

Role and limits of inhibition in an excitatory burst generator

Explaining **levels of synchrony** and **neuron phases**

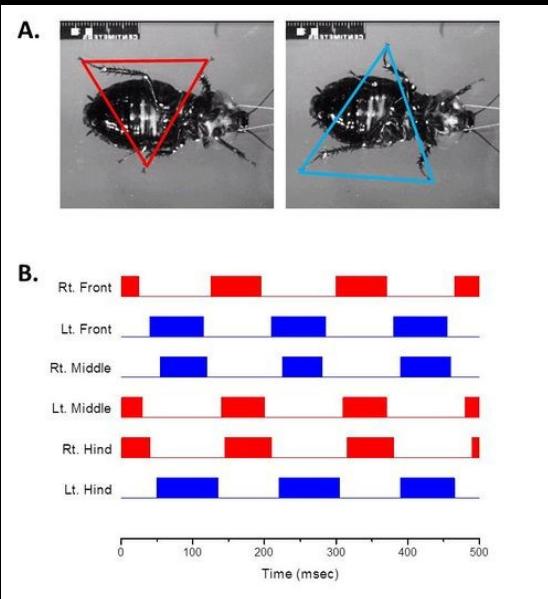
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Applied Mathematics, University of Washington

Banff Networks & Neuroscience 2015

The other people who make it happen

- Experiments at Seattle Children's Research Inst. Center for Integrative Brain Research:
 - Tatiana Dashevskiy
 - Alfredo J. Garcia III
 - Jan-Marino Ramirez
- University of Washington Applied Math
 - Eric Shea-Brown
 - Joshua Mendoza
- NSF Grant #1122106, Boeing fellowship, Big Data Training Grant

Many (semi-)autonomous activities are rhythmic



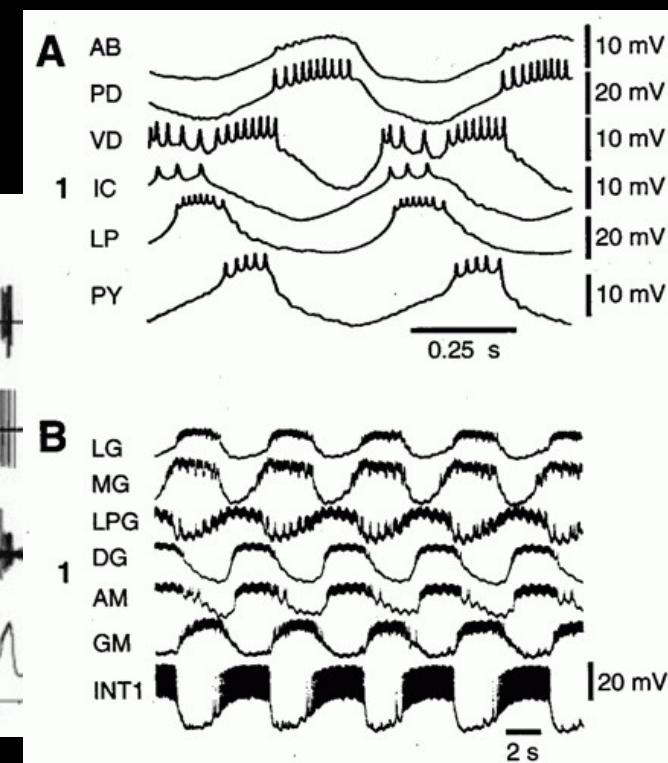
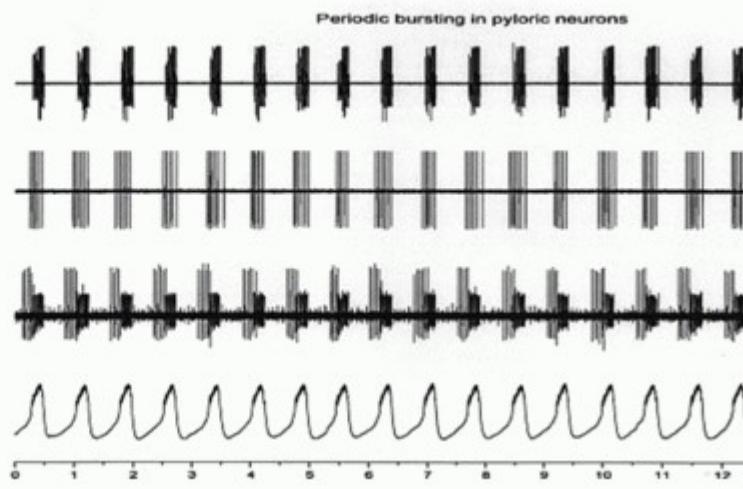
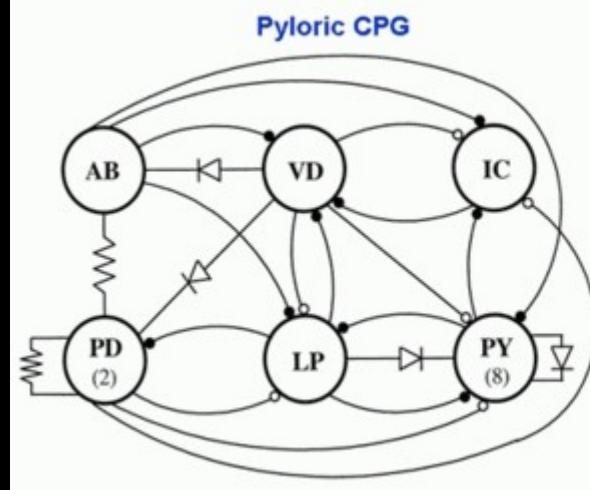
Locomotion
Ritzmann & Zill (2013)

Also:

- Chewing
- Whisking
- Breathing

Consensus view: **CPGs** which generate the patterns that can be controlled

Stomatogastric ganglion
Selverston (2008), Miller & Heinzel



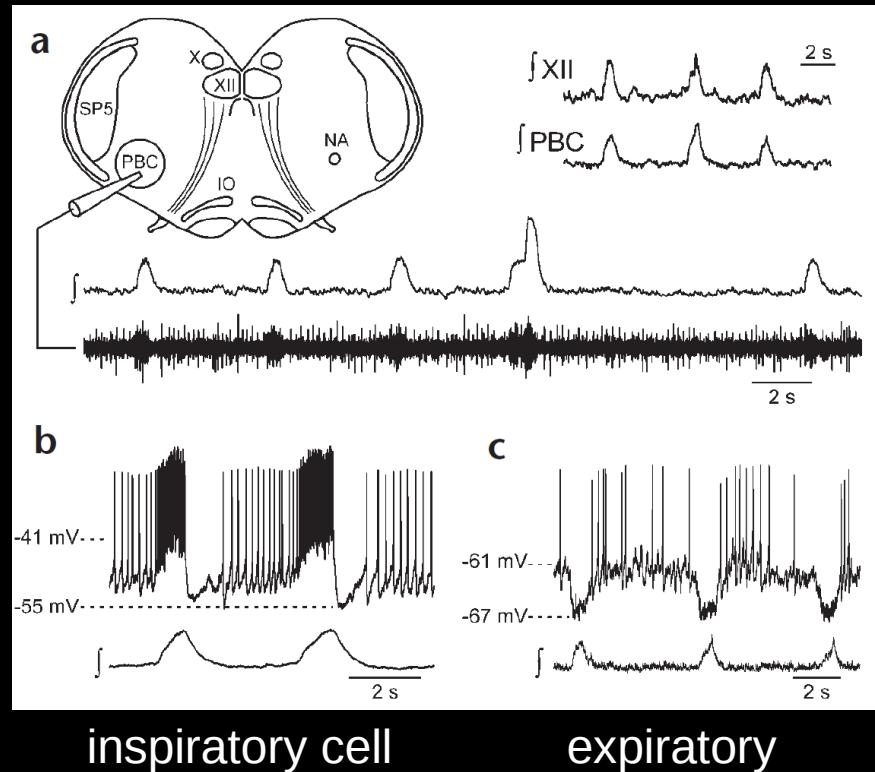
Breathing: an important rhythm Where does it come from?

