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LAVA
An open-source software framework for neuromorphic computing

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Open Neuromorphic
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ONM

intel Neuromorphic Research Community

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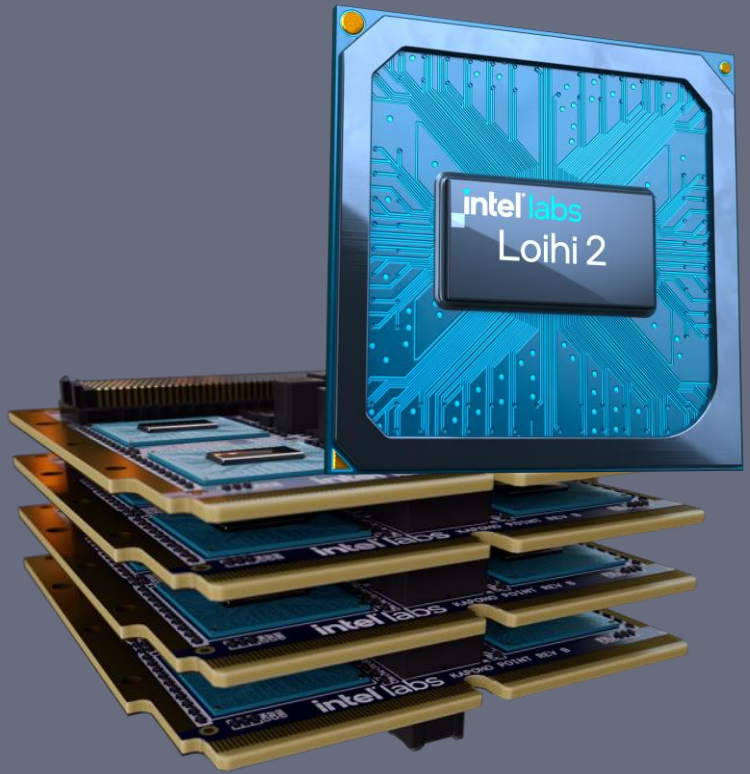
What is Lava?

And why did Intel launch it?

A new SW framework sparked by the arrival of Loihi 2



- Up to 10x faster processing capability*
- Up to 60x more inter-chip bandwidth*
- Up to 1 million neurons with 15x greater resource density*
- Programmable neurons
- Graded spikes
- 3-Factor learning
- 10G Ethernet I/F to host

LAVA

An open-source software framework for neuromorphic computing

* specs and configuration details can be found at intel.com/neuromorphic

What is Lava?

- Full SW stack from runtime, to compiler, to algorithm/application libraries
- Brain-inspired programming model for heterogeneous HW
  - Parallel & asynchronous
  - Event-based computation/communication
- Seeded by Intel but open-source and increasingly community-driven

LAVA

Event-based communication

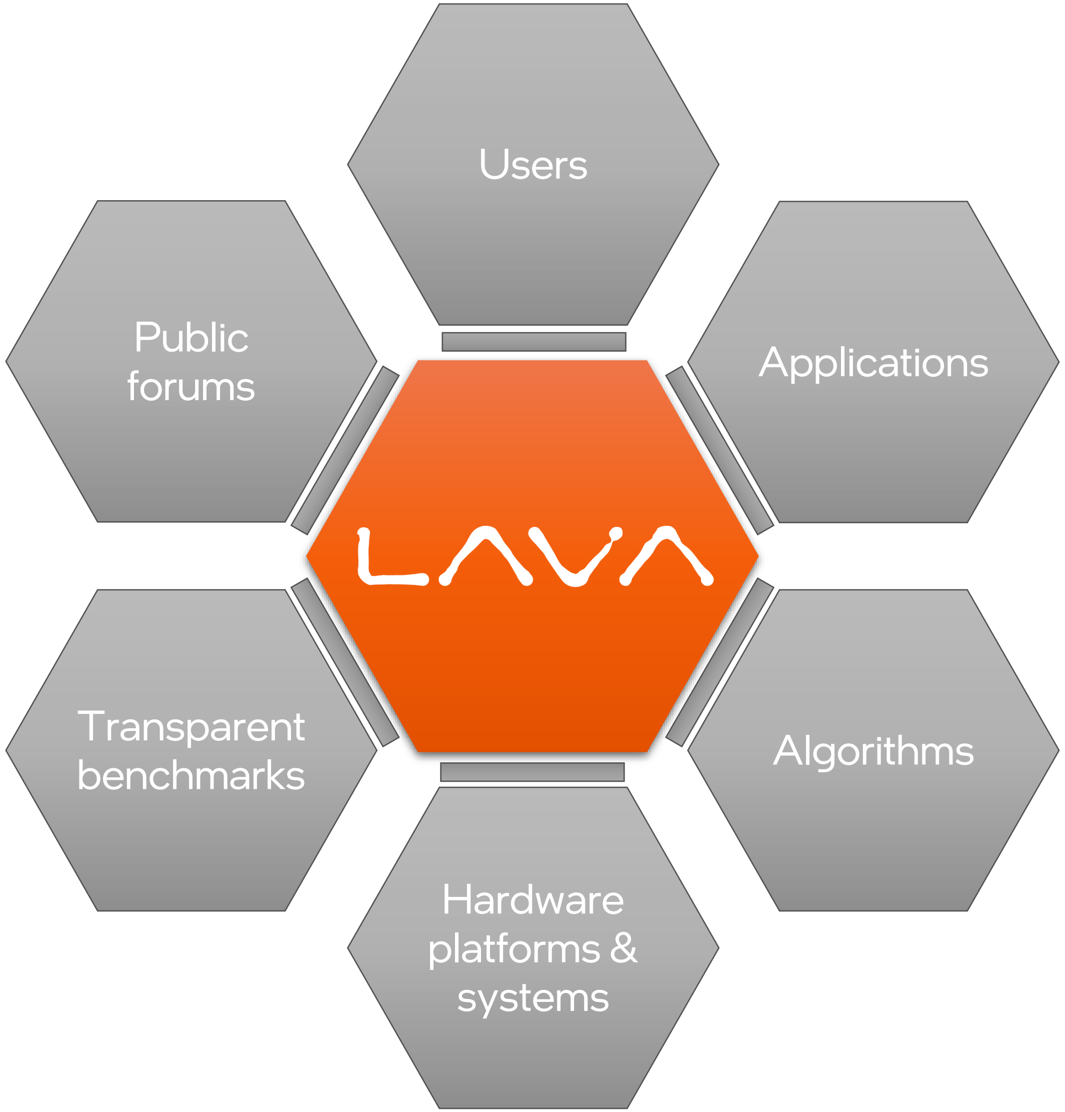
Multi-Paradigm

Multi-Abstraction

Multi-Platform

Why Lava?

