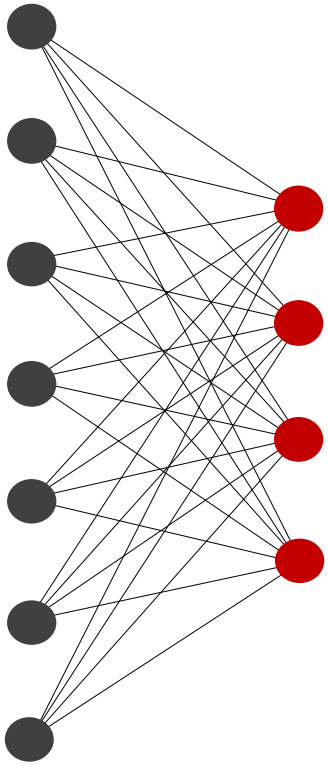
NeuroSTIC
1-2 juillet 2014

Informational neuroscience

Claude Berrou

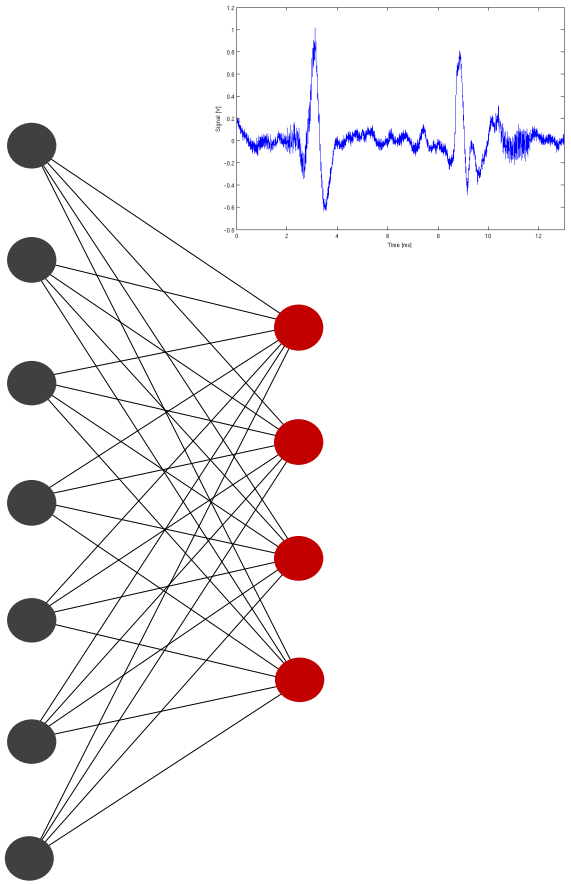
and collaborators

Confronting weighted models and biological facts



perceptron, convolutional
and deep learning networks,
Hopfield-like, etc.

Confronting weighted models and biological facts



Hopfield-like, perceptron, deep belief & deep learning networks, etc.

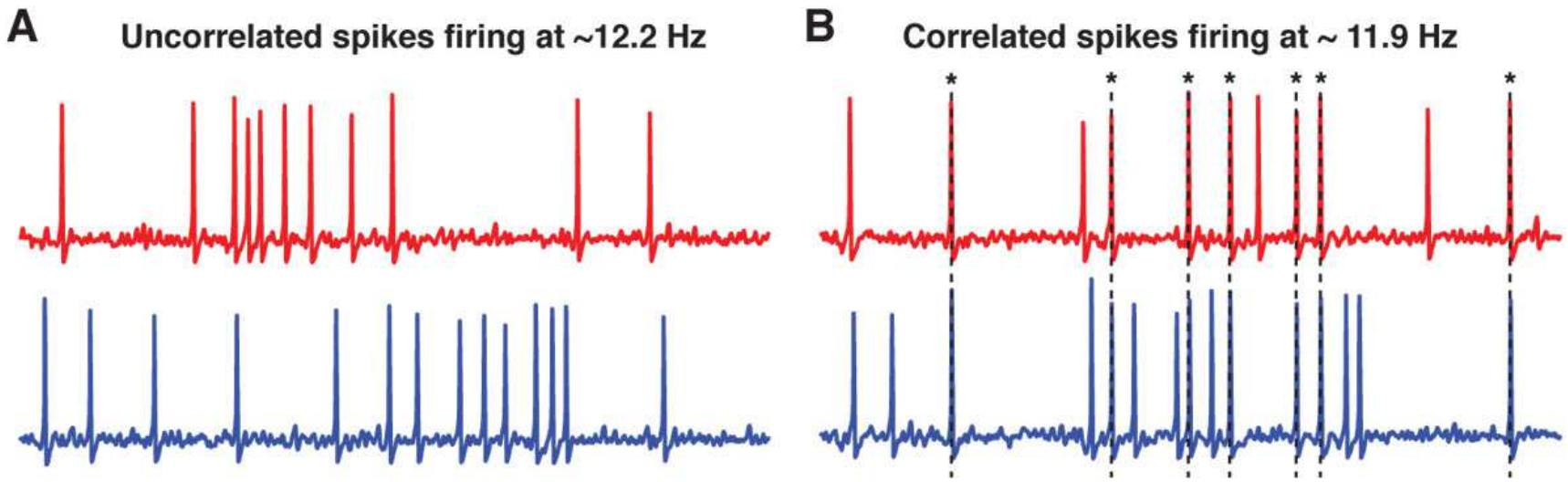
"the probability that a synapse fails to release neurotransmitter in response to an incoming signal is remarkably high, between 0.5 and 0.9"

