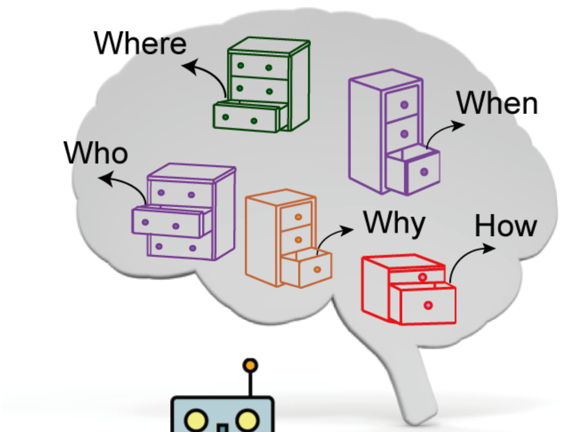
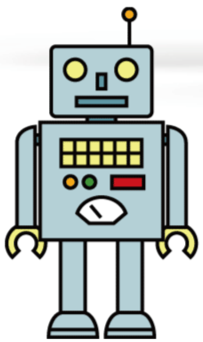
Neural Coding & Brain Computing Unit

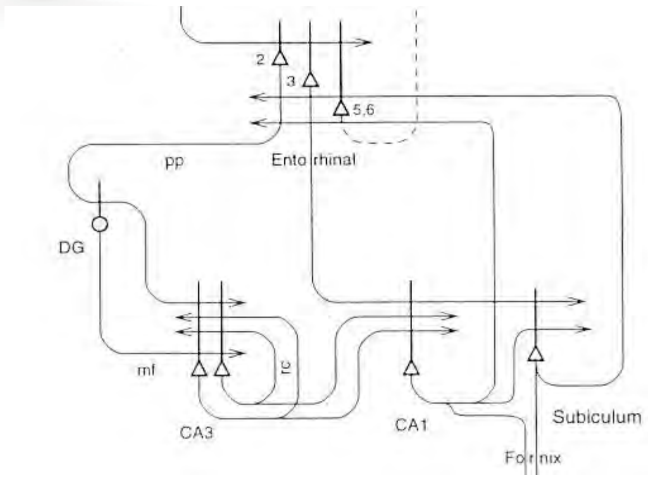
elucidates the computational principles of the brain

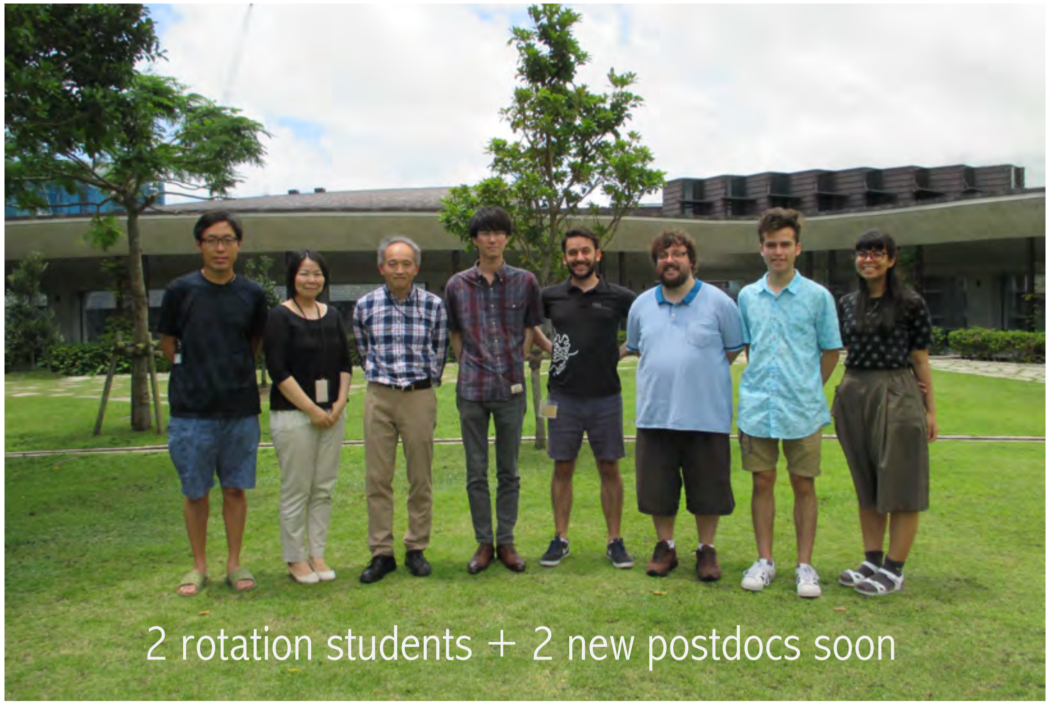
Tomoki Fukai

- Network mechanisms of learning and memory
- Deciphering neural code in large-scale activity data
- Brain-inspired models for AI









OIST

Computational Neuroscience

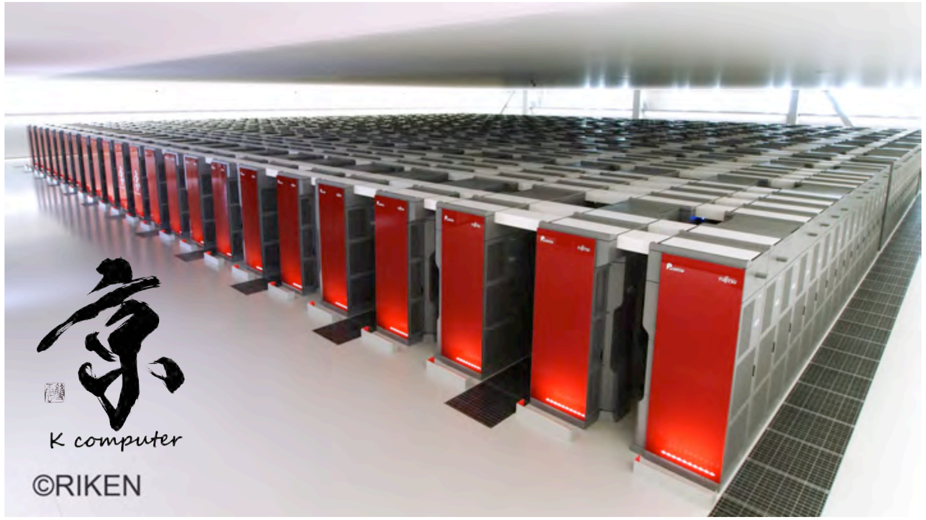
- towards understanding of the principles of brain computing -

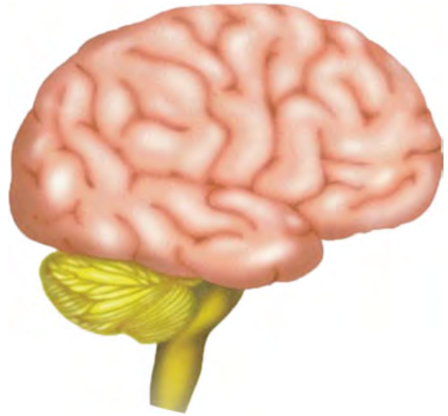
Computational neuroscience is the study of brain function in terms of the information processing properties of the structures that make up the nervous system. It is an interdisciplinary science that links the diverse fields of neuroscience, cognitive science, electrical engineering, computer science, physics and mathematics.

(Wikipedia)

Cognitive Science: the investigation of the mind through a multidisciplinary endeavour

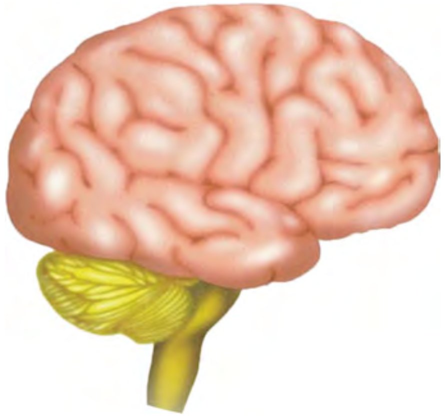
Brain vs Computer





Binary representation (0 and 1)	Action potentials (spike trains)
Serial processing	Parallel distributed processing
Address-based memory (static)	Context-dependent memory (dynamic)
Programmed by humans	Learning from environment

Brain vs Computer



Deterministic processing

No spontaneous activity (no internal states)

Huge energy consumption

(12.7 MW: Use of "K" for a month costs an energy consumption equivalent to 30000 families

Probabilistic processing

Spontaneous activity (noisy internal states)

Highly energy efficient

(20-30 W)

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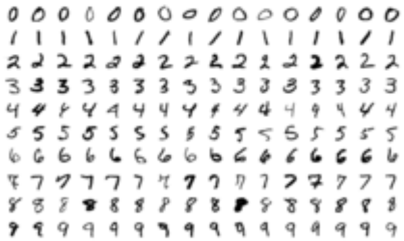
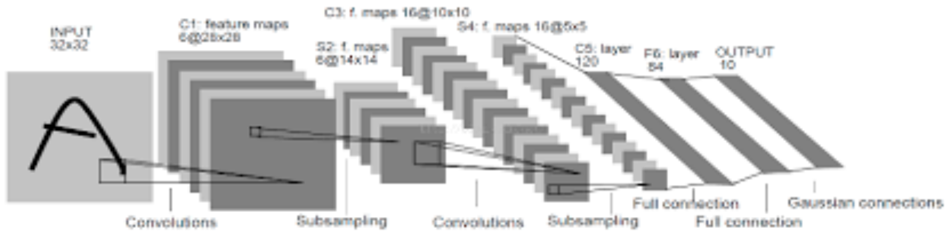
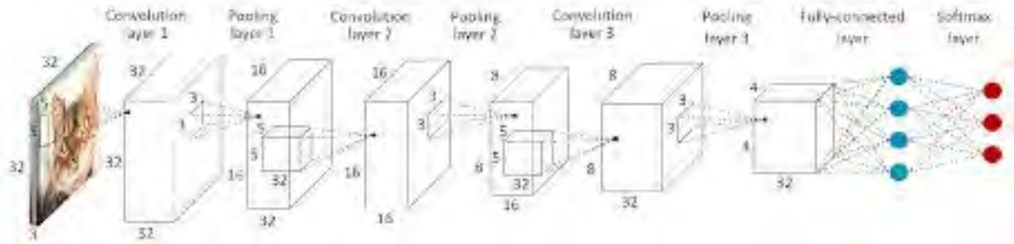
Deep learning: big data & task-specific elaborate networks

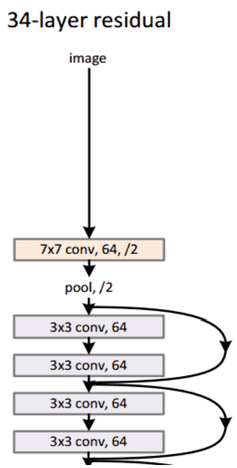


MNIST



CIFAR





Cortical microcircuit

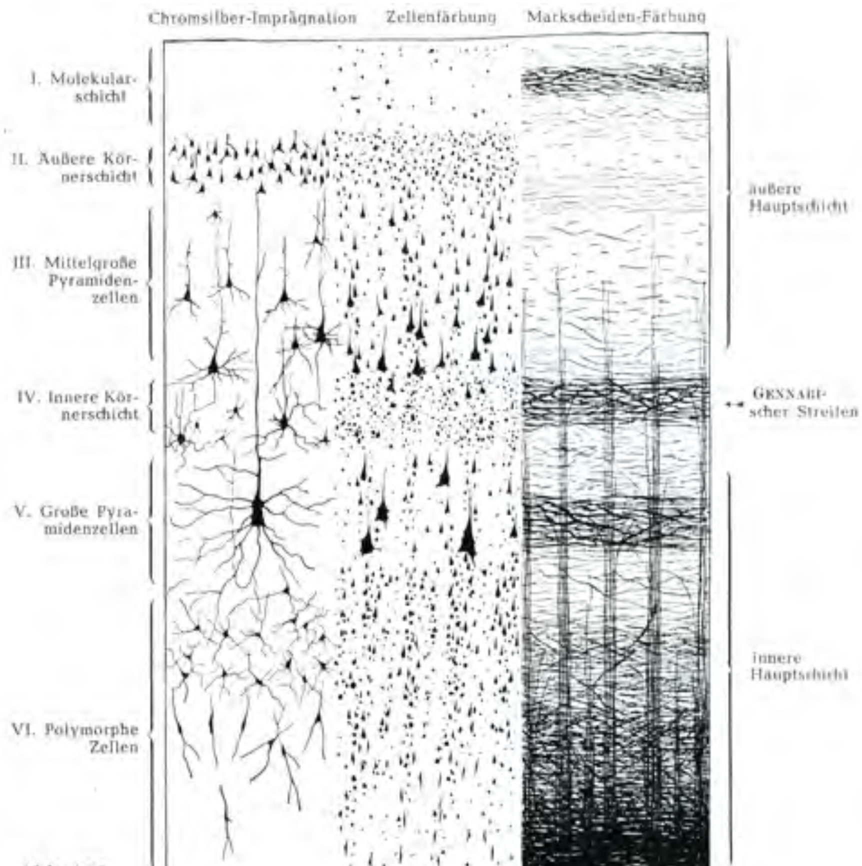
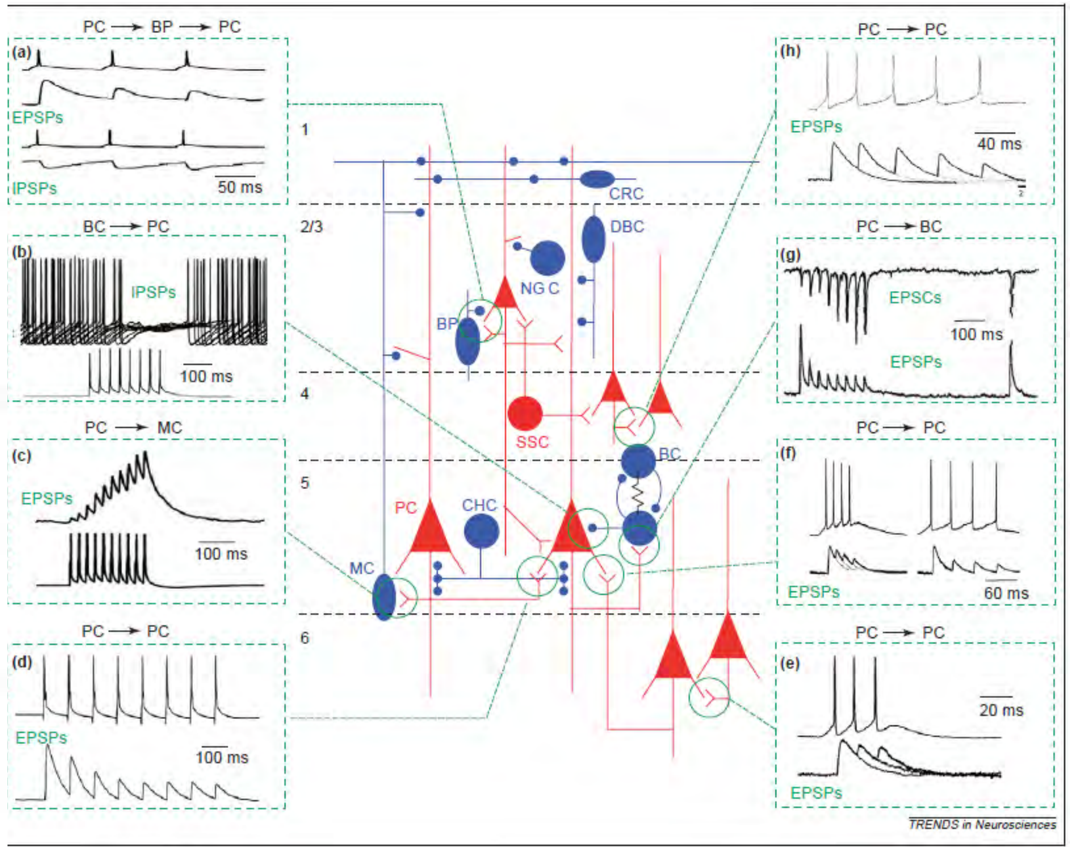


