Spike-based Learning and Cortical Microcircuit Structure

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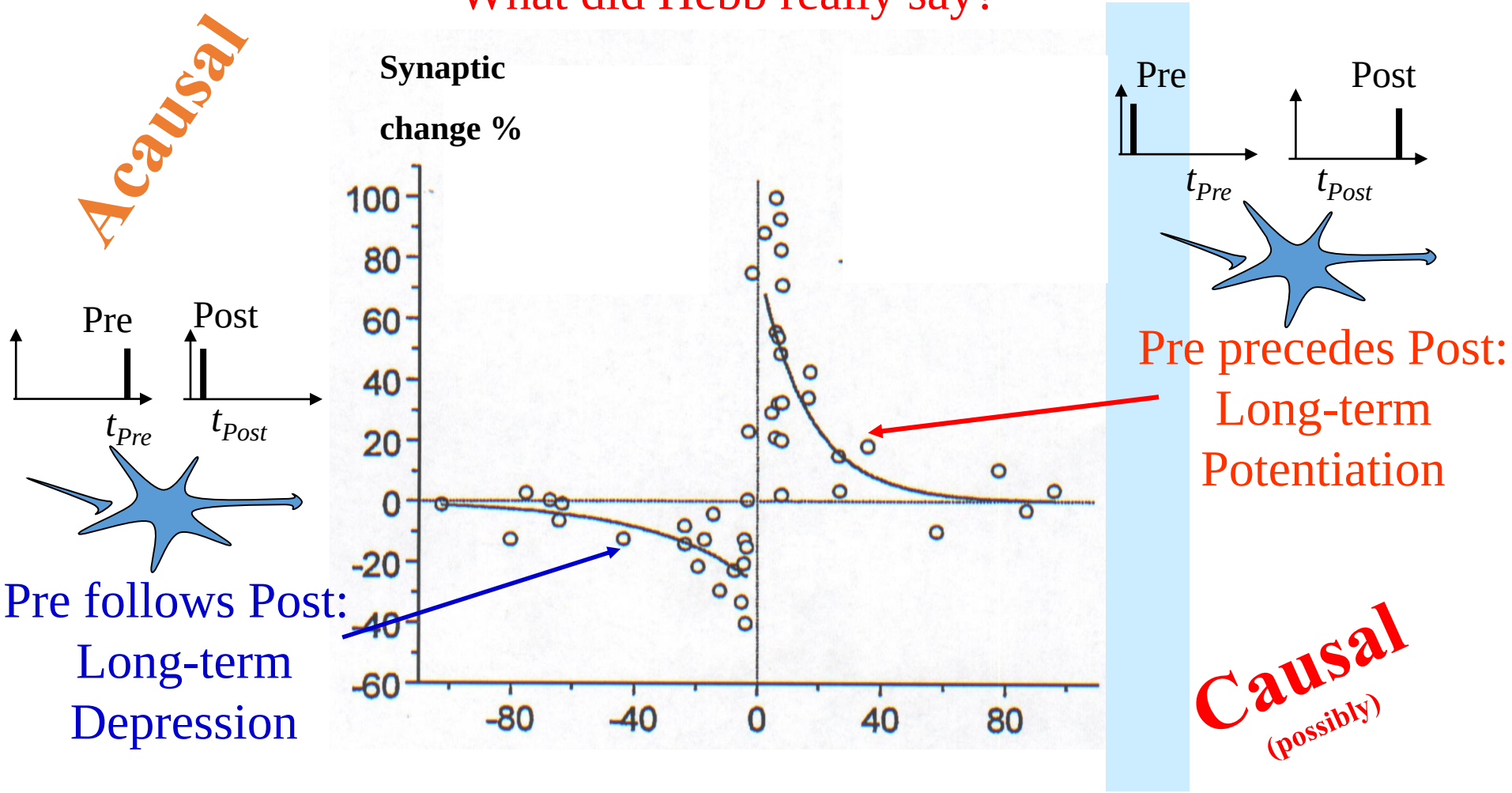
NYU Shanghai Workshop

Spike Timing Dependent Plasticity: Temporal Hebbian Learning

What did Hebb really say?



Weight-change curve

(Bi&Poo, 2001)

Topic 1 Synaptic Plasticity at different time scales
Key molecules at different time-scales

- Fast (milli-seconds)
  -- STDP
  - Calcium CamKII(high-thres) & PKC(low-thres)
- Intermediate
  -- Modulation by Reward
  - cAMP e.g. Modulation by Dopamine
- Within-day
  -- Short-term storage of information to be consolidated during sleep
  - Magnesium e.g. Active Erasure during Sleep, Consolidation
  - Heterosynaptic Plasticity by endocannabinoids
- Days/Months
  - Structural Plasticity, Synapses can be made and break.
  - Interesting part is silent synapse, no synapse is not the same as zero strength synapse.
  - Re-learning is always faster
  - Homeostasis TNF-alpha (Turrigiano)

STDP very sensitive to synchronous events

A PARADOX that exists in auditory and electrosensory neural systems[1,2] is that they encode behaviourally relevant signals in the range of a few microseconds with neurons that are at least one order of magnitude slower.

The importance of temporal coding in neural information processing is not clear yet[3–8].
A central question is whether neuronal firing can be more precise than the time constants of the neuronal processes involved[9]. Here we address this problem using the auditory system of the barn owl as an example.

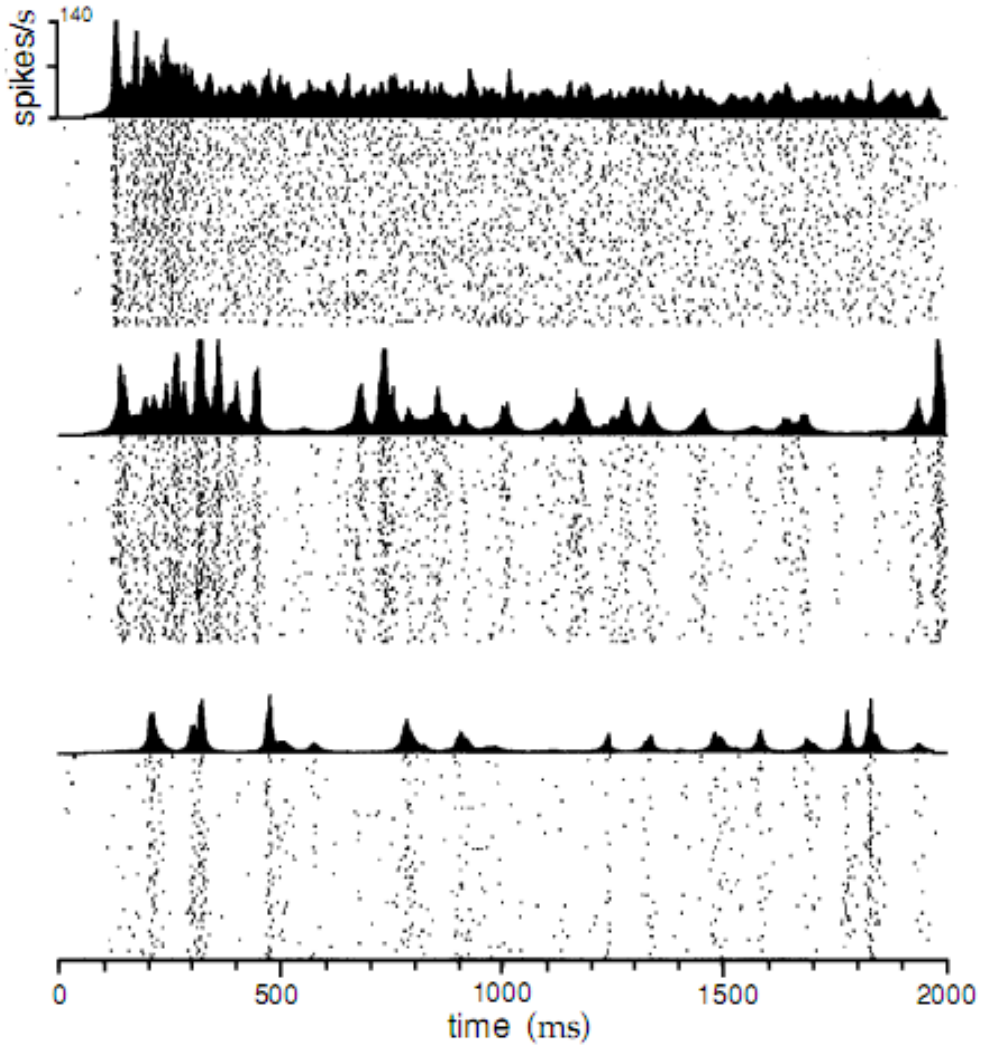
We present a modelling study based on computer simulations of a neuron in the laminar nucleus.

Gerstner *W, Kempter R, van Hemmen JL, Wagner H (1996)*
A neuronal learning rule for ***sub-millisecond*** *temporal coding. Nature 383: 76–81.*

What do Spike Trains Look like

But recent meta-analysis show,
Only in sensory and cognitive parts
Not in motor cortex!

Motor cortex uses more regular spike
Train.



Cortical Spike Trains are Variable

Balance of Excitation and Inhibition

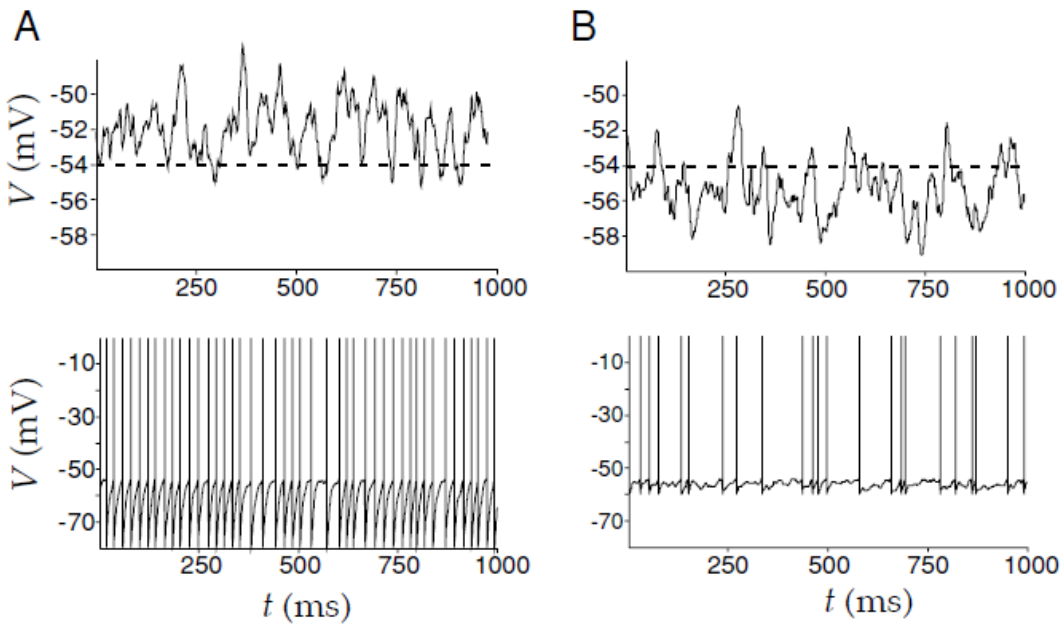


Figure 5.21 The regular and irregular firing modes of an integrate-and-fire model neuron. (A) The regular firing mode. Upper panel: The membrane potential of the model neuron when the spike generation mechanism is turned off. The average membrane potential is above the spiking threshold (dashed line). Lower panel: When the spike generation mechanism is turned on, it produces a regular spiking pattern. (B) The irregular firing mode. Upper panel: The membrane potential of the model neuron when the spike generation mechanism is turned off. The average membrane potential is below the spiking threshold (dashed line). Lower panel: When the spike generation mechanism is turned on, it produces an irregular spiking pattern. In order to keep the firing rates from differing too greatly between these two examples, the value of the reset voltage is higher in B than in A.

