sorn: A Python package for Self Organizing Recurrent Neural Network

Saranraj Nambusubramaniyan$^{1,2}$

$^1$ Indian center for Robotics Innovation and Smart-intelligence(IRIS-i), India $^2$ Institute of Cognitive Science, Universität Osnabrück, Germany

Summary

The self-organizing recurrent neural (SORN) network is a class of neuro-inspired artificial networks. This class of networks has been shown to mimic the ability of neocortical circuits to learn and adapt through neuroplasticity mechanisms. Structurally, the SORN network consists of a pool of excitatory neurons and a small population of inhibitory neurons. The network uses five basic plasticity mechanisms found in the neocortex of the brain, namely, spike-timing-dependent plasticity, intrinsic plasticity, synaptic scaling, inhibitory spike-timing-dependent plasticity, and structural plasticity (Lazar et al., 2009; Papa et al., 2017; Zheng et al., 2013) to optimize its parameters. Using mathematical tools, a SORN network simplifies the underlying structural and functional connectivity mechanisms responsible for learning and memory in the brain.

sorn is a Python package designed for Self Organizing Recurrent Neural Networks. While it was originally developed for SORN networks, it can also serve as an ideal research package for Liquid State Machines (Jaeger, 2002; Jaeger et al., 2007) in general. The detailed documentation can be found at https://self-organizing-recurrent-neural-networks.readthedocs.io/en/latest/. To extend the potential applications of this network architecture, a demonstrative example of a neuro-robotics experiment using OpenAI Gym (Brockman et al., 2016) is provided at sorn package.
Statement of need

Reservoir computing (RC) models are neuroinspired artificial neural networks. RC networks have either sparsely or densely connected units with fixed connection weights. Unlike other RC models, SORN has synaptic weights controlled by neuroinspired plasticity mechanisms. The network has two distinct pools of excitatory and inhibitory reservoirs that compete to remain in a subcritical state suitable for learning. The subcritical state is a state between chaos and order, also called the “edge of chaos.” In this state, the network has momentum with a strong affinity for order, but is sensitive to external perturbations. Through plasticity mechanisms, the network has the ability to overcome the perturbations and return to its subcritical dynamics. This self-adaptive behavior is also referred to as self-organization. To build such a network with a synergistic combination of plasticity mechanisms from scratch requires a deeper understanding of neurophysiology and soft computing.

sorn reduces the cognitive load of theorists, experimenters or researchers by encapsulating all plasticity mechanisms with a high degree of reliability and flexibility.

There are few other open source codes sorn v1, sorn v2, for SORN networks, but they are application-specific and are not general-purpose software packages. However, sorn is a flexible package that allows researchers to develop the network of their interest, providing them the freedom to choose the combination of plasticity rules of their choice. Moreover, it is easy to integrate sorn with machine learning frameworks such as PyTorch and reinforcement learning toolkits such as OpenAI Gym. Overall, sorn provides a research environment for computational neuroscientists to study self-organization, adaptation, learning, memory, and behavior of brain circuits by reverse-engineering neural plasticity mechanisms.

Library Overview

The package sorn is heavily dependent on numpy (Harris et al., 2020) for numerical computation and analysis methods, seaborn and matplotlib (Barrett et al., 2005) for visualization. The network is constructed in five classes; the object SORN encapsulates all the required functions that instantiate network variables such as connection weights and thresholds. Plasticity inherits objects from SORN and implements plasticity rules with methods stdp(), ip(), ss(), sp() and istdp(). NetworkState has methods that evaluate excitatory and inhibitory network states at each time step and finally MatrixCollection objects behave like a memory cache. It collects the network states and keeps track of variables such as weights and thresholds as the network evolves during simulation and training.

The network can be instantiated, simulated and trained using two classes: Simulator and Trainer, which inherit objects from SORN.

