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Neural Networks
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Review

Continual lifelong learning with neural networks: A review

German I. Parisi [a], Ronald Kemker [b], Jose L. Part [c], Christopher Kanan [b], Stefan Wermter [a]

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[b] Chester F. Carlson Center for Imaging Science, Rochester Institute of Technology, NY, USA
[c] Department of Computer Science, Heriot-Watt University, Edinburgh Centre for Robotics, Scotland, UK

Renato Santos Aranha
Nov/2020

many continual learning approaches have been proposed recently!

2016, 2017, 2018…

comprehensive survey on CL → Parisi et al. 2019

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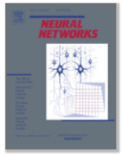

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INTRODUCTION

humans/animals → ability to continually acquir ... espan

(Bremner, Lewkowicz, & Spence, 2012; Tani, 2016). The ability to incrementally acquire, refine, and transfer knowledge over sustained periods of time is mediated by a rich set of neurophysiological processing principles that together contribute to the early development and experience-driven specialization of perceptual and motor skills (Lewkowicz, 2014; Murray, Lewkowicz, Amedi, & Wallace, 2016; Power & Schlaggar, 2016; Zenke, Gerstner and

learning systems process continuous streams of information

stable in order not to catastrophically interfere with consolidated knowledge is known as the *stability–plasticity dilemma* and has been widely studied in both biological systems and computational models (Ditzler, Roveri, Alippi, & Polikar, 2015; Grossberg, 1980, 2012; Mermillod, Bugaiska, & Bonin, 2013). Due to the very chal-

2012; Mermillod, Bugaiska, & Bonin, 2013). Due to the very challenging but high-impact aspects of lifelong learning, a large body of computational approaches have been proposed that take inspiration from the biological factors of learning from the mammalian brain.

lifelong learning remains a long-standing

Ganguli, 2017). In Section 2, we introduce a set of widely studied biological aspects of lifelong learning and their implications for the modelling of biologically motivated neural network architectures. First, we focus on the mechanisms of neurosynaptic plasticity that regulate the stability–plasticity balance in multiple brain areas (Sections 2.2 and 2.3). Plasticity is an essential feature of the brain for neural malleability at the level of cells and circuits (see Power and Schlaggar (2016) a survey). For a stable

knowledge learned from previous tasks

Humans and other animals excel at learning in a lifelong manner, making the appropriate decisions on the basis of

forgetting ☹

Studies on the neurophysiological aspects of lifelong learning have inspired a wide range of machine learning and neural network approaches. In Section 3, we introduce and compare computational

many continual learning approaches have been proposed recently!

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BIOLOGICAL ASPECTS OF LIFELONG LEARNING

The stability-plasticity dilemma

<u>neurophysiological principles</u> regulate stability–plasticity balance!

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The stability-plasticity dilemma

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Neurosynaptic plasticity: brain feature yielding physical changes in neural structure, allowing to learn, remember, and adapt to dynamic environments

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e.g.
somatosensory cortex → new motor learning tasks (DRIVE) without disrupting previously motor skills (RUN)

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plasticity have a consistent tendency: decrease levels of plasticity with increasing age

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The stability-plasticity dilemma

neurophysiological principles regulate stability–plasticity balance!

stability-plasticity dilemma

Model too stable → bad for future training data

Model too plastic → large weight changes blur learned representations

somatosens

skills (RUN)

plasticity profiles have a consistent tendency: decrease levels of plasticity with increasing age

BIOLOGICAL ASPECTS OF LIFELONG LEARNING

Hebbian plasticity and stability

Hubel and Wiesel (1967)

early development:
semantic patterns in visual cortex being established

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early development:
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Additionally:
neural cortical organization can be driven by visual patterns
(Hubel & Wiesel, 1970; Hubel, Wiesel, & LeVay, 1977).

visual input correctly interpreted

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Hebb (1949) → most well-known theory describing neuron adaptation to external stimuli (synaptic plasticity)

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<u>postulate</u>

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$$\Delta w = x \cdot y \cdot \eta$$

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synaptic strength w

pre-synaptic activity x

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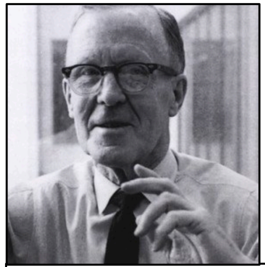