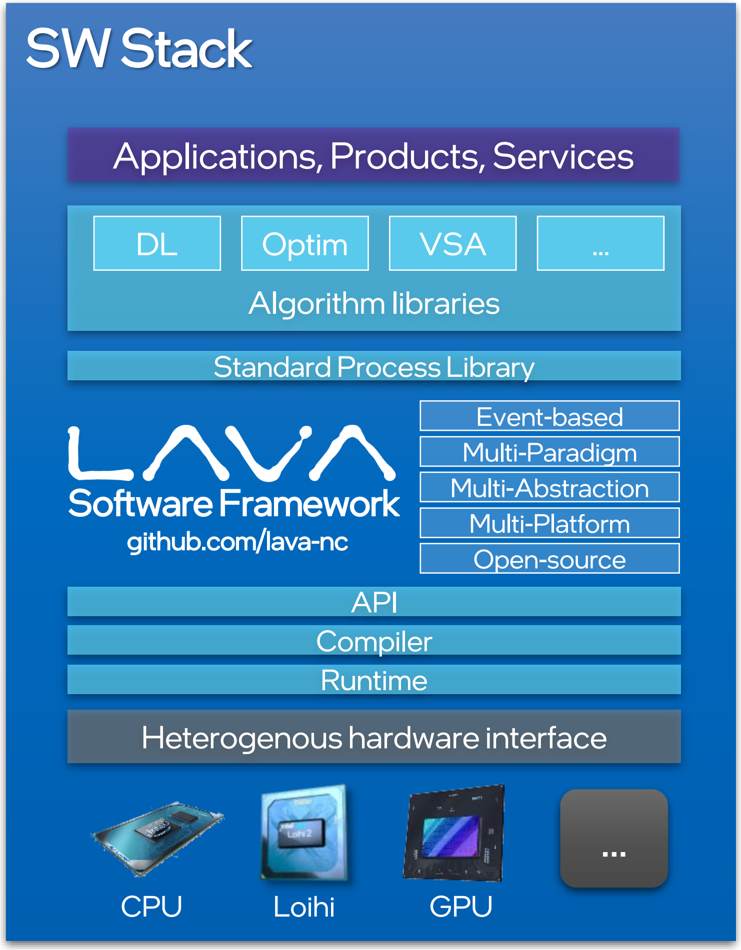
- Converge neuromorphic SW development towards open standard
- Make *exotic* neuromorphic systems accessible to non-expert developers
- Accelerate adoption of neuromorphic technologies
- Enable orders of magnitude gains in compute efficiency



Capabilities

What you can do with Lava today

Lava SW stack

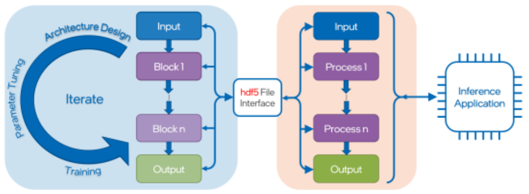


Capabilities today	Platform
▪ Cross-platform compiler/runtime	CPU/Loihi 2
▪ Programming in Python & C	CPU/Loihi 2
▪ "Arbitrary" neuron models via μCode programming	Loihi 2
▪ Synaptic plasticity via 2/3-factor learning rules	CPU/Loihi2
▪ Power, performance, activity, memory profiler	Loihi 2
▪ Lava-dl: Direct training and model deployment	CPU/Loihi 2
▪ Lava-optim: Solvers for QUBO and QP problems	CPU/Loihi 2
▪ Lava-dnf: Connectivity generators for attractor networks	CPU/Loihi 2
▪ Comprehensive documentation and tutorials	CPU/Loihi 2

Lava algorithm libraries

lava-dl

- Direct & HW-aware training of event-based DNNs
- Rich neuron model library (feed-forward & recurrent)

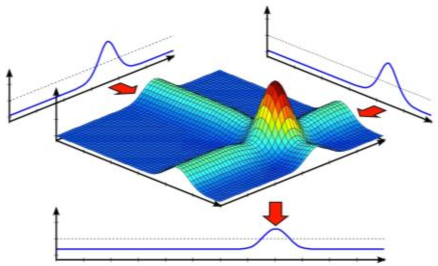


lava-optim

- Family of constraint optimization solvers
- Today: QP, QUBO, LCA, BO
- Future: MPC, ILP, ...
- Standalone use or as part of AI applications

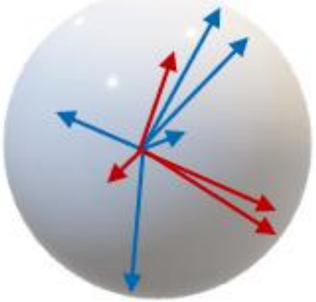
lava-dnf

- Design models with attractor dynamics
- Stabilize temporal data
- Selective data processing
- Dynamic working memories



lava-vsa (WIP)

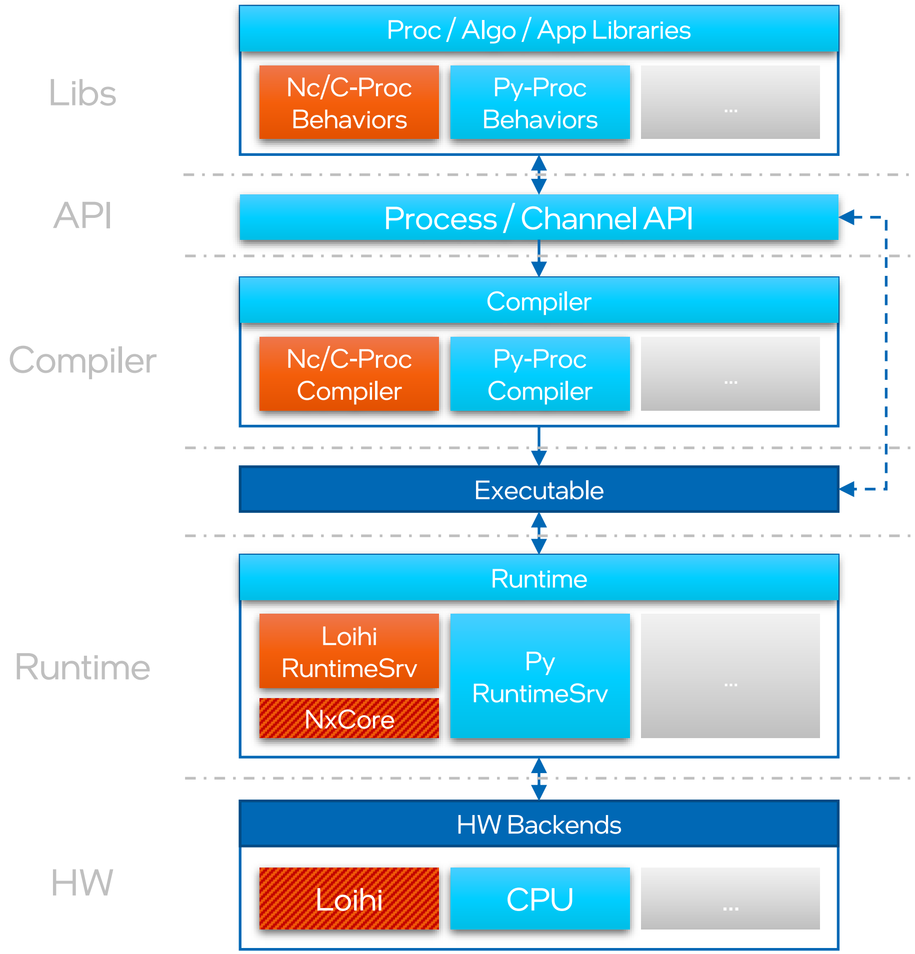
- API for algebraic model description for VSAs
- Library of data types and operations (composition, binding, factorization, ...)



Future directions

- lava-io (sensor/actuator interfaces)
- lava-robotics (control, planning, physical simulator interfaces)
- lava-evolve (evolutionary training methods)
- lava-ui (graphical network creation, visualization, debugging)
- Signal processing
- Off-the-shelf apps (segmentation, tracking, keyword detection, ...)
- Neural simulators (Brian2Lava, ...)

