Exploiting Criticality on HRL's "Latigo" Neuromorphic Device

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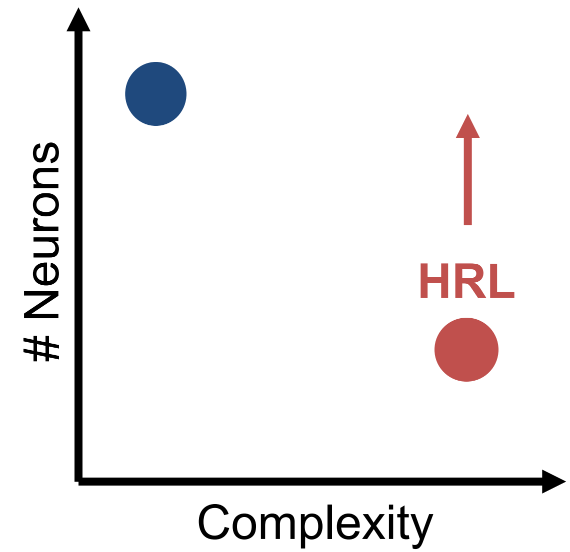
Neuromorphic Computing at HRL

Simple or Complex?
- Trade-offs lead to designs with many simple neurons, or a few complex ones
- HRL, in DARPA SyNAPSE, chose complexity over multiplicity
- Scaling up from there is likely easier



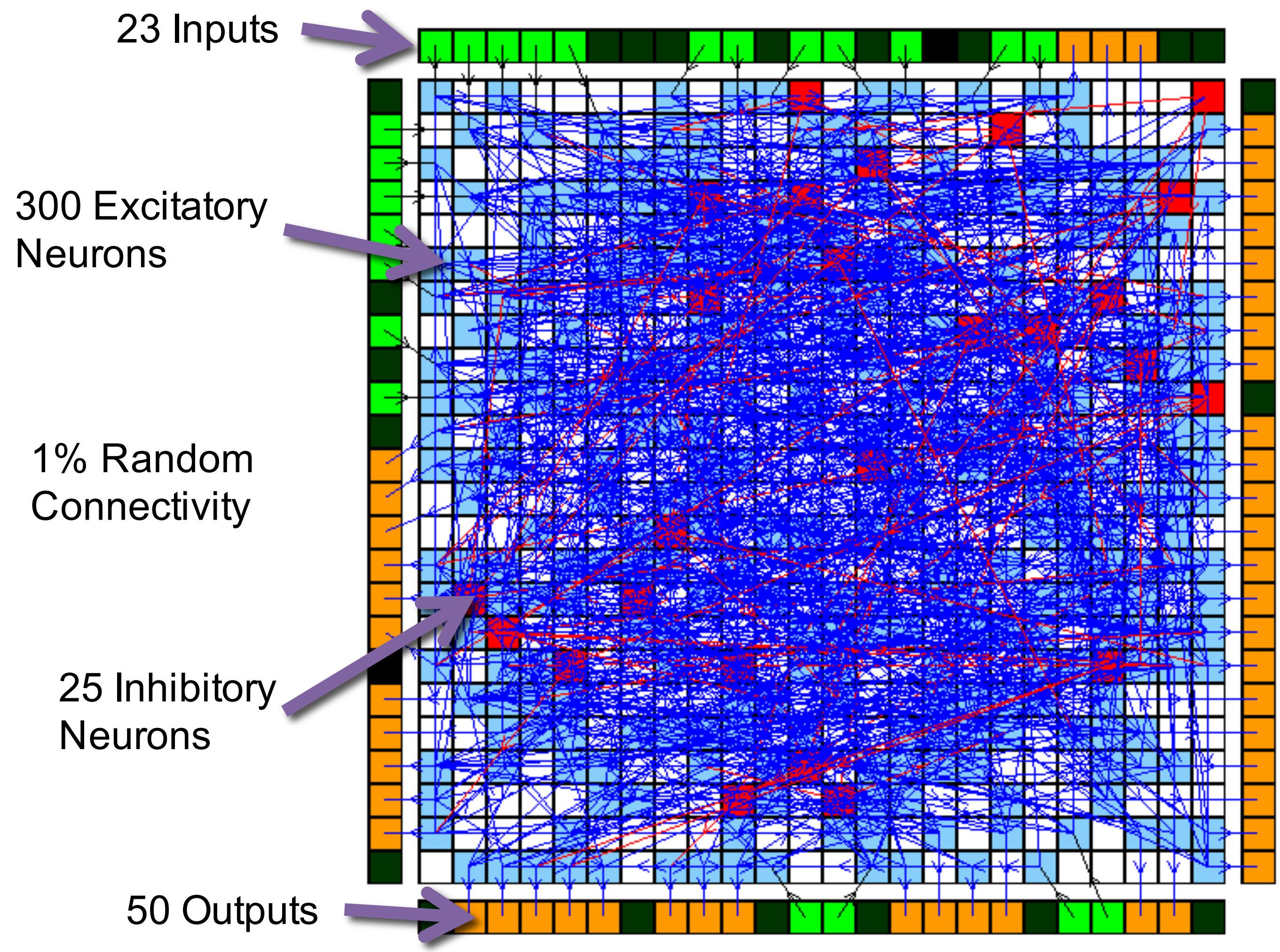
HRL's first real chip – "Surfrider":
- 576 Neurons, 37k Synapses
- Axonal delays
- Synaptic kinetics
- Spike Timing Dependent Plasticity
- Again, complexity over scale