- “Central pattern generator” in brainstem
 - Pre-Bötzinger complex (preBot) [Smith et al. 1991; Ramirez & Richter 1996; Rekling & Feldman 1998; Feldman et al. 2013]
 - Heterogeneous: **bursters**, **tonic (periodic) spikers**, and **quiescent**
 - **Synchronized** population bursts via excitation

Difference from usual CPGs:

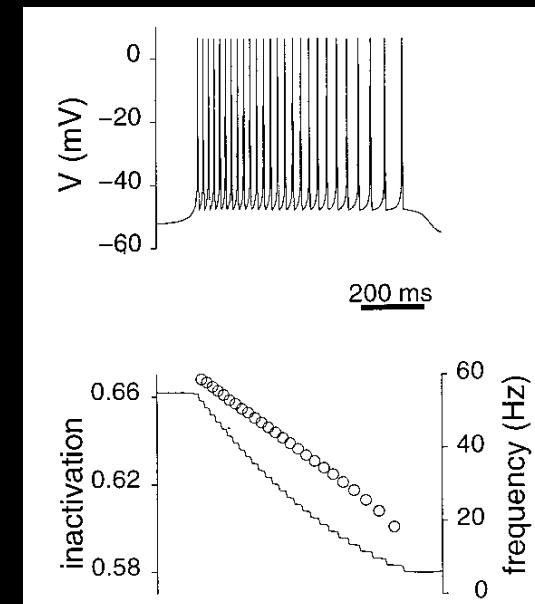
- ~300 neurons... why so many?
- Recurrent E/I network (inh. up to 50% of cells in preBot [Hayes et al. 2012])

S Lieske, M Thoby-Brisson, P Telkamp,
and J-M Ramirez (2000)



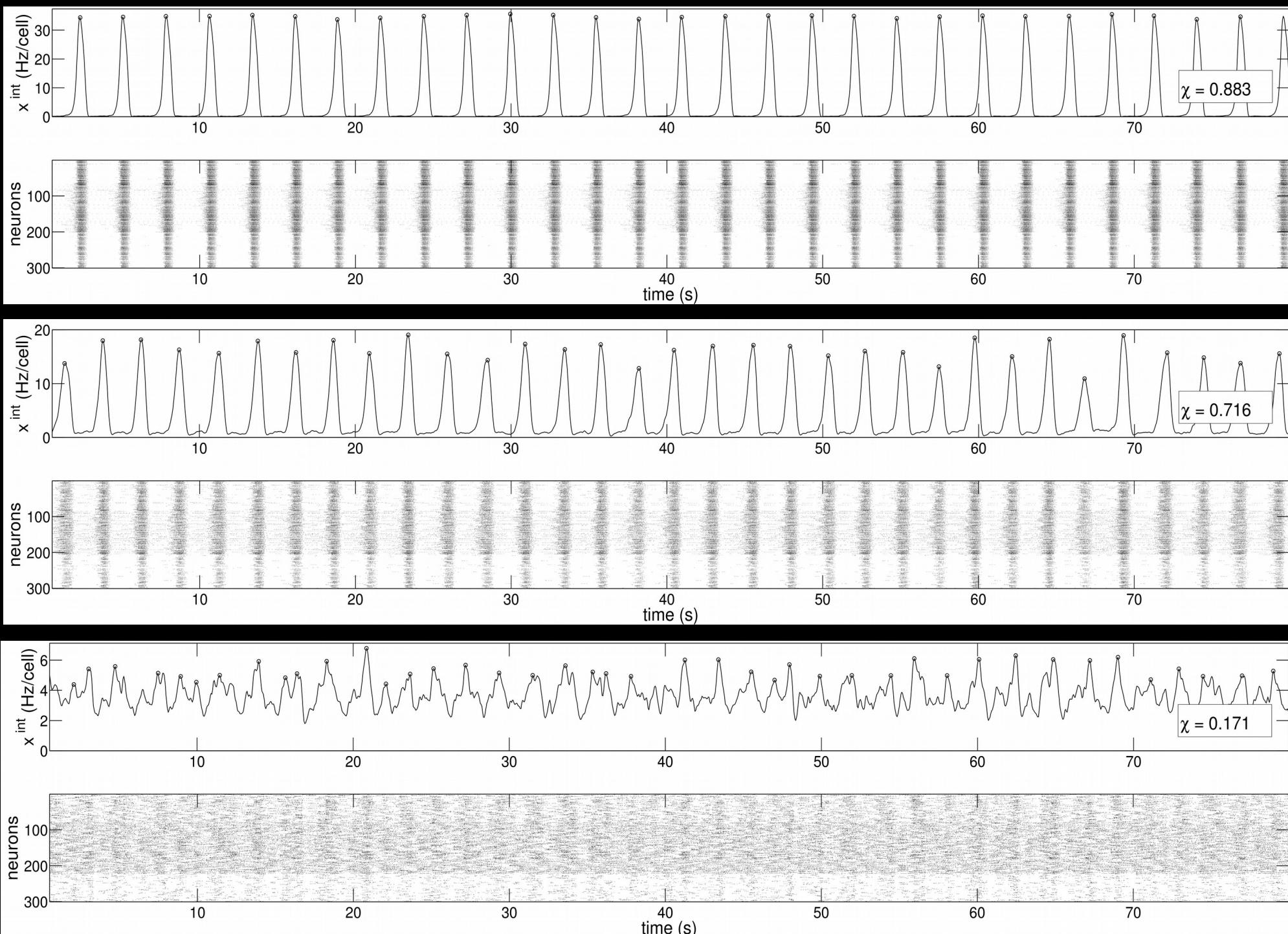
We model the effect of inhibitory cells in the population

- **Heterogeneous neurons** [Butera et al. 1999; see also Best et al. 2005; Rubin et al. 2009; Toporikova & Butera 2011; Park & Rubin 2013]
- Embedded in sparse network ($N=300$, $k=3 - 6$) [Gaiteri & Rubin 2011; Carroll & Ramirez 2013]
- Vary fraction of inhibitory cells p_i (≤ 0.5 [Hayes et al. 2012])
- Look for:
 - Effects on synchrony
 - Rhythm properties
 - Functional role for inhibition?