Abb. 477.



CHC: Chandelier cell
DBC: Double bouquet cell
BP: Bipolar cell
NGC: Neurogliaform cell
MC: Martinotti cell
CRC: Cajal-Retzius cell
SSC: Spiny stellate cell

EPSC: Excitatory postsynaptic current

IPSC: Inhibitory postsynaptic current

Silberberg et al., TINS 2005

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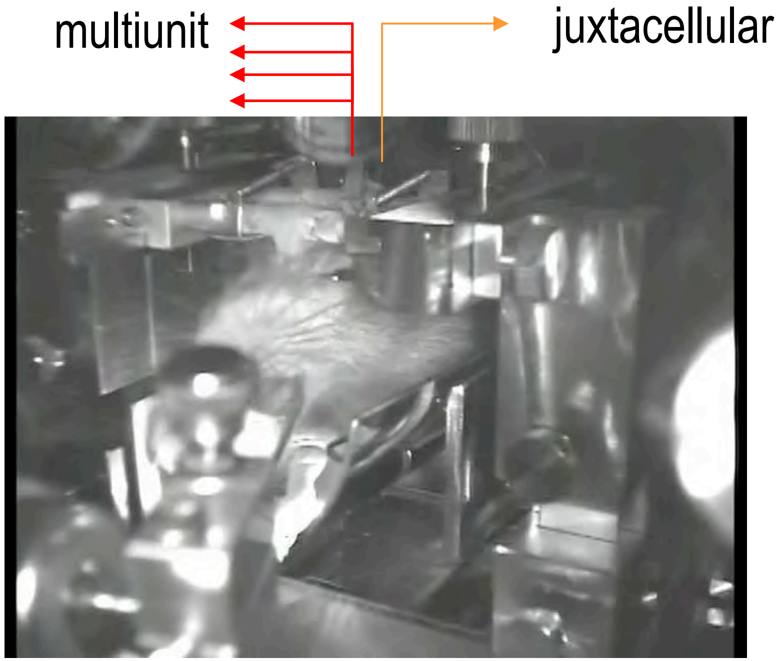
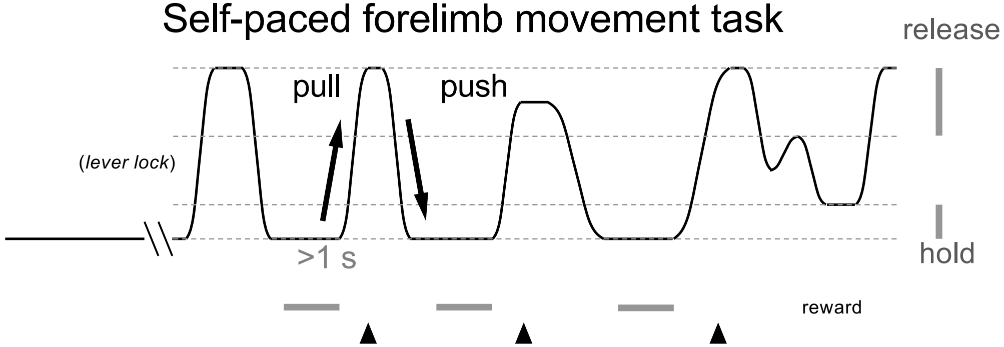
Recordings from head-restrained behaving rats



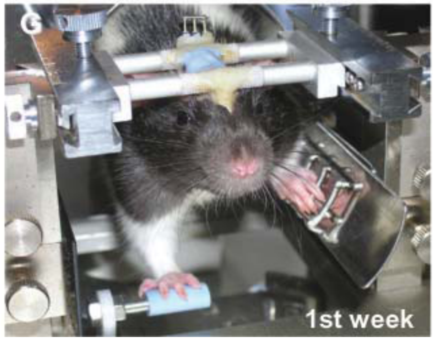
Self-paced forelimb movement task

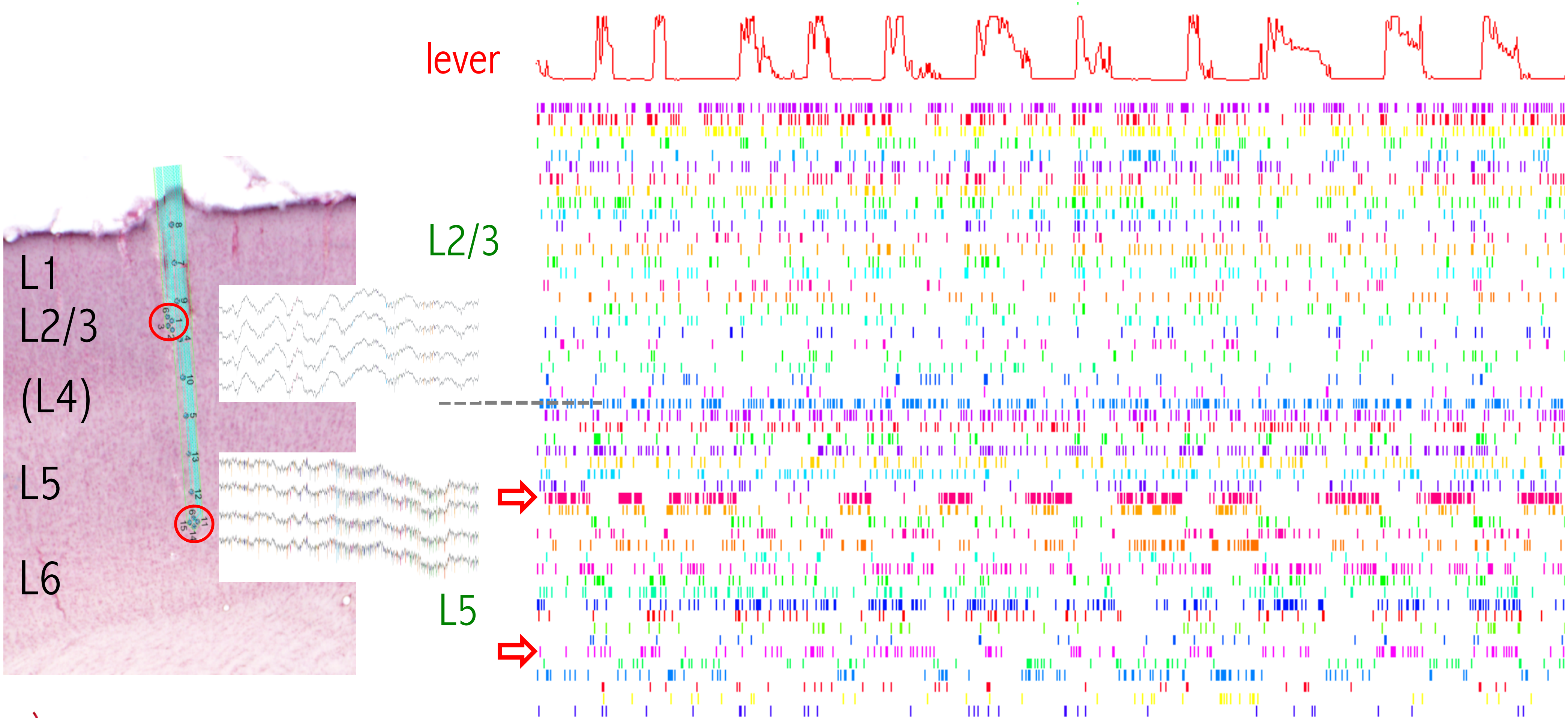


Isomura, Harukuni, Takekawa, Aizawa and Fukai, *Nat Neurosci* (2009)

Asynchronous irregular firing of in vivo cortical neurons

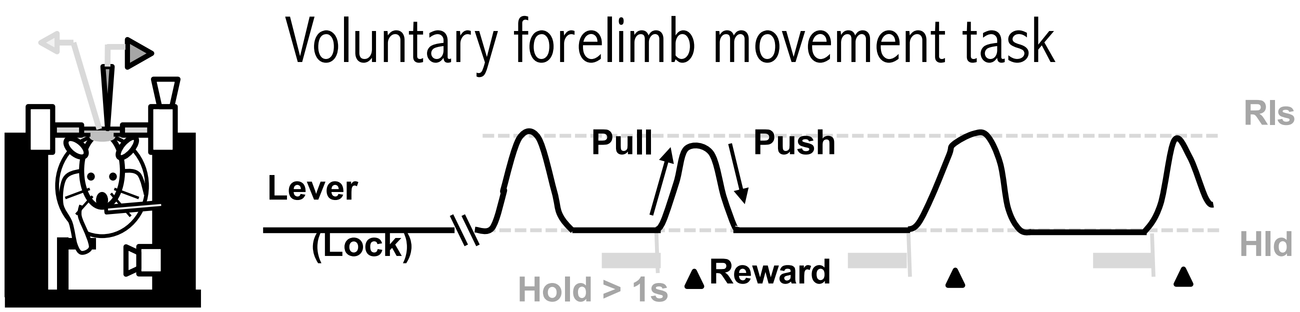
Rat primary motor cortex, spontaneous lever movement task,
multiunit recordings (Isomura et al., Nat Neurosci 2009)

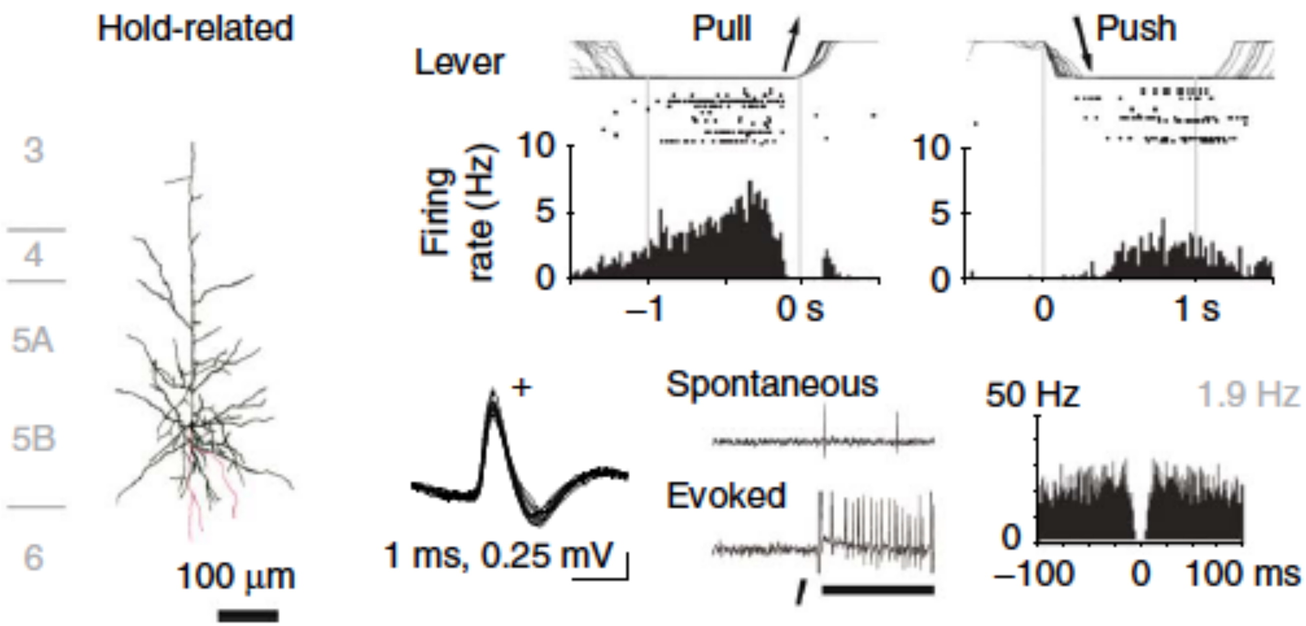




Task-related activities – a classical view

still valid, but insufficient





(Isomura et al., Nat Neurosci 2009)

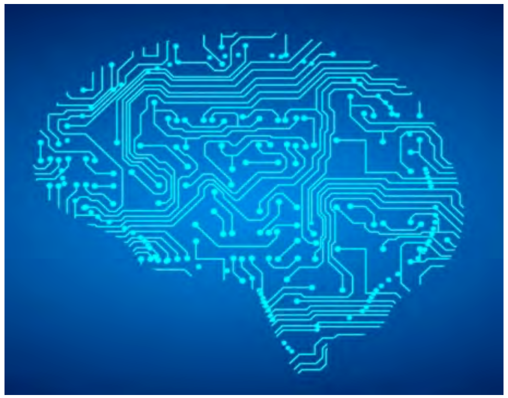
Marr's 3 levels

Computational Theory

Quantities or objectives of brain computing

Algorism

Procedures of brain computing



Implementation

Neural code?

