A Review on Plastic Artificial Neural Networks: Exploring the Intersection between Neural Architecture Search and Continual Learning

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Abstract—Despite the significant advances achieved in Artificial Neural Networks (ANNs), their design process remains notoriously tedious, depending primarily on intuition, experience and trial-and-error. This human-dependent process is often time-consuming and prone to errors. Furthermore, the models are generally bound to their training contexts, with no considerations of changes to their surrounding environments. Continual adaptability and automation of neural networks is of paramount importance to several domains where model accessibility is limited after deployment (e.g IoT devices, self-driving vehicles, etc). Additionally, even accessible models require frequent maintenance post-deployment to overcome issues such as Concept/Data Drift, which can be cumbersome and restrictive.

The current state of the art on adaptive ANNs is still a premature area of research; nevertheless, Neural Architecture Search (NAS), a form of AutoML, and Continual Learning (CL) have recently gained an increasing momentum in the Deep Learning research field, aiming to provide more robust and adaptive ANN development frameworks. This study is the first extensive review on the intersection between AutoML and CL, outlining research directions for the different methods that can facilitate full automation and lifelong plasticity in ANNs.

Index Terms—Plastic Artificial Neural Networks, Adaptive Neural Networks, AutoML, Neural Architecture Search, Continual Learning

I. INTRODUCTION

Deep Learning has led to notable advances across a number of applications, specifically non-procedural tasks, such as image classification or maneuvering autonomous vehicles. By enabling computers to accomplish these tasks at a near (or sometimes even surpassing) human-level performance, a lot of work that previously relied on human-intervention can now become autonomous.

Despite all the incredible achievements accomplished in the field of Artificial Intelligence, there remains a number of hurdles that keep AI models from advancing further. Some Deep Neural Networks have out-performed humans at a number of tasks, such as playing chess [2], reading comprehension [3], audio transcription [4], and several other areas [5–8]. However, even the most advanced models cannot compete with even a child’s cognitive abilities (reasoning, abstract thinking, complex comprehension, etc...). [9]. It is thought that human intelligence arises not only from learned knowledge, but also through innate mechanisms that have evolved over thousands of years [10].

Inspired by the Darwinian evolutionary theory, Neuroevolution evolves neural networks rather than develop them through traditional means (e.g Backpropagation [11]). This evolutionary approach attempts to mimic the brain’s complex structure and capabilities by generating populations of competing individuals (neural networks), essentially simulating the “survival of the fittest” process. By doing so, most features (including the network architecture and its parameters) can be encoded into the evolutionary process and the best fitting combination of features can be searched for in the solution space [12].

Another struggle modern AI faces lies in certain domains where the input changes over the course of time. Typically, Artificial Neural Networks (ANNs) tend to partially or completely overwrite learned knowledge upon retraining for new tasks, a phenomenon referred to as Catastrophic Forgetting, or Catastrophic Interference [13], [14].

Continual Learning (CL) aims to overcome Catastrophic Forgetting by retaining some form of memory within the model, or by having continuous access to the tasks’ datasets. It is worth mentioning that Continual Learning is sometimes referred to as Lifelong Learning [15]–[17], (Task-/Class-)Incremental Learning [18]–[20], and Sequential Learning [13], [21]. To avoid confusion, this paper will only refer to the field as Continual Learning, considering that the other terms might have broader meanings and often overlap with different disciplines.

One of the reasons humans excel at continually adapting to new streams of information without forgetting previously-attained knowledge is that our experiences are generalized and largely overlap [22], [23]. In addition to the human brain’s innate Continual Learning abilities, numerous other plastic features (expanded upon in Section 2) have been a key component in the human evolution to intelligence [24], [25].

A. Use-Cases and Motivation

Although many adaptive qualities the human brain possesses have not been modelled in Artificial Neural Networks yet, there has been a growing interest in Continual Learning as...
well as other fields pertaining to plasticity in computational models [15].

Continually adaptive features in Deep Learning models are becoming more imminent than ever; several fields that have limited access to their deployed models are bound to their fixed, pre-deployment states and cannot improve their functionality to fit their changing surroundings. These fields include autonomous vehicles [20–32], robotics [33–38], Edge and IoT devices [39–42], and numerous others [43–49].

In addition to the importance of Continual Learning in modern Deep Learning applications, the classical process of developing Deep Neural Networks is heavily-reliant on manual human input; from defining a network architecture to tweaking hyperparameters, many values are dependent on experts’ knowledge as well as trial-and-error [50]. The AutoML field was introduced to facilitate more robust Machine Learning solutions for non-experts by pipelining automated optimization techniques, such as Neural Architecture Search (NAS) and Hyperparameter Optimization. This area, however, is still in its infancy and few studies have attempted to achieve an end-to-end self-developing ANN [51], [52].

Intuitively, the more statically-developed or “hard-coded” a neural network is (e.g., fixed architecture, fixed hyperparameters, etc...), the less sensitive it will be to its surrounding environment. By minimizing or completely eliminating manual input from the deployment of ANNs, a network can become significantly less biased and more plastic (or adaptive) to fit a task’s context (formal definition introduced in Section 5).

The aim of this study is to categorize and review the methodologies relating to adaptiveness in ANNs. Although there are some reviews conducted on Continual Learning [16], [18], AutoML [53–55], and NAS [50], [56–58], the intersection between AutoML and Continual Learning has not been formalized or reviewed despite the significant number of existing models in that area. A few related works have established a basis for such a paradigm, but with limited scopes [15], [59].

The next section covers the biological origins and theories of plasticity in the human brain, which can inspire alternative methodologies for agile, self-adaptive ANNs. Following that, the existing Continual Learning approaches are explored and categorized. Section 4 overviews the commonly-used Neural Architecture Search methodologies, which leads up to Section 5 where a new paradigm for adaptive ANNs and their desirable characteristics are proposed. Lastly, the discussion section overviews the limitations of the existing methodologies and delineates potential future research directions.

II. BIOLOGICAL BACKGROUND

Human intelligence is contingent on the acquisition and consolidation of knowledge; research in the field of Evolutionary Neuropsychology has revealed that all the evolutionary advances our species has accomplished are founded upon associative learning and memory [60]. On a cellular level, human brains essentially comprise of neurons and synapses, which are the cells and the connections between them that allow the transmission of signals, respectively. Synaptic Plasticity, or the ability to change synapses’ strengths, is thought to underlie both the learning and memory mechanisms [61–63].

While Synaptic Plasticity is crucial to human intelligence, it is certainly not the only form of neural plasticity [64]. One type of Non-Synaptic Plasticity is Intrinsic Plasticity (IP), or Intrinsic Neuronal Excitability. IP allows neurons themselves to have adaptive qualities pertaining to their electrical properties due to neuronal and synaptic activities, which plays an essential role in maintaining homeostasis [65]. Both Synaptic and Non-Synaptic Plasticity together allow our brains to perform complex tasks, such as learning, thinking, and retaining memories [66], [67].

In this section, an extensive review is conducted on Associative Learning, Memory Formation and Retention, and the Complementary Learning Systems (CLS) in biological neural networks. While the proposed models in these areas are mostly theoretical, some of them have been strongly supported by decades’ worth of subsequent researches.

A. Associative Learning

One of the cornerstones of Biological (as well as Computational) Neuroscience is the Hebbian learning rule, postulated by Donald Hebb in 1949 [68]. The premise behind the rule is that the learning process in biological neural networks is activity-dependent. If a pre-synaptic neuron A is repeatedly successful in activating a post-synaptic neuron B, the strength of the synapse will gradually increase (also referred to as Synaptic Potentiation), which henceforth provides the basis for associative learning.

Hebb’s theory is often inaccurately summarized as the mnemonic “neurons that fire together, wire together”, which can be misleading as the neurons in this context do not activate simultaneously. Temporal precedence is imperative for Synaptic Potentiation to occur; the pre-synaptic neuron must be excited strictly prior to the post-synaptic neuron’s activation. This emphasis on the timing of neuronal activity foreshadowed a form of Synaptic Plasticity called Spike-Timing Dependent Plasticity (STDP), which is considered the underlying mechanism for the Hebbian learning model as well as information storage [69–71].

While Hebb’s postulate is widely considered the foundation of Machine Learning, it had a fundamental flaw that was not addressed for nearly three decades. The most basic form of Hebbian learning is modelled as the product of the pre- and post-synaptic activities, regulated by a learning rate \( \eta \):

\[
\Delta W_{ab} = \eta X_a \cdot Y_b
\]  

Since \( \eta, X_a, Y_b \geq 0 \), the change in synaptic strength \( \Delta W_{ab} \) will always be positive and therefore Equation (1) represents a monotonically increasing function that eventually leads to unstable, runaway neuronal activity.

It was not until 26 years later that Gunther Stent appended a regulatory definition to Hebb’s theory to prevent the perpetual
potentiation of synapses [72]. The mechanism for *Synaptic Depression*, or the weakening of synaptic efficacy, borrows from the causality aspect of Synaptic Potentiation: if neuron A consistently does not take part in firing neuron B, synapse \( W_{ab} \) weakens. This new rule pertaining to synaptic weakening due to lack of co-occurring activity led to the popular adage "use it or lose it".

In addition to Stent’s appendage, *Homeostatic Plasticity* of neuronal excitation persistently regulates the activation of neurons through Intrinsic Plasticity and several other means [73]. While Hebbian Plasticity is responsible for the potentiation or depression of synapses, Homeostatic Plasticity attempts to modulate and maintain the neurons’ original states, or "homeostasis", through the intrinsic properties of the neurons [74], [75].

Another mean to further control and stabilize neuronal activity is through *Neuromodulation*, which is the process of altering the neuron’s intrinsic firing activity through chemical modulators. The most effective neuromodulators on learning and memory are thought to be dopamine (DA), serotonin (5-HT), acetylcholine (ACh), and noradrenaline (also called norepinephrine (NE)) [76], [77]. These modulators (specifically dopaminergic and serotonergic neuromodulation) have been observed to decline in adults, which diminishes their reward-based learning and decision-making skills [78]. These numerous and distinct factors, each affecting the changes in synaptic efficacy in different ways, are vital to the stability of neuronal activity and facilitate the complex mechanisms that underlie intelligence.

Synaptic Plasticity can occur through 2 different means: *Homosynaptic Plasticity* and *Heterosynaptic Plasticity*, which are less often referred to as synaptic *Intrinsic Plasticity* (not to be confused with the previously discussed neuronal Intrinsic Plasticity) and *Extrinsic Plasticity* [79].

