Other system hierarchy examples: Olfaction, Songbird

Odelia Schwartz

2020

Sensory processing in the *Drosophila* antennal lobe increases reliability and separability of ensemble odor representations

Vikas Bhandawat[1], Shawn R Olsen[1,2], Nathan W Gouwens[1,2], Michelle L Schlief[1,2] & Rachel I Wilson[1]

A step toward optimal coding in olfaction

L F Abbott & Sean X Luo

Receptor neurons may not encode sensory information in an efficient manner. A new paper supports the idea that the brain achieves optimal encoding downstream of sensory transduction through additional processing.

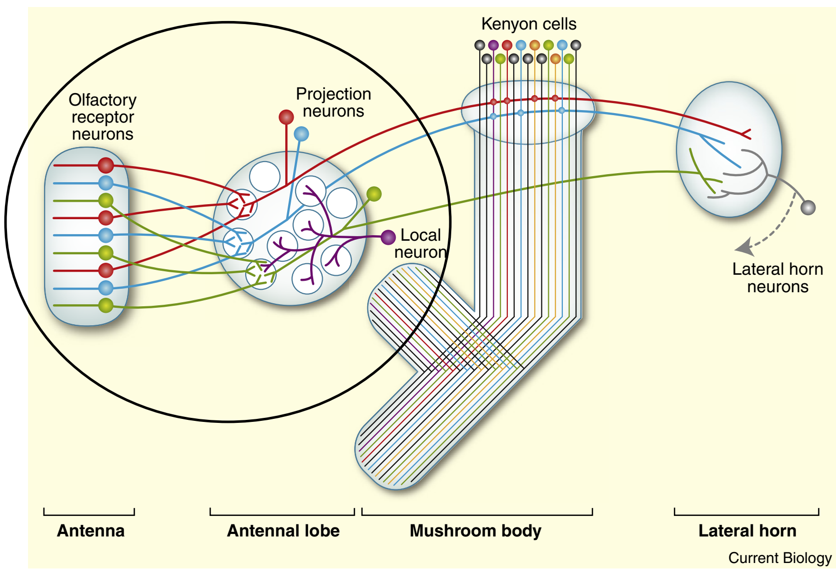
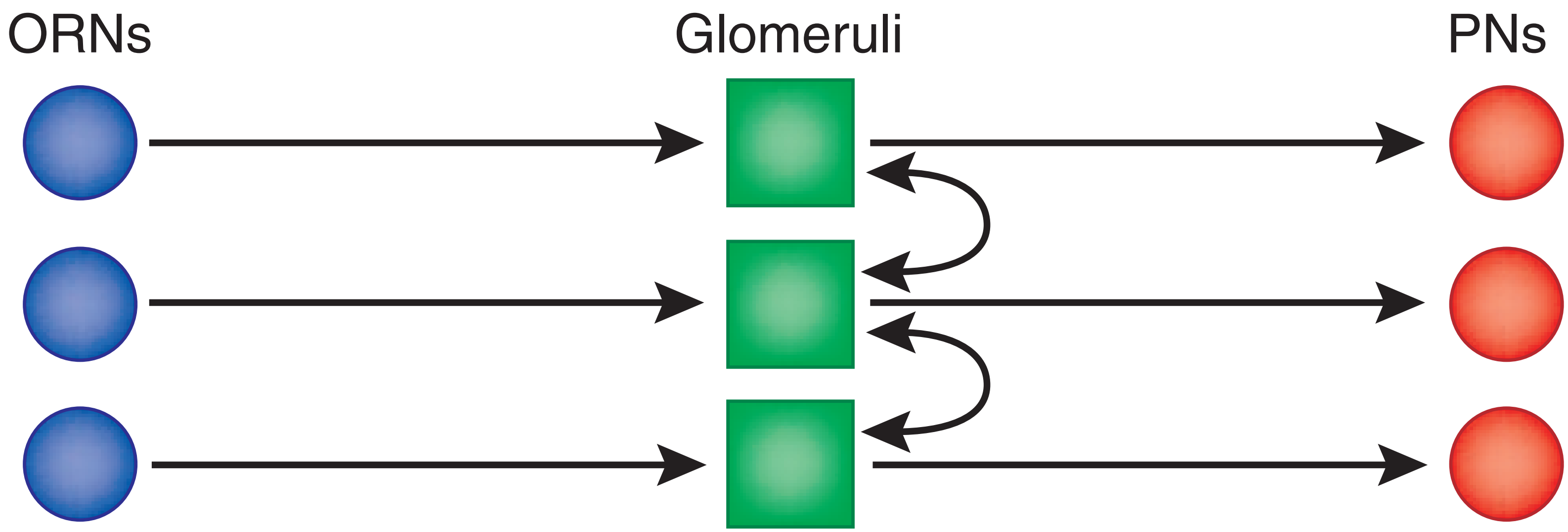


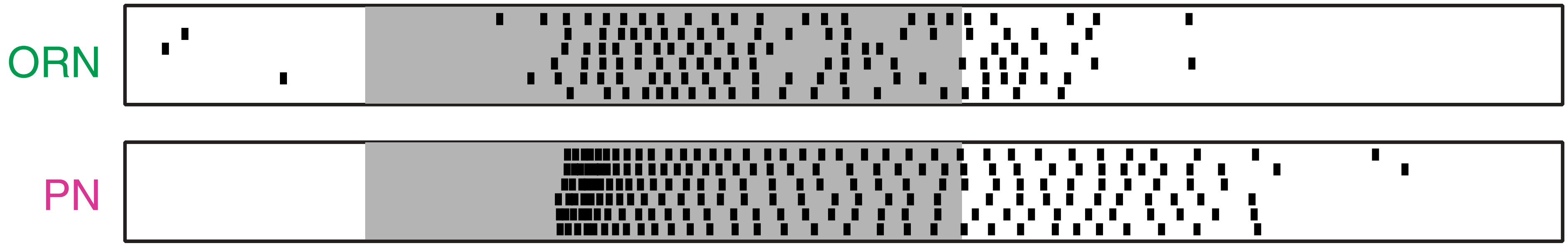
Figure 1. Summary of olfactory anatomy.

Schematic representation of the olfactory system of *Drosophila*. Olfactory receptor neurons in the antennae and maxillary palps send axons to specific glomeruli in the antennal lobe. All olfactory receptor neurons expressing the same odorant receptor complement (same colour) converge at the same glomerulus. There they form synaptic contacts with projection neurons and local neurons. Projection neurons send axons either directly to the lateral horn neuropile (green projection neuron) or indirectly via the calyx of the mushroom bodies (red and blue projection neurons), where they form synapses with Kenyon cells.

Current Biology, 2009

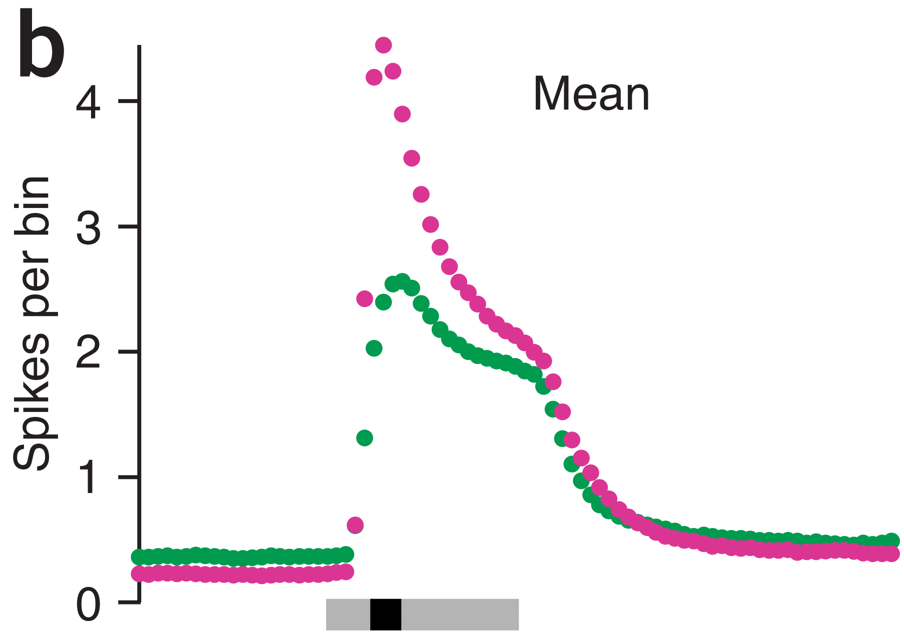

ORNs
Glomeruli
PNs

ORN -> PN



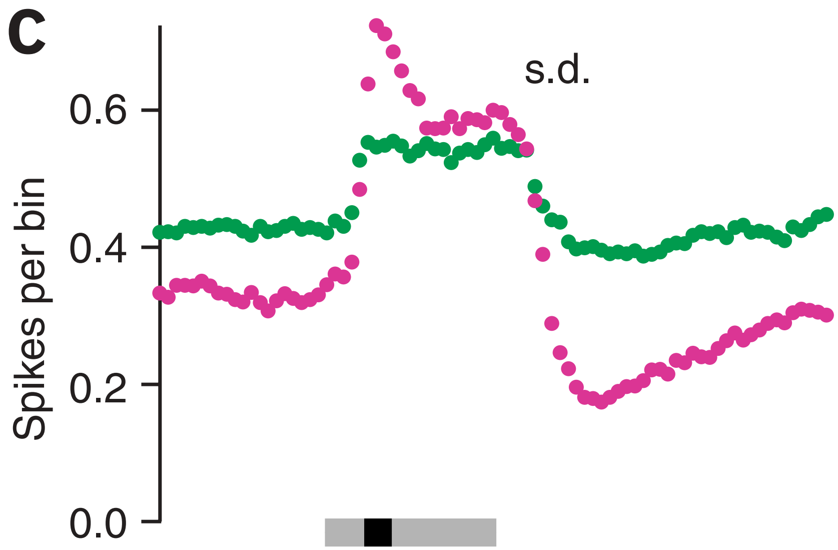
PNs more reliable than ORNs:
Each row repeated trials