Lava stack & open sourcing



Framework components

Lava Framework with CPU backend:
- Open-source
- Code distributed via GitHub
- End user documentation/tutorials
- Python

Lava Loihi backend:
- Proprietary
- For INRC members or selected partners
- Developer documentation
- Mostly Python, some C

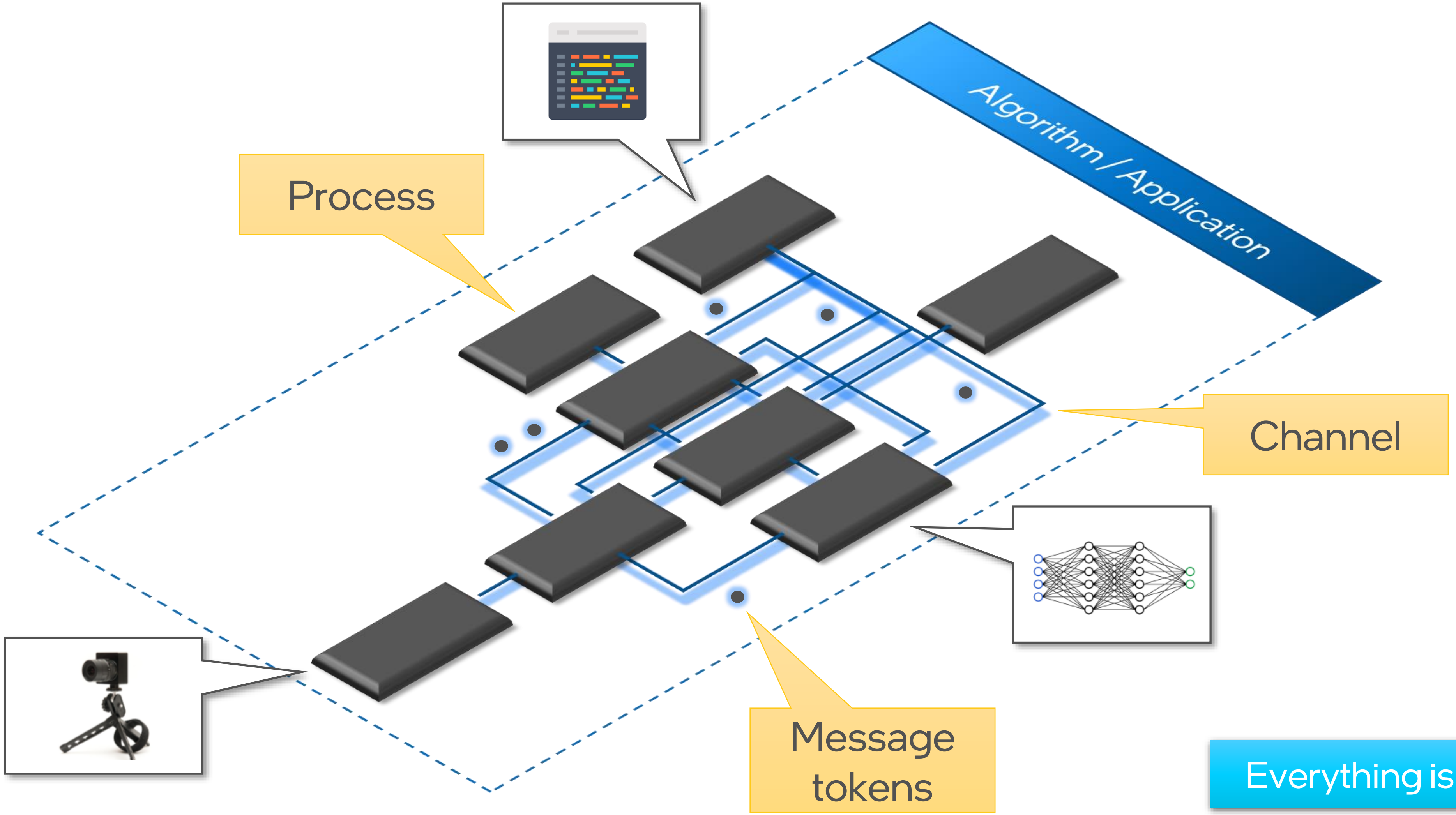
Loihi + NxCore:
- Proprietary
- For INRC members or selected partners
- Developer documentation/tutorials
- Python / C / C++

Using Lava

Basic Lava concepts

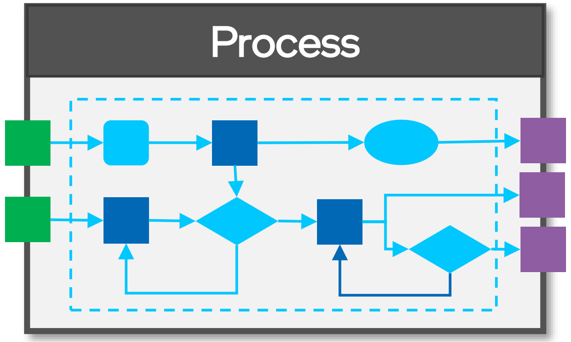
Processes and channels

Lava's fundamental building blocks



Everything is a Process in Lava

Processes



Input Ports Internal Vars Output Ports
Logic

- Implementation-agnostic API
- InPorts/OutPorts for message-based communication via channels
- Internal state & behavior

Example Process definition:

```
class Proc(AbstractProcess):
    def __init__(self, **kwargs):
        super().__init__(**kwargs)
        # Input ports
        self.inp1 = InPort(shape=(2, 1))
        ...
        # Output ports
        self.out1 = OutPort(shape=(10, 1))
        ...
        # Internal variables
        self.var1 = Var(shape=(1, 2), init=10)
        var2_init = kwargs.get("var2_init", 0)
        self.var2 = Var(shape=(1, 1), init=var2_init)

    def an_api_method(self, *kwargs):
        ...
```

All Processes derive from AbstractProcess

__init__ defines Vars and Ports

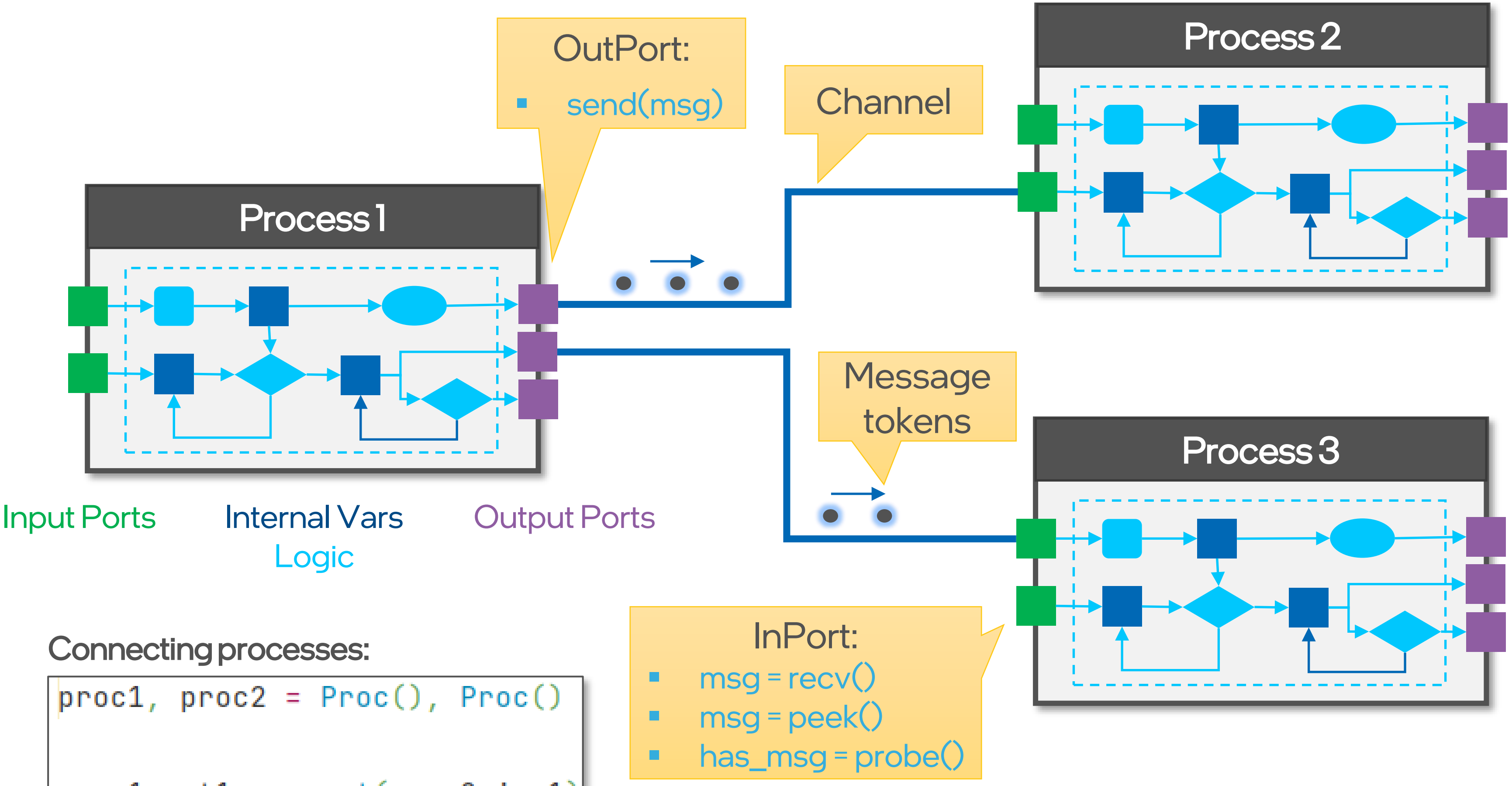
Behavioral implementation defined separately…

