ICMNS 2015, Antibes – Juan les Pins

Binary recurrent neural networks with random coding

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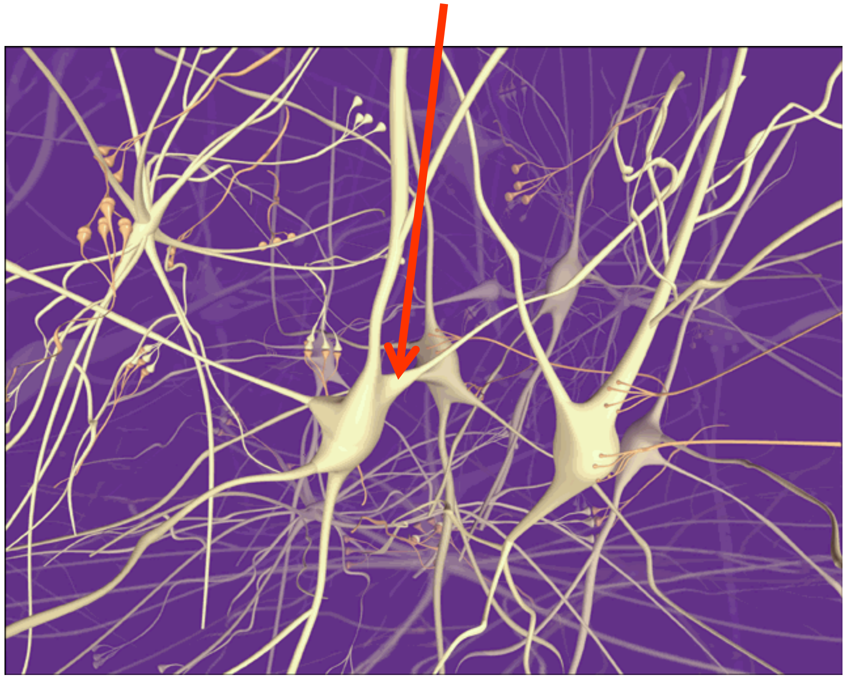
Computational/informational neuroscience
(models of cognition)

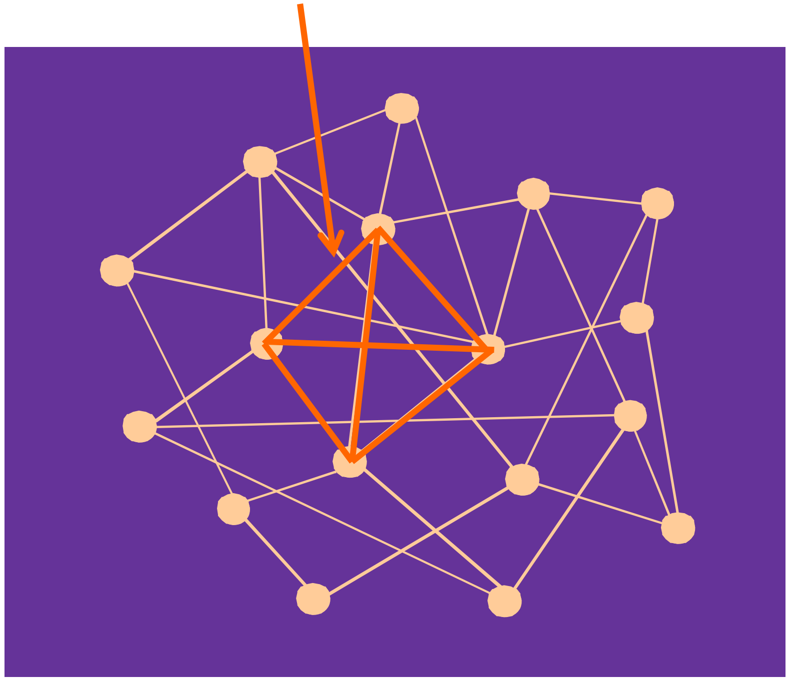
2 schools of thought

Information is borne by
synaptic weights



Analog model

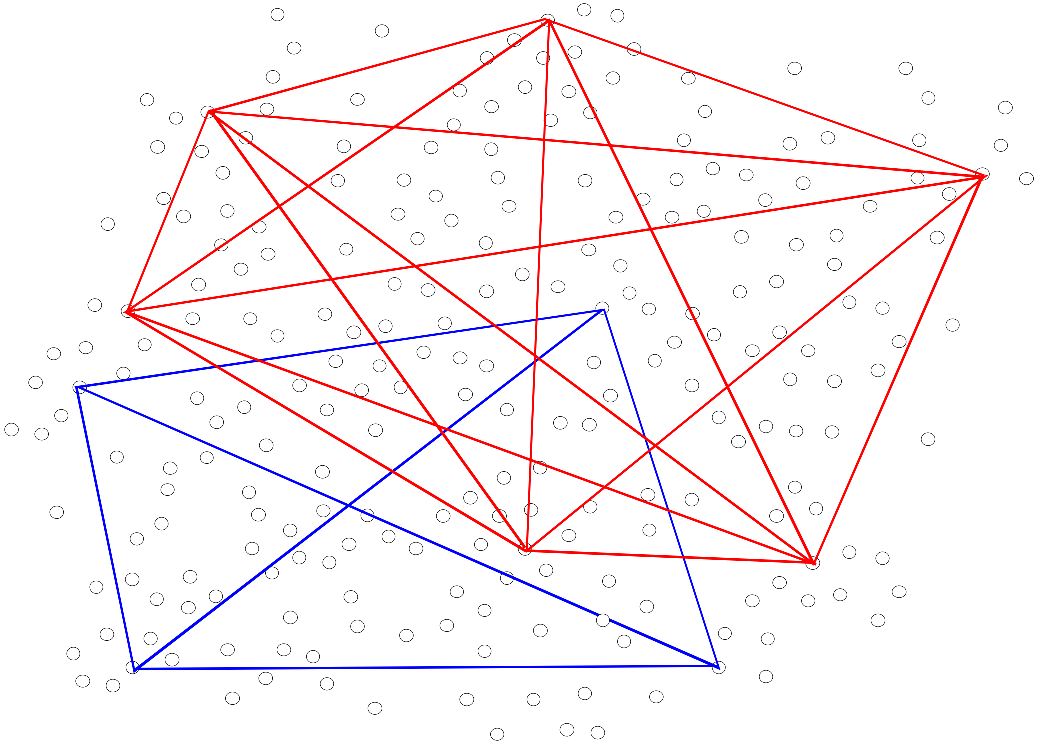
Information is borne by
graphical patterns