ORN -> PN



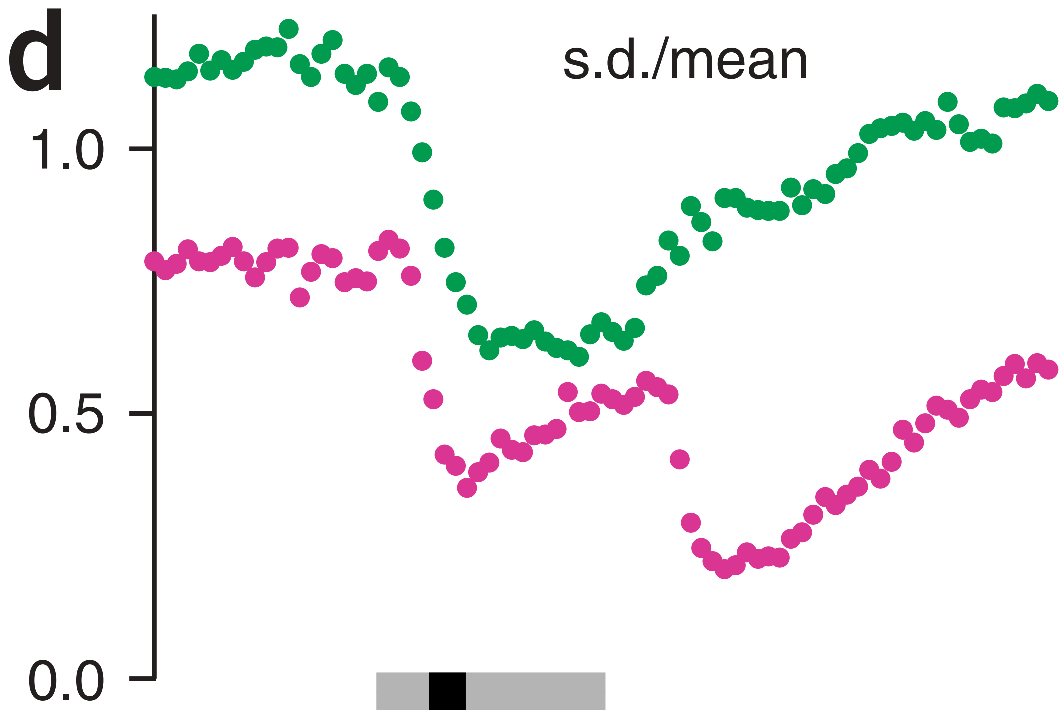
Firing rate PNs on average higher

ORN -> PN



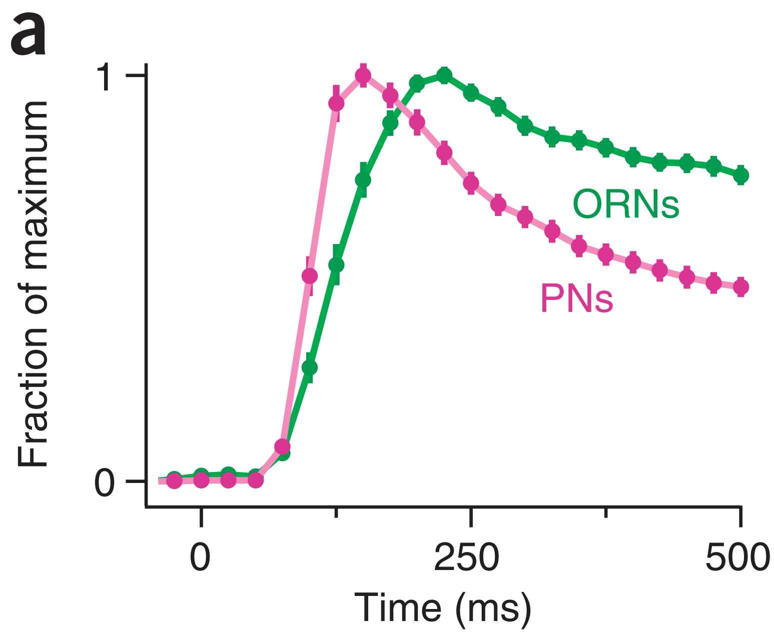
STD of PNs slightly greater than ORN
(spikes counted in 50 msec bin)

ORN -> PN



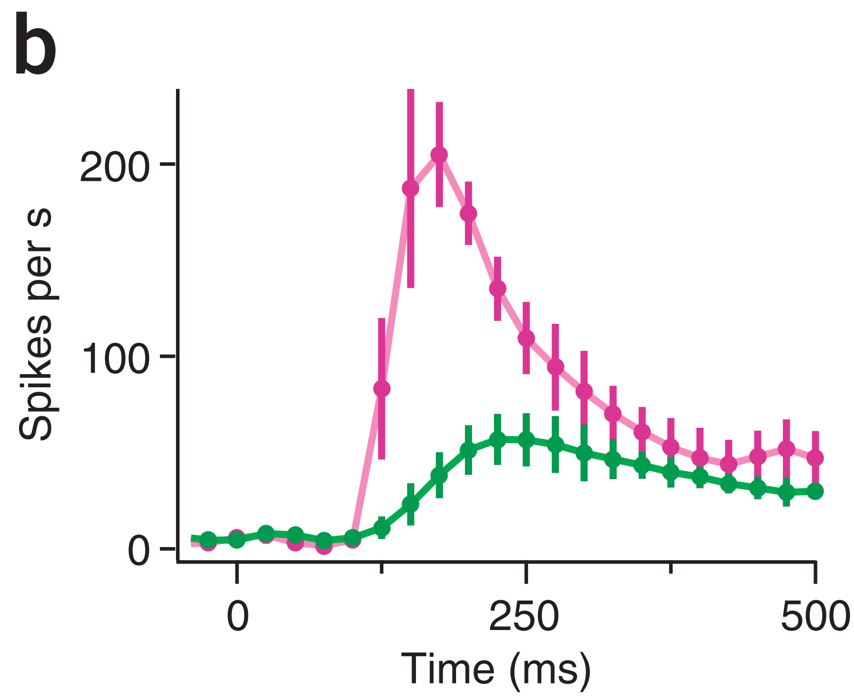
Overall PNs responses less variable (more reliable)

ORN -> PN



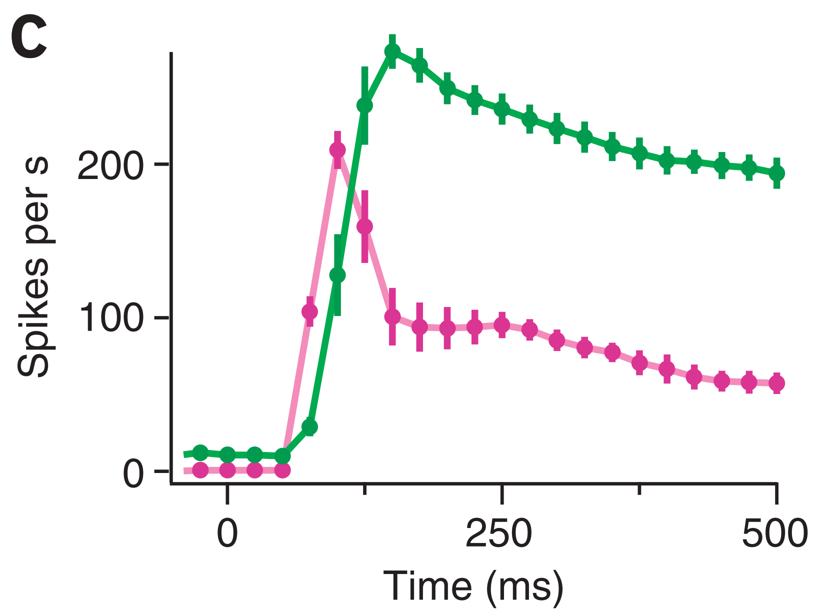
PNs rise more rapidly than ORNs
(averaged across all odors)

ORN -> PN



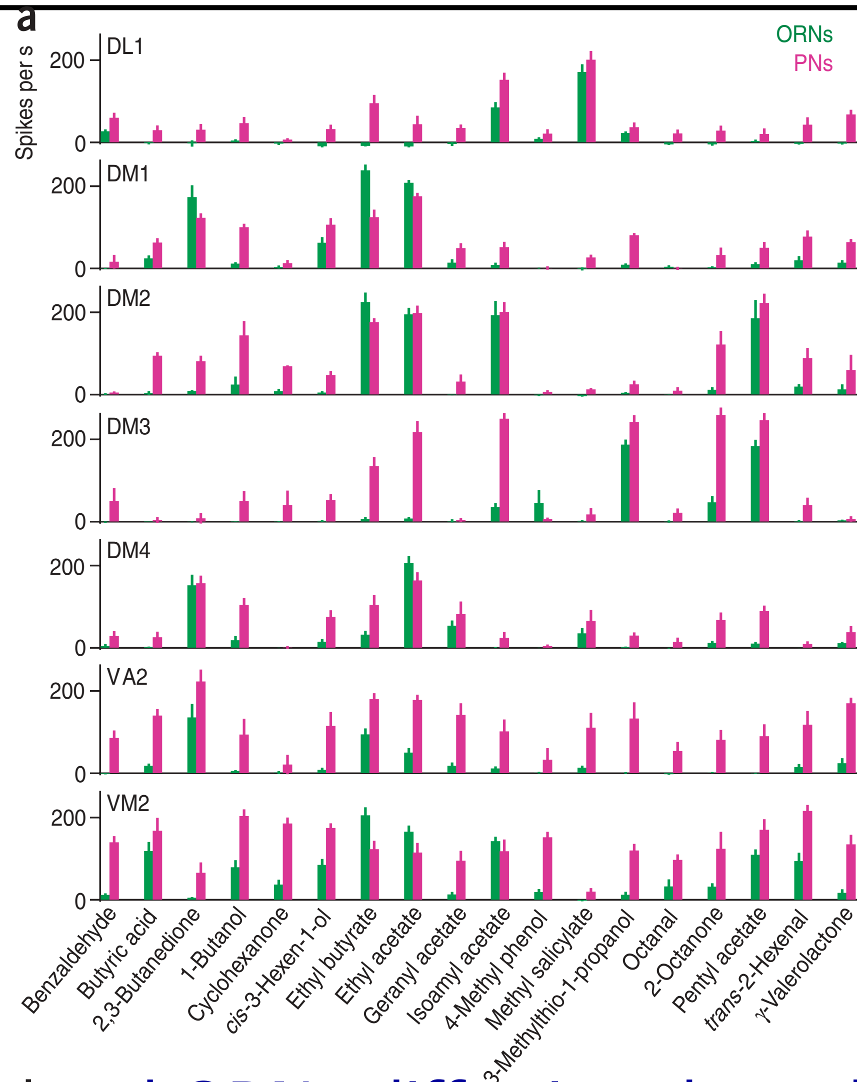
PNs rise more rapidly than ORNs (same odor)

ORN -> PN



"

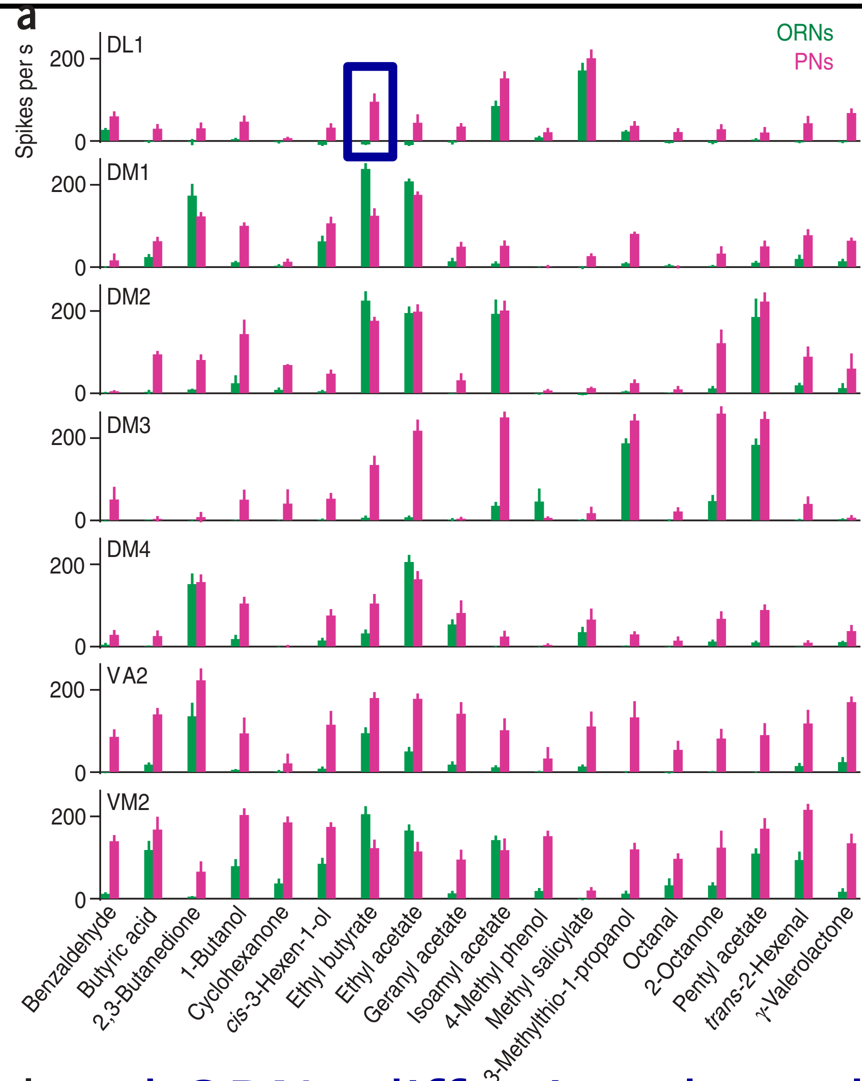
PNs rise more rapidly than ORNs
(another example same odor)