What can Hebbian Learning do?

Basic Hebbian Learning is quivalent to PCA/NMF

Oja's rule

Forging the link to ML/deep learning – a resonable objective function based on multi-dimensional scaling metric

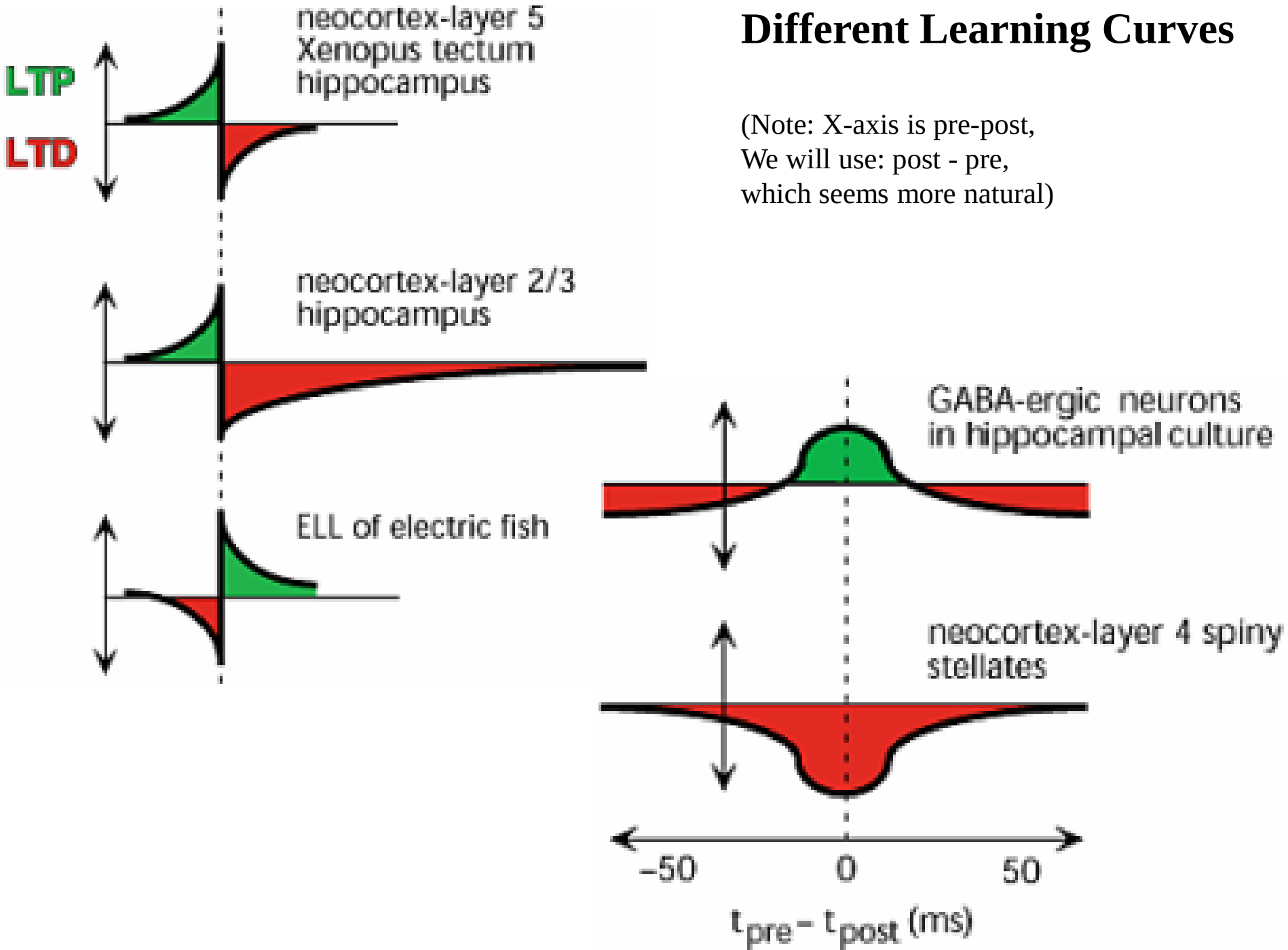
Similarity matching: A new theory of neural computation NIPS 2015
Dmitri (Mitya) Chklovskii

Principled derivation of local learning rules for PCA [Pehlevan & Chklovskii NIPS 2015] and NMF [Pehlevan & Chklovskii 2015].

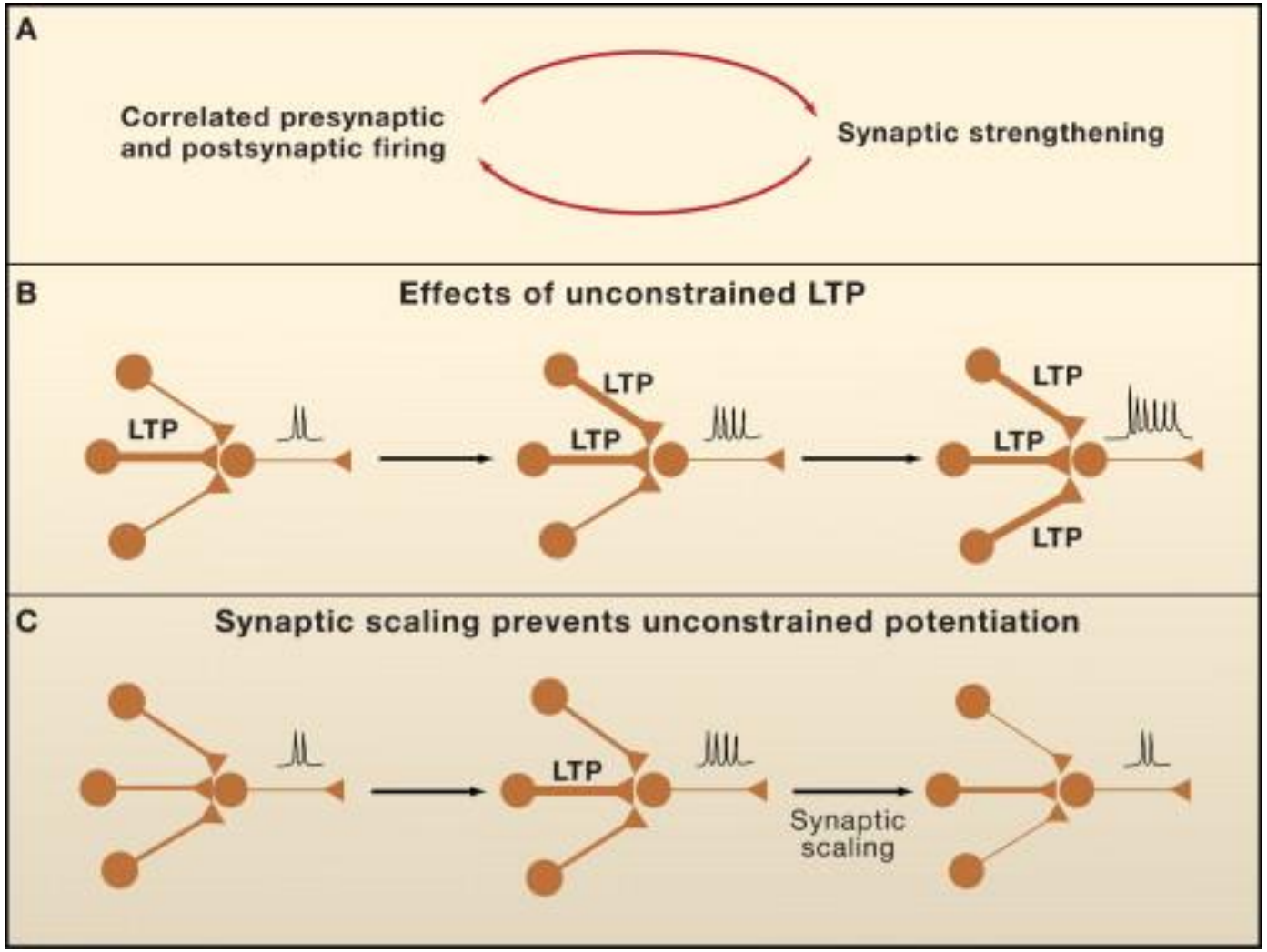
With some tweaking, nonlinearity and sparsity constraints, people have shown it can be ICA

