GPGPU ACCELERATED SIMULATION AND PARAMETER TUNING FOR NEUROMORPHIC APPLICATIONS

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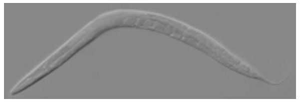
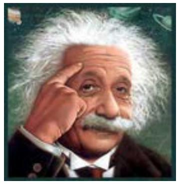
Brains by the Numbers

Species	Neurons	Synapses
Nematode	302	10^3
Fruit Fly	100,000	10^7
Honeybee	960,000	10^9
Mouse	75,000,000	10^{11}
Cat	1,000,000,000	10^{13}
Human	85,000,000,000	10^{15}



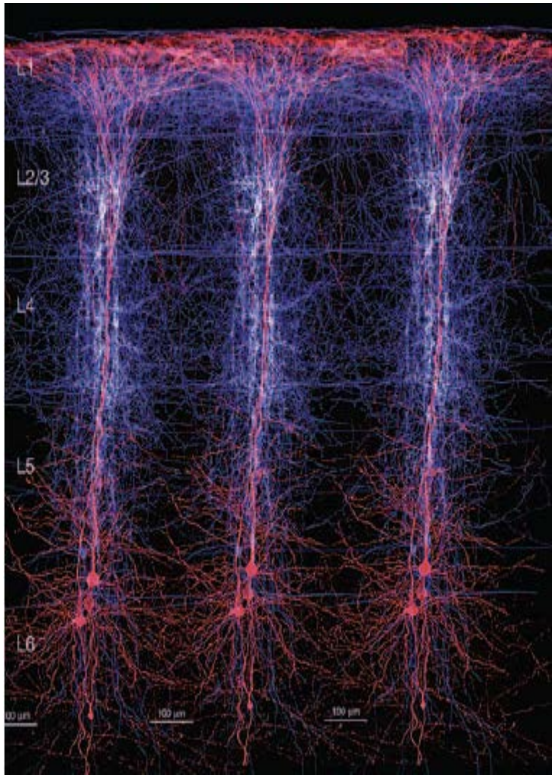


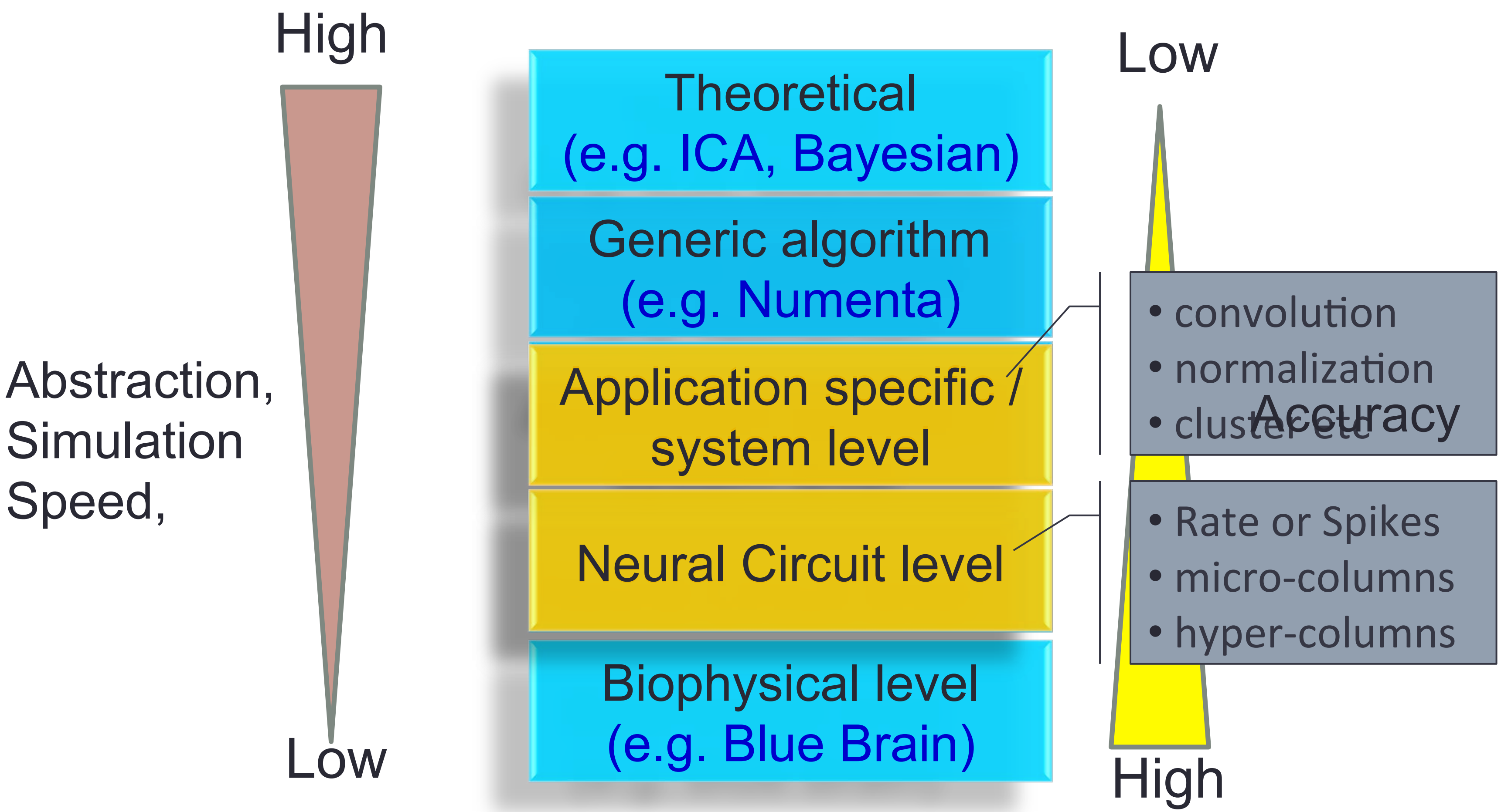
Source – http://en.wikipedia.org/wiki/List_of_animals_by_number_of_neurons

Brain Computations

- Massive parallelism (10^{11} neurons)
- Massive connectivity (10^{15} synapses)
- Excellent power-efficiency
  - ~ 20 W for 10^{16} flops
- Low-performance components (~100 Hz)
- Low-speed comm. (~meters/sec)
- Low-precision synaptic connections
- Probabilistic responses and fault-tolerant
- Autonomous learning



Hierarchy of Brain Model Abstractions



Outline

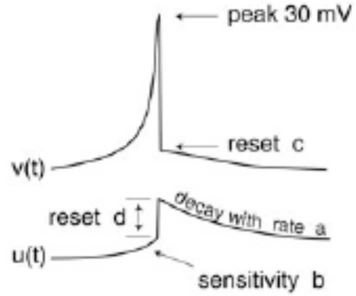
- **What are SNNs?**
- **Neuromorphic Hardware and Simulation Tools**
- **CARLSim SNN Simulator and Applications**
- **Parameter Tuning of Large-Scale SNNs**

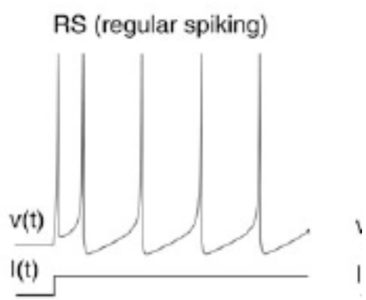
Spiking Neural Networks (SNNs)

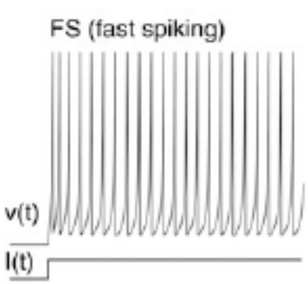
- **What are SNNs?**
  - Neural Networks that model neuronal/synaptic temporal dynamics
  - Spike only when the membrane voltage exceeds a threshold

