Abstract

Recent meta-reinforcement learning work has emphasized the importance of mnemonic control for agents to quickly assimilate relevant experience in new contexts and suitably adapt their policy. However, what computational mechanisms support flexible behavioral adaptation from past experience remains an open question. Inspired by neuroscience, we propose MetODS (for Meta-Optimized Dynamical Synapses), a broadly applicable model of meta-reinforcement learning which leverages fast synaptic dynamics influenced by action-reward feedback. We develop a theoretical interpretation of MetODS as a model learning powerful control rules in the policy space and demonstrate empirically that robust reinforcement learning programs emerge spontaneously from them. We further propose a formalism which efficiently optimizes the meta-parameters governing MetODS synaptic processes. In multiple experiments and domains, MetODS outperforms or compares favorably with previous meta-reinforcement learning approaches. Our agents can perform one-shot learning, approaches optimal exploration/exploitation strategies, generalize navigation principles to unseen environments and demonstrate a strong ability to learn adaptive motor policies.

1. Introduction

The algorithmic shift from hand-designed to learned features that lies at the heart of modern deep learning approaches (Clune, 2020) has been transformative for Reinforcement Learning (RL) (Mnih et al., 2015). By leveraging the versatility of gradient-based optimization, modern RL approaches learn to craft potent internal representations and dynamics to solve increasingly challenging AI problems from video games (Mnih et al., 2013) to multiplayer contests (Jaderberg et al., 2019) or motor control (Levine et al., 2016; Lillicrap et al., 2016). Yet, while deep RL can produce expert agents able to solve complex well-delimited tasks, these agents typically fail when faced with unseen environments that require rapid contextual adaptation. Arguably, this paradox comes from the learning paradigm used to train these agents. The slow gradient-based tuning of an optimal synaptic configuration for a given context is sample inefficient and seems destined to produce highly specialized agents unable to cope with rapidly changing environments or tasks with novel or compositional structures (Lake et al., 2017; Lake & Baroni, 2018; Cobbe et al., 2020).

One potential solution to this challenge is to develop programs which meta-learn cognitive heuristics for storing and articulating episodic information in order to rapidly capture environments’ rules and structure. Meta-learning (Schmidhuber et al., 1997; Thrun, 1998; Vilalta & Drissi, 2002) has emerged as a general approach tackling the higher-order problem of “learning to learn”, i.e., devising efficient strategies to produce learning agents. One additional motivation for casting the learning problem at this higher level of abstraction might be to help identify key neuroscience mechanisms that have been hypothesized to endow humans with their versatile learning abilities (Botvinick et al., 2019). Various classes of models have been recently proposed for on-policy meta-reinforcement learning: Optimization-based methods aim to nest an optimization scheme within the agent lifetime, either through gradient-based tuning of a generic initial parameterization (Finn et al., 2017), or by treating the optimizer as a black-box system (Santoro et al., 2016a; Ravi & Larochelle, 2017). Distinctively, building on the seminal work of Duan et al. (2016) and Wang et al. (2018), which showed that recurrent systems can implement their own reinforcement learning algorithm by carrying task-relevant information in their hidden state, an increasingly popular class of models focuses on endowing neural networks with mnemonic systems adjusting agent decisions by reading and writing from memory (Pritzel et al., 2017b; Lin et al., 2018; Ritter et al., 2018a; Zhu et al., 2020). Despite
formal differences between these different approaches, at a high-level, most of these online meta-learning systems can be synthesized as optimizing a feedback control agents aiming at automatically improving their policy. Hence, the question: “What constitutes a right control rule and how should it be applied to neural networks?”

One neuroscience mechanism hypothesized to orchestrate flexible cognitive functions according to context-dependent rules is fast synaptic plasticity (Abbott & Regehr, 2004; Regehr, 2012; Caporale & Dan, 2008). By tuning neuronal selectivity at fast time scales –from fast neural signaling (milliseconds) to experience-based learning (seconds and beyond)– such synaptic plasticity rules can, in principle, support many cognitive faculties including motor and executive control. Despite the fact that the magnitude of the changes induced by fast synaptic plasticity may be small, such plasticity rules are capable to profoundly alter the network transfer function (Yger et al., 2015) and has led to modern theories of working memory (Mongillo et al., 2008; Masse et al., 2018; Barak & Tsodyks, 2014; Stokes, 2015; Manohar et al., 2019). While such mechanisms are yet to be fully explored for AI applications, short-term plasticity constitutes a plausible mechanism for converting reward and choice history into tuned neural functions (Florian, 2007).

From the machine learning perspective, casting synapses as dynamic variables might serve several purposes. First, from a functional analysis perspective, it can lift neural networks to universal functional approximators, in line with recent results showing that neural networks with learnt local modulations can fit operators on function space (Lu et al., 2019). This ability to produce “functions of functions” can be beneficial in the meta-learning context: it might allow for a computational disentanglement between policy adaptation supported by synaptic variation on the one hand, and optimal mapping from states to actions supported by activation encoding on the other hand. Second, from a dynamical system perspective, synapses can serve as an efficient mechanism for information retention and manipulation. A wide range of models known as associative memory models (see related work) have shown the key benefit of synaptic-based memory: they can produce fast information retrieval (Ramsauer et al., 2020) with a large storage capacity (Krotov & Hopfield, 2016) and perform concept-binding (Schlag et al., 2020). While the ability to continually edit such models is not very well studied, recent results have shown that plasticity parameters can be learnt to dynamically edit and query such models (Chalvidal et al., 2021), making them a potential “substrate” for working memory.

