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2 Theoretical Introduction

"Computational Neuroscience is an approach to understanding the information content of neural signals by modeling the nervous system at many different structural scales, including the biophysical, the circuit, and the systems levels. Computer simulations of neurons and neural networks are complementary to traditional techniques in neuroscience." (Dayan & Abbott, 2005, Series Foreword)

Understanding how the brain works is one of the hardest challenges the humanity has ever faced, and it is crucial in the progress of Science: understanding intelligence, the learning process and consciousness would be groundbreaking for the developing of new technologies. The main issue in the study of the brain right now is retrieving the data: we now have enough computational power to process signals from millions of neurons at the same time, but we can't just put an electrode in everyone of them, although some are going in that direction (Musk, 2019).

Simulations

A less invasive solution is to use our knowledge of the brain to build complex, biologically plausible simulations of the brain, or parts of the brain, and we could retrieve from them all the data that is needed.

However, this approach, deeply analyzed in the past (Smolensky, 1988), doesn't offer assurance that the simulation and the real process could actually be interchangeable. In the present, many of the challenges of that time were overcome, in particular computational power (Djurfeldt et al., 2008), and simulations are used to confirm theoretical models of the brain (Pellionisz & Llinás, 1979).

Still, finding the precise values for all the parameters of neurons in a big model is challenging and time consuming, therefore here is proposed a framework able to autonomously optimize the parameters of a given model, so that a selected output of the simulation will coincide with the desired one. In this case the model, that will be described in more detail later, is an hypothetical column of the sensory cortex of a mammal, developed by Potjans (Potjans & Diesmann, 2014), and the output is the firing rate of the excitatory neurons in four different layers.

Optimization

As it is being showed in other domains, such as predicting protein structure (Senior et al., 2020), Deep Reinforcement Learning is well suited to learn complex features of models and act to modify them in a desired direction. In this work the algorithm selected has been a modified version of Deep Deterministic Policy Gradient (Lillicrap et al., 2015), whose functioning will be explained in the next section.

2.1 Reinforcement Learning

Reinforcement Learning is an area of machine learning which consider a setup consisting of an agent interacting with an environment through actions. The agents receives an input from the environment, chooses and action and receives a reward, based on the state of the environment after the action. The agent behavior is defined by a policy, which maps actions to states. An action-value function tries to predict the reward after taking an action.

Bandits

We consider the simple case of the multi-armed bandit, where the environment reaches the terminal state after one single transition, and the agent has to choose a value for many different actions in a continuous space.

The Actor-Critic

The kind of algorithm we are using belongs to the family of actor-critic algorithms, where the actor is an Artificial Neural Network (ANN) that represents the policy, while the critic is another ANN representing the action-value function. The critic is trained to predict how big the reward will be after an action is taken, and the actor is trained to take the best possible action. The critics try to understand the environment, and the actor uses this knowledge to change it in the desired way.

3 Material and Methods

3.1 The environment

The brain column

The parameters

The reward

3.2 The agent

The algorithm

Adaptation to the bandit problem

4 Results

References

Dayan, P., & Abbott, L. F. (2005). *Theoretical neuroscience: Computational and mathematical modeling of neural systems.* The MIT Press.

Djurfeldt, M., Lundqvist, M., Johansson, C., Rehn, M., Ekeberg, O., & Lansner, A. (2008). Brain-scale simulation of the neocortex on the ibm blue gene/l supercomputer. *IBM Journal of Research and Development*, *52*(1.2), 31-41.

Lillicrap, T. P., Hunt, J. J., Pritzel, A., Heess, N., Erez, T., Tassa, Y., ... Wierstra, D. (2015). Continuous control with deep reinforcement learning. *arXiv preprint arXiv:1509.02971*.

Musk, E. (2019). An integrated brain-machine interface platform with thousands of channels. *bioRxiv*. Retrieved from `https://www.biorxiv.org/content/early/2019/08/02/703801` doi: 10.1101/703801

Pellionisz, A., & Llinás, R. (1979). Brain modeling by tensor network theory and computer simulation. the cerebellum: Distributed processor for predictive coordination. *Neuroscience*, *4*(3), 323 - 348. Retrieved from `http://www.sciencedirect.com/science/article/pii/0306452279900976` doi: https://doi.org/10.1016/0306-4522(79)90097-6

Potjans, T. C., & Diesmann, M. (2014). The cell-type specific cortical microcircuit: relating structure and activity in a full-scale spiking network model. *Cerebral cortex*, *24*(3), 785–806.

Senior, A. W., Evans, R., Jumper, J., Kirkpatrick, J., Sifre, L., Green, T., ... others (2020). Improved protein structure prediction using potentials from deep learning. *Nature*, 1–5.

Smolensky, P. (1988). On the proper treatment of connectionism. *Behavioral and brain sciences*, *11*(1), 1–23.