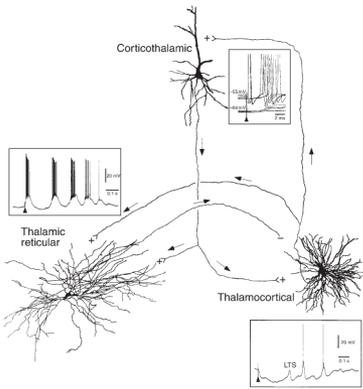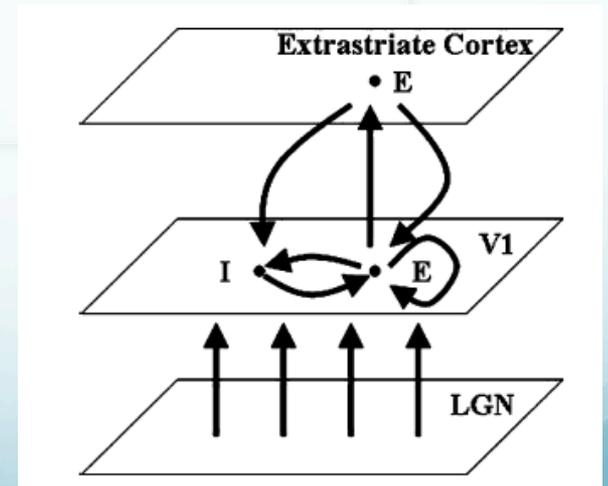# Oscillations, Synchrony, and Noise in Neural Networks

Lawrence Ward
University of British Columbia

$$\tau_E \frac{dm}{dt} = -m + \left[S_{EE}m - S_{EI}n + I_E \right]$$

$$\tau_I \frac{dn}{dt} = -n + \left[S_{IE}m - S_{II}n + I_I \right]$$

Preview

- Gamma bump

- Theta, alpha, beta, gamma oscillations

- Noise effects=>stochastics

- Stochastic phase locking

- Noise affects neural synchronization

- Plethora of models and data.

- Large populations

- What are small neural networks good for?

The gamma bump in LFP

- Jia, Kohn 2011, *PLoS Biol*

- Gamma: 30-50 Hz rhythm in EEG, MEG, LFP

- Gamma power increases with sensory drive, attention, and numerous other cognitive phenomena

- High gamma (>50 Hz) probably reflects MUA (maunsell

- Gamma up => lower frequencies down
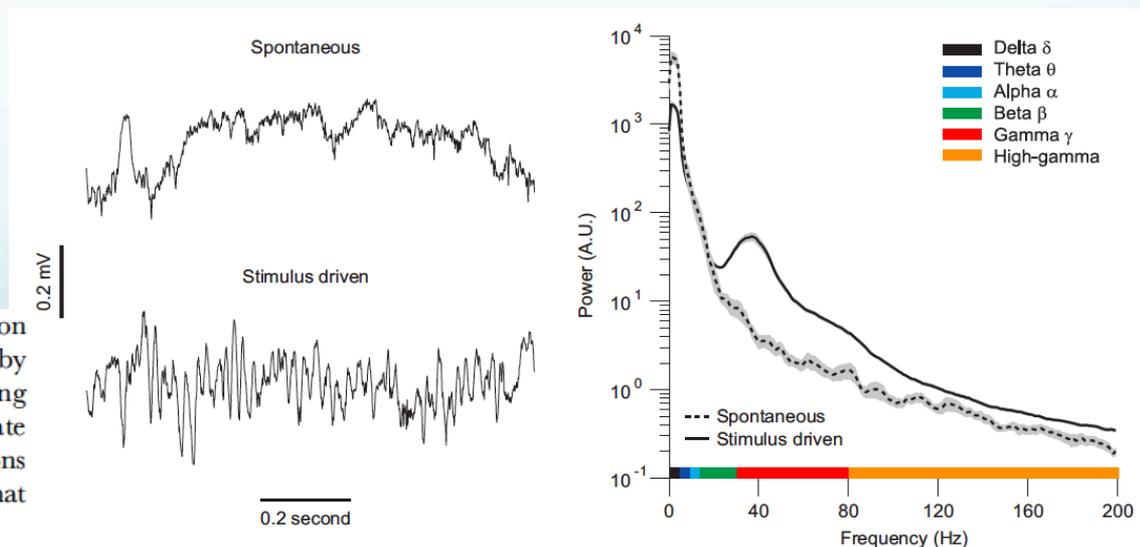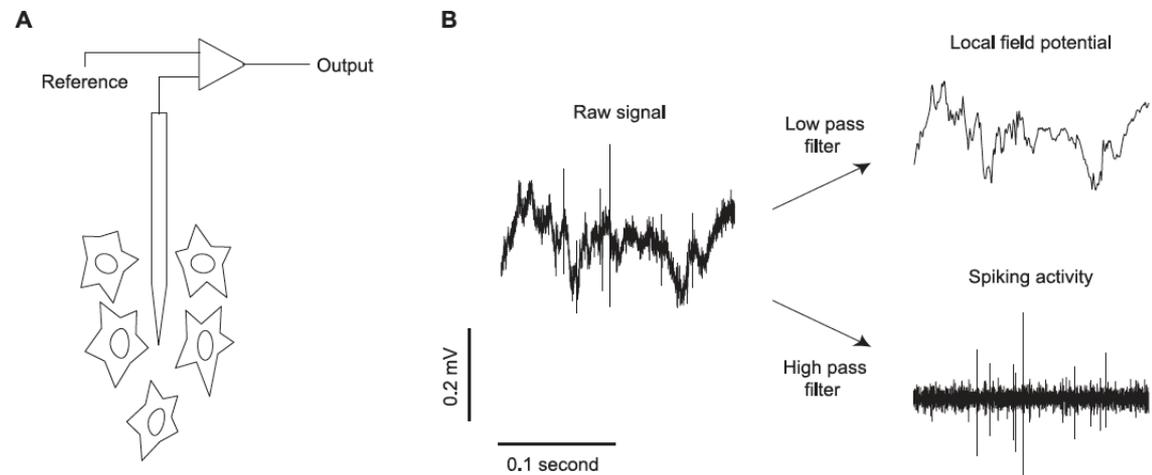
network dysfunction. To move beyond the interesting correlation between these rhythms and brain state, like those first described by Berger, we need a better understanding of the underlying generative mechanisms, the way in which these signals modulate spiking activity, and the effect they have on the computations performed by neuronal networks. Only then will we know what role, if any, gamma plays in cortical function.

