Continual Learning for Embodied Agents: Methods, Evaluation and Practical Use

- a systematic literature review -

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Introduction 1

Background

- **Continual learning** (CL) in AI involves an agent's ability to learn continuously, retaining past knowledge to aid future problem-solving [3].
- **Embodied agents** are physical or virtual entities interact with environments using human-like sensory and cognitive capabilities.
- The main challenge is **catastrophic forgetting** [1]—losing past task-solving abilities upon learning new tasks.

Motivation

- While theoretical research is important, it is crucial to explore the extent to which CL methods have been **applied in practical contexts**.
- An under-explored part of CL is the **context specific characteristics** of CL methods, including the **advantages**, **disadvantages** and **cognitive inspiration** of each method.
- CL is **important** because there is a crucial need for agents that can **dynamically** adjust and learn with **minimal retraining**, paralleling human cognition.

Contribution

- This systematic review focuses on **the methods, the evaluation and the application** of CL in embodied agents, aiming to inspire future research and to shed light on the current underexplored and overlooked aspects of this cognitive framework.

Research questions 2

How has continual and lifelong learning been incorporated into embodied agents, mirroring the human capacity to incrementally acquire new knowledge?

RQ1: What methods and algorithms facilitate continual and lifelong learning in embodied agents, and what are their advantages, drawbacks and cognitive inspiration?

RQ2: How is the performance of systems that are capable of lifelong learning evaluated?

RQ3: How has continual and lifelong learning been integrated into embodied agents in practice?

Method 3

- The **PRISMA** reporting guideline [4] was used to encourage transparency and reproducibility.
- A **reference diagram** was constructed (see Figure 1), which specifies the databases and records included in the review.