Network mechanisms of brain computing

Rapid advances in tools for exploring network functions

LETTER

https://doi.org/10.1038/s41586-019-1641-1

Population imaging of neural activity in awake behaving mice

Kiryl D. Piatkevich[1,2,11], Seth Bensussen[3,11], Hua-an Tseng[3,11], Sanaya N. Shroff[3], Violeta Gisselle Lopez-Huerta[4], Demian Park[1,2], Erica E. Jung[1,5], Or A. Shemesh[1,2], Christoph Straub[6], Howard J. Gritton[3], Michael F. Romano[3], Emma Costa[1], Bernardo L. Sabatini[6], Zhanyan Fu[4], Edward S. Boyden[1,2,7,8,9,10]* & Xue Han[3]*

Nature 574, 413-417 (2019)

RESEARCH

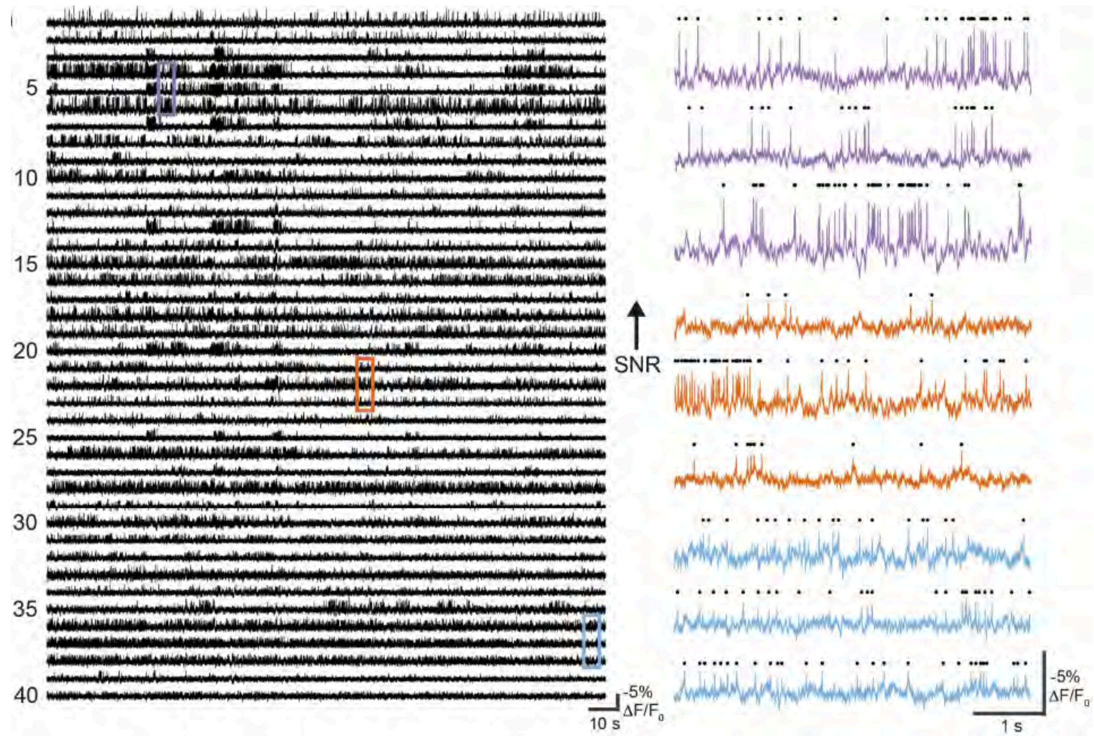
NEUROSCIENCE

Bright and photostable chemigenetic indicators for extended in vivo voltage imaging

Ahmed S. Abdelfattah[1]*, Takashi Kawashima[1]*†, Amrita Singh[1,2], Ondrej Novak[1,3], Hui Liu[1], Yichun Shuai[1], Yi-Chieh Huang[4], Luke Campagnola[5], Stephanie C. Seeman[5], Jianing Yu[1], Jihong Zheng[1], Jonathan B. Grimm[1], Ronak Patel[1], Johannes Friedrich[6,7,8], Brett D. Mensh[1], Liam Paninski[6,7], John J. Macklin[1], Gabe J. Murphy[5], Kaspar Podgorski[1], Bei-Jung Lin[4], Tsai-Wen Chen[4], Glenn C. Turner[1], Zhe Liu[1], Minoru Koyama[1], Karel Svoboda[1], Misha B. Ahrens[1]‡, Luke D. Lavis[1]‡, Eric R. Schreiter[1]‡§

Science 364, 699-704 (2019)

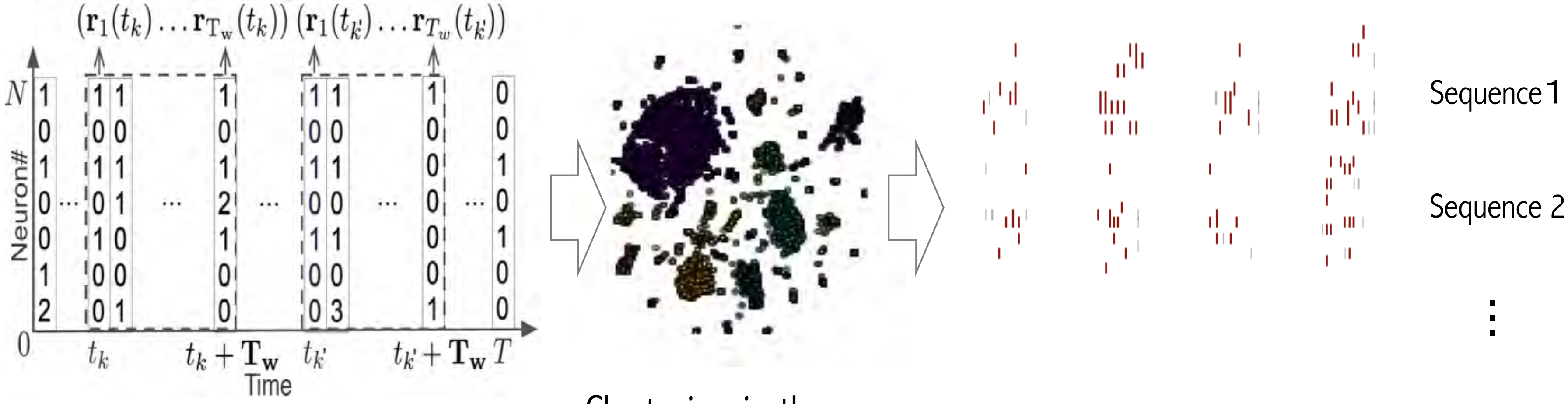
Overall, we imaged a total of 449 neurons (12 fields of view in three mice), demonstrating routine voltage imaging of populations of neurons in superficial mouse cortex (Fig. 3G and figs. S25



Unsupervised detection of cell-assembly sequences with edit similarity score

Keita Watanabe[1,2], Tatsuya Haga[2], David R Euston[3], Masami Tatsuno[3], Tomoki Fukai [1,2,*]
Front Neuroinform (2019)

Temporal patterns of neural population spike firing

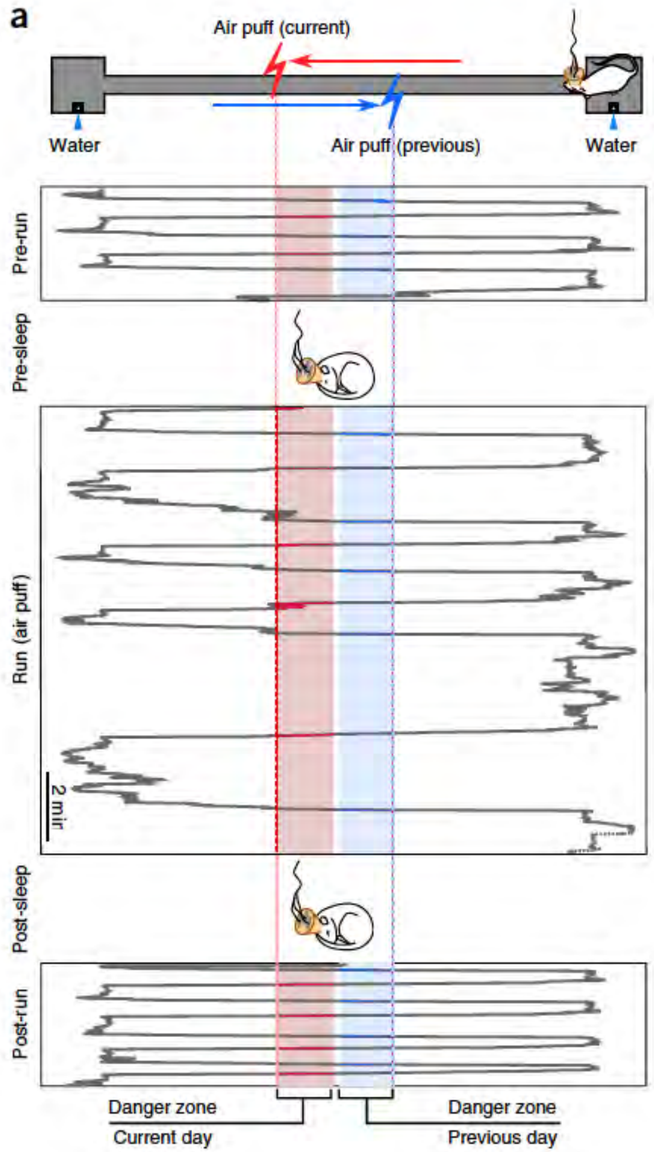


Cell assembly sequences

Clustering in the space of Edit Similarity

Frequently recurring sequences

Applications to neural data

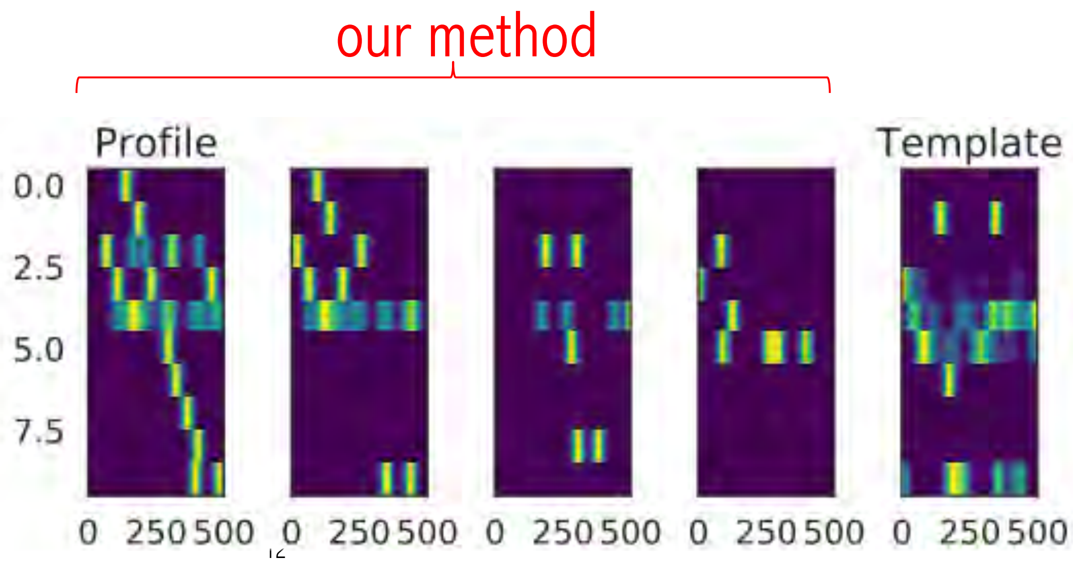


Simultaneous recordings from the basolateral amygdala and hippocampal CA1 of behaving rats

Girardeau, G., Inema, I., & Buzsáki, G. Nat Neurosci (2017).

