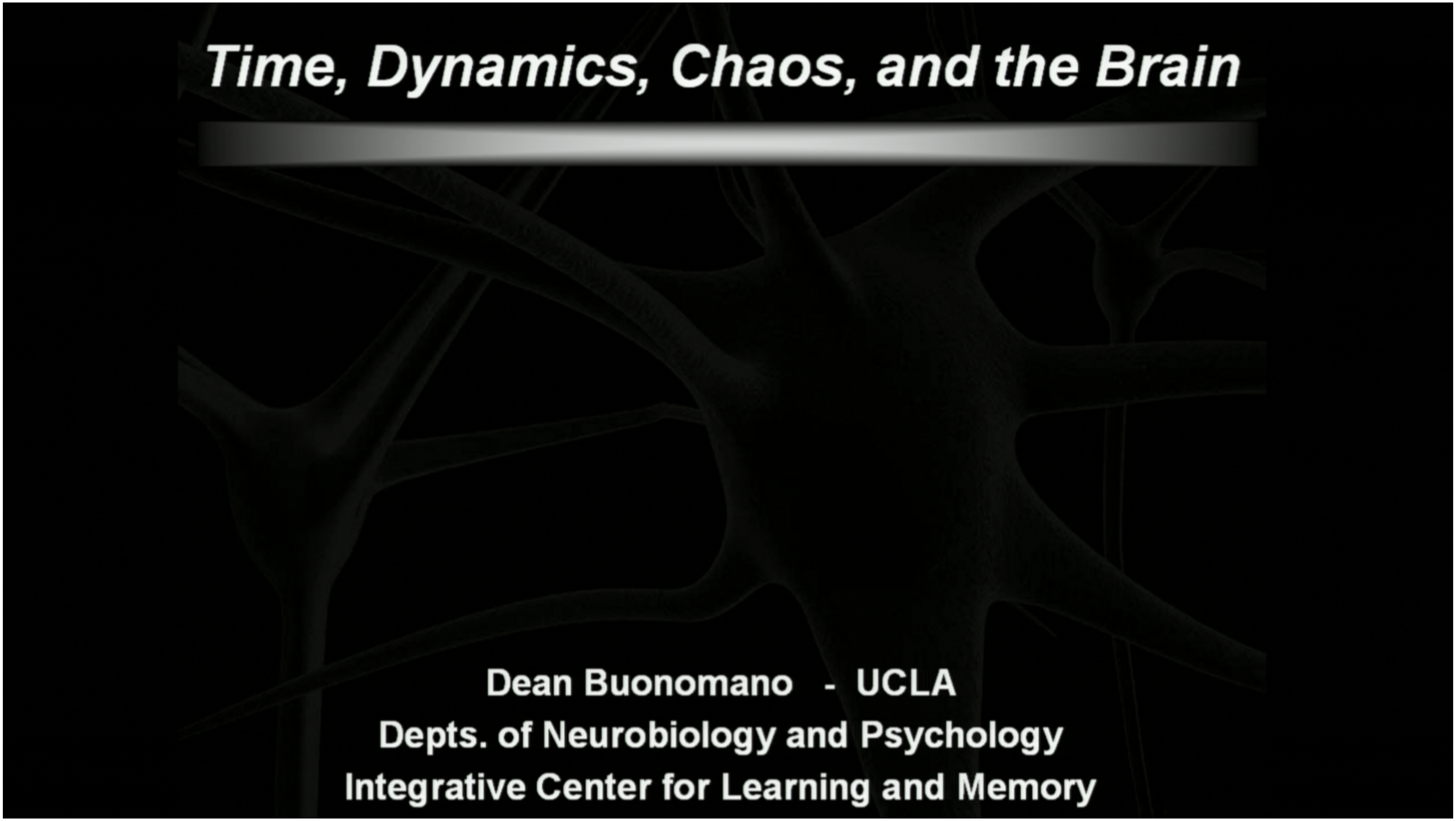
Title: Time, Dynamics, Chaos, and the Brain

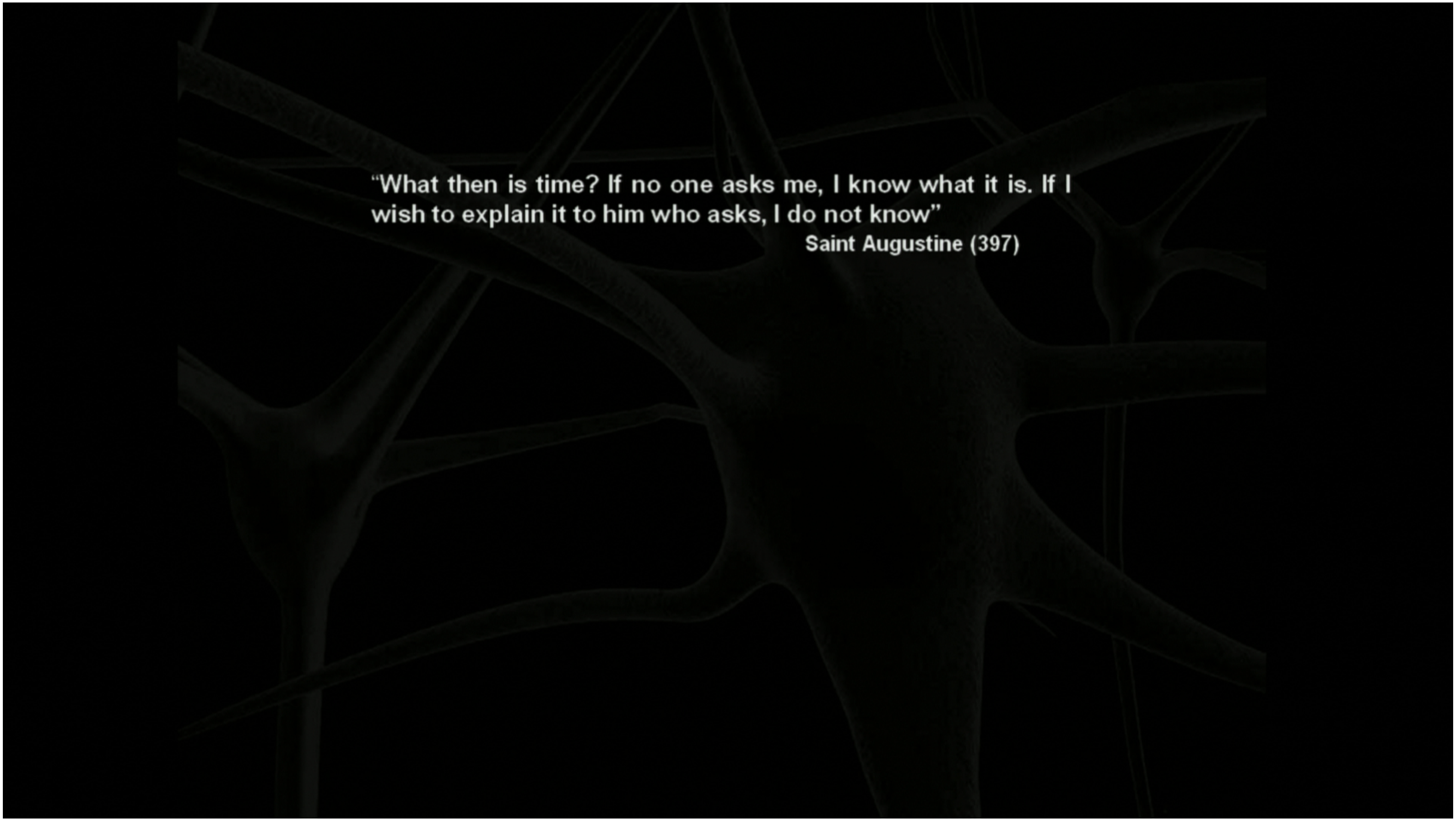
Date: Jan 29, 2014 02:00 PM

URL: http://pirsa.org/13010117

Abstract: Time poses a fundamental problem in neuroscience, in part, because at its core the brain is a prediction machine: the brain evolved to allow animals to anticipate, adapt, and prepare for future events. To accomplish this function the brain tells time on scales spanning 12 orders of magnitude. In contrast to most man made clocks that share a very simply underlying principle-counting the "tics" of an oscillator-evolution has devised many different solutions to the problem of telling time. On the scale of milliseconds and seconds experimental and computational evidence suggests that the brain relies on neural dynamics to tell time. For this strategy to work two conditions have to be met: the states of the neural network must evolve in a nonrepeating pattern over the relevant interval, and the sequence of states must be reproducible every time the system is reengaged. Recurrently connected networks of neurons can generate rich dynamics, but a long standing challenge is that the regimes that create computationally powerful dynamics are chaotic-and thus cannot generate reproducible patterns. We have recently demonstrated that by tuning the weights (the coupling coefficients) between the units of artificial neural networks it is possible to generate locally stable trajectories embedded within chaotic attractors. These stable patterns function as "dynamic attractors" and can be used to encode and tell time. They also exhibit a novel feature characteristic of biological systems: the ability to autonomously "return" to the pattern being generated in the face of perturbations.


Time, Dynamics, Chaos, and the Brain
Dean Buonomano - UCLA
Depts. of Neurobiology and Psychology
Integrative Center for Learning and Memory


Time, Dynamics, Chaos, and the Brain
Dean Buonomano - UCLA
Depts. of Neurobiology and Psychology
Integrative Center for Learning and Memory
PERIMETER
INSTITUTE
FOR THEORETICAL PHYSICS


“What then is time? If no one asks me, I know what it is. If I wish to explain it to him who asks, I do not know”
Saint Augustine (397)

"What then is time? If no one asks me, I know what it is. If I wish to explain it to him who asks, I do not know"

Saint Augustine (397)

"Time is an Illusion, lunchtime doubly so"

Douglas Adams (1979)

"What then is time? If no one asks me, I know what it is. If I wish to explain it to him who asks, I do not know"

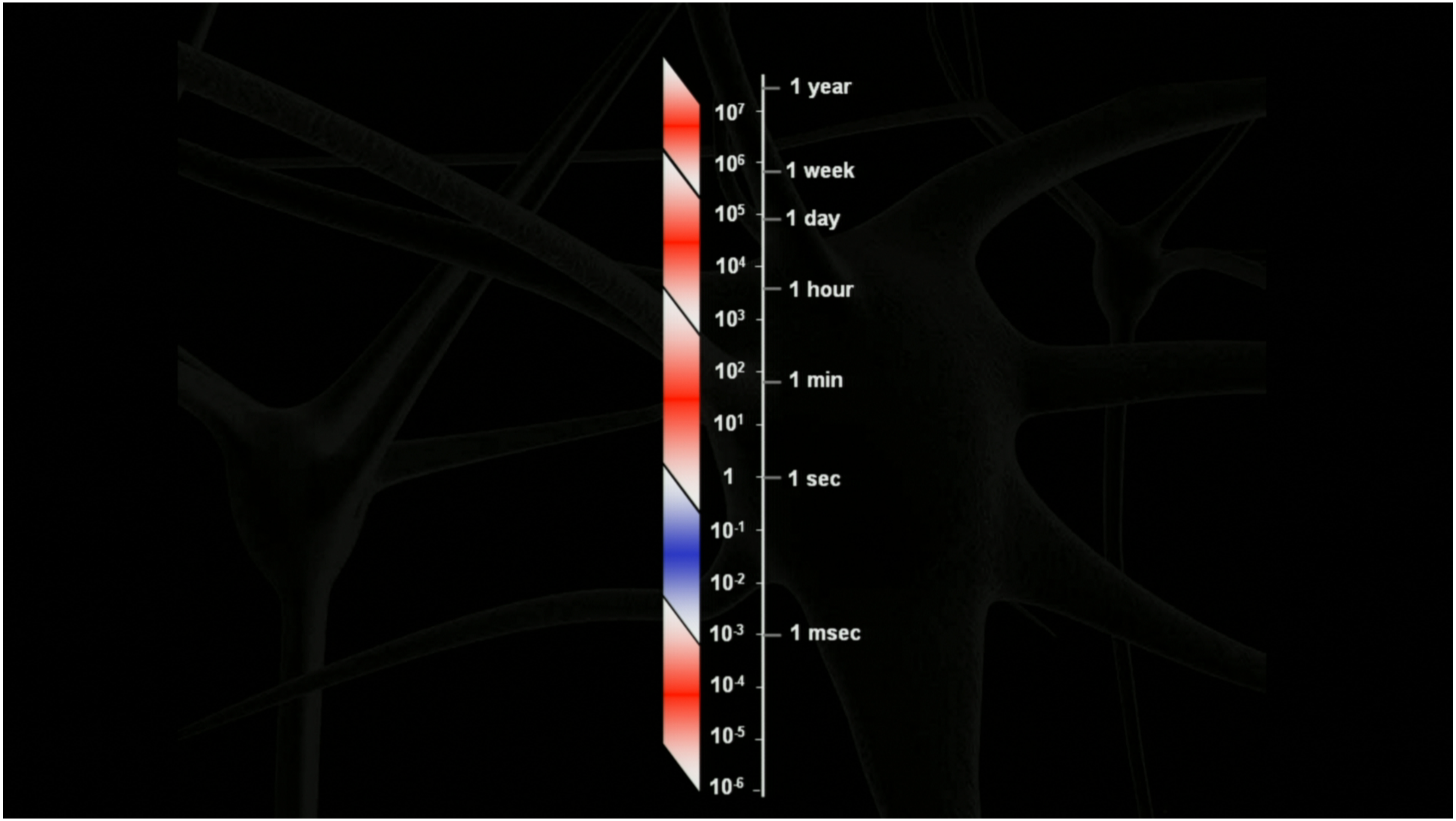
Saint Augustine (397)

"Time is an Illusion, lunchtime doubly so"

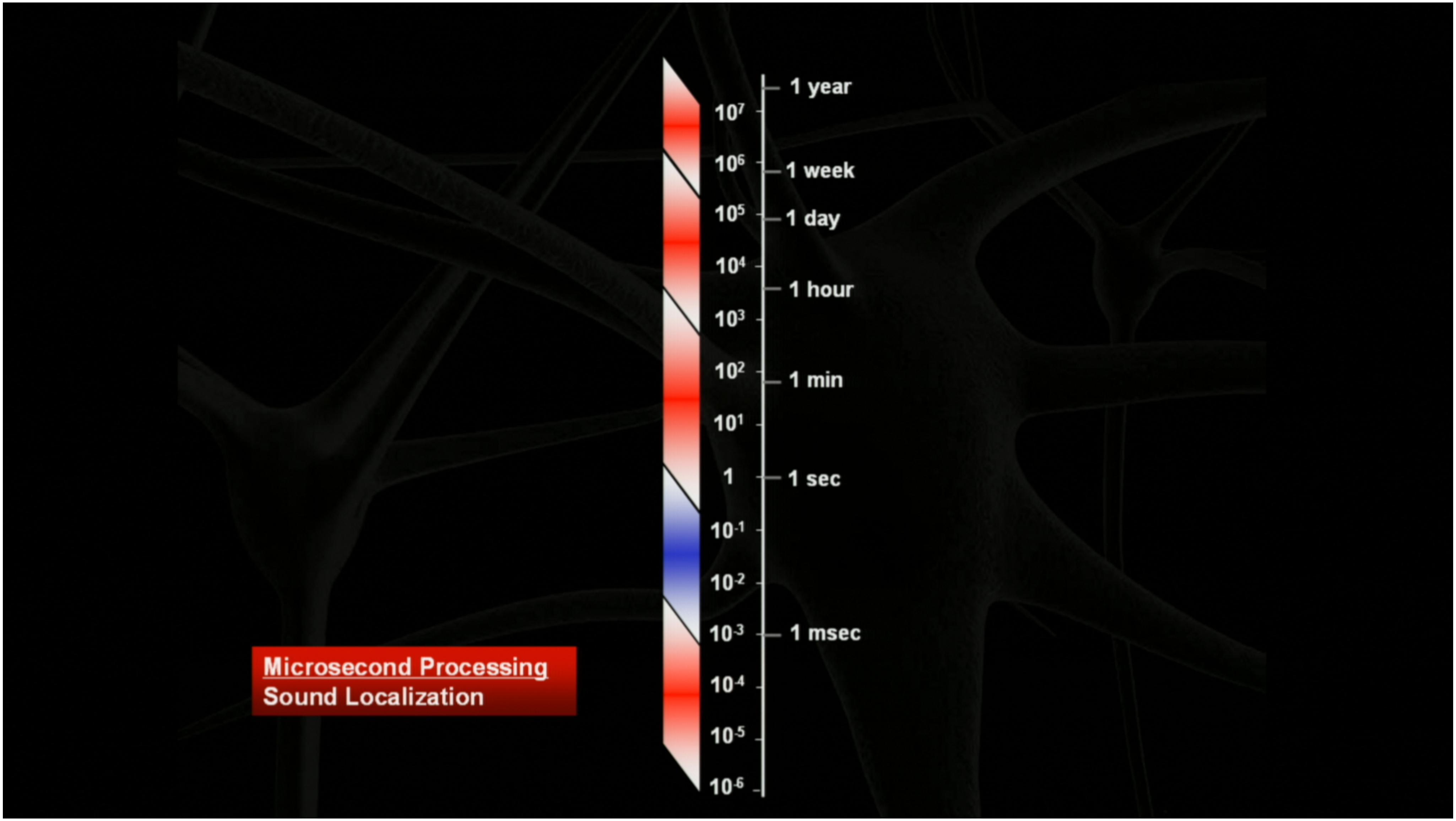
Douglas Adams (1979)

"Maybe it is just as well if we face the fact that time is one of the things we probably cannot define … What really matters anyways is not how we define time, but how we measure it."

