences or stimuli is a significant challenge in the ongoing research (Rao & Sejnowski, 2001; Shine et al., 2019). However, modeling changes in connectivity and their impact on information processing remains elusive.

Learning mechanisms.

Developing accurate and comprehensive models for various learning mechanisms—including STDP (Avram et al., 2010; Barazany et al., 2009; Bermudez et al., 2009; He et al., 2007; Raznahan et al., 2011; Song & Abbott, 2001; Wedeen et al., 2005; Zatorre et al., 2012), reinforcement learning, and metaplasticity—is an ongoing challenge. Understanding how these mechanisms interact and contribute to adaptive behavior is a core neuroscience problem.

Incorporating cognitive functions.

Extending neuroplasticity models to encompass higher-order cognitive functions—such as memory, decision-making, and language processing—poses the challenges of scale integration, dynamic connectivity, and so on (Cope et al., 2017; Gopnik, 2020; Wilson et al., 2014). The connection between low-level plasticity and complex cognitive processes is an ongoing area of research.

Validation and benchmarking.

Establishing reliable methods for validating neuroplasticity models and creating benchmarks for comparing different models is crucial (Chaves et al., 2021; Mulugeta et al., 2018; Spence et al., 2023; Tan et al., 2015). This includes finding appropriate metrics to assess the model's performance in capturing biological phenomena.

Transferability to real-world systems.

Ensuring bio-inspired models' application to real-world systems, such as brain-machine interfaces or neuromorphic hardware, is a challenge. Achieving robustness and adaptability in practical settings remains an open problem. A transferability example is answering the question of how system-level plasticity can be modeled to create optimal retinal neuroprosthesis (Yu et al., 2020).

Individual variability. Accounting for individual variability in neuroplasticity patterns and responses is a challenge (Chrastil et al., 2017; Saletin et al., 2016). Developing models that can capture and predict the diverse ways individuals may adapt to experiences or interventions is an open problem.

Leveraging ML to Solve Open Problems in Neuroplasticity

Many open problems in neuroscience could benefit from ML insights. For instance, a complete description of the mechanistic basis of executive functions remains elusive, even though the brain's prefrontal cortex is identified as responsible for them by various studies, and great advances have been achieved in the last 10 years (Duncan & Owen, 2000; Nord et al., 2020; Nowrangi et al., 2014; Reineberg & Banich, 2016; Zelazo & Carlson, 2023). The integration of Hebbian and homeostatic plasticity is still an open problem (Fox & Stryker, 2017). System-level plasticity models are needed to create advanced retinal neuroprosthesis (Yu et al., 2020). We also described the possible role of replay—which occurs during sleep, rest, and active navigation, aiding memory stabilization, planning, and decision-making—but the mechanisms and relationships involved are complex and not fully understood. Understanding replay's role requires not only manipulating hippocampal replay but also demonstrating its impact on memory maturation, examining the intricate link between awake replay and behavior, and exploring the influence of extra-hippocampal regions and cortical autonomy in initiating and guiding replay. All these tasks require the support of nuanced models that account for intra- and extra-hippocampal function, memory, and place-cell replay process. Many neuroplasticity models are computationally intensive. Improving the efficiency of these models, especially for real-time applications or large-scale simulations, is an ongoing challenge (Dan et al., 1996). Bioinspired neuroplasticity modeling requires collaboration across various disciplines, including neuroscience, computer science, and engineering (Amadio et al., 2018). Integrating these fields and integrating them is still a challenge.

Discussion and Limitations

This chapter explores various aspects of neuroplasticity and brain function through the lens of statistical machine-learning modeling. We discussed the advantages of ML modeling of neural plasticity, highlighting some of the methodological challenges that could be encountered in this process. ML surpasses traditional statistical methods in modeling complex brain plasticity due to its ability to handle large, high-dimensional data and uncover intricate patterns without extensive prior assumptions. Traditional methods often rely on predefined models and assumptions that can limit their applicability and accuracy. Domain-agnostic and scalable ML algorithms can adaptively learn from data and improve over time, making them robust in diverse in dynamic environments (e.g., understanding eye movements and limb control).

ML excels in automatically extracting features from data, a significant advantage over traditional methods. Techniques like convolutional neural networks can autonomously learn hierarchical features from visual data, revealing complex relationships without explicit programming. This automatic extraction capability is crucial for exploring motor control and visual systems, where ML can identify subtle patterns in spike discharge characteristics and sensory feedback that traditional methods might miss.

One of ML's core strengths is its ability to capture nonlinear relationships within data. Neural networks, for instance, can model complex, nonlinear interactions in brain plasticity, such as synaptic changes and motor command history. These models, including recurrent neural networks (RNNs) and Bayesian frameworks, provide a more nuanced understanding of brain function and adaptation compared to linear models like Wiener filters used in traditional statistical approaches.

ML facilitates data fusion by integrating multiple data modalities, enhancing the understanding of brain plasticity. For example, combining neural network architectures with probabilistic models allows for a

comprehensive analysis of how rest influences memory consolidation and learning processes. This multimodal fusion capability enables the synthesis of information from diverse sources, such as EEG, fMRI, and behavioral data, providing a holistic view that traditional methods struggle to achieve. The flexibility of ML is evident in its application across various domains and scales of brain plasticity. ML models, such as reinforcement learning and hierarchical Bayesian frameworks, adapt to different levels of neural complexity, from microscale synaptic changes to macroscale brain network reconfigurations.

This chapter has also covered the application of ML models to understand brain network disruptions in healthy and impaired brains, emphasizing the role of advanced multimodal data processing (e.g., neuroimaging, sequential multimodal data) in understanding plasticity for developing therapeutic strategies. This chapter has discussed the modeling advantages of ML for adaptive plasticity mechanisms such as compensation and neural reserve in motor recovery and cognitive rehabilitation, highlighting the interdisciplinary approach combining neuroscience with computational methods to study brain disorders and rehabilitation techniques.

This chapter aims to serve as a reference for neuroscientists interested in applying data-driven ML models for identifying data patterns to solve neuroplasticity research questions in a scalable manner, but also to serve as a reference for ML practitioners interested in brain plasticity phenomena's current and open problems. We make the following observations:

1. This chapter identifies ML models that aim to emulate, simulate, or abstract brain plasticity instead of simply providing analogies of the mechanisms. Most current literature highlights the similarities of ML with brain plasticity mainly using analogies without a discussion on what is known on plasticity. Our chapter aims to highlight biologically driven ML models that either directly simulate brain plasticity phenomena or represent variables associated with or related to brain plasticity.
2. We create a fivefold characterization of the advantages of ML for modeling plasticity. We highlight some of the key advantages ML and data-driven approaches have that position ML as a critically useful toolbox for fast and scalable advancement of neuroplasticity research by automated pattern identification that could facilitate the “Big Science” of neuroplasticity through data-driven exploration, discovery, and testing. Some insights related to these ML characteristics include:
 - (a) **Model-level flexibility—theory agnosticism and scalability.** The use of hierarchical model-based control and ML for predicting cognitive outcomes in brain plasticity models illustrates domain-agnostic approaches that can scale effectively across different levels of brain function including vision. Functional connectivity patterns in sensorimotor cortical neurons also highlight this level of domain-agnosticism. This is also true for models that aim to represent synaptic plasticity to understand memory storage capacity and accuracy in neural networks. The adaptability and scalability of graph neural networks, as mentioned in the context of representing plasticity effects at both micro and macro levels, further support the criterion of scalability in brain plasticity modeling in motor control, vision, and storage capacity of the mammalian neocortex. Agnosticism is also a characteristic of models of the cortical column that work at different levels of resolution, which is useful also to capture micro-level parameters.
 - (b) **Data-level flexibility.** The brain's use of approximate inference can be modeled using generative models and mesoscale connectomics analysis, which handles diverse data types. These methods adapt to varying data inputs to model brain plasticity effectively. The adaptability of graph mining and relational learning to represent the effects of brain plasticity also demonstrates significant data-driven flexibility, allowing for varied data integration and inference. We discussed various models of the visual cortex, sensory-motor cortex, and mammalian neocortex that automatically capture latent features from neuron stimuli.
 - (c) **Nonlinear representability.** The nonlinear representability is evident in models such as the

cerebellum's three-layer FFNN, which effectively captures the nonlinear dynamics involved in brain plasticity. Nonlinear representation is further highlighted by models that focus on synaptic changes in neural networks, capturing the complex and nonlinear nature of plasticity processes. We discussed various examples from the sensory and motor systems that use three types of coordinate representations to generate and control movements. The models leverage the intrinsic redundancy of the musculoskeletal system for adaptable and successful task completion. Another example of nonlinear representability includes the application of coding theory to determine memory capacity in neural network models, such as Hopfield networks.