S. B. Laughlin and T. J. Sejnowski, "Communication in neuronal networks", *Science*, vol. 301, n° 5641, pp. 1870-1874, Sept. 2003.

Confronting weighted models and biological facts

deletion (failure) + insertion (noise) too intrusive
to "confide information" to synaptic weights

the prevailing theory: assembly coding and correlation



Cerebral Shannon's model

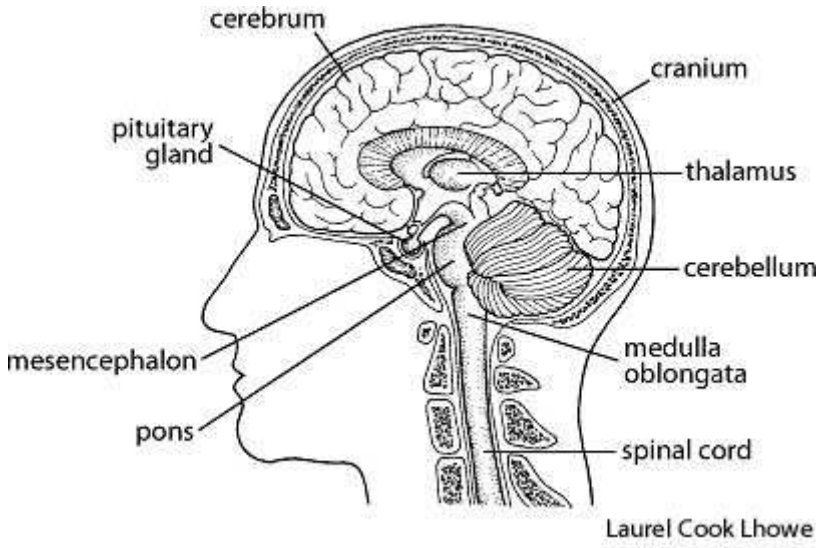
Nervous information

Mental information

Physical world → Source coding → Channel coding → Mental world

richly detailed

fleeting



parsimonious

robust

durable

Mental information is robust and durable, therefore must be redundantly memorized.

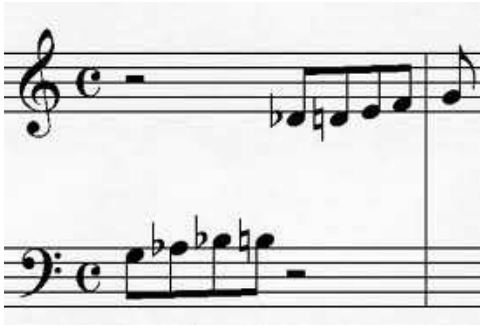
We are interested in

« Pure mental information »

