

## Hold that thought: neural circuits supporting persistent percepts

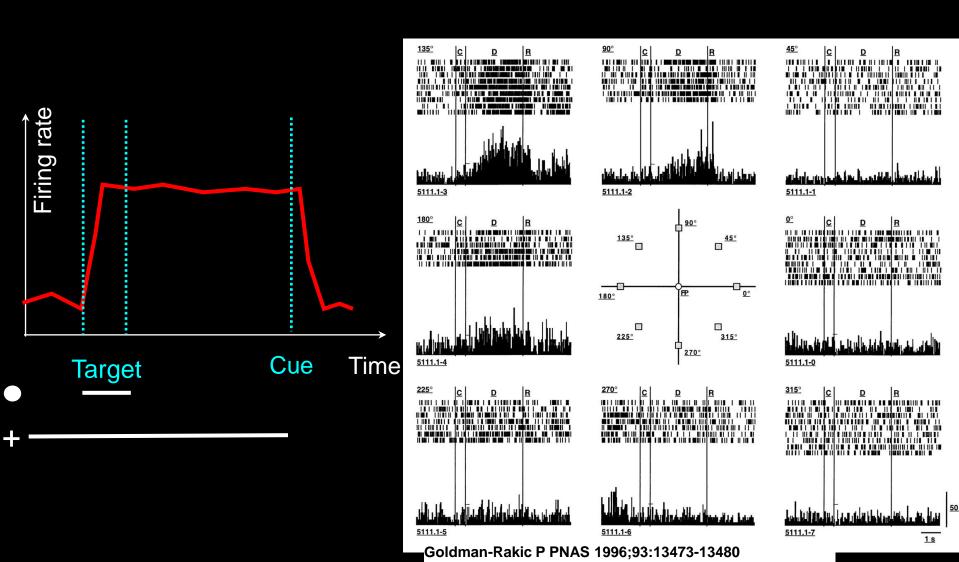
Shaul Druckmann and Dmitri "Mitya" Chklovskii

Janelia Farm

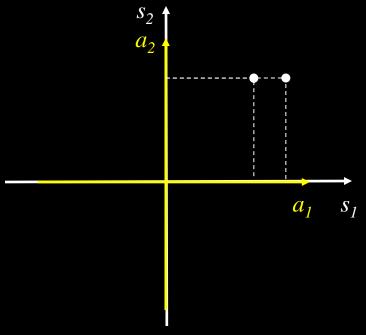
Howard Hughes Medical Institute

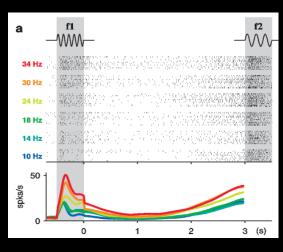
### Working memory task

## Conventional explanation: stimulus memory, or percept, is maintained by persistent activity



## Representation of a sensory percept with neuronal activity





Brody, Hernandez, Zainos, Romo (2003)

Orthogonal representation

Sensory dimensions: 2

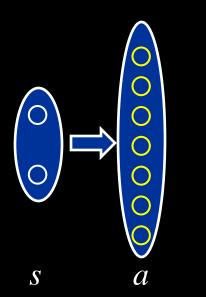
Number of neurons, or activity dimensions: 2

How can time-varying neuronal activity support persistent percepts?

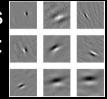
#### Redundant neural representations

#### Primary visual cortex

# thalamic << # cortical inputs neurons

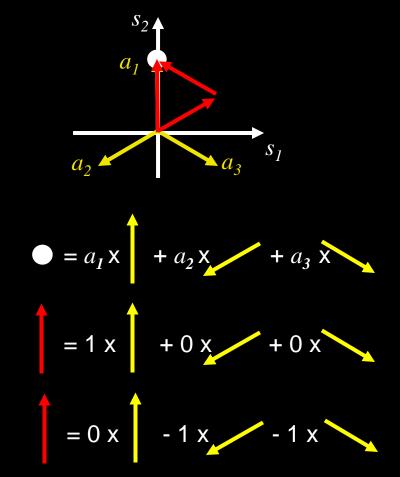


Non-orthogonal receptive fields in monkey V1 (Ringach):

