tinyML® Neuromorphic Engineering Forum

Enabling Ultra-low Power Machine Learning at the Edge

September 27, 2022

TINY ML

www.tinyML.org

Thank you, **tinyML Strategic Partners**, for committing to take tinyML to the next Level, together

TINY ML

Neuromorphic Engineering Forum

Sony Semiconductor Solutions Corporation

TINY ML

Neuromorphic Engineering Forum

Executive Strategic Partners

arm AI

Powering tinyML Innovation

Arm AI Virtual Tech Talks

The latest in AI trends, technologies & best practices from Arm and our Ecosystem Partners.

Demos, code examples, workshops, panel sessions and much more!

Fortnightly Tuesday @ 4pm GMT/8am PT

Find out more:
www.arm.com/techtalks

TINY ML
Neuromorphic Engineering Forum

EDGE IMPULSE

The Leading Development Platform for Edge ML

edgeimpulse.com

Qualcomm AI research

Advancing AI research to make efficient AI ubiquitous

Power efficiency

Model design, compression, quantization, algorithms, efficient hardware, software tool

Personalization

Continuous learning, contextual, always-on, privacy-preserved, distributed learning

Efficient learning

Robust learning through minimal data, unsupervised learning, on-device learning

A platform to scale AI across the industry

Perception

Object detection, speech recognition, contextual fusion

Reasoning

Scene understanding, language understanding, behavior prediction

Action

Reinforcement learning for decision making

Edge cloud

Cloud

IoT/IIoT

Automotive

Mobile

Accelerate Your Edge Compute

SYNTIANT

Making Edge AI A Reality

www.syntiant.com

TINY ML
Neuromorphic Engineering
Forum

Platinum Strategic Partners

Neuromorphic Engineering Forum

Fastest Video Analytics Solutions on Arm CPUs

AI Trailblazers Award Winner

KLIKA·TECH

GLOBAL IOT SOLUTIONS

High-Value or Safety-Critical Use Cases?

For your most important projects, use

Reality AI®

TinyML software that covers the full engineering lifecycle:
Reality AI Tools®

- AutoML for non-visual sensing based on advanced signal processing math
- Hardware design analytics
- Explanation of TinyML models in terms of underlying physics
- Automated Data Readiness assessment

https://reality.ai/ @SensorAI info@reality.ai Reality AI

Renesas is enabling the next generation of AI-powered solutions that will revolutionize every industry sector.

renesas.com

TINY ML
Neuromorphic Engineering Forum

Sony Semiconductor Solutions Corporation

TINY ML

Neuromorphic Engineering
Forum

Gold Strategic Partners

ANALOG DEVICES
AHEAD OF WHAT'S POSSIBLE™

ANALOG DEVICES
AHEAD OF WHAT'S POSSIBLE™

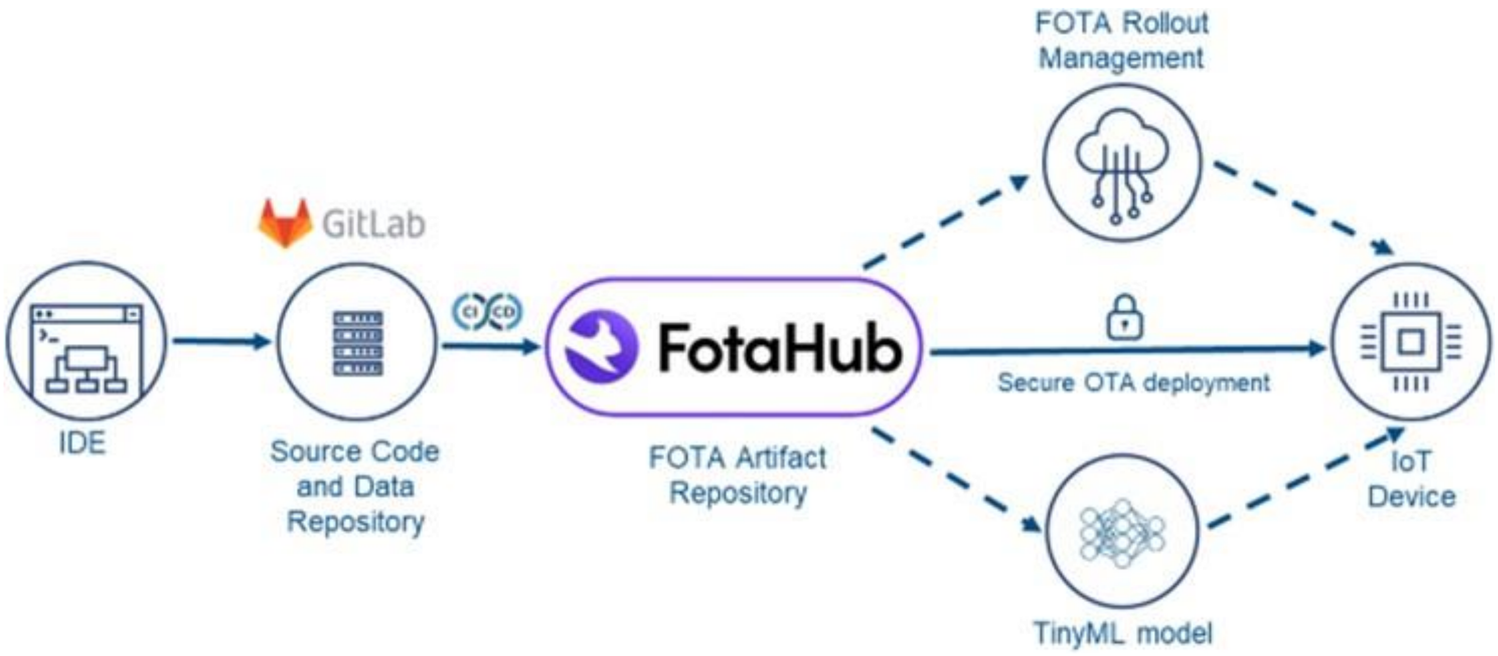
Where what if becomes what is.

Witness potential made possible at analog.com.

FOTAHUB

Making Over-the-Air Firmware and ML models Updates Simple and Accessible!

- Securely update your IoT devices regardless of their Hardware Platform (Silicon) Provider and physical location.
- Unlock TinyML business value through OTA Firmware and ML models update.
- Pay-as you-go



www.fotahub.com

contact@fotahub.com

Microsoft

SECURE CONNECTIONS
FOR A SMARTER WORLD

TOGETHER, WE ACCELERATE THE BREAKTHROUGHS THAT ADVANCE OUR WORLD

www.nxp.com/ai

seeed studio

Deploy TinyML into the Real World - Plug and Play ML

Sensors:
· modulated and ready-to-use sensors to simplify the setup process
· support 500+ grove modules

Wio Terminal:
· completed AI platform --- integrated with a 2.4″ LCD Screen, onboard IMU (LIS3DHTR), microphone, buzzer, microSD card slot, light sensor, infrared emitter(IR 940nm)

Sense

Codecraft:
· no code Programming platform to Get Started With TinML
· supports Arduino, Python, C or JavaScript etc.

Edge Impulse:
· to optimize data utilization and enable deploy a machine learning model faster than ever

TensorFlow Lite:
· to easily train low memory usage machine learning models

Train

Motion /Gesture/Speech /Smell/ Sports
Barcode/Face/Image

Inference

Artificial Nose

AI Thermal Camera for Safe Camping

Azure IoT Squirrel Feeder

Applications

The Right Edge AI Tools Can Make or Break Your Next Smart IoT Product
SensiML
Analytics Toolkit Suite
AutoML
Data Collection
Test & Validation
Data Labeling
Code Generation
Model Building
Team Collaboration
Version Control and Model Management
sensiml.com/tinyML

STMicroelectronics provides extensive solutions to make tiny Machine Learning easy

life.augmented

synaptics

ENGINEERING EXCEPTIONAL EXPERIENCES

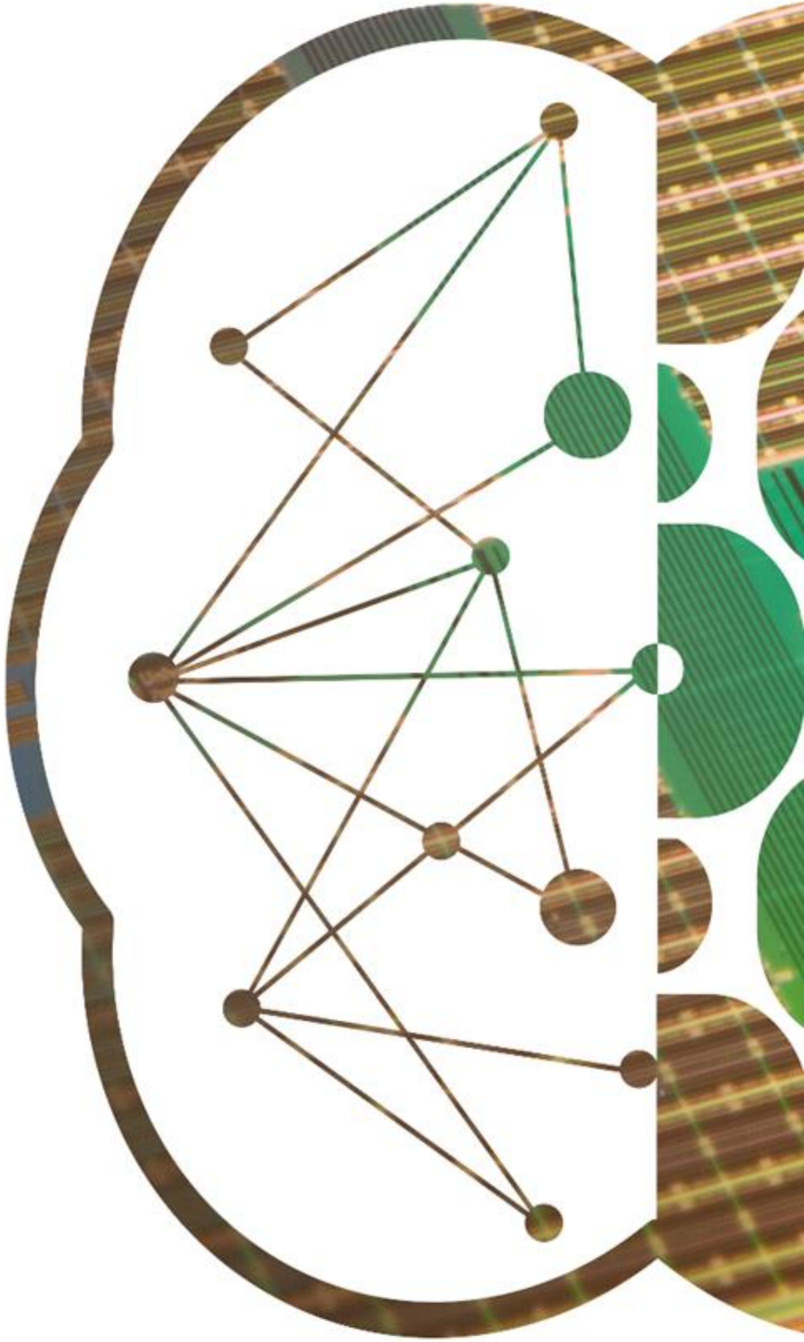
We engineer exceptional experiences for consumers in the home, at work, in the car, or on the go.

www.synaptics.com

SynSense

SynSense builds **sensing and inference** hardware for **ultra-low-power** (sub-mW) **embedded, mobile and edge** devices. We design systems for **real-time always-on smart sensing**, for audio, vision, IMUs, bio-signals and more.

https://SynSense.ai



TINY ML

Neuromorphic Engineering Forum

Silver Strategic Partners

AIZIP

AONdevices

emza visual sense

GREENWAVES TECHNOLOGIES

Grovety Inc.