Hippocampal networks generate gamma (and theta) in vitro

- Bartos, et al., 2007, *Nature Rev Neurosci*

- CA1/CA3 recording of exracellular field in hippocampal slice

- Gamma blocked by $GABA_A$ antagonist bicuculline

- CA1 (c-right) gamma not affected by AMPA antagonist

- CA3 gamma abolished by AMPA antagonist NBOX
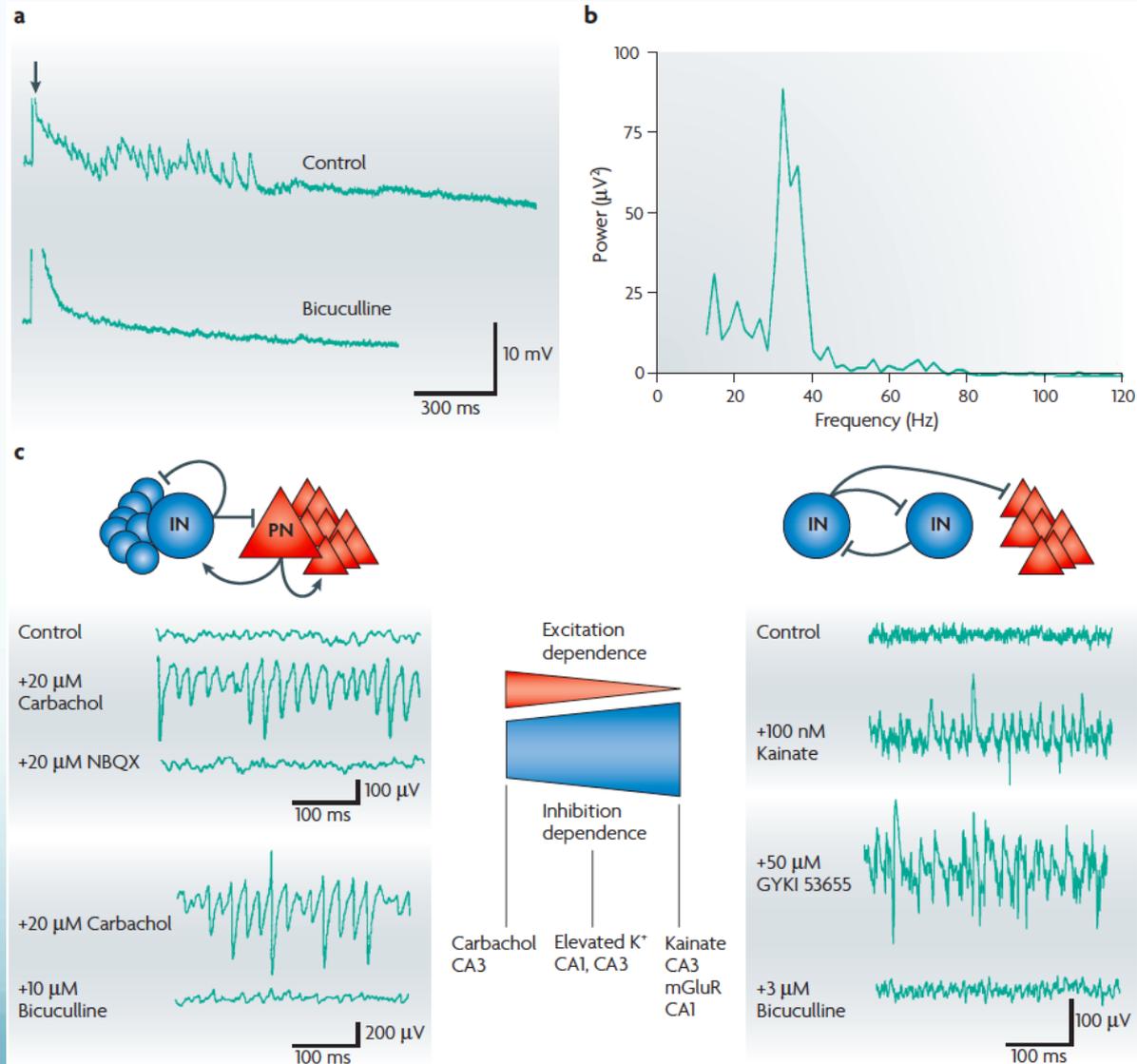
Noise is ubiquitous and various

**Table 2 | Biologically relevant sources of noise that may contribute to stochastic facilitation**

Noise Source	Description
Thermal noise	Also known as Johnson noise, thermal noise arises from random thermal agitation of charge carriers in electrical conductors, and appears as fluctuations in membrane potentials.
Stochastic molecular diffusion	Molecular interactions during calcium signalling in dendritic spines is inherently stochastic owing to diffusion, with potentially important consequences for synaptic plasticity.
Crosstalk noise	Spillover of synaptic vesicles to adjacent neurons can lead to unpredictable variability, as potentially could ephaptic coupling, whereby the electric field produced by adjacent neurons may cause changes in their membrane potentials.
Synaptic neurotransmitter release	Both the number of neurotransmitter molecules released from synaptic vesicles and the number of activated postsynaptic receptors seem to be random variables, and thus lead to stochastic variability in action potential generation.
Short-term plasticity	Several interacting effects can mean that even spikes that arrive regularly at axonal terminals may lead to irregular postsynaptic events. These effects include facilitation, adaptation, depression and recovery as well as the stochastic release of neurotransmitters from vesicles.
Ion channel gating and membrane noise	The stochastic nature of the opening and closing of ion channels is well known. This leads to fluctuations in neuron membrane potentials, and in turn affects action potential generation.
Synaptic barrages	Pyramidal neurons can have many thousands of synaptic connections with other neurons, and the numerous input events from these can lead to the neuron's membrane potential being in a state of increased or decreased, or fluctuating, conductance. This can have profound effects on the neuron's spiking properties.
Diversity owing to stochastic gene expression	Intrinsic biophysical properties vary over populations of neurons and have been shown to benefit neural coding. The notion that this kind of variability can lead to benefits is sometimes called diversity-induced resonance.
Network connectivity	Cortical neurons form connections with many other cortical neurons to form irregularly structured networks.
Sensory inputs	Disturbances can be extrinsic (such as background visual clutter) or intrinsic to biological transduction mechanisms.
Motor noise	Movements induced by muscle fibres are subject to variability through several mechanisms.

