Continuous (Machine) Learning - A Comprehensive Overview

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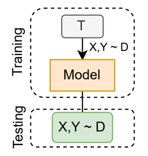
Continuous (Machine) Learning for Artificial Neural Network

1. Knowledge Acquisition

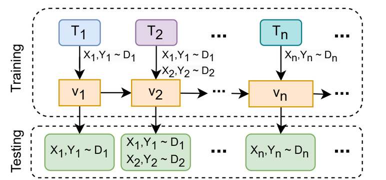
1.A. Data Availability

1.A.I. Offline Learning



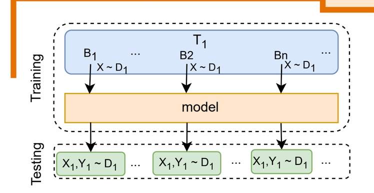
Data were fully collected before training occurred [1].

1.A.II. Continual Learning (CL)



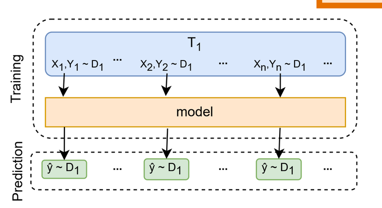
Datasets are acquired over time to encompass new tasks, classes, and domains, prompting model expansion for their support. **Continual learning enables the acquisition of new knowledge while mitigating critical forgetting of prior tasks** [1,2].

1.A.III. Online Learning (OL)



Data are received incrementally, enabling the **models to adjust swiftly and effectively manage data drift** [1].

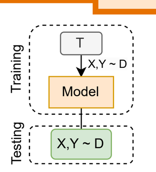
1.A.IV. Stream Learning



Data are **ingested and analyzed sequentially, without any storage**. Models rely on unsupervised learning, generally employing simplified techniques to support analysis and adapt to data drift with reduced delais [3].

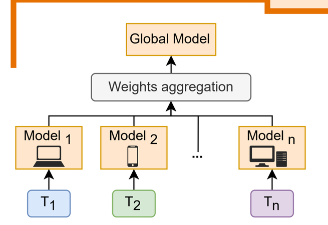
1.B. Ressources Accessibility

1.B.I. Centralized Learning



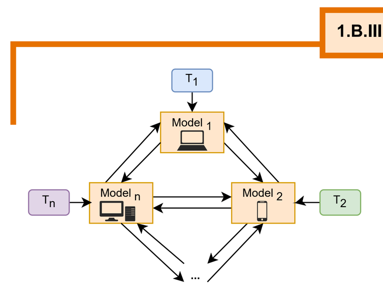
Once all data has been aggregated in a central location, **training is conducted on an individual device** [1].

1.B.II. Federated Learning



Replicas of the model are dispatched to each designated "worker" device to undergo **training on a segmented portion of the dataset,** thereby accelerating the training process before the **aggregation of weights into a unified global model** [4].

1.B.III. Distributed Learning



Each **participant device receives a replica of the model** for localized data training. Upon achieving model stability, participants contribute their respective weights to collaboratively refine the overall solution [4].

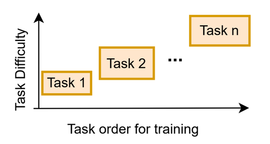
1.C. Learning Mechanism

1.C.I. Hand-Craft

The **architecture** of the Artificial Neural Network is **established prior to the training**, with the intention of modifying only the weights durring the experiment [1].

1.C.II. Curriculum Learning

The efficiency of learning was improved by **refining the sequence in which tasks were presented** [5].

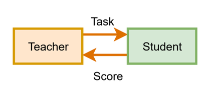


1.C.II.a. Hand-crafted Curriculum

An expert chose the order in which the task will be encountered [5].

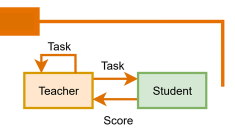
1.C.II.b. Teacher-Student based

The student model **improved its learning by receiving tasks selected by the teacher model** [5].



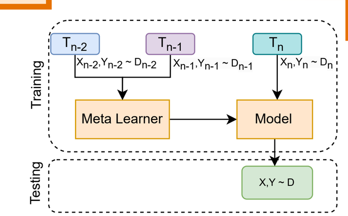
1.C.II.c. Self-Play

The Teacher-Student paradigm was re-examined through the implementation of **competitive tasks.** Within this structure, the 'Teacher' is assigned progressively complex tasks that align with the student's learning progression [5].