Reservoir Computing with HRL Surfrider

Reservoir computing provides a way to use a small network for relatively complex applications:

Pattern Recognition
- Audio
- Video
- Mobile sensor

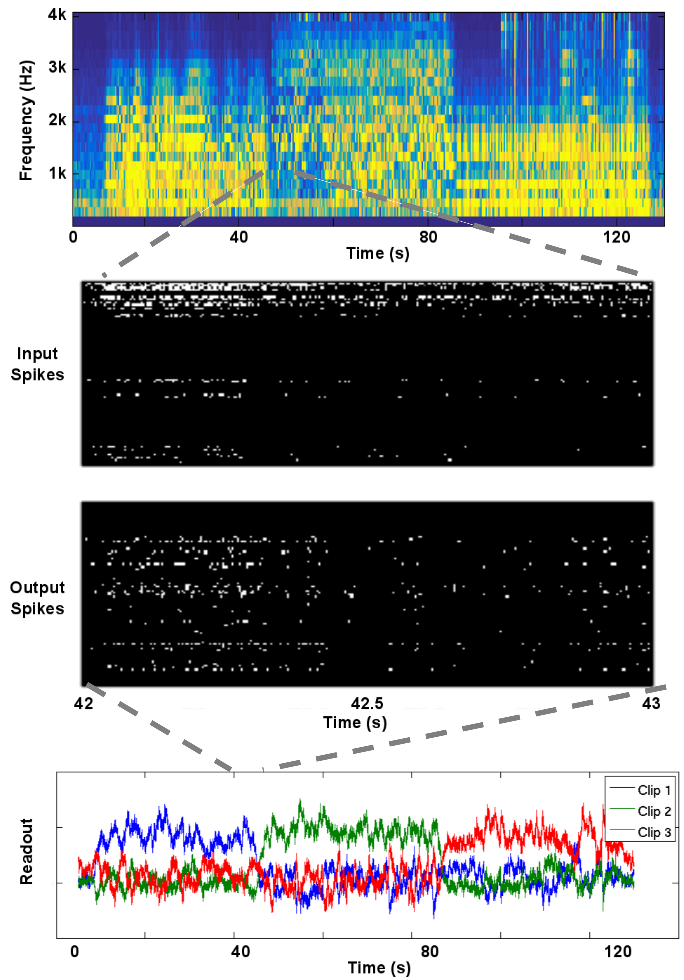
Anomaly Detection



Summary of Surfrider Results

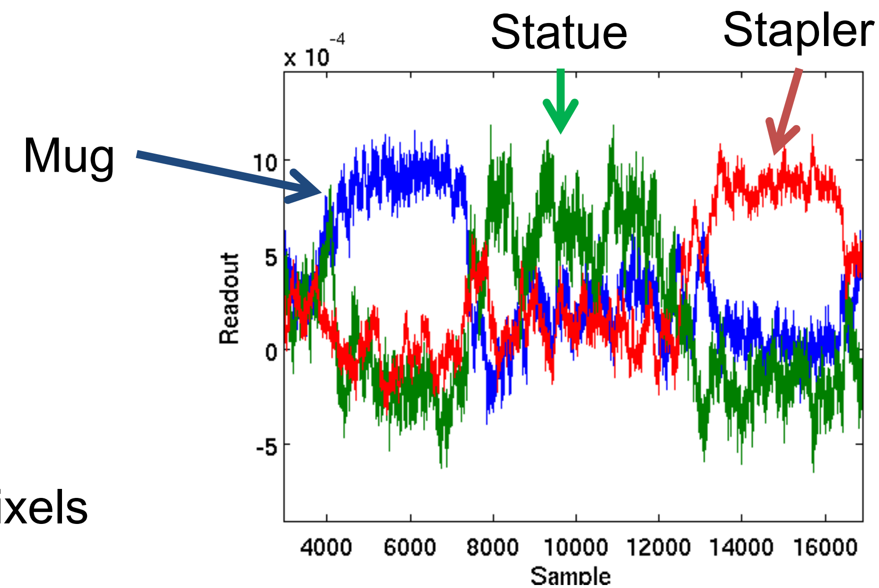
Reservoir computing methods using Surfrider were especially successful for spectral data

Spectrogram
↓
Input Spikes
↓
Output Spikes
↓
Class Readout

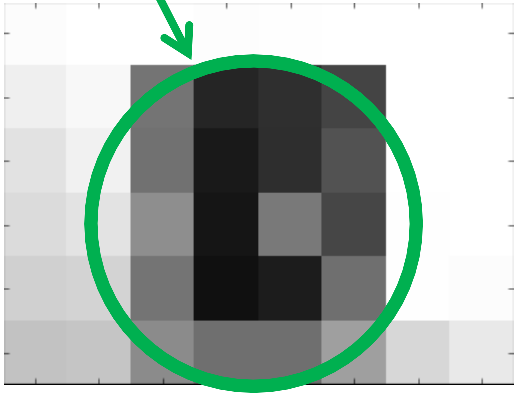


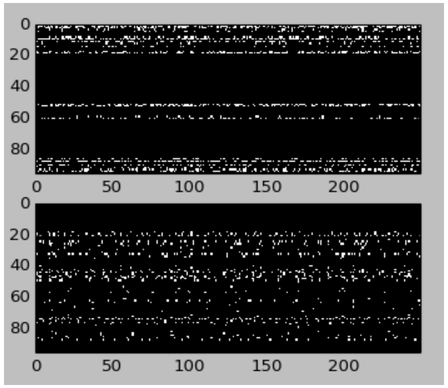
Summary of Surfrider Results

Image data is also usable, but only at extremely low resolutions.