Donald Olding Hebb
(Jul 22, 1904 – Aug 20, 1985)

- canadian psychologist
- influential in the area of neuropsychology
- studied the function of neurons on psychological processes such as learning.

https://can-acn.org/donald-olding-hebb/

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The complementary learning system

“brain learns and memorizes”

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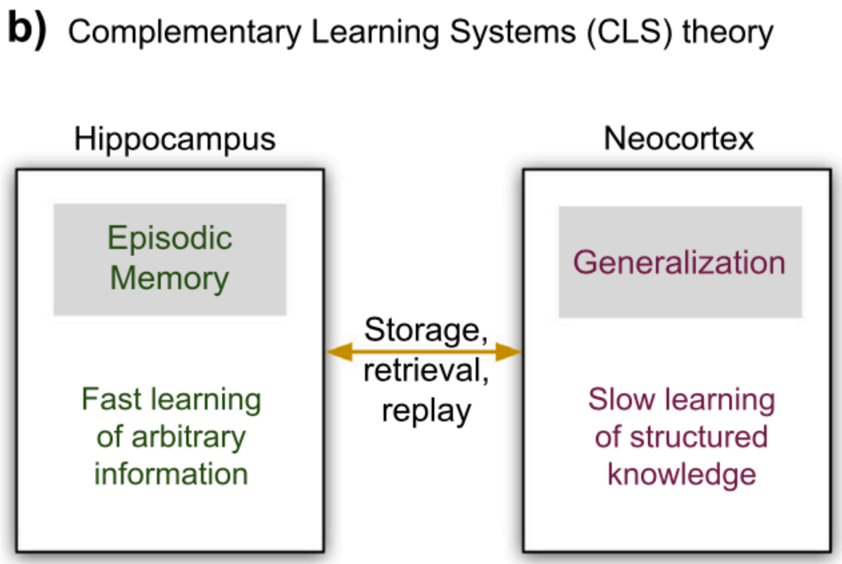
The complementary learning system

"brain learns and memorizes"

McClelland et al., 1995; O'Reilly, 2004; O'Reilly & Norman, 2002
complementary contribution of the neocortex (memory consolidation) and the hippocampus (learning)



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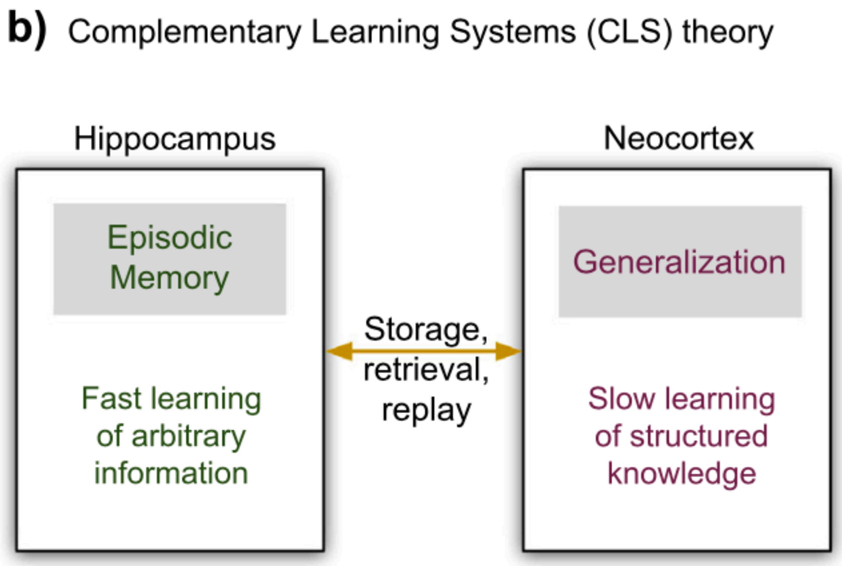

McClelland et al., 1995

2016 → CLS theory updated to incorporate findings from neuroscience (Kumaran et al., 2016)

- replay of hippocampus memories helps learning;
- events can be reactivated during sleep or unconscious memory recall;

