Log-dynamics of cortical networks

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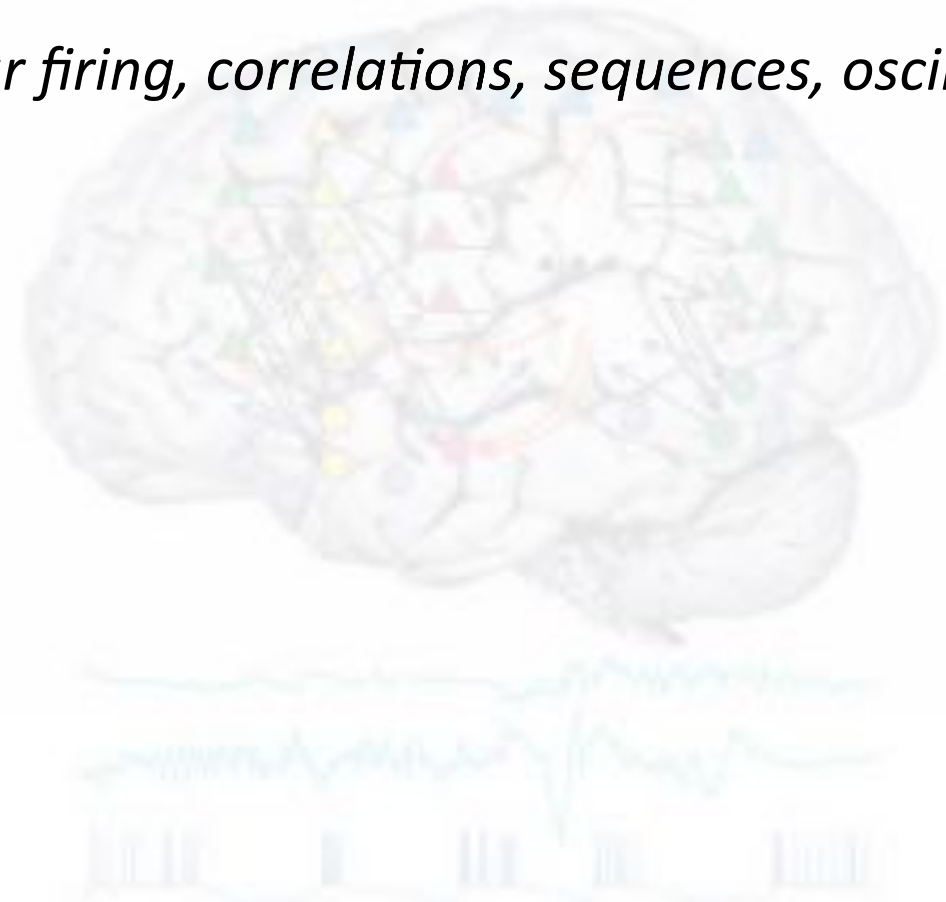
Vladimir Klinshov (Russian Acad Sci)
Vladimir Nekolkin (Russian Acad Sci)

Research talk title

Preplay and replay emerge in a recurrent network of two-compartment neurons

Neural code
Rate, temporal, or multiplexed?

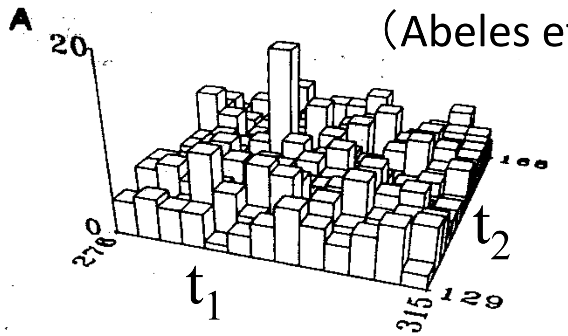
irregular firing, correlations, sequences, oscillations, …

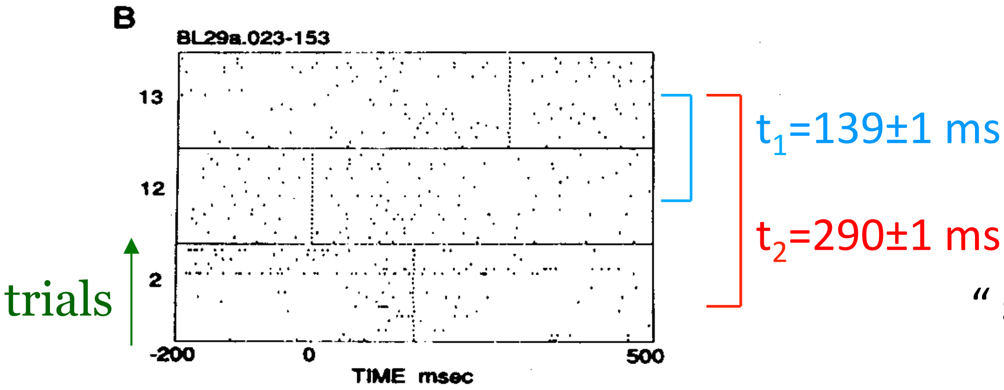


Precise spike sequence

Multiunit recordings from monkey frontal cortex

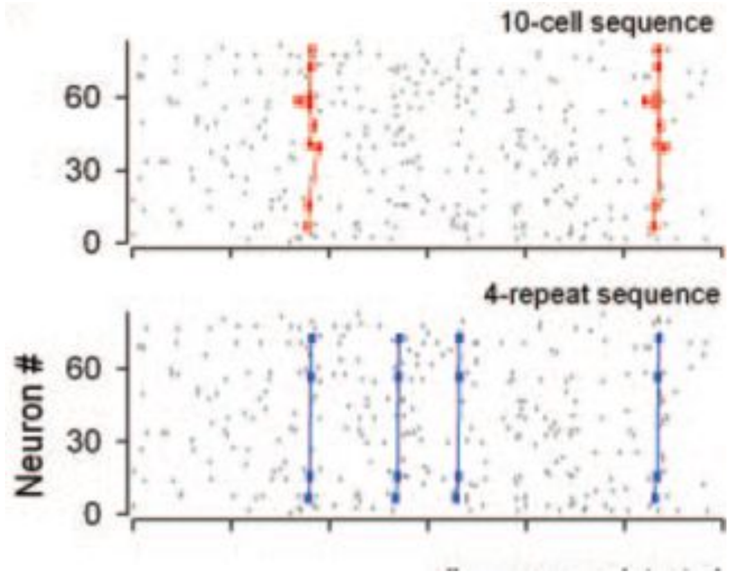
(Abeles et al, 1993)



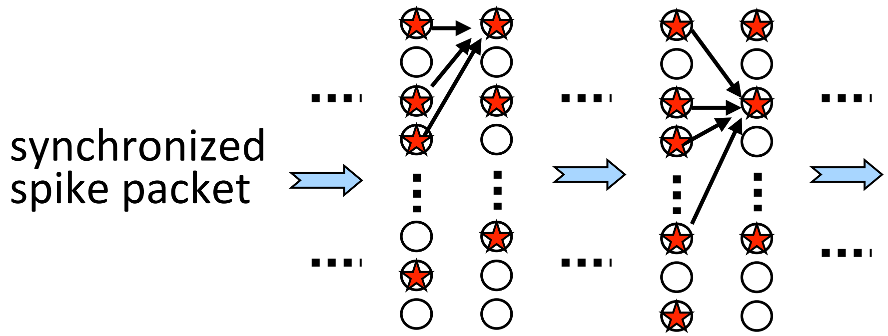


Precisely-timed spike triplets

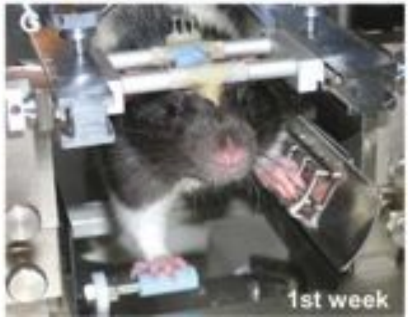
Cortical songs (Ikegaya et al. 2004)



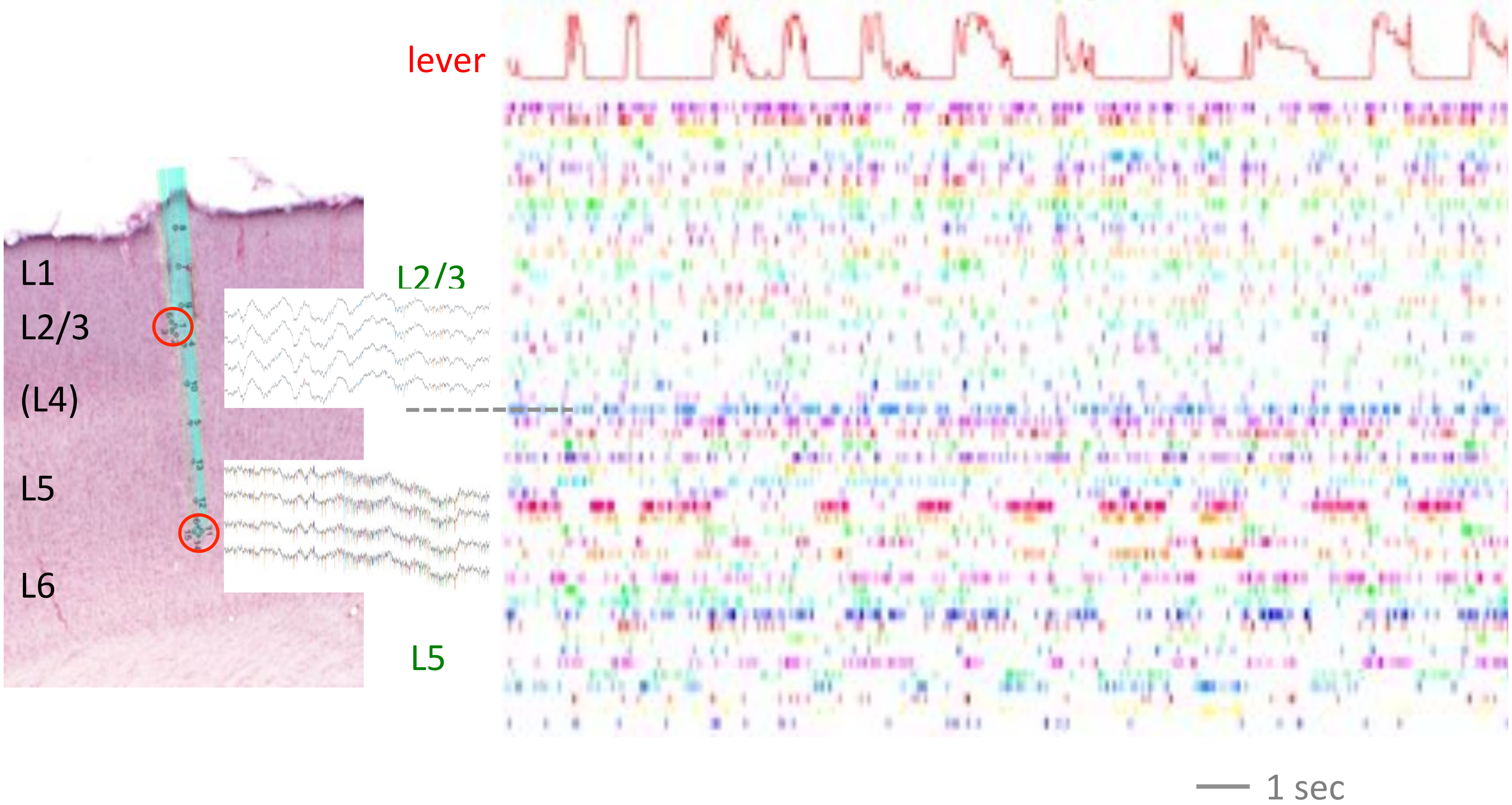
“ synfire chain” (Diesmann et al., 1999)



Firing of in vivo cortical neurons is highly irregular



Rat primary motor cortex, spontaneous lever movement task, multiunit recordings (Isomura et al., Nat Neurosci 2009)

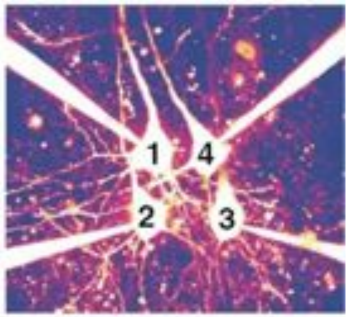


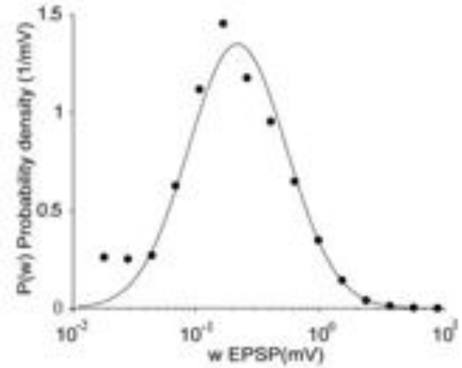
Heavy-tailed EPSP distributions of cortical synapses

Strong-sparse synapses vs. weak-dense synapses

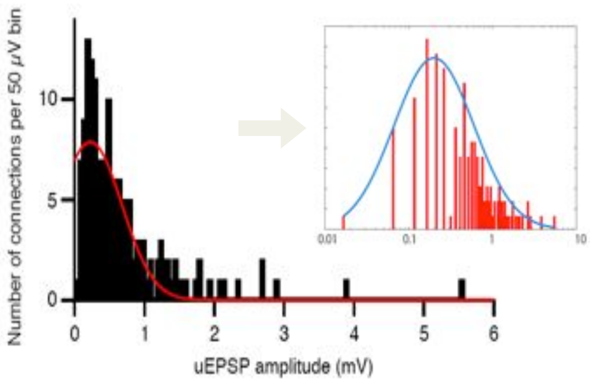
Brain's machinery to generate noise?

rat visual cortex
Song et al., PLoS Biol (2005)

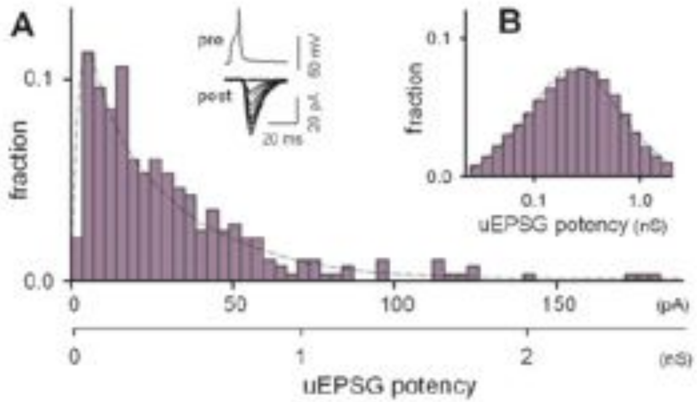




mouse somatosensory cortex
Lefort et al. Neuron (2009)



rat hippocampus
Ikegaya et al., Cereb Cortex (2013)

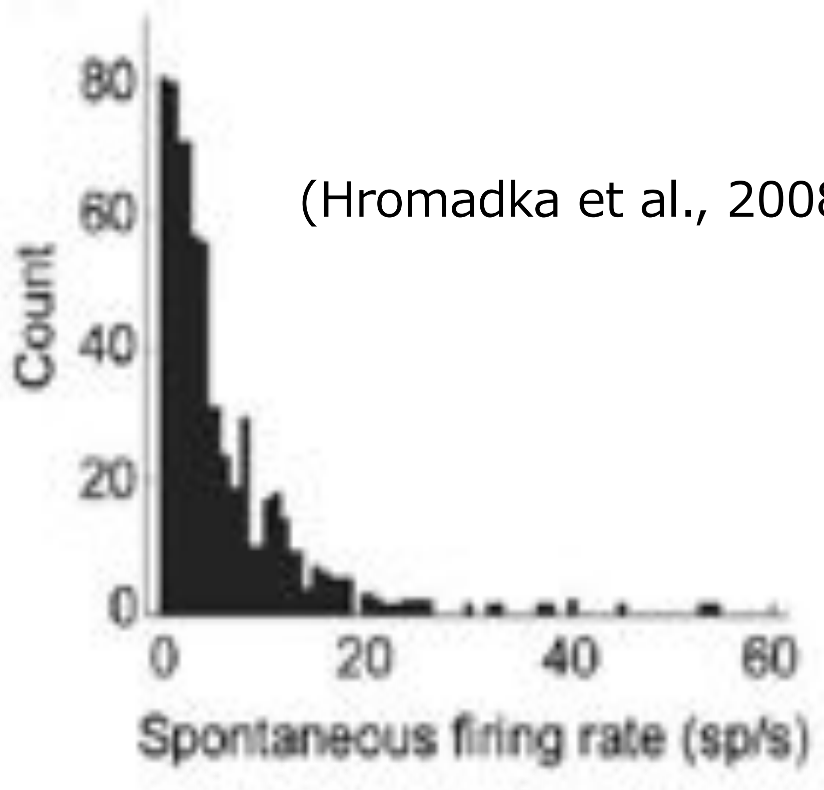


Models of spiking neurons and their networks

1. Spiking neuron models
2. Spontaneous cortical activity
3. A lognormal associative model
4. Synchronous bursting activity in the hippocampus
5. Explore cell assemblies in real data (if time allows)

Q1. Sparse asynchronous irregular states

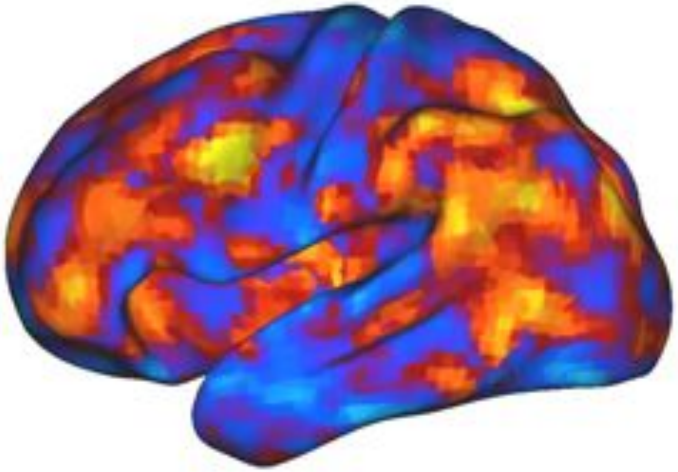
Q2. Sequence vs asynchronous irregular firing



(Hromadka et al., 2008)

Bed 22%
Park 18%
Washroom 7%
Toilet 32%
Bathroom 29%
Bus 17%
Stage 1%
Airport 4%
Poolside 2%
Meeting room 0%

!