Stochastic phase locking

- Gray & Singer, 1989, PNAS synch at 40 Hz in cat V1

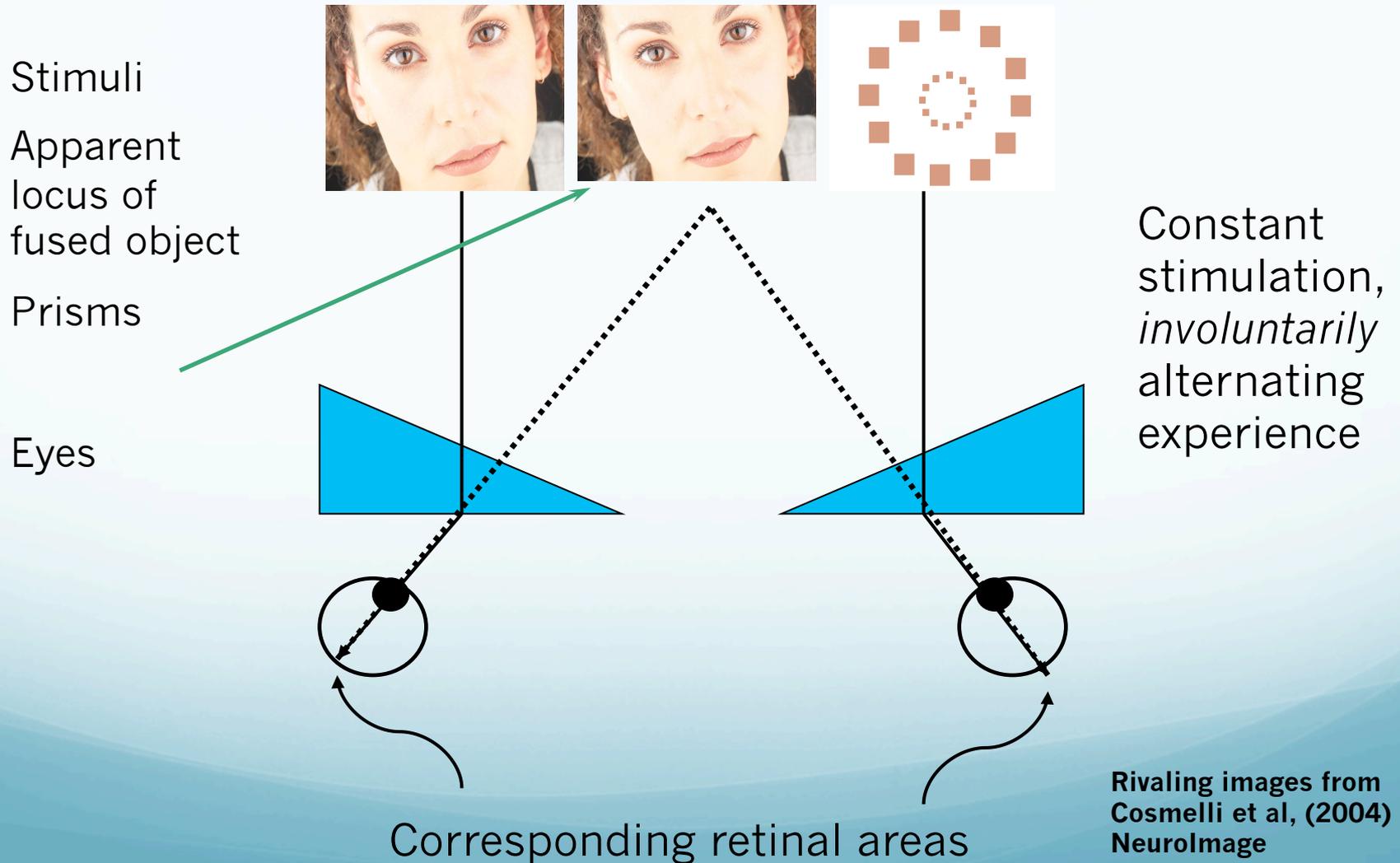- Found in spikes, LFPs, MUAs (but not always)

