Neuron and synapse models in NESTML:
From specification to simulation

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JÜLICH
Forschungszentrum
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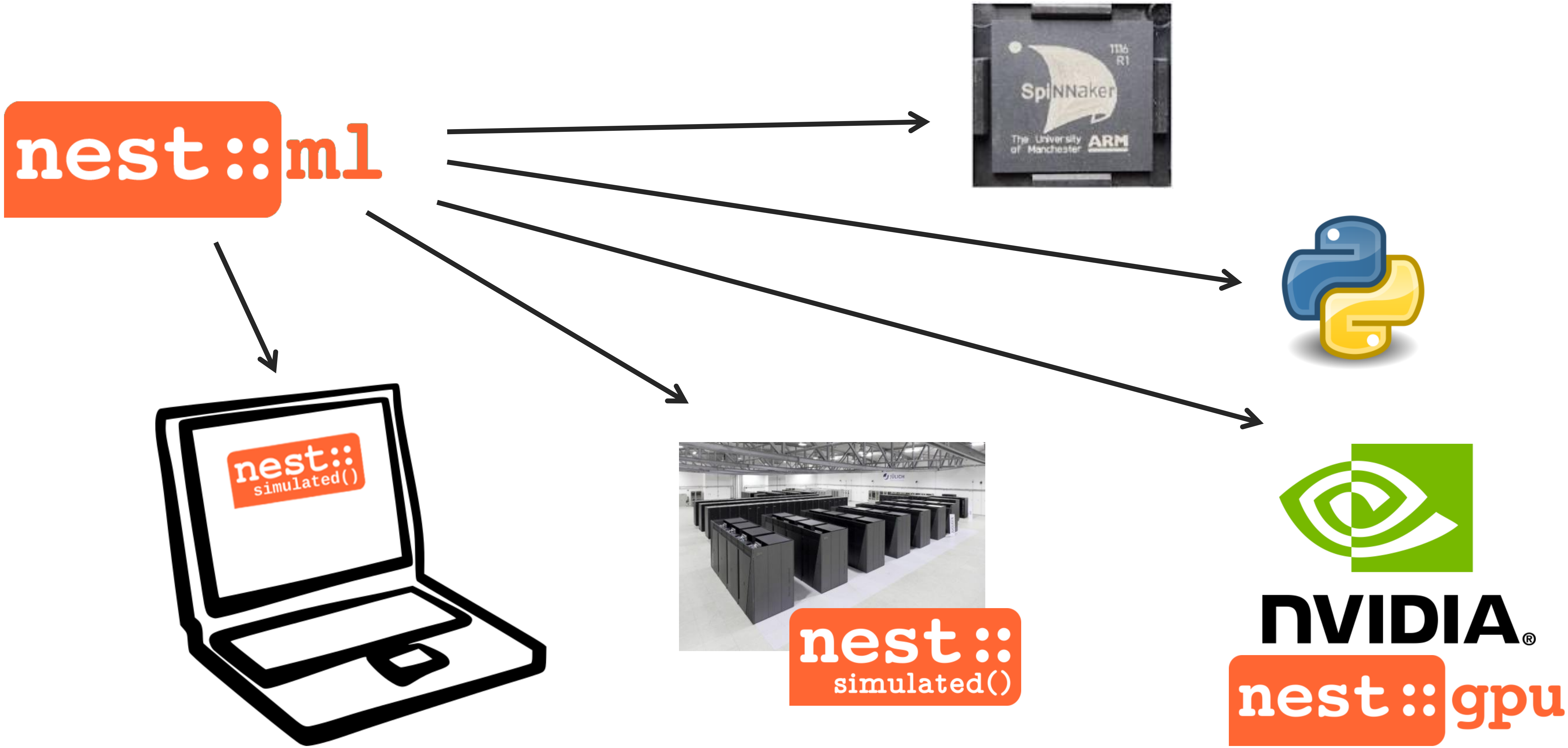
Image credit: (c) S. Spreizer

NESTML AUGMENTS THE SIMULATION ENGINE



WHY NESTML?

