The growth and form of knowledge networks by kinesthetic curiosity

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Throughout life, we might seek a calling, companions, skills, entertainment, truth, self-knowledge, beauty, and edification. The practice of curiosity can be viewed as an extended and open-ended search for valuable information with hidden identity and location in a complex space of interconnected information. Despite its importance, curiosity has been challenging to computationally model because the practice of curiosity often flourishes without specific goals, external reward, or immediate feedback. Here, we show how network science, statistical physics, and philosophy can be integrated into an approach that coheres with and expands the psychological taxonomies of specific-diversive and perceptual-epistemic curiosity. Using this interdisciplinary approach, we distill functional modes of curious information seeking as searching movements in information space. The kinesthetic model of curiosity offers a vibrant counterpart to the deliberative predictions of model-based reinforcement learning. In doing so, this model unearths new computational opportunities for identifying what makes curiosity curious.

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Seeking information with the potential value to learn diverse skills, understand the world, form social relations, and promote individual well-being is essential to flourishing throughout life [1,2,3•,4–7]. Humans encounter information in an ever-expanding and shape-shifting search space of knowledge that is vast and complex [8,9]. The stream of encounters can bring about averse states of uncertainty, pleasurable states of interest, or expectations of usefulness for learning and action, thereby guiding future exploratory strategies [1,4]. However, inferring the hedonic or utilitarian value of information to guide behavior is costly and time-consuming in complex spaces [10,11,3•]. Curiosity may have evolved to overcome these costs, promoting efficient search strategies to encounter potentially valuable information without prior knowledge of the information's identity and location [12,13,3•].

We propose to understand the kinesthetic modes of search strategies associated with curiosity using network science, statistical physics, and philosophy [14,15•,16•,17]. Since antiquity, investigations of curiosity have contemplated its essential components [15•]. However, we argue that curiosity is best characterized by its searching function [15•]. In a model called *kinesthetic curiosity*, we distill three major modes of potentially many functions described by movement embedded within information landscapes: the *busybody* scouts for loose threads of novelty, the *hunter* pursues specific answers in a projectile path, and the *dancer* leaps in creative breaks with tradition [15•]. Each mode of function is linked with a distinct signature of searching movement (Figure 1). The paths of movement from one piece of information to another are threads creating webs of interlinked information, which we call *knowledge networks*. As the byproduct of searching movement, knowledge network structures may support learning, creativity, and social behavior, without the need for task-specific goals, utility, and feedback [18–25,26•,27,28].

In this review, we first describe the kinesthetic curiosity model of efficient search (Section 'Knowledge network growth principles'). We then explain how kinesthetic curiosity integrates existing theories of curiosity and reinforcement learning (Section 'Integrating models of curiosity and learning'). Next, we consider the evolutionary origins of kinesthetic curiosity and hypothesize neural mechanisms (Section 'Neural implementation and

