BrainScaleS-2 Software

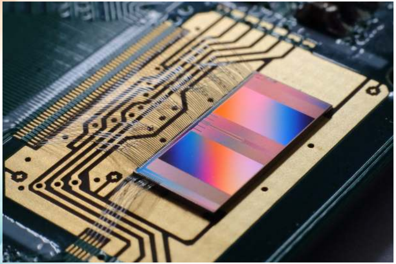
Use Cases, Access and Integration into EBRAINS

Eric Müller
mueller@kip.uni-heidelberg.de

2022-03-31
NICE 2022

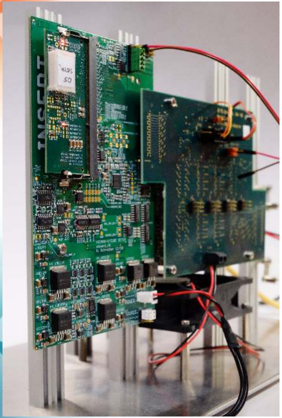
EBRAINS

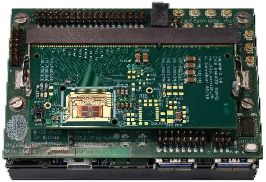
BrainScaleS-2

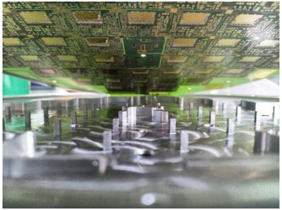


- Physical model, mixed-signal implementation
- AdEx neurons, short-term plasticity
- Structured neurons & nonlinear effects of dendrites
- Accelerated model dynamics ($\sim 10^3$)
- Support for online updates of neuron parameters, synapses (and network topology)
- Programmable plasticity
- Non-spiking operation mode (analog MAC)

BrainScaleS-2 Systems







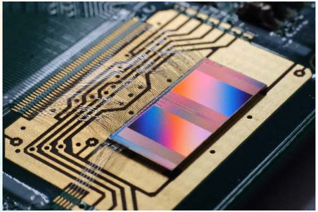
- Setup types
  - “Lab” — local and remote usage
  - Mobile — embedded operation
  - Multi-chip / “Frankenstein Wafer”

→ (Network-attached) Accelerators

- Software stack providing varying abstraction levels
  - `PyNN`, `hxtorch.snn`, ...
  - hardware abstraction layers (configuration and control)
  - communication

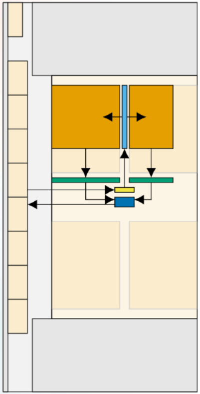
→ APIs for modeling, commissioning and development

Experiments? Configuration & “Protocol”



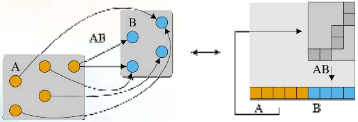
- Synapses, Neurons
- I/O (On-chip/off-chip)
- Observables, Controllables
- Controllers:
    - Host computer
    - FPGA
    - Embedded processors

Experiments? Configuration & “Protocol”



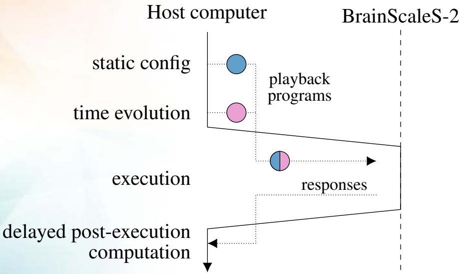
- Synapses, Neurons
- I/O (On-chip/off-chip)
- Observables, Controllables
- Controllers:
  - Host computer
  - FPGA
  - Embedded processors