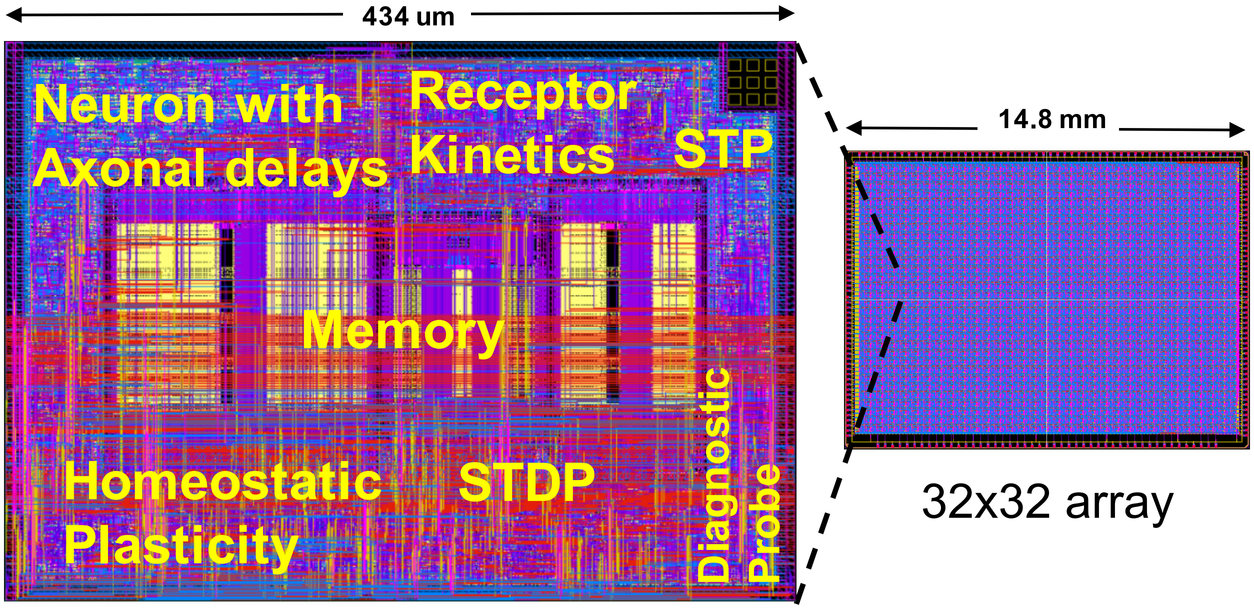


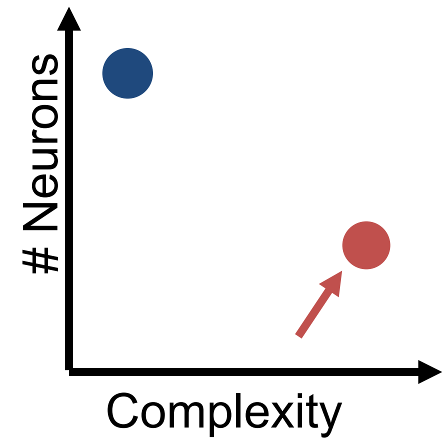
Take 23 pixels





Neuromorphic Computing at HRL
Latigo Chip





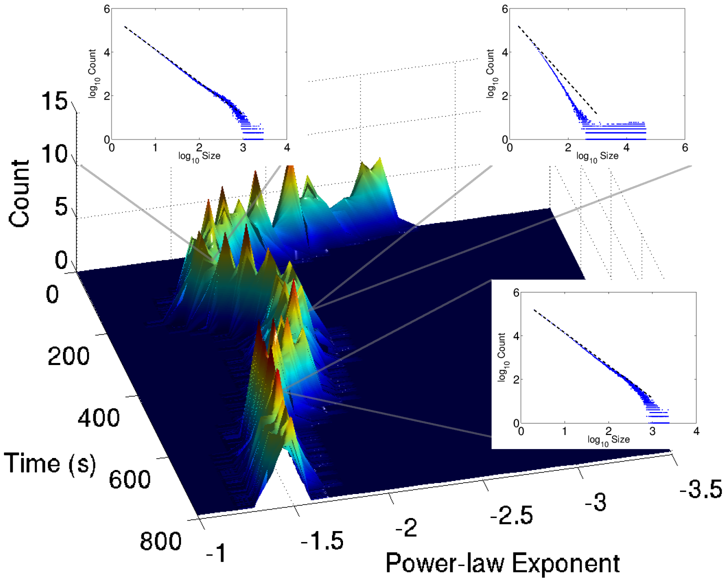
"Latigo" contains 1024 neurons, 131k synapses

- Increase from 96 I/Os to at least 512 – Thousands with additional board dev