The brain is spontaneously cycling through distributed patterns of activity, which mimic activity patterns associated with sensory, motor, or cognitive events.

Vincent et al., J Neurophysiol (2006)

Asynchronous sparse irregular firing
(1~2 Hz)

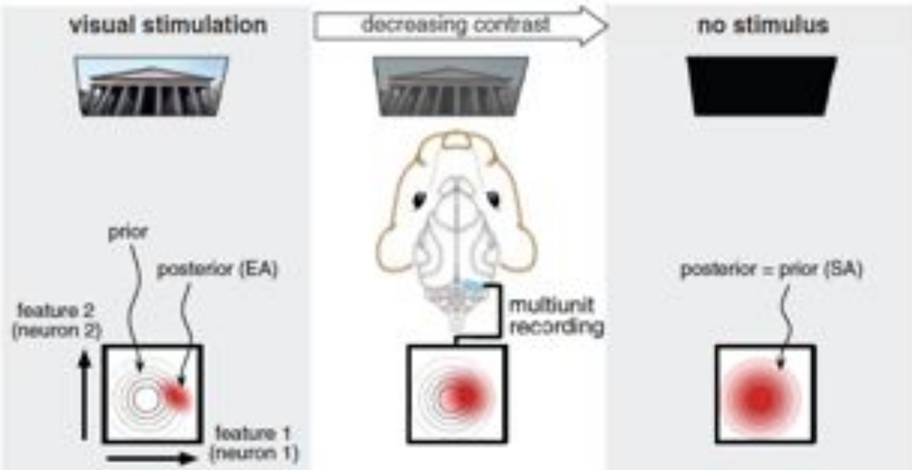
Spontaneous activity gives prior knowledge on external world

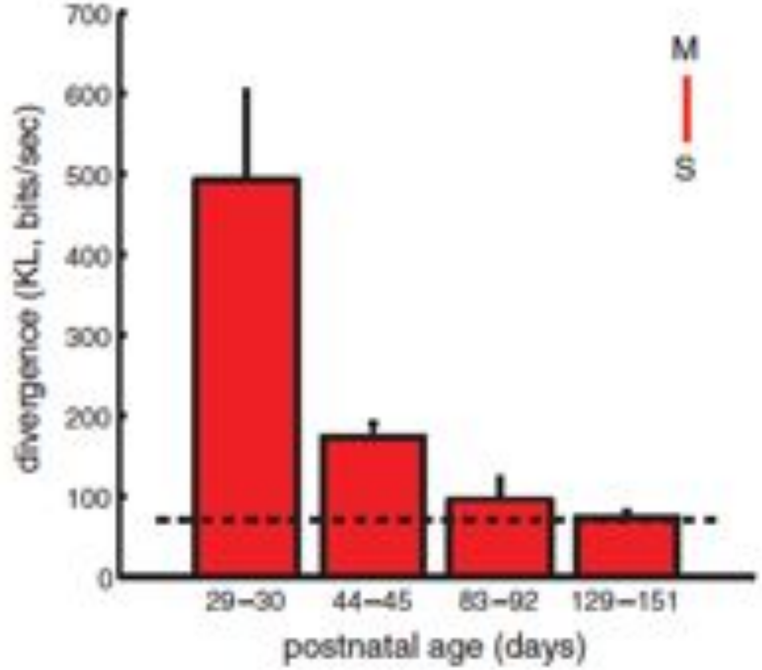
Spontaneous Cortical Activity Reveals Hallmarks of an Optimal Internal Model of the Environment

Pietro Berkes,[1]† Gergő Orbán,[1,2,3] Máté Lengyel,[3]* József Fiser[1,4,5]*

Science 2011

$$\langle P(\text{features}\,|\,\text{input, model})\rangle_{P(\text{input})} \approx P(\text{features}\,|\,\text{model})$$

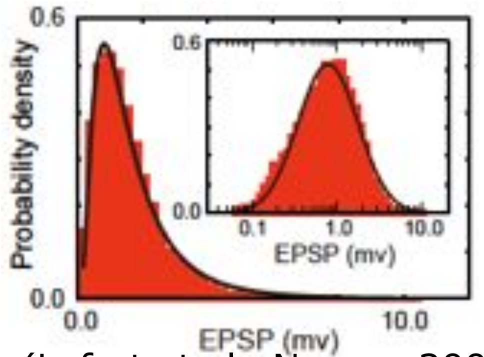




Asynchronous irregular firing in recurrent networks

(Teramae, Tsubo and Fukai, Sci Rep, 2012)

●10000 excitatory + 2000 inhibitory LIF neurons



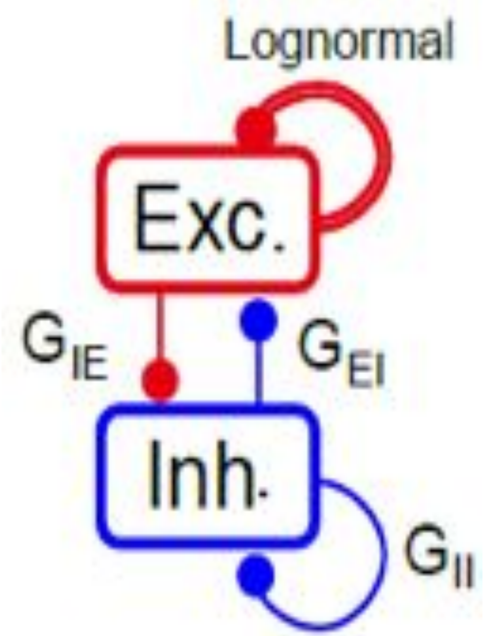
(Lefort et al., Neuron 2009)

●AMPA synapses

Lognormal weight distribution for E-E connections
EPSP size-dependent transmission failure rate

●GABA-A synapses

Gaussian

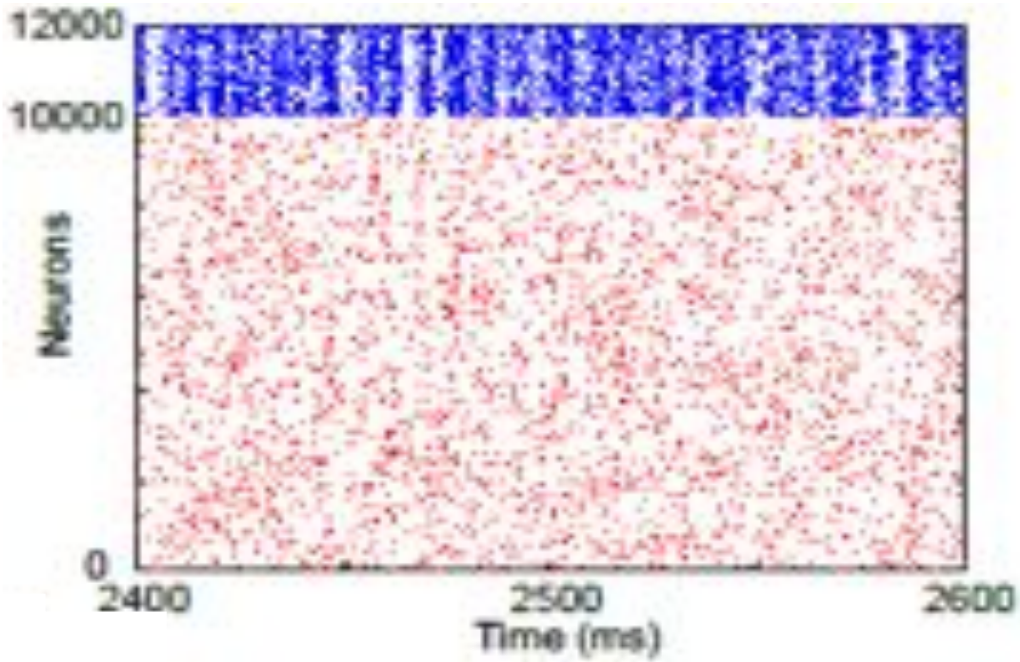


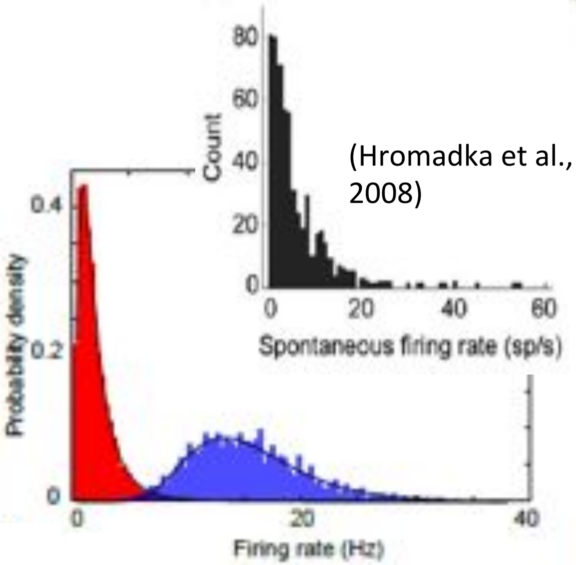
●Transmission delays are 1~3 ms

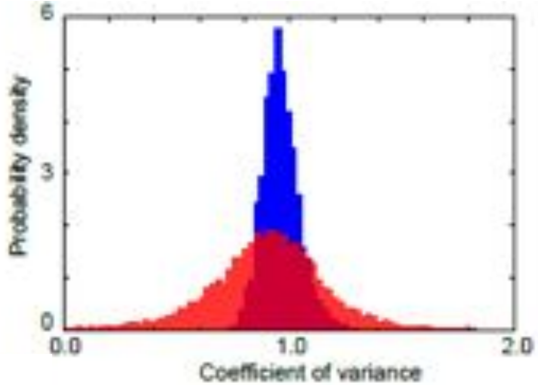
●No external input

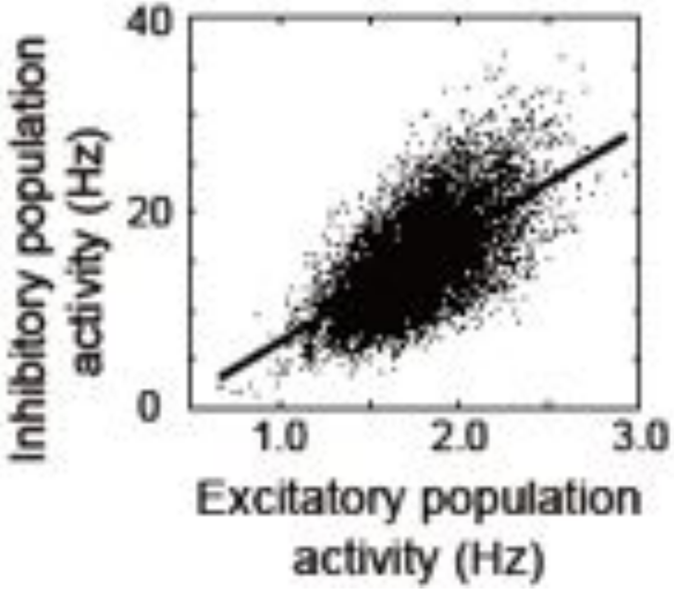
Jun-nosuke Teramae
(-> Osaka Univ)