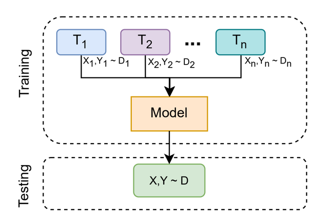
1.C.III. Meta Learning

An AutoML approach that **leverages dataset metadata through iterative learning to enhance performance**, employing metric-based, model-based, and optimization-based strategies [1].



1.C.IV. Multi-Task Learning

Models trained concurrently on a variety of discrete tasks [1].

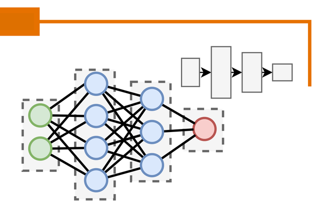


1.C.V. Modular Learning

Sub-units are defined in the model's architecture [6].

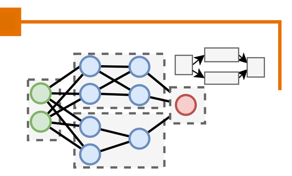
1.C.V.a. Layer Modular Network

It mirrors a conventional Artificial Neural Network, with its **neurons organized into distinct layers** *[6]*.



1.C.V.b. Path Modular Network

Within the Artificial Neural Network subcategory, **specific pathways are allocated for individual tasks** *[6]*.



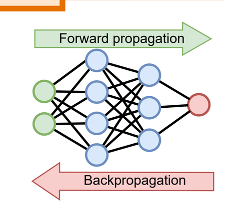
1.C.VI. NeuroEvolution

The model is developed during training, abstaining from layer dependencies, and replicates the principles of **genetic evolution** observed in a population [7].

1.D. Learning Assessment

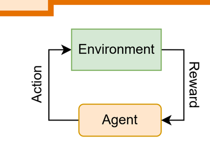
1.D.I. Backpropagation

Weights in the Artificial Neural Network are adjusted based on **δ(y_pred,y)**, which represents the difference between the predicted output (y_pred) and the target value (y). This adjustment is achieved by **propagating the error backward through the network** [7].



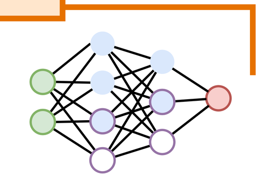
1.D.II. Reinforcement Learning

Specify the goals and the **reward** mechanism that require optimization. The model will **evaluate its architecture using the received reward** signal rather than the δ(y_pred,y) [7].



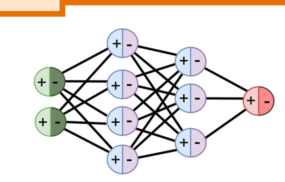
1.D.III. Hebbian Learning

Review the weights using the principle that neurons **firing together wire together**. ΔWij= n×xi×yi, where *xi* is the activation of the pre-synaptic neuron, *yi* is one of the post-synaptic neurons, and *n* is the learning rate [7].



1.D.IV. Predictive coding

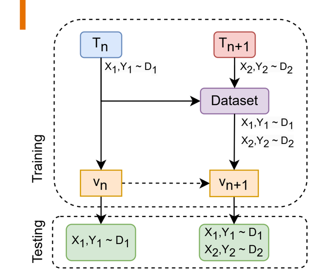
To emulate the brain's unsupervised learning, the network consistently predicts subsequent inputs. This is accomplished by **employing positive and negative neurons to simulate simultaneous forward and backward activations** [8].



2. Knowledge Retention

2.A. Replay-based

Expand the training dataset with stored / generated examples from prior task to maintain prior knowledge retention [1, 9].



2.A.I. Real Data Replay

Retain essential data for reincorporation into the training dataset [1,9].

2.A.II. Real Feature Replay

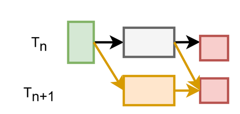
Utilize a feature extraction model to **retain and replay salient features from prior tasks,** analogous to data replay mechanisms [1,9].

2.A.III. Generative Replay

A generative model is employed to create synthetic data, which is then used to augment the training dataset for a separate model, expanding its learning resources [1,9].