SORN Network Model

As defined in (Lazar et al., 2009; Zheng et al., 2013) the activity of neurons in the excitatory and inhibitory pool is given by the following state equations,

$$x_i(t+1) = \Theta \left( \sum_{j=1}^{N_E} W_{ij}^{EE}(t)x_j(t) - \sum_{j=1}^{N_I} W_{ij}^{EI}(t)y_k(t) + u_i(t) - T^E_i(t) + \xi_E(t) \right)$$  (1)

$$y_i(t+1) = \Theta \left( \sum_{j=1}^{N_I} W_{ij}^{IE}(t)x_j(t) - T^I_i(t) + \xi_I(t) \right)$$  (2)

$W_{ij}^{EE}$ - Connection strength between excitatory neurons

$W_{ij}^{EI}$ - Synaptic strength from Inhibitory to excitatory network

Nambusubramaniyan, S., (2021). sorn: A Python package for Self Organizing Recurrent Neural Network. Journal of Open Source Software, 6(65), 3545. https://doi.org/10.21105/joss.03545
$W_{EE}^{ij}$ - Synaptic strength from Excitatory to inhibitory network

$x_j(t)$ - Presynaptic excitatory neuron state at $t$

$y_k(t)$ - Presynaptic inhibitory neuron state at $t$

$x_i(t)$ - Postsynaptic neuron state at $t$

$u_i$ - External stimuli

$T_i(t)$ - Firing threshold of the neuron $i$ at time $t$

**Plasticity Rules**

**Spike Timing Dependent Plasticity**

Spike Timing Dependent Plasticity (STDP) alters synaptic efficacy between excitatory neurons based on the spike timing between presynaptic neuron $j$ and postsynaptic neuron $i$.

\[ \Delta W_{ij}^{EE} = \eta_{\text{STDP}} (x_i(t)x_j(t-1) - x_i(t-1)x_j(t)) \]  

(3)

where,

$W_{ij}^{EE}$ - Connection strength between excitatory neurons

$\eta_{\text{STDP}}$ - STDP learning rate

$x_j(t-1)$ - Presynaptic neuron state at $t-1$

$x_i(t)$ - Postsynaptic neuron state at $t$

**Intrinsic Plasticity**

Intrinsic Plasticity (IP) updates the firing threshold of excitatory neurons based on the state of the neuron at each time step. It increases the threshold if the neuron is firing and decreases it otherwise.

\[ T_i(t+1) = T_i(t) + \eta_{\text{IP}} (x_i(t) - H_{\text{IP}}) \]  

(4)

where,

$T_i(t)$ - Firing threshold of the neuron $i$ at time $t$

$\eta_{\text{IP}}$ - Intrinsic plasticity step size

$H_{\text{IP}}$ - Target firing rate of the neuron

**Structural Plasticity**

Structural Plasticity (SP) is responsible for creating new synapses between excitatory neurons at a rate of about 1 connection per 10th time step.

**Synaptic Scaling**

Synaptic Scaling (SS) normalizes the synaptic strengths of presynaptic neurons and prevents network activity from declining or exploding.

\[ W_{ij}^{EE}(t) = \frac{W_{ij}^{EE}(t)}{\sum W_{ij}^{EE}(t)} \]  

(5)


**Inhibitory Spike Timing Dependent Plasticity**

Inhibitory Spike Timing Dependent Plasticity (iSTDP) is responsible for controlling synaptic strengths from the inhibitory to the excitatory network.

\[
\Delta W_{EI}^{ij} = \eta_{\text{STDP}} \left( y_j(t-1)(1-x_i(t)(1 + \frac{1}{\mu_{IP}})) \right)
\]

(6)

where,

- \( W_{EI}^{ij} \) - Synaptic strength from Inhibitory to excitatory network
- \( \eta_{\text{STDP}} \) - Inhibitory STDP learning rate
- \( \mu_{IP} \) - Mean firing rate of the neuron

Note that the connection strength from excitatory to inhibitory (\( W_{IE}^{ij} \)) remains fixed at the initial state and also the connections between inhibitory neurons are not allowed.