- (d) **Data integration via multimodal fusion.** An example of a distribution-alignment decoding algorithm aims at integrating data from various sources to create a movement decoding framework without jointly measuring neural activity and motor activity. Probabilistic fusion is also used in visual cortex modeling. Parametric probabilistic data fusion in cortical and subcortical regions has been explored for some disorders (DeRamus et al., 2022). The integration of micro- and macro-level plasticity, such as STDP and brain network reconfigurations, showcases multimodal analysis in brain plasticity models. This integration allows for comprehensive modeling of brain dynamics across different scales. The use of fMRI data to model brain dynamics, alongside neural-level plasticity and metaplasticity, further exemplifies integrating data modalities into a cohesive model.
- (e) **Adaptability and flexibility.** The adaptability and flexibility of graph neural networks, Bayesian models, and so on—which can represent brain network function changes at both micro and macro levels—highlight the robust adaptability of these models to different aspects of brain plasticity. The proposal that the brain uses approximate inference with generative adversarial models demonstrates the powerful adaptability and flexibility of these models in capturing the dynamic and complex processes of brain plasticity. Modeling approaches for cortical networks and memory—in, for example, Roberson et al. (2023) and Xu and Tenenbaum (2001)—illustrate the adaptability and flexibility of various models on memory.

Other systems for which we discussed these fivefold characteristics include neuron-level plasticity phenomena (synaptic and homeostatic) and the cortical column. For this, we devoted a full subsection that included examples of modern simulations that had led to impressive practical applications in video analysis and computer vision. Furthermore, we presented some examples of work where adaptability and flexibility have been critical for developing models to capture and represent changes in brain plasticity as it develops. This chapter has included a discussion of various modeling aspects associated with behavior, cognition, decision-making, and memory, including a subsection devoted to models of the striatum and the midbrain and the effects of dopamine on plasticity. Finally, we cited works on adaptive and maladaptive plasticity and discussed a selection of open problems in neuroplasticity modeling.

Ethical challenges.

In general, ethical considerations related to privacy, security, and the potential societal impact of applying these models need careful attention (Amadio et al., 2018), both in terms of the experimental design (Fry, 2019) and ML modeling (Ienca & Ignatiadis, 2020). In addition to the ethical challenges associated with data collection and model training, the use of such models is an area that requires attention. For instance, translating methods such as memory editing technology (Phelps & Hoffman, 2019) from animal models to humans can have some medical applications in therapeutics but they could also pose ethical and practical challenges in terms of protection of human subjects.

Limitations. Despite the opportunities, some constraints must be considered when applying ML to neuroplasticity research. In addition to the experimental challenges, ML can pose challenges associated with the data used for building the models and with the interpretability of some ML models. First, ML models

require large amounts of high-quality data to train effectively. In neuroplasticity research, obtaining such data can be challenging due to the variability and complexity of brain functions, the difficulty of precise measurements, and the ethical and practical constraints of extensive data collection from human subjects. Inadequate or noisy data can significantly hinder the performance and reliability of ML models. Second, ML may lead to difficulties in interpretation. For instance, latent variables could lead to spurious variable relations. Another example of ML interpretability challenges is that some architectures are considered black boxes due to their complex and nontransparent internal workings, which can be a considerable obstacle in neuroscience. Despite these potential issues, ML can offer substantial advantages that outweigh its constraints—by acknowledging possible latent dependencies and by highlighting the resulting dependencies at the model level that are not evident at the data level.

In summary, machine learning's domain-agnostic capabilities, automatic feature extraction, ability to capture nonlinear relationships, data fusion capabilities, and flexibility can provide additional and complementary advantages to traditional statistical methods in studying brain plasticity and related neurological processes. While much work is still needed to take full advantage of these properties of ML—particularly for the integration of neuroplasticity at various resolution levels—we highlight a fivefold analysis of the strengths of current ML and emphasize the important role these characteristics play in facilitating the creation of automated tools for high-scale neuroplasticity exploration, discovery, and testing. This chapter aims to serve as a link for neuroscientists interested in applying ML models on neuroplasticity research questions, and a reference for ML practitioners interested in brain plasticity.

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References

Acharya, J., Basu, A., Legenstein, R., Limbacher, T., Poirazi, P., & Wu, X. (2022). Dendritic computing: Branching deeper into machine learning. *Neuroscience*, *489*, 275–289.

[Google Scholar](#) [WorldCat](#)

Agrawal, M., Mattar, M. G., Cohen, J. D., & Daw, N. D. (2022). The temporal dynamics of opportunity costs: A normative account of cognitive fatigue and boredom. *Psychological Review*, *129*(3), 564–585.

[Google Scholar](#) [WorldCat](#)

Alagapan, S., Choi, K. S., Heisig, S., Riva-Posse, P., Crowell, A., Tiruvadi, V., Obatusin, M., Veerakumar, A., Waters, A. C., Gross, R. E., Quinn, S., Denison, L., O'Shaughnessy, M., Connor, M., Canal, G., Cha, J., Hershenberg, R., Nauvel, T., Isbaine, F., ... Rozell, C. J. (2023). Cingulate dynamics track depression recovery with deep brain stimulation. *Nature*, *622*(7981), 130–138.

[Google Scholar](#) [WorldCat](#)

Albert, M. V., Catz, N., Thier, P., & Kording, K. (2012). Saccadic gain adaptation is predicted by the statistics of natural fluctuations in oculomotor function. *Frontiers in Computational Neuroscience*, *6*, Article 96, 1–7.

[Google Scholar](#) [WorldCat](#)

Alexander-Bloch, A. F., Gogtay, N., Meunier, D., Birn, R., Clasen, L., Lalonde, F., Lenroot, R., Giedd, J., & Bullmore, E. T. (2010). Disrupted modularity and local connectivity of brain functional networks in childhood-onset schizophrenia. *Frontiers in Systems Neuroscience*, *4*, 147.

[Google Scholar](#) [WorldCat](#)

Alexandre, F., Guyot, F., Haton, J.-P., & Burnod, Y. (1991). The cortical column: A new processing unit for multilayered networks. *Neural Networks*, *4*(1), 15–25.

[Google Scholar](#) [WorldCat](#)

Amadio, J., Bi, G.-Q., Boshears, P. F., Carter, A., Devor, A., Doya, K., Garden, H., Illes, J., Johnson, L. S. M., Jorgenson, L., Jun, B.-O., Lee, I., Michie, P., Miyakawa, T., Nakazawa, E., Sakura, O., Sarkissian, H., Sullivan, L. S., Uh, S., ... Singh, I. (2018). Neuroethics questions to guide ethical research in the international brain initiatives. *Neuron*, *100*(1), 19–36.

[Google Scholar](#) [WorldCat](#)

Andersen, M., Winther, O., Hansen, L. K., Poldrack, R., & Koyejo, O. (2018). Bayesian structure learning for dynamic brain connectivity. In A. Storkey & F. Perez-Cruz (Eds.), *International Conference on Artificial Intelligence and Statistics* (pp. 1436–1446). PMLR.

[Google Scholar](#) [Google Preview](#) [WorldCat](#) [COPAC](#)

Anderson, E. D., & Barbey, A. K. (2023). Investigating cognitive neuroscience theories of human intelligence: A connectome-based predictive modeling approach. *Human Brain Mapping*, *44*(4), 1647–1665.

[Google Scholar](#) [WorldCat](#)

Ascoli, G. A., Botvinick, M. M., Heuer, R. J., & Bhattacharyya, R. (2014). Neurocognitive models of sense-making. *Biologically Inspired Cognitive Architectures*, *8*, 82–89.

[Google Scholar](#) [WorldCat](#)

Avram, A. V., Guidon, A., & Song, A. W. (2010). Myelin water weighted diffusion tensor imaging. *Neuroimage*, *53*(1), 132–138.

[Google Scholar](#) [WorldCat](#)

Balleine, B. W., Daw, N. D., & O'Doherty, J. P. (2009). Multiple forms of value learning and the function of dopamine. In Paul W. Glimcher, C. F. Camerer, E. Fehr, & R. A. Poldrack (Eds.), *Neuroeconomics* (pp. 367–387). Elsevier.

[Google Scholar](#) [Google Preview](#) [WorldCat](#) [COPAC](#)

Barazany, D., Basser, P. J., & Assaf, Y. (2009). In vivo measurement of axon diameter distribution in the corpus callosum of the rat

brain. *Brain*, 132(5), 1210–1220.