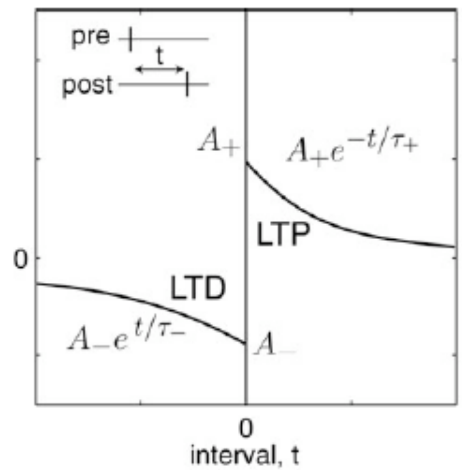
- **Why use SNNs?**
  - Speed of processing hypothesis
    - processing with a wave of spikes
  - Spikes are rare: average brain activity < 1Hz
    - "rates" are not energy efficient
  - SNNs use temporal coding but can still use rate coding
  - Event-driven nature of SNNs fits well with neuromorphic hardware
    - Use "**Address Event Representation**" (**AER**) to minimize communication
  - SNNs model important unsupervised learning algorithm: Spike Timing-Dependent Plasticity (STDP)
    - Precise spike firing has been found at almost all levels of the mammalian visual pathway
    - The exact timing of spike changes plasticity

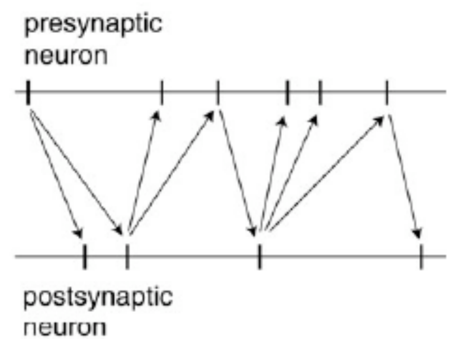
Modeling Components at the Neural Circuit Level

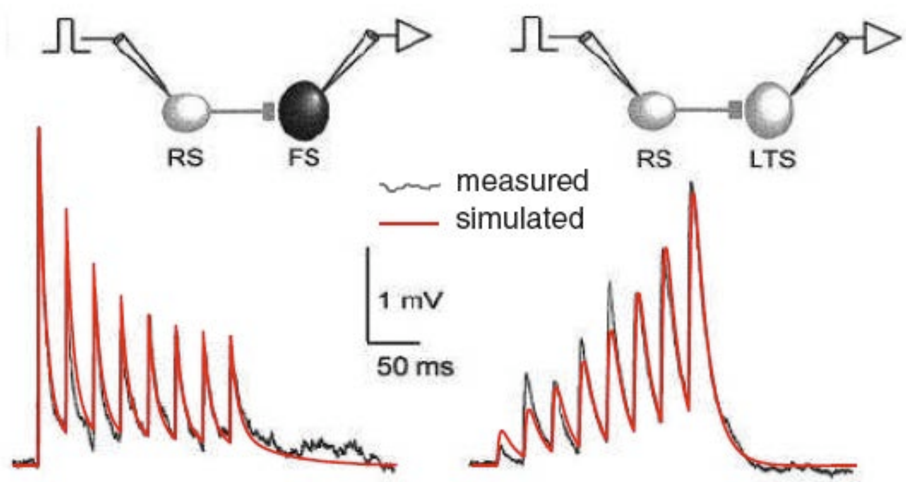












Many Parameters!

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Neuromorphic Hardware Devices

Hardware Project: Hardware Group	Hardware Description	Neuron Models	Synaptic Plasticity	Max Neurons	Max Synapses
SpiNNaker: Industry and UK universities	- Completely digital - Consists of array of nodes - Each node has 18 ARM9 cores - Final goal: 1,036,800 cores	Spiking: Izhikevich and non-spiking	Yes: STDP	1,000 neurons per ARM9 core*	10k synapses per ARM9 core*
Neurogrid: Stanford University	- Analog/digital hybrid - Full board has 16 neurochips - Operates on only 5 W	Spiking: Two-compartment neurons	No	65,536 neurons per neurochip	375M synapses per neurochip
True North Cog. Architecture: IBM SyNAPSE Team	- Completely digital - Consists of hierarchical design - Neurosynaptic core is basic building block	Spiking: many behaviors including LIF	No	256 neurons per neuro-synaptic core	256K binary synapses per neuro-synaptic core
HRL neural chip: HRL Labs, LLC SyNAPSE Team	- Analog/digital hybrid - Synaptic weights stored in memristors	Spiking: Izhikevich	Yes: STDP	576 neurons per chip	70k virtual synapses per chip
HiCANN: BrainScaleS Team	- Analog/digital hybrid - Each wafer has 384 chips - Neurons are analog - Synapses are digital	Spiking: AdExp and I&F	Yes: STDP	512 neurons per chip*	16k synapses per chip*

* Indicates the max. number of neurons are synapses are not independent

Neuromorphic Software Tools: SNN Simulators

Software Project	Features	Parallelized Implementations	Implementation Language	Parameter Tuning Tools
NENGO	- Uses neural engineering framework (NEF) - Set weights to perform specific computations - Uses both rate-based and spiking neurons - Uses neural plasticity rules (STDP) as well	None	- Core: Java - Python scripting	NEF
NEST	- Mature codebase for multiple platforms - Includes many neuron and plasticity models - Built-in simulation language interpreter - Module for creating complex networks	Parallelized MPI CPU implementation	- Core: C++ - Interface: Python - PyNN support	None
Brian	- Multiple integration methods - Multiple neuron and plasticity models - Uses Python plotting packages - Good documentation	Parallelized CPU support Parallelized GPU support only for tuning component	- Core: Python - PyNN support	Support for tuning neuron models
CARLsim	- Fast and efficient CUDA GPU implementation - Support for key ion channels - GPU parallelized general tuning framework - Includes highly optimized CUDA vision frontend	Parallelized CUDA GPU implementation	- Core: C++ and CUDA - Syntax similar to PyNN	General tuning framework using EAs

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CARLsim

frontiers in
NEUROINFORMATICS

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An efficient simulation environment for modeling large-scale cortical processing

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We have developed a spiking neural network simulator, which is both easy to use and computationally efficient, for the generation of large-scale computational neuroscience models. The simulator implements current or conductance based Izhikevich neuron networks, having spike-timing dependent plasticity and short-term plasticity. It uses a standard network construction interface. The simulator allows for execution on either GPUs or CPUs. The simulator, which is written in C/C++, allows for both fine grain and coarse grain specificity of a host of parameters. We demonstrate the ease of use and computational efficiency of this model by implementing a large-scale model of cortical areas V1, V4, and area MT. The complete model, which has 138,240 neurons and approximately 30 million synapses, runs in real-time on an off-the-shelf GPU. The simulator source code, as well as the source code for the cortical model examples is publicly available.

