



# Analysis of external world by stochastic synapses and neurons



Tomoki Fukai  
Twin workshops@Sao Paulo, Brazil

High-Performance Computing, Stochastic modeling,  
and Database in Neuroscience

# Brain Science Institute

*Main BSI Facilities*

Brain Science Central Bldg, East Research Bldg,  
West Research Bldg, Ikenohata Research Bldg,  
Neural Circuit Genetics Bldg

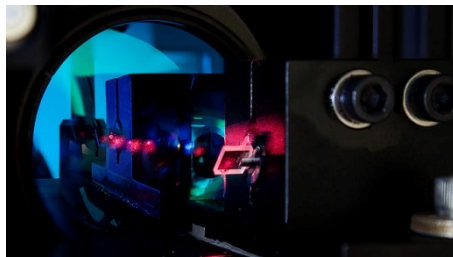


Neural circuit functions (17)  
Higher Cognitive Functions (7)  
Brain Diseases (10)  
Advanced technology (5)

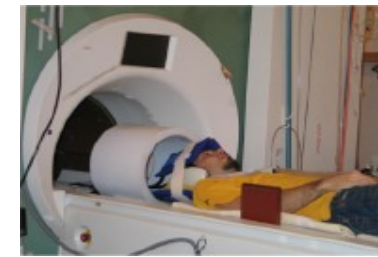
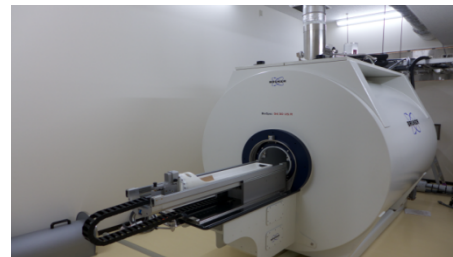


Circuit Genetics Research Bldg was launched in 2011.  
The building accommodates many labs studying the  
functions of rodent's brain circuits.

## Examples of Common Research Resources



**High resolution  
microscopy**



**Functional MRI for animals (left)  
and humans (right)**



# BSI-Neuroinformatics

RIKEN BSI RESEARCH DATABASE PORTAL

State-of-the-Art



2012 -  
Yoko Yamaguchi

## Original Databases from RIKEN-BSI

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**Degu-3D atlas**

[• Detail](#)



**Marmoset-3D atlas**

[• Detail](#)



**Marmoset-the MRI Standard brain**

[• Detail](#)



**Japanese Macaque Monkey-the MRI standard brain**

[• Detail](#)



**Microarray DB**

[• Detail](#)



**BrainTx (Former CDT-DB)**

[• Detail](#)



**Neurotycho**

[• Detail](#)



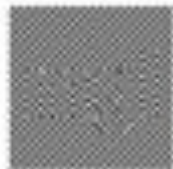
**Multichannel EEG data for Brain Machine Interface (BMI) and/or Human Emotions (HE)**

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**EToS (Efficient Technology of Spike-Sorting)**

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**MGL - matlab package for displaying visual psychophysics stimuli**

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**CellLoc-3D**

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## ■ Tools

### Multichannel EEG data for Brain Machine Interface (BMI) and/or Human Emotions (HE)



#### <Summary>

Main objective is to develop software (algorithms) for analysis of multidimensional brain data, especially multichannel EEG data. Multi-way array (tensor) factorizations and decompositions have emerged as new tools with a wide range of important potential applications, including bioinformatics, brain computer interface (BCI), text mining, image understanding and classification. We will provide experimental raw EEG data for BCI and classification of human emotions. The experimental brain data will be systematically upgraded depending on progress in recording and analyzing new brain data.

[EMOTIONS CLASSIFICATION USING EEG DATA](#) **NEWS**

#### <Contact Information>

Lab. for Advanced Brain Signal Processing (Andrzej Cichocki [a.cichocki@riken.jp](mailto:a.cichocki@riken.jp))

#### <URL>

<http://www.bsp.brain.riken.jp/>

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### EToS (Efficient Technology of Spike-Sorting)



#### <Summary>

Extra-cellularly recorded signals by single or multi electrodes contain the spike events of a number of adjacent or distant neurons. Spike-sorting methods are techniques to sort detected multi-unit activities into spike trains of individual neurons and important step for analysis of multi-neuron activities. "EToS" is a high performance spike-sorting system using latest technologies concerned with signal processing and machine learning and can accurately sort spikes into many neurons. Programs in EToS are all parallelized using OpenMP and efficiently calculate on the computers with multi-core processors.

#### <Contact Information>

Lab. for Neural Circuit Theory (Takashi Takekawa [takekawa@users.sourceforge.net](mailto:takekawa@users.sourceforge.net))

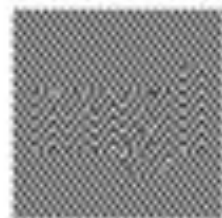
#### <URL>

<http://etos.sourceforge.net/>

[↑ Page Top](#)



### MGL - matlab package for displaying visual psychophysics stimuli



<Summary>

Mgl is a suite of mex/m files for displaying visual psychophysics stimuli and writing experimental programs in Matlab. Runs on Mac OS X (G4/5 and Intel 32 and Intel 64 bit OS Versions 10.5-10.7) Version 2.0. An older version 1.5 runs on Linux.

<Contact Information>

Gardner Research Unit (Justin L. Gardner [jlg@stanford.edu](mailto:jlg@stanford.edu))

<URL>

<http://gru.stanford.edu/doku.php/mgl/overview>

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### mrTools - matlab package for analyzing fMRI data



<Summary>

mrTools provides a set of Matlab tools to analyze fMRI data. It can do basic analyses like correlation analyses used in retinotopy experiments, event-related and GLM analyses. It can display the results of analyses on inplane anatomies, flat maps and surfaces. It is designed to make it easy to write your own script and programs in Matlab to analyze your data.

<Contact Information>

Gardner Research Unit (Justin L. Gardner [jlg@stanford.edu](mailto:jlg@stanford.edu))

<URL>

<http://gru.stanford.edu/doku.php/mrTools/overview>

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### Two-Color Bioarray Analysis



<Summary>

"Two-Color Bioarray Analysis Software" for Gene Expression analysis using the microarray "3D-Gene" (Toray Industries, Inc.) developed by the RRC is capable of detecting gene expression differences in 2 samples using a scatter plot.

<Contact Information>

RRC/BMA (Bioarray Staff [RRC-Bioarray@at1brain.riken.jp](mailto:RRC-Bioarray@at1brain.riken.jp))

<URL>

<http://common.brain.riken.jp/rrc/cominstue/subaeng/service/3dg.html>

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## Marmoset-3D atlas



### <Summary>

Common Marmoset (*Callithrix jacchus*) is a novel primate model animal with transgenic line. Common Marmoset is a small new world primate that, because of its size, availability, and unique biological characteristics, has attracted considerable attention as a potentially useful biomedical research animal in fields such as neuroscience, stem cell research, drug toxicology, immunity and autoimmune diseases, and reproductive biology. This project aims to create the world's first digital 3-D brain atlas of Marmoset, comprising of combined histological and MR images.

### <Progress>

**NEWS** We have already opened the 3D atlas of Marmoset and are available at this web-site. Information such as the correction of structure names and software are updated whenever necessary.

### <Contact Information>

Lab. for Symbolic Cognitive Development (Atsushi Iriki) [iriki@brain.riken.jp](mailto:iriki@brain.riken.jp)

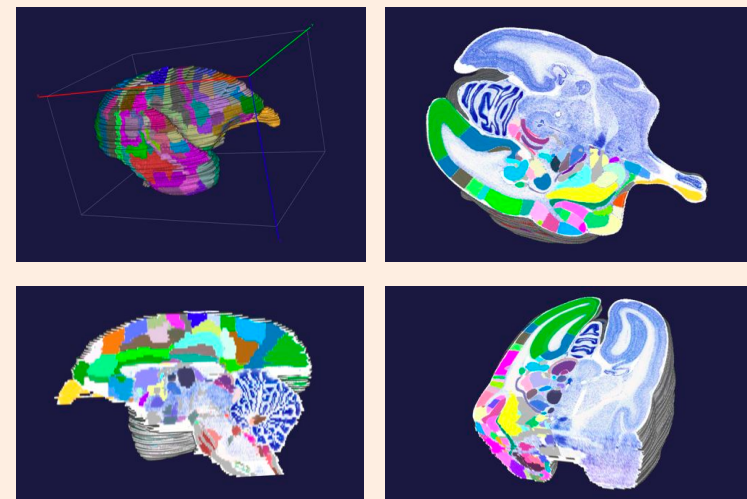
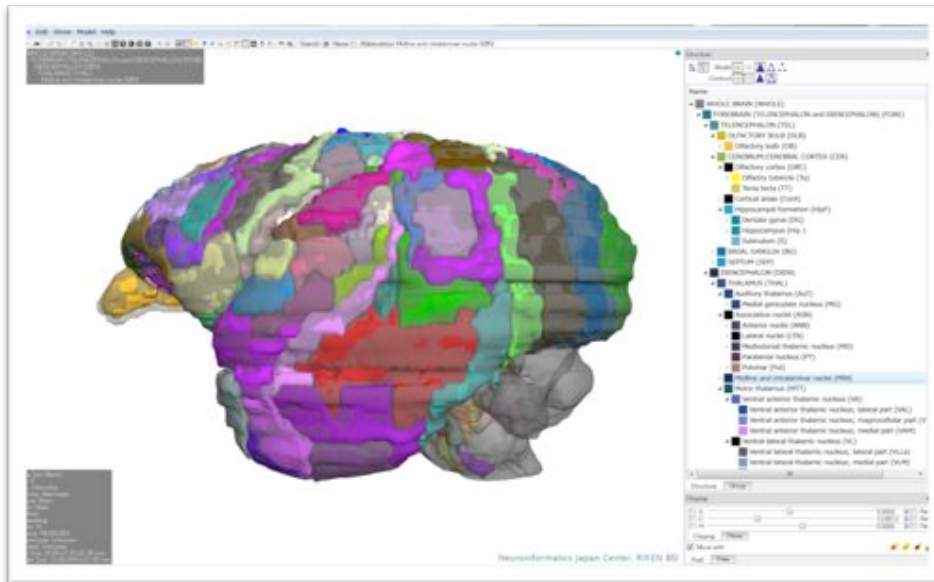
### <URL>