Different Learning Curves

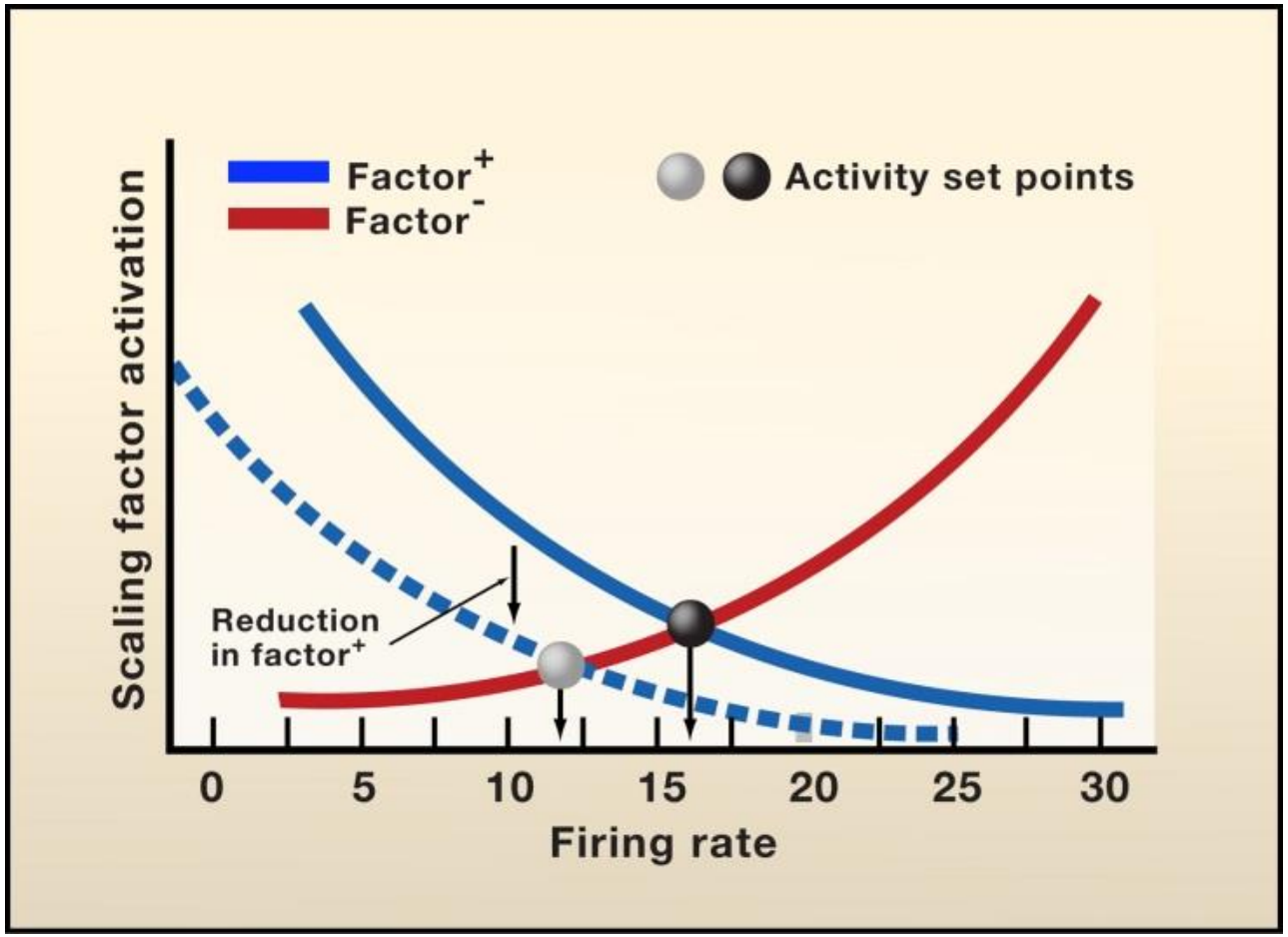
(Note: X-axis is pre-post,
We will use: post - pre,
which seems more natural)



Homeostatic Plasticity



Homeostatic Plasticity

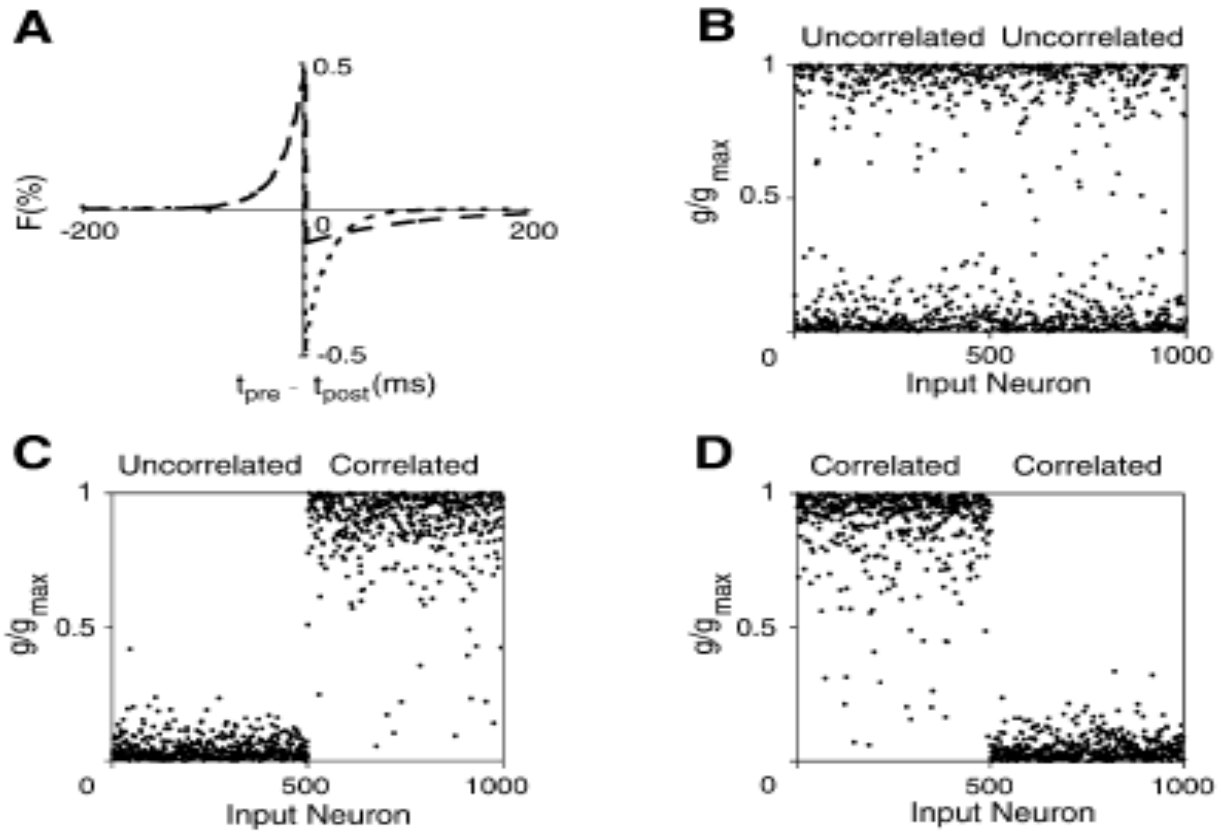


Factor is TNF-alpha

STDP is a Competitive Learning Rule

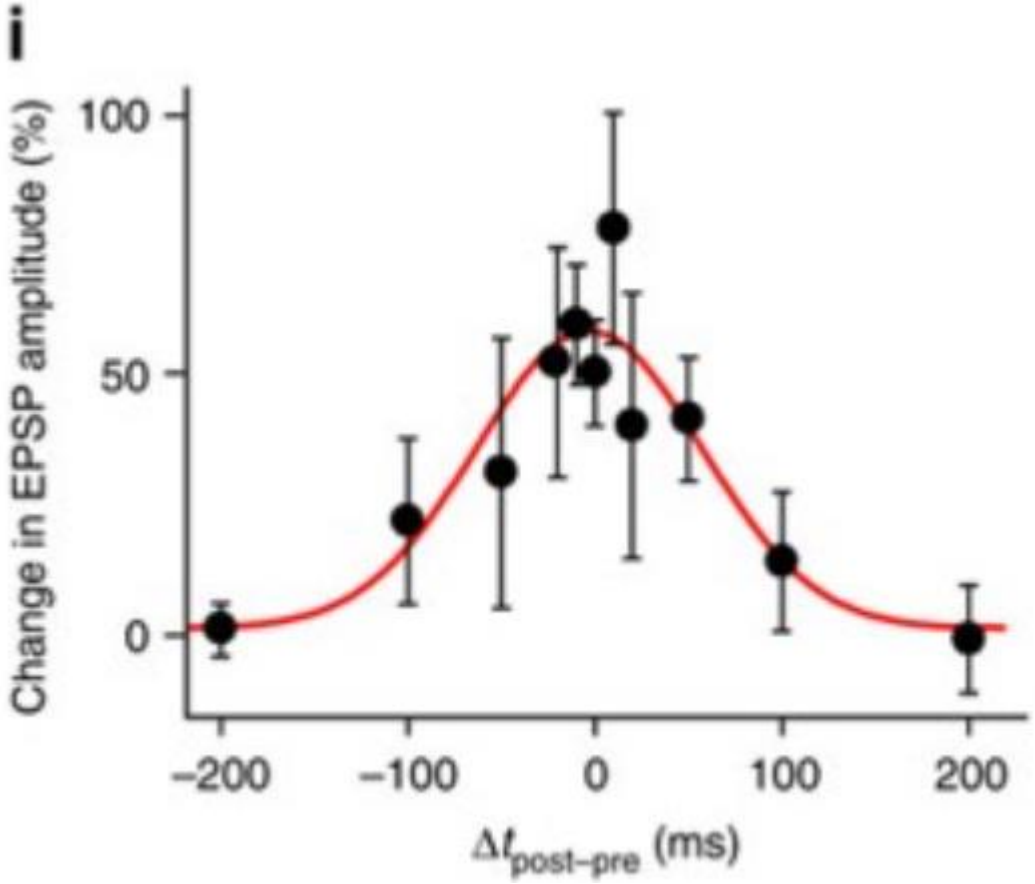
Subtractive Normalization:

$$\tau_w \frac{d\mathbf{w}}{dt} = \mathbf{Q}\mathbf{w} - \frac{(\mathbf{w}\cdot\mathbf{Q}\mathbf{n})\mathbf{n}}{N_u}$$



Additional Hetereosynaptic LTD Mechanisms: mGluR, endocannabinoids

Learning at Recurrent Synapses
Symmetric STDP in Hippocampus

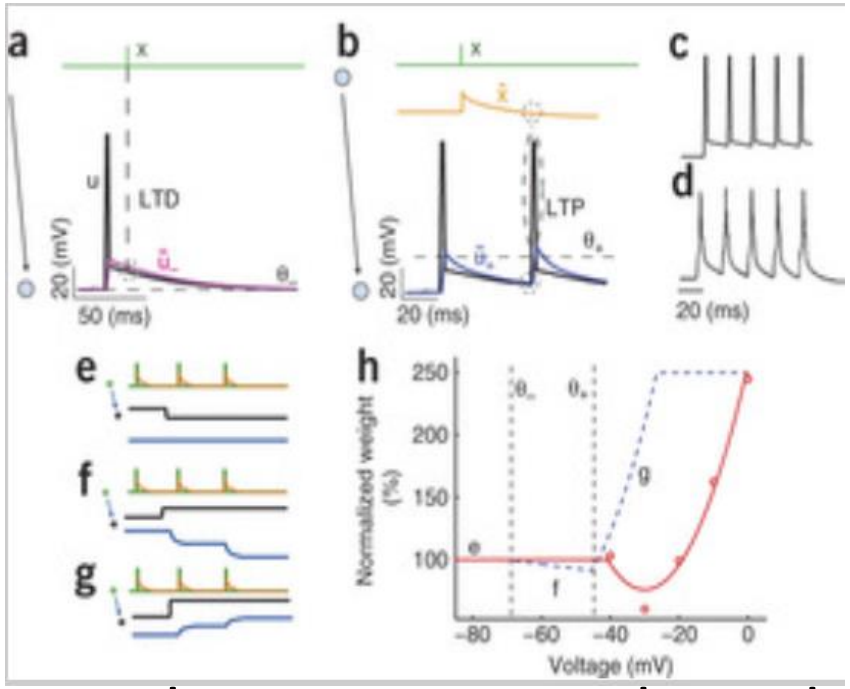


Hippocampal neurons tend to fire in bursts.

