Continual Learning through Evolvable Neural Turing Machines

Benno Lüders, Mikkel Schläger, Sebastian Risi
IT University of Copenhagen
Copenhagen, Denmark
{blde, mihs, sebr}@itu.dk

Abstract

Continual learning, i.e. the ability to sequentially learn tasks without catastrophic forgetting of previously learned ones, is an important open challenge in machine learning. In this paper we take a step in this direction by showing that the recently proposed *Evolving Neural Turing Machine* (ENTM) approach is able to perform *one-shot learning* in a reinforcement learning task without catastrophic forgetting of previously stored associations.

1 Introduction

A hallmark ability of humans is to continually learn from experience. However, creating artificial agents that can continuously adapt to novel situations and learn new skills within their lifetime without catastrophic forgetting of previous learned skills remains an unsolved challenge in machine learning [1]. The recently introduced progressive neural network approach [2], which creates a new neural network for each task, takes a step towards continual learning, but requires the manual identification of tasks. Another example is the cascade-correlation algorithm [3] that can incrementally learn new feature detectors while avoiding forgetting. Ellefsen et al. [4] showed that by encouraging the evolution of modular neural networks, catastrophic forgetting in networks can be minimized, allowing them to learn new skills while retaining the ones already learned. In contrast to their approach, in which associations are learned over multiple network presentations, our method can learn new associations in one-shot.

The presented approach builds on the recently developed *Neural Turing Machine* (NTM) [5] that enables agents to store long-term memories by augmenting neural networks with an external memory component. The differentiable architecture of the original NTM can be trained through gradient descent and is able to learn simple algorithms such as copying, sorting and recall from example data. In the work presented here we build on an evolvable version of the NTM (ENTM) that allows the approach to be directly applied to reinforcement learning domains [6, 7].

While gradient-based methods have shown to scale to highly complex problems, a *neuroevolutionary* approach (i.e. training neural networks through evolution; [8]) that does not rely on differentiability, offers some unique advantages. First, in addition to the network's weights, the optimal neural architecture can be learned at the same time. Second, a hard memory attention mechanism is directly supported and the complete memory does not need to be accessed each time step. Third, a growing and theoretically infinite memory is now possible. Together these mechanisms are especially important for a continual learning system, in which the optimal network architecture is not known a priori, memory is ideally unbounded, and a hard attention mechanism only changes specific memory locations at a time, thereby reducing the chances of overriding previously learned information.

In this paper, we demonstrate that by evolving the network's topology and weights starting from a minimal structure, the optimal structure for a continually learning network can be found automatically. The evolved NTM solutions are able to perform one-shot learning of new associations and

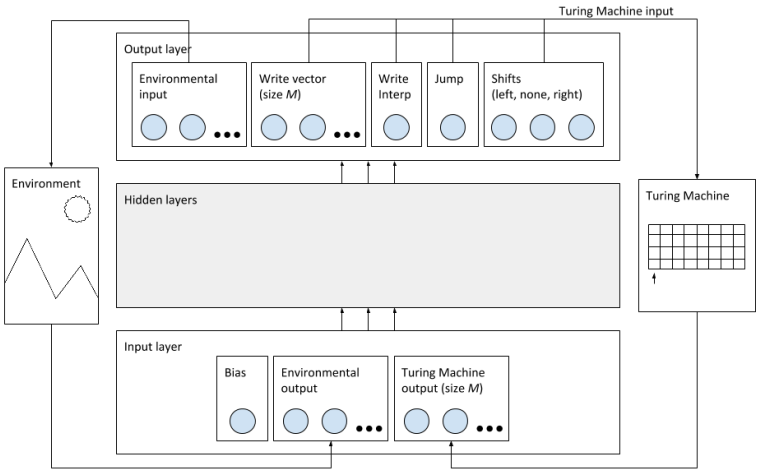


Figure 1: Evolvable Neural Turing Machine. In addition to the NTM specific inputs and outputs, the ANN has domain dependent actuators and sensors. The structure of the networks hidden layers is automatically determined by the NEAT algorithm.

learn to avoid catastrophic forgetting by using their external memory component. Additionally, we present a new ENTM *default jump* technique that facilitates the evolution of high-performing solutions. With increasing computational resources it might now be feasible to combine the strength of gradient-based approaches with the ability of evolutionary approaches to optimize mechanisms that are difficult to differentiate.