Keywords: visual cortex, spiking neurons, STDP, short-term plasticity, simulation, computational neuroscience, software, GPU

Code available at: http://www.socsci.uci.edu/~jkrichma/CARLsim

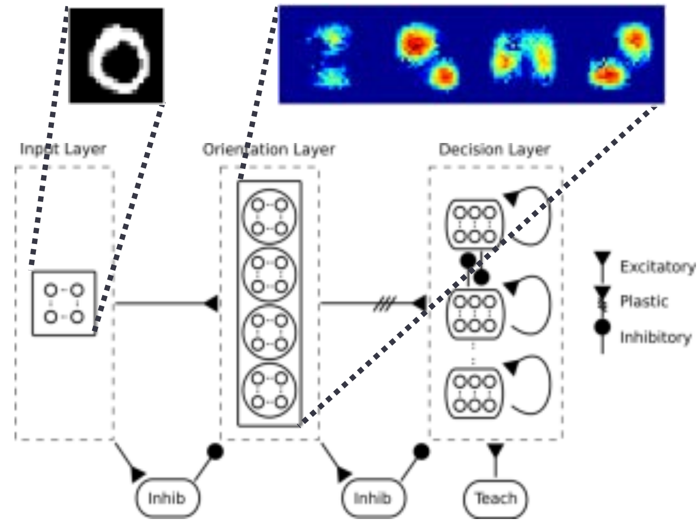
CARLsim Applications

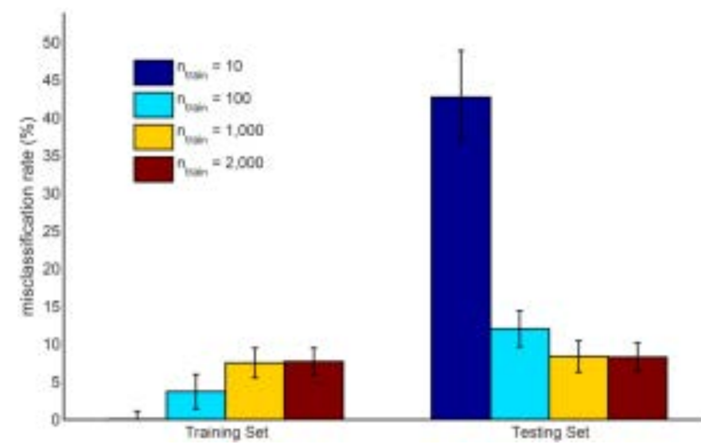
- Used to create large-scale simulations of cognitive processes
  - 10k – 100K neurons with millions of synapses

- Sample Applications
  - Visual Processing
    - Large-scale model of cortical areas V1, V4, and area MT *[Richert et al. 2011]*
  - Neuromodulation
    - Top-down and bottom-up attention *[Avery et al. 2013a]*
    - Working memory and behavior *[Avery et al. 2013b]*
  - Object Categorization
    - Classifying handwritten digits *[Beyeler et al. 2013]*
  - Neural Plasticity
    - Biologically plausible STDP and Homeostatis *[Carlson et al. 2013]*

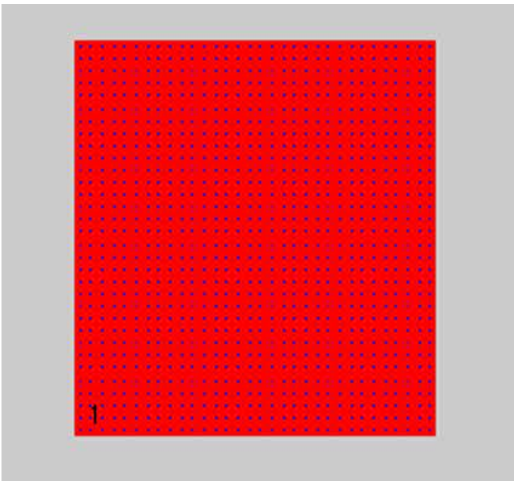
CARLsim Example: MNIST Classification

- MNIST database of handwritten digits
  - 60,000 training / 10,000 test patterns
- Neurofidelity
  - Network: spiking neurons, ion channels
  - Training: Calcium-based learning rule (STDP-like)
  - Classification: decision-making (drift-diffusion / race model)
- Accuracy
  - 92 % correct classifications
  - Biologically plausible reaction times
- Efficiency
  - 71,026 neurons, ~133 million synapses
  - Real-time processing on a single NVIDIA Tesla M2090
- Scalability
  - Modular approach
  - Extend to more general neuromorphic implementation

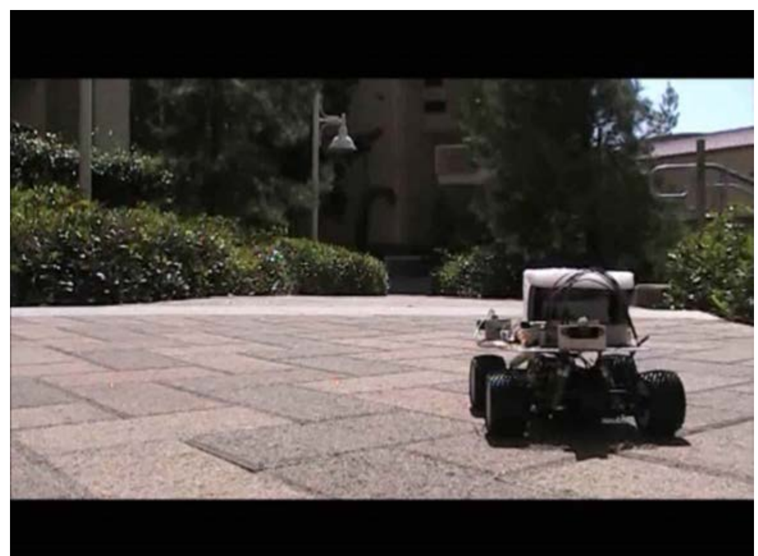




CARLsim Example: Vision Processing System



- Implemented motion selectivity in spiking model of Area MT
- 32x32 Resolution, 138,240 neurons; ~30 million synapses (shown on the left)
  - Running in real-time on single GPU card.
- Higher resolution, ~550K neurons; ~120M synapses (shown below)



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- **Parameter Tuning of Large-Scale SNNs**

Parameter Tuning of Neurobiologically Inspired Networks: Time Consuming!

- **Example 1*:** Tuning a small, lobster pyloric circuit:
  - Tuned 3-neuron, 5 synapse circuit
  - Database of 20M configurations was generated, with only 20% functional
- **Example 2+:** Tuning small SNN:
  - 5 parameters with 10 values, each needs 10^5 simulations
  - Simulation Time: ~15 days for 1K network with 5 parameters
- **Lesson:**
  - Even for small networks, search space is extremely large with many solutions!
- ***Biology provides some constraints, BUT***
  - designer must choose many parameter values ***manually*** to achieve appropriate neuronal dynamics.
- ***Our Solution: Automated Parameter Tuning using GPUs and EAs***

