Neuroscience to Applications

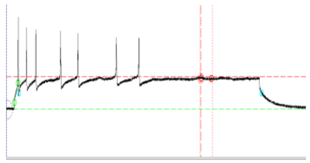
Computational Neuroscience at Sandia National Laboratories

Brad Aimone

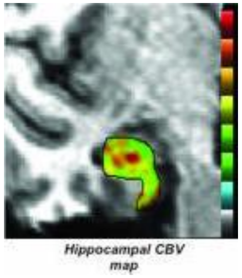
Neuroscience

Molecular

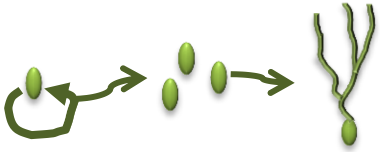
Electro-physiology



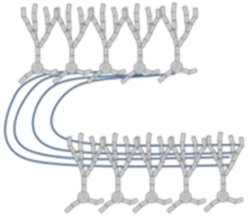
Cognitive



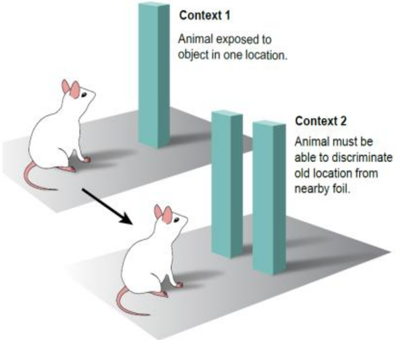
Developmental



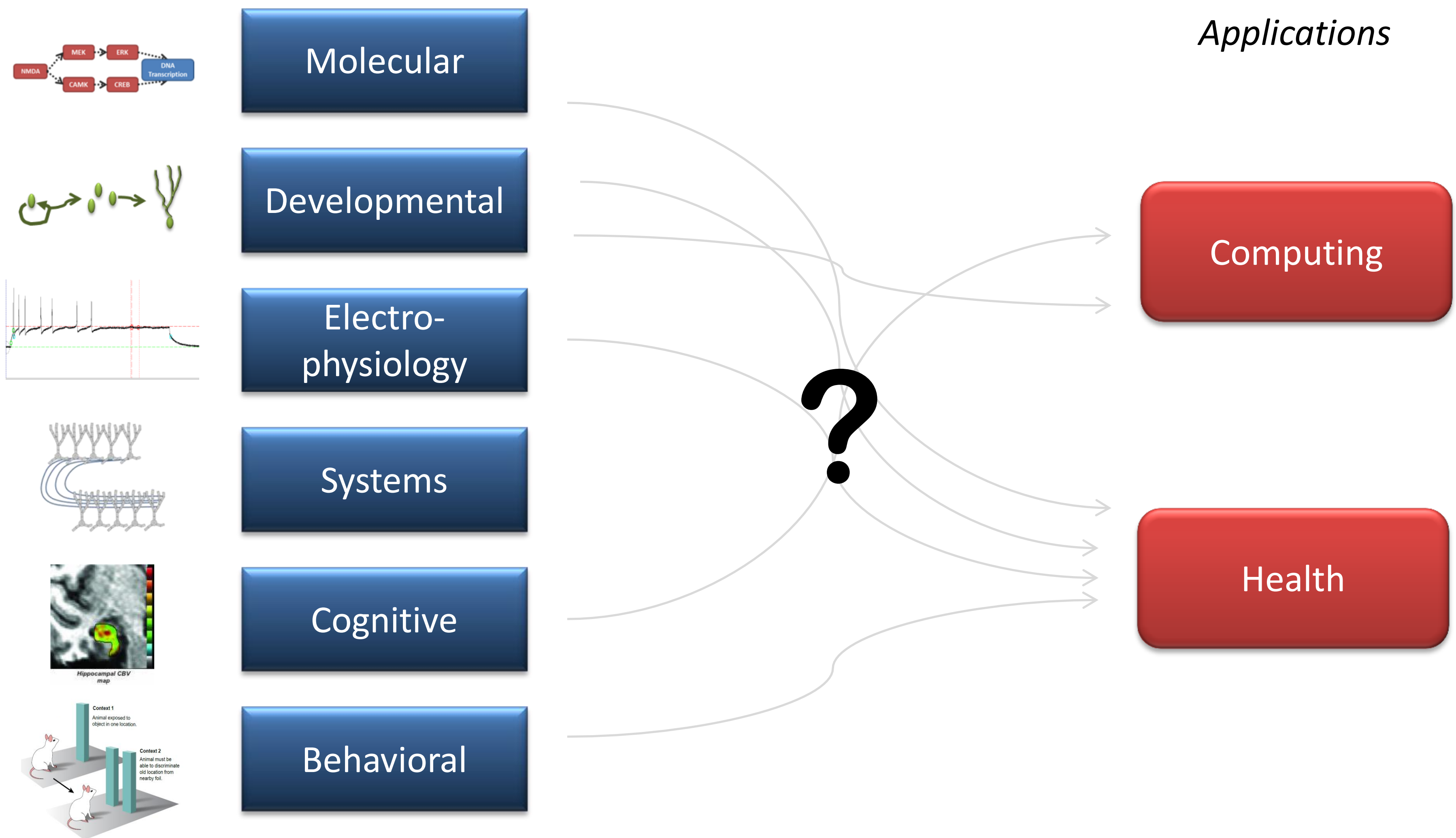
Systems



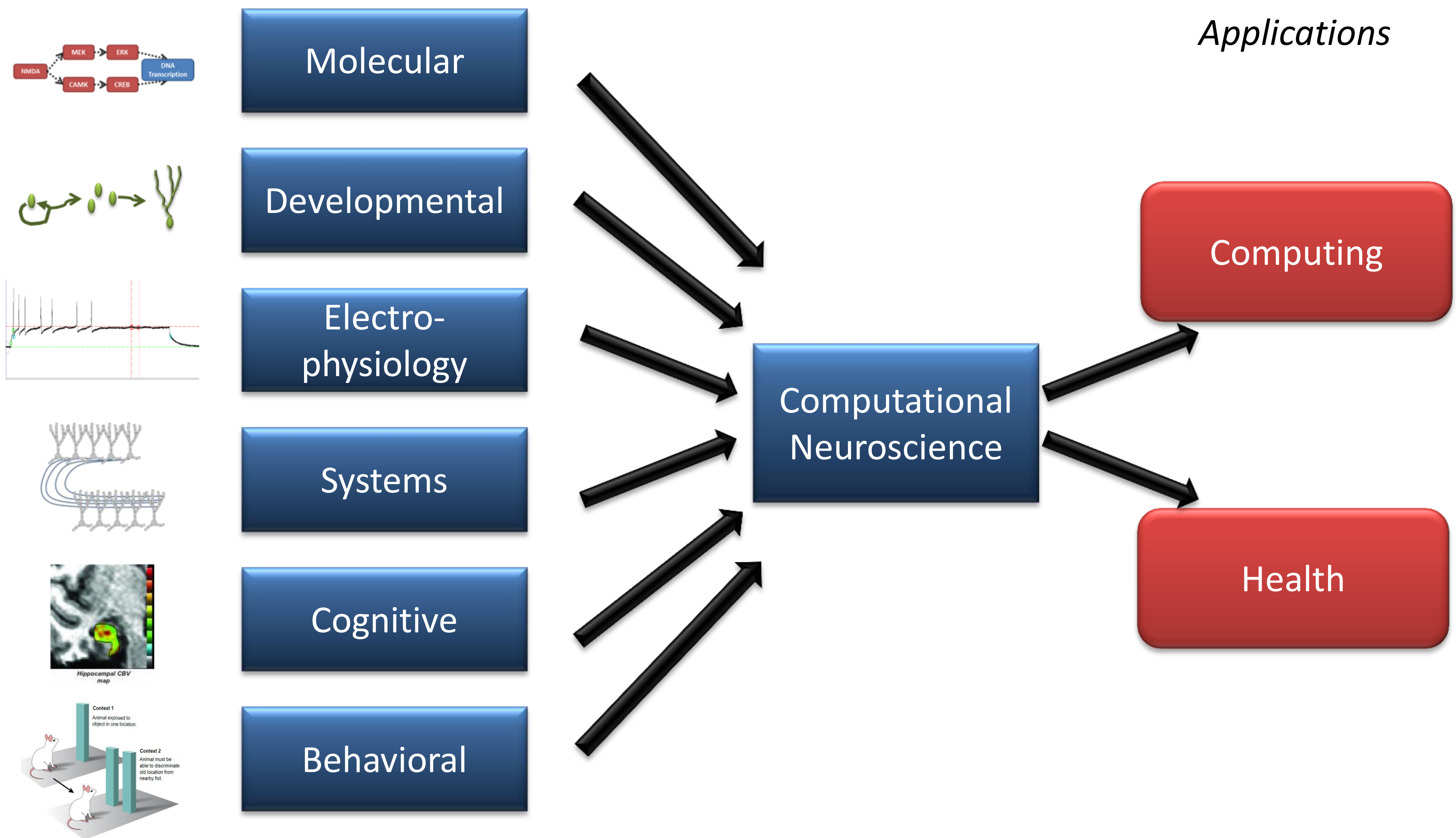
Behavioral



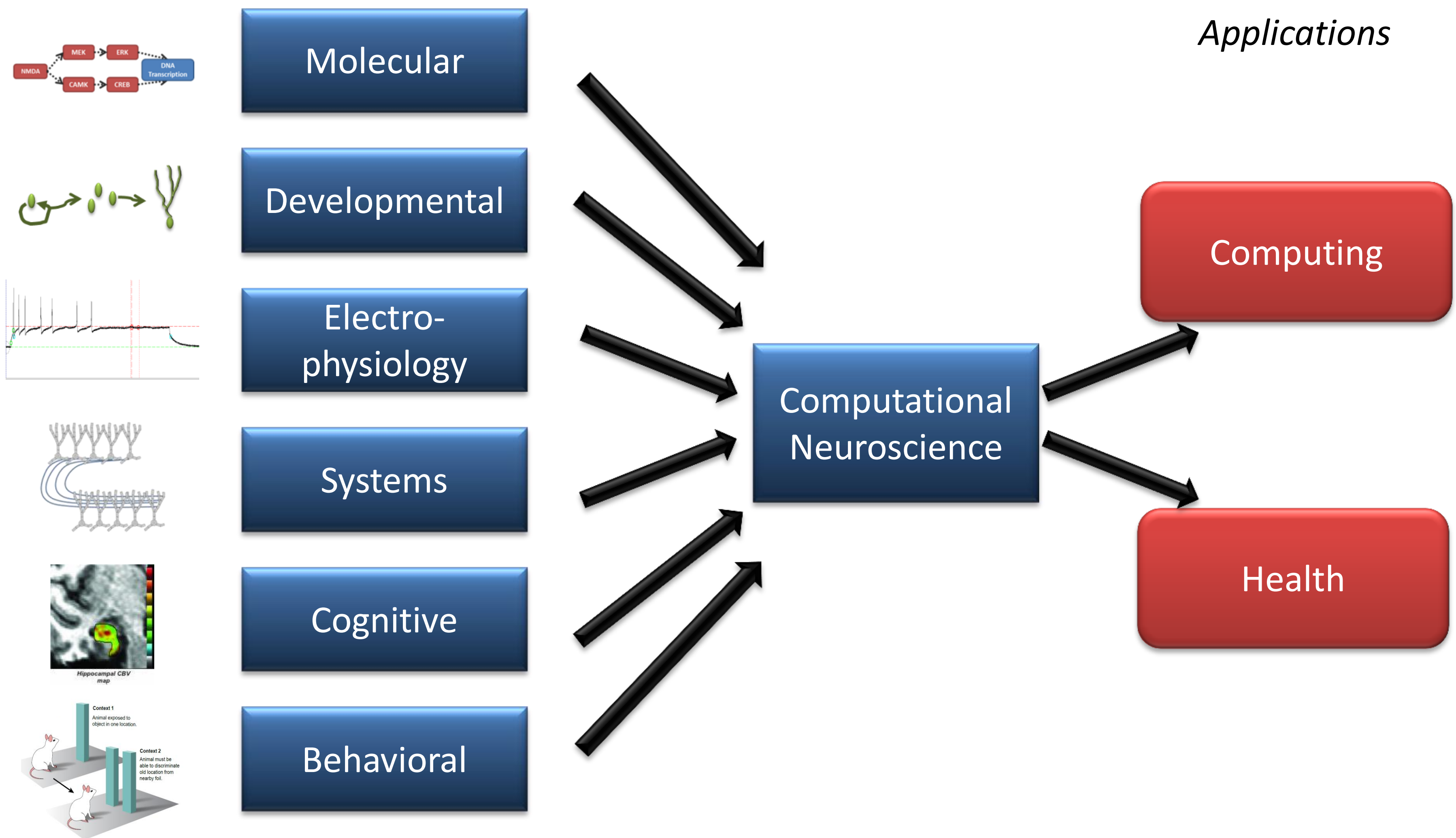
Neuroscience to Applications



Neuroscience to Applications

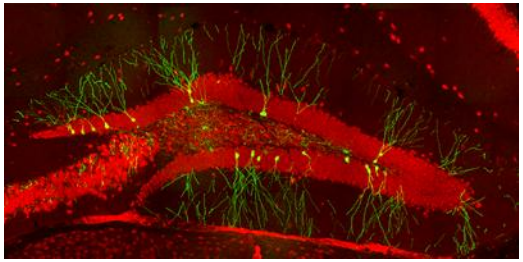


Neuroscience to Applications



Neuroscience at Sandia

- Computational Neuroscience



Adult Neurogenesis

- Simulation Design Platform

N2A

Neurons to Algorithms

- Simulation Engine and Analysis

Xyce™ PARALLEL ELECTRONIC SIMULATOR

Stretching from data to a useful model

Case study: adult neurogenesis

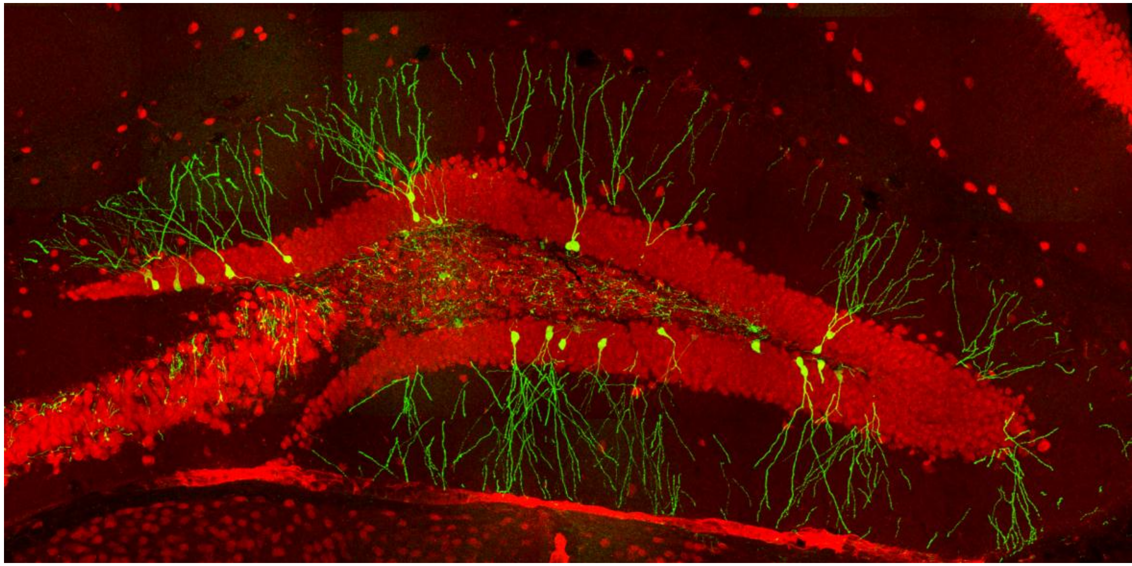
- Biologically very well characterized at low levels

- Big questions
  - Relevance in humans
  - What types of cognition would it affect?

- Substantial application impact
  - Target for in psychiatric and neurological therapeutics
  - Novel form of algorithm – plasticity at neural scales?

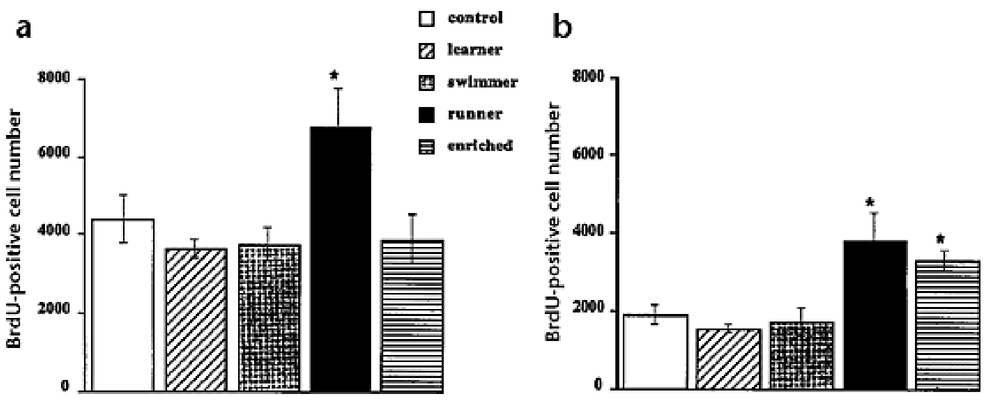
What is adult neurogenesis?