LogN network generates biologically realistic spontaneous activity

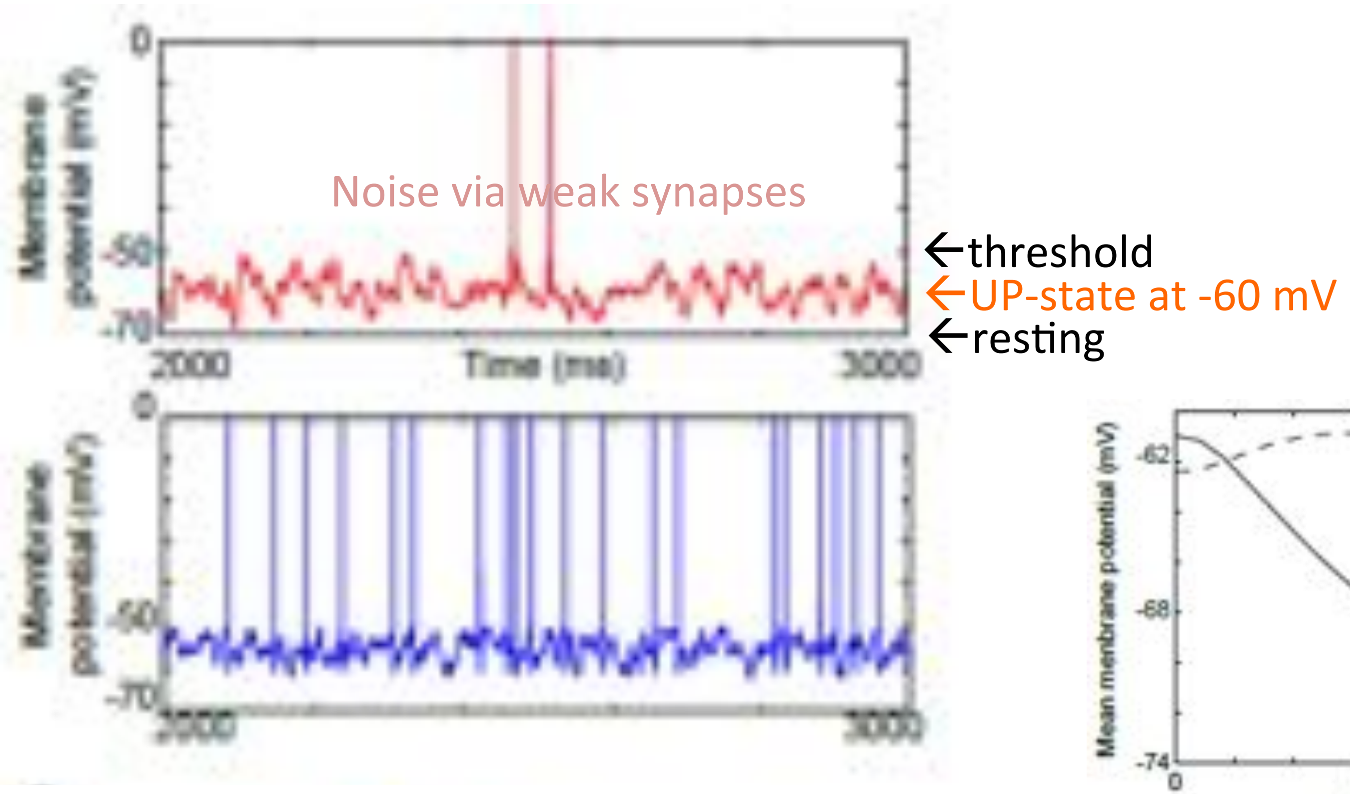


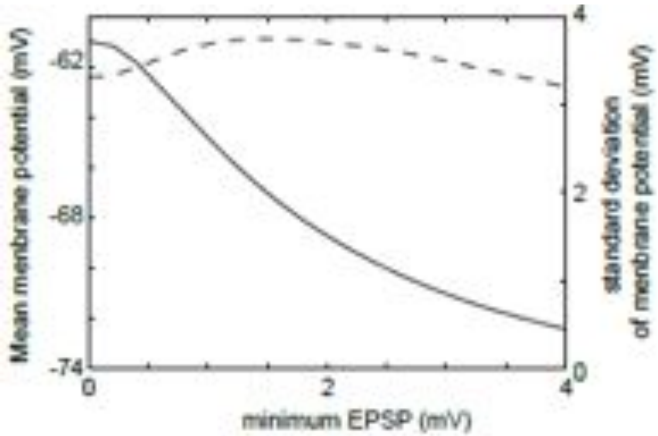


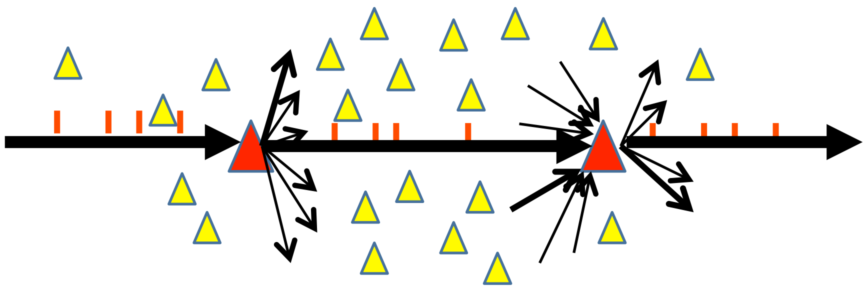




Membrane potential fluctuates around -60 mV

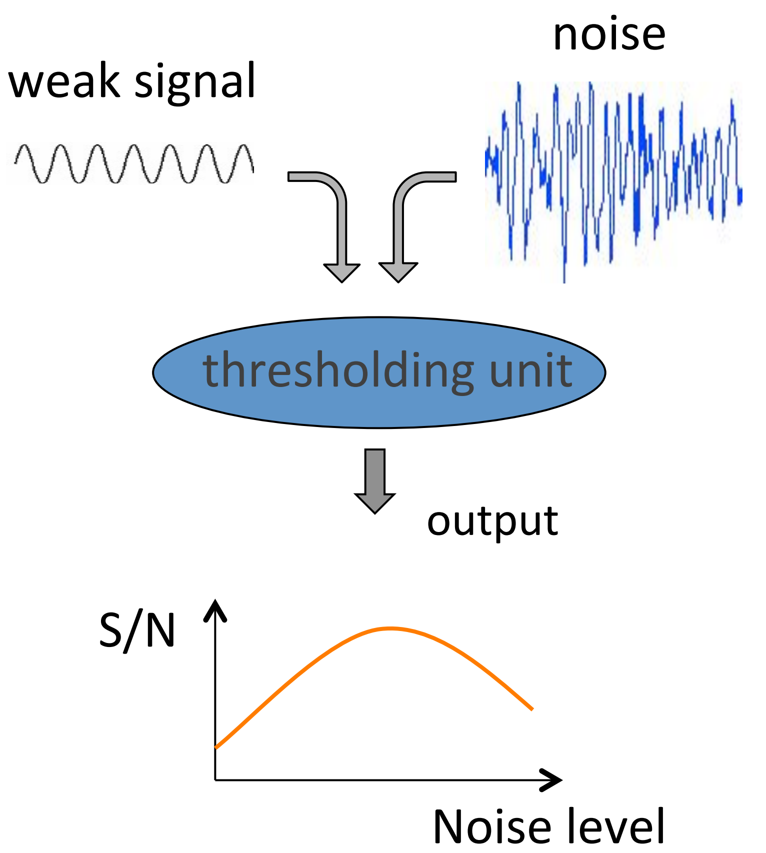


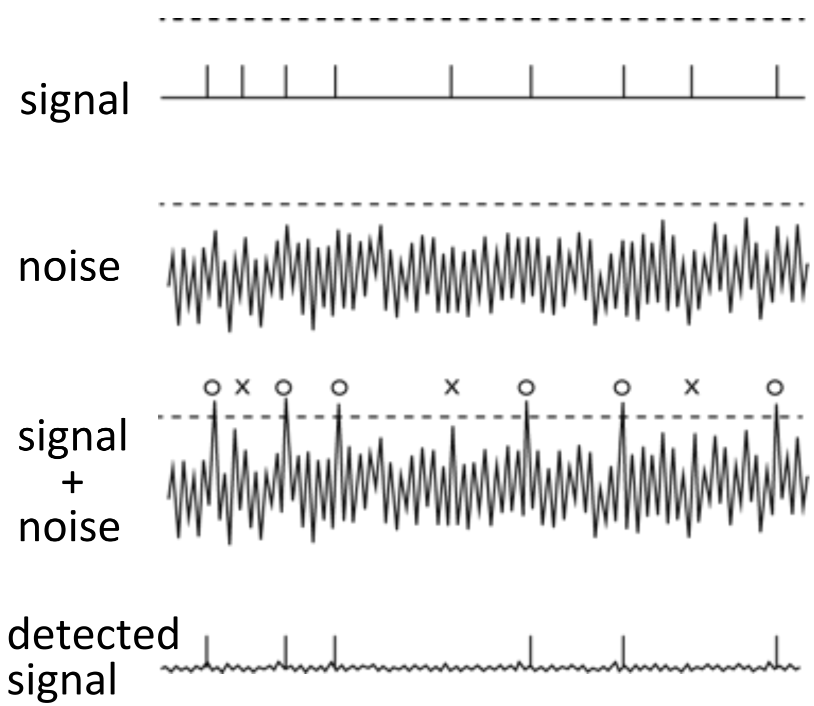




Stochastic resonance（確率共鳴）

Optimal noise helps detection of weak signals

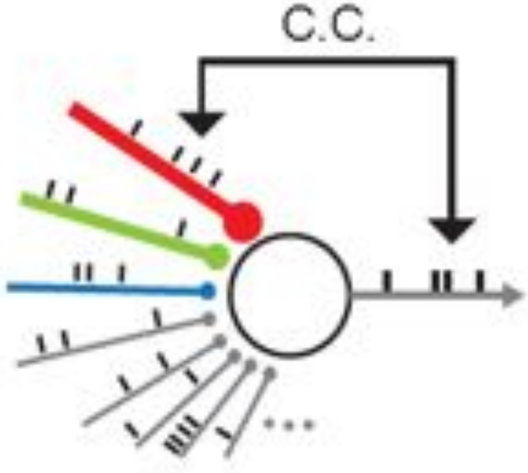


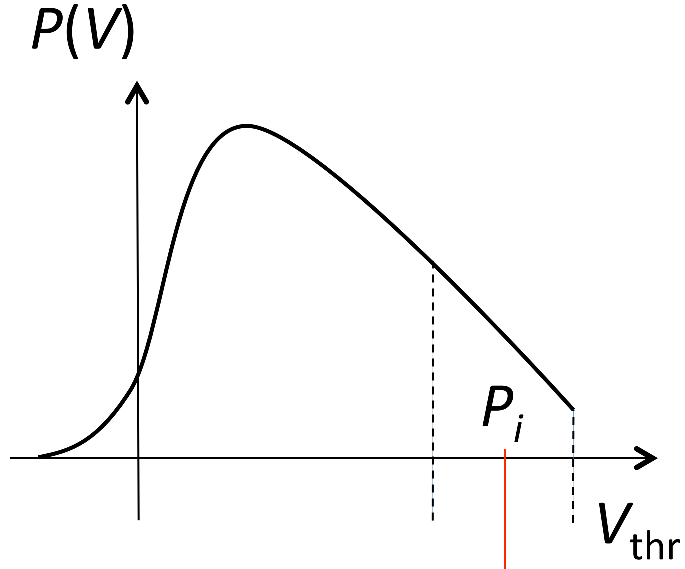


Noise improves our visual perception!

E. Simonotto et al., Phys Rev Lett (1997)

Analysis of spike transmission





$$C.C. = P_i(x_{out} \mid x_{i,in})\sqrt{\frac{r_{i,in}}{r_{out}}}$$

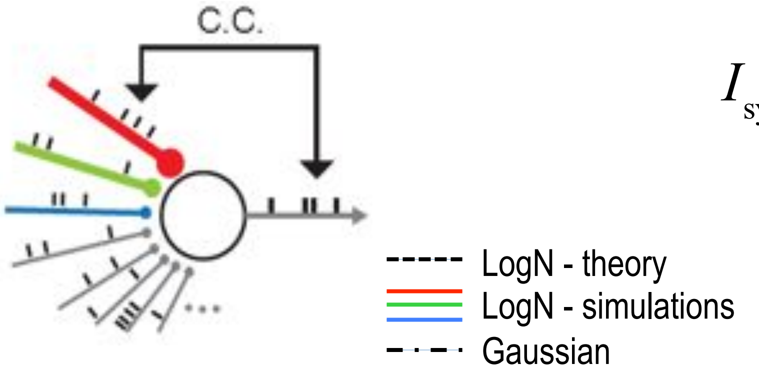
$$P_i(E_i) = \int_{\frac{(V_E - V_L)V_{thr} + \beta E_i V_E}{(V_E - V_L) + \beta E_i}}^{V_{thr}} P(V)\, dV$$

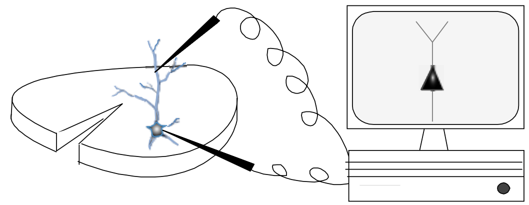
E_i = EPSP amplitude of input synapse

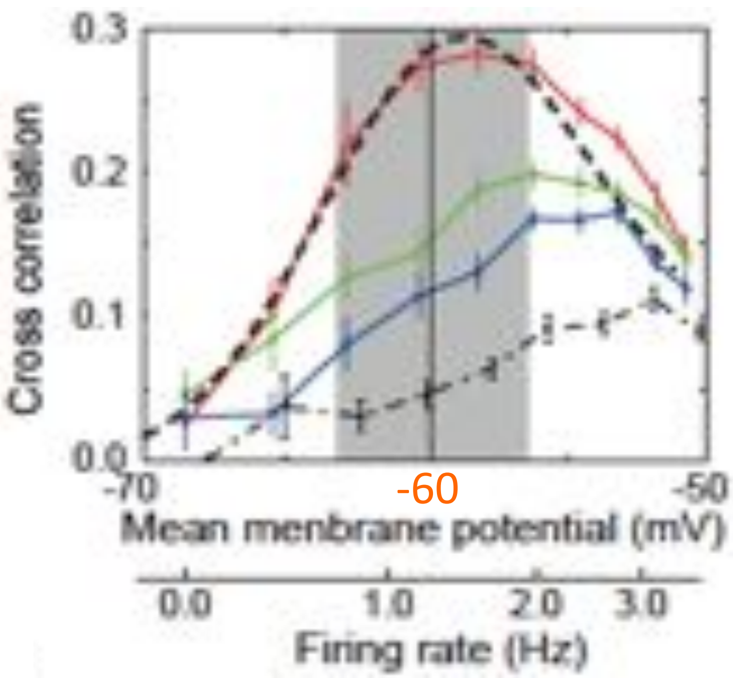
Lognormal EPSP distribution generates *optimal internal* noise in recurrent circuits

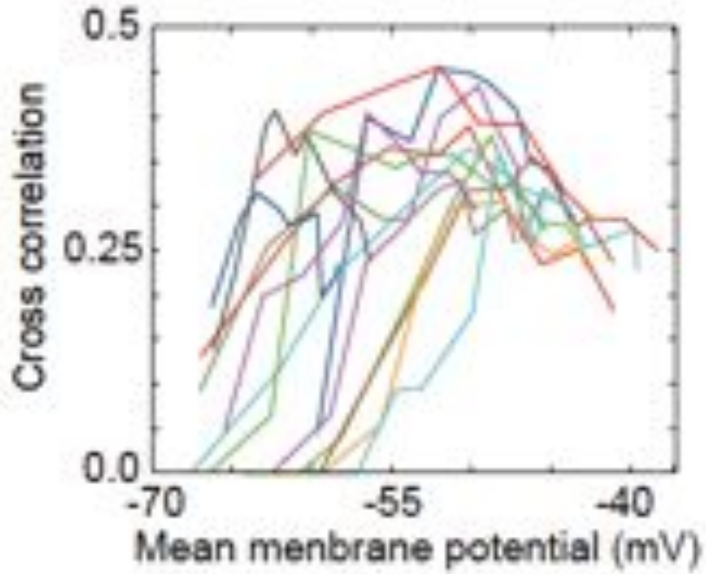
Dynamic clamp

$$I_{\mathrm{syn}}(t) = -\sum_j g_{\mathrm{E},j}(t)(V - E_{\mathrm{E}}) - \sum_j g_{\mathrm{I},j}(t)(V - E_{\mathrm{I}})$$







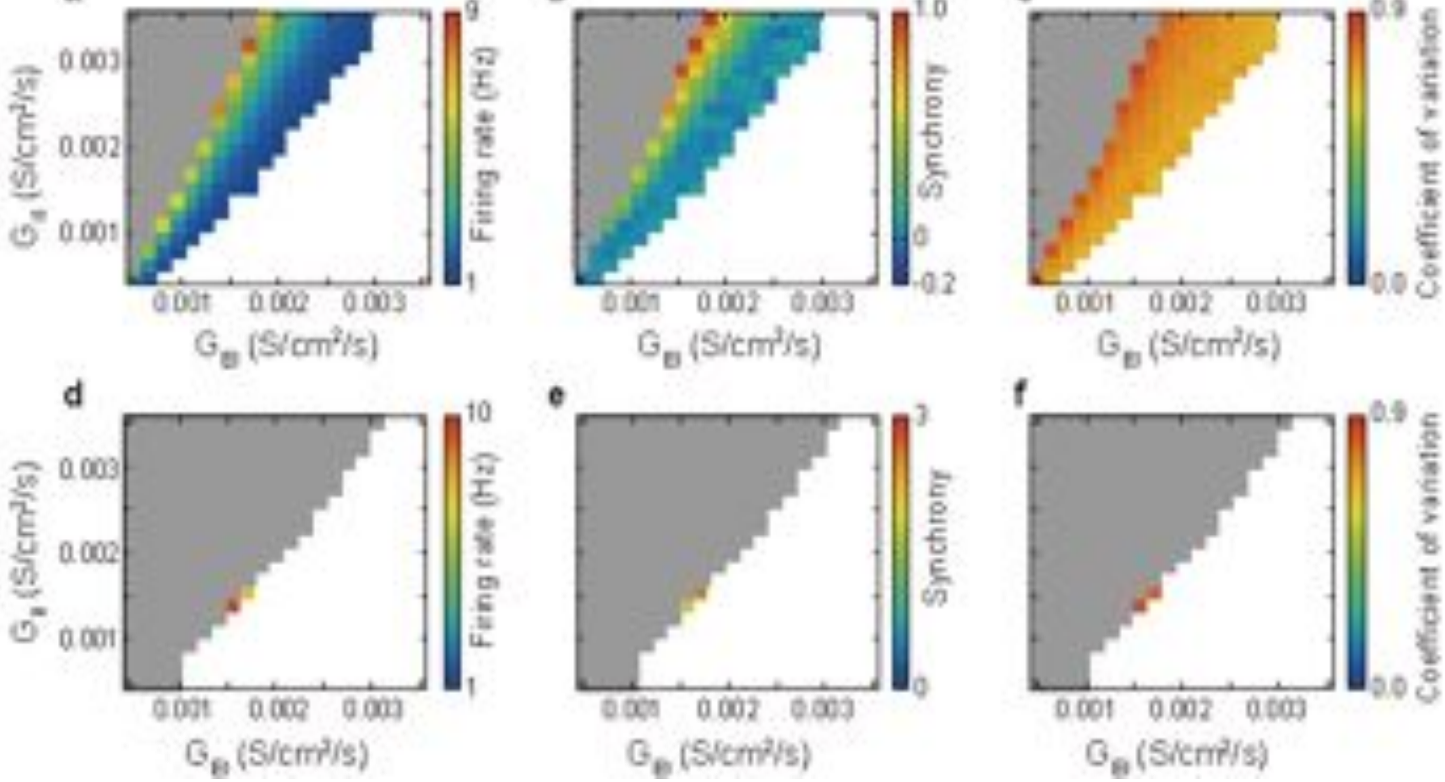


Synaptic delay enhances the stability (LIF neuron)