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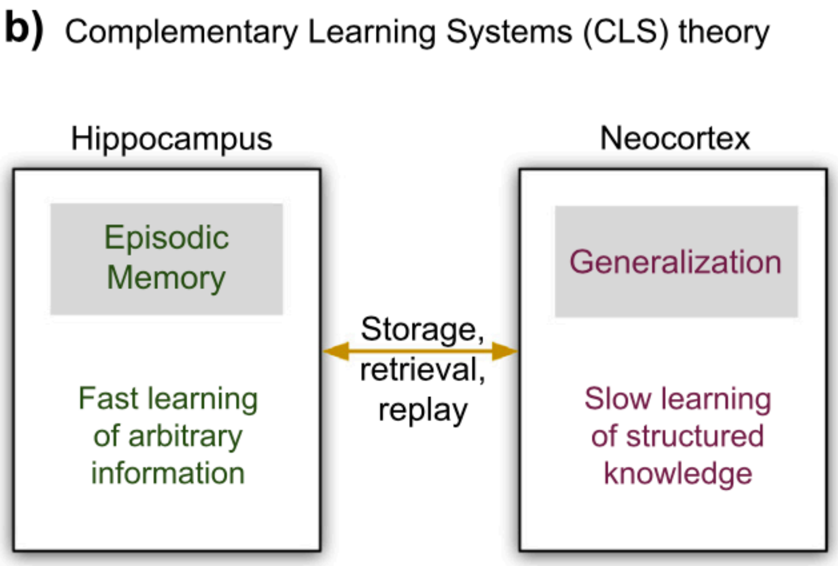

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generative replay!

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Up to now: specialized neurocognitive mechanisms can acquire and protect knowledge

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this asymmetric effect reflect the relative
similarity of the two categories

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Hypothesis: prior knowledge of Korean impact the formulation of language skills to facilitate reacquisition of Korean

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Lifelong machine learning

Learning models:
tendency to catastrophically forget existing knowledge when learning from novel observations

lifelong learning system checklist

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Lifelong machine learning

Learning models:
tendency to catastrophically forget existing knowledge when learning from novel observations

main approaches	some drawbacks
"memory systems" store previous data and replay along new data samples	storage of old information
allocating additional neural resources	increased computational efforts for neural architectures
specialized mechanisms to protect knowledge from being overwritten	not so good for multi modality

LIFELONG LEARNING AND CATASTROPHIC FORGETTING IN NEURAL NETWORKS

Lifelong machine learning

Learning models:
tendency to catastrophically forget existing knowledge when learning from novel observations

	main approaches	some drawbacks
memory replay	"memory systems" store previous data and replay along new data samples	storage of old information
dynamic architecture	allocating additional neural resources	increased computational efforts for neural architectures
regularization	specialized mechanisms to protect knowledge from being overwritten	not so good for multi modality

Regularization approaches

typically inspired by theoretical neuroscience models

avoid forgetting through different levels of synapse plasticity

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computational perspective:

“regularization” approaches alleviate catastrophic forgetting by imposing **constraints** on the update of the **neural weights**

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examples

Learning Without Forgetting

Elastic Weight Consolidation

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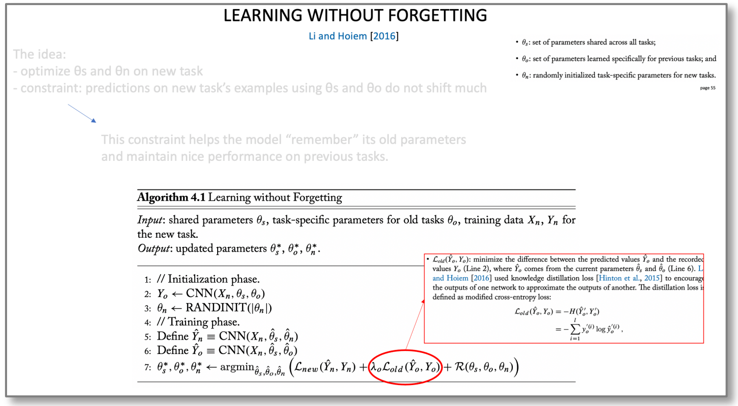
<u>computational perspective:</u>