IBM

imagimob

itemis

Nota AI

OctoML

PROPHESEE

Qeexo

REEXEN technology

SAP

SILICON LABS

STREAM ANALYZE

TDK InvenSense

Neuromorphic Engineering Forum

tinyML EMEA Innovation Forum 2022

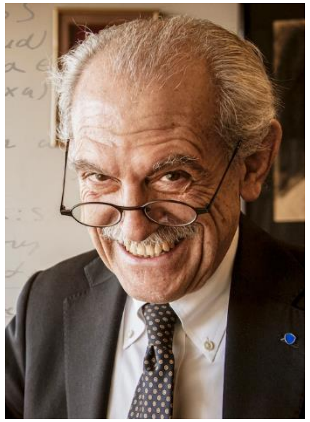
Chair: Prof. Francesco Conti (Univ of Bologna)

Connect, Unify, and Grow the tinyML EMEA Community

October 10-12, 2022

Keynote speakers:

Massimo BANZI
CTO, Arduino



Alberto L. SANGIOVANNI-VINCENTELLI,
UC-Berkeley, Cadence & Synopsys

https://www.tinyml.org/event/emea-2022

in person *in Cyprus, Grand Resort, Limassol*

More sponsorships: sponsorships@tinyML.org

Join Growing tinyML Communities:

11.4k members in
46 Groups in 37 Countries

tinyML - Enabling ultra-low Power ML at the Edge

https://www.meetup.com/tinyML-Enabling-ultra-low-Power-ML-at-the-Edge/

3k members
&
9.3k followers

The tinyML Community

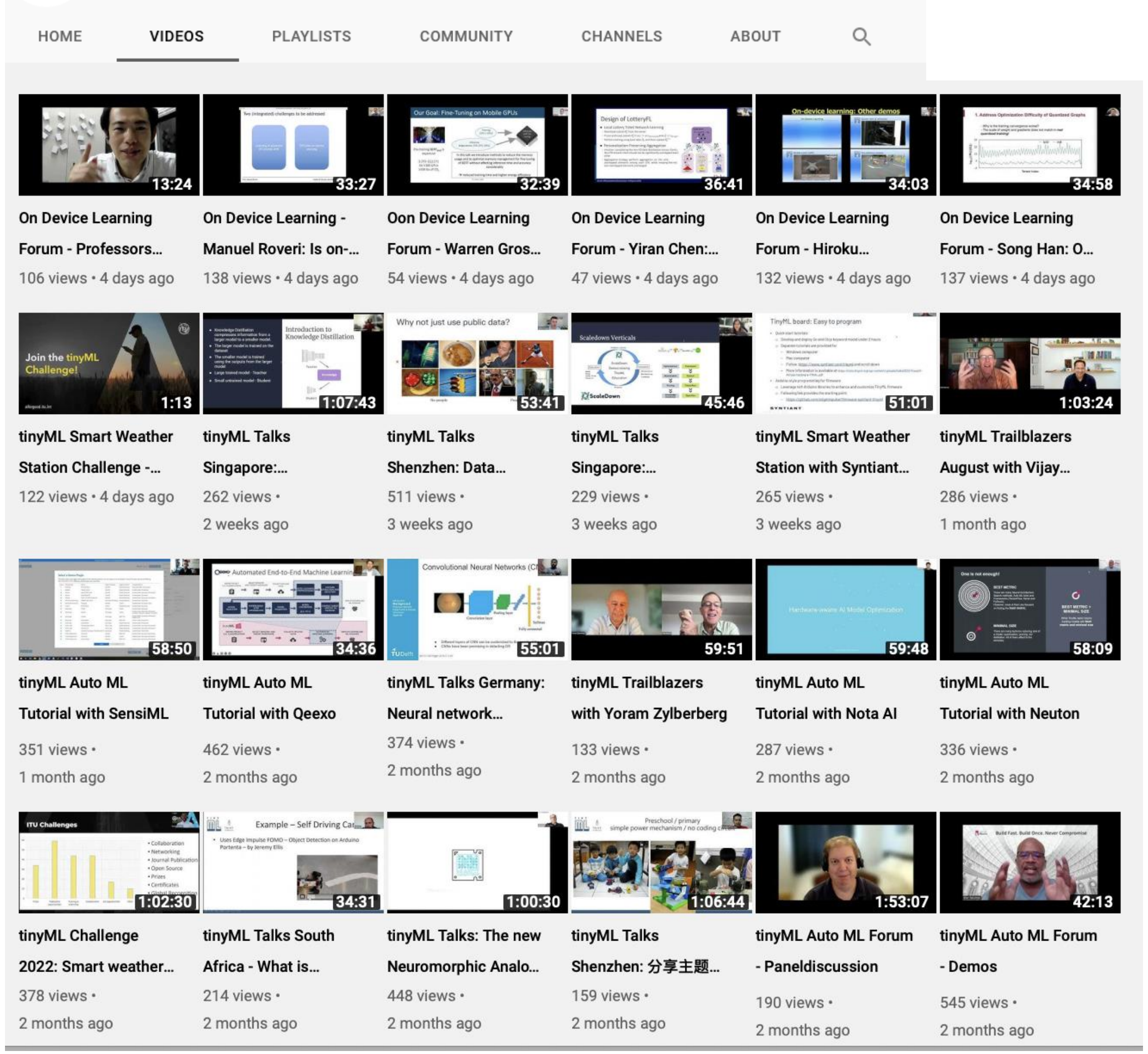
https://www.linkedin.com/groups/13694488/

TINY ML

Neuromorphic Engineering Forum

YouTube

7.7k subscribers, 457 videos with 248k views



Subscribe to
tinyML YouTube Channel
for updates and notifications
(including this video)

www.youtube.com/tinyML

TINY ML
Neuromorphic Engineering Forum

Reminders

Videos will be posted next week

youtube.com/tinyml

Please use the Q&A window for your questions

TINY ML

Neuromorphic Engineering Forum

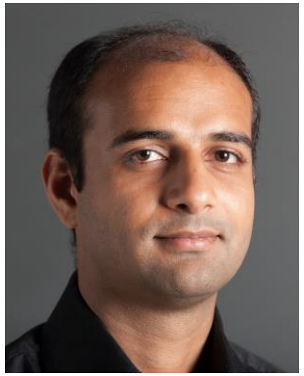
Technical Program Committee

Charlotte Frenkel - Chair
Delft University of Technology

Christoph Posch
PROPHESEE

Jae-sun Seo
Arizona State University

Priya Panda
Yale University



Sadique Sheik
SynSense AG

Yulia Sandamirskaya
Intel

Friedemann Zenke
University of Basel

Andre van Schaik
Western Sydney University

Neuromorphic Intelligence and Learning in Robotics

Yulia Sandamirskaya
Neuromorphic computing Lab, Intel Labs (Munich)
TinyML Neuromorphic Forum, Sept. 27, 2022

intel labs

Legal Information

Performance varies by use, configuration and other factors. Learn more at www.Intel.com/PerformanceIndex.

Performance results are based on testing as of dates shown in configurations and may not reflect all publicly available updates. See backup for configuration details. No product or component can be absolutely secure.

Your costs and results may vary.

Results have been estimated or simulated.

Intel technologies may require enabled hardware, software or service activation.

Intel does not control or audit third-party data. You should consult other sources to evaluate accuracy.

Intel disclaims all express and implied warranties, including without limitation, the implied warranties of merchantability, fitness for a particular purpose, and non-infringement, as well as any warranty arising from course of performance, course of dealing, or usage in trade.

Algorithms for Artificial Intelligence Today

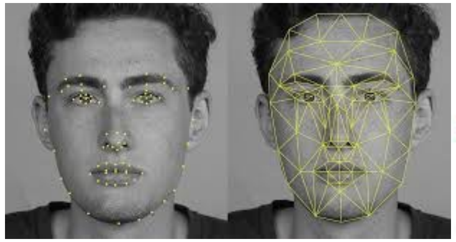


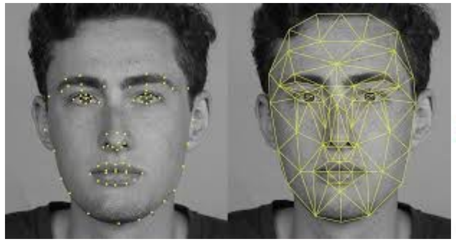
Image (vide

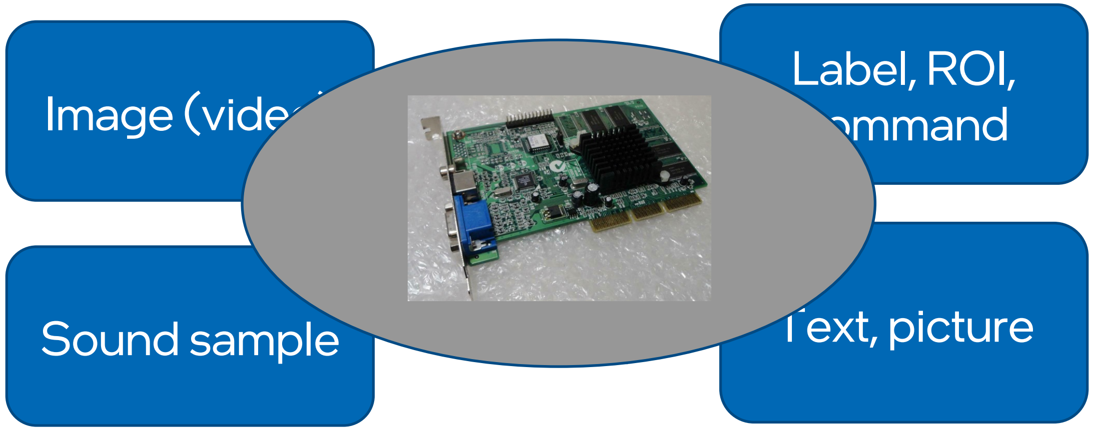
Label, ROI,
ommand

Sound sample

ext, picture

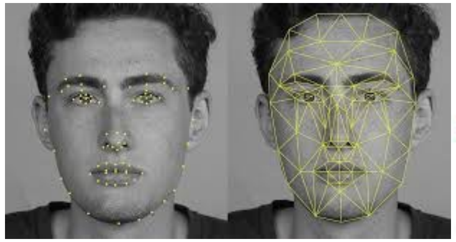
Algorithms for Artificial Intelligence Today and Tomorrow