Figure 1
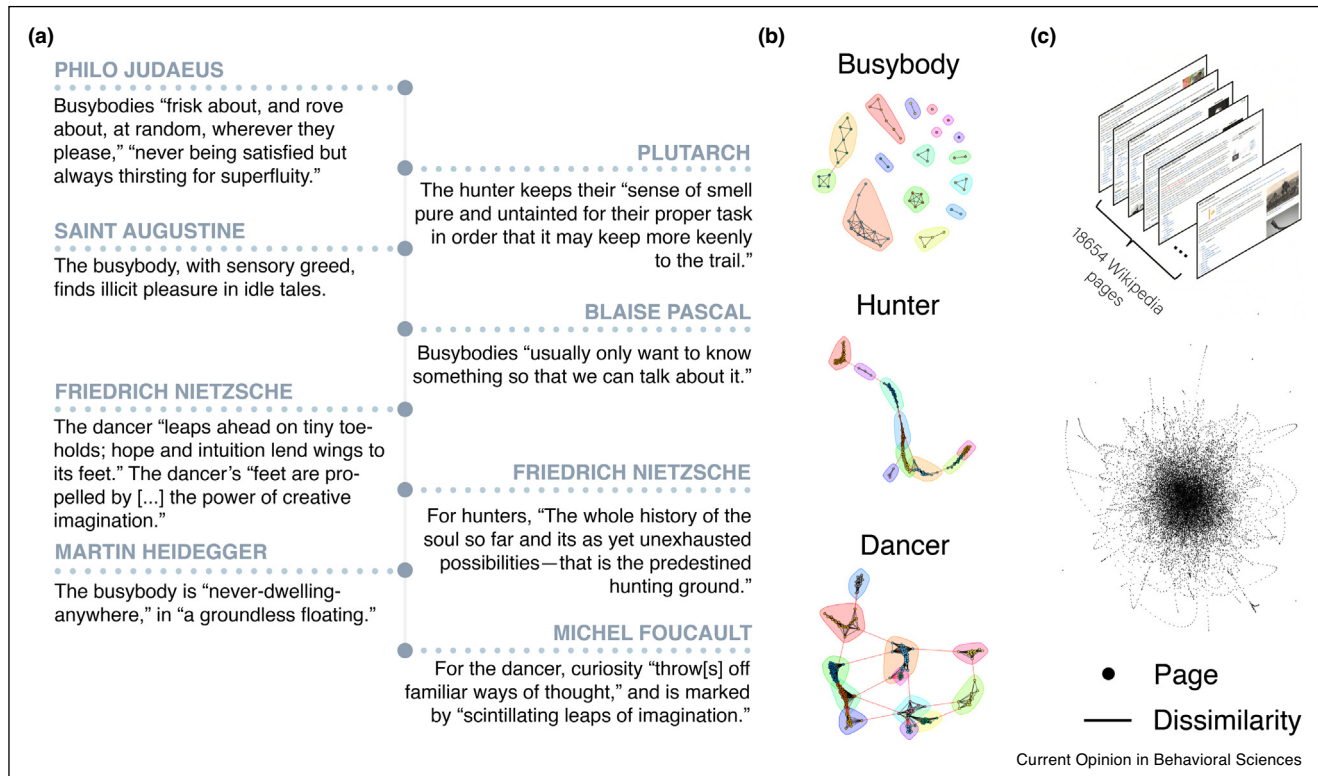
The kinesthetic curiosity model: the concept, associated network representations, and an operationalization in an ecological experiment. **(a)** The kinesthetic curiosity model posits that curiosity is best explained by movement through information space. Three such movements are conceptually operationalized by the historical archetypes of the *busybody*, the *hunter*, and the *dancer* [15•]. Selected quotes from the 1st to 20th centuries describe each of the modes [29–35]. **(b)** The information-seeking movements of the kinesthetic curiosity model can be formalized in the abstract. Each movement is a walk on an underlying collective (or otherwise *a priori* existing) knowledge network. As each person takes this walk, they build their own individualized knowledge network composed of informational units (nodes) and informational relations (edges) [14,17]. Busybodies construct loose networks, hunters build tight networks, and dancers bridge seemingly disparate modules [14,15•]. By adjusting two parsimonious model parameters distilling movement principles of discovery and search, a person may shift continuously between these three modes. Here we show simulated knowledge networks that we generated using a computational model of network growth (see main text) [16•]. Modules are colored according to the WalkTrap algorithm [36]. **(c)** To make the kinesthetic curiosity model concrete to the reader, we consider the example information network of Wikipedia, whose 5.8 million nodes are articles and whose edges are article-to-article hyperlinks. As humans browse, they walk from article to article by hyperlinks, the search bar, or the random page generator; the distance traversed by the walk reflects the similarity of word usage between documents. The sequence of steps can be used to test and validate the kinesthetic curiosity model of knowledge network growth [16•]. Individual differences in the sequence reflect a unique architectural style of information seeking [16•]: knowledge networks with more hunter-like dynamics (versus busybody-like) were associated with higher sensitivity to uncertainty, lower enjoyment of exploration, and lower sensation seeking.

evolutionary origins'). Last, we propose that analyses of knowledge network structure and growth quantify previously qualitative descriptions of curiosity and test contemporary theories of information seeking (Section 'Expanding current taxonomies of curiosity'). Broadly, we offer a perspective that expands our understanding of the practice of curiosity beyond states and traits by positing a computational model of kinesthetic curiosity.