02 29 00 13 06

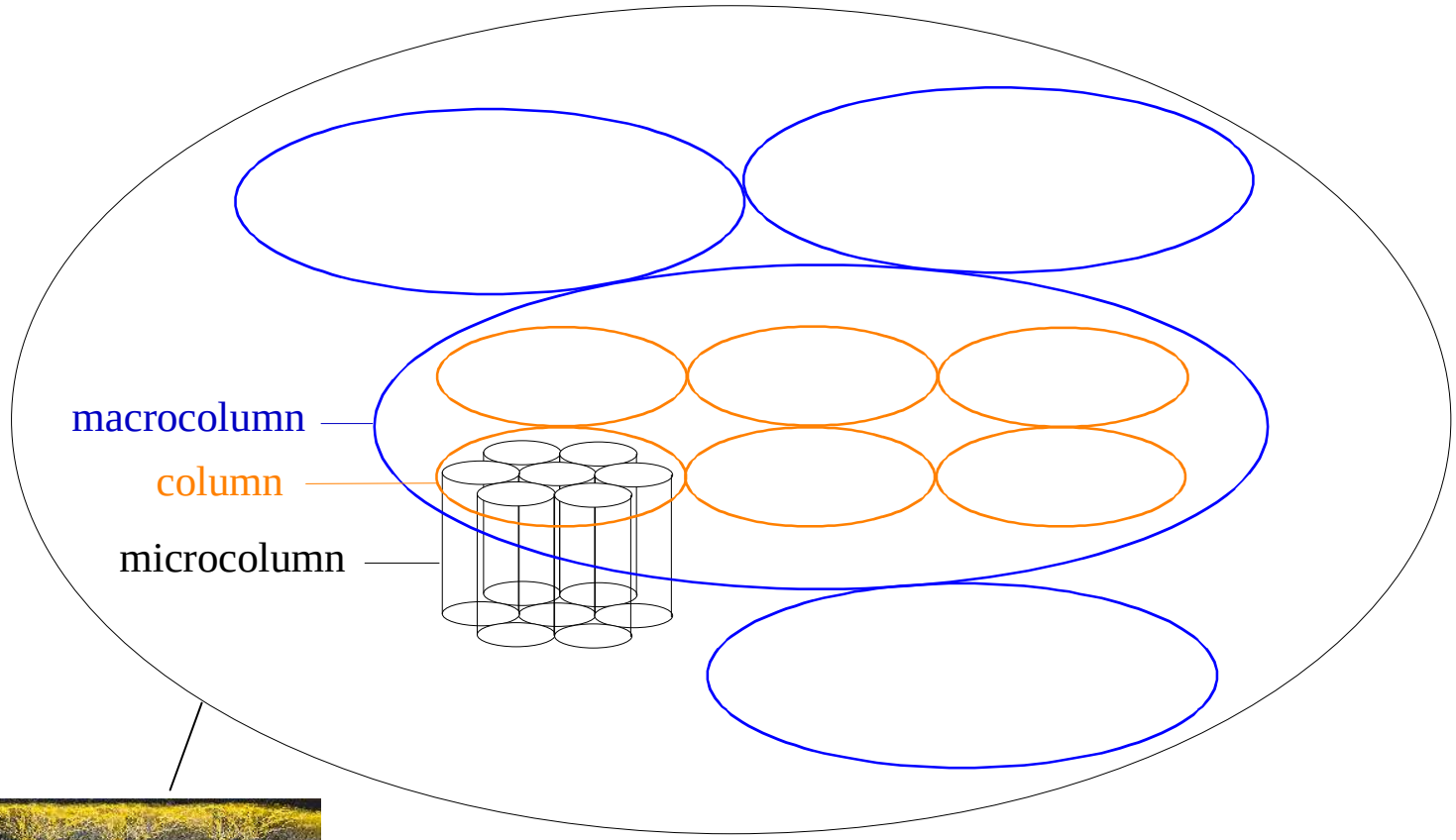
9x8 = 72

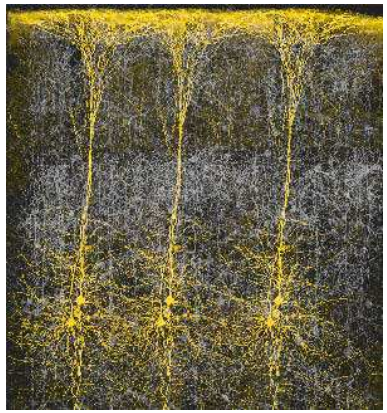
« It so happens I am sick of being a man… »



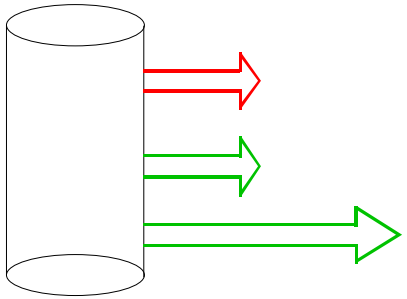
$$H = -\sum_{i=1}^{n} p_i \log_2(p_i)$$

Functional area of the cerebral cortex





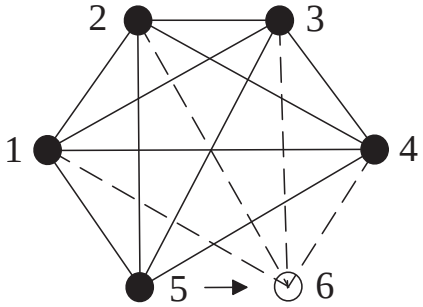
=



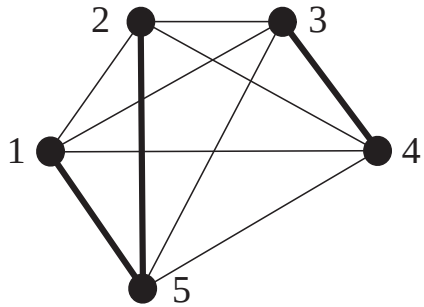
What is the code?

grandmother cell (symbol: node) vs. assembly coding (symbol: edge)

(repetition code)



(a)



(b)

