Brian 2 An Intuitive & Efficient Neural Simulator

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Overview

- Introduction
- Design implementation
- Case study 1: Pyloric network
- Case study 2: Ocular model
- Case study 3: Threshold finding
- Case study 4: Real-time audio
- Drawbacks

Introduction

Want your simulator to attract as many neuro-researchers as possible.

Performance

Is it *benefiting* from:

- Vectorization techniques
- Pre-compiled models

Flexibility

Is it *easy* to define:

- Non-standard models
- Arbitrary protocols

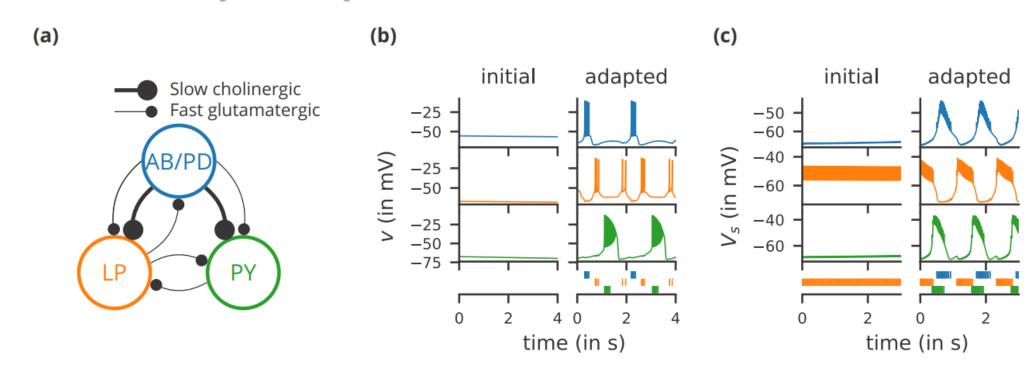
Brian 2 solves this trade-off.

- > Flexibility: User-written Python script
 - No limit on the experiment structure
- ➤ Performance: Code generation
 - Transform high-level model into low-level executable code

Design Implementation

- 1. Non-standard models
 - Mathematical equations should be explicitly written.
- 2. Complete computational experiment
 - Models must interact with general control flow.
- 3. Efficient code generation
 - Generated code can integrate into the simulation flow.
- 4. Extensibility of code
 - Code can be extended either at high- or low-level.

Case Study 1: Pyloric Network



Generate a stereotypical triphasic motor pattern.