[http://brainatlas.brain.riken.jp/marmoset/modules/xoonips/listitem.php?index\\_id=66](http://brainatlas.brain.riken.jp/marmoset/modules/xoonips/listitem.php?index_id=66)



Marmoset-the MRI Standard brain

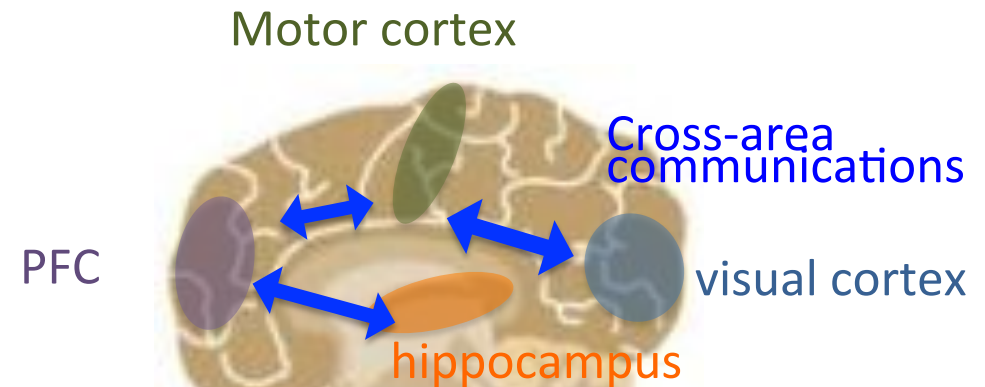
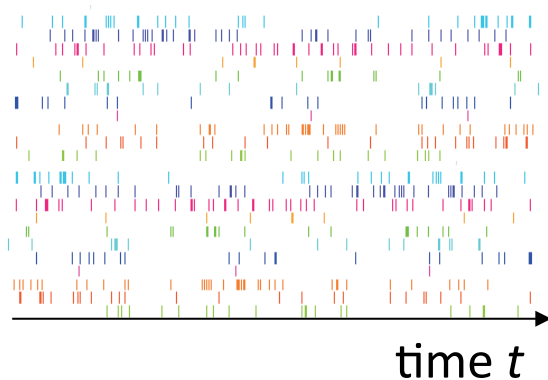
Detail



Nissle Brain (Hashikawa et al. 2015)

# Related on-going projects in my lab

- Detection of highly noisy repeated sequences without referring to external events (Brain Mind Project)



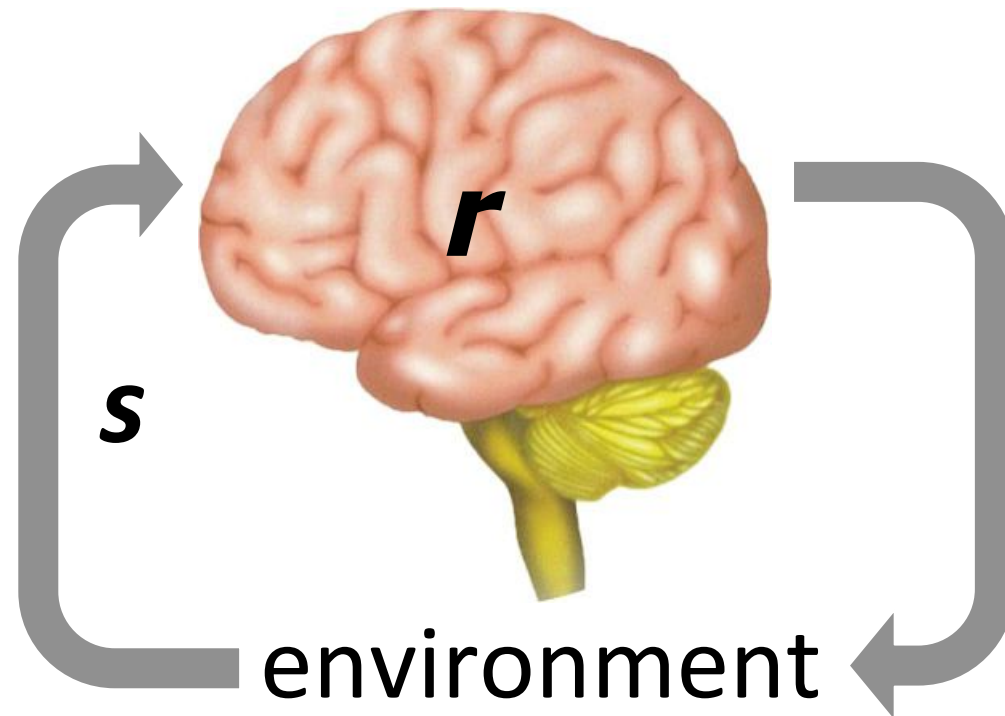
- (1) edit similarity
- (2) sparse kernel PCA

K. Watanabe, T. Hayakawa, T. Haga, T. Fukai

- Semi-automatic detection of neural ensemble activity from imaging data (CREST, JST)

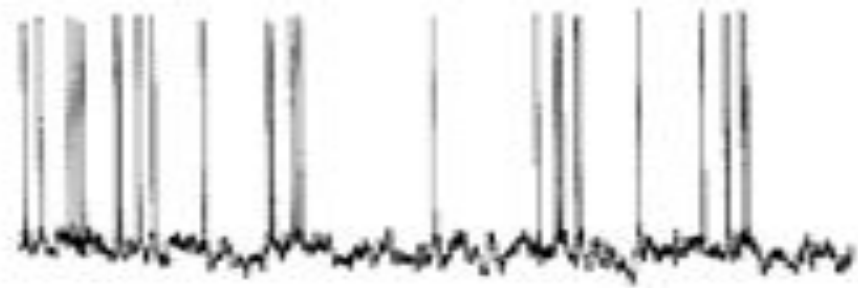
T. Takekawa, K. Inokuchi, Y. Hayashi, T. Fukai, ....

The brain models the external world through bi-directional interactions



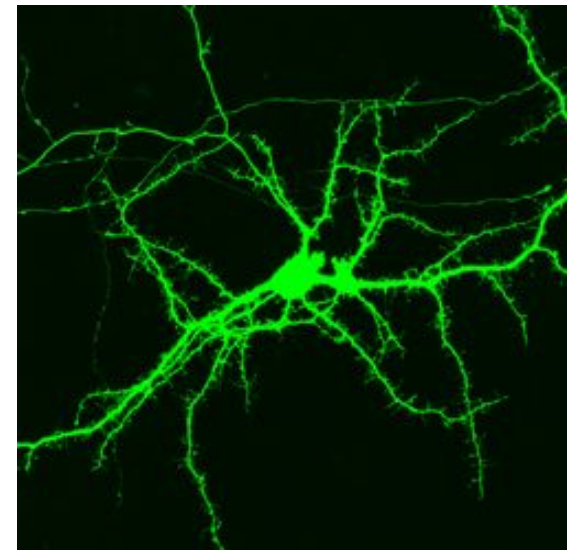


While biological neurons generate spikes, rate-based neurons already perform quite well (e.g., deep learning).  
*When are individual spikes useful?*

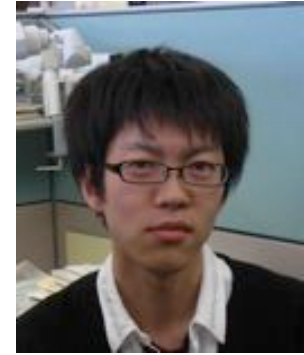


from Timofeev et al., 2001

Complex dendrites are part of neural circuits. *What can neurons perform with dendrites and synapses?*



from NIBB Web magazine



Naoki Hiratani

*Feedforward network of spiking neurons for  
blind source separation*

## Cocktail Party Problem



## Cocktail Party Effect (Blind Source Separation)

Independent component analysis ICA (Common, 1994)

Nonlinear PCA (Oja and Karhunen, 1995)

Entropy maximization (Bell and Sejnowski, 1995)

Natural gradient approach (Amari, Cichocki and Yang, 1995)

...

Yet, how the brain solves this problem is not known.

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t)$$

$\mathbf{A}$  :  $n \times n$  nonsingular mixing matrix

The problem is to find out a good estimate  $\mathbf{W}$  of  $\mathbf{A}^{-1}$

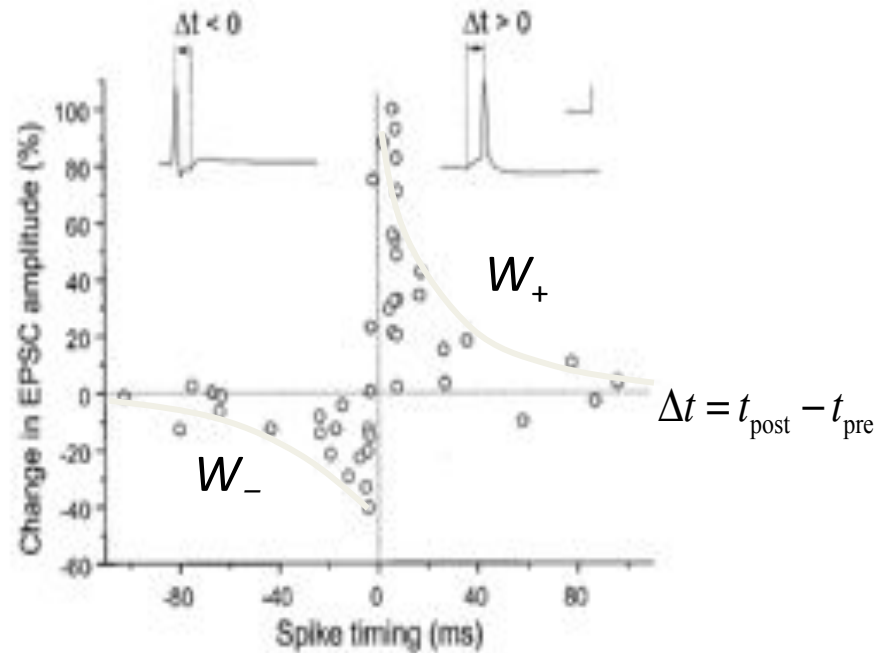
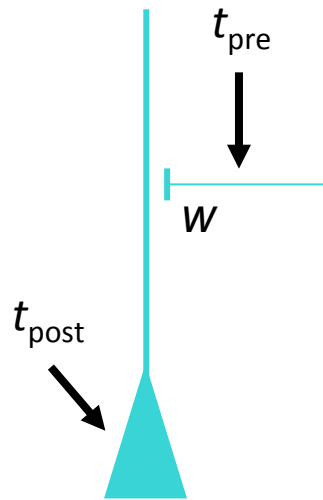
$$\tilde{\mathbf{s}}(t) = \mathbf{W}\mathbf{x}(t)$$