Tensor-valued Vars and Ports

Additional API methods

Processes provide implementation-agnostic API but separate behavioral implementation

Processes and channels



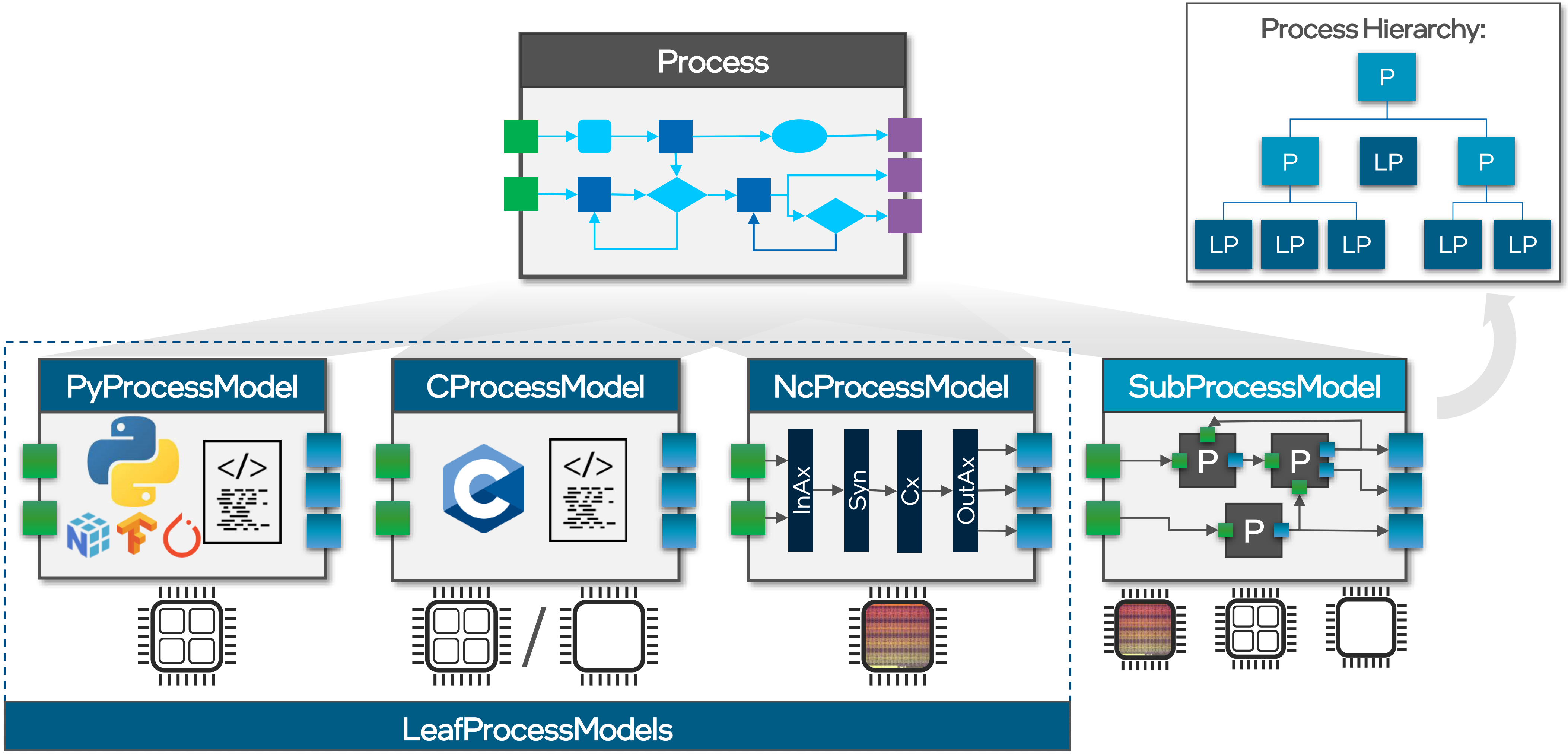
Connecting processes:

```
proc1, proc2 = Proc(), Proc()

proc1.out1.connect(proc2.inp1)
```

Processes communicate through channels via message tokens

Behavioral models → ProcessModel



Two classes of ProcModels: LeafProcModels vs. hierarchical SubProcModels

Examples

Examples

- Tour through Lava
  - lava / tutorials / end_to_end / tutorialX00_tour_through_lava.ipynb
- Low level tutorial library
  - lava / tutorials / end_to_end , in_depth
- Lava-dl: PilotNet
  - lava-dl / tutorials / lava / lib / dl / slayer / pilotnet / train.ipynb
- Lava-optimization: QUBO
  - lava-optimization / tutorials / tutorial_02_solving_qubos.ipynb