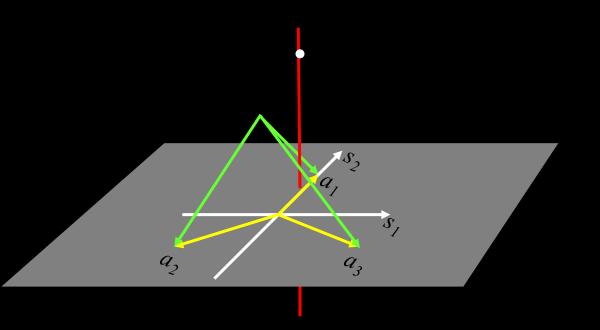


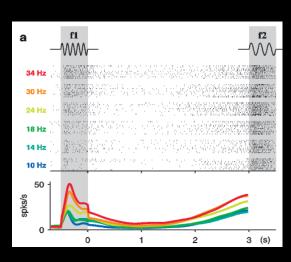
#### The Mercedes-Benz frame

s - sensory percept: 2 dimensions a - neural activity: 3 dimensions



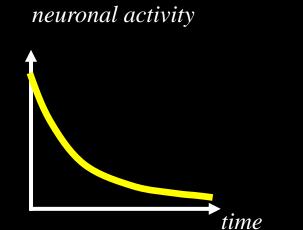
### In a redundant representation, multiple neuronal activity patterns correspond to the same percept

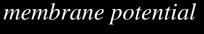


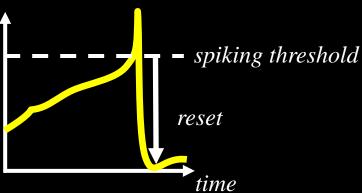


Brody, Hernandez, Zainos, Romo (2003)

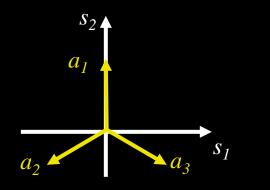
How can percept-preserving dynamics be generated in neurons?