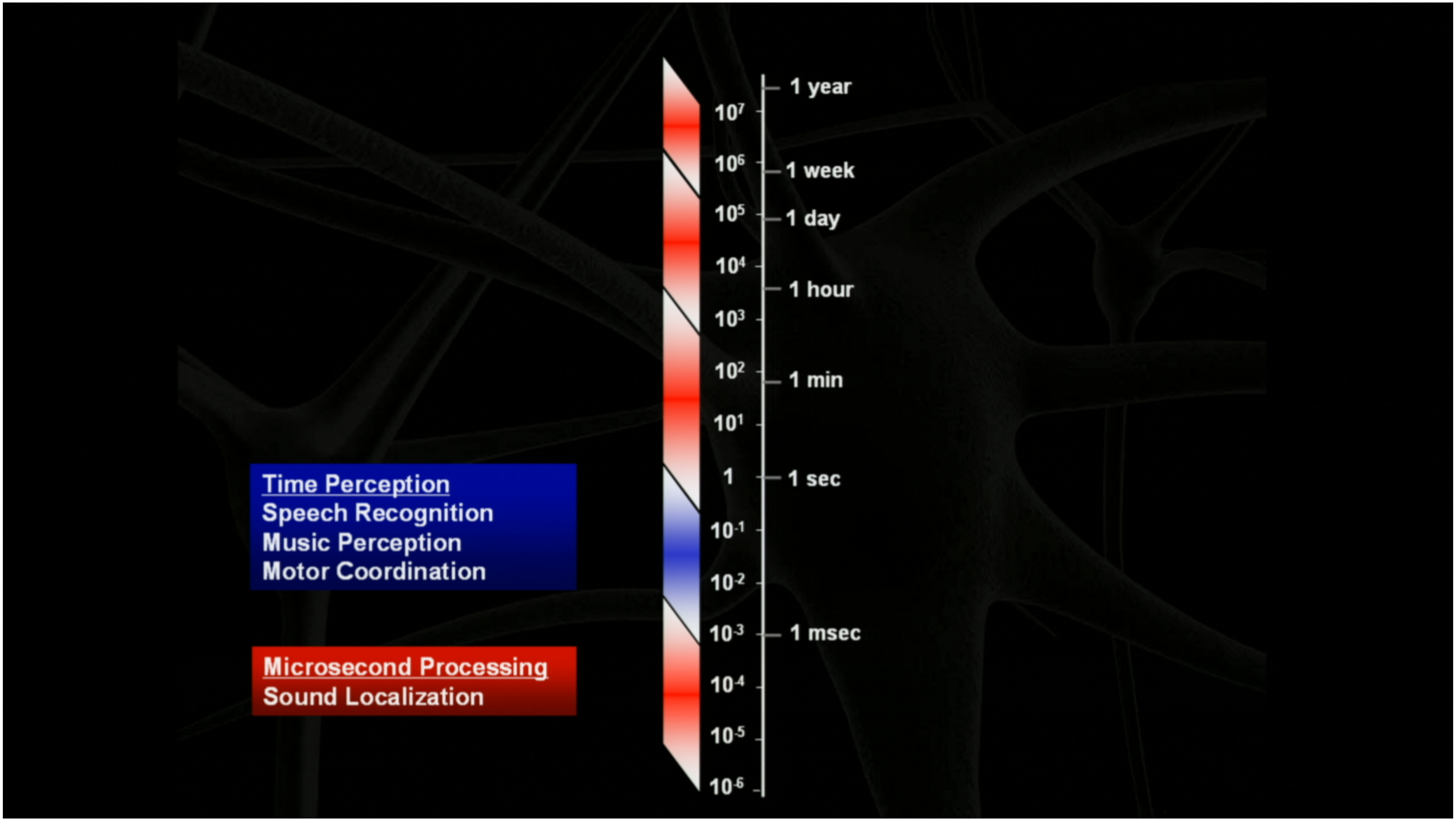
Richard Feynman (1963)

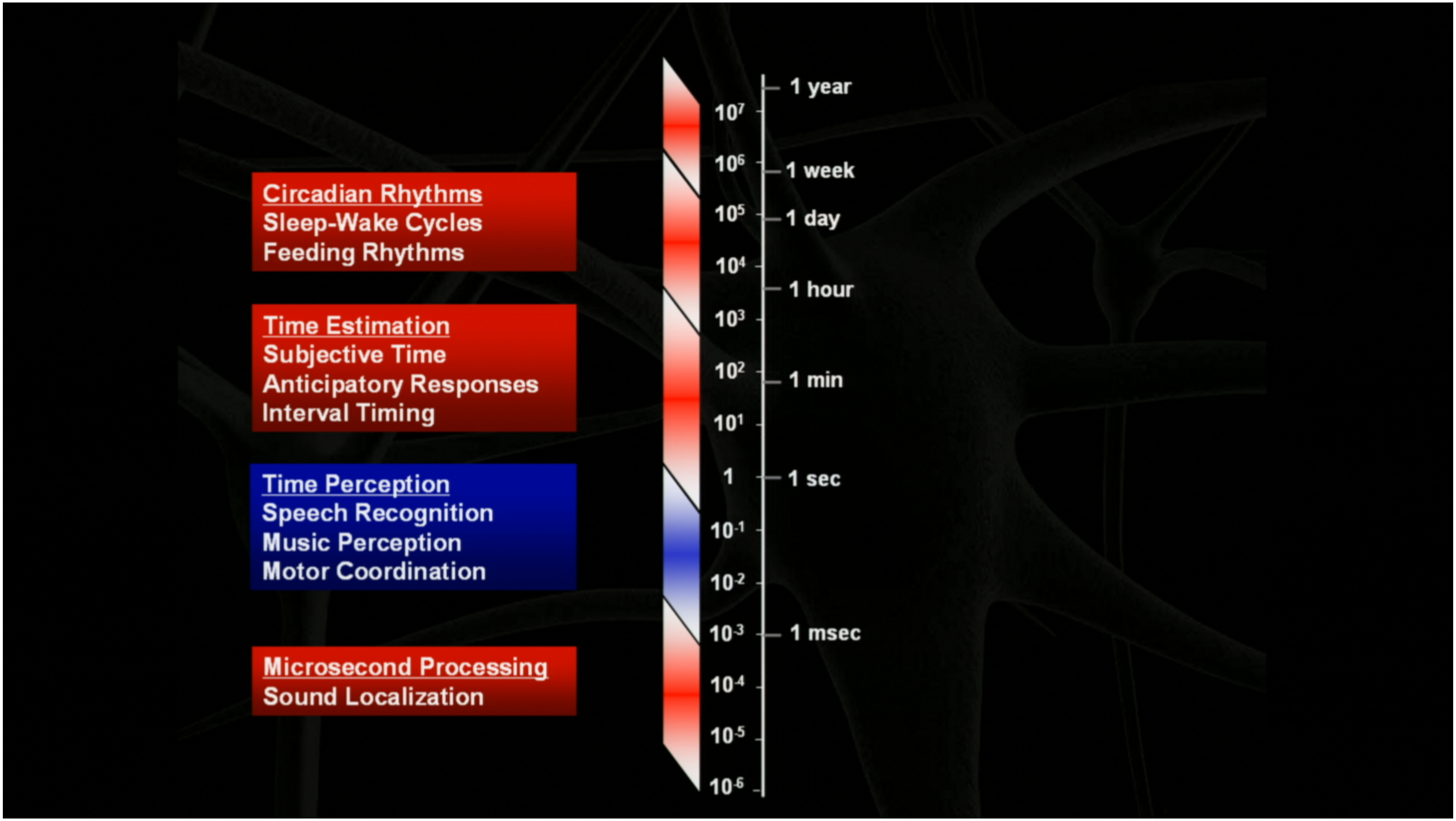


1 year
1 week
1 day
1 hour
1 min
1 sec
1 msec
10^{7}
10^{6}
10^{5}
10^{4}
10^{3}
10^{2}
10^{1}
1
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}

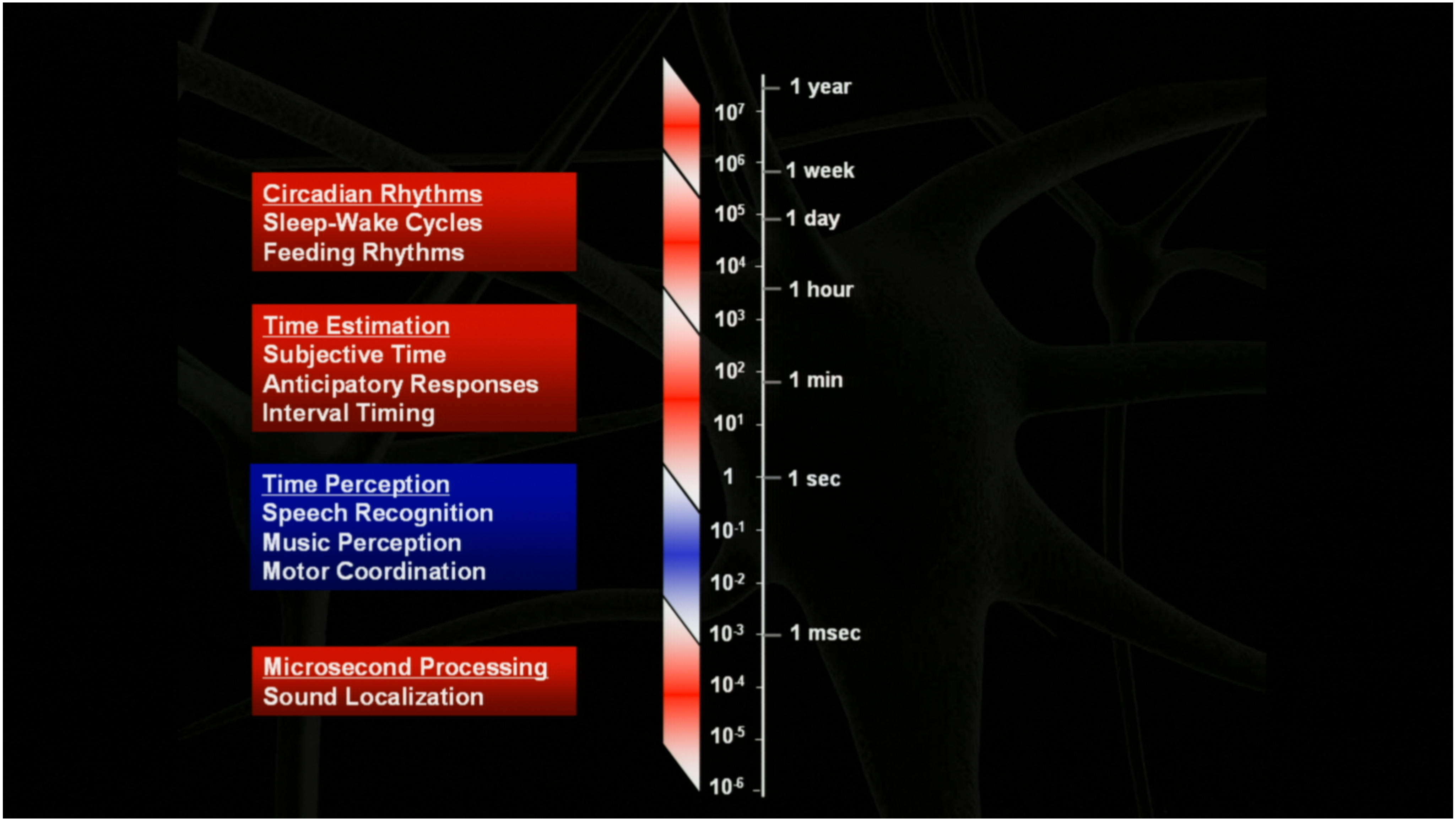


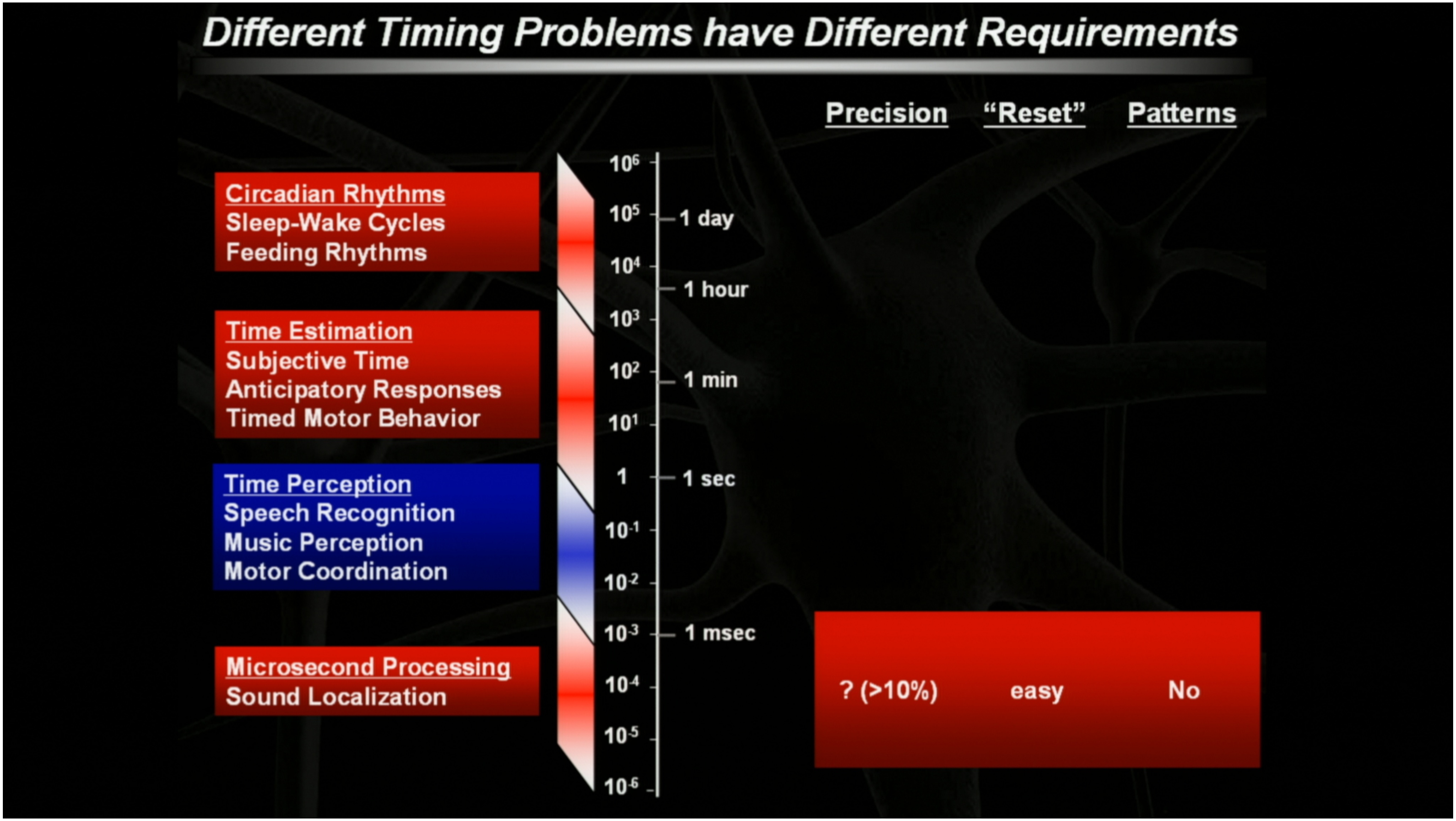
Microsecond Processing
Sound Localization
10^7
10^6
10^5
10^4
10^3
10^2
10^1
1
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
1 year
1 week
1 day
1 hour
1 min
1 sec
1 msec

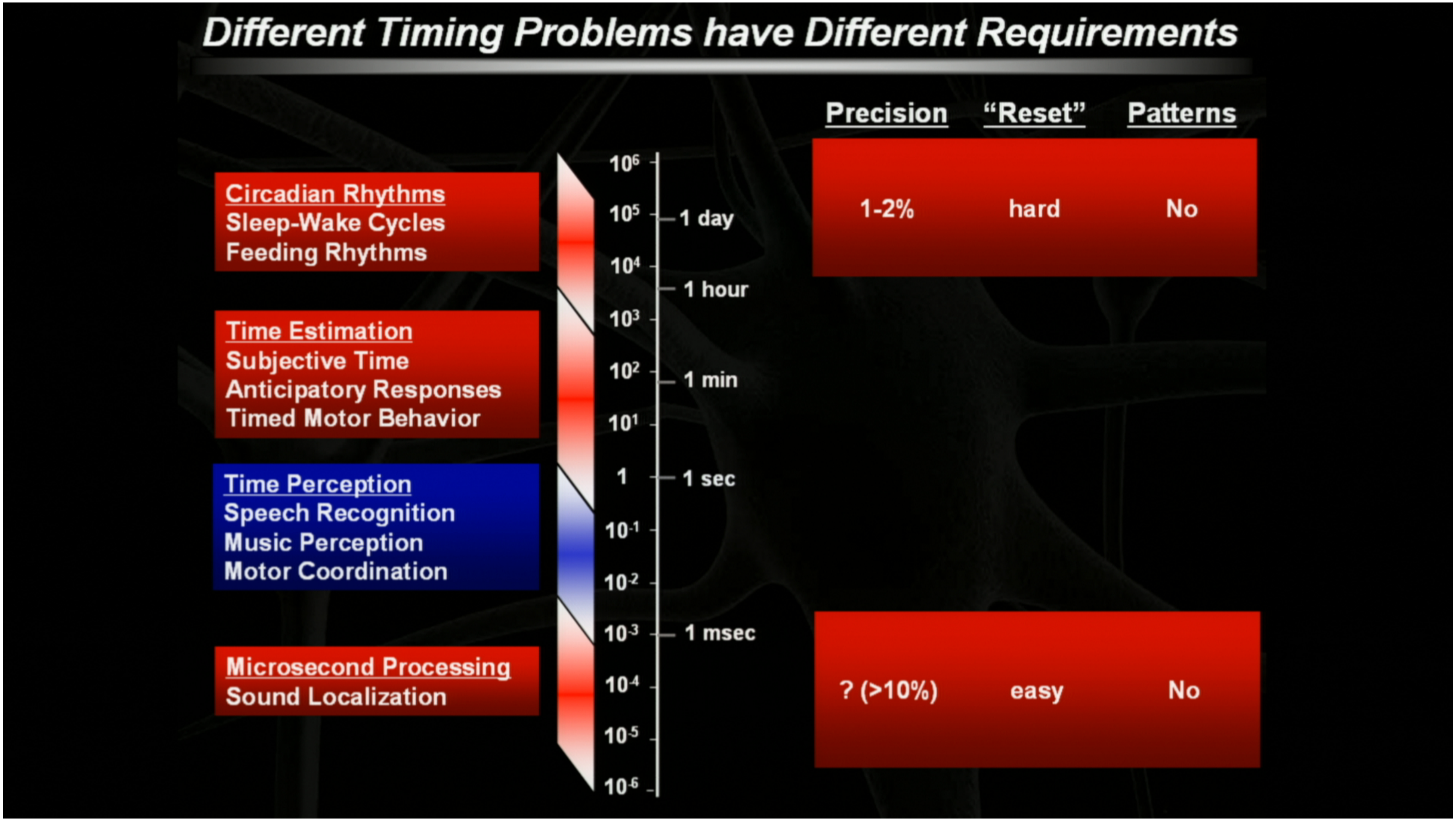

Time Perception
Speech Recognition
Music Perception
Motor Coordination
Microsecond Processing
Sound Localization
10^7
10^6
10^5
10^4
10^3
10^2
10^1
1
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
1 year
1 week
1 day
1 hour
1 min
1 sec
1 msec