CNCRS data sharing website

Our method revealed repeated activation of BLA cell assemblies encoding fear memory

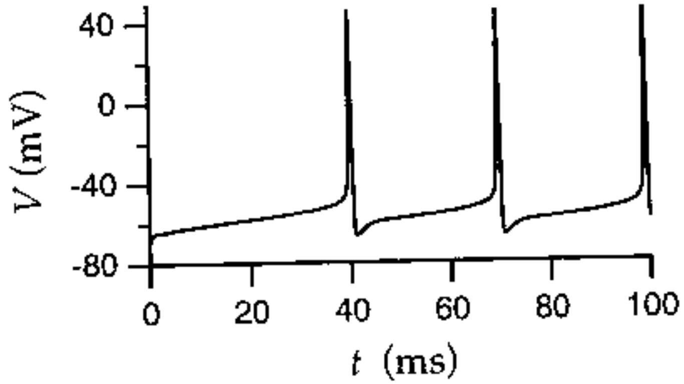


OIST

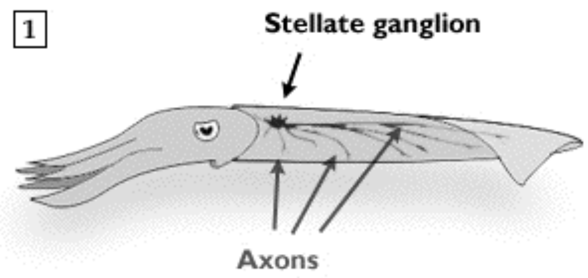
Model neurons at various levels of biological reality

Hodgkin-Huxley-type model:

$$C_m \frac{dV}{dt} = -g_{Na}(V - E_{Na}) - g_K(V - E_K) - g_L(V_m - E_L) + I$$

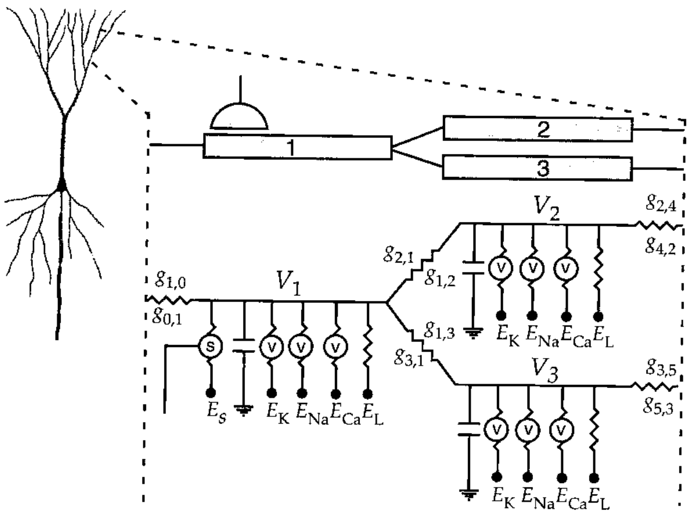


Complex



Simplify

Multi-compartmental model

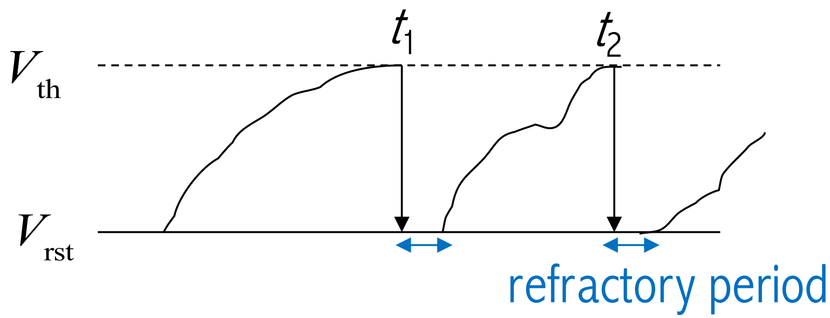


Leaky integrate-and-fire (LIF) neuron

$$C_m \frac{dV}{dt} = -g_L(V - V_{\mathrm{rest}}) + I$$

$V_{\mathrm{th}} = -50\ \mathrm{mV}$, $V_{\mathrm{rest}} = -70\ \mathrm{mV}$,

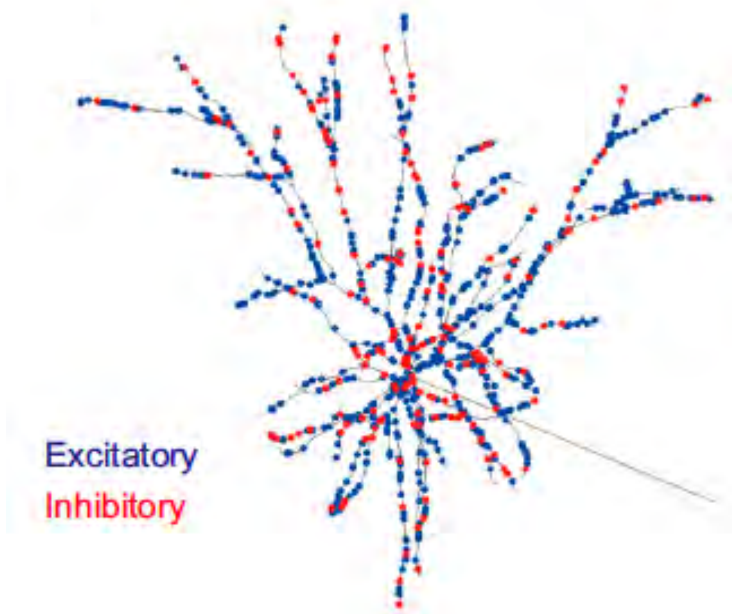
$\tau_m = C_m / g_L = 10 \sim 15\ \mathrm{ms}$



ModelDB

Yale Univ

Vertebrate	Amygdala
	Auditory brainstem
	Auditory cortex
	Basal ganglia
	Brainstem
	Cerebellum
	Dentate gyrus
	Enteric nervous system
	Entorhinal cortex
	Hippocampus
	Inferior Colliculus
	Lamprey, Spinal cord, Brainstem
	Medial Septum
	Neocortex
	Olfactory bulb
	Olfactory cortex
	Prefrontal cortex (PFC)
	Spinal motoneuron
	Striatum
	Subthalamic Nucleus
	Superior colliculus
	Thalamus
	Turtle cortex
Invertebrate	Aplysia
	Hawkmoth Deilephila elpenor
	Helix pomatia (snail)
	Leech
	Stomatogastric ganglion
	Tritonia
Miscellaneous	Egg-laying circuit
	Generic
	Retina
	Unknown

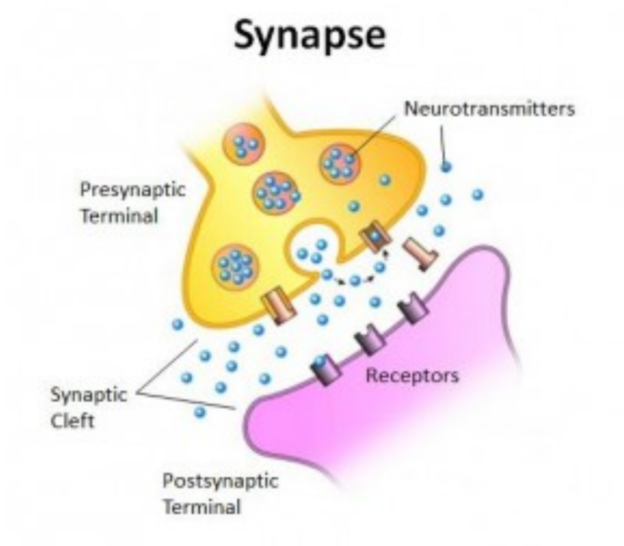


Model of V1 L2/3 pyramidal cell (model)
(Smith et al., Nature 2013)

→ Optimal inference of sensory stimuli
(Hiratni and Fukai, PNAS 2018)

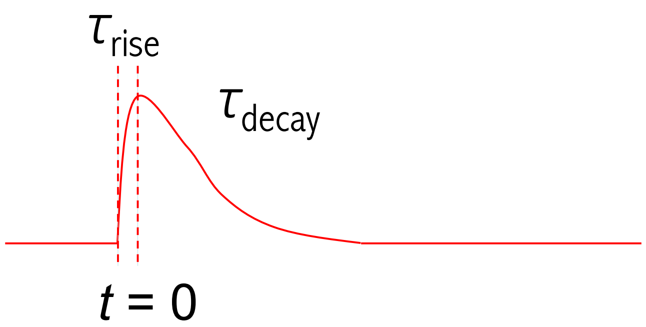
Ionic channels and biologically realistic neuron models
→ Erik DeSchutter@OIST

Excitatory and inhibitory synaptic currents



$$I_s = -g_{\text{AMPA}}(t)(V - E_{\text{AMPA}}) - g_{\text{NMDA}}(t,V)(V - E_{\text{NMDA}})$$
$$- g_{\text{GABA-A}}(t)(V - E_{\text{Cl}})$$

(Ohmic current)

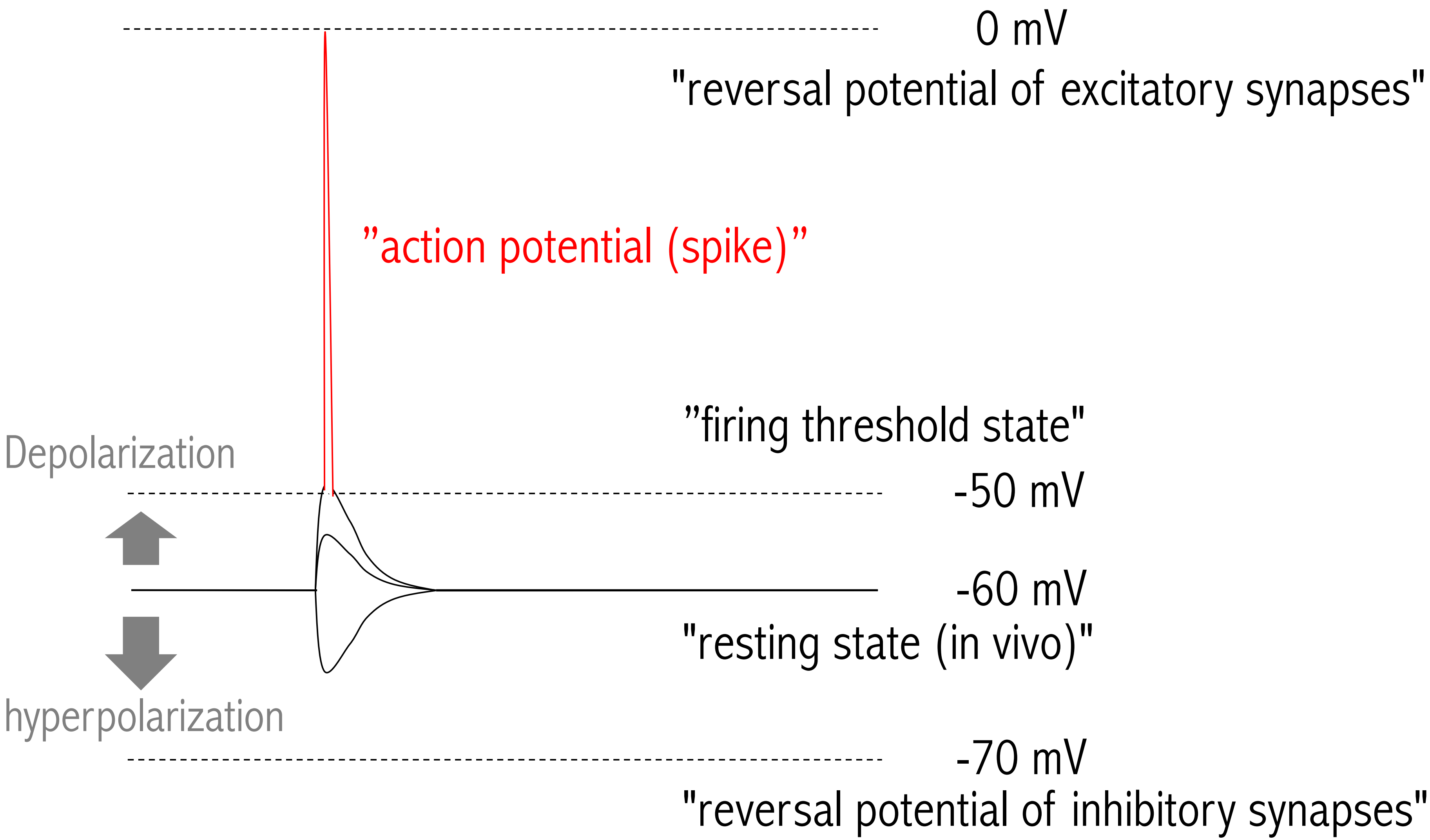


$$g(t) = \frac{1}{\tau_{\text{decay}} - \tau_{\text{rise}}}\left(\exp\left(-\frac{t}{\tau_{\text{decay}}}\right) - \exp\left(-\frac{t}{\tau_{\text{rise}}}\right)\right)$$

$$\tau_{\text{rise}} = 0.1 \text{ ms},\ \tau_{\text{decay}} = 2-3 \text{ ms (AMPA)},$$
$$\tau_{\text{rise}} = 1.5 \text{ ms},\ \tau_{\text{decay}} = 150 \text{ ms (NMDA)},$$
$$\tau_{\text{rise}} = 0.3 \text{ ms},\ \tau_{\text{decay}} = 4-5 \text{ ms (GABA)}$$

$$E_{\text{AMPA, NMDA}} = 0 \text{ mV},\ E_{\text{Cl}} = -70 \text{ mV}$$

Depolarizing and hyperpolaring postsynaptic membrane potentials



A sparsely connected network of LIF neurons (Brunel's model)

$$\tau \dot{V}_i(t) = -V_i(t) + RI_i(t), \qquad (1)$$

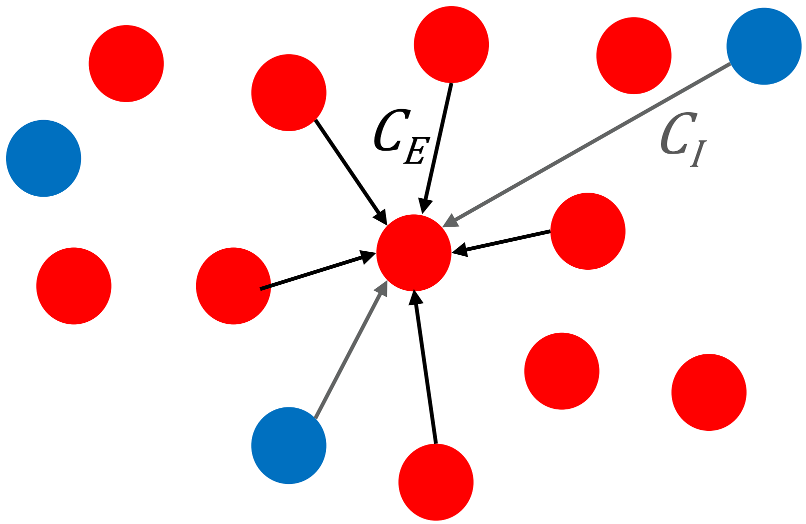
$$RI_i(t) = \tau \sum_j J_{ij} \sum_k \delta(t - t_j^k - D), \qquad (2)$$

excitatory connections per neuron $C_E = \epsilon N_E$

inhibitory connections per neuron $C_I = \epsilon N_I$

$\epsilon \ll 1$ (sparse connectivity)

N. Brunel, J Comput Neurosci (2000)



The network displays a state transition between asynchronous firing (for weak coupling) and synchronous firing (for strong coupling) states.