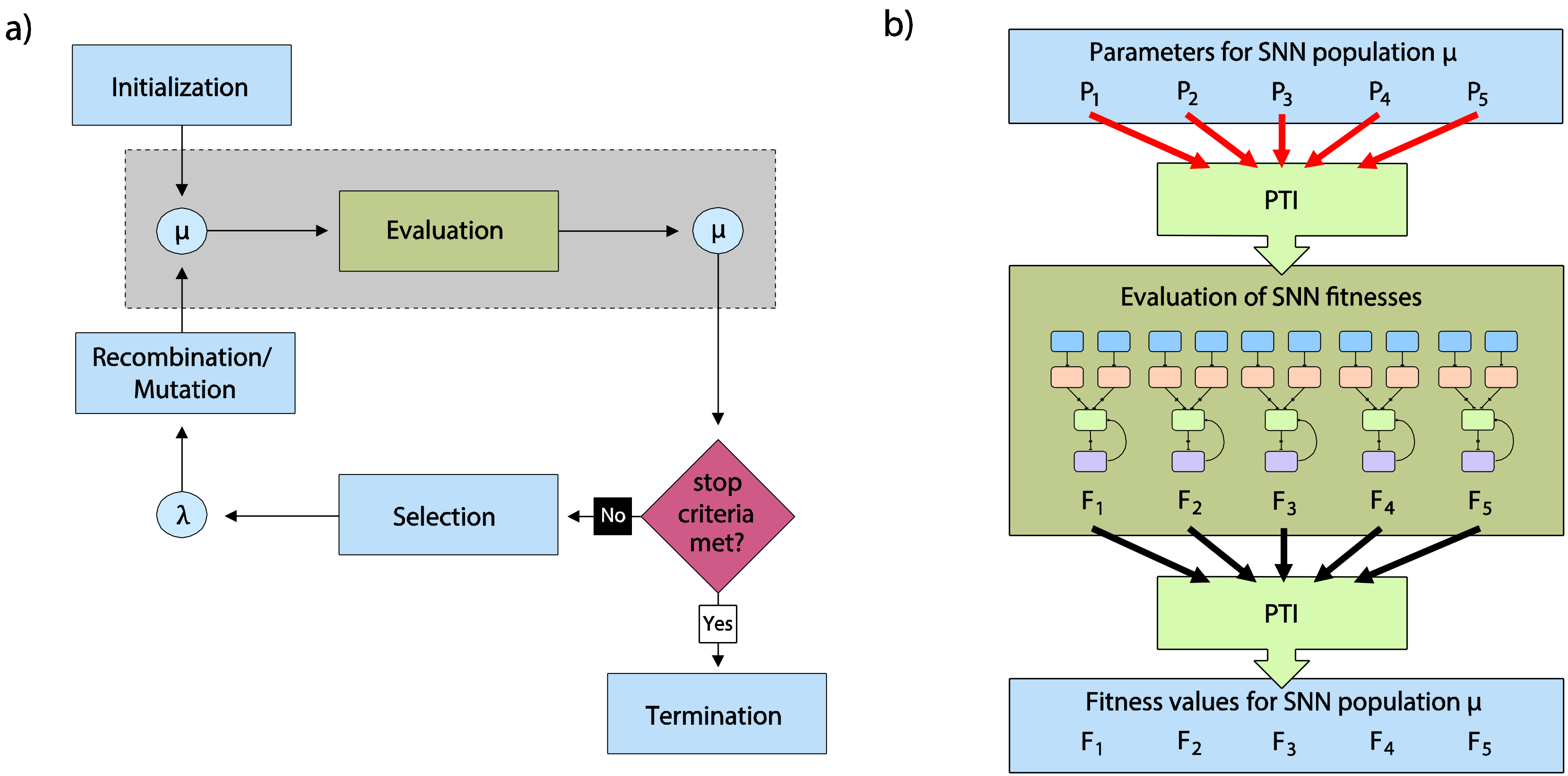
*From Prinz, A.A., Bucher, D., and Marder, E. (2004). Similar network activity from disparate circuit parameters. Nat Neurosci 7, 1345-1352

+From Jayram Moorkanikara's PhD Dissertation at UCI, 2010

Automated Parameter Tuning Framework

- Automated parameter-tuning framework can quickly and efficiently tune large-scale spiking neural networks
- Leverage
  - Recent progress in evolutionary algorithms.
  - Optimization with off-the-shelf graphics processing units (GPUs)
- The parameter search guided by principles of neuroscience
  - Biological networks adapt their responses to
    - increase the amount of transmitted information, reduce redundancies, and span the stimulus space

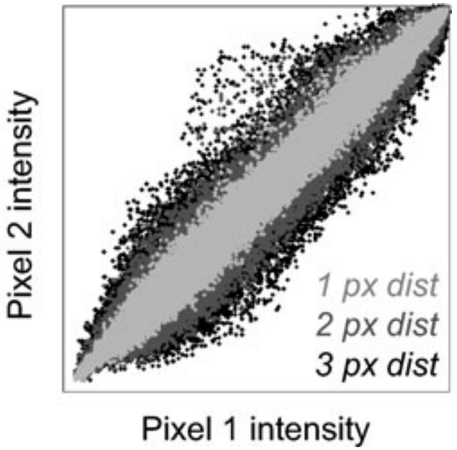
Automated Parameter Framework for Tuning Spiking Neural Networks (SNNs)

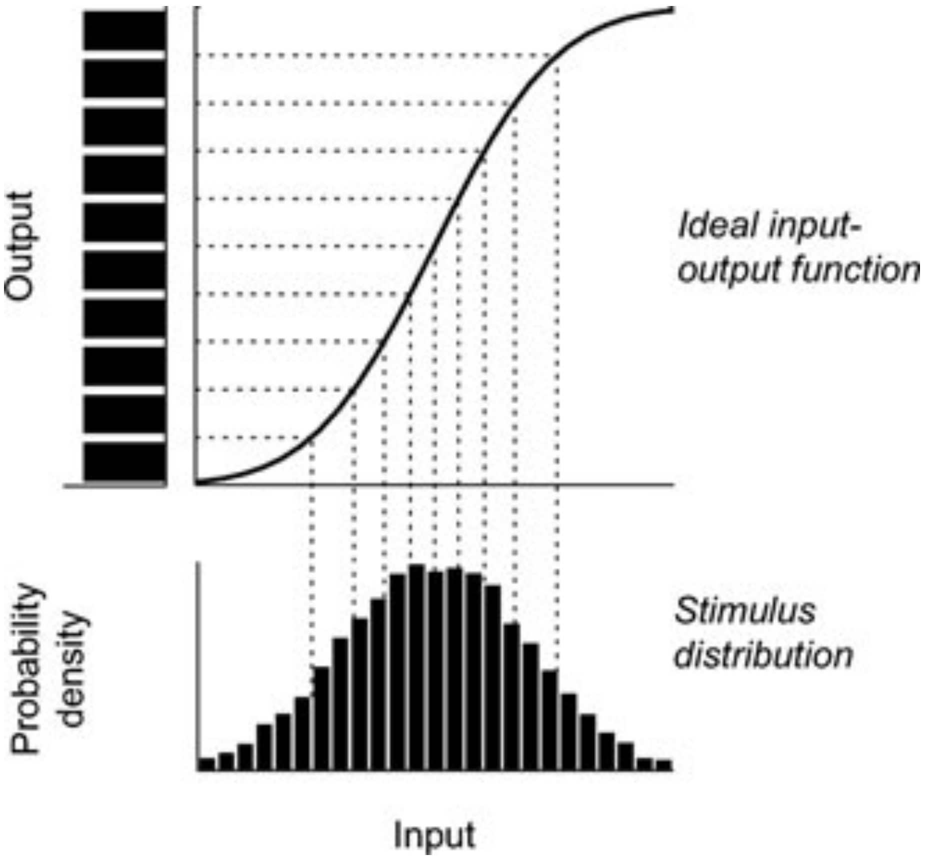


Efficient Coding Hypothesis

- Fundamental idea:
  - Sensory systems adapt their responses to the regularities of their input
  - Increase the amount of transmitted information at any given time

1. Maximize efficiency (*reduce redundancy*)
2. Responses should be independent of one another (*decorrelation*)
3. A stimulus should involve only a small fraction of the available neurons (*sparse*)





Louie, K., and Glimcher, P.W. (2012). Efficient coding and the neural representation of value. Ann N Y Acad Sci *1251*, 13-32.