- Robust process
  - Thousands of new neurons integrate into dentate gyrus monthly



What is adult neurogenesis?

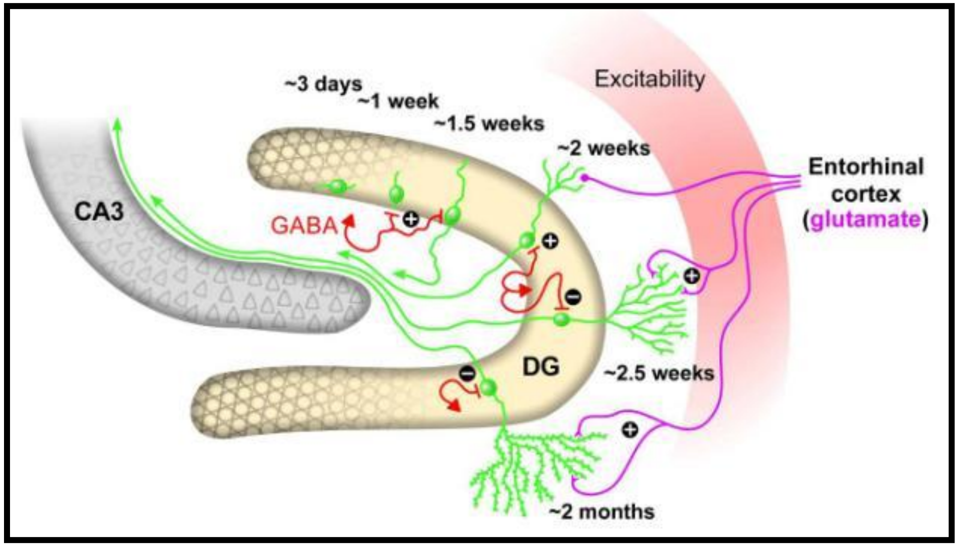
- Robust process
- Highly regulated
  - Both proliferation and survival controlled
  - Activity, enrichment, stress, diet, aging, disease…



van Praag et al., 1999

What is adult neurogenesis?

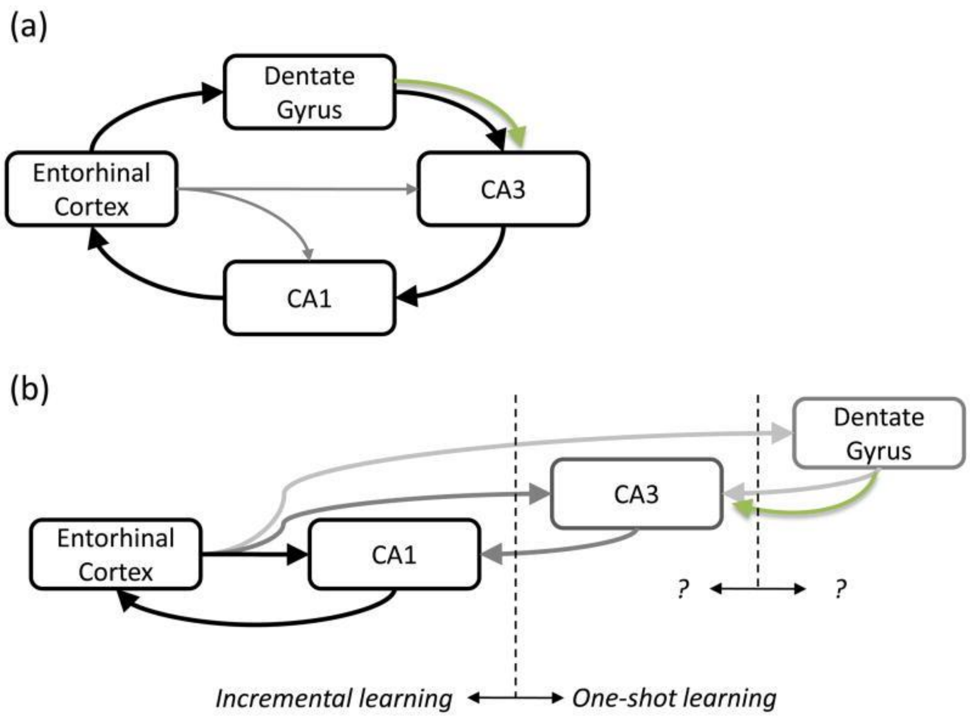
- Robust process
- Highly regulated
- Extended maturation
  - Several weeks to begin integrating into circuit
  - Still "immature" several months later



Aimone et al., Nature Neuroscience 2006

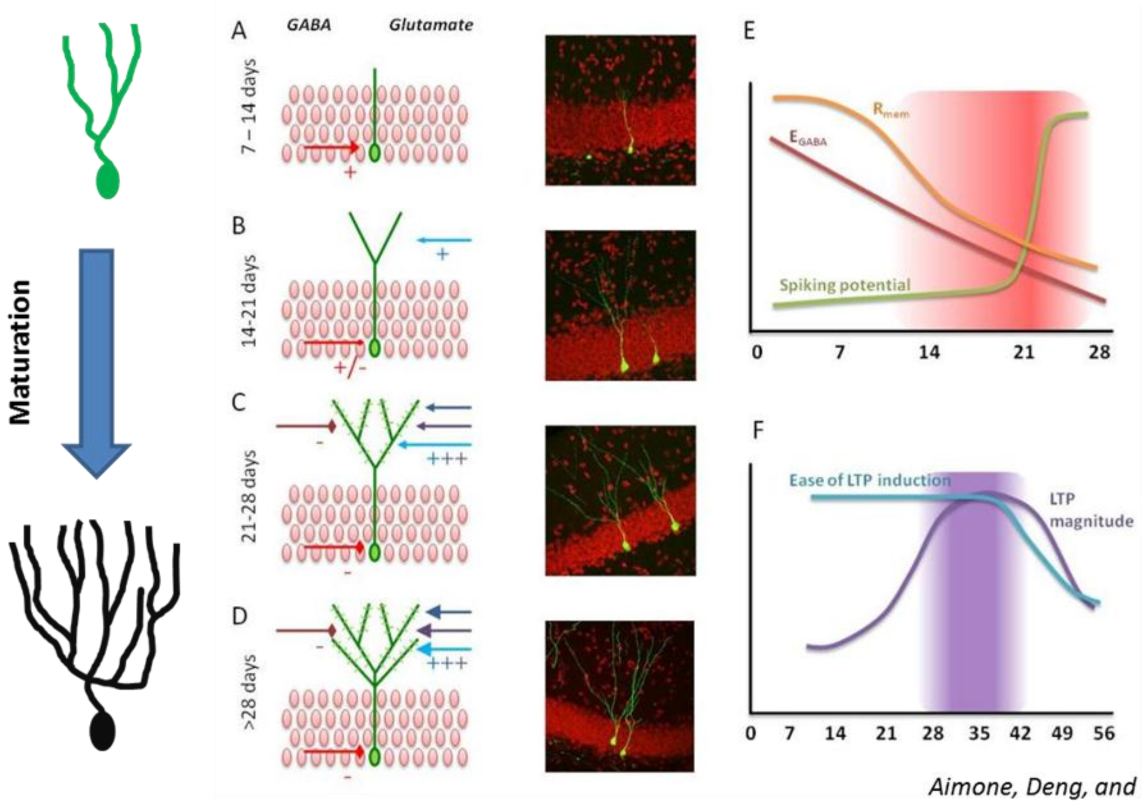
What is adult neurogenesis?

- Robust process
- Highly regulated
- Extended maturation
- Positioned to make an impact
  - Dentate gyrus is initial stage of hippocampus
  - Network amplifies effect of new neurons



Aimone, Deng and Gage
Trends in Cog. Sci., 2010

Maturation process of new neurons



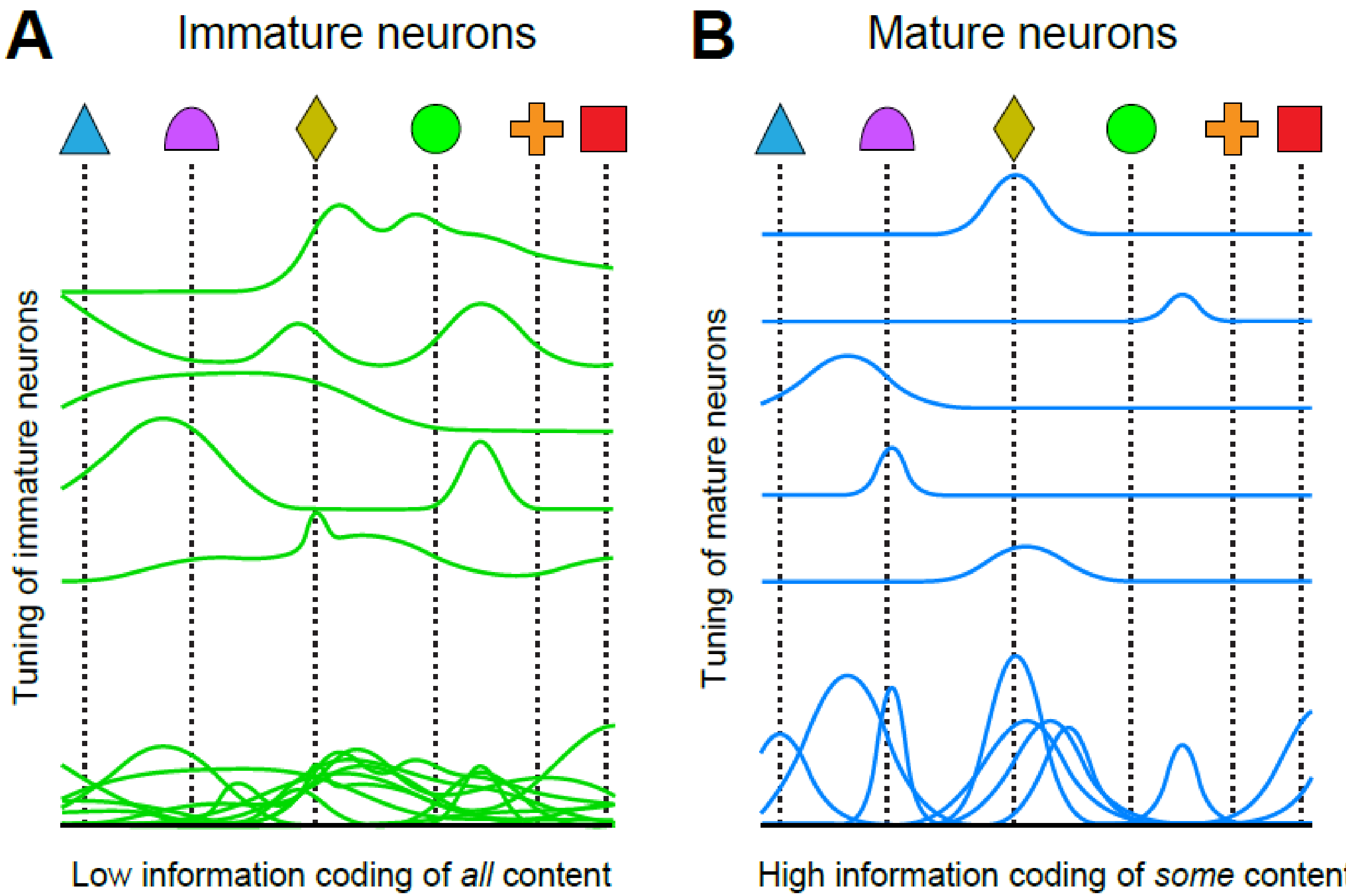
Aimone, Deng, and Gage
Trends in Cog. Sci. 2010

Adult Neurogenesis: Two Big Questions

- What does it do for cognition?

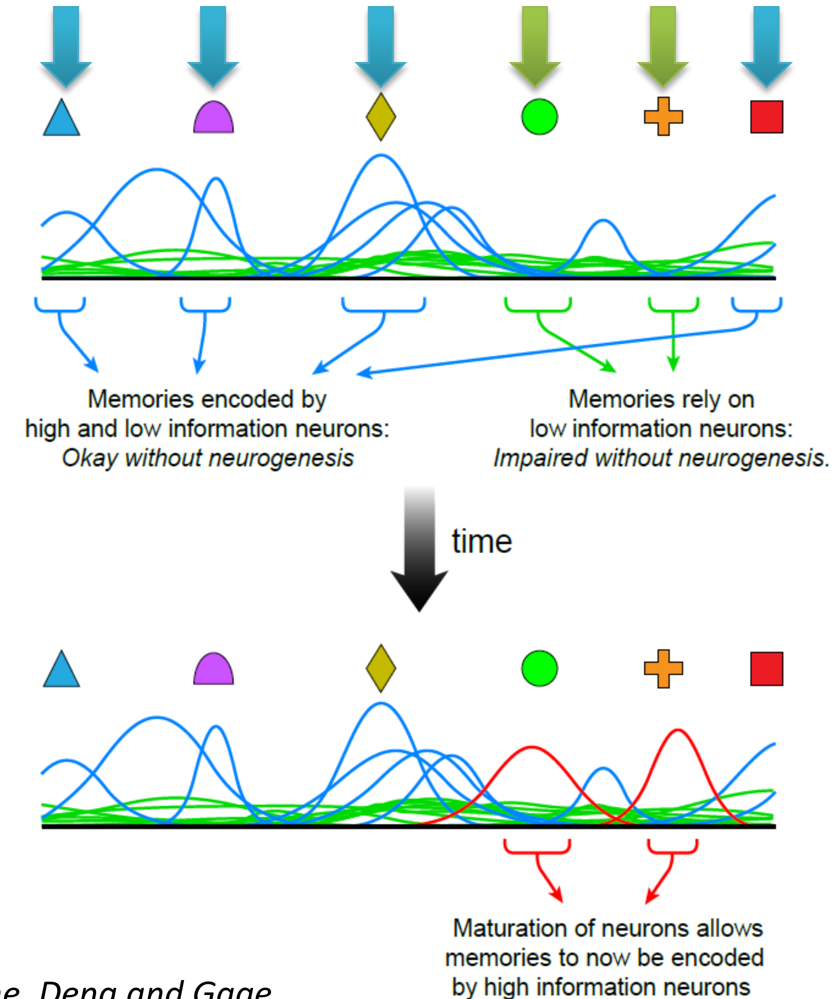
- Relevant in humans?