Digital model

Fixing information in network of cliques

Classical Willshaw network



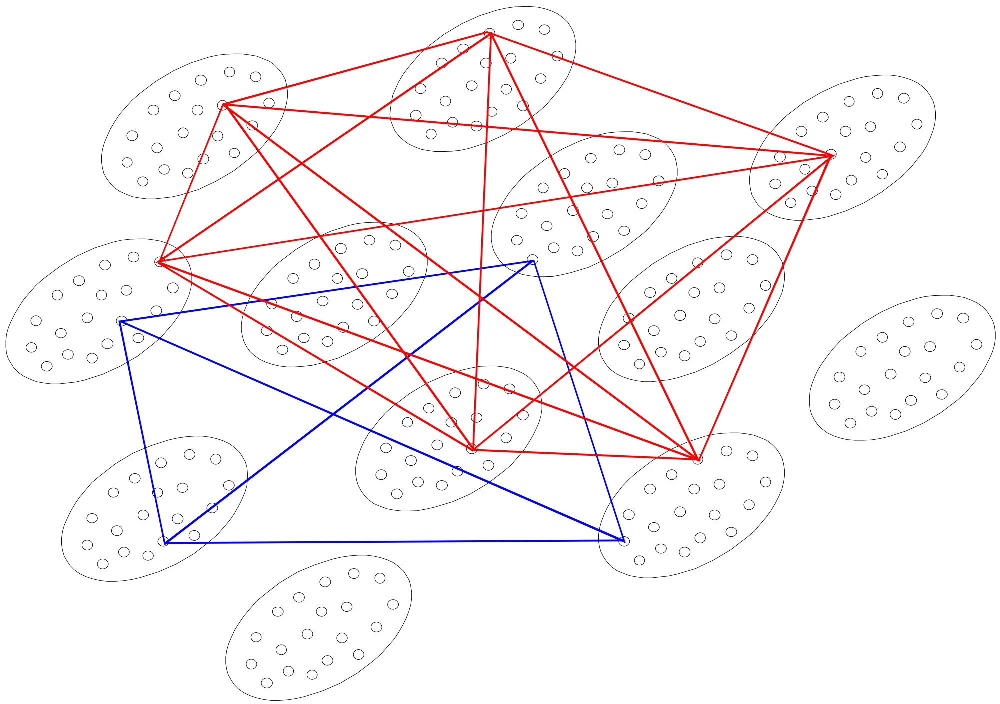
Number of messages proportional to n^2 with robust retrieval

D. J. Willshaw, O. P. Bunetman and H. C. Longuet-Higgins "Non-holographic associative memory," Nature, 222, pp. 960-962, 1969.

G. Palm and F. T. Sommer, "Information capacity in recurrent McCulloch-Pitts networks with sparsely coded memory states", Network: Comput. Neural Syst., vol. 3, pp. 1-10, 1992.

Fixing information in network of cliques

Clustered network



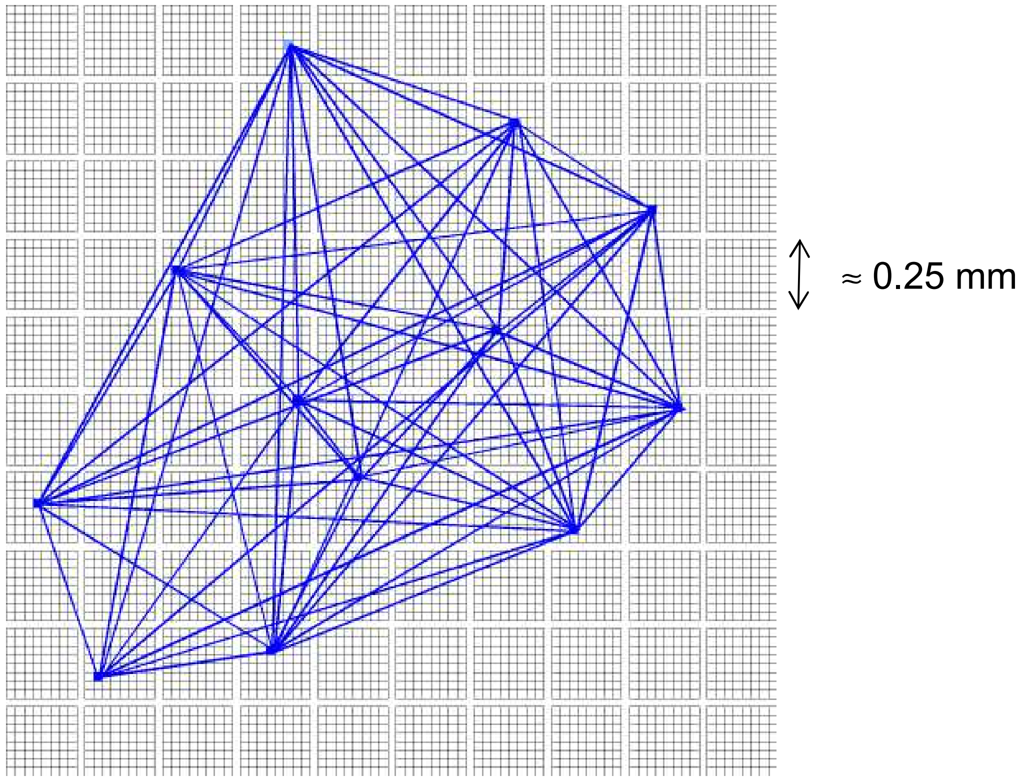
Number of messages proportional to n^2 with even more robust retrieval

V. Gripon and C. Berrou, “Sparse neural networks with large learning diversity”, *IEEE Trans. on Neural Networks*, vol. 22, n° 7, pp. 1087-1096, July 2011

B. Kamary Aliabadi, C. Berrou, V. Gripon and X. Jiang, “Storing sparse messages in networks of neural cliques”, *IEEE Trans. on Neural Networks and Learning Systems*, vol. 25, n° 5, pp. 980-989, Nov. 2013

X. Jiang, V. Gripon, C. Berrou and M. Rabbat, “Storing sequences in binary tournament-based neural networks”, to appear in *IEEE Trans. on Neural Networks and Learning Systems*, 2015