➡ Nest simulators

Question 1.

Check that the Brunel's network model generates distinct patterns of neural activity. How are the different states in a large-scale network related to those of a two-neuron network?

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March 29, 2018

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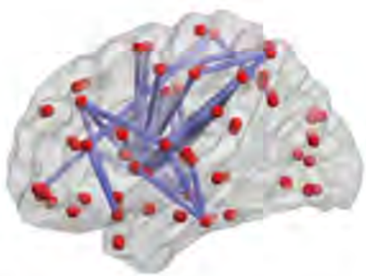
A path to faster large-scale brain simulations

One of the dreams that could be realized with future exascale class supercomputers—meaning machines capable of performing a quintillion calculations per second—is to stimulate the activities of the 100 billion neurons in the human brain. It is a daunting task, however, and one of the major challenges is the amount of computer memory required for such simulations. Recently, an international group including Mitsuhisa Sato and Itaru Kitayama of the RIKEN Advanced Institute for Computer Science and Jun Igarashi of the RIKEN Advanced Center for Computing and Communications has used a new algorithm to make it possible to simulate the actions of neurons on a whole range of computers, from common laptops to exascale supercomputers.

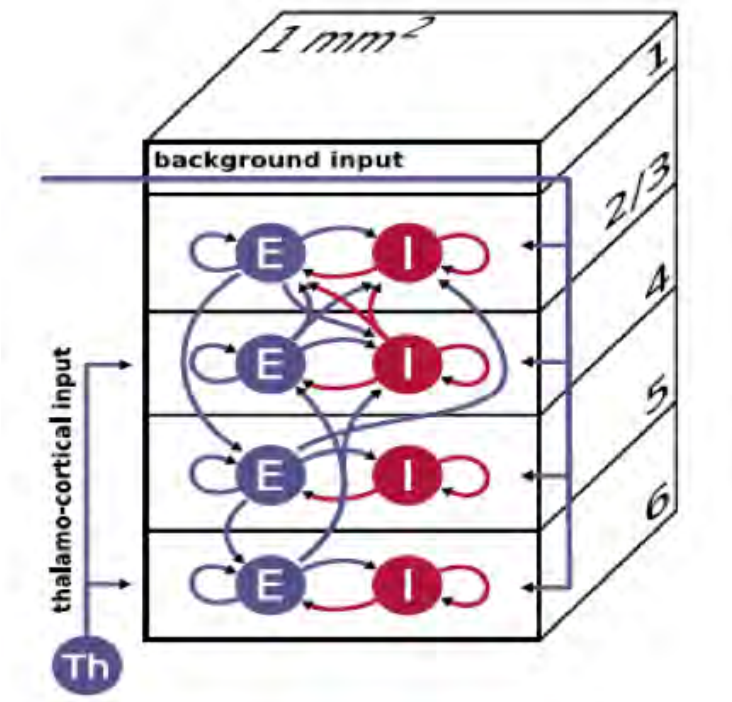


By Soon-Beom HongAndrew ZaleskyLuca CocchiAlex FornitoEun-Jung ChoiHo-Hyun KimJeong-Eun SuhChang-Dai KimJae-Won KimSoon-Hyung Yi [CC BY-SA 3.0 (https://creativecommons.org/licenses/by-sa/3.0)], via Wikimedia Commons

The group was interested in overcoming a stumbling block involving memory usage that will make it difficult to perform such complex simulations on exascale computers. Using powerful supercomputers—the K computer in Kobe and the JUQUEEN computer in Jülich—they streamlined the process, so that there was less communication among the nodes. And according to Susanne Kunkel, an author from the KTH Royal Institute of Technology, “We realized that our novel technology would not only enable simulations on exascale systems, but would also make simulations faster on presently available computers.” According to Dr. Sato, “The study is a wonderful example of the international collaboration in the endeavor to construct exascale computers. It is important that we have applications ready that can use these precious machines from the first day they are available.”

The group plans to publish the algorithm so that researchers around the use can use it to perform better simulations. Collaborators on the project include Jakob Jordan from Forschungszentrum Jülich, Markus Diesmann of the Jülich Institute of Neuroscience and Medicine (INM-6), and Kenji Doya of the Okinawa Institute of Science and Technology (OIST). For more information see the article on the Frontiers news blog.

nest:: simulated()



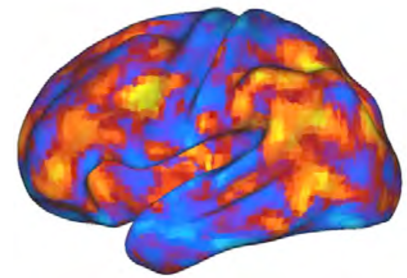
Potjans and Diesmann, Cereb Cortex 2012

- Faster large-scale simulations
- Easy debugging
- Standard platform for simulations

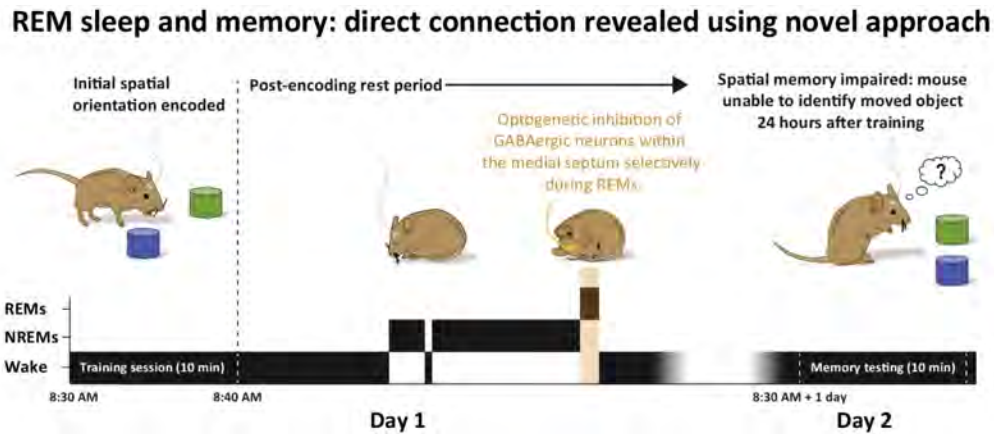
Idling Brain (MEXT KAKENHI for Specially Promoted Research)

● Role of "spontaneous brain activity" in higher cognitive functions

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



● Off-line processing during sleep for memory consolidation "



Boyce et al., Curr Opin Neurobiol 2017

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

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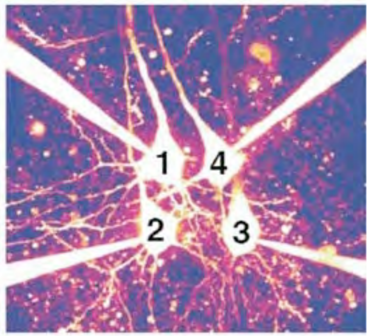
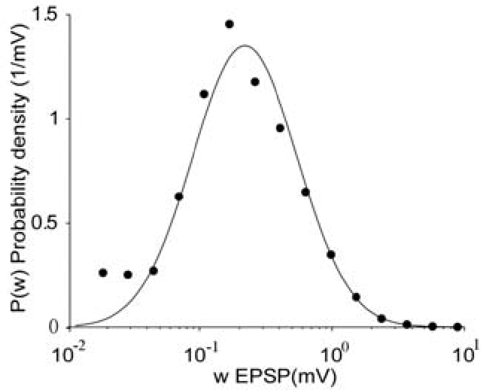
Heavy-tailed EPSP distributions of cortical synapses

Strong-sparse vs. weak-dense synaptic connections

rat visual cortex

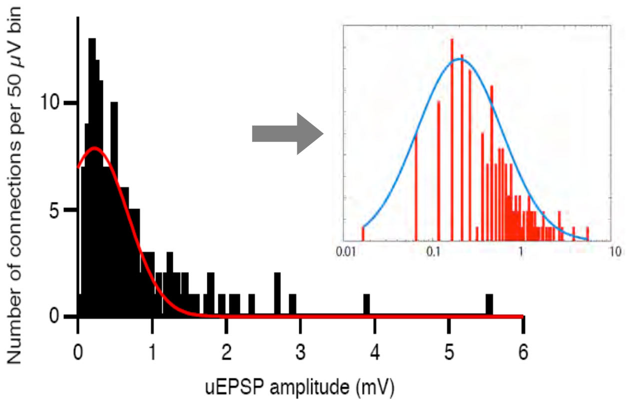
Song et al., PLoS Biol (2005)





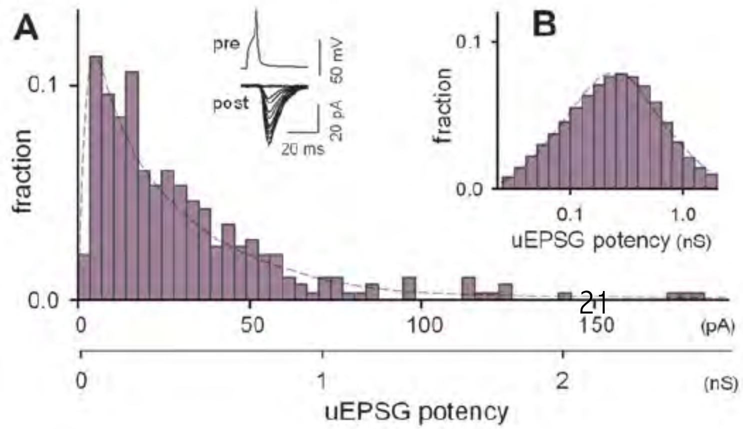
mouse somatosensory cortex

Lefort et al. Neuron (2009)



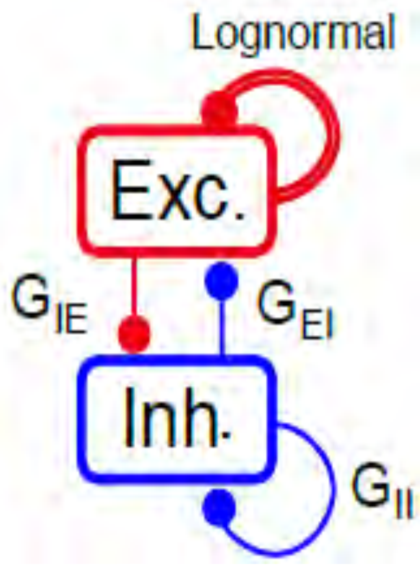
rat hippocampus

Ikegaya et al., Cereb Cortex (2013)



Recurrent network models of spiking neurons

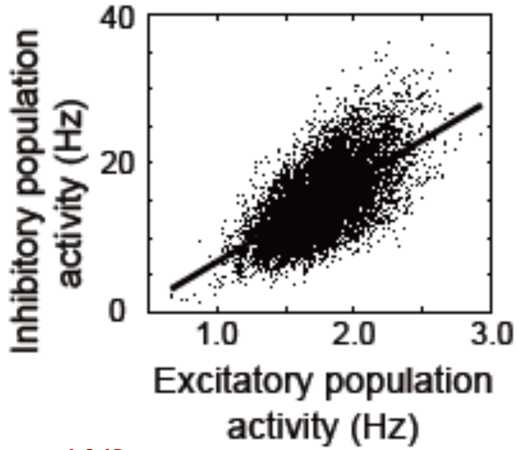
Asynchronous sparse (1~2 spikes/sec) irregular firing

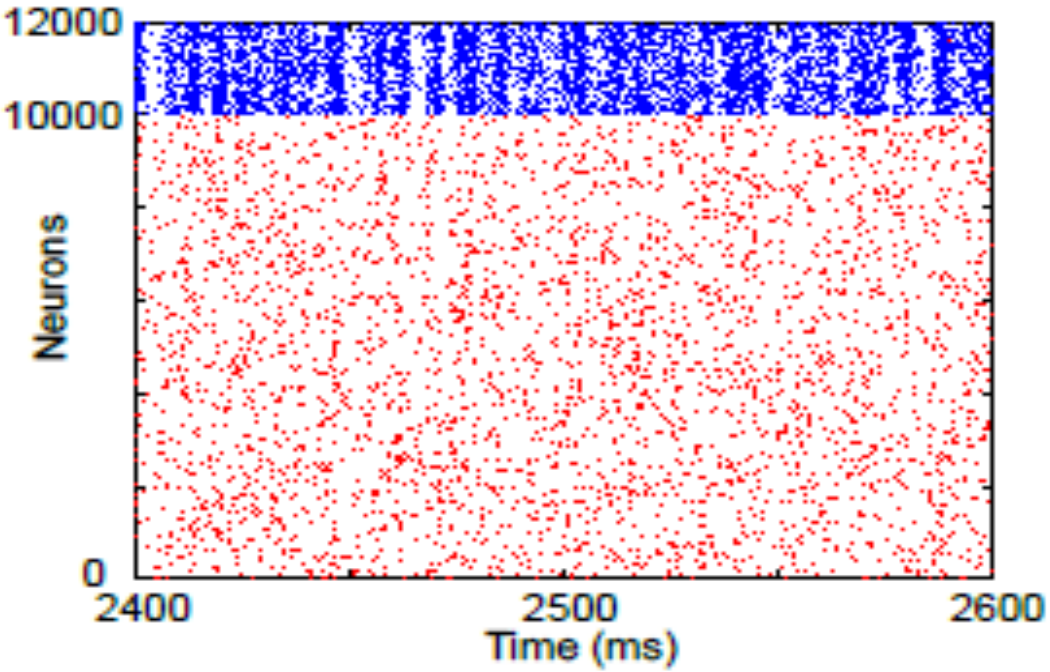


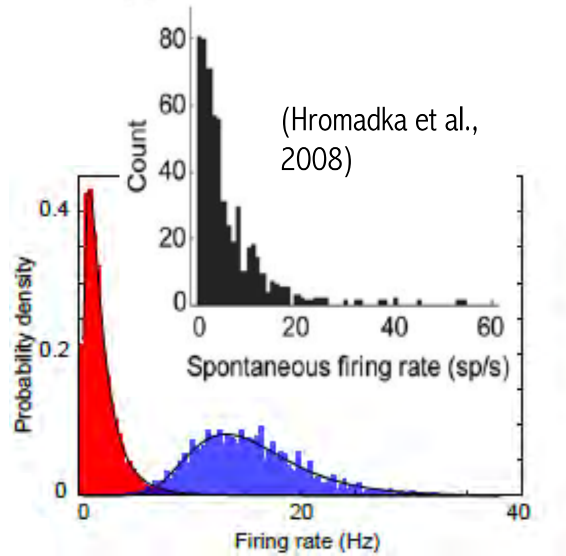
- 10000 excitatory + 2000 inhibitory LIF neurons
- AMPA synapses — Lognormal weight distribution
- GABA-A synapses — Gaussian weight distribution
- Transmission delays ∈ [1, 3] (ms)
- No external input