Contributions: Our work primary contribution is an on-policy meta-RL agent called MetODS (for Meta-Optimized Dynamical Synapses) which can be readily applied to any meta-reinforcement learning task. MetODS consists in a single neural cell leveraging simple synaptic plasticity principles to provide efficient policy adaptation. We theoretically present MetODS as a class of models performing stochastic feedback control in the policy space, interpreting several previous approaches of Meta-RL through this unifying framework. We further offer a method to train MetODS in a memory efficient way leveraging results from control theory. In our experimental evaluation, we demonstrate that a single cell with lightweight parametrization and no hyper-parameter tuning can implement a wide spectrum of cognitive functions, from one-shot learning to long lasting working memory or continuous motor-control, producing better agents than previous meta-RL approaches. We finally investigate and discuss the reinforcement learning strategies implemented by the model.

The remainder of the paper is organised as follows: in Section 2 we review previous approaches of on-policy meta-reinforcement learning and we discuss other models of artificial fast plasticity and their relation to associative memory. In Section 3 we introduce our mathematical formulation of the meta-RL problem and introduce MetODS. In Section 4 we report experimental results in 4 different settings. Finally, in Section 5 we summarise the main advantages of MetODS and outline future directions.

2. Related work

Meta-Reinforcement learning has recently flourished into several different approaches aiming at learning high-level strategies for capturing task rules and structures, effectively improving agent training efficiency. A direct line of work consists in automatically meta-learning components or parameters of the RL arsenal to improve over heuristic settings (Houthooft et al., 2018; Xu et al., 2018; Gupta et al., 2018). Orthogonally, work building on the Turing-completeness of recurrent neural networks has shown that simple recurrent neural networks can be trained to store past information in their persistent activity state to inform current decision, in such a way that the network implements a form of reinforcement learning over each episode. (Hochreiter et al., 2001; Duan et al., 2016; Wang et al., 2018). It is believed that vanilla recurrent networks alone are not sufficient to meta-learn the efficient forms of episodic control found in biological agents (Lenyel & Dayan, 2008; Botvinick et al., 2019). Hence additional work has tried to enhance the system with a better episodic memory model (Santoro et al., 2016b; Pritzel et al., 2017c; Ritter et al., 2018b) or by modeling a policy as an attention module over explicitly stored set of past events (Misra et al., 2018). Optimization based approaches have tried to cast episodic adaptation as an explicit optimization procedure either by treating the optimizer as a black-box system (Santoro et al., 2016a; Ravi & Larochelle, 2017) or by learning a synaptic configura-
tion such that one or a few gradient steps are sufficient to adapt the input/output mapping to a specific task. Recently, (Finn et al., 2017) introduced a generic approach called Model-Agnostic Meta Learning (MAML). MAML learns a task-agnostic initialization that works well after few step gradient update on different tasks.

**Artificial fast plasticity:** Artificial neural networks with plastic synapses have a long history (Hinton & Plaut, 1987; Schmidhuber, 1992; von der Malsburg, 1994; Ba et al., 2016). Recently, networks with dynamic weights that can adapt as a function of neural activation have shown promising results over regular recurrent neural networks to handle sequential data (Munkhdalai & Yu, 2017; Ha et al., 2016; Miconi et al., 2018a; Schlag & Schmidhuber, 2018b; Schlag et al., 2020). However, contrary to our work, these models postulate a persistent neural activity orchestrating weights evolution. On the contrary, we show that synaptic states are the sole persistent components needed to perform fast adaptation while activation variables are freed to perform policy inference. Additionally, the possibility of optimizing synaptic dynamics with evolutionary strategies in randomly initialized networks (Najarro & Risi, 2020) or through gradient descent (Miconi, 2016) has been demonstrated, as well as in a time-continuous setting (Choromanski et al., 2020). However another specificity of this work is that optimization is carried in a controlled functional space allowing to inject a rich reinforcement signal into the weight dynamics.

**Associative memory:** As discussed above, efficient memory storage and manipulation is a crucial feature for building rapidly learning agents. To improve over simple recurrent neural network policies (Duan et al., 2016), some models have augmented recurrent agents with content-addressable dictionaries able to re-instate previously encoded patterns given the current state (Weston et al., 2014; Zaremba & Sutskever, 2016; Pritzel et al., 2017a; Botvinick et al., 2019). However the maintenance and capacity of these slot-based memory systems are subject to interference with incoming inputs to inform policy and their memory cost grows linearly with experience. Contrastingly, attractor networks can be learnt to produce fast compression of sensory information into a fixed size tensorial representation (Bartunov et al., 2019; Zhang & Zhou, 2017). One class of such network are hopfieldian networks (Hopfield, 1982; Koiran, 1994; Demircigil et al., 2017; Krotov & Hopfield, 2016) which can possibly perform concept binding through hetero-associative memory (Schlag & Schmidhuber, 2018a; Schlag et al., 2020) where the retrieved pattern is different from the input pattern. While the ability to continually edit such models is not very well studied, they can produce fast and flexible information retrieval (Ramsauer et al., 2020).

### 3. MetODS: Meta-optimized dynamical synapses

#### 3.1. Preliminaries

Throughout, we refer to “tasks” as Markov decision processes (MDP) defined by the following tuple $\tau = (S, A, \mathcal{P}, r, \rho_0)$, where $S$ and $A$ are respectively the state and action sets, $\mathcal{P} : A \times S \times S \mapsto [0,1]$ is the state transition distribution, $r : A \times S \mapsto \mathbb{R}$ is a bounded reward function, $\rho_0$ is the initial state distribution. For simplicity, we consider finite-horizon MDP with $T$ time-steps although our model can be extended to the infinite horizon case. We specify notation when needed by subscribing with the corresponding task $\tau$ or time-step $t$. We further define a space $T$ of tasks to be learned and a distribution $\mu_T$ over this space, as well as a space $\Pi$ of policies $\pi$. In this work, we adopt an original perspective on meta-reinforcement learning, by showing that it approximates an *optimal transport* problem. Let us define $\mathcal{R} : \mathbb{T} \times \Pi \mapsto \mathbb{R}$ a performance function measuring the average fitness of a policy $\pi$ for a task $\tau$. For instance, $\mathcal{R}$ can be the average accumulated reward:

$$\mathcal{R}(\tau, \pi) = \mathbb{E}_{s_0, \rho_0} \left[ \sum_{t=0}^T r_t(a_t, s_t) \right]$$

where $(s_0, a_0, \ldots, s_T, a_T)$ are action-state trajectories such that the initial state $s_0$ is following the distribution $\rho_0$: $s_0 \sim \rho_0$, state transitions are governed by $s_{t+1} \sim \mathcal{P}_t(\cdot | s_t, a_t)$ and actions are following policy $\pi$: $a_t \sim \pi$. Provided the existence of an optimal policy $\pi^*$ for any task $\tau \in \mathbb{T}$, we can define the distribution measure $\mu_{\pi^*}$ of these policies over $\Pi$. Arguably, an ideal system aims at associating to any task $\tau$ its optimal policy $\pi^*$, that is, finding the transport plan $\gamma$ in the space $\Gamma(\mu_T, \mu_{\pi^*})$ of couplings with marginals $\mu_T$ and $\mu_{\pi^*}$ that maximize $\mathcal{R}$:

$$\max_{\gamma \in \Gamma(\mu_T, \mu_{\pi^*})} \mathbb{E}_{(s, \pi) \sim \gamma} \left[ \mathcal{R}(\tau, \pi) \right]$$

However, most generally, this problem is intractable, since $\mu_{\pi^*}$ has no closed form and cannot be computationally manipulated. Instead, meta-reinforcement learning systems aim to optimize a surrogate problem, by defining an iterative “specialization” procedure which build for any task $\tau$, a sequence $(\pi_t)$ of improving policies (see Fig 1). Defining $\theta$ the parameters governing the evolution of the sequences $(\pi_t)$ and $\mu_{\theta, \tau, t}$, the distribution measure of the policy $\pi_t$ after learning task $\tau$ at test time $t$, the optimization problem amounts to finding the meta-parameters $\theta$ that best adapt every $\pi_t \sim \mu_{\theta, \tau, t}$ over the task distribution:

$$\max_{\theta} \mathbb{E}_{\tau \sim \mu_T} \left[ \mathbb{E}_{\pi \sim \mu_{\theta, \tau, t}} [\mathcal{R}(\tau, \pi)] \right]$$
Such formulation of the problem is powerful because sequences $π_t$ can be constructed in various ways: In most cases, $τ$ can only be known by sampling trajectories $(s_0, a_0, \ldots, s_T, a_T)$, the sequence $π_t$ can be constructed as a stochastic sequence starting from an initial policy $π_0 \sim π_{π_0}$ and such that:

$$π_t = π(.|s_{i\leq t}, a_{i\leq t}, r_{i\leq t}) \sim π^{θ, τ}_{π, t}$$ \hspace{1cm} (4)

Although the autoregressive formulation of the agent’s policy in Eq. (4) is usually implicit in meta-reinforcement learning approaches, it is, however, a crucial condition for the development of an “inner” on-policy reinforcement learning algorithm during the agent exploration of a certain task. We focus hereafter on on-policy sampling to produce states $(s_{i\leq t}, a_{i\leq t}, r_{i\leq t})$ which allows to interpret sequences $π_t$ as a feedback control system where past experiences inform current decisions. Different forms of such control have been previously explored. For instance in MAML, the sequence $(s_{i\leq t}, a_{i\leq t}, r_{i\leq t})$ allows to estimate a few gradient updates of the model weights $w_0$ with respect to a surrogate loss function $L$, yielding a policy $π(a_i|s_{i\leq t}, a_{i\leq t}, r_{i\leq t}, θ) = π(a_i|w_0 + \nabla_w L(s_{i\leq t}, a_{i\leq t}, r_{i\leq t}, w, θ))$. While the gradient update provides theoretical improvement properties, MAML seems inefficient, requiring too many exploration examples in order to compute a good estimate of the gradient. Overall, the question remains as to what the objective function should be or what should trigger an update in the context of an episode. Distinctively, RL² and other solutions based on recurrent neural networks condense the past state trajectory into a hidden state that encode $π(a_i|s_{i\leq t}, a_{i\leq t}, r_{i\leq t}, θ) = π(a_i|h_i, θ)$ where $h_i$ corresponds to the recurrent neural network hidden state. Finally, SNAIL (Mishra et al., 2018) leverages the flexibility of the transformer architecture on sets of inputs by feeding directly the model with a concatenated sequence of states, actions and rewards $π(a_i|s_{i\leq t}, a_{i\leq t}, r_{i\leq t}) = π(a_i|s, a, r)_{i\leq t}, θ)$.

| Method | Memory variable | Computation | Policy form |
|--------|----------------|-------------|-------------|
| MAML   | SYNAPTIC       | GRADIENT    | $π(a_i|w_0 + \nabla_w L(\ldots, w, θ))$ |
| RL²    | HIDDEN STATE   | RECURRENT   | $π(a_i|h_i, θ)$ |
| SNAIL  | STORED OBS     | RECURSIVE  | $π(a_i|s, a, r)_{i\leq t}, θ)$ |
| MetODS | SYNAPTIC       | RECURRENT   | $π(a_i|w_0, θ)$ |

Table 1. Typology of the meta reinforcement-learning systems tested against MetODS in the experimental section

3.2. MetODS

In this work, we explore a new method to build a sequence of reinforcing policies $(π_t)_{t\leq T}$. We would like to leverage the versatility of synaptic-based specialization as in MAML, while retaining the flexibility of RNN-based approaches. Our proposal is to rapidly compress a neural agent experience into its synapses by learning a feedback control rule over its synaptic weights such that the model policy reads:

$$∀ t \leq T, \quad π(a_t|s_{i\leq t}, a_{i\leq t}, r_{i\leq t}, θ) = π(a_t|w_t, θ)$$ \hspace{1cm} (5)

where $w_t$ are instance-particular dynamic weights governed by a function $φ: \mathbb{R}^{|w|} \times S \times A \times R \to \mathbb{R}^{|w|}$ parameterized by $θ$ and controlling the evolution of weights over time with respect to the state trajectory $(s_{i\leq t}, a_{i\leq t}, r_{i\leq t})$:

$$w_t = w_0 + \sum_{i=1}^{t} φ(w_i, s_i, a_{i-1}, r_{i-1}, i, θ)$$ \hspace{1cm} (6)

