



# Epileptogenesis in Small World Neural Networks of the Hippocampus

Rob Clewley<sup>†</sup>

Department of Mathematics, Cornell University

Theoden Netoff<sup>†</sup>, Scott Arno<sup>†</sup>, Tara Keck<sup>†</sup>, John White

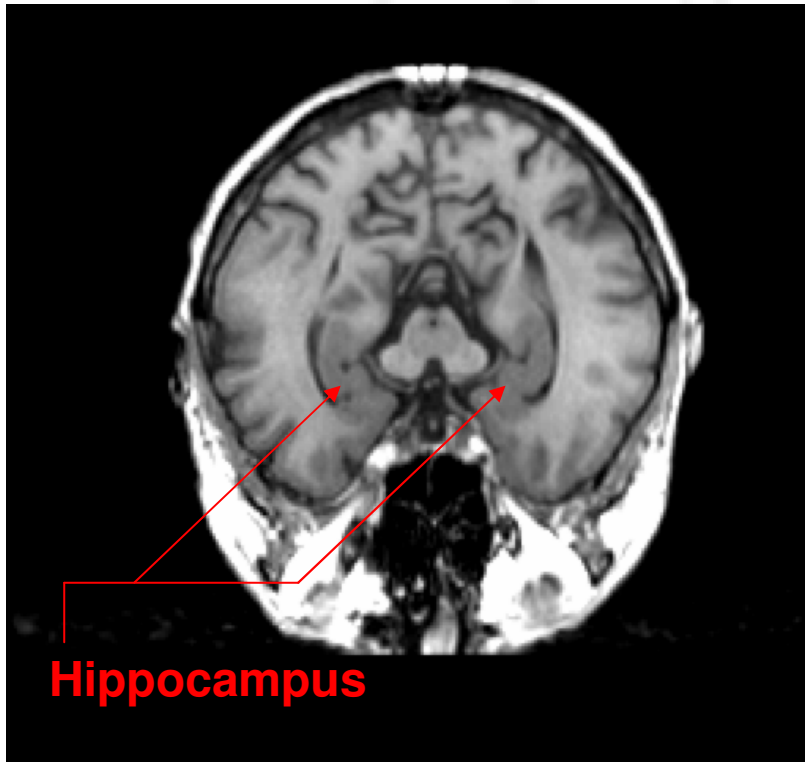
Center for BioDynamics, Boston University

(<sup>†</sup>former members of CBD)

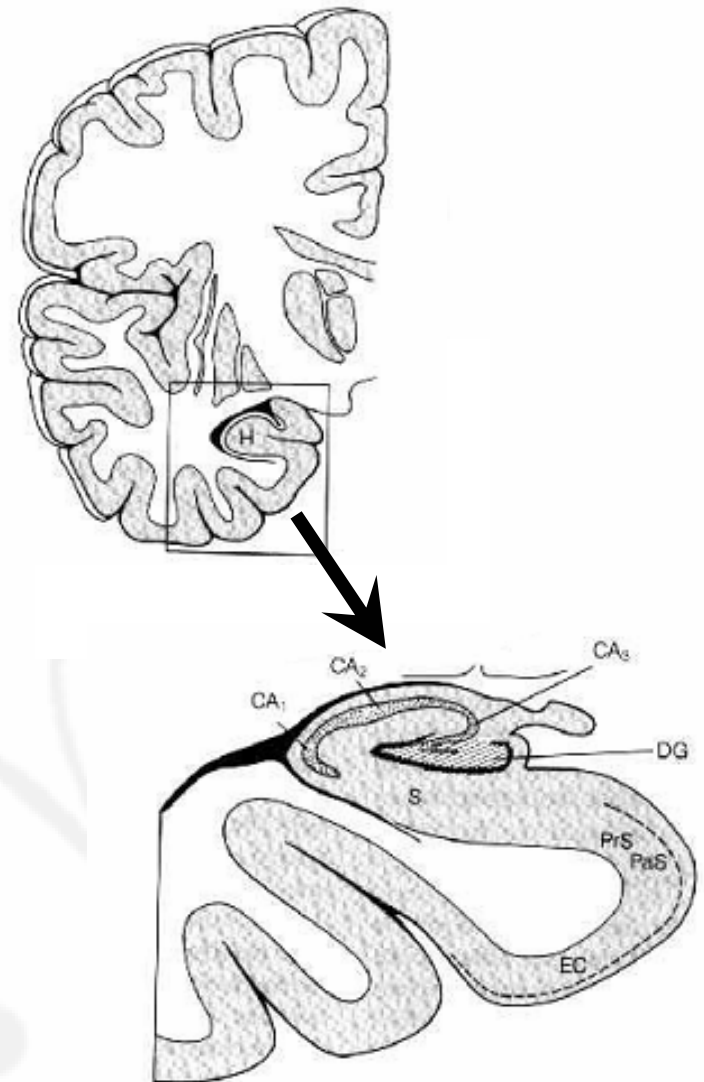
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# The Hippocampus

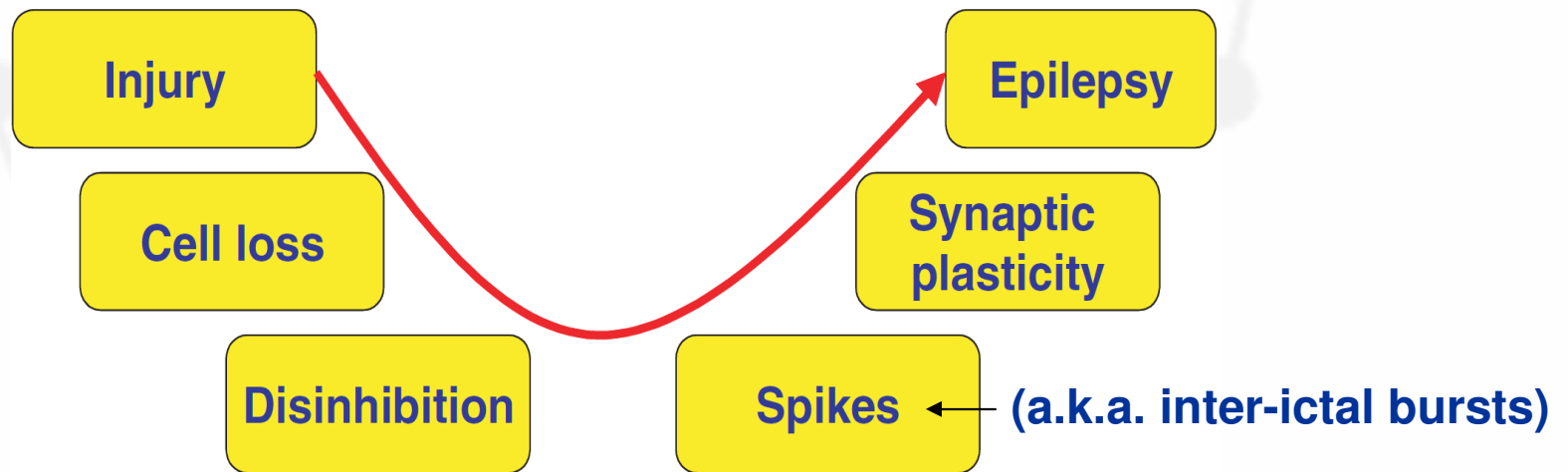


- Memory and learning
- Anatomically well-defined
- Temporal lobe epilepsy



# Models of epileptogenesis

- Typically involve multiple steps ...
- Long-term changes (esp. permanent)
- Short-term changes (esp. non-permanent)
- These involve connectivity changes



(Staley et al, 2005)

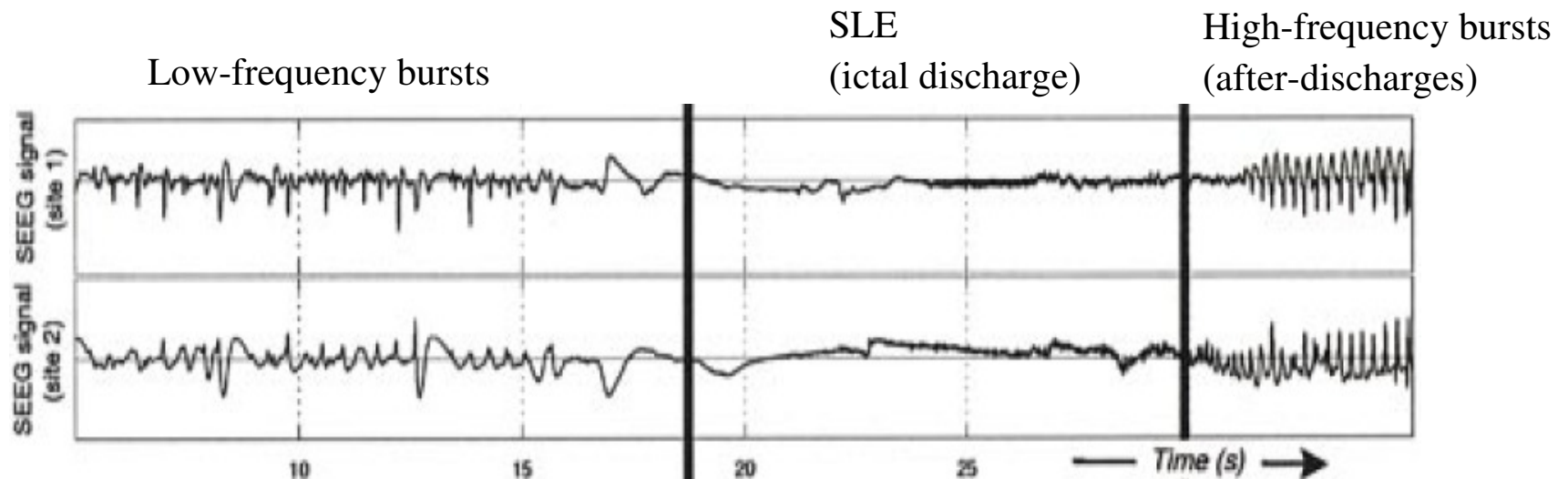
# Primary objectives



- Epilepsy and network connectivity
  - What is the relationship?
  - Can it explain why epileptics have two types of epileptic activity?
    - Some networks “burst”
    - Others “seize”
- How does connectivity interact with other physiological parameters?