- Each neuron has local parameters
- New features: Short term potentiation, homeostatic plasticity
- Intrinsic support for chip tiling

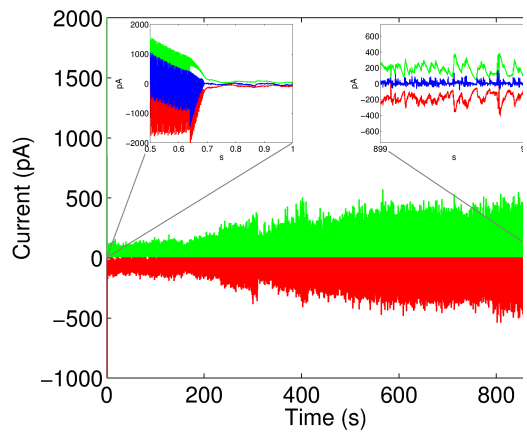
Neurobiological dynamics while maintaining low size, weight, and power

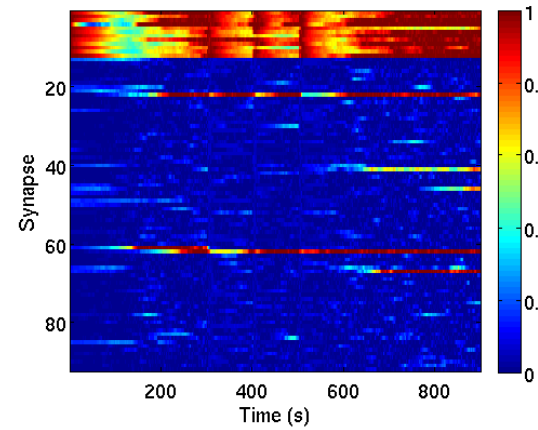
What Can These Features Do?