15 > Hz

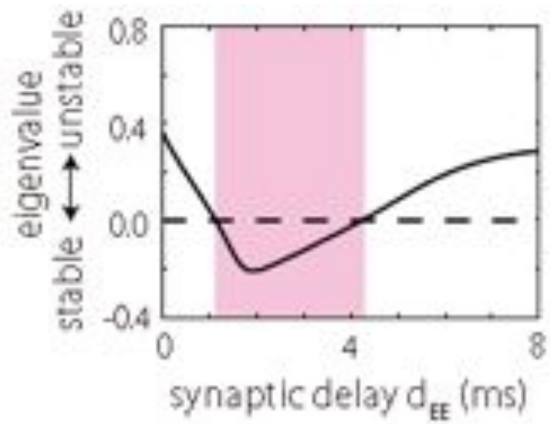
LogN weigh

Gaussian

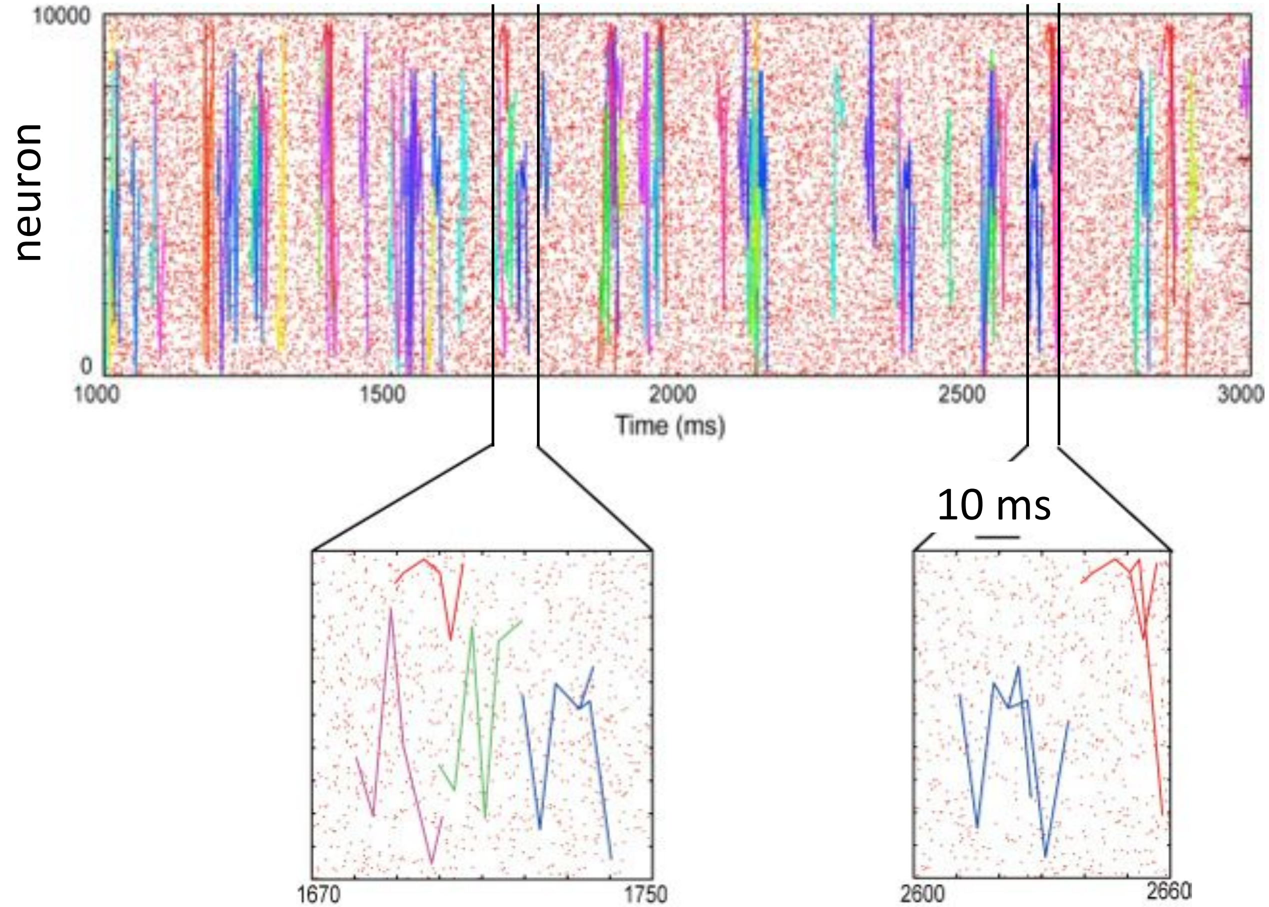


Inhibition arrives a little earlier than excitation

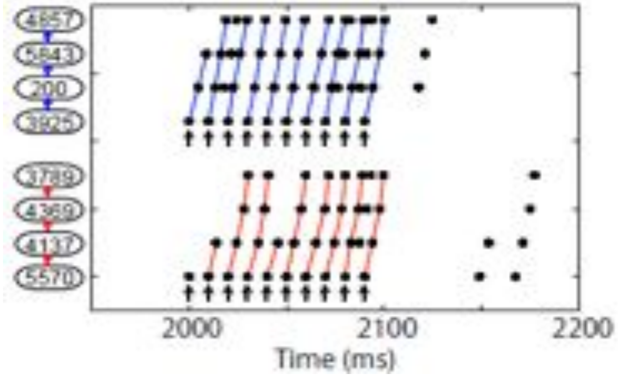
d_{EE} (~ 2ms) > d_{EI}, d_{IE}, d_{II} (~ 1 ms)



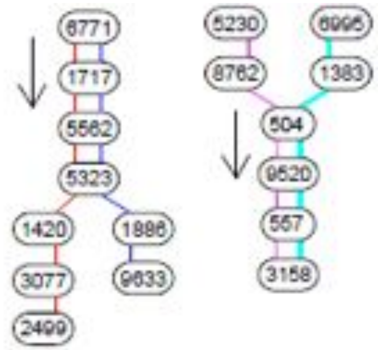
The AI state consists of vast many spike sequences



● Sequence propagation is probabilistic.



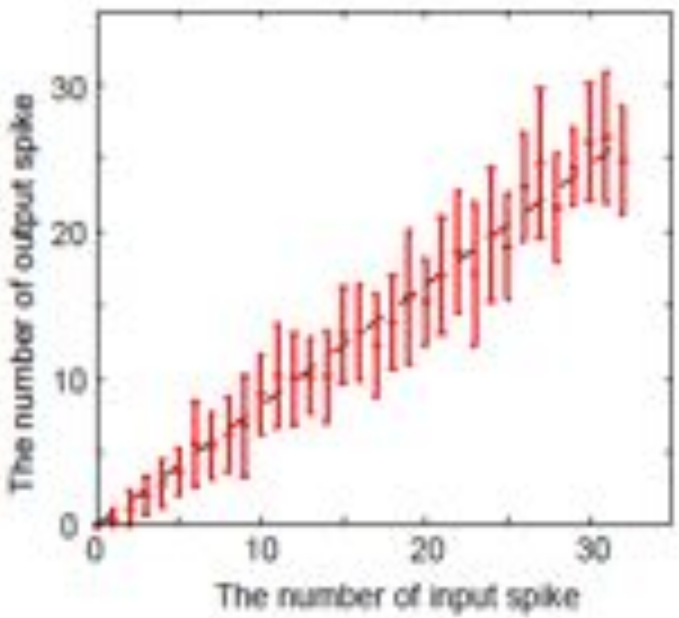
● Sequences can branch or merge.



● Sequences can be stretched or compressed.

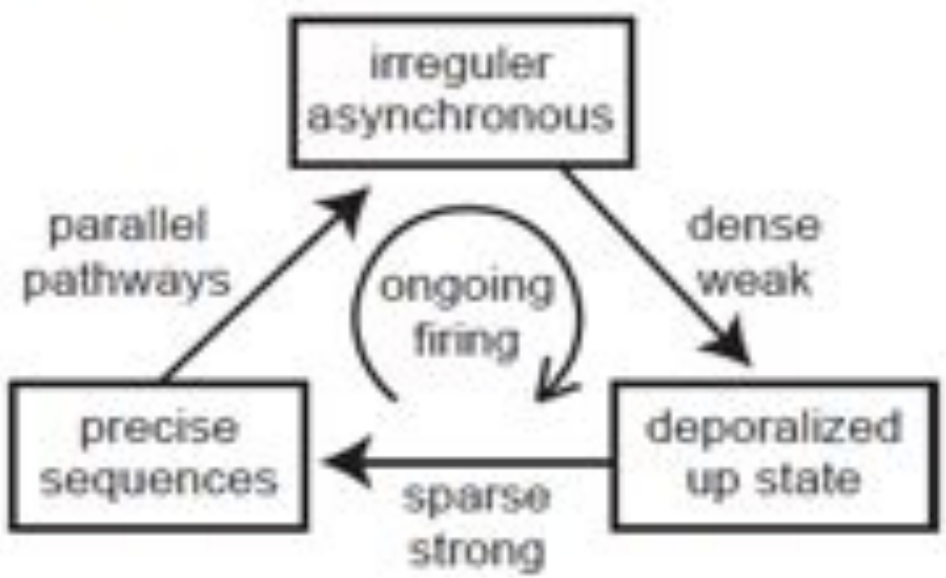
logN network can propagate firing rate information

Efficient spike routing is possible along strong synaptic pathways



Interim Summary

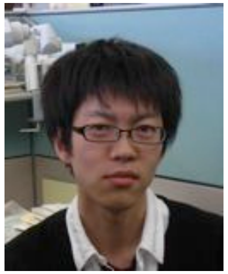
- Long-tailed (lognormal) EPSP distributions achieves asynchronous irregular states by sequences.
- Rate information propagates the pathways of strong synapses.
- Precise spike sequences and irregular firing are two sides of the same coin.



Buzsáki G, Mizuseki K.
The log-dynamic brain: how skewed distributions affect network operations.
Nat Rev Neurosci 15:264-278 (2014).

Lognormal networks for associative memory

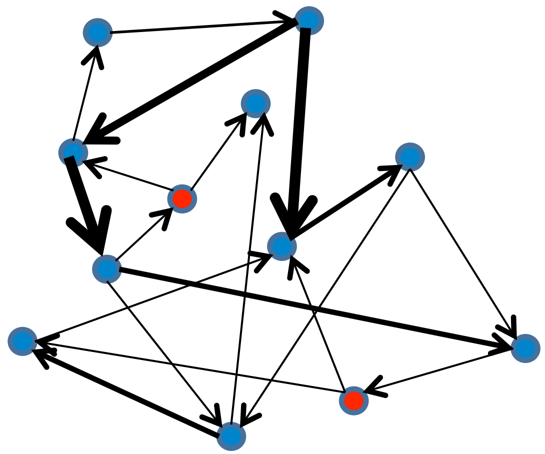
(Hiratani et al., Front Comput Neurosci, 2013)



sparse binary memory patterns

$$\mathrm{Prob}\left[\xi_i^\mu = 1\right] = a,\ \mathrm{Prob}\left[\xi_i^\mu = 0\right] = 1 - a$$

$$J_{ij} = \frac{1}{N}\sum_{\mu=1}^{P} \xi_i^\mu \xi_j^\mu$$ ~ Gaussian

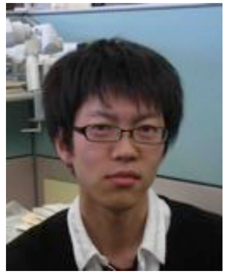


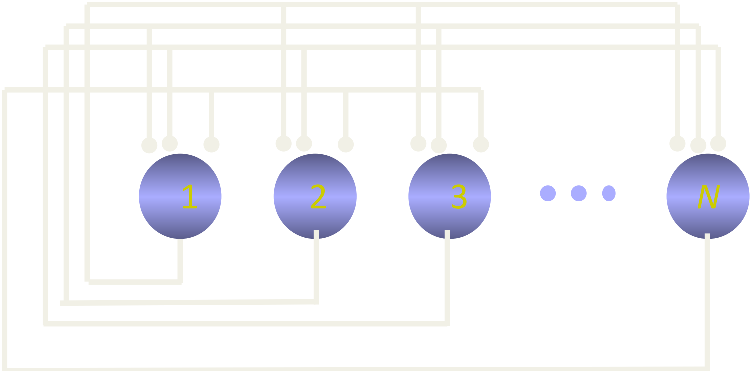
N_E : # of excitatory cells
p : # of stored patterns
a : sparseness (0<a<1)

Use cumulative distributions to map J_{ij} onto a logN distribution, preserving the relative orders between matrix elements

Lognormal associative memory model

(Hiratani et al., Front Comput Neurosci, 2013)





Sparse binary memory patterns

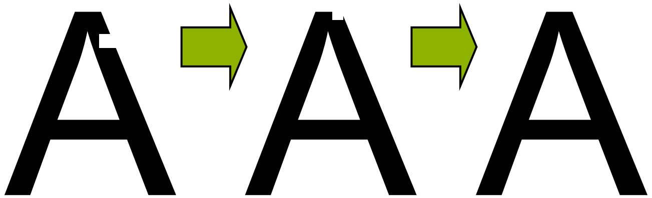
Hebb rule $$G_{ij} = \frac{1}{N}\sum_{\mu=1}^{P} \xi_i^{\mu}\xi_j^{\mu}$$