$d_{\min} = c$

$R = \frac{1}{c}$

$F = Rd_{\min} = 1$

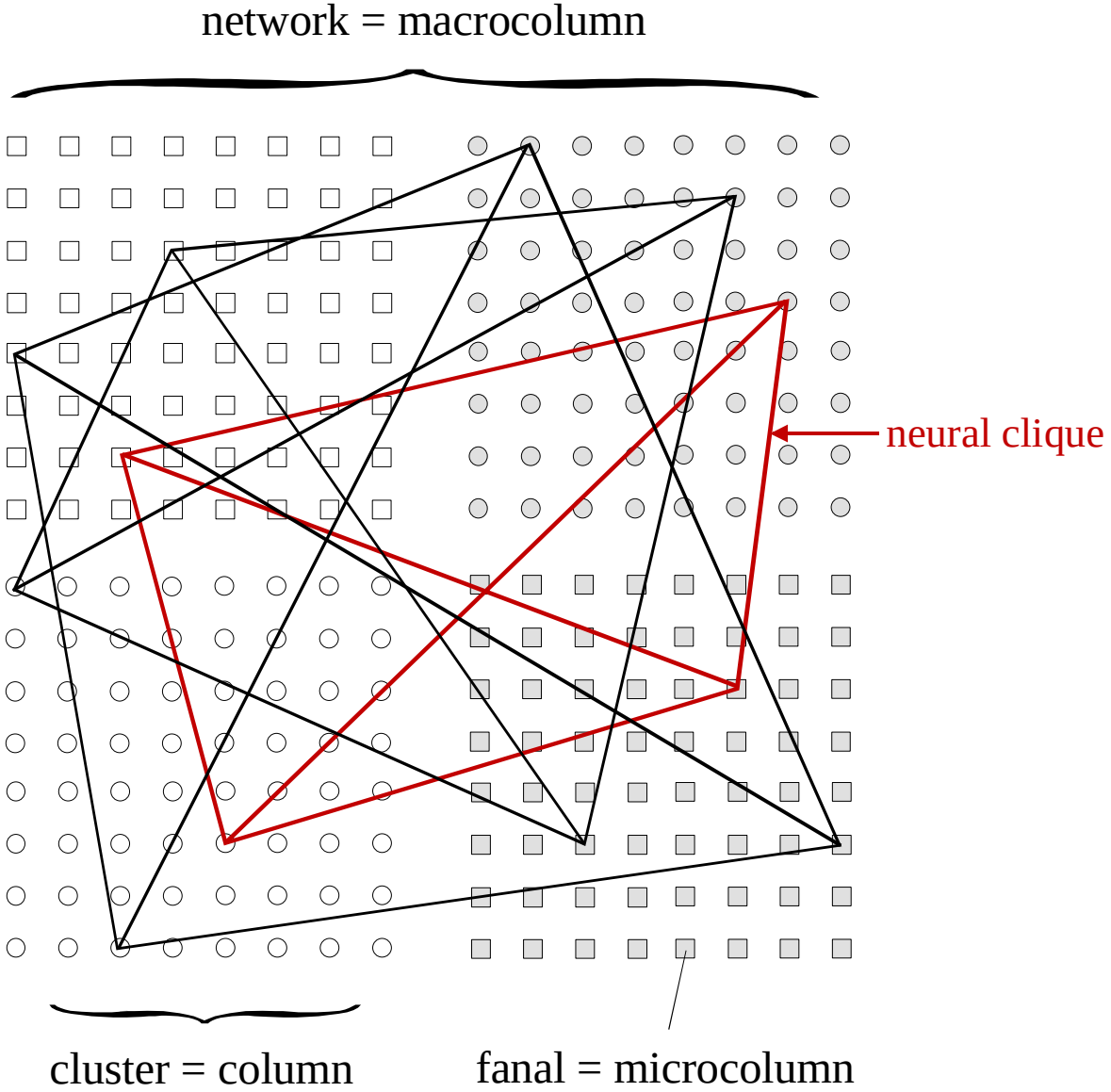
c nodes:

$d_{\min} = 2(c-1)$

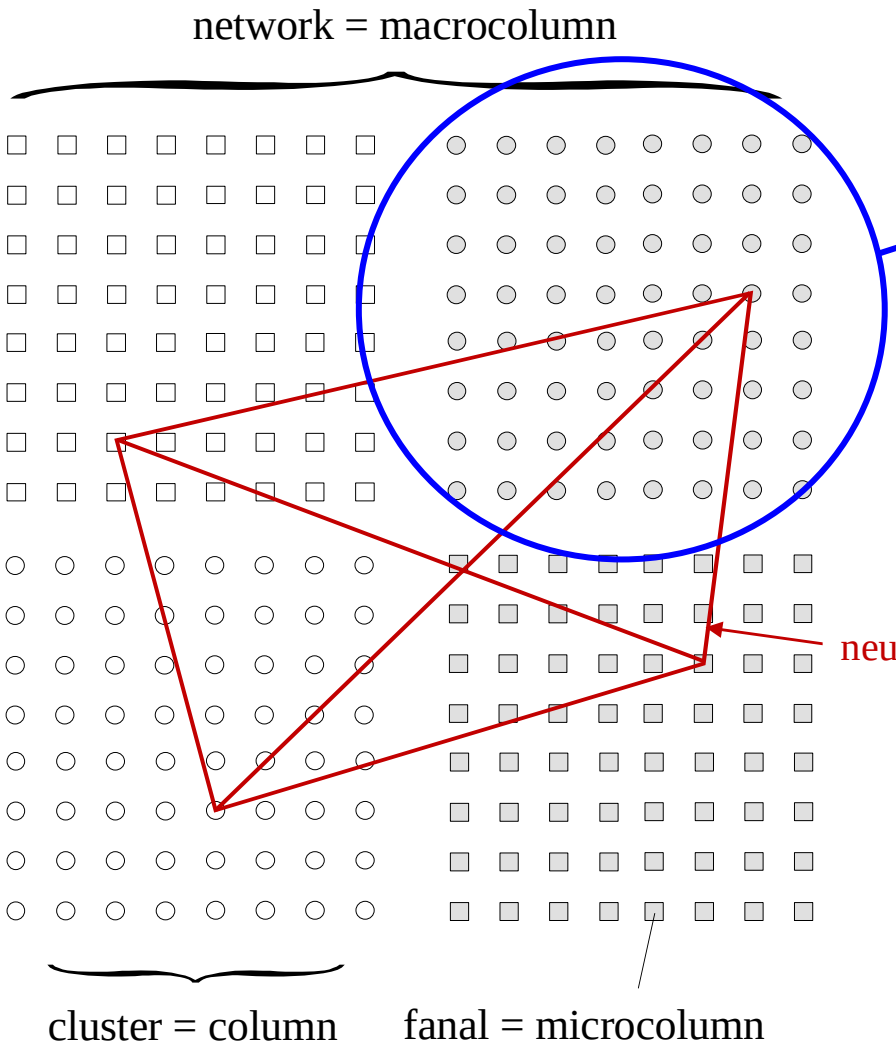
$$R = \frac{\left\lfloor \frac{c+1}{2} \right\rfloor}{\frac{c(c-1)}{2}} = \frac{1}{c-1} \quad (\text{for } c \text{ even})$$

$F = Rd_{\min} = 2$

In order to control the cliques, the graph is structured according to the neocortical architecture