Knowledge network growth principles

The kinesthetic curiosity model posits open-ended and intrinsically motivated movements in an information space (Figure 1). What is the elementary rule of such movements? To answer this question, we observe that

humans often behave quickly and automatically when they must consider many options in complex and changing environments [11]. Thus, a natural rule to consider is that of a random walk. Mathematically, the probability of walking across a path in a network is directly related to the weighted strength of that path. As a computational process, random walk models of behavior can explain several intelligent behaviors including navigation, memory recall, and creativity [18,13,19,24]. As a movement principle, random walks explain patterns of exploration and foraging [13]. When applied to human information seeking, random exploration is economical in that it requires little computational capacity, but can oversample the environment and thus be inefficient [37,38,10].

The random walk model therefore requires additional principles that account for the kinesthetic signatures of discovery and search [39,40,41[•],42[•]]. Two parsimonious movement principles generate the kinesthetic signatures of the busybody, hunter, and dancer, as well as the diverse spectra in between [15[•],16[•]]. First, movements to discover new information can be biased by memory of the familiar; second, search patterns can be biased to efficiently explore a space. The principle of memory for the familiar can be formalized by the notion of *edge reinforcement*, and that of efficient search can be formalized by the notion of a *Lévy flight*. In isolating these principles of discovery and search, it becomes possible to model curious behavior that shifts continuously between the archetypal modes of the busybody, hunter, and dancer, as well as individual differences in preferences for exhibiting each mode [16[•]].

Principle 1: edge reinforcement

How do humans discover knowledge [41[•]]? Put simply, people learn and innovate by revisiting remnants of the past with a fresh perspective. New flickering patterns emerge from well-trodden hubs that shape the flow of information seeking into new directions, expanding the known unknown to explore newly adjacent possibilities [40,41[•]].

In the kinesthetic curiosity model, random walkers individually vary in their preference for either new or familiar information by the mechanism of *edge reinforcement* [41[•]]. Edge reinforcement is a memory of familiarity that increases the probability of taking previously traversed paths. Mathematically, random walks across a path will increase the weighted value of that path, thereby increasing its future transition probability. As a computational process, edge reinforcement is supported by accurate and rapid learning for a vast visual and social memory of familiarity [43,44]. As a movement principle, edge reinforcement resembles the recurrent dynamics of many other existing models for exploration and foraging [45,19,46,47]. When applied to human information seeking, edge reinforcement is associated with the personality trait of *deprivation sensitivity*, a dimension of curiosity associated with aversion to uncertainty and gaps in knowledge [4,1,16[•]].

Seeking information until a chosen knowledge gap is filled characterizes a persistent and effortful form of specific exploration that resolves an unknown by incorporating new information into existing knowledge [1,48,49]. Hunter-like individuals have high deprivation curiosity, creating tighter knowledge networks with greater edge reinforcement as they encounter new information, recognize gaps in their knowledge, and revisit concepts in an iterative cycle of filling in knowledge gaps [50,51,16[•]].

Principle 2: Lévy flight

A pervasive scarcity of resources induces organisms to efficiently search for value despite lacking prior knowledge of the search space, location of targets, and identity of targets [42[•],52–54,45]. Yet, potential value may be unpredictable across the lifespan, between unique individuals, and in high-dimensional environments [55,56]. Therefore, we assume that potentially valuable information is sparsely and randomly (unpredictably) distributed in a complex, unknown environment.