If a change in synaptic strength takes place due to consecutive activity in the pre- and post-synaptic neurons (neuron A and B in Figure (1), respectively), it is considered a result of Homosynaptic Plasticity. Whereas if the change in synaptic efficacy is caused by a different path (a change in \( W_{cb} \) due to stimulation in A), it is categorized as Heterosynaptic Plasticity.

**B. Memory Formation and Retention**

Most models theorized to underlie Associative Learning in biological neural networks can be intuitive and straightforward, while the mechanism underlying memory is significantly more complex and is considered one of the most compelling and challenging research areas in the field of Neuroscience [62], [80]. It is worth noting that researches on cognitive psychology have revealed that memory entails a learning process in itself [60], [81], and thus the mechanisms for both processes are interleaved.

Some studies hypothesized that due to the sheer number of dendrites in every neuron, a masking mechanism naturally occurs that allows most synapses associated with past experiences to be mostly left untouched whilst only a subset of the connections are allocated to learning new information [82].

There are 2 temporal variations of Synaptic Plasticity that are thought to be directly linked to the formation and retention of memories; Long-Term Synaptic Plasticity and Short-Term Synaptic Plasticity [83].

**Long-Term Potentiation (LTP)** is considered the most studied branch of Synaptic Plasticity [64]; ever since its formal description in 1973, it has attracted an increasing attention in the neuroscience research community, especially in relation to learning and the cellular models of memory [62], [84]–[86]. LTP is thought to have both Homo- and Hetero-synaptic components and is caused by persistent strengthening of the synapse over longer periods of time. While there has not been any conclusive proof that memory resides in the synapses and that it is possibly a result of non-synaptic mechanisms [64], numerous studies strongly support the theory that LTP within the hippocampus is at least partially responsible for learning and for the formation and retention of memory [61], [62], [80], [85], [87]–[89].

Intuitively, it is thought that a particularly strong connections between a set of neurons that resulted from high-frequency, persistent strengthening of synapses is a direct representation of memory on a cellular level. On the other hand, lack of access to those memories would result in hippocampal *Long-Term Depression*, which is the weakening of synapses, causing a gradual decay of unused memories over time [85], [90]. Some studies suggest that in the context of developing brains, LTD in already weakened synapses might result in synaptic pruning, which indicates that Long-Term Synaptic Plasticity plays a prominent role in the development of the neural structure [80], [86], [91]. As the brain ages, however, plasticity decays and the brain becomes less prone to drastic changes [92], [93].
Short-Term Synaptic Plasticity, in contrast, refers to the changes in synaptic efficacy that can only last in the order of tens to thousands of milliseconds [94]. There are 3 main categories of Short-Term Synaptic Plasticity: Short-Term Facilitation (STF), Augmentation or Post-Tetanic Potentiation (PTP), and Short-Term Depression (STD) [94]. The short-term counterparts of LTP and LTD are STF and STD, respectively. While the exact impact of Short-Term Synaptic Plasticity on memory and learning is not yet conclusive, it is thought to have a similar effect as Long-Term Synaptic Plasticity, but on relevant timescales [95], [96]. Post-Tetanic Potentiation is also a short-lived increase in the synapses’ strength as a result of repetitive, high-frequency stimulus. Some studies suggest that hippocampal PTP is responsible for short-term memory [97].

Another interesting hypothesis relating to memory-creation and consolidation is through Neurogenesis, which is the generation of new neurons from neural stem cells. Neurogenesis is considered a crucial process in developing brains (embryos in particular), and as with other forms of plasticity, it decays over time [98]. Some studies, however, suggest that Neurogenesis still occurs in adult brains (albeit at a much lower rate [99]) and that when new neurons are integrated into certain parts of the hippocampus, they can be directly related to the formation of new memories [100]. Similar to Neurogenesis, research suggests that newly-developed synapses and synaptic circuits have also been observed in relation to acquiring new memories [80], [101].

C. The Complementary Learning Systems

The Complementary Learning Systems framework, which was articulated by McClelland et al. in 1995, defines the distinct roles of the mammalian hippocampal and neocortical systems on learning and episodic memory [14]. The theory holds that the hippocampus is responsible for rapid learning and retaining short-term, sparse memories, which can later be replayed to the neocortex for more efficient encoding and long-term storage. Although the CLS is characterized as a theory, it has had over 25 years’ worth of empirical data generally supporting its premise [102], [103].

While the hippocampus facilitates the fast and arbitrary episodic learning and memory formation/retrieval, the neocortex (specifically the Prefrontal Cortex (PFC)) tends to be responsible for long-term preservation and recall of memory [104]. Some studies have shown that new memories get encoded in both the hippocampal and neocortical systems simultaneously; the hippocampus would be responsible for short-term recall, and over time the PFC would consolidate the memory and take-over the retrieval duty [105].

Numerous studies found compelling evidence that the consolidation of memories from the hippocampus to the PFC occurs during various stages of sleep [106–110]. While a subject is awake, the hippocampus’ rapid-encoding capabilities accommodate the fact-paced acquisition of information, which are then slowly learned by the PFC and encoded in an overlapped and compressed manner during sleep [107]. Other researches theorize that in addition to memory consolidation, brains tend to also organize and selectively forget older memories during sleep [110].

To varying degrees, both the hippocampus and the neocortex are thought to rely on Hebbian learning due to their tendency to bind co-occurring features of an experience (an episode) together [111]. The hippocampus, more so than the neocortex, is universally assumed to use a Hebbian form of learning, given that short-term memories are thought to share the localized Hebbian nature of proximity-based neural correlated activities [112].

These theoretical models that capture our innate ability to retain important knowledge while gradually forgetting rarely accessed information have inspired numerous computational models, leading to the emergence of the Continual Learning paradigm.

III. CONTINUAL LEARNING APPROACHES

Continual Learning aims to maximize the capacity for simultaneous solutions by generalizing previous experiences to coincide with new tasks (a feature known as Forward Transfer (FWT) of knowledge), whilst also consolidating and maintaining previous knowledge (which is referred to as Backward Transfer (BWT)). Balancing this trade-off between stability and plasticity is essential for a sustainable CL model, and is commonly known as the Stability-Plasticity dilemma [113], [114]. For instance, consider two incremental tasks, $T_i$ and $T_j$, where $T_i \prec T_j$.

Forward Transfer is the impact of $T_i$ on the performance of $T_j$; if a preceding task is advantageous to the learning process of a future task, it is considered positive FWT, which potentially leads to “zero-shot”/“few-shot” learning [115]. Negative FWT, on the other hand, occurs when a previous task hinders the learning process of a future task, essentially making a model less pliable to fit new tasks.

Backward Transfer is the effect the learning process of task $T_j$ has on the performance of task $T_i$. There exists positive BWT if learning $T_j$ increases the performance of the preceding task $T_i$. Conversely, negative BWT exists when learning $T_j$ decreases the performance on $T_i$ (i.e Catastrophic Forgetting) [116], [115].

There are several different approaches to retain memory in CL models. While there has already been a few proposed categorization schemes [15], [116], [117], they were either incomplete or poorly structured.

A. Rehearsal-Based Methods

The first of the two families of methods is Replay-Based Continual Learning. Replay-Based models retain an episodic memory by storing representations that best describe the distribution of the data used for each task. These representations could simply be a raw portion of the datasets (Episodic Rehearsal), or it could be the model itself that was trained on a previous task used to infer and generate the samples used (essentially reverse-engineering the model) (Generative Rehearsal, often called pseudo-rehearsal). Each sub-type of the Replay-based models has its own strengths and weaknesses:
Episodic Rehearsal: store a subset of the datasets used to later "rehearse" them in subsequent training of newer tasks. While this method might be the easiest to implement out of the 2 sub-types, the model can easily overfit to the subsets due to the limited number of samples, and does not scale well in terms of memory cost.

Generative Rehearsal: store the previous tasks' distributions instead of the raw samples, which can later be used to project and generate auxiliary data for replay purposes. Although this method has not been used frequently in recent studies on CL, the recent emergence of generative networks opens a potential for new Generative Rehearsal models [18].

Consider a task-incremental setting with an unending stream of tasks. Since any model is bounded by a certain memory capacity and the number of tasks is unbounded, forgetting is inevitable. As the number of tasks increases, convergence becomes more compromised, leading to a decline in the model performance. This hurdle brings up a desirable feature in CL models: Graceful Forgetting [18], [17], [19]. In order to successfully implement a fixed-capacity network that accepts an unbounded number of tasks, "forgetting" should be allowed through selective means.

Both Replay-Based approaches tend to be computationally-and/or memory-expensive, especially as the number of tasks increases [16], [18], [20], [21]. However, by caching portions of the datasets or the models used for each task, the retraining process can support prioritization for particular tasks, thereby facilitating more control over Graceful Forgetting.

In general, Replay-Based methods draw inspiration from the biological CLS framework, where short-term memory is quickly stored to the hippocampus, to be later learned slowly and in a more generalized fashion by the neocortex (likely during sleep). For a more comprehensive review on the association between biological mechanisms and Replay-Based CL models, the recent work by Hayes et al. covers the topic extensively and in-depth [22].

B. Parameter-Constraint Methods

The latter family of approaches is Parameter-Constraint Continual Learning. By constraining parameters through isolation, regularization, or any form of transfer learning/finetuning, Parameter-Constraint models can efficiently prevent Catastrophic Forgetting whilst not wasting memory on prior data storage. Sub-types of Parameter-Constraint models are split three-fold:

- Data-Focused: constrain parameters through a combination of Fine-Tuning and Knowledge Distillation [23], where a temporary (large and highly regularized) model is trained on a single task and is then used to transfer the knowledge to the main (smaller) network.

- Prior-Focused: constrain parameters through regularization. By penalizing changes to the most influential parameters in the network, Catastrophic Forgetting can be minimized. Geometrically, the model attempts to find the area of best fit (where most solutions coincide) in the solution space.

- Parameter-Isolation: constrain parameters through isolation. Unlike Prior-Focused models, this method completely isolates some of the weights (λ = 0) instead of just applying penalties, hence dedicating portions of the network to individual tasks.

A minor limitation with penalizing changes to the weights or completely isolating them is that the priority will typically be given to the earlier tasks, rendering Graceful Forgetting less attainable using traditional methods [24], [25].

By combining Replay-Based and Parameter-Constraint methods, a third, implicit family of approaches can be defined. The first method to include regularization techniques on top of an episodic memory is Gradient Episodic Memory for Continual Learning (GEM) [15]. GEM aims to constrain the parameter changes pertaining to new tasks by placing an upper-bound limit on the losses of each task; the loss of every task can decrease but cannot increase.