Concatenation of simple and thrifty codes



a constant-weight code(*) with length l and weight $w = 1$

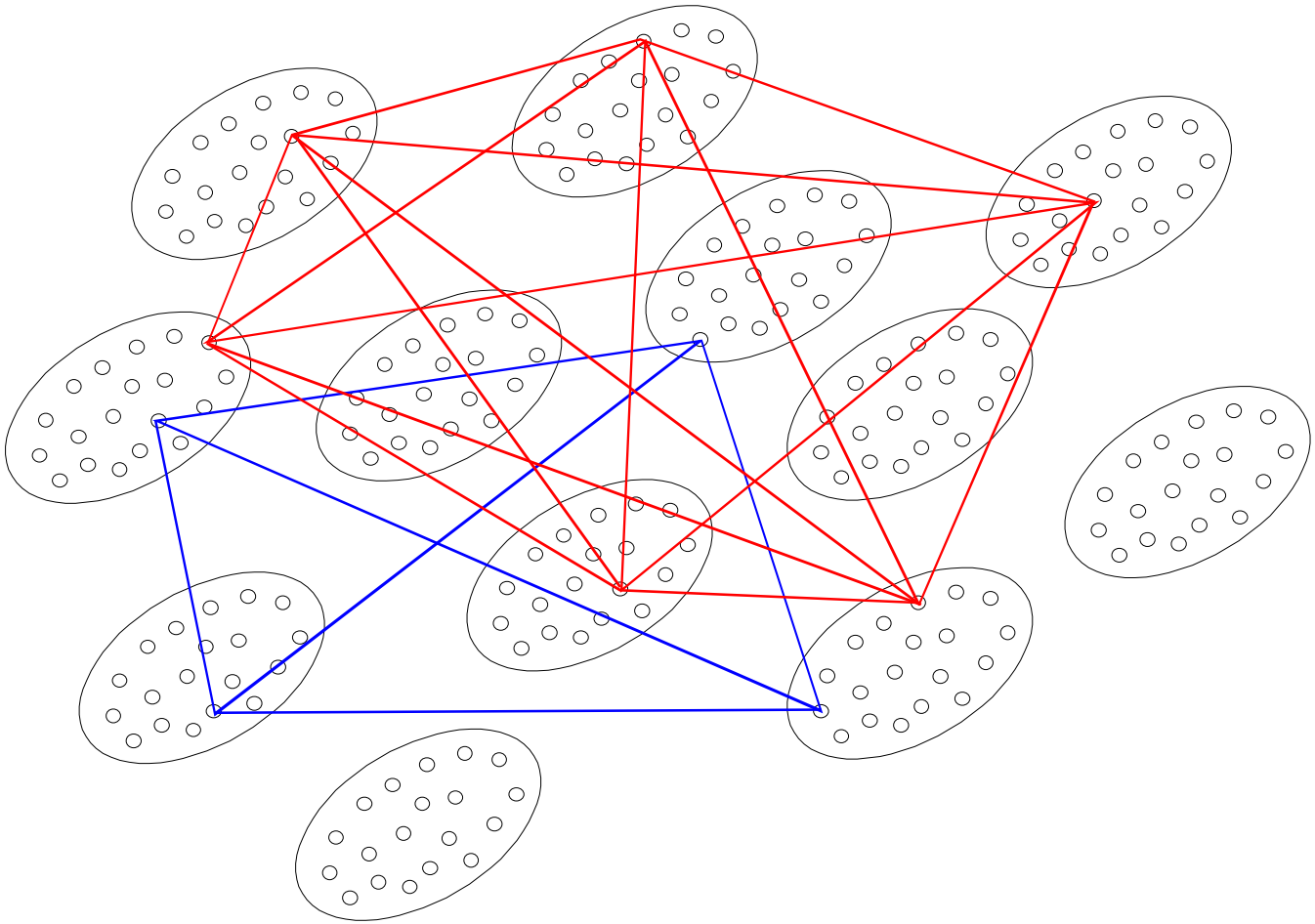
$k = \log_2(l)$ bits $\Rightarrow$

$R = \log_2(l)/l$

$d_{min} = 2$ only but easy to decode according to the *winner-take-all* (WTA) rule (max function)

(*) F. J. MacWilliams and N. J. A. Sloane, *The theory of error-correcting codes*, pp. 526-527, North-Holland, 1979.

