Biological Underpinnings for Lifelong Learning Machines

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Abstract

Biological organisms learn from interactions with their environment throughout their lifetime. For artificial systems to successfully act and adapt in the real world, it is desirable to similarly be able to learn on a continual basis. This challenge is known as *lifelong learning*, and remains to a large extent unsolved. In this perspective article, we identify a set of key capabilities that artificial systems will need to achieve lifelong learning. We describe a number of biological mechanisms, both neuronal and non-neuronal, that help explain how organisms solve these challenges, and present examples of biologically inspired models and biologically plausible mechanisms that have been applied to artificial intelligence systems in the quest towards development of lifelong learning machines. We discuss opportunities to further our understanding and advance the

state of the art in lifelong learning, aiming to bridge the gap between natural and artificial intelligence.

1 Introduction

Learning is a defining ability of biological systems, whereby experience leads to behavioral adaptations that improve performance[1].

The last couple of decades have witnessed astonishing advances in the field of machine learning (ML). Nevertheless, a new generation of applications - self-driving cars and trucks, autonomous drones, delivery robots, intelligent hand-held and wearable devices, and others that we have not yet imagined – will require a new type of machine intelligence that is able to learn throughout its lifetime. Such machines will need to acquire new skills without compromising old ones, adapt to changes, and apply previously learned knowledge to new tasks - all while conserving limited resources such as computing power, memory, and energy. These capabilities are collectively known as lifelong learning (L2).

In contrast with the current generation of intelligent machines, animal species ranging from invertebrates to humans are able to learn continually throughout their lifetime. Neuroscientists and other biologists have proposed a number of mechanisms to explain this ability, and machine learning researchers have attempted to emulate them in artificial systems, with varying degrees of success. In this perspective article, we examine our current understanding of how biological organisms learn continually and review the state of the art in biologically inspired L2 models. We describe a variety of biological mechanisms, both neuronal and non-neuronal, that can improve our ability to create highly functioning lifelong learning machines.

It should be noted that there is also a body of AI research that tackles the lifelong learning problem from a less clearly biological perspective[2–10]. These can be broadly organized into three types: *rehearsal* which store or generate data from past tasks for replay[11–13], *architectural* methods that expand the model parameters[14–17], and *regularization-based* approaches that penalize changes to parameters important to past tasks[18–20] or use meta-learning[8]. Such models , which are not directly inspired by a biological mechanism, fall outside the scope of the present article.

The article is organized as follows: In Section 2, we identify a set of key features of lifelong learning, Section 3 provides an overview of biological mechanisms that are believed to be involved in realizing these features, and in Section 4 we review research where analogous mechanisms have been implemented in ML models with the aim of realizing lifelong learning capabilities in artificial systems. We conclude with a look at future challenges and opportunities in Section 5.

2 Key Features of Lifelong Learning

The vision of *lifelong learning machines* is one of systems that operate much like biological agents: they never stop learning, their performance improves with experience, and - importantly - they make modest demands on energy and compute/memory resources.

Below, we describe six key features of lifelong learning. Successful realization of these features in an AI system would represent a major advance towards true L2 capability. See Figure 1 for an overview.

I. **Transfer and Adaptation** - L2 machines need to be able to transfer and reuse knowledge to improve their performance, and also to rapidly adapt to novel environments, without the need for offline retraining. These capabilities are essential for models deployed in the real world where situations and environmental conditions may vary considerably. Studies focused on few-shot learning (learning from few samples) and meta-learning (learning to learn concepts quickly) have attempted to tackle the adaptation problem[21–23].

II. **Overcoming Catastrophic Forgetting** - A common issue with ML models is their inability to retain previously learned knowledge while training on new tasks. This is known as *catastrophic forgetting*, and it occurs when network parameters are changed to optimize performance for the current task, without adequately protecting previous knowledge.

It is not an issue of insufficient memory, but rather one of rewriting memory areas.

The challenge of acquiring new skills without forgetting old ones is known as the *stability-plasticity dilemma*[24].

III. **Exploiting Task Similarity** - An L2 model needs to learn multiple tasks. Previous work has shown that learning multiple tasks and enabling the transfer of information among them improves performance[25]. *Forward transfer* refers to the application of previously learned skills to new tasks, and *backward transfer* to the case when learning a new task improves performance on a previously learned task. One approach to achieving such forward and backward transfer is compositionality – the ability to decompose complex tasks into more elementary components that can be reused for related tasks[26,27]. The ability to identify and reuse subtasks would accelerate transfer and adaptation.

IV. **Task-Agnostic Learning** - L2 models deployed in the real world cannot rely on an oracle to tell them when training switches from one task to another, or which previously learned task is applicable in any given situation, but must be able
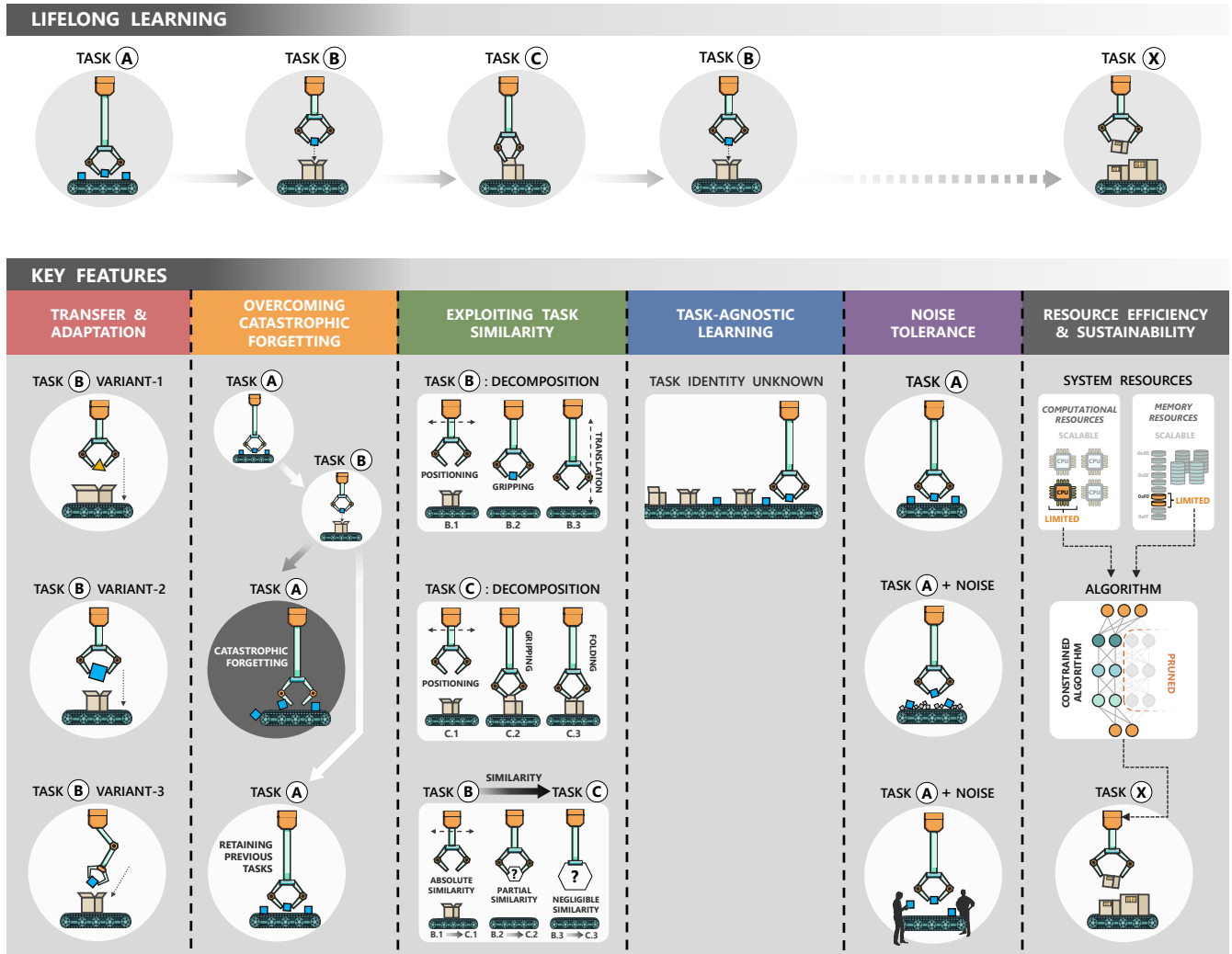
Figure 1. Key features required to achieve lifelong learning. *Top*: a lifelong learning agent encounters a stream of training episodes intermixed with situations where it must apply recently or previously learned skills. In the illustration, a robotic arm is being trained to perform a variety of tasks, and is subsequently able to select from its repertoire of learned skills to apply in different situations that is encounters. *Bottom*: key features for lifelong learning. *From left to right*: **Transfer and Adaptation**: the ability to apply previous knowledge to new tasks and to quickly adapt to changes in the task or the environment. Here, the system is trained on Task B (packing objects in boxes) and is subsequently able to apply the learned skills to facilitate learning of similar but non-identical variants of the task (different sizes and shapes of objects and boxes). **Overcoming Catastrophic Forgetting**: Current AI systems (*grey*) suffer from catastrophic forgetting, the inability to learn new tasks without degradation of performance on ones previously learned. An L2 system (*white*) needs to be able to overcome this problem. In the example, the system is first trained on Task A, then on Task B. After Task B training, the L2 system still performs well on Task A. **Exploiting Task Similarity**: Rather than learning a monolithic representation of a task, an L2 system is able to decompose it into subtasks that can be applied when learning new tasks. In the illustration, the positioning action learned as part of Task B training is directly transferable to Task C, allowing reuse of this skill. The other Task B skills, gripping and translation, are less applicable to Task C. **Task-Agnostic Learning**: the ability to solve a problem without being explicitly told which among several learned tasks the problem belongs to. Here, the L2 system detects that the gripping action that it learned during Task B training is applicable in the current situation. **Noise Tolerance**: the ability to execute a task despite noise that was not present during training. In the example, the system is trained to perform a task without any distractions. It is subsequently able to perform the task in the real world, ignoring irrelevant objects and potentially distracting activity. **Resource Efficiency and Sustainability**: the ability to continually learn new tasks with limited system resources. The figure illustrates that the L2 system is able to perform its tasks with limited memory and compute resources, and with compressed models.

| | KEY FEATURES | | | | | |
BIOLOGICAL MECHANISMS	TRANSFER & ADAPTATION	OVERCOMING CATASTROPHIC FORGETTING	EXPLOITING TASK SIMILARITY	TASK-AGNOSTIC LEARNING	NOISE TOLERANCE	RESOURCE EFFICIENCY & SUSTAINABILITY
NEUROGENESIS	●	●	●	●		●
EPISODIC REPLAY		●		●		●
METAPLASTICITY		●		●		●
NEUROMODULATION	●	●				
CONTEXT-DEPENDENT PERCEPTION AND GATING	●	●	●	●	●	
HIERARCHICAL DISTRIBUTED SYSTEMS			●		●	
COGNITION OUTSIDE THE BRAIN	●		●		●	
RECONFIGURABLE ORGANISMS	●	●	●			
MULTISENSORY INTEGRATION			●		●	

Table 1. Biological mechanisms that support lifelong learning. The matrix illustrates the relationships between the key features of lifelong learning defined in Section 2 (along the top) and the biological mechanisms described in Section 3 (along the left edge). A colored bullet in a cell signifies that the biological mechanism indicated to its left is thought to contribute to the key feature that labels the corresponding column (but not necessarily that the mechanism is sufficient to realize that feature by itself).

to perform well without such information. We refer to this as *task-agnostic learning*. In current state-of-the-art ML, some models require full task identification[28] during training and inference, while others only need to be informed when a task switch occurs. L2M must be able to perform inference without task identifying information.