2.B. Lock-based

2.B.I. Lock & Expand

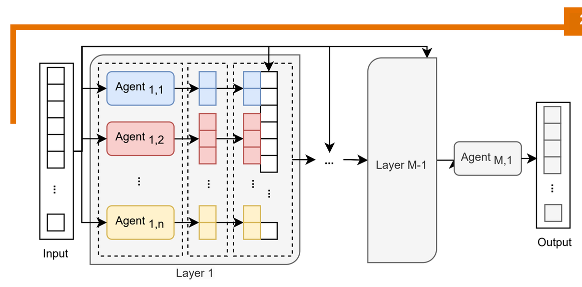


To accommodate a novel task Tn+1, the model introduces **a new pathway and output, thereby leveraging Path Modular Network behavior** to preserve prior knowledge while permitting access to the existing subnetwork to minimize redundancy [1,9].

2.B.II. Multi-Agent based

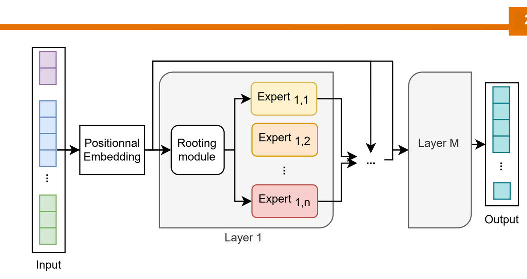
The model architecture contains a **collection of distinct agents** [10].

2.B.II.a. Mixture of Agent (MOA)



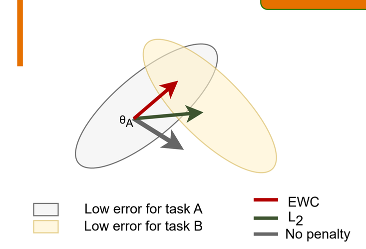
A model featuring a **collection of agents that work collaboratively** to accomplish each task [10].

2.B.II.b. Mixture of Expert (MOE)



The architecture of a model consists of a **routing mechanism and a set of expert models**, wherein the routing system directs specific experts to execute a given prediction [10].

2.C. Regularisation-based



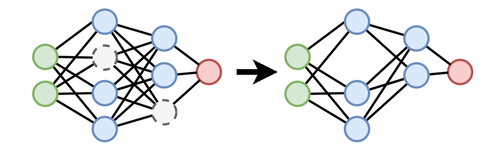
Inspired by neuroplasticity and neuromodulation, **synapse/neurone relevance is calculated for the previous task**. This allows freezing or restricting their plasticity to retain knowledge [9].

3. Knowledge Transfert

3.A. Model Compression

3.A.I. Prunning

To enhance efficiency, elements within the structure exhibiting negligible influence on task performance, indicated by **near-zero neuronal or synaptic weights, are eliminated** [11].



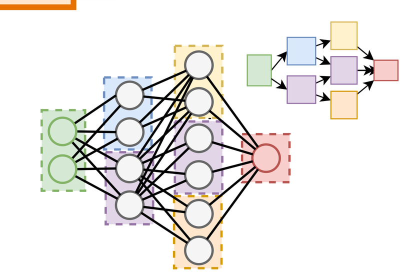
3.A.II. Quantisation

The model's **precision is diminished through the rounding of its numerical values** [11].

Ex: 3.75 → 4

3.A.III. Modular Network based

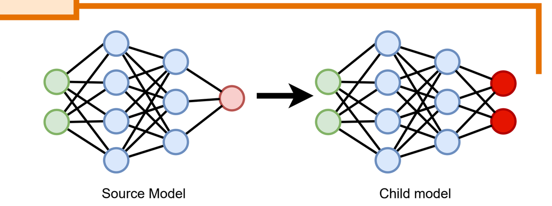
Rely on Neural Modular Network and Principal Component Analysis to **merge the redundant components together** [6].