[Google Scholar](#) [WorldCat](#)

Benjamin, A., Rolnick, D., & Kording, K. (2019). Measuring and regularizing networks in function space. In *International Conference on Learning Representations* (pp. 1–8). New Orleans, LA. <https://openreview.net/forum?id=SkMwpiR9Y7>

[Google Scholar](#) [WorldCat](#)

Bermudez, P., Lerch, J. P., Evans, A. C., & Zatorre, R. J. (2009). Neuroanatomical correlates of musicianship as revealed by cortical thickness and voxel-based morphometry. *Cerebral Cortex*, 19(7), 1583–1596.

[Google Scholar](#) [WorldCat](#)

Botvinick, M., Barrett, D. G. T., Battaglia, P., de Freitas, N., Kumaran, D., Leibo, J. Z., Lillicrap, T., Modayil, J., Shakir, M., Rabinowitz, N. C., Rezende, D. J., Santoro, A., Schaul, T., Summerfield, C., Wayne, G., Weber, T., Wierstra, D., Legg, S., & Hassabis, D. (2017). Building machines that learn and think for themselves. *Behavioral and Brain Sciences*, 40, e255.

[Google Scholar](#) [WorldCat](#)

Botvinick, M., Ritter, M. S., Wang, J. X., Kurth-Nelson, Z., Blundell, C., & Hassabis, D. (2019). Reinforcement learning, fast and slow. *Trends in Cognitive Sciences*, 23(5), 408–422.

[Google Scholar](#) [WorldCat](#)

Botvinick, M., & Weinstein, A. (2014). Model-based hierarchical reinforcement learning and human action control. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 369(1655), 20130480.

[Google Scholar](#) [WorldCat](#)

Boutet, A., Germann, J., Gwun, D., Loh, A., Elias, G. J. B., Neudorfer, C., Paff, M., Horn, H., Kuhn, A. A., Munhoz, R. P., Kalia, S. K., Hodaie, M., Kucharczyk, W., Fasano, A., & Lozano, A. M. (2021). Sign-specific stimulation “hot” and “cold” spots in Parkinson’s disease validated with machine learning. *Brain Communications*, 3(2), fcab027.

[Google Scholar](#) [WorldCat](#)

Bowe, A. K., Lightbody, G., Staines, A., & Murray, D. M. (2023). Big data, machine learning, and population health: Predicting cognitive outcomes in childhood. *Pediatric Research*, 93(2), 300–307.

[Google Scholar](#) [WorldCat](#)

Braitenberg, V., & Schüz, A. (2013). *Cortex: Statistics and geometry of neuronal connectivity*. Springer Science & Business Media.

[Google Scholar](#) [Google Preview](#) [WorldCat](#) [COPAC](#)

Breton-Provencher, V., Drummond, G. T., & Sur, M. (2021). Locus coeruleus norepinephrine in learned behavior: Anatomical modularity and spatiotemporal integration in targets. *Frontiers in Neural Circuits*, 15, 46.

[Google Scholar](#) [WorldCat](#)

Brunel, N., Hakim, V., Isope, P., Nadal, J.-P., & Barbour, B. (2004). Optimal information storage and the distribution of synaptic weights: Perceptron versus Purkinje cell. *Neuron*, 43(5), 745–757.

[Google Scholar](#) [WorldCat](#)

Cain, N., Iyer, R., Koch, K., & Mihalas, S. (2016). The computational properties of a simplified cortical column model. *PLOS Computational Biology*, 12(9), e1005045.

[Google Scholar](#) [WorldCat](#)

Callaway, F., Jain, Y. R., van Opheusden, B., Das, P., Iwama, G., Gul, S., Krueger, P. M., Becker, F., Griffiths, T. L., & Lieder, F. (2022). Leveraging artificial intelligence to improve people’s planning strategies. *Proceedings of the National Academy of Sciences*, 119(12), e2117432119.

[Google Scholar](#) [WorldCat](#)

Carandini, M., Demb, J. B., Mante, V., Tolhurst, D. J., Dan, Y., Olshausen, B. A., Gallant, J. L., & Rust, N. C. (2005). Do we know what the early visual system does? *Journal of Neuroscience*, 25(46), 10577–10597.

[Google Scholar](#) [WorldCat](#)

Chaves, A. R., Snow, N. J., Alcock, L. R., & Ploughman, M. (2021). Probing the brain-body connection using transcranial magnetic stimulation (TMS): Validating a promising tool to provide biomarkers of neuroplasticity and central nervous system function. *Brain Sciences*, *11*(3), 384.

[Google Scholar](#) [WorldCat](#)

Chiou, N., Günal, M., Koyejo, S., Perpetuini, D., Chiarelli, A. M., Low, K. A., Fabiani, M., & Gratton, G. (2024). Single-trial detection and classification of event-related optical signals for a brain-computer interface application. *Bioengineering* (Basel, Switzerland), *11*(8), 781.

[Google Scholar](#) [WorldCat](#)

Chrastil, E. R., Sherrill, K. R., Aselcioglu, I., Hasselmo, M. E., & Stern, C. E. (2017). Individual differences in human path integration abilities correlate with gray matter volume in retrosplenial cortex, hippocampus, and medial prefrontal cortex. *Neuro*, *4*(2), 1–14, article e0346.

[Google Scholar](#) [WorldCat](#)

Cohen, J. D., McClure, S. M., & Yu, A. J. (2007). Should I stay or should I go? How the human brain manages the trade-off between exploitation and exploration. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *362*(1481), 933–942.

[Google Scholar](#) [WorldCat](#)

Conway, C. M. (2020). How does the brain learn environmental structure? Ten core principles for understanding the neurocognitive mechanisms of statistical learning. *Neuroscience & Biobehavioral Reviews*, *112*, 279–299.

[Google Scholar](#) [WorldCat](#)

Cope, T. E., Wilson, B., Robson, H., Drinkall, R., Dean, L., Grube, M., Jones, P. S., Patterson, K., Griffiths, T. D., Rowe, J. B., & Petkov, C. I. (2017). Artificial grammar learning in vascular and progressive non-fluent aphasias. *Neuropsychologia*, *104*, 201–213.

[Google Scholar](#) [WorldCat](#)

Cortes-Briones, J. A., Tapia-Rivas, N. I., D'Souza, D. C., & Estevez, P. A. (2022). Going deep into schizophrenia with artificial intelligence. *Schizophrenia Research*, *245*, 122–140.

[Google Scholar](#) [WorldCat](#)

Dan, Y., Atick, J. J., & Reid, R. C. (1996). Efficient coding of natural scenes in the lateral geniculate nucleus: Experimental test of a computational theory. *Journal of Neuroscience*, *16*(10), 3351–3362.

[Google Scholar](#) [WorldCat](#)

Daw, N. D. & Dayan, P. (2014). The algorithmic anatomy of model-based evaluation. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *369*(1655), 20130478.

[Google Scholar](#) [WorldCat](#)

Daw, N. D., Niv, Y., & Dayan, P. (2006). Actions, policies, values and the basal ganglia. *Recent Breakthroughs in Basal Ganglia Research*, *10*(9), 1214–1221.

[Google Scholar](#) [WorldCat](#)

Daw, N. D., & Tobler, P. N. (2014). Value learning through reinforcement: The basics of dopamine and reinforcement learning. In P. W. Glimcher & E. Fehr (Eds.), *Neuroeconomics* (pp. 283–298). Elsevier.

[Google Scholar](#) [Google Preview](#) [WorldCat](#) [COPAC](#)

Dayan, P., & Daw, N. D. (2008). Decision theory, reinforcement learning, and the brain. *Cognitive, Affective, & Behavioral Neuroscience*, *8*(4), 429–453.

[Google Scholar](#) [WorldCat](#)

Dean, T. (2005). A computational model of the cerebral cortex. In *Proceedings of the National Conference on Artificial Intelligence*, volume 20 (p. 938). AAAI Press; MIT Press, Pittsburgh, Pennsylvania, July 9–13, 2005. <https://aaai.org/wp->

<content/uploads/2023/01/aaai05program.pdf>

[Google Scholar](#) [WorldCat](#)

DeRamus, T. P., Wu, L., Qi, S., Iraj, A., Silva, R., Du, Y., Pearlson, G., Mayer, A., Bustillo, J. R., Stromberg, S. F., & Calhoun, V. D. (2022). Multimodal data fusion of cortical-subcortical morphology and functional network connectivity in psychotic spectrum disorder. *NeuroImage: Clinical*, *35*, 103056.