V. **Noise Tolerance** - Typically, state-of-the-art AI models are trained on datasets collected and cleaned to optimize training, and do not perform well if data encountered during inference differs significantly from the training data. Previous works have focused on building robust models but haven't yet been explored in the context of L2[29]. L2M must be able to handle data which differs from the training data due to variability in the environment or in the agent's own sensors.

VI. **Resource Efficiency and Sustainability** - For ML models to continue learning throughout their service life, serious emphasis needs to be laid on resource constraints. For example, a system that needs to remember (e.g., in a database) all experiences of its past will require ever-increasing storage capacity (e.g. in replay buffers), although there are attempts to compress what needs to be stored across longer timescales[30–32]. Similarly, providing a continual source of clean training data, perhaps even regularized[33], is also impractical. The learning time should not overwhelm the system or slow down its inference. Also, the number of different tasks or behaviors available to the system should not affect its real-time response.

Comprehensive measures of success for lifelong learning are still evolving and are an active area of research. We discuss some of the metrics commonly used in the literature in supplementary material [SM].

Note that this list is presented in a task-centric manner, in that it focuses on *useful* tasks that an agent may want to carry out in the world. As in self-supervised learning[34], curiosity-driven reinforcement learning[35], and works looking at open-ended learning[36], there could be additional tasks (driven by particular objective or reward functions, e.g. reducing uncertainty in predicting the future) that the agent may carry out which are not specific to *useful* tasks. However, even in those cases the features of lifelong learning above hold; for example, during exploration or free play the agent should still not catastrophically forget older tasks, and the skills learned may still be leveraged to improve performance on the useful tasks.

3 Biological Mechanisms that Support Lifelong Learning

Since many animal species appear to be able to learn continuously throughout their lifetime, biologists have tried to identify the underlying mechanisms that enable the features described in Section 2. A number of such mechanisms have been proposed, as described in the following subsections (see Table 1). Most of these mechanisms are attributed to processes in the brain, but some are also from intracellular and intercellular activities – outside the brain.

3.1 Neurogenesis: Dynamically Growing Architectures

Neurogenesis is the process by which new neurons are produced in the central nervous system. It is most active during early development, but continues throughout life. In adults, neurogenesis is known to occur in the dentate gyrus (DG) of the

hippocampal formation[37] and in the subventricular zone (SVZ) of the lateral ventricles[38]. A well-known example of adult neurogenesis is observed in the SVZ of mice, where olfactory interneurons are produced and subsequently migrate to the olfactory bulb (see Figure 2). The rate of neurogenesis in adult mice has been shown to be higher if they are exposed to a richer variety of experiences[39]. This suggests a role for self-regulated neurogenesis in scaling up the number of new memories that can be encoded and stored during one's lifetime without catastrophic forgetting of previously consolidated memories. Neurogenesis may also play an important role during infant development[40], to allow the growth and restructuring needed to accommodate new information and skills.
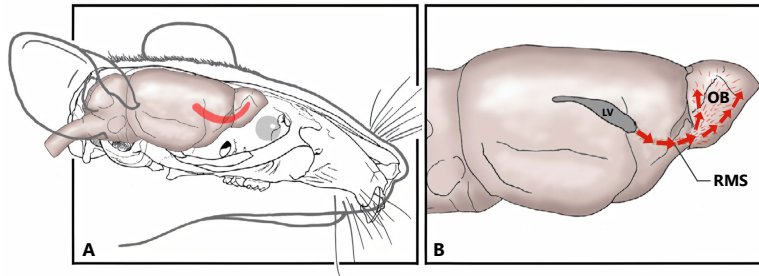

Figure 2. Neurogenesis. (A) Head of a mouse showing the location of the brain and the rostral migratory stream (RMS) (in red) along which newly generated neuroblasts migrate from the subventricular zone of the lateral ventricle into the olfactory bulb (OB). (B) Newly generated neuroblasts begin their migration at the lateral ventricle, continue along the RMS and arrive in the OB, where mature interneuron populations are generated. Adapted from ref.[41].

An extreme example of dynamic architecture and the adaptability of biological organisms to new tasks and functions is the neurogenesis and synaptogenesis that occur during the development cycle of insects. Existing structures are enhanced and repurposed to match the increasing processing demands as they evolve to their mature state[42]. It has been shown that, despite drastic changes in size and configuration, learned responses can be preserved through metamorphosis, for example in the transition from caterpillar to moth[43].

3.2 Episodic Replay: Rehearsal of Previous Memories

Replay is the phenomenon that neuronal activity patterns that had previously occurred during waking are re-occurring during later sleep or rest (shown in Figure 3). Such replay was first observed in the hippocampus[44], and subsequently synchronously in the hippocampus and neocortical areas[45]. An influential hypothesis states that experiences are initially encoded in the hippocampus, and subsequently, during sleep, replayed to the neocortex. The neocortex is hypothesized to interleave these replays, initiated from the hippocampus, with replay of its own (already consolidated) neural patterns, in order to integrate the new information without overwriting previous memory structures[46].
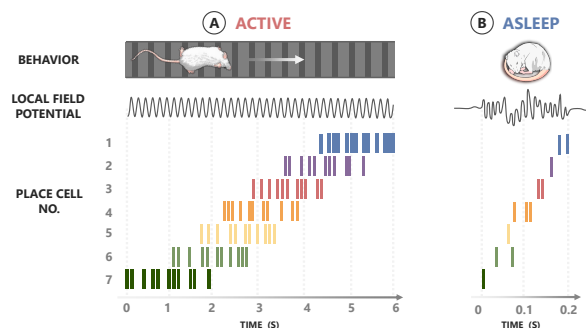
Figure 3. Episodic replay in the hippocampus of a rodent. A) During awake behavior, hippocampal place cells fire in sequence according to the spatial locations visited by the animal. The local field potential (LFP) in the hippocampus shows a theta oscillation, schematically illustrated in this figure (see Refs [47][48] for experimental data) . (B) During sleep and rest following active behavior (and sometimes during brief pauses in active behavior[47]), the hippocampal LFP shows "ripple" activity (brief pulses of 100-200 Hz oscillations) , during which neurons rapidly replay sequences that occurred during behavior [47,49] . Replay of activity sequences observed during behavior have also been observed in other brain regions, in compressed (as shown) or uncompressed form[50] .

Strong experimental evidence has been accumulated in support of a role for replay in memory consolidation in the brain[51–55], and there is a wealth of data indicating that sleep is critically important for learning and memory[56]. Intriguingly, a recent study[57] found that hippocampal activation patterns do not always recapitulate waking experiences; seemingly random activation patterns are also observed. This may suggest a mechanism similar to what is known in machine learning as pseudo-rehearsal[58] or generative replay[59], a way to protect memories from interference without the need to store original input patterns.

While the dual (hippocampo-cortical) memory model (i.e., fast learning in the hippocampus followed by slow learning in the cortex) is widely accepted as a core principle of how the brain learns declarative memories, it is likely not the only memory model the brain uses. For example , procedural, presumably hippocampus-independent memories[60,61] (e.g., some motor tasks) can be learned without forgetting old skills, in which rapid eye movement (REM) sleep plays an important role . The dreams that occur during REM sleep are thought not to be actual replayed experiences, but out-of-distribution elaborations that may also help with generalization[62].

3.3 Metaplasticity: Regulating Synaptic Plasticity

The strength of individual synapses can be modified by neural activity;this is known as synaptic plasticity and is the most widely investigated mechanism by which the brain stores memories[63]. In addition, the ease with which a synapse can be strengthened or weakened may itself vary over time. This "plasticity of plasticity" has been named *metaplasticity*: the ability of a synapse to be modified depends on its internal biochemical states, which in turn depend on the history of synaptic modifications[64,65] and recent neural activity[66]. Metaplasticity has been implicated in multiple aspects of memory maintenance, including mitigation of catastrophic forgetting[67] and regulation of overall neural excitability[65]. In particular, heterosynaptic modulation has been shown to be crucial in synaptic consolidation, allowing for fast learning but slow forgetting[68].

Storage of new memories can interfere with preexisting ones, causing forgetting[46]. The forgetting process can become very rapid when memory resources are restricted, as in the case when synaptic weights can only be stored with limited precision. This is certainly the case with biological synaptic weights, whose values can be preserved on long timescales with a precision of at most 4-5 bits [69]. The consequences of this limited precision on memory capacity can be dramatic[70–72], posing severe restrictions on the performance of any neural system with online learning. One possible solution to this problem may lie in the complexity of biological synapses: the modification of biological synaptic weights involves multiple cascade processes that operate on different timescales. The fast and slow mechanisms permit rapid acquisition of new information combined with a delayed decision whether to make changes permanent, depending on subsequent events. A spurious signal may only result in temporary modifications of synaptic strengths, whereas repeated strong input signals will leave permanent memory traces. In this way, these mechanisms can contribute to solving the stability-plasticity dilemma[24].