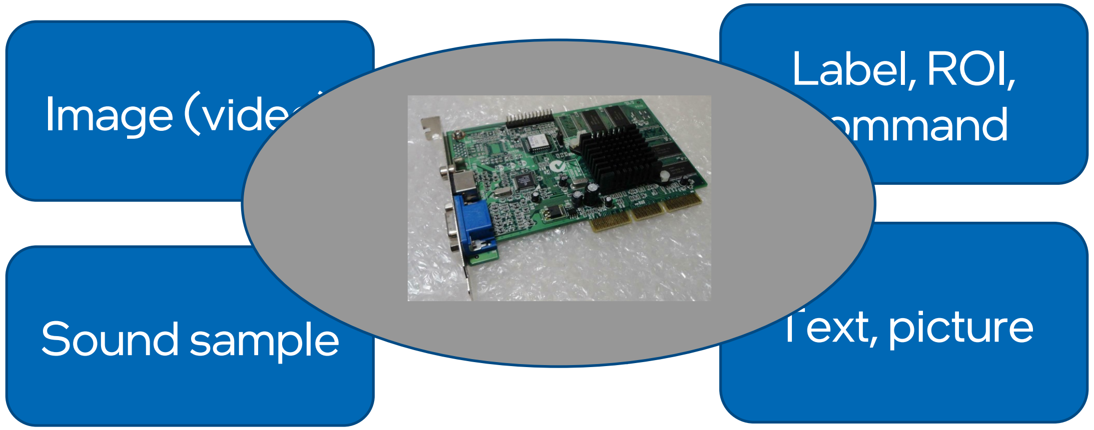




1. Vision
   - Image/Object/Place recognition
   - Localization (IMU, odometry)
   - Estimation of physical parameters (size, shape, weight, surface properties)
   - Spatial reasoning, Scene representation, Map formation (graph-based representations)
   - Language, description
2. Audio, tactile, olfaction
3. Path and motion planning: search, evaluation, decision making
4. Control: task and motor, adaptive, optimization
5. Learning: continual learning, adaptation, context-aware computing

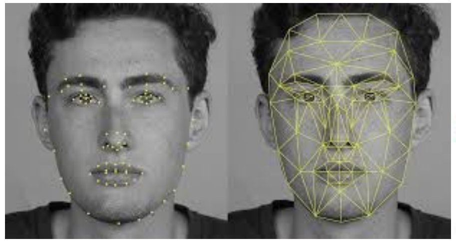
Algorithms for Artificial Intelligence Today and Tomorrow

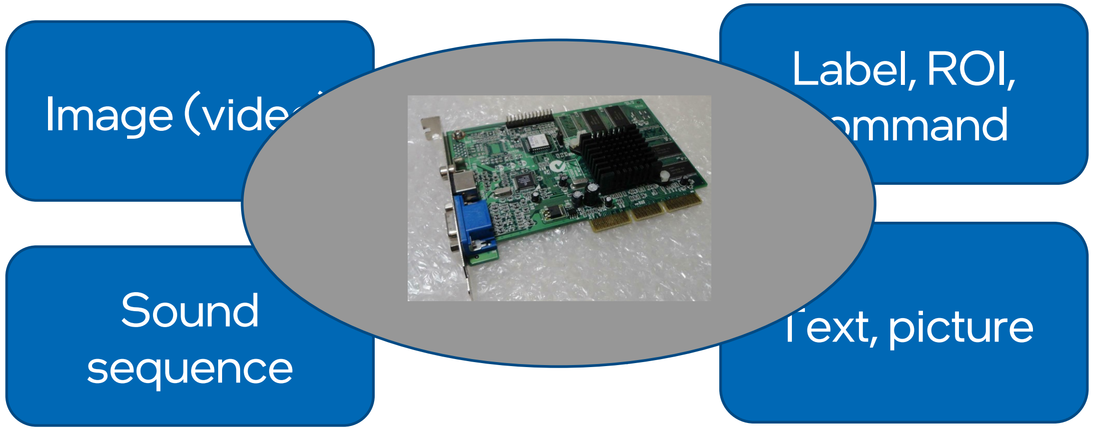


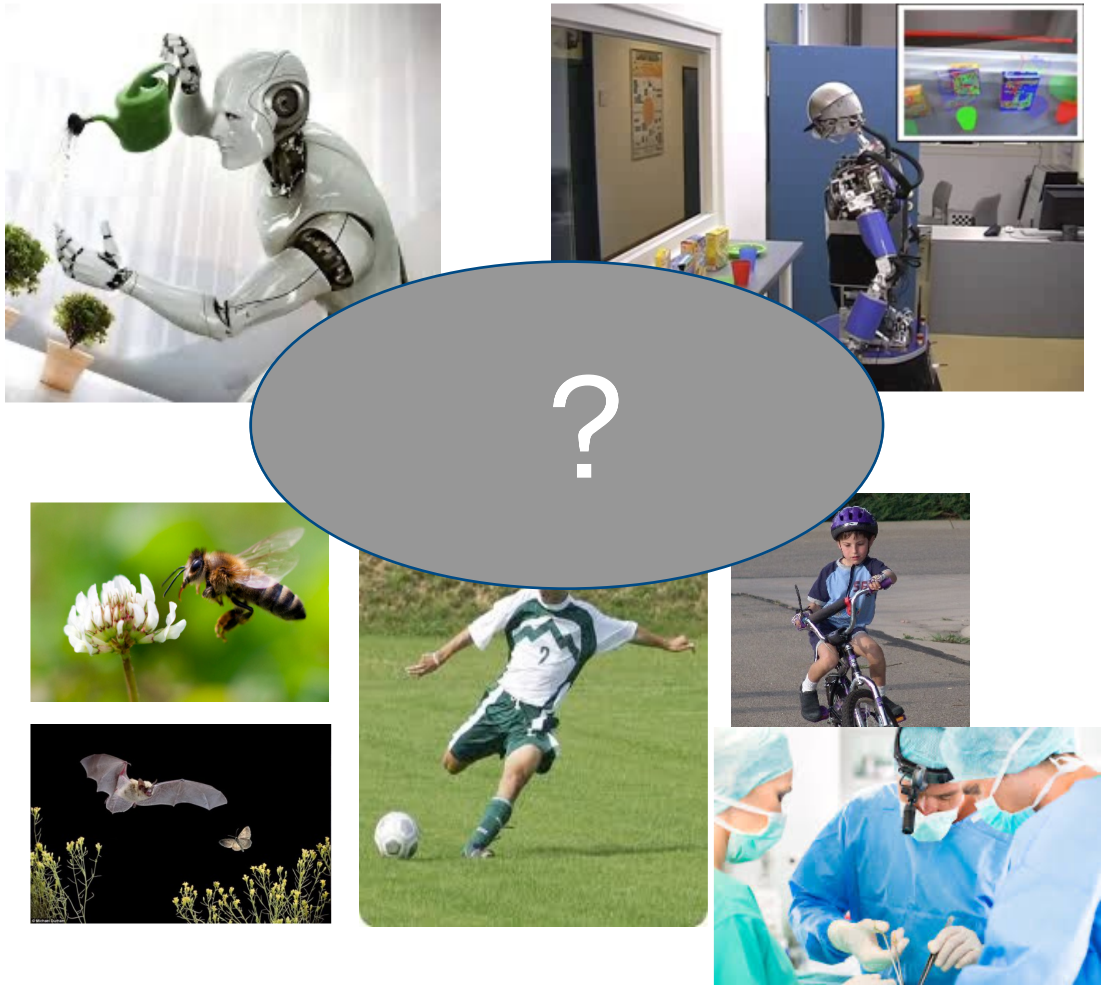


1. Vision
   - Image/Object/Place **recognition**
   - **Localization** (IMU, odometry)
   - **Estimation** of physical parameters (size, shape, weight, surface properties)
   - Spatial **reasoning**, Scene **representation,** Map formation (**graph-based representations**)
   - Language, description
2. Audio, tactile, olfaction
3. Path and motion planning: **search**, evaluation, **decision making**
4. Control: task and motor, adaptive, **optimization**
5. **Learning**: continual learning, adaptation, context-aware computing

Algorithms for Artificial Intelligence Today and Tomorrow







Biological intelligence

- 1g brain, 1M neurons, 1mW
- Navigates and learns in unknown environments “on the fly”

- 2.2g brain, 10 M neurons, 50 mW
- Navigates and learns “on the fly”
- Can learn words
- Can learn to manipulate objects

- 1000g brain, 100 B neurons, 20 W
- Can do amazing things

Biological brains:

Adaptive
Flexible
Fast
Precise
Efficient

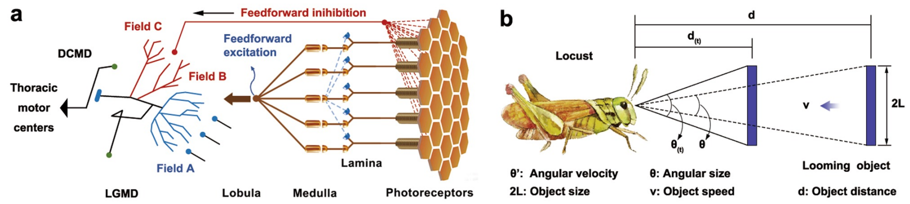
Can deal with real-world complexity

Learn new tasks

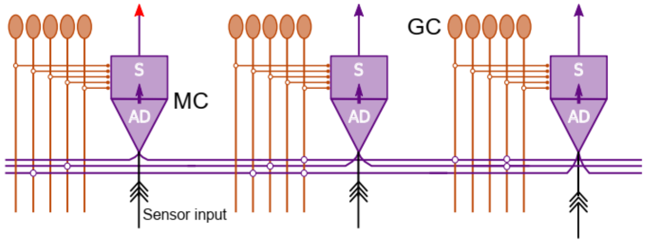
“Cognitive”

What can we learn from biology?

