Mixed-Modality Learning for Lifelong Machine Learning (M2L for L2M)

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Abstract

All modern AI algorithms and advancements fall under the umbrella of Machine Learning. A new framework called Lifelong Machine Learning (L2M) is the next paradigm of research in pursuit of general artificial intelligence. This poster provides a definition of the paradigm and preliminary theoretical research.

Background

All existing machine learning models, regardless of learning modality, follow the same scheme: infer a single model from a set of data. In reinforcement learning (RL), episodic data of state-action-reward sets map to a desirable model of action policy; in supervised learning (SL), labeled inputs map to high-dimensional separability curves; in unsupervised learning, unlabeled data/features map to hierarchical or agglomerative clusters of membership.

Problem Statement

Whether batch or incremental/online, all these methods suffer from **catastrophic forgetting** (maladaptation) when the source data distributions change; old performance suffers when learning new tasks.

Problem Statement: Elucidation

L2M DEFINITION:

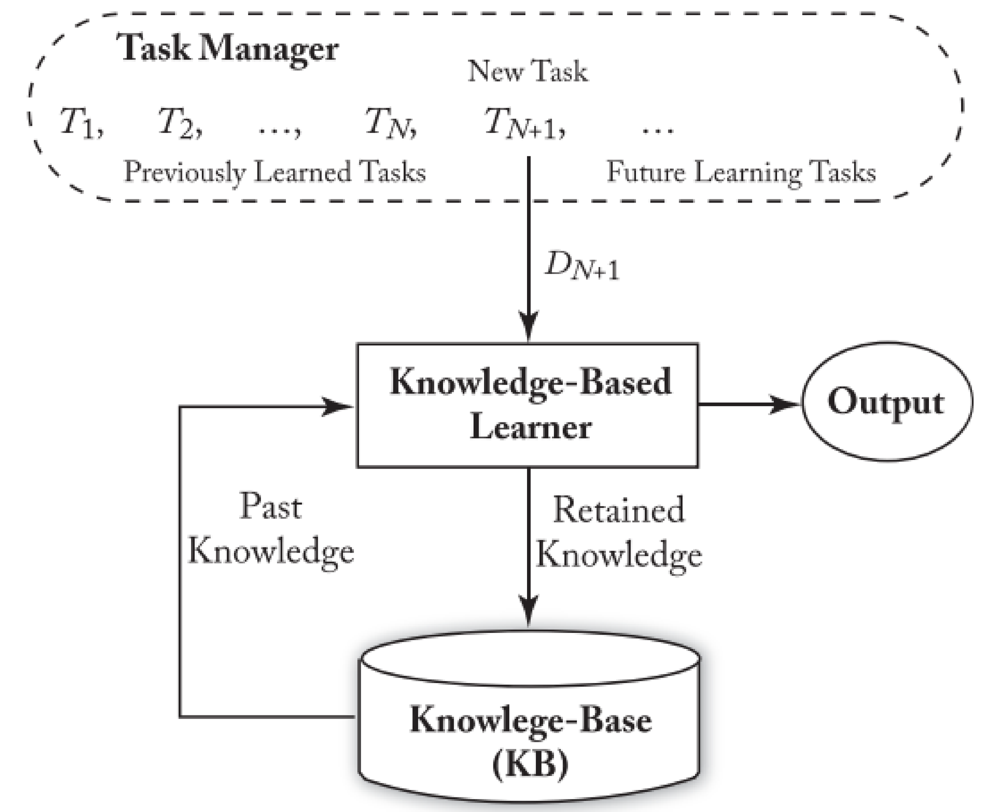
- Environment vs. Task
- Knowledge Base vs. Knowledge-Based Learner
- Forward/backward transfer

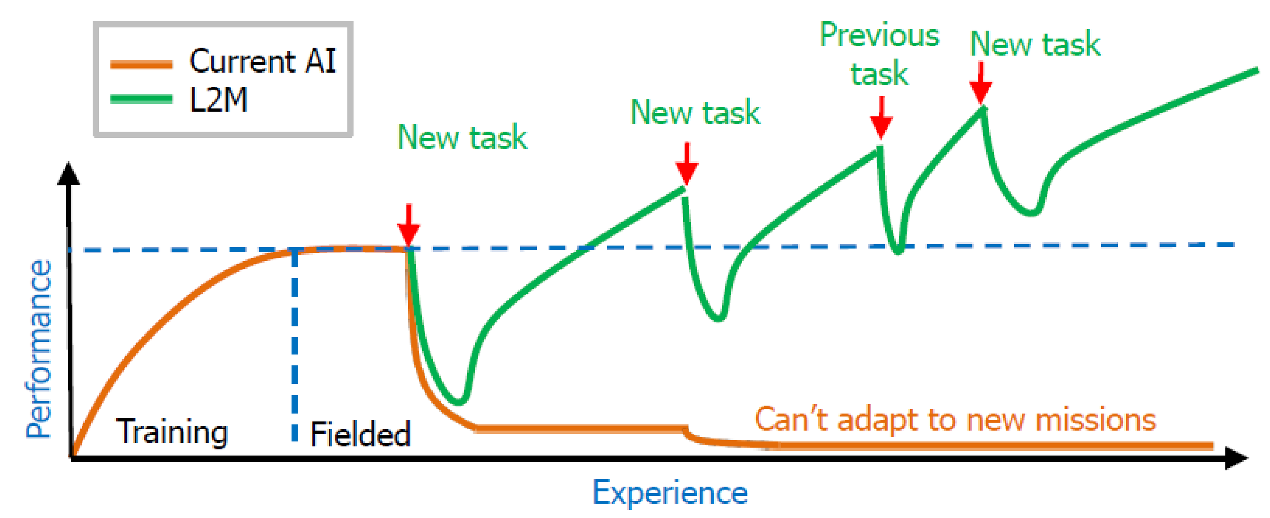
NOT L2M:

- Transfer learning
- Meta learning
- Retraining

GOALS:

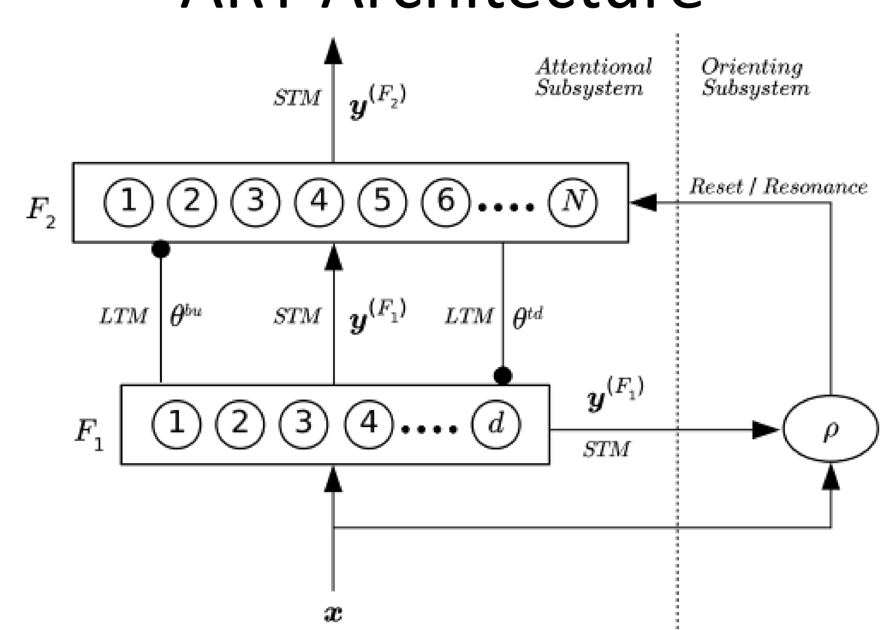
- **Continual Learning**
- **Adaptation to New Tasks**
- **Goal-Driven Perception**
- **Selective Plasticity**
- **Monitoring and Safety**



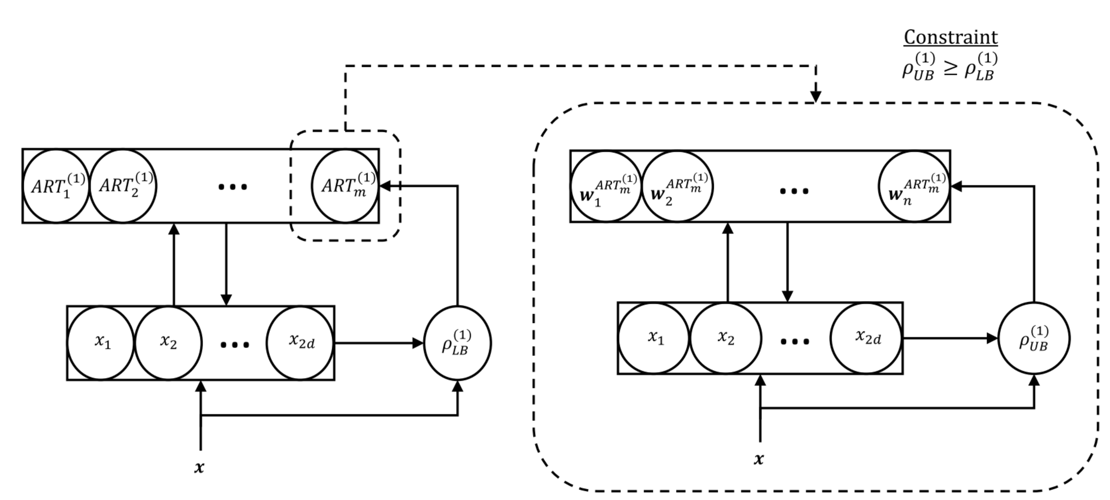


Solution: ART and IVAT

ART Architecture



DDVFA Architecture



Created by Stephen Grossberg and Gail Carpenter of Boston University, Adaptive Resonance Theory (ART) describes how mammalian brains (and other cellular networks outside the brain) solve the **stability-plasticity dilemma** through interactions between bottom-up perception and top-down expectations. The ACIL has contributed Distributed Dual Vigilance Fuzzy ART, which learns online and mitigates order dependence. Furthermore, Incremental Validity Indices (IVAT) provide the first human-interpretable verification of online clustering algorithms.

Conclusion

The realm of L2M is so nascent that there lacks a scientific consensus on definitions and methodology, though it is necessarily the next paradigm towards general AI. Methods like ART and IVATs that mix learning modalities, solve the stability-plasticity dilemma, and "explain" performance are promising pillar stones of this new field.

Summary

Lifelong Machine Learning (L2M) is a genuinely new and promising paradigm in AI. Strictly defining this new problem, mixing learning modalities, and theories explaining how biology has solved the problems of this paradigm are crucial first steps.

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