ORN -> PN

PNs and ORNs differ in odor selectivity

(ethyl butyrate is the 3rd-ranked odor of DL1 PNs,
16th among the odor responses of DL1 ORNs)



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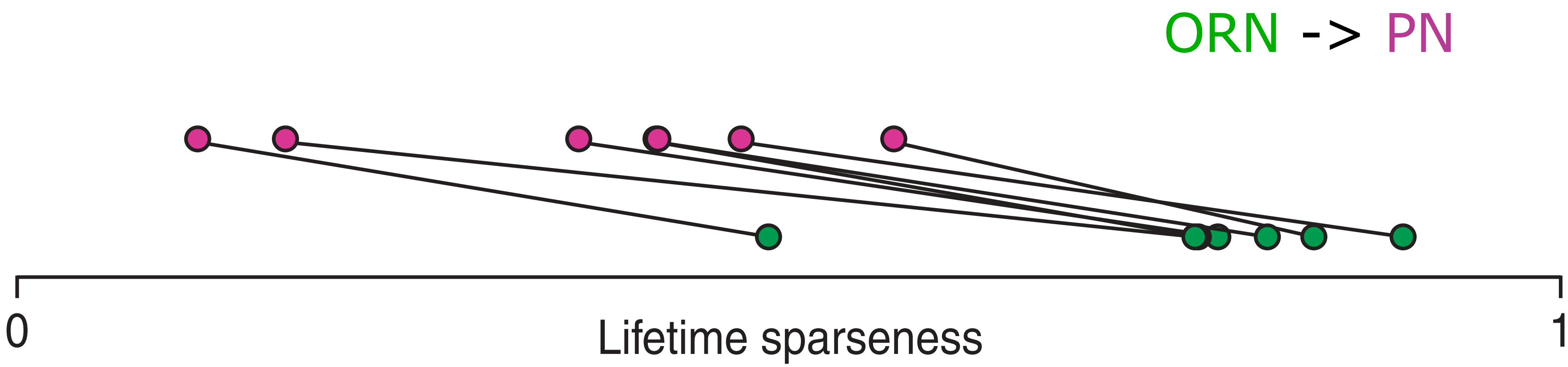
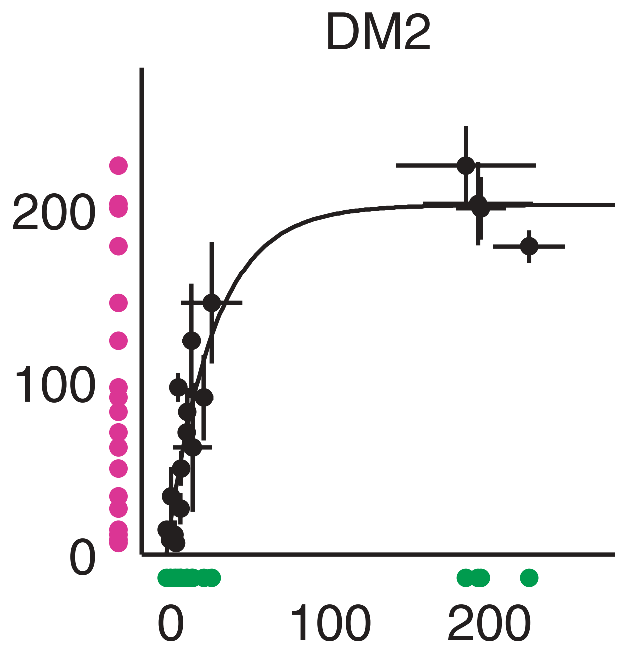


PNs less selective than ORNs

0 nonselective, 1 maximally selective

Same glomeruli connected

ORN -> PN



Nonlinear transformation ORN to PNs

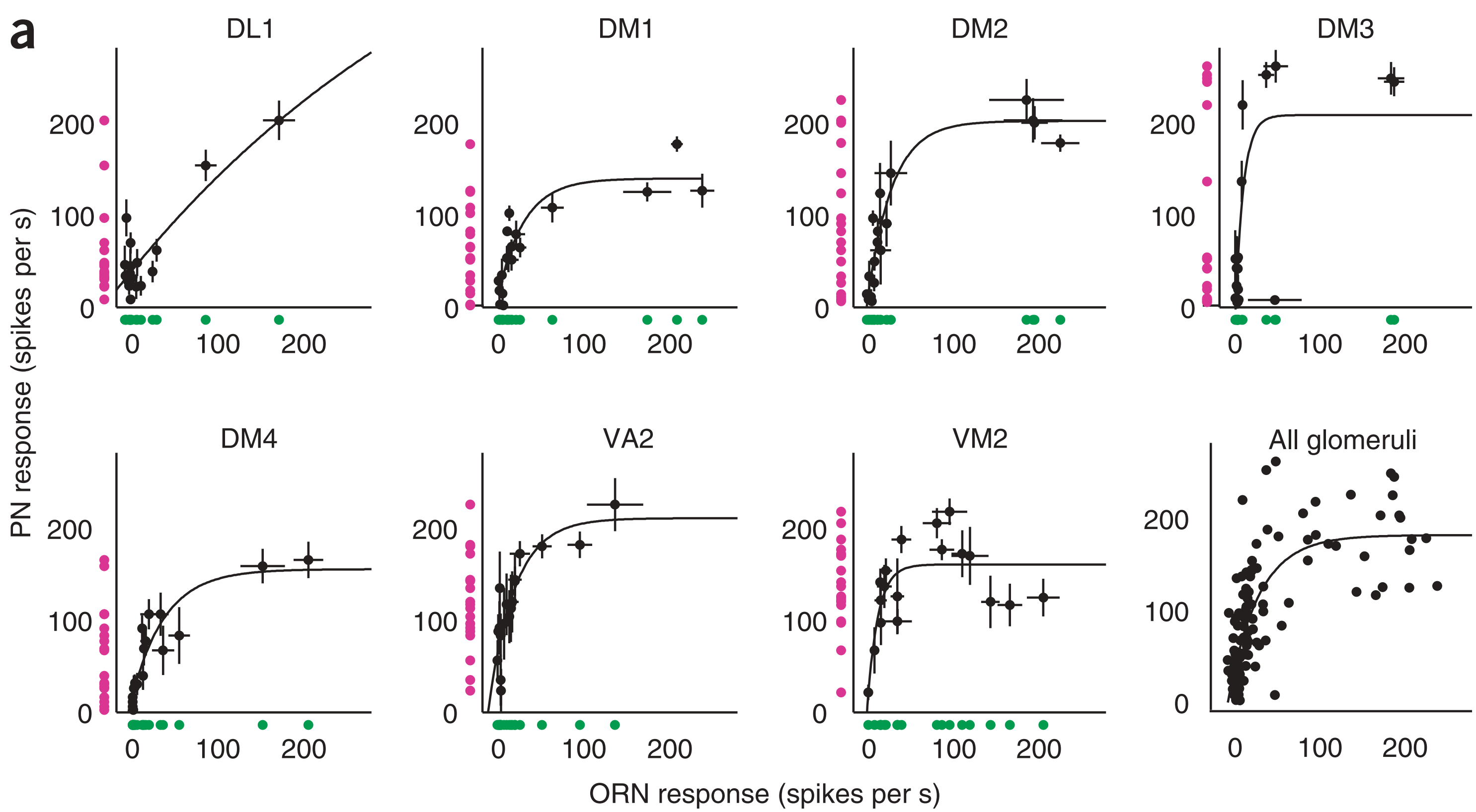
(average response to PN versus ORN for same odor

Curves exponential fits

Green and magenta projection of data onto axes:

Makes use of all available response range)

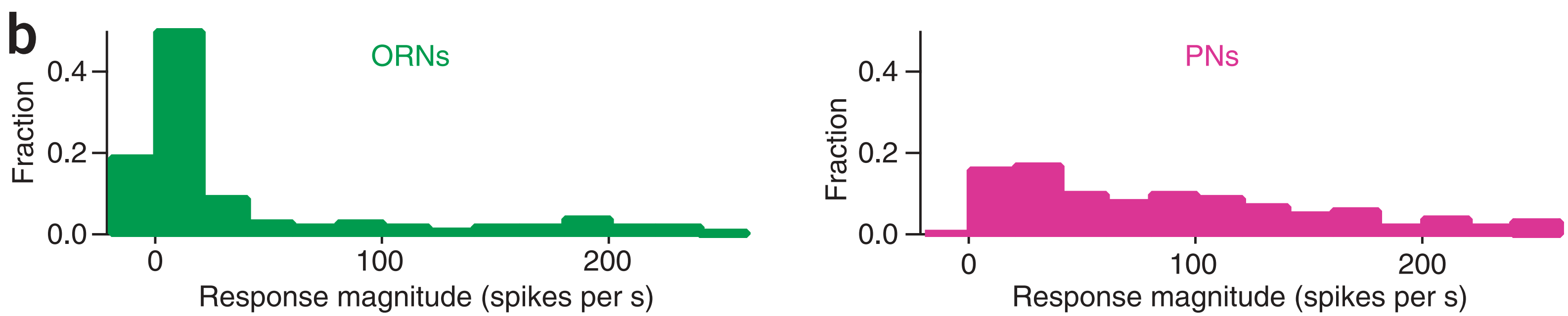
ORN -> PN



Nonlinear transformation ORN to PNs

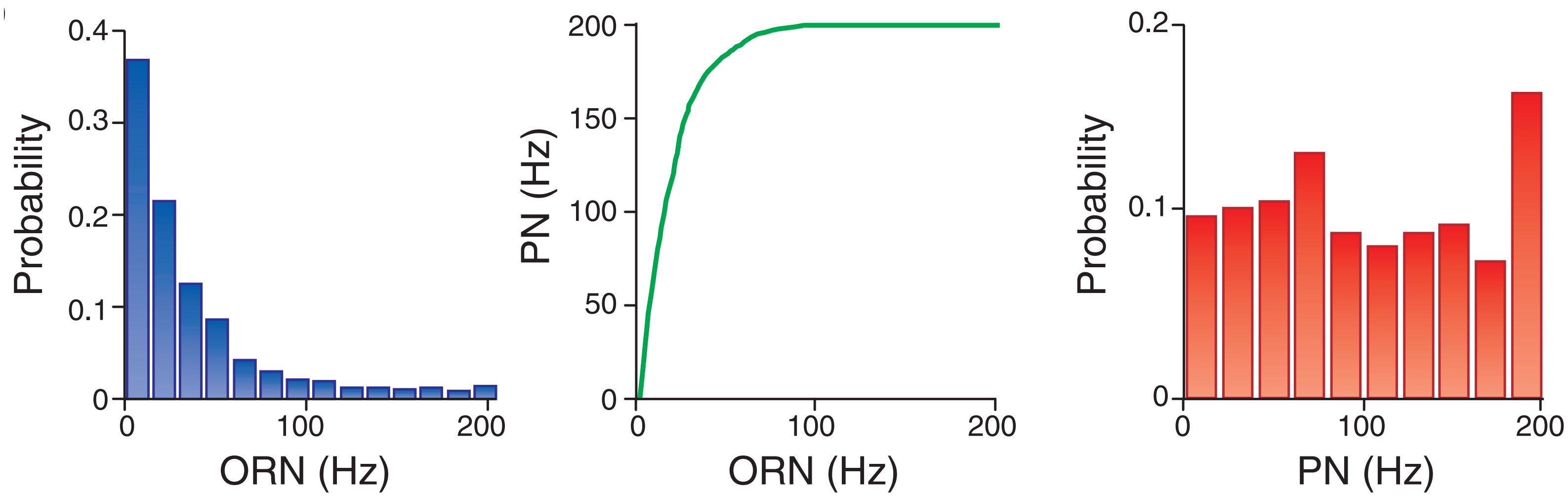
(different glomeruli and all glomeruli)