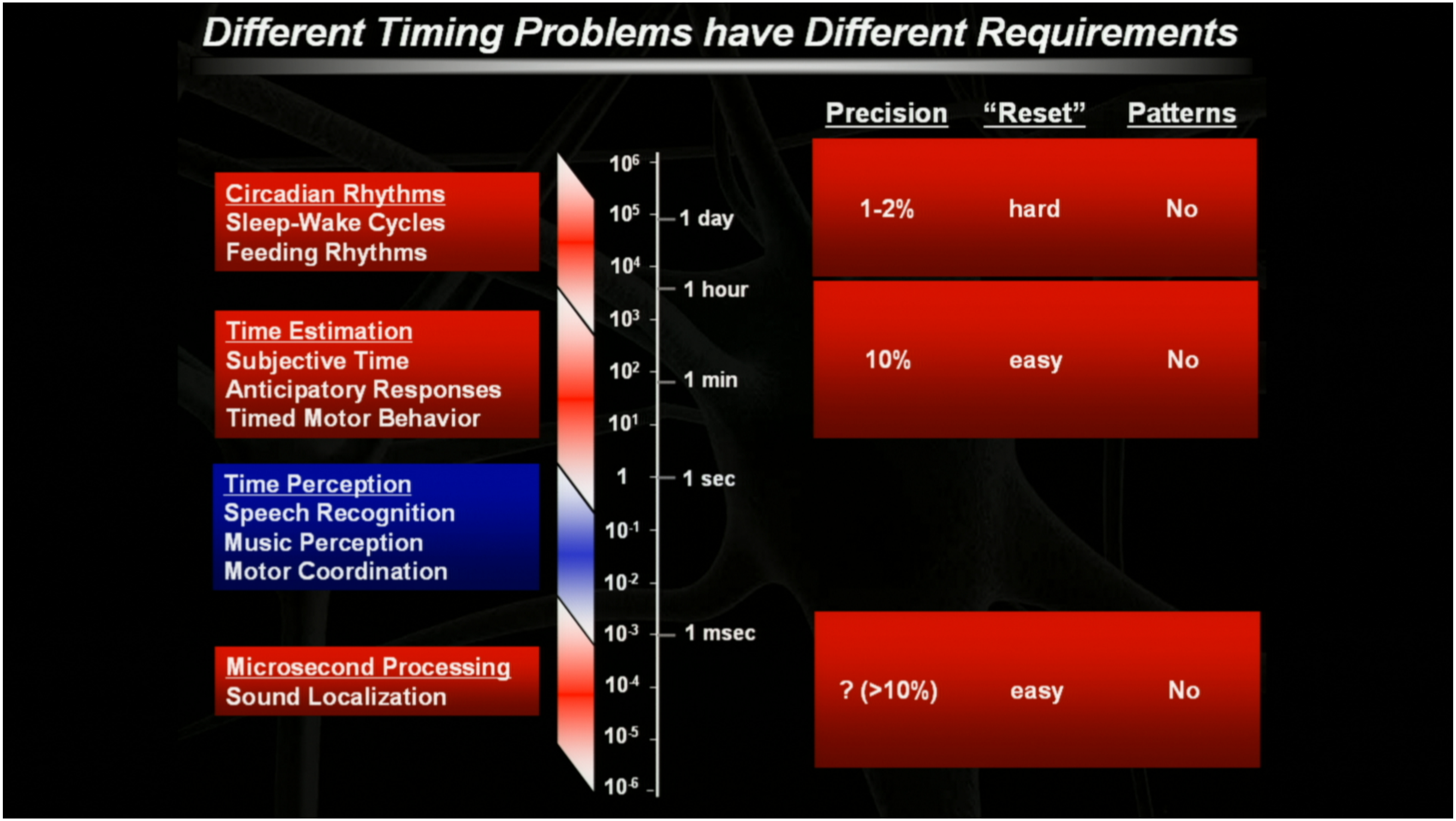


Circadian Rhythms
Sleep-Wake Cycles
Feeding Rhythms
Time Estimation
Subjective Time
Anticipatory Responses
Interval Timing
Time Perception
Speech Recognition
Music Perception
Motor Coordination
Microsecond Processing
Sound Localization
10^7
10^6
10^5
10^4
10^3
10^2
10^1
1
10^-1
10^-2
10^-3
10^-4
10^-5
10^-6
1 year
1 week
1 day
1 hour
1 min
1 sec
1 msec


Circadian Rhythms
Sleep-Wake Cycles
Feeding Rhythms
Time Estimation
Subjective Time
Anticipatory Responses
Interval Timing
Time Perception
Speech Recognition
Music Perception
Motor Coordination
Microsecond Processing
Sound Localization
10^7
10^6
10^5
10^4
10^3
10^2
10^1
1
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
1 year
1 week
1 day
1 hour
1 min
1 sec
1 msec


Different Timing Problems have Different Requirements
Precision
"Reset"
Patterns
Circadian Rhythms
Sleep-Wake Cycles
Feeding Rhythms
Time Estimation
Subjective Time
Anticipatory Responses
Timed Motor Behavior
Time Perception
Speech Recognition
Music Perception
Motor Coordination
Microsecond Processing
Sound Localization
10^6
10^5
1 day
10^4
1 hour
10^3
10^2
1 min
10^1
1
1 sec
10^-1
10^-2
10^-3
1 msec
10^-4
10^-5
10^-6
? (>10%)
easy
No


Different Timing Problems have Different Requirements
Precision
"Reset"
Patterns
Circadian Rhythms
Sleep-Wake Cycles
Feeding Rhythms
1-2%
hard
No
Time Estimation
Subjective Time
Anticipatory Responses
Timed Motor Behavior
Time Perception
Speech Recognition
Music Perception
Motor Coordination
Microsecond Processing
Sound Localization
? (>10%)
easy
No
10^6
10^5
1 day
10^4
1 hour
10^3
10^2
1 min
10^1
1
1 sec
10^{-1}
10^{-2}
10^{-3}
1 msec
10^{-4}
10^{-5}
10^{-6}

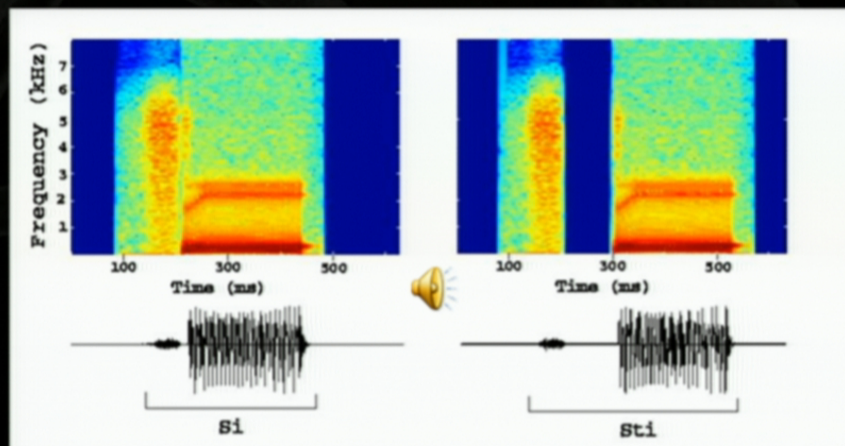

Different Timing Problems have Different Requirements
Precision
"Reset"
Patterns
Circadian Rhythms
Sleep-Wake Cycles
Feeding Rhythms
1-2%
hard
No
Time Estimation
Subjective Time
Anticipatory Responses
Timed Motor Behavior
10%
easy
No
Time Perception
Speech Recognition
Music Perception
Motor Coordination
Microsecond Processing
Sound Localization
? (>10%)
easy
No
10^6
10^5
1 day
10^4
1 hour
10^3
10^2
1 min
10^1
1
1 sec
10^-1
10^-2
10^-3
1 msec
10^-4
10^-5
10^-6

Timing in Speech and Language

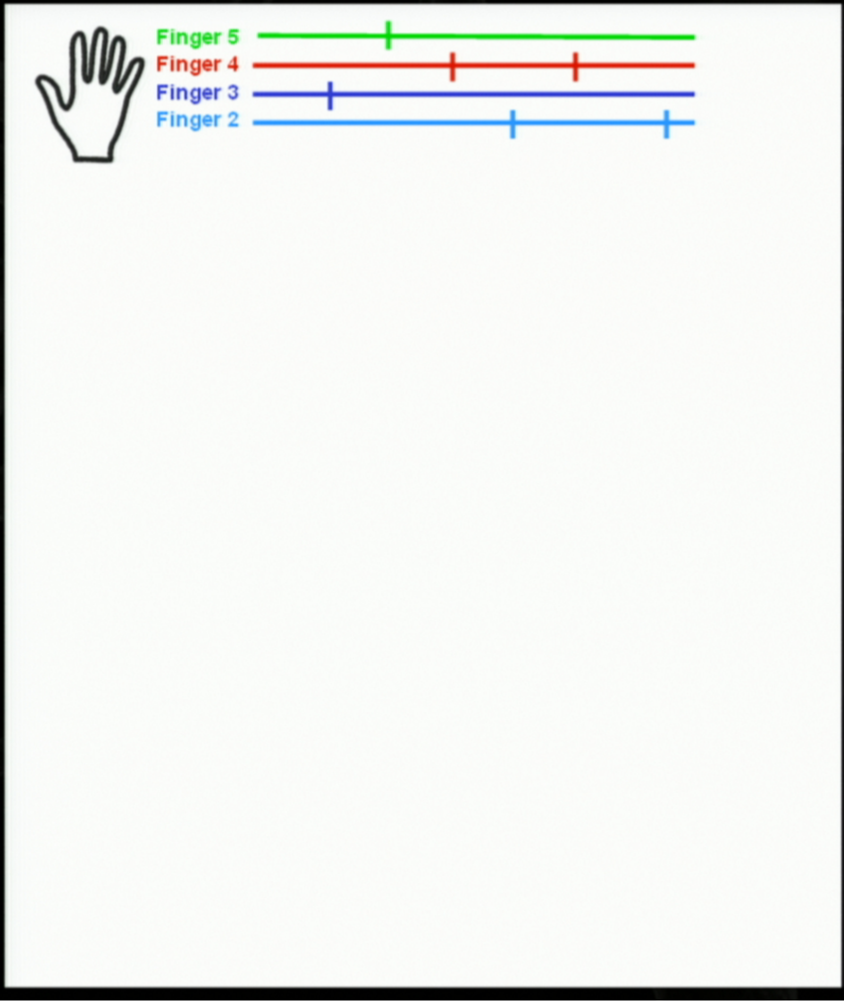
"He gave her cat food"

x

"He gave her cat food"

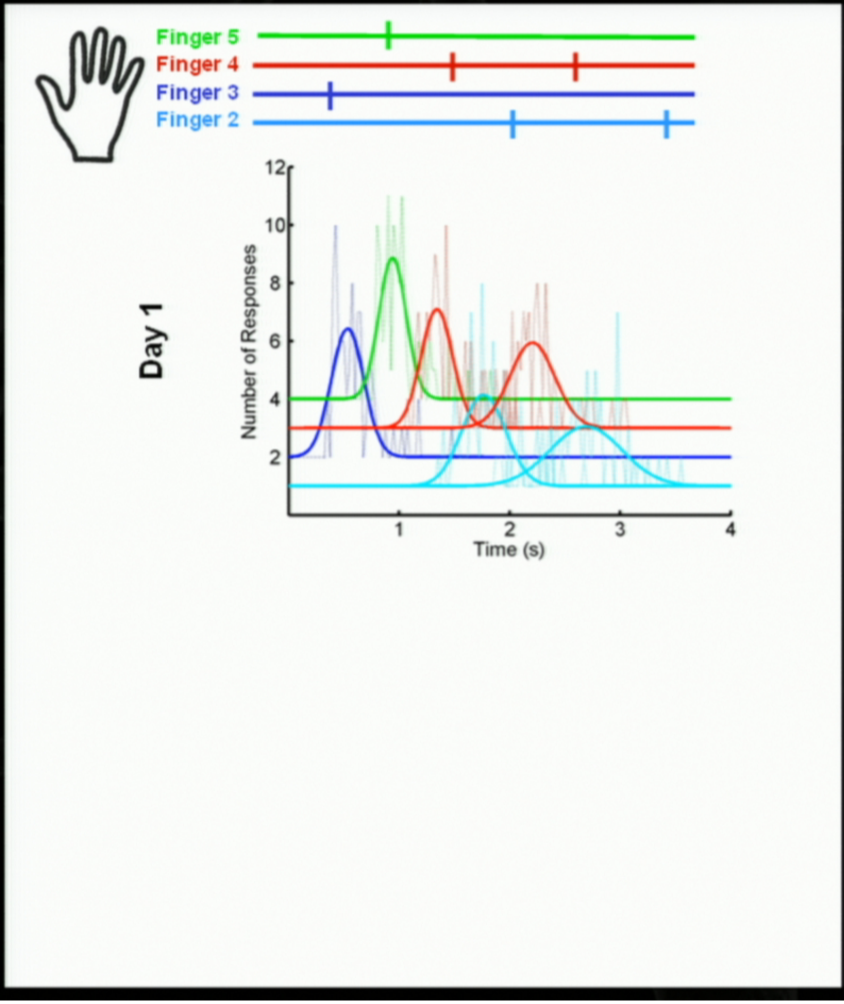


Motor Timing: Production of Complex Temporal Patterns



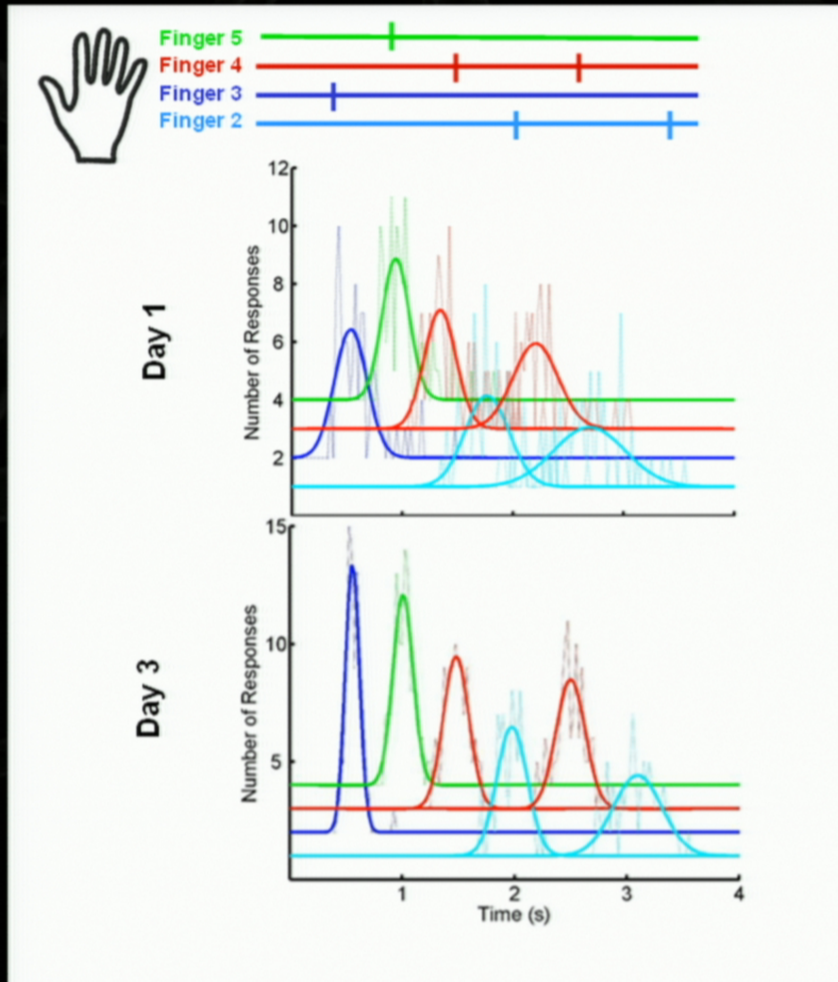
Laje, Cheng, Buonomano, 2011
(Front Intergr Neurosci)

Motor Timing: Production of Complex Temporal Patterns



Laje, Cheng, Buonomano, 2011
(Front Intergr Neurosci)

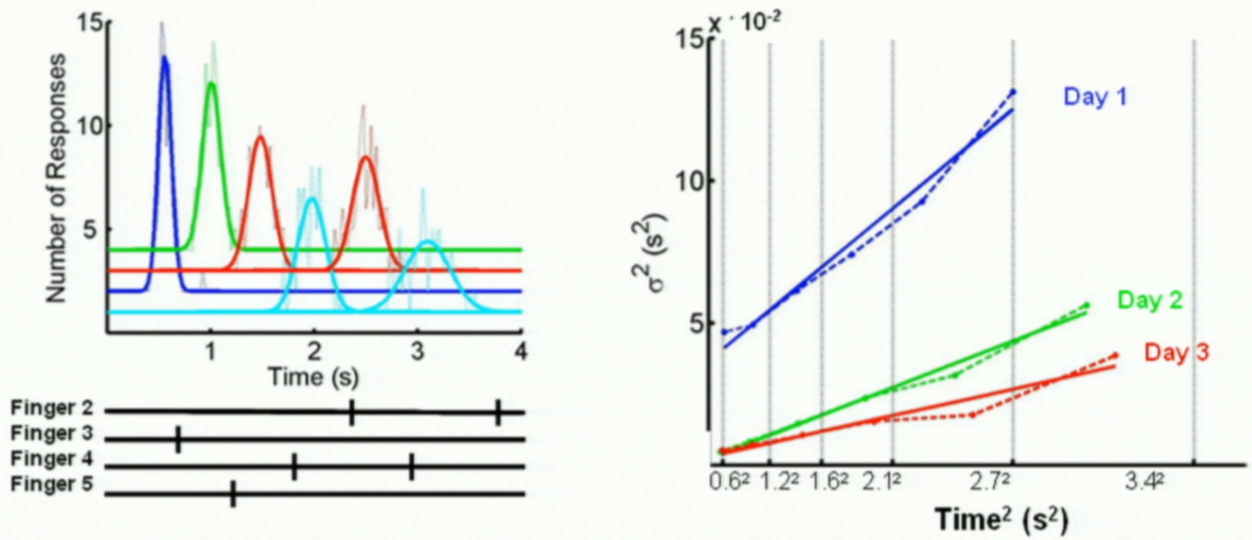
Motor Timing: Production of Complex Temporal Patterns



Laje, Cheng, Buonomano, 2011
(Front Intergr Neurosci)

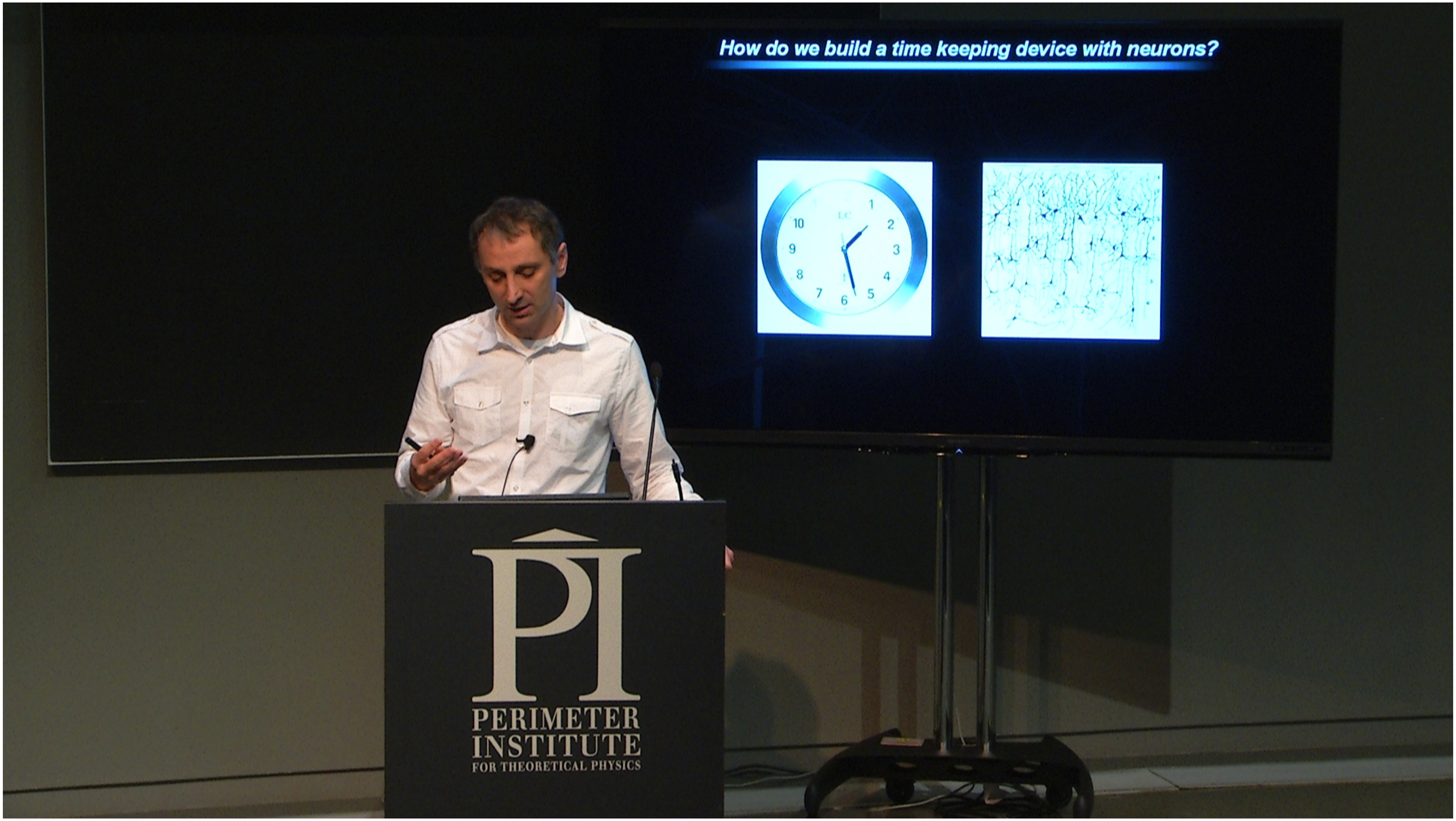
Signature of the Brain's Clocks: Weber's Law ($\sigma^2 \uparrow$ linearly with t^2)

$$\sigma^2 = k\,T^2 + \sigma^2_{\text{indep}} \quad \text{(Generalized Weber's law)}$$



Laje et al, 2011 (Front Integr Neurosci)

How do we build a time keeping device with neurons?