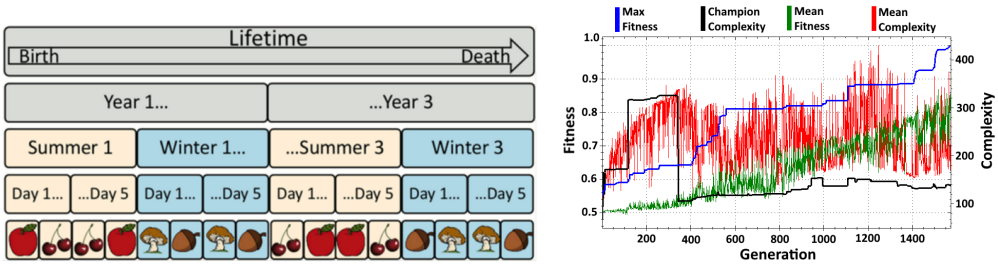
2 Neuroevolution

The weights and topologies of the networks in this paper are trained by the Neuroevolution of Augmenting Topologies (NEAT) approach [9]. The main challenge with evolving neural networks is that some of the primary principles of Evolutionary Algorithms (EAs), mainly crossover, are difficult to apply to networks with arbitrary topologies. NEAT solves this problem by using historical markers for all genes in the chromosome; every time a new mutation is performed it receives a historical marking, which is a unique identifying number. This way networks with arbitrary topologies can be combined in a meaningful way. Additionally, NEAT begins with simple networks (i.e. networks with no hidden nodes and inputs directly connected to the network's outputs), and augments them during the evolutionary process through mutations (adding nodes and connections) and crossover. The NEAT implementation in in this paper (SharpNEAT) uses a complexity regulation strategy for the evolutionary process: A threshold defines how complex the evolving networks can be, before the algorithm switches to a simplifying phase, in which it gradually reduces complexity.

In order to enable these evolving ANNs to learn during their lifetime, efforts have been made to allow them to adapt online and learn from past experience [10, 11, 12, 13, 14]. However, a common problem for these techniques is their inability to sustain long-term memory. The weights that encode a particular task are often overridden when a new task is learned, resulting in catastrophic forgetting [15]. The ENTM approach aims to overcome this challenge.

3 Evolvable Neural Turing Machines (ENTMs)

Based on the principles behind the NTM, the recently introduced Evolvable Neural Turing Machine (ENTM) uses NEAT to learn the topology and weights of the neural controller [6, 7]. That way the topology of the network does not have to be defined a priori (as is the case in the original NTM setup) and the network can grow in response to the complexity of the task. The ENTM often finds compact network topologies to solve a particular task, thereby avoiding searching through unnecessarily high-dimensional spaces [6]. Because the network does not have to be differentiable, it can use hard attention and shift mechanisms, allowing it to generalize perfectly to longer sequences in a copy task. Additionally, a dynamic, theoretically unlimited tape size is now possible.



(a) (b)

Figure 2: (a) Season task environment for one individual's lifetime. Figure from [4]. (b) Fitness and complexity progress during evolution. Notice the low champion complexity relative to the mean.