C. Improvements on Previously-Proposed Taxonomies

While the proposed categorizations in some of the early works provided a stepping stone for research in Continual Learning [16], [17], [18], they were later shown to be incomplete taxonomies [18]. Note that the categorization proposed in Figure (3) is inspired by De Lange et al. [18], with the following improvements:

- Some studies consider "Architectural Methods" (i.e CL models that rely on dynamic topologies) to be a distinct family of methodologies [18], [133], [134]. This study claims that whether or not a network's topology is dynamic cannot be associated with a single family of memory-retention techniques. For instance, some replay-based approaches have fixed network architectures (e.g iCaRL [20]), while others have dynamic network architectures (e.g DEN [15]); structural changes to the network can be applied to any of the proposed approaches in Figure (3). Therefore, in this study, Structural Plasticity is regarded as a separate, global feature that does not pertain to one family of CL approaches, but can still assist in memory-retention (as well as several other qualities in a neural network) nonetheless.

- Furthermore, [18] proposed a third sub-type of Replay-Based methods (Constrained methods), which simply
Learning Without Forgetting (LwF)

- Parameter-Constraint
- Data-Focused
- Highly dependent on the relevance of the tasks
- Training time gradually increases with the number of tasks
- Architecture grows linearly with each task-increment

Incremental Classifier and Representation Learning (iCaRL)

- Replay-Based
- Episodic Rehearsal
- Requires explicit storage for older tasks
- Can easily overfit on the tasks’ exemplars subset
- The exemplars chosen may not be representative of the entire dataset

Elastic Weight Consolidation (EWC)

- Parameter-Constraint
- Prior-Focused
- Strictly requires a fixed network architecture (known in advance)
- Numerically unstable for a large number of tasks

Gradient Episodic Memory for Continual Learning (GEM)

- Replay-Based & Parameter-Constraint
- Episodic Rehearsal & Prior-Focused
- Requires explicit storage for older tasks
- Highly dependent on the relevance of the tasks
- No memory-management policy

Memory-Aware Synapses (MAS)

- Parameter-Constraint
- Prior-Focused
- Strictly requires a fixed network architecture (known in advance)

Progressive Neural Networks (PNN)

- Parameter-Constraint
- Parameter-Isolation
- Does not facilitate positive BWT

Experience Replay for Continual Learning (CLEAR)

- Replay-Based
- Episodic Rehearsal
- Built on the assumption that input data stream is always iid

Continual Learning through Synaptic Intelligence (SI)

- Parameter-Constraint
- Prior-Focused
- Inefficient when applied to a pretrained network
- Tasks’ order affects performance
- The importance of the weights is not properly estimated in some cases (as noted by the authors)

Deep Generative Dual Memory Network for Continual Learning (DGR)

- Replay-Based
- Generative Rehearsal
- Strictly requires a fixed network architecture (known in advance)
- Model saturates with tasks over time (performance declines as the number of tasks increases)

Incremental Moment Matching (IMM)

- Parameter-Constraint
- Prior-Focused
- Requires explicit storage for previous tasks’ models

Less-Forgetting Learning (LFL)

- Parameter-Constraint
- Data-Focused
- Highly dependent on the relevance of the tasks
- Susceptible to data-distribution (domain) shift

Expert Gate

- Parameter-Constraint
- Parameter-Isolation
- Does not facilitate positive BWT due to gating mechanism

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**TABLE I**

| Model | Memory-Retention Strategy | Limitations |
|-------|---------------------------|-------------|
| Learning Without Forgetting (LwF) | Parameter-Constraint | Data-Focused | Highly dependent on the relevance of the tasks |
| | | | Training time gradually increases with the number of tasks |
| | | | Architecture grows linearly with each task-increment |
| Incremental Classifier and Representation Learning (iCaRL) | Replay-Based | Episodic Rehearsal | Requires explicit storage for older tasks |
| | | | Can easily overfit on the tasks’ exemplars subset |
| | | | The exemplars chosen may not be representative of the entire dataset |
| Elastic Weight Consolidation (EWC) | Parameter-Constraint | Prior-Focused | Strictly requires a fixed network architecture (known in advance) |
| | | | Numerically unstable for a large number of tasks |
| Gradient Episodic Memory for Continual Learning (GEM) | Replay-Based & Parameter-Constraint | Episodic Rehearsal & Prior-Focused | Requires explicit storage for older tasks |
| | | | Highly dependent on the relevance of the tasks |
| | | | No memory-management policy |
| Memory-Aware Synapses (MAS) | Parameter-Constraint | Prior-Focused | Strictly requires a fixed network architecture (known in advance) |
| Progressive Neural Networks (PNN) | Parameter-Constraint | Parameter-Isolation | Does not facilitate positive BWT |
| Experience Replay for Continual Learning (CLEAR) | Replay-Based | Episodic Rehearsal | Built on the assumption that input data stream is always iid |
| Continual Learning through Synaptic Intelligence (SI) | Parameter-Constraint | Prior-Focused | Inefficient when applied to a pretrained network |
| | | | Tasks’ order affects performance |
| | | | The importance of the weights is not properly estimated in some cases (as noted by the authors) |
| Deep Generative Dual Memory Network for Continual Learning (DGR) | Replay-Based | Generative Rehearsal | Strictly requires a fixed network architecture (known in advance) |
| | | | Model saturates with tasks over time (performance declines as the number of tasks increases) |
| Incremental Moment Matching (IMM) | Parameter-Constraint | Prior-Focused | Requires explicit storage for previous tasks’ models |
| Less-Forgetting Learning (LFL) | Parameter-Constraint | Data-Focused | Highly dependent on the relevance of the tasks |
| | | | Susceptible to data-distribution (domain) shift |
| Expert Gate | Parameter-Constraint | Parameter-Isolation | Does not facilitate positive BWT due to gating mechanism |

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refers to Replay-Based methods with added regularization constraints. Considering that Constrained methods are essentially a combination of the two proposed families in Figure 3, this sub-type was deemed redundant; hybrid approaches should not be classified as entirely new categories.

These improvements led to a simpler and more concise classification for memory-retention approaches in Continual Learning models, which can help future researchers identify gaps or unexplored areas/hybrid approaches more clearly.

**D. Evaluation of Continual Learning Performance**

Despite the large body of research on Continual Learning, the benchmark tests and evaluation metrics for Continual Learning models are largely heterogeneous and very few works have been devoted to formalize an evaluation framework that captures the models’ performance in dynamic environments. The majority of the early works relied on a rather uninformative evaluation approach, measuring only the average accuracy across all tasks. While accuracy is generally considered a reliable measure of the overall model performance, Continual Learning should be ranked based on more robust criteria that are specific to dynamic scenarios.

Lopez-Paz & Ranzato proposed one of the first formal evaluation methods for Continual Learning models. Their methodology revolves around more “human-like” test environments, where the models’ evaluation should be based on a large number of tasks, each with a relatively small number of examples, and the reported metrics should include not only accuracy, but also a measure of forward/backward transfer.
Given that some models can yield the same accuracies, FWT and BWT can provide a better insight on the model’s long-term performance. Following the same direction, Díaz-Rodríguez et al. later proposed a similar evaluation framework, with the addition of 3 metrics: model-size efficiency, samples storage-size efficiency, and computational efficiency [136]. While these metrics are not directly related to the tasks’ performance (i.e., accuracy, stability, plasticity, etc...), they are vital indicators to a model’s scalability.

While the measure of FWT and BWT can provide extensive information on the behavior of a model, they do not directly estimate how well a model retains memory. Kemker et al. focused on assessing a model’s ability to overcome Catastrophic Forgetting particularly [137]. The study establishes 3 (normalized AUC-ROC curve) metrics that jointly measure memory retention, the model’s ability to acquire new knowledge, and the model’s overall performance: \( \Omega_{\text{base}}, \Omega_{\text{new}}, \) and \( \Omega_{\text{all}} \). The base metric evaluates how well the first/base task is retained after subsequent tasks have been learned. \( \Omega_{\text{new}} \) measures the performance of a new task immediately after it is learned, which shows the model’s few-shot learning ability. Lastly, \( \Omega_{\text{all}} \) evaluates the model’s overall performance in terms of retention and acquisition of knowledge.

Inspired by the aforementioned approach, Hayes et al. proposed a similar evaluation framework that is split into 3 experimental paradigms [138]. The first benchmark test simply measures the model’s ability to quickly learn new tasks through continual iid data. While real-world scenarios tend to comprise of non-iid streams of data, this test is used to establish a baseline metric that can be compared with offline models. The second test evaluates the model’s ability to incrementally learn new classes whilst measuring the tasks’ test accuracies with each increment, which can also indicate when Catastrophic Forgetting occurs. Finally, the last test consists of a stream of organized non-iid data, resembling a realistic stream of stimuli that could be experienced by a deployed model. This framework also uses the \( \Omega_{\text{all}} \) metric to measure stability, plasticity, and overall performance.

It is important to highlight that Continual Learning environments can vary to great extents. A robust evaluation framework should accommodate these variations and yield consistent metrics regardless of the application’s environment. Farquhar & Gal introduced the first desiderata for CL ranking [116]. The proposed desiderata suggests that data from later tasks should resemble earlier tasks to some extent, arguing that some evaluation approaches use permuted datasets (permuted MNIST in particular [137], [138]), which is an unnecessarily excessive test. The study also claims that the output vector used in the training phase should be the same as the one used during testing. Another desirable feature in the evaluation of a CL model is to restrict retraining for older tasks; the model should not be allowed unconstrained access to early tasks’ examples. Last but not least, the test should include more than 2 tasks, as success on such a small sample size cannot yield reliable performance metrics that can be applicable to larger scales.

IV. NEURAL ARCHITECTURE SEARCH APPROACHES

Most popular Deep Neural Networks are designed by human experts, where the potentially hundreds of layers are manually specified [139]–[142]. The architecture design process usually depends on the experts’ educated intuition and a tedious trial-and-error process. As the tasks become more complex, the networks are normally expected to be deeper and thus their architectures become trickier to design and optimize.

In addition to the extensive knowledge required to design neural architectures, humans tend to have a fixed thinking paradigm that limits the exploration of the search space and leads to unvaried solutions. These drawbacks of manual Deep Neural Networks’ design were further recognized when an automatically-tuned neural network (Auto-Net 1.0) won against human experts’ designs in the ChaLearn AutoML challenge in 2015 [143]–[145].

