DO WHAT NATURE DID TO US: EVOLVING PLASTIC RECURRENT NEURAL NETWORKS FOR TASK GENERALIZATION

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Paper under double-blind review

ABSTRACT

While artificial neural networks (ANNs) have been widely adopted in machine learning, researchers are increasingly obsessed by the gaps between ANNs and biological neural networks (BNNs). In this paper, we propose a framework named as *Evolutionary Plastic Recurrent Neural Networks* (**EPRNN**). Inspired by BNN, **EPRNN** composes Evolution Strategies, Plasticity Rules, and Recursion-based Learning all in one meta learning framework for generalization to different tasks. More specifically, **EPRNN** incorporates with nested loops for meta learning — an outer loop searches for optimal initial parameters of the neural network and learning rules; an inner loop adapts to specific tasks. In the inner loop of **EPRNN**, we effectively attain both long term memory and short term memory by forging plasticity with recursion-based learning mechanisms, both of which are believed to be responsible for memristance in BNNs. The inner-loop setting closely simulates that of BNNs, which neither query from any gradient oracle for optimization nor require the exact forms of learning objectives. To evaluate the performance of **EPRNN**, we carry out extensive experiments in two groups of tasks: *Sequence Predicting*, and *Wheeled Robot Navigating*. The experiment results demonstrate the unique advantage of **EPRNN** compared to state-of-the-arts based on plasticity and recursion while yielding comparably good performance against deep learning based approaches in the tasks. The experiment results suggest the potential of **EPRNN** to generalize to variety of tasks and encourage more efforts in plasticity and recursion based learning mechanisms.

1 INTRODUCTION

While Artificial Neural Networks (ANNs) were initially inspired from Biological Neural Networks (BNNs), ANNs have achieved great success in handling machine learning tasks due to the strong capacity of handling large datasets. To learn from data, ANNs proposed to use gradient-based optimizers to minimize various loss functions as differentiable learning objectives. Compared to ANNs, BNNs are evidenced to learn through plastic rules (Gerstner et al., 1993), aka Hebb's rule (Hebb, 1949), where the differentiable objectives are not required. In addition to the use of gradient oracles, ANNs usually need overconsumption of datasets as training samples, acquire manual efforts in designing loss functions as the objective, and also suffer from catastrophic forgetting. All these technical issues suggest us rethinking BNNs for further development of machine intelligence.

Recent studies show the learning mechanisms of BNNs, such as plasticity (Soltoggio et al., 2008; Najarro & Risi, 2020) and recursion (Santoro et al., 2016; Mishra et al., 2018), under appropriate meta-parameter optimization, can facilitate meta-learning of ANNs for task generalization. Unlike gradient-based methods, these mechanisms simulate the learning behaviors of BNNs in a mimic manner and don't require any explicit-form objectives for task generalization. More recently, authors in (Miconi et al., 2019) proposed a recurrent plastic framework for lifelong learning of ANNs, where a so-called *"neuromodulated plasticity"* has been used to implement Hebbian plasticity with differentiable objectives and gradient-based optimization. Though above studies have investigated meta-learning of ANNs using the two mechanisms derived from BNNs with gradient-based methods (Miconi et al., 2019) optionally, in this work, we aim at further improving task generalization using both plasticity and recursion mechanisms, in a *gradient-free fashion* that fits BNNs more (Lillicrap et al., 2020).

Backgrounds. Though learning in BNNs has not been fully understood, some of the learning mechanisms and rules, such as plasticity (Gerstner et al., 1993) and recursion (Pollen, 2003), have been observed in brains and adopted by ANNs. Typically, Recursion-based learning employs recurrent neural networks (*RNN*), *LSTM* (Hochreiter & Schmidhuber, 1997), and self-attention (Mishra et al., 2018; Chen et al., 2021) layers as learners. Learning takes place within the feed forward pass. The information are updated in the hidden states instead of the parameters. Recursion are found to be extremely sample efficient in generalized supervised tasks (Santoro et al., 2016), zero-shot generalization in language (Brown et al., 2020), and reinforcement learning (Mishra et al., 2018; Chen et al., 2021) when compared with various type of gradient descent methods. So far among those learners, though self-attention based learners such as *Transformers* have state-of-the-art performance, the computational costs for inference per step grow linearly with the sequence length, which makes them only available to relatively short sequences. On the other hand, recurrent learners such as *RNN* and *LSTM* have constant per-step inference costs, but suffer form poor asymptotic performances. That is, when sequences are getting longer, performances no longer improve or even deteriorate. This is partly due to the limitation of the memory spaces. For instance, an recurrent hidden layer of size n has a memory of scale $O(n)$. In contrast, its parameters scale with $O(n^2)$, which makes parameter-updating more powerful as learning mechanisms than recursion-only.