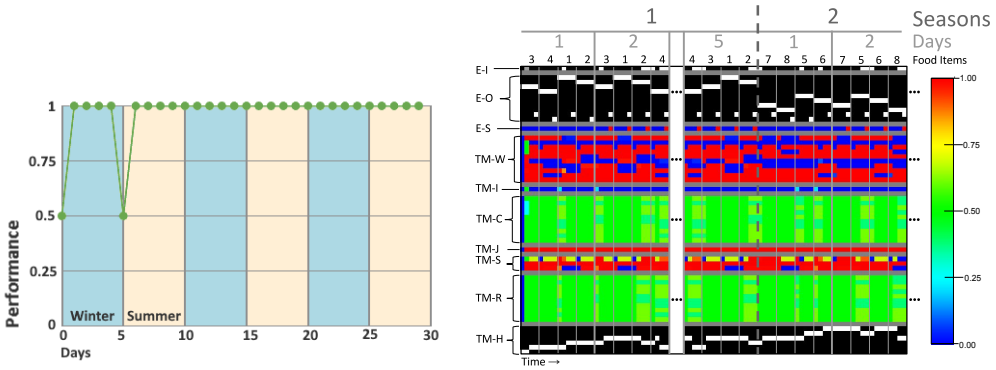
Figure 1 shows the ENTM setup in more detail. The ENTM has a single combined read/write head. The network emits a write vector w of size M, a write interpolation control input i, a content jump control input j, and three shift control inputs s_l, s_0, and s_r (left shift, no shift, right shift). The size of the write vector M determines the size of each memory location on the tape. The write interpolation component allows blending between the write vector and the current tape values at the write position, where $M_h(t)$ is the content of the tape at the current head location h, at time step t, i_t is the write interpolation, and w_t is the write vector, all at time step t: $M_h(t) = M_h(t-1) \cdot (1 - i_t) + w_t \cdot i_t$.

The content jump determines if the head should be moved to the location in memory that most closely resembles the write vector. A content jump is performed if the value of the control input exceeds 0.5. The similarity between write vector w and memory vector m is determined by: $s(w, m) = \frac{\sum_{i=1}^{M} |w_i - m_i|}{M}$. At each time step t, the following actions are performed in order: (1) Record the write vector w_t to the current head position h, interpolated with the existing content according to the write interpolation i_t. (2) If the content jump control input j_t is greater than 0.5, move the head to location on the tape most similar to the write vector w_t. (3) Shift the head one position left or right on the tape, or stay at the current location, according to the shift control inputs s_l, s_0, and s_r. (4) Read and return the tape values at the new head position.

In the original ENTM setup [6, 7], the tape has an initial size of one and its size is increased if the head shifts to a previously unvisited location at either end. This is the only mechanism to increase the tape size in the original setup. Thus to create a new memory, the ENTM write head has to first jump to one end of the tape, and then perform a shift into the correct direction to reach a new, untouched memory location. This procedure also requires marking the end of the tape, to identify it as the target for a subsequent content jump. In this paper we introduce a new *default jump* mechanism that should facilitate creating new memories without catastrophic overriding learned associates. The default jump utilizes a single pre-initialised memory location (initialized to values of 0.5), which is always accessible at one end of the tape. It can provide an efficient, consistent opportunity for the write head to find an unused memory location during a content jump, in which a new memory must be recorded. Once the default memory location is written to, a new default memory is created at the end of the tape. Additionally, we introduce a minimum similarity threshold for the content jumps; if a content jump is performed, and no location on the tape meets the minimum similarity threshold, the head will instead jump to the default location.

Season Task: Agents in this paper are evaluated on the *season task* [4], which tests an agent's ability to withstand catastrophic forgetting (Figure 2a). During its lifetime, the agent is presented with a number of different food items. Some are *nutritious*, some are *poisonous*. The goal of the agent is to learn and remember which food items can be eaten. The task is split into *days*, *seasons* and *years*. Each day, every food item will be presented in a random order. After a certain number of days, the season will change from summer to winter. During winter, a different set of food items will be presented. When the seasons switch the agent now has to remember what it learned during the previous season to achieve the highest possible score.

