

Is V1 actively sparsifying visual input?

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Introduction to sparse coding

It is widely believed that one of the main principles underlying functional organization of the early visual system is the reduction of the redundancy of relayed input from the retina. Sparse coding refers to a possible implementation of this general principle, whereby each stimulus is encoded by a small subset of neurons.

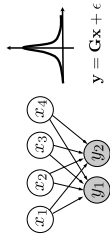
- Advantages of a sparse representation:
- low metabolic cost
 - improved signal to noise ratio
 - easier detection of co-activation patterns
 - improved storage capacity in associative memories
- lifetime sparseness }
population sparseness }
information in input }
easier detection of co-activation patterns }
improved storage capacity in associative memories }

Sparse coding model reproduce simple cell RFS

prior: iid, sparse distribution (Student-t)

$$p(x_k) = \frac{1}{Z} \left(1 + \frac{1}{\alpha} \left(\frac{x_k}{\lambda} \right)^2 \right)^{-\frac{\alpha+1}{2}}$$

(Olshausen & Field, 1996)



Sparse coding models reproduce main characteristics of simple cells RFS (Olshausen & Field, 1996, 1997; Bell & Sejnowski, 1997; van Hateren and van der Schaaf, 1997). They reproduce changes due to manipulation of visual environment (Hsu & Dayan, 2007).

Sampling-based, sparse coding neural network

Assuming that neural activity represents Gibbs samples from posterior distribution:

$$p(x_k | I_{1:k}, \mathbf{y}) \propto \exp \left(-\frac{1}{\sigma^2} \sum_{j,k} G_{jk} \theta_j x_k + \sum_{j,k} R_{jk} x_k \right) p_k - \frac{1}{2\sigma^2} \sum_k x_k^2 + f(x_k)$$

with $\mathbf{R} = -\mathbf{G}^T \mathbf{G}$

This expression can be translated in a simple, one-layer neural network, with feed-forward and recurrent connections (of Dayan and Abbott, 2001; Hoyer and Hyvarinen, 2003; Rozell et al., 2009):



Sparseness measures

Population sparseness measures are normalized to discard the effect of global firing rate changes. Alternative sparseness measures are highly correlated.

lifetime/population sparseness: sum over time/neurons

$$TR = \frac{\sum_{i=1}^N |r_i| / N}{\sum_{i=1}^N r_i^2 / N} \cdot (1 - 1/N)$$

• invariant to additive changes in firing rate

• neural responses normalized by standard deviation for population sparseness

AS = $1 - n_i / N$

• population sparseness: n_i is the number of neurons above threshold (t standard deviation)

• invariant to additive and multiplicative changes

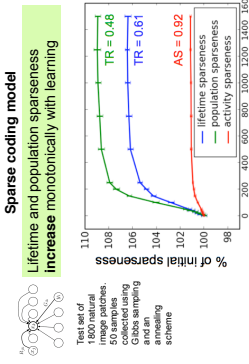
Experimental evidence for sparseness in visual cortex

Animal	References	Awake	Lifetime	Population
	Tohura et al., J Neurosci, 2009	✗	✓	✗
	Yen et al., Neurophysiol, 2007	✗	✓	✓
	Welky et al., Vision Res, 2005	✗	✓	✗
	Welky et al., Neuron, 2003	✗	✓	✗
	Vinje and Gallant, J Neurosci, 2002	✓	✓	✗
	Vinje and Gallant, Science, 2000	✓	✓	✗
	Bardley, Proc R Soc London B, 1997	✗	✓	✗
	this poster	✗	✓ ^{lifetime}	✗

Outstanding issues

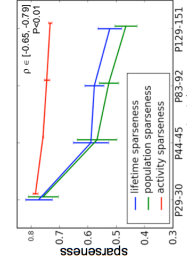
1. Sparseness measurements under anesthesia are not representative of values in awake condition
2. Efficient coding ideas are related to population sparseness, yet this has not been measured in the awake condition.
3. Is high sparseness due to optimal sparse representation or just neural selectivity? (Lehky et al., 2005) We need a relative measurement of sparseness