# Spike-Timing-Dependent Plasticity

(Bi and Poo, 1998)

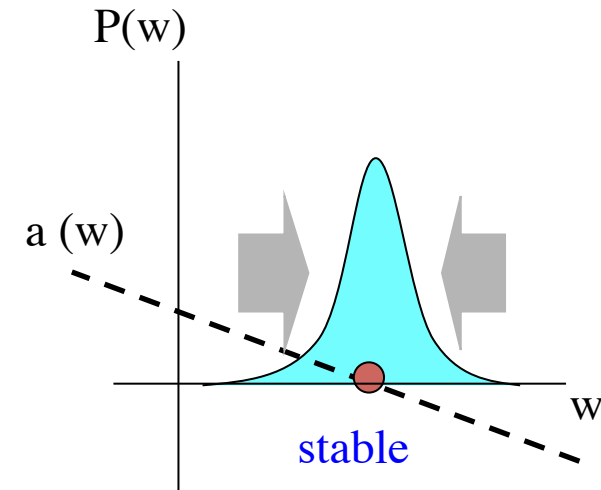


*Gaussian weight dist.*

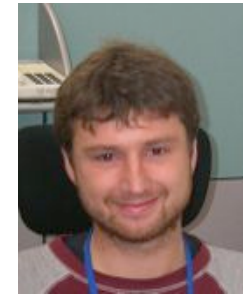
*Multiplicative rule*

$$\Delta w = \begin{cases} (c_+ + wn) \exp(-\Delta t / \tau_+) & \text{LTP} \\ (-c_- w + wn) \exp(\Delta t / \tau_-) & \text{LTD} \end{cases}$$

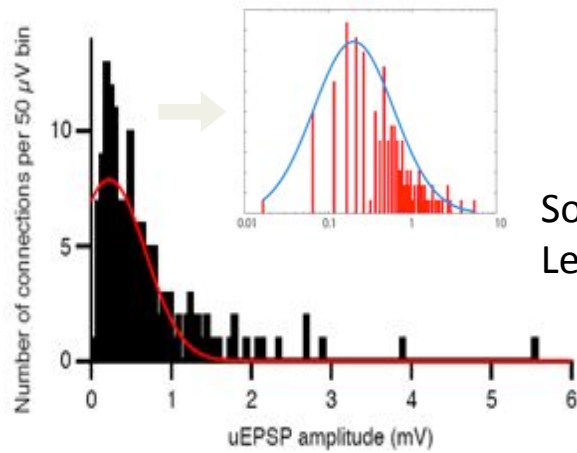
(van Rossum et al., 2000)



# Log spike-timing-dependent plasticity

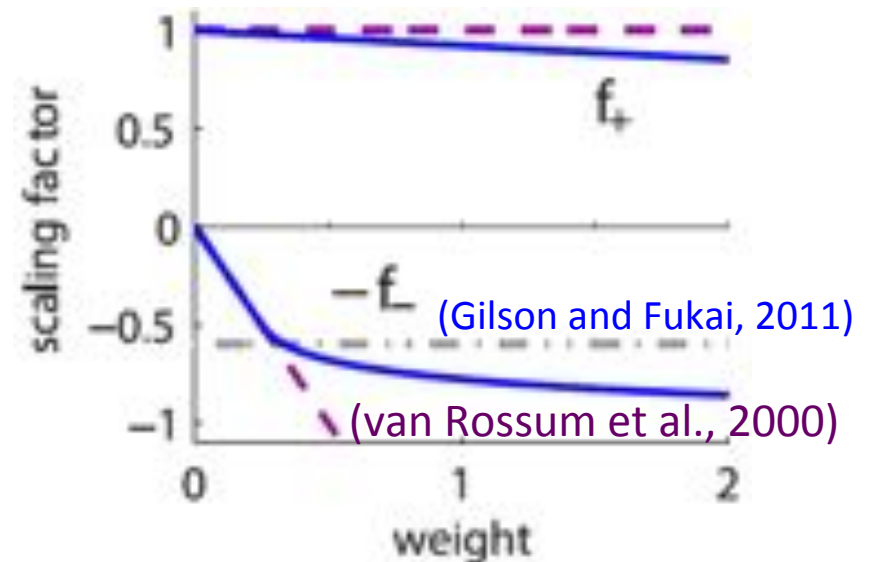
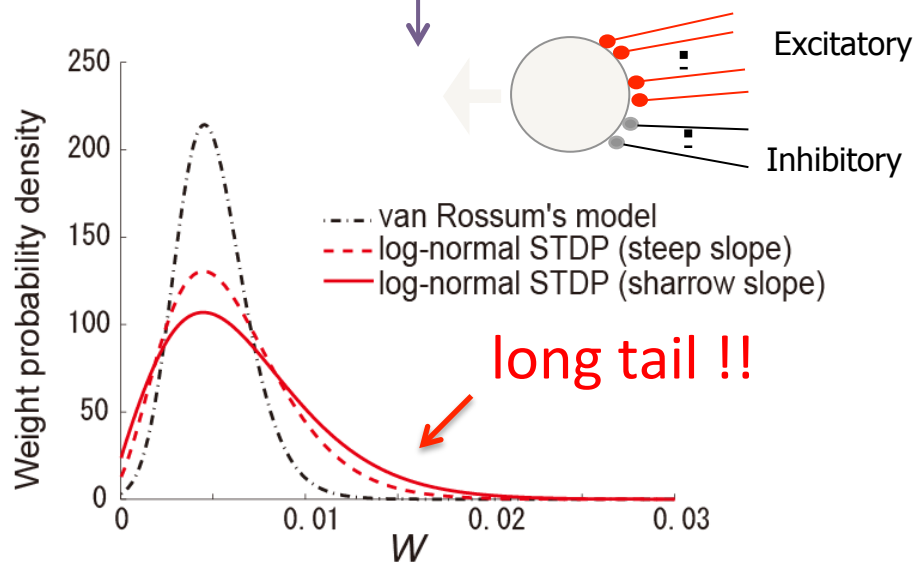


Matthieu Gilson

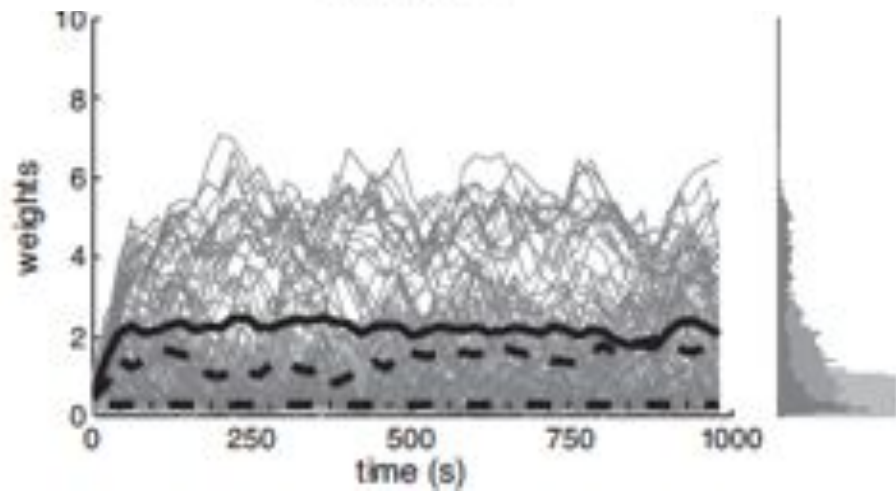
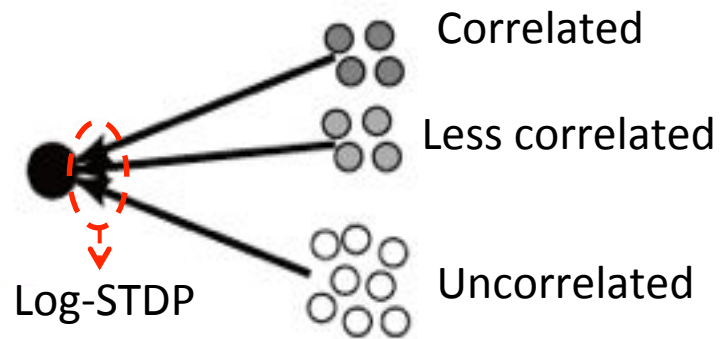
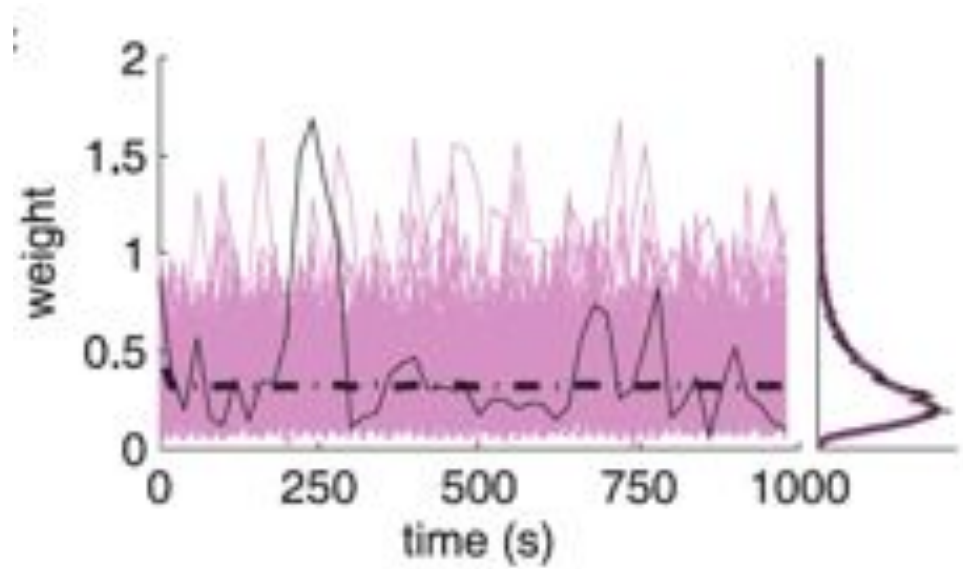
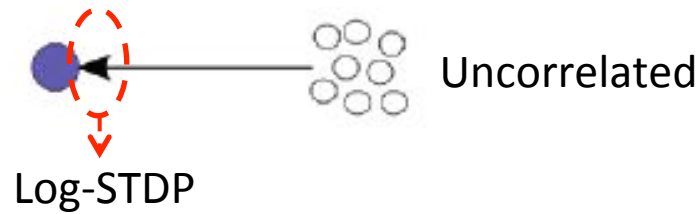