The field of Neural Architecture Search (NAS) emerged to minimize or completely eliminate the limitations posed by the human factor in neural architecture-design whilst providing more robust means of finding optimal topologies. The NAS process comprises of defining 3 main components: a Search Space, a Search Algorithm, and an Evaluation Strategy [50], [56].

![Fig. 4. The general Neural Architecture Search framework](image)

A. Search Spaces

The first step in a typical NAS approach is defining the search space. The search space dictates the potential solutions’ boundary and can have a detrimental impact on the outcome of the entire search process [146]. An over simplified search space will likely lead to shallow networks that are only capable of solving simple tasks, while a non-continuous and high dimensional space can yield more complex networks, but is difficult to optimize and is typically computationally expensive.

1) Chain-Structured Space: One of the simplest search spaces is the Chain-Structured space (sometimes referred to as the Layer-Wise/Stage-Wise/Global search space [50], [147]–[149]), as seen in the iconic early works of Zoph & Le and Baker et al. [56], [150], [151]. As implied by the name, the Chain-Structured space is used to sample a sequentially-built network from a global space of components. For a
simple Chain-Structure-based architecture \( A \) consisting of \( n \) layers, the \( i^{\text{th}} \) layer \( L_i \) would receive its input from \( L_{i-1} \), and its output would feed into \( L_{i+1} \), forming the chain \( A = L_{n-1} \circ \cdots \circ L_1 \circ L_0 \).

\[ A = L_1 \circ L_2 \circ \cdots \circ L_L \]  

**Fig. 5. Chain-Structured Neural Architecture Search samples**

Some studies, however, have more recently started introducing more complex design elements, such as Skip-Connections [56], [150]–[154]. The addition of Skip-Connections allows the search algorithms to build multi-branch networks (similar to ResNet [141] and DenseNet [155]) and significantly expand the search space. These multi-branch networks are sometimes defined as a separate search space, given that they no longer form a standard "chain" of layers [56], [150].

A Chain-Structured search space can be defined through 3 parameters: The number of layers \( n \), the type of layer (e.g. convolution, pooling, flattening, the number of units (in a fully-connected network), etc...), and the hyperparameters associated with the previously-defined layer types. While hyperparameter-optimization is often considered a field on its own, most NAS models consider hyperparameters to be a part of the network’s structure and optimize them along with the topology [56], [150].

Although they offer enormous representation capabilities, Chain-Structured spaces tend to be very expensive computationally. Some studies have attempted to limit the search area by restricting the number of layers or the operation types [151], however, the global and expansive nature of this search space is inherently greedy and resource-intensive.

2) **Cell-Based Space:** To circumvent the high performance requirements posed by the Chain-Structured space, more recent works took advantage of the repeated fixed sub-structures in neural networks, creating cells (i.e groups of layers) that can be reused as individual units. This modular approach to neural architecture design was manually implemented in some popular networks, such as ResNet and InceptionNet [139], [141], and is also one of the most common search spaces in NAS models. The Cell-Based Space (often referred to as the Modular Search Space and the Block-Based Space) drastically reduces the resource cost by compounding the building-blocks that can be used; in other words, the network is optimized on a cell-basis rather than the more granular layer-basis [50], [56], [153], [157], [158].

Zoph et al. introduced one of the top-performing popular NAS frameworks, Google’s NASNet, which was developed using a Cell-Based NAS model [153]. The search space that was used in the design of NASNet is called the NASNet Search Space, and it comprises of only 2 modules: a **Normal Cell**, and a **Reduction Cell**. The Normal Cell performs feature extraction whilst preserving the input dimensionality, whereas the Reduction Cell down-samples the given feature map to half its size. By manually defining a fixed **macro-architecture** (the structure comprising of Normal/Reduction cells), optimal operations for each cell-type can be searched for.

In addition to the reasonable resource usage the Cell-Based Space offers, the modular nature of the space enables the transferability of cells back and forth between networks (i.e cell-based Transfer Learning). For instance, individual cells from NASNet were optimized on CIFAR-10 then transferred and used on ImageNet, achieving a 2.4% error rate [153]. By adopting a higher-level design paradigm and shifting the design focus from an elementary-unit level to the macro-architecture, several studies have attained state-of-the-art performance [152], [153], [158]–[161].

3) **Hierarchical Space:** Another search space that also focuses on macro-architecture optimization is the Hierarchical Space, first introduced by Liu et al. [162]. Similar to the aforementioned modular approach, the Hierarchical Space’s concept is to construct sub-graphs of a topology, then use them to recursively compose an architecture. The key difference between the Cell-Based and Hierarchical spaces is that the latter uses recursive composition to build the topology rather than modular stacking.

At the core, the Hierarchical Space uses primitive operations (e.g 1x1 convolution, 3x3 maxpooling, ReLU, etc...) to set up the first level, \( \ell_1 \). The next level \( \ell_2 \) would consist of sub-graphs, each composed of multiple primitive elements from \( \ell_1 \), and so on for each subsequent level.

Moreover, the composition process yields a new operation in the form of a Directed Acyclic Graph (DAG), which are typically encoded as upper-triangular adjacency matrices. In other words, each level \( \ell \) in the Hierarchical Space comprises of \( n \) adjacency matrices \( O^{(\ell)} = \langle o_1^{(\ell)}, o_2^{(\ell)}, \ldots, o_n^{(\ell)} \rangle \), such that:

\[
o_i^{(\ell)} = \text{compose}(O^{(\ell-1)}), \forall \ell = 2, \ldots, L
\]  

Where the \text{compose}(\cdot) function constructs an operation using a combination of multiple motifs from the given set of operations (the previous level). The Hierarchical Space has proven to be an efficient search space, even when optimized by naïve Search Algorithms, such as Random Search and Grid Search [56], [162].
4) Other Search Spaces: Although the Chain-Structured, Cell-Based, and Hierarchical search spaces are considered some of the most commonly used spaces in the literature, there has been a surge of alternative methodologies recently. For instance, rather than manually designing a static search space, Ci et al. proposed a novel approach to evolve progressively-growing search spaces, which they call Neural Search-space Evolution (NSE) [163]. The authors of NSE claim that traditional search space-design approaches cannot effectively handle large spaces, stating that using existing state-of-the-art algorithms could take up to 27,000 (Nvidia GTX 1080Ti) GPU hours for 100 epochs’ worth of search through a large, 27-operations space. However, using NSENet, that number diminishes to 4,000 GPU hours, with slightly better Top-1 accuracy score.

Inspired by NASNet and the Cell-Based Space, Differen
tiable Architecture Search (DARTS) uses a Cell-Based Space-like search space, where each cell represents a node in a sequentially-built DAG [164]. DARTS also uses the interesting idea of transforming the Cell-Based Space (which is essentially a discrete set of possible solutions) into a continuous and differentiable search space, often denoted as the Continuous Search Space (first introduce by Shin et al. [165]). To make the space continuous, a relaxation process takes place, transforming all categorical operations into a continuous choice of probabilities using softmax. The differentiable nature of the Continuous Search Space also enables DARTS to jointly optimize the architecture and the weights of the network using gradient descent.

Another interesting Search Space-design approach is Memory-Bank Representation (MBR), introduce by Brock et al. [166]. MBR-based networks contain several memory banks (zero-filled tensors) which the network can read/write to. Each layer in the network is viewed as an operation that reads data from a subset of memory tensors, computes the result, then finally write said results to a different subset of memory banks.

B. Search Algorithms

After defining a Search Space, the next step in a standard NAS pipeline is to create and optimize a structure using a Search Algorithm. A Search Algorithm is the approach used to sample the candidate network(s) from a given solution space to be evaluated thereafter and further optimized if needed. Most NAS Search Algorithms are based are based on approaches used for hyperparameter optimization as both areas are inherently similar [167].

1) Random/Grid Search: Although widely considered a naïve optimization approach due to its exhaustive nature, Random Search (RS) has proven to be useful for hyperparameter tuning [168], [169]. RS algorithms for NAS work by selecting a candidate network at random (using a given distribution, e.g: uniform, normal, poisson, etc…) from the search space [170]. The glaring downside of such an approach is that the selection process is statistically independent and cannot be optimized given the feedback from the Evaluation Strategy. However, the lack of complexity leads to a much faster selection process and therefore great exploration capabilities, which can yield high-performing results [146], [162].

Another popular exhaustive search technique used for Neur
al Architecture Search is Grid Search (GS). By defining the number of layers and a set of operations per layer (i.e $L_i = \{conv2x3, maxpool3x3, dense256\}$), GS can select network architectures by trying different combinations of options from the given sets of operations. As with Random Search, the values are independent of each other in Grid Search approaches, meaning the algorithm can be parallelized. However, out of the two exhaustive algorithms, Random Search often outperforms Grid Search [167].

2) Surrogate Model-Based Optimization: Surrogate Model-Based Optimization (SMBO) (often interchangeable with Bayesian Optimization (BO) [157], [171]) has been consistently successful in many areas for almost a decade [144], [172]–[175]. Based on Bayes Theorem, BO works by building a probabilistic model (called the surrogate model) of the objective/cost function. A selection/acquisition function can then be used to sample data points from the posterior, which would iteratively approximate the solution surface. There are numerous surrogate model and acquisition function definitions; however, most BO models use Gaussian Processes (GPs) as surrogate models and Expected Improvement Criterion (modelled below) as selection functions [171].

$$E.I_y(x) = \int_{-\infty}^{\infty} \max(y - y^*, 0) \ p(y|x) \ dy \quad (3)$$

As shown in Equation (3), the Expected Improvement (EI) function is built over the surrogate model $p(y|x)$, where $y$ is the objective function, $y^*$ is the maximum observed value of $y$, and $x$ is the data-point (the hyperparameter in the case of hyperparameter optimization, or the network in case of NAS). The integral (or, in practice, a bounded variation of which) yields the approximate solution space surface, where the maximum observed value $y^*$ represents the global maximum, or the optimal solution. Note that the definition of EI can vary, and could trivially be changed into a minimization problem instead of the current maximization form.

Despite the fact that Auto-Net – the first automatically-tuned ANN to win in a competition against human experts – was tuned using Bayesian Optimization [144], the low-dimensional and continuous nature of most BO surrogate models (GPs in particular) make this an inadvisable approach for NAS applications [56]. However, Zhou et al. proposed the first BO-based NAS model (BayesNAS), which outperformed the famous NASNet in some cases [174]. BayesNAS’s impressive metrics can be attributed to an interesting probabilistic model that promotes sparsity (unlike GPs), thereby proving that Bayesian Optimization can indeed be a powerful search strategy for NAS models.