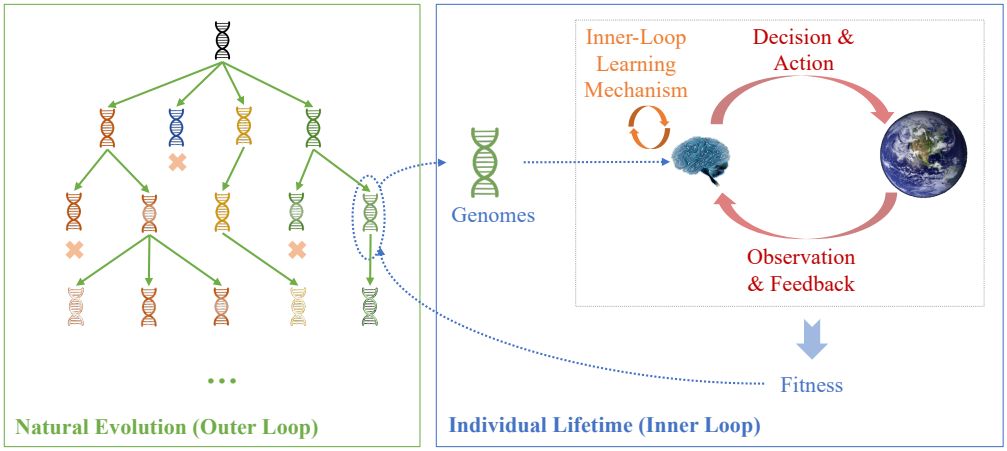


Figure 1: An illustration of the natural evolution: The evolution takes place in the outer loop, where the genomes are mutated and selected, and the population either thrive or become extinct based on the *Fitness*. Lifetime of each individual composes the inner loop. At the beginning, the genomes decide the learning mechanisms and initial neural configurations of the brain in the new born life. As the neural networks interact with the environment through actions and observations, its connections and hidden neuron states are further updated to better adapt to the environment. Plasticity are believed to be important part of the learning mechanisms. The fitness depends on the learning and adapting capability of each individual.

In addition to recursion-based learning, evolving plasticity (Soltoggio et al., 2008; 2018; Lindsey & Litwin-Kumar, 2020; Yaman et al., 2021) has been proposed to reproduce the natural evolution and plasticity in simulation, as shown in Figure 1. Implementing plasticity is not straight-forward, unlike gradient-based learning methods, plastic rules are not universal but have to be optimized beforehand, which is not possible without a further outer-loop optimizer over the inner-loop learning. Evolutionary algorithms (Zhang et al., 2011) are typically applied in the outer loop to search for meta-parameters shaping the learning rules, which can be regarded as information carried by genomes during evolution. Those optimized plasticity rules are then applied in the inner loop to further tune the parameter of NN for better adaptions to the environment. Another line of works tries to bring gradient-based learning algorithms to plasticity rule optimization (Miconi et al., 2018; 2019). Although gradient-based learning approaches are regarded to be more sample efficient compared with Evolutionary methods in most supervised learning cases, it is found that evolution can be more efficient in cases of very long horizon in reinforcement learning (Salimans et al., 2017b).

Our Works. In this work, inspired by the previous works (Cabessa & Siegelmann, 2014; Miconi et al., 2018; 2019) that improve recursive neural networks using plastic rules for capacity of learning,

Methods	Inner Loop	Outer Loop
Memory Augmented NN, (Santoro et al., 2016)	Recursion	Gradient
MAML, (Finn et al., 2017)	Gradient	Gradient
Reptile, (Nichol et al., 2018)	Gradient	Average
Conditional Neural Processes, (Garnelo et al., 2018)	Average	Gradient
SNAIL, (Mishra et al., 2018)	Attention	Gradient
ES-MAML, (Song et al., 2019)	Gradient, Hill Climbing	Evolution
EPMLP, (Najarro & Risi, 2020)	Plasticity	Evolution
Differential Platicity, (Miconi et al., 2018)	Plasticity & Recursion	Gradient
Backpropamine, (Miconi et al., 2019)	Plasticity & Recursion	Gradient
EPRNN (ours)	Plasticity & Recursion	Evolution

Table 1: A brief review of meta learning methods

we propose a novel meta-learning framework namely *Evolutionary Plastic Recurrent Neural Networks* (**EPRNN**) for task generalization. Specifically, this work makes contributions as follows.

- We study the problem of task generalization through simulating BNNs without the need of gradient oracles. To the best of our knowledge, this work is the first to address plasticity, recursion and natural evolution for meta-learning in an entirely gradient-free setting.
- The proposed **EPRNN** consists of nested loops for meta-learning under natural evolutions. The inner loop constructs RNNs applying plastic rules in recurrent connections by utilizing the information of time-dependent hidden states. The outer loop employs evolution strategies that search for proper initial parameters and plastic rules (Fig. 1) to tune the RNN.
- We carry out experiments on two groups of tasks: *Sequence Predicting* and *Wheeled Robot Navigating*, and compare **EPRNN** with other BNN-inspired and gradient-based learners. The results show **EPRNN** surpasses decent models under the same gradient-free settings.

The most relevant works to our study are (Miconi et al., 2018; 2019; Lindsey & Litwin-Kumar, 2020; Yaman et al., 2021). Compared to (Miconi et al., 2018) that leverage gradient oracles to efficiently search plastic rules, the proposed **EPRNN** could work well in gradient-free settings (i.e., when the overall goal of meta-learning is non-differentiable). Compared to (Lindsey & Litwin-Kumar, 2020; Yaman et al., 2021) that use evolutionary strategies to learn plastic rules, **EPRNN** also incorporates a RNN-based inner loop for recursion-based learning. The work (Miconi et al., 2019) also uses recursion (i.e., RNN) and differentiable plasticity in nested loops to train self-modifying neural networks, **EPRNN** replaces the outer loop with evolutionary strategies to generalize tasks with non-differentiable objectives. Though **EPRNN** is not as competitive as gradient-based methods, which is capable of optimizing advanced neural networks with large datasets, our work still demonstrates the potential of using plasticity and recursion for meta-learning through natural evolution.