Immature and mature neurons encode information differently



Aimone, Deng and Gage
Neuron; 2011

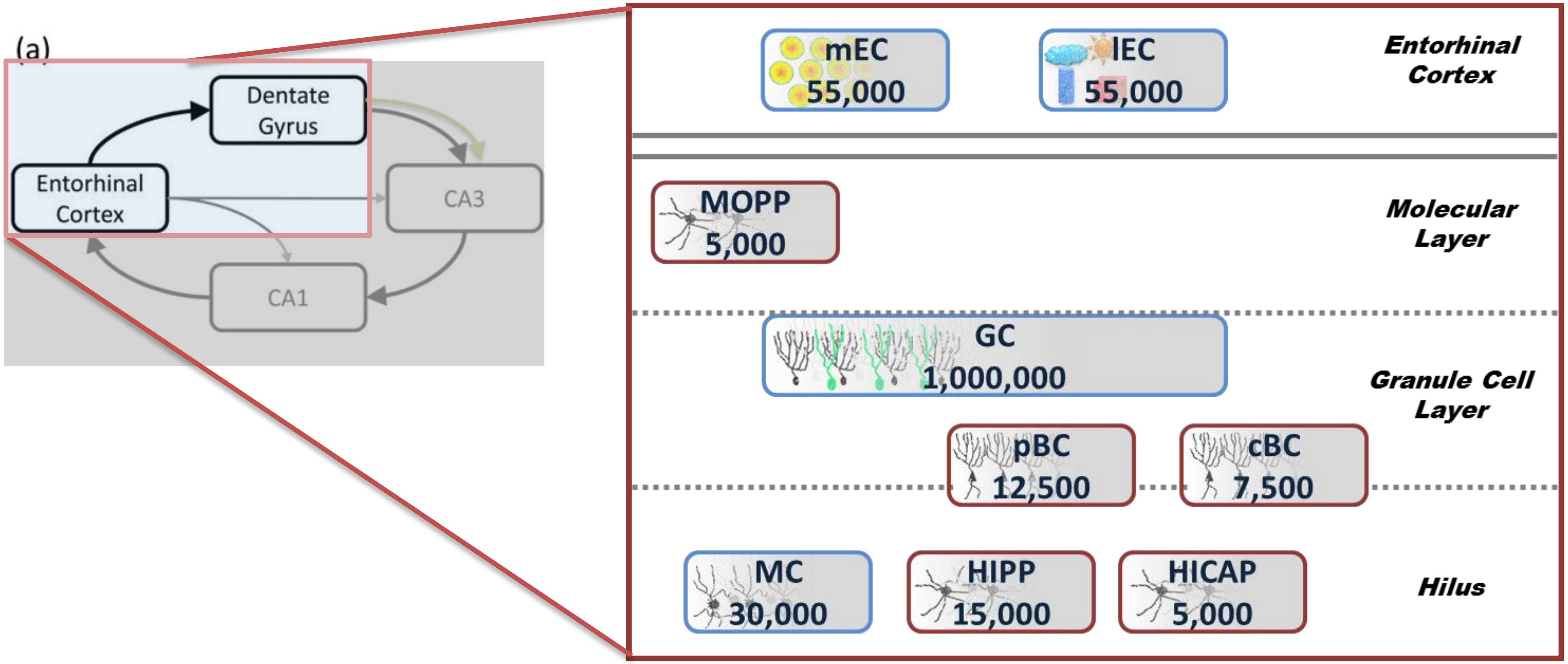
Mixed coding scheme in DG is potentially very powerful



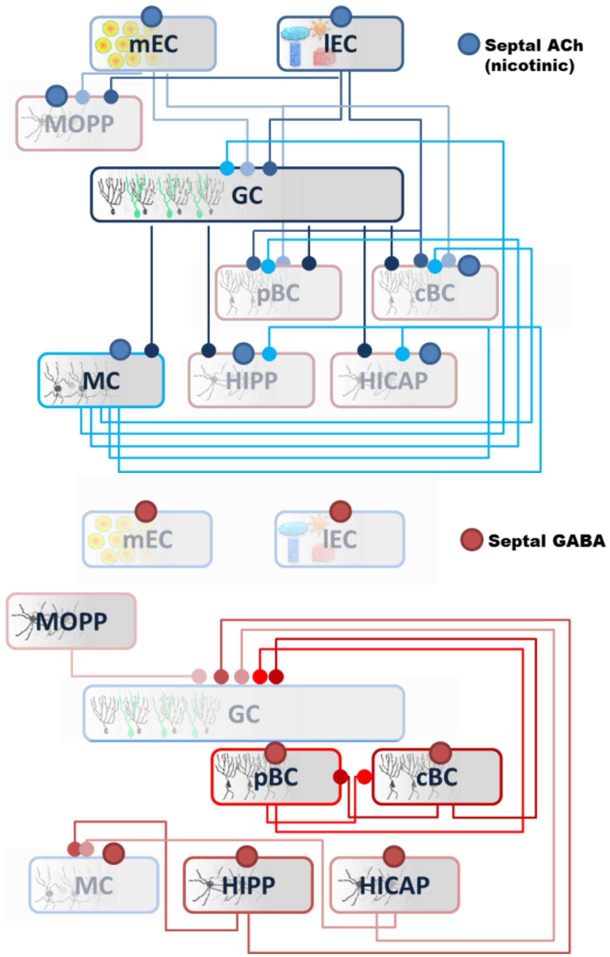
Aimone, Deng and Gage
Neuron; 2011

- Dentate Gyrus performs sparse coding for episodic memories
- Mature neurons are tightly tuned to specific features
  - *Not all events will activate mature neurons*
- Immature neurons are broadly tuned
  - *All events will activate some immature neurons*
- Neurons mature to be specialized to those events later
  - *Coding range of network gets more sophisticated over time*