Somatosensory Cortex  
Lefort et al., Neuron (2009)

$$\Delta w_{ij}^{EE} = \begin{cases} +c_p e^{-\Delta t/\tau_p} \\ -c_d e^{-\Delta t/\tau_d} \log\left(1 + \alpha w_{ij}^{EE} / w_{EE}\right) / \log(1 + \alpha) \end{cases}$$



# Correlated spike input drives synaptic weight to long tail





Sound → Cochlear = Frequency analyzer  
→ Cascade of thalamic nuclei → Auditory cortex

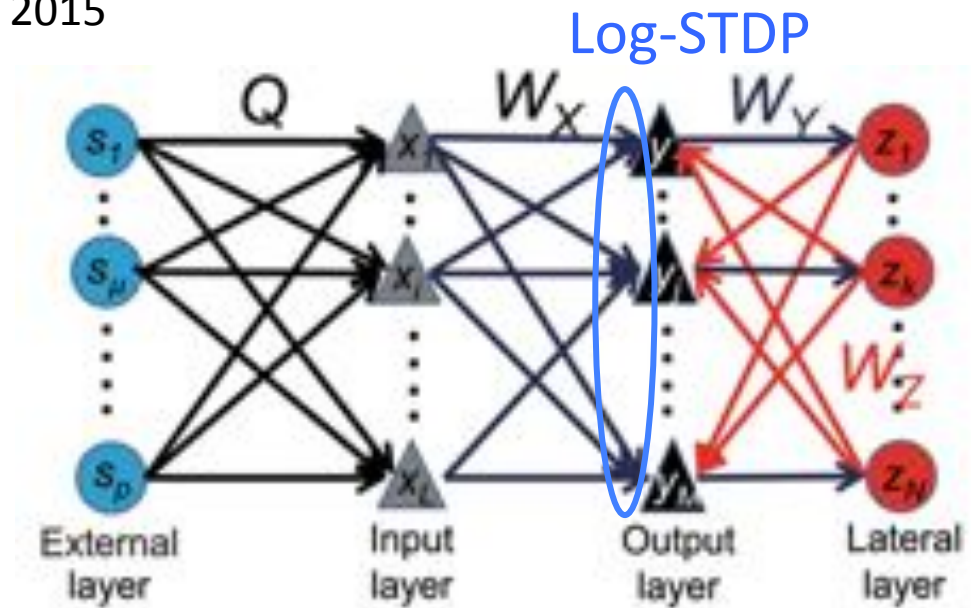
Assumption:

Frequency components belonging to the same auditory source should exhibit larger correlations compared to those belonging to other sources.

# A feedforward network model for signal demixing

Hiratani and Fukai, PLoS Comput Biol, 2015

*Unbalance* between excitatory and inhibitory correlations drives synaptic dynamics



$$\dot{\mathbf{W}}_X \approx \mathbf{W}_X (g_1^X \mathbf{I} - g_2^X \mathbf{W}_Y \mathbf{W}_Z) \mathbf{C}^T$$

Response kernel

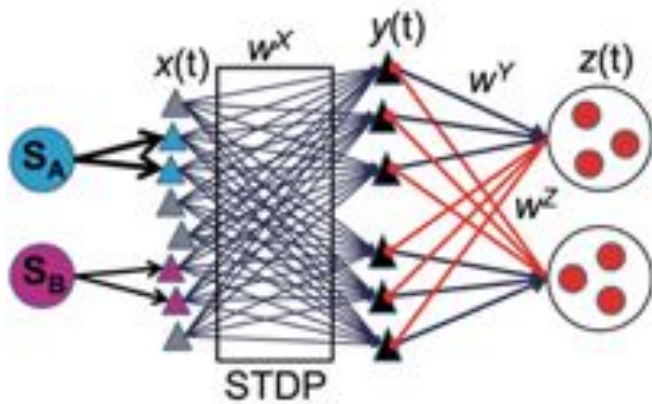
$$g_1^X, g_2^X \xleftarrow{\text{STDP}} h(\tau) = \int_{\max(\tau, 0)}^{\infty} \phi(t) \phi(t - \tau)$$

$$\phi(t) = \text{graph of a bell-shaped curve}$$

$$C_{ij} = \sum_{\mu} q_i^{\mu} q_j^{\mu} \quad \text{Input correlations}$$

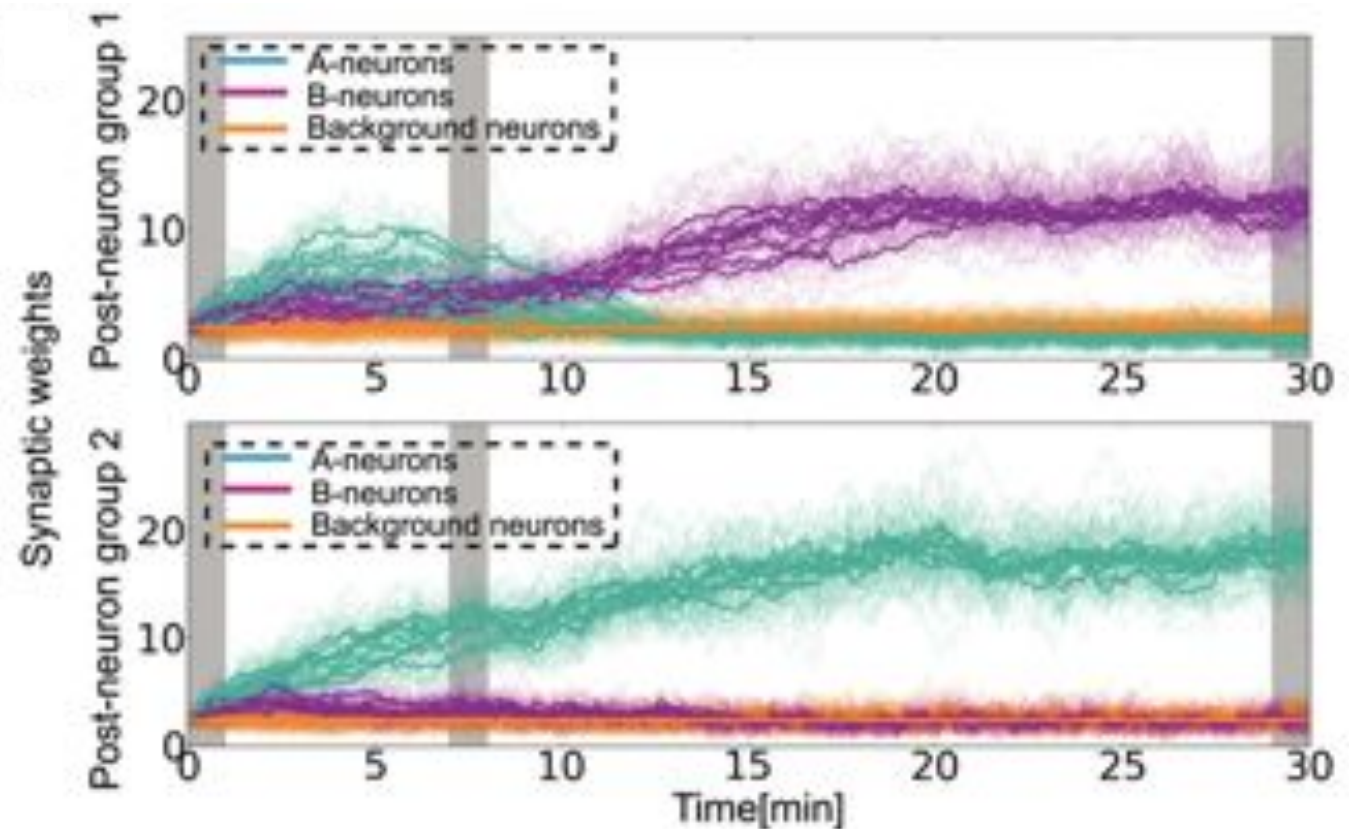
$q_i^{\mu}$  = response probability of neuron  $i$  to input pattern  $\mu$