[Google Scholar](#) [WorldCat](#)

DiCarlo, J. J., Zoccolan, D., & Rust, N. C. (2012). How does the brain solve visual object recognition? *Neuron*, *73*(3), 415–434.

[Google Scholar](#) [WorldCat](#)

Diehl, P. U., & Cook, M. (2015). Unsupervised learning of digit recognition using spike-timing-dependent plasticity. *Frontiers in Computational Neuroscience*, *9*, 99.

[Google Scholar](#) [WorldCat](#)

Dormal, G., Rezk, N., Yakobov, E., Lepore, F., & Collignon, O. (2016). Auditory motion in the sighted and blind: Early visual deprivation triggers a large-scale imbalance between auditory and “visual” brain regions. *NeuroImage*, *134*, 630–644.

[Google Scholar](#) [WorldCat](#)

Dumoulin Bridi, M. C., Aton, S. J., Seibt, J., Renouard, L., Coleman, T., & Frank, M. G. (2015). Rapid eye movement sleep promotes cortical plasticity in the developing brain. *Science Advances*, *1*(6), e1500105.

[Google Scholar](#) [WorldCat](#)

Duncan, J., & Owen, A. M. (2000). Common regions of the human frontal lobe recruited by diverse cognitive demands. *Trends in Neurosciences*, *23*(10), 475–483.

[Google Scholar](#) [WorldCat](#)

Durstewitz, D., Huys, Q. J. M., & Koppe, G. (2021). Psychiatric illnesses as disorders of network dynamics. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, *6*(9), 865–876.

[Google Scholar](#) [WorldCat](#)

Dyer, E. L., Azar, M. G., Perich, M. G., Fernandes, H. L., Naufel, S., Miller, L. E., & Körding, K. P. (2017). A cryptography-based approach for movement decoding. *Nature Biomedical Engineering*, *1*(12), 967–976.

[Google Scholar](#) [WorldCat](#)

Einhäuser, W., Hipp, J., Eggert, J., Körner, E., & König, P. (2005). Learning viewpoint invariant object representations using a temporal coherence principle. *Biological Cybernetics*, *93*(1), 79–90.

[Google Scholar](#) [WorldCat](#)

Engelhard, B., Finkelstein, J., Cox, J., Fleming, W., Jang, H. J., Ornelas, S., Koay, S. A., Thiberge, S. Y., Daw, N. D., Tank, D. W., & Witten, I. B. (2019). Specialized coding of sensory, motor and cognitive variables in VTA dopamine neurons. *Nature*, *570*(7762), 509–513.

[Google Scholar](#) [WorldCat](#)

Fahy, F. L., Riches, I. P., & Brown, M. W. (1993). Neuronal activity related to visual recognition memory: Long-term memory and the encoding of recency and familiarity information in the primate anterior and medial inferior temporal and rhinal cortex. *Experimental Brain Research*, *96*, 457–472.

[Google Scholar](#) [WorldCat](#)

Farashahi, S., Donahue, C. H., Khorsand, P., Seo, H., Lee, D., & Soltani, A. (2017). Metaplasticity as a neural substrate for adaptive learning and choice under uncertainty. *Neuron*, *94*(2), 401–414.

[Google Scholar](#) [WorldCat](#)

Fedorenko, E., Hsieh, P.-J., Nieto-Castañón, A., Whitfield-Gabrieli, S., & Kanwisher, N. (2010). New method for fMRI investigations of language: Defining ROIs functionally in individual subjects. *Journal of Neurophysiology*, *104*(2), 1177–1194.

[Google Scholar](#) [WorldCat](#)

Finn, C., Abbeel, P., & Levine, S. (2017). Model-agnostic meta-learning for fast adaptation of deep networks. In D. Precup & Y. Whye Teh (Eds.), *International Conference on Machine Learning* (pp. 1126–1135). International Convention Centre, Sydney, Australia, August 6–11, 2017.

[Google Scholar](#) [Google Preview](#) [WorldCat](#) [COPAC](#)

Flint, R. D., Scheid, M. R., Wright, Z. A., Solla, S. A., & Slutzky, M. W. (2016). Long-term stability of motor cortical activity: Implications for brain machine interfaces and optimal feedback control. *Journal of Neuroscience*, *36*(12), 3623–3632.

[Google Scholar](#) [WorldCat](#)

Fornito, A., Zalesky, A., & Bullmore, E. (2016). *Fundamentals of brain network analysis*. Academic Press.

[Google Scholar](#) [Google Preview](#) [WorldCat](#) [COPAC](#)

Fox, K., & Stryker, M. (2017). Integrating Hebbian and homeostatic plasticity: Introduction. *Philosophical Transactions of the Royal Society B*, *372*(1715), rstb 20160413.

[Google Scholar](#) [WorldCat](#)

Frank, M. J., Seeberger, L. C., & O'Reilly, R. C. (2004). By carrot or by stick: Cognitive reinforcement learning in Parkinsonism. *Science*, *306*(5703), 1940–1943.

[Google Scholar](#) [WorldCat](#)

Frankenhuis, W. E., & Gopnik, A. (2023). Early adversity and the development of explore-exploit tradeoffs. *Trends in Cognitive Sciences*, *27*(7), 616–630.

[Google Scholar](#) [WorldCat](#)

Friston, K., Moran, R. J., Nagai, Y., Taniguchi, T., Gomi, H., & Tenenbaum, J. (2021). World model learning and inference. *Neural Networks*, *144*, 573–590.

[Google Scholar](#) [WorldCat](#)

Fritsche, M., Lawrence, S. J. D., & De Lange, F. P. (2020). Temporal tuning of repetition suppression across the visual cortex. *Journal of Neurophysiology*, *123*(1), 224–233.

[Google Scholar](#) [WorldCat](#)

Fry, J. P. (2019). Sport, neuroplasticity, and freedom. *Journal of Cognition & Neuroethics*, *6*(1), 17–29.

[Google Scholar](#) [WorldCat](#)

Fukushima, K. (1980). Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position. *Biological Cybernetics*, *36*(4), 193–202.

[Google Scholar](#) [WorldCat](#)

Gallego, J. A., Perich, M. G., Chowdhury, R. H., Solla, S. A., & Miller, L. E. (2020). Long-term stability of cortical population dynamics underlying consistent behavior. *Nature Neuroscience*, *23*(2), 260–270.

[Google Scholar](#) [WorldCat](#)

Gardner, E. (1987). Maximum storage capacity in neural networks. *Europhysics Letters*, *4*(4), 481.

[Google Scholar](#) [WorldCat](#)

Gershman, S. J. (2019). The generative adversarial brain. *Frontiers in Artificial Intelligence*, *2*, 18.

[Google Scholar](#) [WorldCat](#)

Glaser, J. I., Benjamin, A. S., Chowdhury, R. H., Perich, M. G., Miller, L. E., & Kording, K. P. (2020). Machine learning for neural decoding. *Eneuro*, *7*(4), 1–16.

[Google Scholar](#) [WorldCat](#)

Gopnik, A. (2020). Childhood as a solution to explore-exploit tensions. *Philosophical Transactions of the Royal Society B*, 375(1803), 20190502.

[Google Scholar](#) [WorldCat](#)

Gopnik, A., O'Grady, S., Lucas, C. G., Griffiths, T. L., Wente, A., Bridgers, S., Aboody, R., Fung, H., and Dahl, R. E. (2017). Changes in cognitive flexibility and hypothesis search across human life history from childhood to adolescence to adulthood. *Proceedings of the National Academy of Sciences*, 114(30), 7892–7899.

[Google Scholar](#) [WorldCat](#)

Grafman, J. (2000). Conceptualizing functional neuroplasticity. *Journal of Communication Disorders*, 33(4), 345–356.

[Google Scholar](#) [WorldCat](#)

Grant, E., Finn, C., Levine, S., Darrell, T., & Griffiths, T. (2018). *Recasting gradient-based meta-learning as hierarchical Bayes*. In *International Conference on Learning Representations*. Vancouver, Canada, April 30 – May 3, 2018.

[Google Scholar](#) [Google Preview](#) [WorldCat](#) [COPAC](#)

Griffiths, T. L. (2020). Understanding human intelligence through human limitations. *Trends in Cognitive Sciences*, 24(11), 873–883.