In autoassociative network models, storage and recall are more robust with symmetric than with asymmetric STDP rules. Thus, a specialized STDP induction rule allows reliable storage and recall of information in the hippocampal CA3 network.

Symmetric spike timing-dependent plasticity at CA3–CA3 synapses optimizes storage and recall in autoassociative networks
Peter Jonas Nature Comm 2016

Unification of Asymmetric and Symmetric STDP

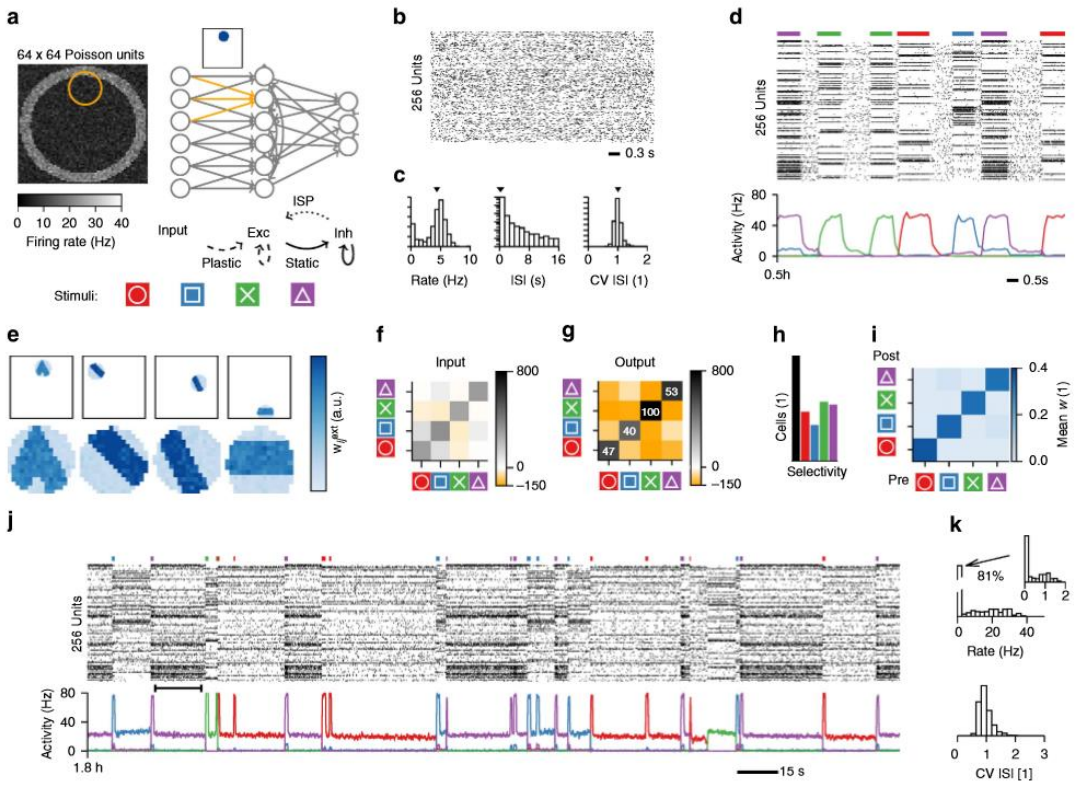


Longer timescale symmetric rule realized through residual Calcium in the synapse

For temporal coding procedures with spatio-temporal input correlations, strong connections were predominantly unidirectional, whereas they were bidirectional under rate-coded input with spatial correlations only.
Thus, variable connectivity patterns in the brain could reflect different coding principles across brain areas

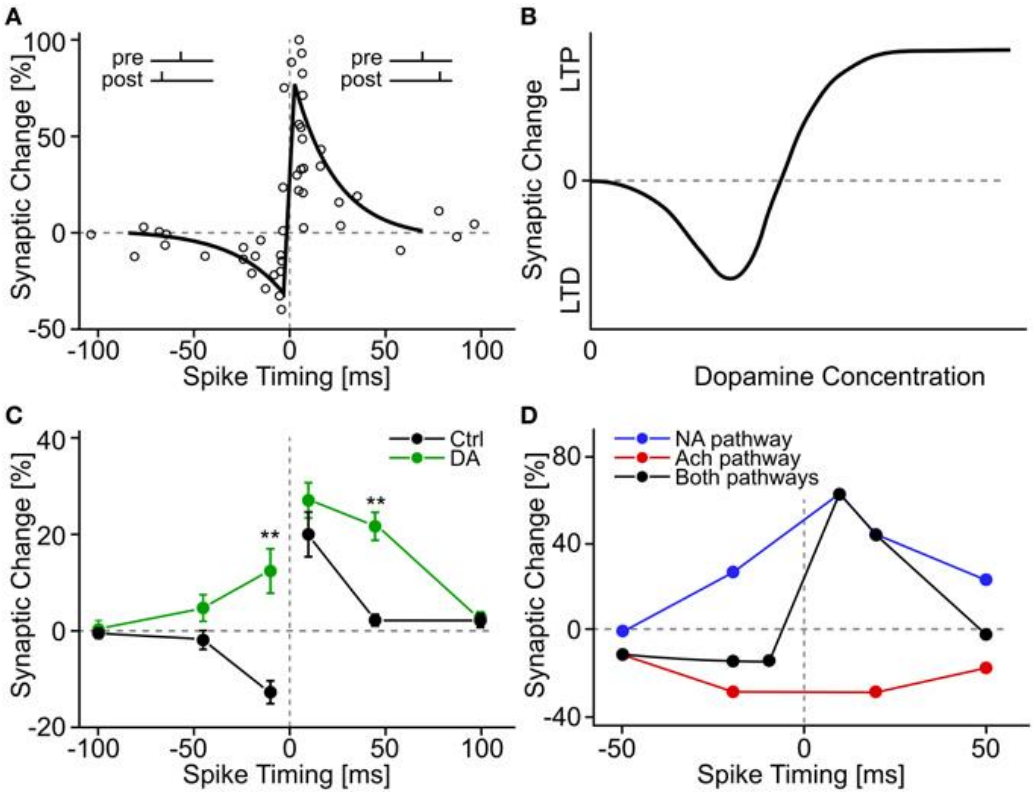
Connectivity reflects coding: a model of voltage-based STDP with homeostasis
Claudia Clopath,Wulfram Gerstner Nature Neuroscience 2010

Unification of Diverse Plasticity for Unsupervised Learning of Hebbian Assemblies



F. Zenke and E.J. Agnes and W. Gerstner (2015)
[Diverse synaptic plasticity mechanisms orchestrated to form and retrieve memories in spiking neural networks]
Nature Comm. 6: 6922

Reward Modulated STDP



- **Retroactive modulation of spike timing-dependent plasticity by dopamine**

Time scale of several seconds, depend on cAMP pathway

Neuromodulated Spike-Timing-Dependent Plasticity, and Theory of Three-Factor Learning Rules
Wulfram Gerstner Front. Neural Circuits, 19 January 2016

Supervised Learning?

- Key components:
  - 1 Forward Pass - OK
  - 2 calculating difference/error – some evidence this is possible
  - 3 backprop – problematic
  - 4 update step – probably implementable with some kind of modified Hebbian rule

- Problems with Backprop:
- 1 no evidence that error is backpropagated
- 2 Same weight for feedforward and feedback pass

Potential Solutions

Hinton's idea

- 1 no evidence that error is backpropagated
  - Backpropagate activity, instead of error

1 Use an autoencoder type of architecture to backprop

Biological evidence that local circuit or feedback circuit can generate some kind of prediction – so not reconstruction but prediction.

Probably possible to propagate back also the correct answer -- Target propagation. Cross modal teaching/integration scenario

Potential Solutions

Hinton's idea

- 1 no evidence that error is backpropagated
  - Backpropagate activity, instead of error

2 Calculate the difference/error using STDP

STDP as discussed above seems unrealistic as time scale is too short

But STDP like plasticity exist on longer time scale.

e.g. coincidence detector between synaptic activity and big somatic deplorization at time scale of 20-40s.

Richard Tsien Science 2016

Sequential ionic and conformational signaling by calcium channels drives neuronal gene expression

So maybe possible, but need a plausible circuit.

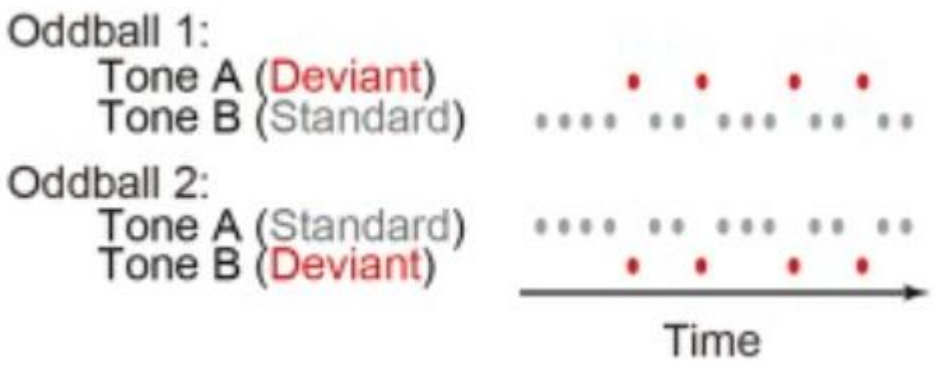
Potential Solutions

Hinton's idea

- 1 no evidence that error is backpropagated
  - Backpropagate activity, instead of error

2 Possibly Calculate the difference/error using inhibitory circuitry

Stimulus Specific Adapation (Mismatch Negativity)
Mechanism for Novelty Detection: Involves specific Inhibitory neurons
Complementary control of sensory adaptation by two types of cortical interneurons
Maria Neimark Geffen Elife 2015