Fitness Function Based on the Efficient Coding Hypothesis

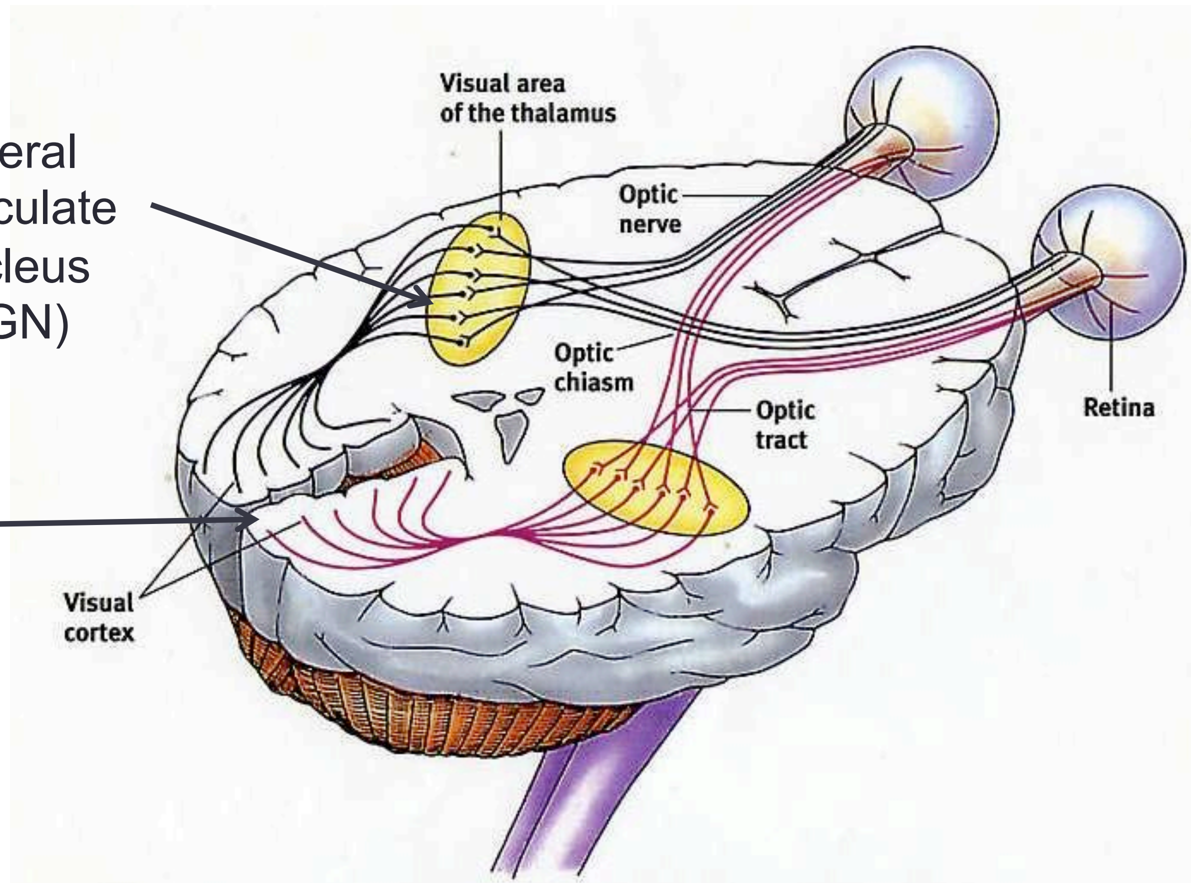
$$Fitness_{\text{total}} = \frac{1}{Fitness_{\text{decorr}} + Fitness_{\text{Gauss}} + K_{\text{scaling factor}} \cdot Fitness_{\text{maxRate}}}$$

- *$Fitness_{\text{decorr}}$* ensured decorrelation by forcing each neuron to respond maximally to different stimuli
- *$Fitness_{\text{Gauss}}$* required Gaussian tuning curves. Also lead neurons to employ their full response range to describe the stimulus
- *$Fitness_{\text{maxRate}}$* limited the maximum firing rate of each neuron which contributes to sparsity

Visual Pathway in the Brain

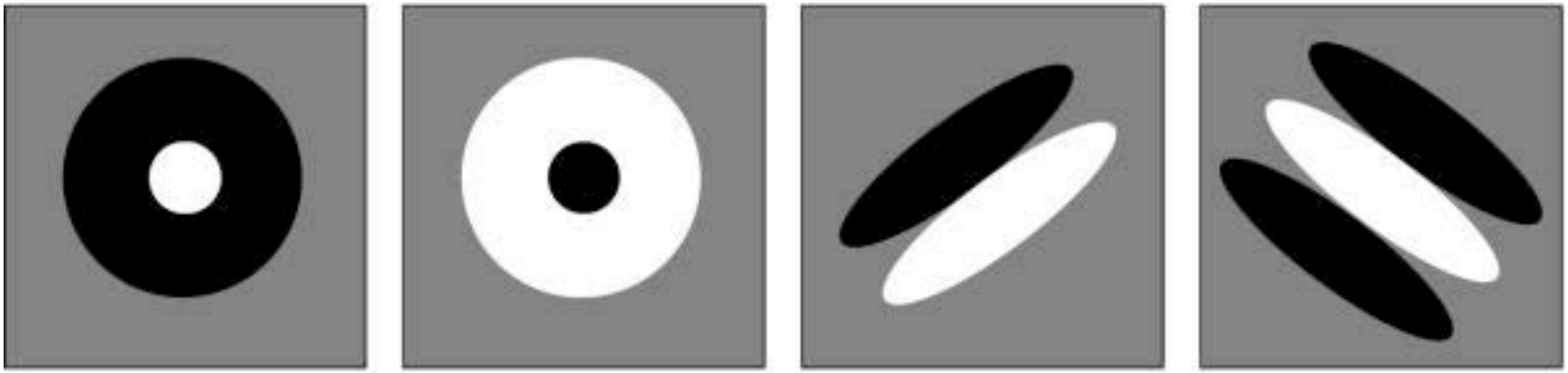
Lateral Geniculate Nucleus (LGN)

Primary Visual Cortex (V1)



- Sample Parameter Tuning Example for Homeostasis and STDP:
  - Unsupervised learning of V1 simple cell receptive fields in response to patterned inputs.