While the formulation presented in Eq. (6) is generic and allows for the definition of any type of synaptic dynamics defined by the control $φ$, we explore hereafter a simple and lightweight definition emulating Hebbian learning. Specifically, MetODS cells consist in a system of $N$ neurons with activations $h$ and synaptic connections $w$. At every
time-step \( t \in [1, T] \), state information \([s_t, a_{t-1}, r_{t-1}]\) is encoded as a vector \( h_t \) by a feedforward mapping \( f \). Altogether, the synaptic control as well as the state-value and action policy estimate of MetODS consists in the following update relating \( w \) and \( h \). For all \( t \in [1, T] \):

\[
\begin{align*}
\mathbf{h}_t &= f(s_t, a_{t-1}, r_{t-1}) \\
\mathbf{w}_{t+1} &= \mathbf{w}_t + \eta \odot (\mathbf{h}_t \otimes \beta \mathbf{h}_t) \\
[a_t, v_t] &= g(h_t + \sigma(h_t \mathbf{w}_t))
\end{align*}
\] (7)

where, \( \eta \) and \( \beta \) are matrices in \( \mathbb{R}^{N \times N} \), \( \odot \) denotes the outer-product, \( \otimes \) is the element-wise multiplication, \( \sigma \) is a non-linear activation function and \( g \) is a read-out function. Hence, in this case, \( \theta = [\eta, \beta, f, g] \). It is worth noting that \( \mathbf{w}_t \) are persistent variables from one state to the next while activation vectors \( h_t \) are discarded after every state transition, and re-encoded through the feed-forward mapping \( f \). We believe that this formulation allows for an efficient multiplexing of information in the agent neural network by explicitly freeing the activation space \( \mathbb{R}^{|\mathbf{h}|} \) from interference between input signals and persistent hidden state as in classical recurrent neural networks. Instead, the activation space can perform computation of the current state-transition, while relevant episodic information has to be retained in the synaptic configuration of the system. Additionally, the initial synaptic configuration \( \mathbf{w}_0 \) can be learnt. Inspecting the second equation of (7), we see that for every couple \((i, j)\) of neurons, the synaptic evolution \( \Delta \mathbf{w}_{i,j} = \mathbf{w}_{i,j}^{t+1} - \mathbf{w}_{i,j}^{t} \) is driven by a multiplicative rule between presynaptic activation \( h_i \) and the linear transformation \( (\beta \mathbf{h}_t)^j \). Moreover, \( \eta_{i,j} \) defines a synapse-specific plasticity gain that allows for different plasticity amplitude at every connection \( w_{i,j} \). This specific definition makes the hidden layer of MetODS an original dynamical form of modern Hopfield network (Ramsauer et al., 2020) with hetero-associative memory that can rapidly store and read useful patterns representations driven by observations, rewards and actions. Unrolling the expression of the weight readout in equation (7), we get, for every coordinate \( i \) of the vector and any time \( t \leq T \) the following equation:

\[
[h_t \mathbf{w}_t]^i = \left[ \sum_{s=0}^{t-1} (h_s \cdot \eta^s \odot \mathbf{h}_s) \beta \mathbf{h}_s + h_t \mathbf{w}_0 \right]^i
\] (8)

where \( \langle \cdot \rangle \) corresponds to the scalar product between two activation vectors \( h \) and \( \eta^s \) correspond to the \( i \)-th column of matrix \( \eta \). Hence, the vector to be read-out to perform action and state-value inference is the contribution of the impulse vector \( h_t \) and a temporal average of the linear transformations \( (\beta \mathbf{h}_s)_{s \leq t} \) weighted by the alignment between current activation \( h_t \) and past activation pattern filtered by \( \eta \). We believe that this computational mechanism allows the agent to reinstate information from previous similar experience, to better inform current policy. Additionally, to prevent runaway of the synaptic variables, we compute a column-wise normalization of \( \mathbf{w}_t \) after every update, which in effect, slowly dissipates the influence of oldest activation patterns stored in the synapses.
3.3. Optimization

Defining the weight parameters $w$ of MetODS as dynamic variables lift the optimization problem (3) into a functional space of control functions $\varphi$ parameterized by $\theta$. Hence, optimizing $\varphi$ necessitates the estimation of gradients with respect to $\theta$ over the space $\mathbb{T}$ and for any possible trajectory $\pi_t$ in $\Pi$. Interestingly, previously discussed approaches have sampled a single policy trajectory $\pi_t \sim \mathcal{M}_\theta(\tau)$ over $M$ multiple tasks, showing that it is sufficient to obtain correct gradient estimates on $\theta$. We proceed in the same way, by estimating the gradient policy update integrated over the space of tasks as mini-batches over tasks.

$$\frac{\partial}{\partial \theta} \mathbb{E}_{\tau \sim \mu_\theta} \left[ \mathbb{E}_{\pi \sim \mu_\phi(\tau, \cdot)} \left[ R(\tau, \pi) \right] \right] \approx \sum_{\tau_1, \ldots, \tau_n} \sum_{t=0}^T \frac{\partial \log \pi_t(a_t | w_t, \theta)}{\partial \theta} r_{\tau_t}(a_t, s_t) \tag{9}$$

