

Kwabena Boahen Spring 2013

Why build <u>large-scale</u> spiking neural models?

* Qualitatively different behaviors emerge, simply scaling a neural network's size.

* A bee's million-neuron brian can't do what a human's hundred-billion neuron brain can.

* Down-scaling exaggerates the influence of single neurons, introducing spurious correlations and requiring external "noise".

Why build large-scale spiking neural models?

- Although most past models ignore spike-timing, evidence is accumulating that the brain exploits spike-timing (e.g., STDP).
- * Neuroscientists are recording spikes from hundreds of neurons simultaneously, revealing spike-timing correlations and synchrony.
- Only spiking models can account for the brain's noisy and stochastic behavior, which set the ultimate limits on performance.

SPAUN: The state-of-the-art



Eliasmith et al. 2013

* 2.5M-neuron functioning whole brain model

* Performs 8 different task autonomously

Brian Simulator

Random network

```
from brian import *
egs = ' ' '
dv/dt = (ge+gi-(v+49*mV))/(20*ms) : volt
                                                                          300
dge/dt = -ge/(5*ms) : volt
dqi/dt = -qi/(10*ms) : volt
1 1 1
                                                                        Neuron nome
Neuron 1200
P = NeuronGroup(4000, eqs, threshold=-50*mV, reset=-60*mV)
P \cdot v = -60 \times mV + 10 \times mV \times rand(len(P))
Pe = P.subgroup(3200)
Pi = P.subgroup(800)
Ce = Connection(Pe, P, 'ge', weight=1.62*mV, sparseness=0.02)
                                                                          1000
Ci = Connection(Pi, P, 'gi', weight=-9*mV, sparseness=0.02)
M = SpikeMonitor(P)
                                                                          50
run(1*second)
raster plot(M)
                                                                                                     250
                                                                                                               300
show()
                                                                                            200
                                                                                                 Time (ms)
```

* Easy to use: Python-based simulation environment

* Flexible: Interprets mathematical descriptions

Neurogrid Simulator

Spatial Attention Model

Step 1: Describe Neuron Model

```
fef_layer1_soma = Soma("quadratic", {"tau_ref": 1e-3, "tau":
    fef_layer1_neuron = Neuron("quadratic", fef_layer1_soma)
```

Step 2: Describe Network Heirarchy

```
fef_v4_group = Group("FEF V4 Group")
fef_layer1 = Pool(fef_layer1_neuron, width, height)
fef_layer2 = Pool(fef_layer2_neuron, width, height)
v4_layer1 = Pool(v4_layer1_neuron, width, height)
v4_layer2 = Pool(v4_layer2_neuron, width, height)
fef_v4_group.AddChild(fef_layer1)
fef_v4_group.AddChild(fef_layer2)
fef_v4_group.AddChild(v4_layer1)
fef_v4_group.AddChild(v4_layer2)
```

Step 3: Describe Connections

fef_v4_group.VerticalProject(fef_layer1.Output(0), v4_layer1.

64K neurons & 70M synapses



* Powerful: Simulates up to a million neurons connected by billions of synapses in real-time

* Also Python-based—but still buggy!

Oculomotor delayedresponse task



* Introduced in first physiological demonstration of working memory (Funahashi, Bruce & Goldman-Rakic 1989).

* The monkey couldn't move its eyes during the delay period, so it had to remember the cue's location.

Prefrontal cortex recordings



a Stimulus 1 Memory Stimulus 2



Working memory models

 * Early models relied on synaptic plasticity couldn't store novel patterns (Amit & Brunel 1997).

* Lisman, Fellous & Wang (1998) pointed out that including NMDA allows novel patterns to be stored.

* Compte et al. (2000) introduced a ring model with stereotyped connectivity that stored memories in the form of activity bumps.

NMDA Current Kinetics



* CNQX blocks AMPA current * Mg blocks NMDA current * AP5 blocks

FIG. 1 Rebinding of transmitter does not contribute to the duration of the NMDA receptor-mediated e.p.s.c. a, Superimposed records of e.p.s.cs recorded in control medium and the presence of 2.5 µM CNQX that selectively blocked the fast component (each trace is an average of 10 responses). b, Diagram of the flow pipe apparatus used to switch the superfusate in the synaptic field. Solution changes were effected by closing the flow pipe containing control medium 20 ms before the adjacent drug-containing pipe was opened. Medium from only one pipe was flowing at a time. c, The flow pipe containing Mg²⁺ was opened for 400 ms at 140, 100, 60 and 20 ms (arrows) after the beginning of each trial as determined by tip potential changes measured after the experiment. The presynaptic neuron was always stimulated at 60 ms. Individual trials were separated by 5 s. The e.p.s.cs recorded in control medium and during Mg²⁺ application are superimposed. d, The same paradigm as in c was used except AP5 (100 μ M) was substituted for Mg²⁺. Traces in c and d were recorded in the presence of 5 μ M CNQX and are each an average of 3-5 trials.

NMPA current

Friday, April 5, 13



Friday, April 5, 13

Feedback C recurrent ofk with NMPA



Friday, April 5, 13

rrent



Ring network simulation



Summary of results



* Bump is cued (C) by focal external input

- * Bump converges to a fixed size that matches E-E profile
- * Bump drifts during delay period (D) due to noise and heterogeneity

* Bump is extinguished (R) by diffuse external input —recruits inhibition

Matches experimental data



Dynamical systems' view

Point Attractor

Line Attractor





* Decision making: How do neurons evaluate sensory evidence to make the right choice?