

Learning to Learn in the Context of Spiking Neural Networks

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Abstract—L2L abstract - I will write it in the end

I. INTRODUCTION

Introduction to the topic

II. RECURRENT NEURAL NETWORKS

A. Subheading

B. Subheading2

III. SPIKING NEURAL NETWORKS (SNN)

Second generation neural networks, as commonly described in the literature, base their neurons activation on various continuous functions and allow a larger space of operations. Maass et al. (Maass et al.) introduced a third setup for designing neural network models. This setup is based on a neuron model that integrates a different conception on how neurons are activated, thus allowing a more accurate representation of biological neurons and their inner workings. This model of Spiking Neural Networks (SNN) employs integrate-and-fire neurons (Maass et al.) which allow timing of activation pulses and therefore a potentially higher capability of representing information.

A. *Neurons - Activation and Signal Processing*

The process of signal transportation within biological neurons ...(figures and Gruning and Bohte)

The fundamental idea behind the computational units of an SNN revolves around integrating a temporal factor in the representation of information. Various models of these spiking neurons, such as the integrate-and-fire model (Abbott), the Hodgkin-Huxley model (Hodgkin and Huxley), the model by Izhikevich (Izhikevich) and the Spike Response Model by Gerstner (Gerstner) exist and vary in their attempt to trade off biological accuracy and computational complexity (Grunte and Bohte). The Leaky-Integrate-and-Fire model is nowadays the most widespread approach due to its simplicity and computational advantages. The representation of the activation process of the neuron is modeled by an electrical circuit in which the membrane potential, threshold voltage, resting potential and leak rate are realized through a capacitor, gate, battery and resistance respectively. (Abbott and fig. Ponulak) At any moment, an LIF neuron has a drive v , which depends on its bias current, b ; its inputs $a_{(in)j}$ (where the index j runs from 1 to the number of inputs); and its synaptic weights, W_j (Eliasmith and Anderson, 2002). (... and so on)

B. *Spike-based Neural Codes*

Whilst encoding and decoding of the desired information is much simpler and intuitive in second generation neural network models, this is a larger challenge for the time-dependent neurons in an SNN, as there is an arbitrary number of theoretically possible ways of encoding information in the neurons. In fact the biological process of information decoding is still being researched, whereas various methods have been introduced Neuroscience Engineering.

- Rate Coding is an approach aiming at recording spike rates during fixed time frames. This implementation of spike encoding can be seen as an analog way of interpreting spike trains in SNNs.
- Latency Coding encodes spikes based on their timing rather than their multiplicity. This encoding has for example been used in unsupervised learning [43], and supervised learning methods like SpikeProp (S. Bohte, J. Kok)
- Fully temporal codes are a more general term which includes the above mentioned approaches. It encodes information based on the precise timing of each spike in a spike train. (Gruning and Bohte)
- Gaussian Coding applies a gaussian distribution over recorded spikes of each neuron and encodes information based on their stochastic occurrence.
- ...

C. *Learning in Spiking Neural Networks - Synaptic Plasticity*

Whilst conventional neural networks employ a stochastic version of gradient descent to backpropagate errors throughout the network, the same approach is difficult to apply in the realm of SNNs due to their temporal dependence and the non-differentiability of spike trains. Whereas multiple learning rules addressing SNNs exist (such as Hebbian Rule, Binarization of ANNs, Conversion from ANNs and Variations of backpropagation (Pfeiffer and Pfeil)), a more biologically realistic training rule is introduced with the spike-timing-dependant plasticity (STDP). The key feature of this approach is to adjust weights between a pre- and post-synaptic neuron according to their relative spike times within an interval of roughly tens of milliseconds in length (S. Bohte, J. Kok) ... more on STDP

1) *Backpropagation and Feedback-alignment:*

2) *Error Feedback:*

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D. Performance of SNNs)

IV. LEARNING TO LEARN (L2L)

The field of reinforcement learning (RL) has recently celebrated great success at reaching human-like and even surpassing human abilities on complex environments such as Atari and Go (Mnih et al. and Silver et al.) with the implementation of Deep Neural Networks to account for non-linear function approximation over high-dimensional action and state spaces. However Artificial Intelligence in general (Landsell and Kording) and Reinforcement Learning in particular (Dual et al.) currently suffer from two major drawbacks, that are limiting their application and design (J. Wang et al.):

- Firstly the immense volume of required training data and the relatively expensive generation of this data in often simulated environments.
- Secondly RL-algorithms often have to be heavily tailored to a specific range of tasks and various algorithms, each of which depending on numerous hyperparameters and thus requiring immense efforts compared to currently reached results.