2 Related Works

Meta Learning. Meta learning aims at building learning machines that gain experience using task-specific data over a distribution of tasks. Inspired by human and animal brains that are born with both embedded skills and capability of acquiring new skills, meta learning implements two nested learning loops: The outer learning loops optimize the meta that typically involves initial parameters (Finn et al., 2017; Song et al., 2019), learning rules (Zoph & Le, 2017; Najarro & Risi, 2020; Pedersen & Risi, 2021), and model structures (Soltoggio et al., 2008; Li & Malik, 2016) over a distribution of tasks; The inner learning loops adapt the model to specific task by utilizing the meta. According to different inner-loop optimizers, we roughly classify the methods into *model-based* and *parameter-updating* methods. The *model-based* methods do not update the parameters in the inner-loop, where learning is accomplished by updating the hidden states (e.g., recursion); The *parameter-updating* methods update the parameter in the inner-loop (e.g., gradient descent (MAML), plasticity). From this point of view, our method can be classified into both groups. A brief review of the typical meta learning paradigms is presented in Table 1.

Plasticity-based Learning. The proposal of the learning mechanism of BNNs is initially raised by Hebb's rule (Hebb, 1949), the most well-known part of which is "neurons fire together wire together". It is further polished by Spike Time-Dependent Plasticity (STDP) (Gerstner et al., 1993) indicating that the signal of learning is dependent on the temporal patterns of the pre-synaptic spike and post-synaptic spike. Learning could also appear in inhibitory connections, also known as anti-hebbian (Barlow, 1989). Also, relationships between STDP and memristance are also investigated (Linares-Barranco & Serrano-Gotarredona, 2009). Since many of those rules are related to spiking neural networks (Ghosh-Dastidar & Adeli, 2009), to apply them to ANNs, simplifed rules are proposed (Soltoggio et al., 2008) instead: given the pre-synaptic neuron state X and post-synaptic neuron state Y, the connections between X and Y are updated by

$$\delta W = m[A \cdot XY + B \cdot X + C \cdot Y + D], \tag{1}$$

m is the output from neuron modulators that adjust the learning rates of plasticity. Most of the existing rules are sub-classes of Equation 1. For instance, some works neglect the neural modulator m (Najarro & Risi, 2020; Miconi et al., 2018), others have set B, C, and D to 0 (Miconi et al., 2018; 2019). The learned rule A, B, C, D will inevitably be dependent on initial parameter of W, however, learning plastic rules that is not dependent on the initial parameters was also investigated (Najarro & Risi, 2020; Yaman et al., 2021).

3 ALGORITHMS

Problem Settings. We consider an agent (learner) that is dependent on meta-parameter θ. It has the capability of adapting itself to a distribution of tasks $T_j \in \mathcal{T}$ by interacting with the environment T_j through observation i_t and action a_t. In K-shot learning, the agent is allowed to first observe samples of length K (this stage can be referred as *meta-training-training*, see Beaulieu et al. (2020)), then its fitness is calculated in *meta-training-testing* rollouts. In Generalized Supervised Learning tasks (**GSL**), the observations typically include features (x_t) and labels (y_t) in *meta-training-training* stage ($i_t = \{x_t, y_t\}$), and the labels are left out for predicting in the *meta-training-testing* stage (Santoro et al., 2016; Garnelo et al., 2018). In Generalized Reinforcement Learning tasks (**GRL**), the observations typically include states (s_t), actions (a_{t-1}), and feedbacks (r_{t-1}) ($i_t = \{s_t, a_{t-1}, r_{t-1}\}$, sometimes r_{t-1} can not be observed) (Mishra et al., 2018). The goal of *meta-training* is to optimize θ such that the agent achieves higher fitness in *meta-training-testing*. In *meta-testing*, similarly, the learned parameters are given *meta-testing-training* and *meta-testing-testing* in order, the performances in *meta-testing-testing* are evaluated.

Plastic Recurrent Neural Networks (PRNN). Given a sequence of observations $i_1, ..., i_t, ...$, we first consider an recurrent neural network (*RNN*) that propagates forward and yields sequence of outputs a_t following:

$$h_{t+1} = \sigma(W_t \cdot h_t + W_i \cdot i_t + b), \tag{2}$$

$$a_t = f(h_{t+1}) \tag{3}$$

where h_t is the hidden states at step t. In PRNN, we kept W_i stationary, but we set W_t to be plastic, so that we add a subscript t to mark different W_t at different steps. Regarding h_t as pre-synaptic neuron states, and h_{t+1} as post-synaptic neuron states, by applying Equation 1, we update W_t with:

$$W_{t+1} = W_t + \delta W_t \tag{4}$$

$$\delta W_t = W_A \odot (\hat{h}_{t+1} \cdot h_t^{\mathrm{T}}) + W_B \odot (m_t \cdot h_t^{\mathrm{T}}) + W_C \odot (\hat{h}_{t+1} \cdot \mathbf{1}^{\mathrm{T}}) + W_D \cdot m_t \tag{5}$$