Realistic scale model

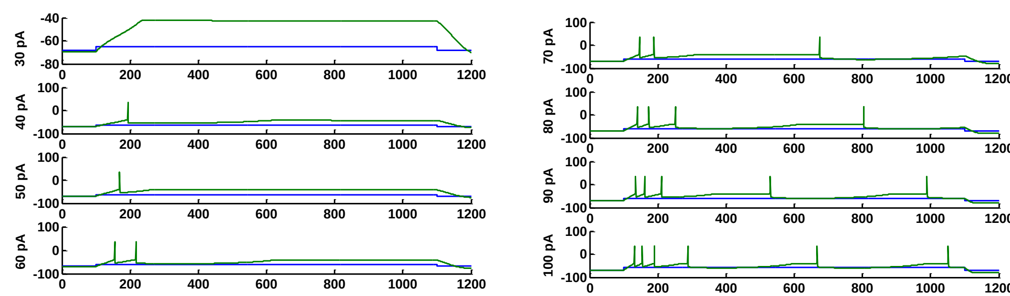


Realistic connectivity and dynamics

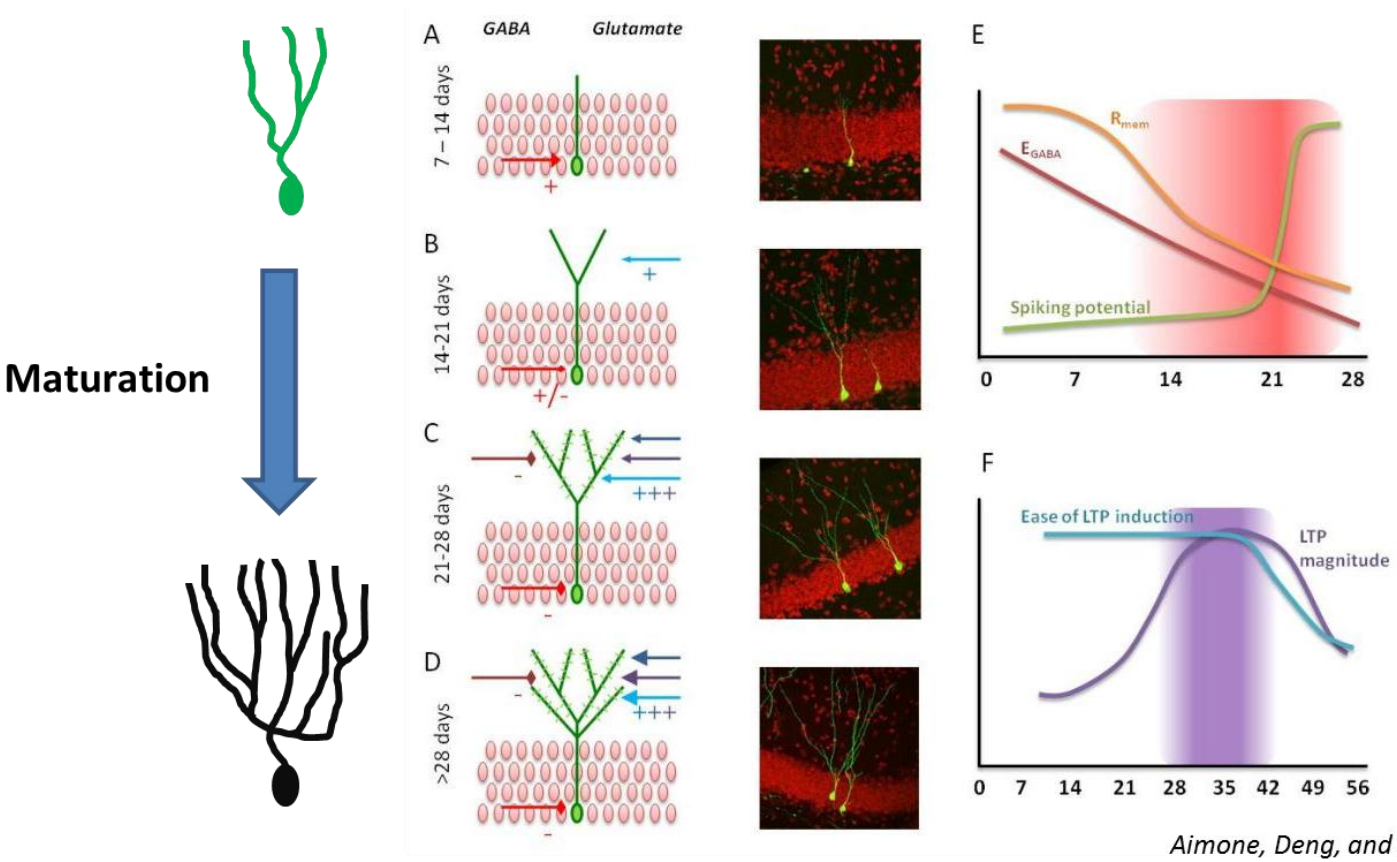


Physiology data

Modeled neuronal dynamics

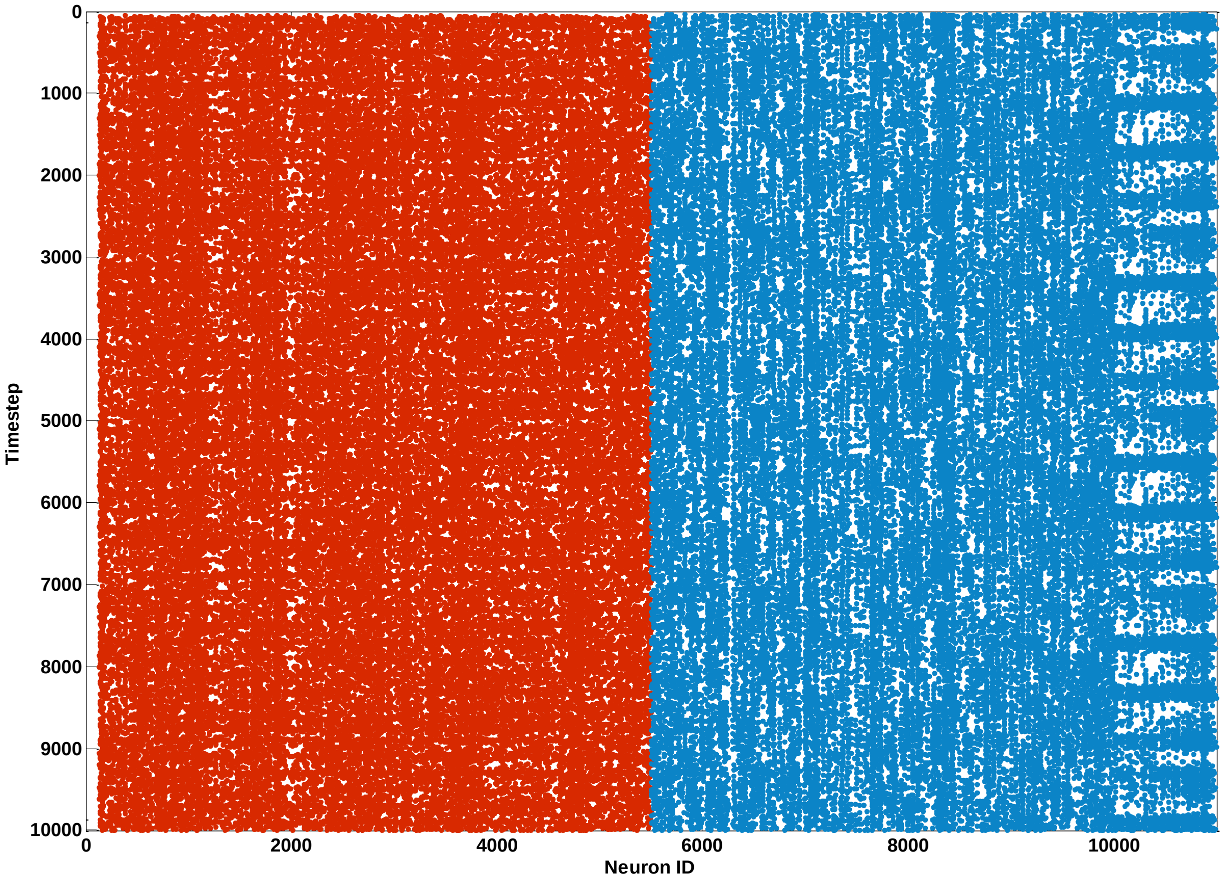


Neurogenesis Process

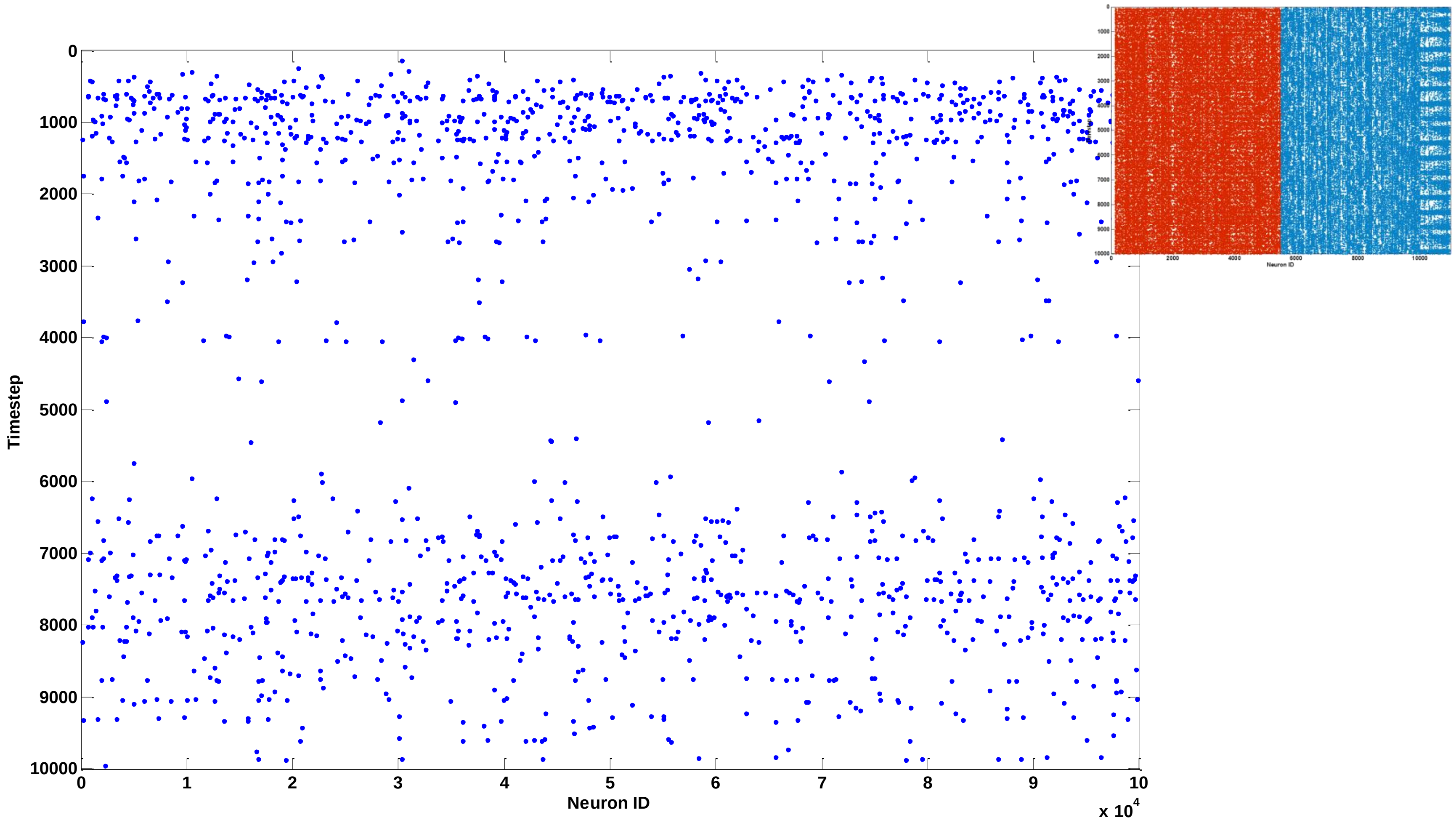


Aimone, Deng, and Gage
Trends in Cog. Sci. 2010

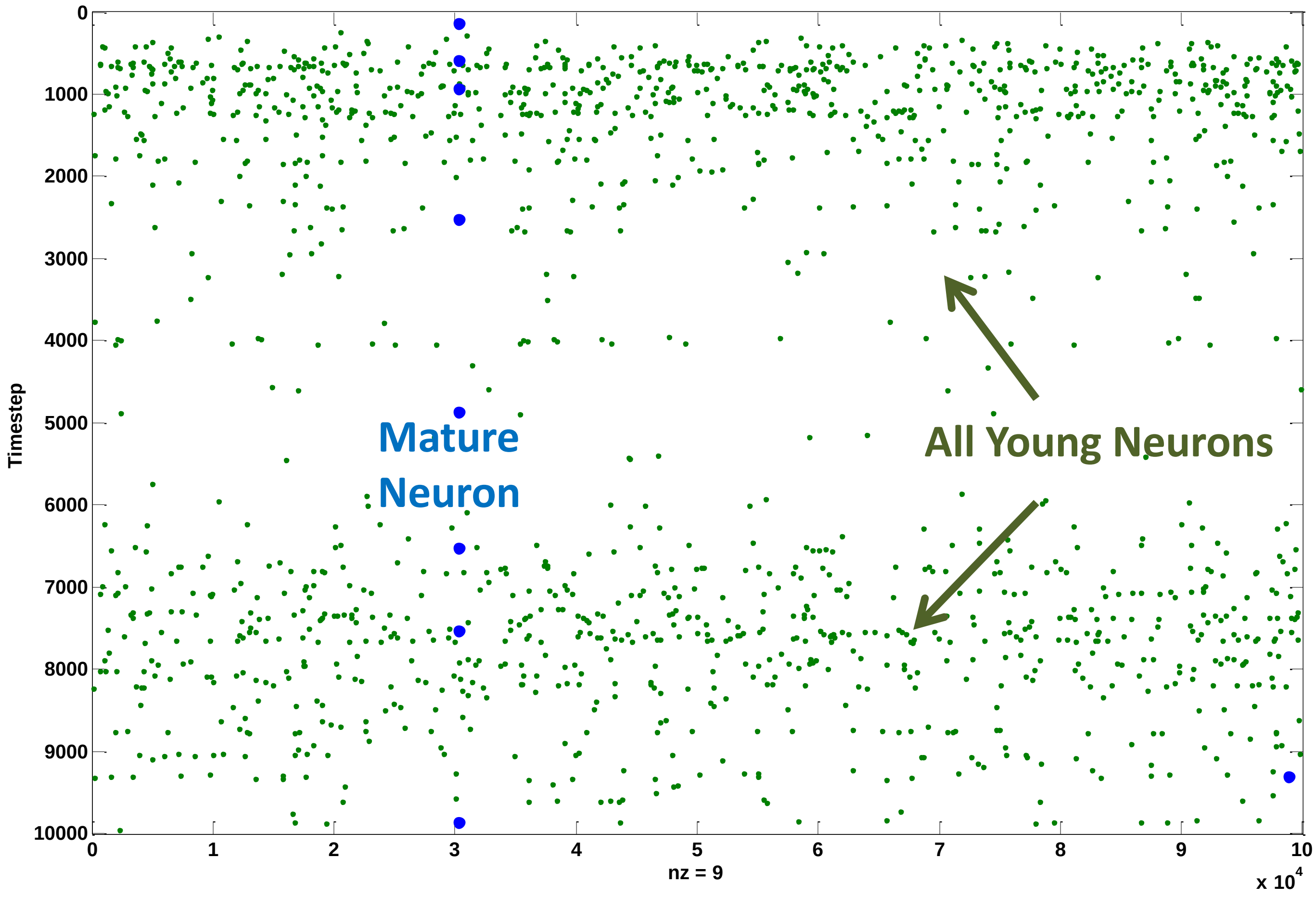
Activity of network – EC Inputs



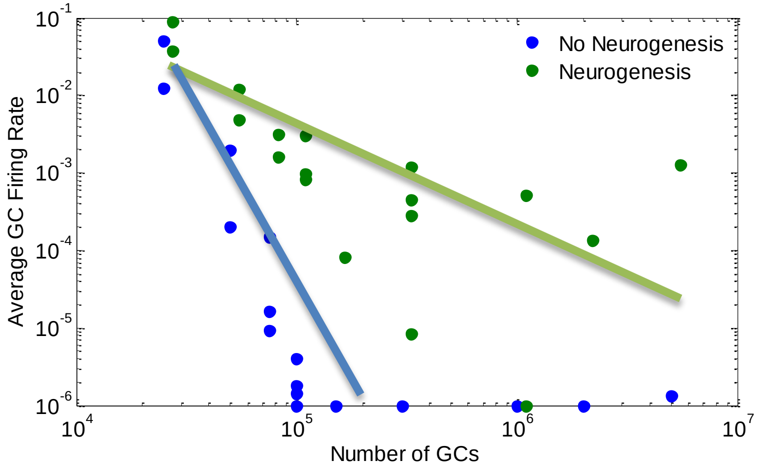
Activity of network – GC Outputs



Young GCs dominate

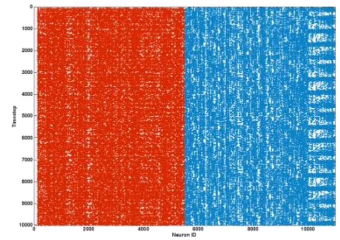


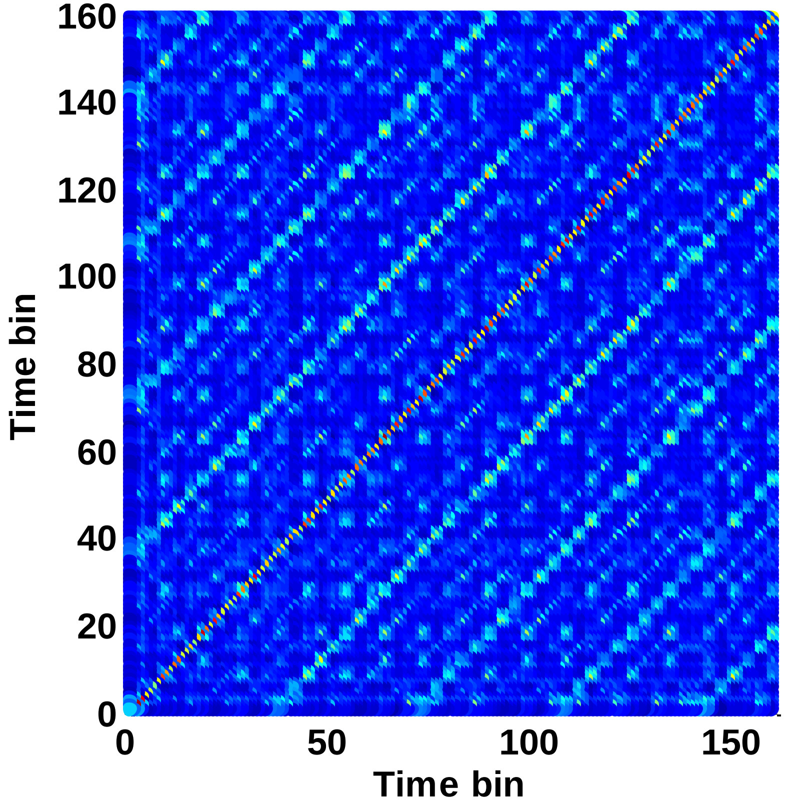
Lack of neurogenesis in large networks correlates with much lower activity

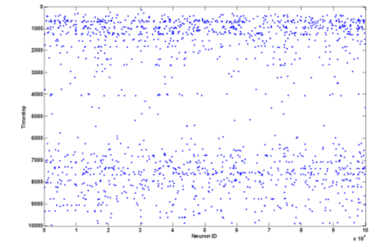


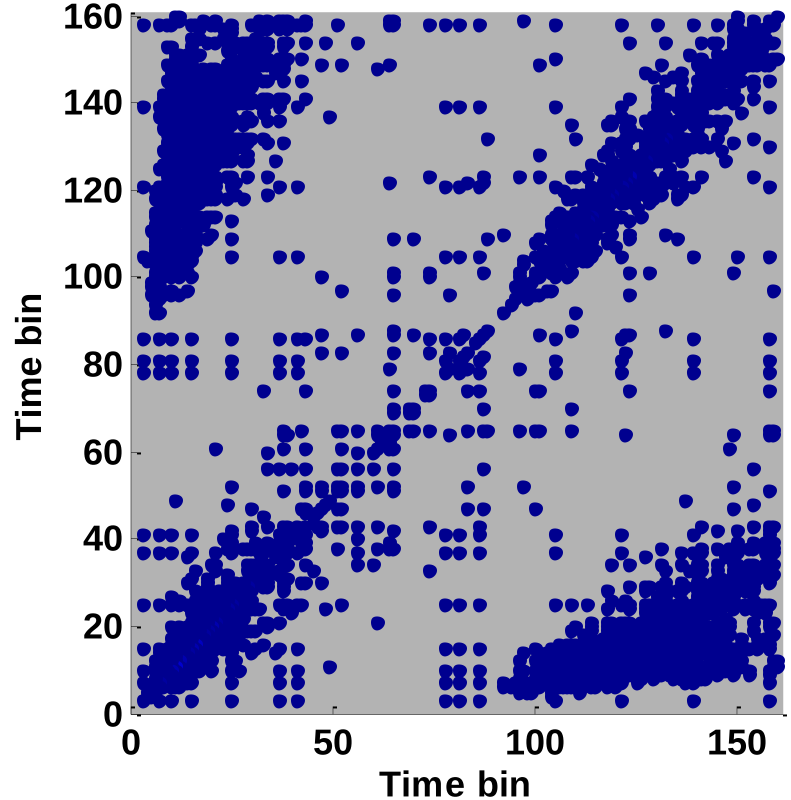
- Neurogenesis networks show activity to novel information at much higher scales
- As we approach human scales, mature neurons appear essentially silent in response to novel information
- Signal (immature) to noise (mature) is amplified in larger networks

Information processing in large networks

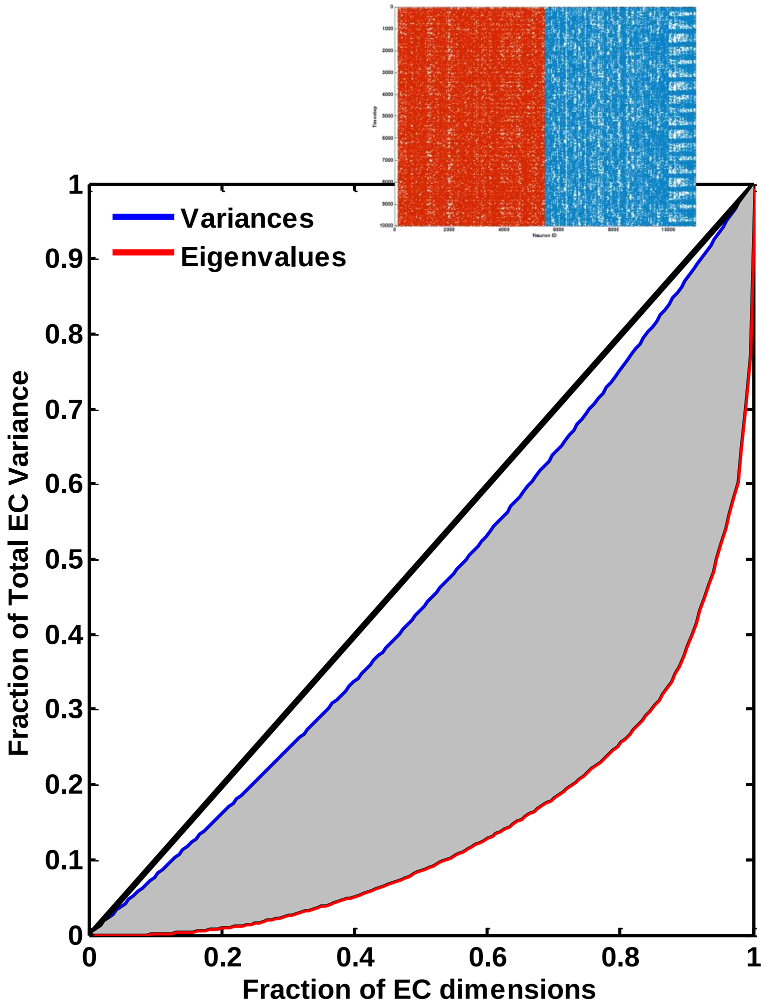


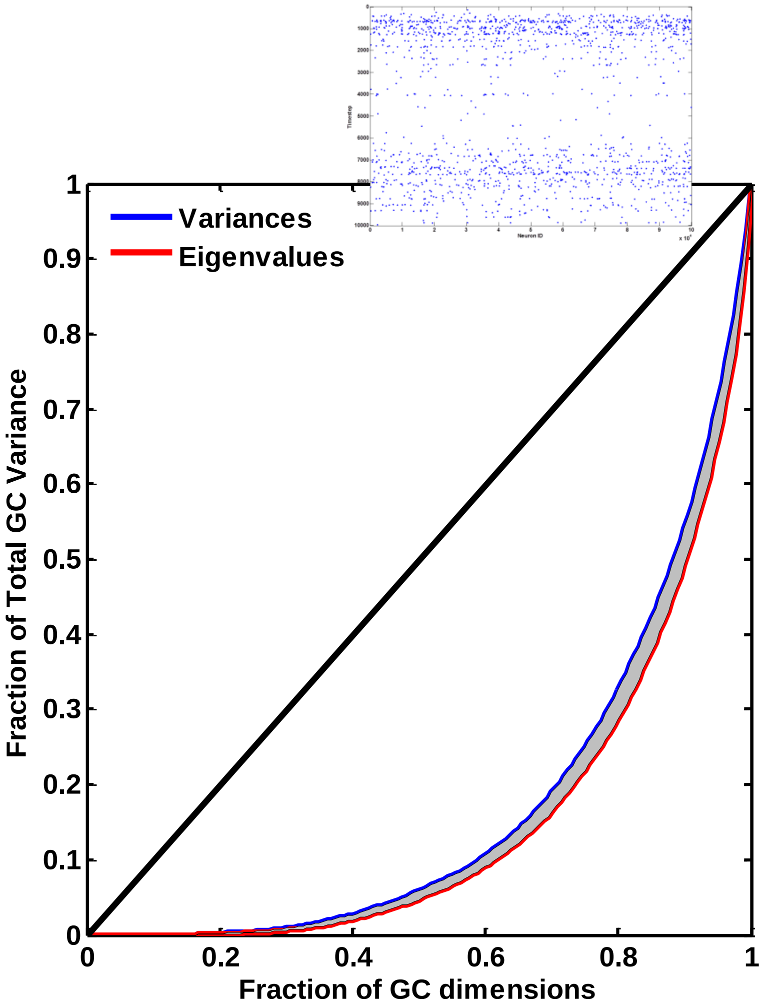




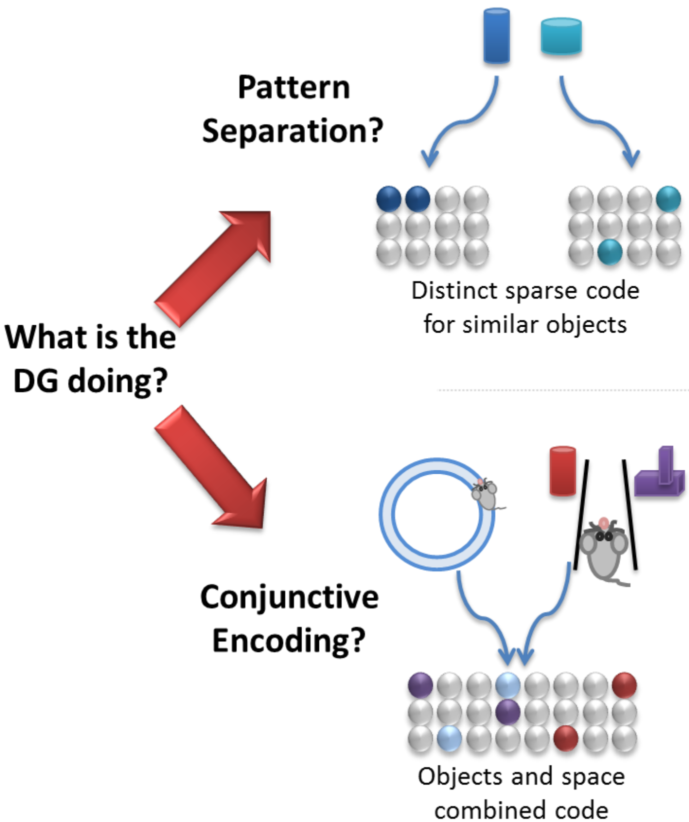


Information processing in large networks





Metrics for understanding NG model



- Pairwise correlation / dot product

$$Sim_{t1,t2} = \frac{\left\| f_{GC,t1} \cdot f_{GC,t2} \right\|}{\left\| f_{GC,t1} \right\| \left\| f_{GC,t2} \right\|}$$

- Average covariance

$$\sigma_{t1,t2} = \sum_{GC} \left(f_{GC,t1} - \overline{f_{t1}} \right) \cdot \left(f_{GC,t2} - \overline{f_{t2}} \right)$$

How to combine over observations?

