Meta-learning stabilizes excitatory-excitatory plasticity in spiking neural networks

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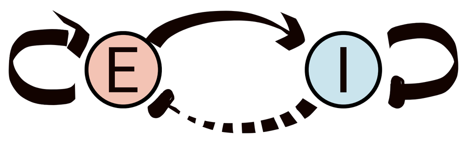
Introduction

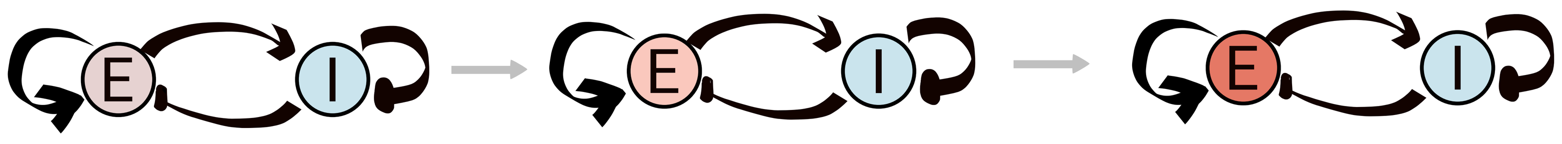
Background

Synaptic plasticity is the activity dependent change in the strength of connections between neurons.

Inhibitory synaptic plasticity is known to provide a homeostatic mechanism to stabilize neural networks[1]

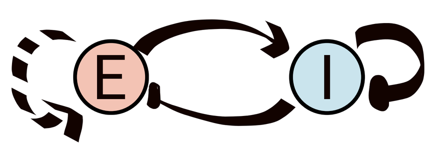


But in the absence of inhibitory plasticity, recurrent excitatory connections can potentially lead to runaway activity.



Question

We let only the excitatory-excitatory connections be plastic and ask if the network can be stable at a fixed firing rate with asynchronous irregular activity.



Attempt

The large search space of parameters and potentially small solution space means that hand tuning is not feasible. We use meta-learning[2][3] to find these parameters automatically.

Methods

Model

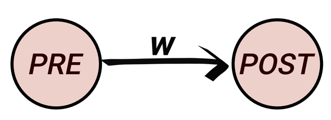
A network of 10,000 randomly connected leaky-integrate-fire neurons where a neuron is either excitatory or inhibitory. Each neuron is governed by the equations :

$$\frac{dv}{dt} = \frac{(V_r - v) + g_e(-v) + g_i(E_{rev} - v) + I_{bg}}{\tau_m}$$
$$\frac{dg_e}{dt} = -\frac{g_e}{\tau_e}$$
$$\frac{dg_i}{dt} = -\frac{g_i}{\tau_i}$$
$$v \geq \theta \implies v \leftarrow V_r \text{ and } g_{post} \leftarrow g_{post} + w$$

Where,
v is the membrane potential of neuron
g_e and g_i are the excitatory and inhibitory conductances
and the rest terms are constants.

Plasticity rule

The weights are updated by the parametrized STDP learning rule[2]:



$$\boxed{\dot{w} = \alpha S_{pre}(t) + \beta S_{post}(t) + \kappa S_{pre}(t) z_{post}(t) + \gamma S_{post}(t) z_{pre}(t)}$$

Where,
$S_i(t) = \sum_f \delta(t - t_i^f) \quad i \in \text{pre, post}$
$\tau_i \dot{z}_i = -z_i$
$z_i \leftarrow z_i + S_i(t)$

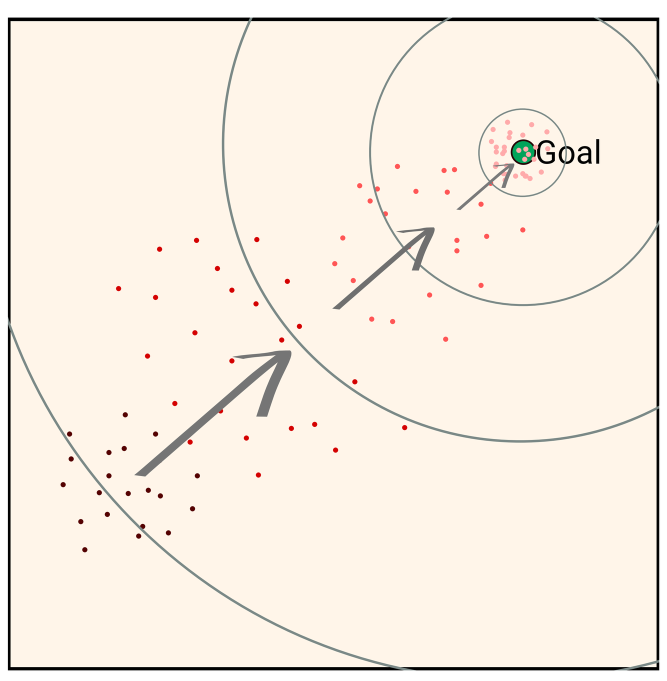
Meta-learning

The parameters of this rule are meta-learned by Covariance Matrix Adaptation Evolutionary Strategy (CMA-ES)

