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The Simons Collaboration on Ecological Neuroscience: Studying how the brain interacts with the world

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The Simons Collaboration on Ecological Neuroscience (SCENE) seeks to uncover general principles of brain function through an ecological perspective: studying perception, cognition, and action in the context of the affordances available to different agents. Here, we introduce SCENE's goals, hypotheses, and approaches outlining a collaborative vision for the next decade.

Introduction

It is an exciting time to be a neuroscientist. The past decade has seen the advent of neurotechnologies that allow us to record from dozens of brain areas simultaneously, at cellular and millisecond resolution. Similarly, the miniaturization of recording devices—both neural and other—now permit rigorous quantitative measurements (e.g., eye and head tracking, inertial motion sensing) while allowing animals to move and sense freely. Advances in computing hardware and software have revolutionized the video tracking of experimental animals,[1] improved our ability to infer latent neural dynamics from sparse spiking observations, and facilitated the visualization of large-scale datasets. Such advances create tremendous opportunities to understand brain function.

These technological leaps have catalyzed a new wave of scientific discoveries, in turn prompting a new set of fundamental questions in neuroscience. For instance, *why* do sensory cortices carry strong motor or decision signals in some species but far less in others?[2] Or, *why* do place and grid cells, thought to support cognitive maps and underpin flexible and adaptive behavior, appear absent—at least in their canonical form—in primates, the most cognitive of animals?

To answer these and similar questions, many of the "why" form, the Simons Collaboration on Ecological Neuroscience (SCENE) has assembled expertise from systems neuroscience, computational neuroscience, cognitive science, machine learning, developmental psychology, and robotics to form a hypothesis-driven, theory-first, multi-species consortium focused on an ecological approach to neuroscience. Because our aims sit adjacent to several prior and existing approaches in ecological psychology and systems neuroscience, we briefly situate SCENE's perspective relative to these traditions to clarify the conceptual space we seek to occupy.

Our definition of "ecological"

We argue that two complementary approaches will become increasingly influential in the next decade of systems neuroscience: a "naturalistic" approach and an "ecological" one. As we use the terms, naturalistic neuroscience emphasizes complex inputs and outputs, whereas ecological neuroscience emphasizes structured interactions between the organism and its environment. For example, naturalistic stimuli may approximate real-world inputs (e.g., fluttering leaves rather than random dot kinematograms) and ethologically valid behavioral outputs (e.g., complex movements rather than saccading to one of two targets). Conversely, ecological tasks need not involve naturalistic stimuli or behaviors: artificial inputs and even highly trained behaviors can be ecological, provided they embody the right organism-environment coupling and a computationally appropriate challenge. Naturalistic and ecological are thus complementary, but not synonymous. Ecological psychology[3] combines both. SCENE emphasizes the latter. In doing so, SCENE focuses on the task structures that animals evolved to solve rather than the detailed input statistics upon which they operate.

In SCENE, we consider a task to be ecological if it includes three elements: (1) a closed perception-action loop, (2) sequences of actions and a delayed reward structure that creates a credit-assignment problem in linking actions to outcomes, and (3) partial observability, requiring brain states that synthesize sensory inputs over time to infer hidden world variables and guide actions. This last element, partial observability, marks a key departure from traditional ecological psychology and its notion of direct perception. We do not espouse Gibson's claim that all information needed for action is directly accessible in sensory inputs,[3] nor do we share his aversion to the concept of a representation. If these were strictly true, one might wonder why we have complex brains at all. With modern connectionist models, the divide between ecological psychology and ecological neuroscience has shrunk[4]: neural networks can rapidly extract features from raw input to guide behavior, blurring the line between direct perception and internal computation. Thus, our use of the term "ecological neuroscience" draws inspiration from ecological psychology,[3] with its emphasis on perception-action loops and environmental affordances, but extends it toward mechanistic neurobiological and computational accounts that can span species and neural systems.

The goal of SCENE is to discover the principles by which interacting with the world shapes neural state representations (see theoretical approach) rather than how a single animal performs a single task or how multiple species perform the exact same task. Over the next decade, we aim to develop an experimentally verifiable, resource-rational "meta-theory" that, from the ecology of a species (i.e., natural input statistics, ecological challenges, bodily and neural constraints), predicts state representations and dynamics across its brain. This meta-theory aims to organize a broad range of observations in different species, tasks, bodies, and brain areas into a coherent, unifying framework. This is an ambitious goal—yet also a verifiable research program building on the recent success in mapping global networks and dynamics (i.e., the "global brain").

Overarching hypotheses

Much of contemporary neuroscience is shaped by two broad computational approaches to perception, cognition, and decision-making: representational models and associative models.