[Google Scholar](#) [WorldCat](#)

Griffiths, T. L., Callaway, F., Chang, M. B., Grant, E., Krueger, P. M., & Lieder, F. (2019). Doing more with less: Meta-reasoning and meta-learning in humans and machines. *Current Opinion in Behavioral Sciences*, 29, 24–30.

[Google Scholar](#) [WorldCat](#)

Habenschuss, S., Bill, J., & Nessler, B. (2012). Homeostatic plasticity in Bayesian spiking networks as expectation maximization with posterior constraints. In F. Pereira, C. J. Burges, L. Bottou, & K. Q. Weinberge (Eds.), *Advances in Neural Information Processing Systems*, 25. Lake Tahoe, December 3–6, 2012.

[Google Scholar](#) [Google Preview](#) [WorldCat](#) [COPAC](#)

He, Y., Chen, Z. J., & Evans, A. C. (2007). Small-world anatomical networks in the human brain revealed by cortical thickness from MRI. *Cerebral Cortex*, 17(10), 2407–2419.

[Google Scholar](#) [WorldCat](#)

Heeger, D. J., Simoncelli, E. P., & Movshon, J. A. (1996). Computational models of cortical visual processing. *Proceedings of the National Academy of Sciences*, 93(2), 623–627.

[Google Scholar](#) [WorldCat](#)

Heit, G., Smith, M. E., & Halgren, E. (1990). Neuronal activity in the human medial temporal lobe during recognition memory. *Brain*, 113(4), 1093–1112.

[Google Scholar](#) [WorldCat](#)

Henkes, A., Eshraghian, J. K., & Wessels, H. (2024). Spiking neural networks for nonlinear regression. *Royal Society Open Science*, 11(5), 231606.

[Google Scholar](#) [WorldCat](#)

Hensch, T. K., & Bilimoria, P. M. (2012). Re-opening windows: Manipulating critical periods for brain development. In *Cerebrum: The Dana forum on brain science*, volume 2012. Dana Foundation 18 pages.

[Google Scholar](#) [WorldCat](#)

Hessler, N. A., Shirke, A. M., & Malinow, R. (1993). The probability of transmitter release at a mammalian central synapse. *Nature*, 366(6455), 569–572.

[Google Scholar](#) [WorldCat](#)

Hill, S., Tononi, G., & Ghilardi, M. F. (2008). Sleep improves the variability of motor performance. *Brain Research Bulletin*, 76(6), 605–611.

[Google Scholar](#) [WorldCat](#)

Hiratani, N., & Latham, P. E. (2020). Rapid Bayesian learning in the mammalian olfactory system. *Nature Communications*, *11*(1), 3845.

[Google Scholar](#) [WorldCat](#)

Ienca, M., & Ignatiadis, L. (2020). Artificial intelligence in clinical neuroscience: Methodological and ethical challenges. *AJOB Neuroscience*, *11*(2), 77–87.

[Google Scholar](#) [WorldCat](#)

Izhikevich, E. M., & Desai, N. S. (2003). Relating STDP to BCM. *Neural Computation*, *15*(7), 1511–1523.

[Google Scholar](#) [WorldCat](#)

Jaegle, A., Mehrpour, V., Mohsenzadeh, Y., Meyer, T., Oliva, A., & Rust, N. (2019). Population response magnitude variation in inferotemporal cortex predicts image memorability. *eLife*, *8*:e47596, August.

[Google Scholar](#) [WorldCat](#)

Jain, Y. R., Callaway, F., Griffiths, T. L., Dayan, P., He, R., Krueger, P. M., & Lieder, F. (2023). A computational process-tracing method for measuring people's planning strategies and how they change over time. *Behavior Research Methods*, *55*(4), 2037–2079.

[Google Scholar](#) [WorldCat](#)

Kara, P., Reinagel, P., & Reid, R. C. (2000). Low response variability in simultaneously recorded retinal, thalamic, and cortical neurons. *Neuron*, *27*(3), 635–646.

[Google Scholar](#) [WorldCat](#)

Kiper, P., Szczudlik, A., Venneri, A., Stozek, J., Luque-Moreno, C., Opara, J., Baba, A., Agostini, M., & Turolla, A. (2016). Computational models and motor learning paradigms: Could they provide insights for neuroplasticity after stroke? An overview. *Journal of the Neurological Sciences*, *369*, 141–148.

[Google Scholar](#) [WorldCat](#)

Krishnan, M. L., Wang, Z., Aljabar, P., Ball, G., Mirza, G., Saxena, A., Counsell, S. J., Hajnal, J. V., Montana, G., & Edwards, A. D. (2017). Machine learning shows association between genetic variability in *PPARG* and cerebral connectivity in preterm infants. *Proceedings of the National Academy of Sciences*, *114*(52), 13744–13749.

Krueger, P. M., Lieder, F., & Griffiths, T. (2017). Enhancing metacognitive reinforcement learning using reward structures and feedback. In *CogSci 2017*. London, July 26–29, 2017.

[Google Scholar](#) [WorldCat](#)

Lee, R. S., Mattar, M. G., Parker, N. F., Witten, I. B., & Daw, N. D. (2019). Reward prediction error does not explain movement selectivity in DMS-projecting dopamine neurons. *eLife*, *8*:e42992.

[Google Scholar](#) [WorldCat](#)

Lee, T. S., & Mumford, D. (2003). Hierarchical Bayesian inference in the visual cortex. *JOSA A*, *20*(7), 1434–1448.

[Google Scholar](#) [WorldCat](#)

Lieder, F., & Griffiths, T. L. (2017). Strategy selection as rational metareasoning. *Psychological Review*, *124*(6), 762.

[Google Scholar](#) [WorldCat](#)

Lieder, F., & Griffiths, T. L. (2020). Resource-rational analysis: Understanding human cognition as the optimal use of limited computational resources. *Behavioral and Brain Sciences*, *43*:e1.

[Google Scholar](#) [WorldCat](#)

Lieder, F., Shenhav, A., Musslick, S., & Griffiths, T. L. (2018). Rational metareasoning and the plasticity of cognitive control. *PLOS*

Computational Biology, 14(4), e1006043.

[Google Scholar](#) [WorldCat](#)

Magee, J. C., & Grienberger, C. (2020). Synaptic plasticity forms and functions. *Annual Review of Neuroscience*, 43, 95–117.

[Google Scholar](#) [WorldCat](#)

Marblestone, A. H., Wayne, G., & Kording, K. P. (2016). Toward an integration of deep learning and neuroscience. *Frontiers in Computational Neuroscience*, 10, 94.

[Google Scholar](#) [WorldCat](#)

Masychev, K., Ciprian, C., Ravan, M., Reilly, J. P., & MacCrimmon, D. (2021). Advanced signal processing methods for characterization of schizophrenia. *IEEE Transactions on Biomedical Engineering*, 68(4), 1123–1130.

[Google Scholar](#) [WorldCat](#)

Mateos-Aparicio, P., & Rodríguez-Moreno, A. (2019). The impact of studying brain plasticity. *Frontiers in Cellular Neuroscience*, 13, 66.

[Google Scholar](#) [WorldCat](#)

McAdams, C. J., & Maunsell, J. H. R. (1999). Effects of attention on the reliability of individual neurons in monkey visual cortex. *Neuron*, 23(4), 765–773.

[Google Scholar](#) [WorldCat](#)

McClelland, J. L., McNaughton, B. L., & O'Reilly, R. C. (1995). Why there are complementary learning systems in the hippocampus and neocortex: Insights from the successes and failures of connectionist models of learning and memory. *Psychological Review*, 102(3), 419.

[Google Scholar](#) [WorldCat](#)

McEliece, R. J., Posner, E. C., Rodemich, E. R., & Venkatesh, S. S. (1987). The capacity of the Hopfield associative memory. *IEEE Transactions on Information Theory*, 33(4), 461–482.

[Google Scholar](#) [WorldCat](#)

Meder, B., Wu, C. M., Schulz, E., & Ruggeri, A. (2021). Development of directed and random exploration in children. *Developmental Science*, 24(4), e13095.

[Google Scholar](#) [WorldCat](#)

Mikhailov, A. M., & Karavay, M. F. (2024). On function of the cortical column and its significance for machine learning. In *ICPRAM 2014* (pp. 461–468). Rome, Italy, February 24–26, 2024.

[Google Scholar](#) [WorldCat](#)

Miller, E. K., & Desimone, R. (1994). Parallel neuronal mechanisms for short-term memory. *Science*, 263(5146), 520–522.

[Google Scholar](#) [WorldCat](#)

Mitra, P. P. (2014). The circuit architecture of whole brains at the mesoscopic scale. *Neuron*, 83(6), 1273–1283.