How do we build a time keeping device with neurons?
PERIMETER
INSTITUTE
FOR THEORETICAL PHYSICS

Random Recurrent Neural Networks

VOLUME 61, NUMBER 3 PHYSICAL REVIEW LETTERS 18 JULY 1988

Chaos in Random Neural Networks

H. Sompolinsky[a] and A. Crisanti
AT&T Bell Laboratories, Murray Hill, New Jersey 07974, and
Racah Institute of Physics, The Hebrew University, 91904 Jerusalem, Israel[b]

and

H. J. Sommers[a]
Fachbereich Physik, Universität-Gesamthochschule Essen, D-4300 Essen, Federal Republic of Germany
(Received 30 March 1988)

REPORTS 2 APRIL 2004 VOL 304 SCIENCE www.sciencemag.org

Harnessing Nonlinearity: Predicting Chaotic Systems and Saving Energy in Wireless Communication

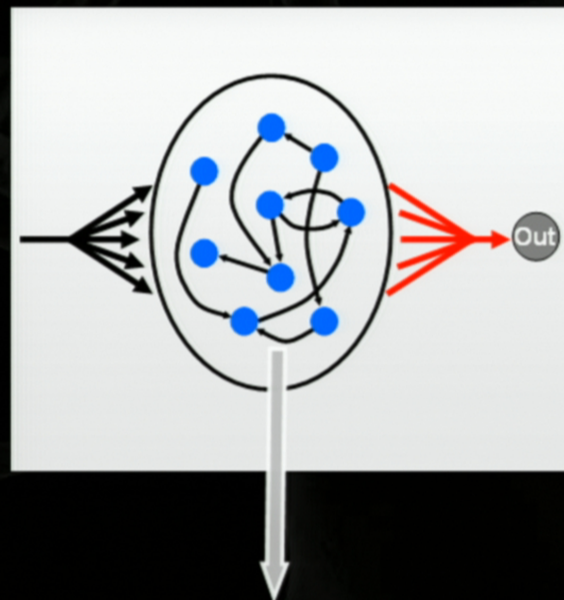
Herbert Jaeger* and Harald Haas

Generating Coherent Patterns of Activity from Chaotic Neural Networks

David Sussillo[1,*] and L.F. Abbott[1,*]
[1]Department of Neuroscience, Department of Physiology and Cellular Biophysics, Columbia University College of Physicians and Surgeons, New York, NY 10032-2695, USA

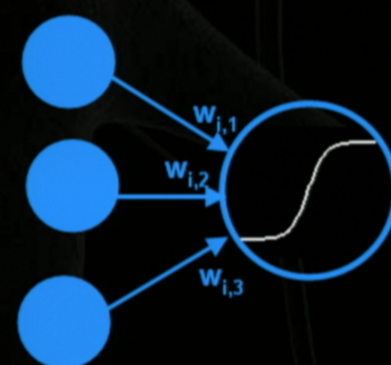
Neuron 63, 544–557, August 27, 2009 ©2009 Elsevier Inc.

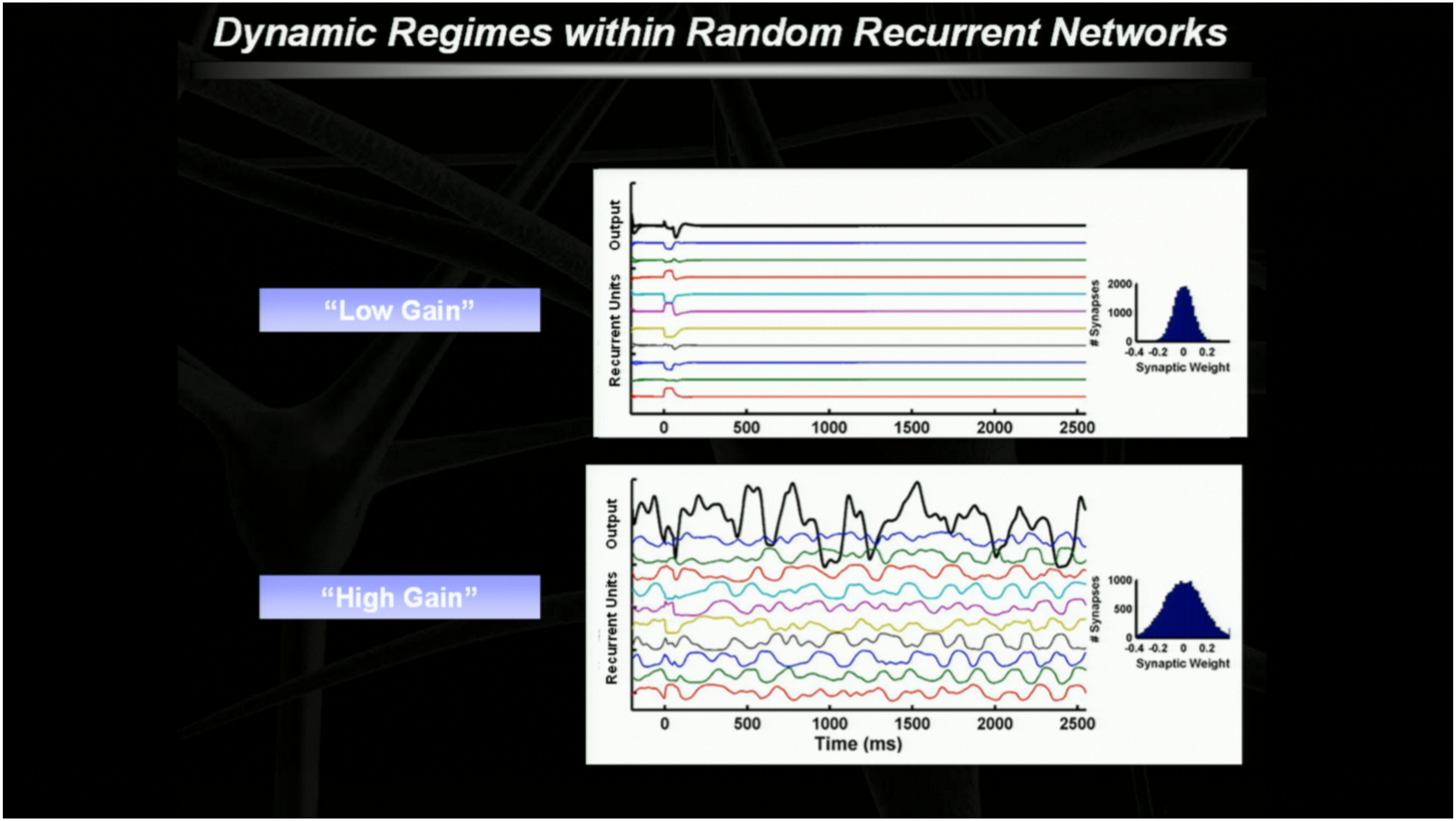
Firing-Rate Models of Recurrent Neural Networks



$$\text{Out} = \sum_{j}^{N} W^{\text{Out}}_{i,j} v_j$$

$$\tau \frac{dv_i}{dt} = -v_i + \sum_{j}^{N} W^{\text{Rec}}_{i,j} \tanh(v_j) + \sum_{j}^{N} W^{\text{In}}_{i,j} v_j + I_{noise}$$

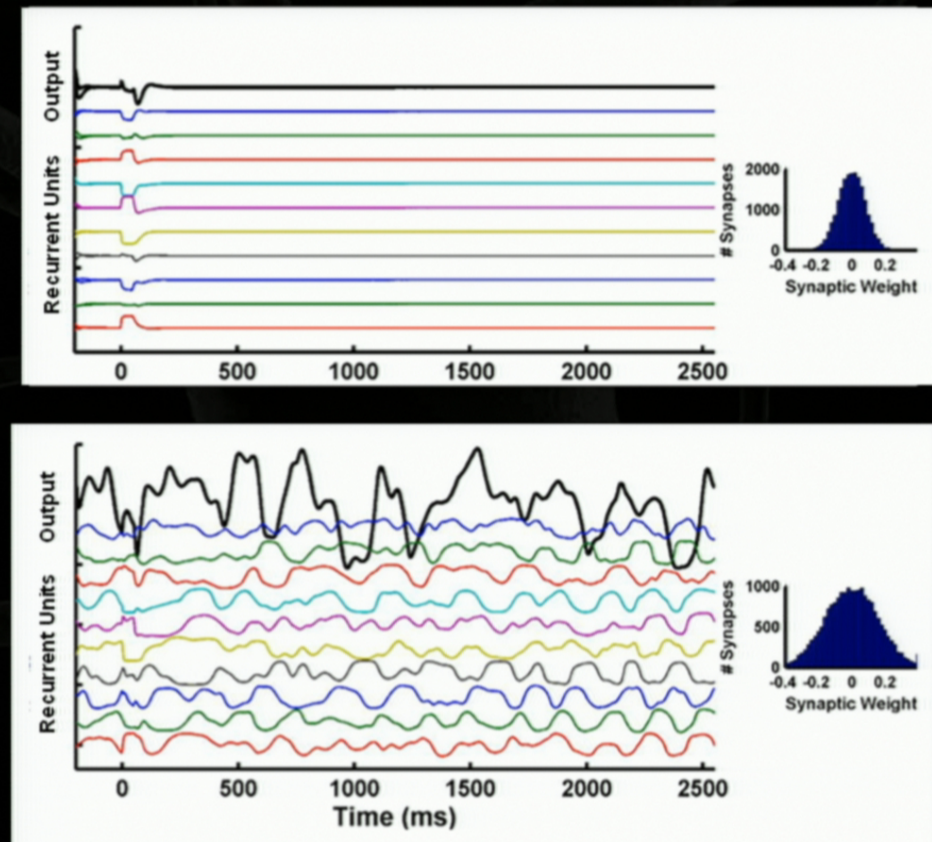



Dynamic Regimes within Random Recurrent Networks
"Low Gain"
"High Gain"
Output
Recurrent Units
Synapses
2000
1000
0
-0.4 -0.2 0 0.2
Synaptic Weight
0
500
1000
1500
2000
2500
Output
Recurrent Units
Synapses
1000
500
0
-0.4 -0.2 0 0.2
Synaptic Weight
0
500
1000
1500
2000
2500
Time (ms)

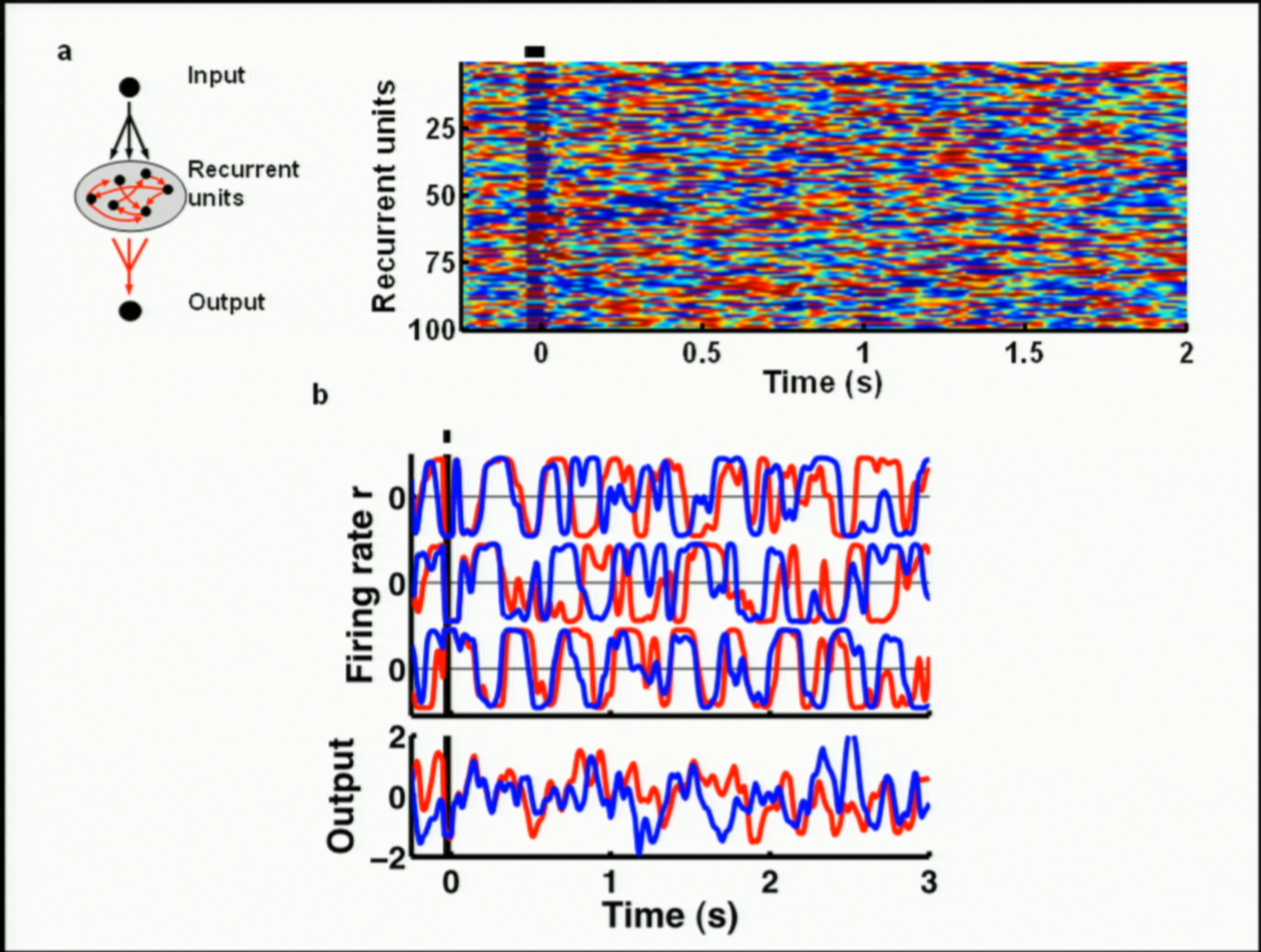
Dynamic Regimes within Random Recurrent Networks

"Low Gain"

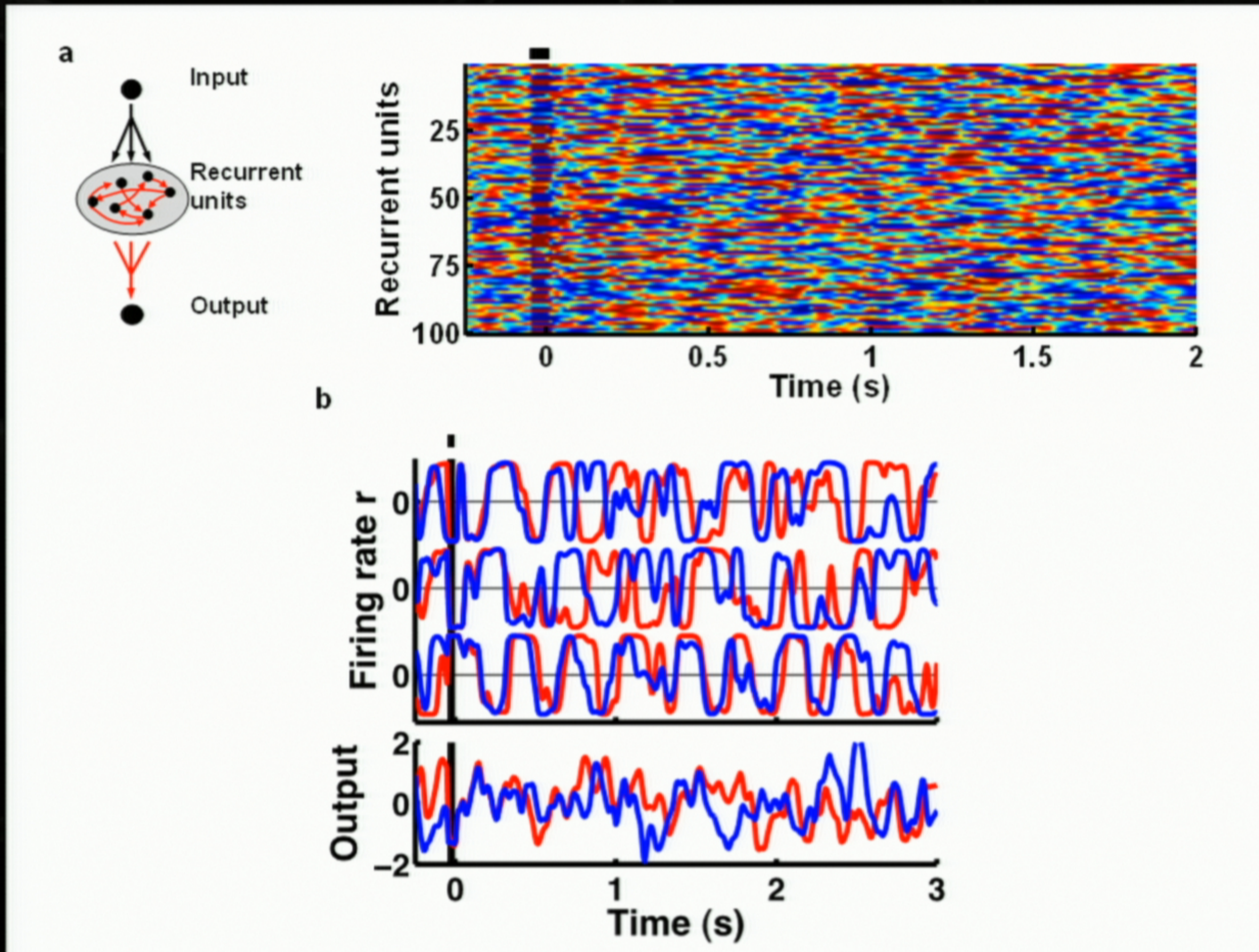
"High Gain"



