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sorn: A Python package for Self Organizing Recurrent Neural Network

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Software

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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, 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 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, 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 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 network, but they are considered publication specific and are not general purpose software packages. However, 'sorn' is a flexible package that allows researchers to develop the network of their interest, provided they have 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 roughly constructed in 5 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.'

The library can be installed as using the Python package manager 'pip';

```
pip install sorn
```

To install all optional dependencies,

```
pip install 'sorn[all]'
```

SORN Network Model

Excitatory network state

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

Inhibitory Network state

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

Plasticity Rules

Spike Timing Dependent Plasticity

It alters synaptic efficacy between excitatory neurons based on the spike timing between pre- j and postsynaptic neuron i.

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

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 - Postsynaptic neuron state at t

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.

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

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

It is responsible for creating new synapses between excitatory neurons at a rate of about 1 connection per 10th time step.

Synaptic Scaling

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

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

Inhibitory Spike Timing Dependent Plasticity

iSTDP is responsible for controlling synaptic strengths from the inhibitory to the excitatory network.

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

where,

W_{ij}^{EI} - Synaptic strenght 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 intial state.

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 last 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 (W_{ij}^{EE},W_{ij}^{EI},W_{ij}^{IE}) ,

```
            Excitatory network activity ('E'),

            Inhibitory network activities('I'),

            Threshold values $T^E,T^I$
```

`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,

```
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

Note: If you pass all above options to freeze, then the network will behave as Liquid State Machine(LSM)

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 intialize new network
`time_steps`	`simulaton` total time steps. For `training` should be 1
`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

kwargs	Description
`_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

`sorn` package also includes necessary methods to investigate network properties. Few methods in `Statistics` 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 coeffecient 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 is found at (https://self-organizing-recurrent-neural-networks.readthedocs.io/en/latest/)

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