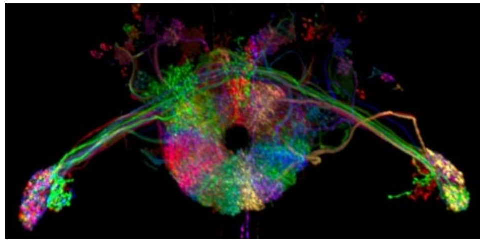
1. Diversity of neuron types, connectivity motives, network structures and topologies



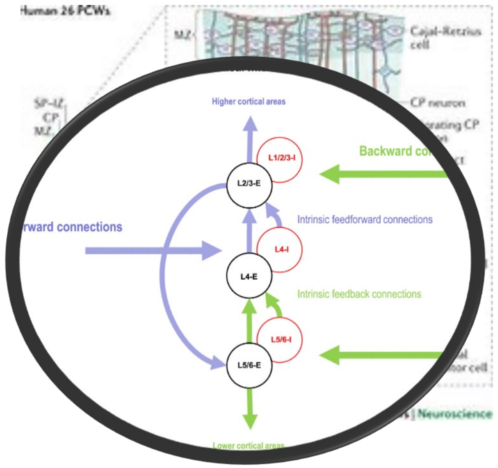
Locust's Giant Motion Detector neuron (LGMD)



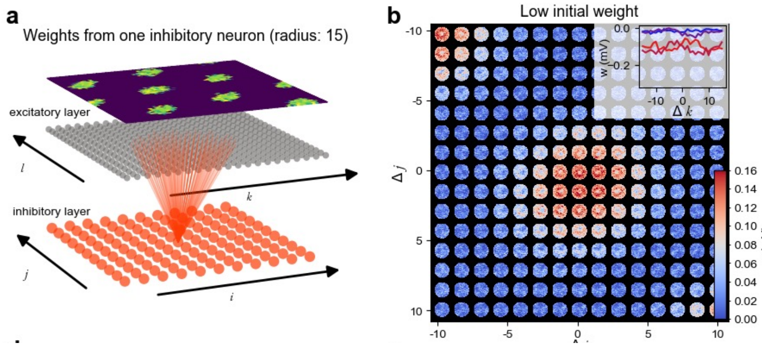
Olfactory circuits



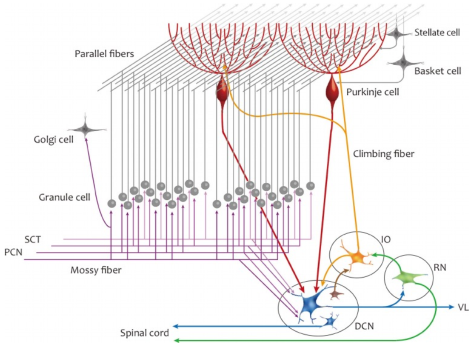
Fly's head direction circuit



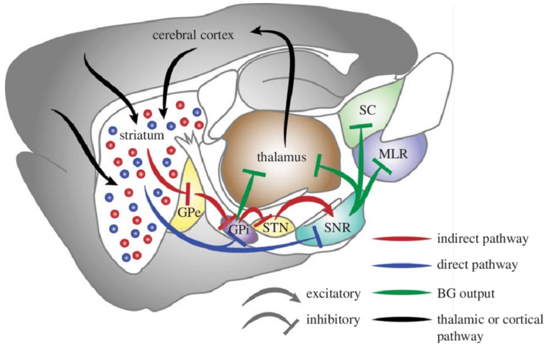
Neocortical layers



Grid cell, hippocampal circuits



Cerebellar architecture



Basal ganglia

2. A lot of predetermined structure augmented with continual learning and plasticity

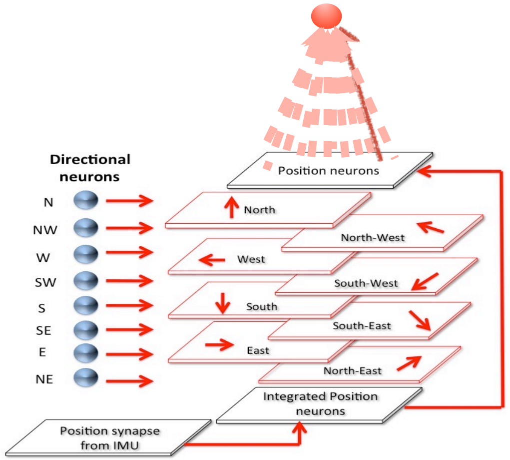
How can we learn from biology?

➢ We can learn specific neural circuits for different tasks

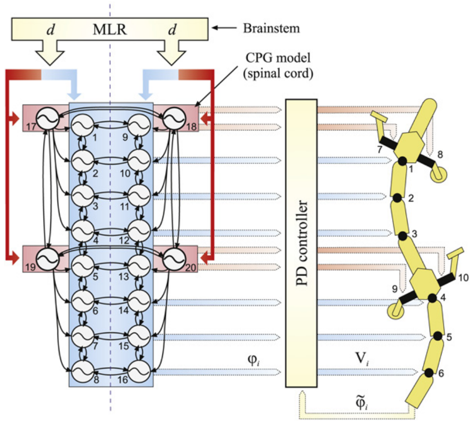
1) Sensing (LGMD, divergence-based landing)
2) Navigation (hippocampal circuits, RatSLAM)
3) CPGs for locomotion

1)

2)



3)



➢ We can learn architectural principles

1) Statful computing; states dynamically stabilitized
2) Loops (predictions, consitency checks)
3) (Autonomous) learning principles

Collection of “solutions” Algorithm, Mechanisms) “Bio”

Principles, laws, building blocks “Phys”

Technology “Eng”

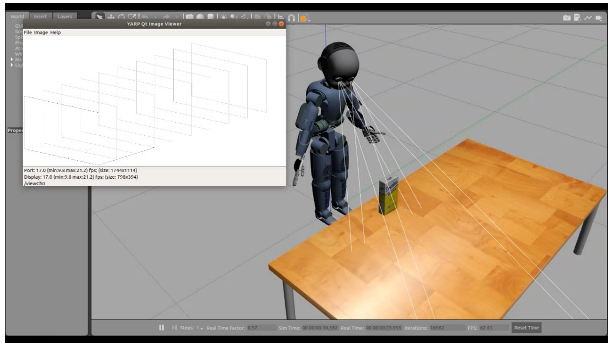
1) Salt, L., Indiveri, G., & Sandamirskaya, Y. (2017, May). Obstacle avoidance with LGMD neuron: towards a neuromorphic UAV implementation. In *2017 IEEE International Symposium on Circuits and Systems (ISCAS)* (pp. 1-4). IEEE.

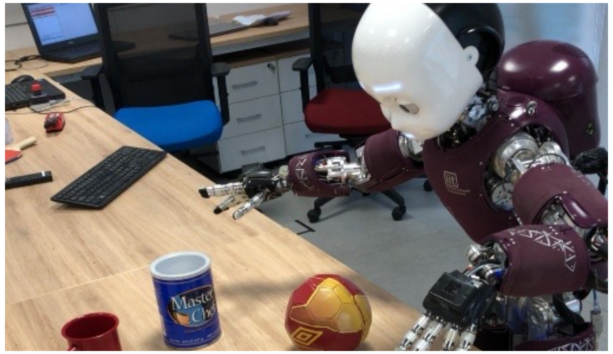
2) Kreiser, R., Renner, A., Sandamirskaya, Y., & Pienroj, P. (2018, October). Pose estimation and map formation with spiking neural networks: towards neuromorphic SLAM. In *IROS* (pp. 2159-2166). IEEE.

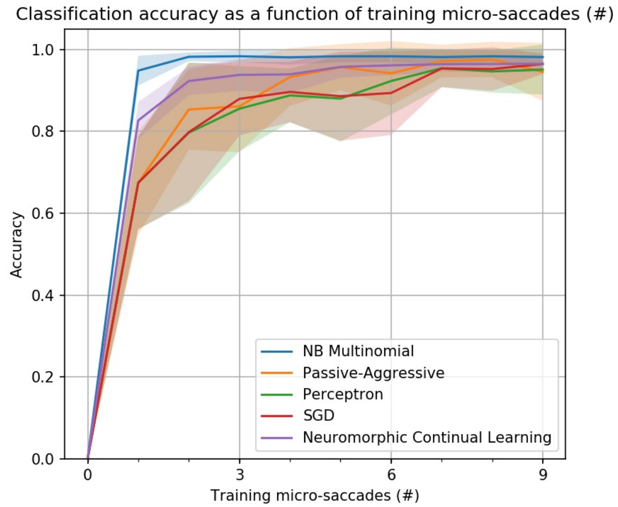
3) A.J. Ijspeert, Central pattern generators for locomotion control in animals and robots: A review. Neural Networks, vol. 21/4, pp. 642-653, 2008

