One Big Net For Everything

Technical Report

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Abstract

I apply recent work on “learning to think” (2015) [77] and on POWER (2011) [75] to the incremental training of an increasingly general problem solver, continually learning to solve new tasks without forgetting previous skills. The problem solver is a single recurrent neural network (or similar general purpose computer) called ONE. ONE may sometimes grow or shrink, e.g., by adding or pruning neurons and connections, as proposed in 1965 [27, 26]. ONE is unusual in the sense that it is trained in various ways, e.g., by black box optimization / reinforcement learning / artificial evolution as well as supervised / unsupervised learning. For example, ONE may learn through neuroevolution to control a robot through environment-changing actions, and learn through unsupervised gradient descent to predict future inputs and vector-valued reward signals [55, 56, 60] as suggested in 1990. User-given tasks can be defined through extra goal-defining input patterns, also proposed in 1990 [79, 57, 58, 80]. Suppose ONE has already learned many skills. Now a copy of ONE can be re-trained to learn a new skill, e.g., through slow trial and error-based neuroevolution without a teacher. Here it may profit from re-using previously learned subroutines, but it may also forget previous skills. Then ONE is retrained in POWER style (2011) [75] on stored input/output traces of (a) ONE’s copy executing the new skill and (b) previous instances of ONE whose skills are still considered worth memorizing. Simultaneously, ONE is retrained on old traces (even those of unsuccessful trials) to become a better predictor. This is done through well-known, feasible, gradient-based methods, without additional expensive interaction with the environment. More and more control and prediction skills are thus collapsed into ONE, like in the chunker-automatizer system of the neural history compressor (1991) [61]. This forces ONE to relate partially analogous skills (with shared algorithmic information) to each other, creating common subroutines in form of shared subnetworks of ONE, to greatly speed up subsequent learning of additional, novel but algorithmically related skills.
1 Introduction

I will first quickly summarize a few relevant concepts discussed in much more detail in previous reports [76, 77]. The reader might profit from being familiar with some of our earlier work on algorithmic transfer learning [69, 75, 77] and recurrent neural networks (RNNs) for control and planning [55, 56, 60, 79] and hierarchical chunking [61].

To become a general problem solver that is able to run arbitrary problem-solving programs, the controller of a robot or an artificial agent must be a general-purpose computer [15, 7, 92, 44]. Artificial RNNs fit this bill. A typical RNN consists of many simple, connected processors called neurons, each producing a sequence of real-valued activations. Input neurons get activated through sensors perceiving the environment, other neurons get activated through weighted connections or wires from previously active neurons, and some neurons may affect the environment by triggering actions. Learning or credit assignment is about finding real-valued weights that make the RNN exhibit desired behavior, such as driving a car. The weight matrix of an RNN is its program.

Many RNN-like models can be used to build general computers, e.g., RNNs controlling pushdown automata [9, 41] or other types of differentiable memory [20] including differentiable fast weights [63, 64], as well as closely related RNN-based meta-learners [66, 25, 51]. Using sloppy but convenient terminology, we refer to all of them as RNNs [77]. In practical applications, most RNNs are Long Short-Term Memory (LSTM) networks [24, 12, 19, 76], now used billions of times per day for automatic translation [106, 43], speech recognition [50], and many other tasks [76]. If there are large 2-dimensional inputs such as video images, the LSTM may have a front-end [95] in form of a convolutional neural net (CNN) [11, 33, 97, 4, 45, 52, 8, 76] implemented on fast GPUs [8, 76]. Such a CNN-LSTM combination is still an RNN.

Without a teacher, reward-maximizing programs of an RNN must be learned through repeated trial and error, e.g., through artificial evolution [39, 107, 83, 49, 48, 18, 103, 14, 89, 88] [76, Sec. 6.6], or reinforcement learning [29, 90, 101, 76] through policy gradients [104, 91, 3, 1, 13, 30, 103, 48, 82, 22, 102, 42, 76, Sec. 6]. The search space can often be reduced dramatically by evolving compact encodings of RNNs, e.g., [67, 87, 32, 94, 76, Sec. 6.7]. Nevertheless, this is often much harder than imitating teachers through gradient-based supervised learning [99, 105, 47, 76] for LSTM [24, 12, 19].