3.4 Neuromodulation: Selective Attention and Selective Plasticity

Neuromodulatory neurons release neurotransmitters that have both a local effect and a global effect on activity and plasticity (Figure 4). Neuromodulation has been studied and modeled in the context of its role in behavioral adaptation in the presence of expected and unexpected uncertainties[73].
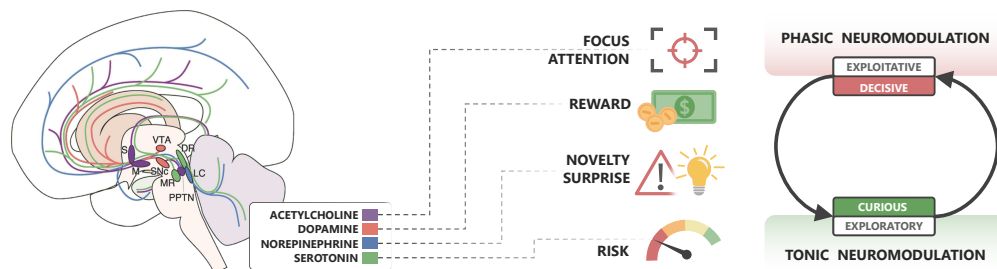
Figure 4. Neuromodulatory systems in the brain. *Left*: the source of neuromodulators are subcortical. Acetylcholine originates in the Substantia Innominata (S) and in the Medial Septum (M). Dopamine originates in the Ventral Tegmental Area (VTA) and the Substantia Nigra Compacta (SNc), Norepinephrine originates in the locus coeruleus (LC), and Serotonin originates in the dorsal (DR) and medial (MR) raphe nuclei. These sources project to large areas of the nervous system. Figure adapted from ref.[74]. *Right*: phasic neuromodulation drives the organism toward more exploitative and decisive behavior, and tonic neuromodulation drives the organism toward more exploratory or curious behavior. The activity of each neuromodulator is related to environmental stimuli. For example, acetylcholine levels appear to be related to attentional effort, dopamine levels appear to be related to reward anticipation, norepinephrine levels appear to be related to surprise or novelty, and serotonin levels appear to be related to risk assessment and impulsiveness. Adapted from ref.[75].

Neuromodulators have a selective effect on learning. For example, acetylcholine (ACh) regulates the trade-off between stimulus-driven and goal-driven attention[76–78], norepinephrine (NE) drives responses to novelty and surprise, serotonin (5-HT) can shift patience and assertiveness depending on the context[79], and dopamine (DA) carries a reward prediction error signal[80], which has been an inspiration for reinforcement learning algorithms[81,82]. Evidence suggests that ACh release is triggered by registering expected uncertainty[83] and unexpected reward[84], while NE release is triggered by surprise[73]. Uncertainty serves as a behaviorally relevant trigger for adaptation and learning, making neuromodulation an ideal mechanism to model AI algorithms capable of self-adaptation by focused attention[77,85], and memory encoding[85,86]. Dopamine allows for associating cues with predicting outcomes, which can be rewards, punishment, and novelty[87,88], and can drive curiosity. It has also been shown to play a role in converting short-term potentiation (STP) to long-term potentiation (LTP) in the synapse. In some cases, only recently activated synapses can have LTP induced by dopamine[89]. Neuromodulation in the mushroom body of the insect brain has been shown to play a key role in regulating activity, forming memory and encoding valence[90]. Neuromodulation can boost learning, help overcome catastrophic forgetting, support adaptation to uncertain and novel experiences, and improve understanding of changes in context[91–96].

3.5 Context-Dependent Perception and Gating: Using Environmental Cues to Modulate Behavior

In biological systems, context plays a significant role in modulating, filtering, and assimilating new information. This is important for tracking changing environments, directing attention to changes, and integrating new information. Context gating, the selective enabling of subpopulations of neurons, helps reduce interference between similar experiences.

For instance, in the olfactory system, context plays a large role in modulating responses and in learning new responses. The olfactory bulb (OB), the cortical area that receives direct sensory input from the nose, receives more input from other parts of the brain than it does from the nose. Primary neurons that project directly to many parts of the brain concerned with memory, context and emotion, are driven mainly by internal states, behavioral expectations, and behavioral context of learned odors[97]. These inputs likely provide the dynamic flexibility associated with task learning, reward association and appropriate motor response[98,99]. They allow for faster learning of new stimuli and gating of responses, including different responses to the same stimulus and stable responses in different environments[90,100,101].

Context modulation and gating is also used for selective attention[102]. For instance, gain modulations have been shown to encode target trajectories in insect vision to locally enhance the gain of relevant areas of its visual field[103]. A top-down task-driven path can effectively direct attention to task-relevant features[104], where it can help filter out less relevant stimuli and focus on critical stimuli that require an immediate response [77]. This procedure of directing attention and tracking expected uncertainty is observable in the cholinergic system in the mammal brain[105,106].

Observations of humans with prefrontal cortical lesions, neuroimaging studies, and animal experiments suggest that prefrontal cortex and connected regions are important in encoding, storing, and utilizing mental schemas, i.e. context-dependent behavioral strategies. While the acquisition of new types of memories (e.g., the first time ever seeing the ocean) requires the creation of new schemas, new memories that are similar to previously learned ones (e.g., one who is familiar with oceans visits a new beach) can be rapidly incorporated into existing schemas, while still retaining old information in other schemas[107–110]. This process requires experiences to be encoded alongside the contextual schemas in which they occur, and suggests a way in which the brain exploits task similarity to achieve transfer and adaptation, to overcome catastrophic forgetting, and to learn in noisy environments.

3.6 Hierarchical Distributed Systems: Decentralized Processing

Many biological organisms have either no centralized brains or extremely small brains.

These control architectures behave as hierarchical systems. This allows processing and learning to be distributed across multiple networks of neurons throughout the body, each having high intra-network yet relatively sparse inter-network connectivity[112–119]. Such decentralized non-von Neumann architectures are starting to be implemented as artificial neural networks in AI and distributed controls[120–122]. By leveraging such hierarchical and distributed architectures, biological systems greatly reduce the input and output dimensionality at each layer to mitigate delays and accelerate learning[120,121,123–126]. As a prime example, consider 'central pattern generators' [127,128] that autonomously respond to perturbations and accomplish locomotion and cyclical movements[129–131].

Such a hierarchical and distributed approach allows animals to achieve enviable levels of performance despite noisy sensors, sluggish actuators (i.e., muscles), and delayed signaling. In particular, there is now an emerging consensus that this is made possible by the brain-body co-evolution of hierarchical and distributed neural circuits—as outlined in Figure 5—that permit effective sensory processing and muscle control [132–134]. Fortunately, it is now becoming possible to map out such widely distributed biological circuits, allowing us to understand how they facilitate task decomposition and detection of task overlap [135–138].
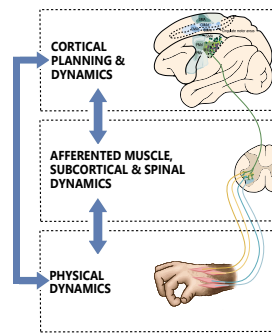
Figure 5. Biological systems use multiple levels of dynamical interactions. Morphological properties and constraints in the body define the feasible low-level dynamics the controller can exploit. Low-level sensorized tissues and feedback loops at the subcortical level (e.g., muscles, brainstem and cerebellum) mediate the interaction with the environment, while high-level cortical brain processes need only plan, select and tune them. This reduces resource utilization by limiting I/O complexity, and allows fast learning in specific layers without affecting the others. Learning and control is thus distributed into subtasks across the entire system. Figure adapted from ref.[111].

3.7 Cognition outside the brain: Bio-electricity Enables Computation in Multiple Media

Much of the focus on functional computation and problem-solving has been on emulating brain-like architectures. However, many biological systems exhibit the ability to learn from experience, anticipate future events, and respond adaptively to novel challenges, without the benefit of a nervous system. This includes organisms and levels of biological organization, such as individual cells and even molecular networks[139, 140], which compute via non-neural bioelectric networks (BEN)[141] or subcellular processes such as transcriptional networks[142]. A simple non-neural bioelectric model [143] that can be trained to perform cognitive tasks like logic and pattern recognition serves as a proof of principle (Figure 6). Because the same bioelectric circuits can control adaptive morphogenesis (e.g., regeneration) and computation (decision-making), this aspect of biology illustrates how the same set of mechanisms can be exploited for adjusting to novelty with respect to changing body structure as well as environmental inputs and conditions. Living systems utilizing this strategy can deal with not only radical changes in the environment such as encounters with toxins that strongly impact cellular physiology[144], but also with changes to their own structure and function[145], such as damage and regenerative remodeling to the original or new[146, 147] architecture. Mechanisms for plasticity and adaptation to new environments and new body configurations, which have been inferred from the field of basal cognition and regenerative biology, offer a rich pool of strategies from which to draw upon in creating novel L2M[148].

Biology exploits the same machinery (bioelectric and other kinds of networks, multi-scale homeostatic mechanisms, cooperation and competition within and across levels of organization) to solve search problems in difficult spaces including transcriptional regulatory networks, morphogenetic and developmental systems, physiological responses, and behavioral goals. Recent data have revealed important commonalities in how information is processed in body-wide neural networks and within single cell pathway networks, which is beginning to be exploited in synthetic biology[149].