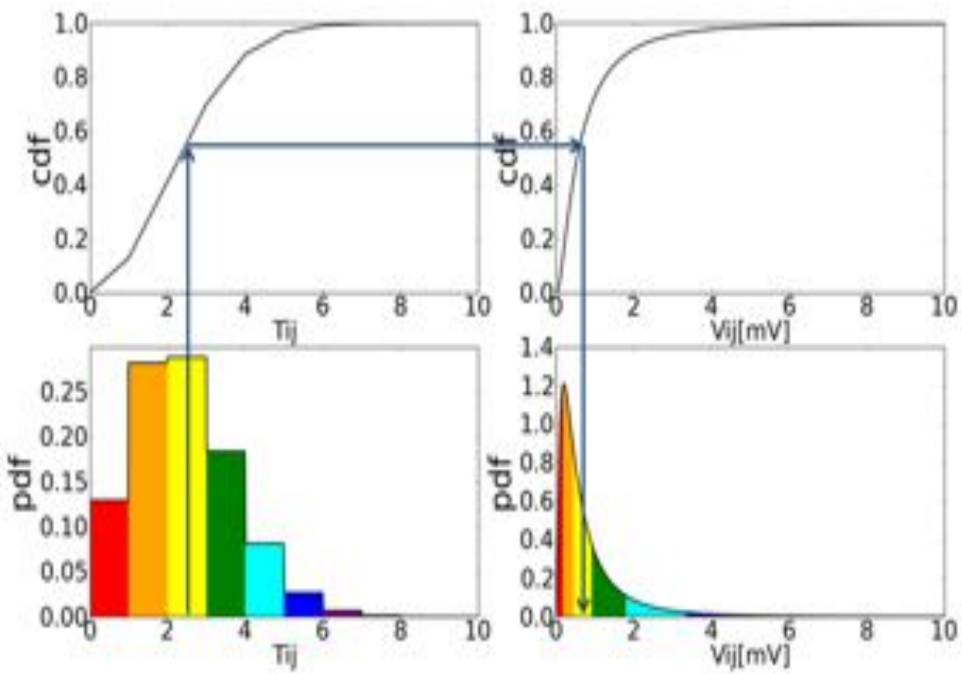
$p/N \rightarrow \infty$

Gaussian

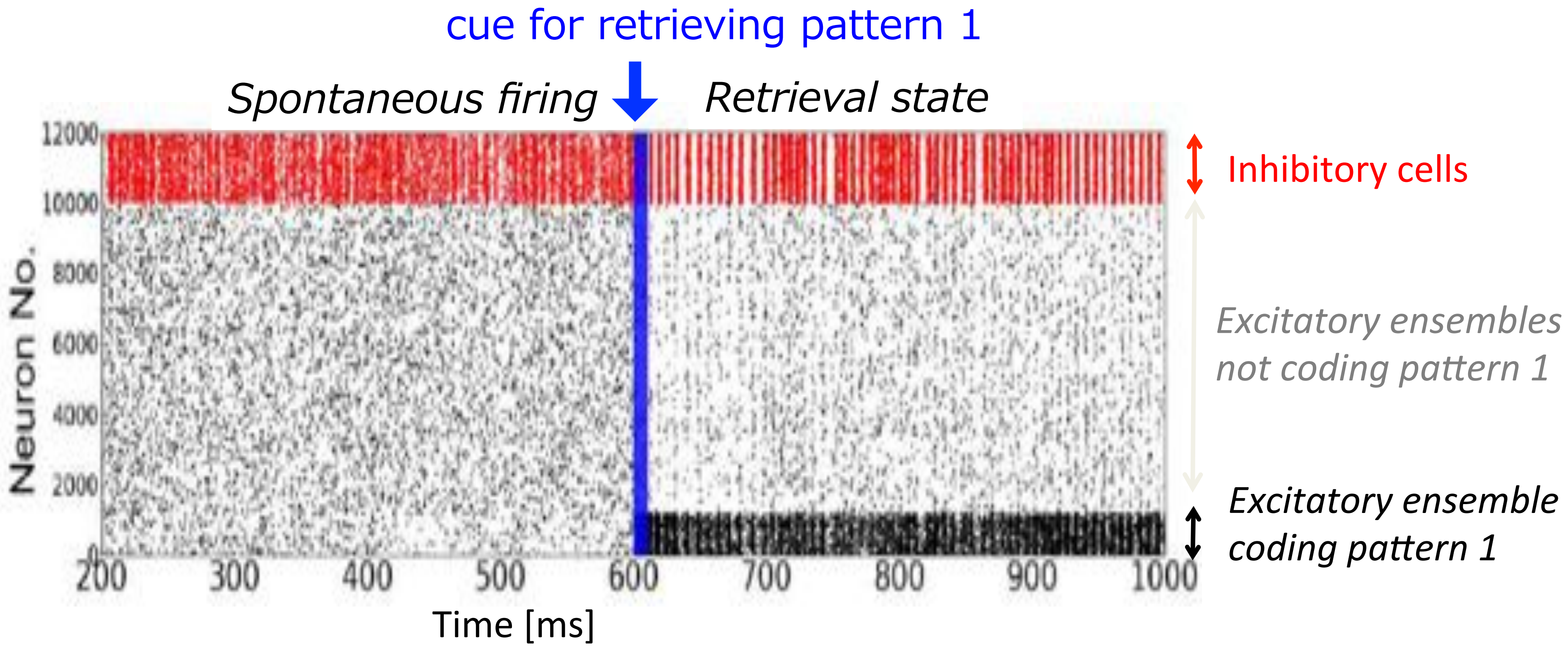
Lognormal

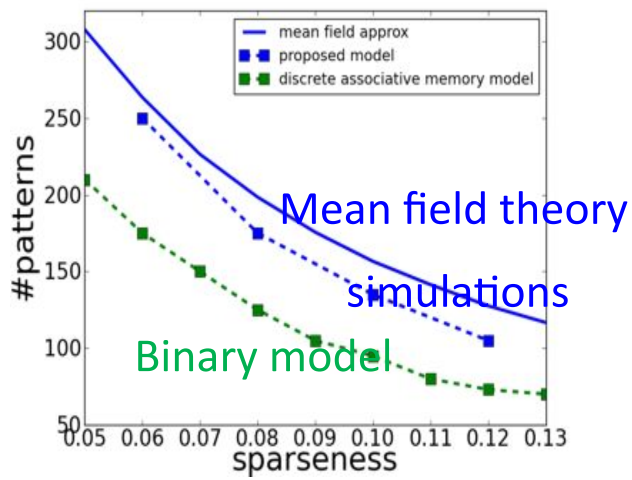
"Pattern completion"



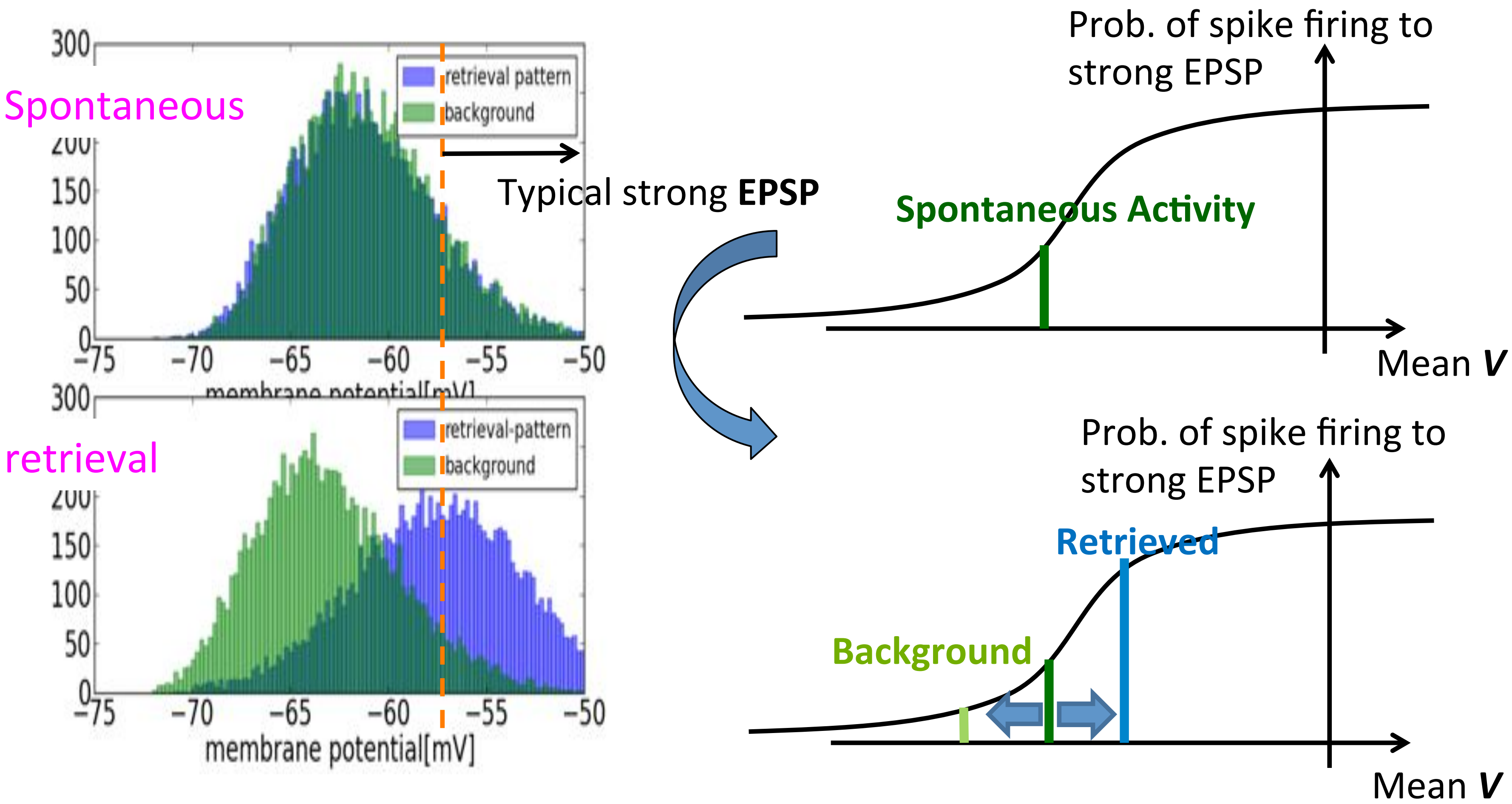


Memory recall





Internal noise structure dynamically changes during retrieval



Model of clustered cortical circuits

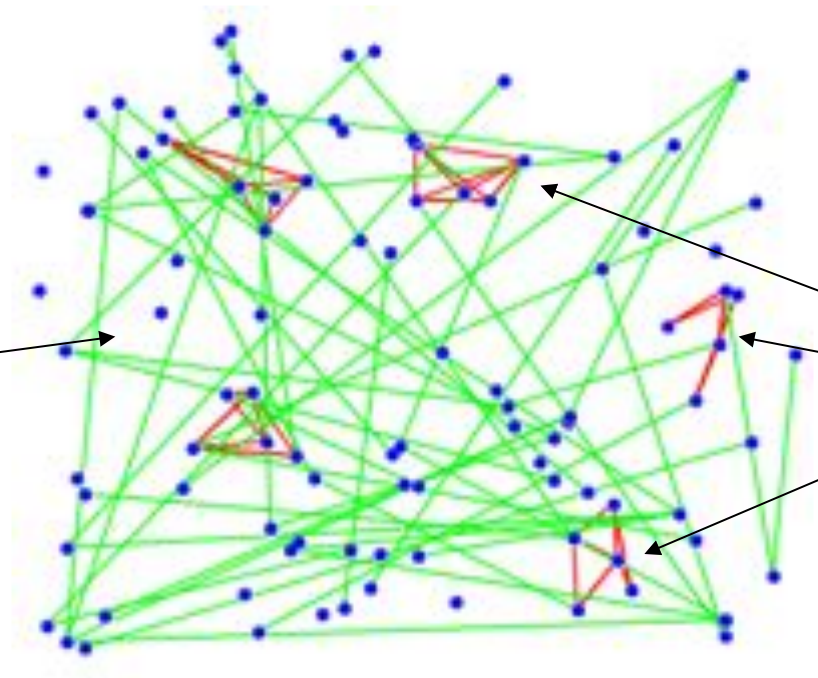
Klinshov, Teramae, Nekorkin, Fukai (PLoS ONE, 2014)

A network of *N* neurons including *K* clusters each involving *M* units
C_1, C_2 : connection probabilities
$f_1(w), f_2(w)$: weight distributions

$(100\ \mu m)^3$

Outside and between clusters

Within a cluster

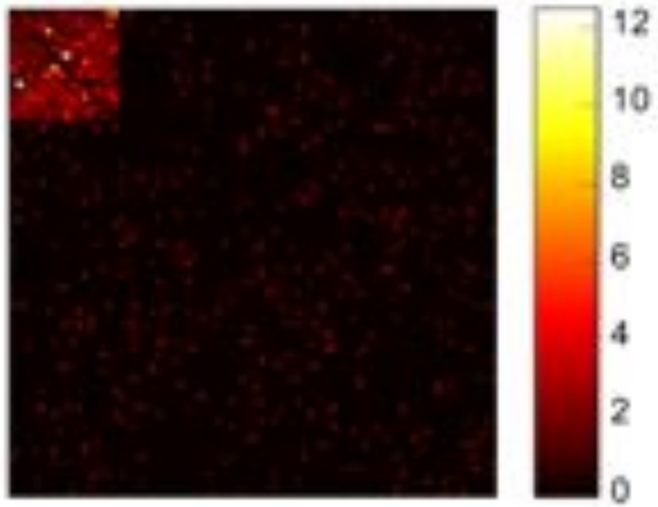


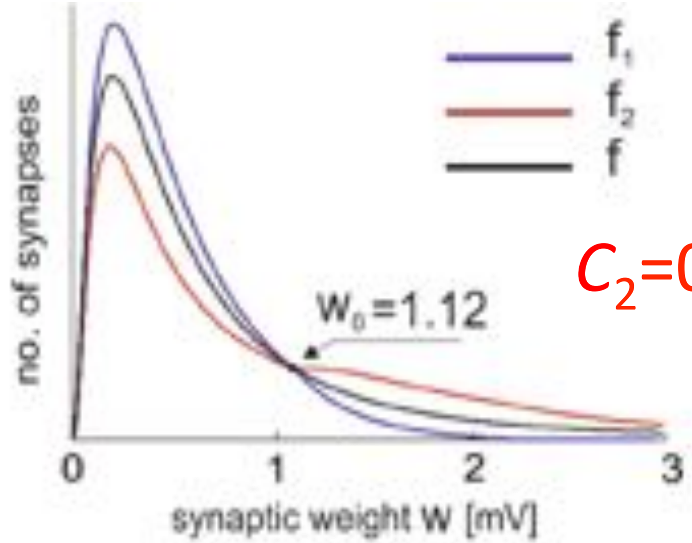
c_1
$f_1(w)$

c_2
$f_2(w)$

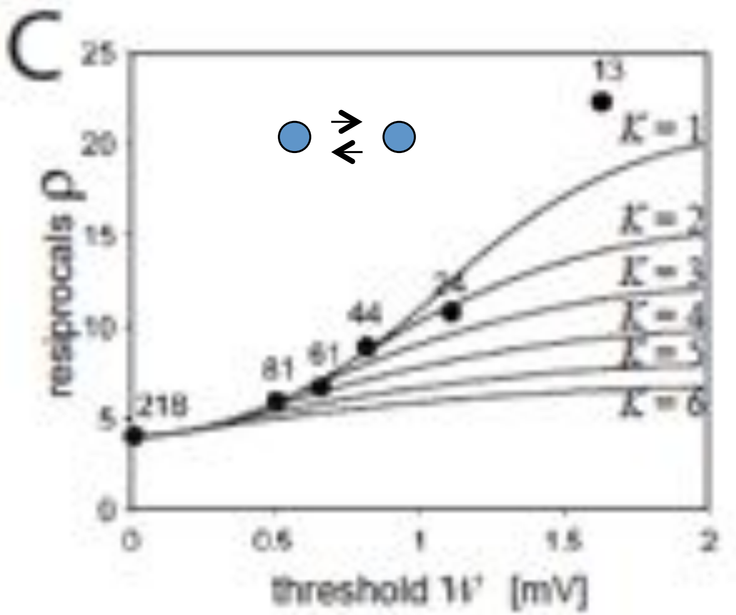
The clustered connection matrix

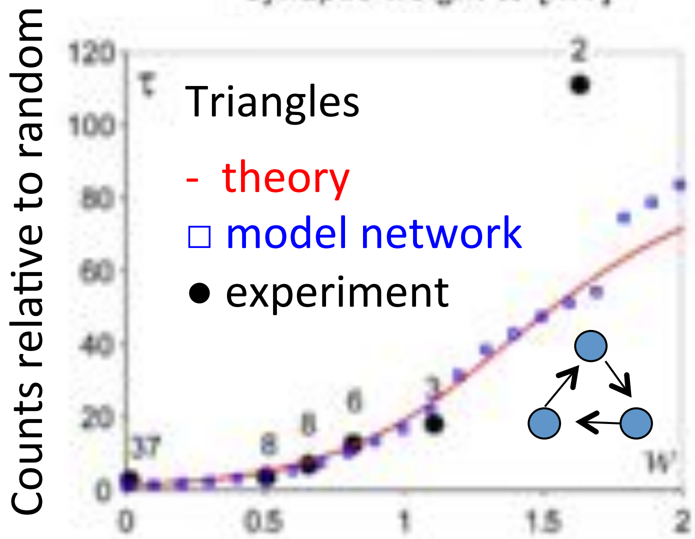
Only K=1 is consistent with all experimental observations.



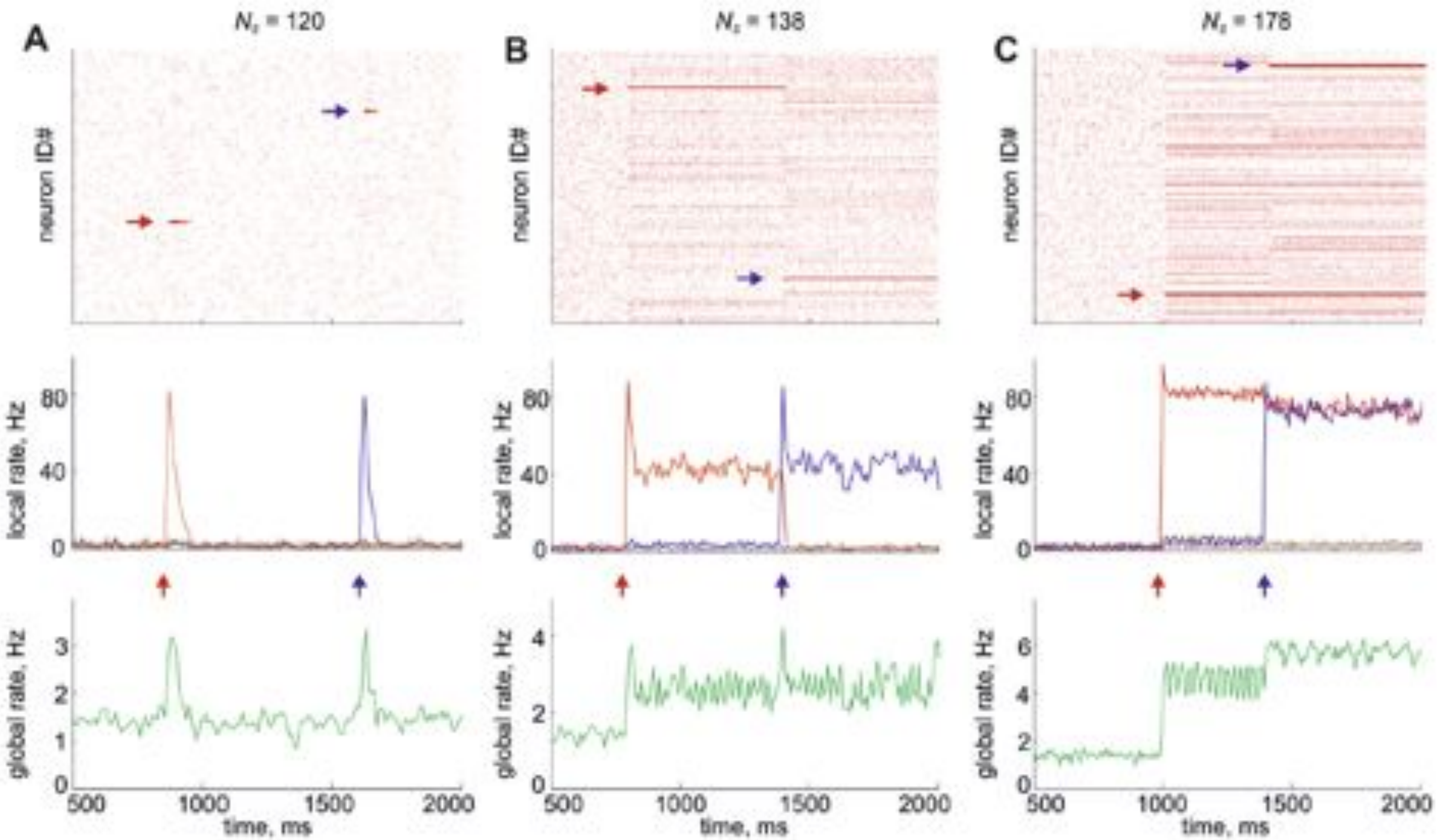


C_2=0.88 !