However, reinforcement learning RNN controllers can profit from gradient-based RNNs used as predictive world models [55, 56, 60, 77]. See previous papers for many additional references on this [76, 77]. In what follows, I will elaborate on such previous work.

2 One Big RNN For Everything: Basic Ideas and Related Work

I will focus on the incremental training of an increasingly general problem solver interacting with an environment, continually [46] learning to solve new tasks (possibly without supervisor) and without forgetting any previous, still valuable skills. The problem solver is a single RNN called ONE.

Unlike previous RNNs, ONE or copies thereof or parts thereof are trained in various ways, in particular, by (1) black box optimization / reinforcement learning / artificial evolution without a teacher, or (2) gradient descent-based supervised or unsupervised learning (Sec. 1). (1) is usually much harder than (2). Here I combine (1) and (2) in a way that leaves much if not most of the work to (2), building on several ideas from previous work:

1. Extra goal-defining input patterns to encode user-given tasks. A reinforcement learning neural controller of 1990 learned to control a fovea through sequences of saccades to find particular objects in visual scenes, thus learning sequential attention [79]. User-defined goals were provided
to the system by special “goal input vectors” that remained constant [79 Sec. 3.2] while the system shaped its incoming stream of standard visual inputs through its fovea-shifting actions. Also in 1990, gradient-based recurrent subgoal generators [57] used special start and goal-defining input vectors, also for an evaluator network predicting the costs and rewards associated with moving from starts to goals. The later POWERPLAY system (2011) [75] also used such task-defining special inputs, actually selecting on its own new goals and tasks, to become a more and more general problem solver in an active but unsupervised fashion. In the present paper, variants of ONE will also adopt this concept of extra goal-defining inputs to distinguish between numerous different tasks.

2. Incremental black box optimization of reward-maximizing RNN controllers. If ONE already knows how to solve several tasks, then a copy of ONE may profit from this prior knowledge, learning a new task through additional weight changes more quickly than learning the task from scratch, e.g., [17, 100, 13], ideally through optimal algorithmic transfer learning, like in the at least asymptotically Optimal Ordered Problem Solver [69], where new solution candidates in form of programs may exploit older ones in arbitrary computable fashion.

3. Unsupervised prediction and compression of all data of all trials. An RNN-based “world model” M of 1990 [55, 56] learned to predict (and thus compress [61]) future inputs including vector-valued reward signals [56] from the environment of an agent controlled by another RNN called C through environment-changing actions. This was also done in more recent, more sophisticated CM systems [77]. Here we collapse both M and C into ONE, very much like in Sec. 5.3 of the previous paper [77], where C and M were bi-directionally connected such that they effectively became one big net that “learns to think” [77]. In the present paper, however, we do not make any explicit difference any more between C and M.

4. Compressing all behaviors so far into ONE. The chunker-automatizer system of the neural history compressor of 1991 [61, 64] used gradient descent to compress the learned behavior of a so-called “conscious” chunker RNN into a separate “subconscious” automatizer RNN, which not only learned to imitate the chunker network, but also was continually retrained on its own previous tasks, namely, (1) to predict teacher-given targets through supervised learning, and (2) to compress through unsupervised learning all sequences of observations by predicting them (what is predictable does not have to be stored extra). It was shown that this type of unsupervised pre-training for deep learning networks can greatly facilitate the learning of additional user-defined tasks [61, 64].

Here we apply the basic idea to the incremental skill training of ONE. Both the predictive skills acquired by gradient descent and the task-specific control skills acquired by black box optimization can be collapsed into one single network (namely, ONE itself) through pure gradient descent, by retraining ONE on all input-output traces of all previously learned behaviors that are still deemed useful [75]. Towards this end, we simply retrain ONE to reproduce control behaviors of successful past versions of ONE, but without really executing the behaviors in the environment (usually the expensive part). Simultaneously, all input-output traces ever observed (including those of failed trials) can be used to train ONE to become a better predictor of future inputs, given previous inputs and actions. Of course, this requires to store input-output traces of all trials [70, 72, 77].