Potential Solutions

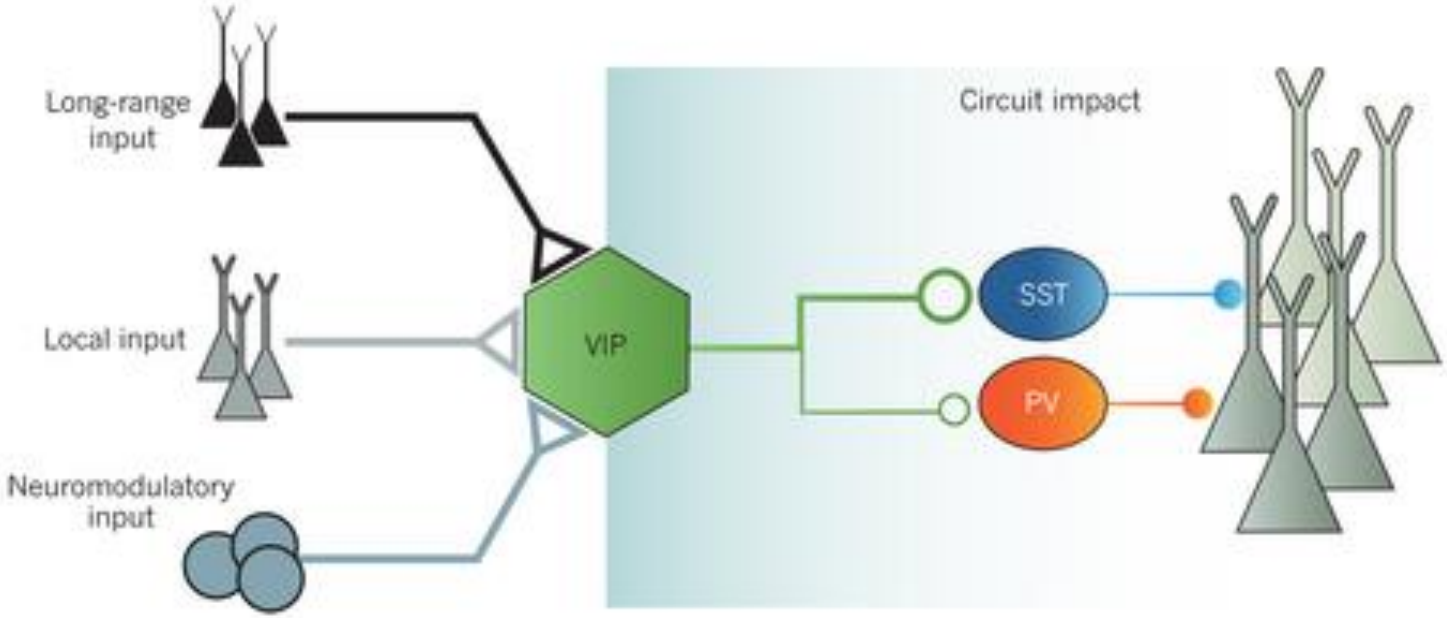
Hinton's idea

2 Feedforward and feedback are separate neurons

- However, controlled by common disinhibitory circuitry so shared learning?

- VIP neurons disinhibit SOM neurons to enable learning
- VIP neurons are targeted by attention related feedback and outcome related feedbacks

- Need to unveil this circui



Potential Solutions

Attention-Gated Reinforcement Learning

- 1 no evidence that error is backpropagated
  - Backpropagate activity, instead of error
  - Use a global error term

Three-stage mechanism for the adaptation of synaptic weights.

1 Feedforward processing determines a winning unit in the output layer of the network that encodes the chosen action.

2 An attentional feedback (AFB) signal originating from the winning unit assigns credit to those connections that were responsible for the chosen action by creating synaptic tags.

3 A global learning signal determines the changes of the weights of those synapses that carry the plasticity tag.

How Attention Can Create Synaptic Tags for the Learning of Working Memories in Sequential Tasks

Pieter R. Roelfsema PLOS Computational Biology 2015

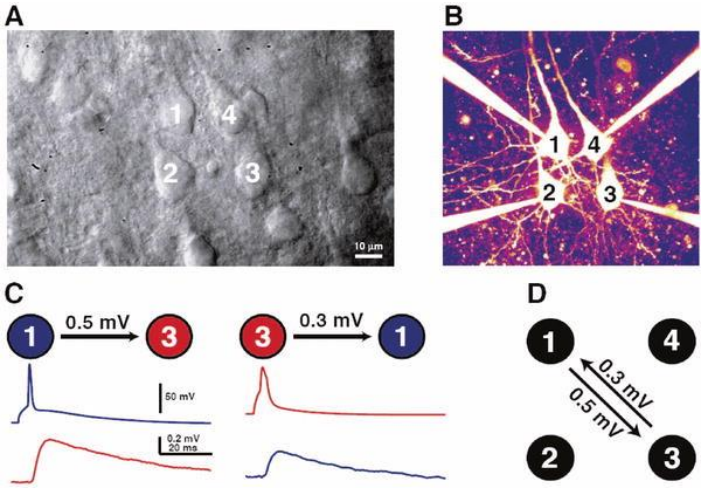
Potential Solutions

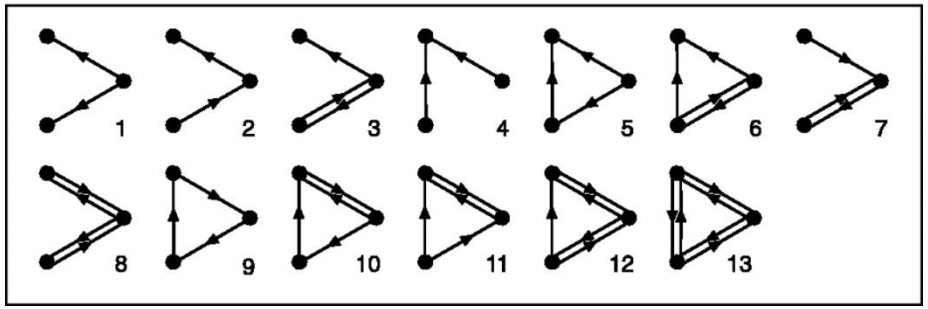
- 2 symmetric feedforward and feedback weights
  - Feedforward and feedback weights do not need to exactly the same

  How Important Is Weight Symmetry in Backpropagation?
  Poggio AAAI-16

- (1) Magnitudes of feedback weights do not matter to performance
- (2) Signs of feedback weights do matter -- the more concordant signs between feedforward and their corresponding feedback connections, the better
- (3) With feedback weights having random magnitudes and 100% concordant signs, we were able to achieve the same or even better performance than SGD.
- (4) Some normalizations/stabilizations are indispensable for such asymmetric BP to work.

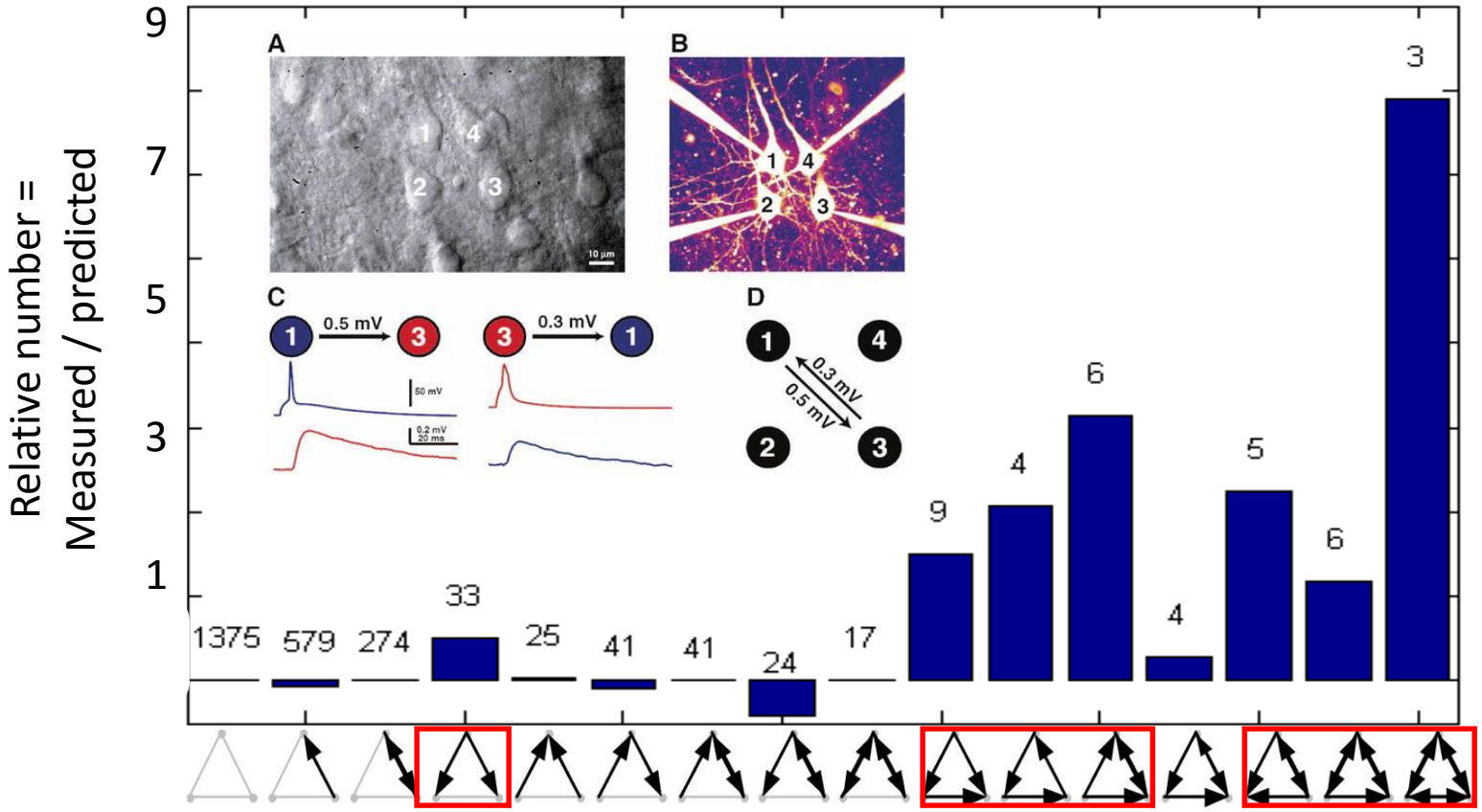
Topic 2 -- Structure of Cortical Microcircuits
Can we constrain model building by quantiative data?