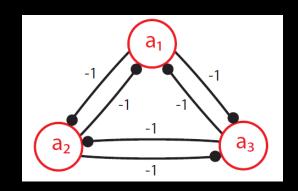


## A circuit supporting persistent percepts in the Mercedes-Benz frame

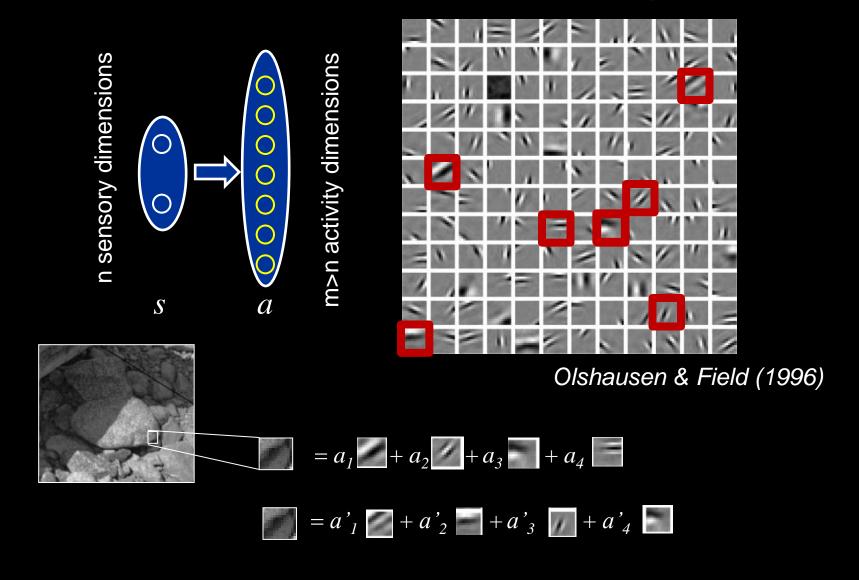


Vector re-expression

$$= -1x - 1x$$

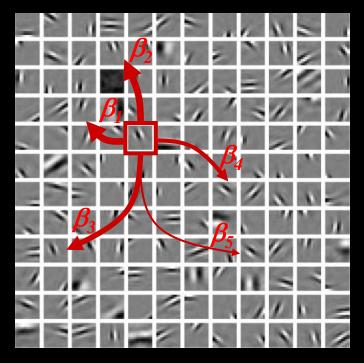


### Representation of a visual percept as a linear combination of V1 feature vectors, or receptive fields



### Neural circuits supporting persistent percepts:

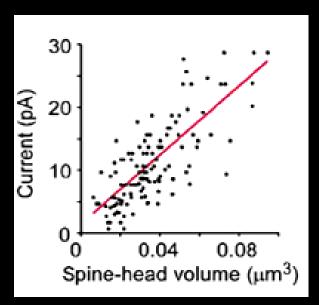
#### REceptive Fleld REcombination (REFIRE) networks



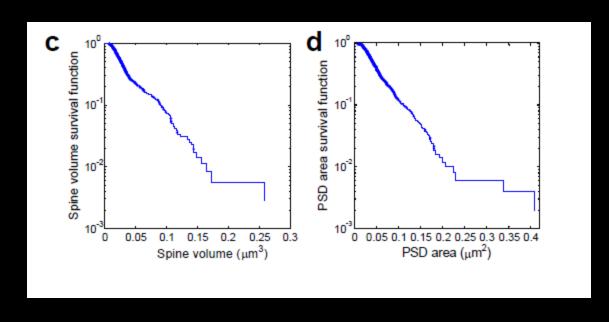
before reset of 
$$a_4$$
:  $= a_1 + a_2 + a_3 + a_4$ 

after reset of  $a_4$ :  $= a_1$   $+ a_2$   $+ a_3$   $+ a_4$   $+ a_4$   $+ a_5$   $+ a_4$   $+ a_5$   $+ a_5$   $+ a_5$ 

# Choosing a particular REFIRE network: economy of synaptic volume/weight



Matsuzaki, Ellis-Davies, Nemoto, Miyashita, Iino & Kasai (2001)



Mischenko, Hu, Spacek, Mendenhall, Harris, Chklovskii (2010)

$$\overrightarrow{\beta}$$
 = argmin {  $\Sigma_i \mid \beta_i \mid$  } such that  $\square = \beta_1 \square + \beta_2 \square + \beta_3 \square + \beta_4 \square + \beta_5 \square$ 

#### Sparsest REFIRE network computed for V1 feature vectors

Choose a sparse decomposition of feature vectors that minimizes total synaptic weight, or volume cost:

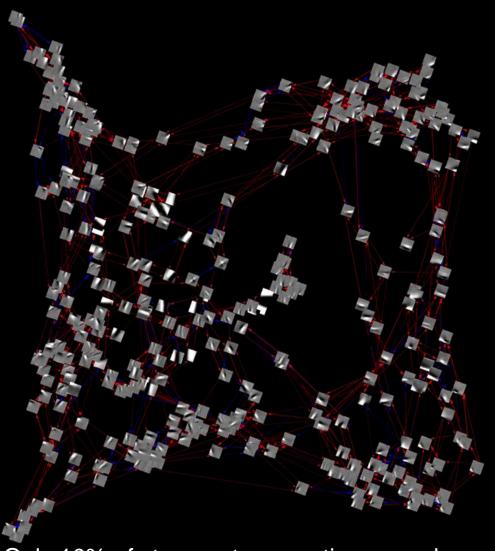
$$\vec{D_j} \ = \ d_1, d_2, \dots d_{j-1}, d_{j+1} \dots d_m$$

$$\beta_j^* = \min_{\beta_{\mathbf{j}} \in \mathcal{R}^{m-1}} ||\mathbf{d_j} - \mathbf{D_j}\beta_{\mathbf{j}}||_2^2 + \lambda_1 ||\beta_{\mathbf{j}}||_1$$