In these environmental conditions, long-term search efficiency across the lifespan and evolution is often modeled with respect to energetic cost [57]. Efficiency is the ratio of resource encounters to energy expenditure, operationalized by the number of steps taken in both spatial and abstract landscapes and the total distance traversed [42[•],58,59[•],60]. Consequently, efficiency depends upon the distribution of step distances. The optimal distribution of step distances is thought to be a power-law [42[•]], which Lévy flights produce in their fractal movement patterns characterized by many small steps and a few large steps [42[•],52,53,45]. While Lévy flights have been frequently studied in environments where reward is sparse and randomly distributed, the dynamics are theoretically optimal in random search across a variety of environmental conditions [42[•],45]. However, especially in smaller spaces or shorter timescales, other qualities of search, such as speed, reliability, and robustness, may prove more relevant for diverse individuals and walks of life [57,61,62]. With respect to other search qualities, the least costly paths are not necessarily the most worthwhile [57,49,63]. Therefore, long-term inefficiency does not imply individual deficiency.

In the kinesthetic curiosity model, a sequence of steps in the random walk weaves a thread through the underlying network. The distance is defined as the number of edges traversed between semantic units [64]. Semantically dissimilar units are connected by paths of greater distance. Mathematically, to assess the existence and extent of Lévy flight dynamics, we consider the manner in which the probability of a step decays as a function of distance. The steepness of decay is directly related to the exponent defining the function's form. Particularly, we measure the exponent of the decaying probability distribution by the step distance of the empirically observed behavior. As a computational process, Lévy flight is supported by widespread observations of its movement signatures across organisms, though its scope and prevalence remain actively debated [62,54]. As a movement principle, optimally efficient Lévy flight dynamics exist if this exponent is approximately 2 [42[•]]. When applied to human information seeking, recent work shows that humans indeed exhibit an average exponent of 2.11 ± 0.15 suggestive of Lévy-like dynamics in curiosity-driven information seeking [16[•]]. Efficiently searching space could explain how

individuals acquire a large repertoire of diverse information with limited resources, while avoiding information that is too difficult or too easy to learn [39,10,21,3•].

Integrating models of curiosity and learning

In this section, we posit that the movement principles of kinesthetic curiosity grow knowledge networks that naturally become cognitive maps. Cognitive maps are internal models learned from the relational structure of a stream of experience [69]. Hierarchically abstracting the structure of cognitive maps at coarser to finer levels can help people to plan, act, and generalize experiences to novel situations [58,70,71]. By using information theory to assess the cost of constructing cognitive maps and of abstracting hierarchies, we propose an integration of curiosity and reinforcement learning.

Map-taking and map-making

The predictive processing approaches, including intrinsically motivated reinforcement learning, propose learning predictive models of the world to flexibly guide optimal actions and further learning [10,72•,3•,70,71]. The predictive models are cognitive maps incorporating prior knowledge of relevant environmental properties [73,74,3•,6]. However, advance knowledge of the environment, including the identity of relevant properties, is often inaccessible.

In unknown environments, inferring the value of potential actions becomes computationally prohibitive due to inefficient scaling with the number of explorable units [66,71]. This limitation prompts us to consider curiosity's function of efficient search [39,52–54,45,3•]. As the search unfolds, information seekers build knowledge networks that naturally become maps due to the emergence of structure from the myriad relationships inherent to sets of semantic units [59•,60] (Figure 2).

Efficient search enhances the learnability of cognitive maps

The cognitive maps arising from kinesthetic curiosity might improve their learnability, conveying information efficiently by omitting unnecessary detail [65•,26•,75,76]. Recent work reported that to efficiently convey information, network representations of that information should be characterized by highly connected hubs and tightly linked modules [26•,77]. Hubs and modules are features of hierarchical organization exhibited by diverse signatures of kinesthetic curiosity (Figure 2). Despite individual differences in edge reinforcement and Lévy flight dynamics, modularity is a core feature of knowledge networks [16•].