- Inferred from correlogram

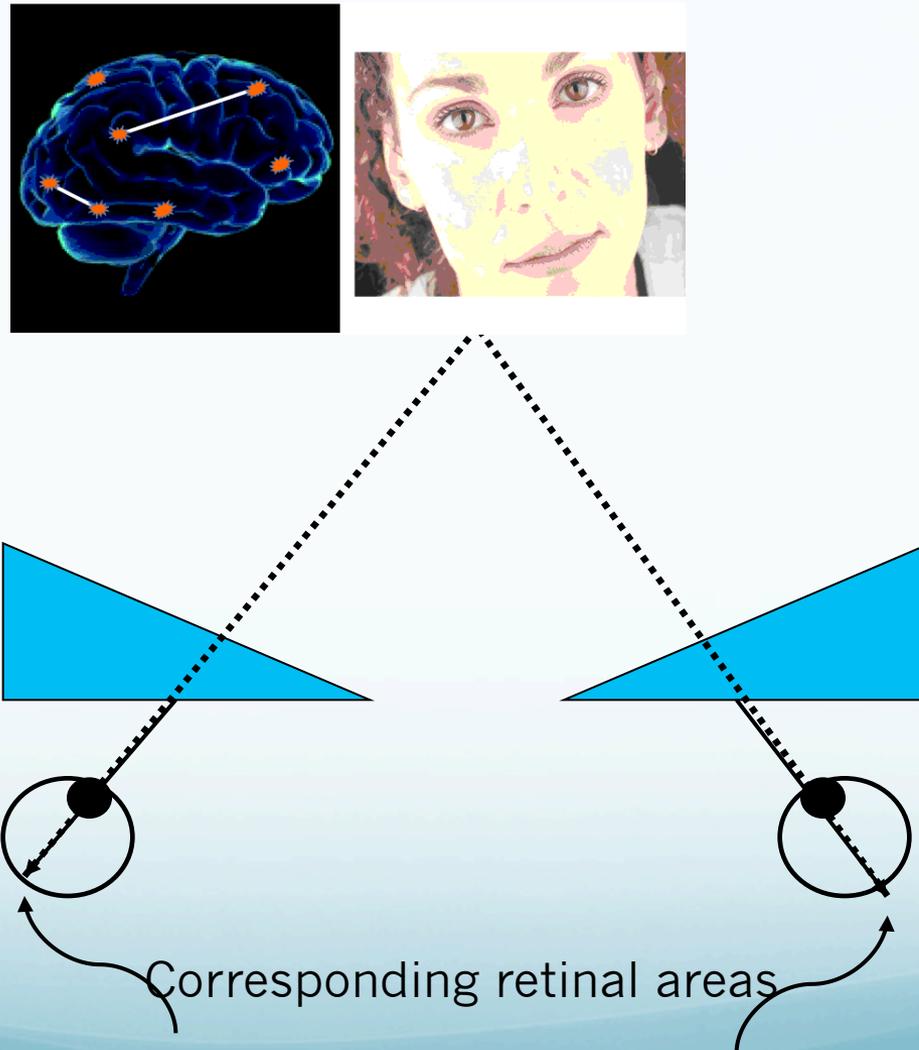Varela et al, 2001, *Nature Rev Neurosci*.
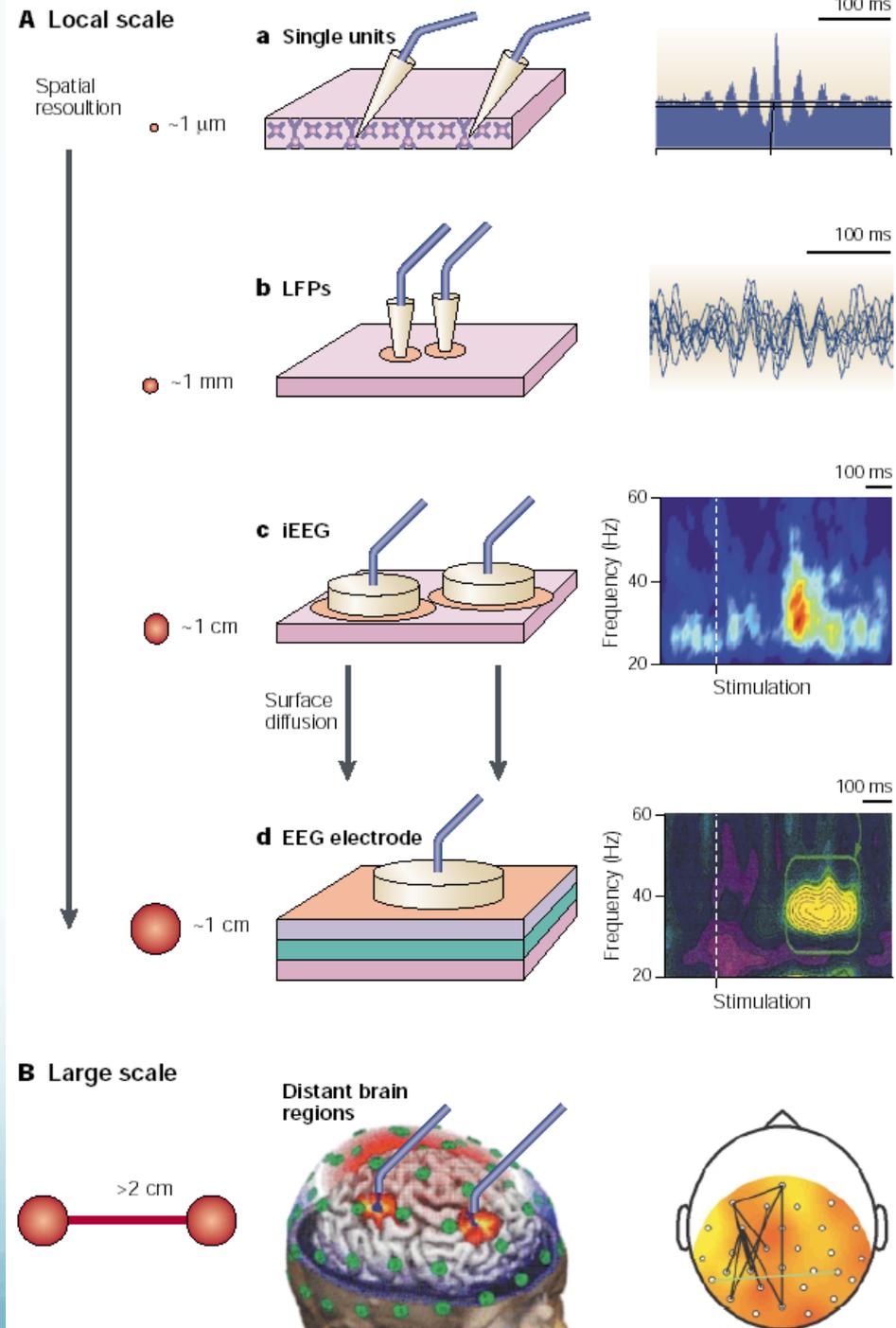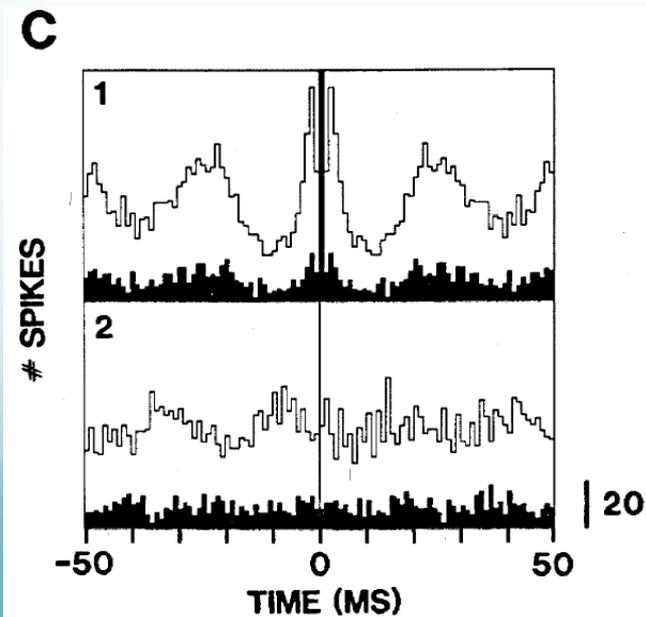
Neural synchrony supports coarse coding
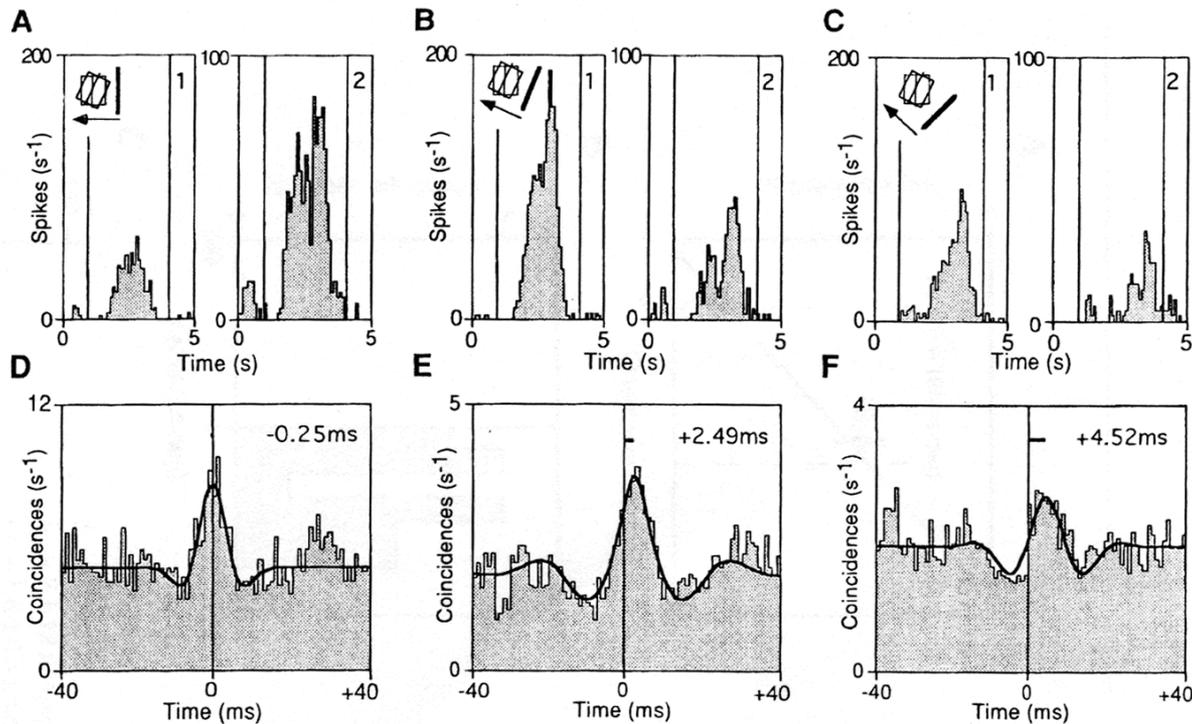
- Optimally and sub-optimally stimulated neurons synch within few ms
- Optimally-stimulated lead in phase
- True for orientation, direction of motion, spatial freq