$$\mathbf{L} = [\tilde{eta_1}, \tilde{eta_2}, \dots \tilde{eta_m}]$$

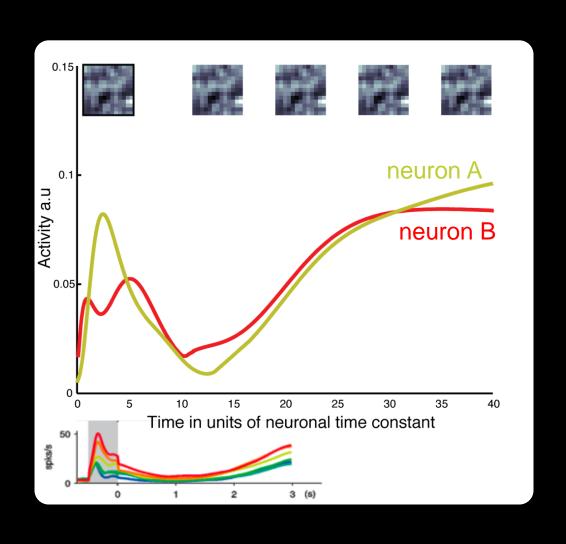
Weights computed using SPAMS package (Mairal et al.)



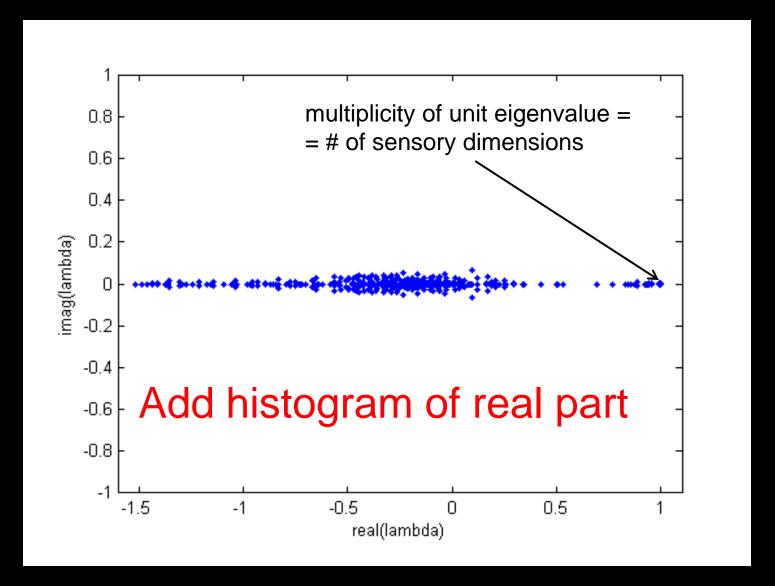


Only 10% of strongest connections are shown

# Computer simulations: despite varying activity, percepts persist



#### Eigenspectrum of the sparsest REFIRE network



# Persistent percepts with non-linear dynamics

$$\begin{cases} s = D \ a \\ \dot{a} = (L-I) f \\ f = spike(a, 1) \end{cases}$$

s - sensory inputs (n)

D - over-complete dictionary

*a* − sub-threshold voltatge(m>n)

L – lateral connectivity matrix

f - supra-threshold voltage

$$spike(a(\tau_0), 1) = \begin{cases} 0, \ a(\tau_0) < 1 \\ \delta(\tau - \tau_0), \ a(\tau_0) \ge 1 \end{cases}$$

$$\dot{s} = D \dot{a} = D(L-I) f = 0$$

# Dynamical properties of the sparsest REFIRE circuit may account for several poorly understood properties of cortical networks

- Wide distribution of firing rates (Koulakov, Hromadka & Zador, 2009)
- Spike counts have high coefficient of variation (Softky & Koch, 1993)
- "Weak thalamic input" dominates neuronal responses despite much more numerous recurrent cortical connections (*Douglas, Koch, Machowald, Martin & Suarez, 1995*)

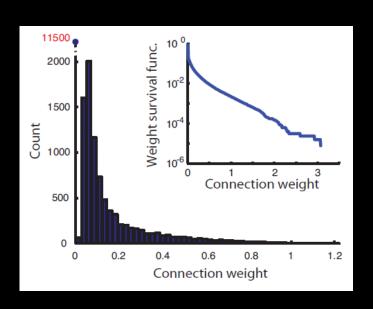
## Sparsest REFIRE circuit computed for V1 receptive fields