- (a) Circuit schematic
- (b) Simulated neuron activity
- (c) Simulated neuron activity (biologically detailed)

```
from brian2 import *
defaultclock.dt = 0.01*ms;
3 Delta_T = 17.5*mV
                          v_T = -40*mV
                                              : tau = 2*ms
                                                                   ; tau_adapt = .02*second
4 tau_Ca = 150*ms
                          ; tau_x = 2*second ; v_r = -68*mV
                                                                   ; tau_z = 5*second
5 a = 1/Delta_T**3
                          ; b = 3/Delta_T**2 ; c = 1.2*nA
                                                                   ; d = 2.5*nA/Delta_T**2
                          S = 2*nA/Delta_T ; G = 28.5*nS
6 \quad C = 60*pF
9 dw/dt = (c - d*(v - v_T)**2 - w)/tau : amp
10 	 dx/dt = (s*(v - v_r) - x)/tau_x : amp
s = S*(1 - tanh(z)) : siemens
g = G*(1 + tanh(z)) : siemens
i3 dCa/dt = -Ca/tau_Ca : 1
14 dz/dt = tanh(Ca - Ca_target)/tau_z : 1
16 I_slow: amp
17 Ca_target : 1 (constant)
18 label : integer (constant)
20 ABPD, LP, PY = 0, 1, 2
circuit = NeuronGroup(3, eqs, threshold='v>-20*mV', refractory='v>-20*mV', reset='Ca += 0.1',
                        method='rk2')
23 circuit.label = [ABPD, LP, PY]
24 circuit.v = v_r
25    circuit.w = '-5*nA*rand()'
26 circuit.z = 'rand()*0.2 - 0.1'
27 circuit.Ca_target = [0.048, 0.0384, 0.06]
29 s_fast = 0.2/mV; V_fast = -50*mV; E_syn = -75*mV
30 eqs_fast = '''
31 g_fast : siemens (constant)
32 I_fast_post = g_fast*(v_post - E_syn)/(1+exp(s_fast*(V_fast-v_pre))) : amp (summed)
34 fast_synapses = Synapses(circuit, circuit, model=eqs_fast)
35 fast_synapses.connect('label_pre != label_post and not (label_pre == PY and label_post == ABPD)')
36 fast_synapses.g_fast['label_pre == ABPD and label_post == LP'] = 0.015*uS
37 fast_synapses.g_fast['label_pre == ABPD and label_post == PY'] = 0.005*uS
38 fast_synapses.g_fast['label_pre == LP and label_post == ABPD'] = 0.01*uS
39 fast_synapses.g_fast['label_pre == LP and label_post == PY'] = 0.02*uS
40 fast_synapses.g_fast['label_pre == PY and label_post == LP'] = 0.005*uS
42 s_slow = 1/mV; V_slow = -55*mV; k_1 = 1/ms
43 eqs_slow = '''
44 k_2 : 1/second (constant)
45 g slow : siemens (constant)
46 I_slow_post = g_slow*m_slow*(v_post-E_syn) : amp (summed)
47 dm_slow/dt = k_1*(1-m_slow)/(1+exp(s_slow*(V_slow-v_pre))) - k_2*m_slow : 1 (clock-driven)
49 slow_synapses = Synapses(circuit, circuit, model=eqs_slow, method='exact')
slow_synapses.connect('label_pre == ABPD and label_post != ABPD')
slow_synapses.g_slow['label_post == LP'] = 0.025*uS
slow_synapses.k_2['label_post == LP'] = 0.03/ms
slow_synapses.g_slow['label_post == PY'] = 0.015*uS
slow_synapses.k_2['label_post == PY'] = 0.008/ms
56 run(59.5*second)
```

```
dv/dt = (Delta_T*g*(-a*(v - v_T)**3 + b*(v - v_T)**2) + w - x - I_fast - I_slow)/C : volt
dw/dt = (c - d*(v - v_T)**2 - w)/tau : amp
dx/dt = (s*(v - v_r) - x)/tau_x : amp

Neuron model is written in differential equation.
```

```
Calcium trace decays.
```

```
circuit = NeuronGroup(3, eqs, threshold='v>-20*mV', refractory='v>-20*mV', reset='Ca += 0.1',
method='rk2')

Calcium trace increases at each spike.
```