According to representational approaches, intelligent systems aim to infer latent causes from their observable effects on sensory inputs. By exploiting the statistical structure of the environment, internal models support flexible prediction, generalization, interpretation, and decision-making (as in model-based reinforcement learning). Representational learning therefore plays a central role in modern neuroscience and machine learning, where both biological and artificial networks can learn generative structures from data, which in turn can be used to explain and produce new observations. In this framing, an intelligent system may create a "perceptual module" to represent sensory information about the world, including information that is not immediately useful. Then, it may use a separate "policy module" to choose actions based on these action- and value-agnostic representations. We call this hypothesis $\mathcal{H}_0$: "encode all causal latent variables."

On the other hand, in associative learning, organisms may form direct connections between stimuli, actions, and rewards without necessarily constructing an internal model of the world: it is about linking experiences through reinforcement or repetition. Classic paradigms for studying it are Pavlovian and Skinnerian (i.e., operant) conditioning. In modern machine learning, this could be classic model-free reinforcement learning algorithms, such as Q-learning, which directly update state-action values through reward prediction errors without learning an internal model of the world. Similarly, some end-to-end approaches to reinforcement learning learn via association, though arguably many such systems may also implicitly learn internal models. Associative learning approaches tend to preferentially learn sensory features that have been rewarding in the past. We call this hypothesis $\mathcal{H}_2$: "encode reward-predictive variables."

We believe there is (at least) a third potential axis in this hypothesis space (Figure 1A). Rather than developing a complete internal model of the world, or narrowly reward-centric representations, our brains may be focused on representing what Gibson called "affordances": the opportunities for action that the environment provides.[3] Although this idea has been explored in both ecological psychology and neuroscience,[5] it has yet to be developed into a mathematical framework comparable in scope to those used for representational or reward-based learning. We formalize this notion as hypothesis $\mathcal{H}_1$: "encode (or prioritize encoding of) controllable latent variables," generalizing the categorical "affordance" to become a continuous "controllability."

To be clear, the goal is not to adjudicate between $\mathcal{H}_0$, $\mathcal{H}_1$, and $\mathcal{H}_2$, and these hypotheses need not be mutually exclusive or "sum to one." We view them as orthogonal axes in the space of all possible internal representations (Figure 1A). In their extremes, these hypotheses are already falsified. We can see the moon, falsifying the extreme $\mathcal{H}_1$ and $\mathcal{H}_2$ hypotheses (we cannot control it and it does not provide reward—at least not in the sense of promoting evolutionary fitness). We do not explicitly perceive the countless air molecules that cause wind or the billions of soil microbes that sustain plant life, falsifying the claim that we encode all causal variables ($\mathcal{H}_0$). Further, it is possible that other axes of this hypothesis space could exist ($\mathcal{H}_3$, $\mathcal{H}_4$, …), and that, as animals learn to negotiate their environments, a representation that was more $\mathcal{H}_0$-like becomes more $\mathcal{H}_2$-like. The goal is to attempt to derive what principles dictate how $\mathcal{H}_0$-like, $\mathcal{H}_1$-like, and $\mathcal{H}_2$-like a state