# Lateral inhibition enhances the detection of weak correlations

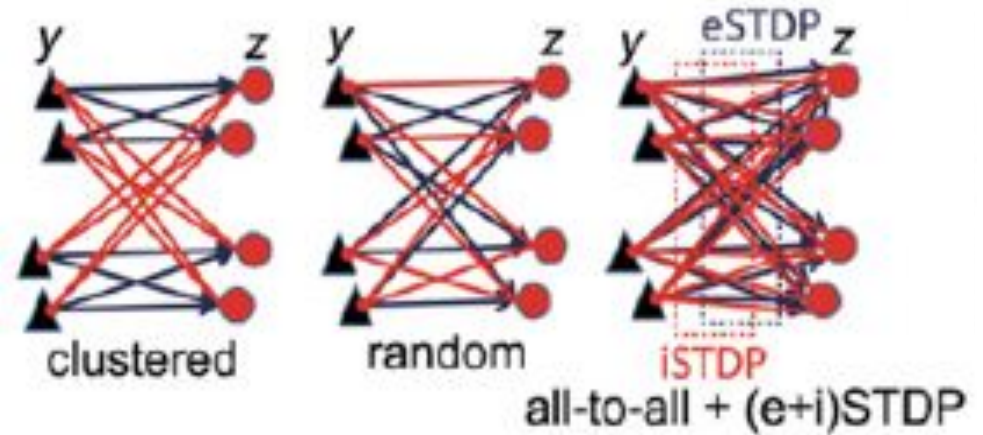
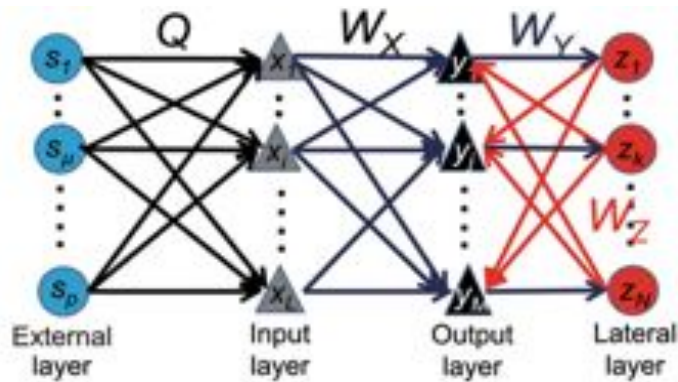


Group A : strongly correlated cell ensemble

Group B : weakly correlated cell ensemble



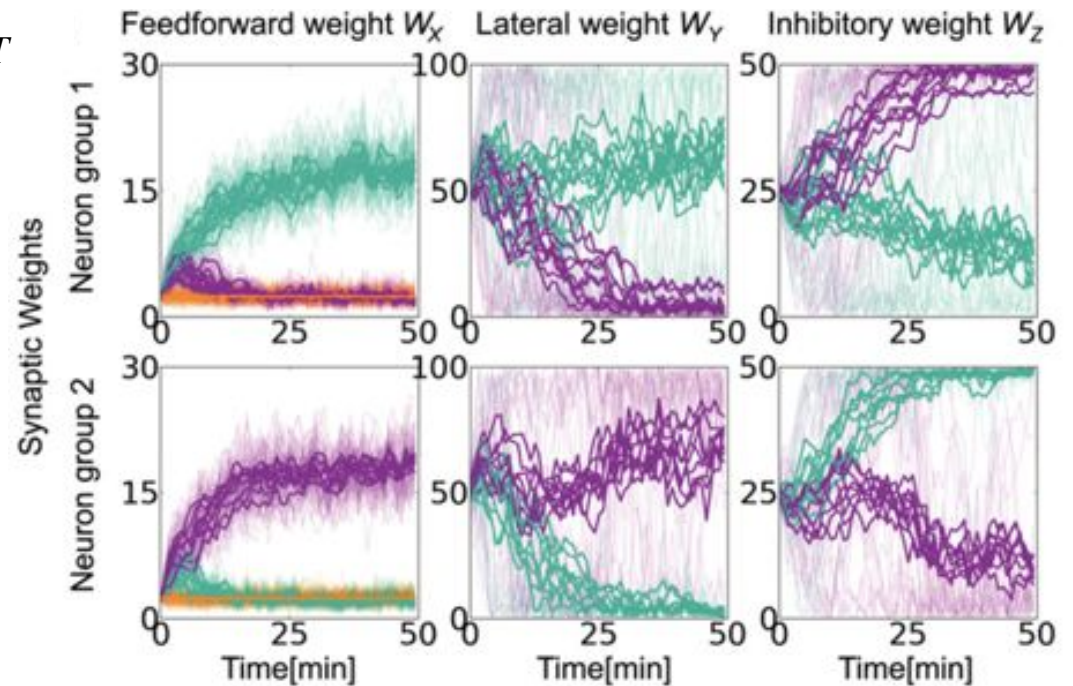
# Inhibitory plasticity generates activity-dependent clusters of inhibitory cells



$$\dot{W}_X \approx W_X (g_1^X \mathbf{I} - g_2^X W_Y W_Z) C^T$$

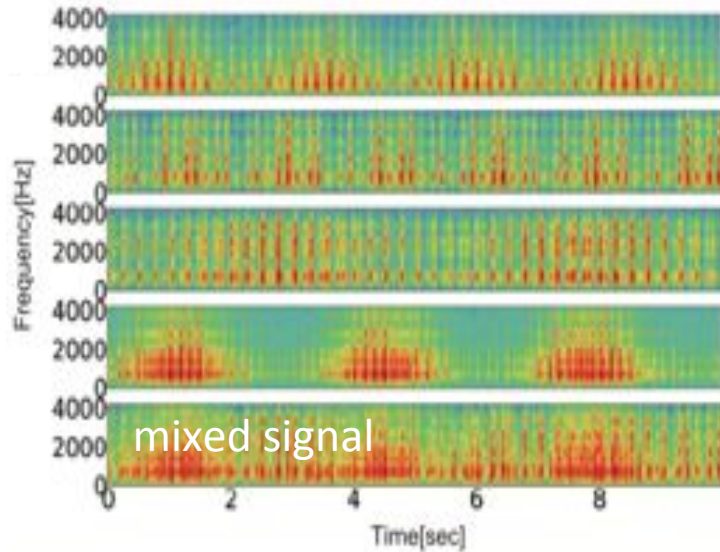
$$\dot{W}_Y \approx g_1^Y W_Y W_X C^T W_X^T$$