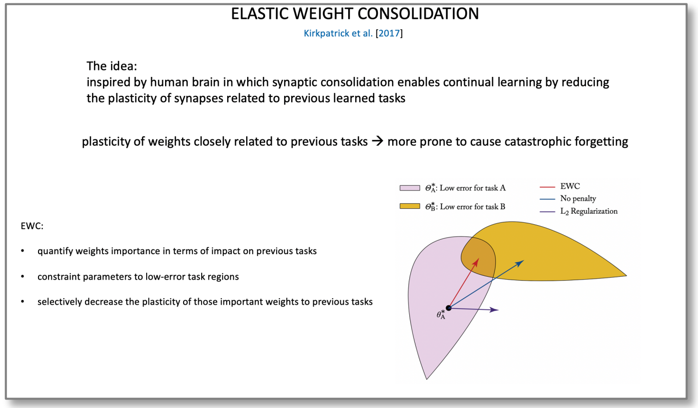
“regularization” approaches alleviate catastrophic forgetting by imposing **constraints** on the update of the **neural weights**

<u>examples</u>

Learning Without Forgetting

Elastic Weight Consolidation





Dynamic architectures

Change **architecture** in response to new information by accommodating novel neural resources

e.g., re-training with an increased number of neurons or network layers.

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Example:

Rusu et al. (2016) → Progressive Neural Networks

PROGRESSIVE NEURAL NETWORKS

Rusu et al. [2016] (Google)

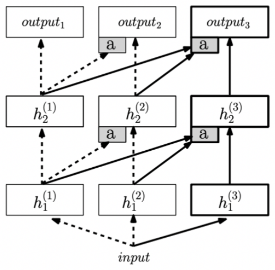
The idea:

- keep a pool of models as “knowledge”
- use lateral connections between them to adapt to the new task.

N past tasks: $T_1, T_2, \ldots, T_N$ → PNN maintain N neural networks

when new task T_{N+1} is created → neural network is expanded with lateral connections

$$h_i^{(N+1)} = \max\left(0, W_i^{(N+1)} h_{i-1}^{(N+1)} + \sum_{n<N+1} U_i^{(n:N+1)} h_{i-1}^{(n)}\right)$$



Complementary learning systems and memory replay

CLS theory (Kumaran et al., 2016; McClelland et al., 1995)

complementary tasks of memorization and generalization mediated by the interplay of mammalian hippocampus and neocortex

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early example: Hinton and Plaut (1987):

each synapse has two weights:
* one with slow changing rate (long-term knowledge)
* one with fast-changing weight (temporary/new knowledge)

Complementary learning systems and memory replay

CLS theory (Kumaran et al., 2016; McClelland et al., 1995)

complementary tasks of memorization and generalization mediated by the interplay of mammalian hippocampus and neocortex

recently: Shin et al (2017)

Inspired by the generative role of the hippocampus, they proposed a deep generative model and a task solver!

Benchmarks and evaluation metrics

many methods addressing continual learning ☺

no established consensus on benchmark
datasets for proper evaluation ☹

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Lopez-Paz and Ranzato (2017) → protocols using accuracy to assess ability to transfer knowledge between tasks

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Lopez-Paz and Ranzato (2017) → protocols using accuracy to assess ability to transfer knowledge between tasks

Kemker et al. (2018) → guidelines for evaluating CL approaches and performed experiments that provide quantitative comparison.

3 benchmark experiments:

data permutation
incremental class learning
multimodal learning

Benchmarks and evaluation metrics

many methods addressing continual learning ☺

no established consensus on benchmark
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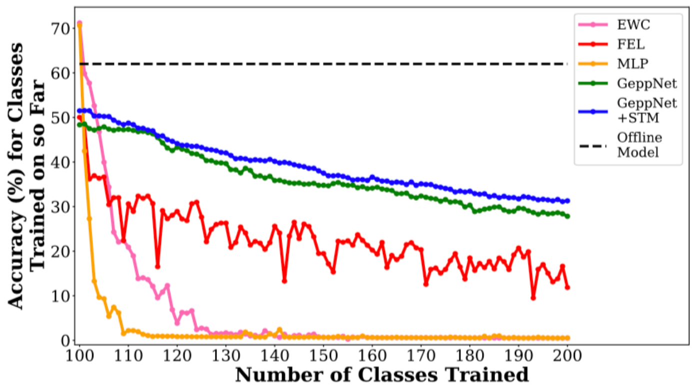
Kemker et al. (2018)

Datasets:

- Caltech-UCSD Birds-200 (CUB-200) (Wah et al. (2011)
- AudioSet dataset (10-s sound clips from 632 classes from YouTube) (Gemmeke et al., 2017)

Approaches (supervised):

- simple MLP as baseline
- EWC (Kirkpatrick et al., 2017)
- PathNet (Fernando et al., 2017)
- GeppNet+STM (Gepperth & Karaoguz, 2015)
- FEL (Coop et al., 2013)