The combination of STDP (excitatory *and* inhibitory) and STP allows self-tuning critical dynamics



Parameter search finds networks that dynamically balance activity to remain in a critical state





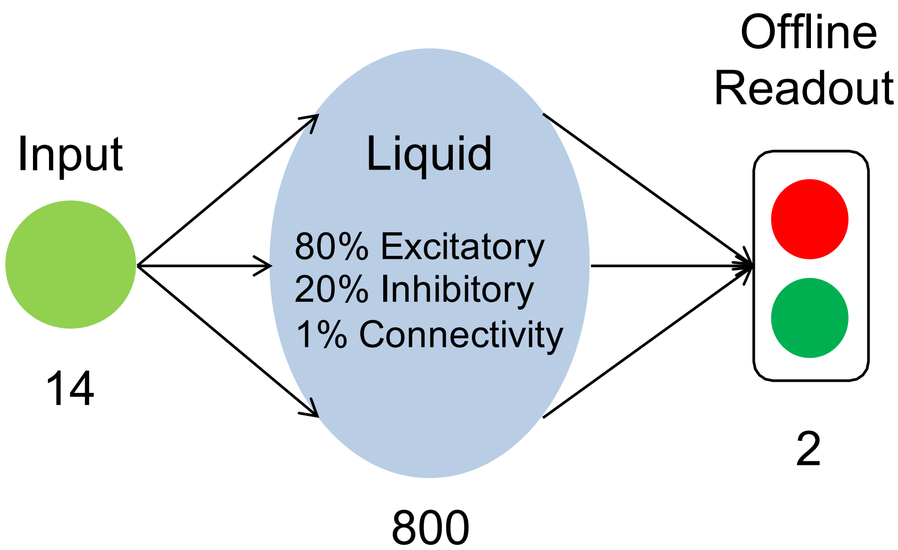
A single high-level parameter search can find networks that look *generally* useful

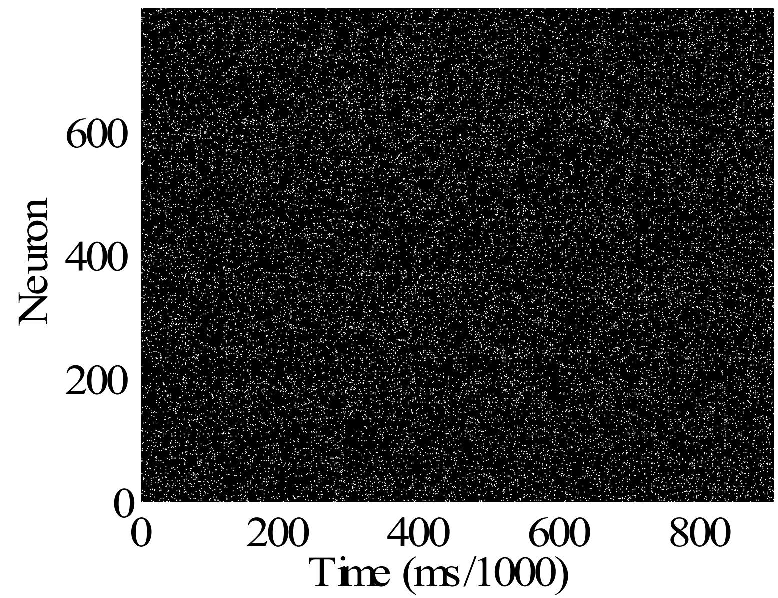
Stepp, N., Plenz, D., & Srinivasa, N. (2015). Synaptic plasticity enables adaptive self-tuning critical networks. PLoS Comput Biol, 11(1), e1004043.