3.8 Reconfigurable Organisms: Adaptive morphology in novel environments.

Biological organisms are highly reconfigurable in that they maintain coherent, adaptive functionality despite drastically changing environments and cellular properties[153]. For example, tadpoles created with an eye on their tail (instead of their primary eyes) can still exhibit efficient visual learning, showing that the brain may adapt to a novel architecture in which the eye is connected to the posterior spinal cord[146]. Similarly, tadpoles re-arrange their face to become normal frogs even when the craniofacial organs are placed in abnormal positions, showing the ability to progressively reduce the error (difference from the correct target morphology) and forge new paths to the correct region of morphospace despite drastically changing circumstances[154]. Planarian flatworms regenerate an entire body from fragments when it is cut into pieces, with very high anatomical fidelity[155]; however, transient modifications of their bioelectric circuits result in 2-headed forms that continue to give rise to 2-headed forms in perpetuity, despite their wild-type genome[156]. This illustrates the ability of somatic bioelectric circuits - precursors of brain networks[157] - to learn from experience and maintain global anatomical information distinct from the default outcomes resulting from their genomically-encoded hardware[140]. Moreover, cells and tissues removed from their normal context can be reconfigured into new organisms - synthetic living constructs - with coherent morphologies and behavior[147, 158] (Fig. 8) - an enviable capacity and design challenge for engineering. Amazingly, not only do living bodies adapt to novel configurations, but they are able to remodel brain tissue while maintaining information content (memories)[145].
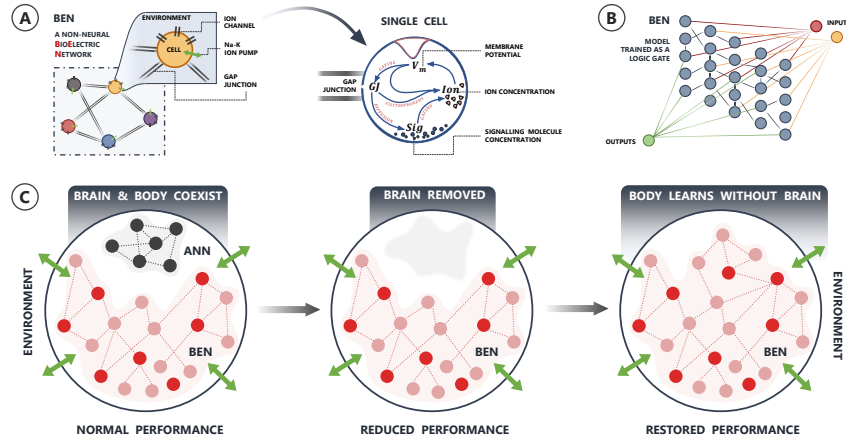
Figure 6. BEN: a non-neural bioelectric network (a mechanism used for control of growth and form during regeneration and repair) that can learn. (A) *Left*: the network architecture consisting of nodes representing non-neural cells that are connected by edges representing gap junctions; *Right*: the architecture of a single cell whose dynamics is driven by a network of generic bio-electric processes such as electrophoresis, diffusion and voltage-gating; bottom: a more detailed view of a two-cell network highlighting the phenomena of voltage-gating of ion channels and gap junctions. Adapted from ref.[143]. (B) A tissue-like BEN model that was trained to function as the AND logic gate. (C) Lifelong embodied learning: a potential future application of BEN where an agent that contains a BEN network modeling its body and an artificial neural network modeling its brain could learn to adapt to its environment even after the brain is removed.

3.9 Multisensory Integration: Creating a Unified Experience from Multimodal Information Streams

Biological organisms are inherently sensorimotor systems whereby motor actions are informed by multiple types of sensory signals. How these distributed, nonlinear, non-collocated, noisy, and delayed sensory signals are integrated to enable versatile motor function remains an active area of research[159–161]. For example, fusing hip and head acceleration signals, as birds are believed to do [162], seems to enhance balance [163]. Also, it has been observed that the superior colliculus integrates sensory information from different senses (i.e., vision, tactile and auditory signals) to produce coordinated eye and head movement [164]. Moreover, sensory signals also drive proprioception (i.e., information about the configuration and state of the body, and its relation to the environment), which provides information for implicit body representations that are fundamental to the sense of self [165]. Our understanding of how organisms handle, filter and process the flood of sensory data in a general task-agnostic way can support L2 [160, 166].

4 Application of Biologically Inspired Models in Lifelong Learning

The following subsections describe biologically inspired algorithms that incorporate the L2 features discussed in Section 2. Each subsection highlights a few examples of works relevant to one feature; Table 2 provides a more complete overview of the referenced works. Details about the cited models, datasets, and limitations can be found in the SM.

It should be noted that important contributions to subsets of L2 have also been made in various ML methods (*e.g.* deep reinforcement learning[82, 167]) that are less clearly biologically inspired, and therefore not included here.

4.1 Transfer and Adaptation

Biology can provide inspiration for systems that generalize, transfer knowledge from one task to the next, and adapt to change without losing that knowledge. Example mechanisms include:

Neuromodulation

The brain's neuromodulatory systems promote rapid learning and the ability to cope with context shifts caused by novel events or changes in motivation.

The role of neuromodulation in ML systems has been extensively explored [86, 91–93, 95, 96, 168, 169]. Specifically in the context of L2, uncertainty-based modulation has been shown to allow flexible adaptation[77], as well as direct and control learning systems[85]. More broadly, artificial evolution of neural networks has shown the key role of neuromodulation in meta-learning[170, 171].

Context-Dependent Perception and Gating

An L2 agent's performance can be improved by tracking contextual variation and using this information to modulate the network during training and/or at inference time. Examples of gating in L2M algorithms include a hierarchical gating mechanism
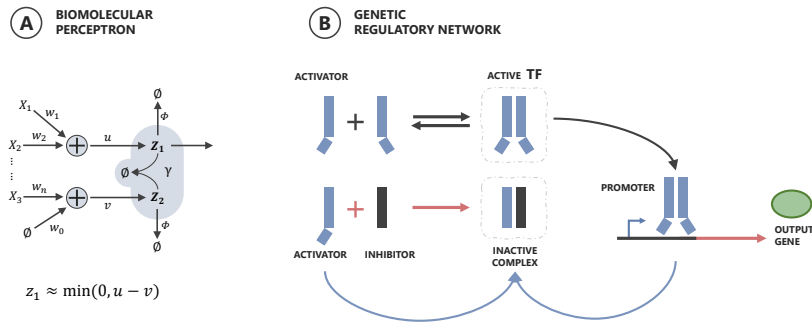
Figure 7. A) **Biomolecular perceptron** based on sequestration reaction between weight sums of inputs. The output Z1 is zero when u < v and u-v when u is greater. Adapted from ref.[150]. B) Genetic regulatory network implementing a sequestration reaction where monomeric molecules that determine the activity of a target (indirect titration, blue reaction arrows) are sequestered by a competing inhibitor (direct titration, red reaction arrows) such that only excess activator results in the output gene[151]. Adapted from ref.[152].
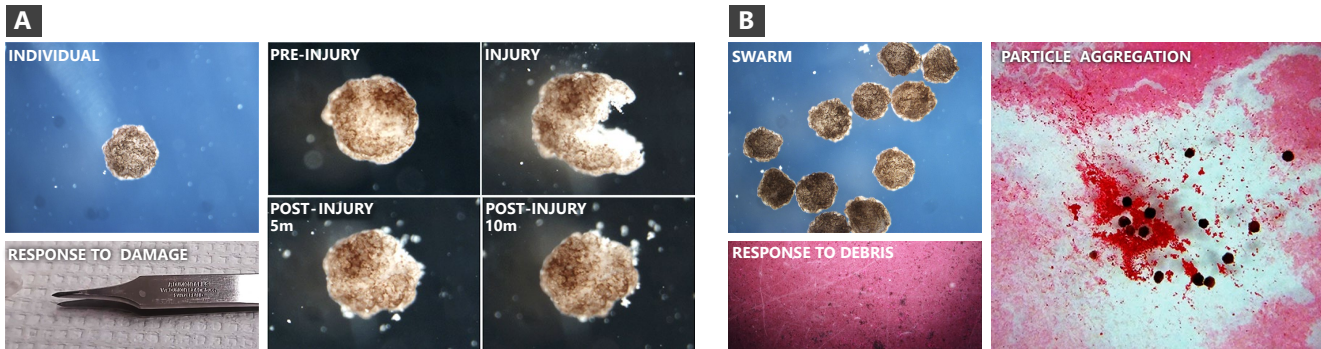
Figure 8. Lifelong learning in reconfigurable organisms. (A) Individuals, when challenged with mechanical injuries, rapidly repair the insult and restore their initial functionality. At the molecular level, repair dynamics can be visualized in real-time using in vivo metabolic reporters, and the resulting signaling networks can be extracted for use in lifetime learning algorithms. (B) Likewise, swarms of reconfigurable organisms demonstrate emergent task performance such as the aggregation of debris from the environment, providing a testbed to further engineer this behavior and determine how such information could be used in transfer and adaptation to a new task.

inspired by schema switching in the prefrontal cortex, which improved transfer learning while reducing memory footprint[172], gating based on a context signal inferred from recently seen inputs[173], and context-based action selection during game playing, enabling quick adaptation [174]. For other works relevant to context-based gating, see refs.[85, 86, 169, 175–178].

4.2 Overcoming Catastrophic Forgetting

Brains incorporate several mechanisms that help mitigate catastrophic forgetting during continual learning. Here we describe a few examples of models that use neurogenesis, metaplasticity, and neuromodulation. See the SM for examples of models that use episodic replay and context-dependent perception and gating.

Context-Dependent Perception and Gating

Context-dependent gating has been used to alleviate catastrophic forgetting by improving separation between the network's representations of patterns belonging to different tasks[179].

Neurogenesis

Neurogenesis, especially in the dentate gyrus of the hippocampus, is thought to support learning new memories without sacrificing old ones[180, 181]. Neurons may be added to represent new memories while leaving existing neurons intact. Several L2M mechanisms have mimicked neurogenesis by adding new neurons as needed[182–185].