$$\hat{h}_{t+1} = m_t \odot h_{t+1}, \tag{6}$$

where we use $\odot$ and $\cdot$ to represent "element-wise multiplication" and "matrix multiplication" respectively. h and $\mathbf{1}$ are column vectors. W_A, W_B, W_C, W_D are collection of plastic rules of A, B, C, D from Equation 1, which has the same shape as W_t. m_t is the neural modulators that adjusts the learning rates of plasticity. We calculate m_t by applying a neuron modulating layer denoted with:

$$m_t = \sigma(W_h^{(m)} \cdot h_t + W_i^{(m)} \cdot i_t + b^{(m)}). \tag{7}$$

A sketch of PRNN is presented in Figure 2. The main difference between PRNN and naive *RNN* is that PRNN updates both the hidden states and the connection weights during the forward pass.

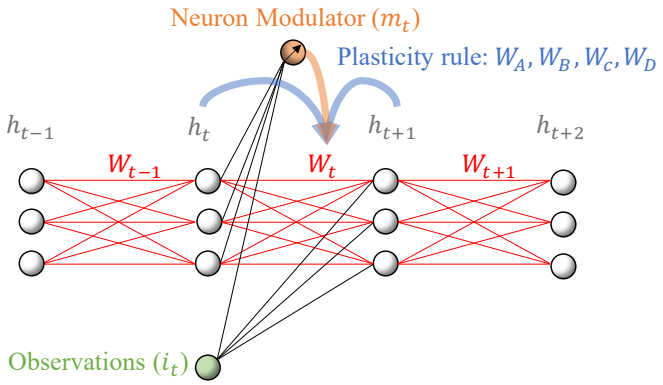


Figure 2: A sketch of the information flow in plastic recurrent neural networks (PRNN)

Evolving PRNN. Given task $T_j \in \mathcal{T}$, by continuously applying Equation 2 to 7 over *meta-training-training* and *meta-training-testing*, the fitness is eventually dependent on the initial parameters, learning rules, and the sampled task T, which is denoted as:

$$\textit{Fit}(\theta, T) = \textit{Fitness}(i_{K+1}, a_{K+1}, i_{K+2}, a_{K+2}, ...,) \tag{8}$$

$$W_i, W_0, W_A, W_B, W_C, W_D, W_h^{(m)}, W_i^{(m)}, b, b^{(m)} \in \theta \tag{9}$$

Following Evolution Strategies (ES) (Salimans et al., 2017a), in kth outer-loop iteration, we sample different tasks from $\mathcal{T}$, and meta-parameters $\theta_{k,i}$ ($i \in [1, n]$) from the neighbourhoods of θ_k. We evaluate the fitness of sampled meta-parameters, and update the meta-parameters by applying:

$$\theta_{k+1} = \theta_k + \alpha \frac{1}{n} \sum_{i=1}^{n} \textit{Fit}(\theta_{k,i}, T_k)(\theta_{k,i} - \theta_k) \tag{10}$$

Why Recurrent Neural Networks? As stated in Equation 1, plasticity in feed-forward-only NNs allows NNs to gain experiences from single-frame observation only. In cases of non-sequential GSL, the plasticity has chances to tune the connection weights to the specific task by relying on observing one single frame of data ($i_t = \{x_t, y_t\}$), since its information of the feature and the supervision is complete. However, in general cases, learning can not happen without summarizing sequences of observations. For instances, a human driver getting used to a new car through continuously interacting and observing. Moreover, in GRL, there are time lag between the observation of states and feed-backs. Recursion helps to summarize historical observations to give the correct update for the connection weights.

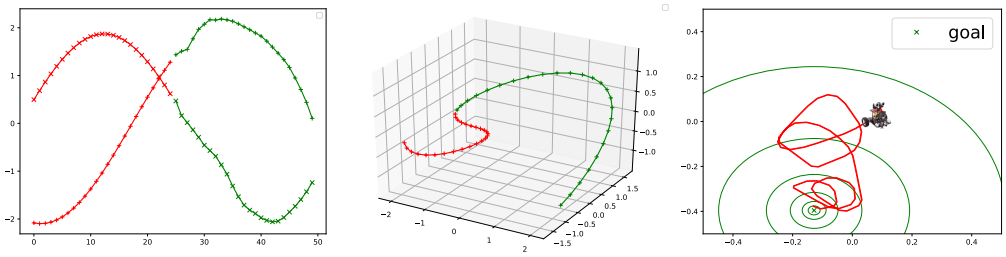
Although, compared with naive *RNN*, there are obviously bunches of more sophisticated neural structure such as *GRU* and *LSTM*, we believe it is more desirable to start from simplest recurrent structure to study the potential of combining recursion and plasticity.

4 Experiments

4.1 Tasks for Evaluation

In generalized tasks, we have each task T_j dependent on some configuration parameters that are hidden from the agent. Below we introduce two groups of generalized tasks that we experiment on.