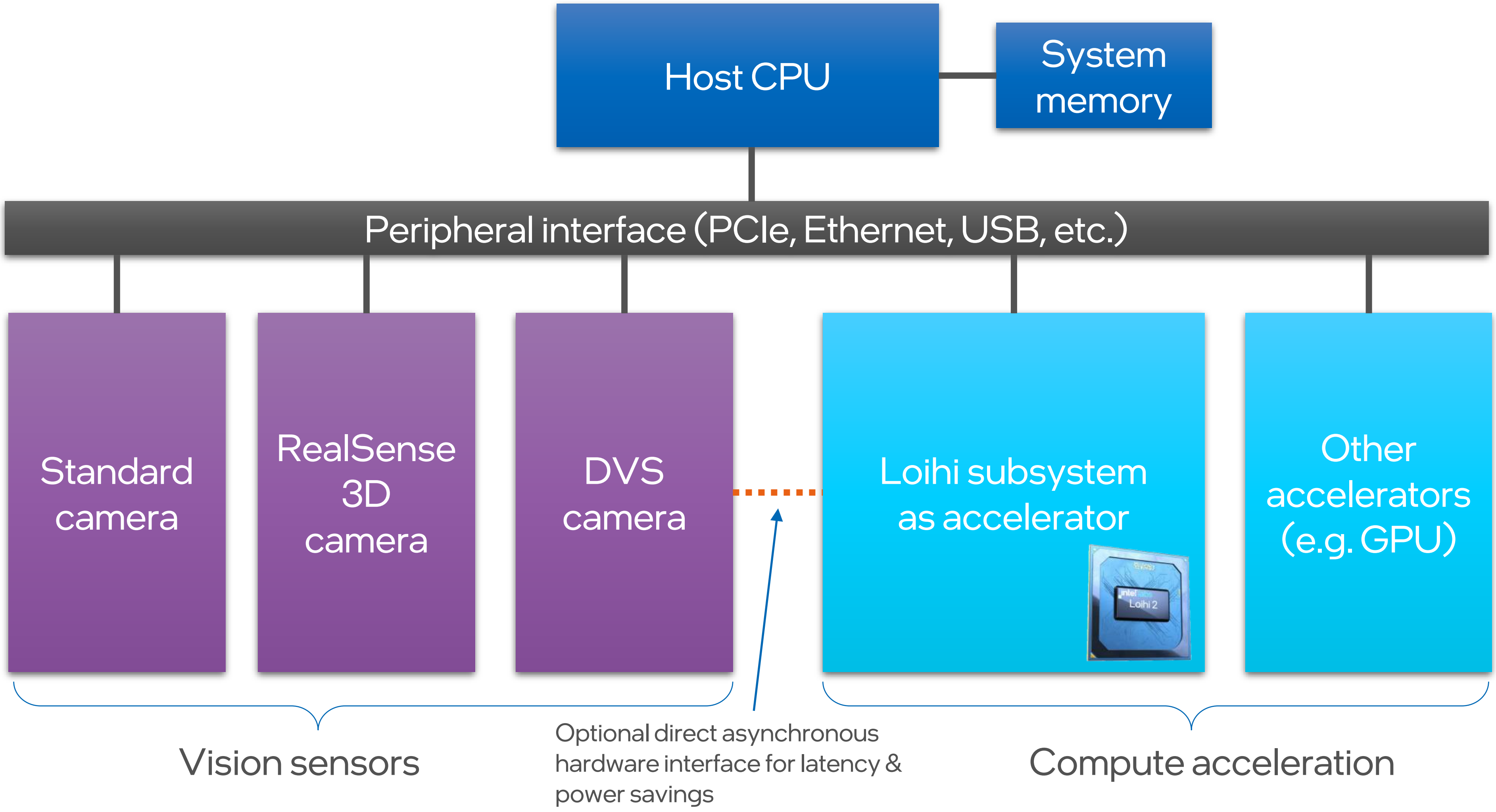
Current development highlights

New SW infrastructure and applications

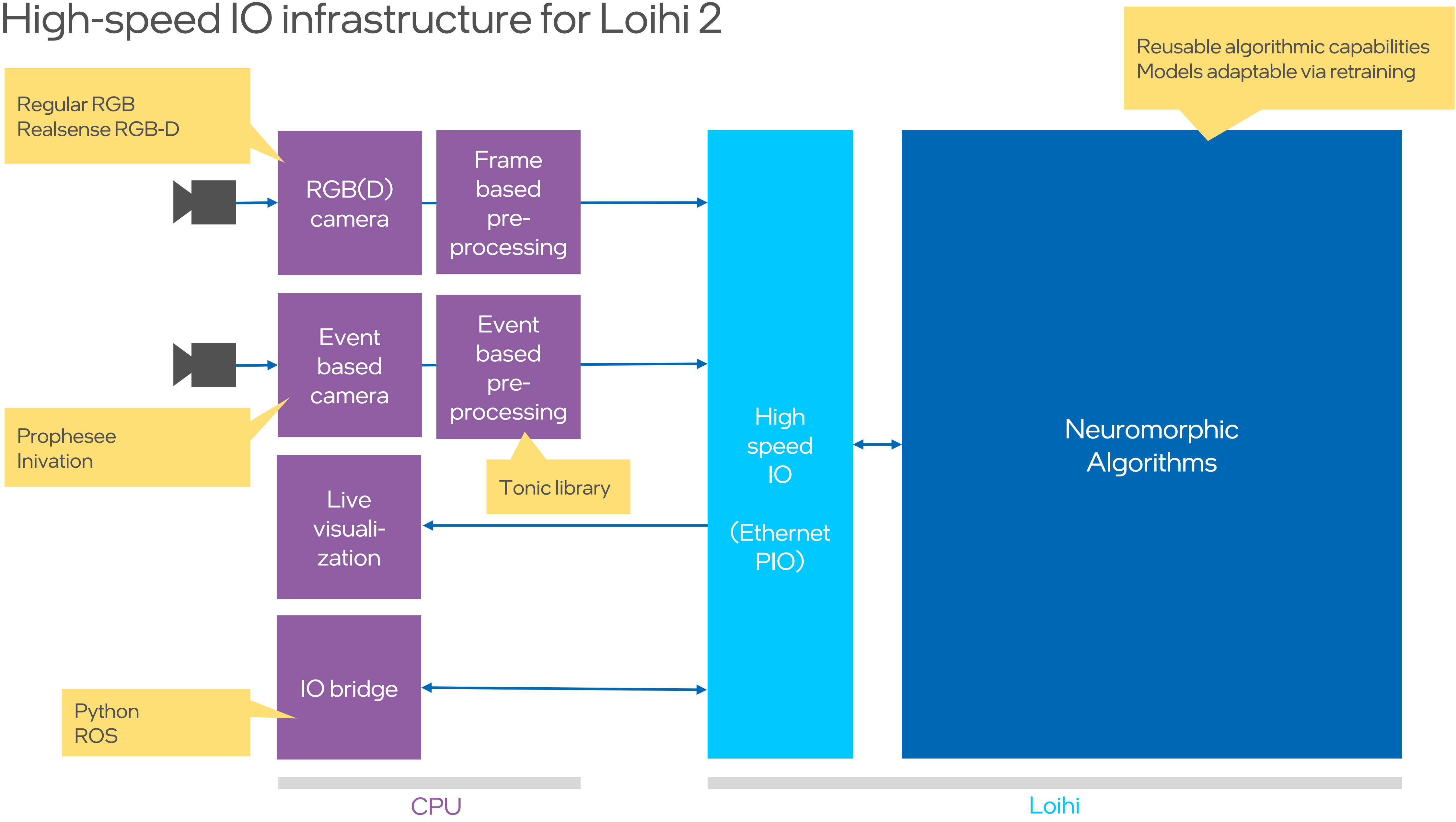
Latest Lava release

- Lava 0.7 – Minor feature additions (April 2023)
  - Tutorial for performance profiling
  - State probes
  - Synaptic delays
  - Bugfixes
- Preparations for larger feature release
  - Sparse compression of connectivity
  - Multiple dendritic accumulators
  - Support for real-time vision capabilities