Exploiting Self-tuning Criticality

Exploiting self-tuning criticality in hardware gets around application specifics

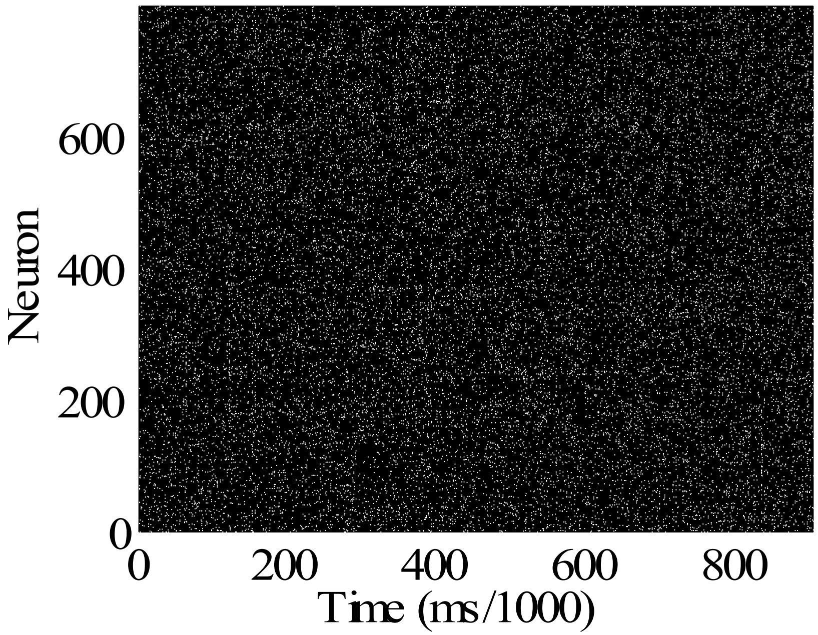
- With lots of complex features, parameter space is large and not smooth
    - Latigo has 4 STDP, 4 STP and 2 HP parameters at every neuron
    - Also voltage thresholds and synaptic time-constants
- A general set-point means one-time parameter tuning

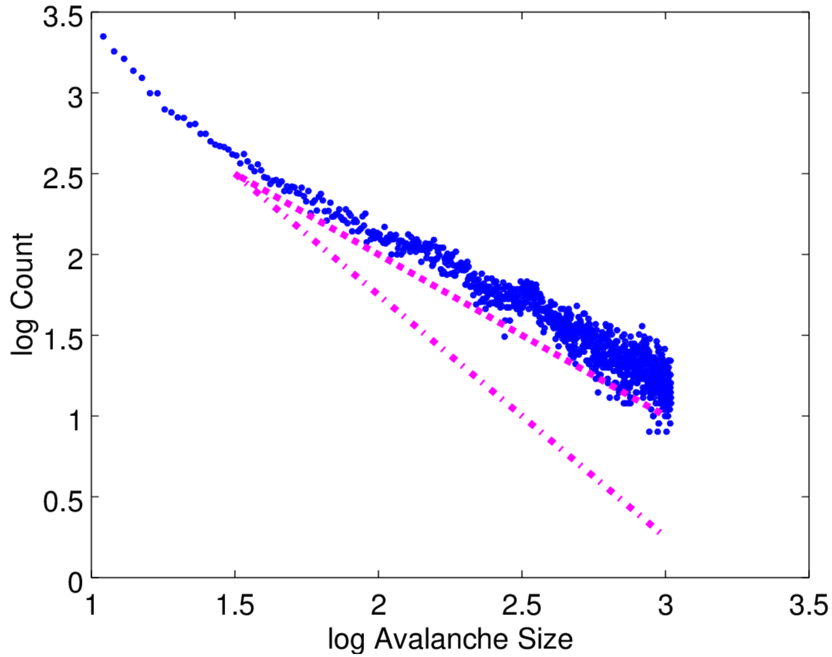




Srinivasa, N., Stepp, N., & Cruz-Albrecht, J. (2015). Criticality as a Set-Point for Adaptive Behavior in Neuromorphic Hardware. Frontiers in neuroscience, 9.

Criticality on Latigo?