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

Excitation-inhibition balance

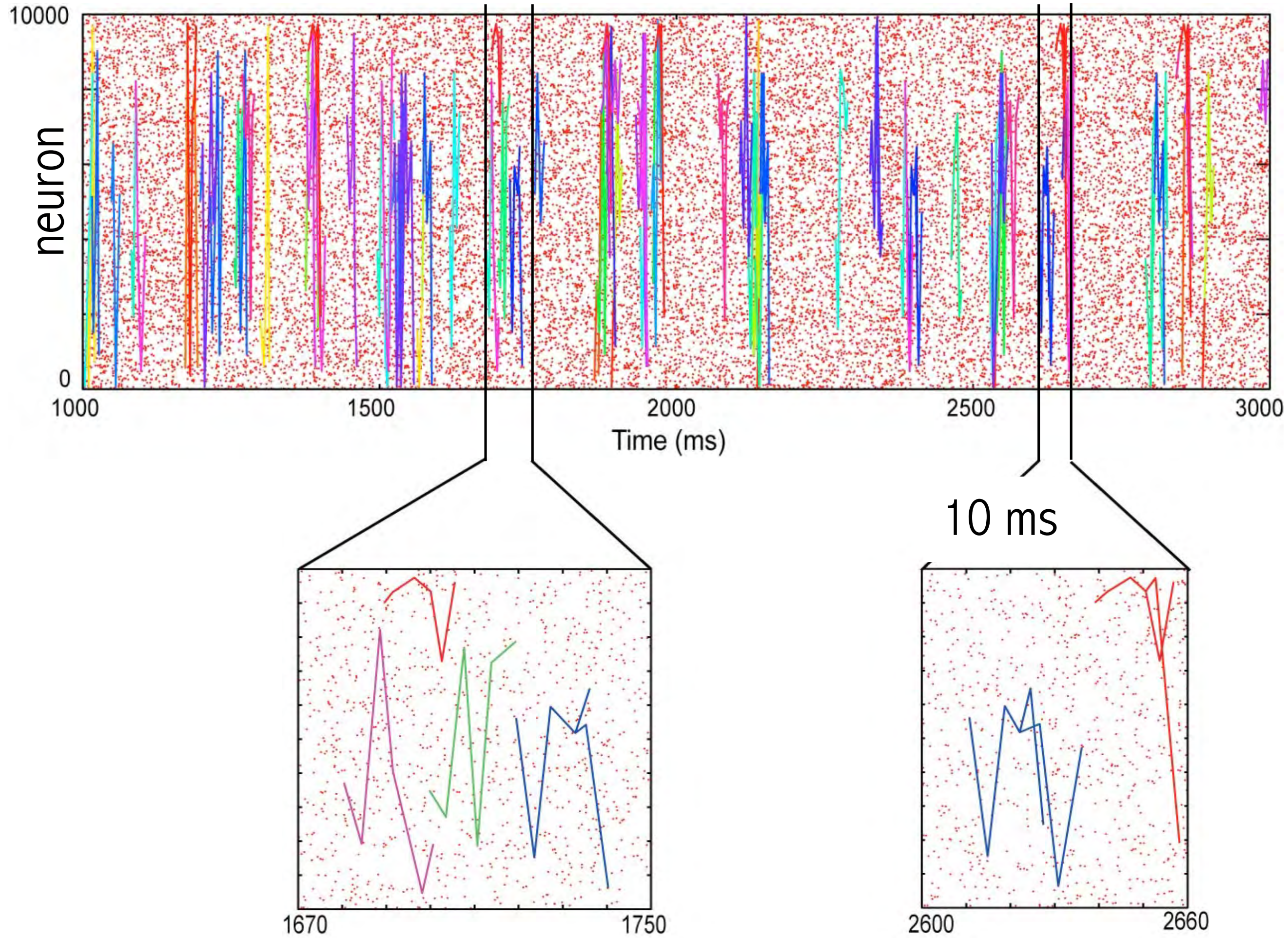






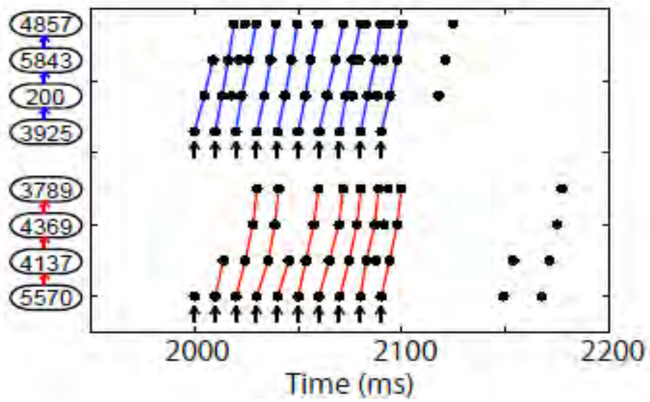
(Hromadka et al., 2008)

AI (asynchronous irregular) state comprises vast many spike sequences

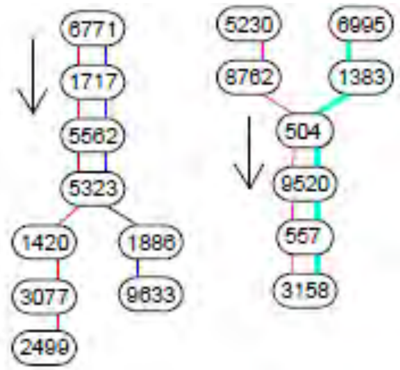


Teramae et al., Sci Rep (2012)

- Probabilistic propagation



- Branching and merging



- Stretching and compression

Question 2.

How does a lognormal neural network spontaneously generate a sparse irregular activity?

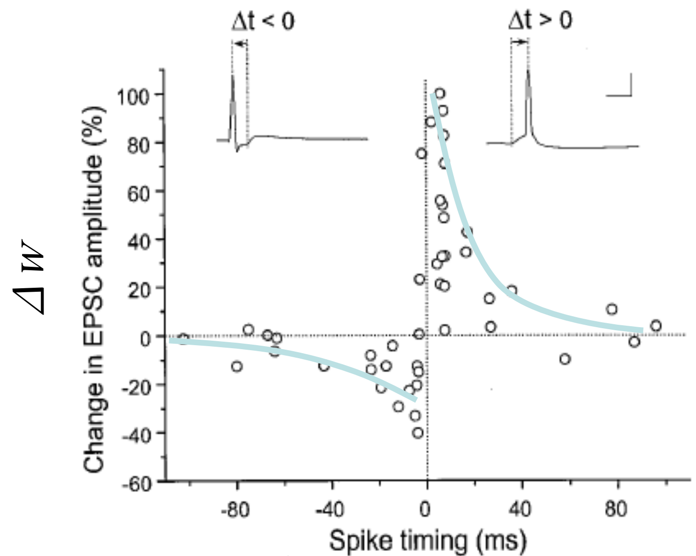
Hebb's cell-assembly hypothesis

Hebb's rule: "Fire together, wire together"

$$A \xrightarrow{w} B$$

(Donald O. Hebb)

Spike-timing-dependent plasticity (STDP)



$$\Delta t = t_{\text{post}} - t_{\text{pre}}$$

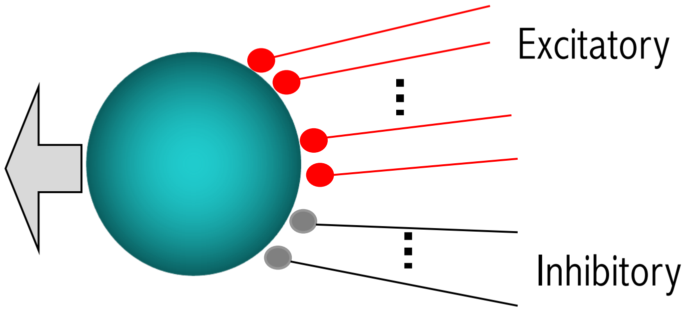
Hippocampal area CA1 (Bi and Poo, J Neurosci, 1998)

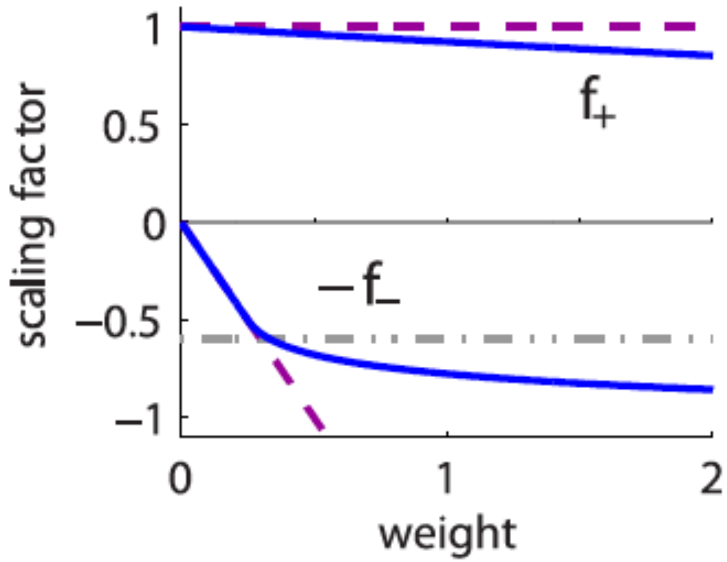
STDP looks convenient for sequence learning

Various STDP rules and synaptic competition

$$\Delta w = \begin{cases} (f_+(w) + \text{noise}) \exp\left(-\Delta t / \tau_P\right) & (\Delta t > 0) \\ -(f_-(w) + \text{noise}) \exp\left(\Delta t / \tau_D\right) & (\Delta t < 0) \end{cases}$$

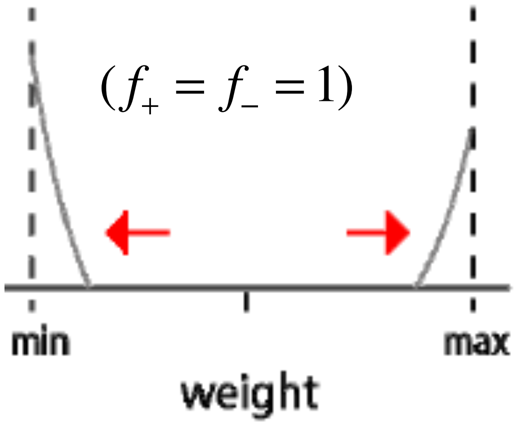
$$\Delta t = t_{\text{post}} - t_{\text{pre}}$$





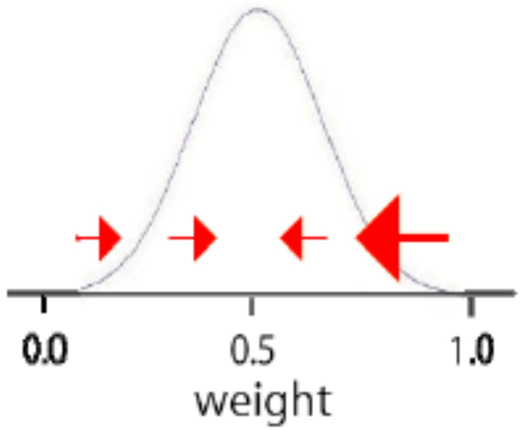
Additive STDP

(Song et al., 2000)



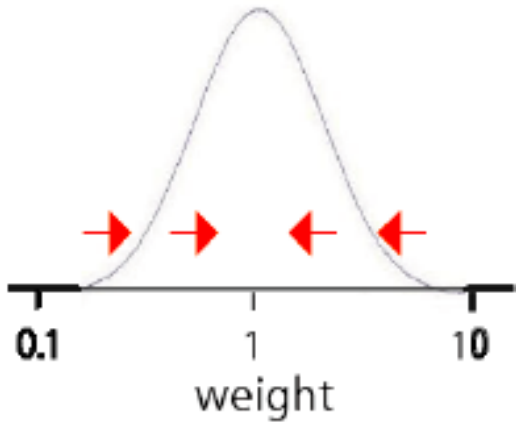
Multiplicative STDP

(van Rossum et al., 2000)



Lognormal STDP

(Gilson and Fukai, 2011)



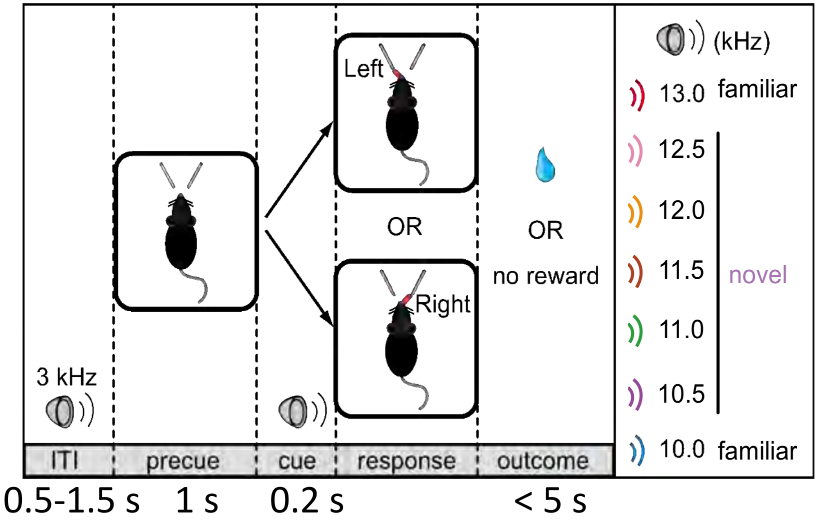
Question 3.