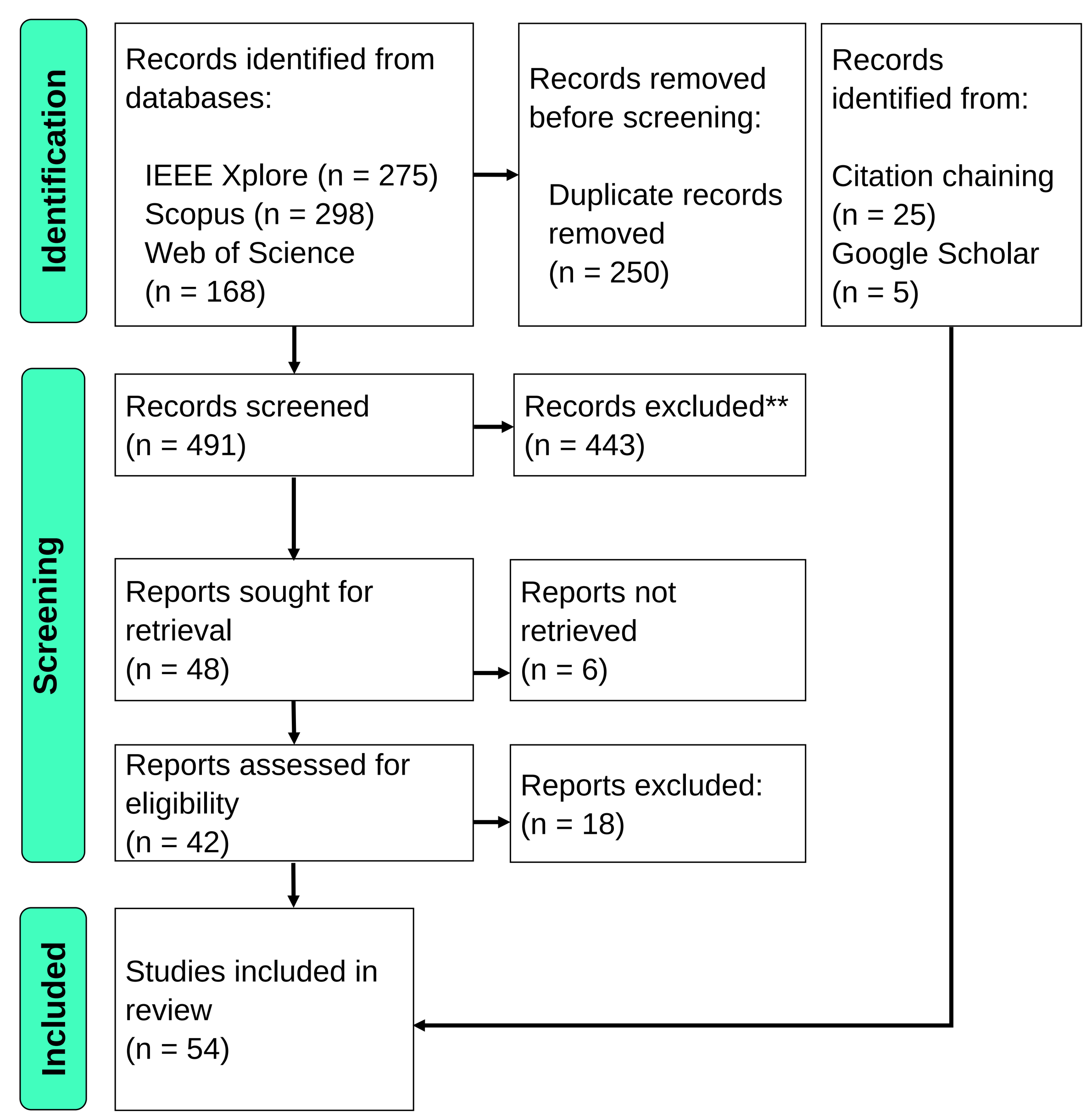

Figure 1: PRISMA flow diagram

- **Query**

("life-long learning" OR "lifelong learning" OR "continual learning" OR "incremental learning" OR "sequential learning") AND (environment OR "3D environment*" OR "virtual environment*") AND (agent* OR multi-agent OR "multi agent" OR "intelligent agent*" OR "autonomous agent*" OR "embodied agent*" OR robot) AND NOT (education)

- **Selection criteria**
  - Study published after 2015
  - Study written in English
  - Study focuses on the integration of CL in embodied agents or methods for achieving CL

References

[1] Robert M. French. Catastrophic forgetting in connectionist networks. Trends in Cognitive Sciences, 3(4):128–135, 1999.
[2] Michael S. Gazzaniga, Richard B. Ivry, and George R. Mangun. Cognitive Neuroscience: The Biology of the Mind. W. W. Norton, 2013
[3] Zhiyuan Chen, Bing Liu, Ronald Brachman, Peter Stone, and Francesca Rossi. Lifelong Machine Learning. Morgan & Claypool Publishers, 2nd edition, 2018.
[4] "PRISMA statement," PRISMA. Available: https://www.prisma-statement.org/. Accessed: May 15, 2024.

Results 4

RQ1: Continual learning can be split into three main families of methods:

Replay methods
Storing past data samples to train models and replaying them continually along with new data to prevent forgetting
- Rehearsal
- Generative

Hippocampal learning
+ : Mitigates catastrophic forgetting effectively
- : Memory overhead for storage

Regularization methods
Imposing constraints on model parameter changes to retain previously learned information while adapting to new tasks
- Weight regularization
- Knowledge distillation

Synaptic plasticity
+ : Space-efficient
- : Balancing retention and learning

Parameter isolation methods
Isolating specific parameters for new tasks, preventing interference with previously learned knowledge
- Dynamic architecture
- Fixed Architecture

Brain modularity
+ : Minimal interference between tasks
- : Scalability issues with growth

RQ2: Evaluation mainly assesses **accuracy**, **forgetting** and **transfer** through various means such as practical adaptation and datasets (Figure 2).