That is, once a new skill has been learned by a copy of ONE (or even by another machine learning device), e.g., through slow trial and error-based evolution or reinforcement learning, ONE is simply retrained in POWERPLAY style [75] through well-known, feasible, gradient-based methods on stored input/output traces [75 Sec. 3.1.2] of all previously learned control and prediction skills still considered worth memorizing, similar to the chunker-automatizer system of the neural history compressor
of 1991 [61]. In particular, standard gradient descent through backpropagation in discrete graphs of nodes with differentiable activation functions [28, 98] [76, Sec. 5.5] can be used to squeeze many exponentially evolved skills into the limited computational resources of ONE. Compare recent work on incremental skill learning [5]. Well-known regularizers [76, Sec. 5.6.3] can be used to further compress ONE, possibly shrinking it by pruning neurons and connections, as proposed already in 1965 for deep learning multilayer perceptrons [27, 26, 77]. This forces ONE even more to relate partially analogous skills (with shared algorithmic information [84, 31, 6, 34, 85, 36, 69]) to each other, creating common sub-programs in form of shared subnetworks of ONE. This may greatly speed up subsequent learning of novel but algorithmically related skills, through reuse of such subroutines created as by-products of data compression, where the data are actually programs encoded in ONE’s previous weight matrices.

So ONE continually collapses more and more skills and predictive knowledge into itself, compactly encoding shared algorithmic information in re-usable form, to learn new problem-solving programs more quickly.

3 More Formally: ONE and its Self-Acquired Data

The notation below is similar but not identical to the one in previous work on an RNN-based CM system called the RNNAI [77].

Let \(m, n, o, p, q, s\) denote positive integer constants, and \(i, k, h, t, \tau\) positive integer variables assuming ranges implicit in the given contexts. The \(i\)-th component of any real-valued vector, \(v\), is denoted by \(v_i\). For convenience, let us assume that ONE’s life span can be partitioned into trials \(T_1, T_2, \ldots\). In each trial, ONE attempts to solve a particular task, trying to manipulate some unknown environment through a sequence of actions to achieve some goal. Let us consider one particular trial \(T\) and its discrete sequence of time steps, \(t = 1, 2, \ldots, T\).

At the beginning of a given time step, \(t\), ONE receives a “normal” sensory input vector, \(in(t) \in \mathbb{R}^m\), and a reward input vector, \(r(t) \in \mathbb{R}^n\). For example, parts of \(in(t)\) may represent the pixel intensities of an incoming video frame, while components of \(r(t)\) may reflect external positive rewards, or negative values produced by pain sensors whenever they measure excessive temperature or pressure or low battery load (hunger). Inputs \(in(t)\) may also encode user-given goals or tasks, e.g., through commands spoken by a user. Often, however, it is convenient to use an extra input vector \(goal(t) \in \mathbb{R}^p\) to uniquely encode user-given goals, as we have done since 1990, e.g., [79, 75]. Let \(sense(t) \in \mathbb{R}^{m+p+n}\) denote the concatenation of the vectors \(in(t), goal(t)\) and \(r(t)\). The total reward at time \(t\) is \(R(t) = \sum_{i=1}^{n} r_i(t)\). The total cumulative reward up to time \(t\) is \(CR(t) = \sum_{\tau=1}^{t} R(\tau)\). During time step \(t\), ONE computes during several micro steps (e.g., [77, Sec. 3.1]) an output action vector, \(out(t) \in \mathbb{R}^o\), which may influence the environment and thus future \(sense(\tau)\) for \(\tau > t\).