# What are seizures?

- Seizure-like events  $> 1s$
- Inter-ictal bursts  $\sim 0.1s$
- Relationship poorly understood
- Population bursting vs. individual neural bursting  
(Shao et al., 2006)



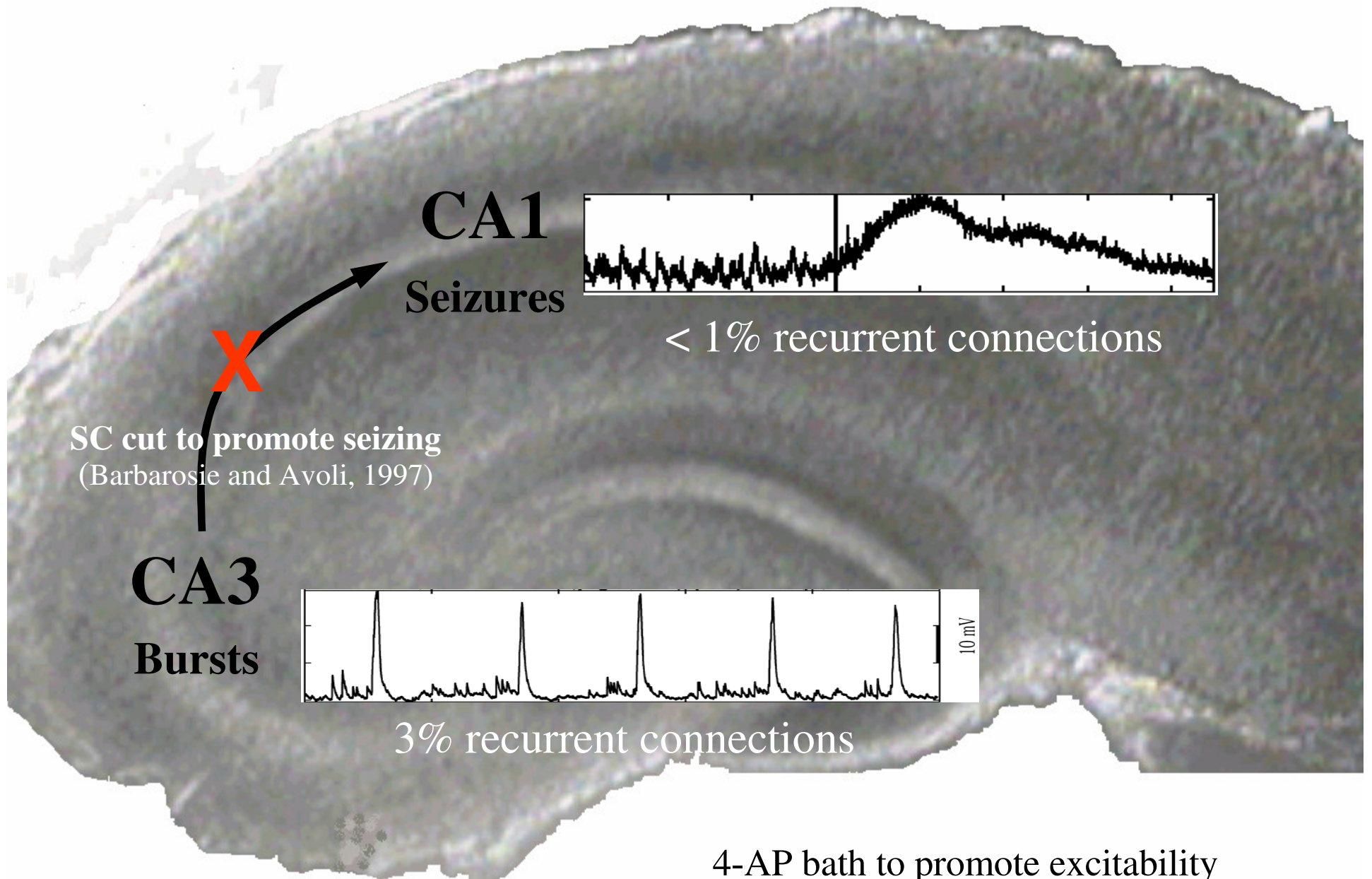
(Wendling et al, 2003)

# What are seizures?

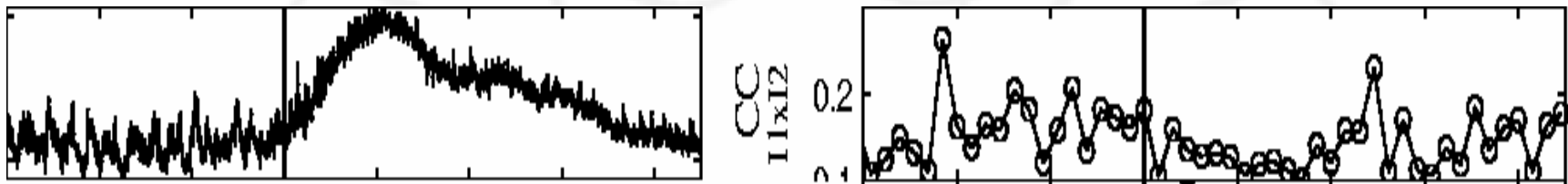


- Prevailing medical dogmas
  - Inter-ictal bursts are precursors to seizures (“damp kindling” hypothesis)
  - Seizure activity involves “hyper-synchronous” co-ordinated firing of many neurons
- Largely based on EEG observations

# Rat hippocampus



# Neuronal activity has low correlation during seizure



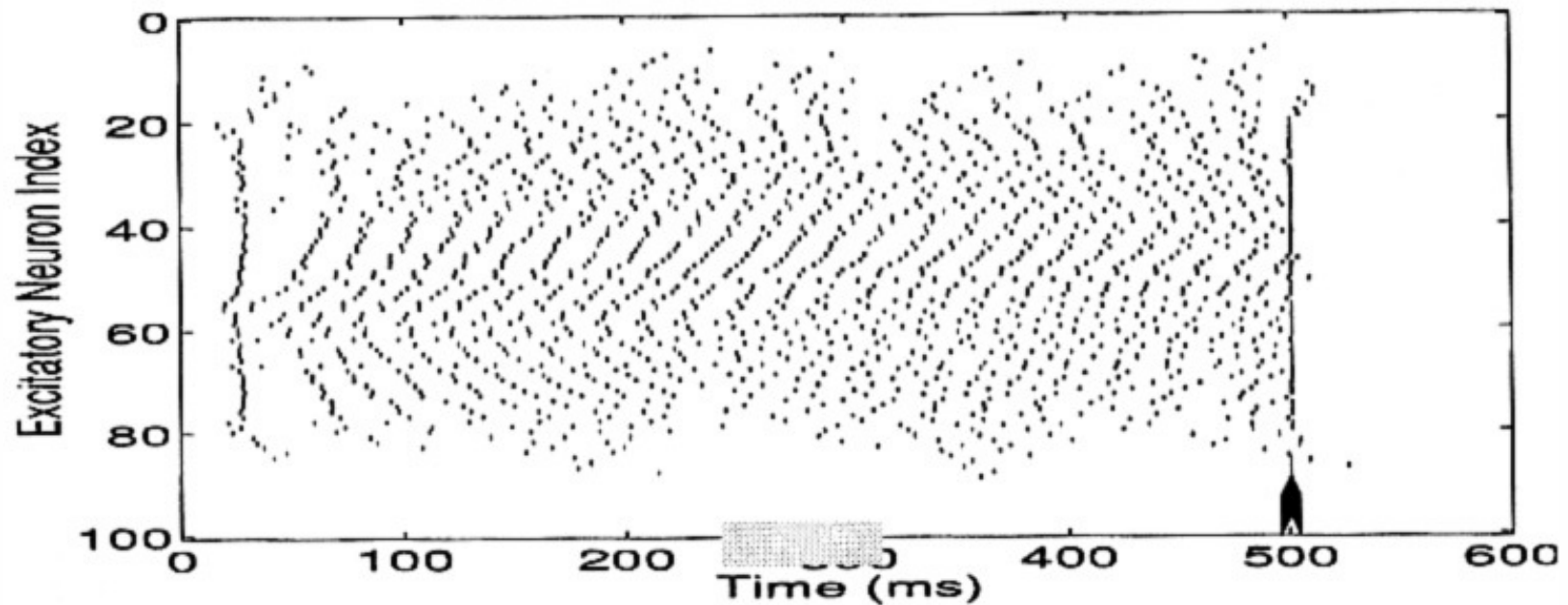
# Neuronal activity is highly correlated during bursts