Conductances are regulated by trace difference.

```
from brian2 import *
defaultclock.dt = 0.01*ms;
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                          v_T = -40*mV
                                              ; tau = 2*ms
                                                                   ; tau_adapt = .02*second
4 tau_Ca = 150*ms
                          ; tau_x = 2*second ; v_r = -68*mV
                                                                   ; tau_z = 5*second
5 a = 1/Delta_T**3
                          ; b = 3/Delta_T**2 ; c = 1.2*nA
                                                                   ; d = 2.5*nA/Delta_T**2
                          S = 2*nA/Delta_T ; G = 28.5*nS
6 \quad C = 60*pF
9 dw/dt = (c - d*(v - v_T)**2 - w)/tau : amp
10 	 dx/dt = (s*(v - v_r) - x)/tau_x : amp
s = S*(1 - tanh(z)) : siemens
g = G*(1 + tanh(z)) : siemens
i3 dCa/dt = -Ca/tau_Ca : 1
i4 dz/dt = tanh(Ca - Ca_target)/tau_z : 1
16 I_slow: amp
17 Ca_target : 1 (constant)
18 label : integer (constant)
20 ABPD, LP, PY = 0, 1, 2
circuit = NeuronGroup(3, eqs, threshold='v>-20*mV', refractory='v>-20*mV', reset='Ca += 0.1',
                        method='rk2')
23 circuit.label = [ABPD, LP, PY]
24 circuit.v = v_r
25 circuit.w = '-5*nA*rand()'
26 circuit.z = 'rand()*0.2 - 0.1'
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30 eqs_fast = '''
31 g_fast : siemens (constant)
32 I_fast_post = g_fast*(v_post - E_syn)/(1+exp(s_fast*(V_fast-v_pre))) : amp (summed)
34 fast_synapses = Synapses(circuit, circuit, model=eqs_fast)
35 fast_synapses.connect('label_pre != label_post and not (label_pre == PY and label_post == ABPD)')
36 fast_synapses.g_fast['label_pre == ABPD and label_post == LP'] = 0.015*uS
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38 fast_synapses.g_fast['label_pre == LP and label_post == ABPD'] = 0.01*uS
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slow_synapses.k_2['label_post == LP'] = 0.03/ms
slow_synapses.g_slow['label_post == PY'] = 0.015*uS
slow_synapses.k_2['label_post == PY'] = 0.008/ms
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fast_synapses = Synapses(circuit, circuit, model=eqs_fast)

Nonlinear (graded) fast synapse
```

```
s_slow = 1/mV; V_slow = -55*mV; k_1 = 1/ms
eqs_slow = '''

k_2 : 1/second (constant)

I_slow_post = g_slow*m_slow*(v_post-E_syn) : amp (summed)

dm_slow/dt = k_1*(1-m_slow)/(1+exp(s_slow*(V_slow-v_pre))) - k_2*m_slow : 1 (clock-driven)

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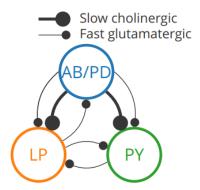
Nonlinear (graded) slow synapse
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slow_synapses.k_2['label_post == PY'] = 0.008/ms
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fast_synapses.g_fast['label_pre == LP and label_post == PY'] = 0.02*uS
fast_synapses.g_fast['label_pre == PY and label_post == LP'] = 0.005*uS

slow_synapses.g_fast['label_post == LP'] = 0.025*uS
slow_synapses.k_2['label_post == LP'] = 0.03/ms
slow_synapses.g_slow['label_post == PY'] = 0.015*uS
slow_synapses.k_2['label_post == PY'] = 0.008/ms

Set up initial values.
```



```
fast_synapses.connect('label_pre != label_post and not (label_pre == PY and label_post == ABPD)')

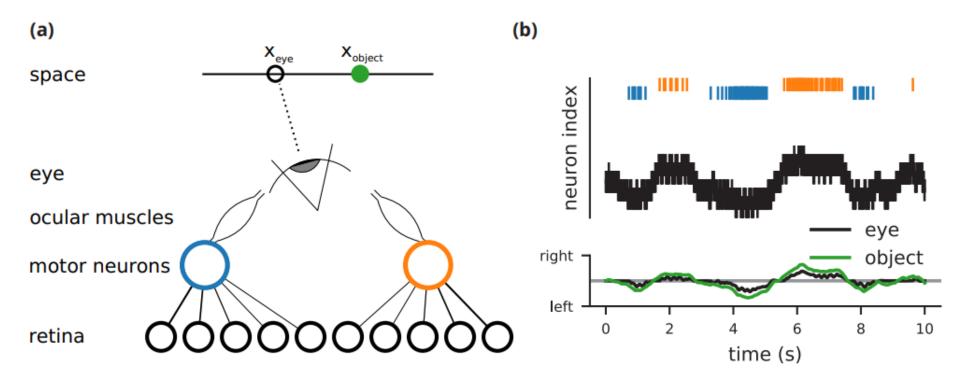
slow_synapses.connect('label_pre == ABPD and label_post != ABPD')

Connectivity pattern
```

Comparison to other approaches

- ➤ Implement in a language like C++?
 - Requires significant technical skill
 - Justified if iteration is done thousands of times
 - Difficult to adapt for other purposes
- ➤ Use description language such as LEMS / NeuroML2?
 - Like Brian2, but somewhat more verbose
- ➤ Use NMODL language in NEURON simulator?
 - Requires learning new language
- ➤ Use NESTML language in NEST simulator?
 - Doesn't support graded synapse

Case Study 2: Ocular Model



Two antagonistic muscles are modelled mechanically as elastic spring with friction.