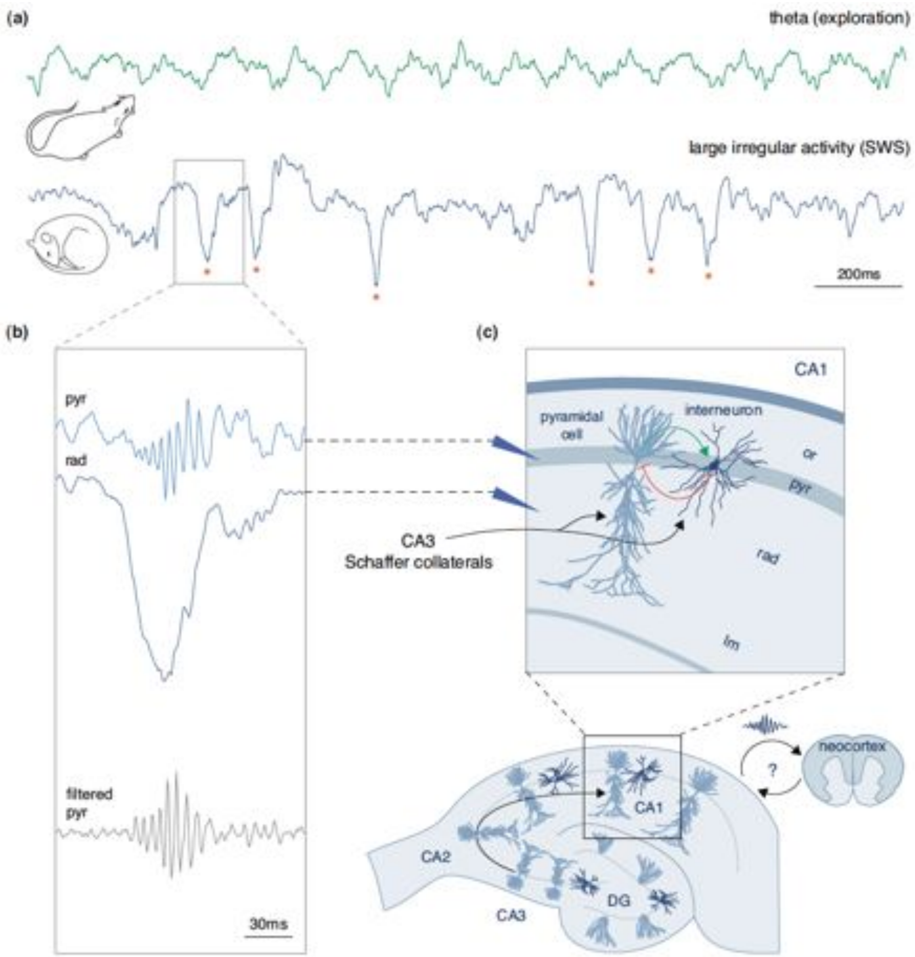




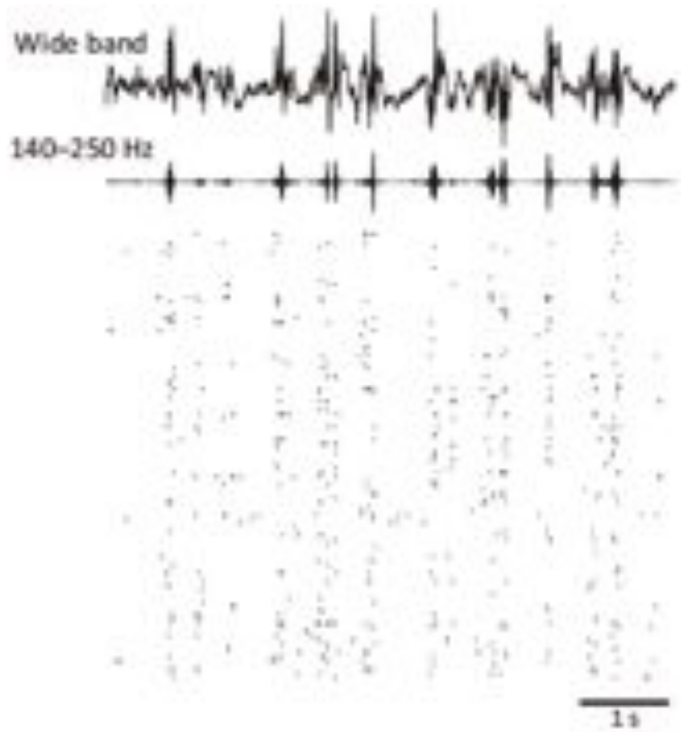
Competing working memory



Burst firing during sharp wave ripples



Girardeau and Zugaro, Curr Opin Neurobiol, 2013



McNamara et al., Nat Neurosci 2014

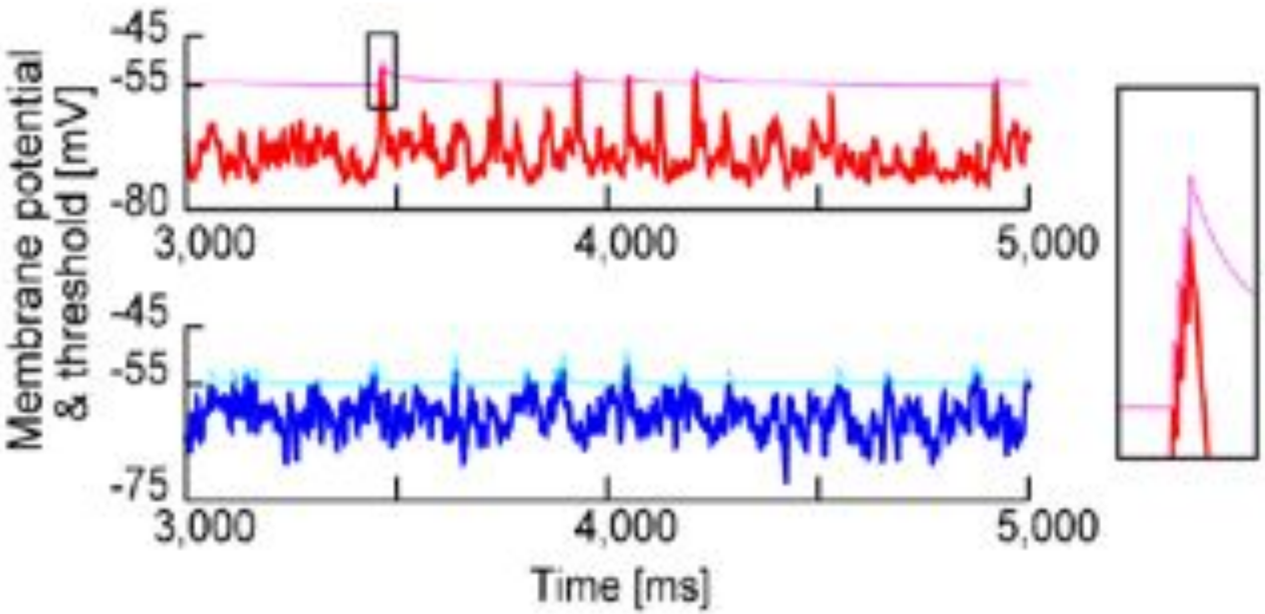
- Ripples are crucial for memory consolidation.
- Ripples are generated by CA3 input.

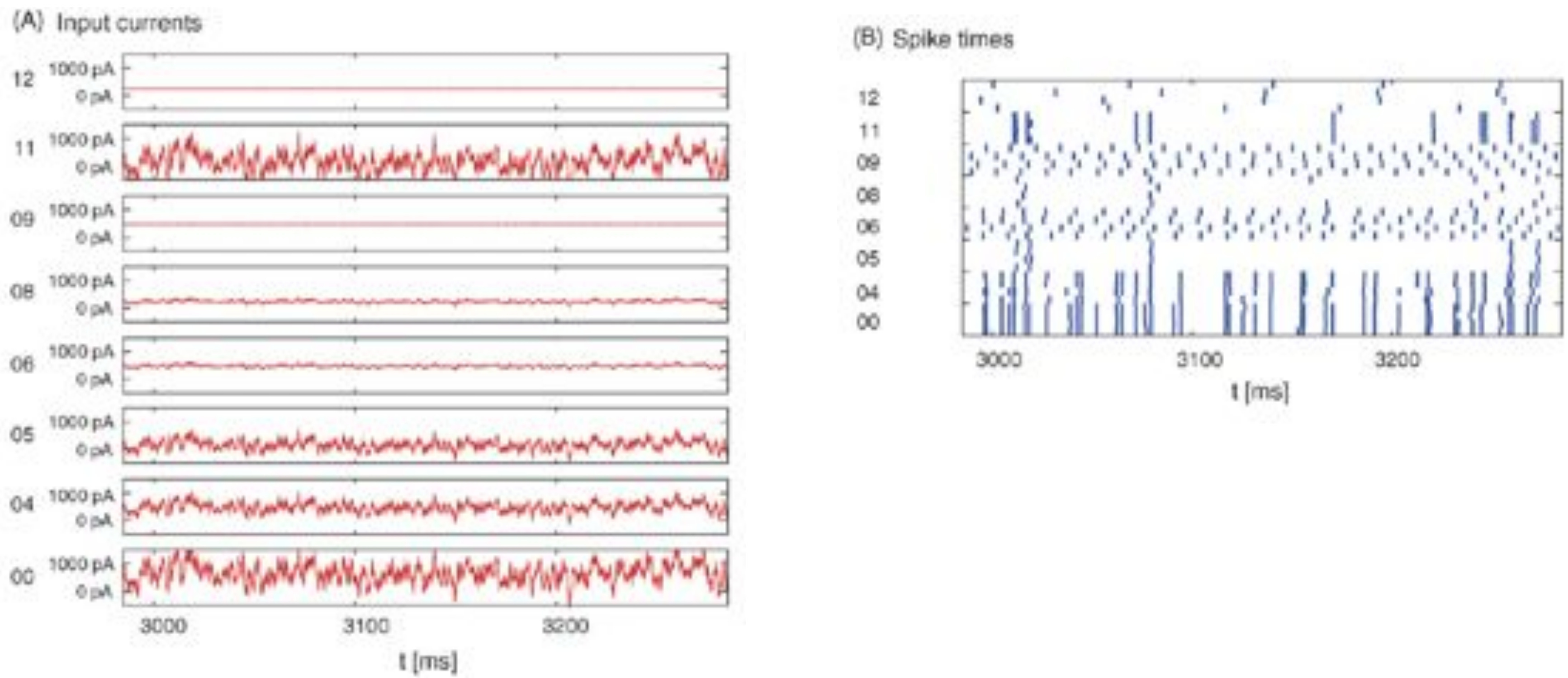
Multi-time scale adaptive threshold (MAT) model

MAT neuron has dynamical threshold and fires when $V(t)$ exceeds $\theta(t)$.

$$\theta_i(t) = \sum_j H(t - t_j) + \omega \qquad H_i(t) = \sum_{k=1,2} \alpha_k \exp(-\frac{t}{\tau_k})$$

Kobayashi et al., 2009





Results of the challenge on intrinsically reliable data only

Submission	Group	Reference	Raw Γ	Performance (Γ_A)
Submission 1	Kyoto/Kobayashi (AR)	See Section 2.4.1	0.60	0.73
Submission 2	Kyoto/Shinomoto (CC)	See Section 2.4.2	0.71	0.84
Submission 3	Anonymous 1	–	0.48	0.56
Submission 4	Anonymous 2	–	0.33	0.40
Reference 1	Lausanne/Jolivet (SRM)	See Section 2.4.3	0.70	0.84
Reference 2	Lausanne/Naud (aEIF)	See Section 2.4.4	0.70	0.83

Jolivet et al., 2008

Modeling population synchrony in the hippocampus

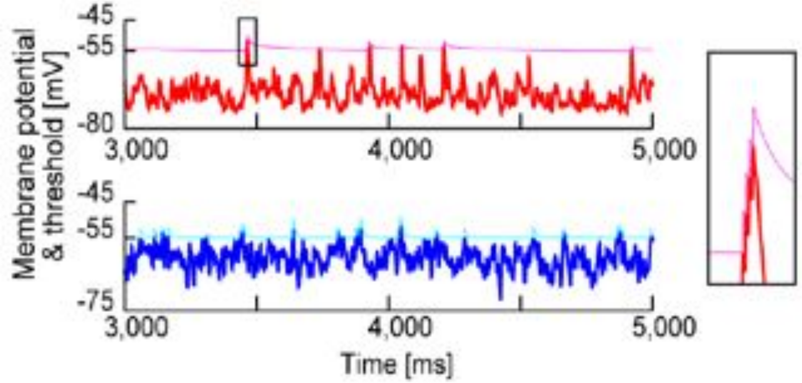
Ohmura, Carvalho, Inokuchi, Fukai (J Neurosci 2015)

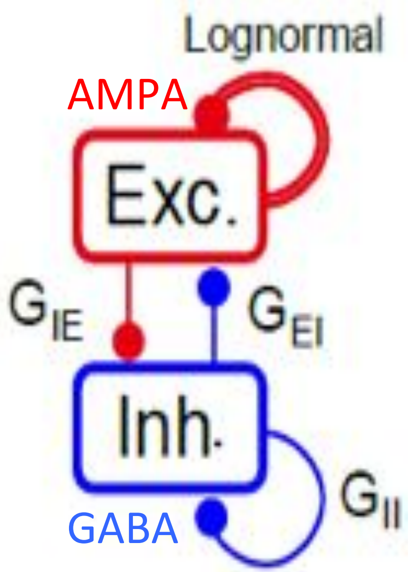
Multi-time scale Adaptive Threshold (MAT) model