People who experience a random sequence of sensory units from a network can learn the network's emergent structure [78,79,59•,80–82,26•,83]. Similarly, current models of learning and decision-making, such as the successor representation and model-based reinforcement learning, propose to predict, plan, and generalize by hierarchically abstracting structure from sequences of experience [84,66,70,71]. A sequence of experiences can be direct, such as in information seeking; or it can be indirect, as in the memory replay of recollected experiences [71]. To flexibly abstract hierarchical structure from a direct or indirect sequence of experiences, individuals would benefit from cognitive maps that are diversely yet economically organized with hubs and modules [84,70,58].

Compression progress theory integrates curiosity and learning

Let us now consider how to operationalize the learnability of cognitive map structure. We begin by noting that kinesthetic curiosity is consistent with the *compression progress theory* of curiosity but differs from the *learning progress hypothesis* [85•,3•]. Compression progress theory posits that individuals practice curiosity to seek information that improves compression of their mental model of the world or a sector thereof. Information compression balances the compactness and accuracy of representations, possibly by exploiting redundancy of knowledge network connections in hubs and modules [65•,86,26•]. Whereas compression progress prioritizes compactness, learning progress prioritizes accuracy [85•,3•]. The compression or abstraction of information in many models of learning, memory, and decision-making is achieved by discounting potentially irrelevant information that is more distant in space or time [87,74,66,72•,26•].

We hypothesize that kinesthetic curiosity increases learnability by producing knowledge network growth with increasing compressibility. Compressibility is operationalized as the information theoretic codelength (bits per step) required to minimally encode random walks in the knowledge network [65•]. Recalling that humans and reinforcement learning algorithms abstract structure from random sequences of experience, the codelength of a random walk in the knowledge network can be used to measure the cost, or learnability [65•]. A decrease in codelength corresponds to a compression gain. Note, however, that coarser abstractions do not always entail compression gains, because inaccurate coarseness demands overly frequent usage of fewer abstracted components in the encoding.

We propose using the operationalization of compressibility as reduced codelength to make three predictions testing the link between curiosity and learning. First, if kinesthetic curiosity is linked with compression progress theory, then random walks biased by the two movement principles of edge reinforcement and Lévy flight will grow knowledge networks with increasing compressibility. Second, if kinesthetic curiosity is linked with the learnability of cognitive maps, then the strength of hubs