Netoff and Schiff, 2002 (Similar conclusions by Wendling et al, 2003;  
van Drongelen et al, 2003; Schindler et al, 2007)

# De-correlation can be required for sustained network activity

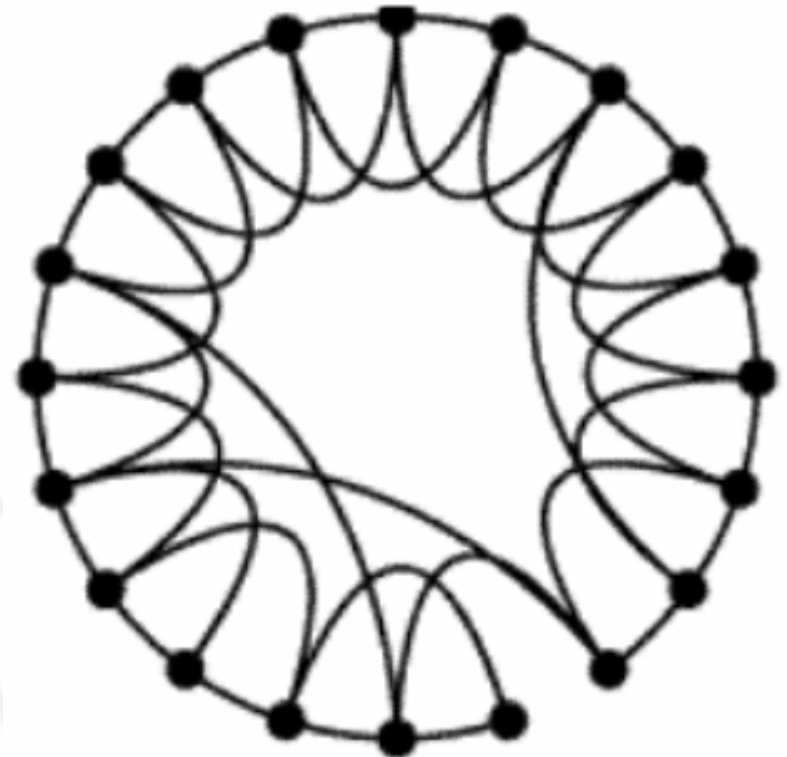
(Gutkin and Ermentrout, 1998)



Hypothesis: To sustain activity there needs to be a reserve of recruitable neurons

# Model networks: small worlds

- Hippocampus
  - Neither a lattice nor randomly connected
  - Detailed anatomy emerging
- “Small world networks” can statistically mimic this
- Randomly rewired connections
  - Decrease average path length between two nodes
  - Maintain clustering
- Only three parameters needed



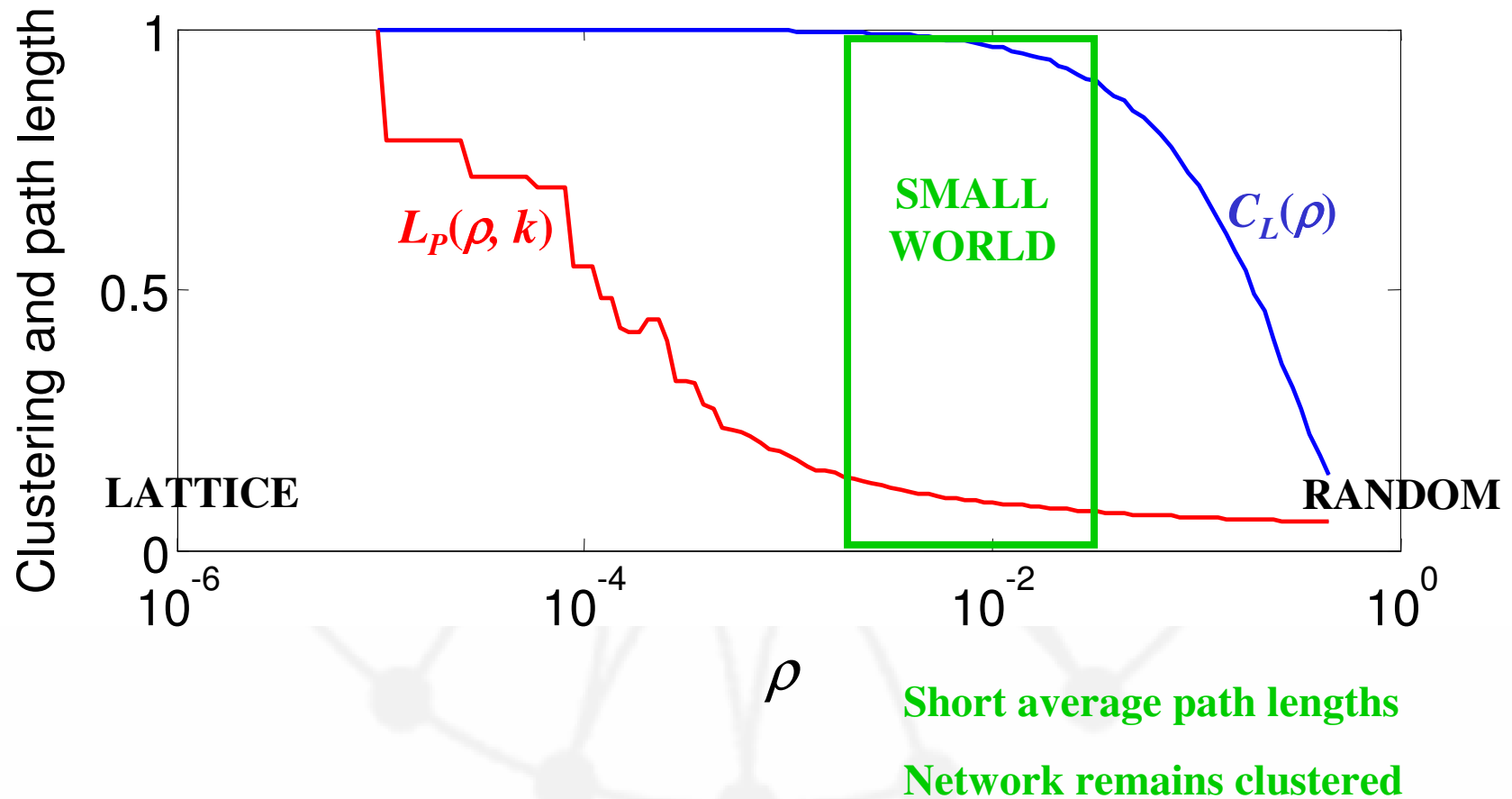
(Watts & Strogatz, 1998)

# Connectivity parameters



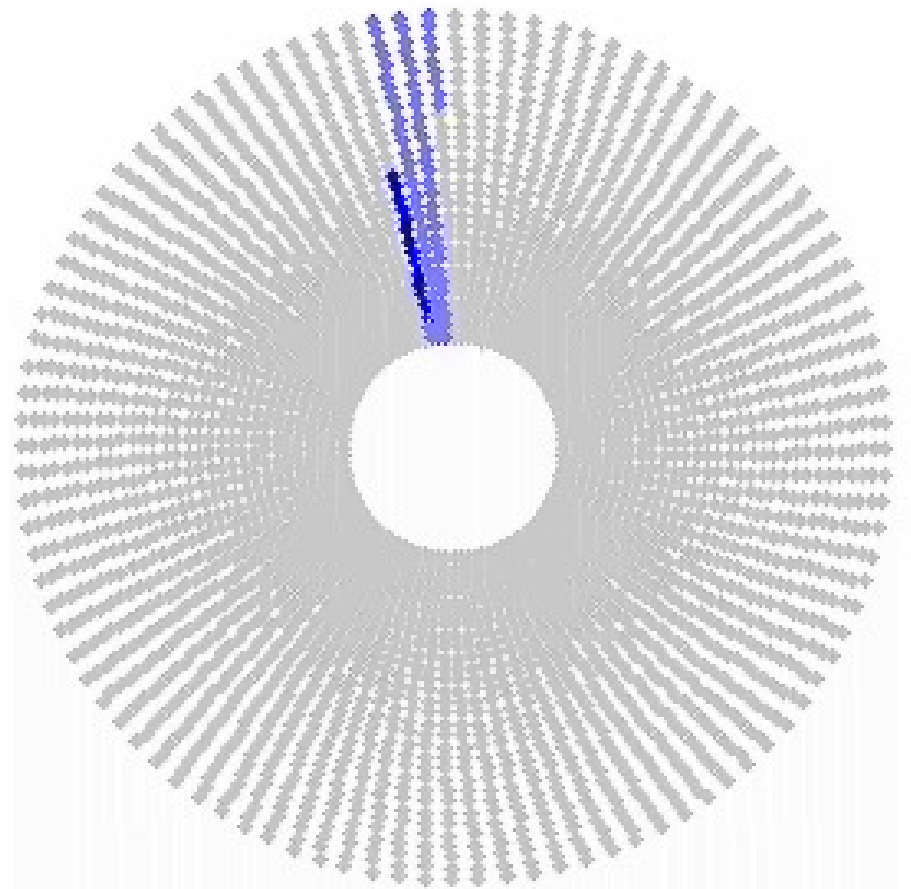
- $N$ 
  - Number of nodes
- $\rho$ 
  - Probability a synapse is randomly rewired
  - “Proportion of long-distance connections”
- $k$ 
  - Proportion of  $N$  to which each neuron synapses
  - Also expressed as synapses/neuron