Configuration & Protocol



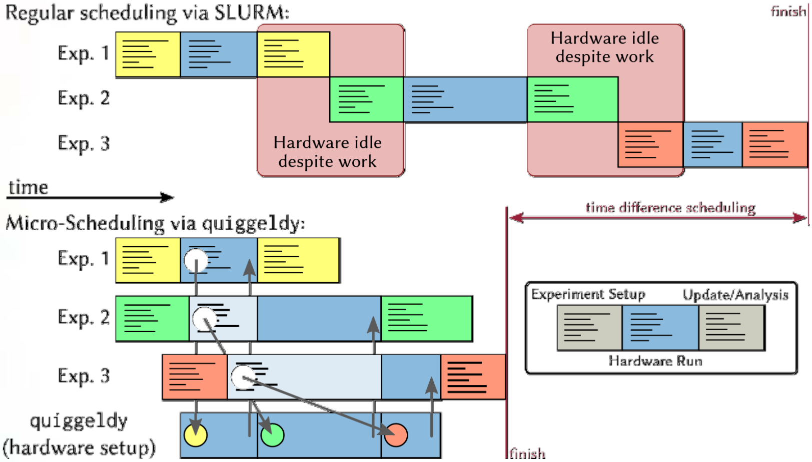
- Experiment Description → Initial Configuration
  - Topology
    - → Placement & Routing
  - Cell Parameterization
    - → Parameter Translation (Calibration)
  - Plasticity Kernels
- Experiment Description → Experiment Protocol
  - Off-chip I/O (input/stimulus, output/recording)
  - On-chip I/O (Poisson spike sources, . . .)
  - Other dynamics (e.g., via embedded processors)

Experiment “Execution”



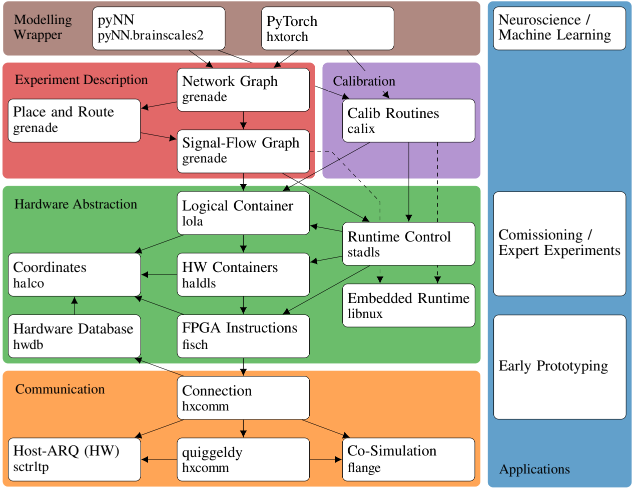
- Initial Configuration
- Execution of the ‘Experiment Protocol’
- Host-centric view here but multiple controllers do co-exist

Time Sharing — Experiment Scheduling



[Oliver Breitwieser (2021). Learning by Tooling: Novel Neuromorphic Learning Strategies in Reproducible Software Environments. Chapter II-10. Ph.D. thesis. Ruprecht-Karls-Universität Heidelberg]

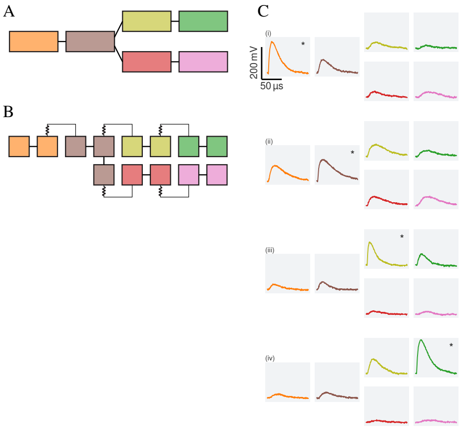
Layers


Modelling Wrapper
pyNN
pyNN.brainscales2
PyTorch
hxtorch
Neuroscience / Machine Learning
Experiment Description
Network Graph
grenade
Place and Route
grenade
Signal-Flow Graph
grenade
Calibration
Calib Routines
calix
Hardware Abstraction
Logical Container
lola
Runtime Control
stadls
Coordinates
halco
HW Containers
haldls
Embedded Runtime
libnux
Hardware Database
hwdb
FPGA Instructions
fisch
Comissioning / Expert Experiments
Early Prototyping
Communication
Connection
hxcomm
Host-ARQ (HW)
sctrltp
quiggeldy
hxcomm
Co-Simulation
flange
Applications