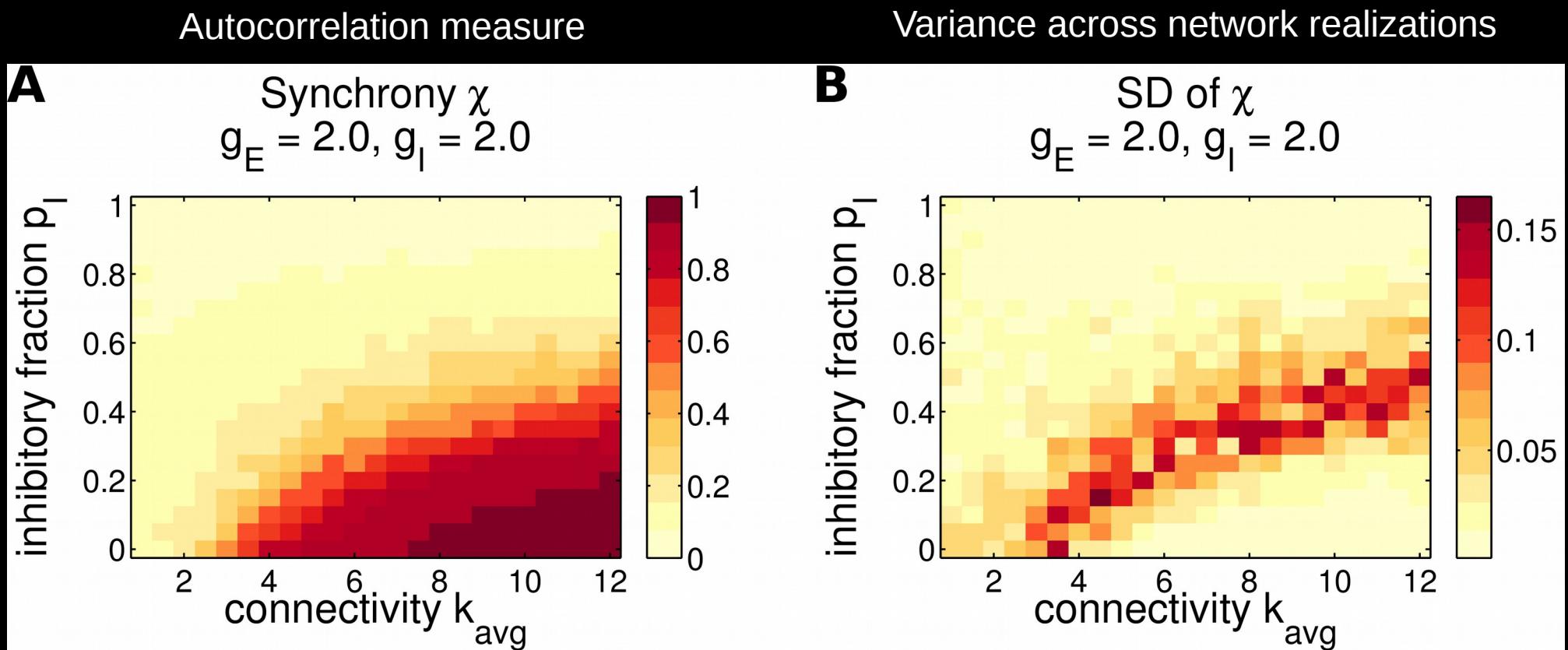
Avg degree = 6, $g_E = g_I = 2.0$ nS

Increasing inhibition ↓



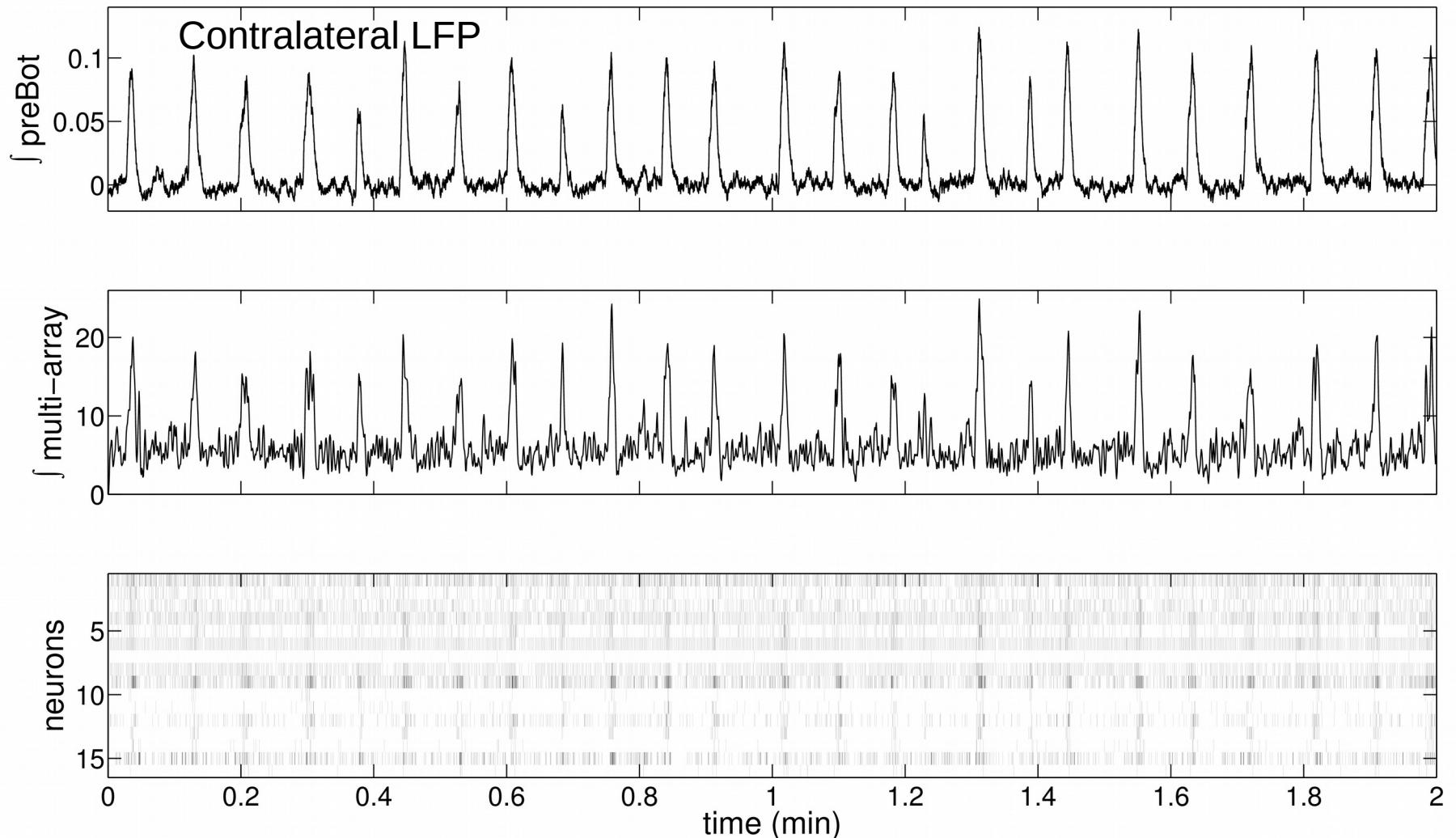
Sparsity & inhibition both degrade the rhythm – (E/I balance)

- Synchronous network oscillation from excitatory interactions
- Stronger with more/stronger connections
- Same effect changing g_E / g_I ... E/I balance what matters



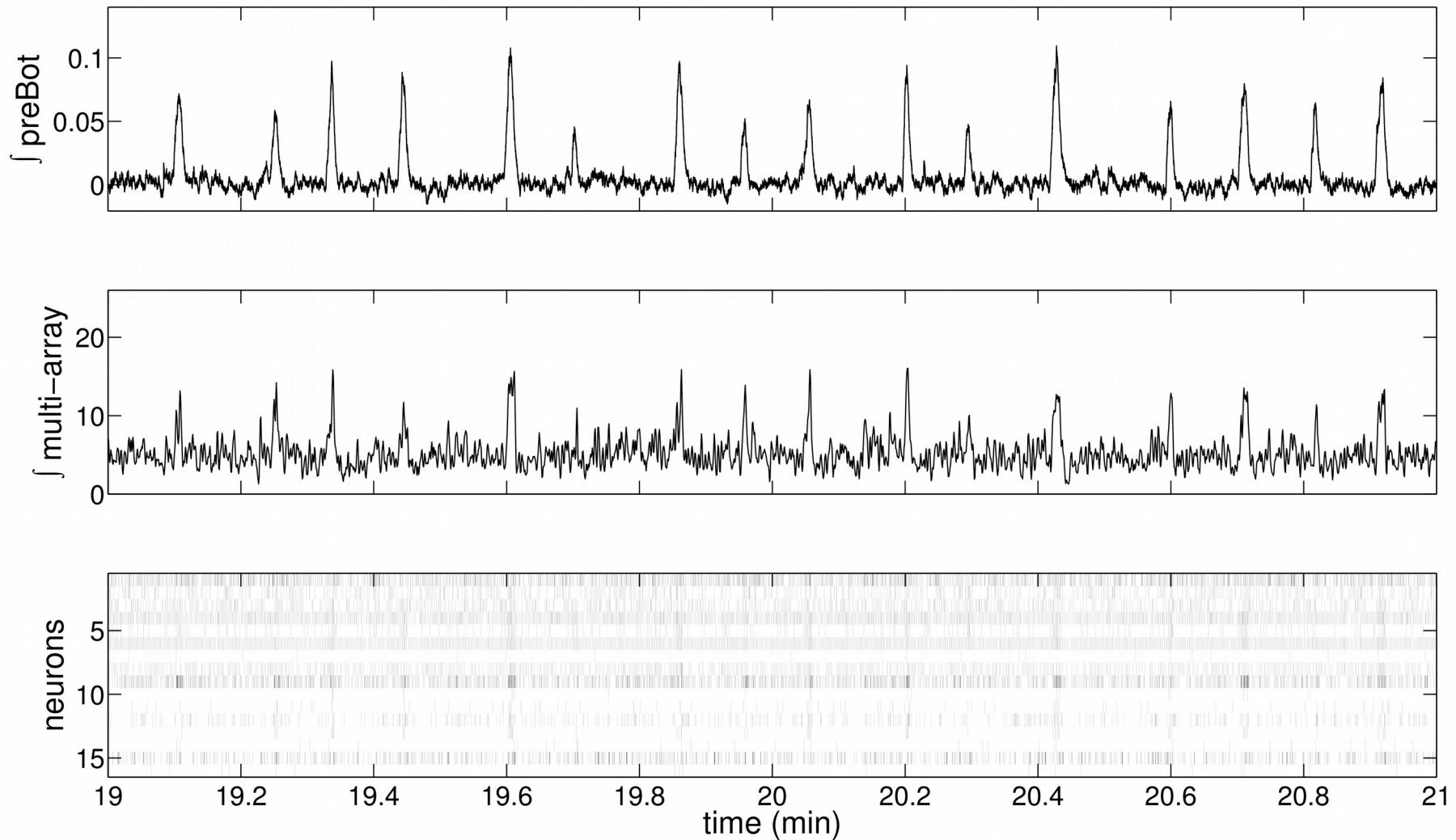
Experiments confirm E/I balance determines synchrony