Avalanche sizes are consistent with a power-law

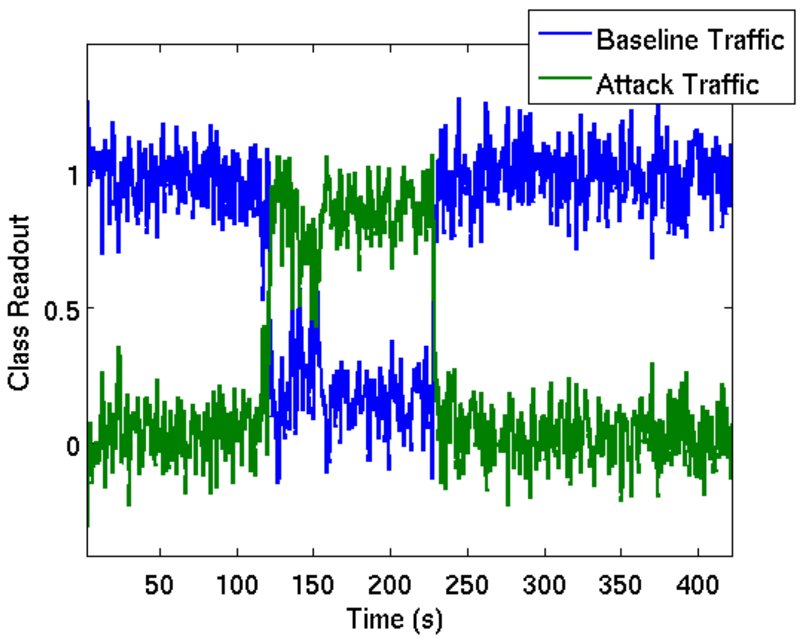
- Small avalanches are near critical branching exponent -1.5
- Larger avalanches fall near -1, literal 1/f
- Consistent with Stepp et al (2015) – input causes deviation from criticality, but self-tuning force is still present

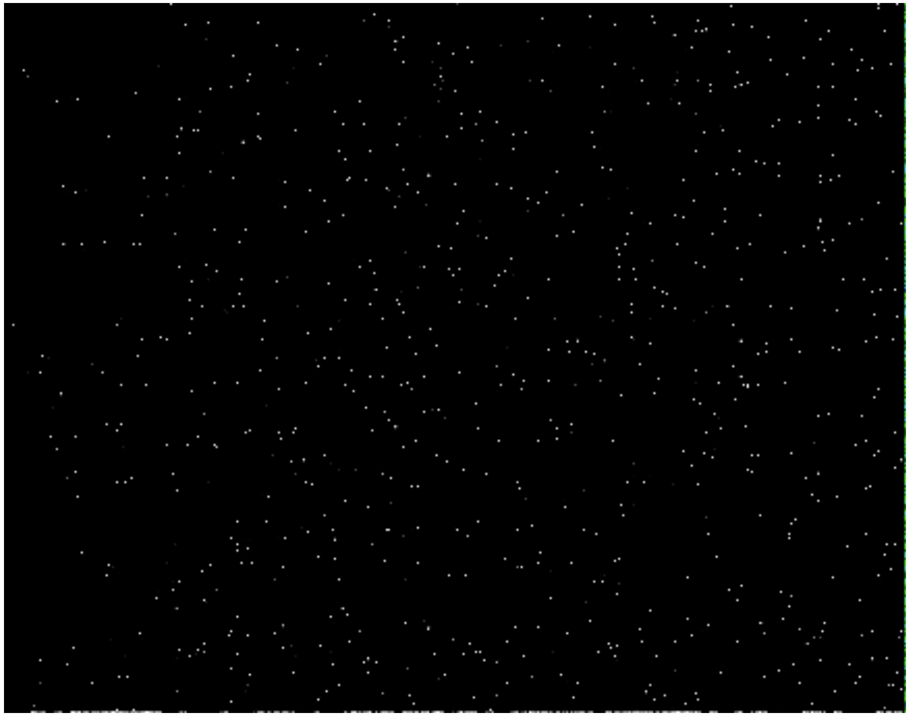
Self-tuning criticality is achievable on the Latigo hardware

Exploiting Criticality for Reservoir Computing

The central claim of Srinivasa et al (2015) is that self-tuning criticality is general purpose

Here we apply the critical network to an intrusion detection problem:





The self-tuning critical reservoir is able to perform well **without problem-specific tuning**

Complicated Hardware for Complex Dynamics

Advanced neurobiological features support complex dynamics in neuromorphic hardware

Complex behavior such as criticality and self-organization promise non-algorithmic solutions where algorithms are hard to write, e.g.
- Problem agnostic parameter tuning
- Adaptable inverse kinematics

When contained in extremely low SWAP hardware, these features enable capabilities on small or unattended platforms beyond simpler neuromorphic systems