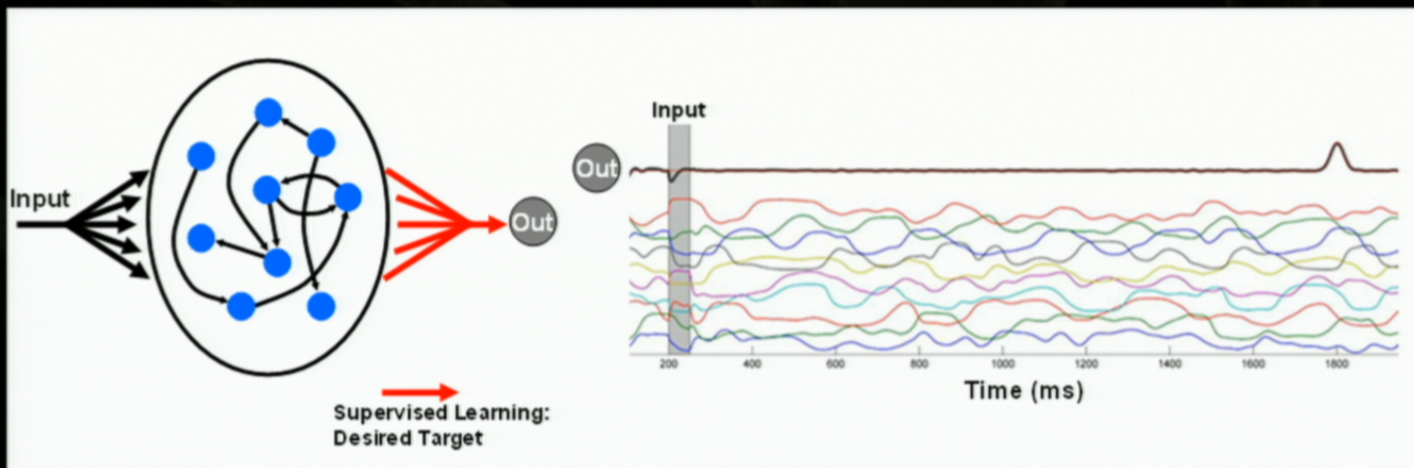
High Gain Regimes are Chaotic

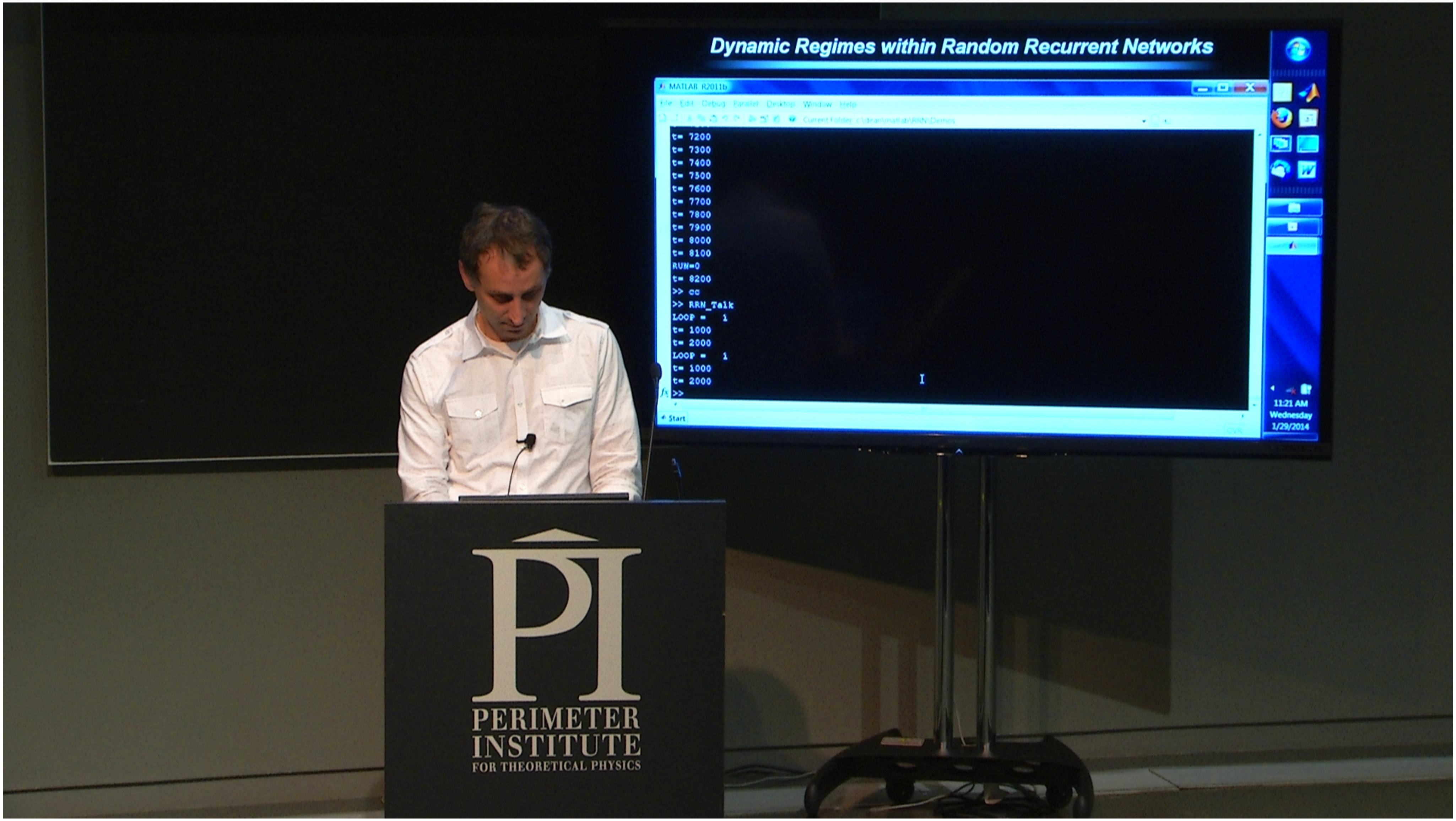


High Gain Regimes are Chaotic



The High Gain Regime has High Computational "Potential" (e.g., telling time)




Dynamic Regimes within Random Recurrent Networks
MATLAB R2011b
t= 7200
t= 7300
t= 7400
t= 7500
t= 7600
t= 7700
t= 7800
t= 7900
t= 8000
t= 8100
RUN=0
t= 8200
>> cc
>> RRN_Talk
LOOP = 1
t= 1000
t= 2000
LOOP = 1
t= 1000
t= 2000
>>
11:21 AM
Wednesday
1/29/2014
PERIMETER
INSTITUTE
FOR THEORETICAL PHYSICS

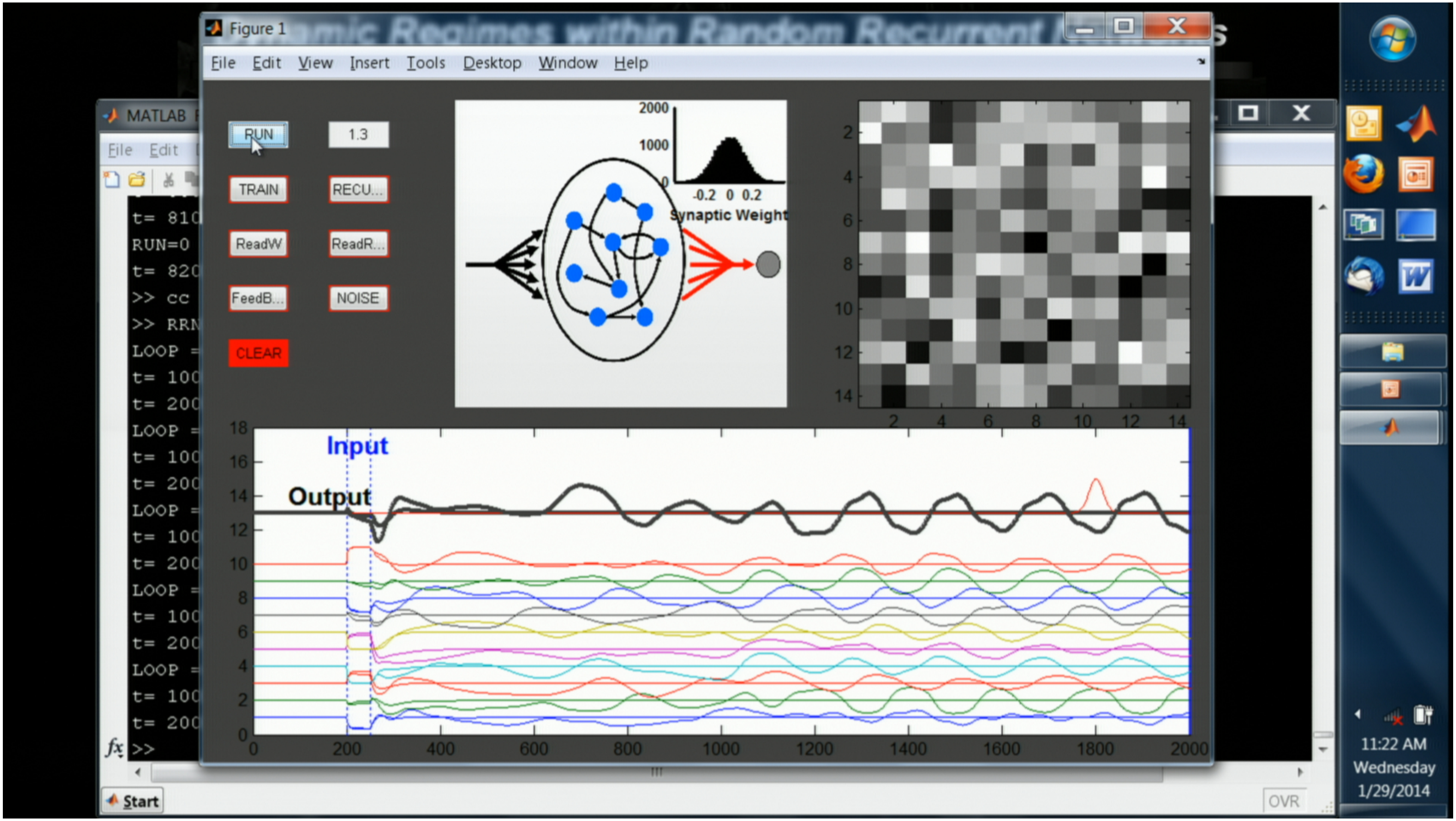


Figure 1
File Edit View Insert Tools Desktop Window Help
RUN
1.3
TRAIN
RECU...
ReadW
ReadR...
FeedB...
NOISE
CLEAR
2000
1000
0
-0.2 0 0.2
Synaptic Weight
Input
Output
MATLAB
t= 810
RUN=0
t= 820
>> cc
Start
OVR
11:22 AM
Wednesday
1/29/2014

Tuning Recurrent Connections Through "Innate Training"

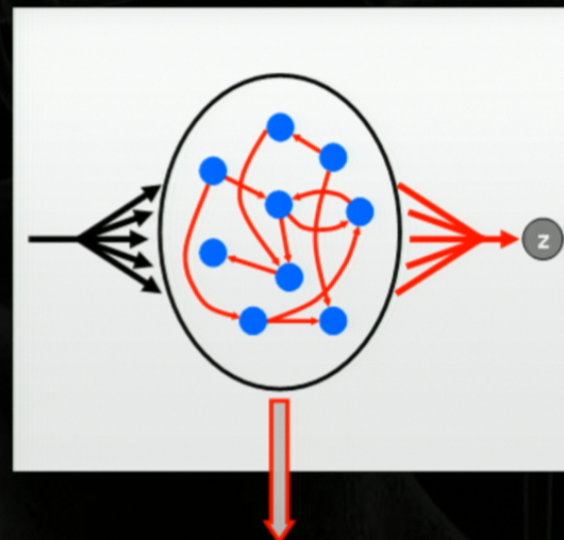
1. Traditional supervised learning rules require a target pattern in order to calculate the error (used to adjust the weights) But what is the target pattern of the recurrent network?

2. In the current framework (SDN / reservoir computing) it does not matter what the network does! As long as the pattern is high-dimensional and reproducible.

3. Innate training trains the network to do what it can already to by picking an "innate" pattern as the target.

Tuning Recurrent Connections Through "Innate Training"

Train the network to do what it can already to by picking an "innate" pattern as the target.

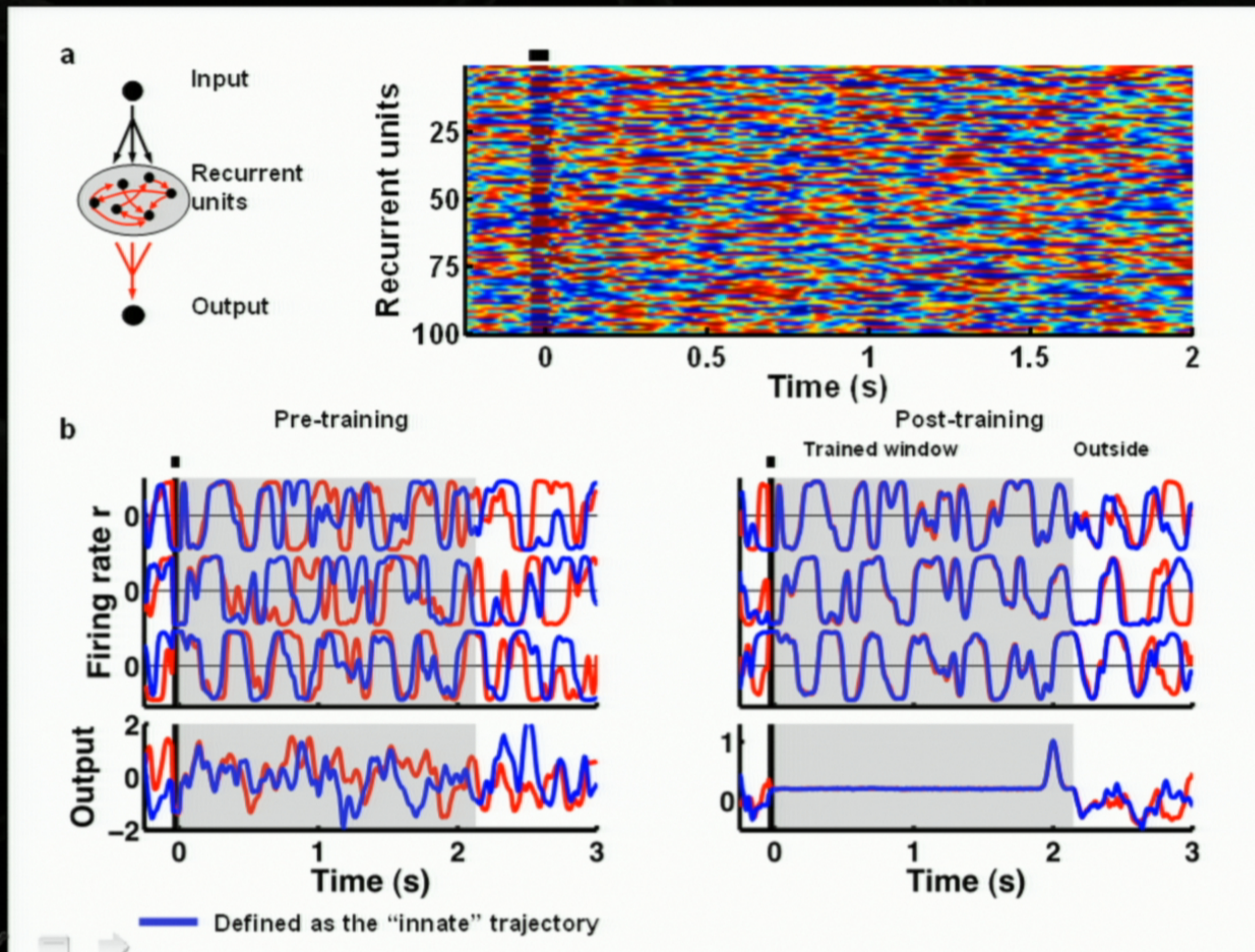


Supervised Learning:
"Continuous" RLS (FORCE)

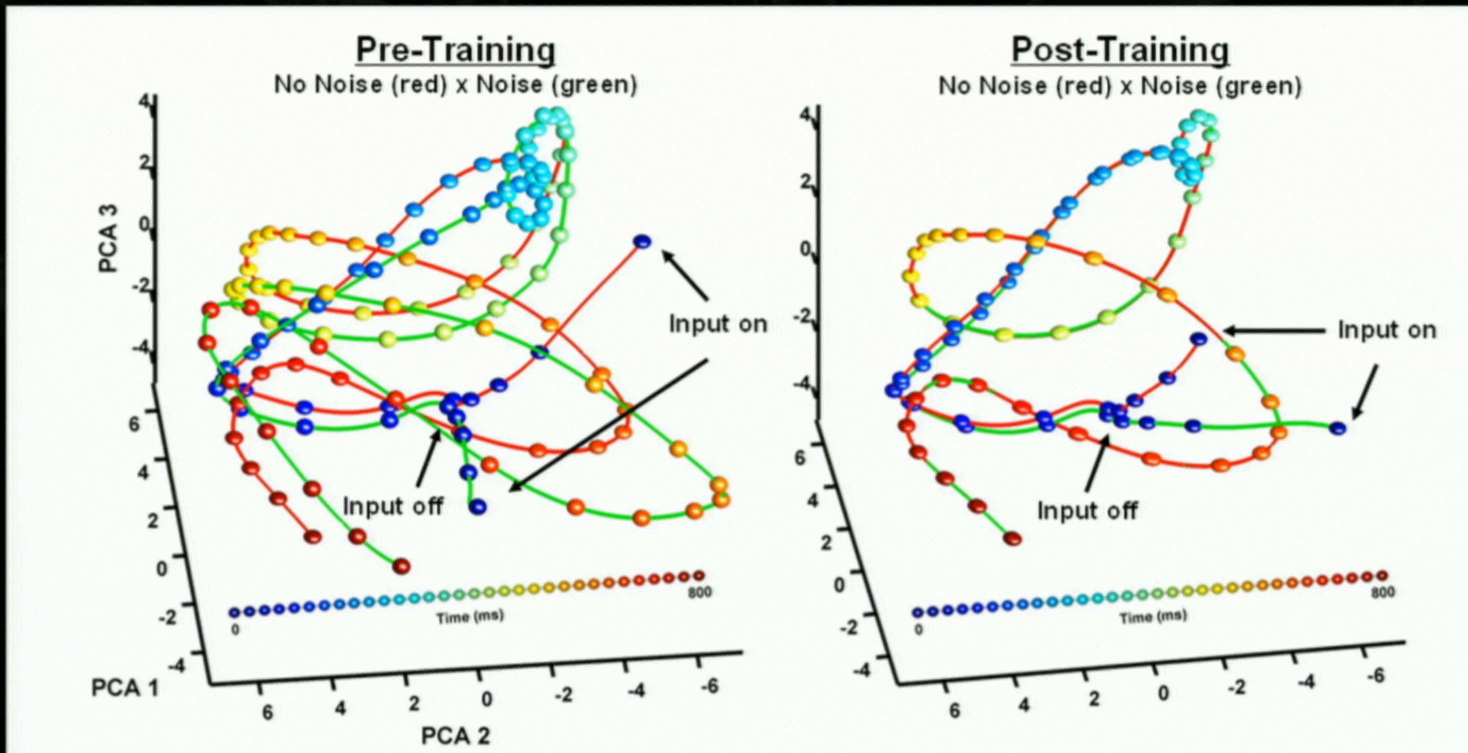
$$w_{ij} = w_{ij}(t - \Delta t) + \mathrm{error}_i(t) \sum_{k}^{\mathrm{Pre}} P_{j,k}(t) r_k(t)$$