NESTML is a **domain-specific modeling language** for the dynamical simulation of point neurons (spiking and rate-based), as well as synapses and synaptic plasticity rules.

- Low on boilerplate; concise yet precise and expressive syntax
- Direct language support for (spike) events, differential equations and algorithms
- NESTML models library contains a variety of neuron models and (third factor) synaptic plasticity rules

NESTML comes with a **code generation** toolbox.

- Code generation (model definition but not instantiation)
- Automated ODE analysis and solver selection
- Flexible addition of targets using Jinja templates
- Automated testing (CI): models are behaviorally validated in simulation runs

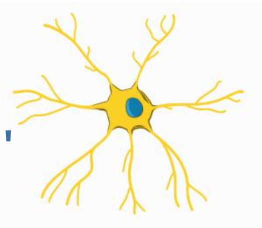
nest::ml

NESTML WORKFLOW FOR NEST

nest::simulated()

```
>>> import nest
>>> nest.Install('my_nestml_module')
>>> pre, post = nest.Create('my_hodgkin_huxley', 100)
>>> nest.Connect(pre, post,
     'all_to_all', syn_spec={'synapse_model': 'my_stdp'})
>>> nest.Simulate(1000)
```

'my_hodgkin_huxley'



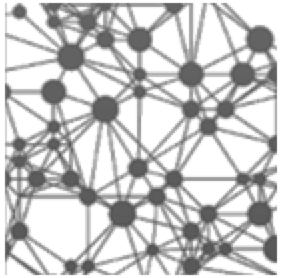
nest::ml
neuron model

nest::ml
synapse model

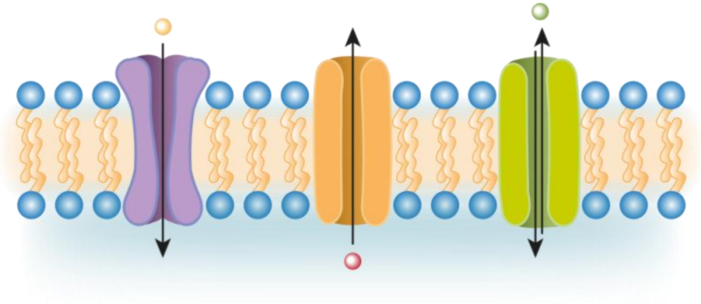
'my_stdp'

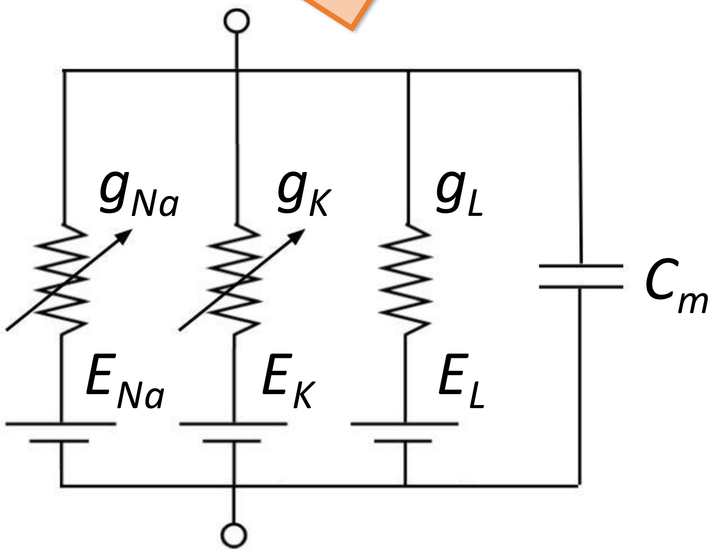
→ PyNESTML → Generated and compiled code → Simulation