3.1 Training a Copy of ONE on New Control Tasks Without a Teacher

One of ONE’s goals is to maximize \(CR(t_T)\). Towards this end, copies of successive instances of ONE are trained in a series of trials through a black box optimization method in Step 3 of Algorithm[1] e.g., through incremental neuroevolution [17], hierarchical neuroevolution [100, 93], hierarchical policy gradient algorithms [13], or asymptotically optimal ways of algorithmic transfer learning [69]. Given a new task and a ONE trained on several previous tasks, such hierarchical/incremental methods may create a copy of the current ONE, freeze its current weights, then enlarge the copy of ONE by adding a few new units and connections [26] which are trained until the new task is satisfactorily solved. This process can reduce the size of the search space for the new task, while giving the new weights the opportunity to learn to somehow use certain frozen parts of ONE’s copy as subroutines. (Of course,
it is also possible to simply retrain all weights of the entire copy to solve the new task.) Compare a recent study of incremental skill learning with feedforward networks [5].

In non-deterministic or noisy environments, by definition the task is considered solved once the latest version of the RNN has performed satisfactorily on a statistically significant number of trials according to a user-given criterion, which also implies that the input-output traces of these trials (Sec. 3.7) are sufficient to retrain ONE in Step 4 of Algorithm 1 without further interaction with the environment.

### 3.2 Superseded ONE Learning to Predict/Compress Observations

ONE may further profit from unsupervised learning that compresses the observed data [61] into a compact representation that may make subsequent learning of externally posed tasks easier [61,78]. Hence, another goal of ONE can be to compress ONE’s entire growing interaction history of all failed and successful trials [70,73], e.g., through neural predictive coding [61,78]. For this purpose, ONE has \( m + n \) special output units to produce for \( t < t_T \) a prediction \( \text{pred}(t) \in \mathbb{R}^{m+n} \) of \( \text{sense}(t+1) \) from ONE’s previous observations and actions, which are in principle accessible to ONE through (recurrent) connections. In one of the simplest cases, this contributes \( \|\text{pred}(t) - \text{sense}(t+1)\|_2^2 \) to the error function to be minimized by gradient descent in ONE’s weights, in Step 4 of Algorithm 1. This will train \( \text{pred}(t) \) to become more like the expected value of \( \text{sense}(t+1) \), given the past. See previous papers [78,70,77] for ways of translating such neural predictions into compression performance. (Similar prediction tasks could also be specified through particular prediction task-specific goal inputs \( \text{goal}(t) \), like with other tasks.)

### 3.3 Training ONE to Predict Cumulative Rewards

We may give ONE yet another set of \( n \) special output units to produce for \( t < t_T \) another prediction \( \text{PR}(t) \in \mathbb{R}^{n+1} \) of \( r(t+1) + r(t+2) + \ldots + r(t_T) \) and of the total remaining reward \( \text{CR}(t_T) - \text{CR}(t) \) [55]. Unlike in the present paper, predictions of expected cumulative rewards are actually essential in traditional reinforcement learning [29,90,101,76] where they are usually limited to the case of scalar rewards (while ONE’s rewards may be vector-valued like in old work of 1990 [55,56]). Of course, in principle, such cumulative knowledge is already implicitly present in a ONE that has learned to predict only next step rewards \( r(t+1) \). However, explicit predictions of expected cumulative rewards may represent redundant but useful derived secondary features that further facilitate black box optimization in later incarnations of Step 3 of Algorithm 1 which may discover useful subprograms of the RNN making good use of those features.

### 3.4 Adding Other Reasonable Objectives to ONE’s Goals

We can add additional objectives to ONE’s goals. For example, we may give ONE another set of \( q \) special output units and train them through unsupervised learning [62] to produce for \( t \leq t_T \) a vector \( \text{code}(t) \in \mathbb{R}^q \) that represents an ideal factorial code [2] of the observed history so far, or that encodes the data in related ways generally considered useful, e.g., [23,28,81,68,21].