General Loihi system architecture

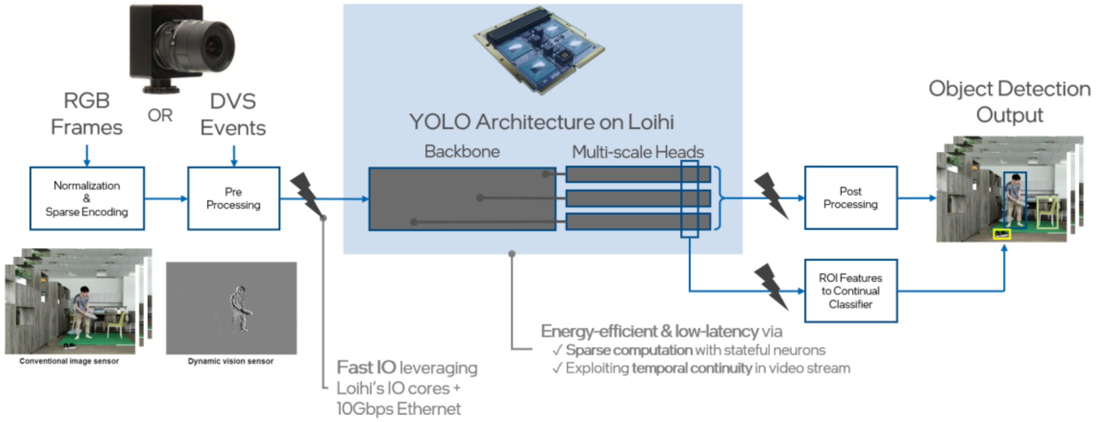


High-speed IO infrastructure for Loihi 2

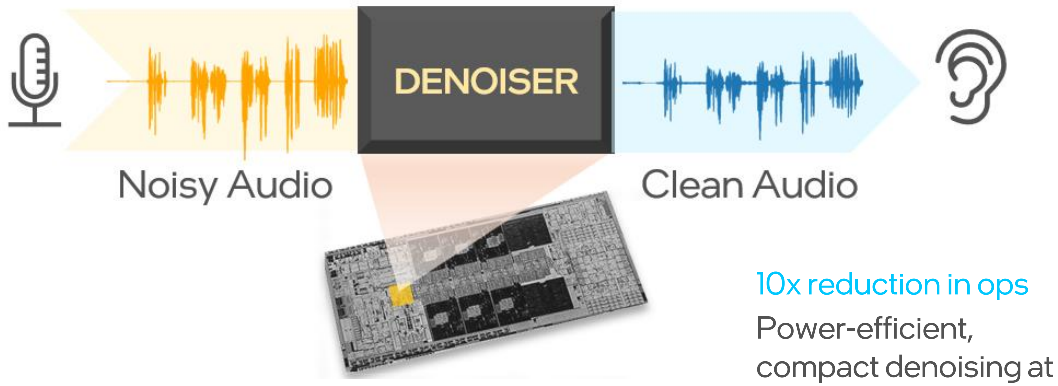


Upcoming signal processing application examples

DNN-based object detection & localization



Audio denoising

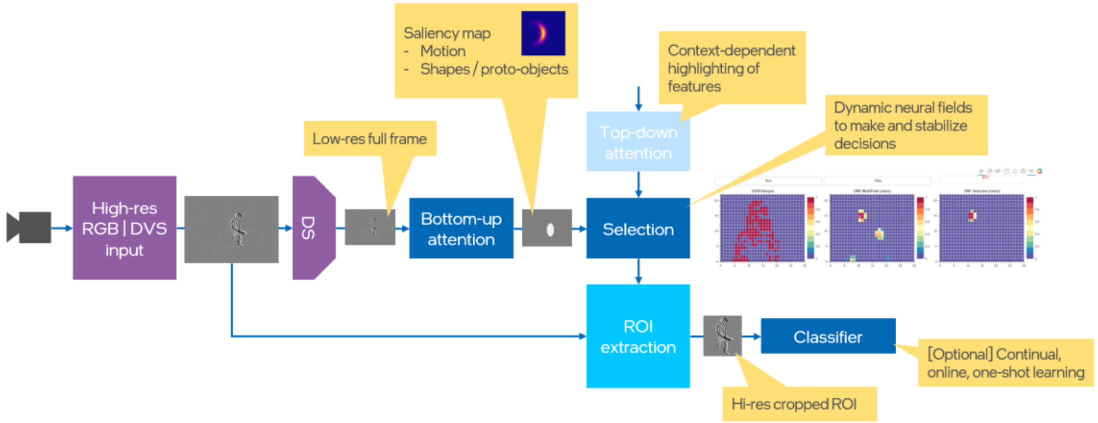


10x reduction in ops

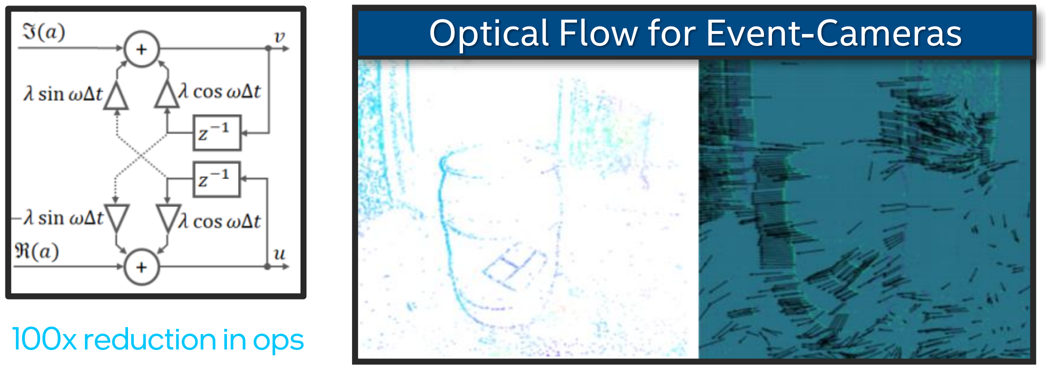
Power-efficient, compact denoising at comparable quality

Timcheck et al, Intel DNS challenge, arXiv:2303.09503

Feedback-driven attention object detection



Optical flow with RF neurons



100x reduction in ops

G. Orchard et al, "Efficient Neuromorphic Signal Processing with Loihi 2"

New online/on-chip learning in Lava

Learning rules as sum-of-products:

$$Z_l(t) = Z_l(t - t_E) + \sum_{r=1}^{N_P} D_r^h \left(S_r \cdot \prod_{s=1}^{N_F} F_{l,r,s}^f \right)$$