**Sample Simulation methods**

```python
# Sample input
num_features = 10
time_steps = 200
inputs = numpy.random.rand(num_features, time_steps)
state_dict,E,I,R,C = Simulator.simulate_sorn(inputs=inputs, phase='plasticity',
                                          matrices=None, noise=True,
                                          time_steps=time_steps, ne=200,
                                          nu=num_features)
```

simulate_sorn returns the dictionary of network state variables of the previous time steps, the excitatory and inhibitory network activity of the whole simulation period, and also the recurrent activity and the number of active connections at each time step. To continue the simulation, load the matrices returned in the previous step as,

```python
state_dict,E,I,R,C = Simulator.simulate_sorn(inputs=inputs, phase='plasticity',
                                          matrices=state_dict, noise=True,
                                          time_steps=time_steps,
                                          ne = 200, nu=num_features)
```

**Network Output Descriptions**

- state_dict - Dictionary of connection weights (‘Wee’, ‘Wei’, ‘Wie’),
  - Excitatory network activity (‘X’),
  - Inhibitory network activities (‘Y’),
  - Threshold values (‘Te’, ‘Ti’)

Nambusubramaniyan, S., (2021). sorn: A Python package for Self Organizing Recurrent Neural Network. Journal of Open Source Software, 6(65), 3545. https://doi.org/10.21105/joss.03545
E - Collection of Excitatory network activity of entire simulation period
I - Collection of Inhibitory network activity of entire simulation period
R - Collection of Recurrent network activity of entire simulation period
C - List of number of active connections in the Excitatory pool at each time step

**Sample Training methods**

```python
from sorn import Trainer
inputs = np.random.rand(num_features,1)

# Under all plasticity mechanisms
state_dict,E,I,R,C=Trainer.train_sorn(inputs=inputs,phase='plasticity',
                                       matrices=state_dict,
                                       nu=num_features,time_steps=1)

# Resume the training without any plasticity mechanisms
state_dict,E,I,R,C=Trainer.train_sorn(inputs=inputs,phase='training',
                                       matrices=state_dict,
                                       nu=num_features,time_steps=1)
```

To turn off any plasticity mechanisms during the simulation or training phase, you can use the argument `freeze`. For example, to stop intrinsic plasticity during the training phase,

```python
state_dict,E,I,R,C=Trainer.train_sorn(inputs=inputs,phase='plasticity',
                                       matrices=None,noise=True,
                                       time_steps=1,ne=200,
                                       nu=num_features,freeze=['ip'])
```

The other options for `freeze` argument are,
- `stdp` - Spike Timing Dependent Plasticity
- `ss` - Synaptic Scaling
- `sp` - Structural Plasticity
- `istdp` - Inhibitory Spike Timing Dependent Plasticity

The `simulate_sorn` and `train_sorn` methods accepts the following keyword arguments:

| kwarg   | Description                                                                 |
|---------|-----------------------------------------------------------------------------|
| inputs  | External stimulus                                                           |
| phase   | plasticity or training                                                      |
| matrices| state_dict to resume simulation otherwise None to intialize new network    |
| time_steps | simulation total time steps. For training should be 1                      |
| kwargs         | Description                                                                 |
|---------------|-----------------------------------------------------------------------------|
| noise         | If True, Gaussian white noise will be added to excitatory field potentials  |
| freeze        | To drop any given plasticity mechanism(s) among ['ip', 'stdp', 'istdp', 'ss', 'sp'] |
| ne            | Number of Excitatory neurons in the network                                  |
| nu            | Number of input units among excitatory neurons                                |
| network_type_ee | sparse or dense connection between excitatory neurons                           |
| network_type_ei | sparse or dense connection from inhibitory and excitatory neurons             |
| network_type_ie | sparse or dense connection from excitatory and inhibitory neurons            |
| lambda_ee     | Connection density between excitatory networks if network type is sparse      |
| lambda_ei     | Density of connections from inhibitory to excitatory networks if network type is sparse |
| lambda_ie     | Density of connections from inhibitory to excitatory networks if network type is sparse |
| eta_stdp      | Hebbian learning rate of excitatory synapses                                   |
| eta_inhib     | Hebbian learning rate synapses from inhibitory to excitatory                 |
| eta_ip        | Learning rate of excitatory neuron threshold                                  |
| te_max        | Maximum of excitatory neuron threshold range                                  |
| ti_max        | Maximum of inhibitory neuron threshold range                                  |
| ti_min        | Minimum of inhibitory neuron threshold range                                  |
| te_min        | Minimum of excitatory neuron threshold range                                  |
| mu_ip         | Target Mean firing rate of excitatory neuron                                  |
| sigma_ip      | Target Standard deviation of firing rate of excitatory neuron                 |