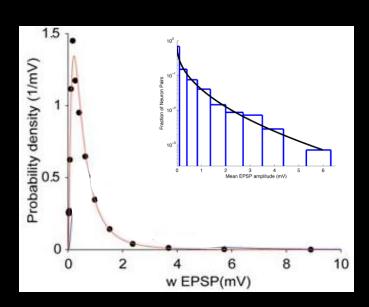


#### Distribution of connection weights

#### Model network



#### Experiment: rat visual cortex



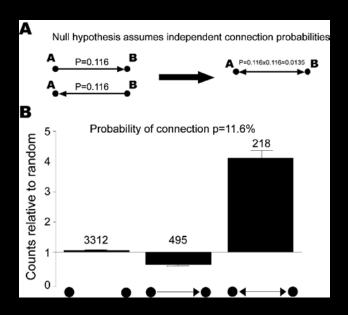
Song, Sjostrom, Reigl, Nelson, Chklovskii (2005)

## Frequency of reciprocal connections matches experiments

Model network

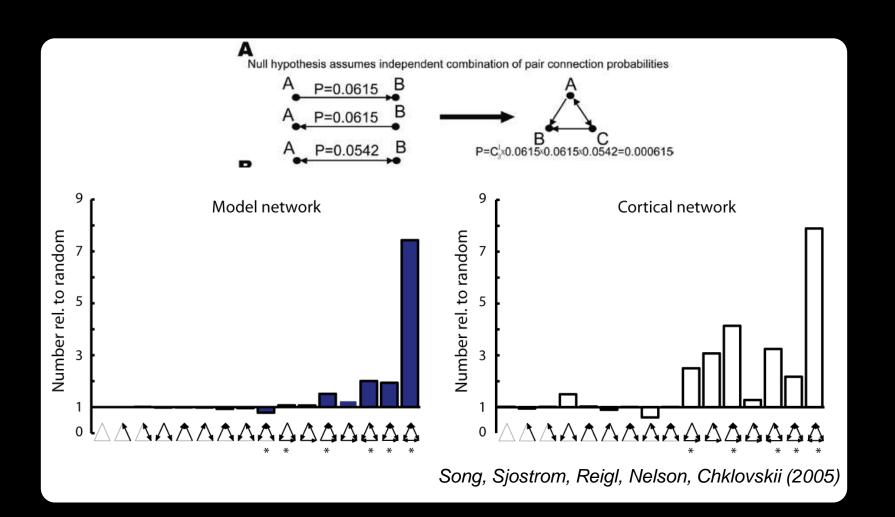
$$P_{=>} = 0.09$$
  $P_{\Leftrightarrow} = 0.03$ 

Experiment: rat visual cortex

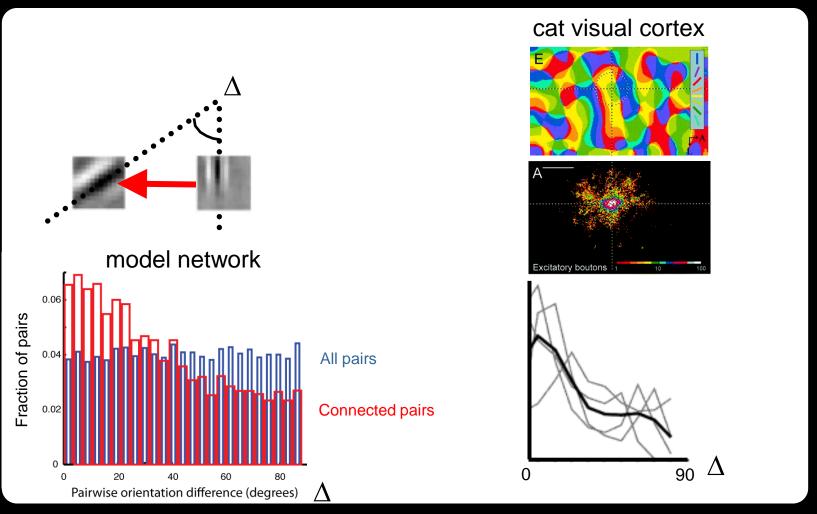


Song, Sjostrom, Reigl, Nelson, Chklovskii (2005)