A model of cortical macrocolumn

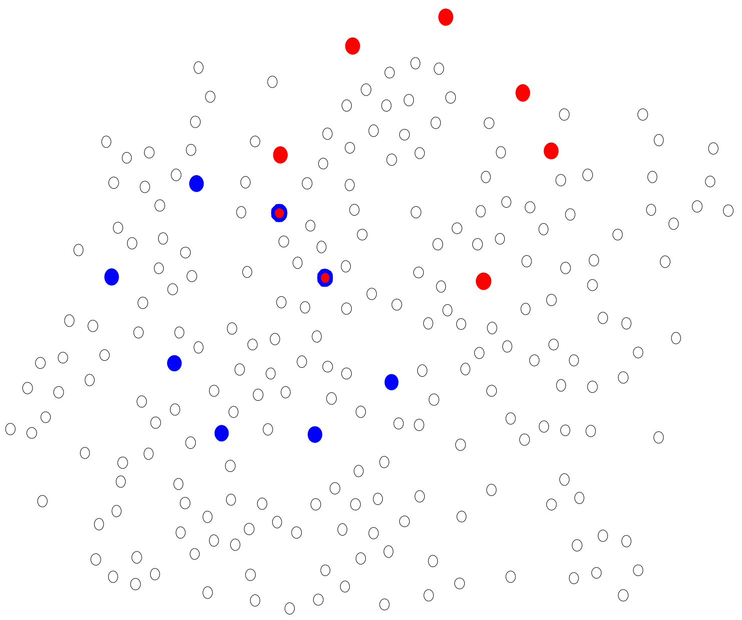


100 clusters of 64 fanals (microcolumns) each: about 10^{-5} x human cortex

Cliques with c = 12 vertices

More than 100.000 possible messages with robust retrieval in presence of errors, intrusions or approximate stimuli

The effects of correlation on clique retrieval

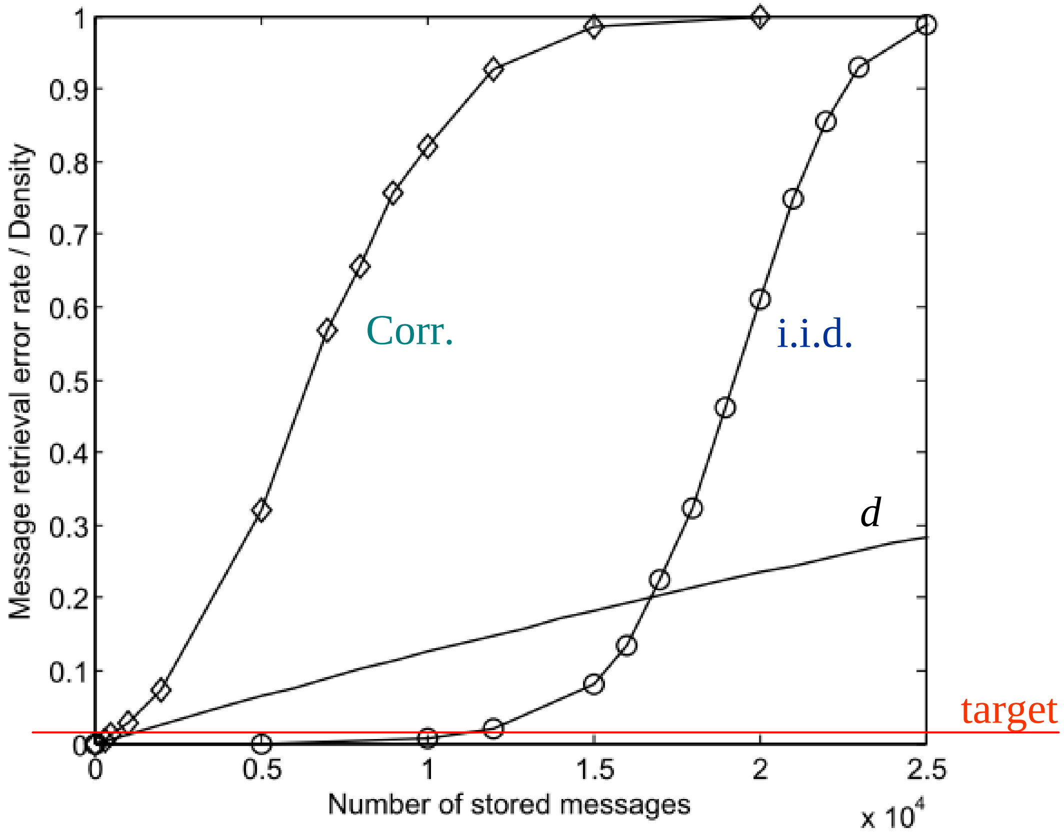


$n = 2048$, $k = 8$, $k_e = 4$

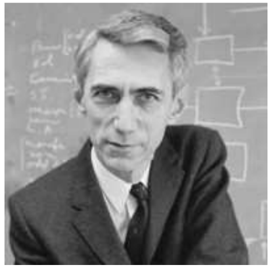
M messages

Corr.: each group of 100 shares 2 nodes

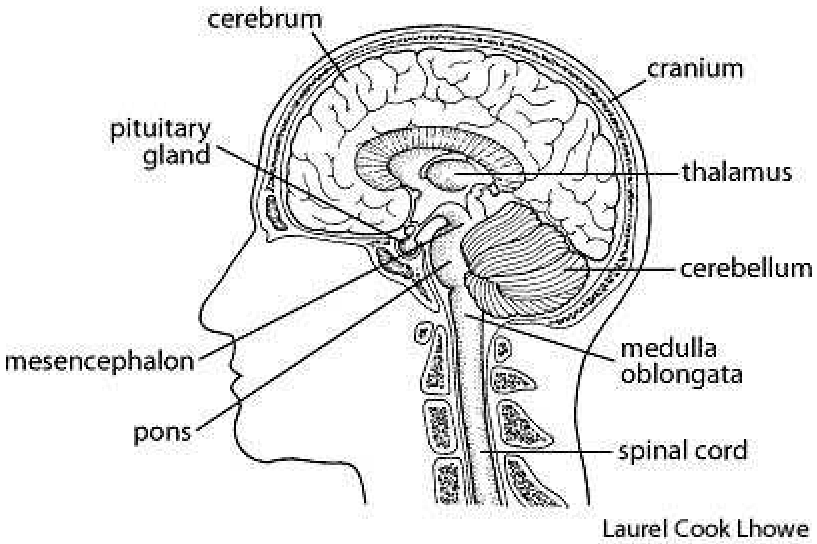
Retrieval according to k-WTA algorithm



density (i.i.d.) $d = 1 - \left(1 - \frac{k(k-1)}{n(n-1)}\right)^M$

Shannon model  applied to the brain

Richly detailed and fleeting external world	→	Useless redundancy is removed Source coding	→	Smart redundancy is added Channel coding	→	Parsimonious and robust mental world