ORN -> PN

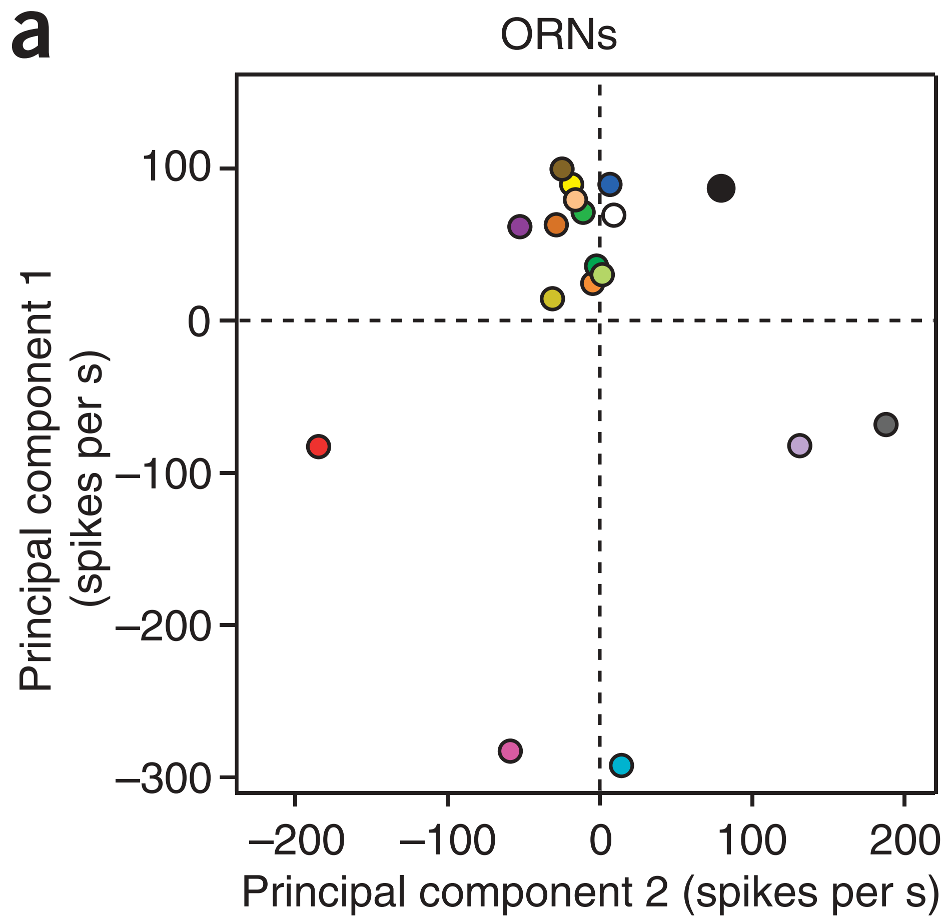


Nonlinear transformation ORN to PNs

(Makes use of all available response range; histogram Equalization
Histogram across 7 glomeruli, 18 odors = 126 points of collected response magnitude)



Abbott News and Views

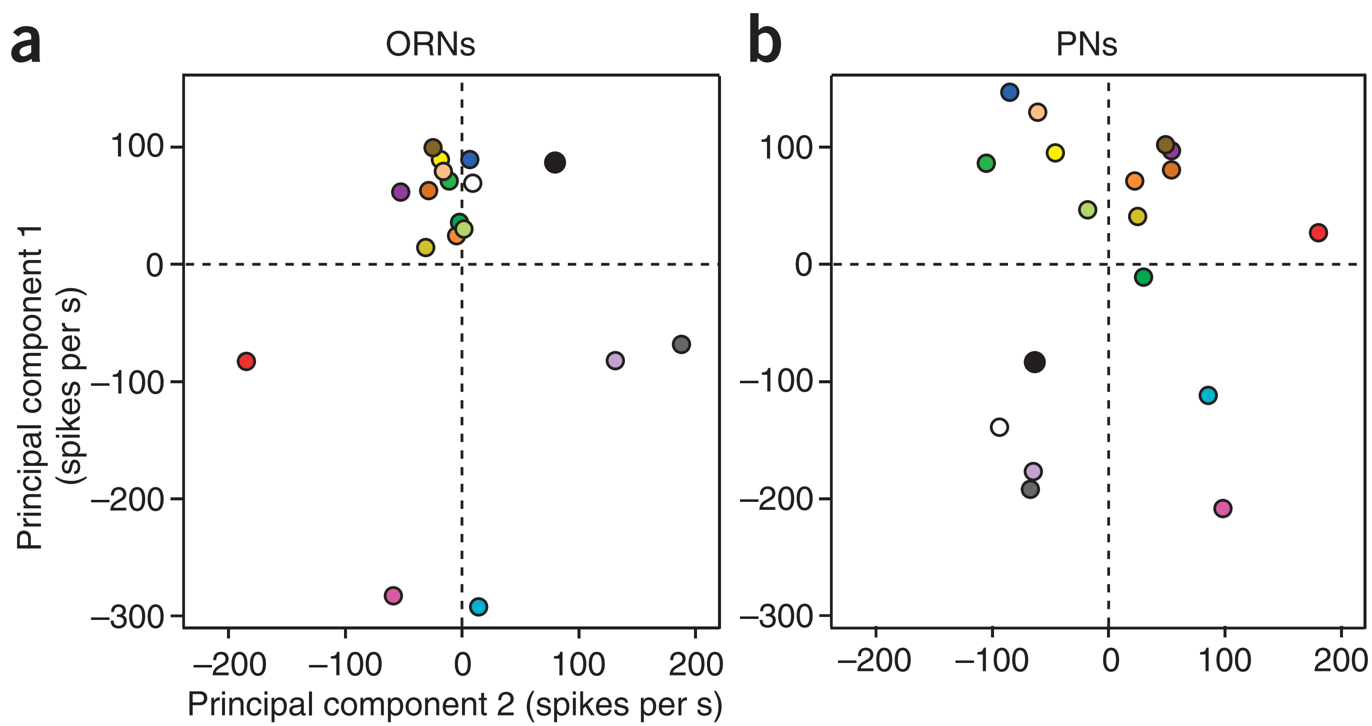


ORN -> PN

Odors non uniform in ensemble ORN coding space

(each point average odor response projected onto first two principal components)

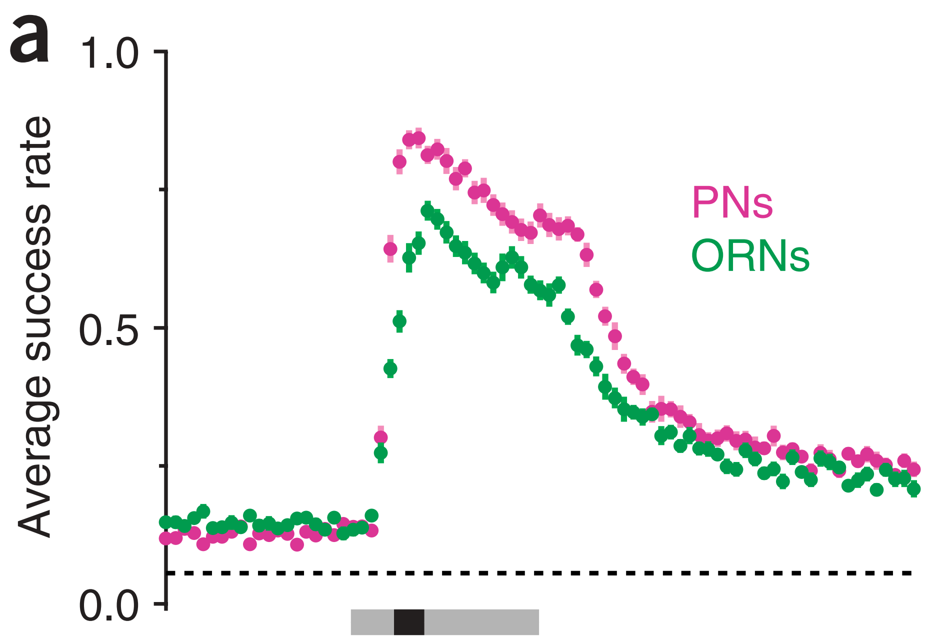
ORN -> PN



Odors are distributed more uniformly in ensemble PN coding space than in ensemble ORN coding space

(each point average odor response projected onto first two principal components)

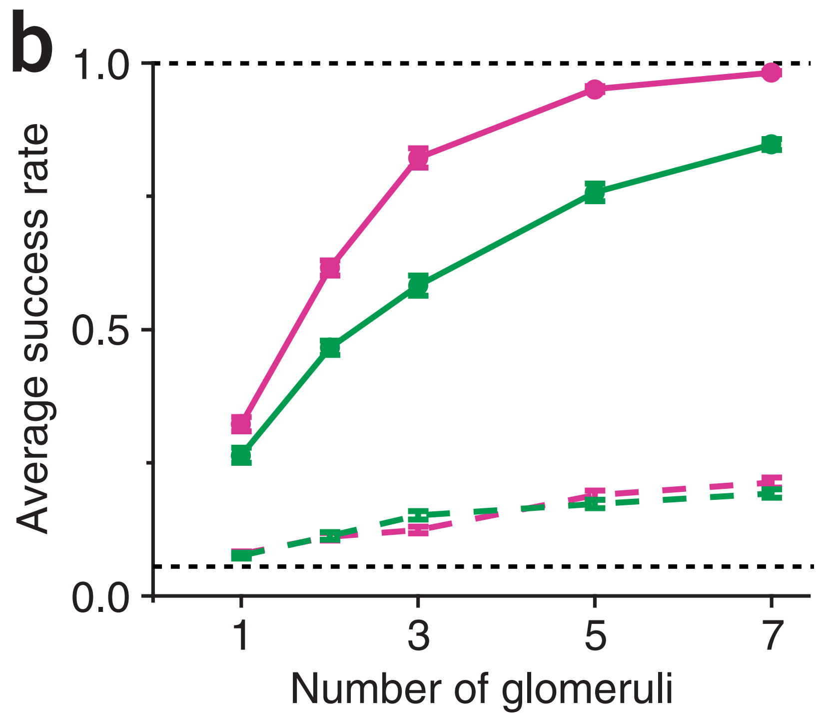
Linear discriminator (3 Glomeruli)



ORN -> PN

PN responses more linearly separable than ORN
(success rate classifying odor; total 18 odors)

Linear discriminator



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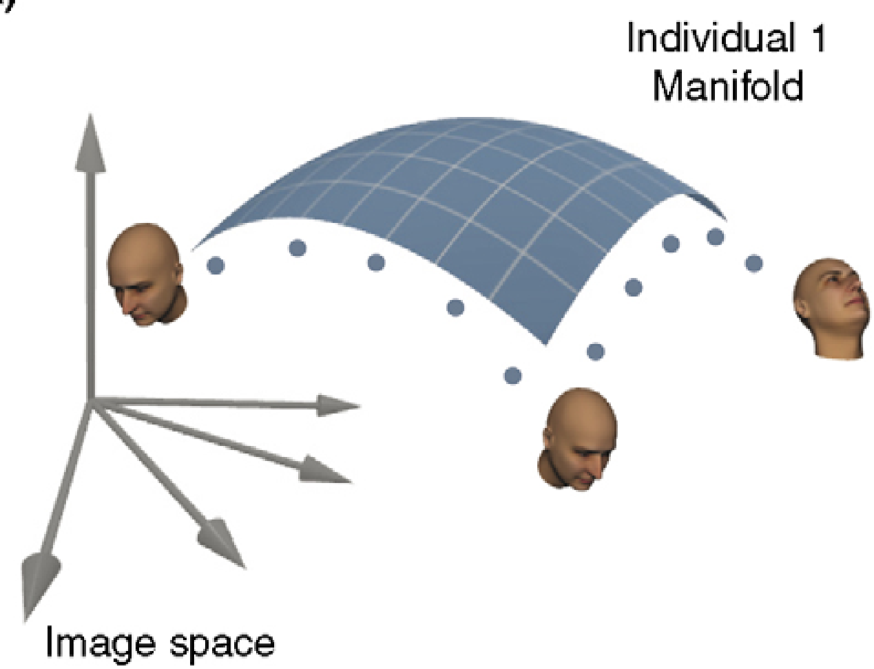
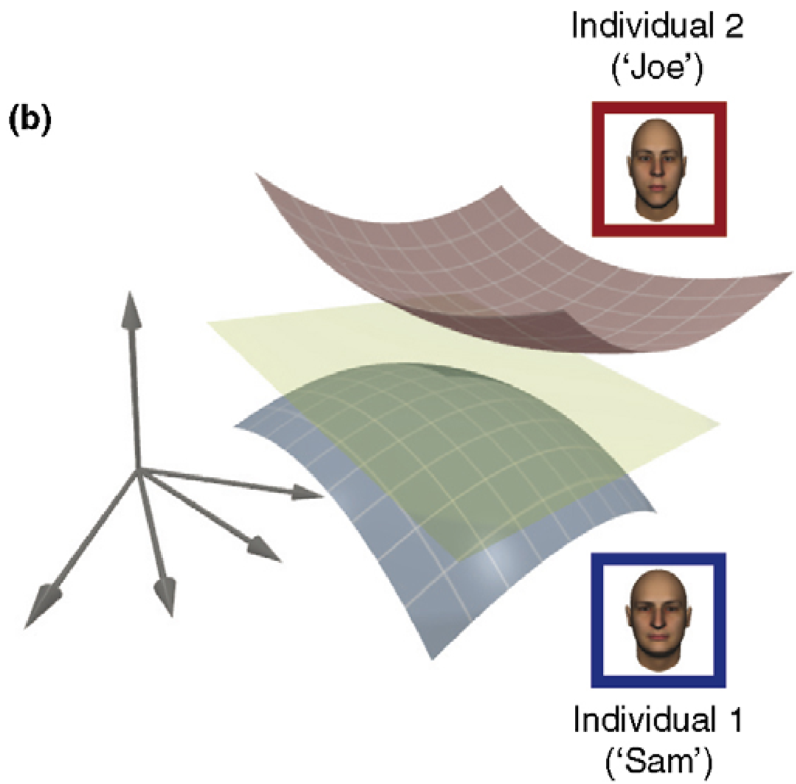
Rust and Di Carlo, Trends Cog Sci 2007