Synaptic state variables

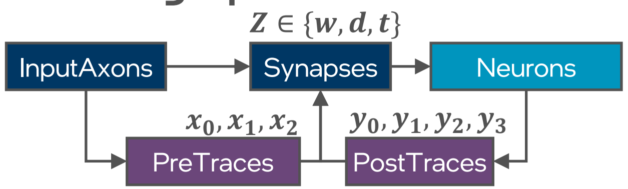
Learning epoch

Dependency operator/factor

Scaling factor

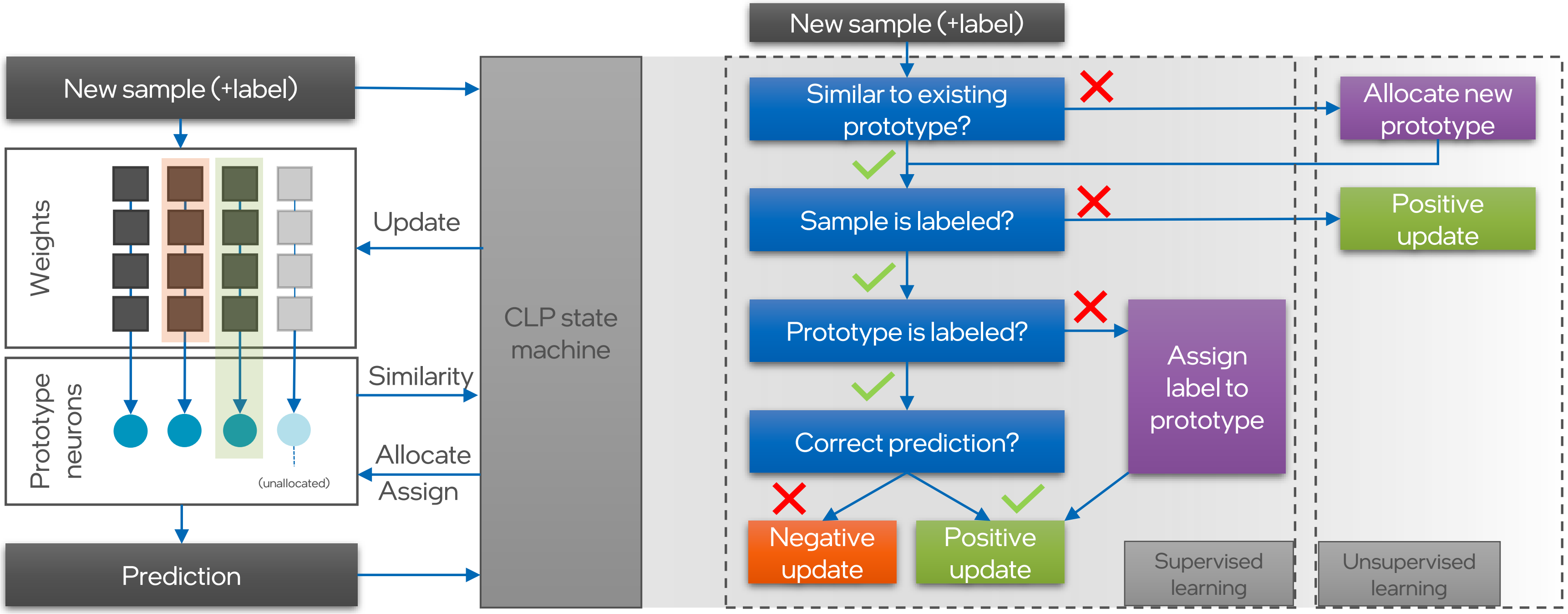
Factor

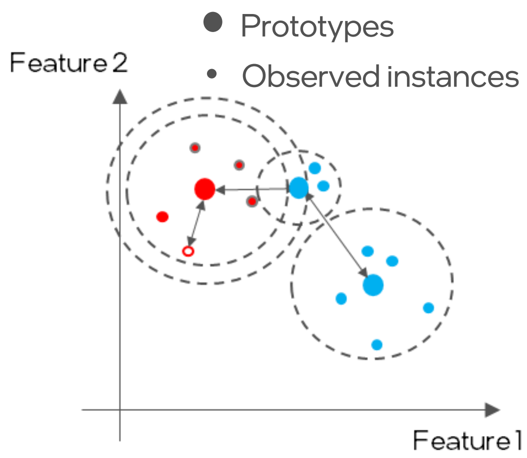
Computational graph:



- Learning supported on CPU/Loihi 2
- Local, 3F-online/on-chip learning
- Currently applied to:
  - Continual Learning Prototype classifier
  - Differentiable neural plasticity

Generic *Continual Learning Prototype* classifier





Characteristics:

- Single-layer, local updates
- Interpretable
- Adjustable memory capacity
- Performant & energy efficient

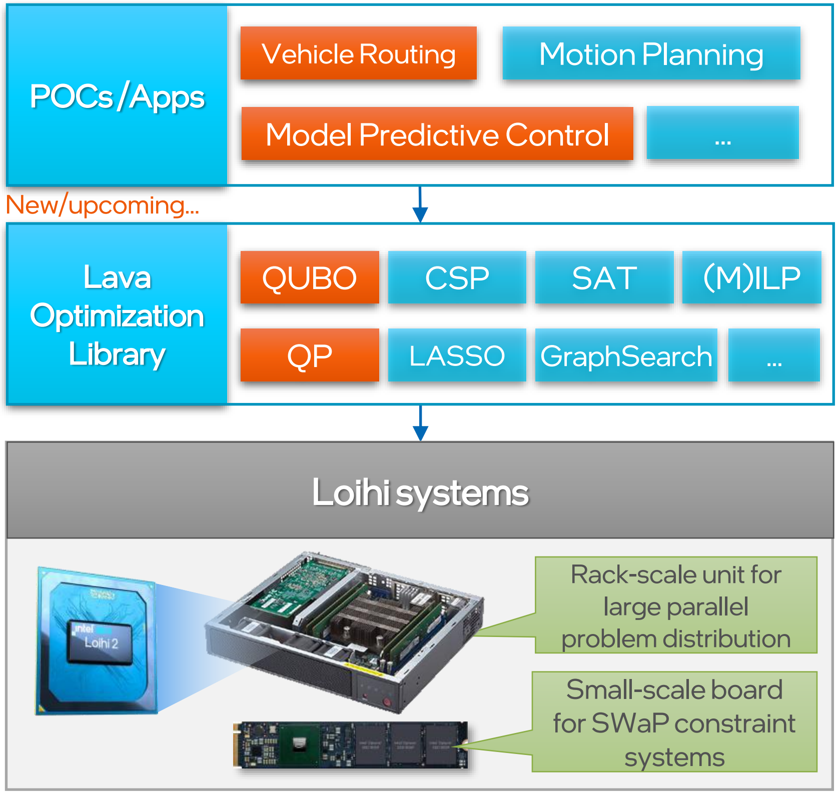
Capabilities:

- Novelty detection
- One-shot learning
- Continual online learning
- Open-set recognition

Enhanced constraint optimization solvers and POCs

Solving optimization problems with orders of magnitude gains in speed and power

Lava-Optimization Library



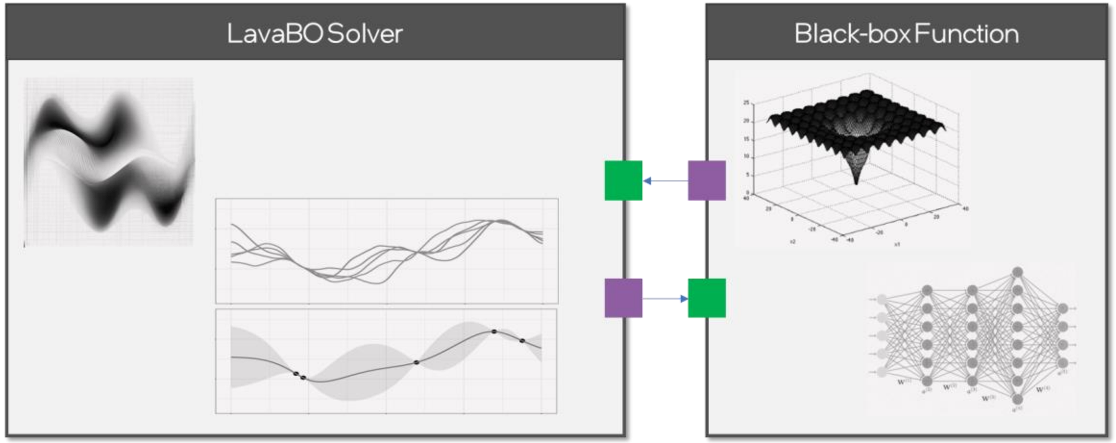
Capabilities:

- Up to 10^5 × EDP gains on Loihi 2 vs. SotA CPU solver
- Scalability from edge to cloud
- Productive HW-agnostic API

Community projects

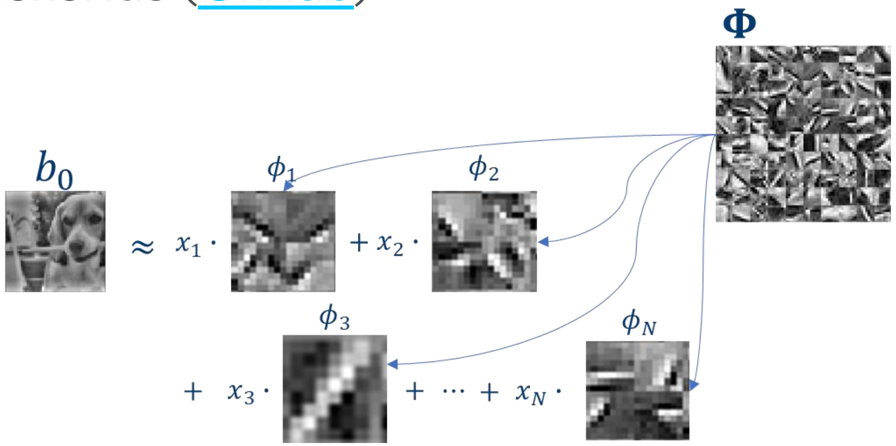
Bayesian Optimization
(George Mason University)