### Network motifs match experiments

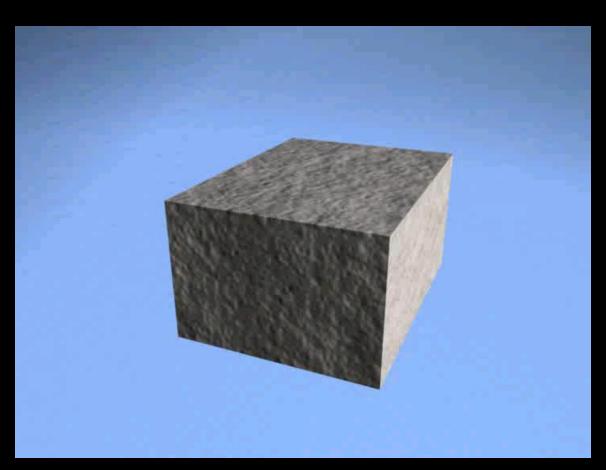


# Orientation preference of lateral connections



Youssef et al. (1999)

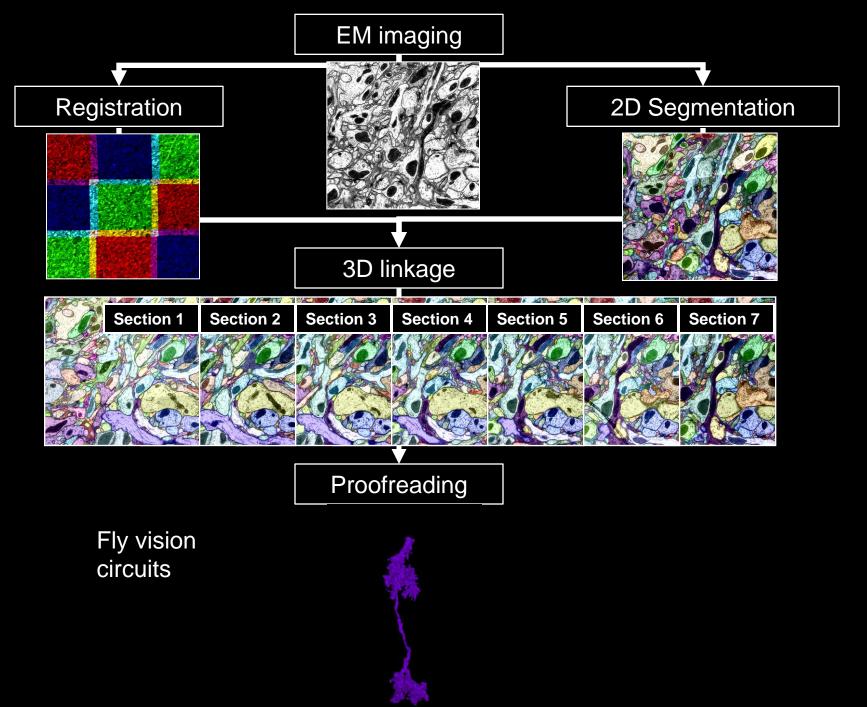
# Reconstruction of neural circuits using electron microscopy (EM)



Volume 10x10x10 micron<sup>3</sup>

- Tissue preparation and sectioning ~ days
- Image acquisition ~ days
- Circuit reconstruction ~ year

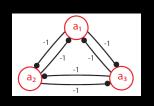
Grand challenge for computer vision



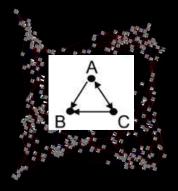
### Summary



In a redundant representation, some changes in activity do not change the percept. Such decoupling of representation and activity offers computational advantages



Contribution of a neuron to a representation lost to post-spiking reset, or leakiness, can be compensated by distributing activity to other neurons via appropriately weighted connections (REFIRE circuit)



Sparsest REFIRE circuit shares many anatomical and physiological properties with the cortical network in V1 and other cortical areas

Test the REFIRE hypothesis by large scale circuit reconstructions



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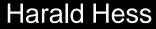
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Shiv Vitaladevuni



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Mathew Saunders

**Pete Davies** 

Goran Ceric

Pat Rivlin

Bruce Kimmel

Reed George

Victor Shapiro

Margaret Jefferies



























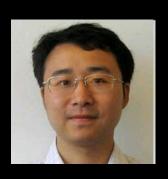
### The Chklovskii group



Arjun Bharioke



Shaul Druckmann



Tao Hu



Juan Nunez-Iglesias



Postdoctoral and research scientist positions available