# Small is a relative term



# Stochastic network model

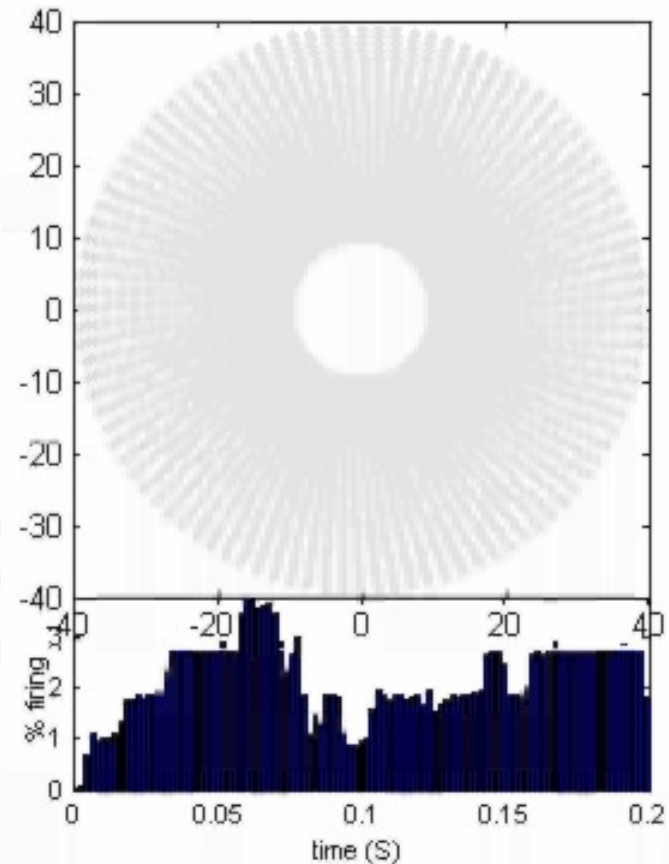
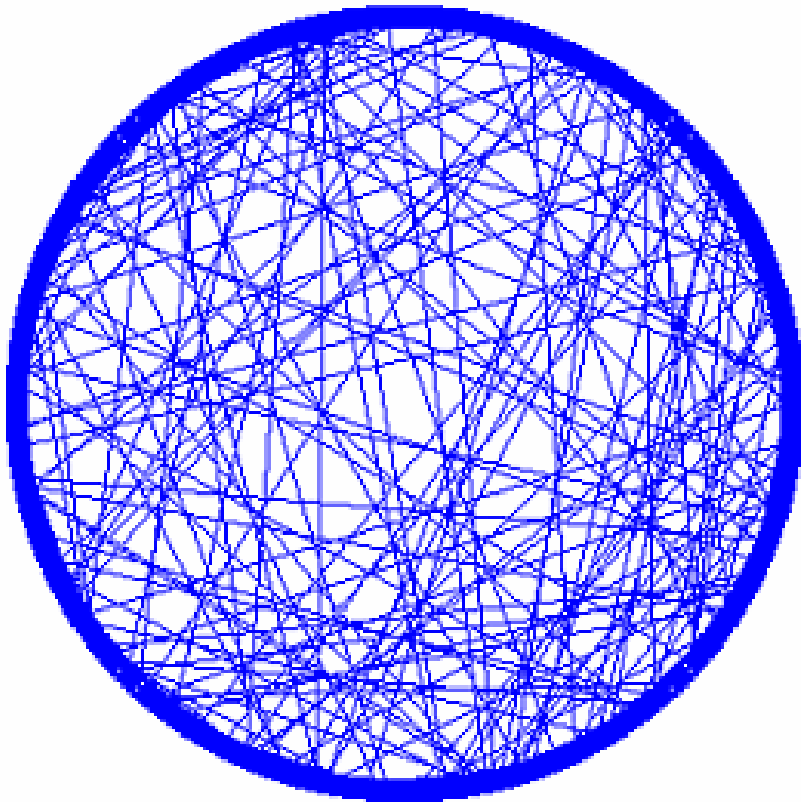
- Ring of excitatory neurons in SWN
  - Eliminates boundary conditions
  - Test broad ideas
  - Compare 3 neuron models
  - *Visual representation to see individual nodes*



# LIF network simulations: CA1

## Seizing activity

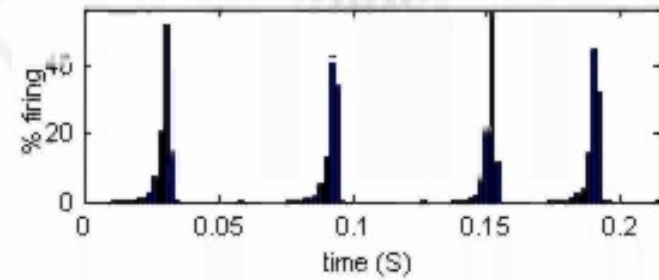
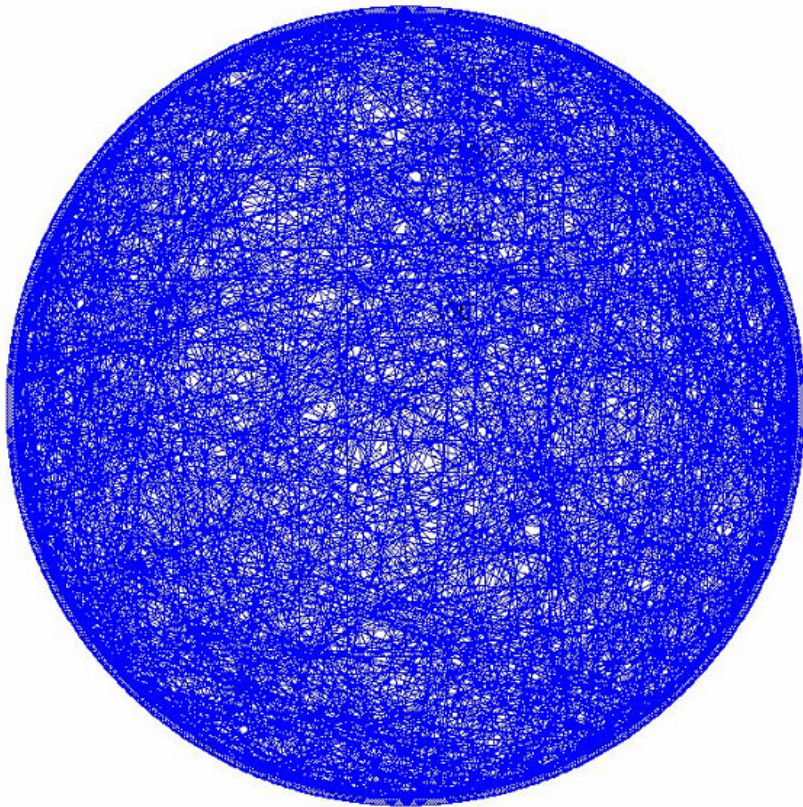
$N=3000$ ,  $k = 30$  synapses/neuron (1%), Proportion rewired  $\rho=0.005$



# LIF network simulations: CA1

## Bursting activity

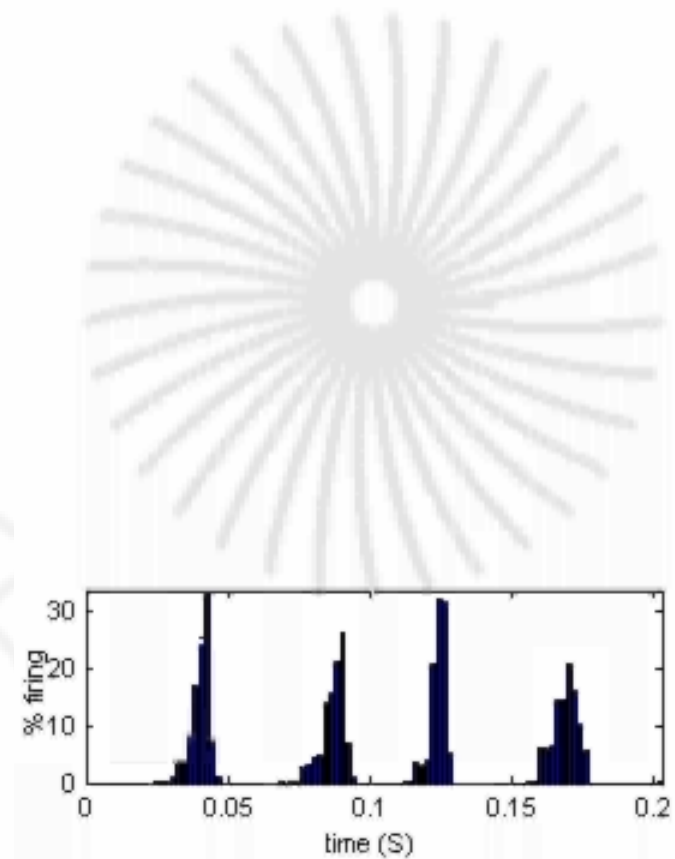
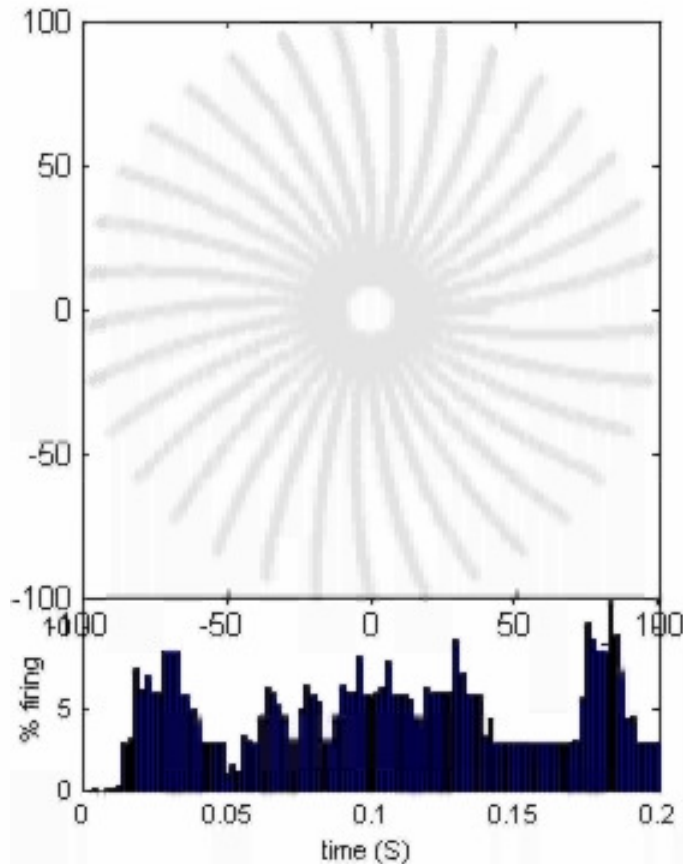
$N=3000$ ,  $k = 30$  synapses/neuron (1%), Proportion rewired  $\rho=0.2$