(a)



Rust and Di Carlo, Trends Cog Sci 2007



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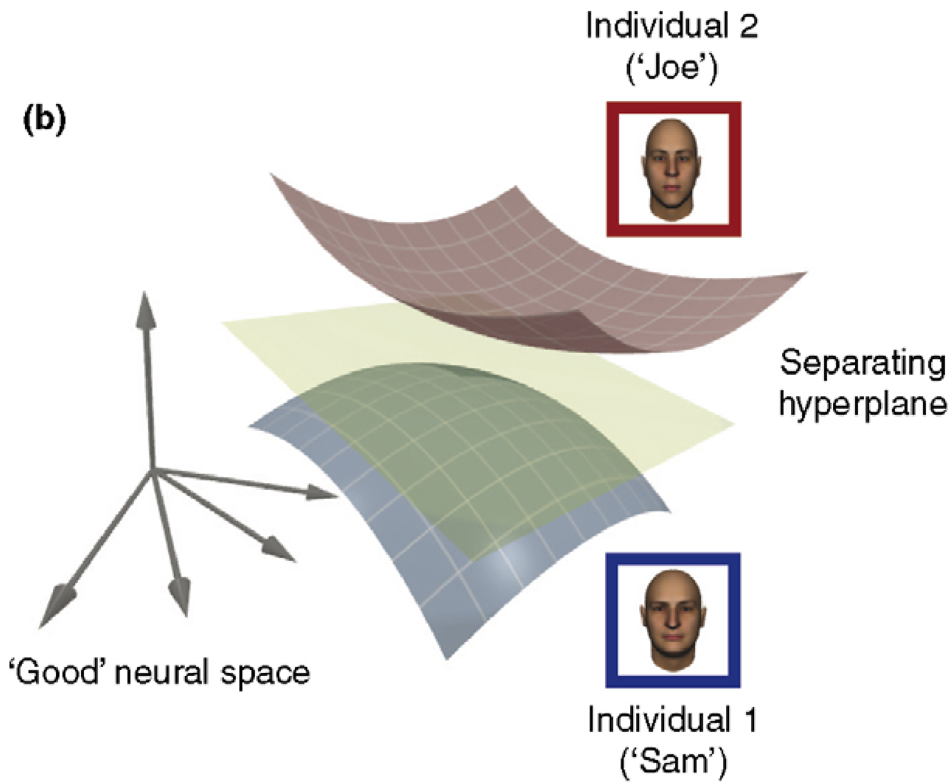

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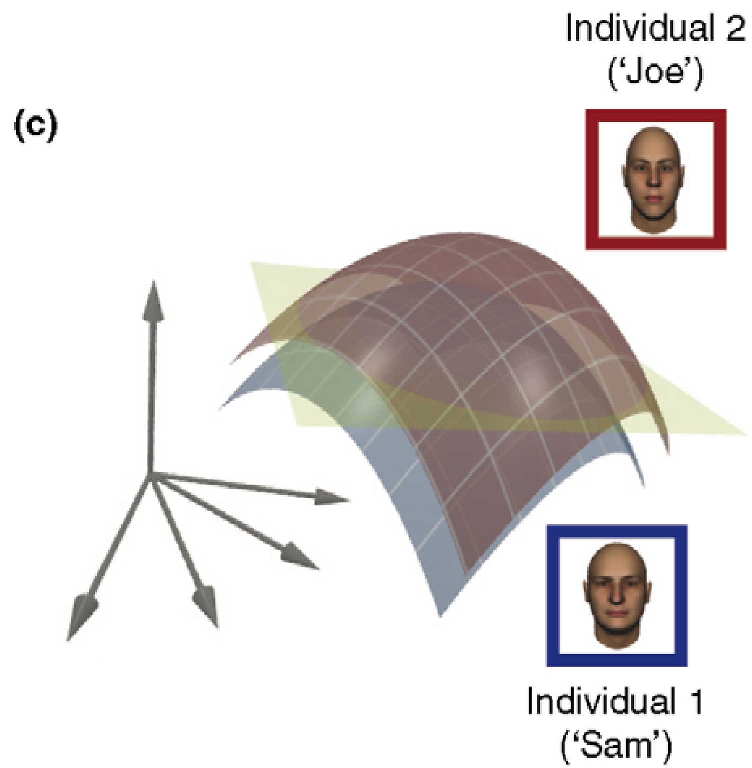
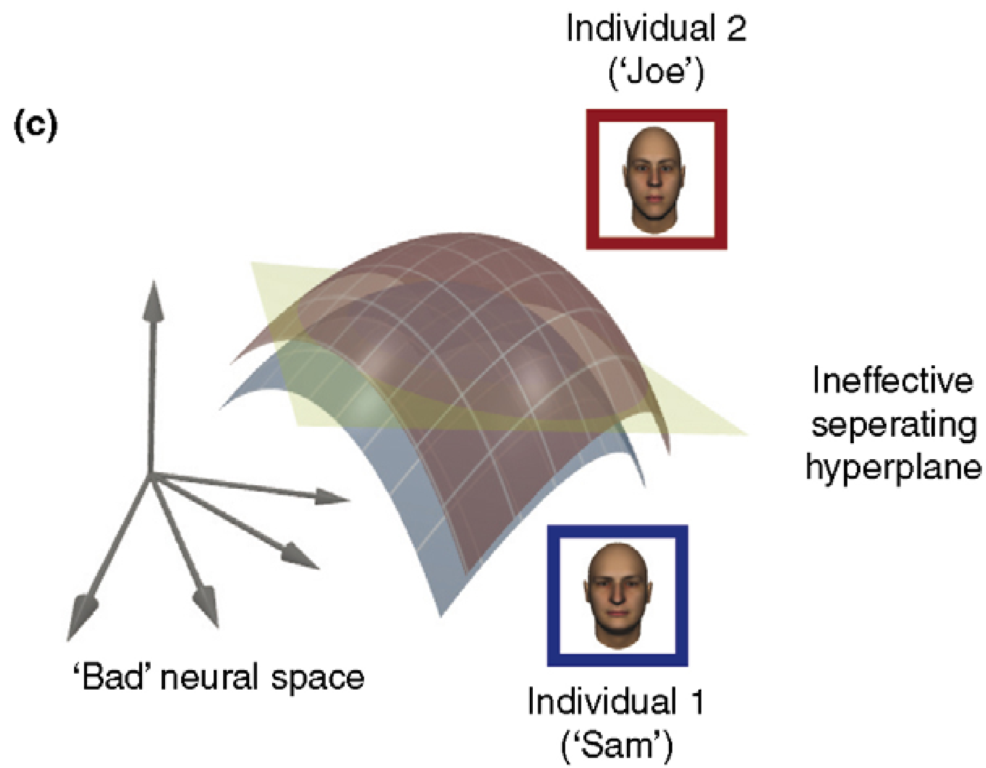
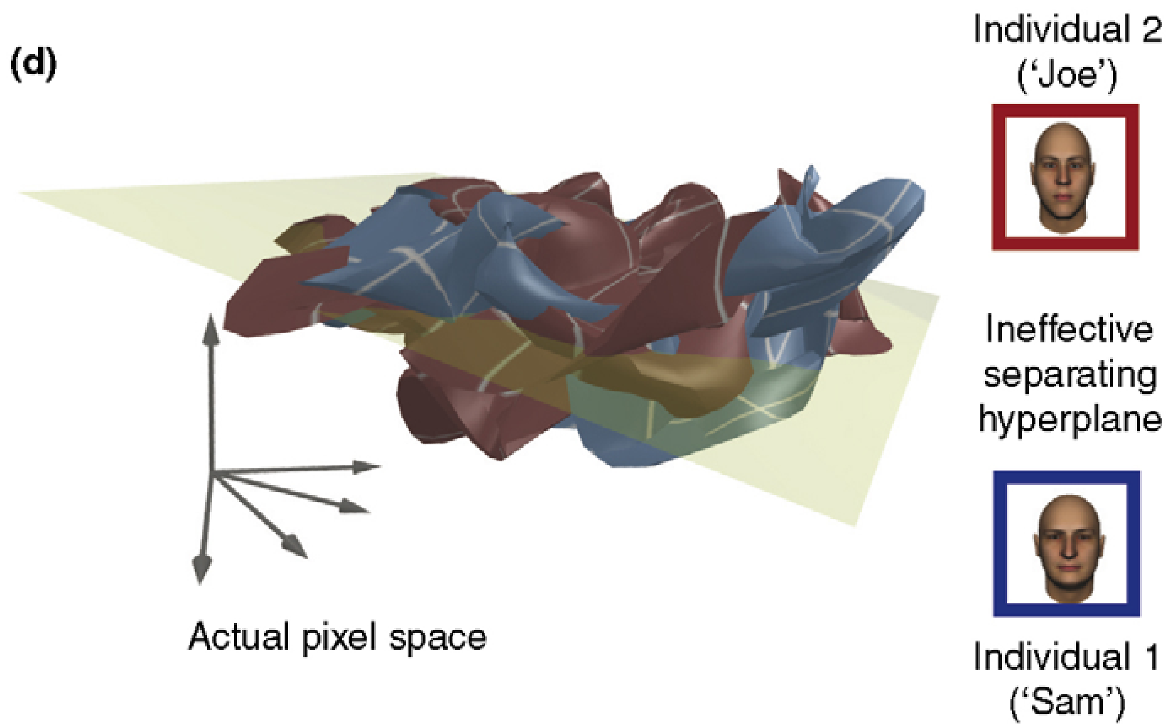