Control: $\chi=0.56$



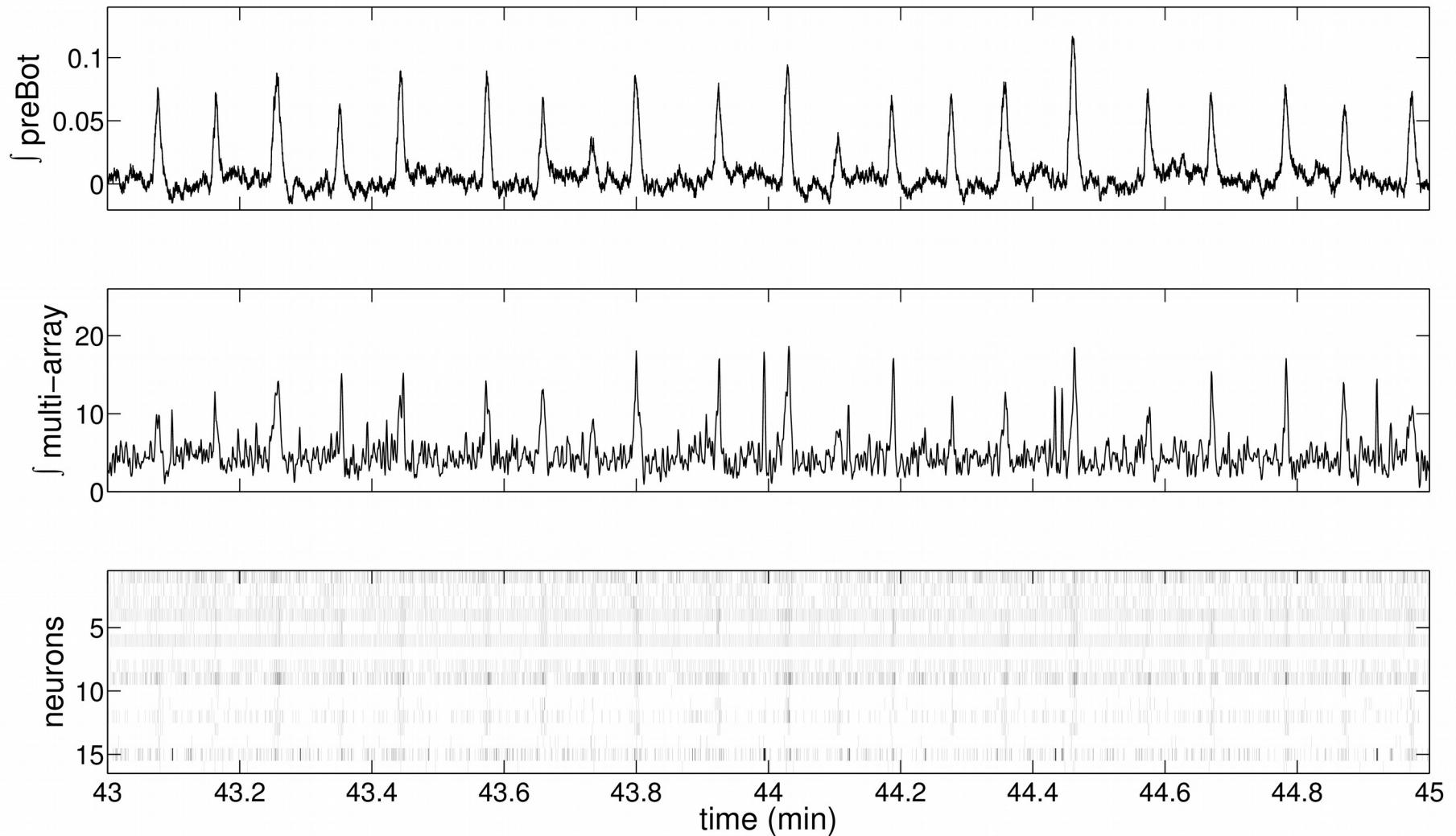
Experiments confirm E/I balance determines synchrony

DNQX @ 0.7 μM : $\chi=0.43$



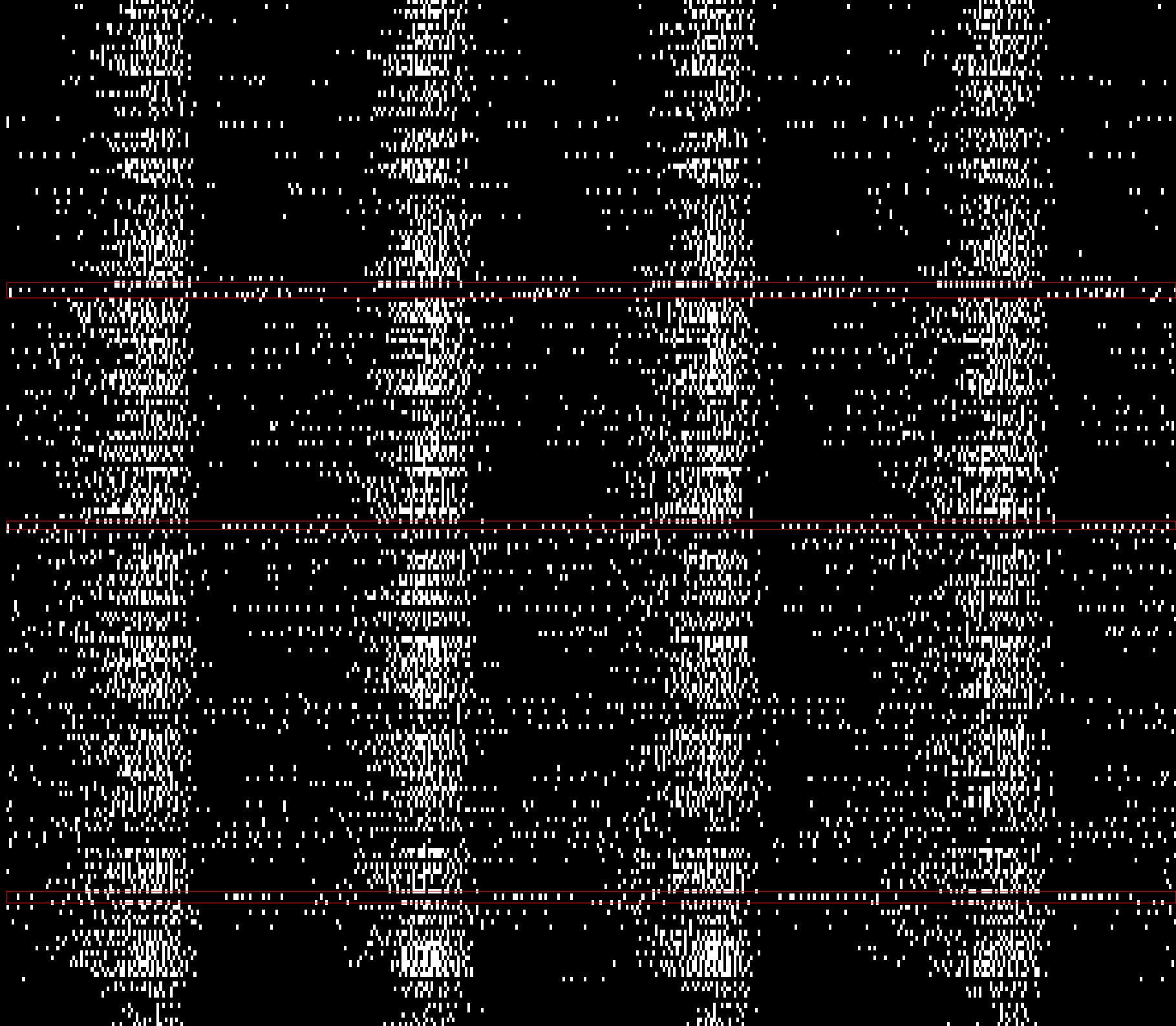
Experiments confirm E/I balance determines synchrony