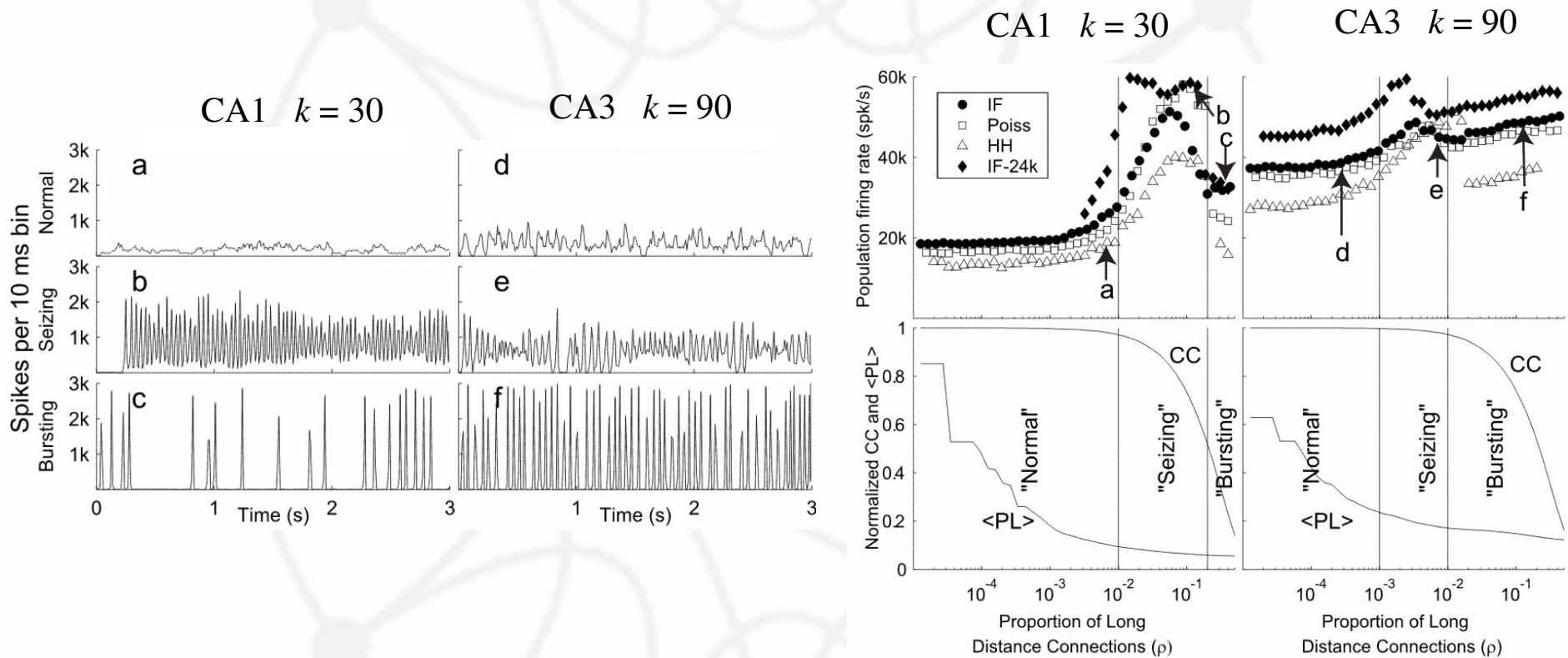
# LIF network simulations: CA3

Proportion rewired  $\rho = 0.0001$   
Synapses/neuron  $k = 90$

Proportion rewired  $\rho = 0.01$   
Synapses/neuron  $k = 90$



# Network properties define transition from bursting to seizing



- Neuron models tested (parameters matched):
  - Leaky integrate-and-fire
  - Poisson spike train
  - Stochastic Hodgkin-Huxley

# Param's for Poisson neuron model

$N$  - **number of neurons** in the network (3000)

$k$  - **number of synapses/neuron** (all synapses start with coupling only to immediate neighbors)

$\rho$  - **probability** that a synapse is broken and **rewired** to random location in the network

$p_1$  - **synaptic efficacy** (0.025):

P(neuron fires | one synaptic spike input)

e.g.  $\propto$  ratio of excitation to inhibition

$p_2$  - P(two or more local neurons fire | one neighbour fires)

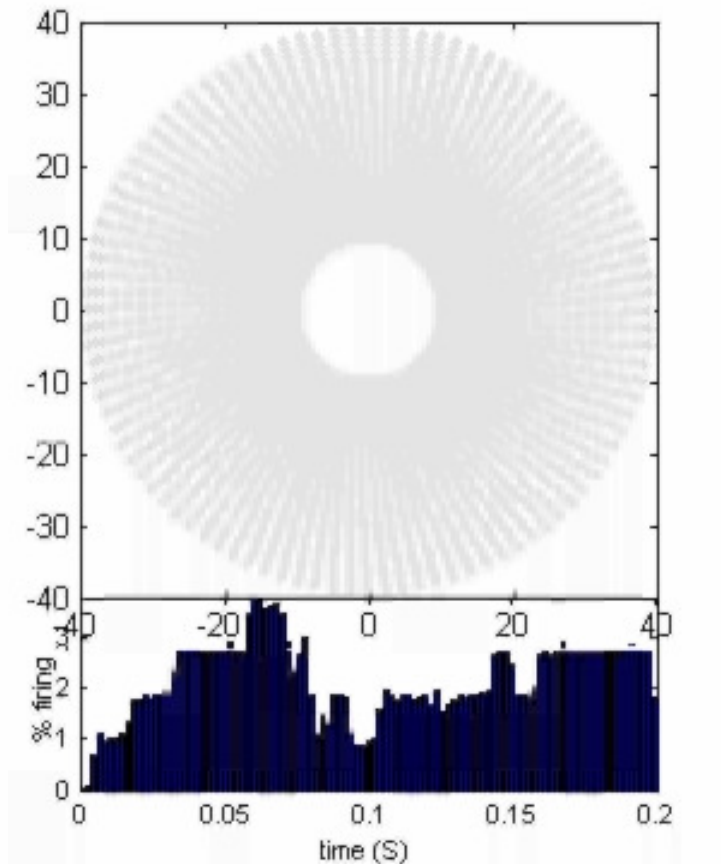
(using Binomial theorem)

$$p_2 = 1 - (1 - p_1)^k - (k - 1)p_1(1 - p_1)^{k-1}$$

$S$  - **spontaneous neuron firing rate**

$R$  - **refractory period** (multiple of delay time)

# How does activity propagate through the network?



- Discrete-time dynamical systems analysis of **average number of waves** in network at any given time
- Qualitative description of the stochastic simulated models
- “Forest fire” model (Bak et al, 1990)

**New # of waves = current # of waves**

**+ new waves**

**– dying waves**

# Difference equation for waves

- Essentially a discretized “master equation”
- Include recent history of activity in dynamics?