König, Engel, Roelfsema, Singer, *Neural Computation*, 1995, Fig 2

Synchronization: Binocular rivalry

Stimuli

Apparent locus of fused object

Prisms

Eyes

Constant stimulation, *involuntarily* alternating experience

Corresponding retinal areas

Rivaling images from Cosmelli et al, (2004) NeuroImage

Binocular rivalry: a window to the neural correlates of consciousness

Constant stimulation, *involuntarily* alternating experience

Corresponding retinal areas

Rivaling images from Cosmelli et al, (2004) NeuroImage

Noise affects synch
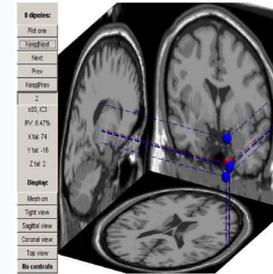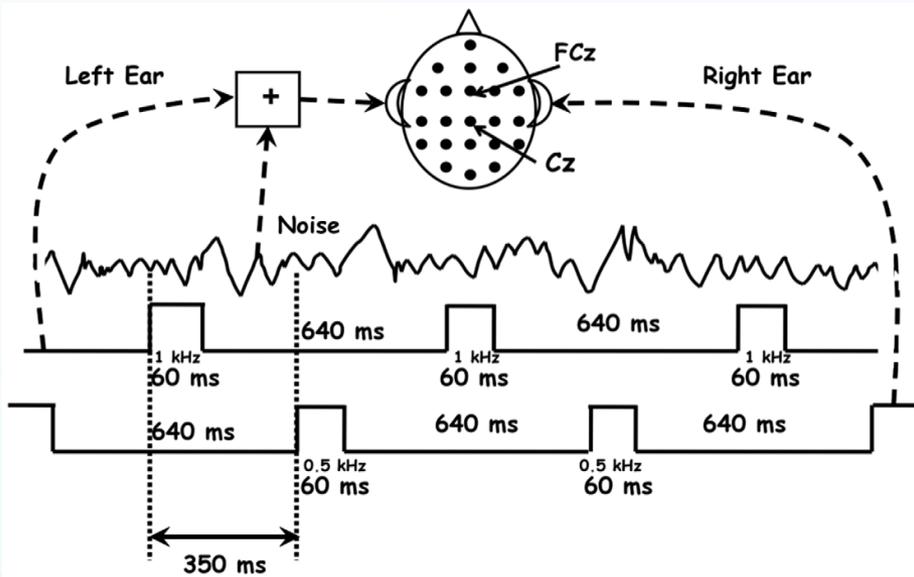
Right Superior Temporal Gyrus
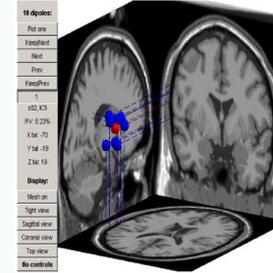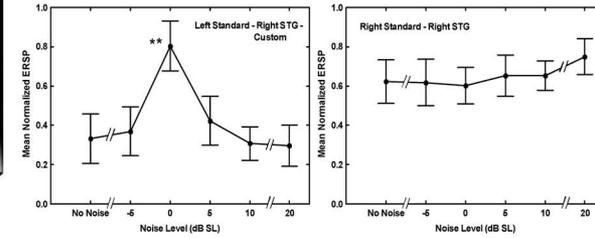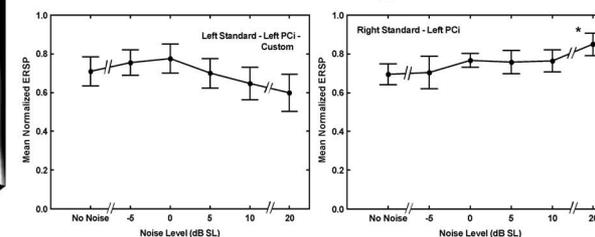
Left Superior Temporal Gyrus
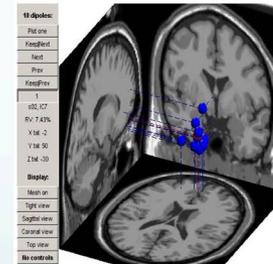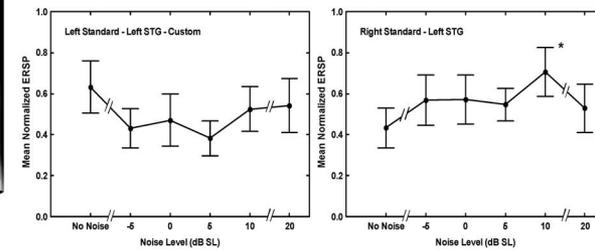
Left Superior Frontal Gyrus
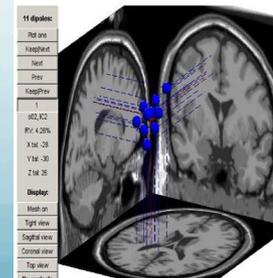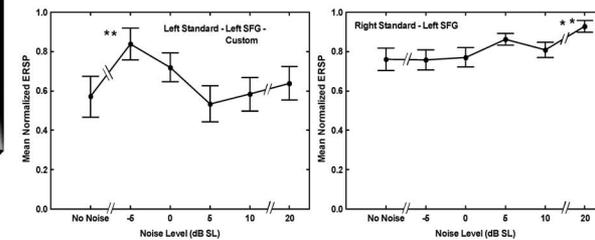
Left Posterior Cingulate