P = running inverse correlation of vector r (presynaptic elements)

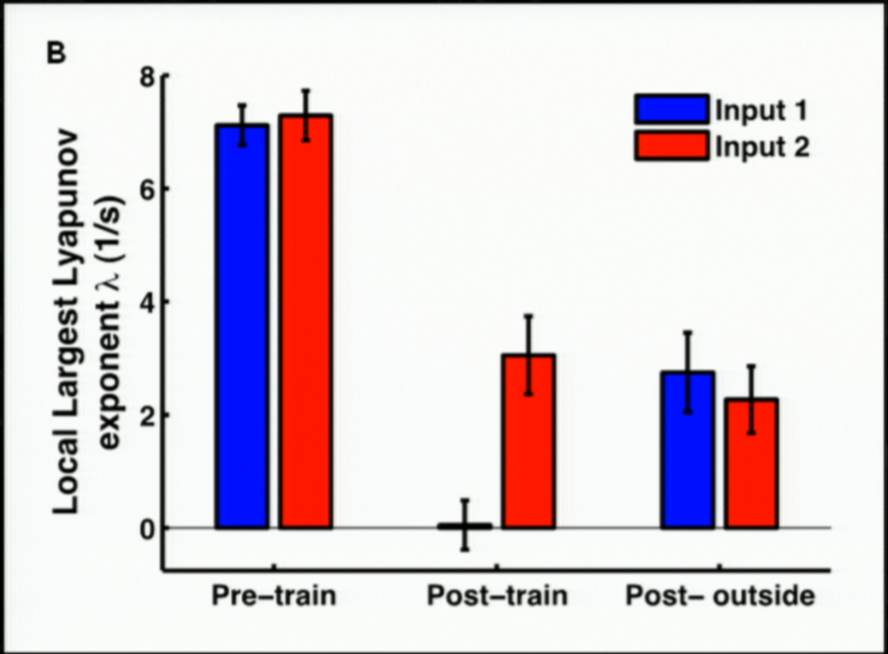
Trained Trajectories are Locally Stable



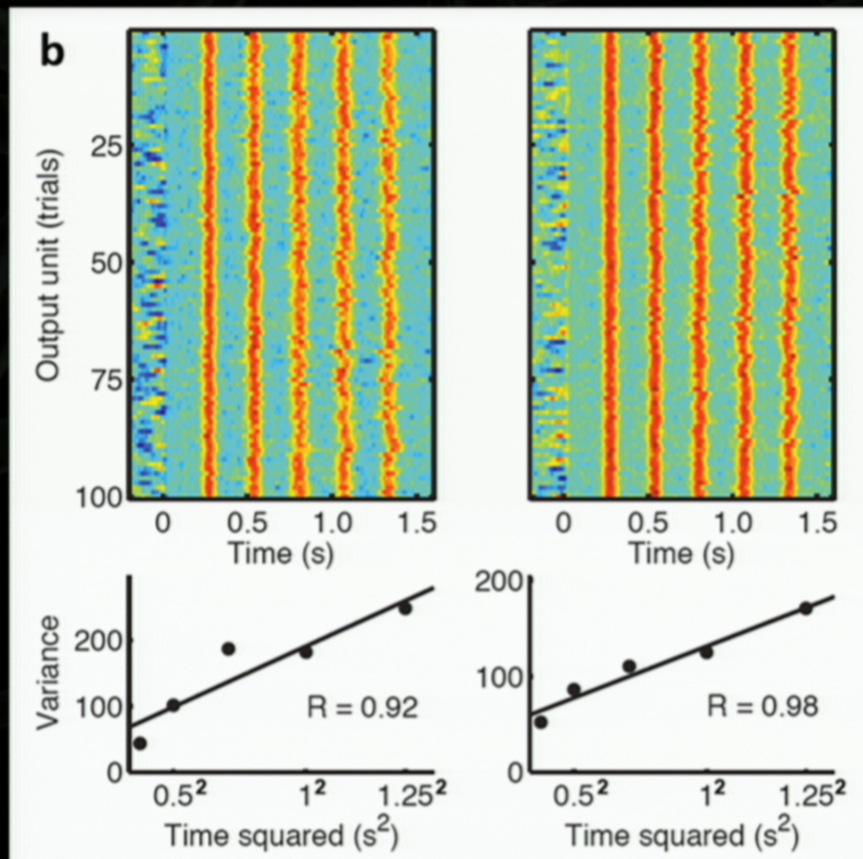
Trained Trajectories are Locally Stable



Trained Trajectories are Locally Stable

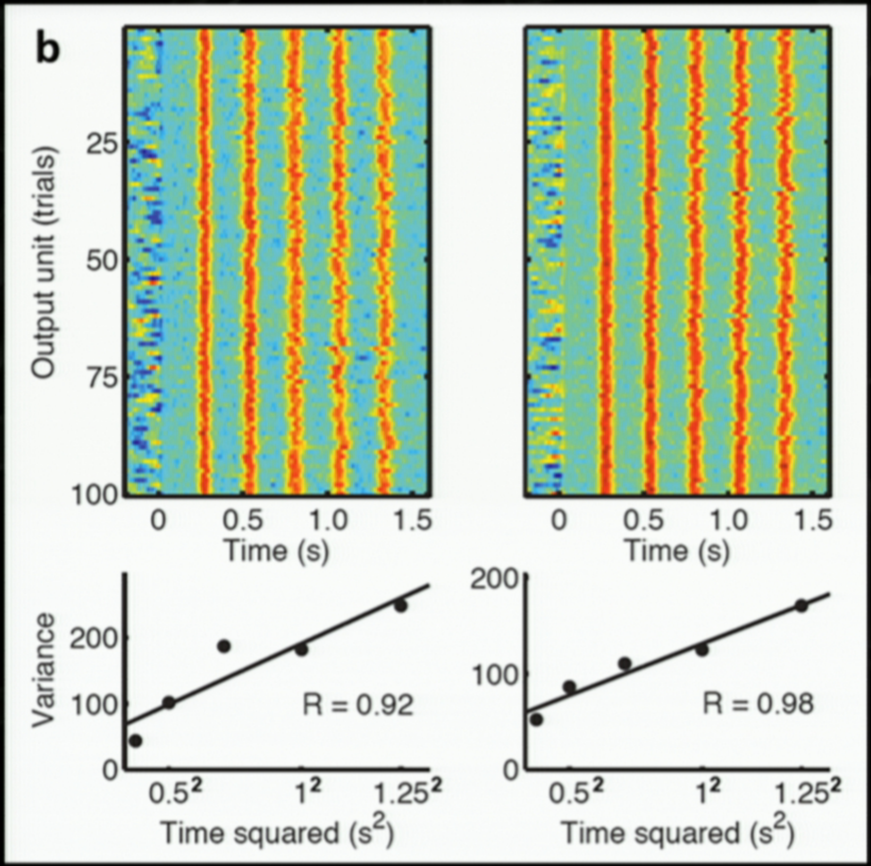


Stable Trajectories can Account for the Experimentally Observed Variance Signature (Weber's Law)



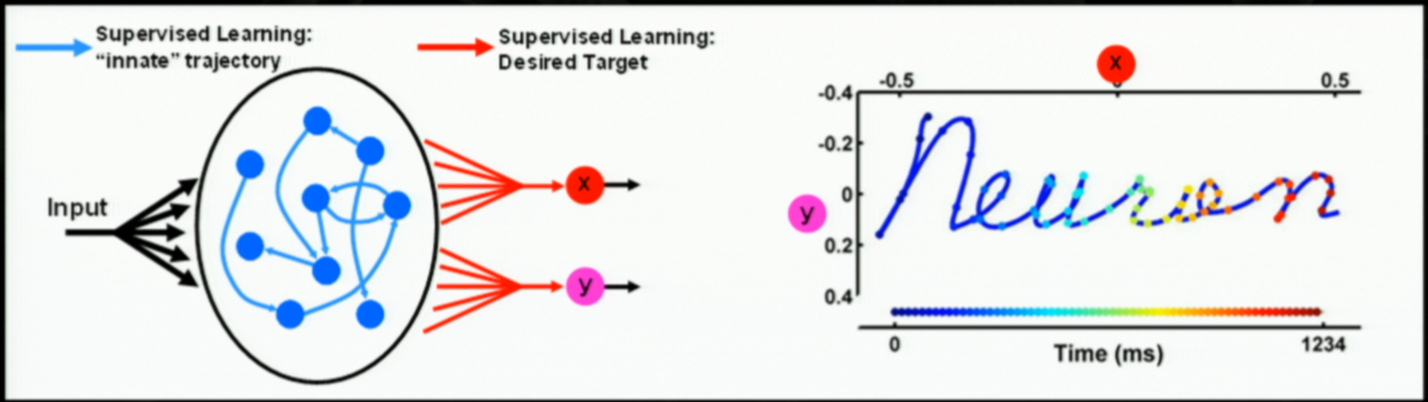
Laje, Buonomano, 2013 (Nat. Neurosci.)

Stable Trajectories can Account for the Experimentally Observed Variance Signature (Weber's Law)

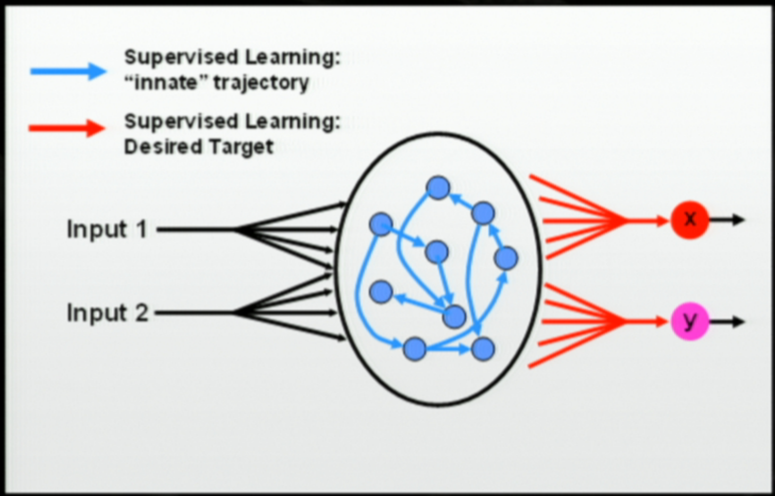


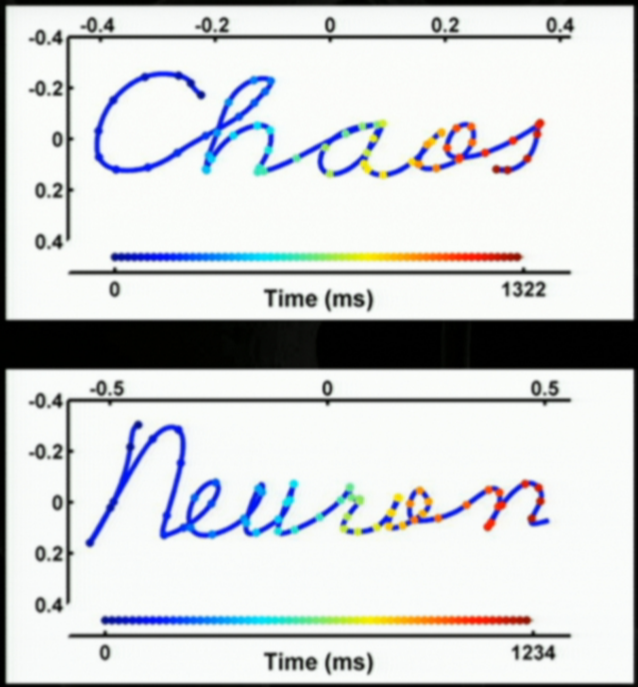
Laje, Buonomano, 2013 (Nat. Neurosci.)

Using Stable Transient Dynamics to Generate Motor Patterns

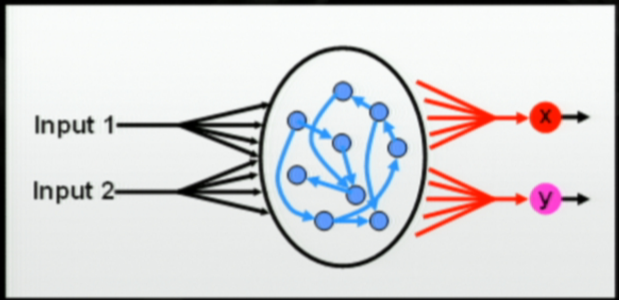


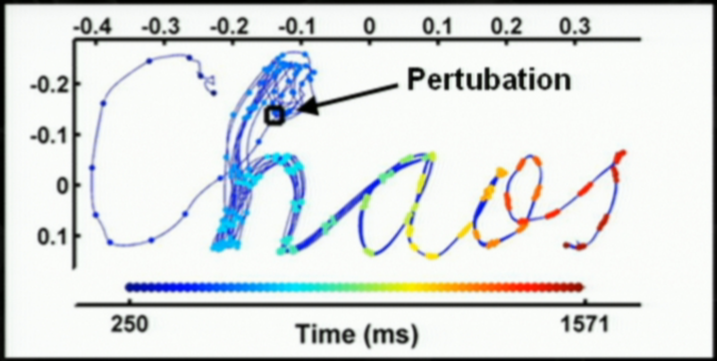
Complex Spatiotemporal Patterns: Handwriting