No  $\rightarrow$  1-dimensional map

$$w_{i+1} = w_i + n_i - d_i \equiv f(w_i)$$

Yes  $\rightarrow$   $(1+R)$ -dim map

$$\begin{aligned} w_{i+1} &= w_i + n_i - d_i \\ &\equiv f(w_i, w_{i-1}, \dots, w_{i-R}) \end{aligned}$$

$w_i$  = number of wave fronts

$n_i$  = number of new wave fronts

$d_i$  = number of dying wave fronts due to collision/annihilation

# Assumptions of the maps

- Two post-synaptic neurons fire within a local neighbourhood ( $k$  neurons)  $\Rightarrow$  all  $k$  will fire at time  $i+1$ 
  - Creates two wave fronts on ring
  - Reasonable because of the large overlap of local connections
- Travelling wave front contains exactly  $\alpha = k/2 - 1$  neurons
- Refractory tail has size  $\alpha R$  in 1D map
  - Or sum activity over previous  $R$  steps in  $(1+R)$ -dim map
- Maps valid only at low activity levels
  - Derivation of  $n_i$  and  $d_i$  require assumption that network activity was far from saturation

# The one-dimensional map

$$w_{i+1} = w_i + n_i - d_i \equiv f(w_i)$$

$$n_i = \theta w_i e_i + s_i$$

$$d_i = 2w_i \alpha / e_i$$

$$e_i = N - w_i \alpha (1 + R)$$

$$s_i = 2S p_2 e_i$$

$$\theta = \frac{2\alpha \rho k p_1 p_2}{N}$$

This parameter contains  
all the network  
properties that are fixed

$w_i$  = number of wave fronts

$n_i$  = number of new wave fronts

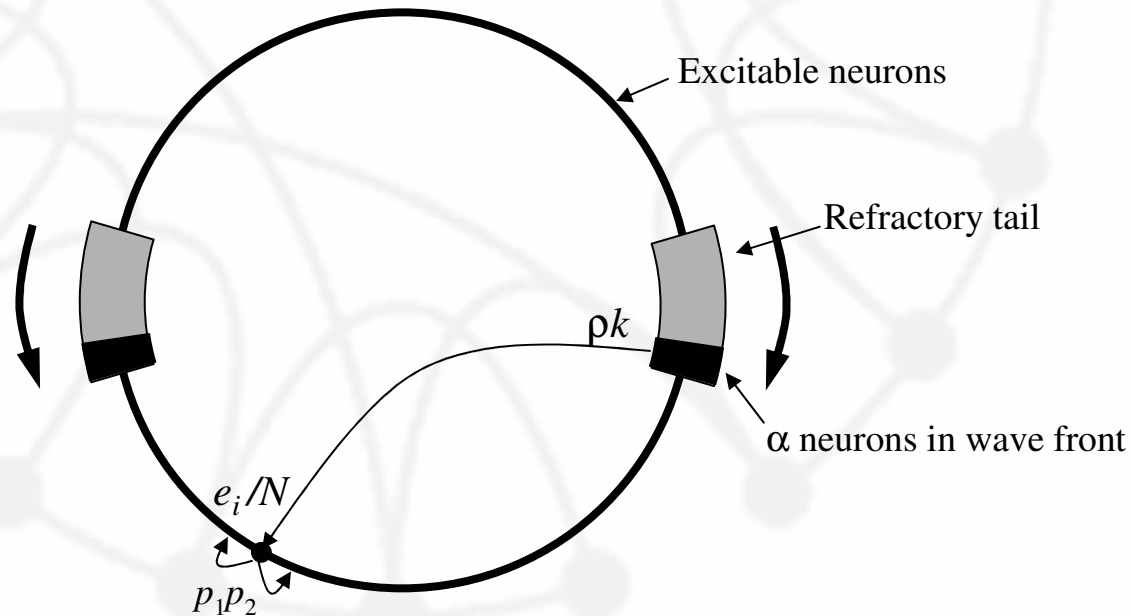
$d_i$  = number of dying wave fronts due to collision/annihilation

$e_i$  = number of excitable neurons

$s_i$  = number of spontaneous waves (  $\ll$  those due to coupling)

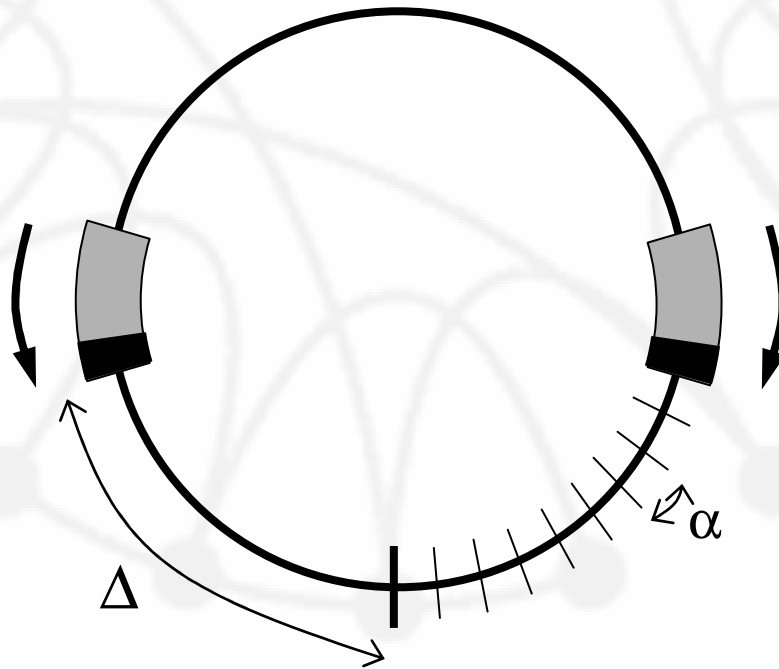
# Derivations: new waves

- Each wave front =  $\alpha$  neurons, each having  $k$  connections
- On average,  $\rho k$  of these are long-distance, of which only the proportion  $e_i/N$  arrive at excitable cells
- Activity along these connections spark 2 wave fronts with probability  $p_1 p_2$  (condensing two time-steps worth of synaptic transmission into one)



# Derivations: dying waves

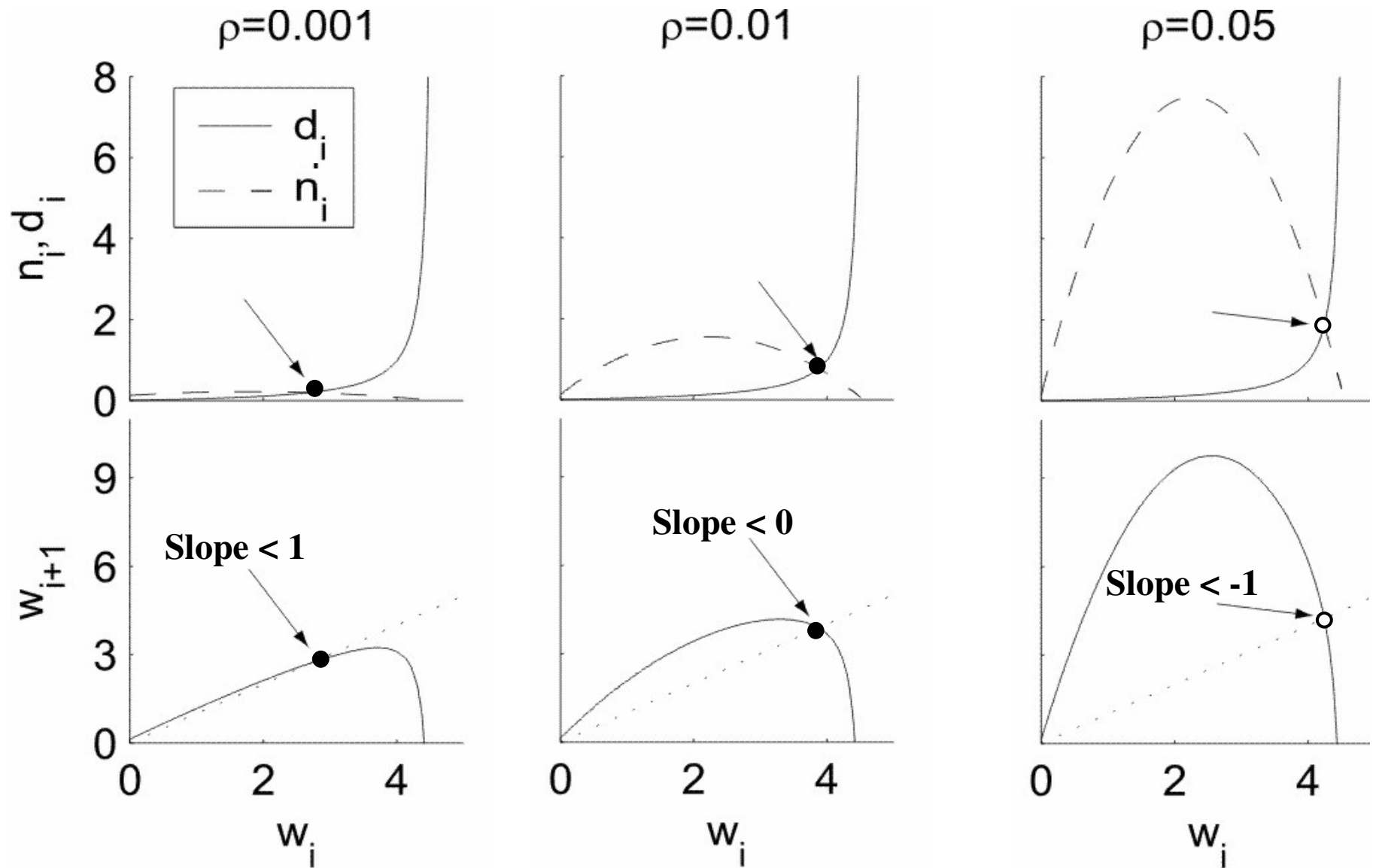
- Assume all waves evenly spaced on average
- # of gaps (containing excitable cells) = # waves
- Each wave travels  $\Delta = \frac{1}{2}$  the excitable neurons per gap before annihilation, i.e.  $\Delta = e_i / (2w_i)$
- ... traversed in  $\Delta/\alpha$  time steps
- Thereby killing waves at a rate of  $e_i / (2w_i\alpha)$  per step