- (a) Circuit schematic
- (b) Simulated activity of sensory neurons (black) & motor neurons (blue, orange)

```
1 from brian2 import *
   alpha = (1/(50*ms))**2; beta = 1/(50*ms); tau_muscle = 20*ms; tau_object = 500*ms
   eqs_eye = '''dx/dt = velocity : 1
                dvelocity/dt = alpha*(x0-x)-beta*velocity : 1/second
                dx0/dt = -x0/tau_muscle : 1
                dx_object/dt = (noise - x_object)/tau_object: 1
                dnoise/dt = -noise/tau_object + tau_object**-0.5*xi : 1'''
   eve = NeuronGroup(1, model=eqs_eve, method='euler')
   motoneurons = NeuronGroup(2, model='dv/dt = -v/taum : 1', threshold='v>1', reset='v=0',
                             refractory=5*ms, method='exact')
   motosynapses = Synapses(motoneurons, eye, model='w : 1', on_pre='x0_post += w')
   motosynapses.connect() # connects all motoneurons to the eye
   motosynapses.w = [-0.5, 0.5]
   N = 20; width = 2./N; gain = 4.
   eqs_retina = '''dv/dt = (I-(1+gs)*v)/taum : 1
                   I = gain*exp(-((x_object-x_eye-x_neuron)/width)**2) : 1
                   x_neuron : 1 (constant)
                   x_object : 1 (linked) # position of the object
                   x_eye : 1 (linked) # position of the eye
                   gs : 1 # total synaptic conductance'''
   retina = NeuronGroup(N, model=eqs_retina, threshold='v>1', reset='v=0', method='exact')
   retina.v = 'rand()'
   retina.x_eye = linked_var(eye, 'x')
   retina.x_object = linked_var(eye, 'x_object')
   retina.x_neuron = '-1.0 + 2.0*i/(N-1)'
   sensorimotor_synapses = Synapses(retina, motoneurons, model='w : 1 (constant)',
                                    on_pre='v_post += w')
   sensorimotor_synapses.connect(j='int(x_neuron_pre > 0)')
   # Strength scales with eccentricity:
   sensorimotor_synapses.w = '20*abs(x_neuron_pre)/N_pre'
38 run(10*second)
```

```
eqs_eye = '''dx/dt = velocity : 1
dvelocity/dt = alpha*(x0-x)-beta*velocity : 1/second
dx0/dt = -x0/tau_muscle : 1

Position of eye follows 2<sup>nd</sup>-order differential equation.
```

```
dx_object/dt = (noise - x_object)/tau_object: 1

dnoise/dt = -noise/tau_object + tau_object**-0.5*xi : 1'''

Stimulus moves in a stochastic process.
```

```
taum = 20*ms
motoneurons = NeuronGroup(2, model='dv/dt = -v/taum : 1', threshold='v>1', reset='v=0',
refractory=5*ms, method='exact')

Muscles are controlled by two motoneurons.
```

```
1 from brian2 import *
   alpha = (1/(50*ms))**2; beta = 1/(50*ms); tau_muscle = 20*ms; tau_object = 500*ms
   eqs_eye = '''dx/dt = velocity : 1
                dvelocity/dt = alpha*(x0-x)-beta*velocity : 1/second
                dx0/dt = -x0/tau_muscle : 1
                dx_object/dt = (noise - x_object)/tau_object: 1
                dnoise/dt = -noise/tau_object + tau_object**-0.5*xi : 1'''
   eye = NeuronGroup(1, model=eqs_eye, method='euler')
   motoneurons = NeuronGroup(2, model='dv/dt = -v/taum : 1', threshold='v>1', reset='v=0',
                             refractory=5*ms, method='exact')
   motosynapses = Synapses(motoneurons, eye, model='w : 1', on_pre='x0_post += w')
   motosynapses.connect() # connects all motoneurons to the eye
   motosynapses.w = [-0.5, 0.5]
   N = 20; width = 2./N; gain = 4.
   eqs_retina = '''dv/dt = (I-(1+gs)*v)/taum : 1
                   I = gain*exp(-((x_object-x_eye-x_neuron)/width)**2) : 1
                   x_neuron : 1 (constant)
                   x_object : 1 (linked) # position of the object
                   x_eye : 1 (linked) # position of the eye
                   gs : 1 # total synaptic conductance'''
   retina = NeuronGroup(N, model=eqs_retina, threshold='v>1', reset='v=0', method='exact')
   retina.v = 'rand()'
   retina.x_eye = linked_var(eye, 'x')
   retina.x_object = linked_var(eye, 'x_object')
   retina.x_neuron = '-1.0 + 2.0*i/(N-1)'
   sensorimotor_synapses = Synapses(retina, motoneurons, model='w : 1 (constant)',
                                    on_pre='v_post += w')
   sensorimotor_synapses.connect(j='int(x_neuron_pre > 0)')
   # Strength scales with eccentricity:
   sensorimotor_synapses.w = '20*abs(x_neuron_pre)/N_pre'
38 run(10*second)
```

```
eqs_retina = '''dv/dt = (I-(1+gs)*v)/taum : 1

I = gain*exp(-((x_object-x_eye-x_neuron)/width)**2) : 1

Retinal neurons receive visual input.
```