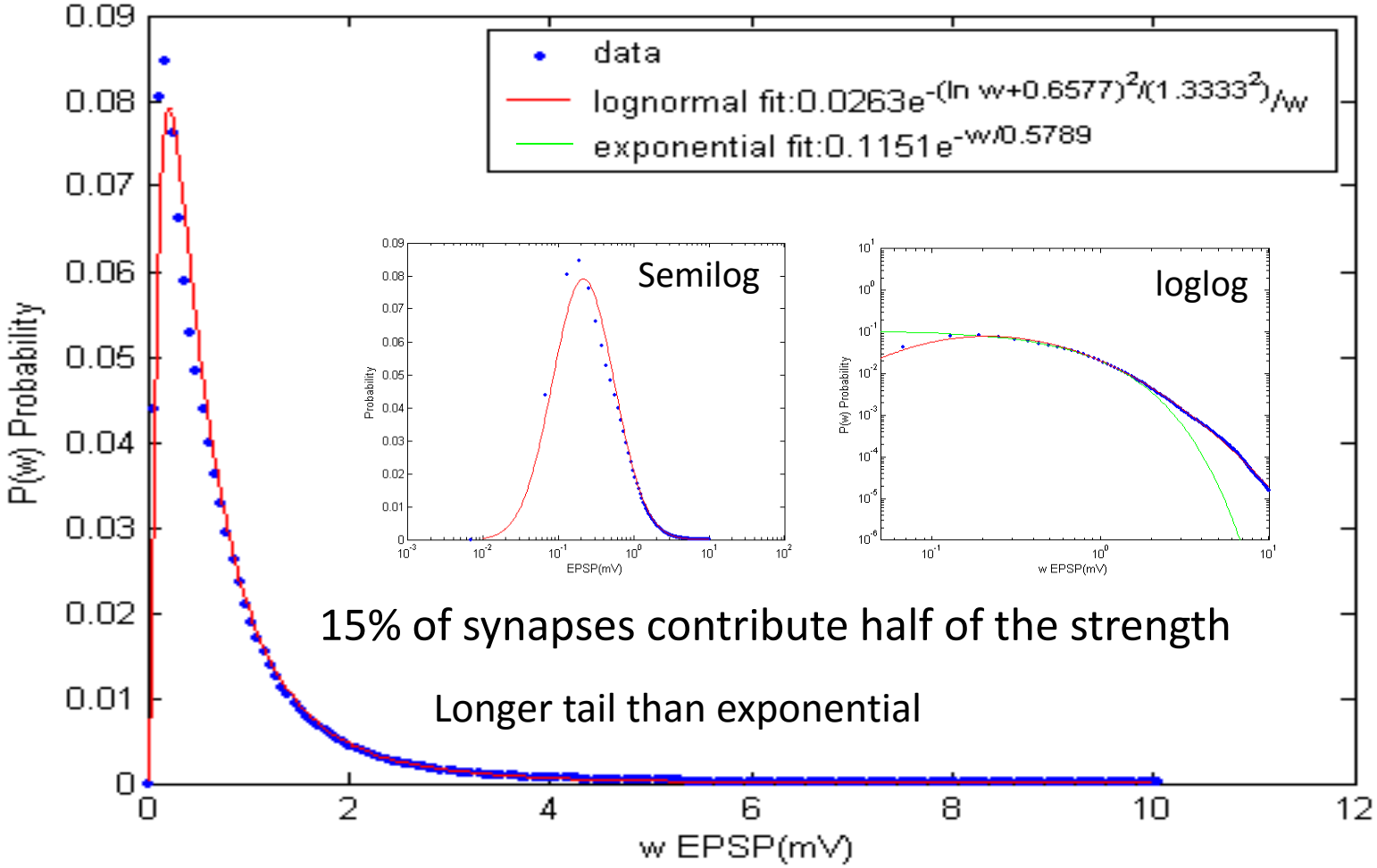
Song S, Sjöström PJ, Reigl S, Nelson S, Chklovskii DB. – PLoS Biology 2005

Three-neuron motifs



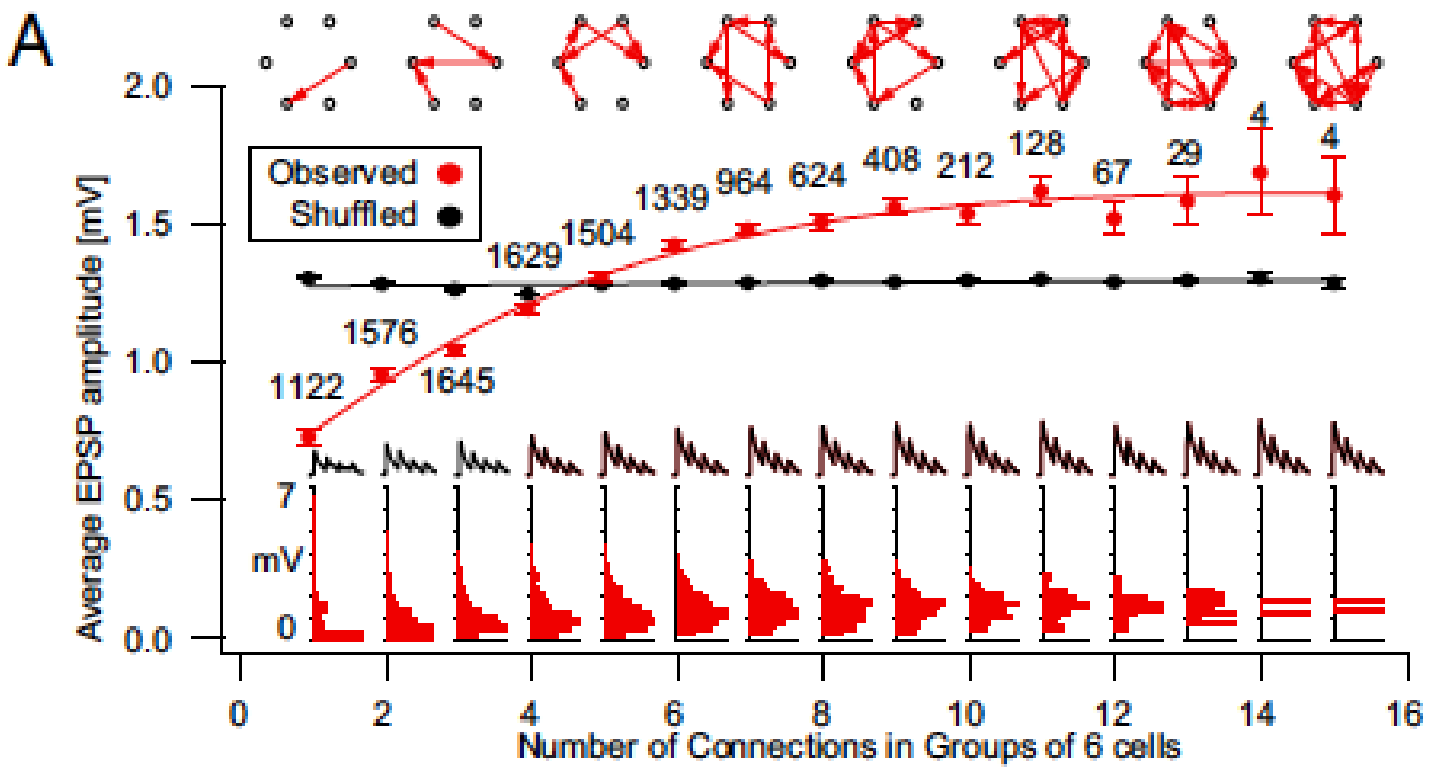
Actual numbers of triplets recorded are shown above the bars

Lognormal Distribution of Connection Strengths



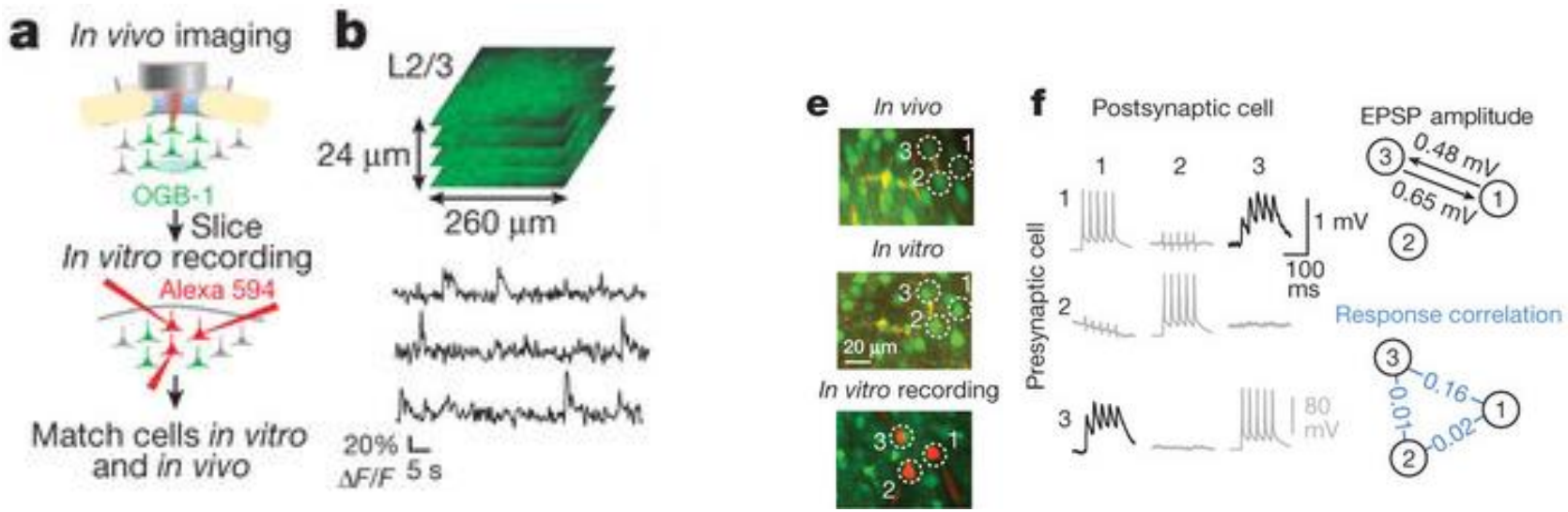
Exponential distribution of mini amplitude noticed before by Bekkers et

Hebbian Assembly



Perin R, Berger TK, and Markram H. – PNAS 2011
Estimated it to be on the order of 50 cells

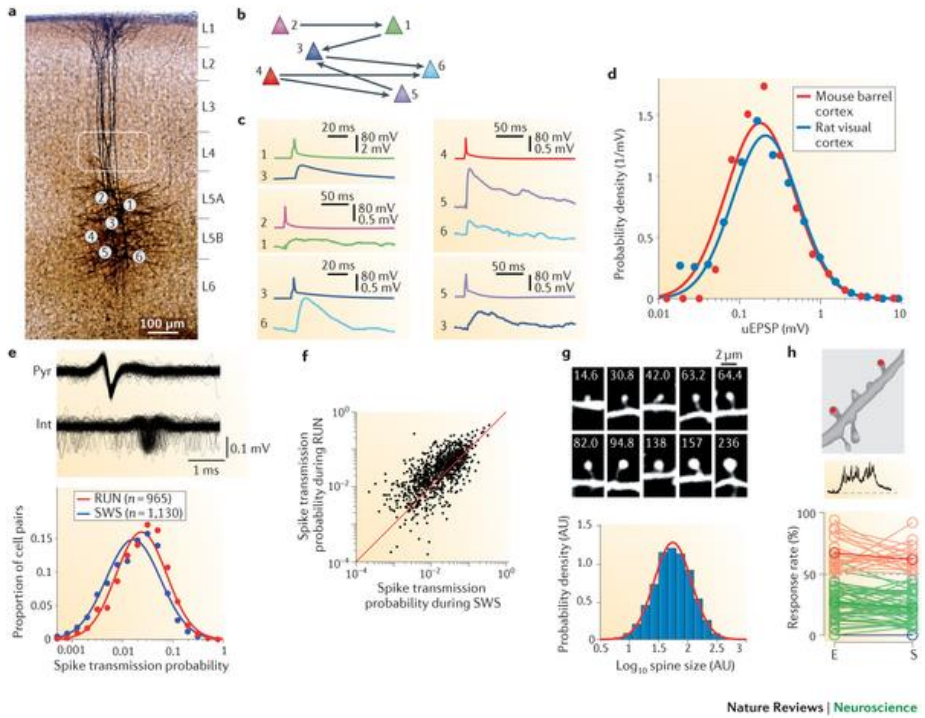
Acquisition and Integration of Functional and Structural Information



