OpenBrain: Massiveley Asynchronous Neurocomputation

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Todo list

Abstract

The OpenBrain white paper.

Produce a 4-6 sentence abstract about the paper.

Note: Most of the sections for this document are included as submodules using the following command.

```
\input{section} %imports section.tex
```

The main file should not be modified, except to change the abstract, add new sections, or modify packages!

1 Introduction

Note: We need to motivate substantially the proposal of a drastically different framework of neurocomputation. This motivation should be given according to the latest neuroscience, and a general problem in the field.

Argue against the current state of ML's approach to the problem of AGI by surveying field.

1.1 Intelligence as an Emergence Phenomenon

Establish Conwaynian philosophy on emergent neurocomputation.

Motivate asynchrynous neurocomputation.

2 Asynchronous Neurocomputation

Note: This section will essentially lay out our model minus learning rules. This means we must give theoretical, biological justifications for the algorithm.

2.1 The Core Framework

This section needs an actuall discussion. For now here are the working definitions of Openbrain.

Definition 2.1.1. *A **neuron** $n \in N$ is defined by*

- *a voltage $V_n(t)$,*
- *a decay time τ_n,*
- *a refactory period ρ_n*
- *a voltaic threshold θ_n.*

Definition 2.1.2. *A **connection** $c \in C$ is a tuple $(n_i, n_j, w_{ij}) \in N \times N \times \mathbb{R}$ where n_i is the **anterior neuron**, n_j is the **posterior neuron**, and $w_i j$ is the standard synaptic weight.*

Make connection diagram.

For a neuron n, we denote the set of anterior neurons A_n and the dendritic connections, C_n^a. In the same light we will use the notations P_n and C_n^p to denote the sets of posterior neurons and posterior connections for n respectiveley.

Definition 2.1.3. *A neuron n is said to **fire** if it is not in its refractory period and $V_n(k) > \theta_n$. Then for all $m \in P_n$,*

$$V_m(k+1) \leftarrow V_m(k+1) + w_{nm}\sigma(V_n(k)); \tag{2.1.1}$$

*that is, voltage is propagated to the posterior neurons. Immediately after n fires, it enters a **refractory period** until $k + \frac{\rho_n}{\Delta t}$.*

Definition 2.1.4. *We say that a neuron n experiences **voltage decay** so that for all k,*

$$V_n(k+1) \leftarrow V_n(k+1) + V_n(k)e^{-\Delta t/\tau}. \tag{2.1.2}$$

Combining (2.1.1) and (2.1.2) we get that for a neuron m at time $k+1$

$$V_m(k+1) = V_m(k)e^{-\Delta t/\tau} + \sum_{n \in A'_m} w_{nm}\sigma(V_n(k)) \tag{2.1.3}$$

such that A'_m is the set of anterior neurons which fired at time k.

2.2 Continuous Time Universal Intelligence Measure

In alignment with the philosophy which predicates OpenBrain, we wish to extend the evaluation of our algorithm well beyond its performance in supervised learning tasks; that is, what can be said about the intelligence of OpenBrain as an agent in an environment? The answer will motivate an important discussion of representation theory annd learning rules.

A well established[1, 3, 4] machine intelligence measure is the Universal Intelligence Measure proposed by Legg and Hutter [2]. Drawing from a large amount of disparate literature on the subject they develop a consise definition of the intelligence of an *agent* in an *environment*.

The following exposition may be unnecessary, and we should consider just stating the result of Legg and Hutter.

Environment-agent interaction is defined with respect to an observation space, $\mathcal{O}$, and an action space, $\mathcal{A}$, both of which consist of abstract symbols. The perception space, $\mathcal{P} \subset \mathcal{O} \times \mathbb{R}$, is the combination of observations and rewards.

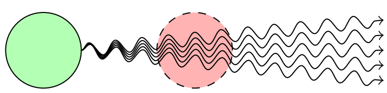
Definition 2.2.1. *An* ***environment*** μ *is a probability measure, specifically defining*

$$\mu(o_k r_k | o_1 r_1 a_1 \dots o_{k-1} r_{k-1} a_{k-1}), \tag{2.2.1}$$

the probability of observing $o_k r_k \in \mathcal{P}$ *given a history, a string* $o_1 \dots a_{k-1} \in \bigtimes_{i=1}^{k} \mathcal{P} \times \mathcal{A}$.

Let E be the space of all turing complete reward environments, and $K : E \to \mathbb{R}$ be the Kolmogorov complexity of an environment. This complexity is calculated with respect to the length of the string with which a reference machine $\mathcal{U}$ generates the environment.

Definition 2.2.2. *Given an agent* π



2.3 Universal Approximation and Representation

2.4 (optional) Multiprocess Turing Completeness

If we decide to go down this route, we'll add it's own TEXfile.

3 Conwaynian Learning Rules

4 Experimentation

4.1 Implementation

4.2 Results

5 Conclusion

5.1 Future Work

References

[1] Shane Legg. "Machine super intelligence". PhD thesis. University of Lugano, 2008.

[2] Shane Legg and Marcus Hutter. "Universal intelligence: A definition of machine intelligence". In: *Minds and Machines* 17.4 (2007), pp. 391–444.

[3] Volodymyr Mnih et al. "Human-level control through deep reinforcement learning". In: *Nature* 518.7540 (2015), pp. 529–533.

[4] Samuel Rathmanner and Marcus Hutter. "A philosophical treatise of universal induction". In: *Entropy* 13.6 (2011), pp. 1076–1136.

Appendices

A Universal Intelligence Definitions