# Explore parameter roles

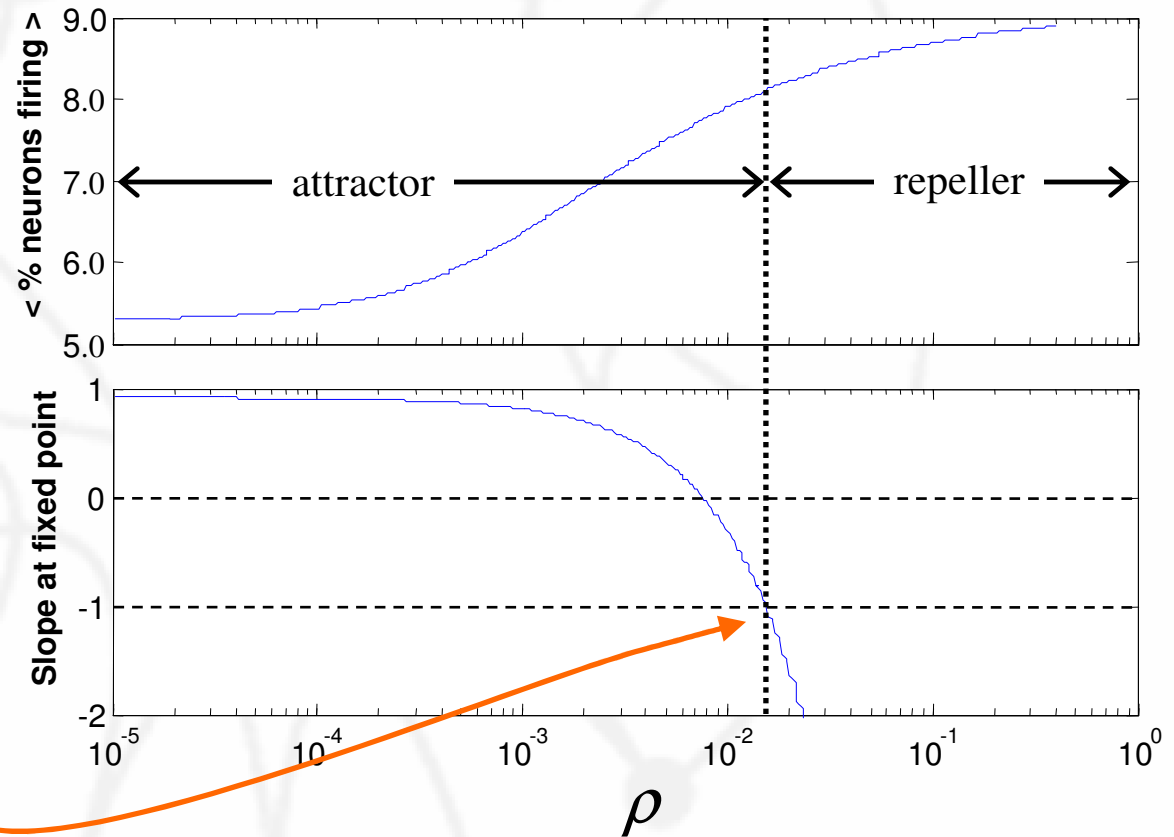
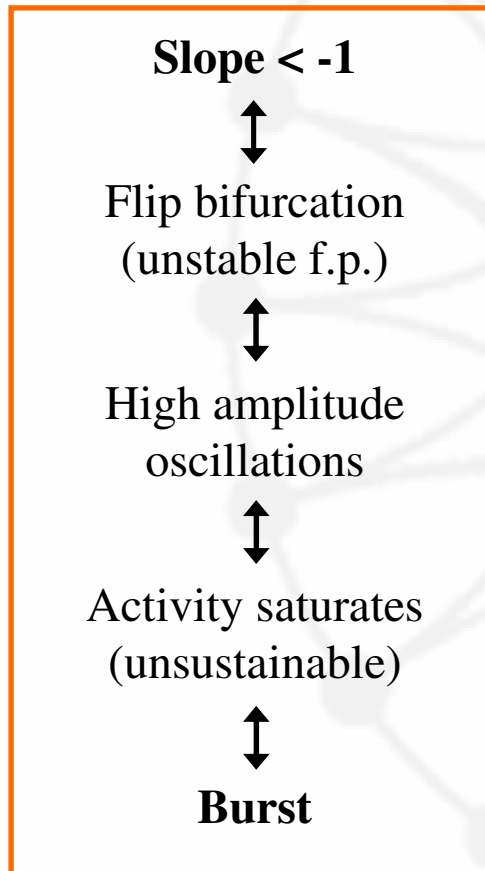
- How do parameters affect network behaviour?
  - e.g. corroborate and predict simulation outcomes
- Qualitative analysis of discrete dynamics
  - Equilibria  $\sim$  expected number of waves  
( $f(w^*) = w^*$  for fixed points)
  - Stability  $\sim$  sustainability of network activity  
( $|\lambda| \equiv |f'(w^*)| < 1$  for attracting)
  - Strength of stability  $\sim$  variance (indicates fluctuations)
- Exemplify by varying  $\rho$  and  $p_1$  for 1D map

# Stability analysis at equilibrium



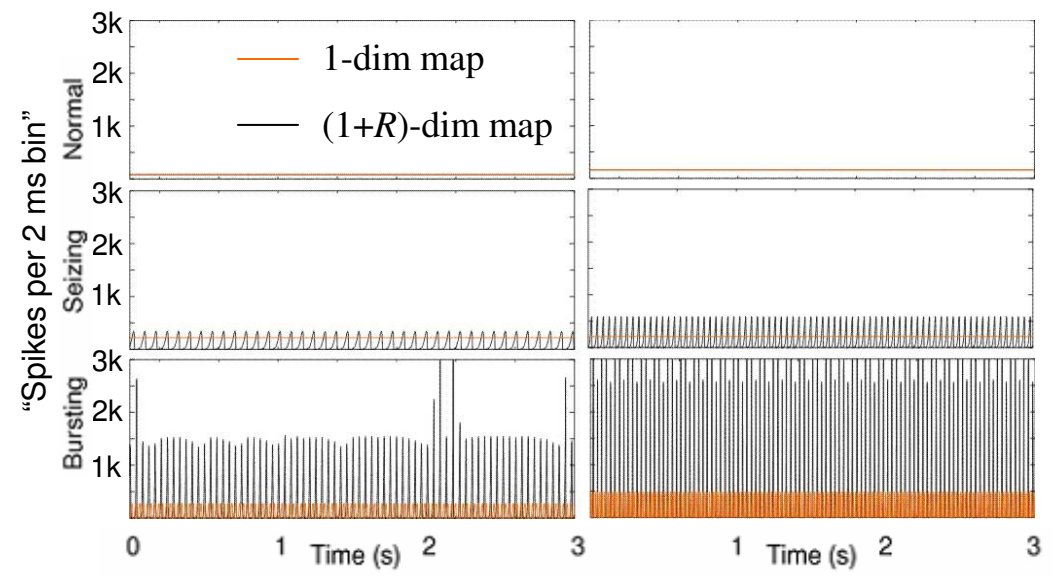
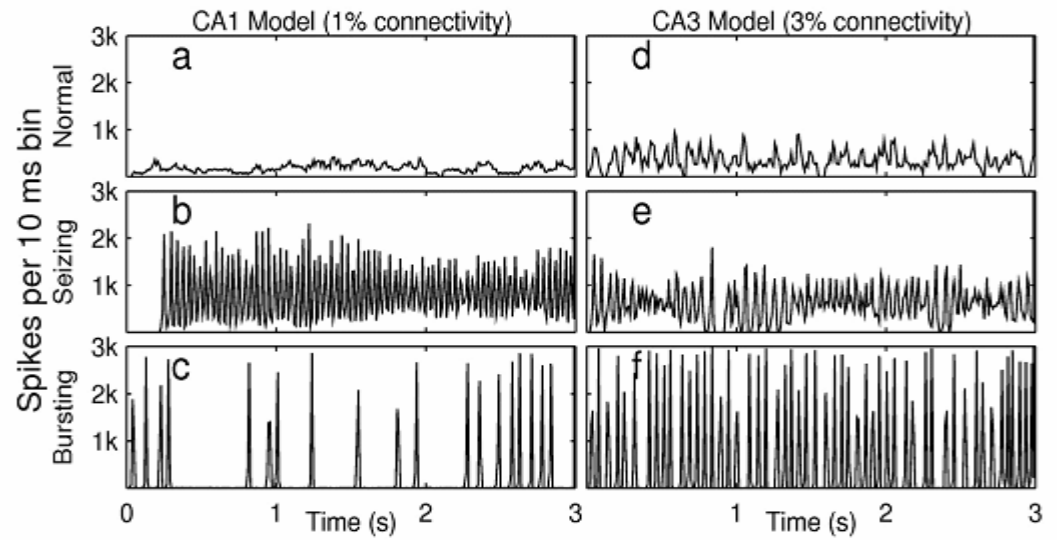
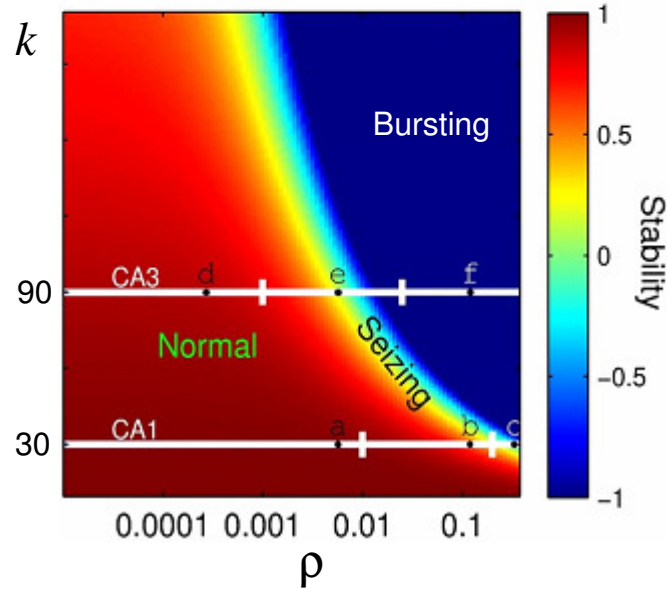
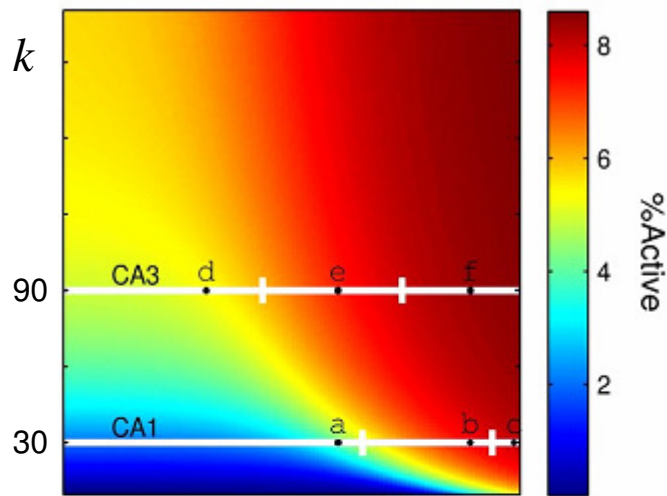
# Stability analysis at equilibrium