- **Linear compressability**

$$\kappa_{GC} = \sum_{i=1..d} (\sigma_i - \lambda_i) \Big/ \sum_{i=1..d} \sigma_i$$

- Average firing rate

$$f_{GC} = {}^{1}\!/_{N_{GC}} \sum_{GC} {}^{N_{spikes}}\!/_{T}$$

- Total variance

$$\sigma_{GC} = \sum_{T} \sigma_{GC,T}$$

- Information Content

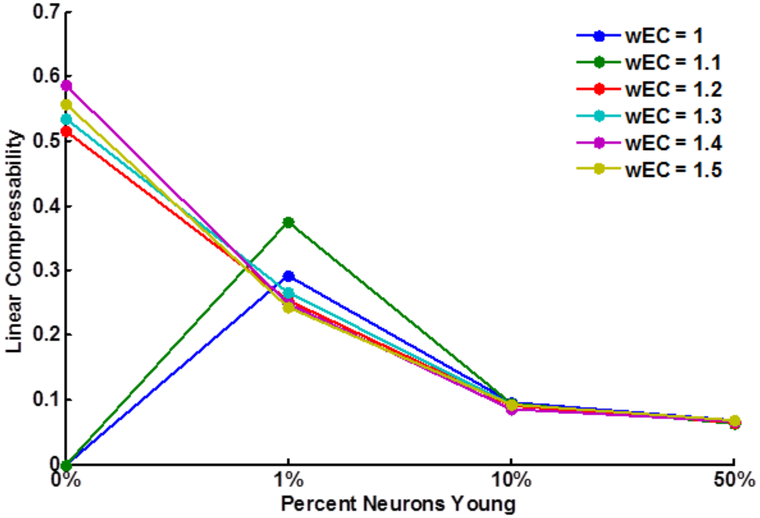
$$I = \sum_{ctx} p_{ctx} \, {}^{f}\!/_{\bar{f}} \log_2 {}^{f}\!/_{\bar{f}}$$

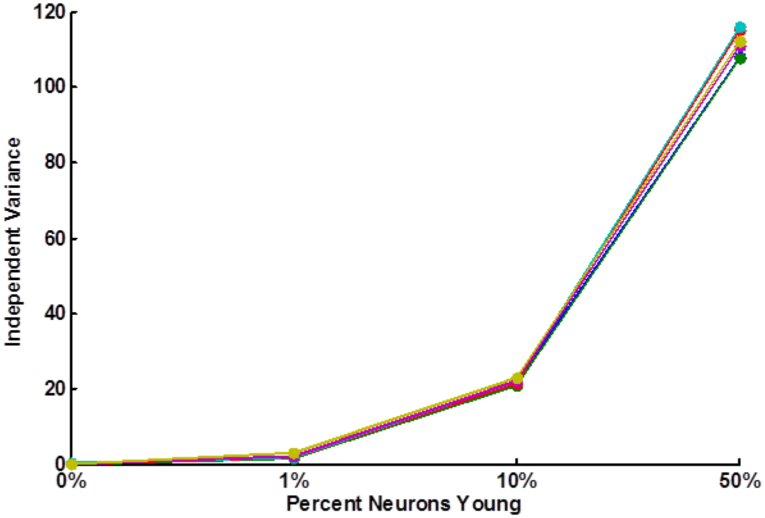
How to combine over neurons?

- **Independent variance**

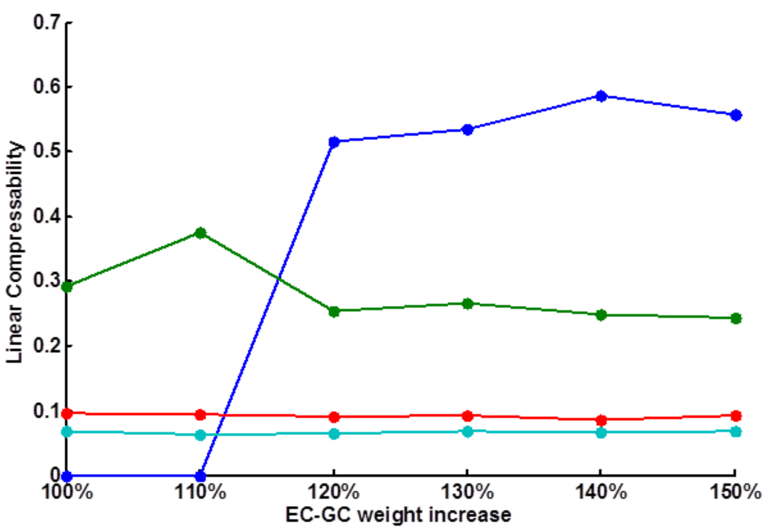
$$\varphi_{GC} = \sigma_{GC} \times \kappa_{\lambda}$$

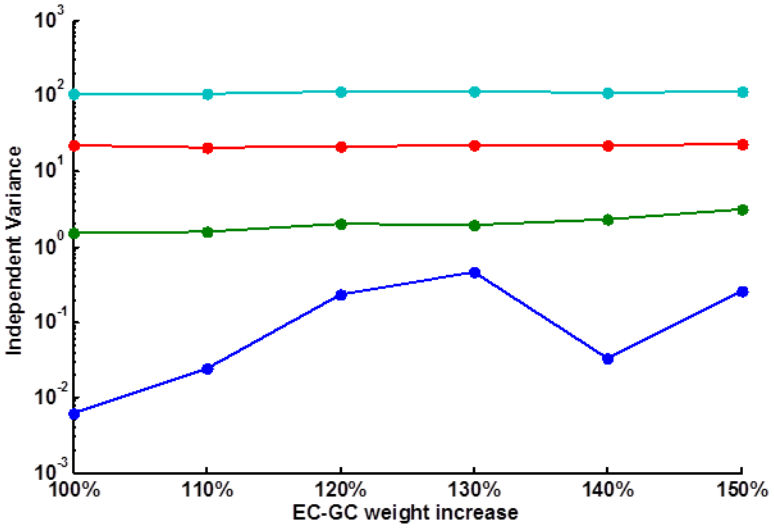
Neurogenesis decreases compressibility and increases total representation



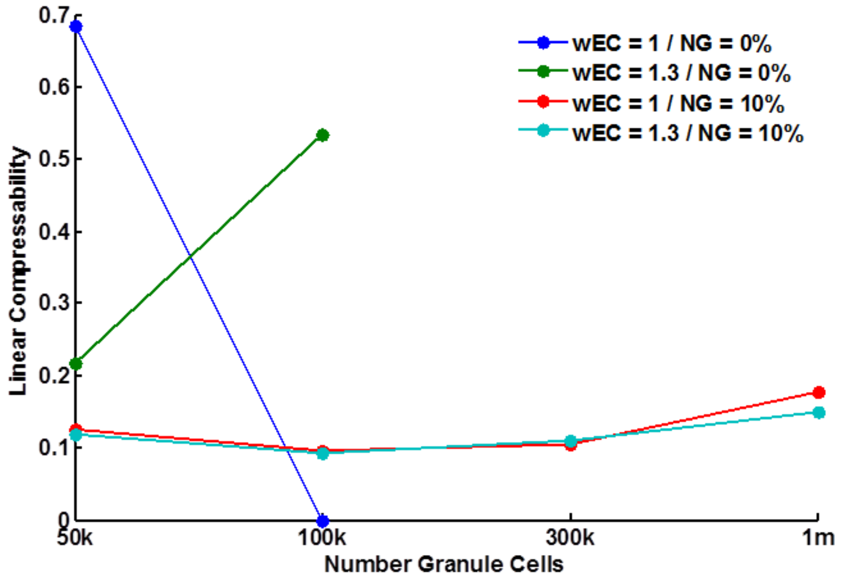


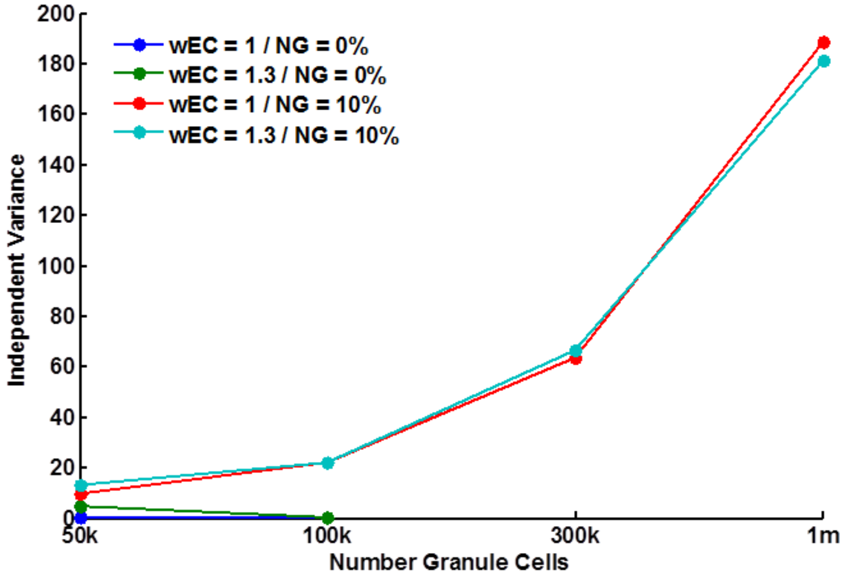
Increasing EC-GC weights impairs separation without improving coding



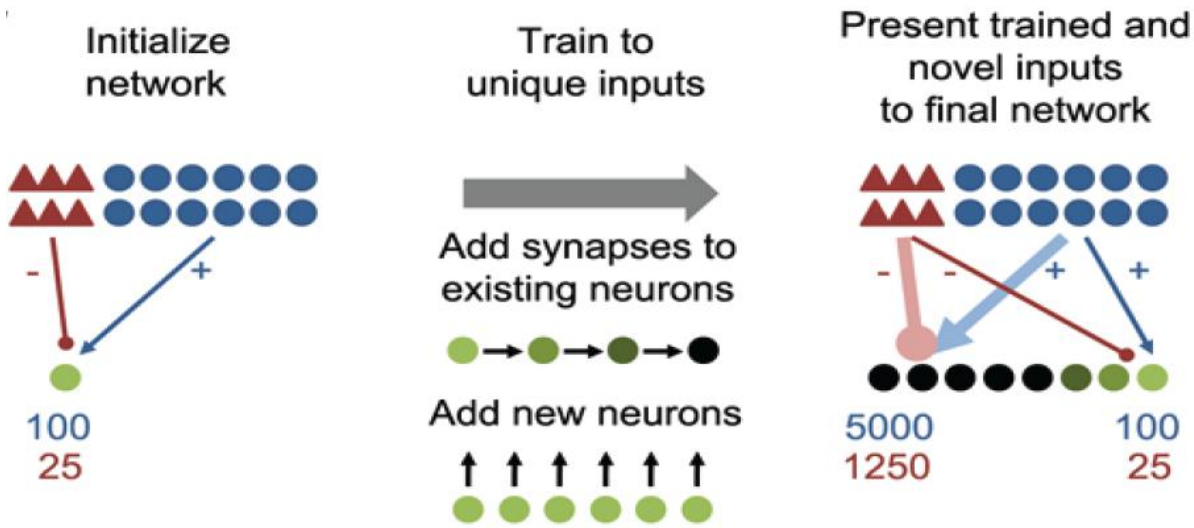


Increased size networks need neurogenesis for balancing separability and representations



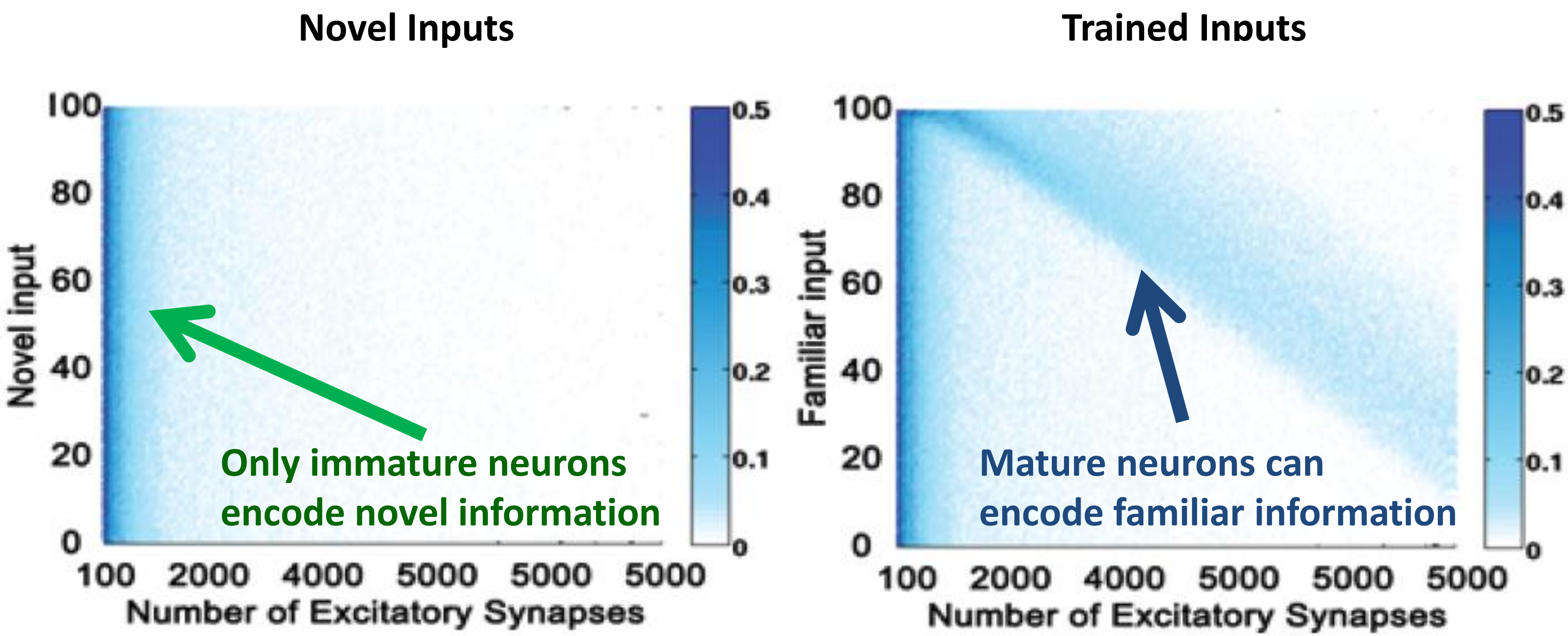


Abstract model: scaling neuron sizes yields neurogenesis effect



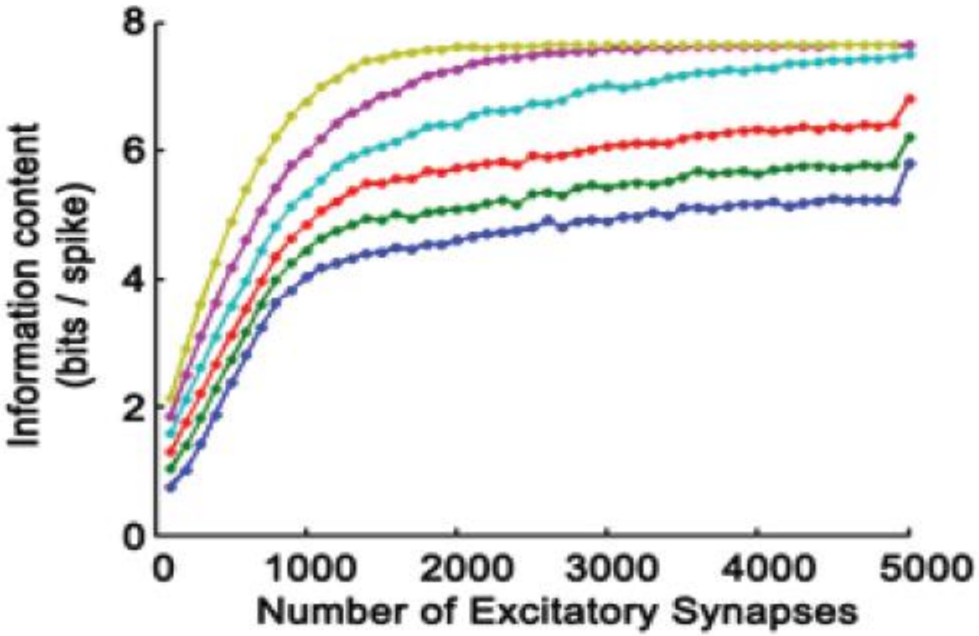
Li, Aimone et al., PNAS 2012

Neurons maturing to large number of synapses contain high information about maturation cues



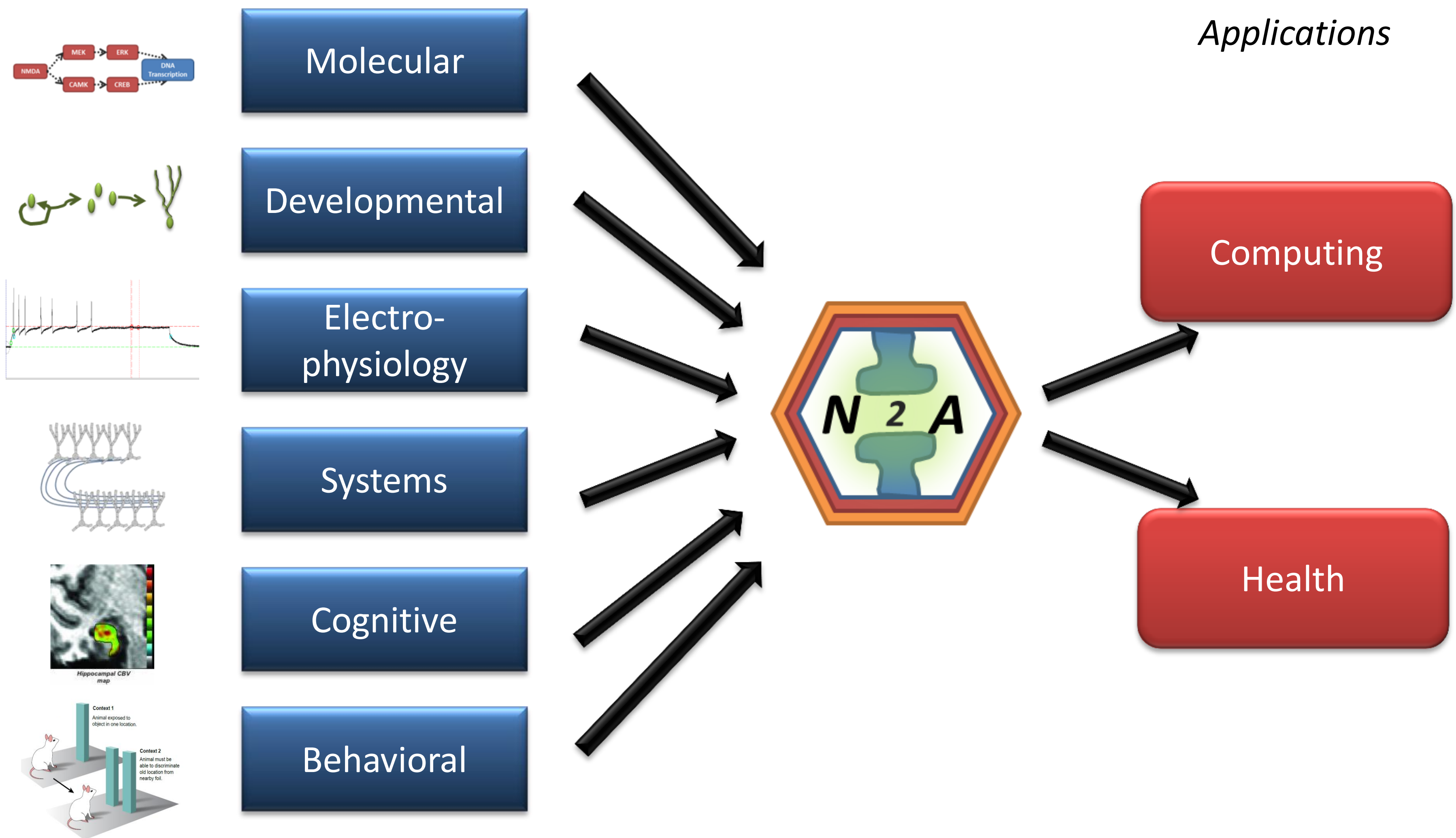
Li, Aimone et al., PNAS 2012

High synapse neurons have higher information content



Li, Aimone et al., PNAS 2012

Neuroscience to Applications



The Challenge

Society for Neuroscience
>30,000 scientists attend
>1,000 topic areas presented

Need to integrate all this knowledge. Beyond capacity of anyone to comprehend.