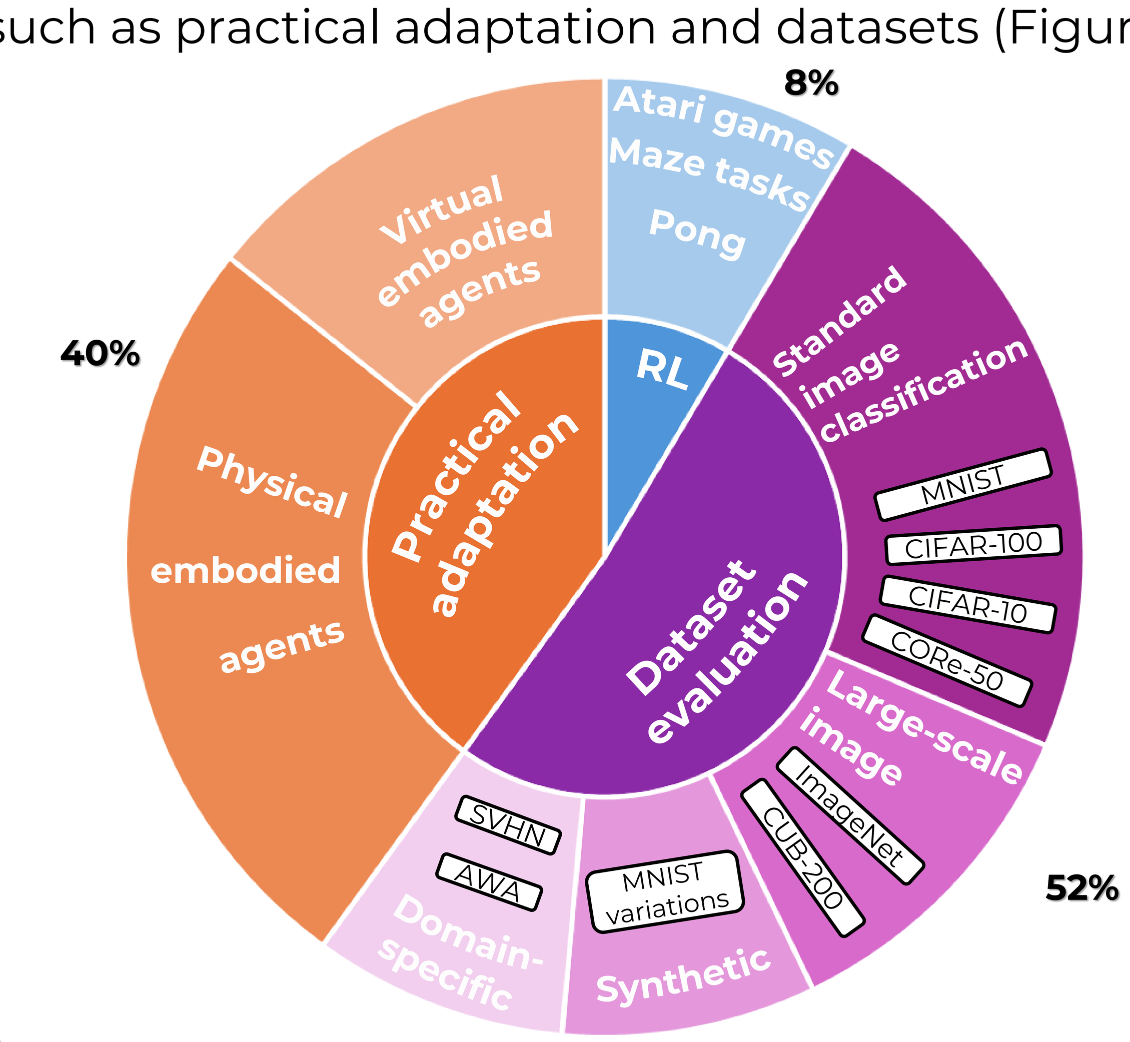

Figure 2: Distribution of evaluation methods used in CL research.

RQ3: Practical uses of CL, categorized into **physical** and **virtual embodied agents**, show how autonomous systems employ this framework to adapt and learn new tasks over time.

Physical agents
- Robots, autonomous vehicles, drones
- Lifelong navigation
- Object classification
- Robotic limb adaptation

Virtual agents
- Simulated limbs, agents, drones
- Lifelong navigation
- Simulated robotic task learning
- Sim2real

Discussion 5

- Approaches for CL vary significantly, each having contextual (dis)advantages
- Current evaluation mostly relies on datasets, and does not capture complexities & entropy
- Limited number of studies discuss the use of CL in embodied agents

Conclusion 6

- CL shows promise for creating adaptive agents
- Heavily reliant on standardized datasets, lack of real-world complexity in testing
- Future work should focus more entropic settings
- Nonetheless, advancements already demonstrate the potential of CL