Simulation script ↓ Simulation



A NEURON MODEL IN NESTML






```
neuron hodgkin_huxley:
  state:
    V_m mV = -65 mV     # membrane voltage
    Act_m, Act_n, Inact_h [...]

  equations:
    kernel syn_kernel = exp(-t / tau_syn)         # postsynaptic kernel
    inline I_Na pA = g_Na * Act_m**3 * Inact_h * (V_m - E_Na)
    inline I_K pA = g_K * Act_n**4 * (V_m - E_K)
    inline I_L pA = g_L * (V_m - E_L)
    Act_n' = (alpha_n(V_m) * (1 - Act_n) - beta_n(V_m) * Act_n) / ms
    Act_m' = (alpha_m(V_m) * (1 - Act_m) - beta_m(V_m) * Act_m) / ms
    Inact_h' = (alpha_h(V_m) * (1 - Inact_h) - beta_h(V_m) * Inact_h) / ms
    V_m' = -(I_Na + I_K + I_L) / C_m + convolve(syn_kernel, spikes)

  function alpha_n(V_m mV) real:
    return -0.05 * (V_m / mV + 34.) / (exp(-.1 * (V_m / mV + 34.)) - 1.)

  function alpha_m(V_m mV) real:
    [...]

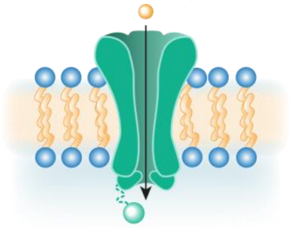
  parameters:
    C_m pF = 250 pF
    V_threshold mV = 40 mV
    [...]

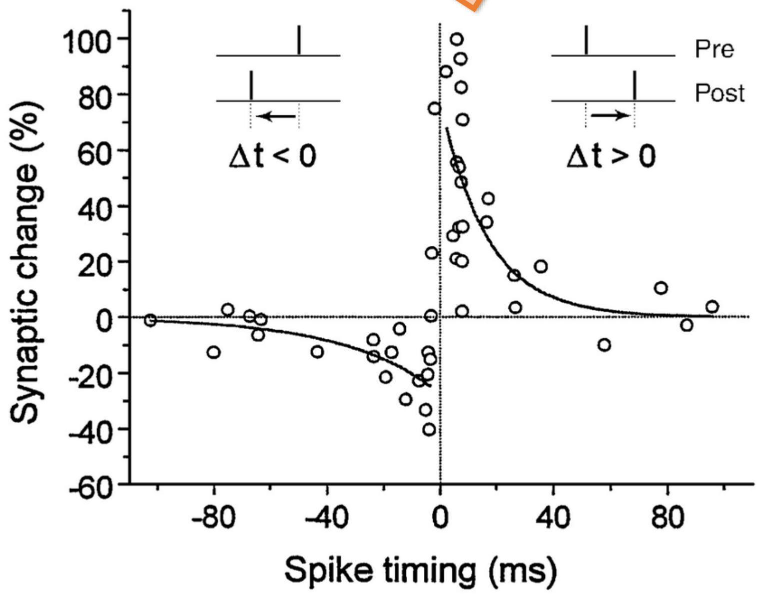
  update:
    integrate_odes()
    if V_m >= V_threshold:
      emit_spike()
```

Image credit: (c) S.B.C. Lehmann, FZ Jülich, (m) C. Linssen

A MODEL OF SYNAPTIC PLASTICITY

NMDA (Ca^{2+})





nest::ml

```
synapse stdp:
  state:
    w real = 1
    tr_post real = 0
    tr_pre real = 0

  equations:
    tr_pre' = -tr_pre / tau_tr
    tr_post' = -tr_post / tau_tr

  input:
    pre_spikes real <- spike
    post_spikes real <- spike

  onReceive(pre_spikes):
    w -= alpha * tr_post          # depress synapse
    tr_pre += 1                   # update presynaptic trace
    deliver_spike(w, delay)       # to postsynaptic partner

  onReceive(post_spikes):
    w += alpha * tr_pre           # potentiate synapse
    tr_post += 1                  # update postsynaptic trace

  parameters:
    delay ms = 1 ms               # dendritic delay
    tau_tr ms = 50 ms             # pre/post trace time const.
    alpha real = .02              # learning rate
```