The community needs powerful computer tools, which Sandia has to offer.

In return, the community will give us far richer models (crowd-sourcing) that we can leverage in mission applications.

How to do it

- Contributed models
- Neurophysiology literature
- Online databases

Database of Neural Structure & Dynamics

Simulate

Xyce

PARALLEL ELECTRONIC SIMULATOR

DAKOTA

Fit parameters

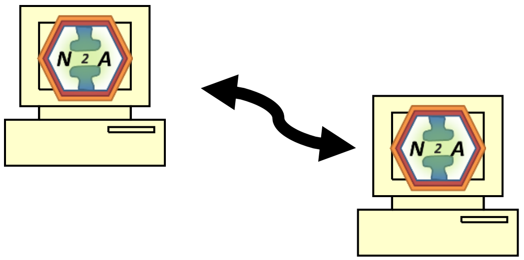
- Visualization
- Automatic analysis

Characterize model behavior

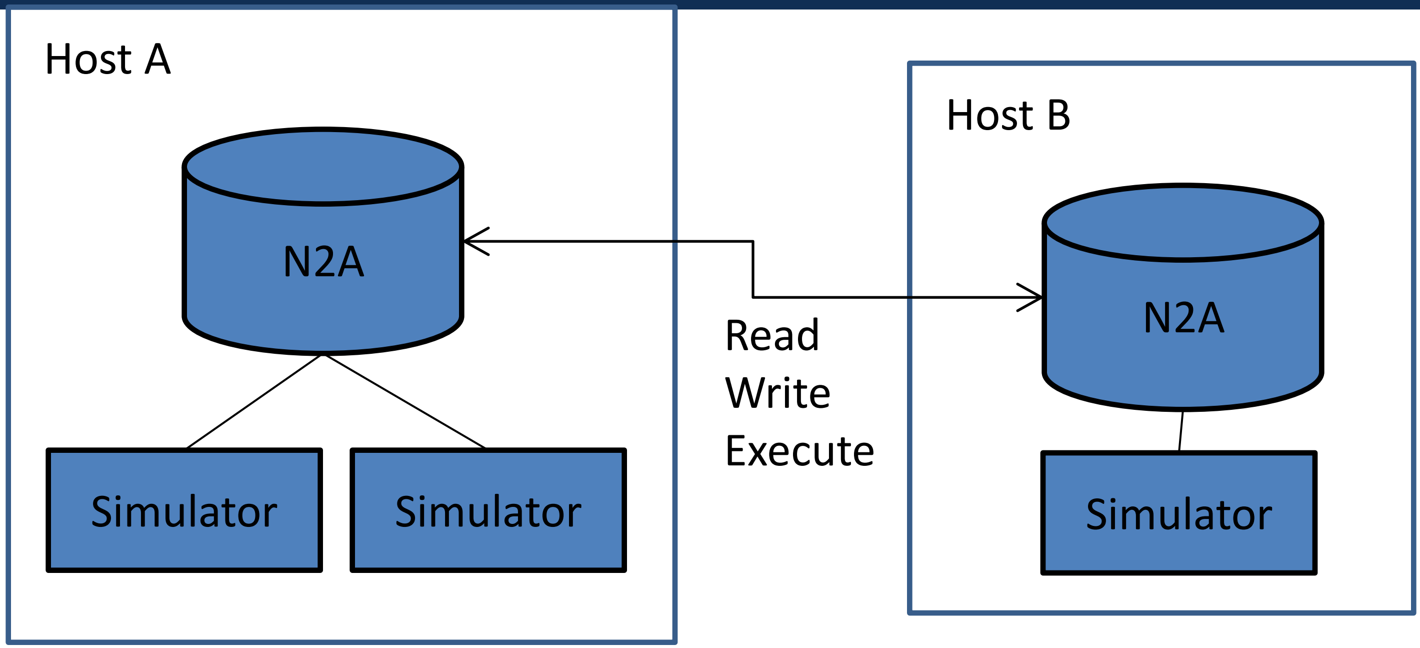
Algorithmic motifs

Vision of N2A

- Open Source
- Peer-to-peer model sharing
- Versioning of models (repeatability)
- Sensitivity Analysis and Streamlined Parameter Estimation
- Interface into Neuroinformatics tools and frameworks (e.g., NeuroML, NIF)
- Ability to incorporate existing published models



(soon) P2P Sharing

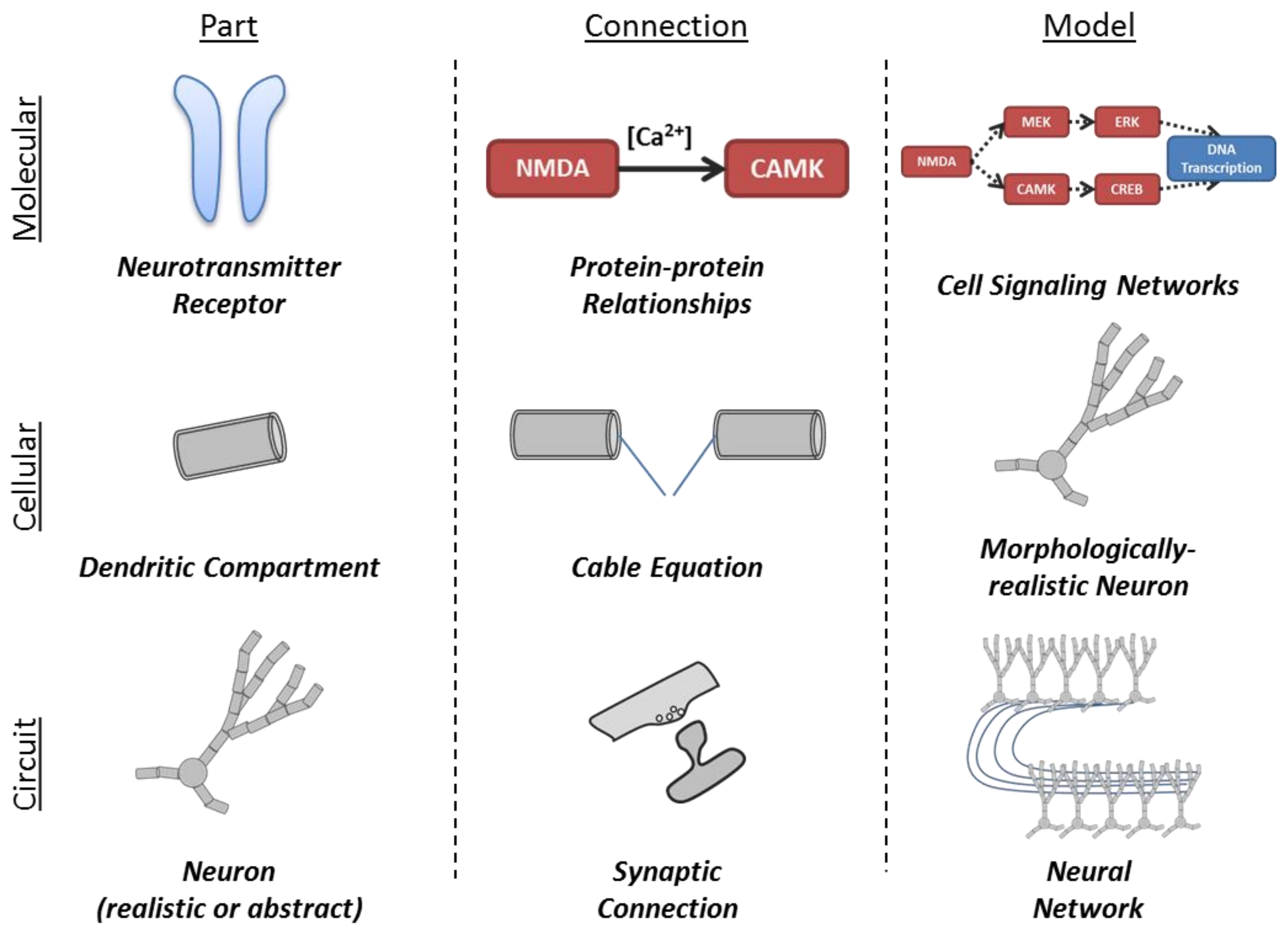


A remote system may be another desktop, a cluster-computer, or a “cloud” service.

You may upload your models to another N2A system,
download models from it,
or ask it to simulate a model on your behalf.

Simulator may be any tool (Xyce, Neuron, PyNN, Brian, ...) for which there is a backend wrapper.

Different scales, same approach



Model Structure

Dynamical Systems
AND Parts-Relations

Many things can be modeled in this form, including biology and cognition.

Connection

A.V’ += B.V – A.V
B.V’ += A.V – B.V
...

Structural dynamics: express quantity and arrangement of Parts, as well as their internal state.

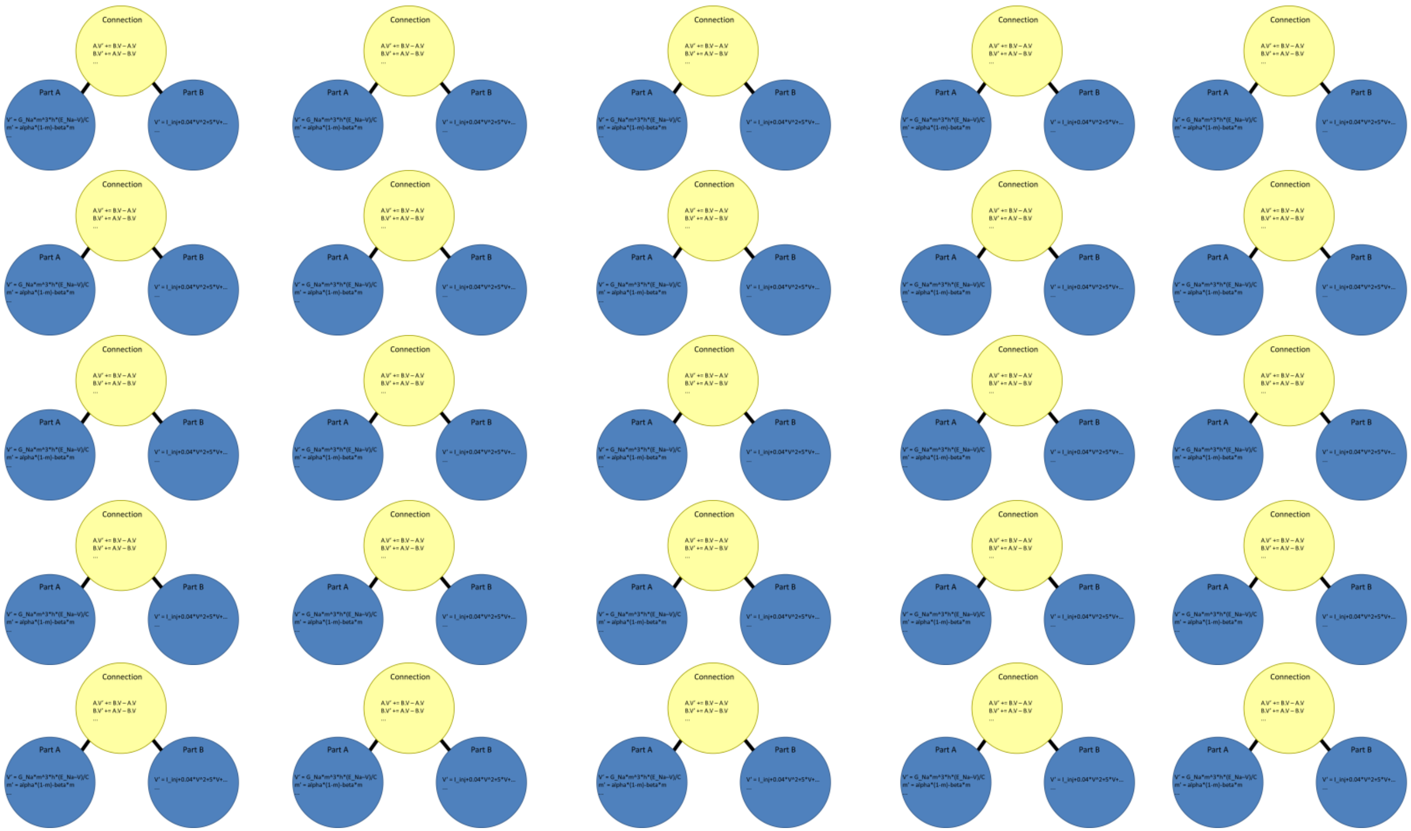
Part A

V’ = G_Na*m^3*h*(E_Na–V)/C
m’ = alpha*(1-m)-beta*m
...

Part B

V’ = I_inj+0.04*V^2+5*V+...
...