Ward, McLean, Kirschner, 2010, *PLoS One*

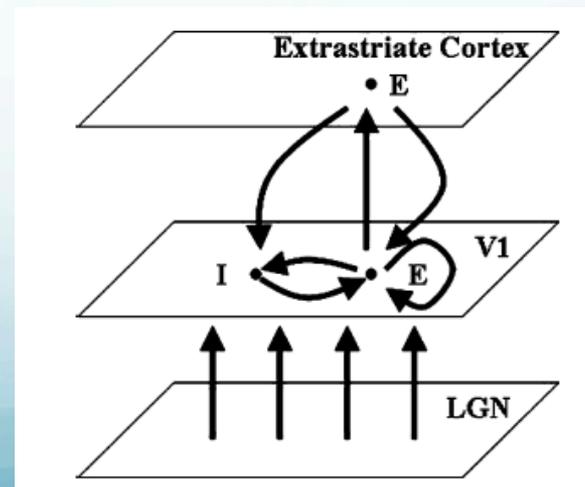# Plethora of models

- Neuron models: IF, LIF, FN, HH, ML, Iz, etc.
  - 1-2 differential equations, stochastic or not, V, V^2, V^3, resetting or oscillating
 - Class 1 (output follows input) vs Class 2 (no low frequency spike trains)
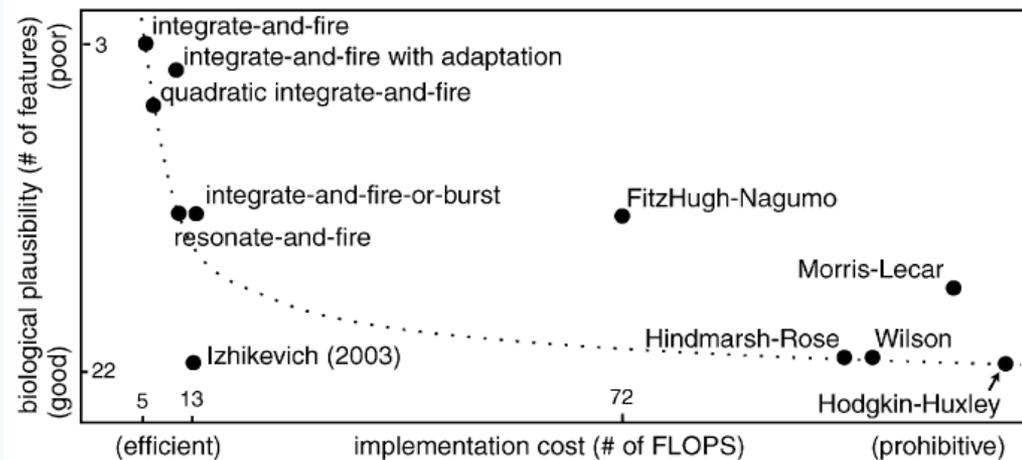
- Motifs

- Topologies

- Populations

- Regional interactions

Large networks popular for population coding

- Two channels: mean and variance

- Mean firing rate increases if excitation up and inhibition down or vice versa

- If both in same direction, variance increases

- Population firing rate encodes input changes that single neuron can't

Tchumatchenko, Wolf, 2011, *PLoS Comp Biol*
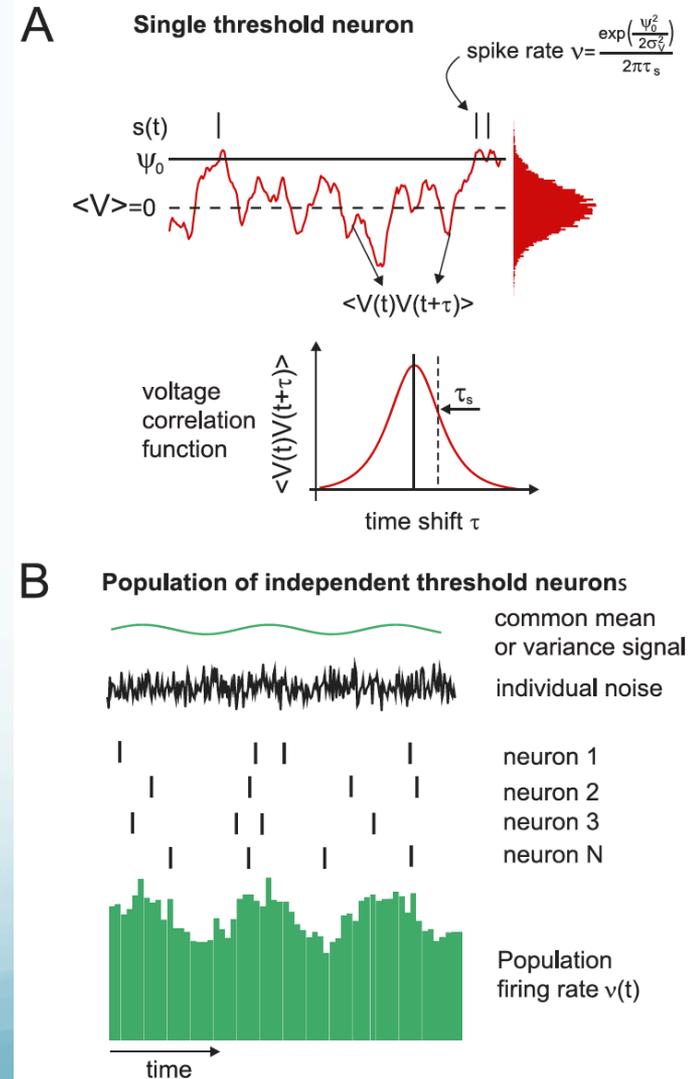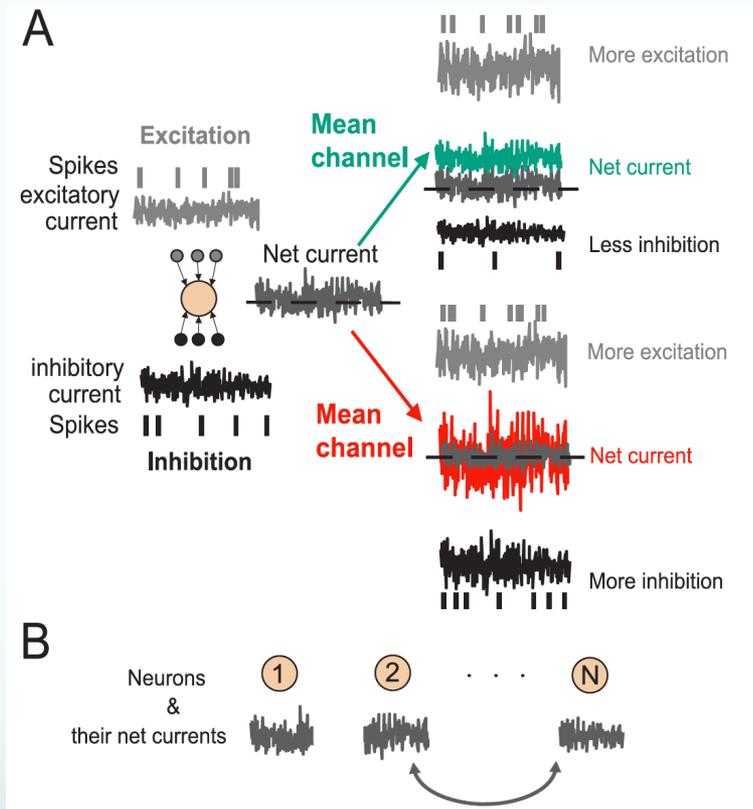
"Large" population model of V1