Botvinick et al. explain these weak spots in AI with a need for low learning rates and the bias-variance trade-off. Low learning rates are necessary to prevent both catastrophic interference (discarding previously reached successful configurations) and overfitting (Hardt, M. et al.). The bias-variance trade-off is a phenomenon describing the contrary working directions of efficiency-driving biases or priors and performing on a wider range of tasks.

—— maybe more basics from hochreiter et al. ——

With some approaches addressing these issues existing, Landsell and Kording argue, that these L2L approaches can be categorized into either Learning to Optimize or Structure Learning (Landsell and Kording). Learning to Optimize focusses on the general adaption of network parameters to achieve efficient learning rules on arbitrary Task classes without hand-selection. Similarly to the way gradient descent applies small changes of the weights in an NN in order to minimize loss functions, the design of AI systems can be viewed as an optimization problem itself, that requires parameter optimization to ensure a well performing algorithm. Structure Learning on the other hand makes use of structural similarities within a finite family of tasks to reach higher data efficiency due to its prior adaptiveness to the given family of tasks (Landsell and Kording).

A. Learning to Reinforcement Learn (metal-RL) and RL

A high level architecture consisting of a learner (performing on the task itself) and a meta-learner (adjusting the learner) is inherent to most implementations of L2L (Landsell and Kording) and has been refined in various ways to create new L2L Systems, as will be explained in the following section.

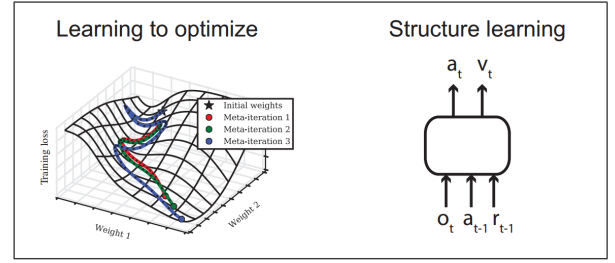


Fig. 1. Types of learning-to-learn in AI. Learning-to-learn can be roughly divided into learning to optimize and structure learning. In AI, hyperparameter optimization is an example of learning to optimize (Maclaurin et al. 2015), while a recurrent neural network taking rewards, actions and observations can often be used to perform structure learning (Wang et al.) (Landsell et al.).

Wang et al. as well as Duan et al. introduced frameworks that can be thought of as generating an RL algorithm of their own and provide agents, who are given a predesigned prior to efficiently learn any task $T \in \mathcal{F}$ (in the original papers denoted as a Markov Decision Process (MDP) $m \in \mathcal{M}$) from a family of interrelated tasks \mathcal{F} (i.e. a set of MDPs \mathcal{M}).

In their attempt to design an algorithm, capable of performing well on a set \mathcal{M} of Markov Decision Processes (MDPs), Duan et al. implement a nested system in which learning an RL algorithm is regarded as a reinforcement learning problem itself, hence the name RL (Duan et al.). The agent performing on a randomly drawn separate MDP $m \in \mathcal{M}$ from the distribution $\rho_{\mathcal{M}} : \mathcal{M} \rightarrow R_+$ is represented as a recurrent neural network (RNN) which outputs the probability distribution over the tasks action-space π (policy) based on a function $\phi(s, a, r, d)$ of the tuple (state, action, reward, termination flag) (Duan et al.). On a higher abstraction layer, this RNN is being optimized by an implementation of Trust Region Policy Optimization (TRPO), a state-of-the-art DRL algorithm (Schulman et al., 2015) with several advantages regarding stability and hyperparameter dependence.

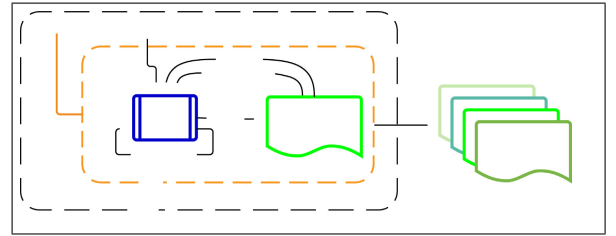


Fig. 2. Schematic of Meta-reinforcement Learning, Illustrating the Inner and Outer Loops of Training. The outer loop trains the parameter weights θ , which determine the inner-loop learner (Agent, instantiated by a recurrent neural network) that interacts with an environment for the duration of the episode. For every cycle of the outer loop, a new environment is sampled from a distribution of environments, which share some common structure (Botvinick et al.).