3) Reinforcement Learning: Reinforcement Learning (RL) problems generally comprise of (i) an Agent that uses an optimization algorithm to take certain actions and achieve a given task, (ii) a Policy that defines the set of possible actions, (iii) an Environment (sometimes called an Action/Observation
Space) that the Agent can interact with, and finally (iv) a Reward Function that incentivizes the Agent every iteration to reach an optimal solution. When applied to NAS, these components remain the same; the architecture generator/controller (the Agent; typically an RNN controller model) uses a set of possible operations/layers (the Policy) in a given Search Space (the Environment), which can then be assessed using an Evaluation Strategy (the Reward Function).

NAS is widely considered to have gained popularity after the groundbreaking work by Zoph & Le in 2017, which was one of the earliest models to achieve impressive performance on the CIFAR-10 and the Penn-Treebank datasets using an automatically-searched neural architecture [150]. Their model was based on a Reinforcement Learning search algorithm that used a Recurrent Neural Network (RNN) with the REINFORCE Policy Gradient algorithm [175] as an Agent/controller that samples a Convolutional Neural Network (CNN) from a given set of CNN operations (convolutional layers with a variable number of kernels and kernel sizes, ReLU, Batch Normalization, and Skip-Connections). Some of the generated models using this approach achieved an error-rate of 3.65% on the CIFAR-10 image dataset, outperforming ResNet and some variations of DenseNet. The highly criticized aspect of this approach is its vast computational requirements, using 800 (Nvidia K40) GPUs for 4 weeks (i.e over half a million GPU hours in total) [150], [153].

Also considered one of the turning-points of NAS research is MetaQNN, introduced by Baker et al. in 2016 [151]. MetaQNN trains an Agent using Q-Learning with an ϵ-greedy Policy to sequentially build a CNN (composed of convolutional, pooling, and dense layers). MetaQNN’s Agent uses an iterative form of Bellman’s Equation as an optimization algorithm, where a state \( s_t \) represents a tuple of layer operations and an action \( u \) specifies the connections between the operations. Although not attaining a competitively low error-rate like the work by Zoph & Le, MetaQNN’s still-reasonable error rate of 6.92% can nevertheless be celebrated given the model’s substantially lower resource requirements, using only 10 GPUs for 8 to 10 days (i.e slightly over 2k GPU hours on average).

Google Brain’s famous NASNet by Zoph et al. was also built using an RL Search Algorithm [153]. NASNet mainly differs from the initial NAS model by Zoph & Le in that the controller uses Proximal Policy Optimization [177] instead of REINFORCE Policy Gradient, and the Search Space is Cell-Based rather than Chain-Structured. More impressively, NASNet obtained an even better error-rate (as low as 2.40%) on the same CIFAR-10 benchmark, with the copious amount of computational requirements (as low as 2k GPU hours).

4) Neuroevolution/Evolvable-NAS: Two of the most prominent Search Algorithms for NAS are Neuroevolution (NE) and Evolvable Neural Architecture Search (ENAS); while both methodologies are based on Evolutionary Algorithms (EAs), NE aims to optimize both the structure and the weights of a network, whereas ENAS is only concerned with the architecture [178]. NE and ENAS draw inspiration from biological evolution, where an architecture corresponds to an individual in a population that could breed (other architectures with similar features) if it is well-performing, or get removed from population otherwise. Simulating this “survival of the fittest” approach in-silico has continued to show promising results for over 3 decades [161], [179]–[181].

The main distinction between NE/ENAS (along with other population-based approaches) and the aforementioned Search Algorithms is that the evolutionary approaches use an initial population of networks, each of which residing on a different position on the optimization surface, whereas the other approaches discussed start off with a single point (i.e a single network). Some of the most commonly used EAs for both NE and ENAS are Genetic Algorithms (GAs), Evolution Strategies (ES), and Differential Evolution (DE) [182].

| Algorithm 1: A typical Evolvable NAS pseudocode (adapted from [183]) |
|---------------------------------------------------------------|
| **input**: A dataset \( D \), number of generations \( T \), number of individuals in a generation \( N \), and the probabilities of mutation and crossover \( P_m \) and \( P_c \) |
| **initialization**: Generate a set of randomized individuals (ANNs) \( \{M_{0,n}\}_{n=1}^{N} \) and evaluate their fitness |
| **for** \( t = 1, 2, ..., T \) **do** |
| **Selection**: select a new generation \( \{M'_{t,n}\}_{n=1}^{N} \) based on the fitness scores of \( \{M_{t-1,n}\}_{n=1}^{N} \) |
| **Crossover**: for each pair \( \{M_{t,2n-1}, M_{t,2n}\}_{n=1}^{\lfloor N/2 \rfloor} \), perform crossover with a probability of \( P_c \) |
| **Mutation**: for each non-crossover individual \( \{M_{t,n}\}_{n=1}^{N} \), perform mutation with a probability of \( P_m \) |
| **Fitness evaluation**: compute the fitness for all individuals \( \{M_{t,n}\}_{n=1}^{N} \) |
| **Output** the last generation \( \{M_{T,n}\}_{n=1}^{N} \) with their fitness scores |

Although there is a number of different types of EAs, they all predominantly revolve around certain key genetic operators: Selection, Crossover (or Recombination), and Mutation [184]. The Selection operator is responsible for sampling fit individuals from the population to pass on to the next generation. Furthermore, Crossover essentially breeds an offspring from two selected individuals by swapping certain features (or genes) in the parents’ genomes, mimicking the biological Genetic Recombination process to some extent. Finally, Mutation is a stochastic operator that randomly modifies the gene pool, ensuring diversity and henceforth promoting the exploration of the search space.

When Genetic Algorithms were first introduced by Holland et al. in 1962 [185], they were merely used for parameter-optimization (i.e training) in the context of ANNs. This ap-
The first model to optimize both the weights and the network architecture using EAs was proposed by Miller et al. in 1989 [179], which spawned a sub-field of NE referred to as Topology and Weight Evolving Artificial Neural Network (TWEANN).

Stanley and Miikkulainen proposed one of the leading-edge TWEANN models titled NeuroEvolution of Augmenting Topologies (NEAT) that addressed several flaws in the Neuroevolution area [186], which is thought to have reignited the interest in the field. NEAT’s significance in the area was mainly attributed to the model’s ability to overcome the issue of competing conventions, where 2 selected parents would have similar genomes, making it difficult to have a successful Crossover. Using a simple and inexpensive feature called historical markings, NEAT ensured coherent Crossover results by keeping track of the newly created structures throughout the evolution process. Moreover, NEAT also proposed the interesting idea of Speciation, or grouping certain individuals with similar characteristics into species. This feature protects some individuals from premature extinction before their potential is realized, and it also promotes diversity within a population (which brought about another area within NE called Novelty Search [187], [188]).

Despite its considerable impact on Neuroevolution, NEAT used a representation method called Direct Encoding, which was highlighted as a significant drawback in later studies [12], [180]. Genetic Algorithms require an encoding technique to map the genotype (the individual’s set of genes; a representation of the neural network in the form of a vector of binary bit strings) to the phenotype (the actual network components). Direct Encoding is a 1-to-1 mapping between the genotype and phenotype, whereby each component in an ANN has to be distinctly described in the genome, posing a scalability problem.

Stanley et al. later recognized this crucial setback and proposed a new model that uses Indirect Encoding named HyperNEAT [180]. Inspired by the human genome’s relatively small capacity (about 30,000 genes [189]) and the astronomical brain structure that comprises of trillions of connections [190], HyperNEAT was able to simulate this 1-to-1 many approach between the genotype and the phenotype using Compositional Pattern-Producing Networks (CPPNs), ultimately outperforming and out-scaling NEAT [180], [191].

The Evolution Strategies paradigm works very similarly to GAs, with two main distinguishing factors: individuals are encoded as vectors of real numbers (instead of binary bitstrings), and the paradigm adopts the concept of Endogenous and Exogenous parameters [192], [193]. Endogenous parameters are values encoded within an individual’s genome (i.e., get optimized in the evolutionary process as part of the individual), whereas Exogenous parameters are static, global hyperparameters that apply to the entire population. For example, the mutation strength in standard GAs is an Exogenous parameter that is uniformly applied to all individuals; however, an ES model could endogenize that value and provide a varied mutation strength that is optimized per individual. This powerful feature offers more individualistic control and encourages self-adaptiveness through the inclusion of hyperparameters into the optimization process. Some of the most popular ES-based models for Neuroevolution include Evolutionary Acquisition of Neural Topologies (EANT) [194], Natural Evolution Strategy (NES) [195], and several Covariance Matrix Adaptation Evolution Strategy-based (CMA-ES) models [196–199] (we refer the reader to Hansen et al. for the latest comprehensive review on Evolution Strategies [199]).

Evolutionary NAS, although a relatively newer area than Neuroevolution, has gained increasing momentum since 2017 [160–162], [181], [183], [200]. ENAS models typically use GAs to evolve and optimize the neural structure, then train the network using Stochastic Gradient Descent (SGD) [178]. AmoebaNet, proposed by Real et al. in 2019 [161], applied the Tournament Selection [201] method, where the best candidate is selected out of a random sample set S and the candidate’s mutated offspring gets put back into the population (sample size |S| = 1 would turn this into a Random Search algorithm). AmoebaNet also implements a selection approach called aging evolution that favors younger genotypes, which puts the exploration of the search space ahead of the exploitation (i.e., prevents the search algorithm from narrowing down on networks that perform well early). Tournament Selection has also been used in a number of other successful ENAS models [162], [181], [202]. On the other hand, Elsken et al. employed a multi-objective Pareto front optimization approach to sample parents inversely proportional to their density [160].

Although RL Search Algorithms tend to be the focus of attention in the NAS research community, a survey conducted by Real et al. on RL, NE/ENAS, and RS has concluded that Reinforcement Learning and evolutionary approaches perform similarly in terms of final test accuracies. Moreover, Neuroevolution and Evolutionary NAS had a slightly better anytime-performance and were more inclined to find smaller, more efficient models [161]. These findings suggest that further research is needed in the NE/ENAS domain to explore its full potential.