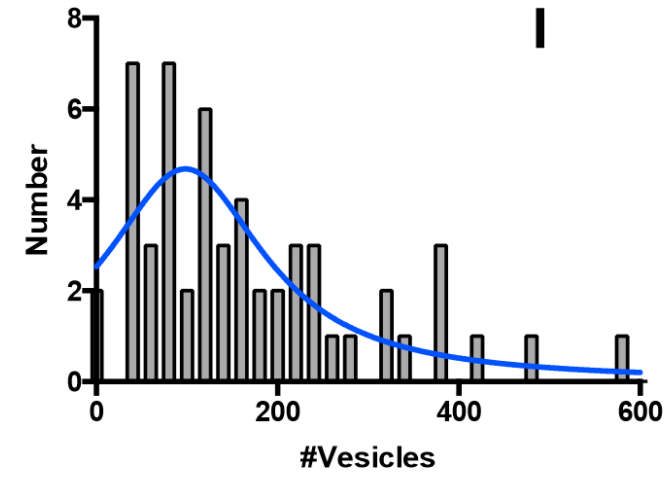
Cells with Similar Receptive Fields are Preferentially Connected

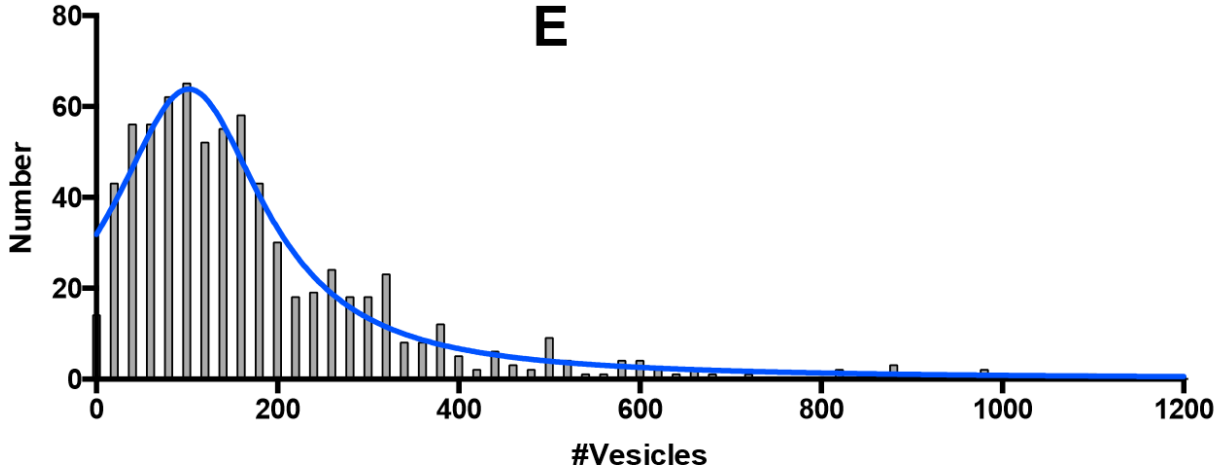
Functional organization of excitatory synaptic strength in primary visual cortex.
Cossel L, Mrsic-Flogel TD. (2015) Nature

Lognormal distribution of synaptic weights and spike transfer probability.



Inhibitory Synapses also have lognormal distribution

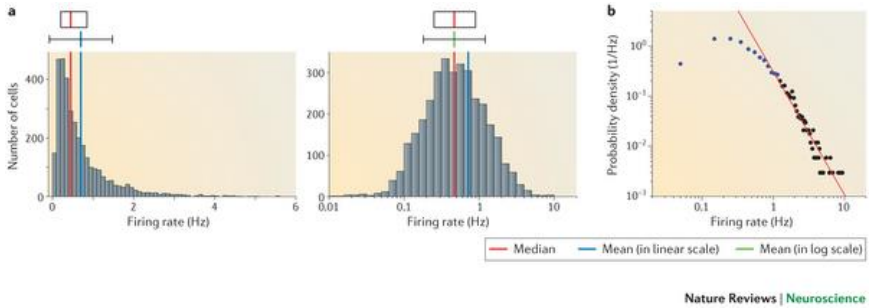


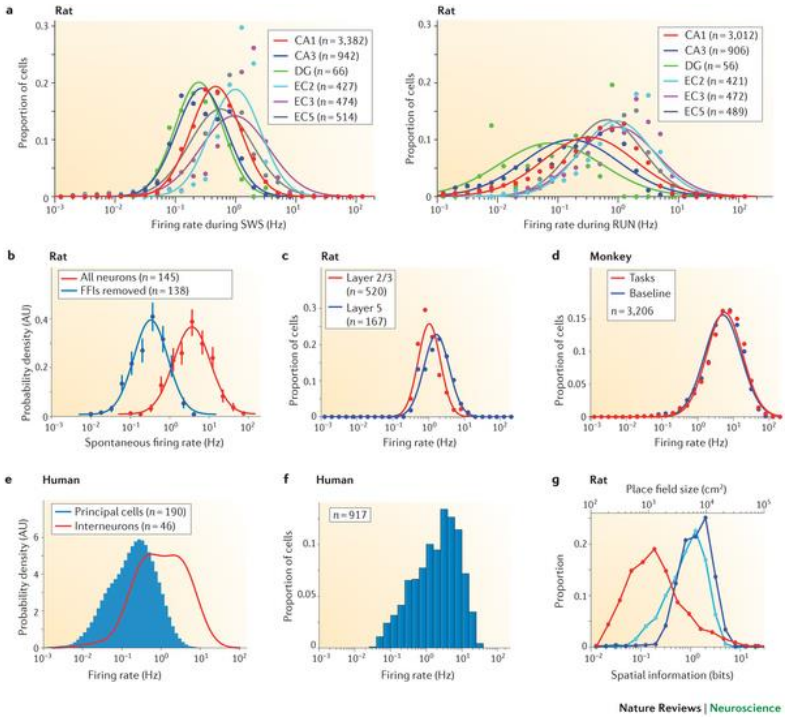


Data from connectomics study published from Jeff Lichtman lab

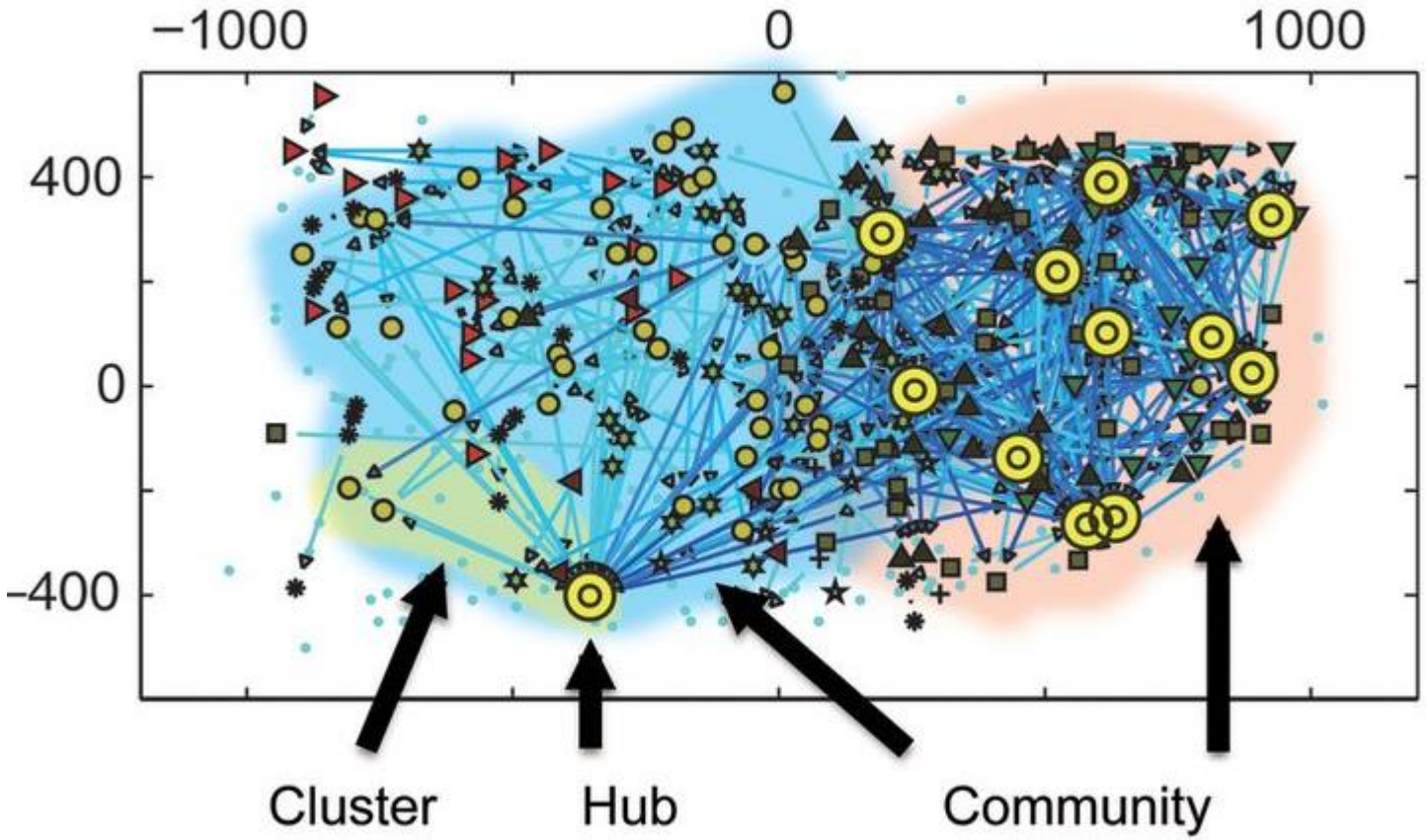
Saturated Reconstruction of a Volume of Neocortex Cell 2015

Lognormal distribution of firing rates in the cortex.