Receptive Fields in LGN and V1



(*a*) ON cell in retina or LGN

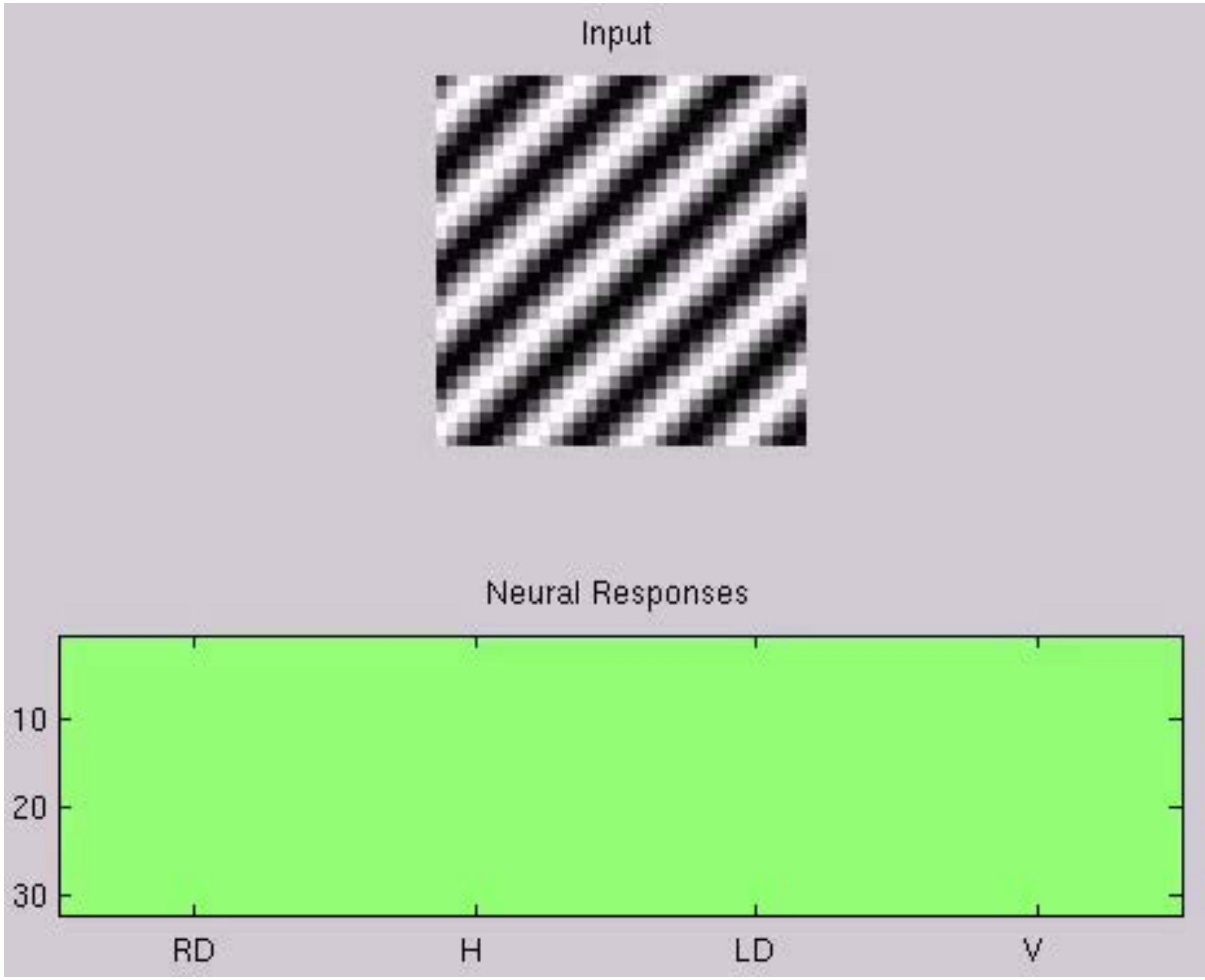
(*b*) OFF cell in retina or LGN

(*c*) 2-lobe V1 simple cell

(*d*) 3-lobe V1 simple cell

K.D. Carlson, M. Richert, N. Dutt and J.L. Krichmar, "Biologically Plausible Models of Homeostasis and STDP: Stability and Learning in Spiking Neural Networks," in Proc. IJCNN 2013

Simulated Visual Cortex Responses to Sinusoidal Gratings



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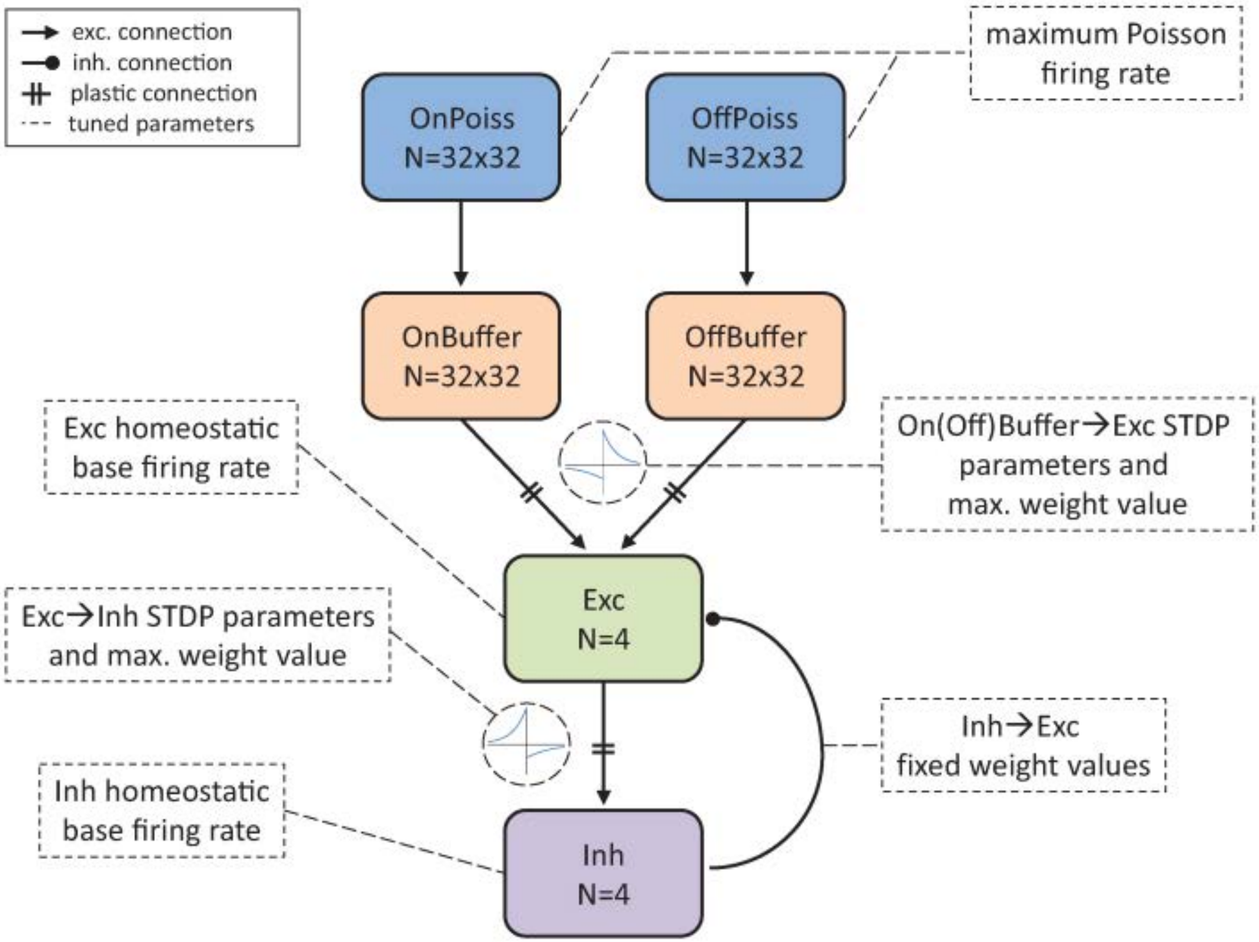
Tuning SNNs that Generate Self Organizing Receptive Fields (SORF)



- Network size
  - 4104 neurons
- Indirect encoding
  - 14 parameters to search
- Training phase
  - 40 sinusoidal orientations presented
  - 2400 presentations
- Testing phase
  - 8 sinusoidal orientations presented to the network
  - Responses of the Exc neurons were evaluated using the ECH fitness function

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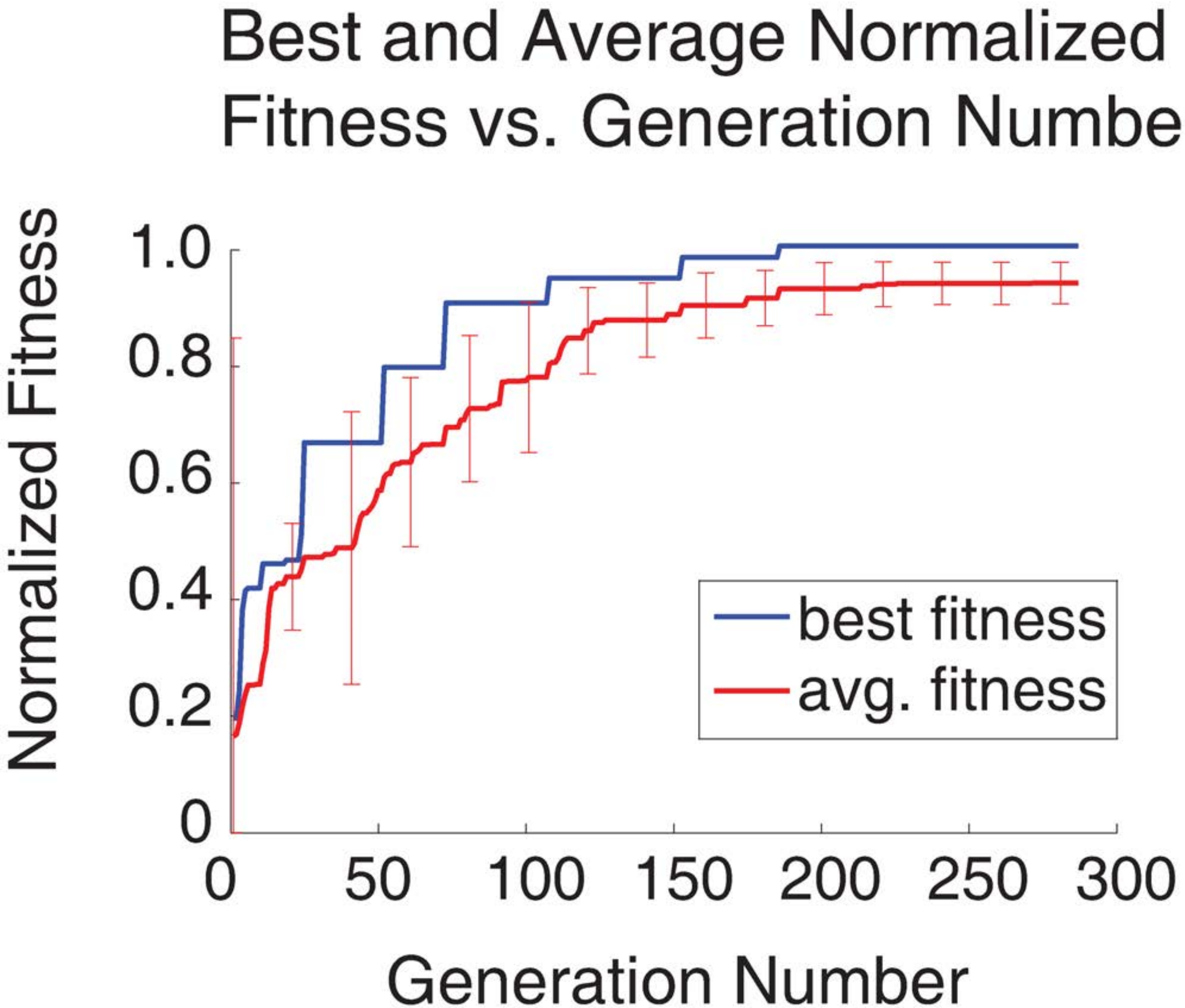