$$\dot{W}_Z \approx g_1^Z W_X C W_X^T W_Y^T$$

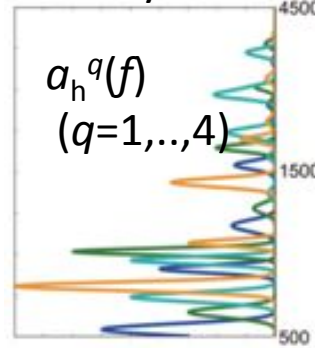




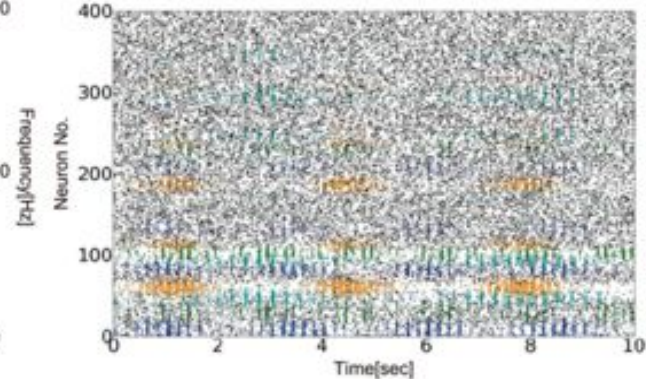
# A solution to Cocktail Party Effect



Spectrums of auditory sources



$X(t)$

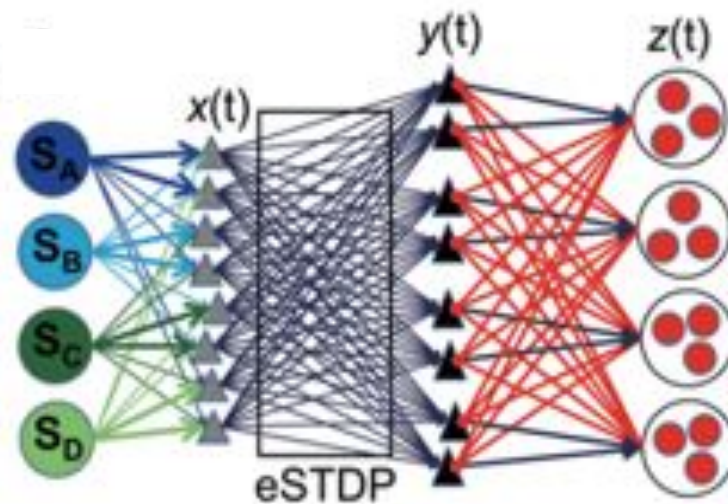


preferred frequency

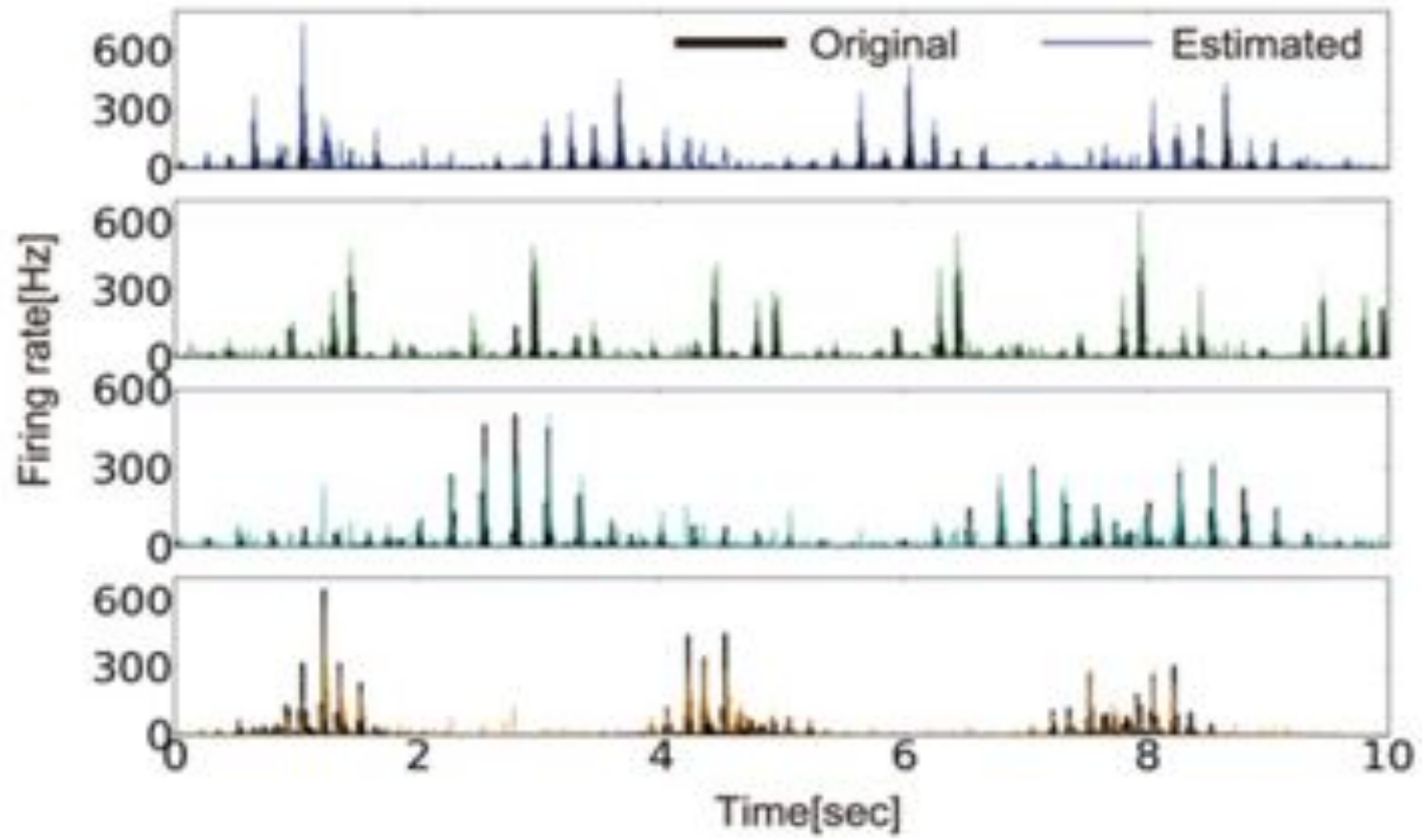
$$\log f_i = \log f_{\min} + (i / L)(\log f_{\min} - \log f_{\max})$$

Time-dependent response probability

$$q_i(t) = q_0 \sum_q a_{\text{sound press}}^q(t) a_h^q(f_i)$$

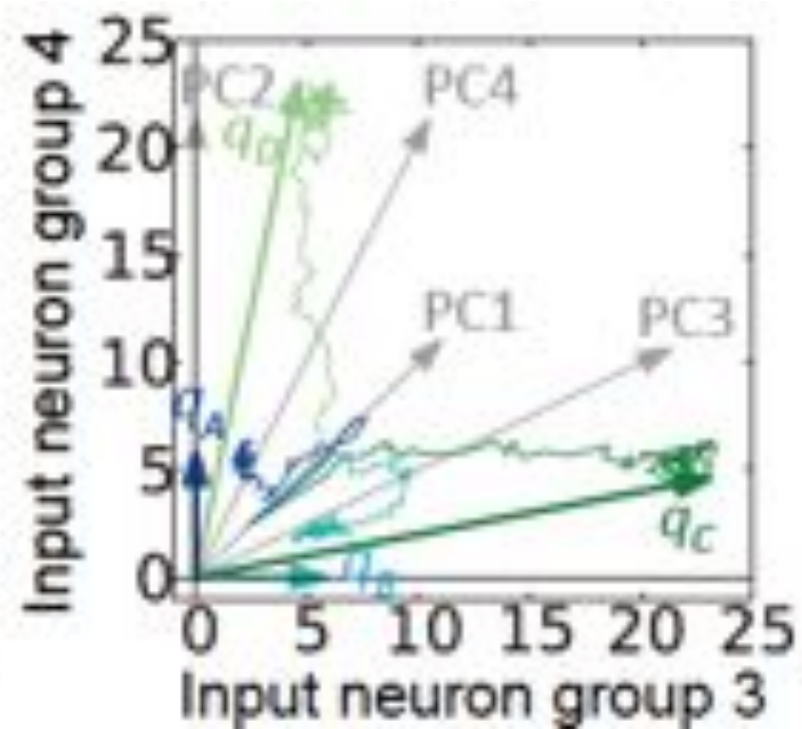
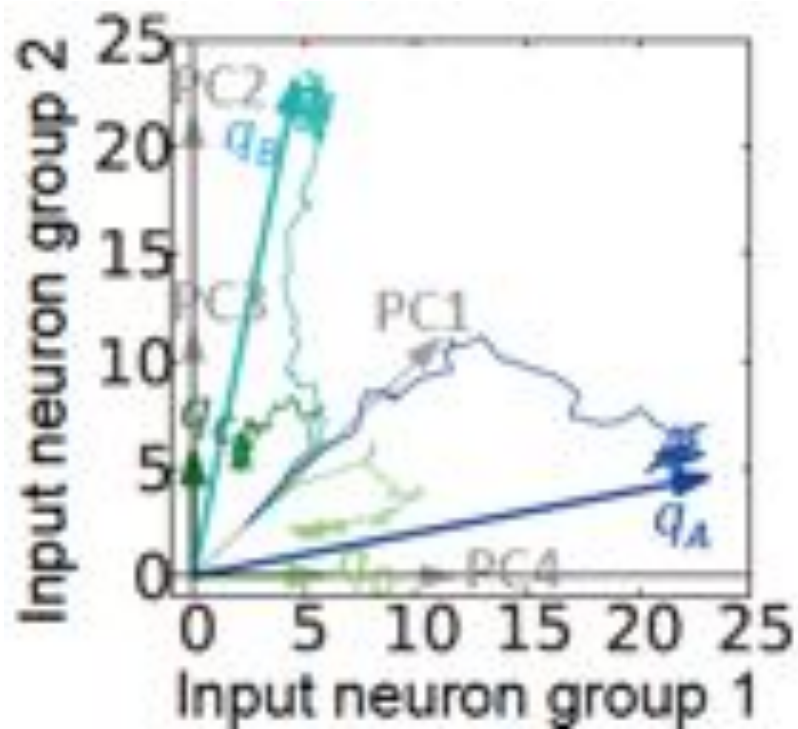


$y(t)$



Our spiking network approximates Bayesian ICA

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \sigma\xi$$



# *Interim summary*

We constructed a theoretical framework to analyze the propagation of spike correlations

In blind source separation, spike correlations provide a cue to recombine components belonging to the same source.

Deep spiking neuron networks for improved performance?

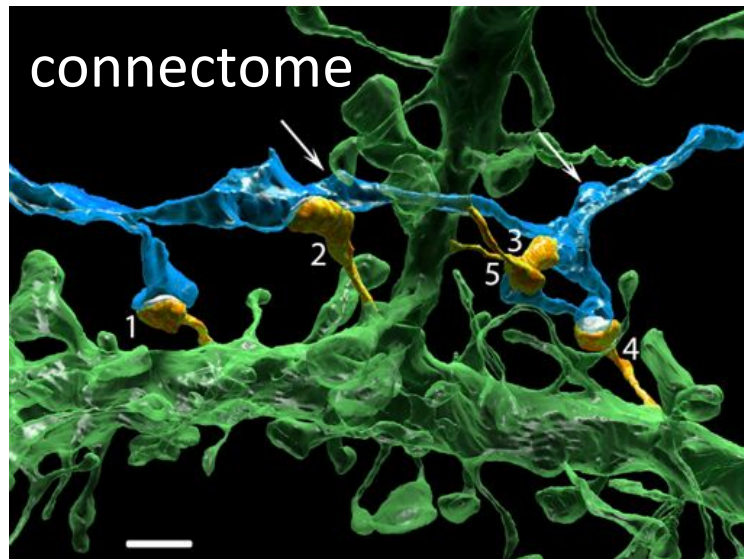


# Optimal learning with redundant synapses in single neurons

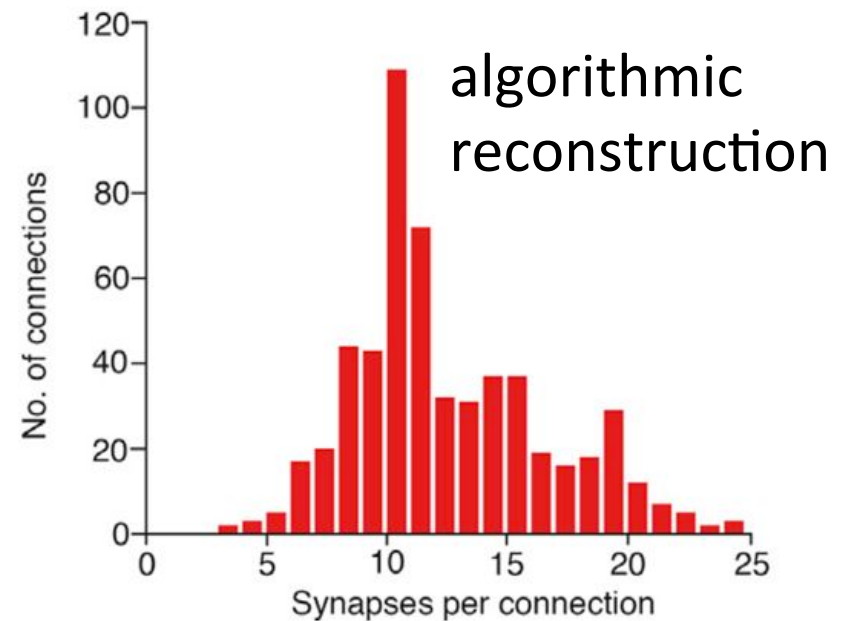


Naoki Hiratani

A cortical neuron pair are connected with multiple synaptic contacts



(Kasthuri et al., Cell, 2015)