Define a hand-tuned loss function based on desired network properties

$$\boxed{\mathcal{L} = \lambda_1 (r_{tgt} - r)^2 + \lambda_2 (std_{rate}) + \lambda_3 (1 - \langle ISICV \rangle)^2}$$

The loss function is minimized by iteratively sampling the parameters.



Broadly,

1. Sample a population of $(\alpha, \beta, \kappa, \gamma)$ from the normal distribution $N(\mu, C)$
2. Simulate the system and calculate $\mathcal{L}$
3. Update (μ, C) such that the distribution moves towards the best performers of the population
4. Resample the population and repeat until the loss is sufficiently small.

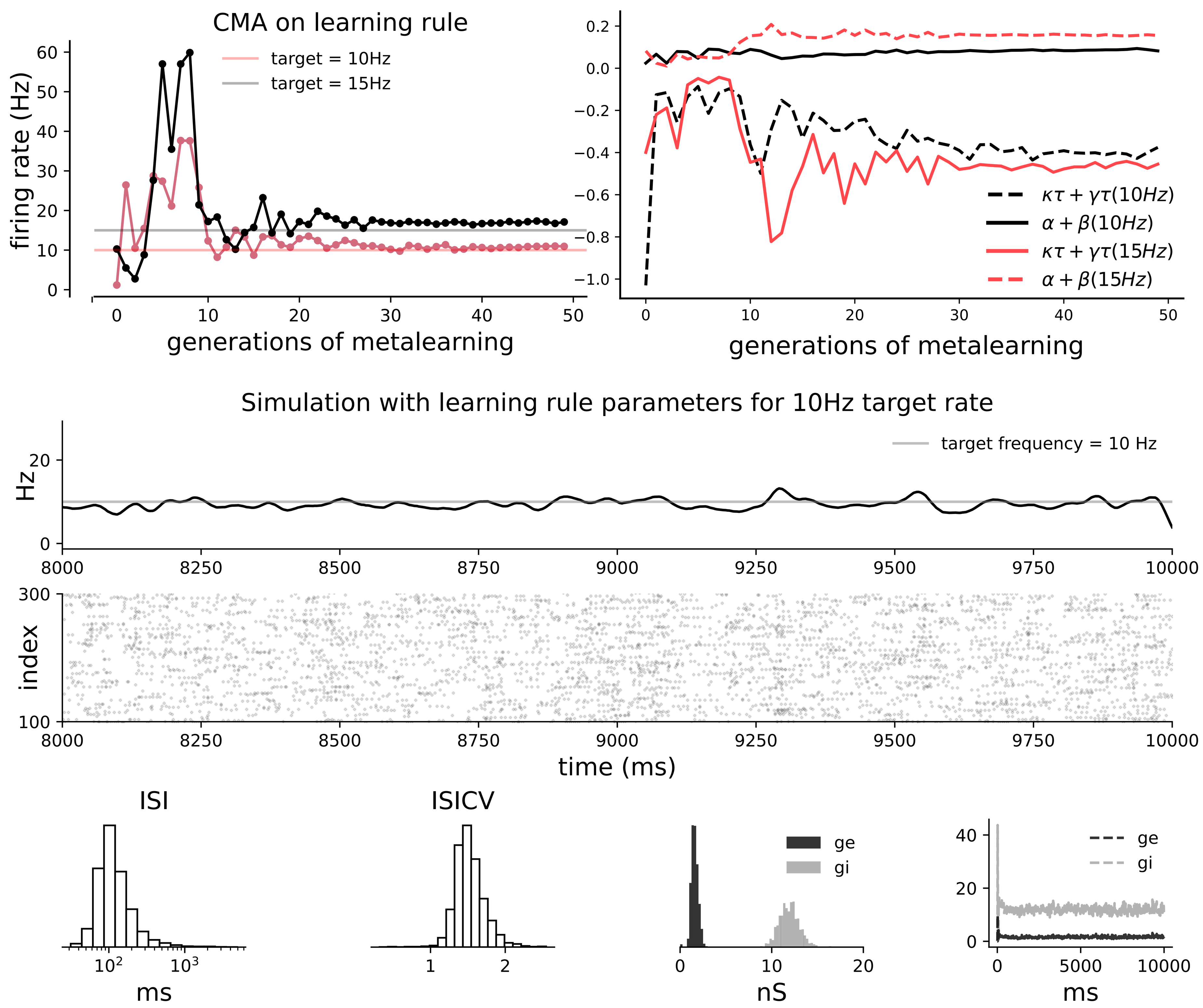
Results

1. Mean field approximations to the learning rule

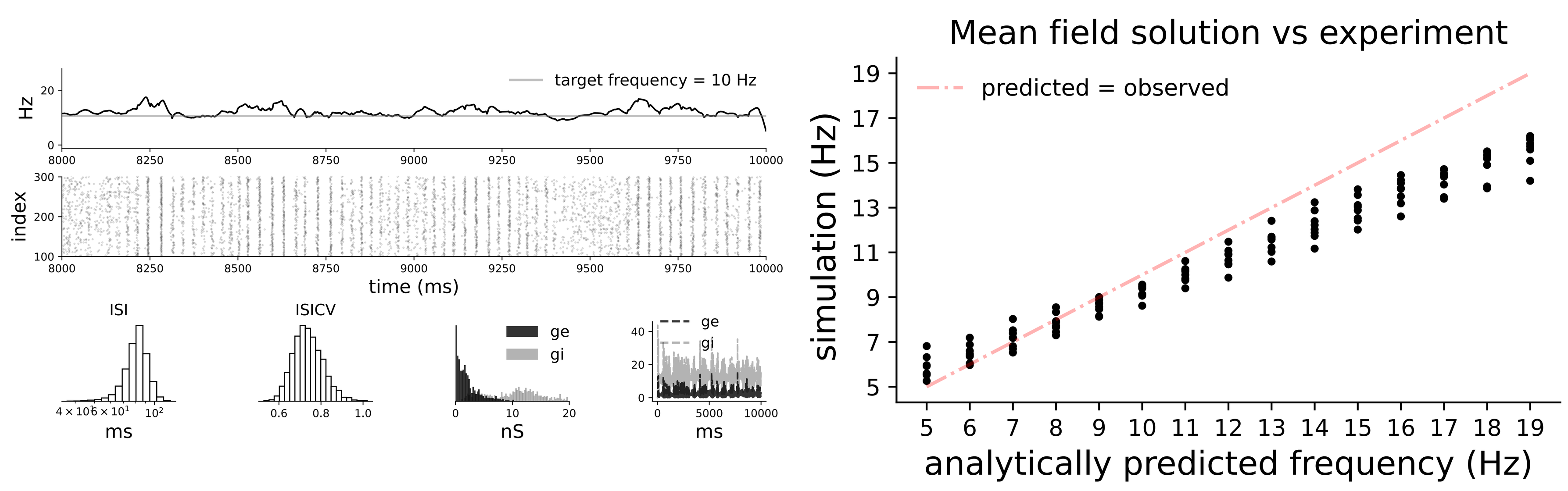
Assuming that: $\frac{d\nu}{dt} \propto \frac{dw}{dt}$, the fixed point of firing rate and stability constraints are given by:

$$\boxed{\nu^* = -\frac{(\alpha+\beta)}{\kappa\tau + \gamma\tau}} \quad \boxed{(\alpha+\beta) > 0 \;\&\; (\kappa\tau + \gamma\tau) < 0}$$

2. CMA-ES finds learning rules that lead to stable network activity at a fixed firing rate and agrees with the mean field constraints on the parameters.



3. Mean field solutions are not necessarily asynchronous irregular. Experiment shows less agreement with mean field solutions at higher target frequencies.



Summary

Excitatory-excitatory plasticity can lead to runaway activity due to positive feedback.

We want to find plasticity rules for E-E connections that lead to stable, asynchronous and irregular activity at a desired firing

Solutions predicted by mean field arguments are not sufficient for desired network activity, thus we meta-learn the parameters by minimizing a loss function by CMA-ES

Meta-learnt rule agrees with the mean field constraints on the parameters, however experiment does not agree with mean field prediction at higher target frequencies.

Future Work and References

Meta-learn more complex tasks, and reduce the dependency on having heuristic terms in the loss function and having to tune it.

Explore the effect of multiple rules acting together in the same network and accomplishing a desired task.

1. Vogels, Tim P., et al. Science (2011)
2. Confavreux, Basile et al. Advances in Neural Information Processing Systems (2020)
3. Hansen, Nikolaus. arXiv preprint (2016).