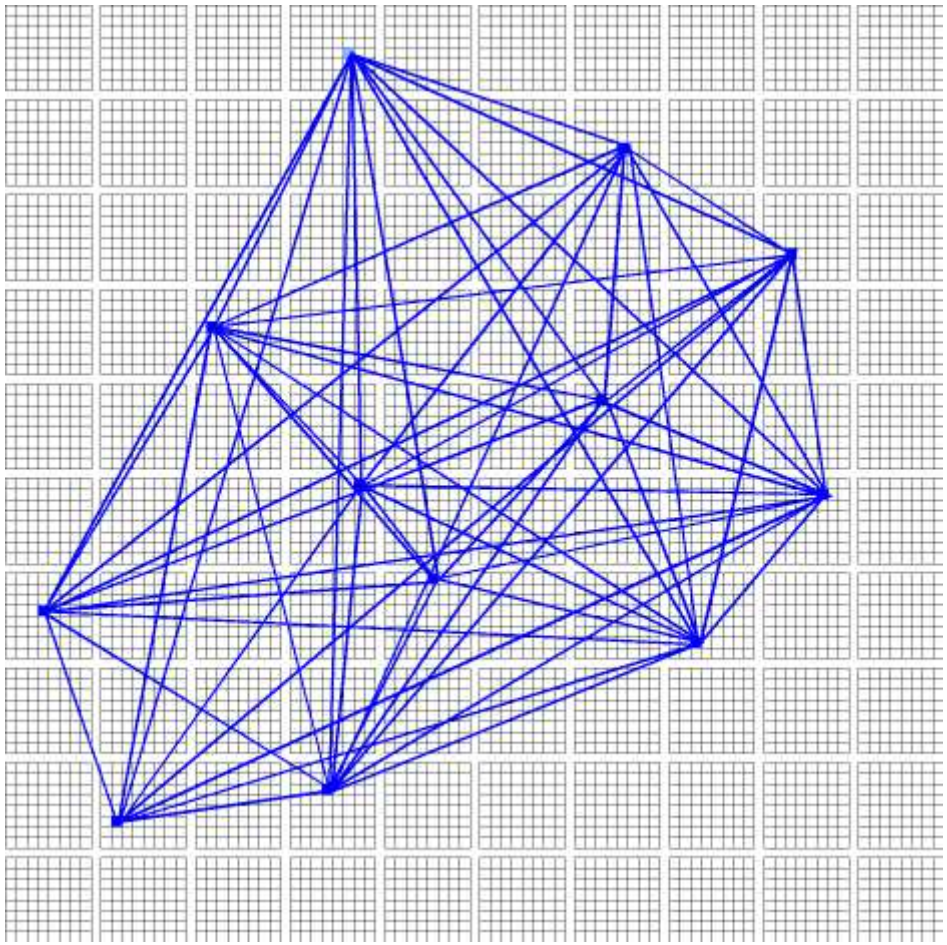
Sparse messages



M proportional to n^2

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, May 2014

Sparse messages in a cortical macrocolumn

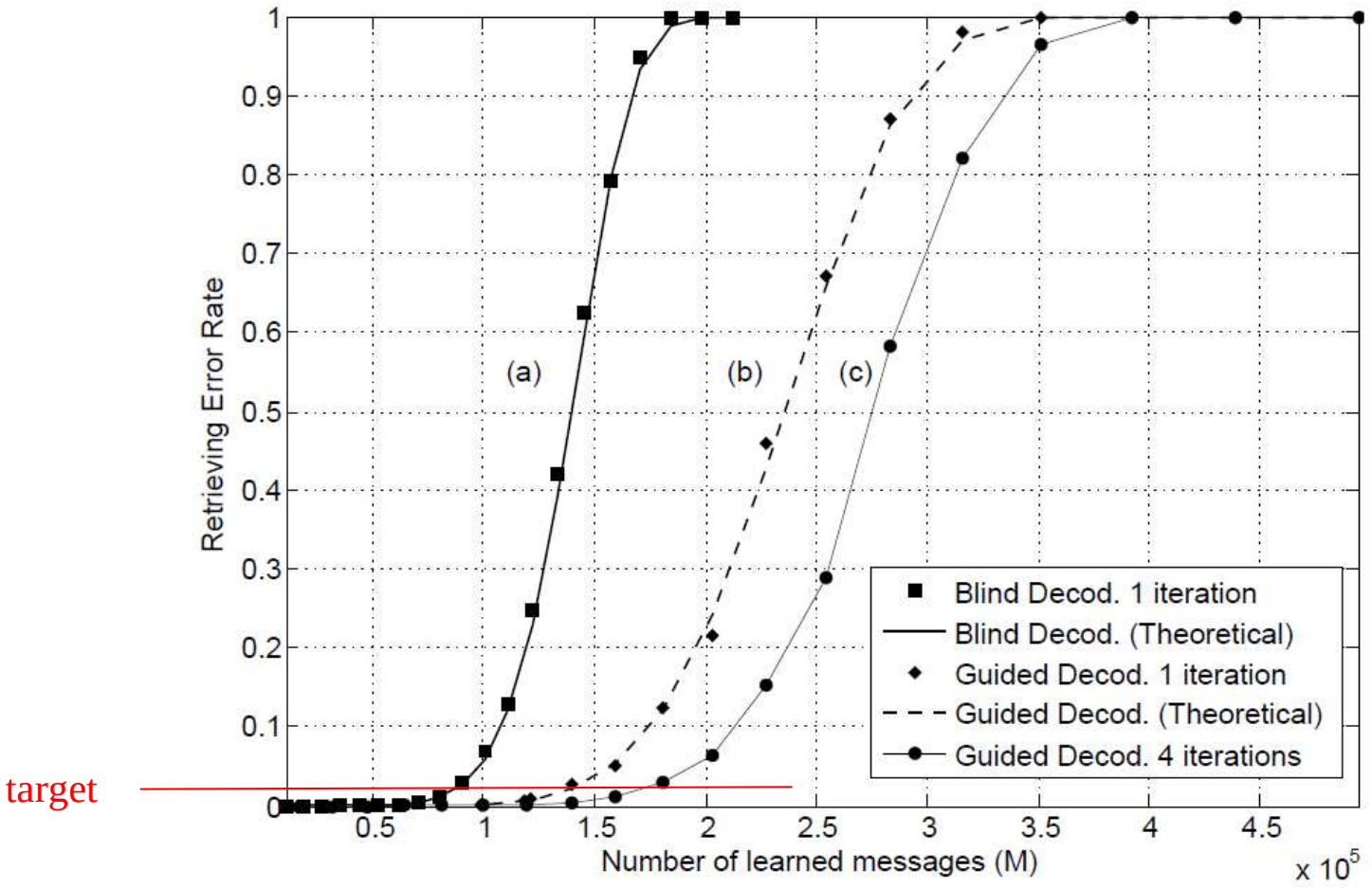


100 clusters of 64 fanals (microcolums) each: about 10^{-5} x human cortex

Cliques with $c = 12$ vertices

about 10^{5} possible messages

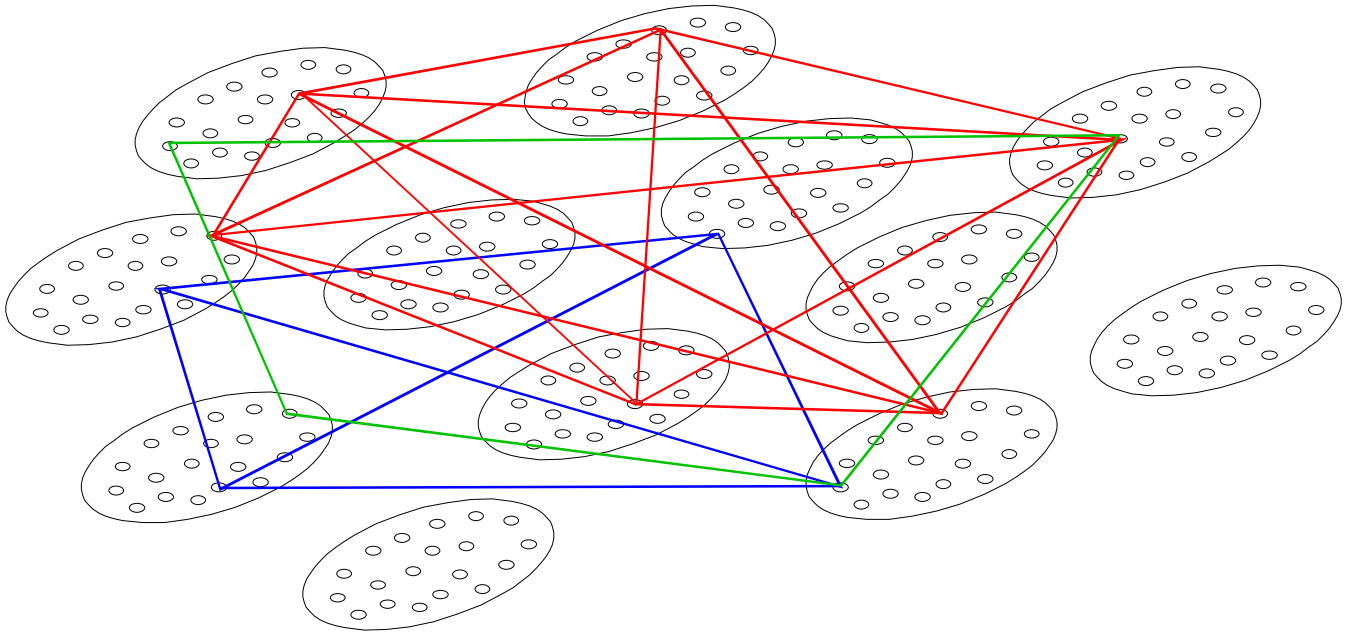
Sparse messages in a cortical macrocolumn