5) Other Search Algorithms: Although the previously discussed 4 major families of Search Algorithms amount to the majority of the models in the literature, there are several different optimization approaches that have been or can potentially be used in NAS applications. Given the fact that Search Spaces are typically discrete in nature, Gradient Optimization (GO) is not usually considered a valid optimization approach. However, an interesting approach introduced by Liu et al. is to relax the structural parameters of the network (transform the discrete search space into a continuous and differentiable space) so that they can be optimized using Gradient Descent [164]. The relaxation of a particular operation \( \bar{o}(i,j) \) is performed using softmax over all possible operations \( \mathcal{O} \) as follows:

\[
\bar{o}(i,j)(x) = \sum_{\alpha \in \mathcal{O}} \frac{e^{\alpha_s(i,j)}}{\sum_{\alpha' \in \mathcal{O}} e^{\alpha_s(i,j)}} \alpha(x^{(i)})
\]  

(4)
Closely related to NE/ENAS, Swarm Intelligence (SI) optimization approaches also have been applied to NAS and yielded impressive results. Niu et al. proposed a Particle Swarm Optimization (PSO)-based NAS model that has achieved state-of-the-art accuracy (95.38% on CIFAR10) in just 0.2 GPU days whilst maintaining an incredibly small model size [203]. Other SI algorithms, such as Ant Colony Optimization [204–206], have also been briefly explored in the NAS context. Further research might be needed, however, to cover the unexplored SI approaches (Artificial Bee Colony, Microbial Intelligence, Fish School Search, Glowworm Algorithm, etc...) for NAS.

In addition to NE/ENAS and SI, other Metaheuristic Optimization (MO) algorithms fit the parallel optimization nature of NAS. Popular optimization techniques, such as Reinforcement Learning and Gradient Optimization, often eclipse less commonly-used approaches; Simulated Annealing (SA), for instance, has outperformed most state-of-the-art NAS models [207], and yet has not been covered in most purportedly comprehensive surveys [50], [56]. Results from other MO-based NAS models, including Cuckoo Search and Tabu Search [208], [209], also show promising potential and should be investigated further.

C. Evaluation Strategies

In order to obtain feedback to guide the Search Algorithm and further optimize the sampled solutions, an Evaluation Strategy is needed to estimate the samples’ performance. The choice of Evaluation Strategy does not significantly affect the search process, rather it can have a great impact on the computational demands of the model as the evaluation process is performed at every iteration [218].

1) Full Training: Considered the simplest form of performance estimation, Full Training (often dubbed as the “Training from Scratch” evaluation) simply trains every candidate network until convergence and then estimates the models’ accuracy and/or other metrics. This approach, although straightforward and providing the most accurate feedback, can be the most computationally demanding Evaluation Strategy: every candidate network has to undergo a full training and testing phase to produce a single feedback data sample.

Models using this naïve approach of evaluation normally require a large number of GPUs running in parallel, leading to excessively high resource demands (in the order of thousands of GPU days) [150], [153], [161], [219], [220]. These widely unfeasible requirements prompted the development of new evaluation methodologies that reduce the performance estimation time.

2) Lower Fidelity Estimation: One way to effectively reduce the evaluation time is by training each candidate architecture on (i) just a subset of the data [221], [222], (ii) for a fewer number of epochs (early-stopping) [153], (iii) using a down-scaled version of the dataset (lower resolution images, etc...) [154], and/or (iv) using a compressed version of the candidate model [153], [161], [223]. This method is commonly referred to as Lower Fidelity Estimation (LFE; sometimes denoted as Proxy Task Metrics).

Lower Fidelity Estimation, although significantly faster and cheaper than the traditional Full Training approach, has its downsides as well. Compressing the evaluation training set/model presents an obvious risk of bias in the candidates’ performance estimation process [224]. The resulting bias, however, can be negligible given that the Search Algorithms can typically be guided using the relative performance rankings of the candidate networks. Nevertheless, if the difference between the biased and fully-trained metrics is too large, the candidates’ rankings might become relatively inconclusive and a multifidelity approach might be needed [225–227].

3) Weight Inheritance: Another way to circumvent high computational demands is to rely on Weight Inheritance from a parent model (often denoted as Network Morphism), an approach similar to Net2Net’s knowledge transfer [228]. By initializing each candidate network to a relevant function, or by simply using the Full Training approach once and then only fine-tuning the weights every subsequent generation, the evaluation time can be cut down significantly.

Furthermore, because most Search Algorithms (specifically ENAS-based models [173]) do not tremendously disrupt the architectures of new individuals, Weight Inheritance can be applied to the unchanged areas of the topology and most of the parameters can be swiftly passed down across generations without requiring retraining from scratch. This method has been proven to efficiently evaluate candidate networks by numerous NAS models [152], [159], [160], [229].

4) Learning Curve Extrapolation: An alternative Evaluation Strategy is Learning Curve Extrapolation (LCE), which initializes the candidate networks through partial training (early-stopping) and then uses a surrogate model to estimate the generalization of the final learning curve. Some studies consider Learning Curve Extrapolation to be a subset of Lower Fidelity Estimation given its early-stopping nature [230]: however, an argument could be posed that the use of fewer epochs to train candidate networks is only one step in this Evaluation Strategy rather than its whole premise, hence Learning Curve Extrapolation is typically considered its own family of methods [56], [231].

While many models implementing Learning Curve Extrapolation have achieved state-of-the-art performance with impressively low computational requirements [232–234], the surrogate model often requires extensive training (both weight and hyperparameter optimization) to yield satisfactory extrapolation performance. Nevertheless, Ru et al. have shown that sufficient surrogate model performance can be achieved under a fixed-hyperparameter framework [231].

5) One-Shot Models: A particularly unique approach to search for neural architectures is One-Shot (OS) models, which heavily rely on weight-sharing (not to be confused with the

1Although regularly used as a performance metric in the literature, GPU models vary across the experiments conducted. These numbers serve only as an approximate estimation of computational-demands.
| Search Algorithm | Reference / Model                                                                 | Year | Search Space           | Evaluation Strategy       | GPU Usage (days) | Params (millions) | CIFAR10 Error (%) |
|------------------|------------------------------------------------------------------------------------|------|------------------------|----------------------------|------------------|-------------------|-------------------|
| RS               | Liu et al. (Hierarchical EAS-Random) [162]                                         | 2018 | Hierarchical           | Full Training             | 8.33             | -                 | 4.04              |
|                  | Luo et al. (NAONet Random-WS) [210]                                                | 2018 | Hierarchical           | OS                         | 0.25             | 3.90              | 3.92              |
|                  | Brock et al. (SMASHv1) [166]                                                       | 2018 | MBR                    | OS                         | -                | 4.60              | 5.53              |
|                  | Li & Talwalkar (RandomNAS) [170]                                                    | 2020 | Cell-Based             | OS                         | 2.7              | 4.30              | 2.85              |
|                  | Zhang et al. (RandomNAS-NSAS) [211]                                                | 2020 | Cell-Based             | OS                         | 0.7              | 3.08              | 2.64              |
| SMBO             | Liu et al. (PNAS) [157]                                                            | 2018 | Cell-Based             | LFE                        | -                | 3.20              | 3.41              |
|                  | Kandasmy et al. (NASBOT) [212]                                                     | 2018 | Chain-Structured       | LFE                        | 1.6              | -                 | 12.09             |
|                  | Zhou et al. (BayesNAS) [174]                                                       | 2019 | Hierarchical           | OS                         | 0.1              | 3.40              | 2.41              |
| RL               | Baker et al. (MetaQNN) [151]                                                       | 2016 | Chain-Structured       | Full Training              | 90 ± 10           | 11.20             | 6.92              |
|                  | Zoph & Le (NAS) [150]                                                             | 2017 | Chain-Structured       | Full Training              | 22,400           | 37.40             | 3.65              |
|                  | Zoph et al. (NASNet-A) [153]                                                       | 2018 | Cell-Based             | LFE                        | 2,000            | 3.30              | 3.41              |
|                  | Cai et al. (EAS) [152]                                                            | 2018 | Hierarchical           | Weight Inheritance         | 17.5 ± 7.5       | 23.40             | 4.23              |
|                  | Pham et al. (Efficient NAS) [213]                                                  | 2018 | Cell-Based             | OS                         | 0.45             | 4.60              | 2.89              |
|                  | Ding et al. (BNAS) [214]                                                           | 2021 | Cell-Based             | OS                         | 0.19             | 4.80              | 2.88              |
| NE/ENAS          | Stanley & Miikkulainen (NEAT) [186]                                               | 2002 | Chain-Structured       | Full Training              | -                | -                 | -                 |
|                  | Stanley et al. (HyperNEAT) [189]                                                   | 2009 | Chain-Structured       | Full Training              | -                | -                 | -                 |
|                  | Real et al. (Large-Scale Evolution) [181]                                          | 2017 | Chain-Structured       | Weight Inheritance         | 2,600 [50]       | 5.40              | 5.40              |
|                  | Liu et al. (Hierarchical EAS-Evolution) [162]                                      | 2018 | Hierarchical           | Full Training              | 300              | 15.70             | 3.75              |
|                  | Real et al. (AmoebaNET-A) [161]                                                    | 2019 | Cell-Based             | Full Training              | 3,150            | 3.20              | 3.34              |
|                  | Elsken et al. (LEMONADE) [160]                                                     | 2019 | Cell-Based             | Weight Inheritance         | 40 ± 16          | 3.40              | 3.60              |
|                  | Lu et al. (NSGA-Net) [215]                                                        | 2019 | Continuous             | Weight Inheritance         | 4                | 3.30              | 2.75              |
|                  | Guo et al. (SPOS) [216]                                                           | 2020 | Cell-Based             | OS                         | -                | -                 | -                 |
|                  | Yang et al. (CARS) [217]                                                          | 2020 | Cell-Based             | OS                         | 0.4              | 3.60              | 2.62              |
| MO               | Niu et al. (PNAS) [203]                                                           | 2019 | Cell-Based             | Weight Inheritance         | 0.2              | 2.44              | 4.62              |
|                  | Byla & Pang (DeepSwarm) [204]                                                      | 2019 | Chain-Structured       | Weight Inheritance         | -                | -                 | 11.31             |
|                  | Mo et al. (SA-NAS-c) [207]                                                        | 2021 | Cell-Based             | LFE                        | 0.1              | 3.20              | 2.53              |

**TABLE II
NAS Models’ Comparison Table**

One-Shot Learning paradigm that seeks to train a model using one instance. The premise of OS methods is to build a single over-parameterized network (a large DAG, often defined as the super-network/supernet) whose sub-graphs are individual candidate models, sharing their weights on common edges. This approach can be considered a Search Space as well as an Evaluation Strategy given that both components of the NAS pipeline are enveloped in the model [235].

One-Shot models’ evaluation consists of a single full-training of the super-network (hence the term "One-Shot"), which takes place during the search process, thereby greatly reducing the evaluation time down to just the testing/validation
time. The training process for one super-network is only slightly more complex than that of any individual candidate in the search space \[58\].