Figure 2
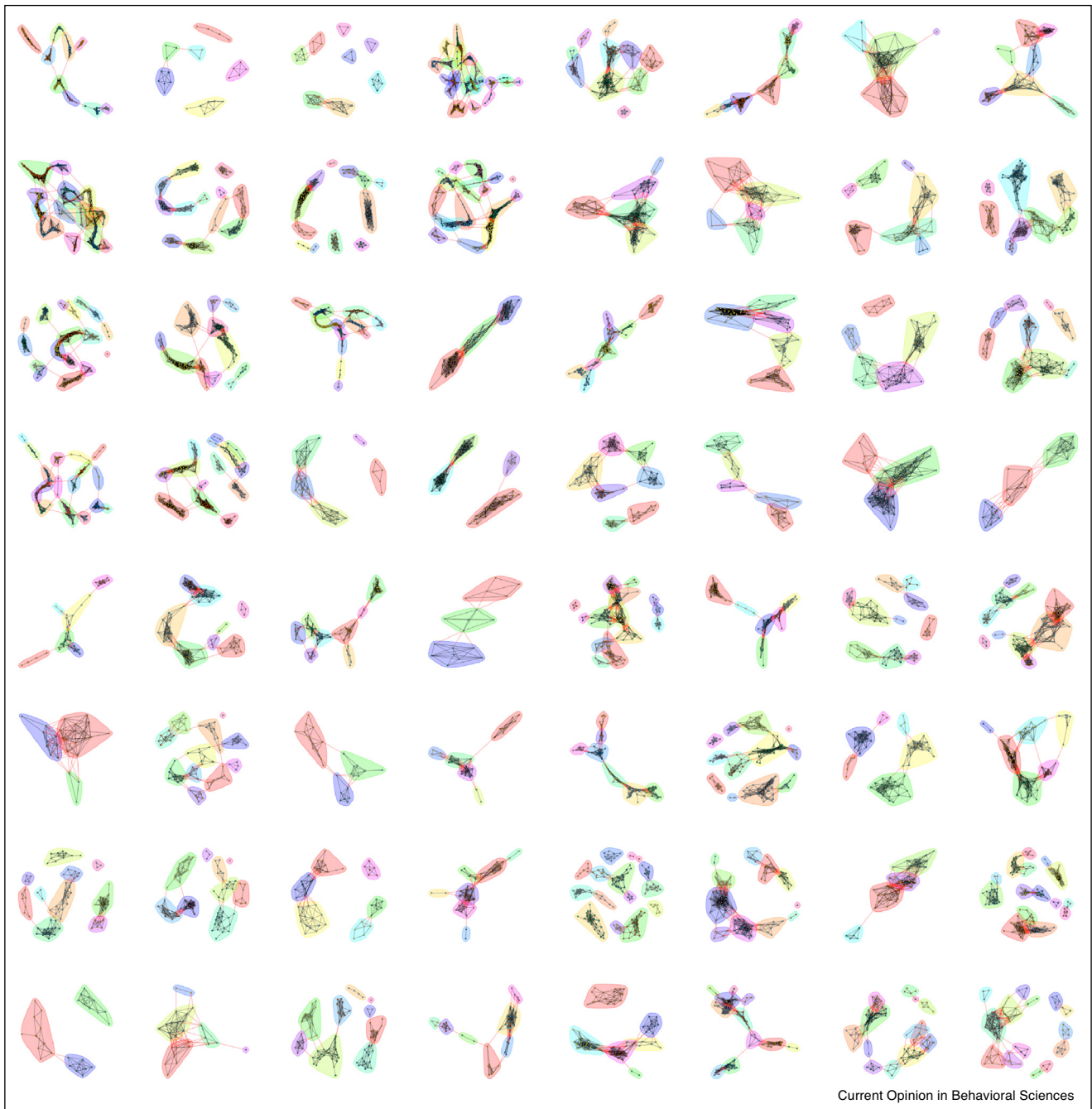
Current Opinion in Behavioral Sciences

Knowledge network growth, form, and individual variation. A few simple principles generate diverse kinesthetic signatures of curiosity. Here we show knowledge networks that were randomly generated using the kinesthetic curiosity model encoded as a random walk biased by principles of edge reinforcement and Lévy flight. Modules are colored by the WalkTrap algorithm [36], and edges connecting modules are colored red. Varying two parameters modeling these principles can characterize the archetypal modes of curious practice and the continuous patterns of behavior in between. The variation evident in these graphs emphasizes the flexibility of the model to fit individual differences. Differing kinesthetic modes may produce dynamics that grow knowledge networks to be efficiently compressible by exploiting the network structure of hubs and modules [65•,66,26•,16•]. Kinesthetic curiosity emphasizes ecological modes of function. Ecologically relevant behaviors are those that individuals are expected to perform in interaction with their daily environments or with similar complexity [67]. Greater ecological relevance instills confidence that theories derived from the carefully designed self-report measures and laboratory tasks generalize to some scope of real-world contexts. It equips researchers to study the evolving practice of curiosity in differing contexts throughout recorded history [13,68,15•,9]. Future work can address the cross-cultural limitations of psychological assessments and models which over-sample homogeneous demographics [67]. In practice, the ability to study uncontrived tasks may prove useful for investigations in pediatric or clinical samples, where tasks that are too difficult or unengaging can introduce statistical biases.

and modules in knowledge networks will be linked to compressibility. Third, if kinesthetic curiosity is linked with hierarchical abstraction, then the integrated compressibility that corresponds to finer and coarser abstractions of the same knowledge network will explain how the cost of information motivates discounts according to distance and time. Together, the frameworks of kinesthetic curiosity and predictive processing can be bridged by examining whether knowledge networks are built to be increasingly compressible [65•, 66,72•,27,28,26•,88].