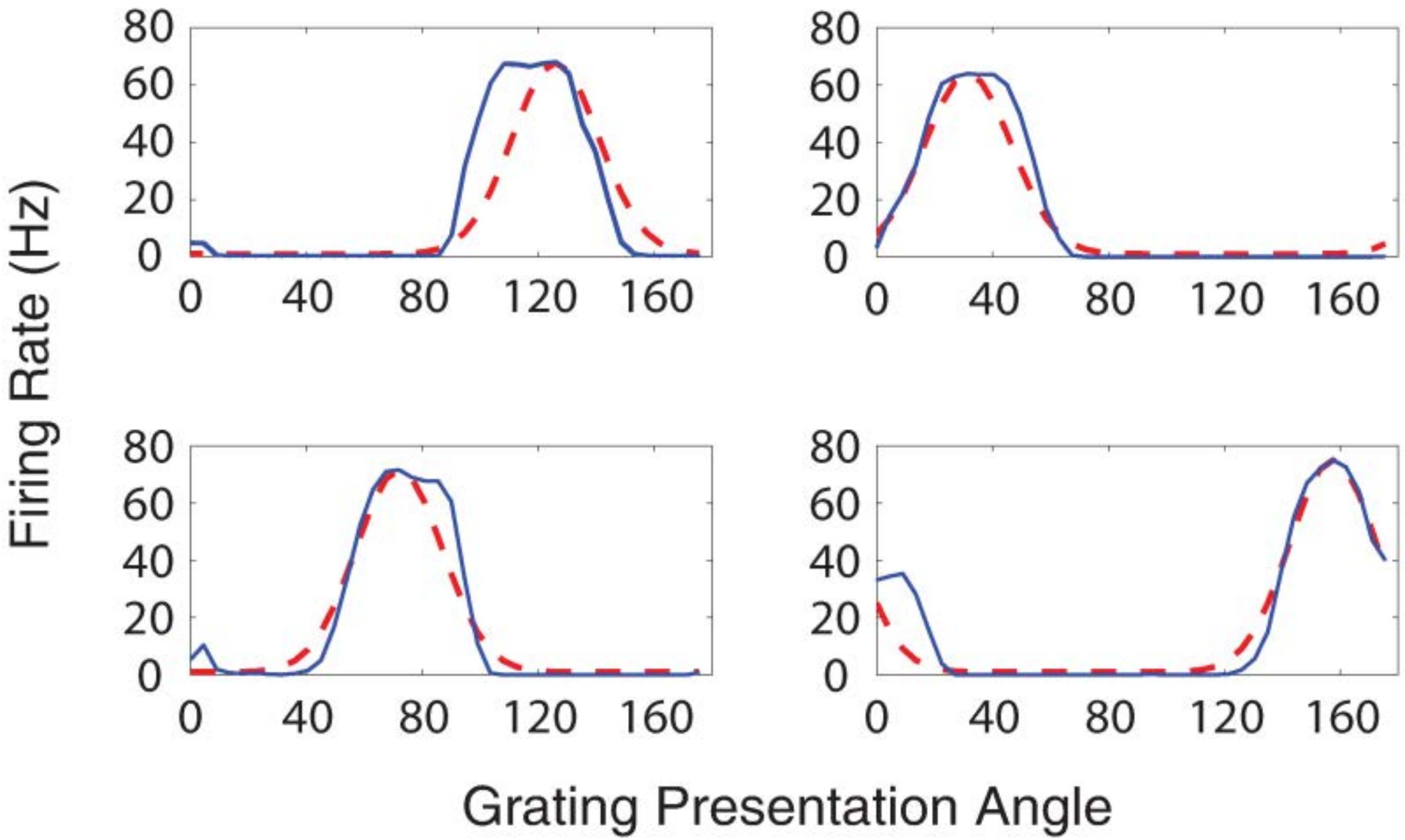
- 10 SNNs in parallel
  - Up to 40.
- 287 EA generations in 127 hours.
- Run on a single NVIDIA Tesla M2090

K.D. Carlson, M. Richert, N. Dutt and J.L. Krichmar, “Biologically Plausible Models of Homeostasis and STDP: Stability and Learning in Spiking Neural Networks,” in Proc. IJCNN 2013