Sequence Predicting (Generalized Supervised Learning tasks). We randomly generate sequences of vectors $\boldsymbol{y}(t) = (y_1(t), ..., y_l(t))$, where $y_i(t) = A_i sin(\frac{2\pi t}{n_i} + \phi_i)$, $t = 1, 2, 3, ...$ and $A_i \sim \mathcal{U}(1, 3)$, $n_i \sim \mathcal{U}(10, 100)$, $\phi_i \sim \mathcal{U}(0, 2\pi)$, and $\mathcal{U}(a, b)$ represents the uniform distribution between a and b. A, n and ϕ are hidden from the agent. The front part of the sequence $\boldsymbol{y}(1), \boldsymbol{y}(2), ..., \boldsymbol{y}(K)$ is exposed to the agent, and the left part $\boldsymbol{y}(K+1), \boldsymbol{y}(K+2), ..., \boldsymbol{y}(N)$ is to be predicted. The fitness



(a) *Sequence Predicting* (l=1,K=25,N=25)

(b) *Sequence Predicting* (l=3,K=25,N=25)

(c) *Wheeled Robot Navigating*

Figure 3: A sketch of the trajectories of three sampled tasks.

is the opposite of mean square error (MSE) between the predicted sequence and the ground truth. We test the methods for comparison in four groups of tasks including $(l = 1, K = 10, N = 20)$, $(l = 1, K = 25, N = 50)$, $(l = 3, K = 10, N = 20)$, and $(l = 3, K = 25, N = 50)$ (see Figure 3(a)(b)).

Wheeled Robot Navigating (Generalized Reinforcement Learning tasks). The agent is to navigate a two-wheeled robot to a randomly generated goal in 2-D space $\boldsymbol{g} = (g_x, g_y)$. We assume that there is a signal transmitter on the goal and a receiver on the robot. The robot observes the signal intensity decided by $A_t = A_0 - k \cdot log(d_t/d_0) + \epsilon$ (inspired by the attenuation for electromagnetic wave, see Friis (1946)), where d_t is the current distance between the robot and the goal, $\epsilon \sim \mathcal{N}(0, \sigma)$ is the white noise in the observation. g_x, g_y, A_0, k are environment related configurations that is hidden from the agent. For each task, we sample configurations by $g_x, g_y \sim \mathcal{U}(-0.5, 0.5)$, $A_0 \sim \mathcal{U}(0.5, 2.0)$, and $k \sim \mathcal{U}(0.1, 0.5)$. The action is the rotation speed of its two wheels that controls the orientation and velocity of the robot. The reward at each step is $r_t = -d_t$, an episode terminates when the robot approaches the goal or steps reaches the maximum of 100. We also hide its own position and orientation from the agent, such that the agent relies on recording its own action the signal strength A_t to locate itself. We investigate three types of navigating circumstances with different level of noises in the observed signal: Low Noise ($\sigma = 0.01$), Median Noise ($\sigma = 0.05$), and High Noise ($\sigma = 0.2$) (see Figure 3(c)).

4.2 Experiment Settings

We add the following methods into comparison, the methods share exactly the same outer loop and differ in the inner loop.

- **ES-MAML** (Song et al., 2019) : We use four gradient descent steps in the inner loop, the learning rate of each step is treated as meta-parameters which is to be optimized by the outer loop. As MAML can not utilize instant observation in zero-shot case, we show results of both **ES-MAML (zero-shot)** and **ES-MAML (one-rollout)** in *Wheeled Robot Navigating*. Except for **ES-MAML**, the other methods are measured with zero-shot *meta-testing* score only in *Wheeled Robot Navigating*.
- **ES-RNN**: Vanilla *RNN* as the inner loop learner.
- **ES-LSTM**: Long Short Term Memory (Hochreiter & Schmidhuber, 1997) as the inner loop learner.
- **EPMLP** (Soltoggio et al., 2018): Multi-Layer Perceptrons (MLP) with plasticity rules implemented.
- **EPMLP (Random)** (Najarro & Risi, 2020): The main difference with **EPMLP** is randomly setting the parameters of the plastic layers at the beginning of each inner loop instead of using fixed trainable initial parameters.
- **EPRNN (w/o m)**: Removing neuron modulator (m_t) from the plasticity rule in PRNN.

We add additional non-plastic fully connected layers before and after the plastic layers to increase the representation capability of the models. For fairness, we kept those layers identical for all compared

methods. For every 100 outer loops in *meta training*, we add an extra *meta testing* epoch, evaluating the average fitness of current meta-parameters on testing tasks. Each run includes 15000 outer loops and 150 meta-testing epochs. Each result is concluded from independent 3 runs. Our code[1] relies on PARL[2]for parallelization. We leave the detailed illustration of the model structures and hyper-parameters in the Appendices.

4.3 RESULTS

We present the experiment results in Figure 4 (In Table 2, and Table 3, we also list the summarized performance by averaging the Top-3 *meta-testing* scores in the latest 10 *meta-testing* epochs of each run over 3 independent runs). Generally, we can conclude that PRNN performs substantially better when compared with naive *RNN*. In some cases, it even produces better results compared with *LSTM*, despite the simpler model architecture. It is also interesting to notice that the gap between *RNN* and PRNN are smaller in shorter sequences or low-noise environments, but larger in more challenging tasks with longer sequence or higher noise (In *Wheeled Robot Navigating* tasks, higher noise pushes the agent to maintain a longer memory in order to filter the noise and figure out the way to goal). This phenomenon reaffirms the lack of long-term memories in *RNN*, and shows that PRNN significantly improves this drawback. Comparing **EPRNN (w/o m)** with *RNN* and **EPRNN** clearly demonstrates that simple ABCD rule (without the neural modulator) may also work to some extent, but introducing the neuron modulator m_t can further benefit the learner.