Multiple instantiations to scale up model

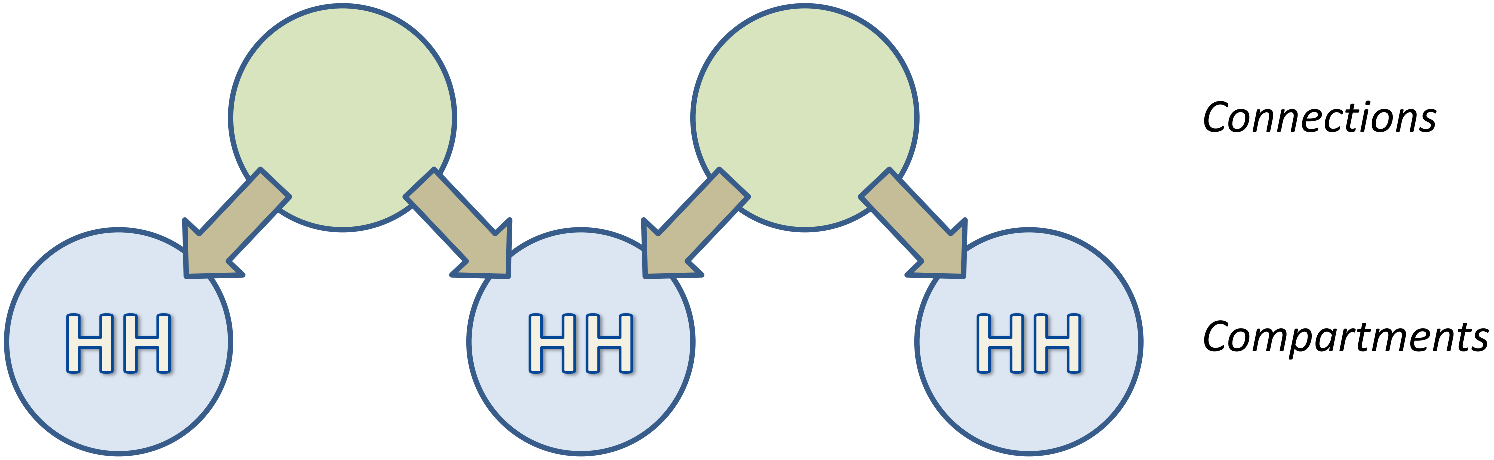


N2A Demo – Example Problem

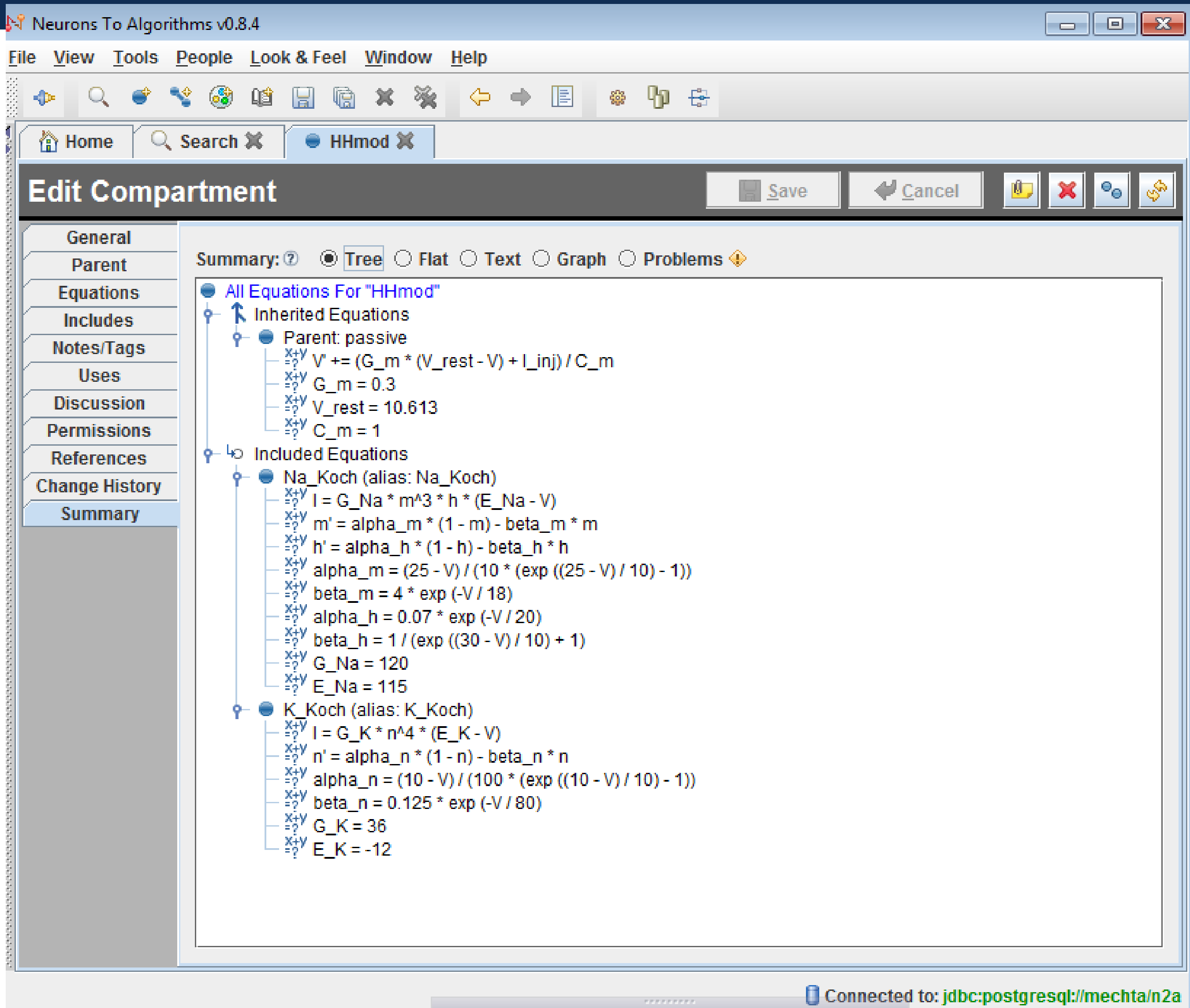
Measure Spike Propagation through Multi-Segment Hodgkin-Huxley Cable

Neuroscientist Representation:

N2A Representation:



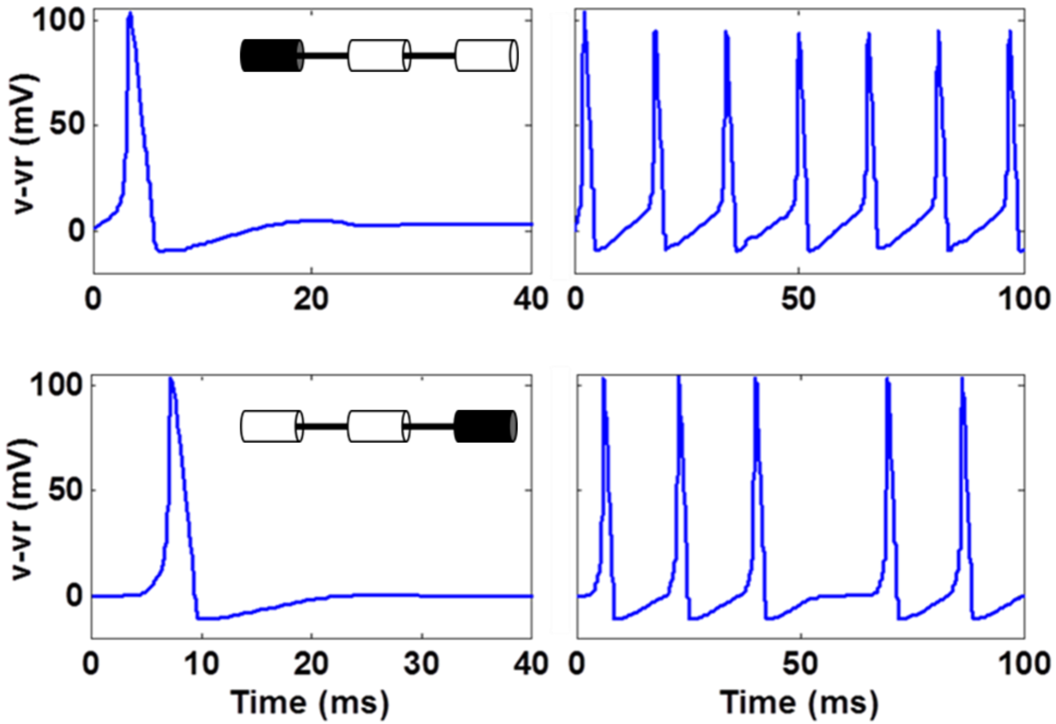
N2A - Demo



Neurons To Algorithms v0.8.4
File View Tools People Look & Feel Window Help
Home
Search
HHmod
Edit Compartment
Save
Cancel
General
Parent
Equations
Includes
Notes/Tags
Uses
Discussion
Permissions
References
Change History
Summary
Summary: Tree Flat Text Graph Problems
All Equations For "HHmod"
Inherited Equations
Parent: passive
V' += (G_m * (V_rest - V) + I_inj) / C_m
G_m = 0.3
V_rest = 10.613
C_m = 1
Included Equations
Na_Koch (alias: Na_Koch)
I = G_Na * m^3 * h * (E_Na - V)
m' = alpha_m * (1 - m) - beta_m * m
h' = alpha_h * (1 - h) - beta_h * h
alpha_m = (25 - V) / (10 * (exp ((25 - V) / 10) - 1))
beta_m = 4 * exp (-V / 18)
alpha_h = 0.07 * exp (-V / 20)
beta_h = 1 / (exp ((30 - V) / 10) + 1)
G_Na = 120
E_Na = 115
K_Koch (alias: K_Koch)
I = G_K * n^4 * (E_K - V)
n' = alpha_n * (1 - n) - beta_n * n
alpha_n = (10 - V) / (100 * (exp ((10 - V) / 10) - 1))
beta_n = 0.125 * exp (-V / 80)
G_K = 36
E_K = -12
Connected to: jdbc:postgresql://mechta/n2a

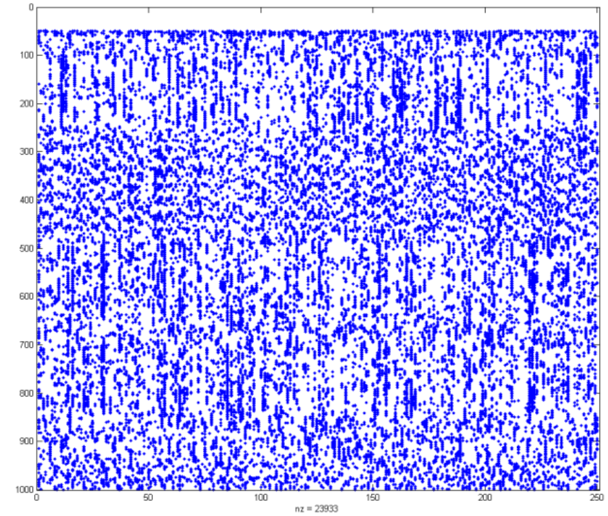
Results

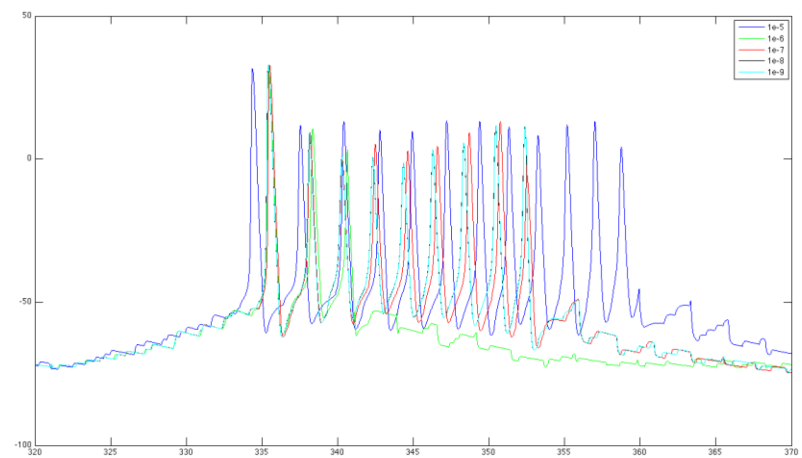

I_inj
V_1
V_3


100
50
0
v-vr (mV)
0
20
40
0
50
100
100
50
0
v-vr (mV)
0
10
20
30
40
Time (ms)
0
50
100
Time (ms)

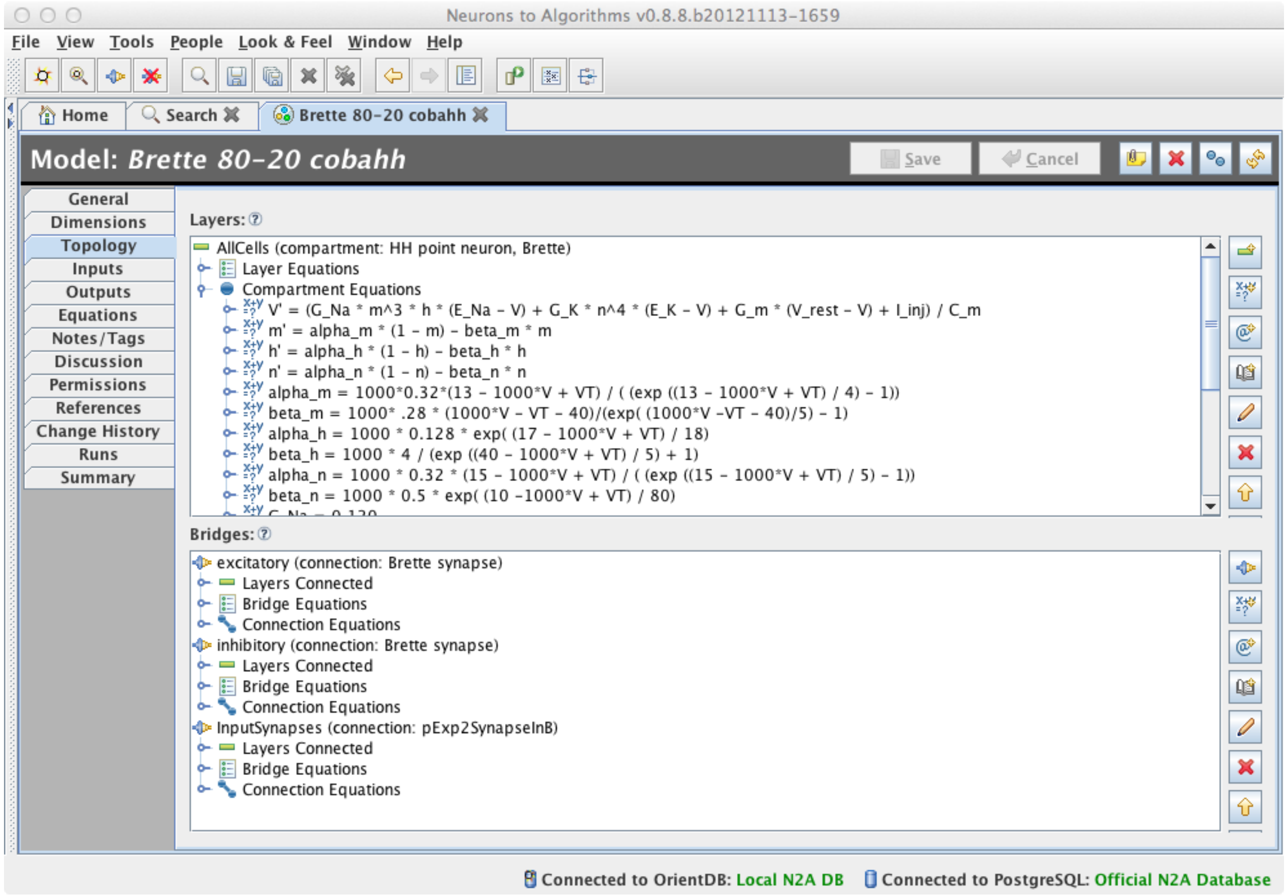
Sensitivity of recurrent spiking neural networks

1. Borderline chaotic dynamics
   – Network is deterministic
   – Very slight deviations in solving get amplified by spiking
2. How do you analyze?
   – Individual neurons diverge over time
   – Need “ground truth”