DNQX @ 0.7 μ M, PTX @ 20 μ M: $\chi=0.50$



In model,
with $p=0.2$

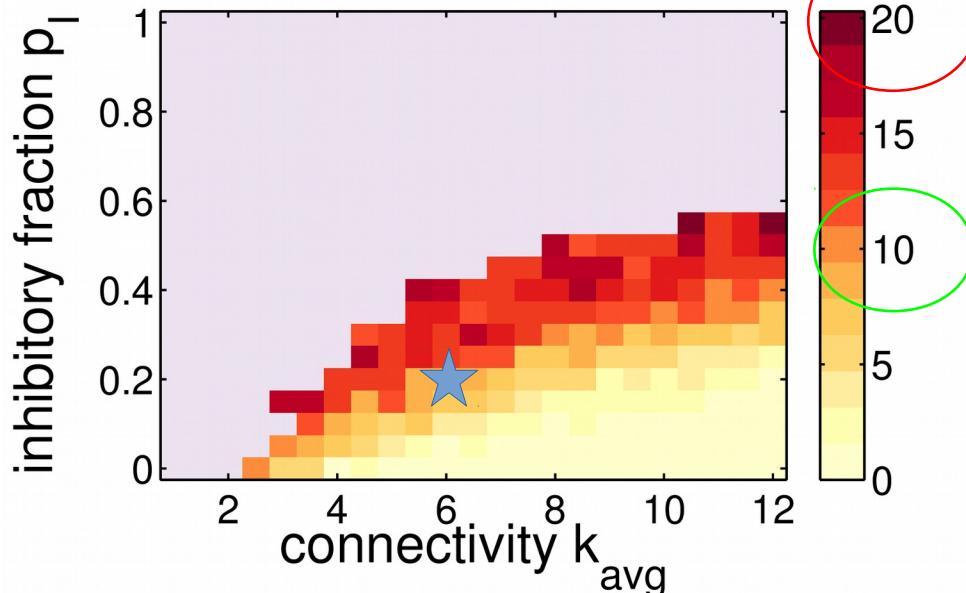
Expiratory
cells



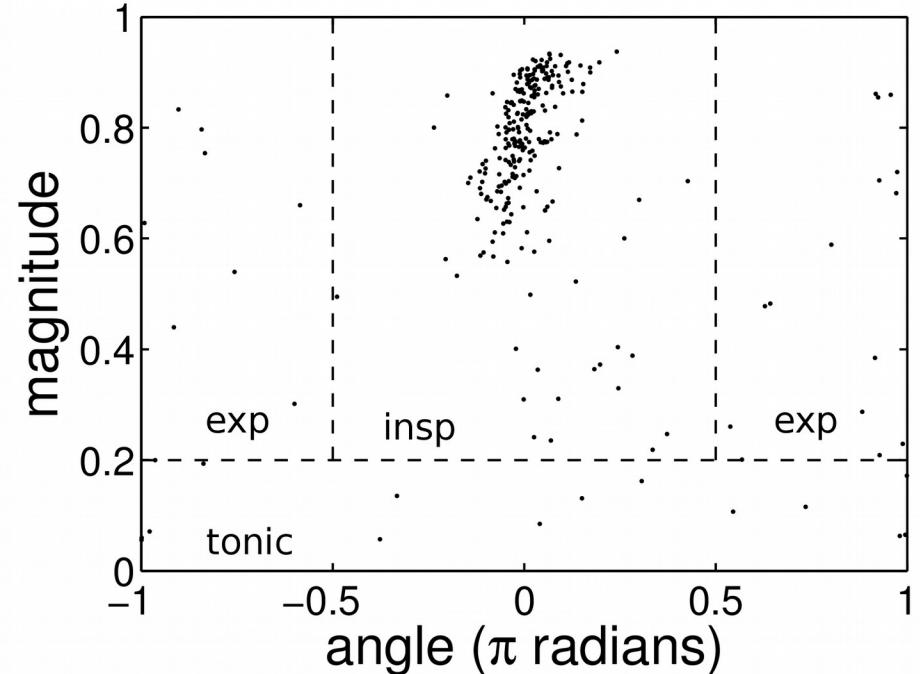
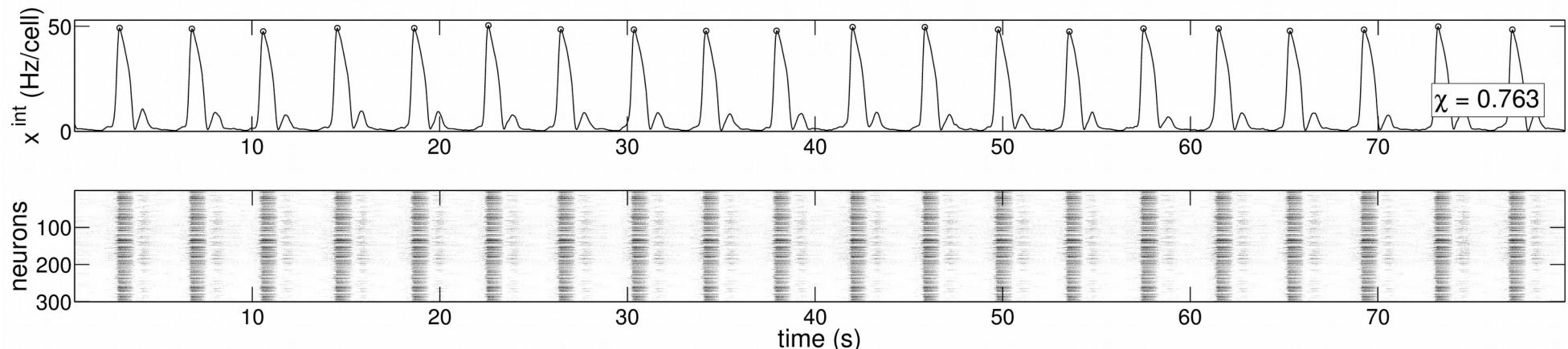
Expiratory neurons arise from inhibition

A

Percent expiratory
 $g_E = 2.0, g_I = 2.0$

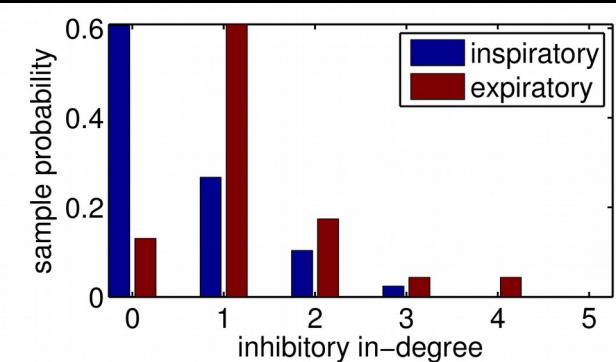
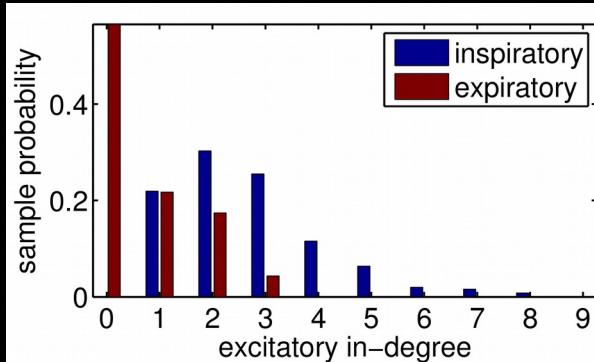
**B**