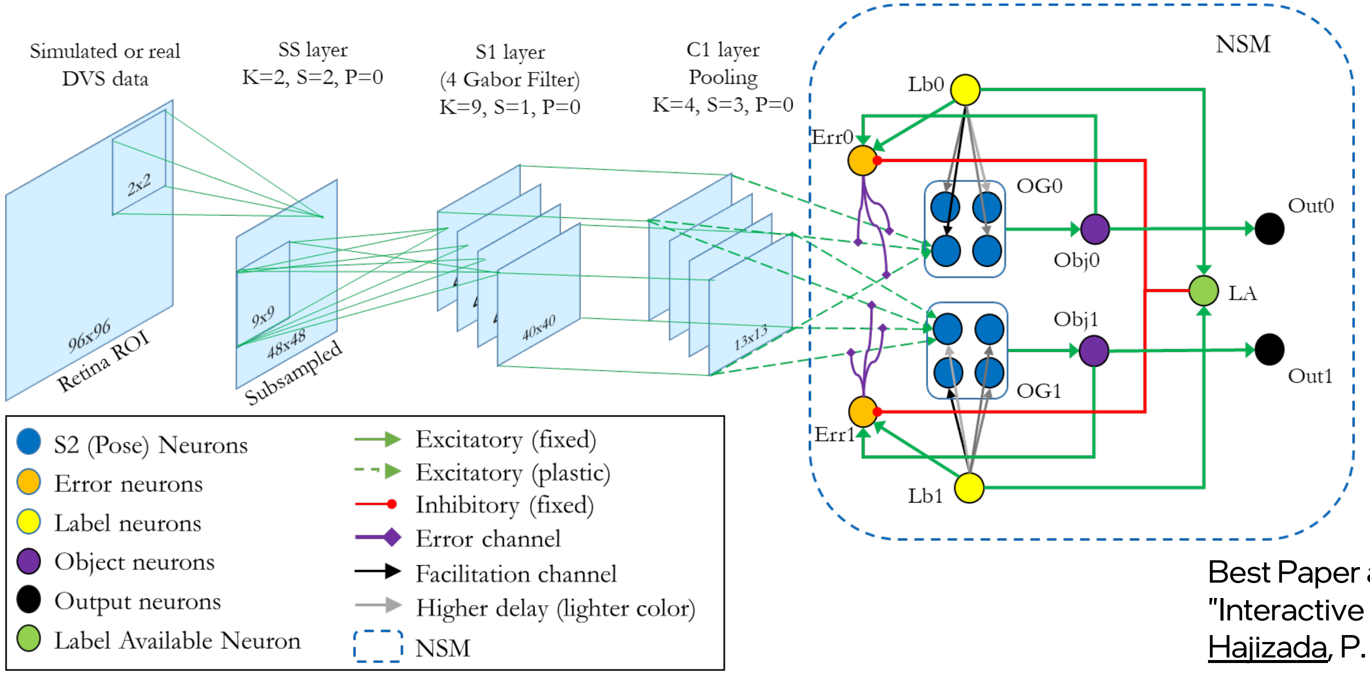
Example: object learning

- Learning objects in a natural way







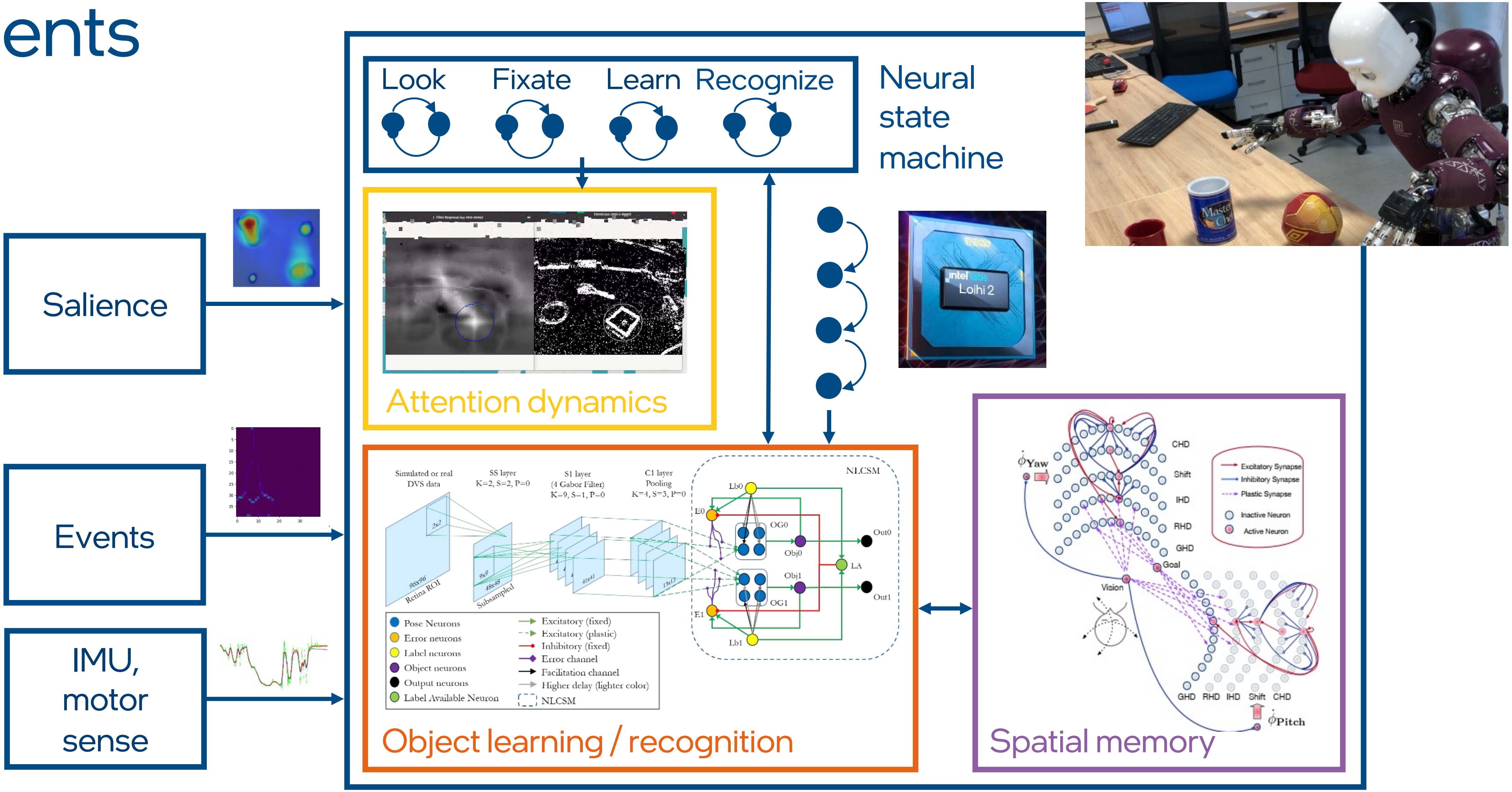


- 200x better energy per learning instance and up to 150x for inference
- The best execution time for learning an instance and being on par with other methods in inference time

Best Paper at International Conference on Neuromorphic Systems (ICONS): "Interactive continual learning for robots: a neuromorphic approach," E. Hajizada, P. Berggold, M. Iacono, A. Glover, Y. Sandamirskaya

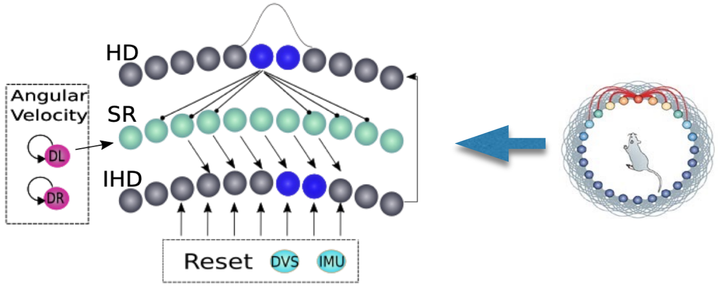
Notice: All experiments run on a machine with Intel(R) Core(TM) i7-9700K CPU @ 3.60GHz x8, 32GB RAM running Ubuntu 20.04.2 LTS, python 3.8.10, and v. 1.0.0 of the Intel NxSDK in Loihi 1 hardware. All performance measurements are based on testing as of October 2021 and may not reflect all publicly available security updates. Results may vary.

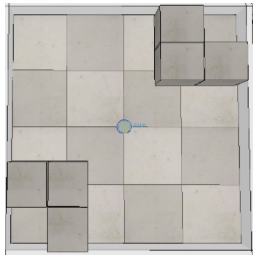
Combining with other behavioral elements

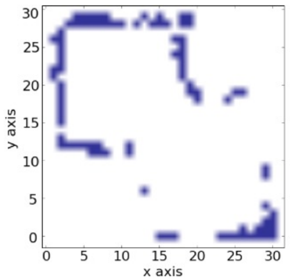


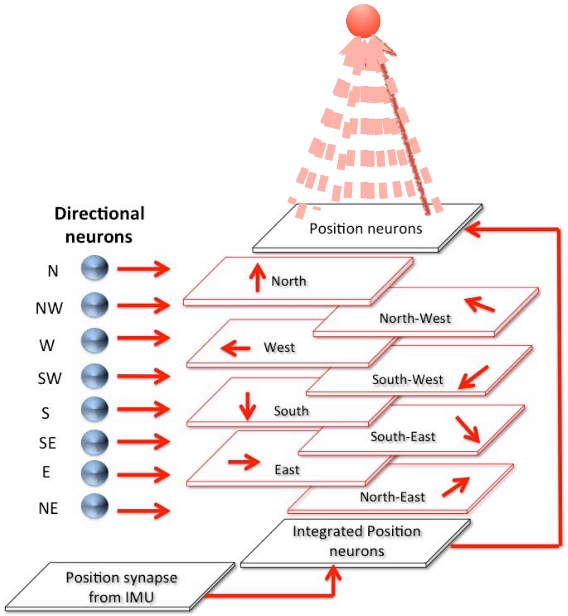
Spatial memories: forming and correcting a memory

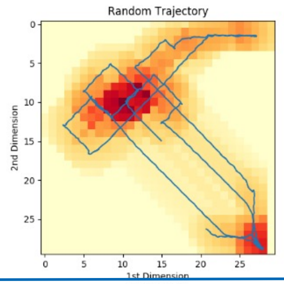
Place cells, Grid cells

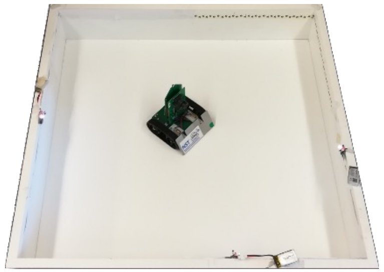


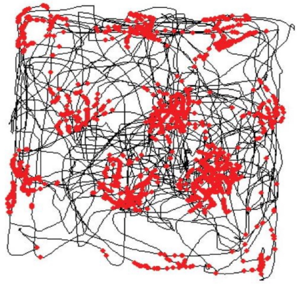






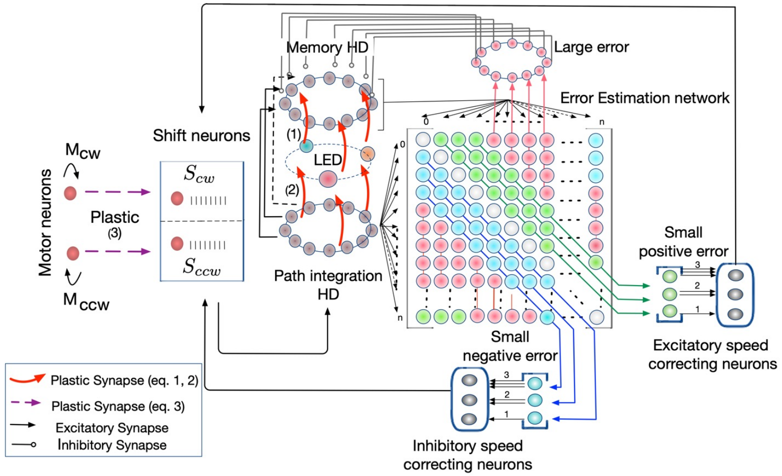


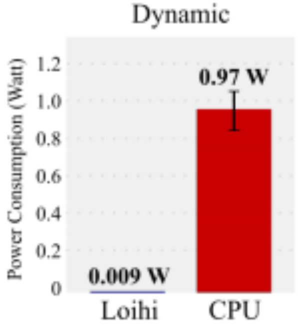




Moser et al. Annual Review of Neuroscience 2008

Error monitoring and correction



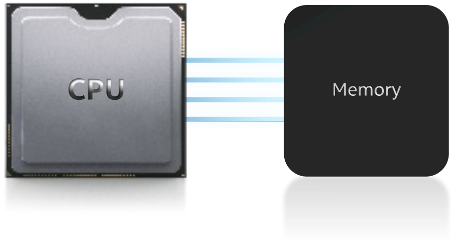


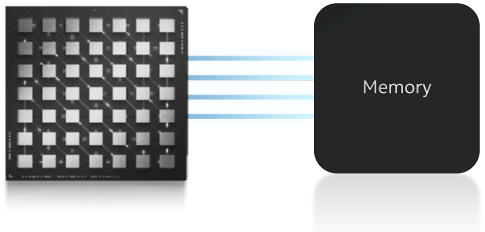
X100 more energy efficient compared to Gmapping on CPU (i7-4850HQ) on 1D SLAM