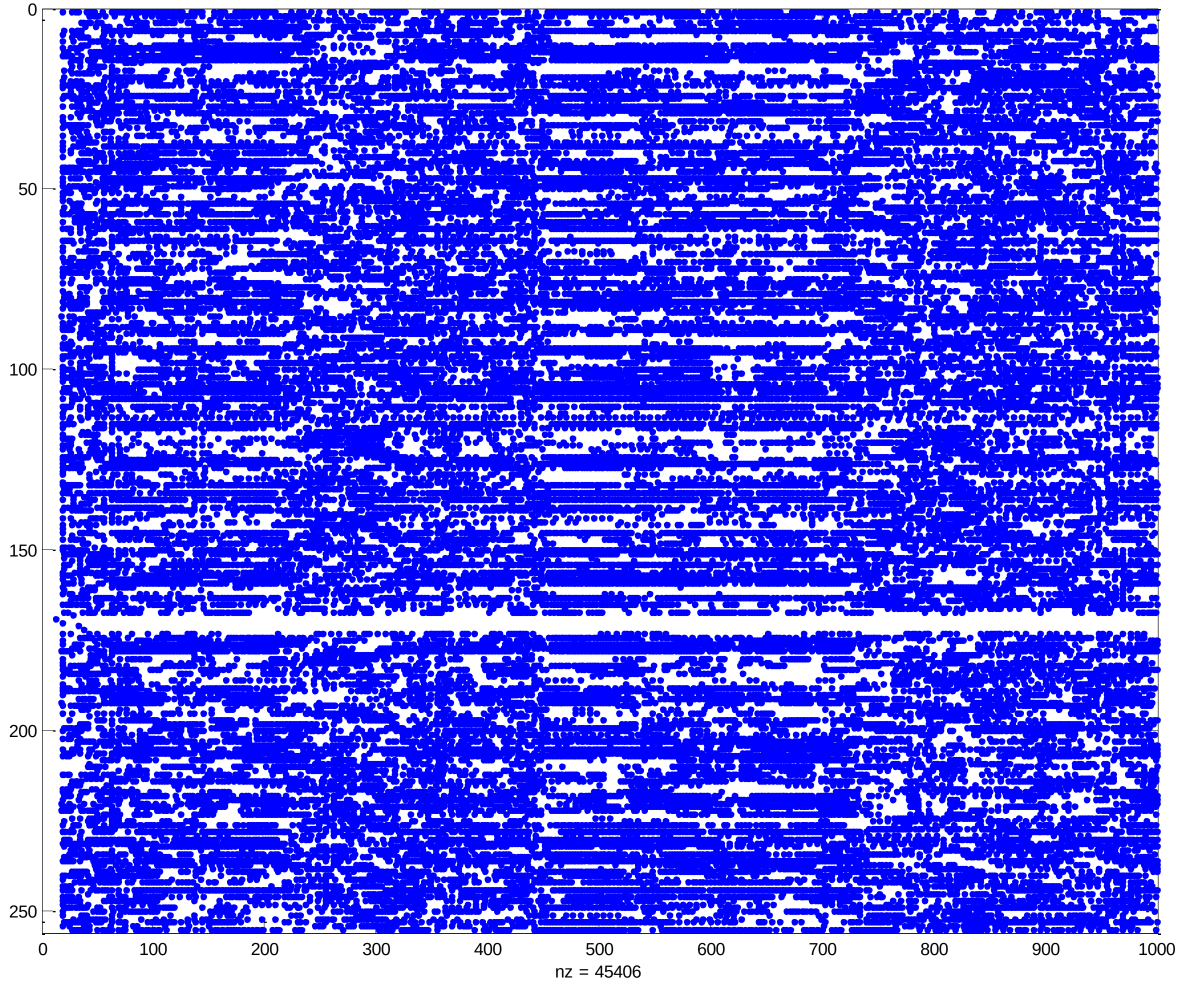




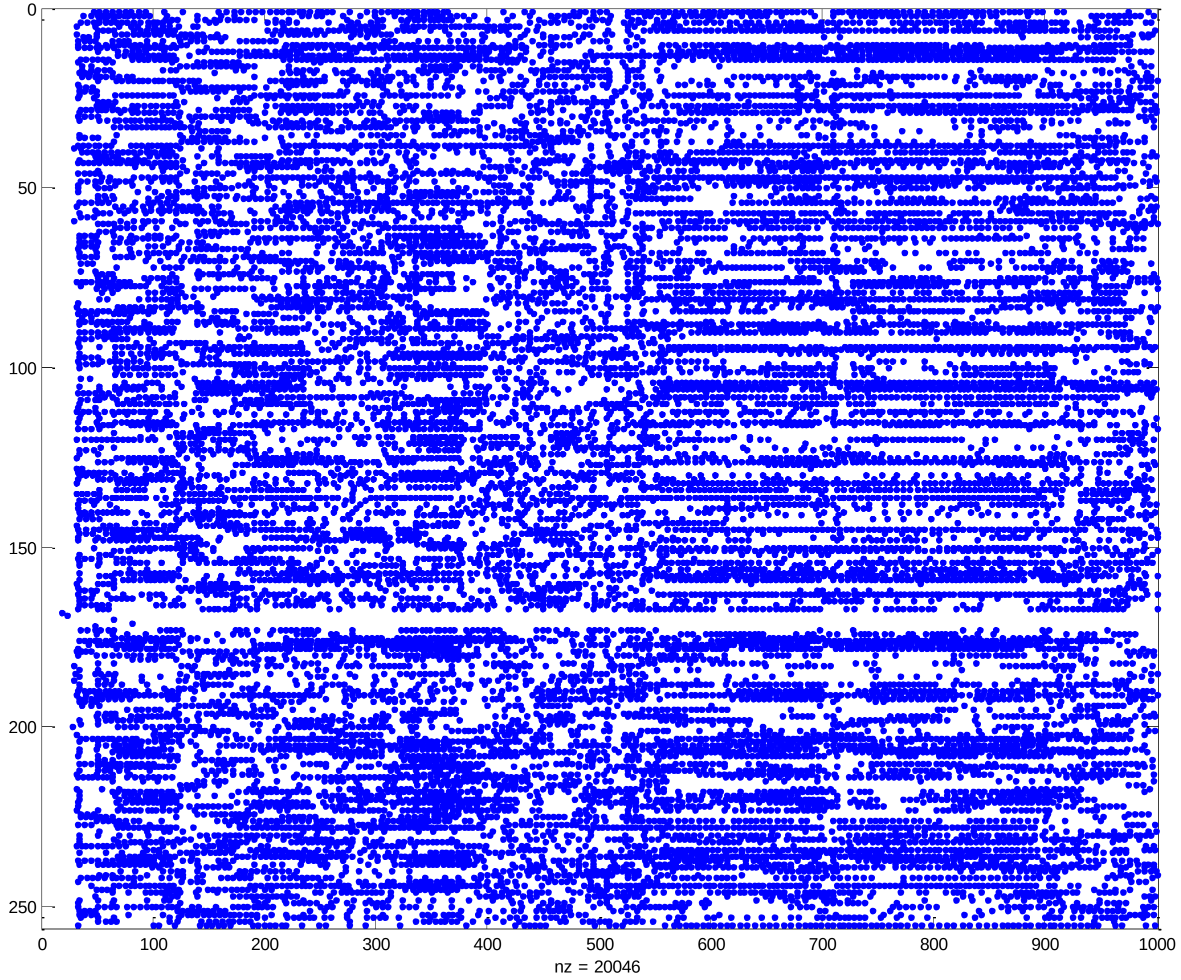
Recurrent model in N2A



Recurrent model in N2A



Recurrent model in N2A



Sandia's Computing Strengths

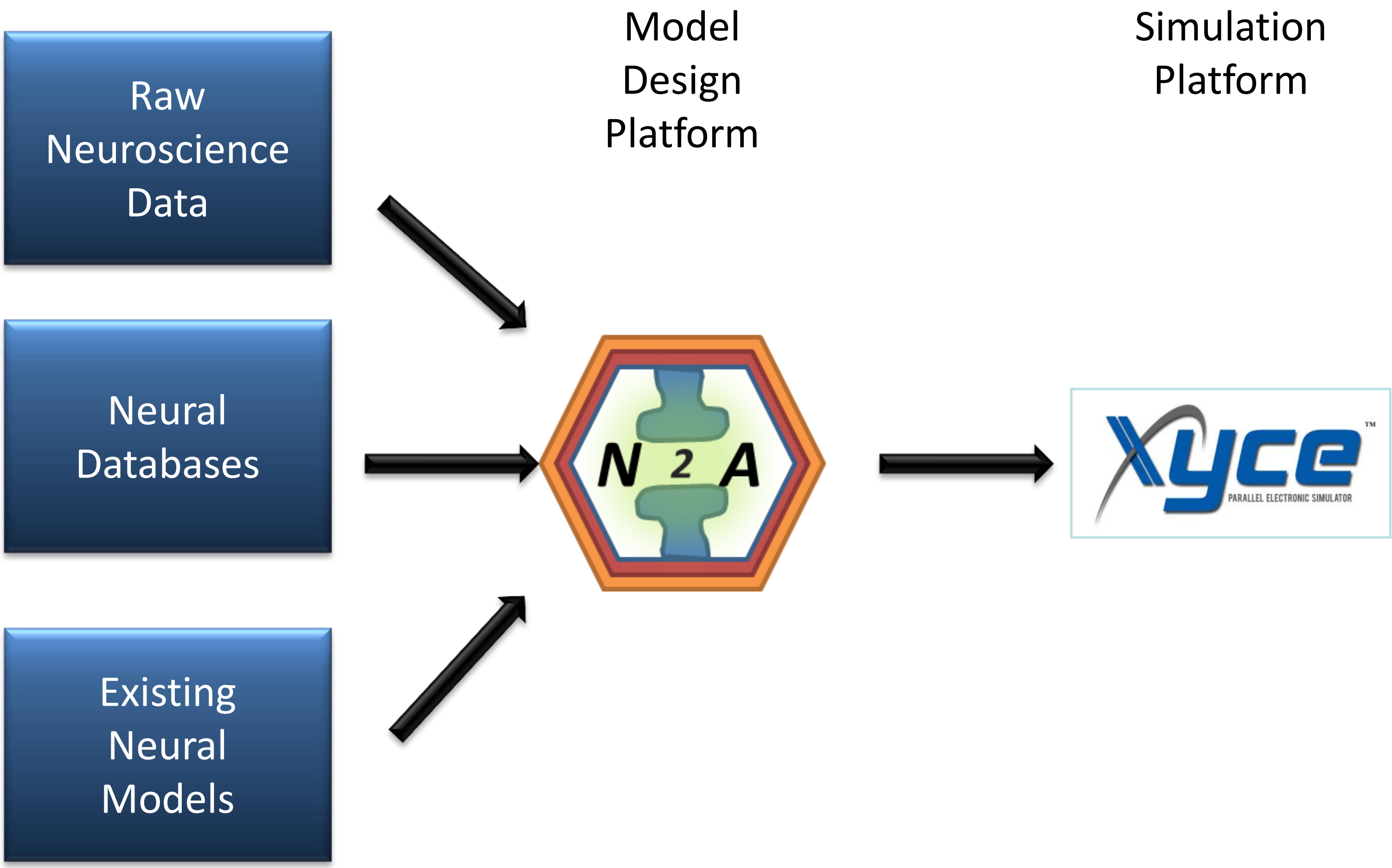
Device Physics
Parallel Network Creation
Time Integration
Parallel Analysis

Parallel & Serial Solvers
Parallel Data Structures
Multicore / Parallel Linear Algebra
Nonlinear Solvers
Parallel Graph Partitioning

Sampling
Optimization
Sensitivity
Job control

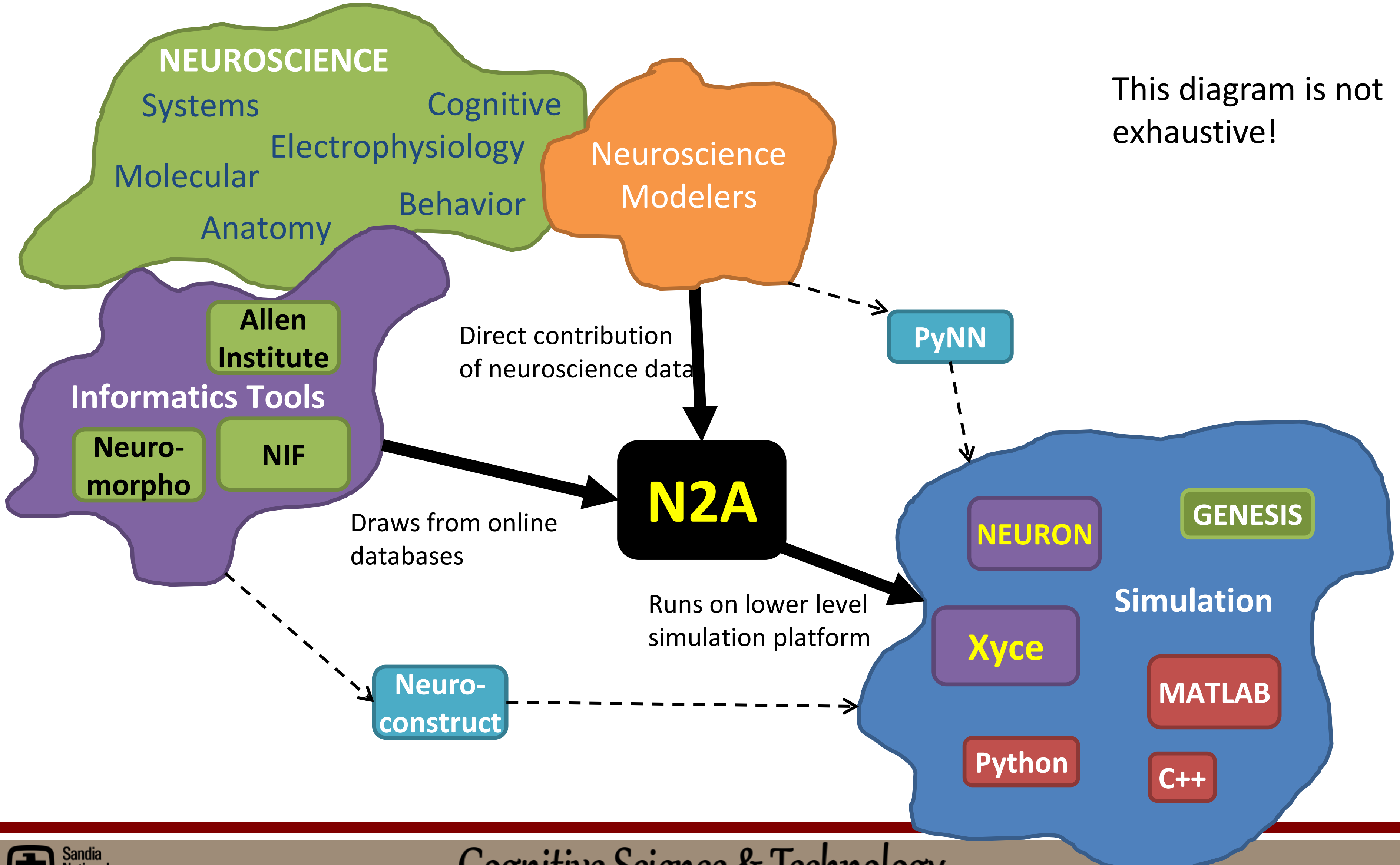
Sandia R&D expertise covers many levels important to computational neuroscience.
Can we leverage this for Xyce and Computational Neuroscience?

Sandia Computational Neuroscience Tools

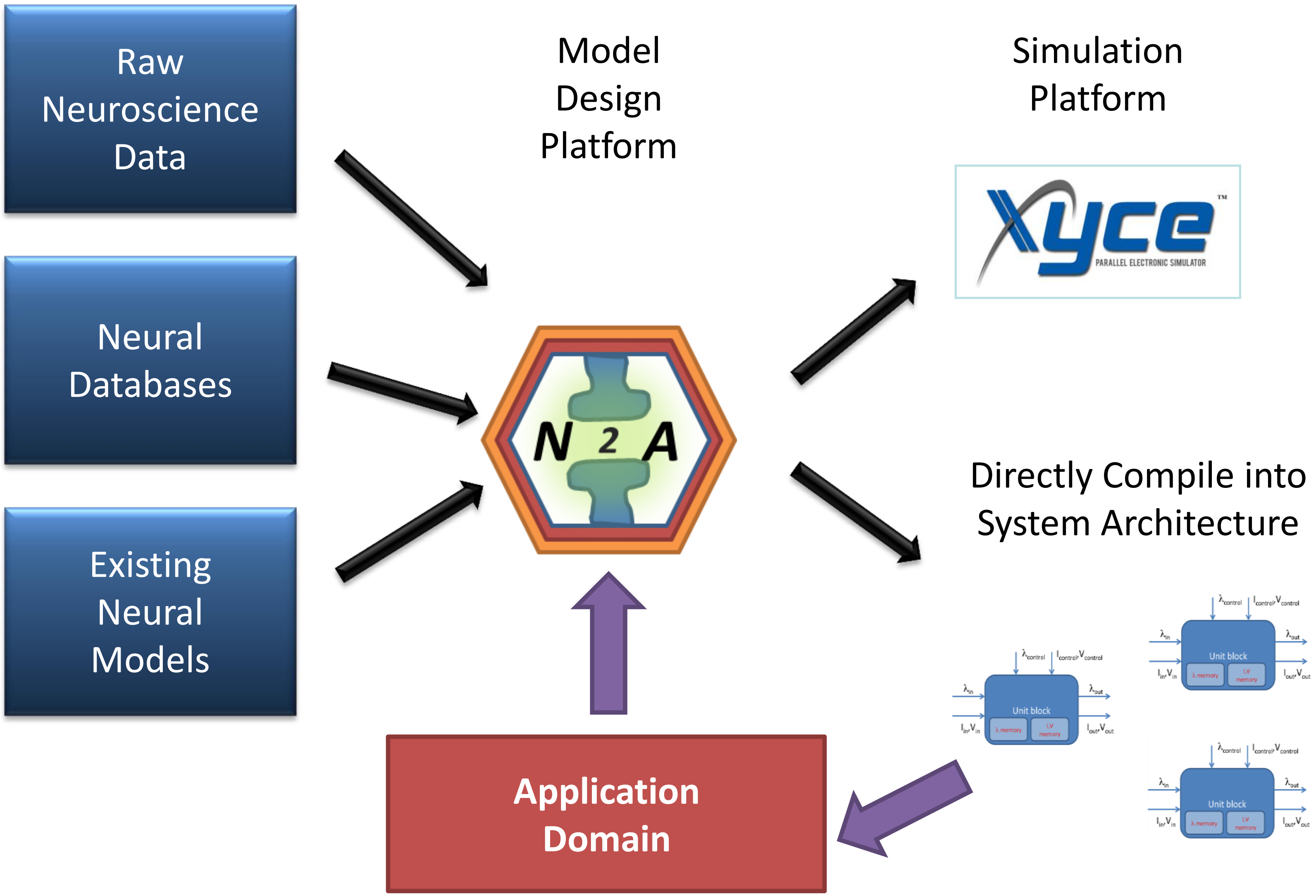


Where Sandia Tools Fit Into Neuroscience

This diagram is not exhaustive!



Direct application of tools to applications



Overview of Sandia Neuroscience

- Computational investigation of neural processes
- Novel tool development for community
- Mapping neural algorithms and insights into computing application

Sandia Comp Neuro Staff

- Michael Bernard
- Fred Rothganger
- Christy Warrender
- Richard Schiek
- Craig Vineyard
- Derek Trumbo
- Steve Verzi
- …and more