[Google Scholar](#) [WorldCat](#)

Montague, P. R., Dayan, P., & Sejnowski, T. J. (1996). A framework for mesencephalic dopamine systems based on predictive Hebbian learning. *Journal of Neuroscience*, 16(5), 1936–1947.

[Google Scholar](#) [WorldCat](#)

Montague, P. R., & Sejnowski, T. J. (1994). The predictive brain: Temporal coincidence and temporal order in synaptic learning mechanisms. *Learning & Memory*, 1(1), 1–33.

[Google Scholar](#) [WorldCat](#)

Mukamel, E. A., Nimmerjahn, A., & Schnitzer, M. J. (2009). Automated analysis of cellular signals from large-scale calcium imaging data. *Neuron*, 63(6), 747–760.

[Google Scholar](#) [WorldCat](#)

Müller-Dahlhaus, F., & Ziemann, U. (2015). Metaplasticity in the human cortex. *The Neuroscientist*, 21(2), 185–202.

[Google Scholar](#) [WorldCat](#)

Mulugeta, L., Drach, A., Erdemir, A., Hunt, C. A., Horner, M., Ku, J. P., Myers, J. G., Jr., Vadigepalli, R., & Lytton, W. W. (2018). Credibility, replicability, and reproducibility in simulation for biomedicine and clinical applications in neuroscience. *Frontiers in Neuroinformatics*, 12, 18.

[Google Scholar](#) [WorldCat](#)

Mussa-Ivaldi, F. A., & Solla, S. A. (2004). Neural primitives for motion control. *IEEE Journal of Oceanic Engineering*, 29(3), 640–650.

[Google Scholar](#) [WorldCat](#)

Na, S., Kolar, M., & Koyejo, O. (2021). Estimating differential latent variable graphical models with applications to brain connectivity. *Biometrika*, 108(2), 425–442.

[Google Scholar](#) [WorldCat](#)

Nere, A., Hashmi, A., Cirelli, C., & Tononi, G. (2013). Sleep-dependent synaptic down-selection (I): Modeling the benefits of sleep on memory consolidation and integration. *Frontiers in Neurology*, 4, 143.

[Google Scholar](#) [WorldCat](#)

Nessler, B., Pfeiffer, M., Buesing, L., & Maass, W. (2013). Bayesian computation emerges in generic cortical microcircuits through spike-timing-dependent plasticity. *PLOS Computational Biology*, 9(4), e1003037.

[Google Scholar](#) [WorldCat](#)

Newman, C. M. (1988). Memory capacity in neural network models: Rigorous lower bounds. *Neural Networks*, 1(3), 223–238.

[Google Scholar](#) [WorldCat](#)

Nord, C. L., Halahakoon, D. C., Lally, N., Limbachya, T., Pilling, S., & Roiser, J. P. (2020). The neural basis of hot and cold cognition in depressed patients, unaffected relatives, and low-risk healthy controls: An fMRI investigation. *Journal of Affective Disorders*, 274, 389–398.

[Google Scholar](#) [WorldCat](#)

Nowrangi, M. A., Lyketsos, C., Rao, V., & Munro, C. A. (2014). Systematic review of neuroimaging correlates of executive functioning: Converging evidence from different clinical populations. *The Journal of Neuropsychiatry and Clinical Neurosciences*, 26(2), 114–125.

[Google Scholar](#) [WorldCat](#)

O'Doherty, J., Dayan, P., Schultz, J., Deichmann, R., Friston, K., & Dolan, R. J. (2004). Dissociable roles of ventral and dorsal striatum in instrumental conditioning. *Science*, 304(5669), 452–454.

[Google Scholar](#) [WorldCat](#)

Ólafsdóttir, H. F., Bush, D., & Barry, C. (2018). The role of hippocampal replay in memory and planning. *Current Biology*, 28(1), R37–R50.

[Google Scholar](#) [WorldCat](#)

Olcese, U., Esser, S. K., & Tononi, G. (2010). Sleep and synaptic renormalization: A computational study. *Journal of Neurophysiology*, 104(6), 3476–3493.

[Google Scholar](#) [WorldCat](#)

Pagan, M., & Rust, N. C. (2014). Dynamic target match signals in perirhinal cortex can be explained by instantaneous computations that act on dynamic input from inferotemporal cortex. *Journal of Neuroscience*, 34(33), 11067–11084.

[Google Scholar](#) [WorldCat](#)

Pagan, M., Simoncelli, E. P., & Rust, N. C. (2016). Neural quadratic discriminant analysis: Nonlinear decoding with V1-like

computation. *Neural Computation*, 28(11), 2291–2319.

[Google Scholar](#) [WorldCat](#)

Parisi, G. I., Kemker, R., Part, J. L., Kanan, C., & Wermter, S. (2019). Continual lifelong learning with neural networks: A review. *Neural Networks*, 113, 54–71.

[Google Scholar](#) [WorldCat](#)

Partridge, J. G., Tang, K.-C., & Lovinger, D. M. (2000). Regional and postnatal heterogeneity of activity-dependent long-term changes in synaptic efficacy in the dorsal striatum. *Journal of Neurophysiology*, 84(3), 1422–1429.

[Google Scholar](#) [WorldCat](#)

Payeur, A., Guerguiev, J., Zenke, F., Richards, B. A., & Naud, R. (2021). Burst-dependent synaptic plasticity can coordinate learning in hierarchical circuits. *Nature Neuroscience*, 24(7), 1010–1019.

[Google Scholar](#) [WorldCat](#)

Phelps, E. A., & Hofmann, S. G. (2019). Memory editing from science fiction to clinical practice. *Nature*, 572(7767), 43–50.

[Google Scholar](#) [WorldCat](#)

Piray, P., & Daw, N. D. (2020). A simple model for learning in volatile environments. *PLOS Computational Biology*, 16(7), e1007963.

[Google Scholar](#) [WorldCat](#)

Potjans, T. C., & Diesmann, M. (2014). The cell-type specific cortical microcircuit: Relating structure and activity in a full-scale spiking network model. *Cerebral Cortex*, 24(3), 785–806.

[Google Scholar](#) [WorldCat](#)

Rao, R. P. N., & Sejnowski, T. J. (2001). Spike-timing-dependent Hebbian plasticity as temporal difference learning. *Neural Computation*, 13(10), 2221–2237.

[Google Scholar](#) [WorldCat](#)

Raznahan, A., Lerch, J. P., Lee, N., Greenstein, D., Wallace, G. L., Stockman, M., Clasen, L., Shaw, P. W., & Giedd, J. N. (2011). Patterns of coordinated anatomical change in human cortical development: A longitudinal neuroimaging study of maturational coupling. *Neuron*, 72(5), 873–884.

[Google Scholar](#) [WorldCat](#)

Rebesco, J. M., Stevenson, I. H., Körding, K. P., Solla, S. A., & Miller, L. E. (2010). Rewiring neural interactions by micro-stimulation. *Frontiers in Systems Neuroscience*, 4, 39.

[Google Scholar](#) [WorldCat](#)

Reineberg, A. E., & Banich, M. T. (2016). Functional connectivity at rest is sensitive to individual differences in executive function: A network analysis. *Human Brain Mapping*, 37(8), 2959–2975.

[Google Scholar](#) [WorldCat](#)

Richards, B. A., & Kording, K. P. (2023). The study of plasticity has always been about gradients. *The Journal of Physiology*, 601(15), 3141–3149.

[Google Scholar](#) [WorldCat](#)

Riches, I. P., Wilson, F. A., & Brown, M. W. (1991). The effects of visual stimulation and memory on neurons of the hippocampal formation and the neighboring parahippocampal gyrus and inferior temporal cortex of the primate. *Journal of Neuroscience*, 11(6), 1763–1779.

[Google Scholar](#) [WorldCat](#)

Riesenhuber, M., & Poggio, T. (1999). Hierarchical models of object recognition in cortex. *Nature Neuroscience*, 2(11), 1019–1025.

[Google Scholar](#) [WorldCat](#)

Roberson, S. N., Nwosu, S., Collar, E. M., Kiehl, A., Harrison, F. E., Bastarache, J., Wilson, J. E., Mart, M. F., Sevransky, J. E., Ely, E. W.

, Lindsell, C. J., & Jackson, J. C. (2023). Association of vitamin C, thiamine, and hydrocortisone infusion with long-term cognitive, psychological, and functional outcomes in sepsis survivors: A secondary analysis of the vitamin C, thiamine, and steroids in sepsis randomized clinical trial. *JAMA Network Open*, 6(2), e230380–e230380.