Rust and Di Carlo, Trends Cog Sci 2007



Rust and Di Carlo, Trends Cog Sci 2007



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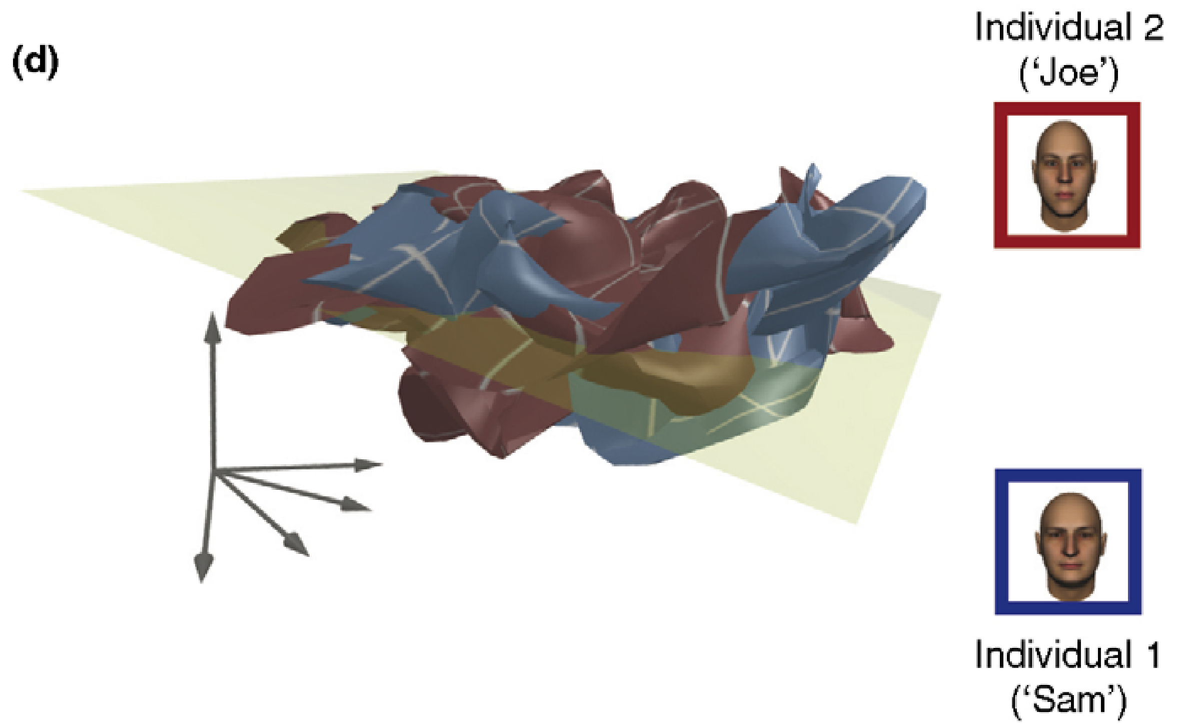

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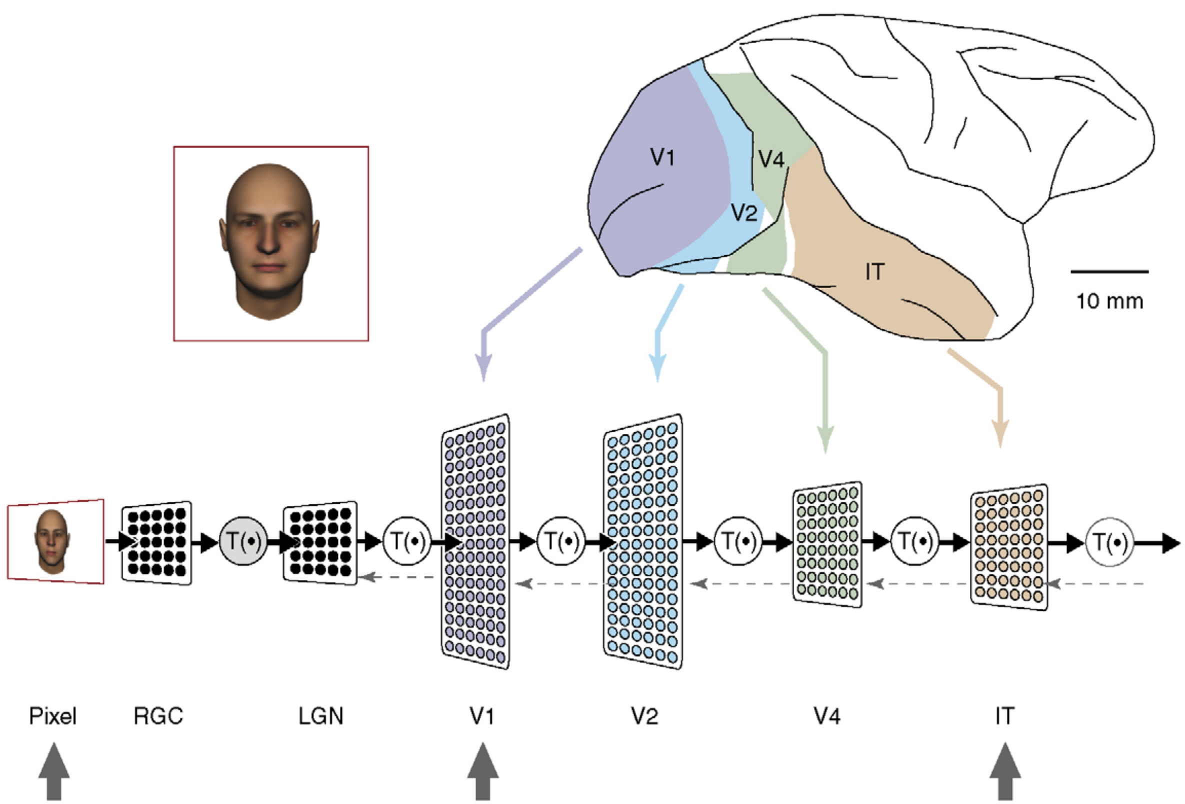

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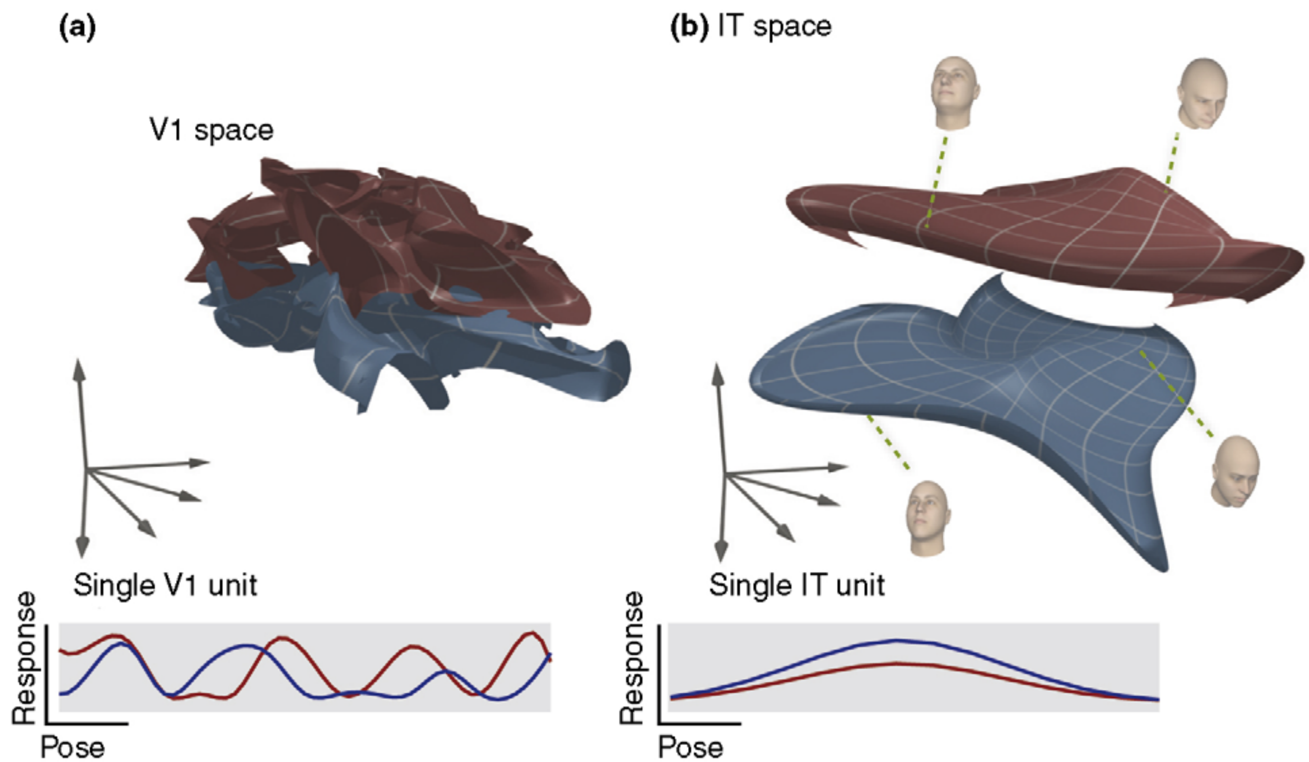
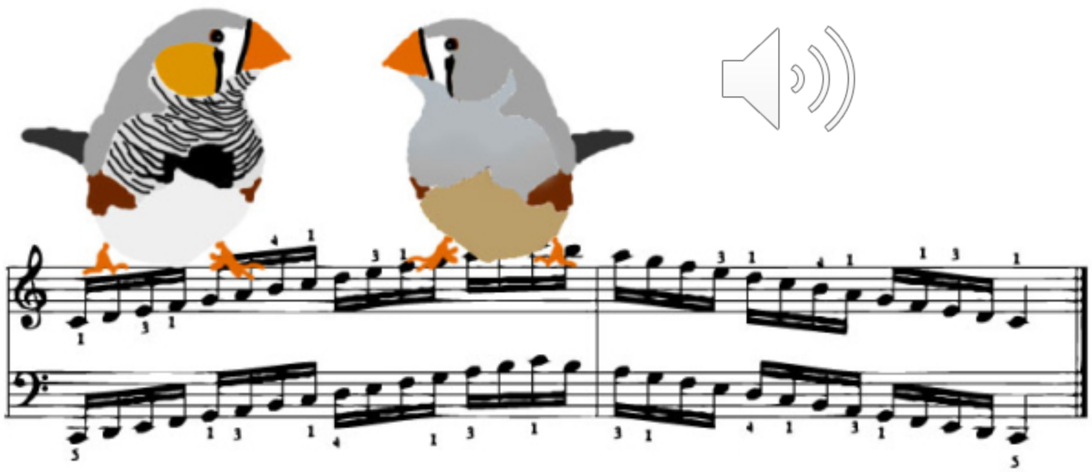


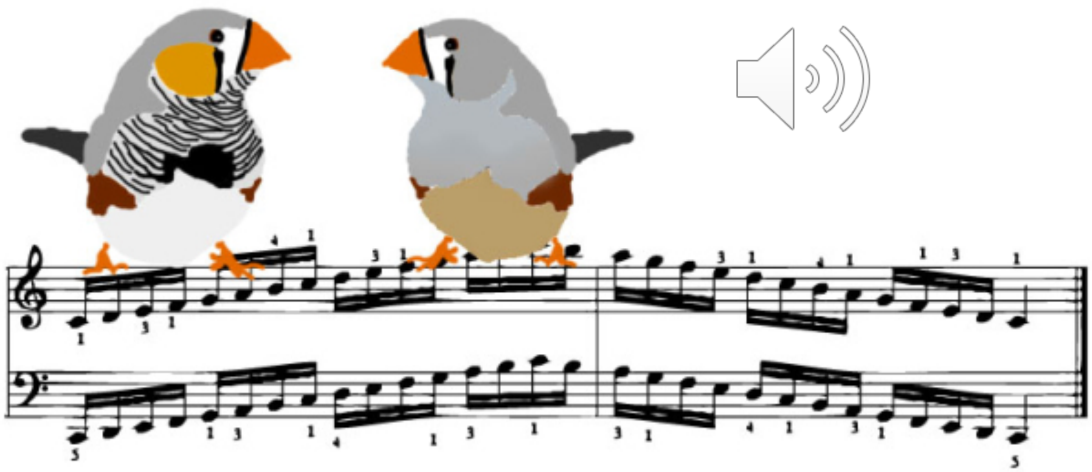
Another example
system and coding, plus hierarchy