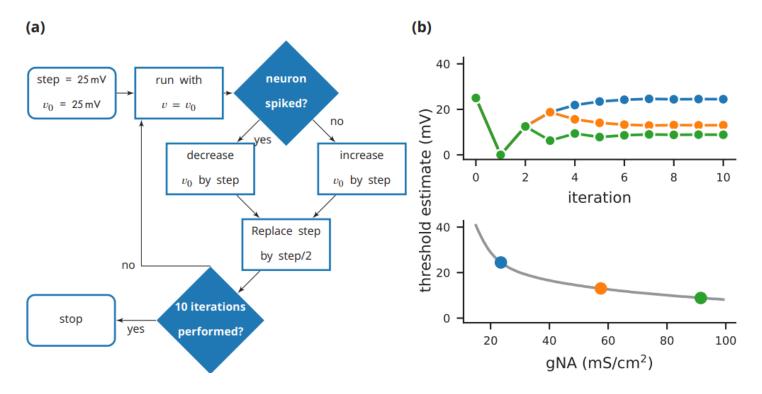
```
sensorimotor_synapses = Synapses(retina, motoneurons, model='w : 1 (constant)',
on_pre='v_post += w')
```

Retinal neurons project on motoneuron to control muscle.

Comparison to other approaches

- ➤ Use language such as LEMS / NeuroML2 / NMODL?
 - Same as "Case Study 1"
- ➤ Use NESTML language in NEST simulator?
 - Doesn't support continuous interaction between single environment & multiple neurons

Case Study 3: Threshold Finding



Determine the voltage firing threshold of a neuron.

- (a) Flowchart of bisection algorithm
- (b) Refinement of threshold over iterations (three different Na densities)

```
from brian2 import *
 defaultclock.dt = 0.01*ms
 4 El = 10.613*mV; ENa = 115*mV; EK = -12*mV
 5 gl = 0.3*mS/cm**2; gK = 36*mS/cm**2; C = 1*uF/cm**2
   gNa_min = 15*mS/cm**2; gNa_max = 100*mS/cm**2
        = '''dv/dt = (gl*(El - v) + gNa*m**3*h*(ENa - v) + gK*n**4*(EK - v)) / C : volt
             gNa : siemens/meter**2
            dm/dt = alpham*(1 - m) - betam*m : 1
            dn/dt = alphan*(1 - n) - betan*n : 1
            dh/dt = alphah*(1 - h) - betah*h : 1
            alpham = (0.1/mV)*(-v + 25*mV)/(exp((-v + 25*mV))/(10*mV)) - 1)/ms : Hz
            betam = 4 * \exp(-v/(18*mV))/ms : Hz
            alphah = 0.07 * exp(-v/(20*mV))/ms : Hz
            betah = 1/(\exp((-v+30*mV) / (10*mV)) + 1)/ms : Hz
            alphan = (0.01/mV) * (-v+10*mV) / (exp((-v+10*mV) / (10*mV)) - 1)/ms : Hz
            betan = 0.125*exp(-v/(80*mV))/ms : Hz'''
   neurons = NeuronGroup(100, eqs, threshold='v > 50*mV', method='exponential_euler')
   neurons.gNa = 'gNa_min + (gNa_max - gNa_min)*1.0*i/N'
   neurons.v = 0*mV
   neurons.m = '1/(1 + betam/alpham)'
   neurons.n = '1/(1 + betan/alphan)'
   neurons.h = '1/(1 + betah/alphah)'
25 S = SpikeMonitor(neurons)
   # We locate the threshold by bisection
        25*mV*ones(len(neurons))
31 step = 25*mV
33 for i in range(10):
        restore()
        neurons.v = v0
        run(20*ms)
        v0[S.count == 0] += step
        v0[S.count > 0] -= step
        step /= 2.0
```

```
30  v0 = 25*mV*ones(len(neurons))
31  step = 25*mV
```