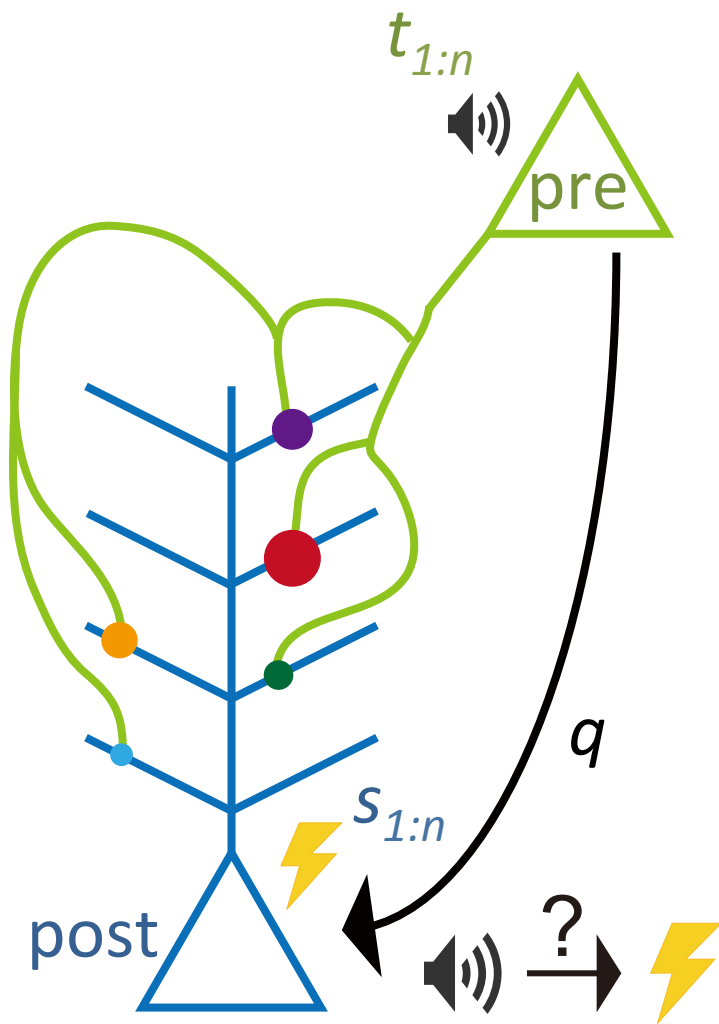


(Markram et al., Cell, 2015)

# Model: Fear conditioning

Task: Optimal learning of the conditional probability  $q$  that a sensory stimulus  $t_{1:n}$  predicts an electric shock  $s_{1:n}$ .  $t, s \in \{0, 1\}$

Challenge: An optimal inference requires *the conditional probability distribution*  $p(q | t_{1:n}, s_{1:n})$ .



$$\bar{q}_n = \langle q_n \rangle_{p(q|t_{1:n}, s_{1:n})} \quad \leftarrow p(q | t_{1:n}, s_{1:n})$$



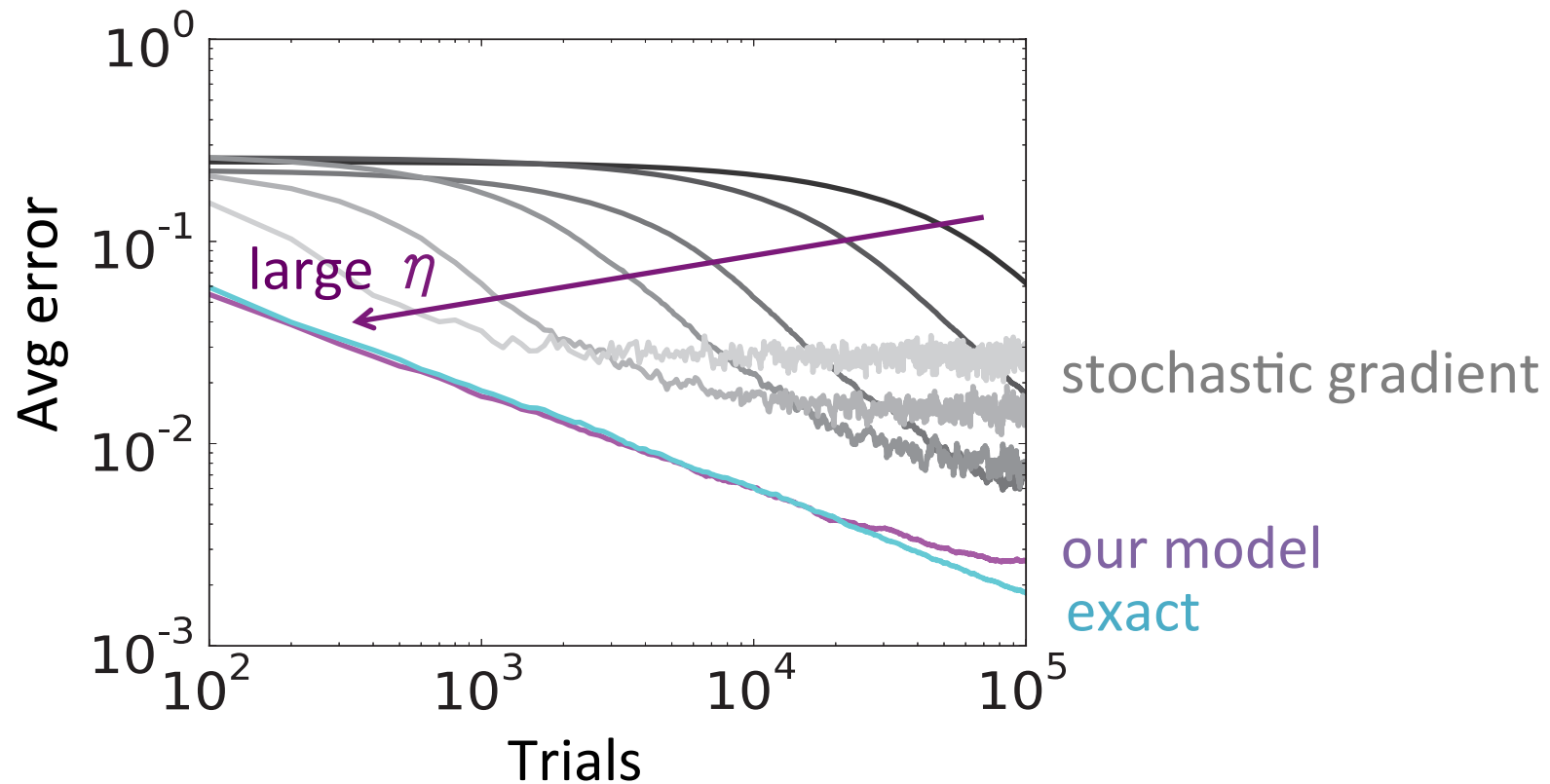
$$\bar{q}_{n+1} = \langle q_{n+1} \rangle_{p(q|t_{1:n+1}, s_{1:n+1})} \quad \leftarrow p(q | t_{1:n+1}, s_{1:n+1})$$

# Evaluation of the model's performance

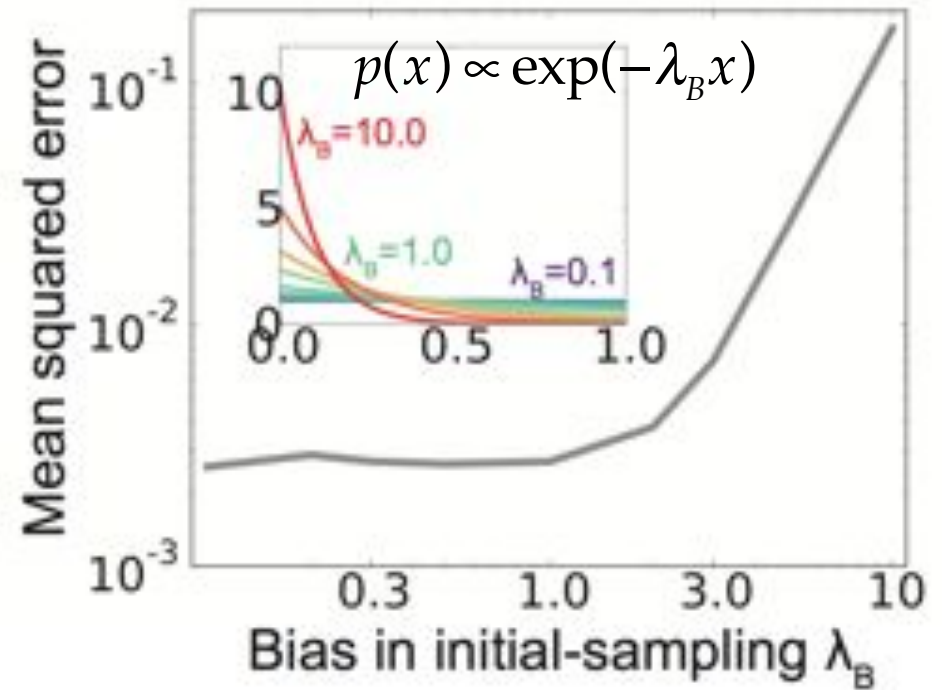
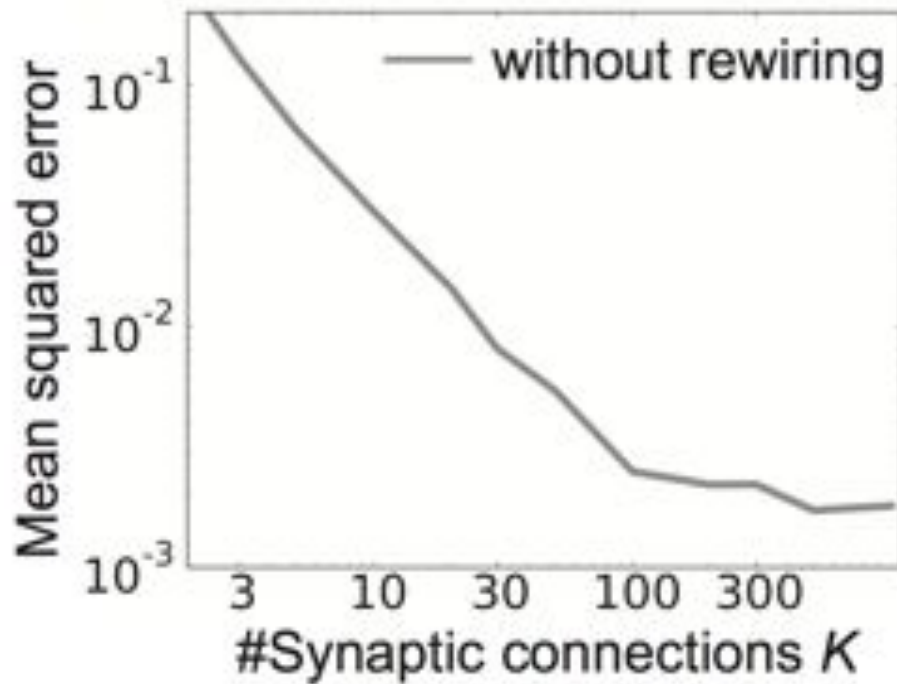
Exact solution:  $\lambda_{\text{exact}}(n) = \sum_{m=1}^n s_m / \sum_{m=1}^n t_m$

