

sorn: A Python package for Self Organizing Recurrent Neural Network

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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.

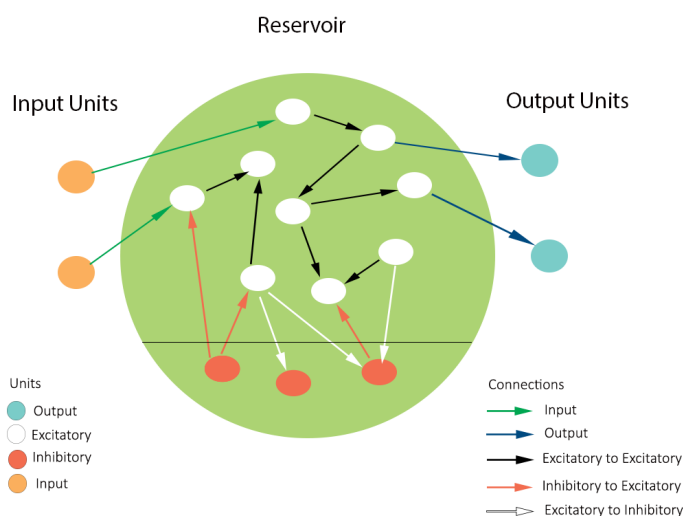


Figure 1: SORN network

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,

$$x_i(t+1) = \Theta \left(\sum_{j=1}^{N^E} W_{ij}^{EE}(t)x_j(t) - \sum_{j=1}^{N^I} W_{ik}^{EI}(t)y_k(t) + u_i(t) - T_i^E(t) + \xi_E(t) \right) \quad (1)$$

$$y_i(t+1) = \Theta \left(\sum_{j=1}^{N_i} W_{ij}^{IE}(t)x_j(t) - T_i^I + \xi_I(t) \right) \quad (2)$$

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

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

$W_{ki}^{!E}$ - Synaptic strenght from Exciatory 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 .

$$\Delta W_{ij}^{EE} = \eta_{\text{STDP}} (x_i(t)x_j(t-1) - x_i(t-1)x_j(t)) \quad (3)$$

where,

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

η_{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.

$$T_i(t+1) = T_i(t) + \eta_{\text{IP}}(x_i(t) - H_{\text{IP}}) \quad (4)$$

where,

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

η_{IP} - Intrinsic plasticity step size

H_{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.

$$W_{ij}^{EE}(t) = W_{ij}^{EE}(t) / \sum W_{ij}^{EE}(t) \quad (5)$$

Inhibitory Spike Timing Dependent Plasticity

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

$$\Delta W_{ij}^{EI} = \eta_{iSTDP} \left(y_j(t-1)(1 - x_i(t)(1 + \frac{1}{\mu_{IP}})) \right) \quad (6)$$

where,

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

η_{iSTDP} - Inhibitory STDP learning rate

μ_{IP} - Mean firing rate of the neuron

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

Sample Simulation methods

```
# 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,

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')

- 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

```
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,

```
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:

kwargs	Description
inputs	External stimulus
phase	plasticity or training
matrices	state_dict to resume simulation otherwise None to initialize new network
time_steps	simulaton 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/>)

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