Set initial estimate and step width.

```
\begin{array}{c} \text{step = 25\,mV} \\ v_0 = 25\,\text{mV} \\ \end{array} \begin{array}{c} \text{run with} \\ v = v_0 \\ \end{array} \begin{array}{c} \text{no} \\ \text{spiked?} \\ \text{no} \\ \end{array} \begin{array}{c} \text{no} \\ \text{decrease} \\ v_0 \text{ by step} \\ \end{array} \begin{array}{c} \text{no} \\ \text{stop} \\ \end{array} \begin{array}{c} \text{stop} \\ \text{yes} \\ \end{array} \begin{array}{c} \text{10 iterations} \\ \text{performed?} \\ \end{array}
```

```
for i in range(10):
    restore()
    neurons.v = v0
    run(20*ms)
    v0[S.count == 0] += step
    v0[S.count > 0] -= step
    step /= 2.0
```

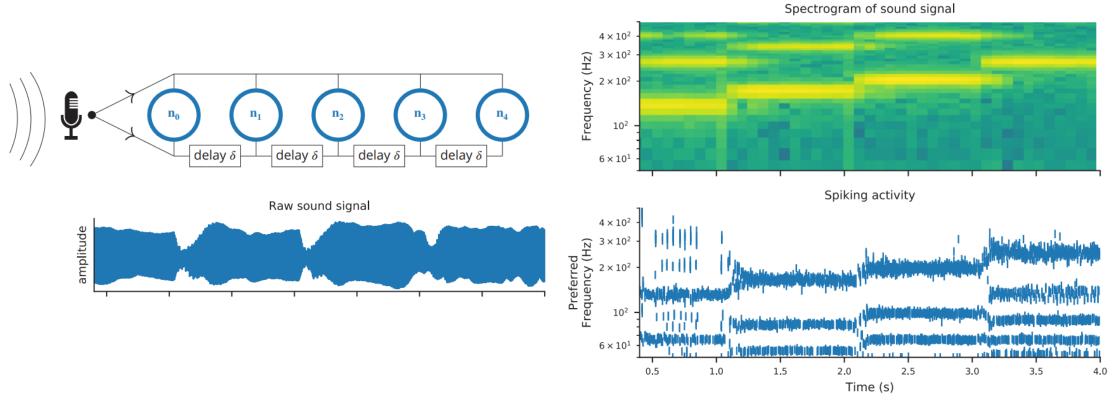
Perform the bisection for a certain #iteration.

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Comparison to other approaches

- ➤ Use language such as LEMS / NeuroML2?
 - Can only specify duration and step size
- ➤ Use NEST simulator?
 - Like Brian2; use SLI or Python
- ➤ Use NEURON simulator?
 - Like Brian2; use HOC or Python

Case Study 4: Real-time Audio



Detect the pitch based on autocorrelation of a signal.