BIOLOGICALLY INSPIRED MECHANISMS	KEY FEATURES						EVALUATION	
	TRANSFER & ADAPTATION	OVERCOMING CATASTROPHIC FORGETTING	EXPLOITING TASK SIMILARITY	TASK-AGNOSTIC LEARNING	NOISE TOLERANCE	RESOURCE EFFICIENCY & SUSTAINABILITY	DATASET CATEGORY	REFERENCES
NEUROGENESIS	*(hatched)*	180—185	249	172	*(hatched)*	185, 212, 213	IMAGE RECOGNITION	7, 59, 77, 85, 91, 95, 96, 171, 176, 177, 179, 182, 183, 186–188, 190, 192, 194, 196, 209, 212, 213, 249
EPISODIC REPLAY		59, 186, 187, 190, 191		59, 187	187, 188	58, 59, 186, 187, 190, 191, 214		
METAPLASTICITY		72, 96, 192—196		7, 192, 196, 209		96, 192—194, 209		
NEUROMODULATION	77, 85, 91—93, 95, 96, 168, 170, 171	85, 86, 91, 96, 175	96	85, 170	85, 169, 210	96	ENVIRONMENT INTERACTION	85, 86, 168, 170, 171, 174, 181, 182, 185, 191, 193, 195, 203
CONTEXT-DEPENDENT PERCEPTION AND GATING	85, 86, 169, 172—178	85, 179	86, 173—177	77, 172	169, 173, 174			
HIERARCHICAL DISTRIBUTED SYSTEMS			199—202		121, 202, 211	202	BIOLOGICAL SIMULATION	147, 158, 206–208
COGNITION OUTSIDE THE BRAIN	*(hatched)*		206—208		*(hatched)*			
RECONFIGURABLE ORGANISMS	147	*(hatched)*	147, 158		147, 158	147, 158	ROBOTICS	121, 163, 171, 175, 200, 201
MULTISENSORY INTEGRATION			163, 166, 203, 204		121, 173		OTHER	58, 72, 92, 93, 166, 169, 172, 173, 178, 180, 184, 199, 202, 204, 210, 211, 214

Table 2. Application of biologically inspired models for L2. The matrix illustrates the relationships between bio-inspired mechanisms that have been implemented in ML models (along the left edge) and key L2 features (along the top). Numbers in a cell indicate referenced works where a mechanism (row) has been applied to realize a key feature (column). The right pane represents the different dataset categories for the models cited in the table. Note that some of the mechanism-feature correspondences attributed to biological systems (as seen in Table 1) are yet to be implemented in ML models (designated using colored hatched lines), while some correspondences (designated using gray hatched lines) have neither biological nor ML implementations [See SM].

Episodic Replay

Building on biological insights related to sleep and replay, it has recently been shown that both mimicking sleep[186–189] and adding internally generated replay[59,190] or rehearsal of stored data [191], can help make deep neural networks more resistant to catastrophic forgetting.

Metaplasticity

Researchers have taken inspiration from the time-varying plasticity of biological synapses to implement metaplasticity in ML models. A cascade model of synaptic plasticity was shown to significantly mitigate catastrophic forgetting[72]. More recently, a model using binarized weights with a real-valued hidden state was able to sequentially learn complex datasets, without forgetting prior learning[192].

The metaplasticity model from ref.[72] has also been shown to mitigate forgetting in a reinforcement learning paradigm[193]. Other examples where metaplasticity is used to overcome catastrophic forgetting include[96,194–196].

Neuromodulation

In simulations and robot memory tasks[86,175], neuromodulation has been used to decide if new stimuli were novel and unfamiliar (i.e., create a new schema) or novel and familiar (i.e., consolidate into an existing schema). Neuromodulation signaling uncertainty has also been used to regulate the stability-plasticity dilemma when encoding memories, thus overcoming catastrophic forgetting[85].

4.3 Exploiting Task Similarity

Several bio-inspired mechanisms contribute to flexible representations that facilitate task overlap and composition.

Context-Dependent Perception and Gating

The disentangling role of the dentate gyrus, as discussed in Section 3.1, is general to a number of architectures and cognitive theories, for example, the disentangled and factorized representations found in autoencoders[176,177], and context-dependent schemas[86,175]. On a more abstract level, few-shot complex object learning can be framed as the combination of parts into wholes based on their relationships, which are captured in capsule networks[197], and has led to the formation of the Omniglot dataset[198].

Hierarchical Distributed Systems

Although layered architectures such as network protocols are typically part of good systems engineering[199], there are certainly combinatorial challenges in applying similar concepts to learning systems. These challenges arise because of diversity across layers in a hierarchy. This makes it difficult to build a system capable of flexibly capturing the entire combinatorial space of diversity.

In refs.[200–202], methods for learning and selecting movement primitives have been demonstrated to accelerate learning in robotic motion.

Multisensory Integration

Leveraging from more than one sensory input enhances robot navigation [203], as well as tunable perception of body configuration [163] and its relation to the environment [204]. For example, a bioinspired spiking multisensory neural network can recognize objects based on multisensory integration as well as imagine never-seen pictures based on an audio input (e.g., a blue apple after learning colors through vision and the association of the word "apple" with the fruit) [166].

Reconfigurable organisms

Cells taken from the skin of an organism, when excised and allowed to recombine in a novel environment, self-assembles into an active construct that exploits similarities in its new environment to implement motility and interactions with conspecifics and objects in the vicinity (such as using cilia for propulsion, and regenerative mechanisms to repair to the new morphology after damage)[147, 158]. Note that these elements overlap and interact; for example, context-dependent perception and disentangled representations enable hierarchical organizations. Also, while the above methods can more effectively leverage task similarity, there are still a number of limitations and open questions. Though notions of neurogenesis, compositionality, and reconfigurability implicitly rely on task similarity, it is not clear whether and how more explicit measures and representations for task similarity[205] could provide further improvements.

Cognition outside the brain

Bioelectric networks found in non-neural tissue have inspired modeling of regulatory and regenerative functions for L2M systems[206–208].Biological tissues that are not neurons form bioelectrical networks to control morphogenesis[206, 207]. Cognition outside the brain is shaped by evolutionary forces just as cognition in the brain. Computational AI systems can mimic and exploit the resulting dynamics by simulating the known mechanisms of non-neural bioelectric communication among cells.

4.4 Task-Agnostic Learning

In real-world deployment, task information is typically not provided and task boundaries are not well defined. A particularly challenging scenario in L2 is when the model is required to infer task identity. Several of the mechanisms described in Section 3 have inspired ML models that can aid task-agnostic learning in L2 systems.

Context-Dependent Perception and Gating

Biological systems often modulate perception through selective attention and can infer task information. Context-dependent perception or gating can utilize network information (local or global), to infer context shifts or identify context information. An example is the detection of context shifts based on the network's error[77, 172].

Metaplasticity

Many metaplasticity-based approaches, especially those that aim to protect knowledge by restricting the plasticity of important synapses[194, 195], require task change notifications during training in order to decide when to update each synapse's estimated importance. Recently, several studies have implemented metaplasticity as a function that only uses information that is local to each synapse, without any need for task information[7, 192, 196, 209].

4.5 Noise Tolerance

L2 agents operating in real-world scenarios must be able to maintain their performance in the presence of spurious and out-of-distribution patterns and data. Mechanisms such as neuromodulation[85, 169, 210], multisensory integration[121, 173], hierarchical distributed systems[121, 202], reconfigurable organisms[147, 158], and episodic replay[187, 188] have been employed to help improve the noise tolerance of L2 systems.

Hierarchical systems can learn higher-tier control policies that accommodate for noise, mitigating its effects on lower-tier controller outputs [121], resulting in algorithms that can perform well in noisy environments[211]. Noisy, spurious correlations can be filtered out by a synaptic consolidation mechanism that extracts cause effects in input-output streams[210]. Finally, cells dissociated from a living organism can self-organize into a novel, functional proto-organism without micromanagement – they tolerate high levels of noise in terms of number and position of cells, and environmental conditions, to reliably construct a motile, regenerative functional system [147, 158].

4.6 Resource Efficiency and Sustainability

A difficult challenge for L2M is to accommodate new information without uncontrolled growth of memory and compute-power requirements. Examples of approaches that have shown promise include:

Neurogenesis

While neurogenesis allows systems to incorporate new information[212], uncontrolled growth needs to be avoided. Distinguishing novel information can help discern whether further neurogenesis is required, and to what degree[185,213]. Network pruning mechanisms have also been shown to be effective in simulated maze environments[185].

Episodic Replay

The replay or rehearsal of previously learned information is an effective and widely used tool in L2[58,59,186,187,190,191]. However, an important concern with replay is its computational efficiency and scalability, as its naive implementation involves constant retraining on all previously seen data. Inspired by neuroscience, recent work in deep learning has addressed the issue of scalability by showing that to avoid forgetting, it can be sufficient to only replay a small subset[59], to just replay old memories that are similar to the new learning[214], or to replay abstract, high-level representations of past experiences[59]. Interestingly, it has also been shown that replay interleaved with new learning can reduce the amount of resources used to represent previously learned information, allowing a growing number of tasks to be learned without memory requirements growing at the same rate[215].

Metaplasticity.

Several metaplasticity-based approaches, also referred to as parameter regularization methods, have been shown to be able to reduce catastrophic forgetting while learning new tasks without increasing resource requirements for memory and compute power[96,192–194,209]. However, because the representational capacity of these approaches is fixed, they will not be able to learn sequences of tasks that are arbitrarily long, and it could be argued that a controlled growth in resource use is desirable[216].

5 Conclusions

In this perspective, we have reviewed insights from biology regarding the abilities of humans and other animals to meet the challenges of lifelong learning, and presented an overview of research that applies such findings toward the development of continual learning in AI systems.

The application of biologically inspired models to lifelong learning has provided some tantalizing examples of the potential that these approaches have to transcend the limitations of current AI. Many of these developments are still in their infancy, involving small-scale demonstrations of individual features to achieve L2 capabilities. Going forward, we can expect significant advances in our understanding of biological learning mechanisms that can continue to inform new methods for AI. We expect that adoption of these ideas by the AI community, and integrating them into standard AI/ML frameworks, will serve as a strong foundation to develop new generations of AI systems with greater autonomy and L2 capabilities. A lesson one can draw from this perspective is the importance of developing composite systems that incorporate several of the mechanisms listed in section 3 (or those yet to be discovered), in contrast to narrowly focusing on a small subset of such mechanisms.

Another crucial factor for the advancement of L2 technology is the development of realistic test environments that specifically address continual learning capabilities, not limited to pre-prepared datasets. Going forward, an L2 system will have to stay active, be aware of external changes and its own operation – as it collects hints for additional learning.

We suggest that future widespread deployment of AI/ML will require the development of compute-efficient L2 architectures. Rapid progress towards this goal is being made through the creation of new hardware substrates, notably neuromorphic accelerators that emulate neural processing [209,217–228]. In particular, bio-plausible L2 models can be well-suited for these neuromorphic accelerators.

We believe that biology will continue to be a rich source of inspiration for the development of novel L2 approaches. Advancements in our understanding of other key biological mechanisms, including dynamic memory updating mechanisms like active forgetting[229], extinction[230], and memory reconsolidation[231] will continue to inspire novel algorithms beyond those described in this perspective. Expanding our knowledge of intra-cellular processes like signaling and gene regulation as well as inter-cellular communication could also provide inspiration for L2 beyond the central nervous system.