Neuron OPs

**C**

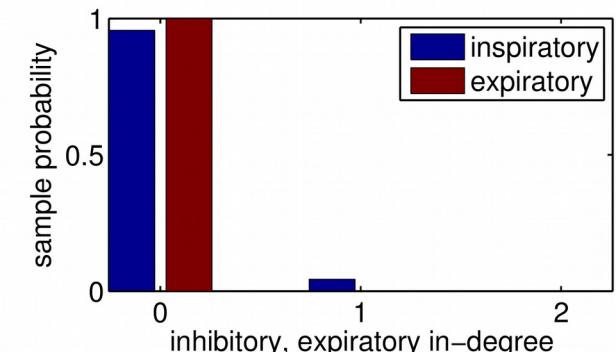
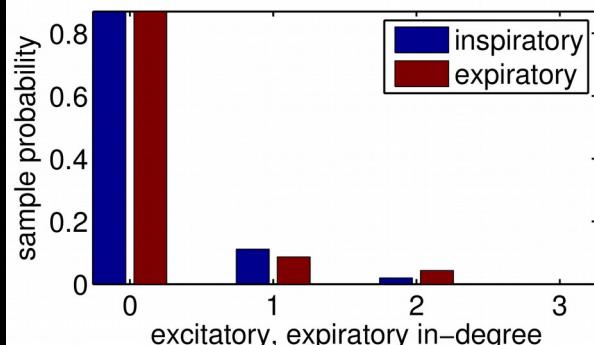
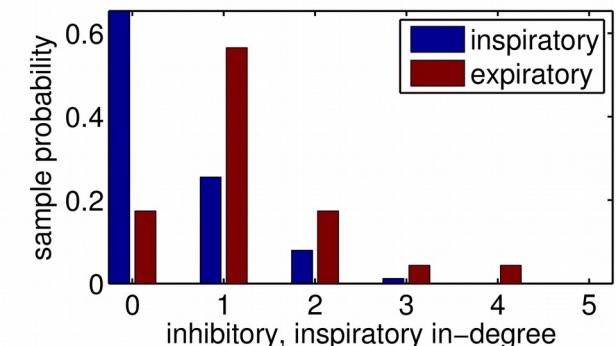
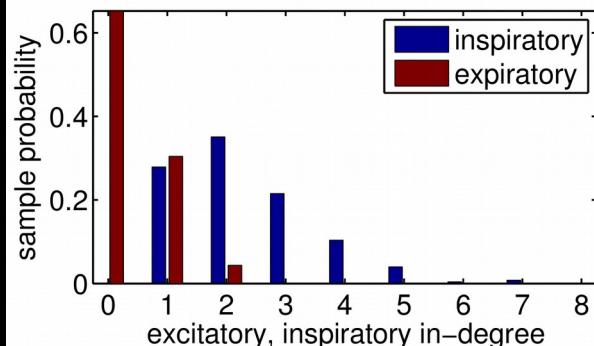
Inputs determine phase

Overall degrees:



Degrees labeled by phase:

- **Expiratory** neurons receive **less excitation**, preferentially from **other expiratory**
- **Expiratory** neurons receive **more inhibition**, preferentially from **inspiratory**
- Inspiratory is reverse



“Phases as spins” model reproduces synchrony phase diagram

Phases align/anti-align based on excitatory/inhibitory inputs

Makes sense with “binary”-like bursting neurons

We construct a spin-type model that includes both effects:

$$H = - \sum_{i < j} A_{ij}^{(E)} \sigma_i \sigma_j + \alpha \sum_{i < j} A_{ij}^{(I)} \sigma_i \sigma_j$$

Mean field theory works on tree-like graphs: sparse ER

[Dembo & Montanari 2010]

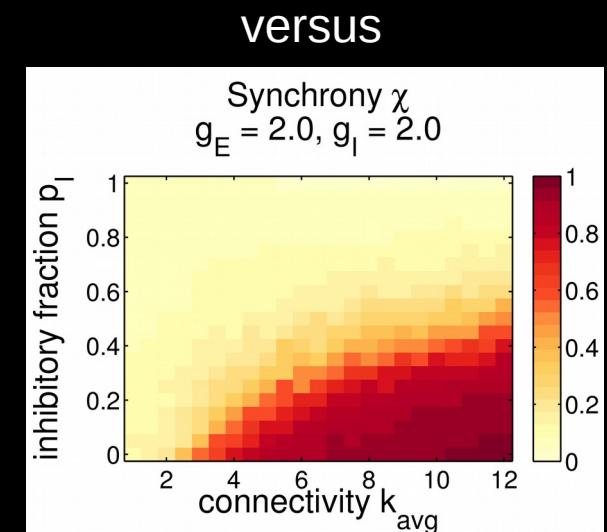
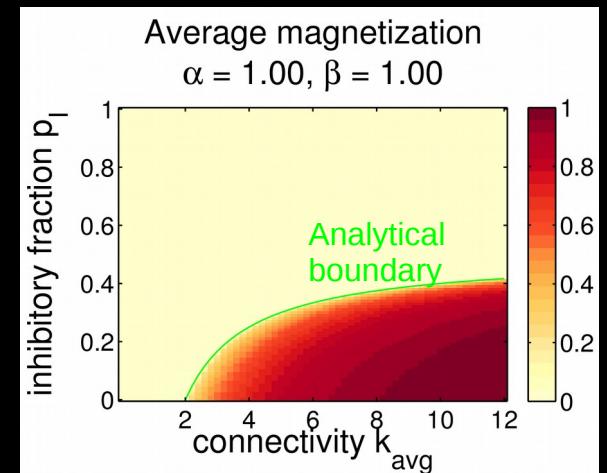
MF synchronization

$$\bar{m} = \sum_k P(k) \tanh(\beta(1 - p_I - \alpha p_I)k\bar{m})$$

Implicit equation for amount of synchronization

Yields phase boundary:

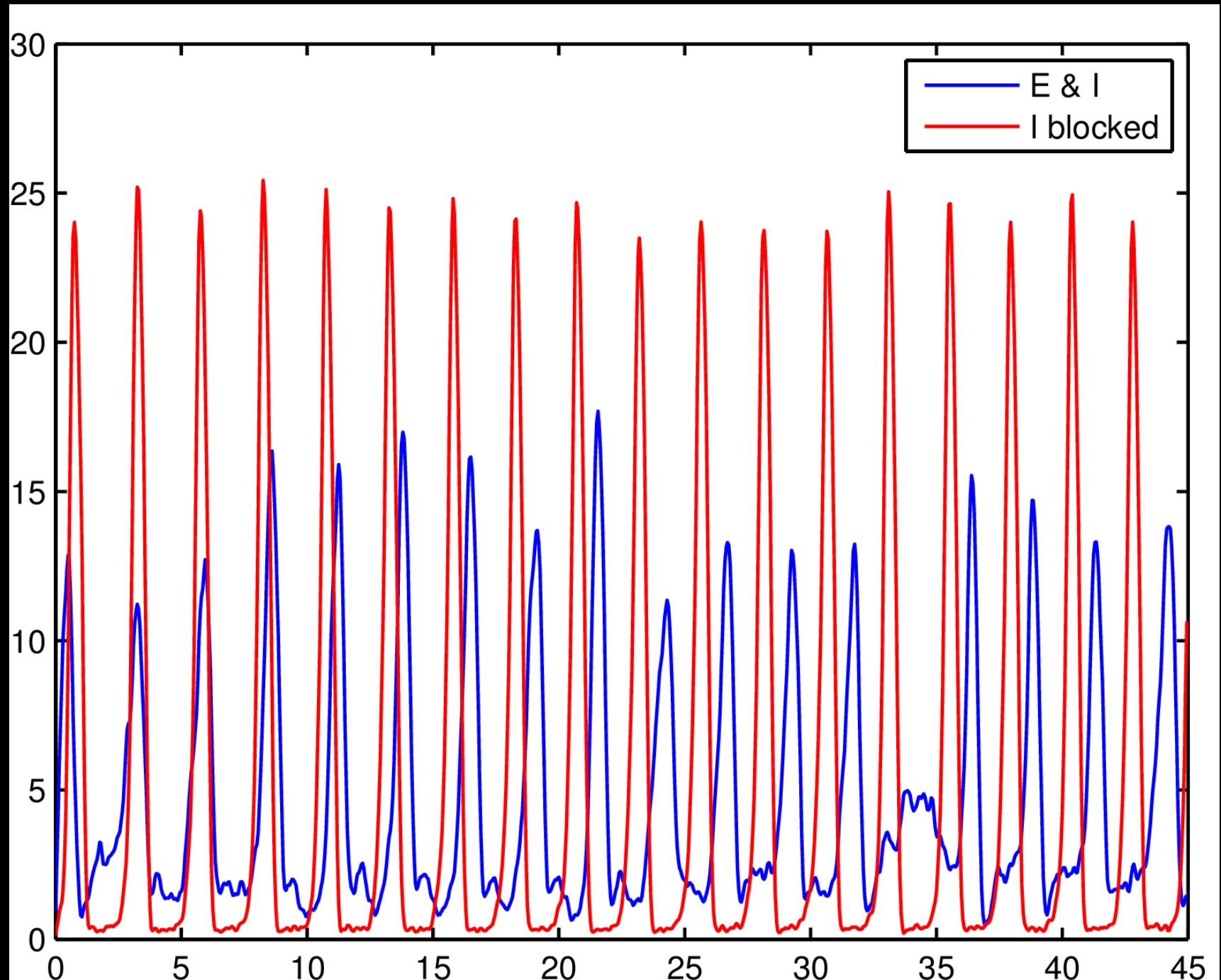
$$p_I < \frac{1}{1 + \alpha} \left(1 - \frac{1}{\beta k_{avg}} \right)$$



So what good is inhibition?

- Diversity of cell types: expiratory cells
- Shapes the rhythm – broader than w/o
- A control knob?
 - Sherman et al. (2015) deactivate rhythm w/ strong optogenetic input to Gly2 cells *in vivo*
 - Has not worked with pulse input to model... can get sharpening as found
- Gain control [e.g., Azim]
 - So far, do not see evidence of the effect in model
- More dynamic range? (have to test)

Example: inhibit I population sharpens

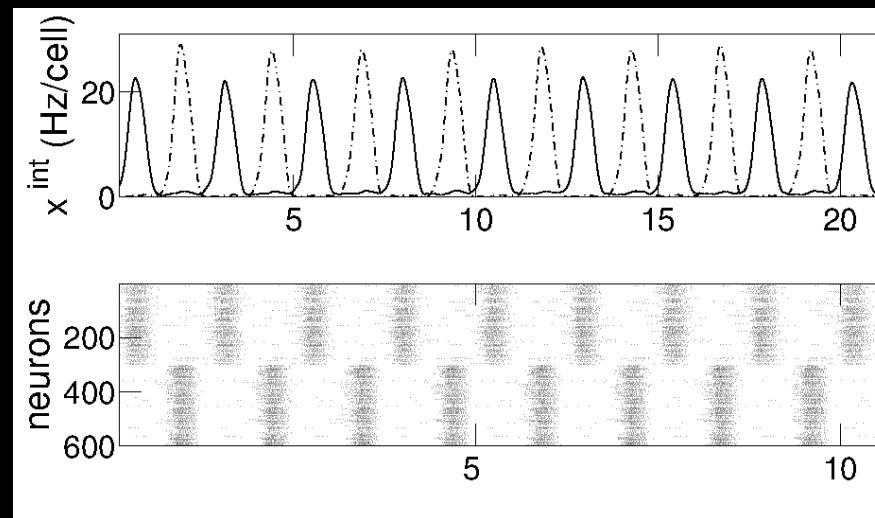
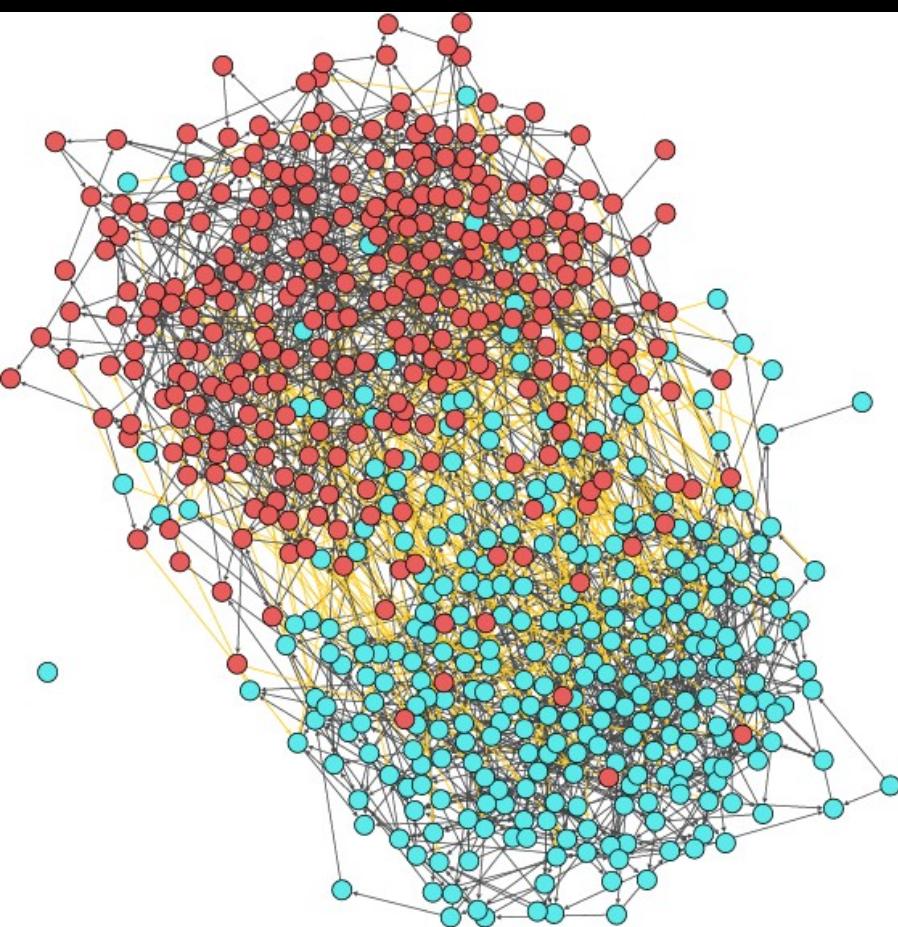


Thank you!

- My dissertation committee and collaborators:
 - Eric Shea-Brown, Ioana Dumitriu, Nino Ramirez, Stefan Mihalas, Adrienne Fairhall
 - Tatiana Dashevskiy, Tatiana Anderson, Alfredo Garcia, Aguan Wei, Joshua Mendoza
- Shea-Brown group: Yu Hu, Guillaume Lajoie, Natasha Caico-Gajic, Tim Oleskiw, Alison Weber, Hannah Choi, Braden Brinkman, Joel Zylberberg, Doris Voina
- Other conversations: Jonathan Rubin, Peter J. Thomas, Bard Ermentrout, Kresimir Josic, Brent Doiron, Chris Danforth, Peter Dodds, Nathan Kutz, Bingni Brunton
- NSF Grant #1122106, Boeing fellowship, Big Data Training Grant
- Computational neuroscience and Applied Mathematics communities at UW

How to get 50% expiratory neurons?