Additionally, the memory cost of storing synaptic weights trajectories instead of hidden activity in a network of $N$ neurons is $O(N^2)$ instead of $O(N)$. This might lead to prohibitively large memory requirements for training with BPTT (Rumelhart et al., 1985) over long episodes. We present an alternative solution by showing that it is possible to train the model through discrete adjoint sensitivity method, leveraging the work of (Betancourt et al., 2020) yielding a memory cost of $O(1)$. The agent’s log-policy total derivative with respect to $\theta$ can be computed as the solution of an augmented adjoint problem (Chalvidal et al., 2021), where $v_t$ is the adjoint variable to $w_t$ who is solution of the following sequence starting from $v_T = 0$ and going backwards:

$$v_{t-1} = v_t - \sum_{\tau_1, \ldots, \tau_n} \frac{\partial \log \pi_t(a_t | w_t, \theta)}{\partial w_t} r_{\tau_t}(a_t, s_t) \tag{10}$$

The derivation of (9) and (10) as well as the gradient estimate are explicited in the supplementary material.

4. Experiments

In all our experiments, we optimize the synaptic meta-parameters $\eta_1, \beta, w_0$, $f$ and $g$ using the Advantage Actor-critic algorithm (Mnih et al., 2016). We chose this online reinforcement learning algorithm because it does not perform sequential policy optimization over fixed rollouts such as in TRPO or PPO (Schulman et al., 2017a;b). We suspect this would not be suitable for our approach because recurrent polices are averse to mismatch between the optimized function and rote hidden variables trajectories during the inner optimization loop of these algorithms. Additionally, since the advantage value estimator used to perform policy gradient updates highly depends on the task performed, we meta-learn it as a second head of the MetODS cell output. Crucially, in order for MetODS to perform credit assignment, we pass to the model the specific state observables along with action and reward of the last state transition. All experiments use the same MetODS model definition with a single densely connected cell. $f$ and $g$ are two-layer perceptrons with hyperbolic tangent as activation functions. All of the experiments were performed using PyTorch (Paszke et al., 2019) which allows us to compute the gradient of all the plasticity parameters using automatic differentiation.

4.1. One-shot reinforcement learning: the Harlow task

![Figure 3. One-dimensional Harlow task](image)

**Figure 3.** One-dimensional Harlow task a): Task overview. An agent moves either left or right along the horizontal axis to reach a fixation target before choosing between two values $x$ and $y$ uniformly sampled in $[0,5]$ for each episode. One of the two value is rewarded and their position are randomly switched across trials, forcing the model to learn the associative value-reward rule. b) A successful episode of the task in which MetODS has consistently selected the value associated with positive reward. The sum of the afferent synapses’ absolute variation for every neuron (green shades) is most impacted at the time when the reward feedback signal is received. c) Comparison of the accumulated reward during training MetODS vs. an Elman RNN with the same number of dynamic variables. MetODS rapidly obtains the maximal possible reward (dashed line) while the RNN is unable to fully solve the task. d) Different synaptic states of the cell at the end of three different episodes. Each neuron presents both excitatory and inhibitory synapses.

To illustrate the idea that dynamic synapses can support fast behavioral adaptation by carrying relevant information over time, we use a classic experimental paradigm from the neuroscience literature originally presented by Harlow (Harlow, 1949) and recently reintroduced in artificial meta-learning by Wang et al. (2018). An episode of the task consists
of several presentations of two values randomly permuted on a one-dimensional line: one value is associated with a positive reward and the other with a negative reward. The trials are presented in alternance with periods of neutral fixation. After five repetitions of this process, two entirely new values are substituted, and the process restarts. An episode is schematized in Figure 3. We note that since the reward location is randomly permuted during an episode, the agent cannot develop a mechanistic strategy to reach high rewards based on initial presentation position. Instead, the agent needs to perform one-shot learning of the task-contingent association rule: i.e. it must learn to consistently select the right reward from the first presentation onward, or learn to switch from the initially chosen stimuli after receiving a penalty. We test a very small network of N=20 neurons which proved to be sufficient to learn to solve the task perfectly. As a comparison, an Elman RNN without any complex memory mechanism and the same number of dynamic variables (hence \( \sim 60 \times \) more parameters) is not able to solve this simple task. We further investigated the policy encoding expressed by the model synaptic states over time steps and episodes. A principal component analysis reveals a differentiation of the synaptic configuration with respect to the initial value choice outcome (see Figure 1). Moreover, the largest synaptic variations measured by the sum of absolute synaptic variations \( \sum |\Delta w_{ij}| \) occur for states that carry the reward signal (see Figure 3).

Theses results suggest that, through their weights dynamics, MetODS agents learn to spontaneously implement a reinforcement learning algorithm that is powerful enough to support one-shot learning of the task association rule.

4.2. Maze exploration navigation

![Figure 4](image.png) Examples of 10 \times 10 maze configurations. The agent receptive field is highlighted in red. To make the exploration and memorization more difficult, the agent is blind to the target location until it reaches the precise location of the reward.

We further test the memorization capabilities of MetODS on a more challenging task in the form of a partially observable Markov decision process (POMDP). In each episode, an agent must locate a target in a randomly generated maze starting from random locations while only being able to observe a small portion of its environment. While visual navigation has been previously explored in meta-RL (Duan et al., 2016; Mishra et al., 2018; Miconi et al., 2018b), we here focus on the mnemonic component of navigation by complexifying the task and reducing the agent’s visual field. The mazes consist in 10 \times 10 pix. areas, with walls and obstacles randomly placed according to a variation of Prim’s algorithm (Prim, 1957). For each episode, a new maze configuration is created (examples can be seen in Figure 4 and code can be found in the supplementary material) and a target location is selected randomly for the entire duration of the episode. The observation performed by the agent consists in a small visual field of size 3x3 pix. (depicted in Figure 4) along with actions and rewards from the last state transition. The agent can take discrete actions in the set \{up,down,left,right\} which moves it accordingly by one coordinate. The agent’s reward signal is solely received by hitting the target location, thus receiving a reward of 10.