### 3.5 No Fundamental Problem with Bad Predictions of Inputs and Rewards

Note that like in work of 2015 [77] but unlike in earlier work on learning to plan of 1990 [55,56], it is not that important that ONE becomes a good predictor of inputs (Sec. 3.2) including cumulative rewards (Sec. 3.3). In fact, in noisy environments, perfect prediction is impossible. The learning of solutions of control tasks in Step 3 of Algorithm 1 however, does not essentially depend on good
predictions, although it might profit from internal subroutines of ONE (learned in Step 4) that at least occasionally yield good predictions of expected future observations in form of of \( \text{pred}(t) \) or \( \text{PR}(t) \).

Likewise, control learning may profit from but does not existentially depend on near-optimal codes according to Sec. 3.4.

To summarize, ONE’s subroutines for making codes and predictions may or may not help to solve control problems during Step 3, where it is ONE’s task to figure out when to use or ignore those subroutines.

### 3.6 Store Behavioral Traces

Like in previous work since 2006 [70, 72, 77], to be able to retrain ONE on all observations ever made, we should store ONE’s entire, growing, lifelong sensory-motor interaction history including all inputs and goals and actions and reward signals observed during all successful and failed trials [70, 72, 77], including what initially looks like noise but later may turn out to be regular. This is normally not done, but feasible today. Remarkably, as pointed out in 2009, even human brains may have enough storage capacity to store 100 years of sensory input at a reasonable resolution [72].

On the other hand, in some applications, storage space is limited, and we might want to store (and re-train on) only some (low-resolution variants) of the previous observations, selected according to certain user-given criteria. This does not fundamentally change the basic setup - ONE may still profit from subroutines that encode such limited previous experiences, as long as they convey algorithmic information about solutions for new tasks to be learned.

### 3.7 Incrementally Collapse All Previously Learned Skills into ONE

Let \( \text{all}(t) \) denote the concatenation of \( \text{sense}(t) \) and \( \text{out}(t) \) and \( \text{pred}(t) \) (and possibly \( \text{PR}(t) \) and \( \text{code}(t) \) if any). Let \( \text{trace}(T) \) denote the sequence \( (\text{all}(1), \text{all}(2), \ldots, \text{all}(t_T)) \). To combine the objectives of the previous, very general papers [75, 77], we can use simple, well understood, rather efficient, gradient-based learning to compress [61] all relevant aspects of \( \text{trace}(T_1), \text{trace}(T_2), \ldots \) into ONE, and thus compress all control [49] and prediction [61] skills learned so far by previous instances of ONE (or even by separate machine learning methods), preventing ONE not only from forgetting previous knowledge, but also making ONE discover new relations and analogies and other types of mutual algorithmic information among subroutines implementing previous skills. Typically, given a ONE that already knows many skills, traces of a new skill learned by a copy of ONE are added to the relevant traces, and compressed into ONE, which is also re-trained on traces of the previous skills. See Step 4 of Algorithm 1.

Note that POWERPLAY (2011) [75] also uses environment-independent replay of behavioral traces (or functionally equivalent but more efficient methods) to avoid forgetting and to compress or speed up previously found, sub-optimal solutions. At any given time, an acceptable (possibly self-invented) task is to solve a previously solved task with fewer computational resources such as time, space, energy, as long as this does not worsen performance on other tasks. In the present paper, we focus on pure gradient descent for ONE (which may have an LSTM-like architecture) to implement the POWERPLAY principle.

### 3.8 Learning Goal Input-Dependence Through Compression

After Step 3 of Algorithm 1 a copy of ONE may have been modified and may have learned to control an agent in a video game such that it reaches a given goal in a maze, indicated through a particular goal input, e.g., one that looks a bit like the goal [79, Sec. 3.2]. However, the weight changes of ONE’s copy may be insufficient to perform this behavior exclusively when the corresponding goal
input is on. And it may have forgotten previous skills for finding other goals, given other goal inputs. Nevertheless, the gradient-based dreaming phase of Step 4 can correct and fine-tune all those behaviors, making them goal input-dependent in a way that would be hard for typical black box optimizers such as neuroevolution.