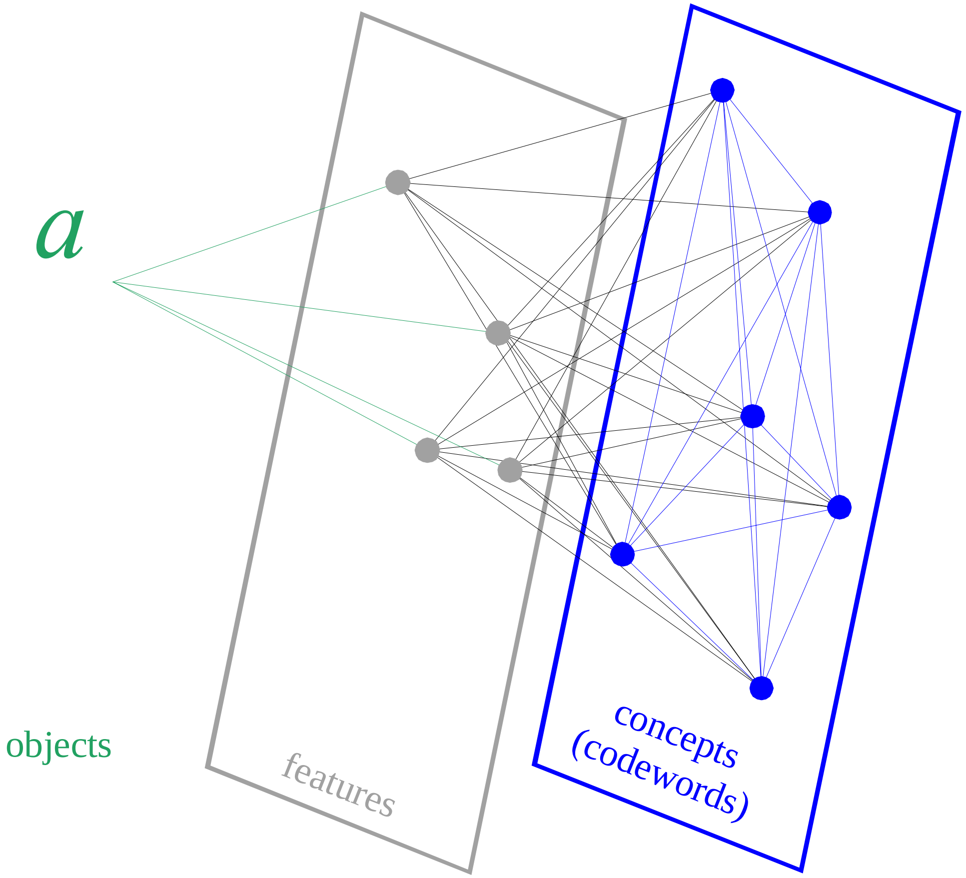


Shannon model applied to the brain

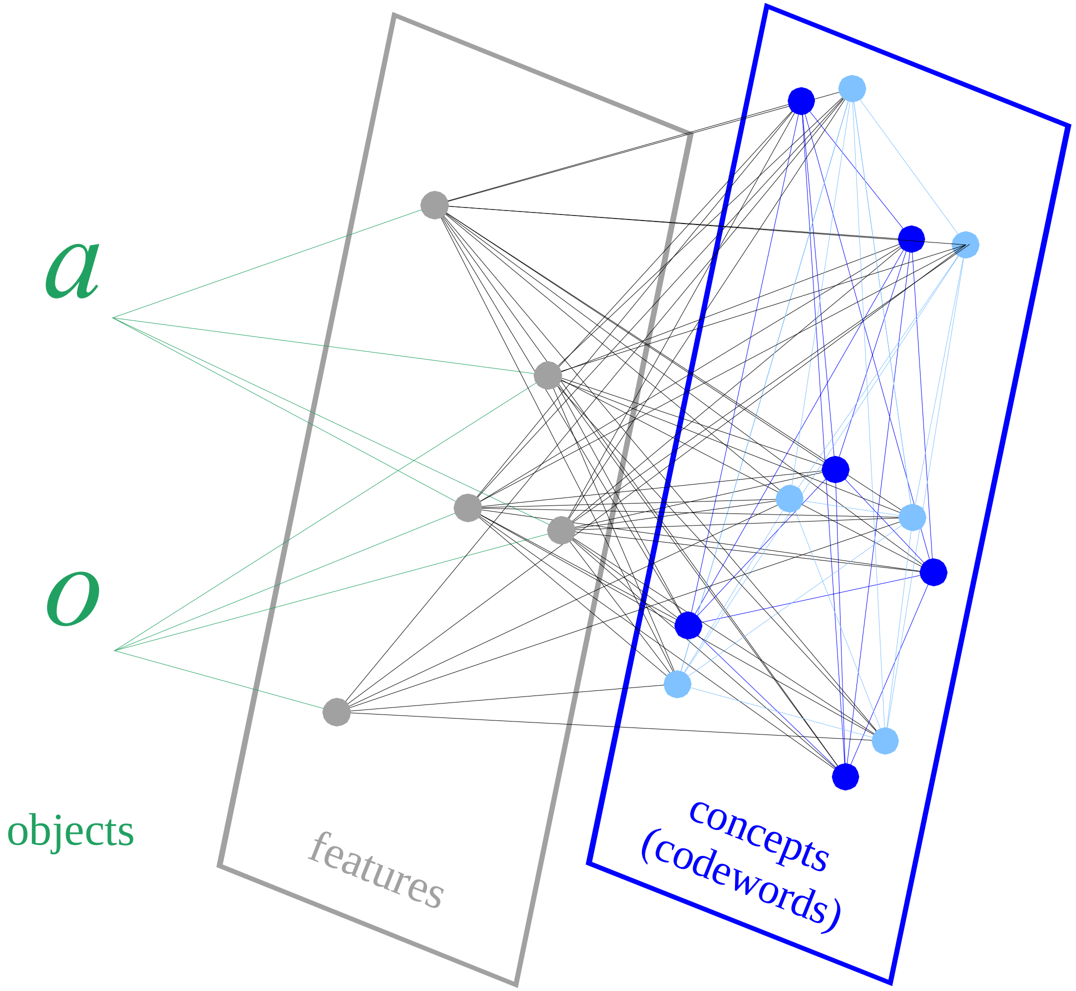
Useless redundancy is removed

Smart redundancy is added

Richly detailed and fleeting external world → Source coding → Channel coding → Parsimonious and robust mental world