Image credit: (c) S.B.C. Lehmann, FZ Jülich, (m) C. Linssen; Bi & Poo 2001

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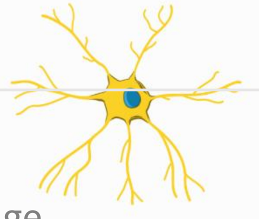

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  state:
    V_m mV = -65 mV    # membrane voltage
    Act_m, Act_n, Inact_h [...]

  equations:
    kernel syn_kernel = exp(-t / tau_syn)
    inline I_Na pA = g_Na * Act_m**3 * [...]
    V_m' = -(I_Na + I_K + I_L) / C_m + [...]

  function alpha_n(V_m mV) real:
    return -0.05 * (V_m / mV + 34.) / (exp(-.1 *
(V_m / mV + 34.)) - 1.)

  parameters:
    C_m pF = 250 pF
    V_threshold mV = 40 mV
    [...]

  update:
    integrate_odes()
    if V_m >= V_threshold:
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nest::ml

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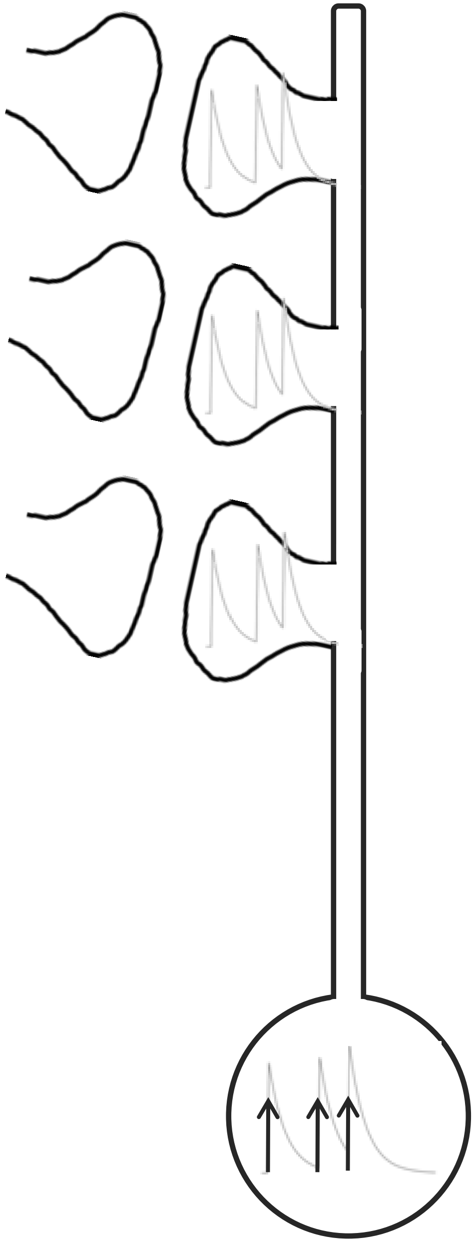
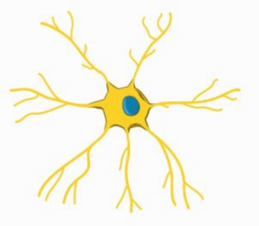
Postsynaptic activity trace is specified in synapse model...



... but needs to be simulated as part of the neuron model to avoid redundant computations.

nest::ml



```
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  state:
    V_m mV = -65 mV    # memb
    Act_m, Act_n, Inact_h ...

  equations:
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    inline I_Na pA = g_Na * Act_m**3 * ...
    V_m' = -(I_Na + I_K + I_L) / C_m + ...

  function alpha_n(V_m mV) real:
    return -0.05 * (V_m / mV + 34.) / (exp(-
.1 * (V_m / mV + 34.)) - 1.)

  parameters:
    C_m pF = 250 pF
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    ...

  update:
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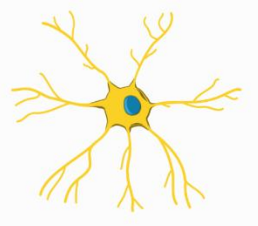