**Algorithm 1** How ONE can learn (without a teacher) one more control skill as well as additional prediction skills, using pure gradient-based learning for avoiding to forget previously learned skills and for learning goal input-dependent behavior. See Sec. [3] for details of steps 3-4.

1. Access global variables (also accessible to calling procedures such as Algorithm 2): the present ONE and its weights, positive real-valued variables $c, \lambda$ defining search time budgets, and a control task description $A \in T$ from a possibly infinite set of possible task descriptions $T$ [75, Sec. 2].

2. Unless goal descriptions are transmitted through normal input units, e.g., in form of speech, select a unique, task-specific [79] goal input $G(A) \in \mathbb{R}^p$ for ONE; otherwise $G(A)$ is a vector of $p$ zeros.

3 (Try to Solve New Task). Make a copy of the present ONE and call it ONE1; make a copy of the original ONE (before training) and call it ONE0 (notation in both cases like for ONE; Sec. [3]). The total search time budget [69] of the present Step 3 is $c$ seconds. In parallel (or interleaving) fashion, apply a trial-based black box optimization method (Sec. [3.1]) to (all or some of the weights of) ONE0 and ONE1, spending equal time on both, until $c$ seconds have been spent without success (then go to Step 4), or until either ONE0 or ONE1 have learned task $A$ sufficiently well, according to some given termination criterion, where for both ONE0 and ONE1 for all time steps $t$ of all trials, $G(A) = \text{goal}(t) = \text{const}$. In case of first success through ONE0, rename it ONE1. If both ONE1 and the environment are deterministic, such that trials are repeatable exactly, mark only the final ONE1’s trace $(T)$ (Sec. [3.7]) as relevant, where $T$ is the final successful trial. Otherwise, to gain statistical significance, mark as relevant the traces of sufficiently many (Sec. [3.1]) successful trials conducted by the final ONE1 on task $A$.

Comment: Previously learned programs and subroutines already encoded in the weight matrix of ONE at the beginning of Step 3 may help to greatly speed up ONE1’s optimization process - see Sec. [3.1]; ONE0, however, is trying to learn $A$ from scratch, playing the role of a safety belt in case ONE1 has become “too biased” through previous learning (following the algorithmic transfer learning approach of the asymptotically Optimal Ordered Problem Solver [69]).

4 (Dream and Consolidate). Since ONE1 may have forgotten previous skills in Step 3, and may not even have understood the goal input-dependence of the newly learned behavior for $A$ (Sec. [3.8]), spend $\lambda c$ seconds on: retrain ONE by standard gradient-based learning (Sec. [13.7]) to reproduce the input history-dependent outputs $\text{out}(t)$ in all traces of all previously learned relevant behaviors that are still deemed useful (including those for the most recent task $A$ learned by ONE1, if any). Simultaneously, use all traces (including those of failed trials) to retrain ONE to make better predictions $\text{pred}(t)$ (Sec. [3.2]) and code$(t)$ (Sec. [3.4]) if any, given previous inputs and actions (but do not provide any target values for action outputs $\text{out}(t)$ and corresponding $PR(t)$ (Sec. [3.3]) in replays of formerly relevant traces of trials of unsuccessful or superseded controllers implemented by earlier incarnations of ONE - see Sec. [3.9]). Use regularizers to compactify and simplify ONE as much as possible [76,77].

Comment: This process collapses all previous prediction skills and still relevant goal-dependent control skills into ONE, without requiring new expensive interactions with the environment. We may call this a consolidation phase or sleep phase [71] or dream phase or regularity detection phase.
The setup is also sufficient for high-dimensional spoken commands arriving as input vector sequences at certain standard input units connected to a microphone. The non-trivial pattern recognition required to recognize commands such as “go to the north-east corner of the maze” will require a substantial subnetwork of ONE and many weights. We cannot expect neuroevolution to learn such speech recognition within reasonable time. However, a copy of ONE may rather easily learn by neuroevolution during Step 3 of Algorithm 1 to always go to the north-east corner of the maze, ignoring speech inputs. In a later incarnation of Step 3, a copy of another instance of ONE may rather easily learn to always go to the north-west corner of the maze, again ignoring corresponding spoken commands such as “go to the north-west corner of the maze.” In the consolidation phase of Step 4, ONE then may rather easily learn the speech command-dependence of these behaviors through gradient-based learning, without having to interact with the environment again. Compare the concept of input injection [5].