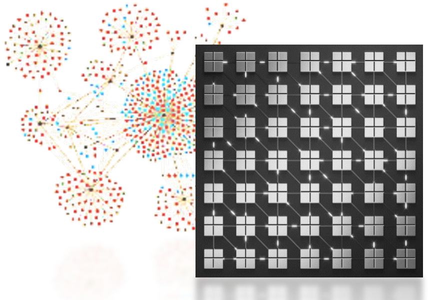
Kreiser et al, ISCAS 2018; Kreiser et al, IROS 2018, 2019; Kreiser at al, RAINR 2019;

Tang, Michmizos, ACM Proc., 2018

Implementing neural architectures efficiently



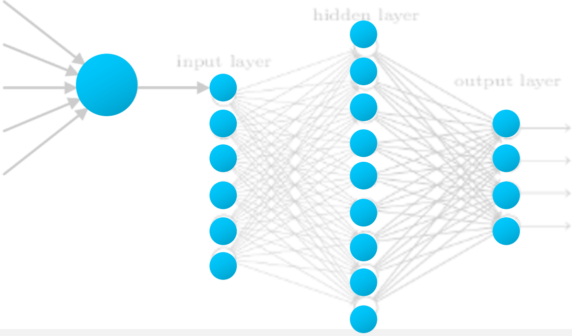


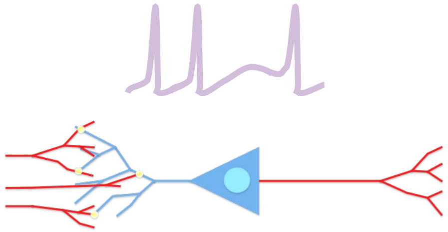


SEQUENTIAL THREADS OF CONTROL	PARALLEL DENSE COMPUTE	PARALLEL SPARSE COMPUTE
SYNCHRONOUS CLOCKING	SYNCHRONOUS CLOCKING	ASYNCHRONOUS EVENT-BASED SPIKES
PROGRAMMING BY ENCODING ALGORITHMS	OFFLINE TRAINING USING LABELED DATASETS	LEARN ON THE FLY THROUGH LOCAL LEARNING RULES

```
if X then
  …
else
 …
```

01100
11010
00100





Neuromorphic hardware marketplace

Digital Chips

- TrueNorth (IBM)
- Loihi (Intel)
- Tianjic (Tsinghua U)
- Darwin 2 (Zhejian Lab)
- SpiNNaker 2 (Human Brain Project)
- DynapCNN (SynSense / Baidu)
- GrAI One (GrAI Matter Labs)
- Akida (BrainChip)

Mixed analog-digital Chips

- ROLLS (ETH Zurich)
- Braindrop (Stanford)
- DynapSEL (SynSense / Baidu)
- Innatera (Delft)

Large-Scale Systems

4M-neuron
BrainScaleS
(HBP)

64M-neuron
NS16e-4 (IBM)

1M-core
SpiNNaker
(HBP)

100M-neuron
Pohoiki Beach/Springs (Intel)

120M-neuron
Darwin Mouse (Zhejiang U)

Event-based Vision

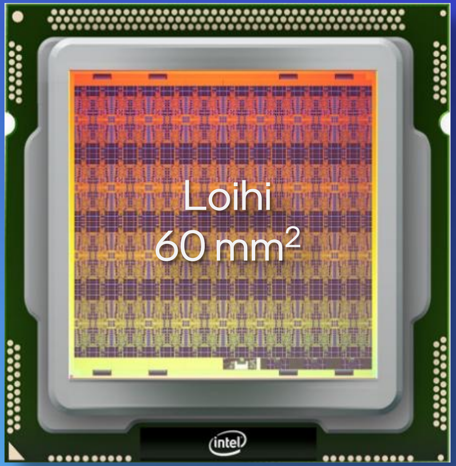
- DAVIS240C (IniVation) 18um
- CeleX-IV (CelePixel) 18um
- DVS-Gen2 (Samsung) 9um
- DVS-Gen3 (Samsung) 6um
- Gen4 (Prophesee/Sony)
- FENCE (DARPA) event-based IR

2014 2015 2016 2017 2018 2019 2020 2021

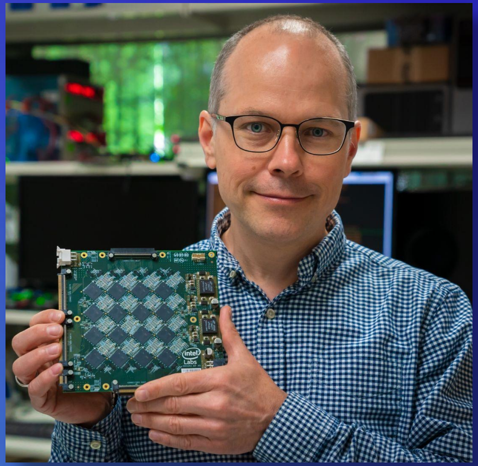
Five years ago, Intel Labs announced the Loihi neuromorphic test chip

Our mission: Pioneer a new programmable computing technology inspired by a modern understanding of the brain

Loihi Neuromorphic Research Chip



Nahuku board with 32 Loihi chips

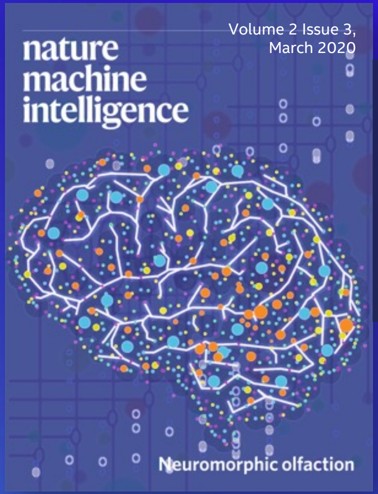


Pohoiki Springs system with 768 Loihi chips

Research Community with 180+ members

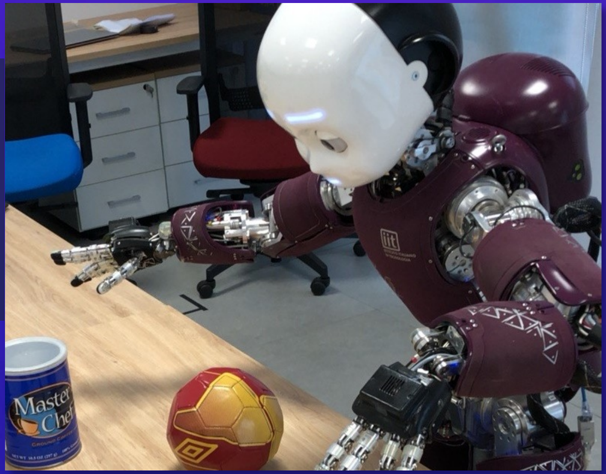
Image: intel.com/content/www/us/en/research/neuromorphic-community.html

Loihi application proof points

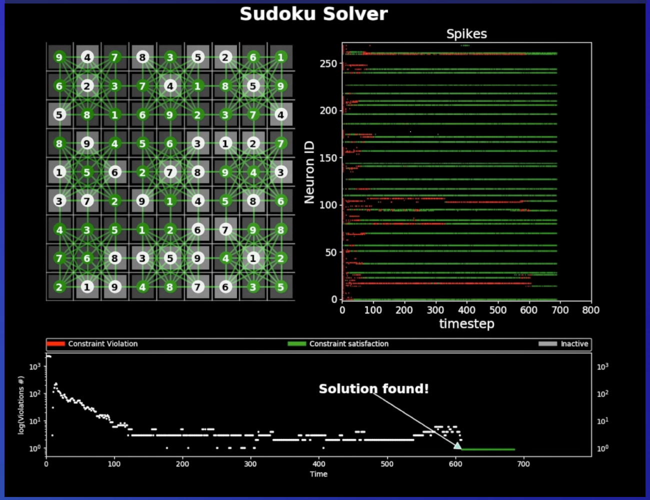


Olfaction-inspired odor recognition and learning
3000x more data efficient learning than a deep autoencoder

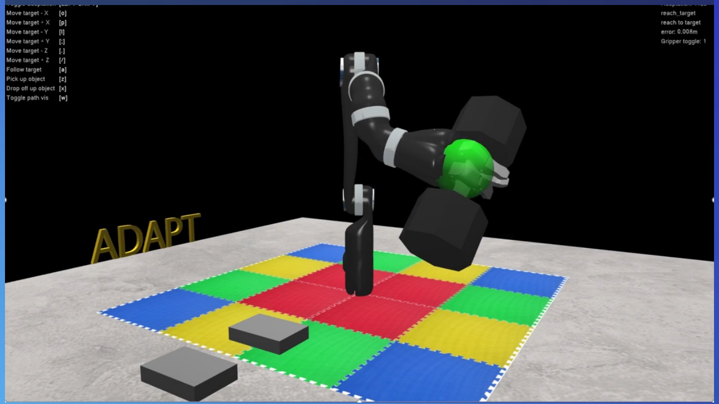
Scene understanding
Integrated behaviors: Object recognition, tracking, learning
100x lower power SLAM vs CPU