Why does additive STDP induce competition among synapses?

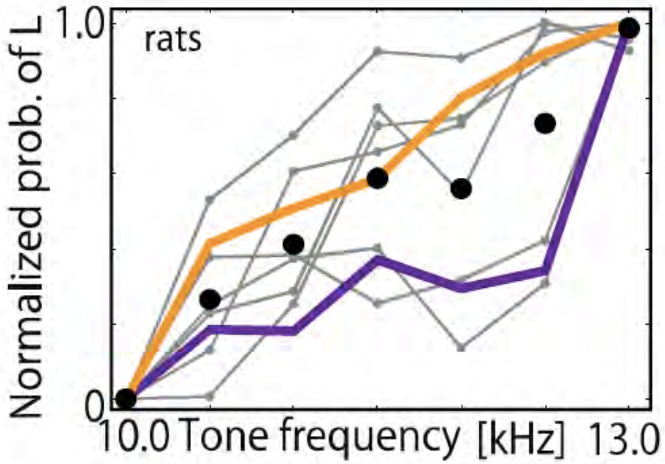
Why is this competition weak in multiplicative STDP?

Neural population dynamics - a recent view

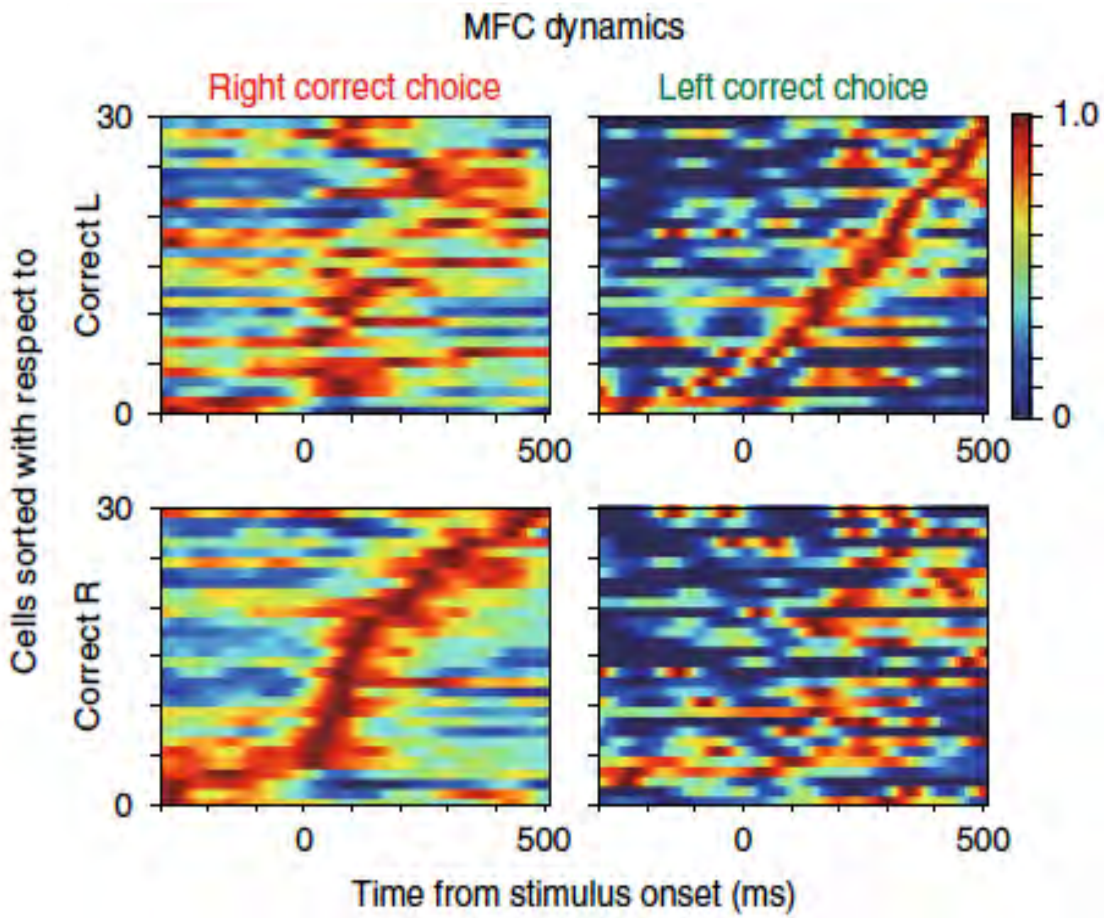
decision-making for ambiguous auditory stimuli



large behavioral variance

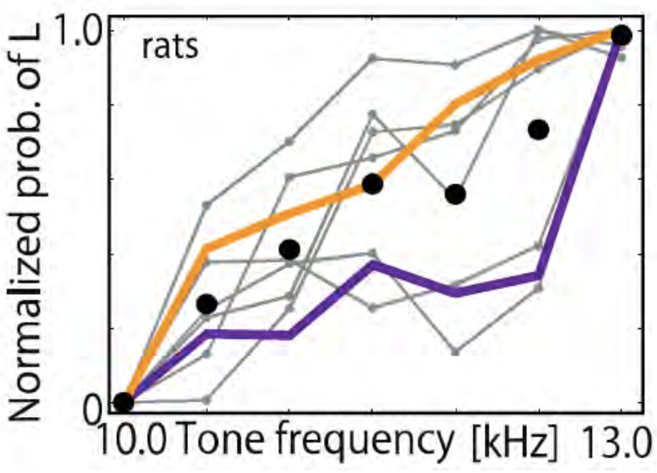


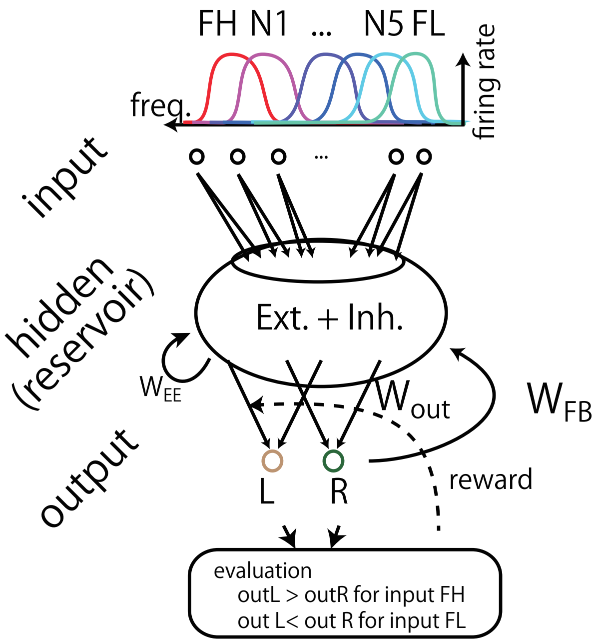
choice-specific trajectories of neural firing in the medial frontal cortex

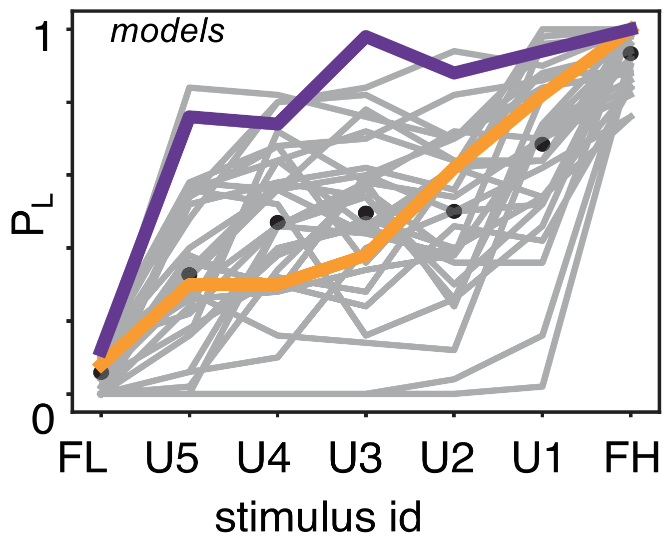


(Handa et al., Cerebral Cortex, 2017; Kurikawa et al., Nat Neurosci 2019)

Same learning rule generates large behavioral variance

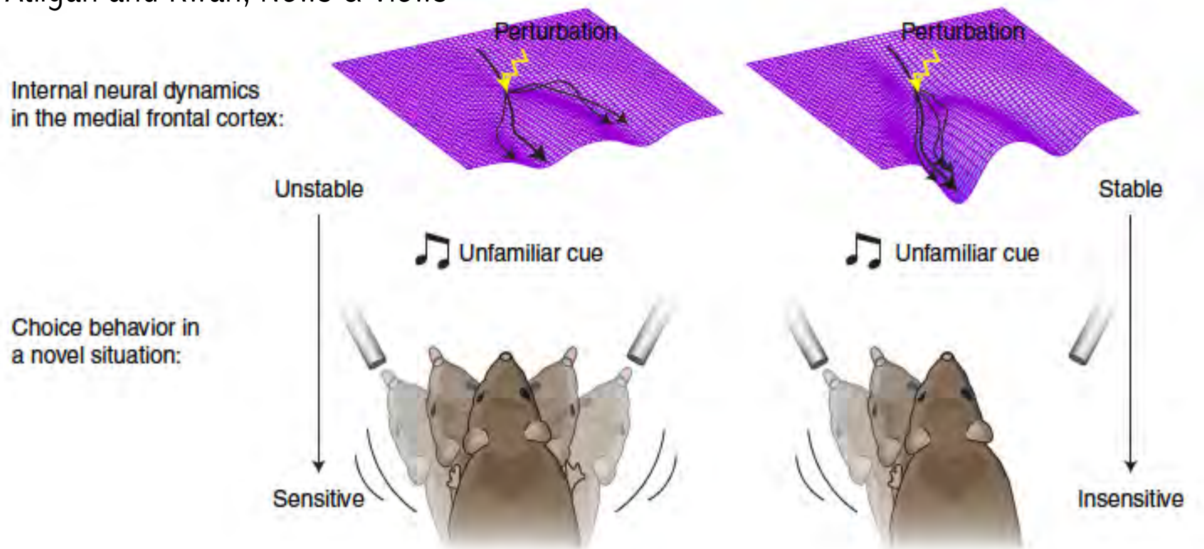






Kurikawa et al. Nat Neurosci (2018)

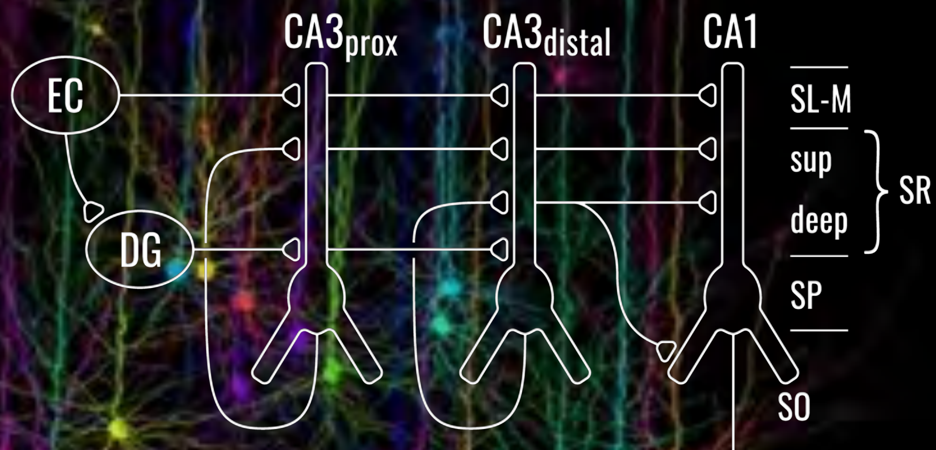
Atilgan and Kwan, News & Views



What's the next step?

We need to unify local circuit computations and whole brain computation

- Predictive coding hypothesis and hierarchical Bayesian computation
- Dendritic processing for brain-wide information routing and temporal feature analysis



We need to uncover "neural code" in which the brain represents information

(http://www.giantfreakinrobot.com/sci/brains-computing-power-originally-thought.html)

What’s the next step?

Predictive coding hypothesis

Bayes rule:

$$P(s|r) = \frac{P(r|s)P(s)}{P(r)}$$

Prior $P(s)$

~ the internal model of external world

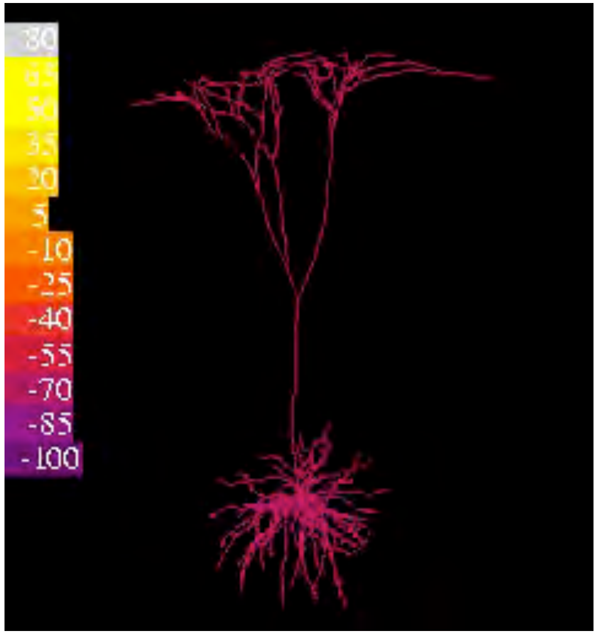
~ spontaneous brain activity?