Brock et al. proposed one of the earliest OS models called SMASH \[169\]. SMASH operates by generating pseudo-random weights through a surrogate "HyperNet", which (although randomly-generated) are sufficiently optimal to provide a relative measure for the candidate sub-graphs. Sampling hundreds of architectures can be done in under 1 GPU day due to the concurrent architecture/weights search, which (compared to other Search Algorithms/Evaluation Strategies) is tremendously fast.

SMASH, however, is limited by the HyperNet’s "low-rank" child-sampling space \[213\]. To overcome this issue, Pham et al. introduced the Efficient NAS model, which (due to its superiority) is thought to have popularized the One-Shot NAS paradigm \[50\], \[213\]. Efficient NAS can be considered a hybrid OS/RL algorithm, where an auxiliary controller network (trained using REINFORCE) samples candidate architectures from a Cell-Based search space.

One apparent limitation of OS models is that the super-network is static and thus constrains the Search Space to its sub-graphs. Furthermore, One-Shot models are (i) immensely restricted by the GPU’s capacity given that the supernet normally needs to be loaded into the memory during the search process, and (ii) they inherently do not enable individual sub-graph optimization due to weight-sharing.

Although numerous studies have been conducted on different combinations of Search Spaces, Search Algorithms, and Evaluation Strategies, there still remains large gaps of unexplored areas. Metaheuristics Optimization, Learning Curve Extrapolation, and Bayesian Optimization have all had minimal coverage in the literature and their full potential is yet to be investigated. Moreover, statistical dependence between iterations in NAS only occurs at the Search Algorithm/Evaluation Strategy level, whereas feedback from the evaluation could also be used to improve the efficiency of the Search Space. Last but not least, NAS frameworks generally assume a non-incremental experimental setup where all data is present prior to architecture generation, which limits their use to static environments.

V. PLASTIC ARTIFICIAL NEURAL NETWORKS

Humans have evolved to be capable of general learning and skill-refinement; the essence of our intelligence is captured by our ability to continuously assimilate new knowledge and adapt to the varying stimuli we are exposed to (i.e Classical Conditioning) \[240\]. Most modern ANNs are models of what is referred to as “dedicated intelligence” \[241\], \[242\], while more recent works either confined the definition to specific areas (i.e domain-adaptive \[243\], mode-adaptive \[244\], etc...) or generalized it to describe certain learning paradigms, such as Online ML and Unsupervised Learning \[18\].

Soltoggio et al. first coined the term Evolved Plastic Artificial Neural Networks (EPANNS) in 2018, introducing a new paradigm of adaptive ANNs based on Evolutionary Algorithms \[15\]. To expand the currently narrow and specialized mindset associated with ANNs, we extend and generalize the inspiring ideas previously proposed beyond the limited scope of Evolutionary Algorithms. Plastic Artificial Neural Networks (PANNs) aim to ultimately eliminate human-intervention from the development and maintenance of ANNs through existing automation and optimization techniques. A neural network is considered plastic if it is:

1) fully-autonomous (including pre-training data preparation as well as model generation and maintenance),
2) inherently continual (i.e have CL attributes), and
3) capable of handling and adapting to an infinite stream of input (with allowed degradation of performance over time; see Section 5.C, Graceful Forgetting).

Criterion 1 can be further captured by the taxonomy proposed in Figure (7). A fully-Plastic ANN implements every component in the diagram on a continual basis, whereas a partially-Plastic ANN covers only a portion of the components continually.

Fig. 7. Proposed taxonomy for Plastic Artificial Neural Networks

There are numerous additional components that could be considered continually adaptive (e.g learning rule plasticity)
and therefore fit our description of PANNs. However, Fig. (7) defines the baseline, mandatory elements that would ensure end-to-end adaptiveness in a typical ANN life-cycle.

Furthermore, it is important to highlight that – according to Criterion 2 – a PANN is not simply a looped AutoML pipeline. While there exists several approaches that can automate pre-training data preparation and model generation, Plastic ANNs require every component to have Continual Learning attributes; the pipeline should not be iterated with statistical independence for every task encountered, but rather enable Forward and Backward Transfer wherever possible.

B. PANN Components

A PANN framework comprises of 2 essential components: Data Automation and Model Plasticity.

The first stage in a standard Machine Learning pipeline is Data Preparation, which includes all procedures required before the training stage. These procedures include Data Acquisition, Data Pre-processing, and Feature Engineering [54], [55], [245].

1) Data Acquisition: In particular real world applications, a continuous source of data (e.g. a sensor, live camera, etc...) is attached to the model, rendering the Data Acquisition step unnecessary. However, in other scenarios, the data-source is either insufficient (provides a limited amount of data) or simply does not exist. Considering the importance of the dataset’s size and its impact on a model’s performance, a number of approaches have emerged to extend limited data sources. The most common techniques to expand small data in an automated setting are Web Search / Scrape and Data Synthesis.

With the increasing availability of public datasets, web-scraping [246] - [248] and dedicated APIs [1], [249] have become viable solutions for automated Data Acquisition. The main concerns with such Data Search approaches are:

- The legality and ethics of web-scraping [250].
- Search results are likely to contain irrelevant data.
- Unpredictable data quality; without a supplementary data-quality verification technique, the acquired data is unreliable.

Data Synthesis, in contrast, offers a more controllable Data Acquisition environment that overcomes all the listed drawbacks posed by Web Search/Scrape. The fast-growing research on generative models and data simulators has shown that synthetic data can be an impressive alternative when real data is unattainable. The mesmerizing realism produced by Generative Adversarial Networks (GANs) [251] also proves that synthetic data can be almost indistinguishable from their real counterpart whilst providing granular control of the results [252]. Moreover, tools like OpenAI Gym, Unreal Engine, and even the Grand Theft Auto game have been successfully used to simulate entire scenes for image classification and segmentation [253], [254]. The apparent limitation of Data Synthesis is that the process (in an automated context) requires an initial dataset to establish a baseline distribution for the synthesizer to match.

2) Data Pre-processing: Whether the data is directly fed to the framework through a continuous source or externally acquired, Data Cleaning is inevitable. The cleaning process includes removing noise/outliers, handling missing data (commonly denoted as NaNs), and eliminating inconsistencies [255]. Although the Data Pre-processing stage is heavily dependent on the domain of the problem (image, text, audio signals, etc...), some data cleaning algorithms, such as BoostClean [256] and AlphaClean [257], are domain-agnostic and therefore enable generic automation. Moreover, Continuous Data Cleaning frameworks that leverage the user’s feedback on cleaning preferences have been briefly explored [258].

Amongst the issues that commonly arise during Data Preparation are class imbalance (uneven data per label), and lack of variability/over-fitting. By augmenting the data (i.e using affine transformations on image datasets or pitch-scaling on audio signals; we refer the reader to the survey by He et al. [55] for a Data Augmentation taxonomy), new data points can be generated to help balance the dataset and increase the generalization ability of the model. A byproduct of Data Augmentation is dataset extension and so it can also be regarded as a Data Acquisition approach. However, the consensus is that augmentation is primarily used for its regularization qualities and is thus considered a part of the Data Pre-Processing stage [55], [259].

3) Feature Engineering: More often than not, a dataset contains redundant features that negatively impact the convergence of the model during training. The function of any

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2 https://www.datasearch.elsevier.com
3 https://datasetsearch.research.google.com/
neural layer is to essentially map an input feature vector \( \vec{x} = [x_1, x_2, \ldots, x_n] \in \mathbb{R}^n \) to an output vector \( \vec{y} = [y_1, y_2, \ldots, y_m] \in \mathbb{R}^m \) with a nonlinearity, which can be modelled as:

\[
\vec{y} = \sum_{i=1}^{n} x_i W_i + b_i ,
\]

\[
\hat{y} = f(\vec{y})
\]

Where \( W = [w_1^T, w_2^T, \ldots, w_n^T] \in \mathbb{R}^{n \times m} \) is the parameter matrix of the network, \( b = [b_1, b_2, \ldots, b_m] \in \mathbb{R}^m \) is the bias vector, and \( f(\cdot) \) is an element-wise nonlinearity (e.g Tanh, Sigmoid, etc...).

A training matrix \( X = [\vec{x}, \vec{y}] \) with correlated features (i.e collinearity or multi-collinearity) is linearly dependent and thus \( X \) is not a full rank matrix. Given the high-dimensional nature of deep neural networks, where \( m \) and \( n \) are often in the order of thousands \[155\], rank-deficiency significantly impacts the training time of the model \[272\]. Feature Selection not only speeds up the convergence of the optimization process, it also enables the use of techniques like Low-Rank Approximation that can significantly reduce the memory-footprint of the model by representing the weight tensor as multiple smaller tensors through low-rank factorization \[273\].

Due its non-trivial and creativity-driven nature, Feature Transformation and Construction is usually considered the most human-dependent Feature Engineering phase \[54\], \[55\]. Constructing new features extends the dataset and its generalization by synthesizing new features from existing ones (as opposed to Data Augmentation, which adds new samples/rows rather than columns), whereas Feature Transformation affects the speed of the optimization process. Linear feature transformations, such as normalization and standardization, boost the convergence of the training process by scaling the raw data
distribution and ensuring the features have similar magnitudes. Additionally, the traditional use of a single learning rate in ANNs upholds the importance of unifying the features’ scale; in a Gradient Descent training scenario, a global learning rate applied to unnormalized data will most likely propel each gradient/dimension at proportionally different magnitudes.

Similar to Feature Selection, Dimensionality Reduction (often called Feature Extraction) aims to separate redundant data from effective information. The primary distinction between the two processes is that Dimensionality Reduction creates new compressed mappings of the original features rather filter them as with Feature Selection. Although neural networks perform Dimensionality Reduction inherently (e.g. pooling or convolution layers extract features from localized regions), methods such as Principal Component Analysis (PCA) can scale a neural network’s input and reduce the number of operations performed, thereby minimizing the computational requirements for training.

Feature Engineering can be regarded as a stochastic optimization problem and therefore a number of traditional optimization algorithms can be used to automate the process. The limited Automated Feature Engineering frameworks that have been proposed are mainly based on Genetic Algorithms and Reinforcement Learning, where both approaches performed impressively well compared to baselines (random- and manual/human-based). With the current lack of a unified benchmark, however, automated Data Preparation frameworks cannot be formally ranked or compared.