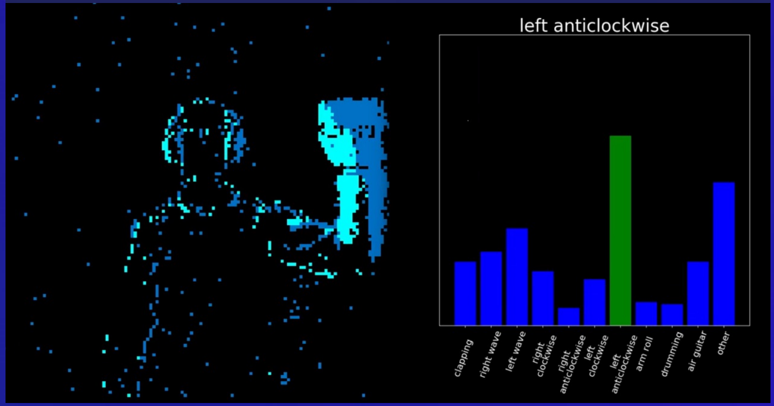
Combinatorial optimization
(CSP, SAT, ILP, QP)
2,800x lower energy and 44x faster vs CPU



Adaptive robotic arm control
40x lower power, 50% faster vs GPU



Gesture recognition + learning
Loihi + DAVIS 240C camera
60 mW total power, 15 mW dynamic

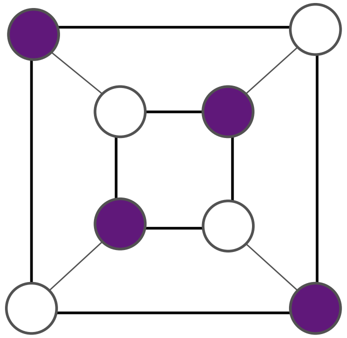


Orders of magnitude gains for optimization workloads

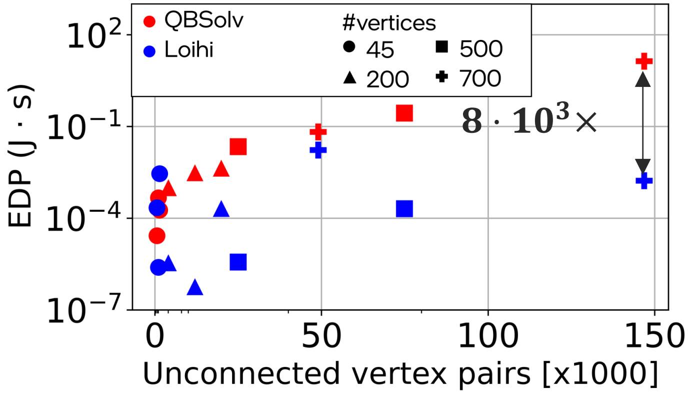
QUBO (Maximum Independent Set)

Workload:
Find the largest possible set of unconnected vertices

Relevance:
- Target of quantum annealing approaches
- NP Hard



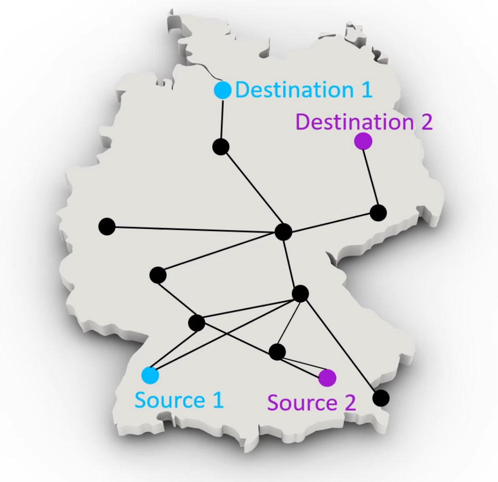
CPU (QBSolv) versus Loihi Energy-Delay-Product



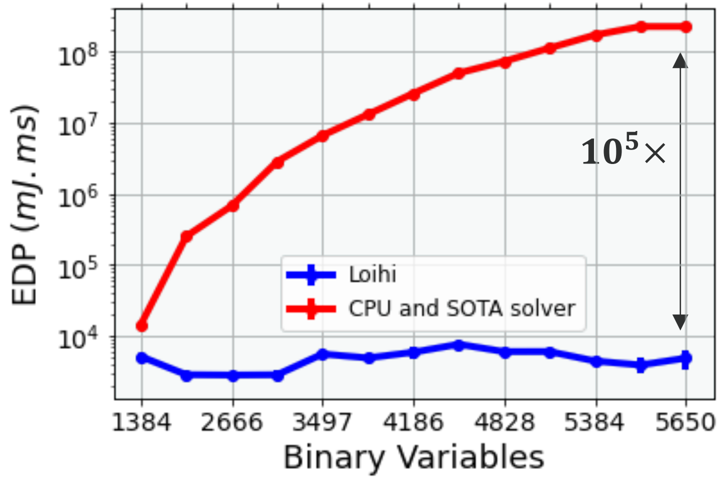
Integer Linear Programing (Train Scheduling)

Workload:
Find the largest possible set of route assignments, given customer requests and railway, time and train constraints.

Relevance:
- Large-scale, real-world use case
- Applicable to resource allocation in warehouses and production lines.



CPU vs Loihi Energy Delay Product



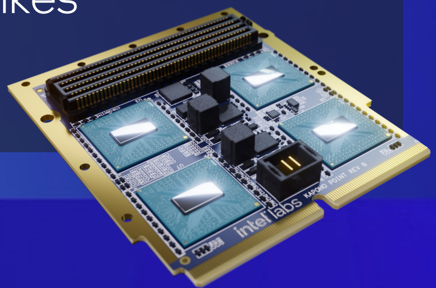
Loihi: Nahuku board running NxSDK 0.95 with an Intel Core i7-9700K host with 128GB RAM, running Ubuntu 16.04.6 LTS
QUBO-QBSolv/CPU: benchmarks ran on an Intel Xeon CPU E5-2699 v3 @ 2.30GHz with 32GB DRAM (https://github.com/dwavesystems/qbsolv)
ILP-CPU: Xeon-based commercial cloud service as used operationally by DB. Solver runtime was measured; energy consumption estimated based on a 100W TDP estimate.

Performance results are based on testing as of September 2021 and may not reflect all publicly available security updates. Results may vary.

Last year, Intel entered a new era with Intel Loihi 2 and open-source Lava framework

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

- Up to 10x faster processing capability*
- Up to 60x more inter-chip bandwidth*
- Up to 1 million neurons with 15x greater resource density*
- 3D scalable
- Native ethernet
- Programmable neurons
- Graded spikes



LAVA

Event-based communication

Multi-Paradigm

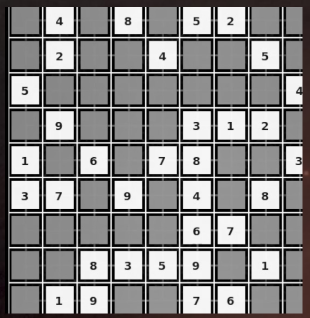
Multi-Abstraction

Multi-Platform

Open-Source and Community-Driven

Multi-Paradigm

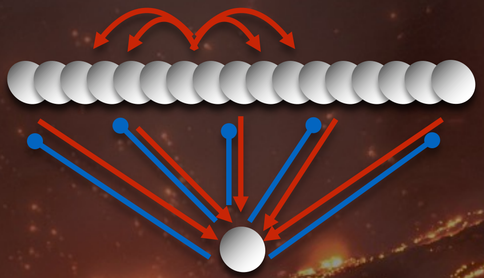
Optimization



LCA, Stochastic SNNs
LASSO, QP,
CSP, ILP, QUBO

+ model learning

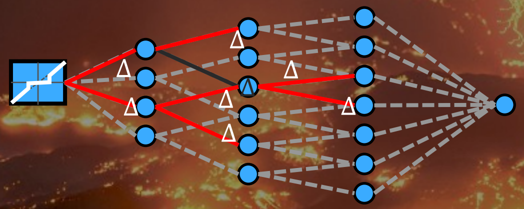
Neural Attractors



Dynamic Neural Fields,
Continuous Attractor NNs,
WTA

+ associative learning

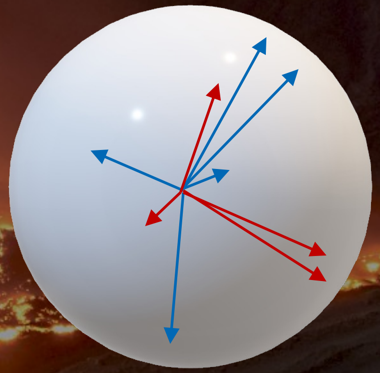
Deep Learning



ANN->SNN rate-coded conversion,
Directly trained SNN ConvNets
Sigma-Delta Neural Networks
TTFS- and Phase-coded SNNs

+ gradient learning

Vector Symbolic



HRRs, MAPs,
Binary Spatter Codes,
Sparse Block Codes,
Resonator Networks

+ HD learning

Many others to come: NEF, Reservoir Computing, STICK, Equilibrium Propagation, evolutionary, ...

Latest Lava Milestones and Results

- Intel added support for Loihi 2 features including **programmable neurons, graded spikes, and continual learning**.
- With the latest release of Lava (v0.5) and Kapoho Point, Intel Labs achieved **15x improved energy efficiency and up to 12x faster throughput** for a deep learning application.

	Loihi 1 SNN [3]	Loihi 2 SNN [2]		Loihi 2 SDNN [1]	
Mean-Square-Error	0.049	0.049	1	0.037	32% lower
Neuron cores	368	70	5x smaller	70	5x smaller
Latency (ms)	15.5	2.56	6x faster	1.22	9-12x faster
Throughput (fps)	808	4877		7404	
Energy (uJ/frame)	1770	270	6.5x better	120	15x more efficient
TOPS/W (DNN equiv)	0.02	0.13		0.28	

Results may vary.

[1] Loihi 2 SDNN results based on Lava v0.5 benchmarks in September, 2022 of 9-layer PilotNet DNN inference workload implemented as a sigma-delta neural network on Loihi 2. Equivalent DNN op counts calculated from a conventional DNN implementation with the same topology and same number of 8-bit parameters. See Bojarski, Mariusz et al. "End to end learning for self-driving cars." arXiv preprint arXiv:1604.07316 (2016).