Synaptic Weight Progression During Training for a High Fitness Individual

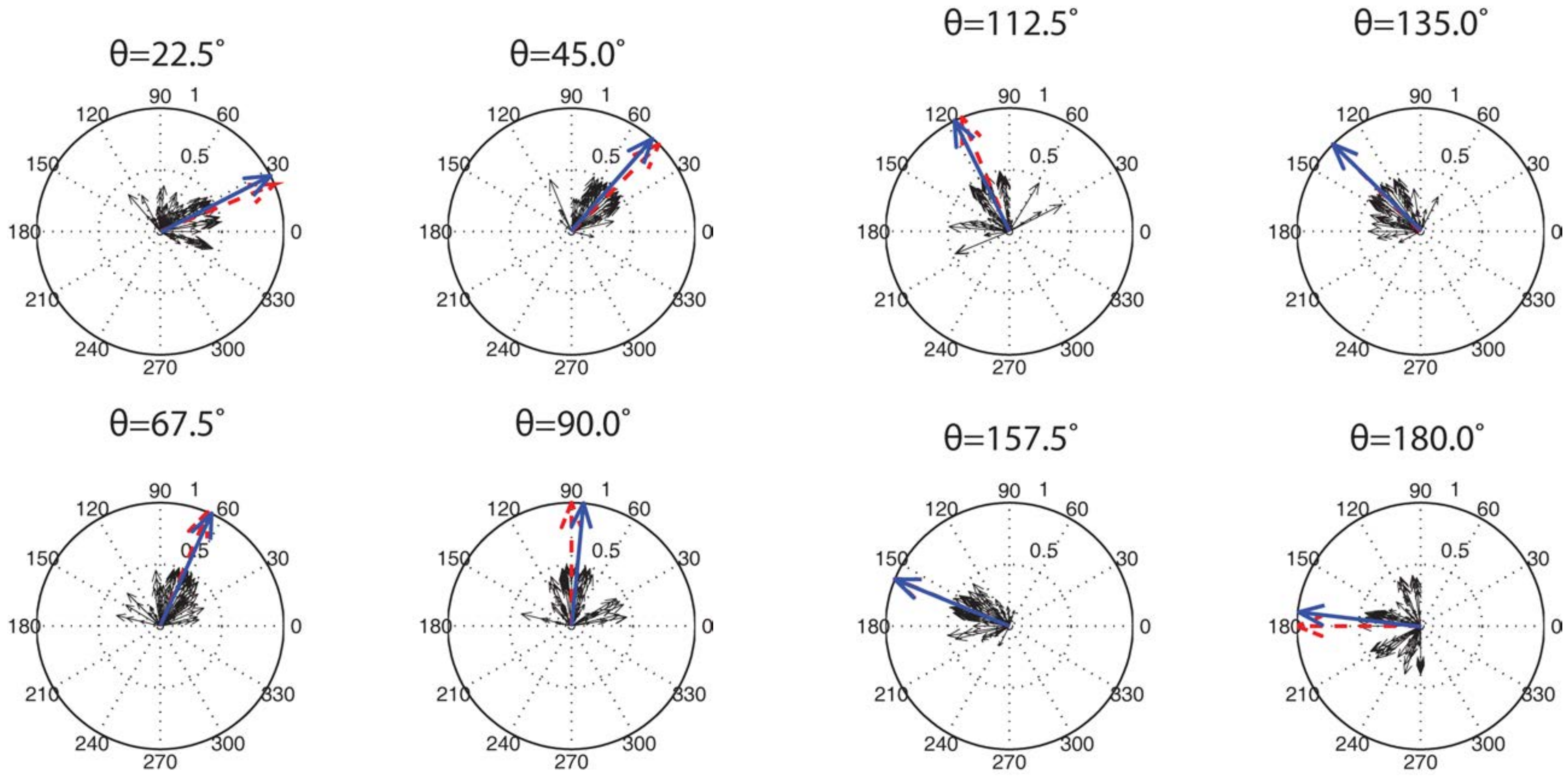
- Synaptic weights for the On(Off)Buffer→Exc connections
  - Light regions denote strong weights, dark regions denote weak weights

Response Of Neurons To Sinusoidal Gratings



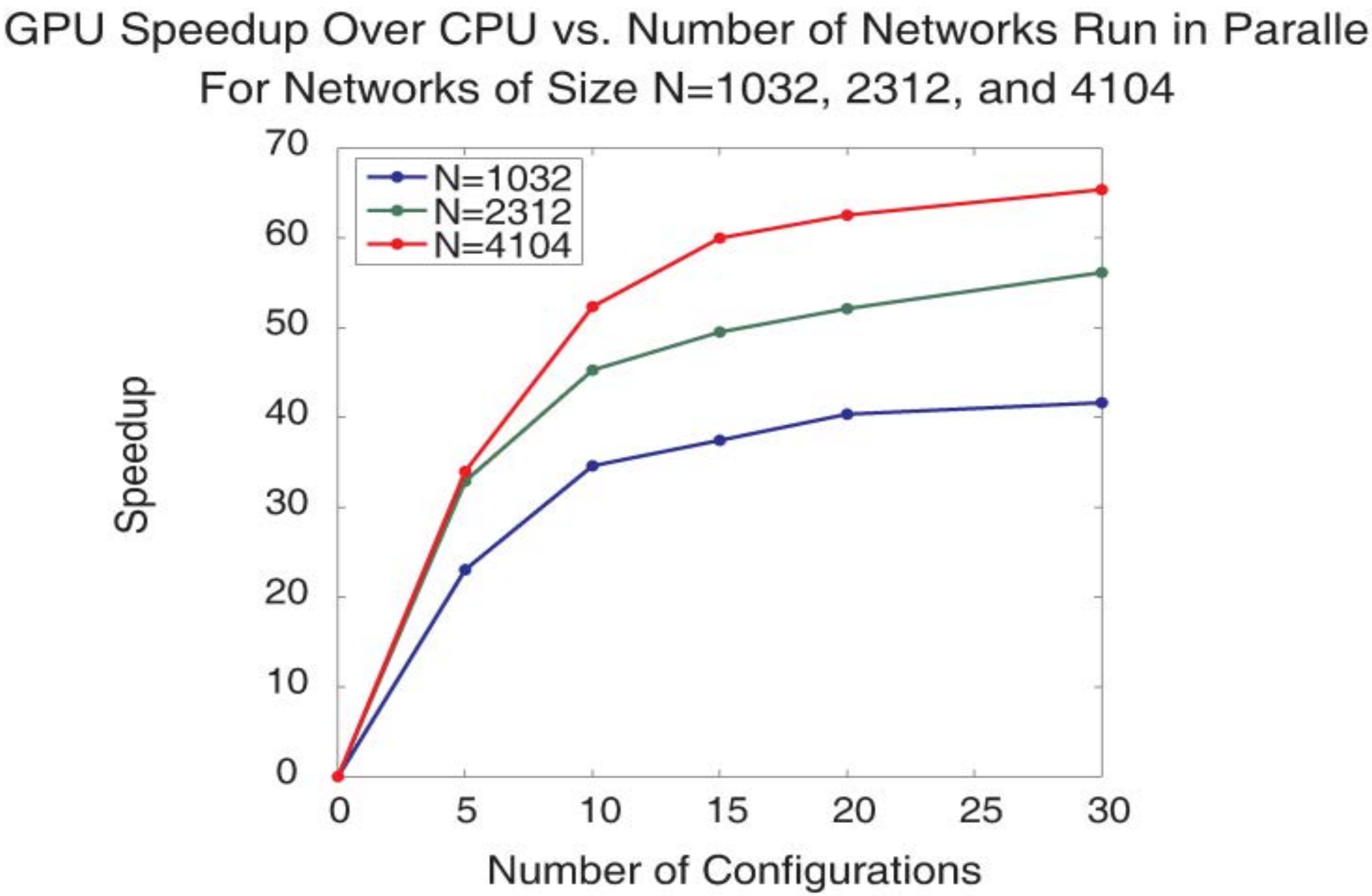
- **Blue line:** firing rate of simulated individual Exc group neuron
- **Red line:** ideal Gaussian tuning curve firing rate response for V1

Population Response After Evolution



- **Population decoding for diff presentation angles (70 sets of 4 exc neurons):**
  - Small black arrows: component vectors for individual neurons
  - **Blue arrow: normalized decoded population vector**
  - **Red arrow: normalized ideal grating presentation vector**

Automated Parameter Tuning Framework Performance



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Conclusions

- Large-scale, complex, realistic brain simulations are necessary:
  - For the field of neuromorphic engineering to produce results and applications of practical value
  - To help computational neuroscientists develop new theories of neural function
- To address this challenge:
  - our approach leverages
    - the optimization capabilities of evolutionary computation
    - exploits graphical processing unit (GPU) parallelism
- The efficient coding hypothesis
  - May provide a metric for tuning networks of simulated spiking neurons
  - May also given insights into how real brain networks process information and achieve homeostasis

Thanks to…

Team CARL Now (2014) – UC Irvine

Front row – Alexis Craig, Emily Rounds, Kris Carlson, Liam Bucci, Ting-Shuo Chou

Back row – Feng Rong, Andrew Zaldivar, Nicolas Oros, Jeff Krichmar, Derrik Asher, Michael Beyeler, Nik Dutt

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Front row – Jay Nageswaran, Mike Avery, Chelsea Guthrie, Micah Richert

Back row – Andrew Zaldivar, Brian Cox, Michael Wei, Jeff Krichmar

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Thanks!

Questions or Comments???