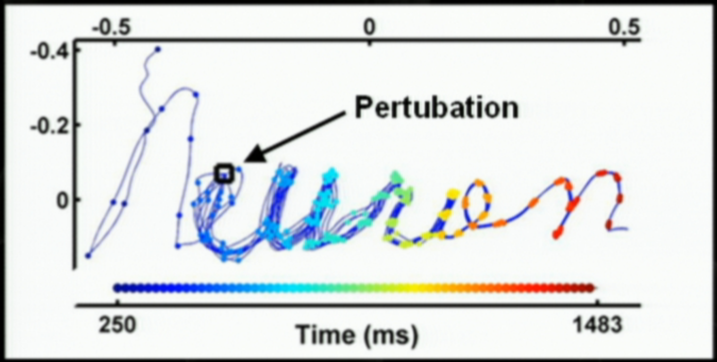


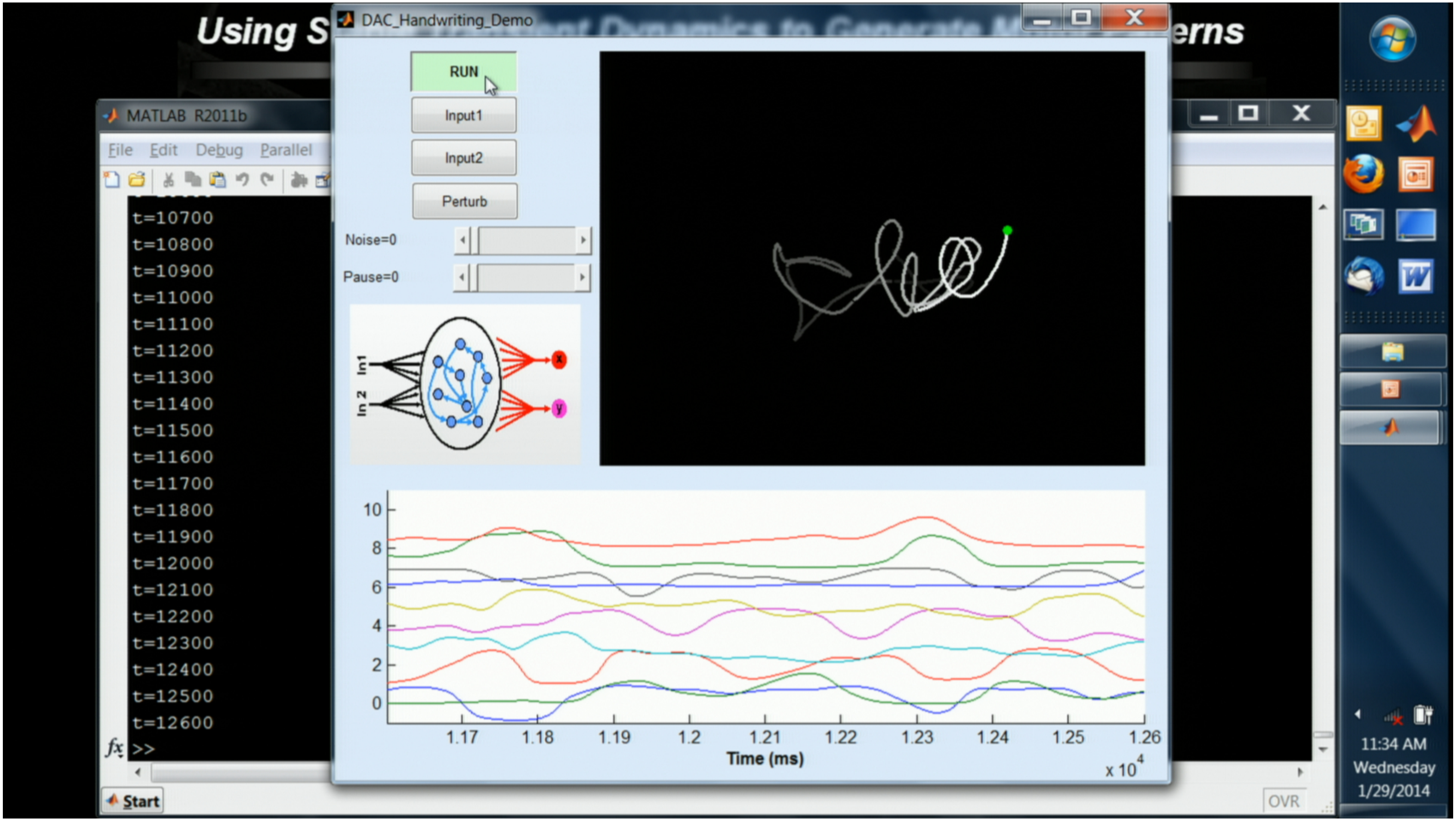


Dynamic Attractor: Return to the Trajectory after Pertubation

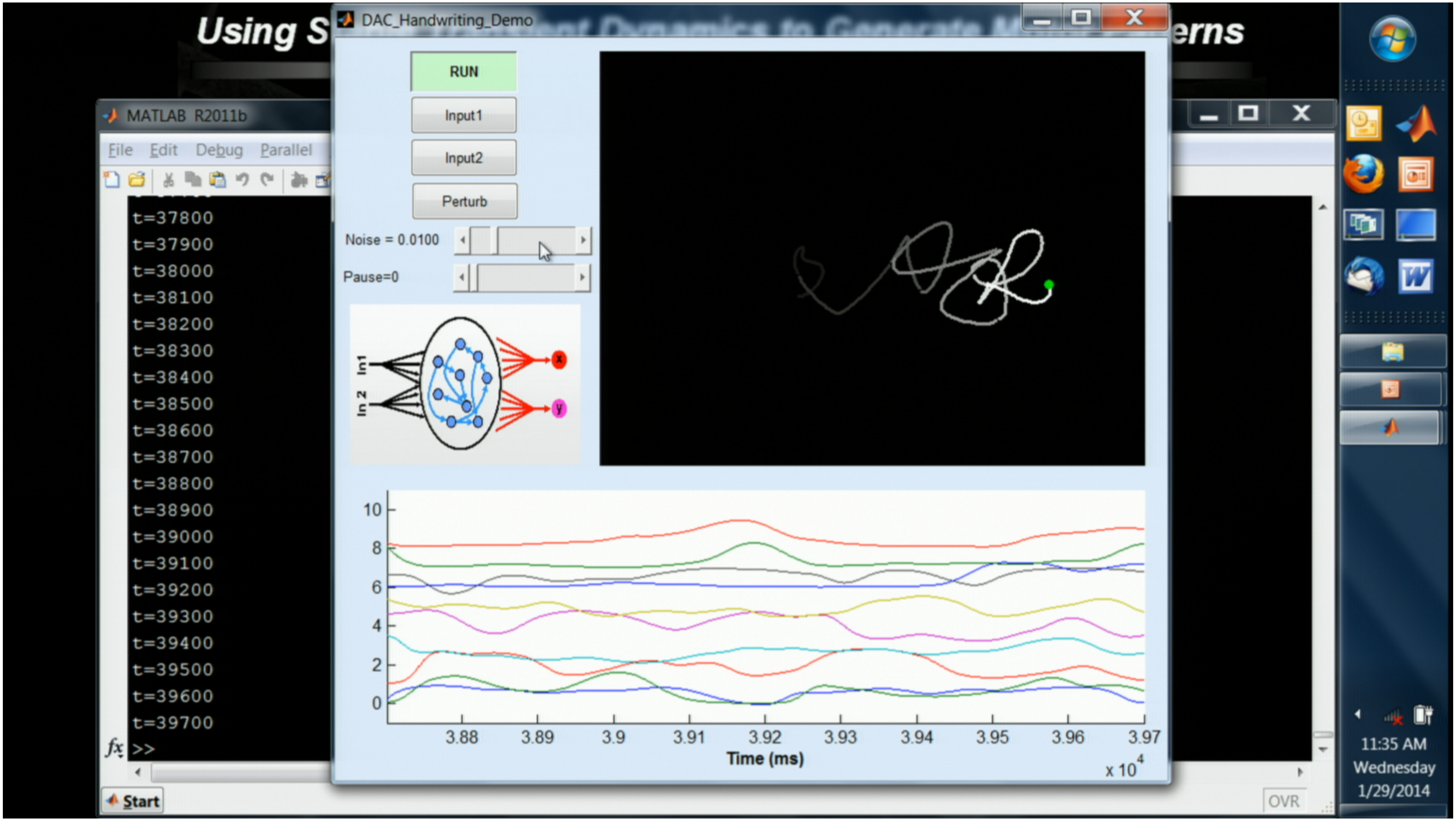




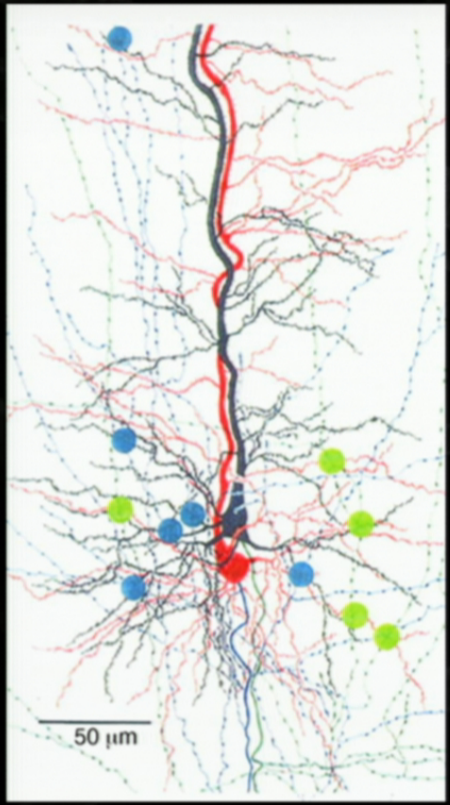


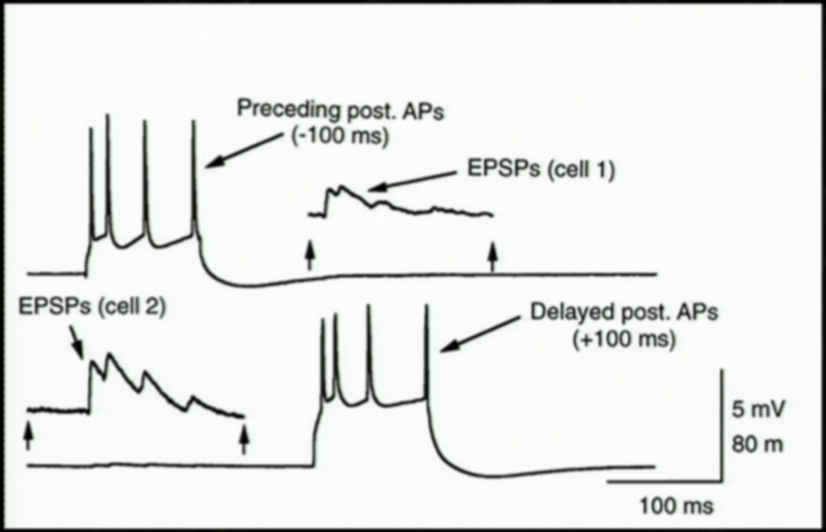


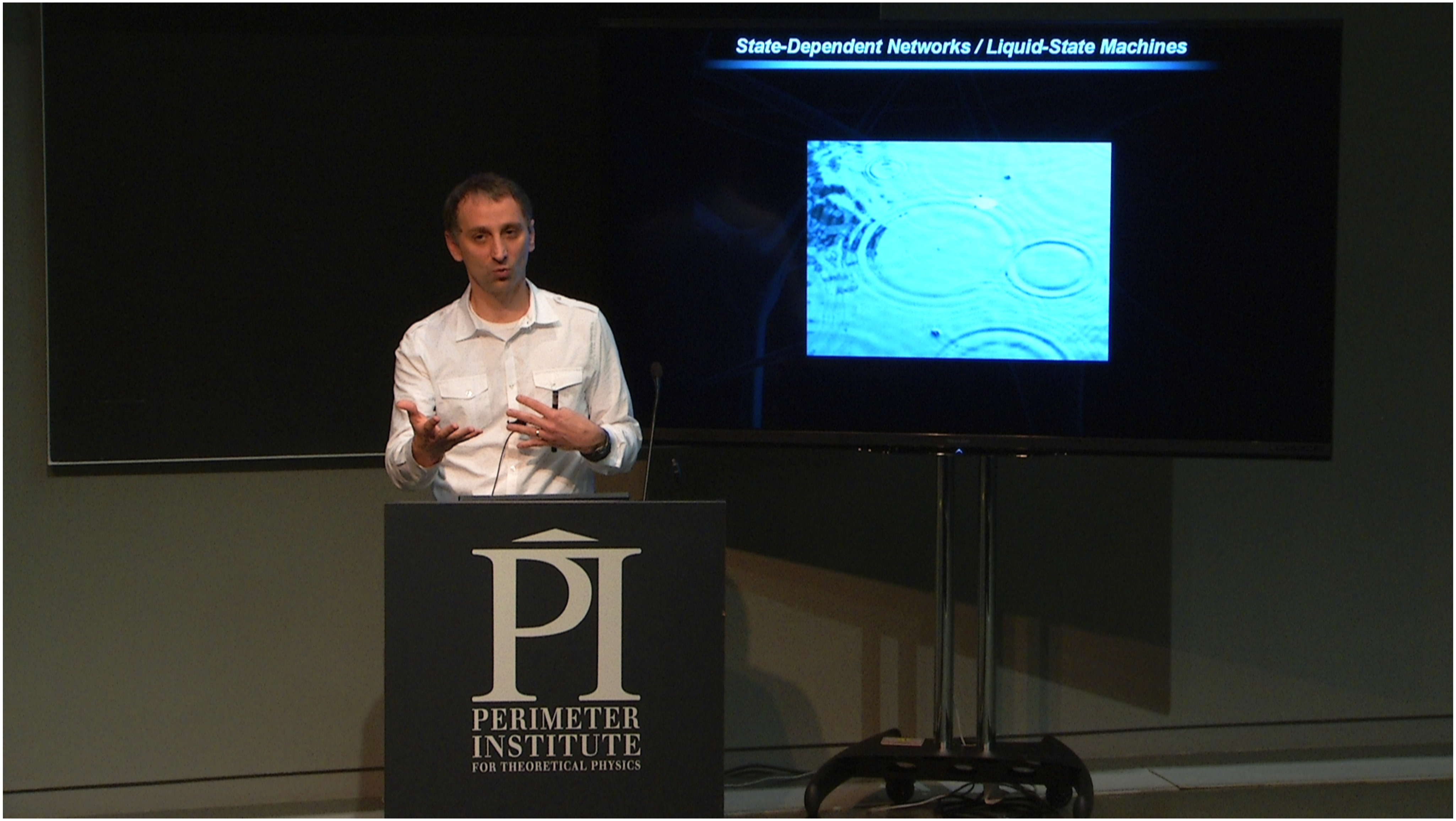
DAC_Handwriting_Demo
MATLAB R2011b
File Edit Debug Parallel
RUN
Input1
Input2
Perturb
Noise=0
Pause=0
In1
In 2
x
y
t=10700
t=10800
t=10900
t=11000
t=11100
t=11200
t=11300
t=11400
t=11500
t=11600
t=11700
t=11800
t=11900
t=12000
t=12100
t=12200
t=12300
t=12400
t=12500
t=12600
Time (ms)
x 10^4
Start
OVR
11:34 AM
Wednesday
1/29/2014


Using S
erns
DAC_Handwriting_Demo
MATLAB R2011b
File Edit Debug Parallel
t=37800
t=37900
t=38000
t=38100
t=38200
t=38300
t=38400
t=38500
t=38600
t=38700
t=38800
t=38900
t=39000
t=39100
t=39200
t=39300
t=39400
t=39500
t=39600
t=39700
>>
RUN
Input1
Input2
Perturb
Noise = 0.0100
Pause=0
In1
In 2
x
y
10
8
6
4
2
0
3.88
3.89
3.9
3.91
3.92
3.93
3.94
3.95
3.96
3.97
Time (ms)
x 10^4
Start
OVR
11:35 AM
Wednesday
1/29/2014

Real Neural Networks are Much More Complicated






State-Dependent Networks / Liquid-State Machines
PERIMETER
INSTITUTE
FOR THEORETICAL PHYSICS

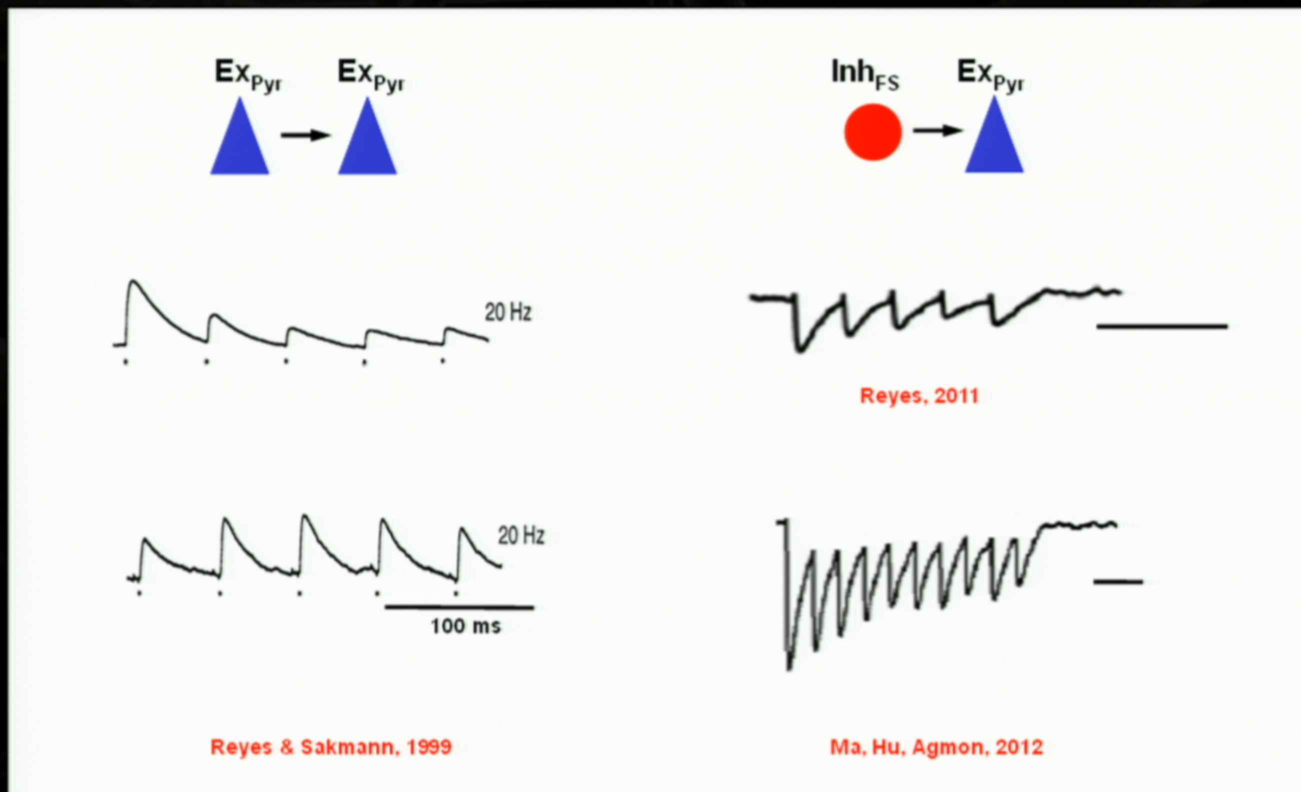
State-Dependent Networks / Liquid-State Machines

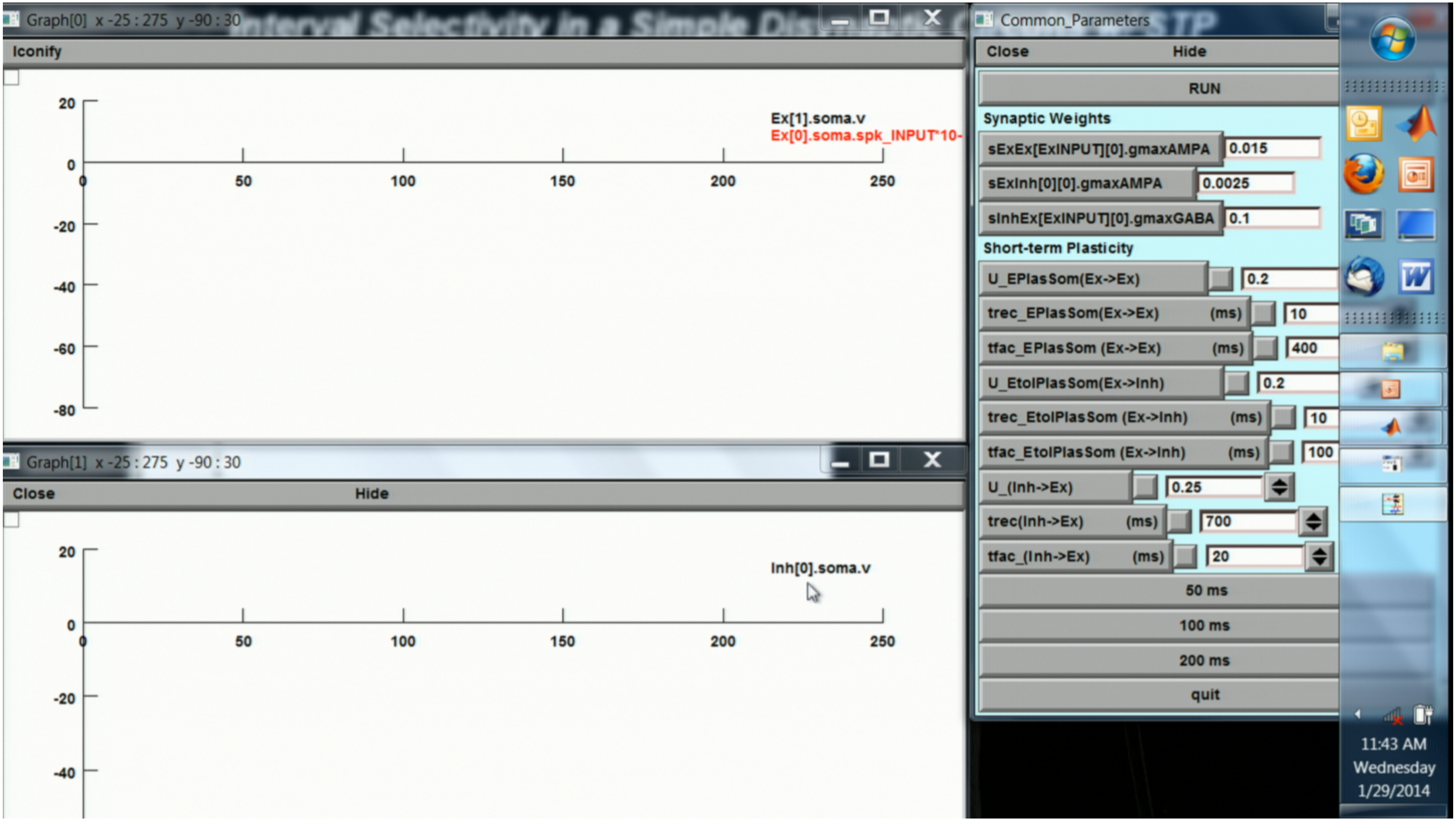
1. In the sensory domain temporal computations arise from the interaction between the internal state of neural networks and incoming stimuli. The state of a network is defined both by it's "active" and "hidden" state.