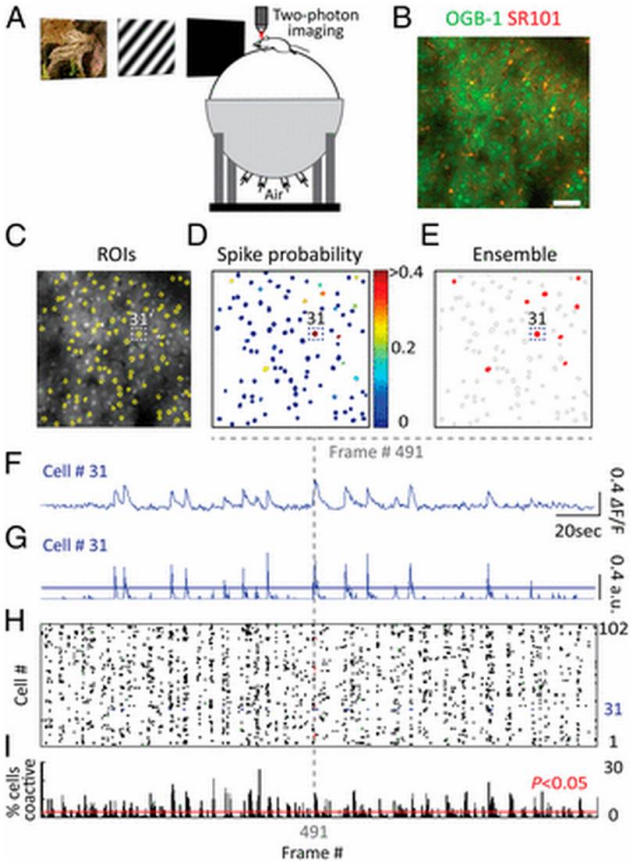




Hubs and Community

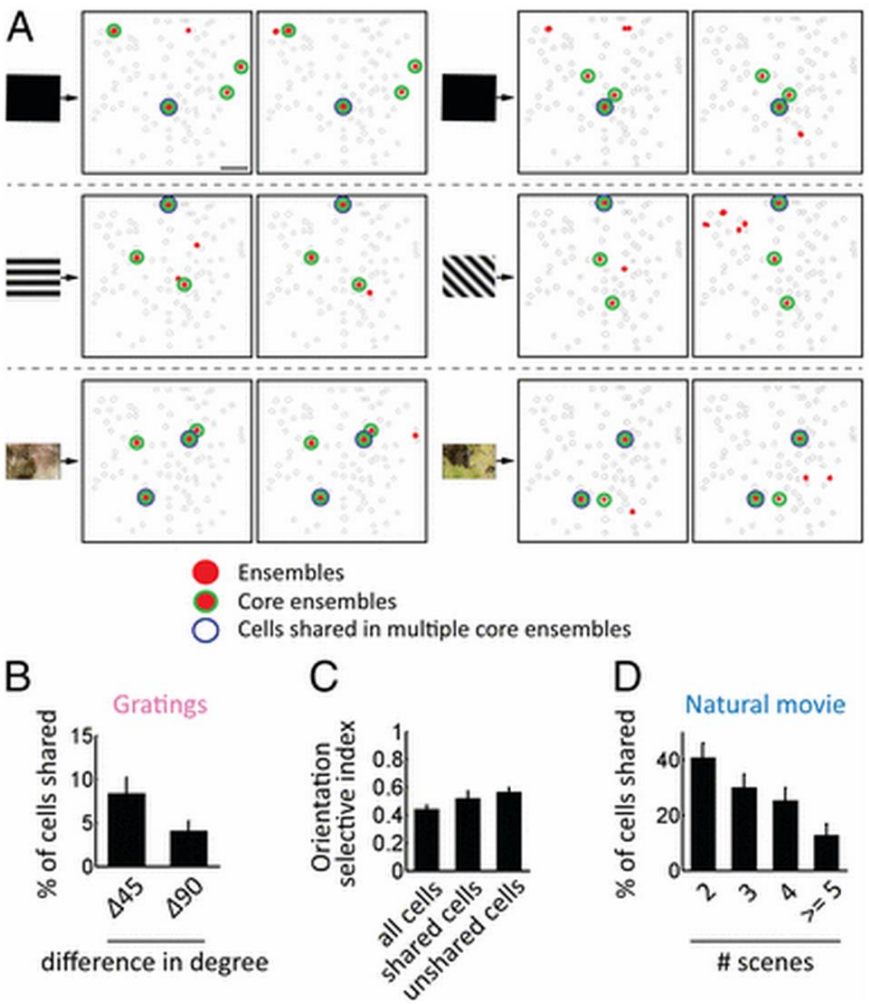


Hub neurons participate in several ensembles?



Visual stimuli recruit intrinsically generated cortical ensembles
Rafael Yuste and colleagues PNAS 2014

Cells participate in multiple assembly

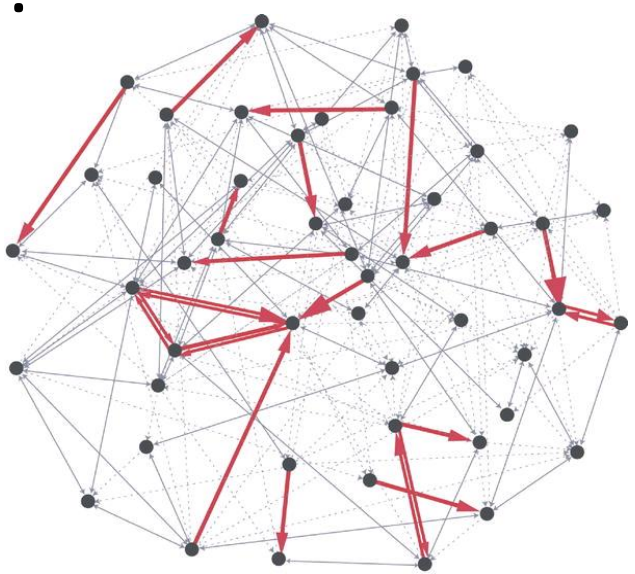


How do those two aspects come together?

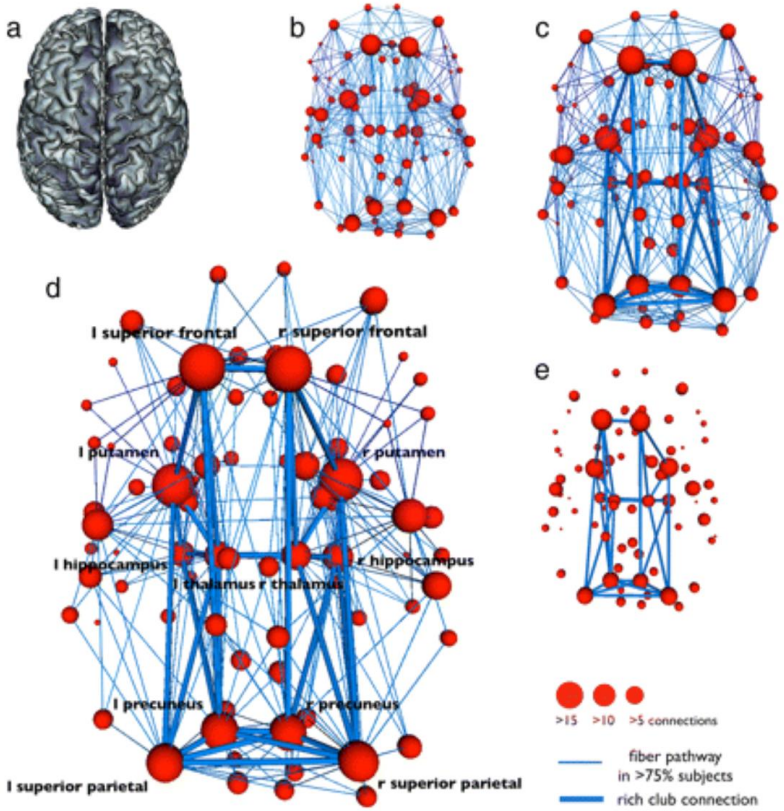
- Stronger connections are few but powerful
- Connections cluster together, especially stronger ones

Skeleton of stronger connections in a sea of weaker ones

How do those two aspects come together?



Rich-Club Organization



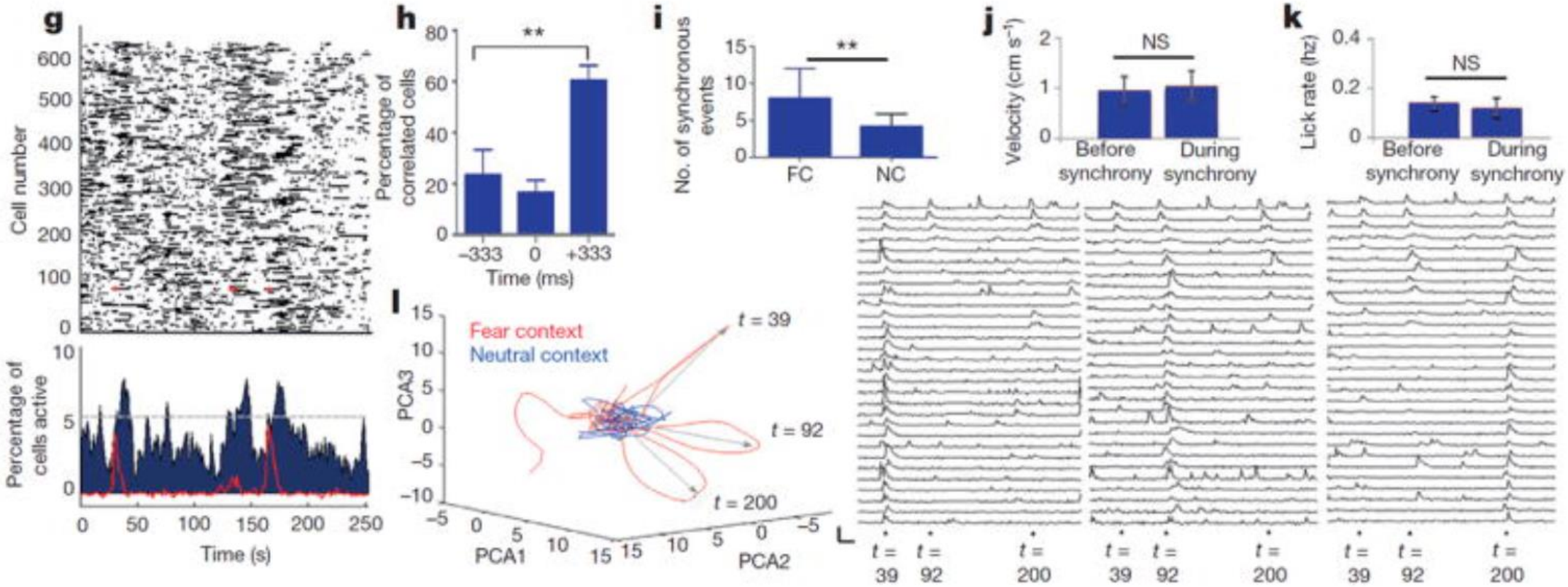
Rich Club in Humans

we define neurons to be rich if their cumulative contribution is 60% of the total outgoing information

Connection strength were calculated with transfer entropy
Neurons with the highest outgoing and incoming information transfer were more strongly connected to each other than chance, thus forming a “rich club.”
The discovery of a small, but information-rich, subset of neurons within cortical regions suggests that this population will play a vital role in communication, learning, and memory.

Rich-Club Organization in Effective Connectivity among Cortical Neurons
John Beggs: Rodent slice culture and in vivo . JNS 2016

Specialized subgroup of cells as pointer?



Projections from neocortex mediate top-down control of memory retrieval.
Nature 2015

Learning drives the emergence of a sparse class of neurons in CA2/CA3 that are highly correlated with the local network and that lead synchronous population activity events;
these neurons are then preferentially recruited by the AC–CA projection during memory retrieval.

Center for Brain-inspired Computation