- Mazzoni et al (2008): gamma oscillation modulated by stimulus intensity (signal rate)

- Information transmission in low and high frequency channels

- 4000 E and 1000 I

- Erdös-Rényi LIF network with p_c=0.2

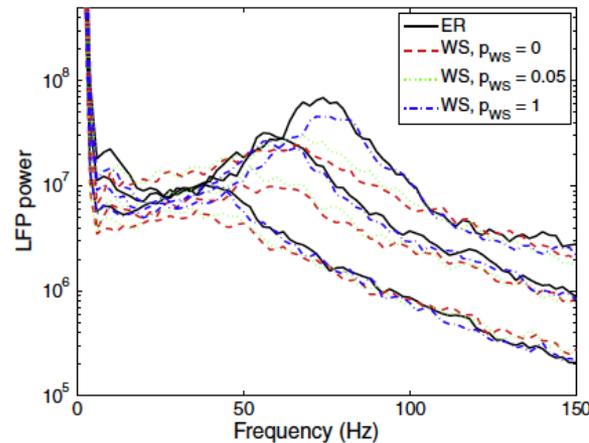- A=AMPA; G=GABA synapses

- Signal and noise from thalamic (LGN) input
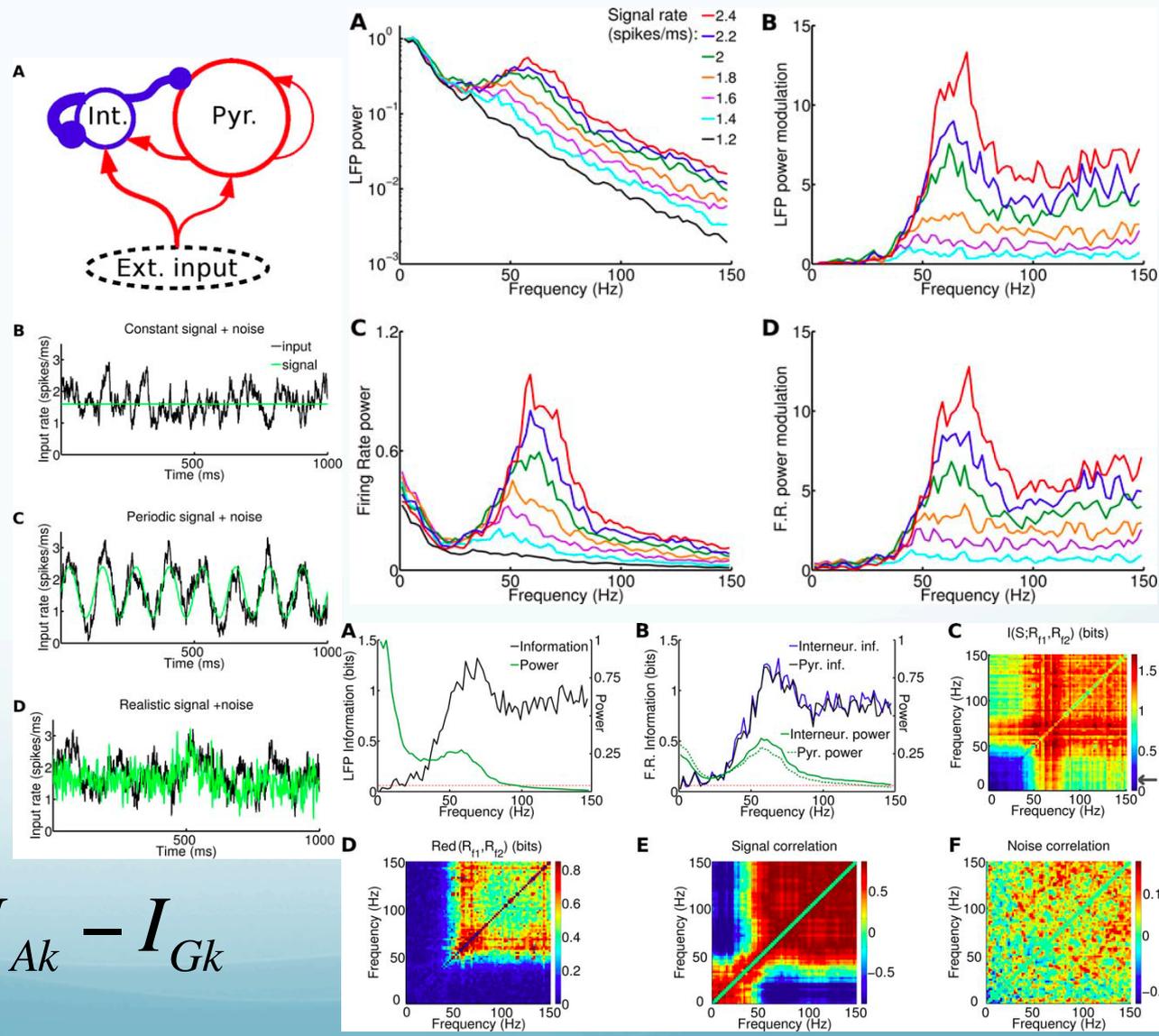
$$\tau_m \frac{dV_k}{dt} = -V_k + I_{Ak} - I_{Gk}$$

Topology, plasticity and motifs

- McDonnell, Mohan, Stricker, Ward (2012, *Brain Res*) studied Mazzoni et al model further

- Erdös-Rényi vs Watts-Strogatz small world: V1 probably E-R as W-S decreases gamma modulation by stimulus intensity