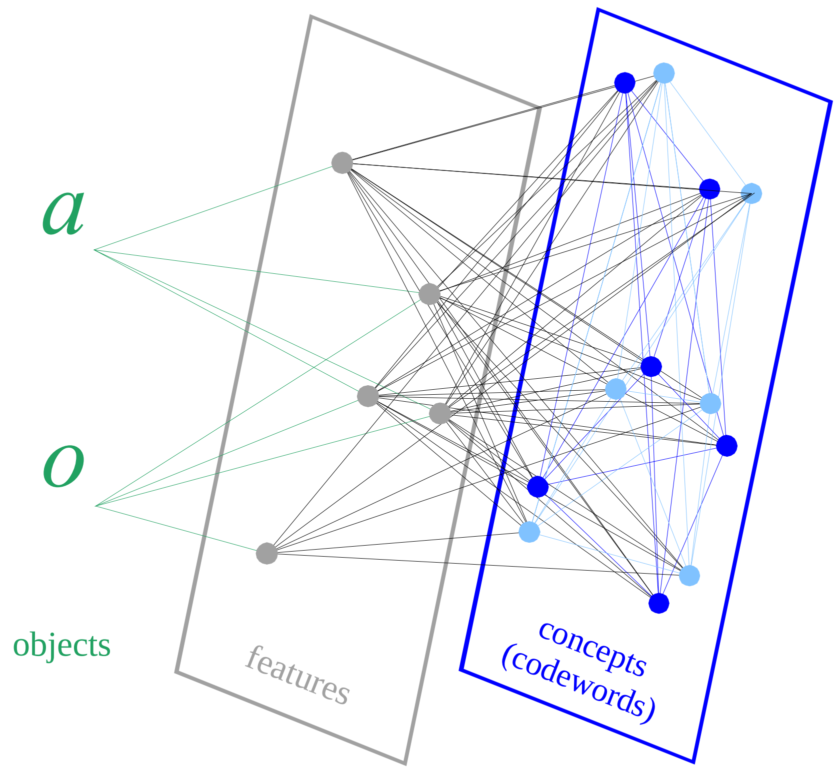
Shannon model applied to the brain

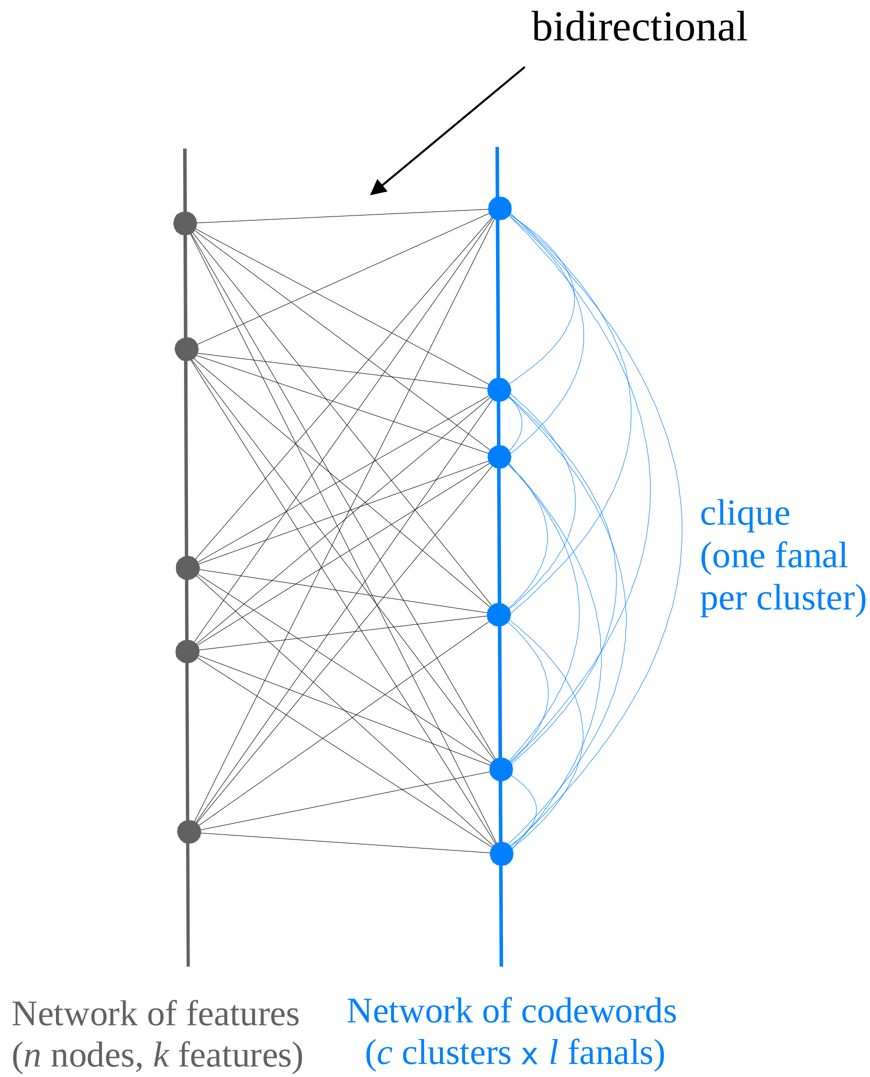


Correlated

Uncorrelated
(random)