[Google Scholar](#) [WorldCat](#)

Rolls, E., & Treves, A. (1997). *Neural networks and brain function*. Oxford University Press.

[Google Scholar](#) [Google Preview](#) [WorldCat](#) [COPAC](#)

Rust, N. C., & Mehrpour, V. (2020). Understanding image memorability. *Trends in Cognitive Sciences*, 24(7), 557–568.

[Google Scholar](#) [WorldCat](#)

Rust, N. C., & Stocker, A. A. (2010). Ambiguity and invariance: Two fundamental challenges for visual processing. *Current Opinion in Neurobiology*, 20(3), 382–388.

[Google Scholar](#) [WorldCat](#)

Saletin, J. M., Goldstein-Piekarski, A. N., Greer, S. M., Stark, S., Stark, C. E., & Walker, M. P. (2016). Human hippocampal structure: A novel biomarker predicting mnemonic vulnerability to, and recovery from, sleep deprivation. *Journal of Neuroscience*, 36(8), 2355–2363.

[Google Scholar](#) [WorldCat](#)

Schaeffer, R., Khona, M., Ma, T., Eyzaguirre, C., Koyejo, S., & Fiete, I. (2024). Self-supervised learning of representations for space generates multi-modular grid cells. *Advances in Neural Information Processing Systems*, 36. New Orleans Convention Center.

[Google Scholar](#) [WorldCat](#)

Schilling, A., Sedley, W., Gerum, R., Metzner, C., Tziridis, K., Maier, A., Schulze, H., Zeng, F.-G., Friston, K. J., & Krauss, P. (2023). Predictive coding and stochastic resonance as fundamental principles of auditory phantom perception. *Brain*, 146(12), 4809–4825.

[Google Scholar](#) [WorldCat](#)

Schmidgall, S., & Hays, J. (2023). Meta-SpikePropamine: Learning to learn with synaptic plasticity in spiking neural networks. *Frontiers in Neuroscience*, 17, 1183321.

[Google Scholar](#) [WorldCat](#)

Schwartz, E., Kasprian, G., Jakab, A., Prayer, D., Schöpf, V., & Langs, G. (2016). Modeling fetal cortical expansion using graph-regularized Gompertz models. In *Medical Image Computing and Computer-Assisted Intervention. MICCAI 2016: 19th International Conference, Athens, Greece, October 17–21, 2016, Proceedings, Part I* (pp. 247–254). Springer.

[Google Scholar](#) [WorldCat](#)

Scott, D. N., & Frank, M. J. (2023). Adaptive control of synaptic plasticity integrates micro- and macroscopic network function. *Neuropsychopharmacology*, 48(1), 121–144.

[Google Scholar](#) [WorldCat](#)

Sehgal, S., Song, C., Ehlers, V. L., Moyer, J. R., Jr. (2013). Learning to learn: Intrinsic plasticity as a metaplasticity mechanism for memory formation. *Neurobiology of Learning and Memory*, 105, 186–199.

[Google Scholar](#) [WorldCat](#)

Serre, T., Oliva, A., & Poggio, T. (2007a). A feedforward architecture accounts for rapid categorization. *Proceedings of the National Academy of Sciences*, 104(15), 6424–6429.

[Google Scholar](#) [WorldCat](#)

Serre, T., Wolf, L., Bileschi, S., Riesenhuber, M., & Poggio, T. (2007b). Robust object recognition with cortex-like mechanisms. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 29(3), 411–426.

[Google Scholar](#) [WorldCat](#)

Shadmehr, R. (2020). Population coding in the cerebellum: A machine learning perspective. *Journal of Neurophysiology*, 124(6),

2022–2051.

[Google Scholar](#) [WorldCat](#)

Shen, J. P., & Nair, H. (2023). Cortical columns computing systems: Microarchitecture model, functional building blocks, and design tools. In Y. (Cindy) Yi & H. An (Eds.), *Neuromorphic Computing*. IntechOpen, 22 pages (Online).

[Google Scholar](#) [Google Preview](#) [WorldCat](#) [COPAC](#)

Shidara, M., Kawano, K., Gomi, H., & Kawato, M. (1993). Inverse-dynamics model eye movement control by Purkinje cells in the cerebellum. *Nature*, 365(6441), 50–52.

[Google Scholar](#) [WorldCat](#)

Shine, J. M., Breakspear, M., Bell, P. T., Ehgoetz Martens, K. A., Shine, R., Koyejo, O., Sporns, O., & Poldrack, R. A. (2019). Human cognition involves the dynamic integration of neural activity and neuromodulatory systems. *Nature Neuroscience*, 22(2), 289–296.

[Google Scholar](#) [WorldCat](#)

Simpson, D. S. A., & Oliver, P. L. (2020). Ros generation in microglia: Understanding oxidative stress and inflammation in neurodegenerative disease. *Antioxidants*, 9(8), 743.

[Google Scholar](#) [WorldCat](#)

Smith, R., Musleh, W., Akopian, G., Buckwalter, G., & Walsh, J. P. (2021). Regional differences in the expression of corticostriatal synaptic plasticity. *Neuroscience*, 106(1), 95–101.

[Google Scholar](#) [WorldCat](#)

Solgi, M., Liu, T., & Weng, J. (2013). A computational developmental model for specificity and transfer in perceptual learning. *Journal of Vision*, 13(1), 7.

[Google Scholar](#) [WorldCat](#)

Song, S., & Abbott, L. F. (2001). Cortical development and remapping through spike timing-dependent plasticity. *Neuron*, 32(2), 339–350.

[Google Scholar](#) [WorldCat](#)

Song, S., Sjöström, P. J., Reigl, M., Nelson, S., & Chklovskii, D. B. (2005). Highly nonrandom features of synaptic connectivity in local cortical circuits. *PLOS Biology*, 3(3), e68.

[Google Scholar](#) [WorldCat](#)

Spence, J. S., Turner, M. P., D’Esposito, M., & Chapman, S. B. (2023). Toward precision brain health: Accurate prediction of a cognitive index trajectory using neuroimaging metrics. *Cerebral Cortex*, 34(1), bhad435.

[Google Scholar](#) [WorldCat](#)

Stevenson, I. H., Rebesco, J. M., Hatsopoulos, N. G., Haga, Z., Miller, L. E., & Kording, K. P. (2008). Bayesian inference of functional connectivity and network structure from spikes. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 17(3), 203–213.

[Google Scholar](#) [WorldCat](#)

Su, Z., & Cohen, J. Y. (2023). Two types of locus coeruleus norepinephrine neurons drive reinforcement learning. [Unpublished doctoral dissertation], p. 199. Available via bioRxiv.

Suri, R. E., & Schultz, W. (2001). Temporal difference model reproduces anticipatory neural activity. *Neural Computation*, 13(4), 841–862.

[Google Scholar](#) [WorldCat](#)

Sussillo, D., Churchland, M. M., Kaufman, M. T., & Shenoy, K. V. (2015). A neural network that finds a naturalistic solution for the production of muscle activity. *Nature Neuroscience*, 18(7), 1025–1033.

[Google Scholar](#) [WorldCat](#)

Sutton, R. S. (1998). Learning to predict by the methods of temporal differences. *Machine Learning*, 3, 9–44.

[Google Scholar](#) [WorldCat](#)

Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction*. MIT Press.

[Google Scholar](#) [Google Preview](#) [WorldCat](#) [COPAC](#)

Sutton, S., Steuber, V., & Schmukeyer, M. (2019). Unsupervised learning of sparse spatio-temporal receptive fields through inhibitory plasticity: A model of the mammalian early visual system. *BMC Neuroscience*, 20(Suppl 1), 278.

[Google Scholar](#) [WorldCat](#)

Takahashi, C. D., & Reinkensmeyer, D. J. (2003). Hemiparetic stroke impairs anticipatory control of arm movement. *Experimental Brain Research*, 149, 131–140.

[Google Scholar](#) [WorldCat](#)

Talukdar, T., Zamroziewicz, M. K., Zwilling, C. E., & Barbey, A. K. (2019). Nutrient biomarkers shape individual differences in functional brain connectivity: Evidence from omega-3 PUFAs. *Human Brain Mapping*, 40(6), 1887–1897.

[Google Scholar](#) [WorldCat](#)

Talukdar, T., Zwilling, C. E., & Barbey, A. K. (2023). Integrating nutrient biomarkers, cognitive function, and structural MRI data to build multivariate phenotypes of healthy aging. *The Journal of Nutrition*, 153(5), 1338–1346.