Commissioner’s View on Structured Neurons

```python
coord = halco.AtomicNeuronOnLogicalNeuron    # relative coordinate
row = halco.NeuronRowOnLogicalNeuron         # 0, 1
column = halco.NeuronColumnOnLogicalNeuron   # 0, 1, ..., 127
morphology = lola.Morphology()
# create compartments: main branch
morphology.create_compartment([coord(0, 0), coord(1, 0)])
morphology.create_compartment([coord(2, 0), coord(3, 0), coord(3, 1)])
# create compartments: sub branches
for row_coord in [0, 1]:
    for column_coord in [4, 6]:
        morphology.create_compartment([coord(column_coord, row_coord),
                                       coord(column_coord + 1, row_coord)])
# enable conductance to shared line
morphology.connect_resistor_to_soma(coord(1, 0))
for row_coord in [0, 1]:
    for column_coord in [3, 5]:
        morphology.connect_resistor_to_soma(coord(column_coord, row_coord))
# direct connection to shared line
morphology.connect_to_soma(coord(2, 0))
for row_coord in [0, 1]:
    for column_coord in [4, 6]:
        morphology.connect_to_soma(coord(column_coord, row_coord))
# connect somatic shared line
morphology.connect_soma_line(start=column(1), end=column(2), row=row(0))
for row_coord in [row(0), row(1)]:
    morphology.connect_soma_line(column(3), column(4), row_coord)
    morphology.connect_soma_line(column(5), column(6), row_coord)

neuron_coordinate, logical_neuron = morphology.done()
```

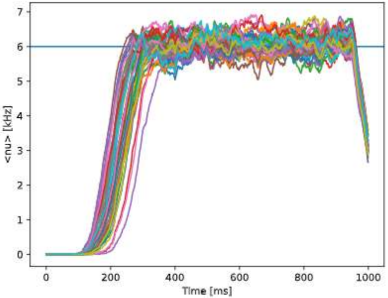


[Work by Raphael Stock and Jakob Kaiser (2021, 2022)]

Programmable Plasticity from PyNN

```
class HomeostaticSynapse(pynn.PlasticityRule,
                         pynn.standardmodels.synapses.StaticSynapse):
    # ...
    def generate_kernel(self) -> str:
        return textwrap.dedent("""
            // C++ ...
            template <size_t N>
            void PLASTICITY_RULE_KERNEL(
                    std::array<SynapseArrayViewHandle, N>& synapses,
                    std::array<PPUOnDLS, N> synrams) {
                    /* embedded processors have access to a set of
                     * observables and controllables ... */
                    }
        """.format(...)

# ...
synapse_type = HomeostaticSynapse(timer=timer, target=60, weight=0)
pynn.Projection(pop_input, nrn, pynn.AllToAllConnector(),
                synapse_type=synapse_type)
# ...
```



[Work by Philipp Spilger (2021, 2022)]

Modeling with Hardware in the Loop

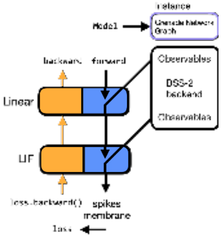
```python
from hxtorch import snn

class Model(torch.nn.Module):
    def __init__(...):
        # Create Instance
        instance = snn.Instance(mock=mock)
        # Add HXModules
        self.linear_h = snn.HXSynapse(
        in_features, out_features, instance=self.instance, ...)
        self.lif_h = snn.HXNeuron(
        hidden_size, instance=self.instance, ...)
        self.linear_o = snn.HXSynapse(
        hidden_size, output_size, instance=self.instance, ...)
        self.li_readout = snn.HXReadoutNeuron(
        output_size, instance=self.instance, ...)

    def forward(self, input):
        current_i = self.linear_h(input)
        spikes_h = self.lif_h(current_i)
        current_o = self.linear(spikes_h)
        membrane_out = self.li_readout(current_o)
        # Run on Hardware
        snn.run(self.instance, runtime=...)
        return membrane_out

# Execute
model = Model(...)
inputs = snn.HXTensorHandle(spikes)
membrane = model(inputs)
```

- PyTorch-like description of SNNs
- Handles for tensors (i.e. not using XLA Tensors)
- Same API for software simulation & hardware emulation
- Maintains auto-differentiation functionality
- Flexibility in backward pass by assigning autograd functions to hardware operations
- Future: Integration into Norse?