4) Neural Architecture Generation and Optimization: The crucial phase of generating a network’s topology for a given task has been discussed in depth in Section 4. Nevertheless, the continuous maintenance of a neural network should not be interpreted as a repeated NAS process; while reiterating a NAS algorithm for each encountered task can indeed result in a fully-autonomous continuous pipeline, the computational cost and time required to repeatedly search for architectures from scratch will likely be unfeasible for most applications. To address the expected high resource demand for continual NAS frameworks, a few models have been recently proposed that incorporate CL techniques within the architecture search process (e.g finding an optimal NAS cell that best fits all encountered tasks and facilitates few-shot learning for future tasks).

Proposed by Gao et al. in 2022, Continual Learning with Efficient Architecture Search (CLEAS) dynamically expands the network architecture whilst preserving previous knowledge through parameter isolation. While this approach experiences no forgetting, it scales poorly; for every encountered task, the network has to expand with no means of compressing superfluous parameters. Similarly, ENAS-S and Learn-to-Grow also experience monotonic expansion without a memory-boundary, which makes them unsustainable for long-term real world deployment.

Moreover, Continual NAS (CNAS), REC, and BNS all require a dedicated memory to store subsets of training data for replay purposes. While this memory-retention strategy offers great control over the retraining of the models as well as the NAS process, they are not capable of handling an infinite stream of input due to the unrestricted external memory requirement.

An alternative approach proposed by Niu et al. (dubbed AdaXpert) dynamically adjusts the neural architecture using a secondary model called the Neural Architecture Adjuster (NAA), which aims to search for a new topology only when deemed necessary (i.e the distance between task boundaries is greater than a given threshold). However, in the experiment proposed for AdaXpert, the NAA uses Wasserstein distance for every input to compute how far the new task boundary is from the existing trained model’s probability distribution, which shows an implicit and unmentioned assumption that the input samples must be grouped prior to training. Given a real world scenario where samples are interleaved, the NAA will be prompted to adjust the network for every increment, rendering it essentially futile.

5) Hyperparameter Optimization: Most NAS frameworks use the same set of hyperparameters over the search process. While static hyperparameters might be viable for single-task NAS problems, they cannot be efficiently generalized for unknown future tasks, therefore continuous Hyperparameter Optimization is needed to maintain efficiency across sequentially encountered tasks.

Furthermore, most NAS frameworks consider the architecture and hyperparameter optimization processes as two separate phases. While NAS frameworks use the same set of hyperparameters over the search process, which exponentially increases the complexity of the framework. To overcome nesting architecture search and hyperparameter tuning, jointly optimizing both the structure and its hyperparameters can significantly reduce the framework’s requirements, especially on a continual basis. A number of studies on evolutionary ANNs suggest that hyperparameters can be endogenous features (i.e encoded as genes) and therefore get bootstrapped into the optimization process.

C. Desiderata for PANNS

Aside from the formal definition previously described, PANNS should ideally possess the following qualities:

1) Domain-agnostic: The model should not rely on a priori task-boundary definition; be capable of adapting to its surrounding environment without exhibiting a preference to a certain domain.
2) Abstract representation: Encoding the network should be represented with a high level of abstraction (i.e in the case of Evolutionary Computation, the genotype-phenotype relation should be indirect). This ensures model-scalability and follows on the biological analogy where the human genome is indirectly mapped to physical body.
3) Dynamic architecture with bounded capacity: The network topology should grow, shrink, or get remapped to accommodate different input complexities and maintain efficiency. However, the architecture-search process should be bounded by a given memory capacity to
avoid overflow and facilitate deployment in real-world applications.

4) **Graceful Forgetting**: With a bounded memory capacity and a potentially unbounded stream of data, forgetting is inevitable. It should, nevertheless, be imposed gracefully through selective means, where the less important tasks’ performance gradually decays rather than catastrophically fails.

5) **Few-Shot Learning capability (positive FWT)**: Positive FWT is not often the focus for most Continual Learning models; however, for PANNs, facilitating Few-Shot Learning is a priority in order to reduce the large computational costs over time.

6) **Multi-Modal input support**: To further pave the way for a more generalized form of AI, a PANN framework should ideally support knowledge-acquisition through different modalities (e.g., image classification, text classification).

7) **No explicit data storage for previous tasks**: Storing subsets of examples from previous tasks usually entails linearly increasing memory-consumption. Parameter-Constrain approaches, where the model’s "memory" is implicitly stored through the training process, are therefore considered a more favorable memory-retention technique. Additionally, the globally growing privacy concerns also dictate less data-storage-based methodologies.

8) **Learning rule plasticity**: The training process for ANNs greatly relies on predefined learning rules (or weight-updating equations) that determine the changes to the network parameters. Jointly optimizing the learning rule with the other network parameters (as suggested by [12], [15]) could effectively cut down the training cost.

Although these desirable features do not directly contribute to end-to-end automation and continuity, they aim to generalize PANNs and facilitate their scalability for real-world deployment.

VI. **Future Directions**

A palpable concern to PANNs is the potentially staggering computational requirements; pipelining multiple automated optimization approaches back-to-back with a possibly expanding network can be expensive. Nevertheless, with the advancements made in NAS (as shown in Table (2)) and the incorporation of Continual Learning within the architecture search and the data preparation processes, resources can be considerably spared. While fully-Plastic ANNs do not currently exist, some models (such as AdaXpert and CLEAS [267, 271]) have made great strides in the direction of full automation and therefore support the feasibility of PANNs and their future potential.

Furthermore, inconsistent with their state-of-the-art performance, Metaheuristic Optimization for NAS is often overlooked in comprehensive surveys/reviews [50], [56]. Scarce coverage of such approaches limits the exploration of the optimization family, which has continued to show great potential in multiple areas [203, 205, 207]. Additionally, other MO approaches, such as Artificial Bee Colony and Glowworm Algorithm, have not been applied to Neural Architecture Search, making them prospective future research directions.

The 3 implicitly agreed-upon metrics for NAS models are (i) CIFAR10 acc./error, (ii) model size (parameter count), and (iii) GPU days, or the amount of GPU time that was needed to the optimal architecture (modelled as GPU Days \( N \times D \), where \( N \) is the number of GPUs used in parallel and \( D \) is the number of days spent). Both (i) and (ii) yield robust and absolute measures of model performance. The "GPU Days" metric, however, is inconsistent across systems; the programming language and paradigms, operating system, and hardware used (mainly the GPU model) could vary tremendously in the experiments performed. For instance, some researchers have used workstation-grade GPUs [210], whereas others have used low-end personal computer GPUs [213]. While most studies
opt to use this evaluation metric to provide a rough estimate of the framework’s efficiency, more absolute measures (such as FLOPs) have been used by a few others \[217\]. Absolute measures, however, usually require additional implementation steps to calculate. A generic evaluation approach for NAS models’ computational efficiency is needed to provide a robust insight on the frameworks’ requirements and rank them appropriately.

Another interesting research area worth exploring is Social Learning (sometimes dubbed collaborative learning). Human intelligence could not have evolved through one individual in a single life-time; similarly, it is unlikely that a complex set of mechanisms could evolve or be learned in a relatively short period of time without knowledge-sharing across multiple artificial models. Recent works on ML started exploring the concept of Social Learning, where a ML model would share information with other models in the same domain to collectively boost performances \[15\], \[238\]. Social Learning can be complementary to P ANNs, especially given their lifelong learning nature.

While AutoML frameworks (NAS specifically) and Continual Learning models have implicitly agreed upon benchmarks in the literature, the intersection between both fields does not (as shown in Table 3). Some works use the average accuracy over all tasks to rank their model \[260\], \[267\]. However, that metric diminishes as the number of tasks approaches infinity. Consider a model with a bounded memory capacity for \(C\) tasks and an unbounded incremental input \(x\), \(s.t\ |x| = +\infty\), the running average of accuracies will reach an inflection point at \(x_C\) where the inevitable forgetting will set in and average accuracy is bound to diminish. Furthermore, in the context of a system that enables an infinite input, the model should not be ranked according to some “final” model metrics; by definition, the framework has no final state and intermediate results might not reflect the framework’s true performance, hence a robust ranking approach for PANNs (potentially based on the rate of change of metrics rather than instantaneous values) needs to be formalized.

A noteworthy research direction for handling forgetting in a graceful manner would be defining a Replacement Policy for PANNs and Continual Learning models in general. Certain tasks should be prioritized over the lifetime of the model, possibly on a Least Frequently Used- / Least Recently Used-basis (as with Cache Replacement Algorithms), which further follows the biological inspiration mentioned in Section 2 (i.e Hebbian learning).

The main hindrance with "full" automation in PANNs is the need for an initial Task Descriptor. A PANN, by definition, should be capable of generating a relational solution given only a problem boundary (e.g a dataset/a model of the task data distribution, or possibly even the keywords for a web-scraping/search algorithm). This indicates that a manual list of descriptions for every task (consisting of the problem distribution, lifetime, etc...) is likely still needed in the PANN pipeline. Automating the Task-Descriptor is contingent on modelling a driving force for the model (i.e equivalent to the evolutionary primal disposition to survival/procreation in biological species), which makes for another interesting research direction.

Notwithstanding the exciting prospect of generalized AI, there are drastic risks associated with such forms of continual automation. Unmonitored data collection introduces the possibility of accidental dataset poisoning, where unwanted samples are fed to the model. In sensitive domains (UAVs, medical applications, industrial IoT devices, etc...), data-integrity must be verified and input data should possibly be restricted to certain distribution boundaries as well. Safeguarding PANNs against potential task deviations is of paramount importance and highly suggested as a future research area.

VII. Conclusion

In this study, we propose a dynamic paradigm that entails full-automation and continual-adaptiveness in neural networks. Despite the existence of several models in the PANNs field (as shown in Table (3)), this intersection between AutoML and Continual Learning has never been formalized or reviewed in depth.

Through self-development and lifelong plasticity, PANNs aim to overcome numerous limitations posed by the human factor and result in more optimal models. In doing so, Plastic ANNs could potentially introduce a new spectrum of applications where the functionality of the model is pliable, even after the deployment phase when remote access is often limited or unavailable.

Additionally, PANNs take a step towards generalizing intelligence; although the definition of “intelligence” has long eluded psychologist and neuroscientists, it has been repeatedly defined as “goal-directed adaptive behavior” and “adaptive self-modification” rather than mere associative inference \[240\], \[278\]. Narrow, Weak AI has indeed led to amazing accomplishments, however, there is an undeniable impending bottleneck to the capabilities that can be achieved with traditional methodologies. Continual adaptability and automation, on the other hand, minimize the static nature of narrow AI and provide an essential basis for Strong AI.

The proposed categorization schemes and analysis of methodologies aim to propel researches towards a less dedicated form of intelligence and facilitate more robust models that are sensitive to their surrounding environments.

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