Implementing random coding





Two-layer network

cliques

$n_c = 2048$, $c = 8$, $l = 256$

Retrieval according to local WTA algorithm

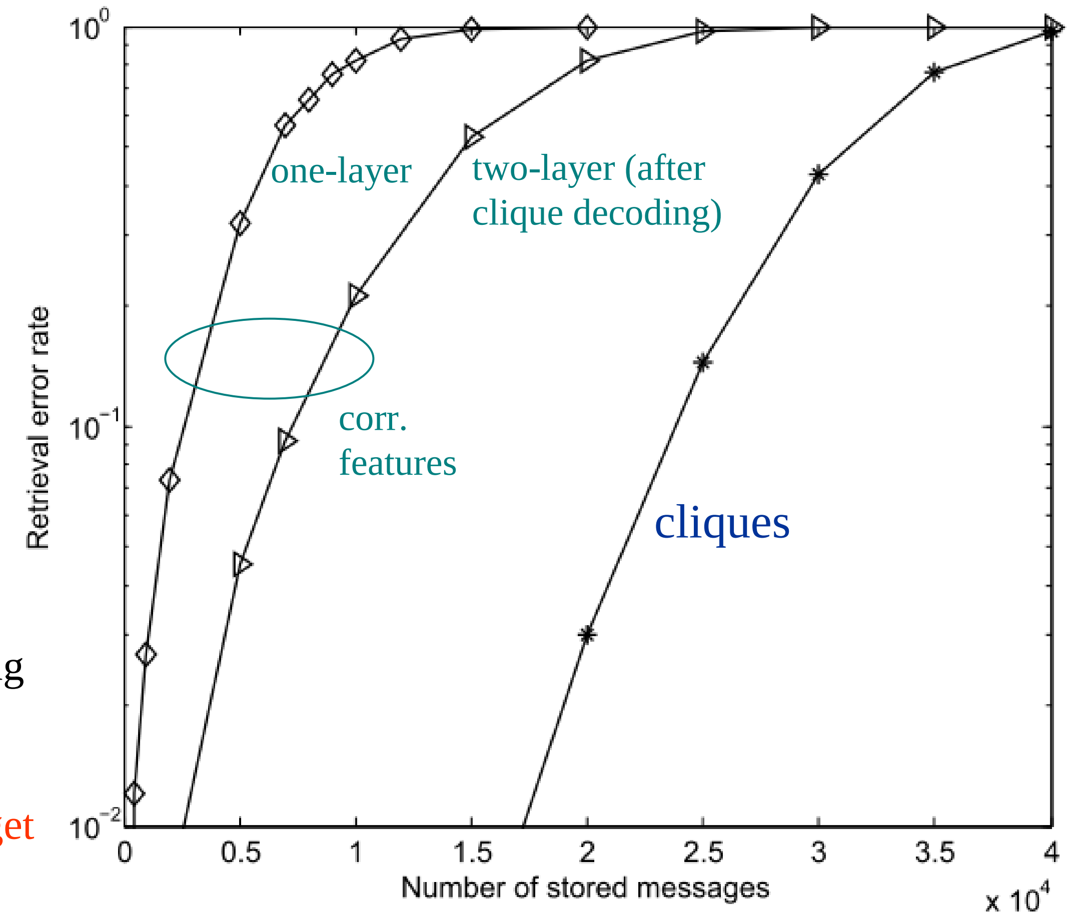
Features

$n = 2048$, $k = 8$, $k_e = 4$

Corr.: each group of 100 shares 2 nodes

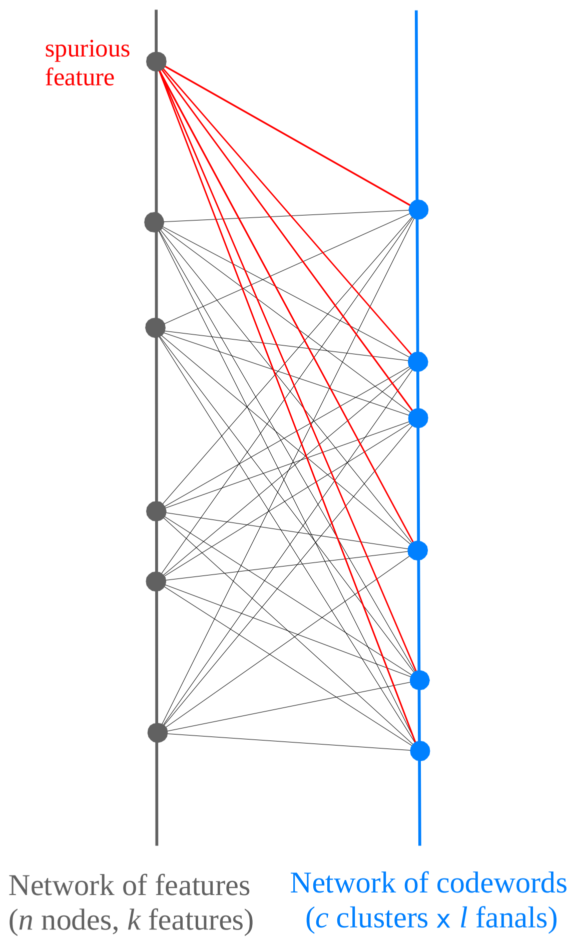
Retrieval according to threshold (c) decoding

target



Remark: the two-layer network uses twice the resource of the single layer network

Two-layer network: analysis



- Spurious features appear after reconstruction in the network of features
- These features are mainly those which are highly appealed to (2 out of 8 in our example)
- Easy to analyze in the i.i.d. case:

Bipartite density: $d_b \approx 1 - \left(1 - \frac{k}{nl}\right)^M$

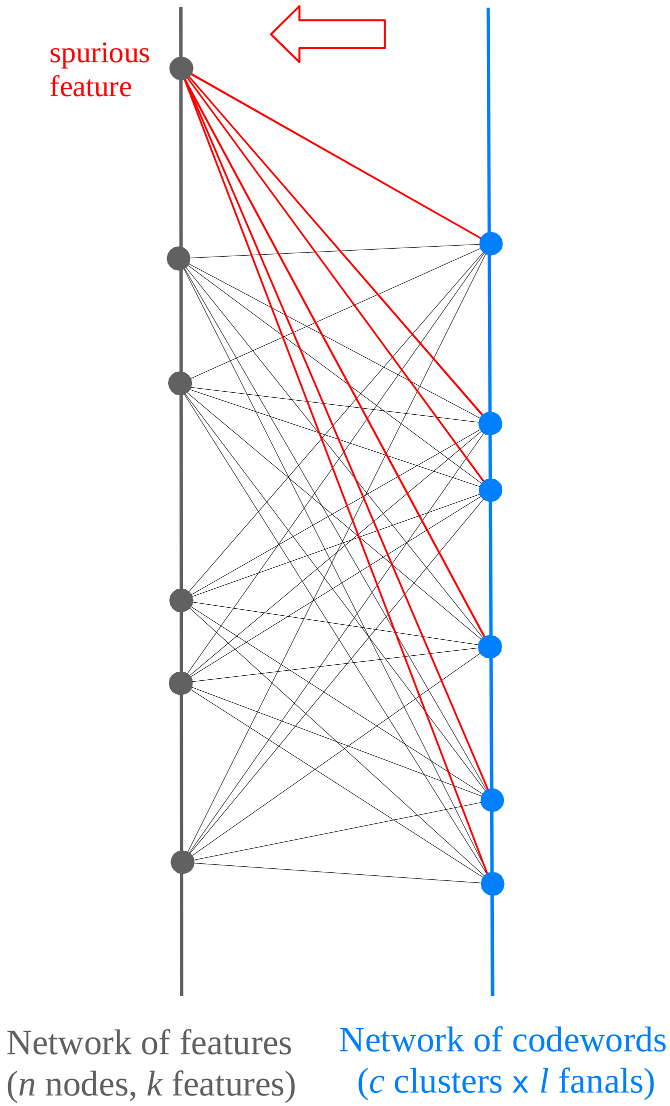
Probability of having at least one spurious feature after reconstruction:

$$P_s = 1 - \left(1 - d_b{}^c\right)^{n-k}$$

(for instance, $n = 2048$, $l = 256$, $c = k = 8$, $M = 15000 \Rightarrow P_s = 6.2\ 10^{-3}$)

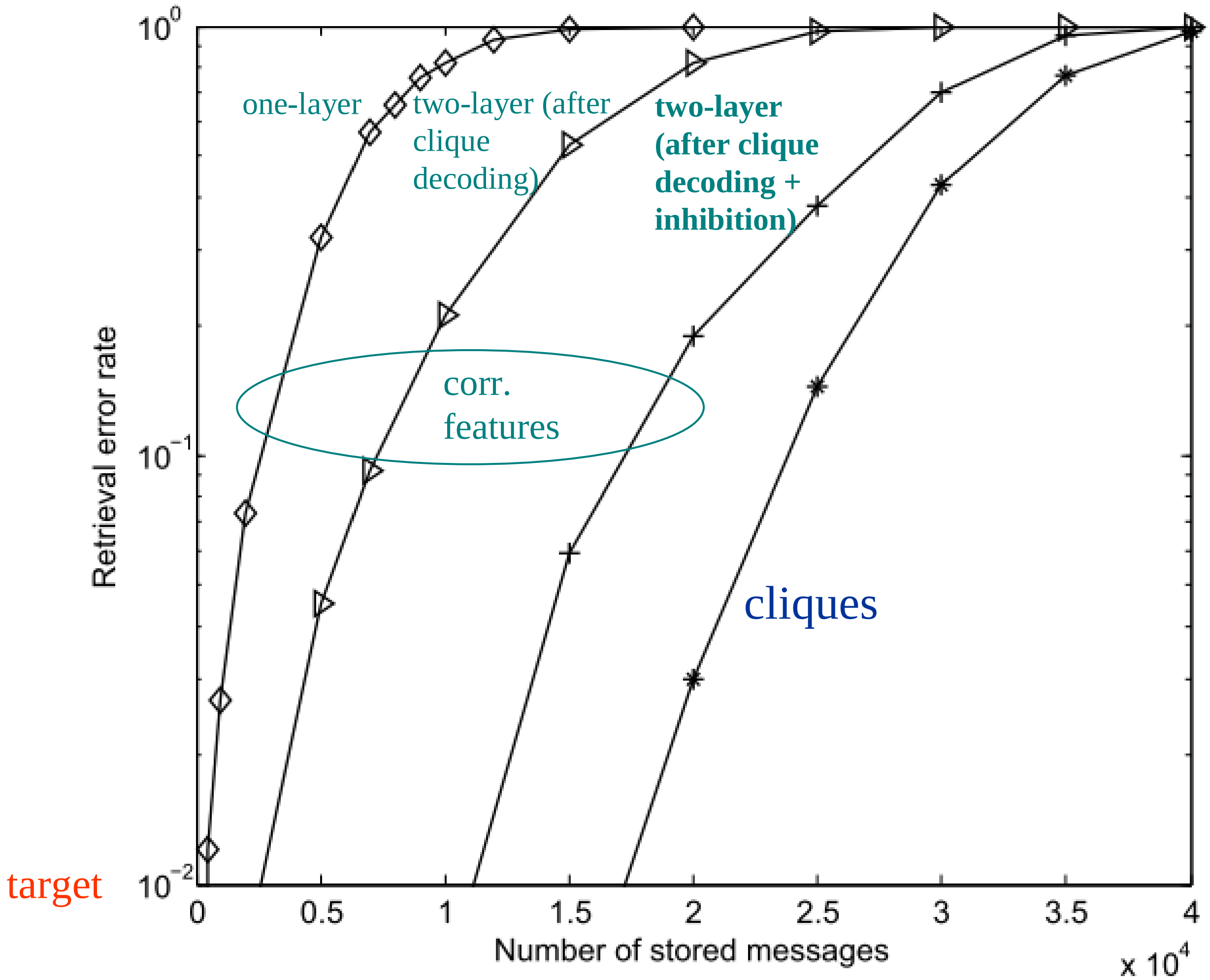
- Not so easy with correlated features (feasible but each correlation model has its specific relations)