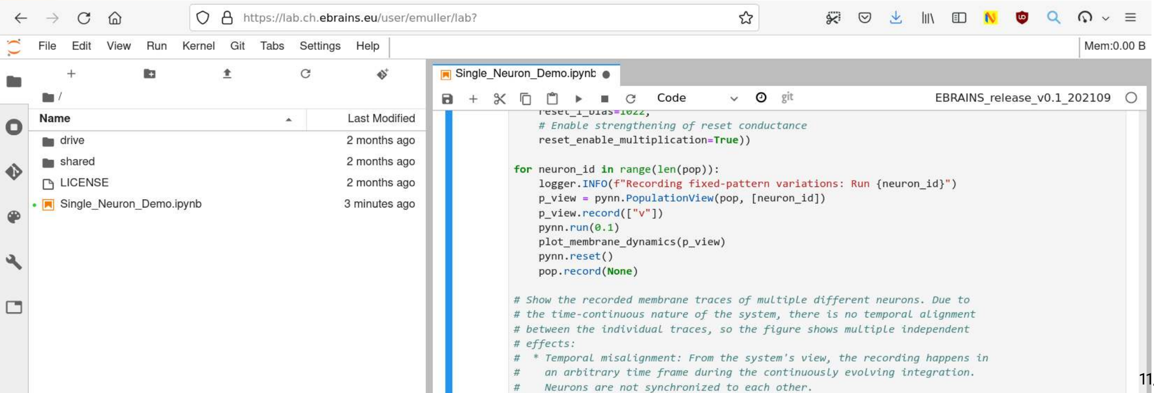
[Work by Elias Arnold & Philipp Spilger (2022)]

Platform Access & Operation

- We leverage EBRAINS central services!
  - AAA, WebIDE hosting (JupyterLab), storage, quota/job reporting, . . . , user support
- Access to BrainScaleS via EBRAINS
  (+ SpiNNaker, as well as many other software packages)
- Dedicated BrainScaleS-2 Experiment Service for interactive experimenting
  ($\mathcal{O}$(10 Hz), limited by specifics of the experiment and I/O)

Platform Access & Operation

- BSS-2 software now integrated into the EBRAINS Software Distribution. . .
- . . .enables a native and “natural” integration of BrainScaleS-2 into EBRAINS ‘Collabs’
  - *We convinced EBRAINS to adopt spack as a package manager :o)*
  - Future: Deployments on EBRAINS HPC sites → multi-site workflows



Disclaimer

- Our software deployment on EBRAINS is somewhat ‘stable’… we expect more recent software in a couple of weeks (and more frequent releases afterwards).
- In addition, there will be a ‘testing’ deployment providing a continuous stream of newer software versions (approx. weekly).
- Many features presented here are still work in progress (MC neurons, programmable plasticity, SNN support in hxtorch), will require some more time to stabilize and materialize in a release.

Conclusion

- We work towards multiple goals:
  - Commissioning of recent BSS-2 hardware features, e.g., structured neurons and multi-chip systems
  - Programmable plasticity (code generation for the embedded processors)
  - Providing ML-friendly interfaces
  - Efficiency (fast reconfiguration) in high-level use cases
  - Parameter Translation (SI hardware & bio units) and integration of 'Calibration'
  - We continue to improve system robustness

  $\Rightarrow$ Transition towards a flatter learning curve for users (deployment, operation & usage)
- Executable Documentation incl. Examples
- Now: BrainScaleS-2 interactive tutorial $\rightarrow$ `PyNN.brainscales2`
  - Link to 'Collab' should have been sent via mail
  - https://wiki.ebrains.eu/bin/view/Collabs/nmc-test-SOMEUSERNAME/

A scalable approach to modeling on accelerated neuromorphic hardware

Eric Müller [*†1], Elias Arnold [†1], Oliver Breitwieser [†1], Milena Czierlinski [†1], Arne Emmel [†1], Jakob Kaiser [†1], Christian Mauch [†1], Sebastian Schmitt [†2], Philipp Spilger [†1], Raphael Stock [†1], Yannik Stradmann [†1], Johannes Weis [†1], Andreas Baumbach [1], Sebastian Billaudelle [1], Benjamin Cramer [1], Falk Ebert [1], Julian Göltz [1], Joscha Ilmberger [1], Vitali Karasenko [1], Mitja Kleider [1], Aron Leibfried [1], Christian Pehle [1], Johannes Schemmel [1]

[1]Electronic Vision(s), Kirchhoff-Institute for Physics, Heidelberg University, Germany
[2]Third Institute of Physics, University of Göttingen, Germany

Preprint available on arXiv: https://arxiv.org/abs/2203.11102

BrainScaleS