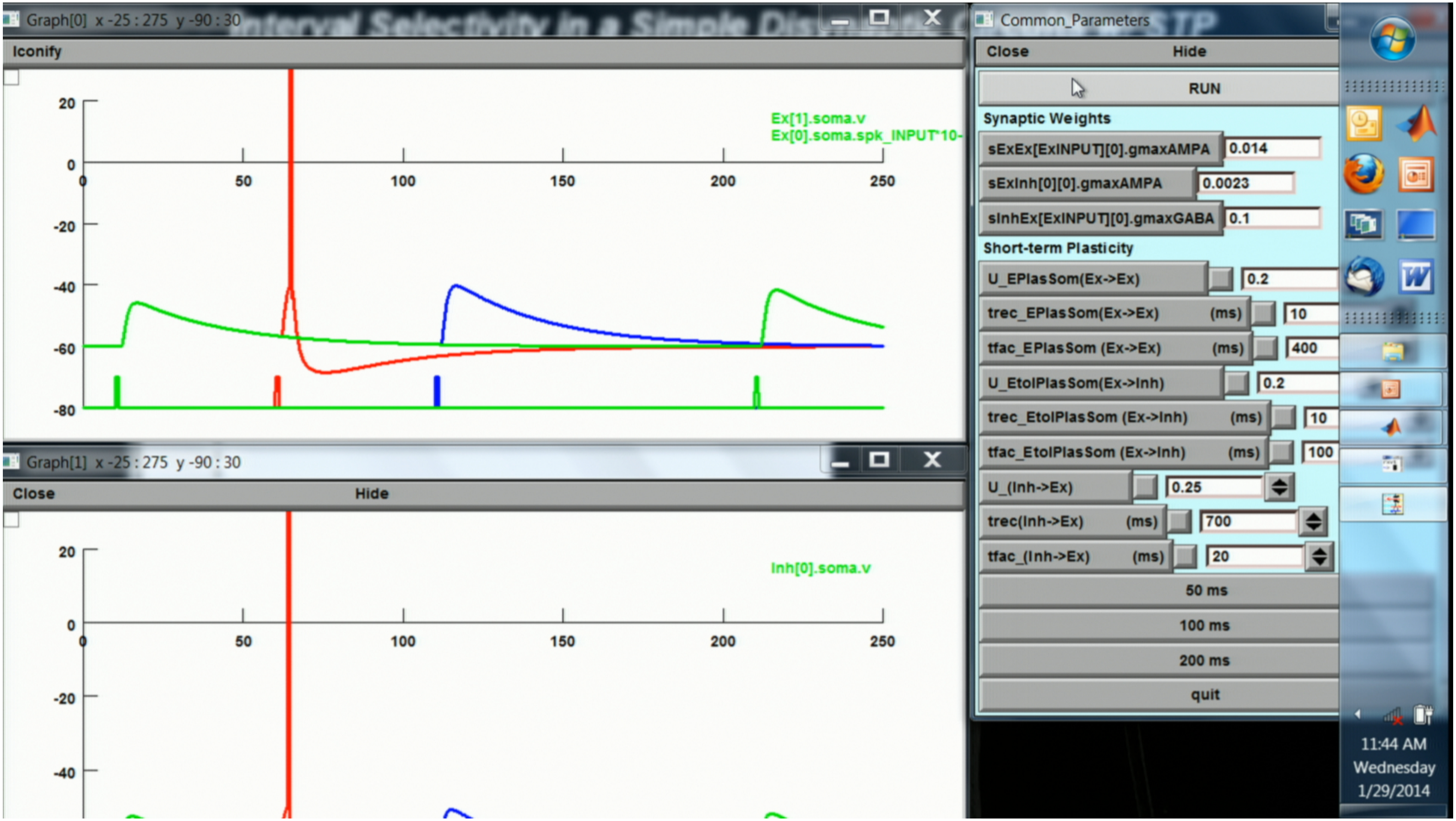
2. The inherent complexity and size of recurrent neural networks ensures that virtually any stimulus set is represented in high-dimensional space—which facilitates the decoding (e.g., support vector machines)

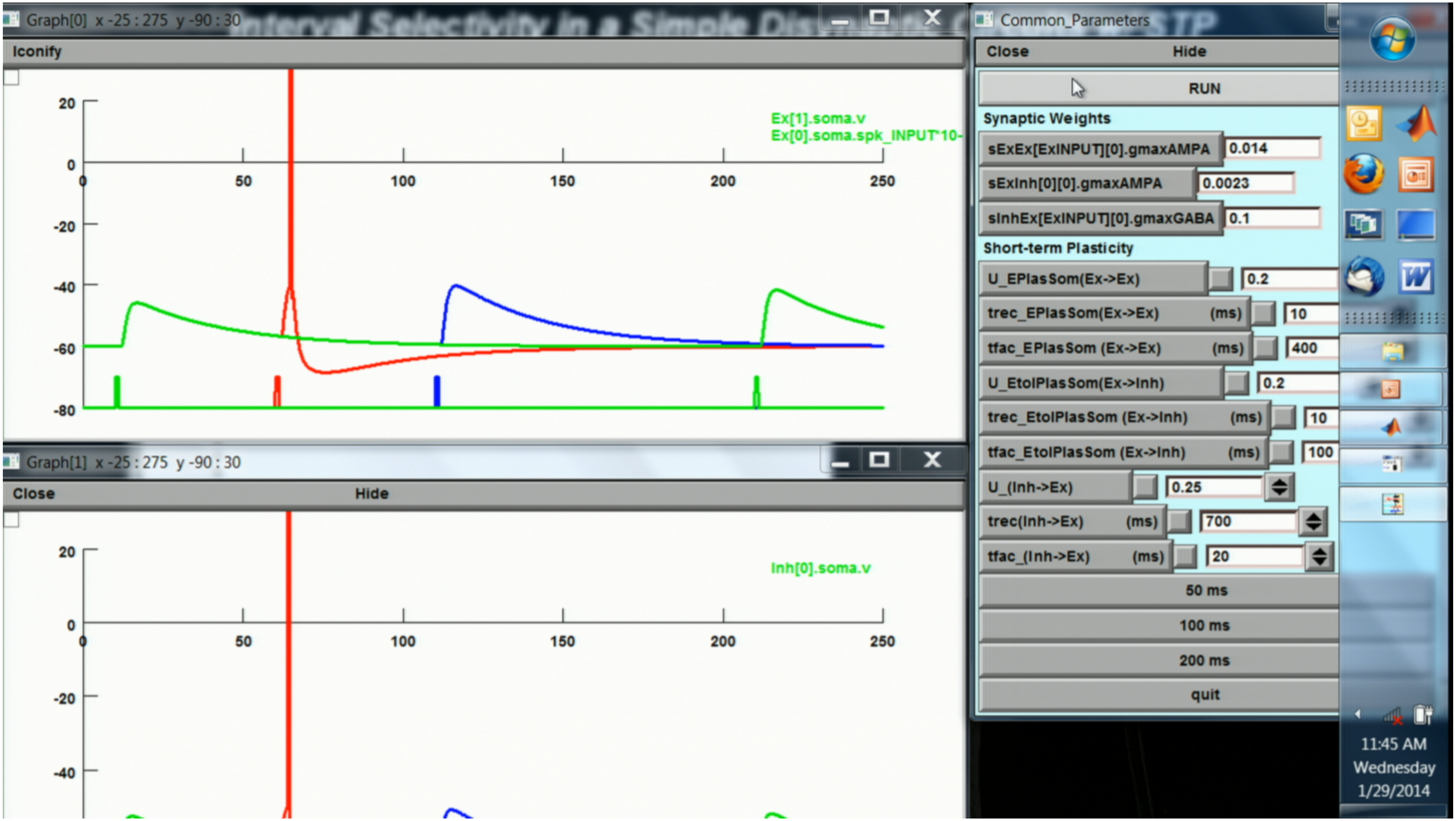
Buonomano & Maass, 2009 (Nat. Neuroscience)

Short-term Synaptic Plasticity



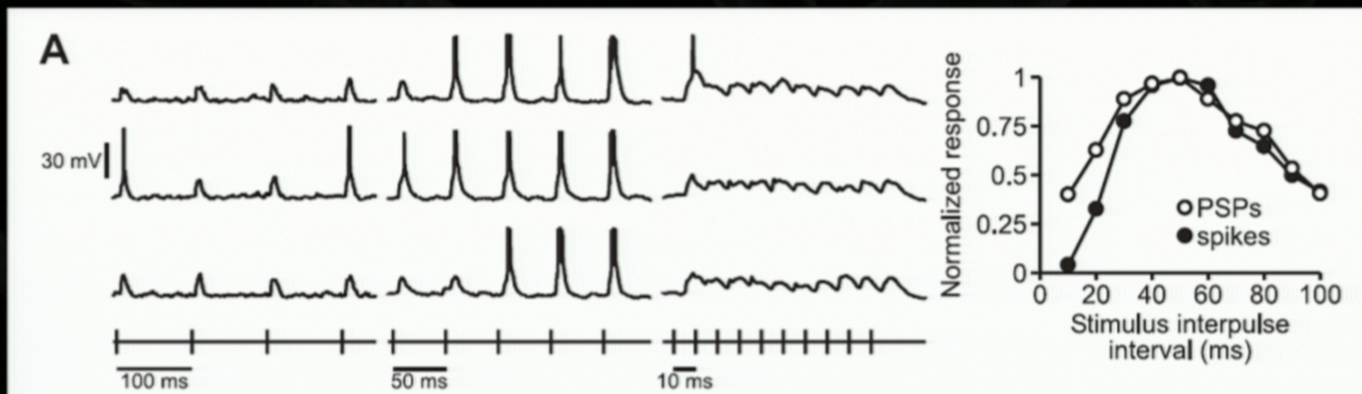

Graph[0] x -25 : 275 y -90 : 30
Iconify
Ex[1].soma.v
Ex[0].soma.spk_INPUT*10-
Graph[1] x -25 : 275 y -90 : 30
Close
Hide
Inh[0].soma.v
Common_Parameters
Close
Hide
RUN
Synaptic Weights
sExEx[ExINPUT][0].gmaxAMPA
0.015
sExInh[0][0].gmaxAMPA
0.0025
sInhEx[ExINPUT][0].gmaxGABA
0.1
Short-term Plasticity
U_EPlasSom(Ex->Ex)
0.2
trec_EPlasSom(Ex->Ex) (ms)
10
tfac_EPlasSom (Ex->Ex) (ms)
400
U_EtoIPlasSom(Ex->Inh)
0.2
trec_EtoIPlasSom (Ex->Inh) (ms)
10
tfac_EtoIPlasSom (Ex->Inh) (ms)
100
U_(Inh->Ex)
0.25
trec(Inh->Ex) (ms)
700
tfac_(Inh->Ex) (ms)
20
50 ms
100 ms
200 ms
quit
11:43 AM
Wednesday
1/29/2014


Graph[0] x -25 : 275 y -90 : 30
Iconify
Ex[1].soma.v
Ex[0].soma.spk_INPUT*10-
Graph[1] x -25 : 275 y -90 : 30
Close
Hide
Inh[0].soma.v
Common_Parameters
Close
Hide
RUN
Synaptic Weights
sExEx[ExINPUT][0].gmaxAMPA 0.014
sExInh[0][0].gmaxAMPA 0.0023
sInhEx[ExINPUT][0].gmaxGABA 0.1
Short-term Plasticity
U_EPlasSom(Ex->Ex) 0.2
trec_EPlasSom(Ex->Ex) (ms) 10
tfac_EPlasSom (Ex->Ex) (ms) 400
U_EtoIPlasSom(Ex->Inh) 0.2
trec_EtoIPlasSom (Ex->Inh) (ms) 10
tfac_EtoIPlasSom (Ex->Inh) (ms) 100
U_(Inh->Ex) 0.25
trec(Inh->Ex) (ms) 700
tfac_(Inh->Ex) (ms) 20
50 ms
100 ms
200 ms
quit
11:44 AM
Wednesday
1/29/2014



Graph[0] x -25 : 275 y -90 : 30
Iconify
Ex[1].soma.v
Ex[0].soma.spk_INPUT*10-
Graph[1] x -25 : 275 y -90 : 30
Close
Hide
Inh[0].soma.v
Common_Parameters
Close
Hide
RUN
Synaptic Weights
sExEx[ExINPUT][0].gmaxAMPA
0.014
sExInh[0][0].gmaxAMPA
0.0023
sInhEx[ExINPUT][0].gmaxGABA
0.1
Short-term Plasticity
U_EPlasSom(Ex->Ex)
0.2
trec_EPlasSom(Ex->Ex) (ms)
10
tfac_EPlasSom (Ex->Ex) (ms)
400
U_EtoIPlasSom(Ex->Inh)
0.2
trec_EtoIPlasSom (Ex->Inh) (ms)
10
tfac_EtoIPlasSom (Ex->Inh) (ms)
100
U_(Inh->Ex)
0.25
trec(Inh->Ex) (ms)
700
tfac_(Inh->Ex) (ms)
20
50 ms
100 ms
200 ms
quit
11:45 AM
Wednesday
1/29/2014

Short-Term Synaptic Plasticity Seems to Underlie Neuronal Interval Selectivity in Some Cases



Behavioral/Systems/Cognitive

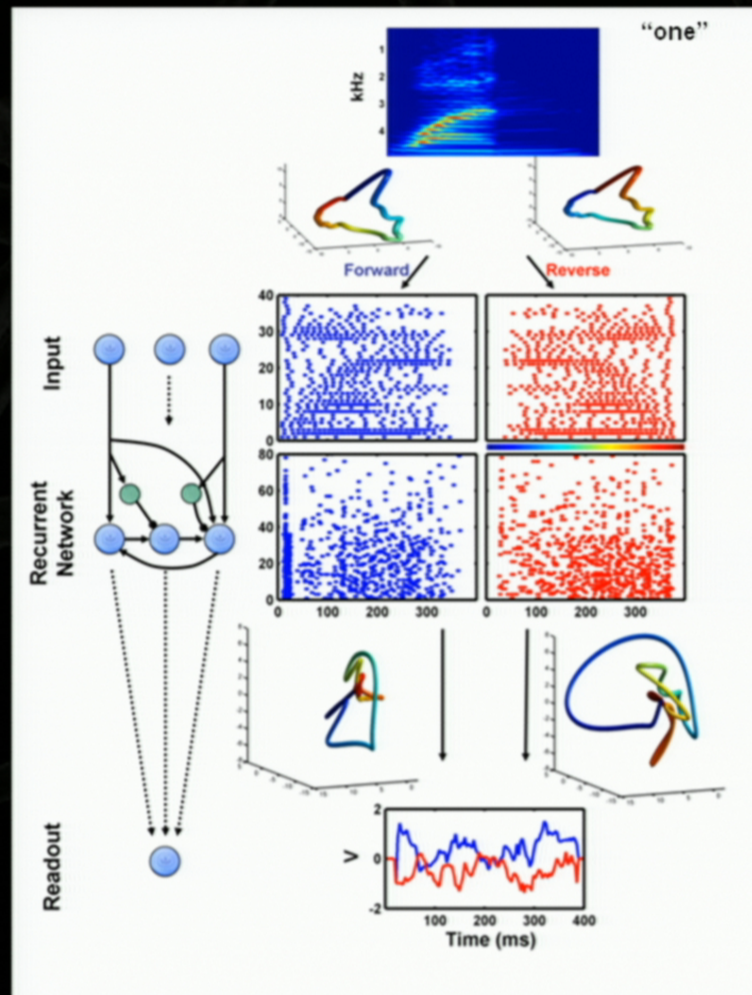
Carlson, 2009 (J. Neurosci)

Temporal-Pattern Recognition by Single Neurons in a Sensory Pathway Devoted to Social Communication Behavior

Bruce A. Carlson

Department of Biology, Washington University in St. Louis, St. Louis, Missouri 63130, and Department of Neurobiology and Behavior, Cornell University, Ithaca, New York 14853

Neural Trajectories are Time Asymmetric



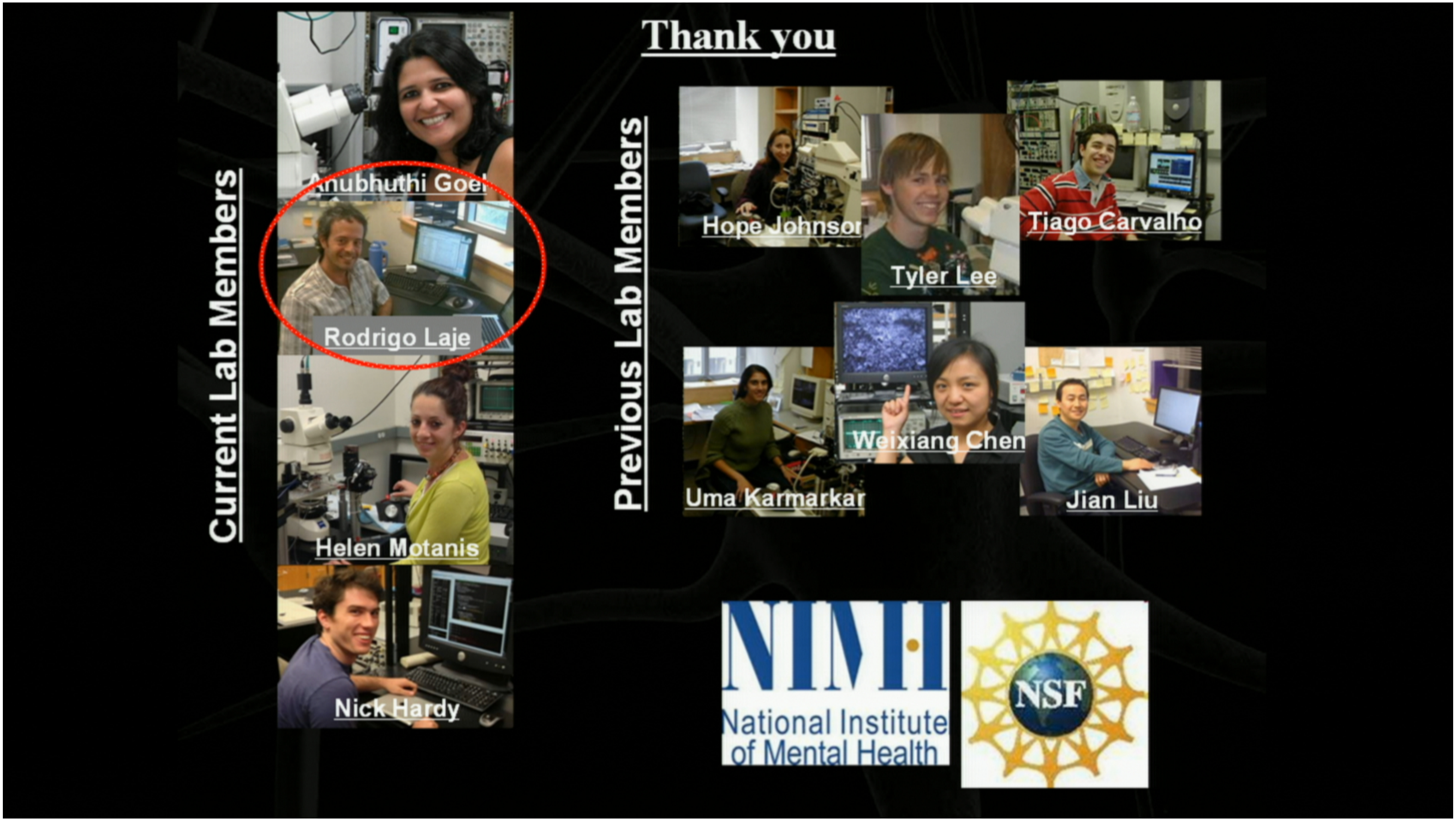
Haeusler & Maass, 2007

Conclusions

- The brain has many different "clocks". Each specialized for different temporal scales and functional needs (precision, reset, patterns, …)

Conclusions

- The brain has many different “clocks”. Each specialized for different temporal scales and functional needs (precision, reset, patterns, …)
- Experimental and theoretical evidence that the brain uses neural dynamics of recurrent neural networks to tell time on the scale of milliseconds and seconds.
- But these networks have traditionally been subject to chaos. We now know that we can “tame” chaos through plasticity of the recurrent connections.
- Recent shift in thinking about how the brain works: Computations arise from the voyage through state space, as opposed to a destination in state space


Thank you
Current Lab Members
Anubhuthi Goel
Rodrigo Laje
Helen Motanis
Nick Hardy
Previous Lab Members
Hope Johnson
Tyler Lee
Tiago Carvalho
Weixiang Chen
Uma Karmarkar
Jian Liu
NIMH
National Institute of Mental Health
NSF