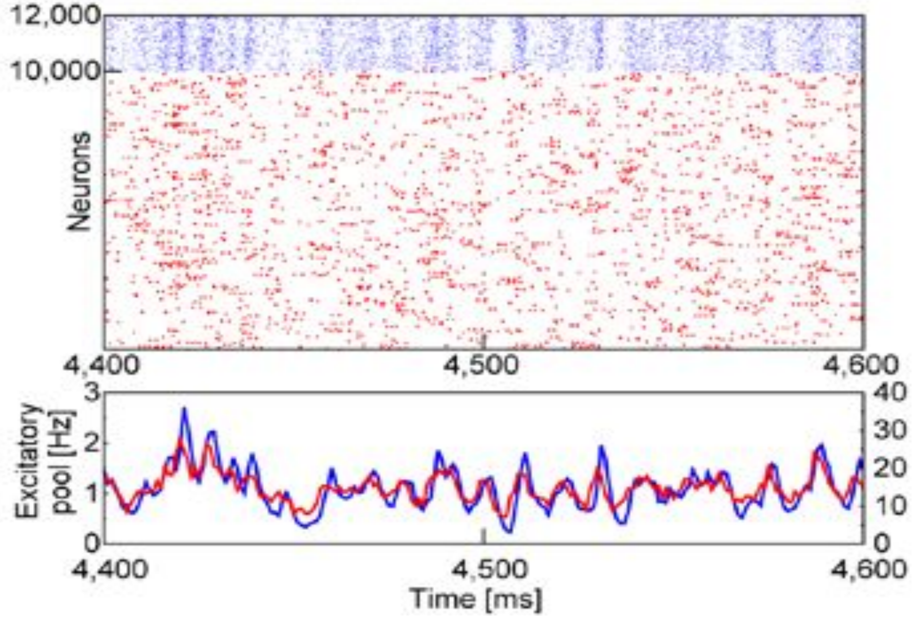
$$\theta_i(t) = \sum_j H(t - t_j) + \omega$$

$$H_i(t) = \sum_{k=1,2} \alpha_k \exp\left(-\frac{t}{\tau_k}\right)$$

Jolivet et al., 2008
Kobayashi et al., 2009

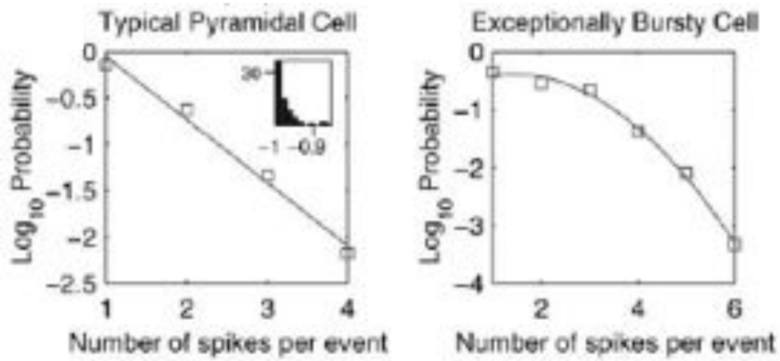




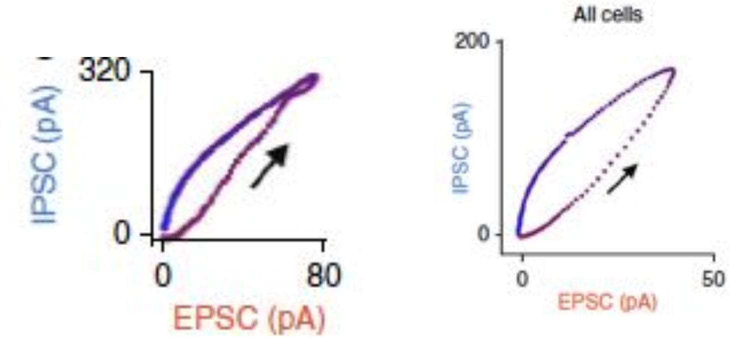


EXP

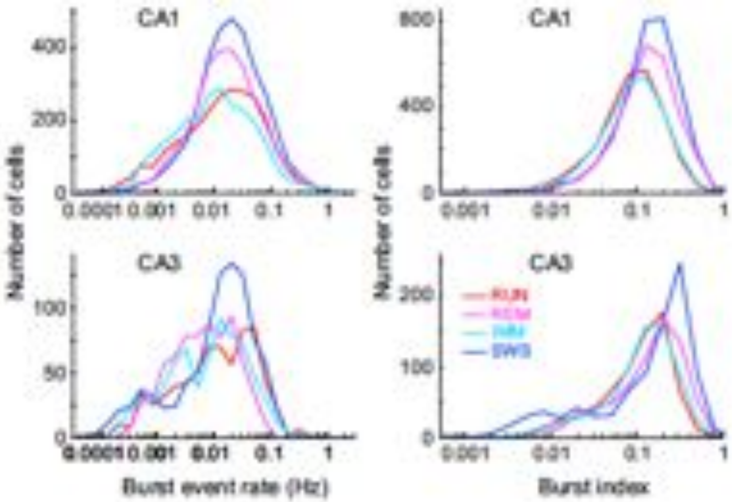
Model



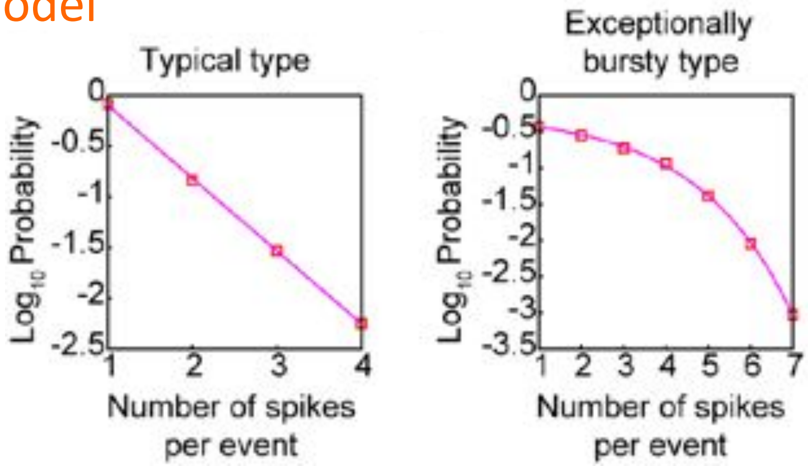
(Harris et al., Neuron 2001: CA1)

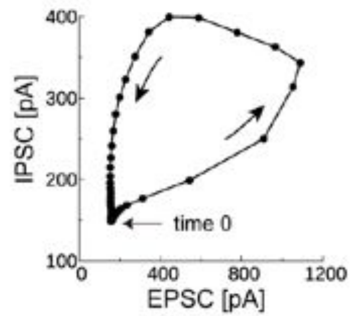


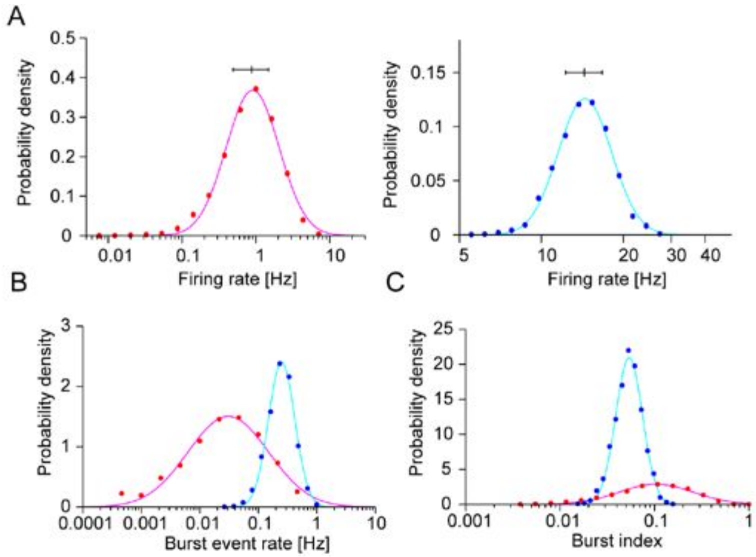
(Mizunuma et al., Nat Neurosci 2014)



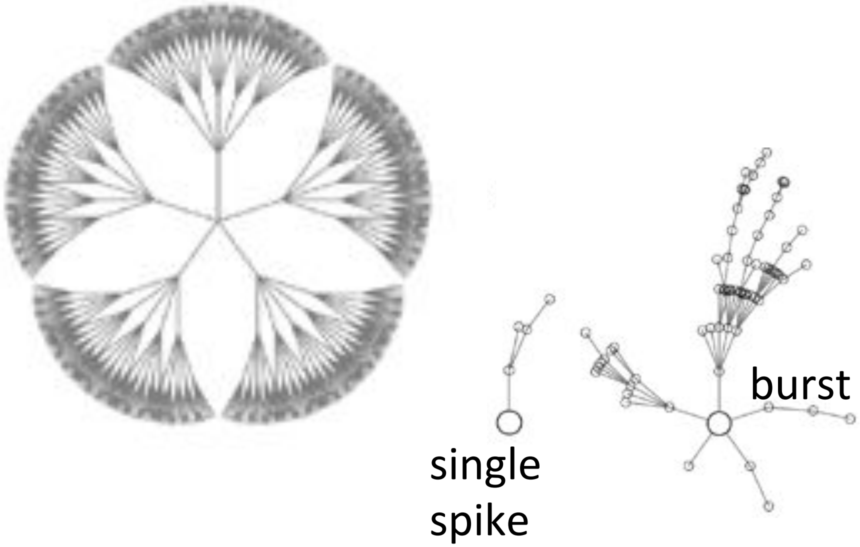
(Mizuseki and Buzsaki, Cell Rep, 2013)

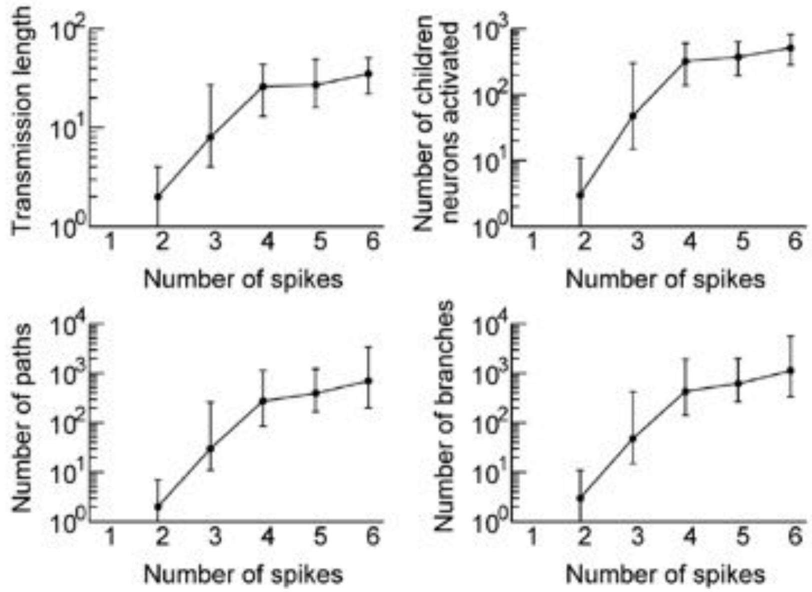


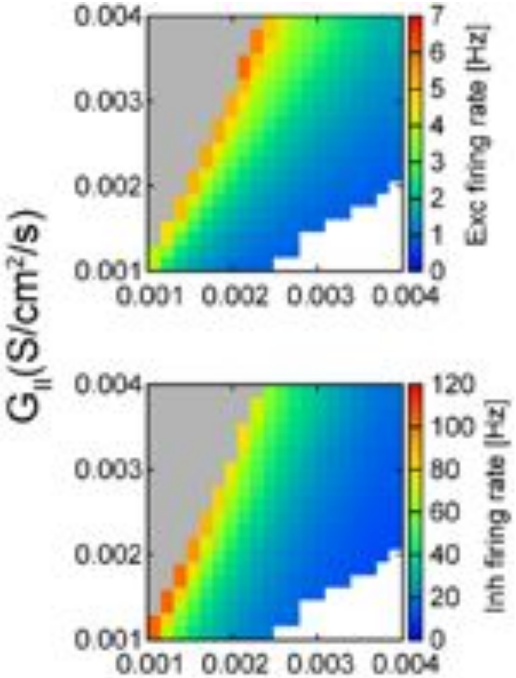




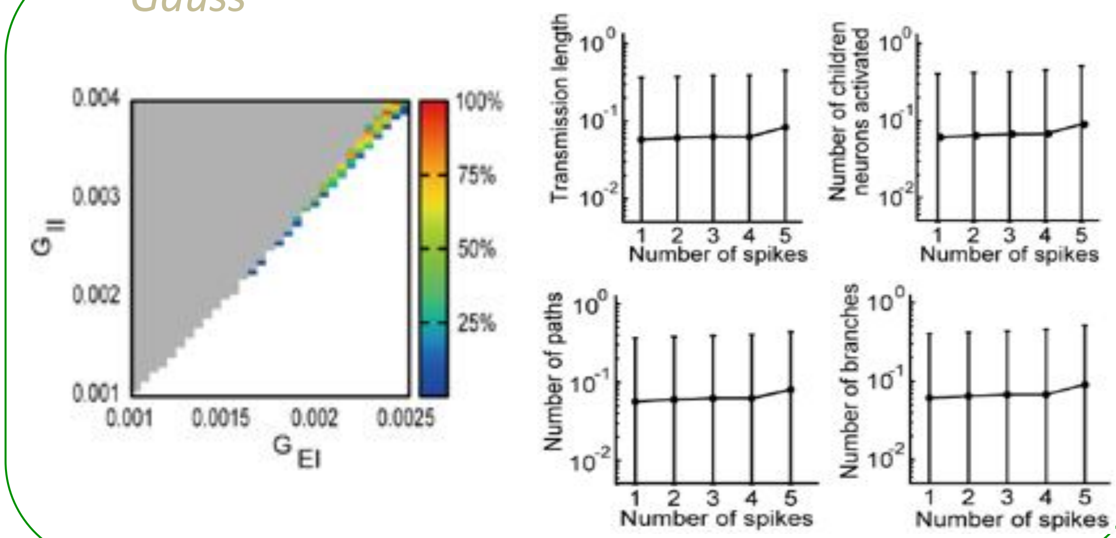
Activity propagation in lognormal networks







Gauss



Summary

Co-existence of *strong sparse synapses* and *weak dense synapses* is a typical feature of neocortical and hippocampal circuits.

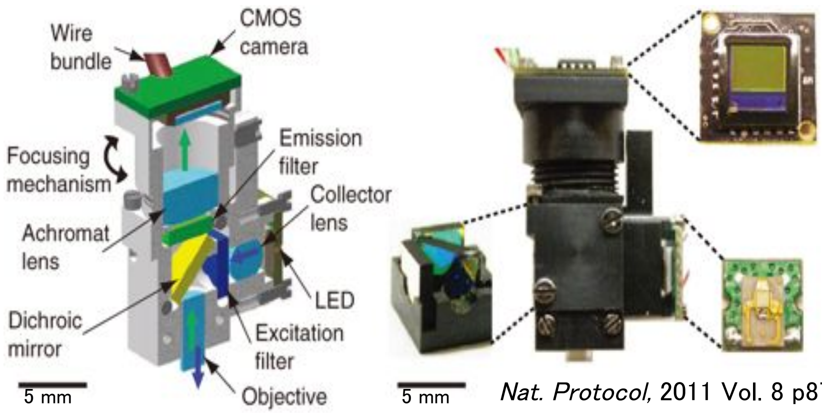
Such distributions support both irregularity and sequence in population neural activity.

Clustered networks with such distributions suggested working memory activity is cluster-size dependent.