3.B. Transfert Learning

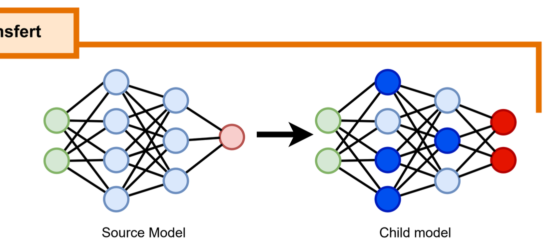
3.B.I. Full Feature Extraction

The revised model **retains the complete input/hidden layer configuration from the prior trained solution**, primarily serving scenarios requiring comparable tasks or learning [11].



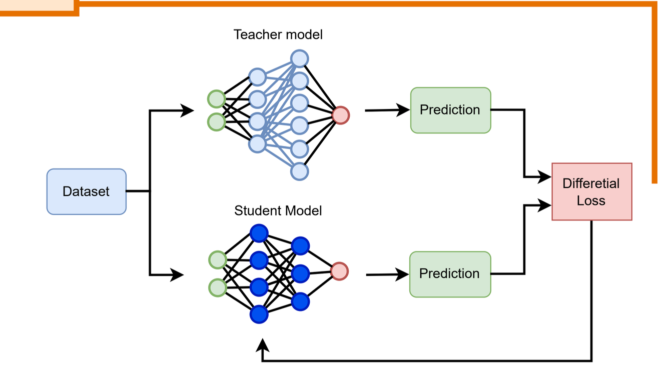
3.B.II. Partial Feature Transfert

Resuing fragments of the previously trained model by maintaining the same weights [11].



3.B.III. Knowledge Distillation

The trained model is used as a teacher to teach a new model [11].



Summary:

Continuous Machine Learning can be viewed as a sub-domain of Machine Learning focused on enabling continuous learning behaviors, drawing inspiration from biological ontogenesis and phylogenesis. Ontogenesis Learning encompasses the learning capabilities exhibited during the lifetime of a single individual, as observed for instance in Continual Machine Learning [1-4,7,9], Online Learning [1,3], and Curriculum Learning [5]. In contrast, Phylogenesis Learning, specifically cover learning related to a group of individuals, it incorporates legacies from ancestors and interactions between individuals/agents. This is emulated by Evolutionary Algorithms, such as NeuroEvolution [7], and can be view to some extend as an inspiration for multi-agent systems [10].

While numerous reviews delineate specific topics, they often lack a comprehensive overview regarding the co-existence, interconnections, and distinct characteristics of these domains. In this overview, a broad definition of Continuous Machine Learning is established based on an the literature review, as illustrated on the right. This framework facilitates the distinction of three primary axes: Knowledge Acquisition [1-8], Knowledge Retention [1,9,10], and Knowledge Transfert [6,11]. These axes collectively form the aforementioned taxonomic representation, which serves to elucidate their key features and enhance the understanding of how Continuous Machine Learning operates:

- Knowledge Acquisition encompasses the mechanisms by which a model acquires knowledge, considering factors such as data availability, resource accessibility, learning mechanisms, and knowledge assessment methodologies. This axis delineates the distinctions among Continual Learning [1-4,7,9], Online Learning [1,3], and Curriculum Learning [5], while also highlighting the reliance of many continuous models on established methods such as Federated Learning [4], Distributed Learning [4], and Incremental Learning [2].
- Knowledge Retention, however, is predominantly addressed within Continual Learning [1-4,7,9], enabling a model to expand its capabilities and support new tasks, classes, and domains over time, while simultaneously mitigating catastrophic forgetting [1]. Nevertheless, recent approaches leveraging multi-agent systems are beginning to emerge, to decrease update times and reduce hallucination risks, thereby supporting more adaptive continuous solutions that permit on-demand updates of specific components [10].
- Knowledge Transmission, lastly, relies on Compression and Transfer Learning techniques employed in domains such as TinyML and Continual Learning to diminish model size and complexity [6,11], thereby mitigating model growth over time before subsequent expansion to accommodate new tasks, classes, or domains.

Continuous (Machine) Learning

1. Inspirations
- A. Ontogenesis
- B. Phylogenesis

2. Caracteristics
- A) Knowledge Acquisition
  - i. Task Learning
  - ii. Task Agnostic Learning
  - iii. Exploit Task Similarity
- B) Knowledge Retention
  - i. Overcoming Catastrophic Forgetting
- C) Knowledge Transfert
  - i. Graceful Forgetting
  - ii. Knowledge Generalisation
  - iii. Knowledge Specialization

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