Each time the agent hits the target, its position is randomly reassigned on the maze and the exploration resumes. Note that the reward is invisible to the agent, and thus the agent only knows it has hit the reward location because of the activation of the reward input. An episode lasts 100 steps during which the agent must accumulate as much reward as possible. The agent only receives very sparse rewards during training since most of the state transitions yield no reward at all. Moreover, the agent has no particular inductive bias for efficient spatial exploration or path memorization. However, as shown in Table 2, a strong policy emerges spontaneously from training, outperforming a human baseline in terms of cumulative reward (see supplementary for details). We additionally test the capability of the learnt navigation skills to generalize to varying maze size in \{6, 8, 10, 12, 14\} unseen during training. We show that MetODS is robust to these variations and is able to retain its advantage between 10 to 25\% over RL\(^2\) across unseen maze sizes (see supplementary for experimental details).

| AGENT   | 1ST REW. (↓) | SUCCESS (↑) | CUM.REW. (↑) |
|---------|-------------|-------------|--------------|
| RANDOM  | 96.8 ± 0.5\(^\) | 5\% | 43.53        |
| HUMAN   | 20.2 ± 18.2 | 100\%       | 55.41        |
| RL\(^2\) | 16.2 ± 1.1 | 96.2\%      | 77.77        |
| MetODS  | 14.7 ± 1.4 | 96.6\%      | 86.54        |

Table 2. Results for the Maze experiments: MetODS explores better the maze as measured by the average number of steps before 1st reward and the success rate in finding the reward at least once. It then exploits better the maze as per the accumulated reward. (*) We assign 100 to episodes with no reward encounter.

4.3. K-armed bandits

Multi-armed bandits constitute a subset of Markov decision processes with no observed state. Originally proposed by Duan et al. (2016) in the context of meta-RL, this task consists in K possible actions (arms) that the agent can execute
$N$ times. Each of the $K$ action yields a reward following the Bernoulli distribution with parameter $p_k$. The agent executes this for a fixed number of steps in order to maximize the total accumulated reward. In each episode, the vector $(p_k)_{k \leq K}$ is drawn from $K$ independent uniform distributions in $[0, 1]$ and fixed for the duration of the episode. To perform well on this task, the agent must explore the reward profile of the arms while favoring the most rewarding options. Hence, it enables us to investigate the exploration/exploitation trade-off implemented by the inner synaptic reinforcement learning algorithm in MetODS. At each timestep, the meta-learner receives the previous reward, along with a one-hot encoding of the corresponding arm selected. It outputs a discrete probability distribution over the $K$ arms and the selected arm is determined by sampling from this distribution. We tested combinations of $N = 10, 100, 500$ and $K = 5, 10, 50$. We report the results from (Mishra et al., 2018) which includes as a baseline the Gittins index (Gittins, 1979), the Bayes optimal solution in the discounted, infinite-horizon, setting. MetODS compare on par with other methods despite using a smaller architecture than the other approaches (in terms of number of trainable parameters) and not being fine-tuned to the task. In addition, we note that unlike SNAIL and MAML, RL$^2$ and MetODS do not explicitly store observables and hence do not lead to a memory cost that grows linearly in time during inference.

| (N,K) | RANDOM | GITTINS | MAML | RL$^2$ | SNAI | METODS |
|-------|--------|--------|------|-------|-------|--------|
| 10 - 5 | 5.0 | 6.6 | 6.5 | 6.7 | 6.6 | 6.6 |
| 10 - 10 | 5.0 | 6.6 | 6.6 | 6.7 | 6.7 | 6.7 |
| 10 - 50 | 5.1 | 6.5 | 6.6 | 6.8 | 6.7 | 6.7 |
| 100 - 5 | 49.9 | 78.3 | 67.1 | 78.7 | 79.1 | 78.8 |
| 100 - 10 | 49.9 | 82.8 | 70.1 | 83.5 | 83.5 | 83.0 |
| 100 - 50 | 49.8 | 85.2 | 70.3 | 84.9 | 85.1 | 83.4 |
| 500 - 5 | 249.8 | 405.8 | 401.6 | 408.1 | 405.0 | |

Table 3. Multi-Armed Bandits results: We compare MetODS total reward averaged over 1,000 different instances of the bandit problem against results reported in (Mishra et al., 2018). MetODS learns strategies that perform on par with previous approaches.

### 4.4. Motor control

Finally, we test MetODS for high-dimensional continuous locomotor control with the MuJoCo simulator (Todorov et al., 2012). In this experiment, we consider a combination of the meta-RL tasks introduced by (Finn et al., 2017) and (Najarro & Risi, 2020), in which a simulated 2D-planar cheetah robot has to move in a particular direction randomly chosen for the duration of the episode. The observations are the robot’s joint angles and velocities, and the actions are its joint torques, while the reward is computed as robot’s velocity multiplied by the current direction rule $(\pm 1)$. As a comparison, we evaluated RL$^2$ and MAML. The latter is highly penalized in this setting because of the rigid nature of its adaptation mechanism: the agent needs to gain enough experience for the gradient estimate to efficiently specialize the policy (we perform gradient update after 100 steps). On the other hand, the online and continual nature of policy updates performed by MetODS and RL$^2$ allows these methods to adapt to rule variations and to perform well after a few timesteps. We show in Fig 4 that MetODS finds the better policy with respect to the average cumulated reward. Finally, we demonstrate the robustness of MetODS learnt reinforcement learning program by evaluating the robot ability to perform in a setting not seen during training. Specifically, we evaluate performance when freezing one of the robots torque. We show that MetODS retains the best his performance ($79.4\%$ vs $60.7\%$ for RL$^2$). These results demonstrate that learning fast synaptic dynamics are not only better suited to support fast adaptation of a locomotory policy in the continuous domain, but they also implement a more robust reinforcement learning program when impairing the agent motor capabilities.