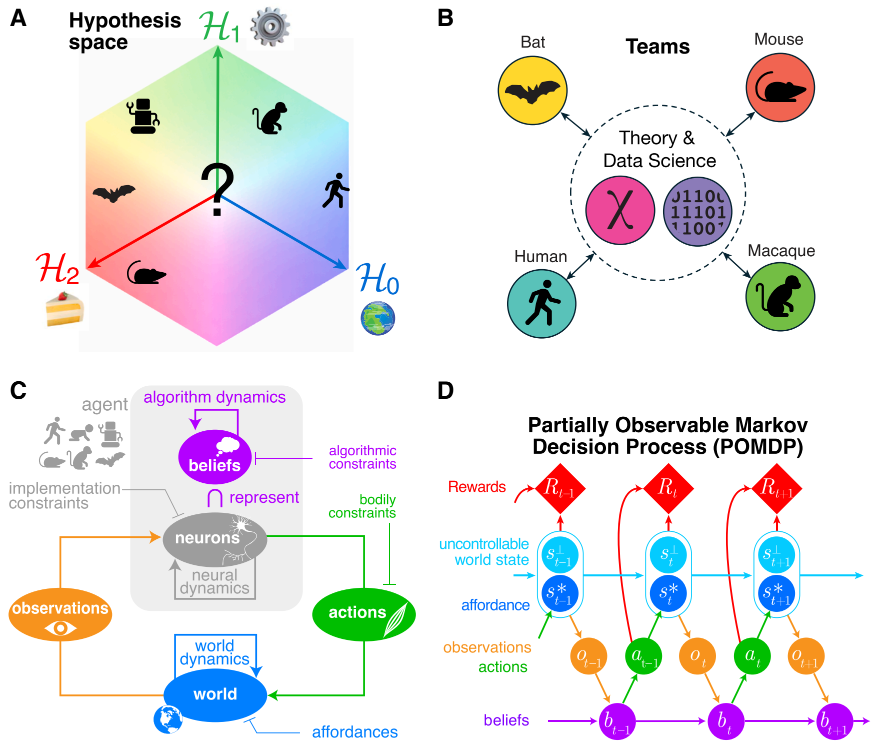

Figure 1. Overview of SCENE

(A) Goals and overall hypotheses of SCENE. The working hypothesis space includes the range from $\mathcal{H}_0$—"encode all latent variables"—to $\mathcal{H}_1$—"encode (or prioritize encoding) of latent variables that are controllable" (i.e., affordances)—and $\mathcal{H}_2$—"encode only what is rewarding." These hypotheses need not be competing, mutually exclusive, or "add to 1."

(B) Our team science approach prioritizes hypothesis-driven, theory-first research. This enables SCENE to leverage the strengths of multiple species by designing (navigation- and manipulation-based) tasks that engage different species with the same computational problem. From a governance perspective, a "hub-and-spokes" approach will allow for a multi-tiered communication schema (reducing burden) and for strong ownership over individual projects in each of the spokes.

(C) Real-world closed loop between observations, beliefs (encoded by neural dynamics), actions, and the environment—affording potential actions.

(D) In partially observable Markov decision processes (POMDPs), a world state (blue) generates observations (orange), which lead an agent to infer the world state. This inference may be erroneous and is probabilistic, leading the knowledge about world states to be summarized by belief states (purple). Based on the latter and a policy, the agent acts on the world (green), which changes the world state. Some actions and world states may lead to reward (red). POMDPs can be constructed to instantiate Gibson's concept of affordances as controllable properties of the world state (darker blue), helping bridge ecological psychology and modern machine learning.

representation and algorithm will be given an organism's ecology, computational challenges, and bodily constraints. Certain state representations may be best for certain learning or planning algorithms, and different brain areas may lie at different positions along the $\mathcal{H}_0$, $\mathcal{H}_1$, and $\mathcal{H}_2$ axes.

SCENE as team science

Both outside (e.g., ATLAS collaboration at CERN or the Human Genome Project) and within (e.g., the Allen Institute, the International Brain Laboratory, or the ABCD project) our field, there is a growing appreciation for how team science can undertake projects that a single "boutique" lab cannot accomplish alone. Team science also fosters multidisciplinarity and enhances scientific rigor (e.g., via the early and frequent sharing of data, code, and protocols).

While previous team-science approaches within neuroscience have focused on a single species, a single task, or a single modality, here, we will test a team-science scheme where scientific hypotheses (above) and theory come first. From these is born an analytical approach and a family of ecological challenges that can be applied across multiple species and measurement modalities. Indeed, we have structured the SCENE consortium after a "hub-and-spokes" model, with theory and data science as the hub and different experimental animals (mouse, bat, macaque, and human) as different spokes (Figure 1B). We believe that this organization will allow for multi-tiered and dynamic communication across the collaboration, with early and frequent communication within a spoke ($\sim$ 6–15 individuals) and more targeted engagement across spokes ($\sim$ 50–75 individuals)—always couched within the broader theoretical framework. This model, we believe, will also allow for increased scientific ownership of projects within each spoke and for each animal to operate within its appropriate niche.

Theoretical approach

The natural language to mathematically formalize the closed loop that exists between (1) using our sensory periphery to make sensory observations, (2) the establishing of subjective beliefs implemented via neural dynamics, (3) actions, and (4) the environment is that of partially observable Markov decision processes[6]

(POMDPs; Figure 1C). In this framework, animals use their observations to guide a sequence of decisions or actions to maximize their total expected value. This presents a fundamental computational challenge to the animal, as it cannot know the future state of the world, which will affect its upcoming choices. Moreover, in a POMDP, even the current world state (Figure 1C, blue) is unknown but must be inferred from partial observations (Figure 1C, orange). Actions (Figure 1C, green) must be based on this incomplete knowledge, often characterized by a probability distribution, or "beliefs" (Figure 1C, purple), about the world state that ideally is updated by rules of Bayesian inference. Indeed, POMDPs are a natural extension of Bayesian decision theory, which is concerned with individual decisions under uncertainty, to sequential decision-making. Conversely, they extend classical reinforcement learning, which has sequential decision making at its core, to environments where the agent does not have full observability of the state, requiring belief-state updates and planning under uncertainty. Within this framework, agents may behave rationally without being optimal—for example, by optimizing within an inaccurate internal model of the world or with respect to a utility function that is unknown to the experimenter. From the perspective of the animal, however, only subjective belief states are accessible. Consequently, understanding brain function requires careful estimation of these belief states.[7] All tasks developed within SCENE will therefore be accompanied by corresponding POMDP models designed to make these latent belief states explicit.