Calcium imaging with ultrasmall endomicroscope

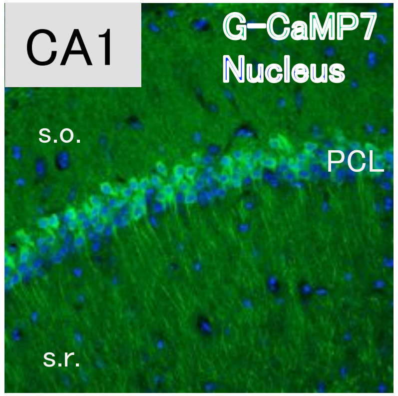
From Inokuchi laboratory
@Toyama University

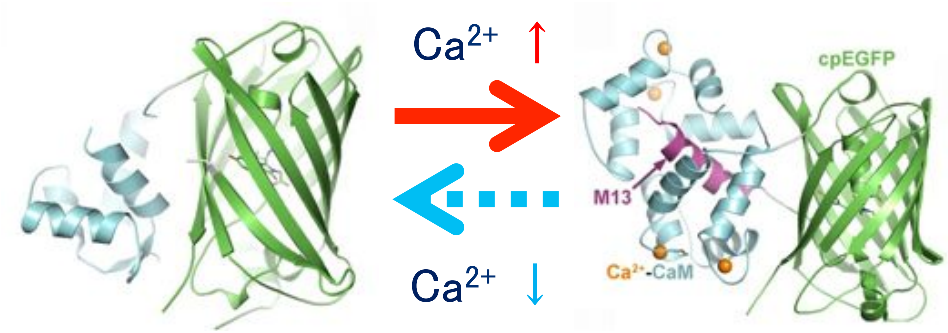
● Optical endomicroscope・*nVista*



Nat. Protocol, 2011 Vol. 8 p871–

● Calcium sensor G-CaMP

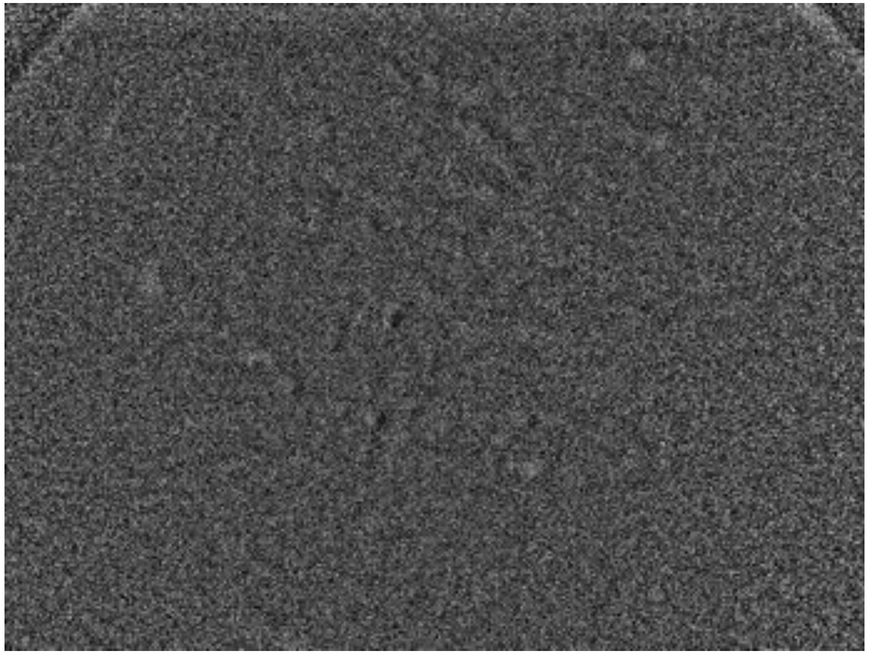




Calcium imaging with an ultrasmall endomicroscope

Novel context exposure
dF/F movie

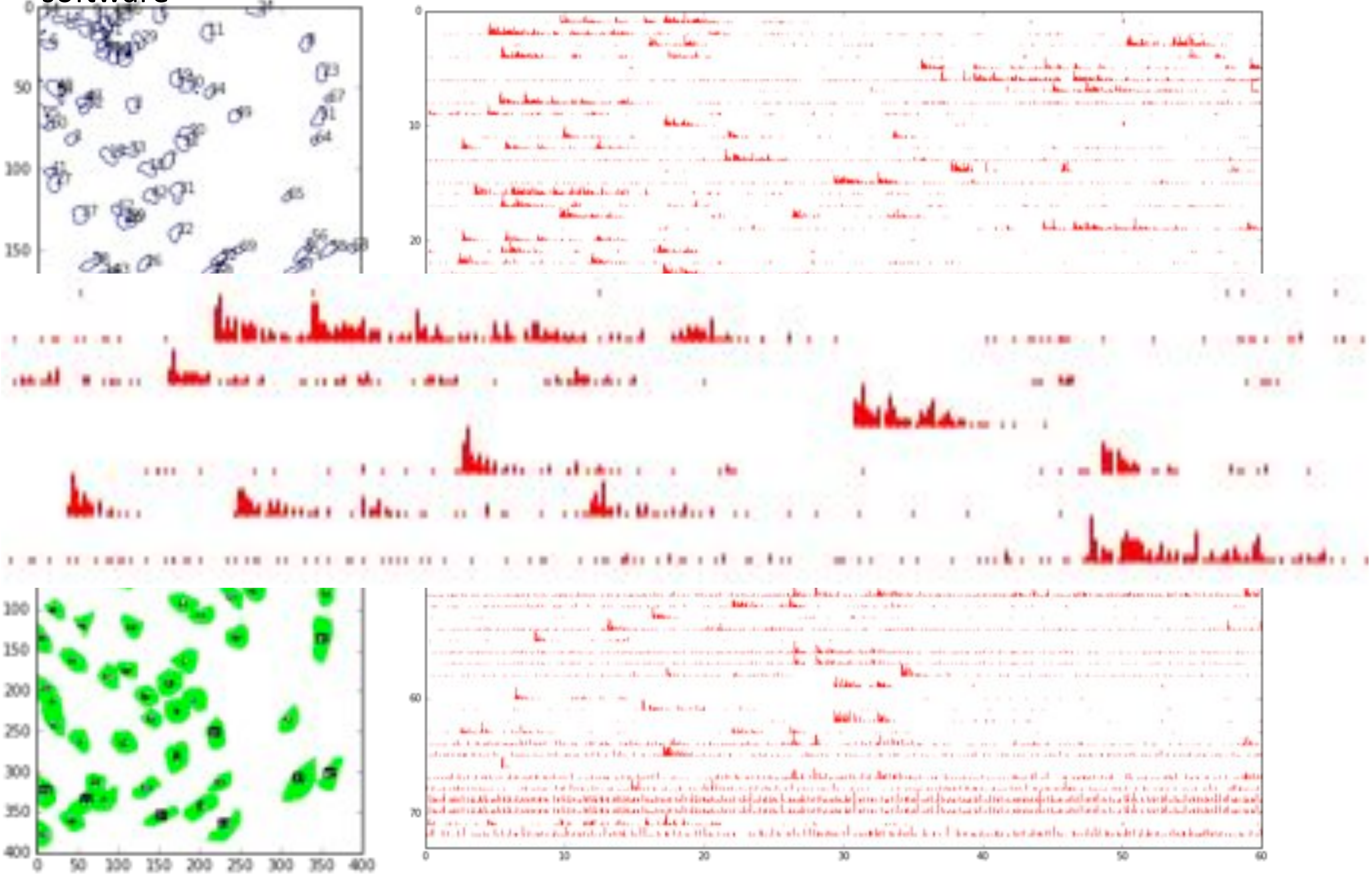
By Inokuchi laboratory
@ Toyama University



–Novel context exposure and Ca^{2+} *dF* movie–

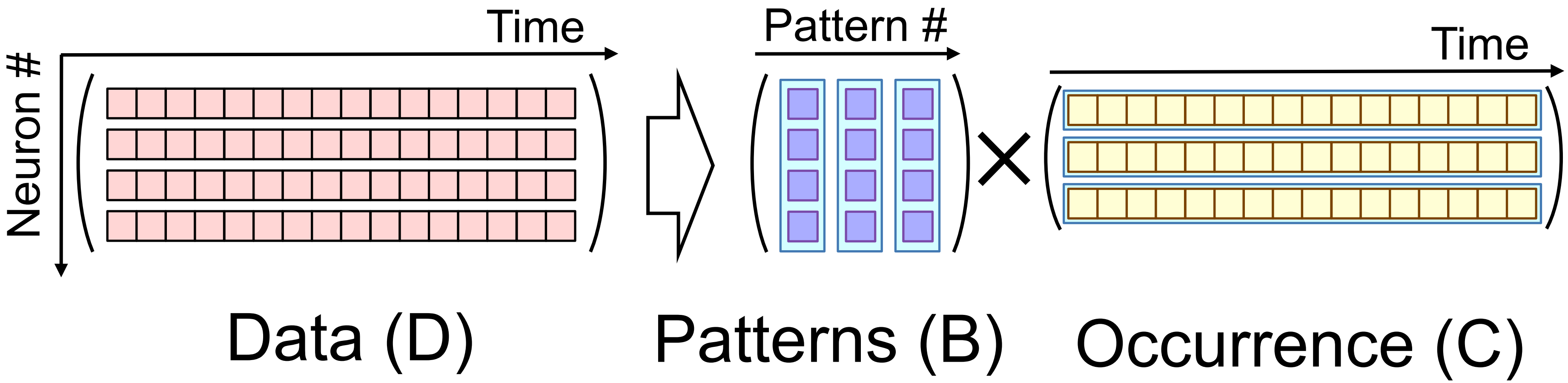
Examples of detected cells and activity patterns

software



Non-negative matrix factorization (NMF) for cell assembly detection

Alan Fung



- Data matrix expressed by a product of non-negative matrices

$$\mathbf{D} \approx \mathbf{BC}$$

- Search matrices B and C that minimize the error.

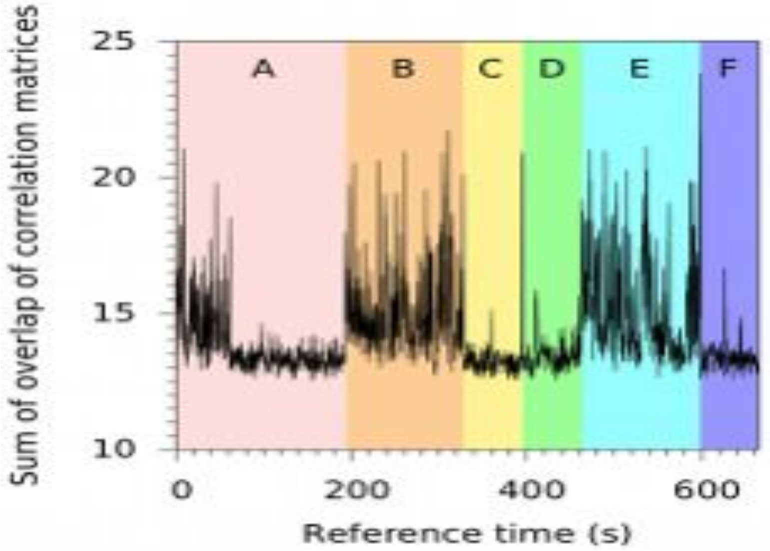
$$E \equiv \sum_{ij} \left(D_{ij} - \sum_k B_{ik} C_{kj} \right)^2$$

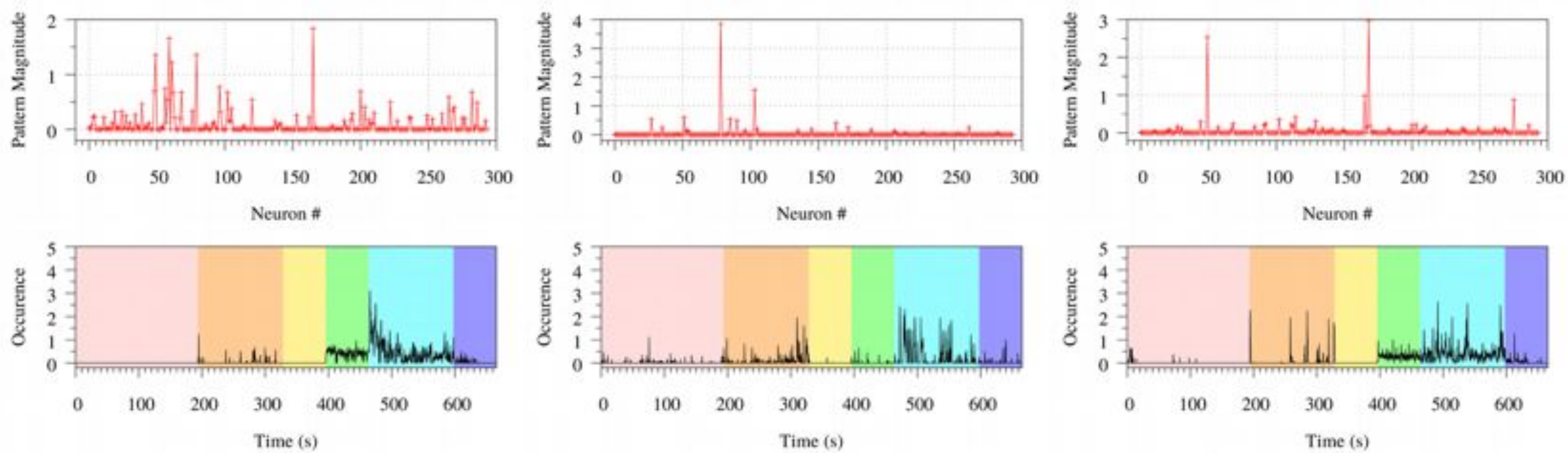
深井G, 未発表

NMF of NV61

Day 1
- A　Pre-exposure sleep
- B　Exposure to a novel context
- C　Post-exposure sleep

Day 2
- D　Pre-exposure sleep
- E　Exposure to a novel context
- F　Post-exposure sleep





Day change
Preplay?

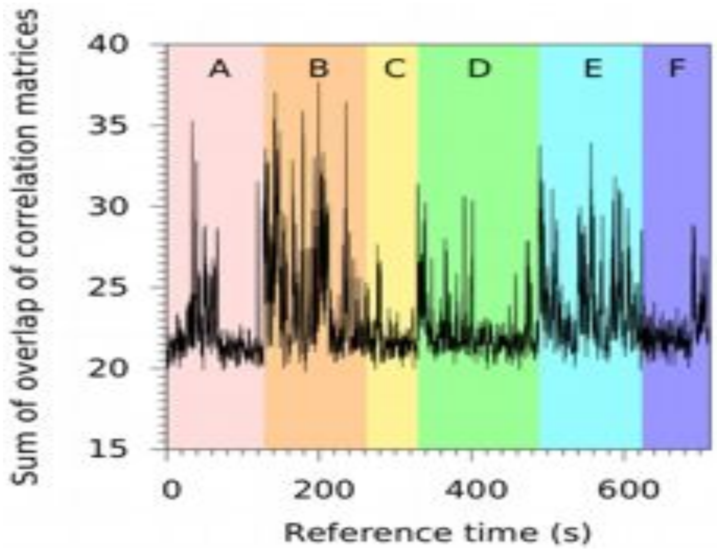
Preplay?
Interaction with previous experience

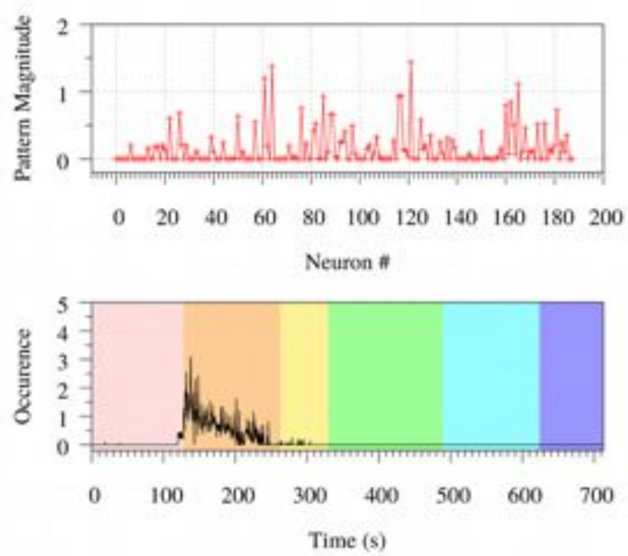
深井G, 未発表

NMF of NV62

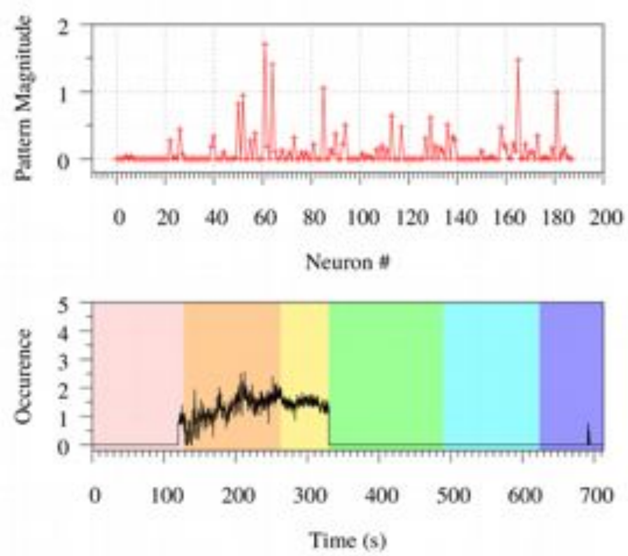
Day 1
- A Pre-exposure sleep
- B Exposure to a novel context
- C Post-exposure sleep

Day 2
- D Pre-exposure sleep
- E Exposure to a novel context
- F Post-exposure sleep

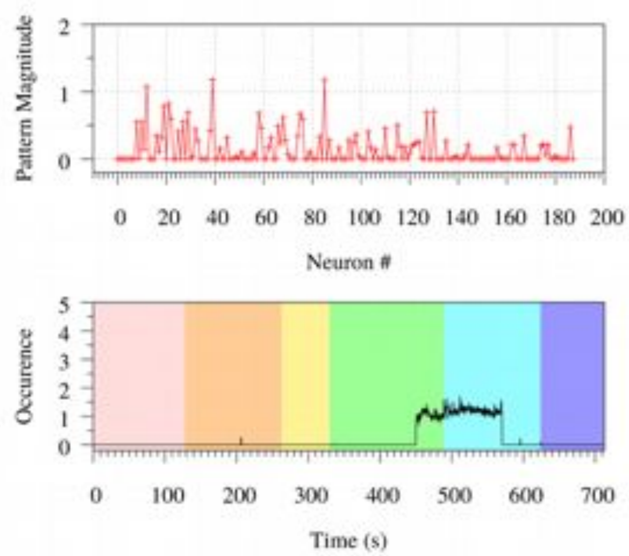




Day change
Context



Day change
Replay



Day change
Preplay

Optimal number of cell assemblies

●Too many cell assemblies does not much improve the fitting accuracy.

●Use Akaike's information criteria for determining the optimal number.