Fixed point position and slope as function of  
% long distance connections in network



$$N = 3000, \quad k = 90$$

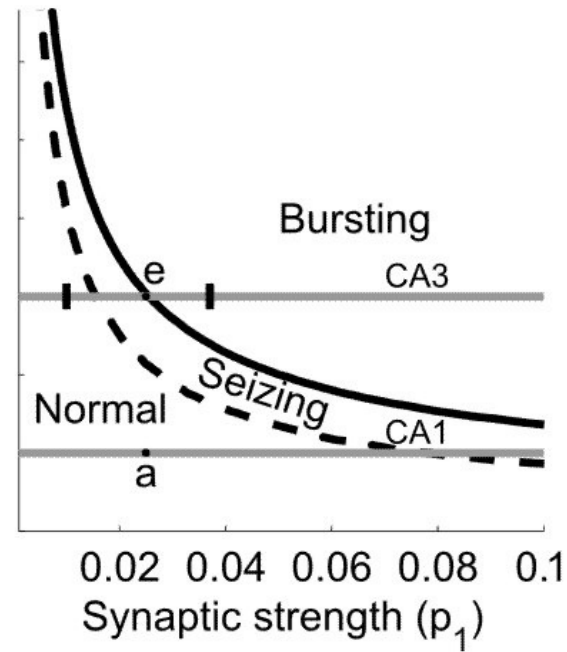
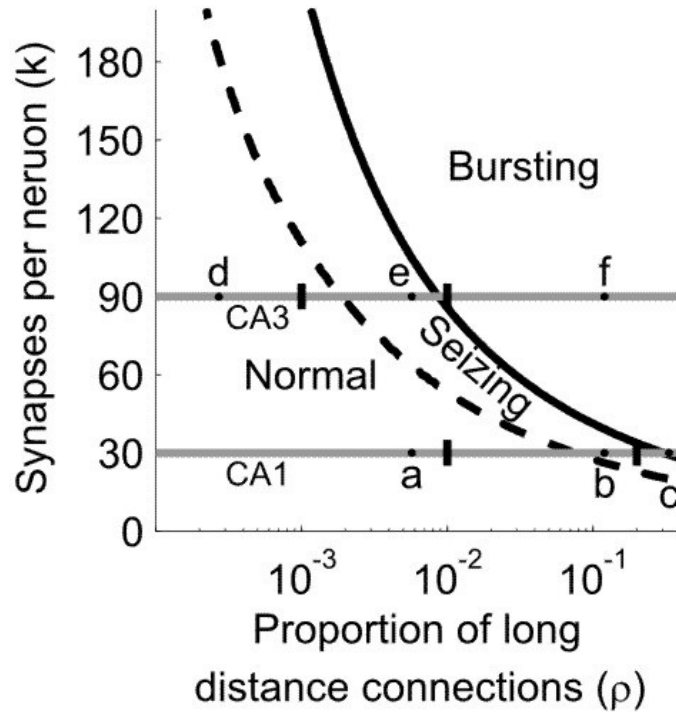
# Maps capture the trends



# Maps capture the trends

Equilibrium loses stability in

(1+R)-D map 1-D map



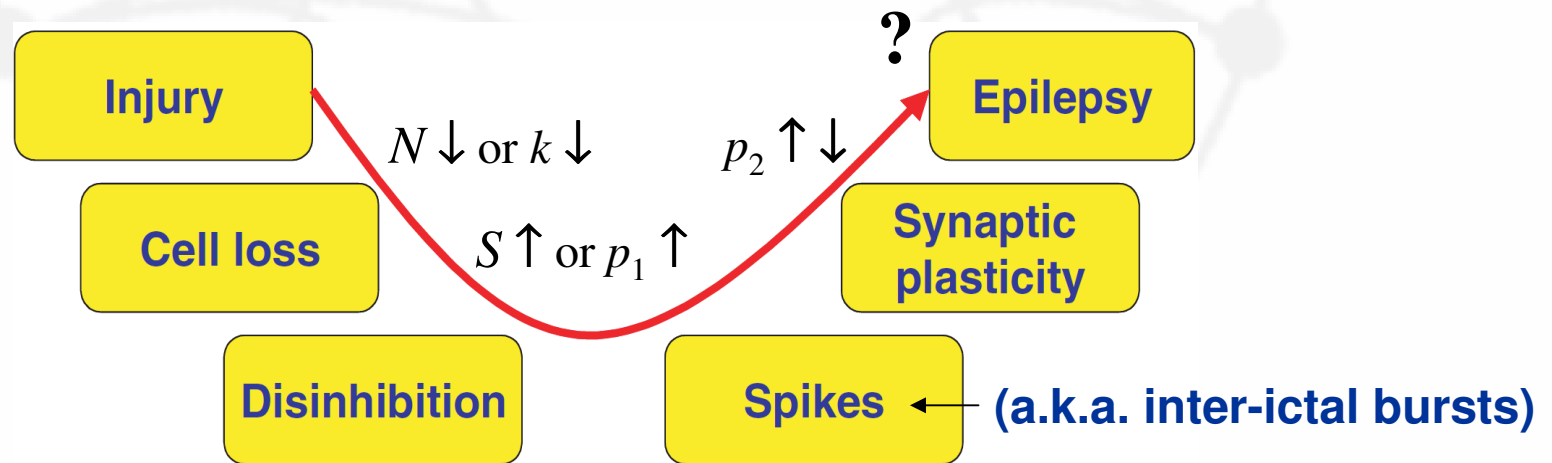
Predicts increasing synaptic efficacy causes network to burst in CA3 before CA1

# Summary of results

- Suggests broad relationship between network connectivity and temporal lobe epilepsy
  - Denser networks burst
  - Sparser networks seize
- Bursts are more synchronous than seizures
- Bursts may not be “pre-seizures”
  - Network-based mechanism
  - Not “damp kindling” in this case

# Physiological implications

- Simple map representation of network dynamics
  - Predicts roles for physiological parameters (alone or in combo)
  - Encodes basic assumptions
  - Validated against our simulations
  - Predictions easier to generate/analyze than using large data-driven simulations
- **Basis for predicting result of parameter changes in mechanistic, computational models**



# Physiological implications

- DG shows SWN connectivity (Dyhrfeld-Johnsen et al., 2006)
  - Specific sclerosis of distantly-projecting hilar neurons
  - Sprouting of mossy fibres
- Neocortex may behave differently
  - Different connectivity
  - Intrinsic bursting neurons (NaP) (van Drongelen et al., 2005)
- Could try this methodology in
  - Developmental networks
  - Migraine models
- Recent work has studied statistics of waves in SWNs and scale-free networks (some in 2D)  
(Roxin et al., 2004; Ursino & La Cara, 2006; Beggs & Plenz, 2004; Singer et al., 2006; Carvunis et al., 2006; French & Gruentstein, 2006)

# Inhibition and excitation



- Hippocampus ~ 80% excitatory, 20% inhibitory
- Inhibition important to study drug effects
  - Slower inhibition may switch off SLEs
- Inhibition + excitation ~ lower excitation?
  - Inhibitory cell connectivity uncertain
  - Synchronous w/ excitation? (P. Velazquez & Carlen, 1999)
- Mark Kramer (B.U.) working on models