Because of their greater abilities and richer range of behaviors when deployed in real world [232], L2 systems have the potential to revolutionize many applications, including fully autonomous vehicles, smart cities, and healthcare. The realization of this potential will require continued multidisciplinary initiatives that support researchers studying at the intersection of biology, neuroscience, psychology, engineering, and AI[233]. Such collaborations are crucial for generating the convergent solutions that this new form of AI demands.

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Supplementary Material

Bio-Inspired Models for Lifelong Learning

We provide brief explanation of the biologically inspired models mentioned in Section 4 and Table 2.

- Brain-Inspired Replay (BI-R)[59] - This model uses a brain-inspired variant of replay in which abstract, high-level representations are replayed that are generated by the network's own feedback connections. This model (1) alleviates catastrophic forgetting because it interleaves new task training data with samples representative of past tasks, (2) it is able to do class-incremental learning (i.e., a form of task-agnostic learning[28]) because its replay mechanism allows for direct comparisons between objects or classes that are not observed together and (3) it enhances the computational efficiency and scalability of replay by only replaying a relatively small number of samples in every mini-batch and by replaying abstract, latent representations rather than detailed, input-level examples. BI-R has been tested on incremental image classification problems based on MNIST and CIFAR-100. A limitation of BI-R is that its internal replay component depends on the availability of a suitable pre-trained feature extractor. Open source code: `https://github.com/GMvandeVen/brain-inspired-replay`.

- Dynamic Generative Memory (DGM)[234] - DGM is a brain-inspired variant of memory replay in which a neuro-modulated generative model is trained to conditionally generate data from previous tasks, and interleave them with new data while training on the new task. One challenge with generative replay approaches is that catastrophic forgetting can happen in the generator. DGM proposes a novel brain-inspired solution to this problem by using neuromodulation via binary synaptic masks to allow continual learning of the generative model itself. The approach is tested on various incremental image classification benchmarks including MNIST, SVHN, and ImageNet.

  Limitations: One limitation of DGM is that this approach requires knowledge of task identity, which is not practical in real-world scenarios.

- Uncertainty-Modulated Learning (UML)[85] - UML utilizes principles of neuromodulation to drive adaptation and learning in response to multiple types of uncertainty. Inspired by mechanisms of neuromodulation, UML compares its internal hypotheses against expectations and adapts its behavior based on the level of mismatch. Under high uncertainty, it re-configures itself and re-evaluates its inputs, allowing robust operation in noisy environments or in the presence of new conditions. Under low uncertainty, the algorithm can more confidently engage long-term adaptation to learn new tasks or tune its knowledge base. Because uncertainty serves to gate learning and the type of adaptation in the system, it can prevent catastrophic forgetting and promote behaviorally-relevant adaptation. Furthermore, under very high uncertainty conditions, UML protects existing knowledge to allow one-shot learning of novel information. Finally, the algorithm can use its internal measures of uncertainty to actively seek new information (active perception) to reduce uncertainty or stop learning (under low uncertainty) to optimize learning and resource utilization. The UML algorithm has been evaluated in multiple machine learning domains, including classification, embodied agents, and reinforcement learning. In the first case, the UML algorithm enabled adaptation to degraded MNIST imagery[235] without requiring complete retraining nor sacrificing performance on the original dataset. In a second case, the UML algorithm promoted adaptation in an embodied agent within a 3D environment[236] trained on ground-level imagery. UML's neurmodulation-inspired mechanisms supported adaptive learning, uncertainty management, and attentional focus in the application, adding functionality to the agent and allowing it to search for and recognize these objects from the air [85]. In the third case, UML monitored the expectations of a deep reinforcement agent, modulating its behavior to recover performance under noisy and perturbed conditions. Finally, UML has been applied in multiple real-world applications, including recyclables sorting and synthetic aperture radar (SAR) -based automatic target recognition (ATR) systems. A limitation of UML is that it requires a robust representation of its inputs. Nonetheless, it has proven to work well when using the output layer of deep neural networks trained on datasets such as ImageNet or COCO. Another limitation is that it learns to recognize tasks by the difference in the context of each task. Therefore, there is a requirement that each task possesses a sufficiently different context.

- Elastic Weight Consolidation (EWC)[195] - EWC performs task-specific synaptic consolidation (a metaplasticity approach to reduce plasticity of synapses considered important for previous tasks) to mitigate catastrophic forgetting. In EWC, a synapse's importance is estimated for each task by the synapse's corresponding diagonal element of that task's Fisher Information matrix. The information matrix for each task is evaluated after finishing training on that task. EWC allows knowledge of previous tasks to be protected thereby addressing catastrophic forgetting of old abilities on a set of image classification tasks based on handwritten digit datasets and learning several Atari 2600 games sequentially.

Limitations: One limitation of this approach pertains to having knowledge of task identity, which is not practical in real-world scenarios. EWC requires storing a synapse's importance per task, which is not scalable as the number of tasks grows. Moreover, EWC inherently assumes that a synapse's importance is independent of all other synapses (i.e., the assumption that task's Fisher Information matrices are diagonal), which is not accurate. Finally, a generic shortcoming for structural plasticity approaches like EWC is the so-called 'intransigence,' which refers to the inability of the network to learn new tasks as it becomes less and less plastic.

- Synaptic Intelligence (SI)[194] - SI incorporates the concepts of brain-inspired metaplasticity and introduces *intelligent synapses* as a way to mitigate catastrophic forgetting. Each intelligent synapse accumulates task relevant information over time, and exploits this information to rapidly store new memories without forgetting old ones. This model reduces forgetting in task-aware scenarios for image classification tasks of handwritten digits and CIFAR-10/100 datasets, while maintaining computational efficiency.

  Limitations: But as observed with most of the metaplasticity based approaches, complex synapses fail to operate well in task agnostic settings. Most of the existing models of metaplasticity are unable to efficiently address the stability-plasticity dilemma for complex tasks. (Synapses become too stable to generally adapt to the changes in the input distribution) Open source code: `https://github.com/ganguli-lab/pathint`

- General-to-Particular algorithm (G2P)[121] - G2P is a bio-inspired algorithm which consists of a sparse kinematic sampling phase (similar to motor babbling in vertebrates) followed by refinements of the inferred kinematic mapping using data collected while performing tasks of interest. Moreover, the modular nature of the G2P algorithm enables it to work with prescribed tasks, imitation learning, or reinforcement learning, where the accuracy of the inverse kinematic model improves as the system explores more task-specific kinematic subspaces. The algorithm was tested on a custom-built physical tendon-driven robotic leg with two joints and three tendons (i.e., actuators). One of the metrics used to quantify performance was the cumulative distance the leg could propel a treadmill. The leg was also tested to imitate various postures and gait patterns in the air. Limitations: The model needs to be tested on more complex physical robot bodies that feature more degrees of freedom (joints and tendons) as well as with richer, more dynamic tasks such as balance-control and locomotion in different environments. Open source code: `https:github.com/marjanin/Marjaninejad-et.-al.-2019-NMI`

- Dynamical Movement Primitives[200, 201] - This is a technique that takes inspiration from biology[138] when building complex movements and actions from the addition of simpler 'movement primitives.' This hierarchical control approach explicitly distinguishes among the plant, the movement primitives and their combination into a more complex action. Each of these layers in the hierarchy is defined as dynamical equations, coming together to produce the system's overall dynamics. Learnable forcing functions then drive this combined dynamical system to perform discrete (point-to-point) and cyclical actions of arbitrary complexity. The advantage of this approach is that certain aspects (dynamical equations) are prescribed while others (like forcing functions, system parameters) are learned and tuned at various levels of the hierarchy. The technique was tested to replicate multi-dimensional movement patterns in simulation and on a physical robotic arm. Limitations: This computationally intensive approach to controlling robotic movement relies on our ability to, at least approximately, model the dynamical equations being controlled under different conditions (e.g., payloads and trajectories), and have a relatively broad stability margin across multiple and potentially unknown conditions. This means these techniques often require explicit training and deployment phases, and have to be extensively tested before being applicable to highly nonlinear systems such as tendon-driven robots for hybrid dynamics such as those for locomotion and manipulation.

- Relational Neurogenesis (RN)[185] - This model demonstrates a dynamic network architecture inspired by neuroevolutionary mechanisms. The network growth is implemented through Neurogenesis (adding of nodes) and Synaptogenesis (adding of edges). However, to prevent unnecessary evolution or explosive growth, neuronal and synaptic termination/pruning mechanisms are used. This work is able to demonstrate continual learning in a task-agnostic manner for reinforcement learning scenarios. RN was evaluated on two photorealistic 3D simulation environments which are customized to support continual learning. Limitations: The algorithm requires extensive real-time computational overheads which make it unsuitable for edge applications. Additionally, the neurogenesis implementation is unbounded (despite relief being provided by pruning mechanisms), and thus, does not fulfill the resource constraint requirements of lifelong learning. Open source code: `https://github.com/Nu-AI/RelationalNeurogenesis`

- Continual Neural Dirichlet Process Mixture (CN-DPM)[183] - CN-DPM applies an expansion-based approach for task-free continual learning. This model consists of a set of experts and decides whether an input sample should be assigned to an existing expert or a new expert should be created for it. CN-DPM expands the number of experts in a principled

way under the Bayesian nonparametric framework. Due to the dynamically growing architecture, the model capacity is determined adaptively depending on the data. Overall, the model not only prevents catastrophic forgetting but also applies to the setting where no task definition and boundaries are given at both training and test time. CN-DPM was evaluated on the CIFAR-10/100 and the MNIST datasets for image classification. Limitations: The approach still has a limitation in selection of the expert (which is necessary in improving the performance of the model) and needs to be evaluated in other domains. Open source code: `https://github.com/soochan-lee/CN-DPM`

- Modulatory Network (ModNet)[95] - In ModNet, neuromodulatory plasticity is embedded with dynamic learning architectures inspired from mushroom body in the insect brain. Neuromodulatory mechanisms are incorporated in two ways, 1) An inbuilt modulatory unit (modulatory layer is introduced in a random projection framework) to regulate and compartmentalize learning based on the context and internal state of the system. This renders the system an ability to perform selective attention and self modify its weights. 2) A modulatory trace based learning rule, that uses a time dependent trace to modify the synaptic connections as a function of ongoing states and activations. The trace itself is updated via simple plasticity rules thus reducing the demand on resources. ModNet demonstrates the ability to learn from few samples, train quickly, and perform few-shot image classification in a computationally efficient manner on handwritten character and digit recognition datasets like Omniglot and MNIST. Limitations :ModNet does not account for the stability of the model and is prone to forget prior learned knowledge. Moreover, the generation of a relevant context signal to realize the effect of neuromodulators is yet to be addressed. Open source code: `https://github.com/Nu-AI/Neuromodulatory_OneShotLearning`

- Continual Learning with Experience and Replay (CLEAR)[191] - CLEAR is a replay-based method that reduces catastrophic forgetting in multi-task reinforcement learning scenarios. CLEAR leverages off-policy learning and behavioral cloning from replay to enhance stability, as well as on-policy learning to preserve plasticity. CLEAR uses on-policy learning on fresh experiences to adapt rapidly to new tasks, while using off-policy learning with behavioral cloning on replay experience to maintain and modestly enhance performance on past tasks. In addition to this, CLEAR does not rely upon the identity of tasks or the boundaries. CLEAR was able to demonstrate these capabilities on the DMLab tasks. Limitations: The reliability of the model in realistic scenarios wherein the amount of constructive or destructive interference between tasks varies is yet to be evaluated.