ss run(10*second)

```
from brian2 import *
set_device('cpp_standalone')
   sample_rate = 48*kHz; buffer_size = 128; defaultclock.dt = 1/sample_rate
  max_delay = 20*ms; tau_ear = 1*ms; tau_th = 5*ms
   min_freq = 50*Hz; max_freq = 1000*Hz; num_neurons = 300; tau = 1*ms; sigma = .1
   @implementation('cpp'.'''
  PaStream *_init_stream() {
       PaStream* stream:
       Pa_Initialize();
       Pa_OpenDefaultStream(&stream, 1, 0, paFloat32, SAMPLE_RATE, BUFFER_SIZE, NULL, NULL);
       Pa_StartStream(stream);
       return stream;
  float get_sample(const double t) {
       static PaStream* stream = _init_stream();
       static float buffer [BUFFER_SIZE];
       static int next_sample = BUFFER_SIZE;
       if (next_sample >= BUFFER_SIZE)
          Pa_ReadStream(stream, buffer, BUFFER_SIZE);
           next_sample = 0;
       return buffer[next_sample++];
   }''', libraries=['portaudio'], headers=['<portaudio.h>'],
         define_macros=[('BUFFER_SIZE', buffer_size),
                        ('SAMPLE_RATE', sample_rate)])
   @check_units(t=second, result=1)
       raise NotImplementedError('Use a C++-based code generation target.')
   eqs_ear = '''dx/dt = (sound - x)/tau_ear: 1 (unless refractory)
                dth/dt = (0.1*x - th)/tau th : 1
                sound = clip(get_sample(t), 0, inf) : 1 (constant over dt)'''
   receptors = NeuronGroup(1, eqs_ear, threshold='x>th',
                           reset='x=0; th = th*2.5 + 0.01'.
                           refractory=2*ms, method='exact')
  receptors.th = 1
   eqs_neurons = '''dv/dt = -v/tau+sigma*(2./tau)**.5*xi : 1
                    freq : Hz (constant) '''
   neurons = NeuronGroup(num_neurons, eqs_neurons, threshold='v>1', reset='v=0', method='euler')
   neurons.freq = 'exp(log(min_freq/Hz)+(i*1.0/(num_neurons-1))*log(max_freq/min_freq))*Hz
   synapses = Synapses(receptors, neurons, on_pre='v += 0.5', multisynaptic_index='k')
   synapses.connect(n=2) # one synapse without delay; one with delay
   synapses.delay['k == 1'] = '1/freq_post'
```

Two modes:

(1) Runtime mode:

- Python controls overall simulation.
- It calls compiled code objects to do heavy lifting.
- Overhead: Repeated switching from Python to another language
 - Justified if flexibility is preferred

(2) Standalone mode:

- Low-level code is generated.
- It controls overall simulation.
- Able to generate code for target platform (GPU)

Comparison to other approaches

- ➤ Use language such as LEMS / NeuroML2?
 - Not possible
- ➤ Use NEST simulator?
 - Utilize MUSIC framework to couple multiple simulators
 - Cannot apply continuous-valued inputs
- ➤ Use NEURON simulator?
 - Can include user-written C code
 - No documented mechanism to link external libraries

Drawbacks

1. Explicit model definitions

- Difficult to design tools to programmatically inspect a model
 - Rebuttal: Reduce risk of difference between implementation & description

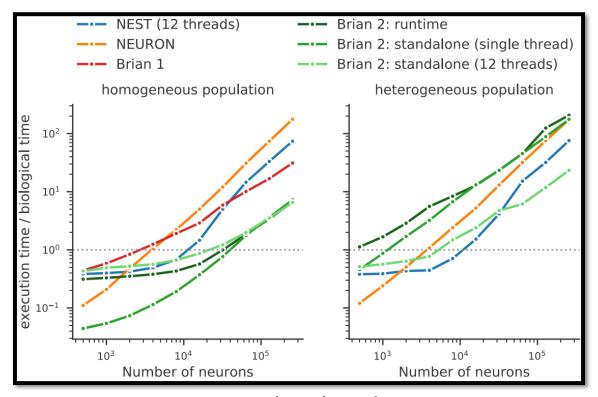
2. Tightly integrated simulation flow

- Difficult to reuse or programmatically compare a model
 - Rebuttal: Reduce complexity & chance of errors

3. No scaling up

- Lack of support for running large networks over multiple machines
 - Rebuttal: Most people use smaller networks for parameter exploration.

- 4. Rudimentary multi-compartmental models
 - Not as mature as NEURON or GENESIS simulator
- 5. Automated optimization techniques
 - Generate optimization for specialization of models



CUBA benchmark

Questions?
Comments?
Concerns?