```
neuron hodgkin_huxley:
  state:
    V_m mV = -65 mV
    Act_m, Act_n, Inact_h ...

  equations:
    kernel syn_psc_kernel = exp(-t / tau_syn)
    inline I_Na pA = ...
    inline I_K pA = ...
    inline I_L pA = g_L * (V_m - E_L)
    V_m' = -(I_Na + I_K + I_L) / C_m
           + convolve(syn_psc_kernel, spikes)
    [...]

  parameters:
    C_m pF = 250 pF
    V_threshold mV = 40 mV
    ...

  update:
    integrate_odes()
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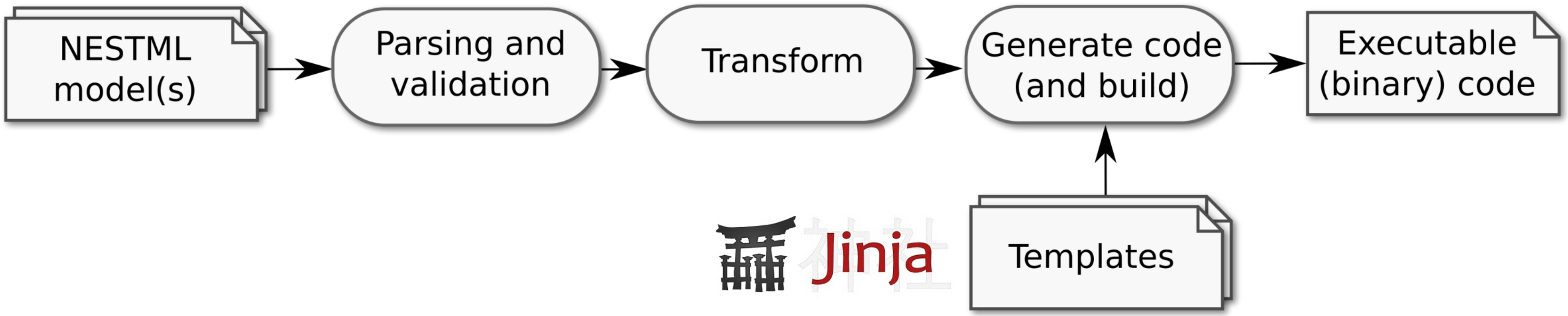
```

PYNESTML TOOLCHAIN: MODULAR AND EXTENSIBLE

- Jinja templates are used for code generation. The toolchain is modular and written in Python, which, taken together, allows for a great deal of flexbility and ease of customizing and adding novel code generation platform targets.

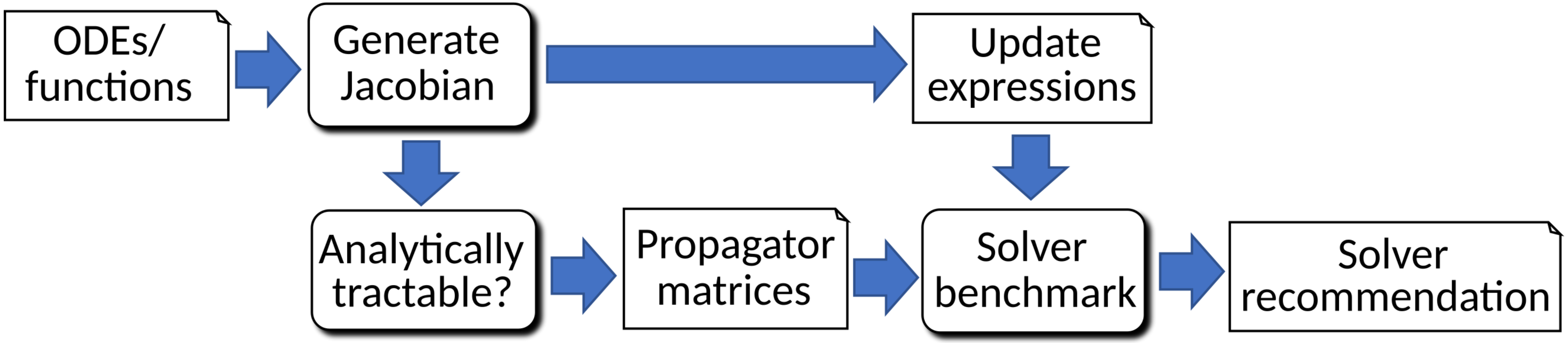
Example snippet from synapse template for Python target:

```
{%- if parameter_syms_with_iv|length > 0 %}
    # initial values for parameters
{%- filter indent(4) %}
{%- for parameter in parameter_syms_with_iv %}
{%-   with variable = parameter %}
{%-     include "directives/MemberInitialization.jinja2" %}
{%-   endwith %}
{%- endfor %}
{%- endfilter %}
{%- endif %}
```



AUTOMATIC SELECTION AND GENERATION OF INTEGRATION SCHEMES FOR SYSTEMS OF ODES

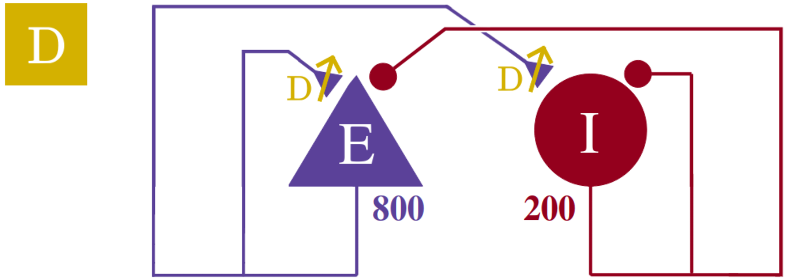
- Fully automated symbolic analysis of systems of ODEs using sympy
- Generates ”propagator” solver for dynamics that admits an analytic solution
- Numeric solver benchmarking and recommendation



ADVANCED SYNAPTIC PLASTICITY RULES

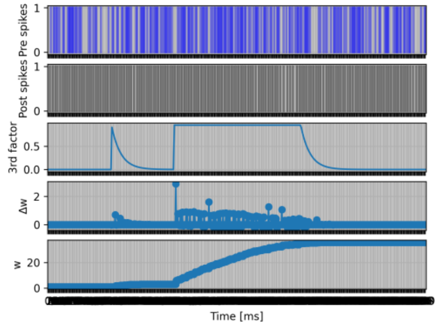
Neuromodulation

Spatially diffuse neuromodulators like dopamine can flexibly be used as “third factors” in synaptic plasticity rules to impement, reinforcement learning.



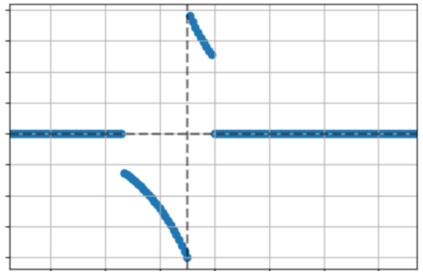
Postsynaptic dendritic current-modulated STDP

Arbitrary postsynaptic quantities, such as (active) dendritic currents, can be used to modulate synaptic plasticity.



Triplet and non-linear STDP

Higher-order STDP rules, such as the triplet rule, as well as non-linear STDP variants, involving for example the clamping of a weight change outside a given window, can be easily and flexibly implemented using the NESTML syntax.



NESTML SOFTWARE DEVELOPMENT USES BEST PRACTICES IN SOFTWARE ENGINEERING

- Automated testing (CI): models are behaviorally validated in simulation runs

- Extensive documentation and automated HTML documentation generation for models in the extensive neuron and synapse models library:

  https://nestml.readthedocs.org/

- Open development:

  https://github.com/nest/nestml

  GNU GPL v2.0 licensed

GitHub

THANK YOU!

Jochen M. Eppler
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Tanguy Fardet
Jessica Mitchell
Sara Konradi
Ayssar Benelhedi

... and to all our users!

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