Sparseness decreases over development

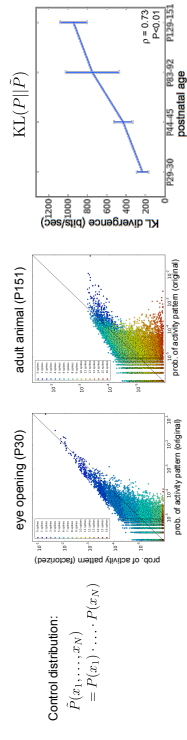


Neural data

Lifetime and population sparseness decrease with visual experience



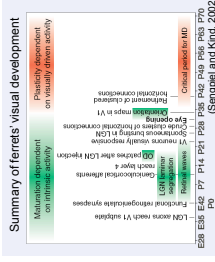
Sparseness decreases over development, in contrast to trend predicted by sparse coding models.



Decrease in sparseness seems to be due to increase in dependencies between neurons.

Could hyperparameters optimization explain a decrease in sparseness?

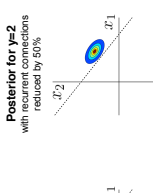
1. We can exclude a strategy like noise annealing, which would make the units sample from the prior
2. Setting the hyperparameters to a strong prior seems to be a counterproductive strategy, as it would distort the representation at the onset of learning
3. We don't explain the anesthetized results



Active sparsification requires competition between units

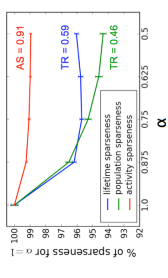
Sparse coding requires an active sparsification process mediated by recurrent connections.

Simple example with higher component mediated by two sparse variables:

$$y = x_1 + 1.3 \cdot x_2 + \epsilon$$


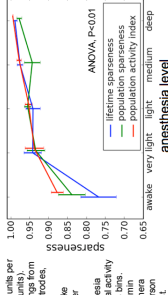
Sparseness increases with anesthesia

Sparseness decreases when lateral connections are weakened



Neural data

Lifetime and population sparseness increase with deeper anesthesia



Sparseness increases with development, in contrast to the trend predicted by sparse coding models.

Increase in sparseness is unlikely to be due to loss of feed-forward information:

- Feed-forward RF properties of neuron in V1 do not change significantly under anesthesia (Sheer et al., 1976; Sheer et al., 1980)
- Light levels of ketofentanyl affect only cortical connections (DeGuz et al., 1999; Hentschke et al., 2005)
- Stimulus-noise ratio of responses to periodic flashing stimulus does not change significantly with anesthesia

Conclusions

Neural data shows trends of lifetime and population sparseness over development and under anesthesia that are opposite to those predicted by the sparse coding hypothesis, suggesting that the sparse responses of visual neurons are not due to an active sparsification process. However, the results are still consistent with a generalization of efficient coding as learning in a hierarchical, probabilistic model of visual input.

D.J. Tibbatt, D.J. Smyth, and I.D. Thompson. The sparseness of neuronal responses in monkey striate cortex. I. Journal of Neurophysiology, 1976.

A.J. Bell and T.J. Sejnowski. The independent components of natural scenes are similar to simple cells in monkey striate cortex. Journal of Neurophysiology, 1997.

J.H. van Hateren and van der Schaaf. Independent component filters of natural images compared with simple cells in primary visual cortex. Proc R Soc B, 1998.

V.A.F. Lamme, K. Ziper, and H. Spoenke. Eye-ground activity in primary visual cortex of awake ferrets. Journal of Neurophysiology, 1999.

O. DeGuz, et al. Isoflurane induces dose-dependent changes of ballistic orientation selectivity in popliteal neurons. Vision Research, 2007.

R. Bardley, et al. Responses of neurons in primary and inferior temporal visual cortex during natural vision. Science, 2000.

W.E. Skaggs and J.L. Culter. Science, 2000.

M. Welky, J. Fisher, R.H. Hunt, and D.N. Wagner. Coding of natural scenes in the primary visual cortex of awake ferrets. Journal of Neurophysiology, 1997.

S.R. Lehky, T.J. Sejnowski, and R. Desimone. Selectivity and sparseness in the responses of striate complex cells. Vision Research, 2005.

C.J. Rozell, et al. Sparse coding with thresholding and local competition in neural networks to natural stimuli in cat striate cortex. Journal of Neurophysiology, 2007.