3.9 Discarding Sub-Optimal Previous Behaviors

Once ONE has learned to solve some control task in suboptimal fashion, it may later learn to solve it faster, or with fewer computational resources. That’s why Step 4 of Algorithm 1 does not retrain ONE to generate action outputs out(t) in replays [37] of formerly relevant traces of trials of superseded controllers implemented by earlier versions of ONE. However, replays of unsuccessful trials can still be used to retrain ONE to become a better predictor or world model [77], given past observations and actions (Sec. 3.2).

3.10 Algorithmic Information Theory (AIT) Argument

As discussed in earlier work [77], according to the Theory of Algorithmic Information (AIT) or Kolmogorov Complexity [84, 31, 6, 34, 85, 36], given some universal computer, U, whose programs are encoded as bit strings, the mutual information between two programs p and q is expressed as $K(q | p)$, the length of the shortest program $\bar{w}$ that computes q, given p, ignoring an additive constant of $O(1)$ depending on U (in practical applications the computation will be time-bounded [36]). That is, if p is a solution to problem $P$, and q is a fast (say, linear time) solution to problem $Q$, and if $K(q | p)$ is small, and $\bar{w}$ is both fast and much shorter than q, then asymptotically optimal universal search [35, 69] for a solution to $Q$, given p, will generally find $\bar{w}$ first (to compute q and solve Q), and thus solve Q much faster than search for q from scratch [69].

In the style of the previous report [77], we can directly apply this AIT argument to ONE. For example, suppose that ONE has learned to represent (e.g., through predictive coding [61, 78]) videos of people placing toys in boxes, or to summarize such videos through textual outputs. Now suppose ONE’s next task is to learn to control a robot that places toys in boxes. Although the robot’s actuators may be quite different from human arms and hands, and although videos and video-describing texts are quite different from desirable trajectories of robot movements, ONE’s knowledge about videos is expected to convey algorithmic information about solutions to ONE’s new control task, perhaps in form of connected high-level spatio-temporal feature detectors representing typical movements of hands and elbows independent of arm size. Training ONE to address this information in its own subroutines and partially reuse them to solve the robot’s task may be much faster than learning to solve the task from scratch with a fresh network.

3.11 Gaining Efficiency by Selective Replays

Instead of retraining ONE in a sleep phase (step 4 of algorithm 1) on all input-output traces of all trials ever, we may also retrain it on parts thereof, by selecting trials randomly or otherwise, and
Algorithm 2 Simple automatic ordering of ONE’s tasks - see Sec. 3.14.1

1. Initialize global variables ONE, a finite set $\mathcal{T}$ of task descriptions [75, Sec. 2], and positive real-valued variables $c$, $\lambda$ used to define training time budgets.
2. Spend $c$ seconds on trying to solve a 1st task in $\mathcal{T}$ through Algorithm 1, then $c$ seconds on trying to solve the 2nd, and so on (here a teacher may or may not suggest an initial ordering of tasks). In line with Algorithm 1, whenever a task gets solved within the allocated time, spend $\lambda c$ seconds on compressing its traces into ONE, while also retraining ONE on previous traces to reduce forgetting of older skills, and even on traces of unsuccessful trials to improve ONE’s predictions (if any).
3. If no task in $\mathcal{T}$ got solved, set $c := 2c$ and go to 2.
4. Set $\mathcal{T}$ equal to the set of still unsolved tasks. If $\mathcal{T}$ is empty, exit. Reset $c$ to its original value of Step 1. Go to 2 (with a “more sophisticated” ONE that already knows how to solve some tasks).

replaying [37] them to retrain ONE in standard fashion [77]. Generally speaking, we cannot expect perfect compression of previously learned skills and knowledge within limited retraining time spent in a particular invocation of Step 4. Nevertheless, repeated incarnations of Step 4 will over time improve ONE’s performance on all tasks so far.