| Setting | CHEETAH | CHEETAH DAMAGED | RESISTANCE (%) |
|---------|---------|-----------------|----------------|
| RANDOM  | $-3.7 \pm 5.4$ | $-2.7 \pm 4.3$ | N.S |
| MAML    | $59.2 \pm 55.8$ | $40.9 \pm 37.8$ | $68.49\%$ |
| RL$^2$  | $979.7 \pm 54.5$ | $594.5 \pm 260.9$ | $60.7\%$ |
| METODS  | $1010.8 \pm 50.5$ | $802.7 \pm 84.7$ | $79.4\%$ |

Table 4. Accumulated reward for the motor control experiment. Results are averaged over 500 rollouts. The locomotion policy learnt by MetODS performs better, suggesting that the system is faster at adapting to fluctuations of the reward signal. The policy specialization remains more robust to damages of the robot unseen during training.

### 5. Discussion

In this work, we introduce a novel meta-RL system, MetODS, which leverages fast activity-induced synaptic plasticity for rapid memorization and specialization at the episodic level. MetODS demonstrates that agents endowed with such plasticity principles implement a potent form of working memory and are capable of spontaneously deploying their own reinforcement learning strategies. Our approach support discrete and continuous domains and give rise to a promising repertoire of skills such as one-shot adaptation, spatial navigation or motor coordination. MetODS compares favorably with prior meta-RL algorithms and we conjecture that tuning further the hyperparameters as well as combining MetODS with more sophisticated reinforcement learning algorithms can boost its performance. Furthermore, the agent can be readily applied to any meta-reinforcement learning problems. Generally, the success of the approach provides evidence for the benefits of fast activity-dependent synaptic plasticity in artificial neural networks, and the exploration of dynamic associative memory models.
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A. Optimization

A.1. Gradient policy update

We derive here the policy gradient update used to train MetODS:

We recall the definition of $\mathcal{R}(\tau, \pi)$ as the average accumulated reward under policy $\pi$ for task $\tau$. We further define $\zeta^\tau = (s_i^\tau, a_i^\tau, r_i^\tau)$ the possible state-action-reward trajectories under policy $\pi$ and write $w = (w_i)_{t \leq T}$ the trajectory of weights such that the trajectory of policies can be written:

$$\pi(\zeta^\tau | w, \theta) = (\pi_i(a_i^\tau | w_i, \theta))_{t \leq T} \sim \mu_{\pi, \tau}$$

(12)

As specified in section 3.3, we do not sample over possible policy distribution $\mu_{\pi, \tau}$ to estimate the inner integral in (11) but rely on a single evaluation yielding, with a slight abuse of notation on $\pi$:

$$\frac{\partial}{\partial \theta} \mathbb{E}_{\pi \sim \mu_{\pi, \tau}} \left( \mathbb{E}_{\pi \sim \mu_{\pi, \tau}} \left[ \mathcal{R}(\tau, \pi) \right] \right)$$

$$\approx \frac{\partial}{\partial \theta} \left( \int_{\zeta} \mathcal{R}(\tau, \pi) \mu_{\pi, \tau} \right)$$

$$\approx \frac{\partial}{\partial \theta} \left( \int_{\zeta} r_i(\zeta^\tau) \pi(\zeta^\tau | w, \theta) \right)$$

$$\approx \int_{\zeta} r_i(\zeta^\tau) \frac{\partial}{\partial \theta} \pi(\zeta^\tau | w, \theta)$$

$$\approx \int_{\zeta} r_i(\zeta^\tau) \frac{\partial}{\partial \theta} \pi(\zeta^\tau | w, \theta)$$

By breaking down over time-steps, this last equation allows us to write the following gradient estimator

$$\frac{\partial}{\partial \theta} \mathbb{E}_{\pi \sim \mu_{\pi, \tau}} \left[ \mathcal{R}(\tau, \pi) \right] \approx \frac{1}{M} \sum_{i=0}^{M} \sum_{t=0}^{T} \frac{\partial}{\partial \theta} \pi_i(a_i^\tau | w_i, \theta) r(a_i^\tau, s_i^\tau)$$

(14)

A.2. Discrete adjoint system

With the previous notation, let us define the total gradient function $\frac{\partial J}{\partial \theta}$ defined as the sum of log-policies:

$$\frac{\partial J}{\partial \theta} = \sum_{i=0}^{M} \sum_{t=0}^{T} \frac{\partial}{\partial \theta} \log \pi_i(a_i^\tau | w_i, \theta) r(a_i^\tau, s_i^\tau)$$

(15)

To clarify, we shall introduce the intermediary cost notation:

$$c_i(w, \theta, t) = \sum_{i=0}^{M} \log \pi_i(a_i^\tau | w_i, \theta) r(a_i^\tau, s_i^\tau)$$

(16)

and we recall that we have the update equation

$$w_{t+1} = w_t + \eta (h_t \otimes \beta h_t) = \delta(w_t, \theta)$$

(17)

This identify a discrete dynamical system with finite sum and differentiable cost, whose gradient can be computed mediating the introduction of an adjoint dynamical system presented in section 2 of (Betancourt et al., 2020). Defining $(\nu_t)_{t \leq T}$ the adjoint sequence, the general gradient equation can be computed as:

$$\frac{\partial J}{\partial \theta} = \left[ \frac{\partial c_0}{\partial w_0} - \nu_0 \cdot \frac{\partial \delta}{\partial \theta} - \nu_0 \right] \frac{\partial w_0}{\partial \theta}$$

$$+ \sum_{i=1}^{T} \left[ \frac{\partial c_i}{\partial \theta} - \nu_i^\dagger \cdot \frac{\partial \delta}{\partial \theta} \right]$$

(18)