- Neuromodulated Attention[77] - In uncertain domains, the goals are often unknown and need to be predicted by the organism or system. An online learning model based on the cholinergic and noradrenergic neuromodulatory systems could quickly learn the context without supervision, flexibly apply attention to the appropriate goal (expected uncertainty), and rapidly detect and re-adapt to context changes (unexpected uncertainty). The predicted goal modulated the attention of a contrastive Excitation Backprop neural network[237] by increasing attention to objects associated with the goal, while decreasing attention to distractors. In particular, the cholinergic system evaluates the trade-off between stimulus-driven and goal-driven attention[238]. The noradrenergic system responds to novelty, surprises or large deviations from priors[83]. When the NE system responds phasically under rapid and transient change increase of goal-related neural activity, it causes a network to reset and allows quick adaptation to a different goal[239,240]. The approach was used in two goal-driven perception tasks – one with pairs of noisy MNIST digits and the other with a Toyota Human Support Robot (HSR)[241] in an action-based attention scenario. For object classification in the action-based robot experiment, the Microsoft COCO dataset[242] was applied to a GoogLeNet[243] via the Caffe framework[244] instead of using the MNIST-pair network as in the first experiment. This neurobiologically plausible model demonstrates how neuromodulatory systems can predict goals in uncertain domains and how attentional mechanisms can enhance the perception for that goal. In the present work, the system guessed the appropriate goal from a known set of possible goal classes. In the future, the system should be more scalable to adapt to unseen goals or goal classes by using a single head that can learn them online with reward feedback without any *a priori* assumptions. The introduction of the cholinergic and noradrenergic neuromodulation should make the goal search fast and flexible.

- Context+Skill model (CS)[173,174] - This model demonstrates how explicit representation of context can modulate performance across related tasks, making it possible to extrapolate to new tasks. The model is inspired by the olfactory system, where context plays a crucial role in recognizing known odors as well as learning to recognize new ones[97,99–101,245]. Context and skill are implemented as different modules: Context integrates information over long time periods and skill responds to current input. A third module, decision-maker, combines their outputs to the final output of the system. The approach is particularly useful in transfering and adapting to new tasks, exploiting task similarity, and dealing with noisy environments. In addition to olfactory search, it has been demonstrated in adapting to new conditions in various control game environments (Poker, FlappyBird, LunarLander;[174]), to new tasks in automated driving[174], and to sensor drift in gas identification[173]. Limitations: The model currently assumes that the skill is applied repeatedly at shorter time scales than

the context. It provides a robust starting point for lifelong adaptation, but adapting the CS model itself over time still needs to be tested. Open source code: `https://github.com/nnrg/ContextSkillDrift`, `https://github.com/nnrg/ContextSkillCarla`, `https://github.com/nnrg/ContextSkillFlappyball`.

- Neural Model of Schemas and Memory Encoding[86, 175] - The ability to rapidly assimilate new information is essential for survival in a dynamic environment. This requires experiences to be encoded alongside the contextual schemas in which they occur. Tse et al.[108] showed that new information matching a preexisting schema could be quickly consolidated from hippocampus to cortex, whereas novel schemas took time to consolidate. To better understand the neurobiological mechanisms for creating and maintaining schemas, a biologically plausible neural network was constructed to learn context in a spatial memory task[86]. The model proposed that this occurs through two processing streams of indexing and representation, in which the medial prefrontal cortex and hippocampus work together to index cortical activity. Additionally, the model demonstrated how neuromodulation contributes to rapid encoding within consistent schemas. Similar to noradernergic and dopaminergic neuromodulation in the hippocampus, the modeled neuromodulators drove rapid learning when new information fit within a familiar context, and slower consolidation when new information did not fit within a context. By separating different information into schemas, the model further provided a basis for creating context-dependent memories while preventing catastrophic forgetting in artificial neural networks. Similar to Tse and colleagues[108], the schema model was tested with odor and place associations[86]. A later study with a physical robot tested the schema idea with objects typically found in an office suite[175]. A limitation of the model was it had a finite number of possible schemas. It remains to be seen if the model could scale up to benchmarks used to test catastrophic forgetting and transfer learning.

- Continual reinforcement learning with complex synapses[193] - This research explores whether a biologically plausible complex synaptic model[72], which abstractly models plasticity over a range of timescales, can be applied to mitigate catastrophic forgetting in a reinforcement learning context. Following the concept of metaplasticity, each parameter of a tabular or deep RL agent is expressed as a dynamical system of interacting variables. This work demonstrates that incorporation of different timescales of plasticity can correspondingly result in improved behavioural memory over distinct timescales. Furthermore, this is achieved even though the process of synaptic consolidation has no prior knowledge of the timing of changes in the data distribution (in a task-agnostic fashion).This work on metaplasticity was evaluated on simple Cart-pole and Catcher environments. The scalability of metaplastic synapses on complex learning tasks and scenarios is still under question and needs to be addressed.

- Sleep Replay Algorithm (SRA)[187–189] - Motivated by biological sleep replay, this work tested if implementing a sleep-like phase in ANNs can protect old memories during new training. To simulate local unsupervised Hebbian plasticity during sleep phase, after each new training we implemented an offline sleep-like phase with noisy input. The model was evaluated on the MNIST, Fashion MNIST, CUB-200 and CIFAR10 image recognition benchmarks. In an incremental learning framework, we demonstrate that sleep was able to recover old tasks that were otherwise forgotten[187]. Previously learned memories were replayed spontaneously during simulated sleep, forming unique representations for each class of inputs. Representational sparseness and neuronal activity corresponding to the old tasks increased while new task related activity decreased following a sleep phase. We further found benefits of SRA on defending against adversarial attacks and increasing ANN classification robustness[188]. For that, the model was evaluated on the MNIST and CUB-200 data sets in two different settings, i) Adversarial attacks designed to fool neural networks and ii) generalization distortions designed to reflect imperfect viewing conditions or other types of noise. The study suggests that local, biologically inspired learning rules applied during spontaneously generated sleep replay are sufficient to alleviate catastrophic forgetting, promote generalization and improve robustness against noise. The main advantage of the SRA is that no old data are needed to be stored or generated to enable continual learning or increase adversarial robustness. The limitation, and possibly trade-off, is that the robustness comes at a cost to the classification accuracy of the model. The next steps would be to address the robustness-accuracy trade-off.

- Sleep replay in spiking neural model[186, 246, 247] - Building upon data suggesting importance of sleep in learning and memory, the work evaluated a hypothesis that sleep protects old memories from forgetting. In the biophysical spiking model, training a new memory interfered with previously learned old memories leading to degradation and forgetting of the old memory traces. Simulating sleep immediately after new learning reversed the damage and enhanced all memories. We found that when a new memory competed for previously allocated neuronal/synaptic resources, sleep replay changed the synaptic footprint of the old memory to allow overlapping neuronal populations to store multiple memories. The study predicts that memory storage is dynamic and sleep enables continual learning by combining consolidation of new memory traces with reconsolidation of old memory traces to minimize interference. The advantage of this model is that it can directly capture biological mechanisms. The limitations lie in the simplicity of tasks the model was evaluated on.

The memory consolidation and reconsolidation experiments were conducted on very simple memory sequences. Scaling up the biophysical models to complex tasks is challenging and computationally expensive. It is possible that the new solutions based on the neuromorphic hardware (e.g., Intel Loihi [248]) could enable a further new avenue for replay with spiking neural networks.

- Neuromorphic Neural Architecture (NNA) [96] - NNA is a biologically-inspired architecture that exhibits excellent performance in various online continual learning tasks. First, this work mimics the heterogeneous plasticity of the insect brain by decoupling our networks into a feature extraction and a learning component. Second, NNA uses local synaptic plasticity rules to carry out supervised learning on data streams, where labels are passed as neuromodulatory signals akin to what happens in ternary synapses. Third, novel local learning rules are introduced that mimic the transition from short term to long term memory taking place in individual synapses. We show that the synaptic plasticity mechanism and neuromodulation combined with other structural features in the invertebrate brain are enough to achieve state-of-the-art online continual learning without the need of keeping a memory buffer of past experiences We evaluated NNA in both the task- and class-incremental learning scenarios on Split-MNIST, Split-CIFAR10 and Split-CIFAR100 datasets. Limitations: The plasticity for the supervised learning is restricted to a single layer in our architecture.