[Google Scholar](#) [WorldCat](#)

Tan, C., Lalle, S., & Orchard, G. (2015). Benchmarking neuromorphic vision: Lessons learnt from computer vision. *Frontiers in Neuroscience*, 9, 374.

[Google Scholar](#) [WorldCat](#)

Telnykh, A., Nuidel, I., Shemagina, O., & Yakhno, V. (2021). A biomorphic model of cortical column for content-based image retrieval. *Entropy*, 23(11), 1458.

[Google Scholar](#) [WorldCat](#)

Tenenbaum, J. B., & Griffiths, T. L. (2001). Generalization, similarity, and Bayesian inference. *Behavioral and Brain Sciences*, 24(4), 629–640.

[Google Scholar](#) [WorldCat](#)

Thomson, R., & Lebiere, C. (2013). Constraining Bayesian inference with cognitive architectures: An updated associative learning mechanism in ACT-R. *Proceedings of the Annual Meeting of the Cognitive Science Society*, 35, 3539–3544.

[Google Scholar](#) [WorldCat](#)

Tyulmankov, D., Fang, C., Vadaparty, A., & Yang, G. R. (2021). Biological learning in key-value memory networks. *Advances in Neural Information Processing Systems*, 34, 22247–22258.

[Google Scholar](#) [WorldCat](#)

Varela, F., Lachaux, J.-P., Rodriguez, E., & Martinerie, J. (2001). The brainweb: Phase synchronization and large-scale integration. *Nature Reviews Neuroscience*, 2(4), 229–239.

[Google Scholar](#) [WorldCat](#)

Varshney, L. R., Sjöström, P. J., & Chklovskii, D. B. (2006). Optimal information storage in noisy synapses under resource constraints. *Neuron*, 52(3), 409–423.

[Google Scholar](#) [WorldCat](#)

Vu, M.-A. T., Adali, T., Ba, D., Buzsaki, G., Carlson, D., Heller, K., Liston, C., Rudin, C., Sohal, V. S., Widge, A. S., Mayberg, H. S., Sapiro, G., & Dzirasa, K. (2018). A shared vision for machine learning in neuroscience. *Journal of Neuroscience*, 38(7), 1601–1607.

[Google Scholar](#) [WorldCat](#)

Vukovic, N., Hansen, B., Lund, T. E., Jespersen, S., & Shtyrov, Y. (2021). Rapid microstructural plasticity in the cortical semantic

network following a short language learning session. *PLOS Biology*, 19(6), e3001290.

[Google Scholar](#) [WorldCat](#)

Wamsley, E. J. (2019). Memory consolidation during waking rest. *Trends in Cognitive Sciences*, 23(3), 171–173.

[Google Scholar](#) [WorldCat](#)

Wang, J. X., Kurth-Nelson, Z., Kumaran, D., Tirumala, D., Soyer, H., Leibo, J. Z., Hassabis, D., & Botvinick, M. (2018). Prefrontal cortex as a meta-reinforcement learning system. *Nature Neuroscience*, 21(6), 860–868.

[Google Scholar](#) [WorldCat](#)

Wedeen, V. J., Hagmann, P., Tseng, W.-Y. I., Reese, T. G., & Weisskoff, R. M. (2005). Mapping complex tissue architecture with diffusion spectrum magnetic resonance imaging. *Magnetic Resonance in Medicine*, 54(6), 1377–1386.

[Google Scholar](#) [WorldCat](#)

Wei, K., Yan, X., Kong, G., Yin, C., Zhang, F., Wang, Q., & Kording, K. P. (2014). Computer use changes generalization of movement learning. *Current Biology*, 24(1), 82–85.

[Google Scholar](#) [WorldCat](#)

Wilcox, R. R., & Barbey, A. K. (2023). Connectome-based predictive modeling of fluid intelligence: Evidence for a global system of functionally integrated brain networks. *Cerebral Cortex*, 33(19), 10322–10331.

[Google Scholar](#) [WorldCat](#)

Wilson, R. C., Geana, A., White, J. W., Ludvig, E. A., & Cohen, J. D. (2014). Humans use directed and random exploration to solve the explore-exploit dilemma. *Journal of Experimental Psychology: General*, 143(6), 2074.

[Google Scholar](#) [WorldCat](#)

Winterer, G., & Weinberger, D. R. (2004). Genes, dopamine and cortical signal-to-noise ratio in schizophrenia. *Trends in Neurosciences*, 27(11), 683–690.

[Google Scholar](#) [WorldCat](#)

Witney, A. G. (2018). Neurostimulation techniques for the modulation of pain. *Transcranial Magnetic Stimulation in Neuropsychiatry* (pp. 103–121). Intech Open.

[Google Scholar](#) [WorldCat](#)

Wolpert, D. M., & Ghahramani, Z. (2000). Computational principles of movement neuroscience. *Nature Neuroscience*, 3(11), 1212–1217.

[Google Scholar](#) [WorldCat](#)

Wu, Y., Dissing-Olesen, L., MacVicar, B. A., & Stevens, B. (2015). Microglia: Dynamic mediators of synapse development and plasticity. *Trends in Immunology*, 36(10), 605–613.

[Google Scholar](#) [WorldCat](#)

Xu, F., & Tenenbaum, J. B. (2001). Rational statistical inference: A critical component for word learning. *Behavioral and Brain Sciences*, 24(6), 1123–1124.

[Google Scholar](#) [WorldCat](#)

Xu, F., & Tenenbaum, J. B. (2007). Word learning as Bayesian inference. *Psychological Review*, 114(2), 245.

[Google Scholar](#) [WorldCat](#)

Xu, W., Morishita, W., Buckmaster, P. S., Pang, Z. P., Malenka, R. C., & Südhof, T. C. (2012). Distinct neuronal coding schemes in memory revealed by selective erasure of fast synchronous synaptic transmission. *Neuron*, 73(5), 990–1001.

[Google Scholar](#) [WorldCat](#)

Yarkoni, T., & Westfall, J. (2017). Choosing prediction over explanation in psychology: Lessons from machine learning. *Perspectives on Psychological Science*, 12(6), 1100–1122.

[Google Scholar](#) [WorldCat](#)

Yildirim, I., Belledonne, M., Freiwald, W., & Tenenbaum, J. (2020). Efficient inverse graphics in biological face processing. *Science Advances*, 6(10), eaax5979.

[Google Scholar](#) [WorldCat](#)

Yoon, H., Bak, M. S., Kim, S. H., Lee, J. H., Chung, G., Kim, S. J., & Kim, S. K. (2022). Development of a spontaneous pain indicator based on brain cellular calcium using deep learning. *Experimental & Molecular Medicine*, 54(8), 1179–1187.

[Google Scholar](#) [WorldCat](#)

Yu, Z., Liu, J. K., Jia, S., Zhang, Y., Zheng, Y., Tian, Y., & Huang, T. (2020). Toward the next generation of retinal neuroprosthesis: Visual computation with spikes. *Engineering*, 6(4), 449–461.

[Google Scholar](#) [WorldCat](#)

Zaadnoordijk, L., Besold, T. R., & Cusack, R. (2022). Lessons from infant learning for unsupervised machine learning. *Nature Machine Intelligence*, 4(6), 510–520.

[Google Scholar](#) [WorldCat](#)

Zatorre, R. J., Fields, R. D., & Johansen-Berg, H. (2012). Plasticity in gray and white: Neuroimaging changes in brain structure during learning. *Nature Neuroscience*, 15(4), 528–536.

[Google Scholar](#) [WorldCat](#)

Zelazo, P. D., & Carlson, S. M. (2023). Reconciling the context-dependency and domain-generalty of executive function skills from a developmental systems perspective. *Journal of Cognition and Development*, 24(2), 205–222.

[Google Scholar](#) [WorldCat](#)

Zhang, S., & Yu, A. J. (2013). Forgetful Bayes and myopic planning: Human learning and decision-making in a bandit setting. *Advances in Neural Information Processing Systems*, 26.

[Google Scholar](#) [WorldCat](#)

Zhu, H., Li, T., & Zhao, B. (2023). Statistical learning methods for neuroimaging data analysis with applications. *Annual Review of Biomedical Data Science*, 6(1), 73–104.

[Google Scholar](#) [WorldCat](#)

Zucchet, N., Schug, S., Von Oswald, J., Zhao, D., & Sacramento, J. (2022). A contrastive rule for meta-learning. *Advances in Neural Information Processing Systems*, 35, 25921–25936.

[Google Scholar](#) [WorldCat](#)