(b) CUB-200

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Parisi et al. 2019

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Towards autonomous agents

Humans → ability to learn and fine-tune skills in a “lifelong manner”

lifelong learning in infants → capacity of autonomously explore and generate goals, driven by intrinsic motivation

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crucial difference between biological and artificial lifelong learning!

next sections:

approaches driven by findings from neuroscience, psychology and cognitive sciences for development of lifelong learning autonomous agents

DEVELOPMENTAL APPROACHES AND AUTONOMOUS AGENTS

Developmental and curriculum learning

Learning and development interact in a very intricate way (Elman, 1993)

Senghas et al, 2004

“sensitive/critical period of development”

- infancy time window sensitive to experiences,
  sometimes with irreversible effects in behaviour

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critical periods in DNN (initial rapid learning phase) → key role in defining final network.

- first epochs critical for resource allocation across layers

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Curriculum learning

Elman 1993, Bengio et al 2009

curriculum of **progressively harder tasks** leads to faster training **performance** in neural networks!

but effectiveness is sensitive to the choice of progression tasks (assuming it can be done)…

DEVELOPMENTAL APPROACHES AND AUTONOMOUS AGENTS

Transfer learning

apply previously domain acquired knowledge to solve a problem in a novel domain

neural transfer learning mechanisms in brain are poorly understood…

Doumas et al 2008 → transfer of abstract knowledge is by means of conceptual representations invariant to individuals, objects, or scene elements.

Rusu et al. [2017]
Progressive neural networks to transfer learned low-level features and high-level policies from a simulated to a real environment.

Tessler et al. [2017]
Hierarchical deep reinforcement learning network that uses an array of skills to reuse and transfer knowledge between tasks

…

DEVELOPMENTAL APPROACHES AND AUTONOMOUS AGENTS

Curiosity and intrinsic motivation

intrinsic motivation models → inspired by the way human infants choose their goals and progressively acquire skills to define lifelong learning frameworks

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Gopnik et al., 1999
Infants select experiences that maximize an intrinsic learning reward through an empirical process of exploration.

Computational models of intrinsic motivation:

- can collect data and acquire skills incrementally through self-generation of a learning curriculum (Baranes & Oudeyer, 2013; Forestier & Oudeyer, 2016)

- this allows selection of tasks to be learned with an active control of the growth of the complexity.

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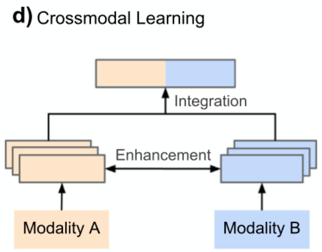

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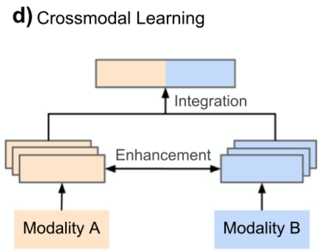

Lewkowicz, 2014; Spence, 2014 → mechanisms of multisensory integration emerge during initial development

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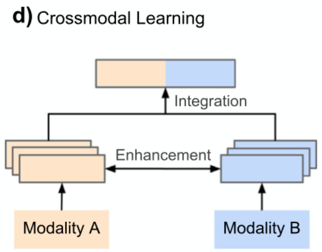

<u>interesting reasons for modelling multisensory learning:</u>

- multisensory functions aim at yielding robust responses in case of uncertain sensory input
- when trained with multisensory data, one modality can be reconstructed from information of another modality.

  e.g.: Moon, Kim, and Wang (2015): Abstract representations obtained from a network encoding the source modality used to fine-tune target modality (audio and images)

many continual learning approaches have been proposed recently!

2016, 2017, 2018…

comprehensive survey on CL → Parisi et al. 2019

Contents

Parisi et al. 2019

CONCLUSION

- mammalian brain and biologically-inspired approaches remains the best model for lifelong learning!
- general notion of structural plasticity is a promising solution to lifelong learning (section 2.2)
- current models of LL are still far from providing the flexibility, robustness, and scalability of biological systems
- most popular continual learning models are restricted to supervised problems (section 3.5)
- critical periods of development can be modelled to determine initial architectures and patterns to improve performance on subsequent learning tasks (section 4.2)
- Multisensory integration models are a key feature for autonomous agents (section 4.5)