Stochastic gradient:

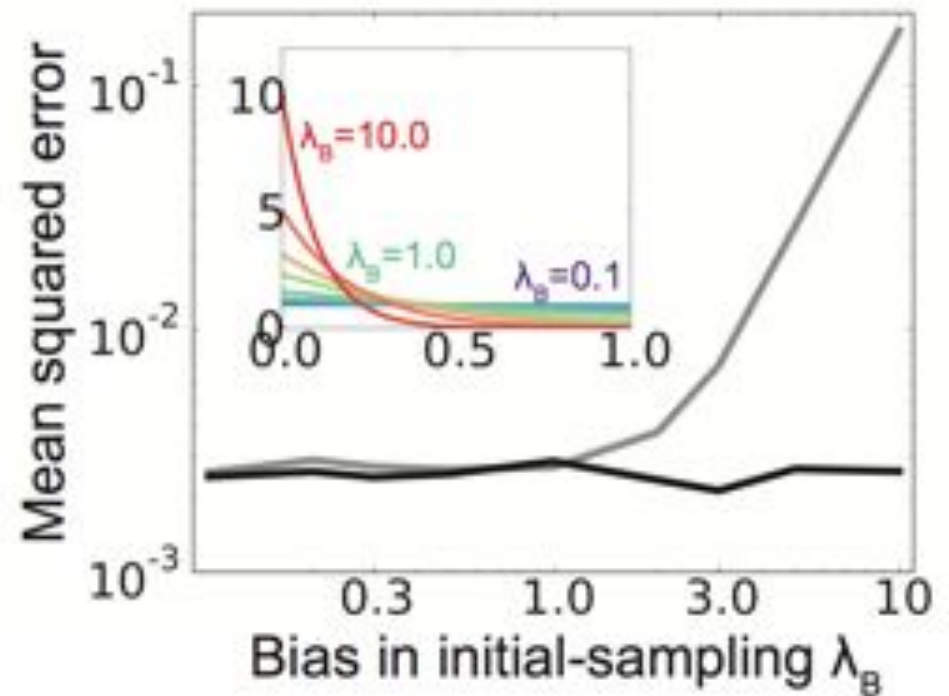
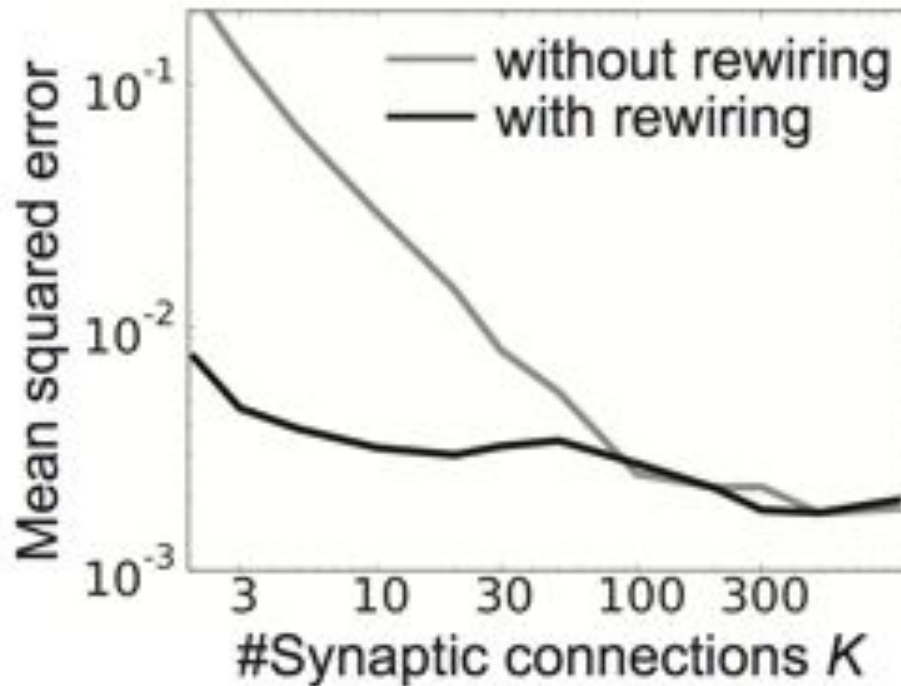
$$\lambda_{\text{approx}}(n) = \lambda_{\text{approx}}(n-1) \left[ 1 + \eta (s_n - \lambda_{\text{approx}}(n-1)t_n) \right]$$



# Particle filtering requires many redundant synapses



# Wiring plasticity enables sub-optimal learning with fewer synapses



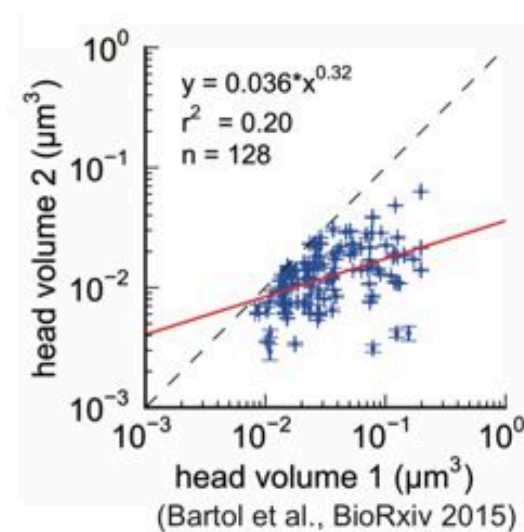
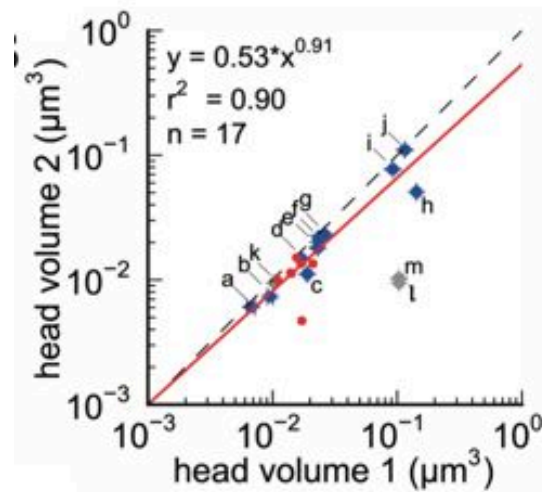


# Our model accounts for correlations between spine size and dendritic location

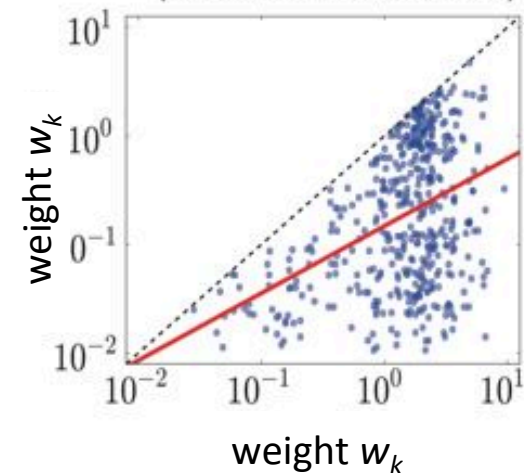
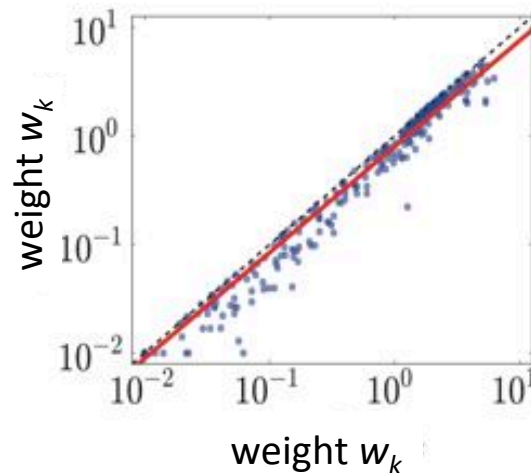
From same axon  
to same branch

From same axon  
to different branches

Exp



Model



# Our model is also consistent with

- Transient increases in spine number during relearning (Xu et al. Nature 2009)
- Dendritic location dependence of synaptic plasticity (Letzkus et al., J Neurosci 2006)
- Dendritic location dependence of spine size in CA1 and neocortex (Williams and Stuart, TINS 2003)

# Summary

Our model proposes that wiring plasticity with redundant synapses perform near-optimal learning

Our model accounts for several experimentally observed features of dendritic spines



The Journal of Neuroscience, October 28, 2015 • 35(42):14585–14601 • 14585

Systems/Circuits

## A Lognormal Recurrent Network Model for Burst Generation during Hippocampal Sharp Waves

Yoshiyuki Omura,<sup>1,2,3</sup> Milena M. Carvalho,<sup>1,4</sup> Kaoru Inokuchi,<sup>1,2</sup> and Tomoki Fukai<sup>1,2</sup>

<sup>1</sup>Department of Biochemistry, Faculty of Medicine, Graduate School of Medicine and Pharmaceutical Sciences, University of Toyama, Toyama 930-0194, Japan, <sup>2</sup>Laboratory for Neural Circuit Theory, RIKEN Brain Science Institute, Suitama 351-8585, Japan, <sup>3</sup>CREST, Japan Science and Technology, Suitama 352-0002, Japan, and <sup>4</sup>São Carlos Institute of Physics, University of São Paulo, 13560-970, São Carlos, São Paulo, Brazil