- Context-dependent gating (XdG)[179] - XdG proposes a gating technique inspired from context-dependent gating mechanism, which can allow networks trained using metaplasticity based techniques to maintain high performance across large numbers of sequentially presented tasks. They are able to achieve this by using a context-dependent signal to gate non-overlapping sets of units to be active for any given task. This ensures maximal separability of the representations across different tasks and is useful in scaling up capabilities of regularization-based approaches. This work was evaluated on larger datasets like CIFAR-100 and ImageNet-1000 with the model being presented 100 tasks sequentially. Despite this work demonstrating the importance of context dependent gating for scaling metaplasticity based approaches, there an issue with the generation of context signal in task unaware settings that is yet to be addressed. Open source code: `https://github.com/nmasse/Context-Dependent-Gating`

- Dynamic Mixture of Experts (DynaMoE)[172] - DynaMoE is a simple neural network framework that incorporates hierarchical context-based gating to model the prefrontal cortex's ability to flexibly encode and use multiple disparate schemas. This model shows how gating leads to transfer learning and robust memory savings. The model is able to encode, store and access multiple schemas from experiences using a mixture of experts and is agnostic of training regimen in addition to not requiring any supervision. DynaMoE is able to add capacity when required and leverage already acquired knowledge to solve new problems, thereby reducing the demand for growth and enabling the model to be scalable. To demonstrate the features, DynaMoE was evaluated on the Wisconsin Card Sorting Task (WCST) dataset, where the model is required to sequentially sort cards according to one of three possible rules. Limitations: DynaMoE needs to be evaluated on complex tasks to measure the efficacy of selection of experts to varying input distributions. Open source code: `https://github.com/tsudacode/DynaMoE`

- A Neuromodulated Meta-Learning Algorithm (ANML)[91,93] - ANML, inspired by the neuromodulatory processes in the brain, enables continual learning without catastrophic forgetting at scale. ANML differentiates through a sequential learning process to meta-learn an activation-gating function that enables context-dependent selective activation within a deep neural network. Specifically, a neuromodulatory (NM) neural network gates the forward pass of another (otherwise normal) neural network called the prediction learning network (PLN). The NM network also thus indirectly controls selective plasticity (i.e. the backward pass of) the PLN. ANML demonstrates effectiveness at reducing catastrophic forgetting at scale on the Omniglot handwritten character recognition dataset. Limitations: The model shows a slight performance drop in task agnostic settings which can be improved and resource efficient ways of modulating the synapses in the PLN can be explored. Open source code: `https://github.com/uvm-neurobotics-lab/ANML`

- Synaptic metaplasticity in binarized neural networks[192] - This work incorporates metaplasticity in binary neural networks to achieve resource and compute efficient continual learning capabilities in deep neural networks. In binary neural networks, every hidden weight is associated with a real value, and the proposed work interprets this value as a metaplastic variable which drives the weights in the network to a more stable state to prevent forgetting. This model implements long-term memory in binarized neural networks and is able to overcome catastrophic forgetting in a task agnostic scenario. Limitations : The proposed metaplastic regularization approach is not scalable to larger networks and evaluation datasets. Moreover, utilizing full-precision real values as metaplastic variables does not entail significant benefits in the energy and resource efficiency of the model for lifelong learning. Open source code:`https://github.com/Laborieux-Axel/SynapticMetaplasticityBNN`

- Deep Generative Replay (DGR)[190] - Inspired by the generative nature of the hippocampus as a short-term memory system in primate brain, DGR introduces a framework with a deep generative model and a task solver model to replay past learned data while being interleaved with current data as a method for reducing catastrophic forgetting. DGR is evaluated on digit recognition benchmarks, namely MNIST and SVHN. Limitations: One defect of the DGR framework pertains to its reliance on the quality of the generator used to create samples of previously seen data. Thereby, significant changes in input distribution might cause the network to either forget previously learned data or learn incorrect generated samples.

- Rapid online learning and robust recall in a neuromorphic olfactory circuit[169] - This research inspired from the architecture of the mammalian olfactory bulb, utilizes spike-timing based learning coupled with neuromodulation and neurogenesis to perform noise robust rapid online learning on edge platforms. This work deploys neuromodulation as a dynamic optimization trajectory and neurogenesis to continually process and learn multiple odours. The proposed model is able to classify odours, even in scenarios when the sensors are fed with noisy inputs. Limitations: This work uses a simplified model to evaluate the rapid learning capabilities in resource and energy constrained platforms. The applicability of this model to multi-sensory inputs with varying input distributions is yet to be evaluated. Open source code:`http://modeldb.yale.edu/261864`

- Evolved Plastic Artificial Neural Networks (EPANN)[171] - This broad approach consists in the evolution of plastic networks with the aim not to optimize an existing learning process, but rather to discover from scratch novel learning algorithms that solve L2 problems. Such autonomously discovered learning can fit lifelong learning scenarios according to the evolutionary settings and environments. They promise to bootstrap AI systems with novel learning paradigms. Limitations: the computational cost of evolving learning networks is high because each fitness evaluation involves long training processes that require repeating across a population of solutions. A second limitation is that the search space of such search algorithms is large. This often results in sub-optimal performance with respect to manually designed networks that undergo a more targeted learning process.

- Consolidation of Hebbian synapses for hypothesis testing and noise tolerance[210] - This research shows that rich information streams can be noisy and true cause-effect relationships between inputs, output, and rewards, are difficult to discover. Such cause-effect relationships can be discovered by a combination of short-term plasticity and consolidation mechanisms, the combination of which contributes to achieve noise tolerance and avoid catastrophic forgetting. Limitations: the process of learning cause-effect relationships under noisy conditions involves multiple repetitions of input-output patters before consolidation occurs. At that point, the consolidated synapses are less plastic and less able to adapt in dynamic conditions. This limitation is common to all consolidation-based approaches.

- Lifelong learning of compositional structures[249] - This research aims to construct compositional structures for storing knowledge and using their novel combinations to perform different tasks. The proposed framework inspired from dynamic architectures in the brain, separates the learning process into two broad stages: learning how to best combine existing components in order to assimilate a novel problem, and learning how to adapt the set of existing components to accommodate the new problem. This separation explicitly handles the trade-off between the stability required to remember how to solve earlier tasks and the flexibility required to solve new tasks. The model was evaluated for classification on the image recognition datasets, namely MNIST, Fashion-MNIST, CUB-200, CIFAR-10 and Omniglot datasets. Limitations: A limitation with this work lies in the lack of proper metric to assess the degree to which the learned structures are compositional.Open source code:`https://github.com/Lifelong-ML/Mendez2020Compositional.git`

- Reconfigurable Organisms[147, 158] - This nascent research program shows how genetically unmodified frog cells can be rearranged into novel organisms that maintain their form and function without human intervention for several weeks before they biodegrade, thus demonstrating the noise tolerance, adaptation, and sustainability of cells and tissues in novel circumstances. To explore the vast space of reconfigurable organisms, an evolutionary algorithm was used to generate and test billions of candidate body plans against a behavioral goal in a physics-based virtual environment. Despite major simplifications inherent in computer simulations, the most performant simulated designs were successfully transferred to reality as biological constructs that exhibited same structure and behavior as their simulated equivalents, further demonstrating the homeostatic capacity of cellular collectives. Open source code: `https://cdorgs.github.io`

- Robot end effector tracking using predictive multisensory integration[204] - This paper shows that combining visual and proprioceptive (i.e., joint angles) information improves eye tracking performance, as it allows the visuo-motor model to predict the visual consequences of its actions. This work is inspired by findings that motor activity can modulate, or even trigger, responses in primary visual cortex neurons[250, 251]. This work shows how a robot that combines proprioceptive

and visual inputs improves smooth pursuit-like eye movements to track its own hand – compared to using only visual information (equivalent to tracking an external object) or only using proprioceptive information (equivalent to generating a target trajectory in the dark). An important limitation is not explicitly including the known *efference copy* of motor commands thought to directly allow the prediction of the sensory consequences of actions. Moreover, the significant delays in neural signal conduction and processing were not included.

- Sensory fusion to enhance perching balance [163]. Birds are believed to use a 'balance organ' in the hip (the lumbosacral organ) to complement their craneal vestibular organ[162]. In ref.[163] the utility of such an organ for perching is evaluated. They created a bird-like bipedal skeletal structure with a compliant neck and placed it on a platform randomly shaken by a robotic arm. They found that fusing accelerations at the head and hip vs. using acceleration signals from the head alone, improved the prediction of the acceleration at the platform. This supports the notion that vestibular and lumbosacral sensory fusion would enhance perching balance. A limitation is that the skeletal structure was passive, whereas we know that active sensing is used by animals to tune sensory function. The utility of this kind of sensory fusion for balance during locomotion and flight remains to be explored.

- Bioelectric networks consisting of non-neural cell types[206, 207]. Brains evolved from ancient bioelectric networks formed from non-neural cells. Prior to the management of behavior in 3D space via control of muscle activity, somatic bioelectric networks managed movements in anatomical morphospace via the control of other kinds of cell activity (proliferation, differentiation, migration, cell shape, etc.). These bioelectric control networks exhibit remarkable robustness and plasticity, able to solve the problem of achieving a specific shape despite perturbations and altered components.

Metrics

There are several metrics that have been used to assess specific aspects of L2 performance. The main measure of performance typically revolves around the mean accuracy across a family of tasks, backwards transfer, and forwards transfer. The mean accuracy (MA) across all tasks, $MA = \sum_{t=1}^{N} \frac{R^{t,N}}{N}$, quantifies the average performance ($R^{t,N}$) on the entire set of tasks (N), after training on the final task T^N. This is one of the most commonly used metrics for comparison between models, but is only capable of giving an abstract view of how an L2 systems does with transfer adaptation, catastrophic forgetting, and exploiting task similarity. A more descriptive metric when studying L2 is backwards transfer (BWT) $BWT = \sum_{t=1}^{k} \frac{R^{t,k}}{k}$, which computes the change in accuracy on task $t < k$, after learning task T^k. Negative BWT reflects catastrophic interference (the smaller the value, the greater the interference), whereas positive BWT reflects the current task improving performance on previous tasks. This provides a greater level of detail into how an L2 system specifically performs at different feature areas discussed in section 2. A third metric of performance is the forwards transfer (FWT) of knowledge; $FWT = \sum_{t=k+1}^{N} \frac{R^{t,k} - b^t}{N-k}$ which computes the performance on all tasks $t > k$, after learning task T^k with respect to the performance of a baseline untrained model b^t. This quantifies if the model is learning features that can facilitate or improve later performance, providing insight into how it handles transfer and adaptation, as well as exploiting task similarity.

For assessing the resource efficiency and sustainability, a common metric is memory overhead (MO) based on the average amount of memory a model requires per task (θ_i), in units of the baseline model's memory size (θ_b): $MO = min\left(1, \frac{1}{N} \sum_{i=1}^{N} \frac{Mem(\theta_i)}{Mem(\theta_b)}\right)$. A second metric is memory growth, which measure how the parameters of a L2 system grows with respect to the number of tasks, or how the number of samples stored grows.

Though these metrics provide a level of insight into how L2 systems meet the features listed in this paper, there are still details not captured (*e.g.* noise tolerance, training time, convergence speed, task agnostic). These details may be reported in specific works, but there is a need for unity and more comprehensive metrics when studying the full performance of L2 systems.