- Objective: Optimize (hyper-) parameters of functions that are non-convex or expensive to evaluate (e.g., entire deep networks)
- Features: Supports three acquisition functions, two acquisition estimators, flexible search space specification
- Status: Solver supports CPU backend; Loihi 2 WIP (Github)



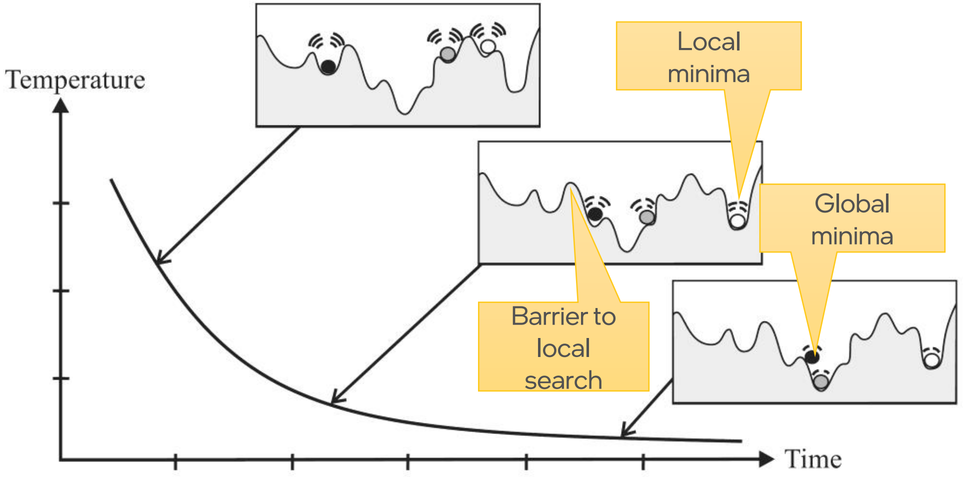
LASSO Optimization
(Pacific Northwest National Lab)

- Objective: Minimize $\frac{1}{2}||\mathrm{b}_0 - \Phi\mathrm{x}||_2^2 + \lambda||\mathrm{x}||_1$, with known feature set Φ to get optimal sparse representations x of input b_0.
- Features: Uses locally competitive algorithm for efficiency. Known to be up to 10^4 times more energy efficient on Loihi than CPU.
- Status: Solver supports CPU & Loihi 2 backends (Github)



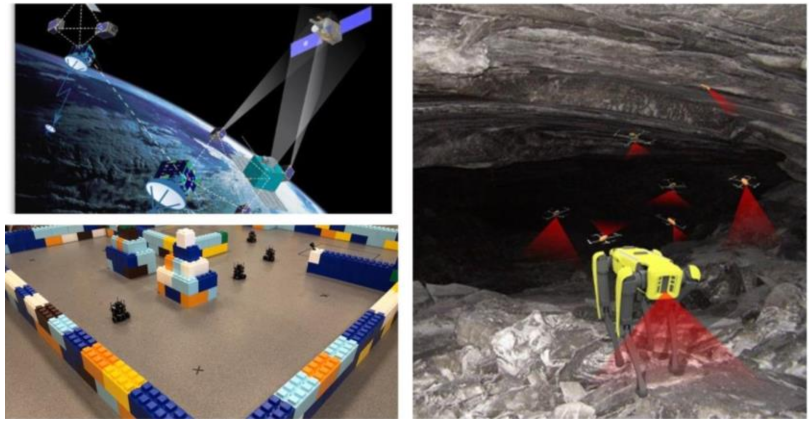
Simulated Annealing
(MIT, ORNL, U. Bonn)

- Objective: Accelerated combinatorial optimization for problems of currently intractable complexity at CERN
- Features: explores overall search space before narrowing down towards global optimum
- Status: POC working on Loihi 2 backend; benchmarking data collected from D-Wave



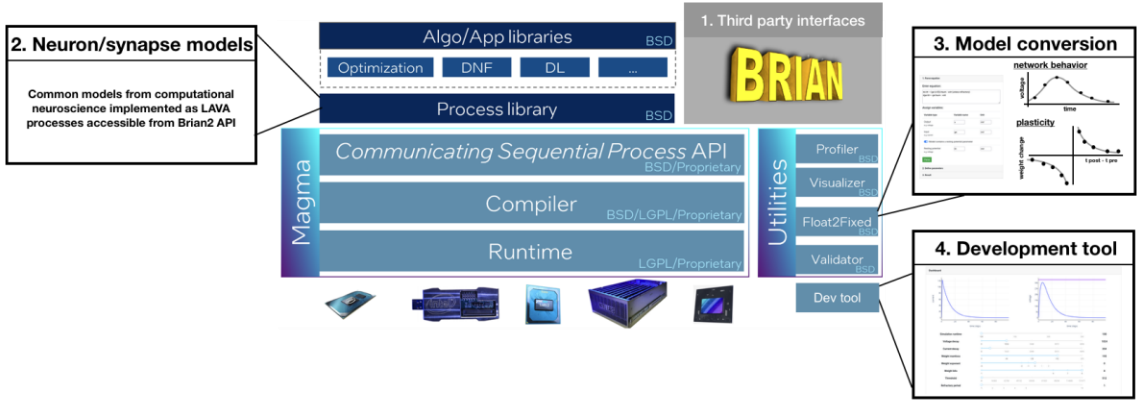
Model Predictive Control
(Lulea University)

- Objective: Model predictive control for planning of swarms of drones and quadrupeds
- Features: builds control algorithms on top of Lava's QP solver, derives stability and convergence guarantees for the solvers under real-time latency constraints. Build demos with physical robots.
- Status: stability analysis for PIPG/MPC algorithm, control loop with Lava's QP solver. CPU for now, Loihi 2 WIP.



Brian2Lava
(U. Goettingen)

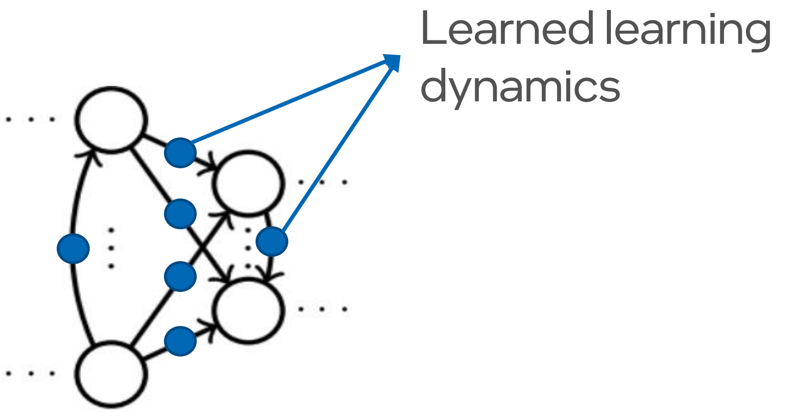
- Objective: Brian 2 interface for Lava to deploy brain-inspired algorithms
- Feature: Automatic conversion of Brian models to Lava/Loihi 2 + Models + Utilities
- Status: Solver supports CPU backend; Loihi 2 WIP



https://brian2lava.gitlab.io/

Differentiable plasticity
(RWTH Aachen, FZ Juelich, NRL)

- Objective: Backpropagating to learn rapid real time weight adaptation on chip
- Features: Gradient through learning dynamics + Learned (via backprop) learning rule coefficients
- Status: Lava-DL supports for DNNs + differentiable local learning rules



Discussion

https://intel-ncl.atlassian.net/wiki/spaces/INRC/overview intel®