Table 2: Summarized performances comparison in *Sequence Predicting* tasks

Methods	l=1,K=10,N=20	l=1,K=25,N=50	l=3,K=10,N=20	l=3,K=25,N=50
ES-RNN	-0.385 ± 0.060	-1.228 ± 0.191	-1.273 ± 0.009	-1.811 ± 0.015
ES-LSTM	-0.165 ± 0.014	-0.283 ± 0.013	-1.229 ± 0.010	-1.475 ± 0.016
ES-MAML	-1.452 ± 0.292	-1.747 ± 0.064	-1.218 ± 0.013	-1.796 ± 0.013
EPMLP	-0.732 ± 0.031	-1.185 ± 0.045	-1.339 ± 0.004	-1.735 ± 0.013
EPMLP-(Random)	-1.233 ± 0.115	-1.319 ± 0.035	-1.489 ± 0.023	-1.788 ± 0.003
EPRNN	$\mathbf{-0.114 \pm 0.012}$	$\mathbf{-0.208 \pm 0.025}$	$\mathbf{-1.107 \pm 0.015}$	$\mathbf{-1.430 \pm 0.019}$
EPRNN (w/o m)	-0.135 ± 0.026	-0.351 ± 0.058	-1.128 ± 0.014	-1.520 ± 0.041

Table 3: Summarized performances comparison in *Wheeled Robot Navigating* tasks

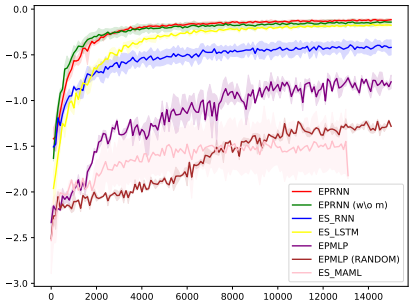
Methods	Low Noise ($\sigma = 0.01$)	Median Noise ($\sigma = 0.05$)	High Noise ($\sigma = 0.2$)
ES-RNN	-16.90 ± 1.30	-18.99 ± 0.14	-31.23 ± 3.95
ES-LSTM	-14.04 ± 0.08	-15.50 ± 0.58	$\mathbf{-22.53 \pm 0.45}$
ES-MAML (zero-shot)	-37.18 ± 0.45	-37.91 ± 0.80	-37.90 ± 0.05
ES-MAML (1 rollout)	-23.10 ± 0.46	-29.21 ± 0.46	-37.12 ± 0.12
EPMLP	-21.24 ± 6.08	-16.65 ± 0.39	-23.75 ± 2.02
EPMLP (Random)	-13.02 ± 0.19	-18.25 ± 0.23	-28.85 ± 1.1
EPRNN	$\mathbf{-12.71 \pm 0.75}$	$\mathbf{-15.07 \pm 0.03}$	-23.79 ± 0.55
EPRNN (w/o m)	-14.93 ± 0.49	-16.72 ± 0.33	-24.11 ± 0.34

Among plasticity based methods, we show that recursion is more advantageous than MLP in evaluated tasks. It is also worth noticing that **EPMLP** and **EPMLP (Random)** perform steadily beyond the gradient-based learner (**ES-MAML**). In **ES-MAML**, the gradient can only be calculated after an episode is completed, while **EPMLP** is able to perform sequential learning even though no feedback is available during its life time. This demonstrates the possibility of surpassing human-designed gradient-based learning rules with automatically learned unsupervised rules. Moreover, comparison

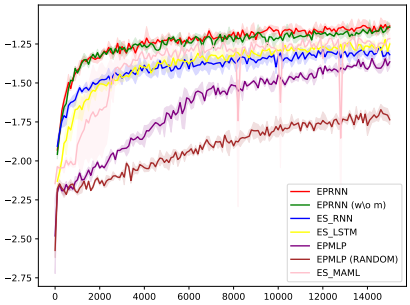
[1]https://github.com/WorldEditors/EvolvingPRNN

[2]https://github.com/PaddlePaddle/PARL

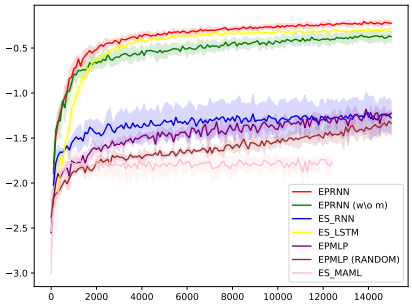
between **EPMLP** and **EPMLP (Random)** validate the proposal of Najarro & Risi (2020), implying the possibility of discovering global plastic learning rules instead of rules coupled with the initial parameters. Yet we see optimization of the initial parameters is still advantageous, which can also be validated by evidences in nature that the newborn lives already have certain embedded skills (e.g., Newborn human babies have reflexes of suckling and grasping; Foals can stand shortly after being born).