- Synaptic delay ≤ 2 ms

- No plasticity vs Type 1 (transmitter-release dependent depletion and constant recovery) vs Type 2 (release-independent depletion and frequency-dependent recovery): Type 2 plasticity decreases gamma power and produces beta modulation
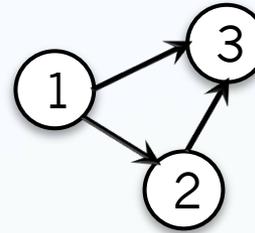
- Latter result may depend on ratio of motifs – loop vs no loop - more later
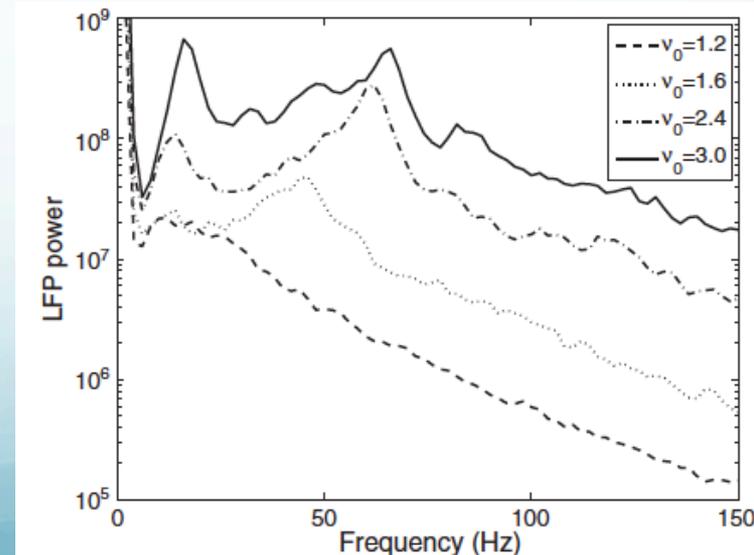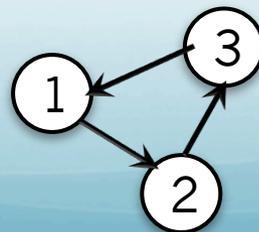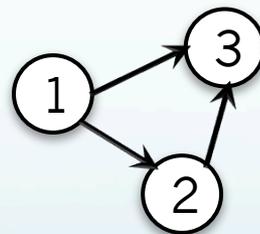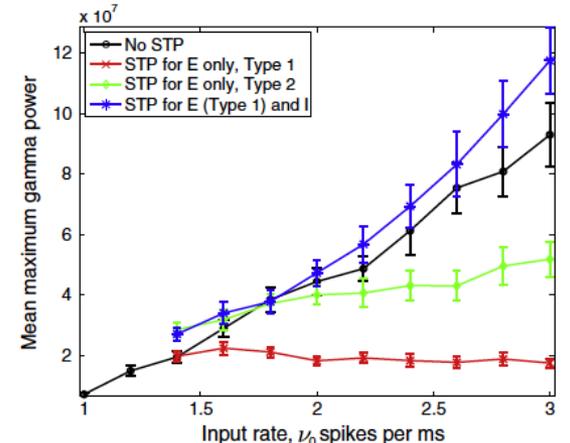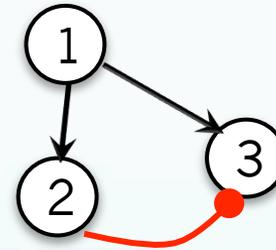
Motifs cont'd

- Guo & Li, 2009 PRE: effect of FFL motif on SR and CR

- 1=input; 3=output

- Izhikevich neurons: E regular spiking, I fast spiking

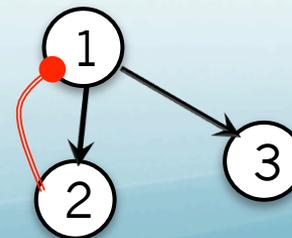- Both SR and CR of membrane potential affected by motif and coupling strength

Feed Forward Loop: FFL EEE

FFL EIE

FFFBL EIE ?

Large population models, cont'd

- Burns et al., 2011, *J. Neurosci*: V1 gamma bump is not a "clock" but filtered noise?

- Kang et al. 2010, *J. Comp Neurosci*: attempt to explain spectral peaks in V1 LFP

- "Large population" of neurons modeled by mean field conductance rate equations

- Power spectrum with peak around gamma

- System resonates at 40 Hz and f_{res} varies with extrastriate feedback as *in vivo*

- Required strong inhibition to get effects seen in data
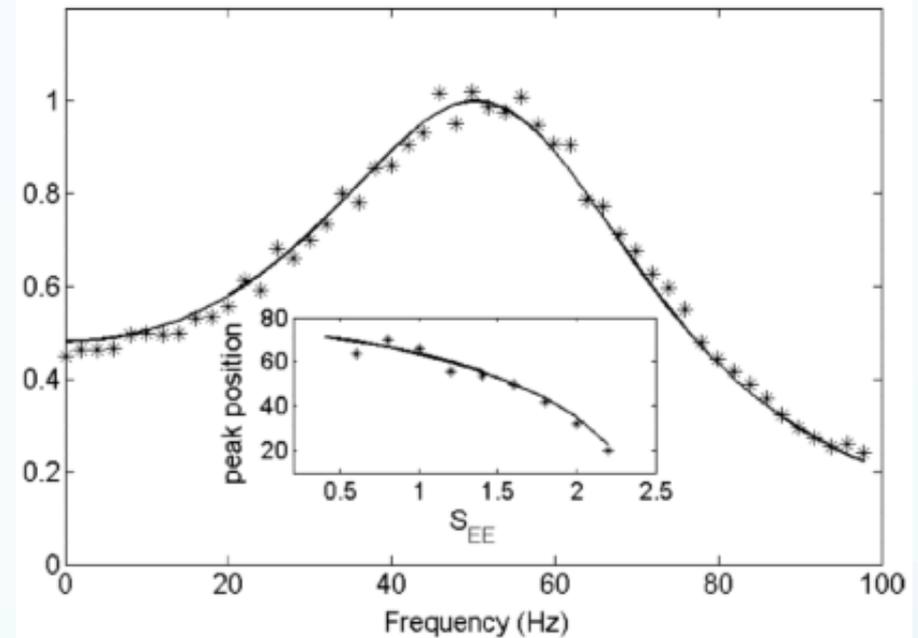
$$\tau_E \frac{dm}{dt} = -m + \left[S_{EE}m - S_{EI}n + I_E \right]$$

$$\tau_I \frac{dn}{dt} = -n + \left[S_{IE}m - S_{II}n + I_I \right]$$
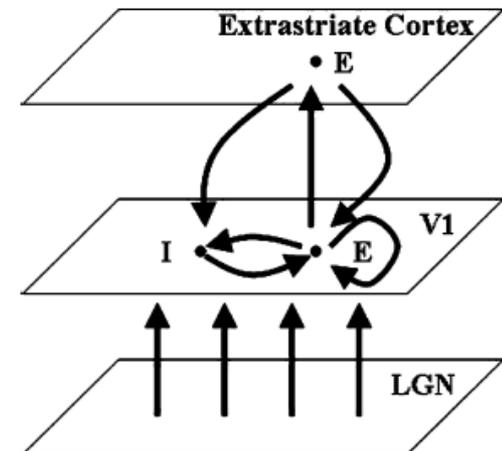
What are small network studies good for?

- Oscillation, timing, synchrony

- Temporal coding

- Motifs

- Computation?

- Information transfer?

- Effects of neuron model properties on network activity

- Which phenomena scale up to large networks?

- ???