**Analysis functions**

The sorn package also includes necessary methods to investigate network properties. A few of the methods in the Statistics module are:

| methods                 | Description                                                                 |
|-------------------------|-----------------------------------------------------------------------------|
| autocorr                | t-lagged auto correlation between neural activity                           |
| fanofactor              | To verify poissonian process in spike generation of neuron(s)               |
| spike_source_entropy    | Measure the uncertainty about the origin of spike from the network using entropy |
| firing_rate_neuron      | Spike rate of specific neuron                                                |
| firing_rate_network     | Spike rate of entire network                                                 |
| avg_corr_coeff          | Average Pearson correlation coefficient between neurons                      |
| spike_times             | Time instants at which neuron spikes                                         |
| spike_time_intervals    | Inter spike intervals for each neuron                                         |
| hamming_distance        | Hamming distance between two network states                                   |

More details about the statistical and plotting tools in the package can be found at [https://self-organizing-recurrent-neural-networks.readthedocs.io/en/latest/](https://self-organizing-recurrent-neural-networks.readthedocs.io/en/latest/)

**References**

Barrett, P., Hunter, J., Miller, J. T., Hsu, J.-C., & Greenfield, P. (2005). Matplotlib—a portable python plotting package. *Astronomical Data Analysis Software and Systems XIV*, 347, 91.

Brockman, G., Cheung, V., Pettersson, L., Schneider, J., Schulman, J., Tang, J., & Zaremba, S. (2021). sorn: A Python package for Self Organizing Recurrent Neural Network. *Journal of Open Source Software*, 6(65), 3545. [https://doi.org/10.21105/joss.03545](https://doi.org/10.21105/joss.03545)
W. (2016). Openai gym. *arXiv Preprint arXiv:1606.01540*.

Harris, C. R., Millman, K. J., Walt, S. J. van der, Gommers, R., Virtanen, P., Cournapeau, D., Wieser, E., Taylor, J., Berg, S., Smith, N. J., & others. (2020). Array programming with NumPy. *Nature, 585*(7825), 357–362.

Jaeger, H. (2002). Adaptive nonlinear system identification with echo state networks. *Advances in Neural Information Processing Systems, 15*, 609–616.

Jaeger, H., Maass, W., & Principe, J. (2007). Special issue on echo state networks and liquid state machines. https://doi.org/10.1016/j.neunet.2007.04.001

Lazar, A., Pipa, G., & Triesch, J. (2009). SORN: A self-organizing recurrent neural network. *Frontiers in Computational Neuroscience, 3*, 23. https://doi.org/10.3389/neuro.10.019.2009

Papa, B. D., Priesemann, V., & Triesch, J. (2017). Criticality meets learning: Criticality signatures in a self-organizing recurrent neural network. *PLoS One, 12*(5), 1–21. https://doi.org/10.1371/journal.pone.0178683

Zheng, P., Dimitrakakis, C., & Triesch, J. (2013). Network self-organization explains the statistics and dynamics of synaptic connection strengths in cortex. *PLoS Computational Biology, 9*(1), e1002848. https://doi.org/10.1371/journal.pcbi.1002848