- PreBot & Botzinger complexes (inspiration + active expiration)
- **Add structure to network**



2-block stochastic block model

Work with undergraduate
Joshua Mendoza

Synchrony measure

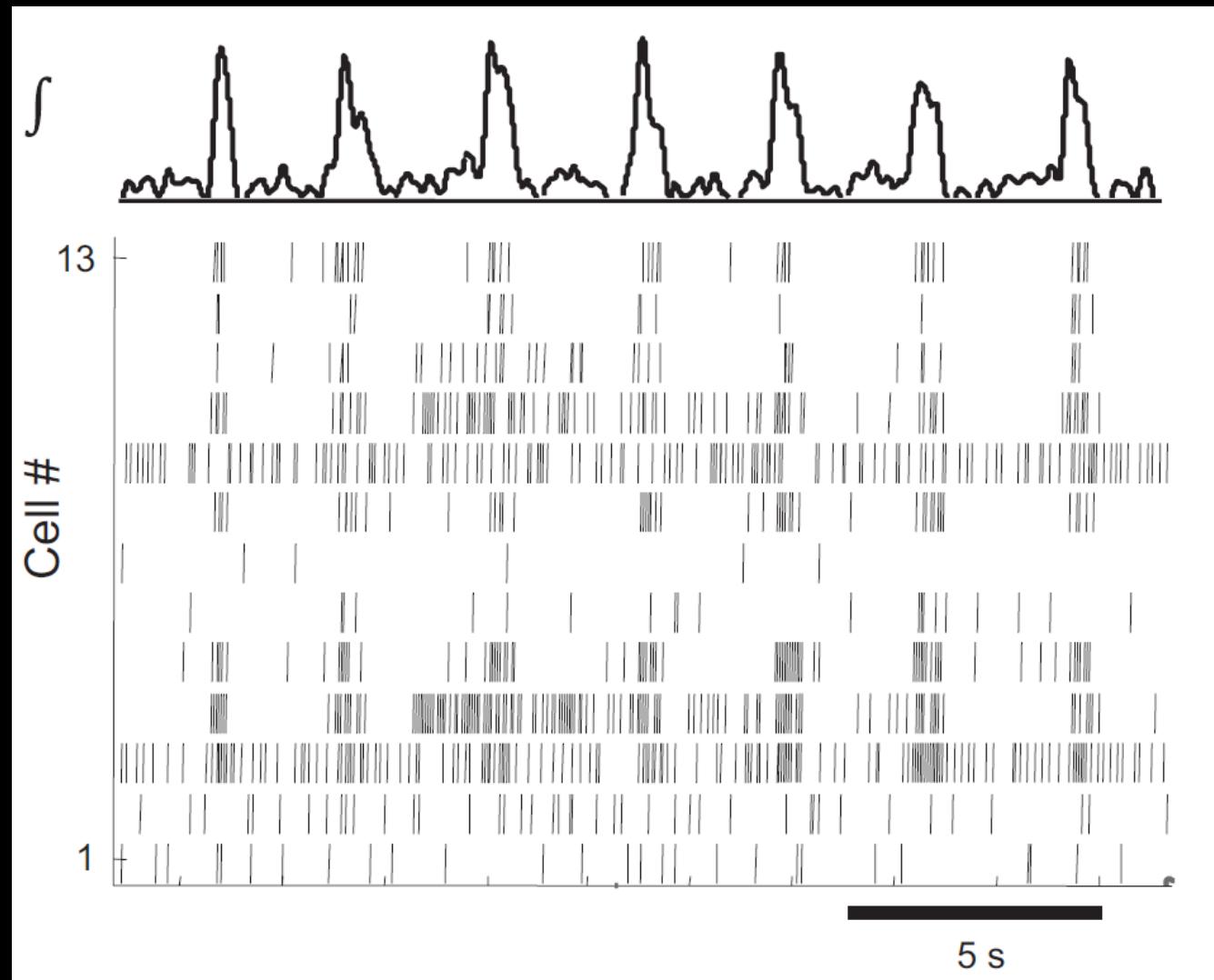
$$\chi = \left(\frac{\langle \bar{x}^{\text{filt}}(t)^2 \rangle_t - \langle \bar{x}^{\text{filt}}(t) \rangle_t^2}{\frac{1}{N} \sum_{i=1}^N [\langle x_i^{\text{filt}}(t)^2 \rangle_t - \langle x_i^{\text{filt}}(t) \rangle_t^2]} \right)^{1/2}$$

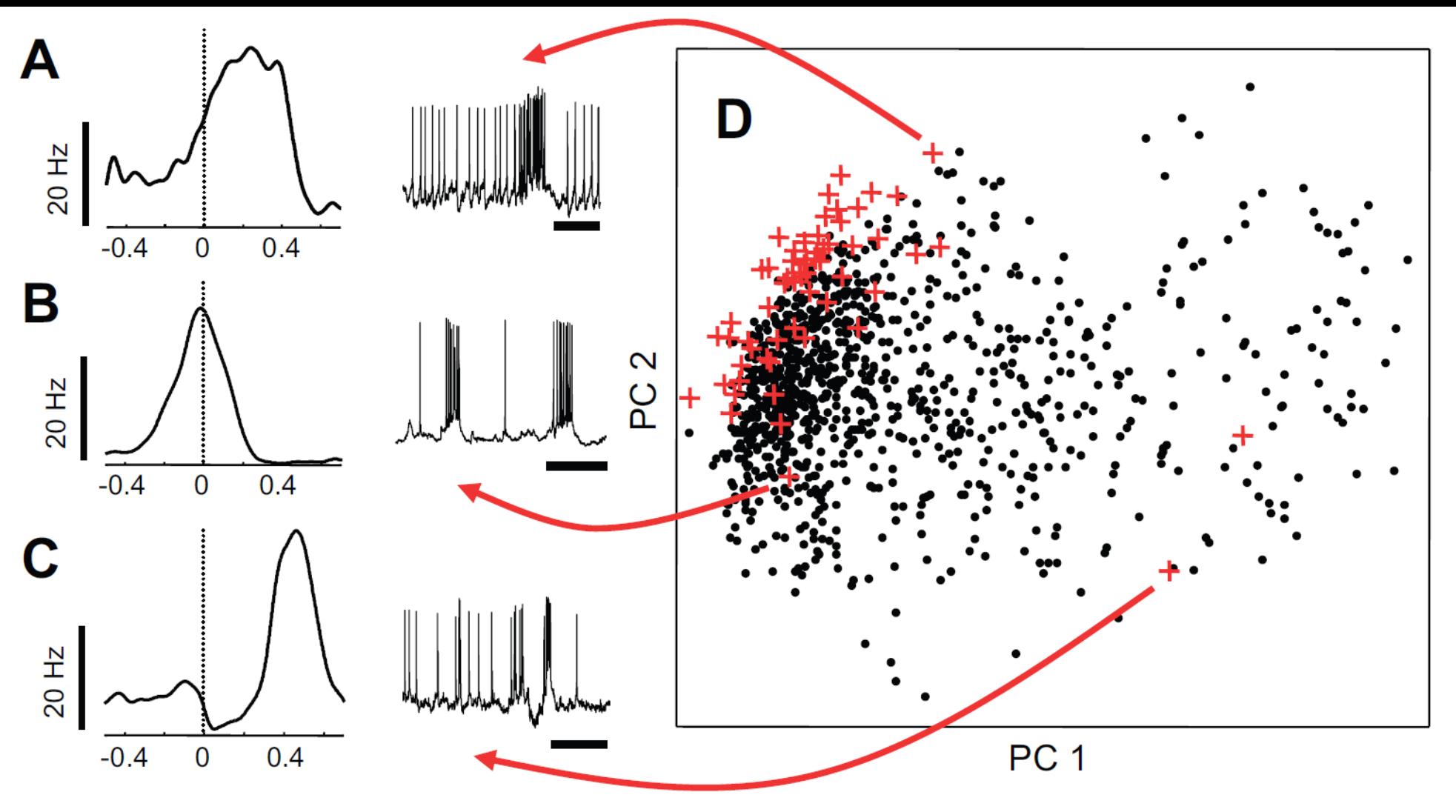
Square root of ratio of

- MS deviations of pop average to
- pop average of MS deviations

Stochastic assembly

Cycle-cycle role of individual neurons is variable





Red dots = intracellular recordings
Black dots = multielectrode