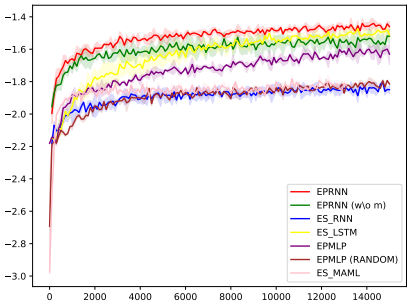
(a) *Sequence Predicting* (l=1,K=10,N=20)



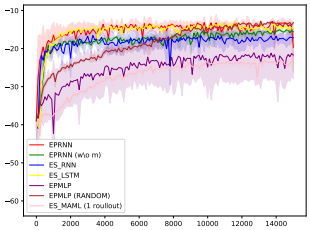
(b) *Sequence Predicting* (l=3,K=10,N=20)



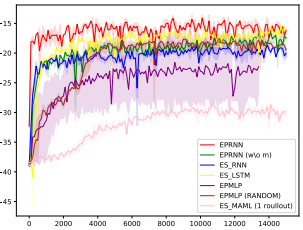
(c) *Sequence Predicting* (l=1,K=25,N=50))



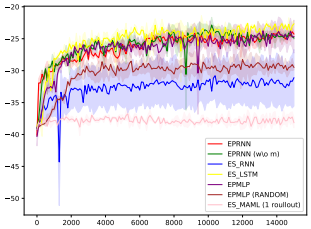
(d) *Sequence Predicting* (l=3,K=25,N=50)



(e) *Wheeled Robot Navigating* (Low Noise)



(f) *Wheeled Robot Navigating* (Median Noise)

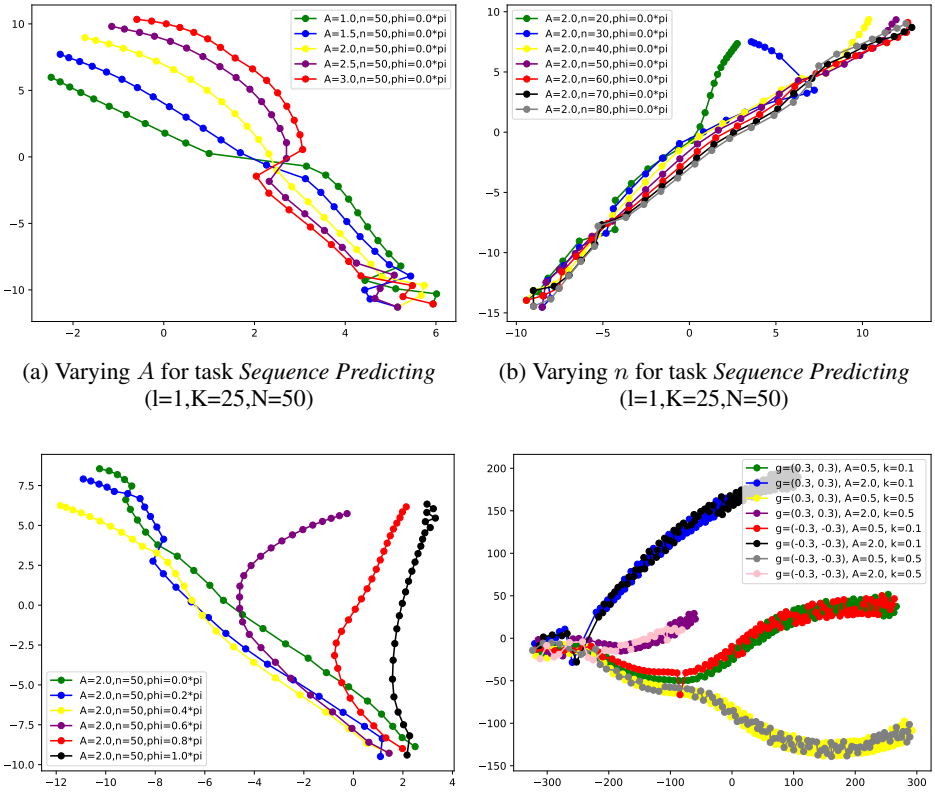


(g) *Wheeled Robot Navigating* (High Noise)

Figure 4: Plotting *meta-testing* scores against *meta-training* iterations.

4.4 Analysis and Discussion

To investigate whether plasticity rules update the connection weights as expected, we test the trained model with different tasks and record the updating trajectories of plastic connection weights W_t. As those weights are in relatively high dimension, we run t-SNE visualization to map W_ts to 2-D space and show their trajectories in Figure 5. We found that W_t start from the same position and gradually move in different directions depending on the tasks. The final weights effectively capture environmental configuration that was hidden from the agent. Particularly, in Figure 5(d) for *Wheeled Robot Navigating* tasks, we can see that W_t captures only the signal transmission patterns (A_0, k), but neglects the position of the goal (g_x, g_y). We guess that A_0, k are important stationary patterns that helps the agent to interpret the observed signal strength (A_t), while the absolute position of



(a) Varying A for task *Sequence Predicting* (l=1,K=25,N=50)

(b) Varying n for task *Sequence Predicting* (l=1,K=25,N=50)

(c) Varying ϕ for task *Sequence Predicting* (l=1,K=25,N=50)

(d) Varying settings for task *Wheeled Robot Navigating* (Low Noise)

Figure 5: t-SNE visualization of the trajectories of the plastic connection weights W_t.

goal is less important as its relative position to the robot is changing continuously. This is clear that plasticity has made meaningful update on the connections weights depending on the tasks.