Wang et al. define a similar setup in which a RL-algorithm is responsible for learning the weights of a nested RNN. Both, inner and outer loop in this framework draw their learning experience from the reward information

generated by the actions of the RNN (Wang et al.), where the RNN holds information on the previously chosen action and the subsequent rewards. However the process of learning in each of these loops is realized differently and results in specializations of different scopes. While the wrapping RL-algorithm used to optimize the weights of the RNN operates over the entire set of episodes, that is to say all MDPs M , learning of the nested RNN within a single task m is based on the inner recurrent dynamics of the network. The policy outputs π of this network can be viewed as an RL-algorithm on its own, resulting in the name meta-RL. For the implementation of this framework Wang et al. used a LSTM according to Hochreiter and Schmidhuber (Hochreiter and Schmidhuber, 1997) to account for the inner RNN, while both synchronous asynchronous advantage actor critics (A2C and A3C) (Mnih et al.) were employed to learn its parameters. The observation vectors of experiment environments were either directly fed to the LSTM one-hot-encoded or passed through an additional deep encoder model (Wang et al.). Experiments on a series of bandit problem and two MDP-centered problems with implementation architectures as described above showed, that meta-RL delivers competitive results compared to problem-specific algorithms (Thompson sampling, UCB, Gittins) while operating on a wider set of tasks.

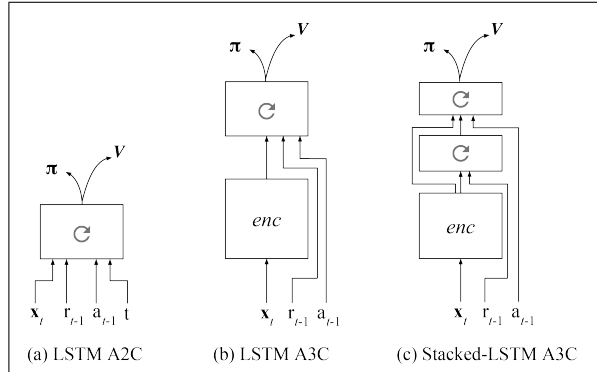


Fig. 3. Advantage actor-critic with recurrence. In all architectures, reward and last action are additional inputs to the LSTM. For non-bandit environments, observation is also fed into the LSTM either as a one-hot or passed through an encoder model [3-layer encoder: two convolutional layers (first layer: 16 8x8 filters applied with stride 4, second layer: 32 4x4 filters with stride 2) followed by a fully connected layer with 256 units and then a ReLU non-linearity. See for details Mirowski et al. (2016)]. For bandit experiments, current time step is also fed in as input. π = policy; v = value function. A3C is the distributed multi-threaded asynchronous version of the advantage actor-critic algorithm (Mnih et al., 2016); A2C is single threaded. (a) Architecture used in experiments 1-5. (b) Convolutional-LSTM architecture used in experiment 6. (c) Stacked LSTM architecture with convolutional encoder used in experiments 6 and 7 (Wang et al.)

A notable characteristic of both previously described setups is that the learning rate of the nested RNN is chosen lower compared to the outer optimization loop, consequently preventing the agent from overfitting to a single task m , yet gathering knowledge from the entire MDP space M (Botvinick et al.).

more from :

Meta-SGD: Learning to Learn Quickly for Few-Shot Learning (Li et al.)

Meta-learning in Reinforcement Learning (Schweighofer and Doya)

Learning to Learn without Gradient Descent by Gradient Descent (Chen et al.)

B. L2L in the Context of Spiking Neural Networks

tbd ... Long short-term memory and Learning-to-learn in networks of spiking neurons (Bellec et al.) Biologically inspired alternatives to backpropagation through time for learning in recurrent neural nets (Bellec et al.) Embodied Neuromorphic Vision with Event-Driven Random Backpropagation (Kaiser et al.)

C. Implications for Neuroscience and Psychology

That is, having to learn their complete knowledge about the world from scratch, whereas the human brain has undergone a long history of evolutionary development, adjusting its learning paradigms to the challenges it faces (Duan et al.).

more from:

Reinforcement Learning, Fast and Slow (Botvinick et al.)

Biologically inspired alternatives to backpropagation through time for learning in recurrent neural nets (Bellec et al.)