Each lifetime has three years, and each year has two seasons. Each season has four food items (presented in a random order), of which two are poisonous. We use a random number of days per season



(a) (b)

Figure 3: Evolved Solution Example. (**a**) The best evolved network quickly learns the correct food associations and reaches a perfect score of 1.0, displaying one-shot learning abilities. Additionally, the associates learned in earlier seasons are still remembered in later seasons. Memory usage during learning is shown in (**b**). Days 3 and 4 of season 1, and everything past day 2 in season 2 are not shown but solved perfectly. Legend: **E-I:** Environment input or ANN output to the environment. **E-O:** Environment output (observation), or ANN input from the environment. **E-S:** Score indicator. **TM-W:** Write vector. **TM-I:** Write interpolation. **TM-C:** Content of the tape at the current head position after write. **E-J:** Content jump input. **TM-S:** The three shift values, in descending order: left, none, right. **TM-R:** Read vector. **TM-H:** Current head position (after control operations).

(between one and five) to prevent overfitting to a certain sequence length. The ANNs environmental inputs consist of inputs 1–4 to encode which summer item is presented, and inputs 5–8 to encode the winter items. Additionally, one reward input is activated when the agent makes the correct decision, and one punishment input is activated when the wrong decision is made. The ENTM read/write vector size M is set to 10. The network has one output o connected to the environment, which determines whether a food item should be eaten ($o > 0.7$) or not ($o < 0.3$).

For the experiments in this paper, population size was set to 250. The selection proportion was 20%, and the elitism proportion was 2%. Connection weight range was $[-10, 10]$. Mutation parameters were 98.8% connection weight mutation probability, 9% connection addition probability, 5% connection removal probability. The node addition probability was set to 0.5%. Each simulation ran for a maximum of $10,000$ generations. A total of 30 independent evolutionary runs were performed.

4 Results

During evolution each individual is evaluated on 50 randomly generated sequences. To avoid noisy evaluations, the same 50 random sequences are used throughout the evolutionary process. However, we also perform a generalization test on the last generation networks on unseen and longer sequences (40 seasons with 4–10 days in testing, compared to six seasons with 2–5 days during evolutionary training). The agents are scored based on how often they choose the correct action for eating or ignoring a food item. The resulting fitness score is scaled into the range $[0.0, 1.0]$. The ENTMs with default jump scores 0.783 on average ($sd = 0.103$) during testing on 50 random sequences, while the method without default jump scores 0.706 ($sd = 0.085$). This difference is significant ($p < 0.05$; according to the Mann-Whitney U test), confirming the benefits of the new jump mechanism.

The best evolved network has a total of 138 connections and six hidden nodes. Figure 2b shows its fitness and complexity during evolution. The periodic increases and decreases in mean fitness mirror the complexification and simplification phases. The champion network is able to learn new associations in *one-shot*, without catastrophic forgetting of earlier learned associations (Figure 3a) and can generalize almost perfectly to never before seen sequences (testing score of 0.988). The network records the information about the food items in four memory locations, two for each season (Figure 3b). The agent initially *ignores* all food items. Since it is punished for ignoring nutritious items, the agent then memorizes the food items it gets wrong and has to eat in the future. Each nutritious

item is saved into its own memory location, summing up to the four locations used. Memorisation is accomplished by connecting the punishment input to the write interpolation output.

5 Conclusion

We showed that the ENTM is able to overcome catastrophic forgetting in a reinforcement learning tasks, taking a step towards continual learning agents. The evolved ENTM solutions allow successful one-shot-learning during the first day and can perfectly distinguish each food item afterwards. Moreover we augmented the ENTM with a default jump mechanism that facilitates the evolution of learning agents. An important next step is to combine the advantages of this evolutionary-based approach (e.g. automatic optimization of network topologies, hard attention mechanism, variable memory size) with the recent success of gradient-based learning methods. Given the increase in computational resources, this combination starts to be a promising research direction [16].

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