Neural implementation and evolutionary origins

Here, we consider kinesthetic curiosity at the levels of evolution, as well as the micro-scale, meso-scale, and macro-scale brain network. We begin by noting that the intrinsic motivation of curiosity purportedly evolved for long-term learning despite rapidly growing complexity in the surrounding habitat [10,2]. It is therefore critical to assess how models of curiosity can contend with ecologically relevant complexity. For animals and organisms with extensive limitations on computational capacity, it is challenging to trace the evolutionary history of uncertainty monitoring [11,89]. In contrast, the dynamics of kinesthetic curiosity have been observed in the foraging movements of organisms and animals, perhaps evolving for a need to navigate habitats with increasing complexity [42•,12,90,13,52–54,45,91].

To modulate foraging behaviors at the micro-scale, the neural mechanisms of kinesthetic curiosity likely involve dopaminergic function [13,92]. Consistent with this proposition, prior curiosity research has reported the involvement of dopaminergic brain areas associated with reward anticipation and subjective value, as well as dopaminergic plasticity of the hippocampus in reward-driven associative learning [93,7]. Dopaminergic function for foraging predates function linked to reward anticipation and learning, suggestive of a potential dual role of dopamine in reinforcement learning and kinesthetic curiosity [13,94,6].

At the meso-scale, and in contrast to prior curiosity research, we hypothesize a central role of the hippocampal-entorhinal circuit in curiosity due to the mechanisms that underpin foraging-oriented locomotion, cognitive maps of space, structure learning, and navigation [69,79,72•,59•,95–98,58,6]. Recent neural and behavioral work has reexamined errors and noise due to limited computational capacity as advantageous features of exploration and learning [57,99,26•,37,38,98]. Similarly, we posit that the limited capacity to optimally choose from potential movement plans for foraging during the hippocampal replay of model-based reinforcement learning results in random movement [99,38,98]. Lévy flight dynamics may emerge from the interaction between

individuals with limited cognitive capacity and complex environments [57,12,90,72•,91,54].

Last, we predict that macro-scale brain network structure and function moderate individual differences in learning related to the compressibility of knowledge networks [85•,26•,27,28]. We hypothesize the involvement of network hubs in the frontoparietal circuit, which are thought to support executive function, learning, and information compression, as well as the default-mode network associated with mind wandering and hierarchical abstraction [66,100–102,88]. A set of brain regions across both networks are associated with the reinforcement learning of implicit and explicit representations of experience [103,98]. Together, the neural circuitry shared by model-based reinforcement learning and kinesthetic curiosity suggests that the models are functional counterparts, enacting more learnable experiences for predicting value.

Expanding current taxonomies of curiosity

An influential psychological taxonomy of curiosity describes the personality trait along the two axes of specific-diversive and perceptual-epistemic [39,1,2,4]. The kinesthetic curiosity framework accommodates traditional state and trait approaches to modeling individual differences by characterizing behavior using a computational model. The computational model can capture tendencies to prefer one mode over another (trait), shifts between modes (state), and shifts between tendencies to prefer one mode over another (between state and trait) [16•]. Here we show how the movement principles and modes of kinesthetic curiosity can quantify and expand these current qualitative frameworks.