POMDPs provide a formal bridge from affordances in ecological psychology to a modern framework. We expect the first contribution of SCENE to be formalizing the $\mathcal{H}_0$, $\mathcal{H}_1$, and $\mathcal{H}_2$ hypothesis landscape into the language of POMDPs and establishing a common application programming interface (API) to develop POMDPs across ecological tasks. Translating these overarching hypotheses into POMDPs can take several forms. For instance, we can explore how splitting world state and/or belief states into uncontrollable and controllable (i.e., affordances) states (Figure 1D) impacts the ability of an agent to perform a given task or the strategy employed in accomplishing this task. Alternatively, within a given neural architecture, we can define different objectives: optimizing for information ($\mathcal{H}_0$), optimizing for reward ($\mathcal{H}_2$), or optimizing empowerment ($\mathcal{H}_1$)—a formal measure of an agent's potential to influence and control its environment.

Experimental approach

We will study multiple species, including rodents, bats, macaques, and humans (Figure 1B). Each of these animals has their own experimental advantages and disadvantages. Perhaps more importantly, they each sense the world differently (e.g., eye movements in macaques, whisking in rodents, echolocation in bats) and have distinct end effectors. Thus, we can use this diversity to understand how sensing and acting constraints may shape state representations. We will conduct the same experiments in a subset of these species where appropriate (e.g., macaque and human). However, more importantly, we challenge each of these species with problems of parallel computational structure, such as accumulating evidence, identifying affordances, or weighing benefits of exploration versus exploitation. These parallel challenges must be adapted to each species' bodily and cognitive abilities to be ecologically valid and engage the species-specific brain circuits selected by evolution.

In each of these species, we will study two broad classes of affordances: navigation and object manipulation. In rodents, this may include examining navigation to target in real and virtual environments as we manipulate the availability of different paths, action costs, rewards, and sensory uncertainty. We will also present objects that may or may not be moved or changed by actions. In bats, we can study prey capture and navigate to target in mazes of differing complexity, as we manipulate navigability and the availability of rewards. We can also track bats in the wild ("outdoor SCENE"[8]). Similarly, we can study freely moving macaques and humans and challenge these animals with manipulation tasks requiring a long sequence of actions prior to reward. In virtual reality, we can also introduce entirely novel objects with novel affordances, perhaps even violating the laws of physics. Lastly, by also studying young children, we can leverage the fact that their action repertoire is naturally and rapidly evolving. In time, we will examine interacting or hierarchical affordances. For instance, manipulation may gate navigation (e.g., doorknob opening a new path) or navigation may gate manipulation (e.g., climbing a ladder to reach a book). We also expect to leverage expertise in robotics where we can directly manipulate the availability of different sensors and effectors, where algorithms may be embodied, and where we can reverse engineer sensorimotor systems constrained by musculoskeletal and other biomechanical models.

Experimental techniques will include on-animal sensors[8]; immersive virtual and/or augmented reality; high-density extracellular recordings,[2] including in freely moving humans[9]; and electroencephalography, among others. To handle, interpret, and openly share these data (within and beyond the consortium), a team of data scientists will develop robust pipelines for data processing, analysis, and visualization. This will include machine learning approaches for pose estimation, dimensionality reduction, and inferring latent dynamics, as well as cloud-based storage solutions for seamless data sharing, and standardized frameworks to ensure reproducibility across studies and laboratories.

Outlook

Allowing animals to operate in a closed loop with the environment, to move and sense freely, and to engage in a long series of open-ended decisions comes with significant experimental and theoretical challenges. We believe the benefits of this approach will outweigh the challenges, ultimately facilitating the understanding of brain function. For theories, our ecological approach forces us to explicitly attempt to invert the internal models that animals may use to accomplish a given task (e.g., via a POMDP[6,7]). Experimentally, a confound we often overlook is that presenting stimuli at an experimenter-defined pace disrupts the natural, and likely critical, timing linking action, perception, cognition, and internal neural dynamics. Indeed, when an animal actively samples from its environment (e.g., saccade), this motor act presumably primes its sensory system to be most receptive to new, incoming information.[10]

Despite its challenges, we believe our ecological approach to the study of brain function comes with incredible opportunities. We will minimize these challenges using a hypothesis-driven and theory-first approach, asking what principles shape state representations to prioritize the encoding of all causal latent variables, rewarding latent variables, and/or controllable latent variables.

We will not come to an answer alone. SCENE is built upon decades of experimental and theoretical work relating to affordances, motor repertoires, dynamical systems, reinforcement learning, and more. SCENE will operate in a closed loop with the rest of the global scientific community. We hope you will join us!

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DECLARATION OF INTERESTS

The authors declare no competing interests.

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