Ultra Sparse Song Bird System

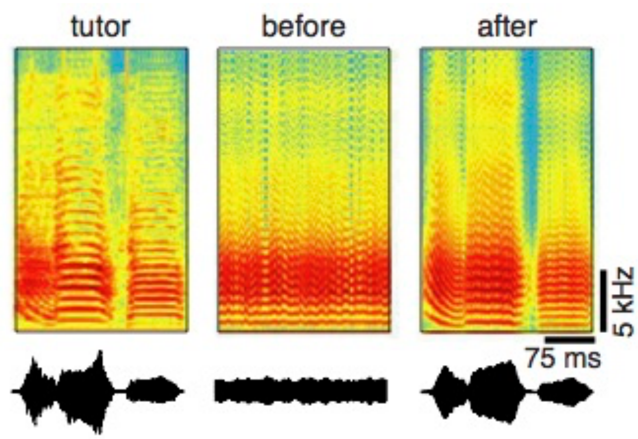
Song before learning



Song after learning



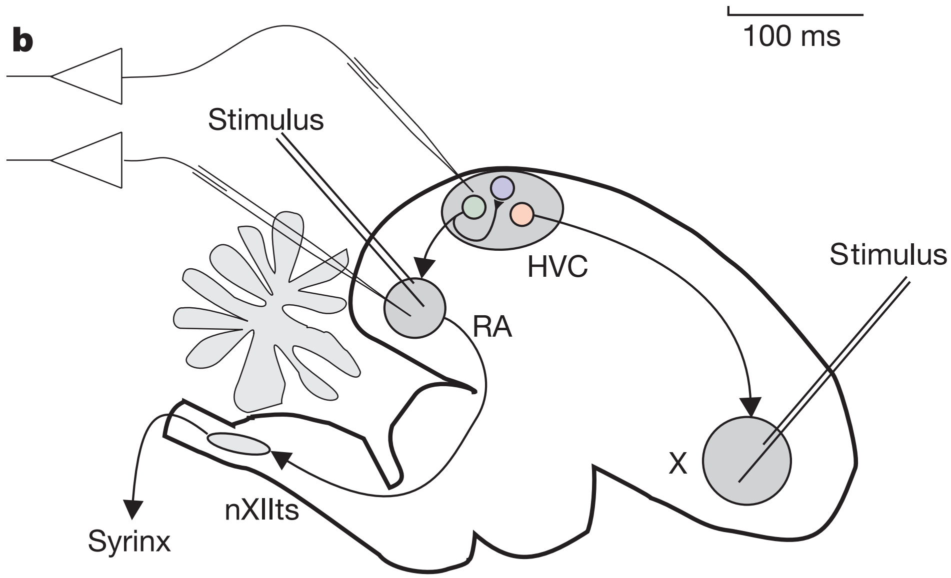
Songbird



Fiete et al. 2009 review paper

Songbird

HVC -> RA

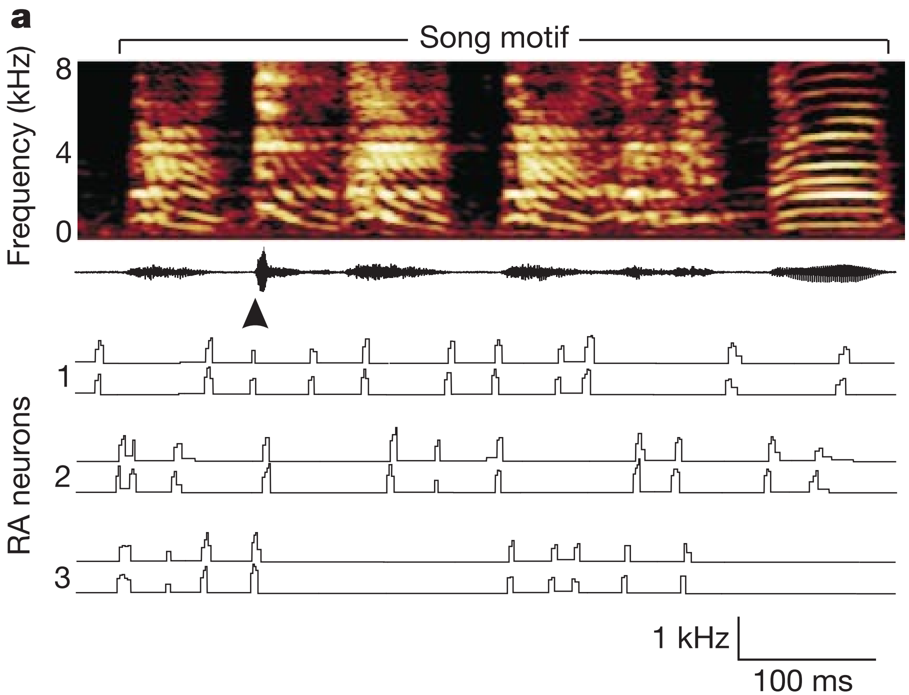


Hahnloser et al. 2002, Nature

HVC neurons connect to RA neurons, which control muscles

Songbird

HVC -> RA

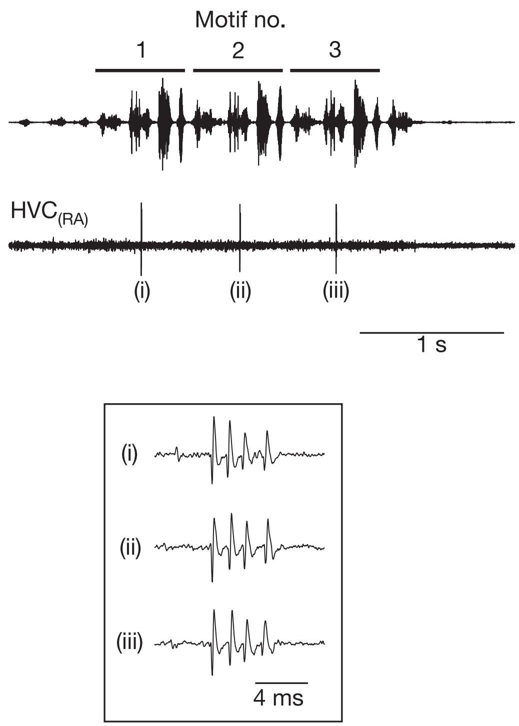


Hahnloser et al. 2002, Nature

RA neurons fire at multiple times during a song

Songbird

HVC -> RA

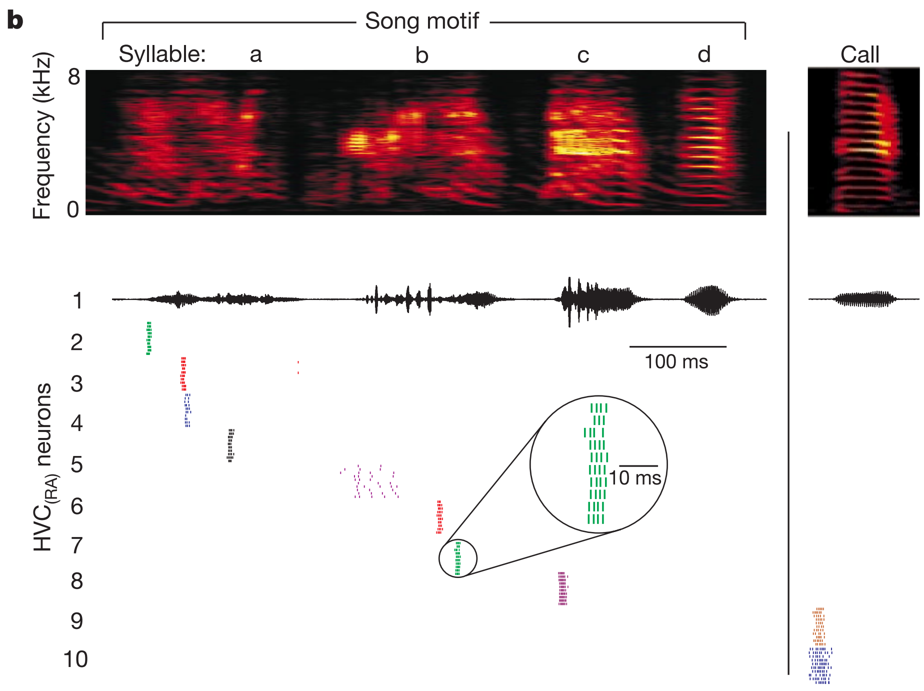


Hahnloser et al. 2002, Nature

HVC neurons burst reliably at a single precise time in the song or call!

Songbird

HVC -> RA



Hahnloser et al. 2002, Nature

HVC neurons burst reliably at a single precise time in the song or call

Songbird model

Why ultra sparse responses in the songbird??

Songbird model

Why ultra sparse responses in the songbird??

"Intuitively … minimizing interference between different synapses during learning … In this paper we make the intuitive argument more concrete."

Fiete et al. 2004: Temporal Sparseness of the Premotor Drive Is Important for Rapid Learning in a Neural Network Model of Birdsong
Also: Doya and Sejnowski 1995 (**considered sparseness in a model before known**)

Songbird model

Why ultra sparse responses in the songbird??

We'll look at modeling work, and also introduce network modeling approaches…

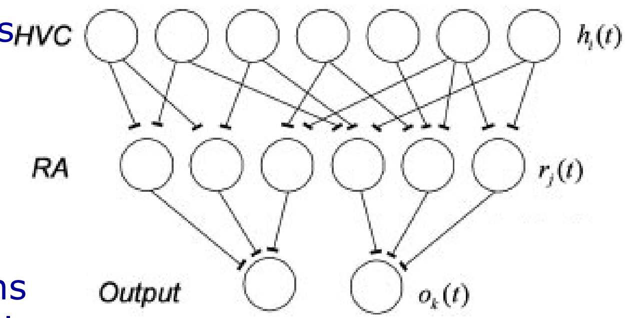
Songbird model

HVC -> RA

500 HVC neurons

800 RA neurons

2 Output Neurons
(number of vocal
muscles controlled;
7 in real system)



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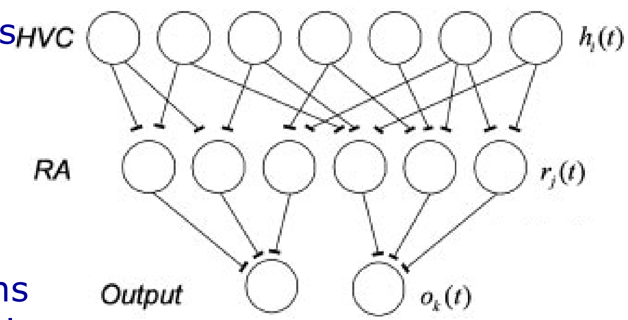

Input known (binary burst
pulses chosen randomly of either
1, 2, 4 or 8 bursts per motif)

Hidden

Desired output known

Fiete et al. 2004: Temporal Sparseness of the Premotor Drive
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Songbird model

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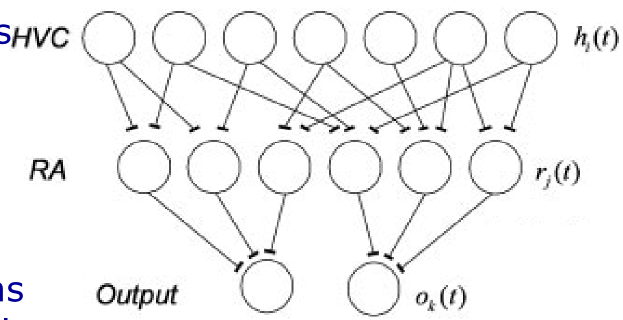

Hidden

Desired output known

Goal: minimize error between network output and desired output

Fiete et al. 2004: Temporal Sparseness of the Premotor Drive
Is Important for Rapid Learning in a Neural Network Model of Birdsong

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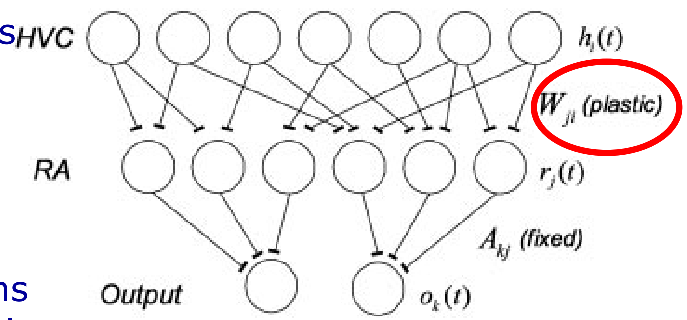