In kinesthetic curiosity, interdigitations of the specific-diversive and perceptual-epistemic axes can be quantified according to movement dynamics producing tight or loose knowledge networks [16•]. Specific curiosity is the desire for particular relevant pieces of information, while diversive curiosity is a general drive to explore different information. These qualitative descriptions underscore the fact that novelty, diversity, and unexpectedness are functions of the sequence or dynamics of information seeking, rather than properties of each element of information [40,41•]. In contrast, the second classical axis of curiosity describes the contents of each element of information with perceptual to epistemic properties [39]. Perceptual curiosity is a drive to seek novel sensory information, whereas epistemic curiosity is the drive to learn conceptual knowledge and regulate uncertainty [2]. Recent work applied kinesthetic curiosity to quantify the specific-diversive axis of epistemic curiosity [16•]. People who sought specific information during Wikipedia browsing constructed knowledge networks that were tighter than those who sought diverse information. Future tests of perceptual curiosity could apply kinesthetic curiosity to assess how people seek images and videos [104,47].

Contemporary theories of epistemic curiosity state that information seeking is governed by a desire to close an information gap between current uncertainty and preferred baseline uncertainty [50]. However, it remains unclear how to define an individual's preference for uncertainty [2,10]. The information gap theory addresses the question of *what* one needs to know, whereas kinesthetic curiosity addresses the question of *how* one comes to know. The latter allows researchers to investigate the growth dynamics that arise from extended preferences. Prior work has reported that individuals with a stronger personality trait of deprivation sensitivity, a preference for certainty, produced tighter knowledge networks with closed cycles and greater edge-reinforcement [4,16•]. Therefore, the preferred uncertainty is linked to the deprivation sensitivity dimension of trait curiosity. A future test of the information gap theory could assess how modes of movement fill topological gaps in the knowledge network, as children fill gaps in semantic networks when learning language or explore when information is incomplete [48,105].

Conclusion

The kinesthetic curiosity model can formalize, assess, and expand the classical psychological taxonomy of curiosity. We present a computational model of curiosity that hues close to its ecological function in naturalistic environments and to its need to efficiently contend with complexity. The implicit construction of learnable knowledge networks accompanies the explicit learning of structure, as random search may arise from the neural capacity limits for learning. The costs of abstracting hierarchical structure from cognitive maps could link curiosity, creativity, social behavior, and learning under the framework of compression progress theory. In our view, the practice of curiosity includes distinct modes of information seeking dynamics that package information into knowledge networks with unique structural signatures. Considering the philosophical archetypes of curiosity embodied in the hunter, busybody, and dancer will help us to understand curiosity throughout history, across cultures, and at the scales of individuals and societies (Box 1).

Box 1 Outstanding questions

How does knowledge network structure and information compression influence learning, creativity, and social interactions?

How could the brain implement kinesthetic curiosity with the mechanisms of foraging, spatial navigation, cognitive maps, and information compression?

How does kinesthetic curiosity differ with individual variation of attention, mood, motivation, learning, and social behavior, and in psychiatric disorders?

How should institutions of science, education, media, and markets create incentives for differing modes of kinesthetic curiosity?

Citation diversity statement

Recent work in neuroscience and other fields has identified a bias in citation practices such that papers from women and other minorities are under-cited relative to the number of such papers in the field [106–110]. Here we sought to proactively consider choosing references that reflect the diversity of the field in thought, form of contribution, gender, and other factors. We obtained predicted gender of the first and last author of each reference by using databases that store the probability of a name being carried by a woman [110,111]. By this measure (and excluding self-citations to the first and last authors of our current paper), our references contain 13.5% woman/woman, 21.3% woman/man, 12.4% man/woman, and 52.8% man/man. This method is limited in that (a) names, pronouns, and social media profiles used to construct the databases may not, in every case, be indicative of gender identity and (b) it cannot account for intersex, non-binary, or transgender people. We look forward to future work that could help us to better understand how to support equitable practices in science.

Conflict of interest statement

Nothing declared.

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Papers of particular interest, published within the period of review, have been highlighted as:

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