[2] Loihi 2 SNN measurements were obtained on Oheo Gulch board ncl-og-06 using an internal version of NxSDK.
[3] Loihi 1 SNN measurements were obtained on Nahuku 32 board ncl-ghrd-01 using NxSDK v1.0.0

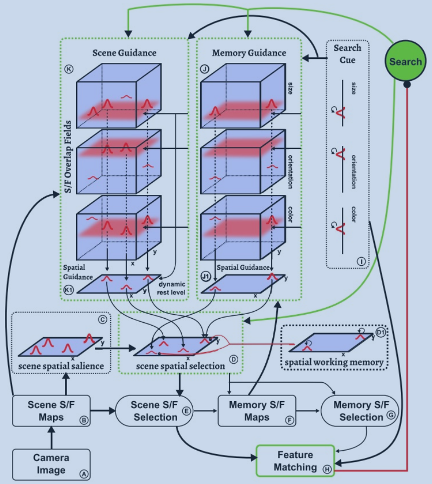
Redefining Artificial Intelligence with Neuromorphic Computing

Diversity of neuronal "algorithms"

- Representation: Sensing, memory
- Evaluation of options: Optimization, planning
- Decision making
- Action: active sensing, sensing for acting

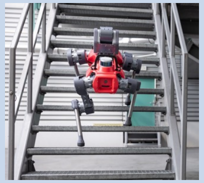
Symbolic processing

Artificial embodied intelligence



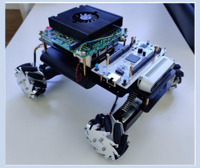
- Building intelligent neural architectures
- With building blocks inspired by bio-computing principles

locomotion



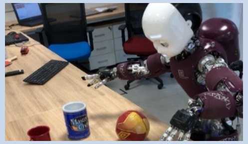
drones

vehicles



- Enabling smart autonomous systems

arms, grippers



cognitive, humanoids

autonomous spaces

Intel Neuromorphic Research Community

To join:
inrc_interest@intel.com

Collaborating to Accelerate the Research

INRC includes over ~~120~~ 170 groups

Other names and brands may be claimed as the property of others

The Future Begins Here

intel labs

References and System Test Configuration Details

[Task 1] P Blouw et al, 2018. arXiv:1812.01739

[Task 2] TY Liu et al, 2020, arXiv:2008.01380

[Task 3] KP Patel et al, "A spiking neural network for image segmentation," *submitted, in review*, Aug 2020.

[Task 4] **Loihi**: Nahuku system running NxSDK 0.95. CIFAR-10 image recognition network trained using the SNN-Toolbox (code available at https://snntoolbox.readthedocs.io/en/latest). **CPU**: Core i7-9700K with 32GB RAM, **GPU**: Nvidia RTX 2070 with 8GB RAM. OS: Ubuntu 16.04.6 LTS, Python: 3.5.5, TensorFlow: 1.13.1. Performance results are based on testing as of July 2020 and may not reflect all publicly available security updates.

[Task 5] **Loihi**: Nahuku system running NxSDK 0.95. Gesture recognition network trained using the SLAYER tool (code available at https://github.com/bamsumit/slayerPytorch). Performance results are based on testing as of July 2020 and may not reflect all publicly available security updates. **TrueNorth:** Results and DVS Gesture dataset from A. Amir et al, "A low power, fully event-based gesture recognition system," in IEEE Conf. Comput. Vis. Pattern Recog. (CVPR), 2017.

[Task 6] T. Taunyazov et al, 2020. RSS 2020

[Task 7] Bellec et al, 2018. arXiv:1803.09574. **Loihi**: Loihi: Wolf Mountain system running NxSDK 0.85. **CPU**: Intel Core i5-7440HQ, with 16GB running Windows 10 (build 18362), Python: 3.6.7, TensorFlow: 1.14.1. **GPU**: Nvidia Telsa P100 with 16GB RAM. Performance results are based on testing as of December 2018 and may not reflect all publicly available security updates.

[Task 8] T. DeWolf et al, "Nengo and Low-Power AI Hardware for Robust, Embedded Neurorobotics," Front. in Neurorobotics, 2020.

[Task 9] Loihi Lasso solver based on PTP Tang et al, "Sparse coding by spiking neural networks: convergence theory and computational results," arXiv:1705.05475, 2017. **Loihi**: Wolf Mountain system running NxSDK 0.75. **CPU**: Intel Core i7-4790 3.6GHz w/ 32GB RAM running Ubuntu 16.04 with HyperThreading disabled, SPAMS solver for FISTA, http://spams-devel.gforge.inria.fr/.

[Task 10] G Tang et al, 2019. arXiv:1903.02504

[Task 11] EP Frady et al, 2020. arXiv:2004.12691

[Task 12] Loihi graph search algorithm based on *Ponulak F., Hopfield J.J. Rapid, parallel path planning by propagating wavefronts of spiking neural activity. Front. Comput. Neurosci. 2013.* **Loihi**: Nahuku and Pohoiki Springs systems running NxSDK 0.97. **CPU**: Intel Xeon Gold with 384GB RAM, running SLES11, evaluated with Python 3.6.3, NetworkX library augmented with an optimized graph search implementation based on Dial's algorithm. See also http://rpg.ifi.uzh.ch/docs/CVPR19workshop/CVPRW19_Mike_Davies.pdf

[Task 13] **Loihi**: constraint solver algorithm based on *G.A. Fonseca Guerra and S.B. Furber, Using Stochastic Spiking Neural Networks on SpiNNaker to Solve Constraint Satisfaction Problems. Front. Neurosci. 2017.* Tested on the Nahuku 32-chip system running NxSDK 0.98. **CPU**: Core i7-9700K with 32GB RAM running Coin-or Branch and Cut (https://github.com/coin-or/Cbc). Performance results are based on testing as of July 2020 and may not reflect all publicly available security updates.

Loihi 2 Performance Analysis Details

[2] Based on comparisons between barrier synchronization time, synaptic update time, neuron update time, and neuron spike times between Loihi 1 and 2. Loihi 1 parameters measured from silicon characterization (see below); Loihi 2 parameters measured from both silicon characterization with N3B1 revision and pre-silicon circuit simulations using back-annotated timing for Loihi 2.

[3] Based on Lava simulations in September, 2021 of a nine-layer variant of the PilotNet DNN inference workload implemented as a sigma-delta neural network on Loihi 2 compared to the same network implemented with SNN rate-coding on Loihi. The Loihi 2 SDNN implementation gives better accuracy than the Loihi 1 rate-coded implementation.

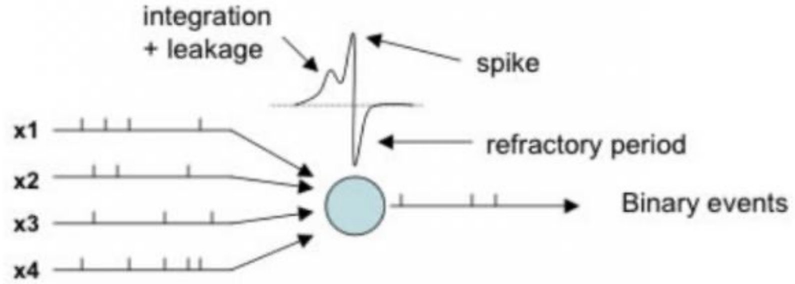
[4] Circuit simulations of Loihi 2's wave pipelined signaling circuits show 800 Mtransfers/s compared to Loihi 1's measured performance of 185 Mtransfers/s.

[5] Based on analysis of 3-chip and 7-chip Locally Competitive Algorithm examples.

The Lava performance model for both chips is based on silicon characterization in September 2021 using the Nx SDK release 1.0.0 with an Intel Xeon E5-2699 v3 CPU @ 2.30 GHz, 32GB RAM, as the host running Ubuntu version 20.04.2. Loihi results use Nahuku-32 system ncl-ghrd-04. Loihi 2 results use Oheo Gulch system ncl-og-04. Results may vary.

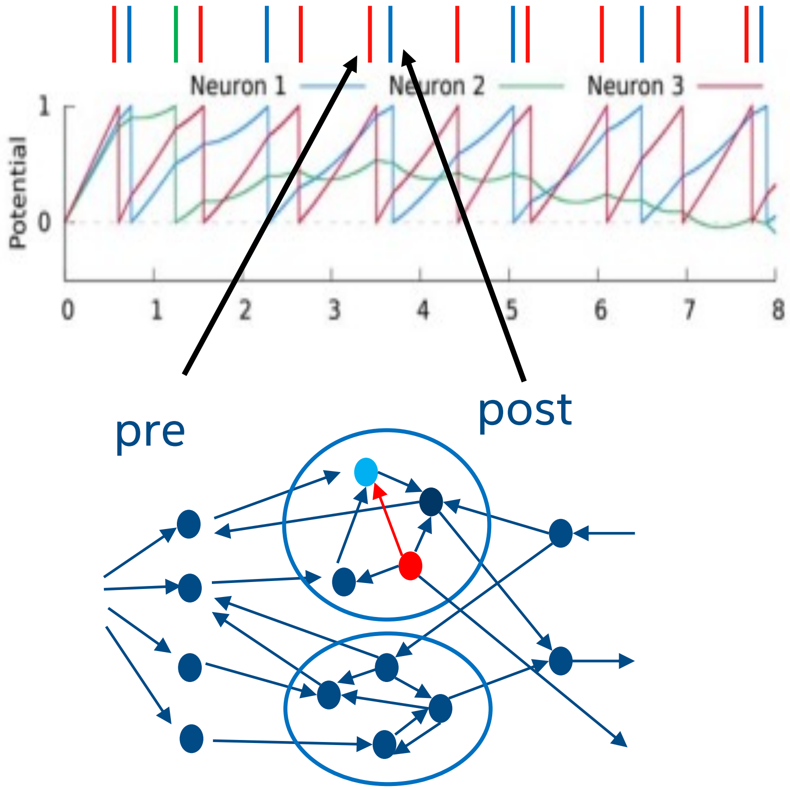
Neuromorphic computing: Core elements

Spiking neuron: leaky integrate and fire

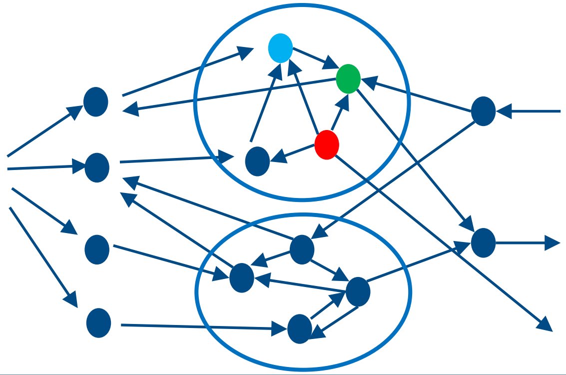


- Time is explicitly included in computation
- Events (spikes) transmit activation
- Spatial-temporal patterns

Learning: synaptic plasticity



- Local learning rules



Network topology

- Fine-grained parallelism
- Modularity, recurrence

TINY ML

Neuromorphic Engineering Forum

Copyright Notice

www.tinyml.org