Note that we did not compare **EPRNN** with many gradient-based solutions such as differentiable plasticity (Miconi et al., 2018; 2019), since the classic Hebbian plasticity has been observed and confirmed from neurons for more than half century (Hebb, 1949) — there is not evidences that the nature do differentiation or backpropagation (Lillicrap et al., 2020) to update plastic rules. The purpose of our work is to reveal the potential of natural evolution of plasticity, and we don't hope to claim that **EPRNN** could outperform gradient-based solutions on machine learning tasks.

5 Conclusions

In this paper we present **EPRNN** a nature-inspired learning framework composed of Evolution Strategies, Plastic rules, and Recursion. Experiment results show that plasticity can be effectively forged with recursion to enhance the learning capability. The proposed framework can achieve equivalent or even better performances compared with more sophisticated neural structures, by applying the simplest recurrent neural structures. Moreover, we also show that under proper meta parameters, plasticity has a chance to surpass gradient descent methods.

We believe the learning framework of Figure 1 can be extended to more sophisticated plastic rules and model structures, uncovering better learners in the future. Also, it would be more interesting if such framework can be validated in more complex environments such as natural language processing tasks and vision-related tasks. Finally, we are looking forward that this work can shed light to new paradigm of building intelligent machines and inspire more efforts in this line of research.

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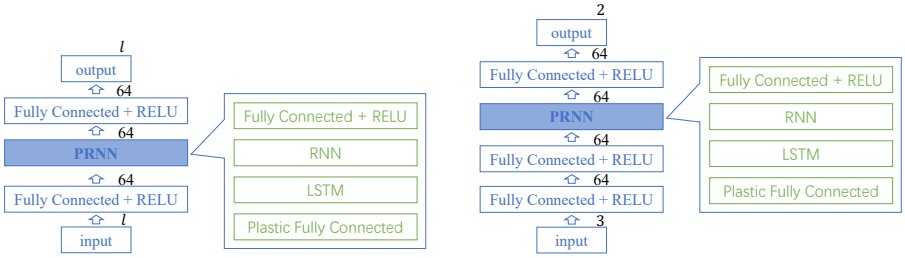
A APPENDICES

A.1 MODEL ARCHITECTURE AND TRAINING DETAILS

To maintain fairness for comparison, the model architectures of the compared methods are similar, where the differences lie in only one of their layers (Figure 6). We use 3 hidden layers for *Sequence Predicting* tasks and 4 hidden layers for *Wheeled Robot Navigating* tasks. For **ES-MAML**, we replace the PRNN layer with fully connected layer; For **ES-RNN** and **ES-LSTM**, we replace it with *RNN* and *LSTM* respectively; For **EPMLP**, we replace it with plastic fully connected layer, where the plasticity rule is stated by Equation 1, and the neural modulator m is calculated by an additional dense layer with sigmoid activation. The hidden sizes of all the hidden layers are 64 (for LSTM it is 64 hidden states and 64 cell states).



(a) *Sequence Predicting* (b) *Wheeled Robot Navigating*

Figure 6: A sketch of the model architectures for evaluated tasks

For *Sequence Predicting* tasks, the input observation and the output action has the dimension of l. In the *meta-training-training* and *meta-testing-train* stages, we use the ground truth $\boldsymbol{y}_{t-1}$ as input observation; In the the *meta-training-test* and *meta-testing-test* stages, its previous action (a_{t-1}) are taken as inputs. For *Wheeled Robot Navigating* tasks, the output action is the control command of its two wheels (a length 2 vector), the input observation is the concatenation of its previous action and the current observed signal intensity (A_t).

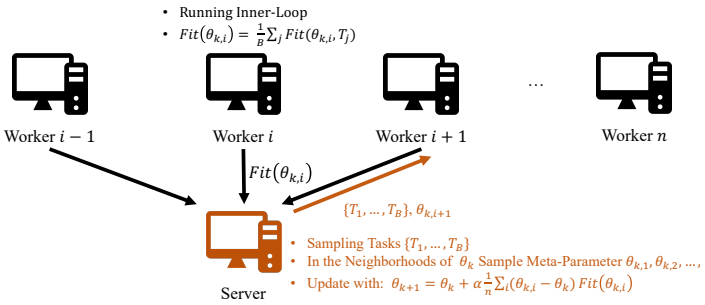


Figure 7: A sketch of the parallel training framework.

The training process is accelerated by utilizing the paralleling mechanism of PARL. We employ 400 workers (400 Intel(R) Xeon(R) CPU E5-2650) running inner-loops for 400 off-springs in each generation of the evolution, and additional 1 CPU to perform evolutionary update (shown in Figure 7(b)). It takes 3 to 12 hours for each run depending on the length of the inner loop and model architectures. Following the previous work (Salimans et al., 2017a), we rank normalize the fitness among 400 workers. The learning rate α is set to 0.2. The mutation is performed by adding independent Gaussian noises to each parameter. During the *meta-training*, we sample B different tasks and 400 meta-parameters. Each worker run B *meta-training-training* and B *meta-training-testing* given the assigned meta-parameter, then the fitness is averaged. We set $B = 16$ for *Sequence*

Predicting tasks, and $B = 4$ for *Wheeled Robot Navigating* tasks. For each *meta-testing* epoch, we evaluated the current meta parameters in newly sampled 1600 tasks.