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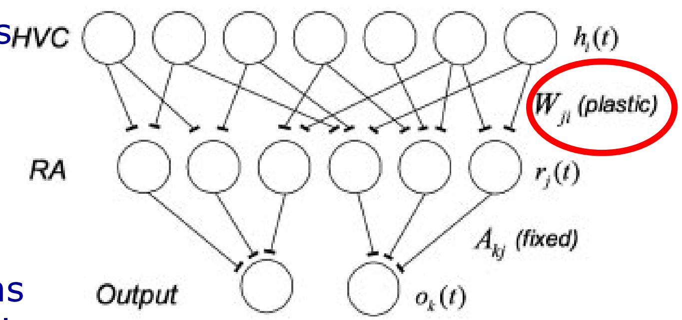

$$r_j(t) = f\left[\sum_{i=1}^{N_h} W_{ji} h_i(t) - \theta_j\right]$$

$$O_k(t) = \sum_{j=1}^{N_r} A_{kj} r_j(t)$$

Fiete et al. 2004: Temporal Sparseness of the Premotor Drive
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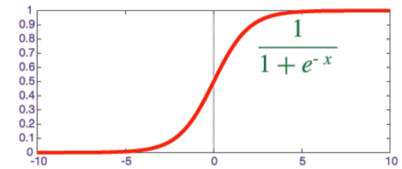

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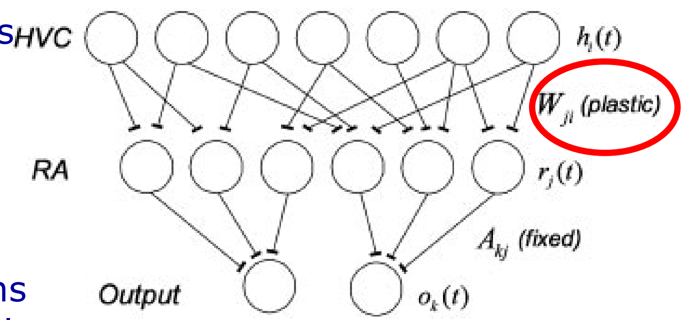


sigmoid

threshold

$$r_j(t) = f[\sum_{i=1}^{N_h} W_{ji}h_i(t) - \theta_j]$$

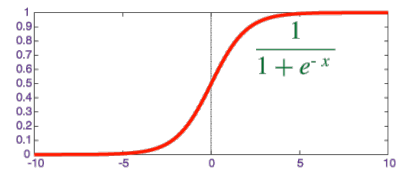
$$O_k(t) = \sum_{j=1}^{N_r} A_{kj}r_j(t)$$

We know inputs and desired outputs

Compare outputs with correct answer to get error (what kind of learning is this?)

Fiete et al. 2004: Temporal Sparseness of the Premotor Drive
Is Important for Rapid Learning in a Neural Network Model of Birdsong

Songbird model



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2 Output Neurons
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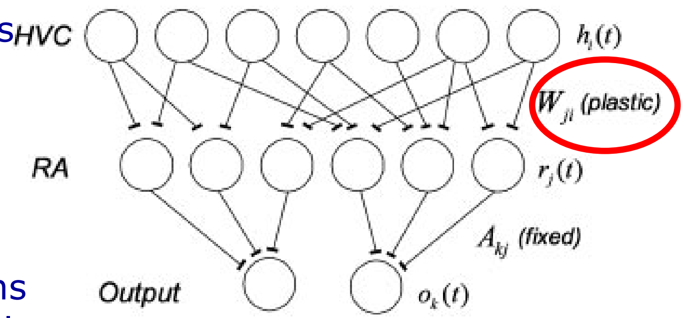

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$$O_k(t) = \sum_{j=1}^{N_r} A_{kj} r_j(t)$$

We know inputs and desired outputs

Compare outputs with correct answer to get error
(what kind of learning is this? Supervised)

Fiete et al. 2004: Temporal Sparseness of the Premotor Drive
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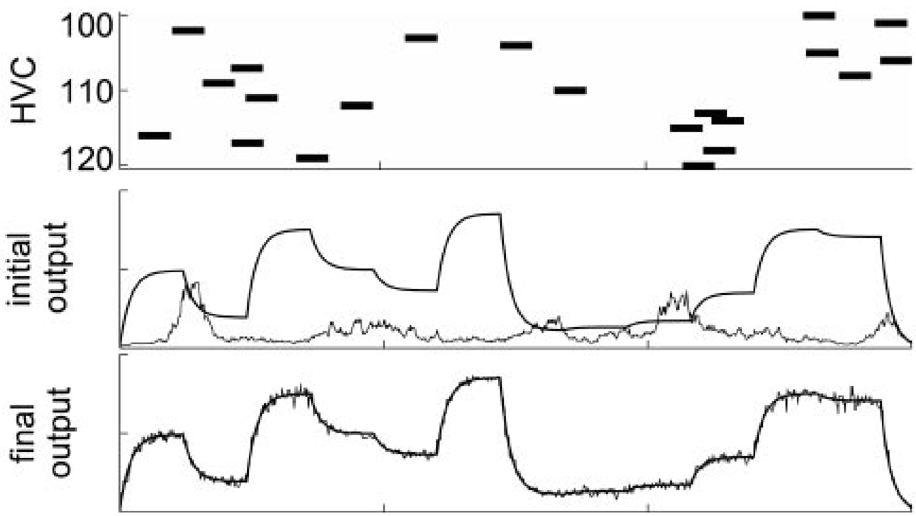
Songbird model



20 HVC neurons
each bursting once

Initial versus desired

final versus desired

Top: HVC units; middle: initial network output; and bottom: final network output matching desired output for one of the two output units
output units

Fiete et al. 2004: Temporal Sparseness of the Premotor Drive
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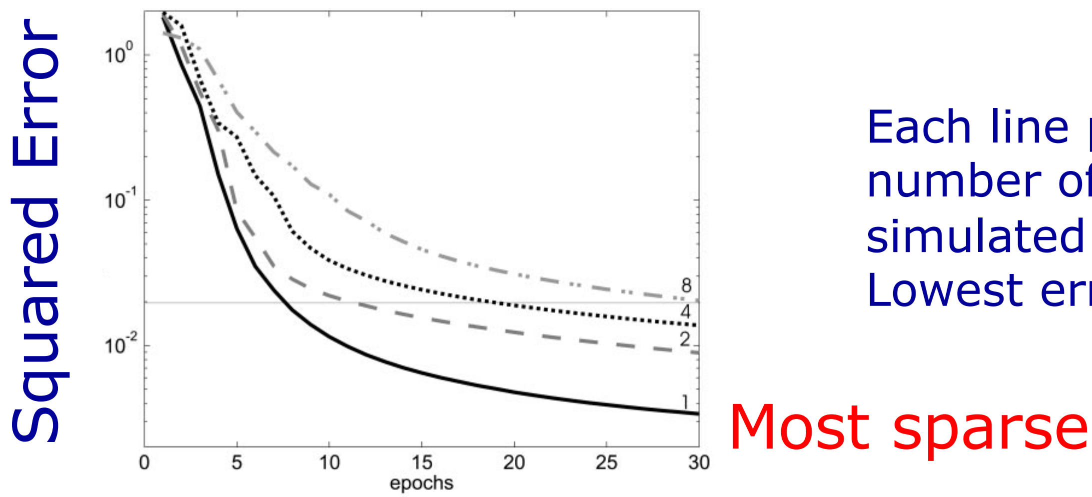
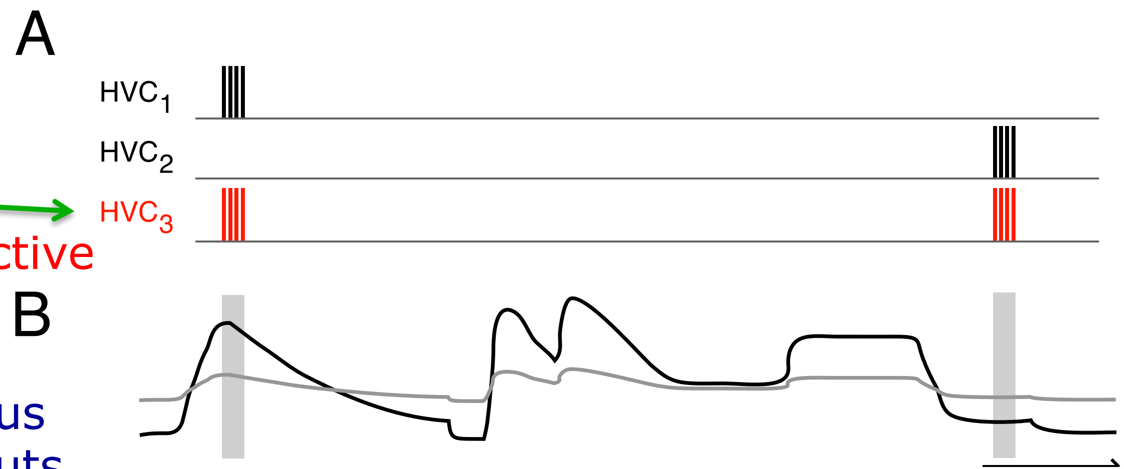
Songbird model



Each line plot: Varying number of bursts per motif of simulated HVC neurons.
Lowest error for 1 burst per motif.

Fiete et al. 2004: Temporal Sparseness of the Premotor Drive
Is Important for Rapid Learning in a Neural Network Model of Birdsong

Songbird model

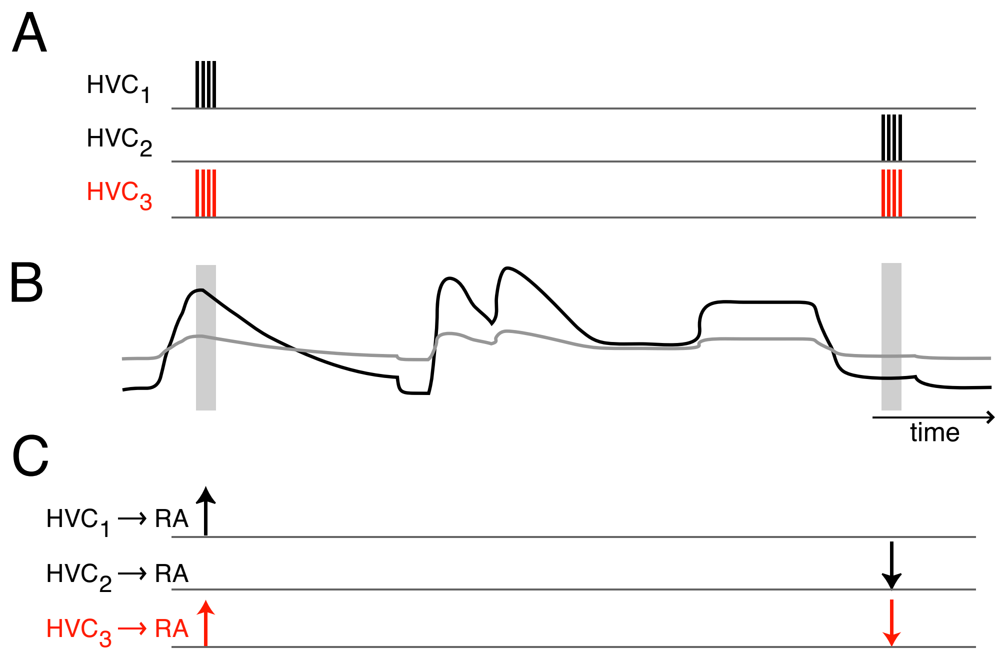


Mixed (neuron active twice)

Tutor versus pupil outputs

Fiete et al. 2009, review

Songbird model



Synapse should be strengthened and weakened -> Conflicting demands causes slowdown of learning

Fiete et al. 2009, review