3.12 Heuristics: Gaining Efficiency by Tracking Weight Variance

As a heuristic, we may track the variance of each weight’s value at the ends of all trials. Frequently used weights with low variance can be suspected to be important for many tasks, and may get small or zero learning rates during Step 3 of Algorithm 1, thus making them even more stable, such that the system does not easily forget them during the learning of new tasks. Weights with high variance, however, may get high learning rates in Step 3, and thus participate easily in the learning of new skills. Similar heuristics go back to the early days of neural network research. They can protect ONE’s earlier acquired skills and knowledge to a certain extent, to facilitate retraining in Step 4.

3.13 Gaining Efficiency by Tracking Which Weights Are Used for Which Tasks

To avoid forgetting previous skills, instead of replaying all previous traces of still relevant trials (the simplest option to achieve the POWERPLAY criterion [75]), one can also implement ONE as a self-modularizing, computation cost-minimizing, winner-take-all RNN [53, 74, 86]. Then we can keep track of which weights of ONE are used for which tasks. That is, to test whether ONE has forgotten something in the wake of recent modifications of some of its weights, only input-output traces in the union of affected tasks have to be re-tested [75, Sec. 3.3.2]. First implementations of this simple principle were described in previous work on POWERPLAY [75, 86].

3.14 Ordering Tasks Automatically

So far the present paper has focused on user-given sequences of tasks. But in general, given a set of tasks, no teacher knows the best sequential ordering of tasks, to make ONE learn to solve all tasks as quickly as possible.

The POWERPLAY framework (2011) [75] offers a general solution to the automatic task ordering problem. Given is a set of tasks, which may actually be the set of all tasks with computable task descriptions, or a more limited set of tasks, some of them possibly given by a user. In unsupervised mode, one POWERPLAY variant systematically searches the space of possible pairs of new tasks and modifications of the current problem solver, until it finds a more powerful problem solver that solves
all previously learned tasks plus the new one, while the unmodified predecessor does not. The greedy search of typical PowerPlay variants uses time-optimal program search to order candidate pairs of tasks and solver modifications by their conditional computational (time and space) complexity, given the stored experience so far. The new task and its corresponding task-solving skill are those first found and validated. This biases the search toward pairs that can be described compactly and validated quickly. The computational costs of validating new tasks need not grow with task repertoire size.

3.14.1 Simple automatic ordering of ONE’s tasks

A related, more naive, but easy-to-implement strategy is given by Algorithm 2, which temporally skips tasks that it currently cannot solve within a given time budget, trying to solve them again later after it has learned other skills, eventually doubling the time budget if any unsolved tasks are left.

4 Conclusion

Supervised learning in large LSTMs works so well that it has become highly commercial, e.g., [50, 106, 96, 43]. True AI, however, must continually learn to solve more and more complex control problems in partially observable environments without a teacher. In principle, this could be achieved by black box optimization through neuroevolution or related techniques. Such approaches, however, are currently feasible only for networks much smaller than large commercial supervised LSTMs. Here we combine the best of both worlds, and apply the AIT argument to show how a single recurrent neural network called ONE can incrementally absorb more and more control and prediction skills through rather efficient and well-understood gradient descent-based compression of desirable behaviors, including behaviors of control policies learned by past instances of ONE through neuroevolution or similar general but slow techniques. Ideally, none of the “holy data” from all trials is ever discarded; all can be used to incrementally make ONE an increasingly general problem solver able to solve more and more tasks.

Essentially, during ONE’s dreams, gradient-based compression of policies and data streams simplifies ONE, squeezing the essence of ONE’s previously learned skills and knowledge into the code implemented within the recurrent weight matrix of ONE itself. This can improve ONE’s ability to generalize and quickly learn new, related tasks when it is awake.

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