Applying formula (18) to MetODS yield the following gradient formula:

$$\frac{\partial J}{\partial \theta} = \left[ \frac{\partial c_0}{\partial w_0} - \nu_0 \right] + \sum_{i=1}^{T} \left[ \frac{\partial c_i}{\partial \theta} - \nu_i^\dagger \cdot \frac{\partial \delta}{\partial \theta} \right]$$

(19)

where $(\nu_t)_{t \leq T}$ follows the following update rule backwards:

$$\begin{cases}
\nu_T = 0 \\
\nu_{t-1} = \nu_t - \frac{\partial c_t}{\partial w_t}
\end{cases}$$

(20)

B. Experiment details

As specified in section 4, and common to all experiments, we follow regular practice in meta-reinforcement learning with recurrent network by passing a concatenation of current state observables, as well as actions and rewards of the previous
state to the network. For discrete action space, actions are encoded as one-hot vectors while continuous action values are directly passed as inputs. For every initial step, we pass a null vector in place of previous actions and rewards. For the neural network architecture, we use hyperbolic tangent as activation functions. For the mappings $f$ and $g$, weights initialization are performed with Xavier initialization.

We use a single cell to infer both policy and advantage value function red-out from two different heads. We define the global objective function as a sum of the accumulated reward and advantage value regression weighted with a parameter $\lambda \in [0, 1]$. The advantage value baseline is computed for each episode through the Generalized Advantage Estimation (GAE) (Schulman et al., 2018).

**B.1. MetODS**

**B.2. Experimental hyperparameters**

| Experiment | Harlow | Maze | Bandits | Motor Control |
|------------|--------|------|---------|---------------|
| Network size | 20     | 200  | 100     | 100           |
| Learning rate | 5e-4   | 5e-4 | 5e-4    | 1e-4          |
| Meta-batch size | 20     | 20   | 20      | 50            |
| Discount factor $\lambda$ | 9e-1   | 9e-1 | 9e-1    | 9.5e-1        |
| GAE | 1.1 | 1.1 | 3e-1 | 9.5e-1 |
| Loss value factor | 4e-1 | 1e-1 | 4e-1 | 4e-1 |
| Entropy reg. factor | 3e-2 | 3e-2 | 1e-2 | 1e-2 |

Table 5. Training hyperparameters for the 4 presented experiments.

**B.3. Harlow task**

In this experiment, we explored a 1-dimensional simplification of the task presented in (Wang et al., 2018) and inspired from https://github.com/bkhmsi/Meta-RL-Harlow. The agent action space is the discrete set $\{-1, 1\}$ moving him accordingly on the discretized line. The state space consist in 17 positions while the agent receptive field is eight dimensional. Values are place at 3 positions from the fixation target position. The fixation position yield a reward of 0.2 while the values are drawn uniformly from $[0, 100]$ and randomly associated with a reward of $-1$ and $1$ at the beginning of each episode. The maximal duration for an episode is 250 steps, although the model solve the 5 trials in $\sim 35$ steps on average.

**B.4. Maze Navigation task**

The maze environments are created following Prim’s algorithm which randomly propagates walls on a board of $N \times N$ cells. We additionally add walls to cell location were no walls has been created at any of the neighboring 8 cells to avoid null inputs to the agent. The reward and agent locations are selected at random at the beginning of an episode. The reward location does not change during the episode while the agent is restarting from a random location after every encounter with reward. The agent does not “see” the reward during exploration but can only detect it through the feedback signal.

We show in Fig 8 the accumulated reward of MetODS and RL2 agents trained on $10 \times 10$ mazes for different size variations $N \in \{6, 8, 10, 12, 14\}$ over 1000 episodes. Agents performances are highly varying within a size setting due to differences in maze configurations and across maze sizes due to increasing complexity. However, MetODS and RL2 are able to generalize at least partially to these new settings (see table 6). MetODS outperforms RL2 in every setting, and generalize better, retaining an advantage of up to 25% in accumulated reward in the biggest maze. In order to roughly estimate a human baseline on this task, we implemented a platform to replicate the maze setting and play from the agent viewpoint. We collected 25 games from 5 different players. A picture of the environment as seen by the player is given in Fig 9.
B.5. Multi-Armed Bandits

We report baseline results from (Mishra et al., 2018) in this experiment as no code has been released to the best of the authors knowledge for the bandits problem. However, we reimplemented a GRU baseline with comparable number of parameters and shared policy/value function network to compare MetODS in the context of varying Bandits returns. Specifically, this experiment consisted in 100 time-steps with 10 arms whose Bernouilli parameters \( p_k \) are resampled with a 5% probability at every time-steps. This setting yield an average return of 70.4 for MetODS and 69.2 for the GRU-based control.

B.6. Motor control

We consider the half-cheetah agent from the MuJoCo robotic suite. We apply standard reinforcement learning practice for continuous control by paramterizing the stochastic policy as a product of independent normal distributions with fixed standard deviation \( \sigma = 0.1 \) and mean inferred by the agent network. A training episode consists in 200 steps with random sampling of the reward direction for each episode.

We further tested our trained agents over 5 consecutive episodes with randomly changing rewarded direction to investigate their ability to perform several chained policy adaptation. We show in Fig 10 the average reward profile of the three meta-RL agents over 1000 test episodes.

| MAZE SIZE | RL\(^2\) | MetODS | RELATIVE IMP. |
|-----------|---------|--------|---------------|
| 6         | 317.7 ± 136.2 | 344.3 ± 146.6 | 8%            |
| 8         | 149.3 ± 66.7 | 169.1 ± 66.1 | 13%           |
| 10        | 72.1 ± 45.6  | 87.3 ± 48.3  | 20%           |
| 12        | 28.1 ± 29.7  | 34.9 ± 34.9  | 21%           |
| 14        | 11.1 ± 15.8  | 13.9 ± 19.8  | 25%           |

Table 6. Average accumulated reward of MetODS and RL\(^2\) for different maze sizes unseen during training over 1000 episodes.