~ important for learning with small data

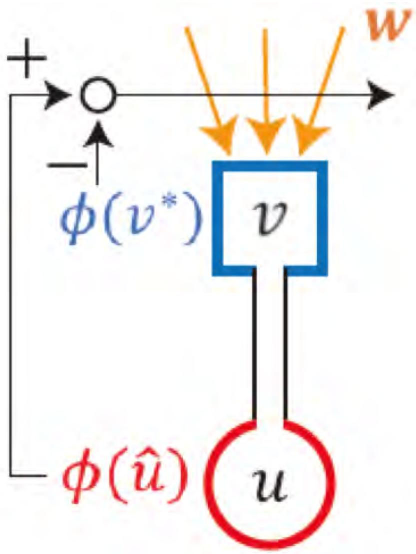
(http://www.giantfreakinrobot.com/sci/brains-computing-power-originally-thought.html)

Somatodendritic discrepancy detection for temporal feature analysis

(Pare et al., Neurosci 1998)



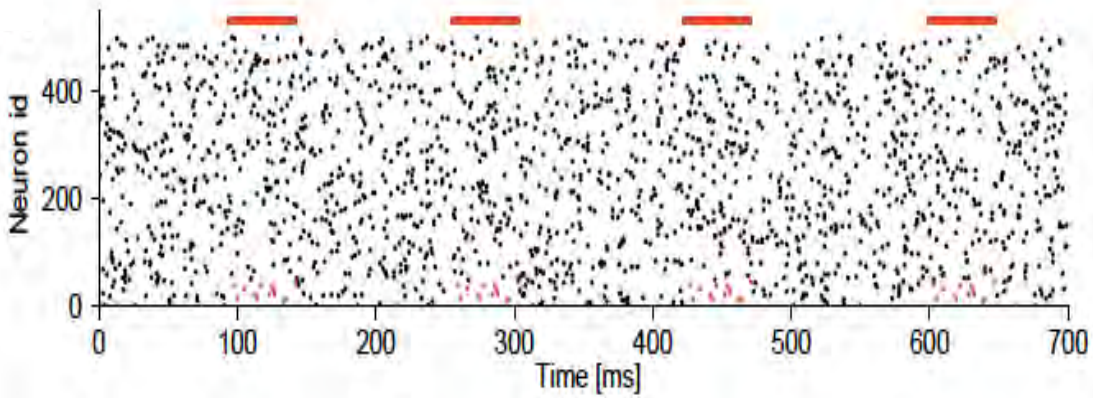
(Asabuki and Fukai, bioRxiv)

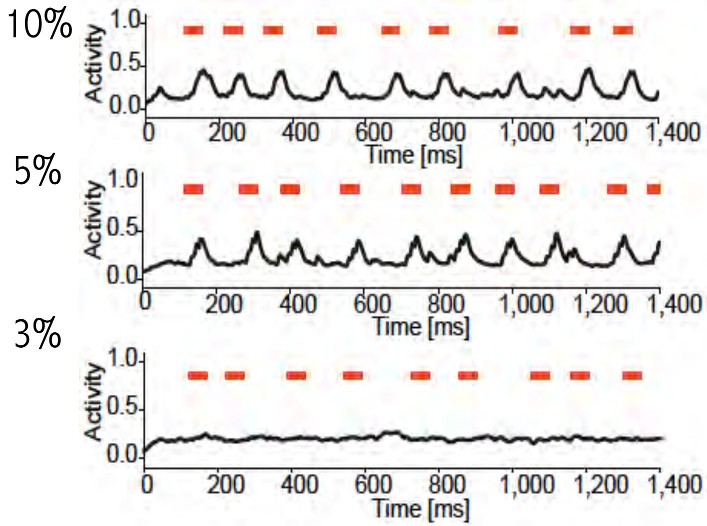


$$\frac{d}{dt}w \propto \psi(v^*(t))[\phi(\hat{u}(t)) - \phi(v^*(t))]e(t)$$

Dendrite generates a statistical model of the somatic responses

Temporal pattern detection

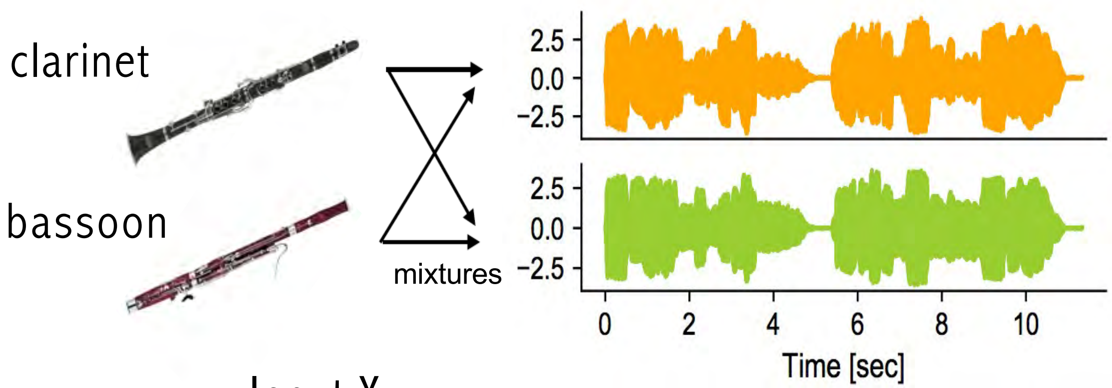


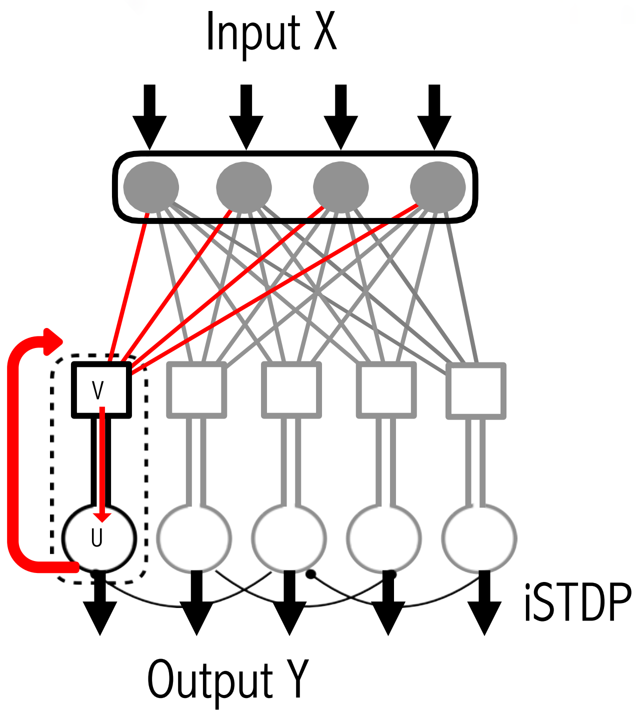


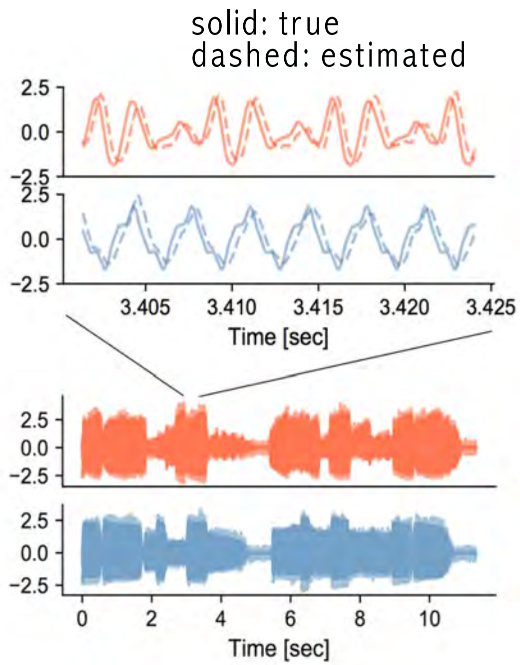
Asabuki and Fukai, bioRxiv

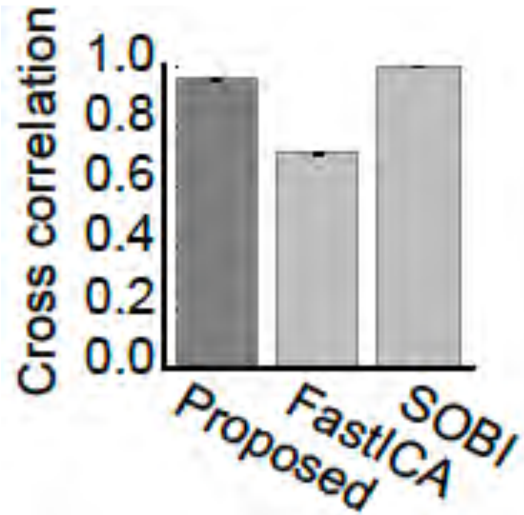
OIST

A new solution to cocktail party problem



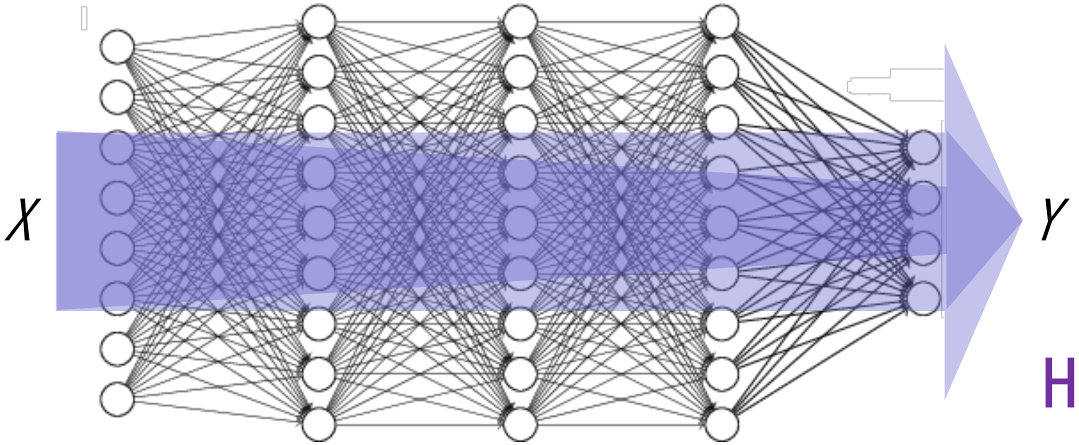






Asabuki and Fukai, bioRxiv

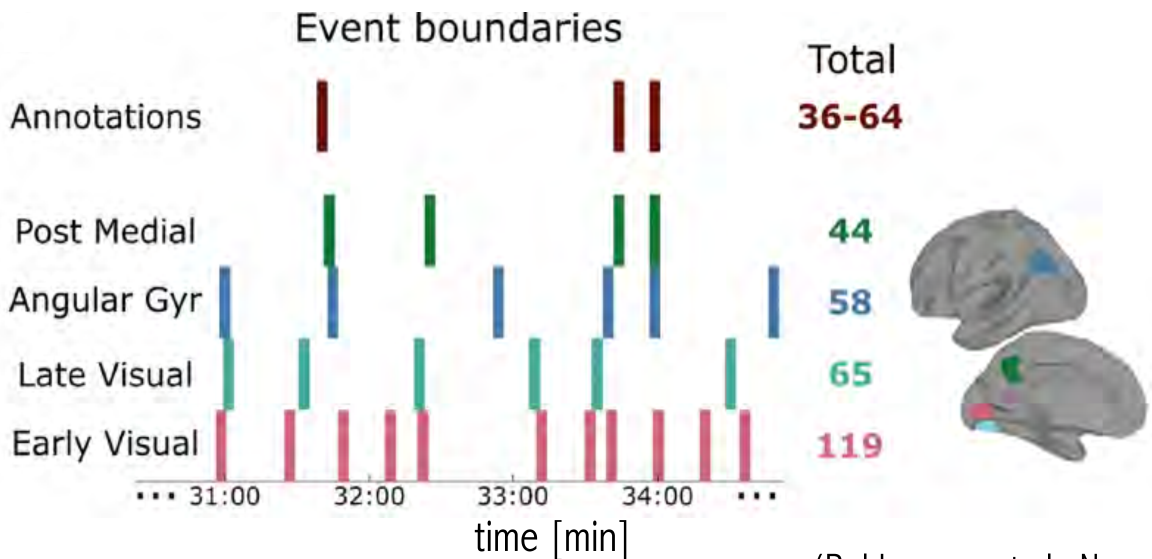
Multi-timescale processing with information compression



Mutual Information Maximization

$$I(X;Y) = \sum_{y \in Y} \sum_{x \in X} p(x,y) \log \frac{p(x,y)}{p(x)\,p(y)},$$

How does the brain compress information?

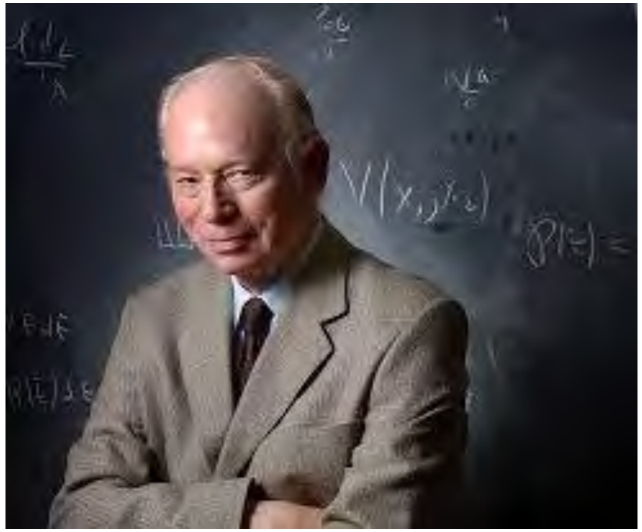


(Baldassano et al., Neuron 2017)

Steven Weinberg (1933 -)

Nobel Prize (Physics), 1979

A unified theory of weak and electromagnetic forces



It is often necessary to forget one’s doubts and to follow the consequences of one's assumptions wherever they may lead - the great thing is not to be free of theoretical prejudices, but to have the right theoretical prejudices.

Thank you for your listening and enjoy the Skill Pills+!