Towards learning-to-learn (Landsell and Kording)

V. APPLICATIONS OF L2L AND SNNs IN ROBOTICS

While the development of robots has shown great success in the recent past with advances being pushed from numerous different fields of engineering, including that of machine learning and especially classic DNNs, it is still a tedious and highly tailored process, requiring many domain experts. Many of the underlying algorithms in the control, motion planning and sensoric interpretation require suitable setups of the environment with little room for variation. For example industrial manipulator robots can perform outstandingly when placed in a fixed production line, yet recognizing and grasping everyday objects in a kitchen or workshop poses a much higher challenge, as it requires the skill to make sense of broad environments with numerous imaginable tasks. Furthermore the dominating problems of applying RL in robotics can be summarized by the following problem classes (<https://towardsdatascience.com/reinforcement-learning-for-real-world-robotics>):

- Sample efficiency
- Sim2Real
- Reward Specification
- Safety

The previous sections revealed the potential of L2L frameworks in terms of sample efficiency and generalization, thus constituting feasible answers to expensive data generation or overfitting to simulator-specific features.

However this further implies a reflection on the scalability of said L2L approaches in order to evaluate their applicability in the often very high-dimensional task spaces faced in robotics.

Wang et al. examine meta-RL’s ability to detect abstract task structures in large scale problems by adapting a well-known behavioural experiment described by Harlow (Harlow, 1949) to a visual fixation task. In Harlows experiment, monkeys were presented two unfamiliar objects, with each being assigned a bowl filled with food and an empty bowl respectively. The monkeys were allowed to choose one of the objects and received the reward, if present. Despite switching the objects for new unknown objects in each episode, upon replaying several trials in several episodes of this game, the animals showed a general understanding of the underlying structure of the problem. After beginning a new episode with new objects, the monkeys inevitably took one random guess but managed to succeed in the following trials of the episode (Botvonick et al.).

A. Tasks in high-dimensional spaces

Motion and path planning is a fundamental problem in all of robotics, whether it be within a space of rich visual input, sensory data or configuration/join-spaces. Similiar to the problem described by Harlow, the navigational task in the I-maze environment as described by Mirowski et al. and Jaderberg et al. requires a understanding of the general structure of the problem in order to learn sample-efficiently on the specific task. In this case the same maze spawns a goal location on random position within the maze where the agent has to learn a motion path to the goal in as few trials as possible. The results of Wang et al. show, that an architecture of stacked LSTM is able to solve the task after having conducted one exploration run (finishing the episode in 100 timesteps) notably faster (30 timesteps) within few explotation runs. A so to say proof of concept is the fact, that a feedforward architecture A3C learner is not able to solve the problem at all.

more from :

Meta-SGD: Learning to Learn Quickly for Few-Shot Learning (Li et al.)

Meta-learning in Reinforcement Learning (Schweighofer and Doya)

Learning to Learn without Gradient Descent by Gradient Descent (Chen et al.)

B. Speed Improvement and Few-Shot Learning

VI. CONCLUSION AND CHALLENGES

APPENDIX

Appendixes should appear before the acknowledgment.

REFERENCES

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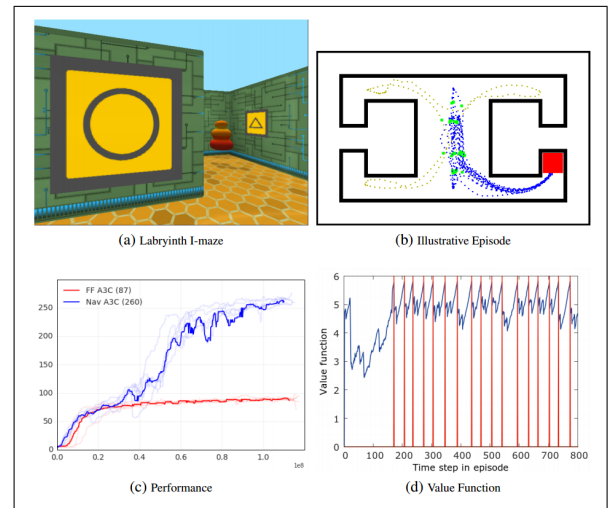


Fig. 4. a) view of I-maze showing goal object in one of the 4 alcoves b) following initial exploration (light trajectories), agent repeatedly goes to goal (blue trajectories) c) Performance of stacked LSTM (termed Nav A3C) and feedforward (FF A3C) architectures, per episode (goal = 10 points) averaged across top 5 hyperparameters. e) following initial goal discovery (goal hits marked in red), value function occurs well in advance of the agent seeing the goal which is hidden in an alcove. Figure used with permission from Mirowski et al. (2016).