Implementing inhibitory feedback



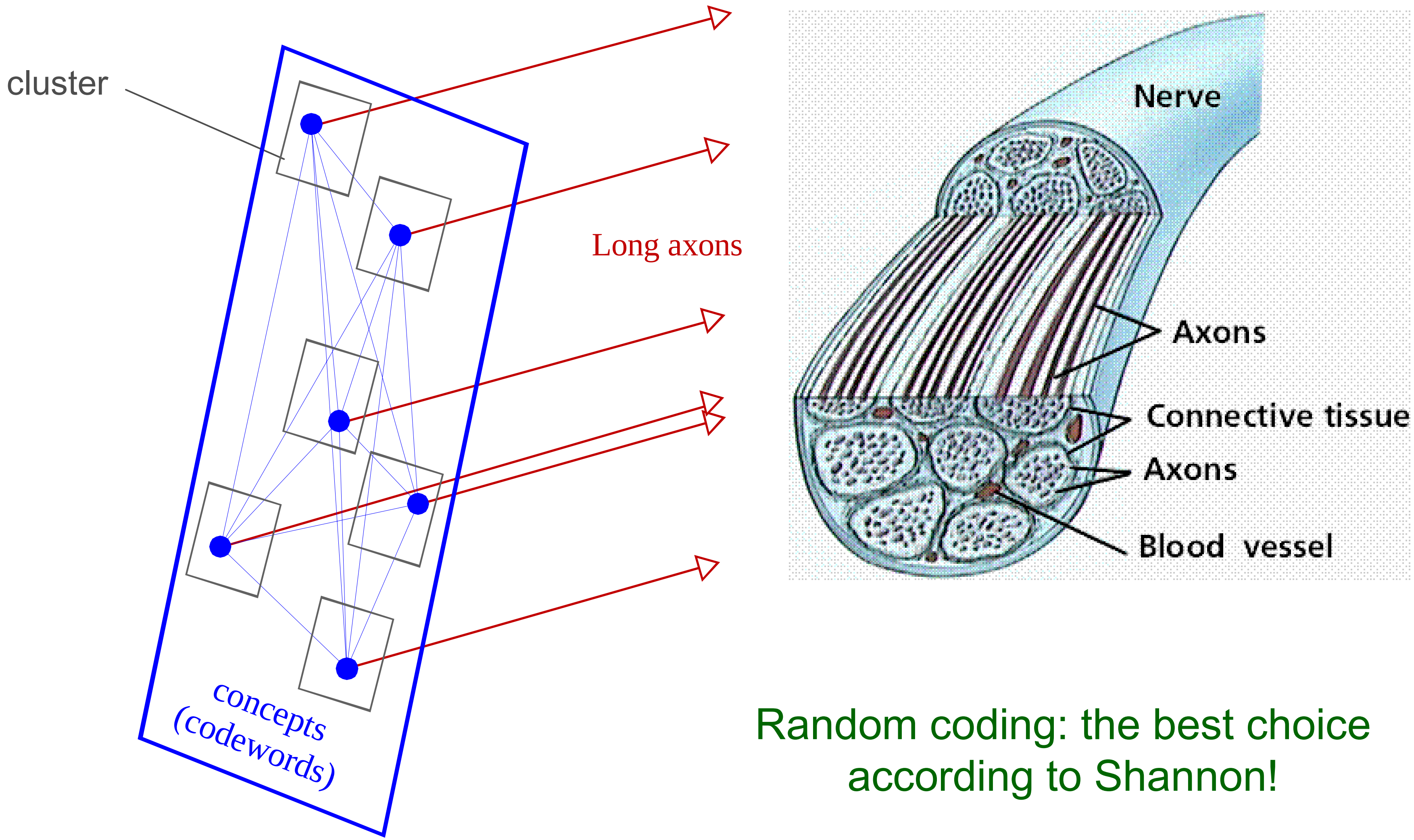
1. Learning/storing
2. Training
3. Retrieving

Implementing inhibitory feedback



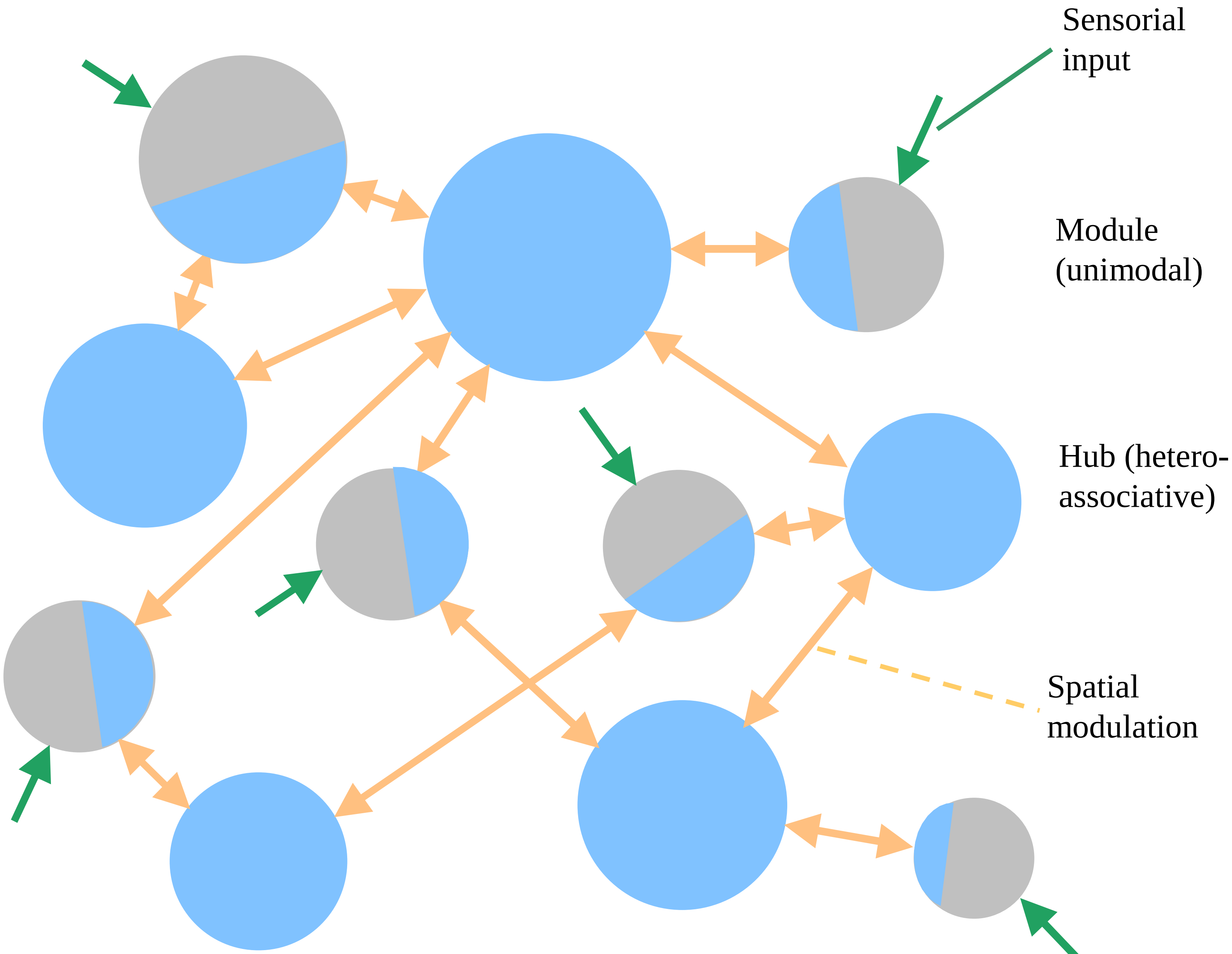
Remark: the two-layer network with inhibitory feedback uses four times the resource of the single layer network

Communication



Random coding: the best choice according to Shannon!

As a conclusion: a model of cortical network



Outputs not displayed

Random is best (and natural)!