100 clusters of 64 fanals each. Cliques with order 12.

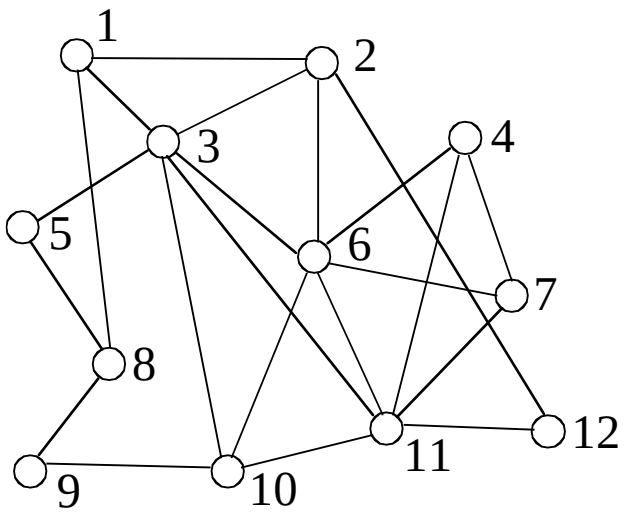
3 clusters have no initial information

The concept of assembly coding raises fundamental questions such as the negation

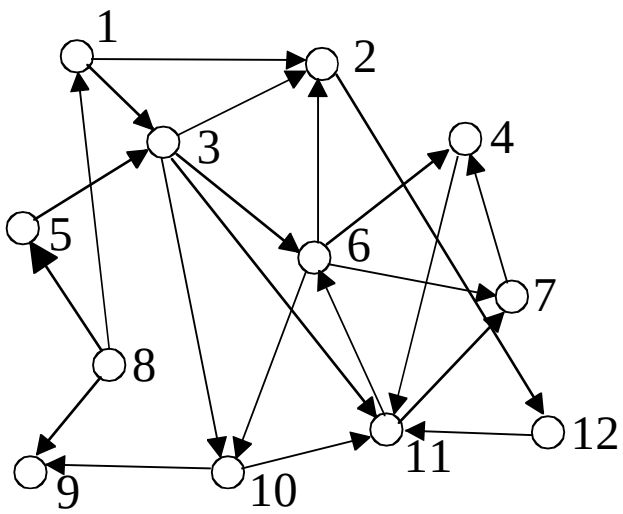


How to validate $\overline{\text{blue}}.\overline{\text{red}}.\text{green}$?

To store sequences instead of atemporal messages: replace cliques with tournaments



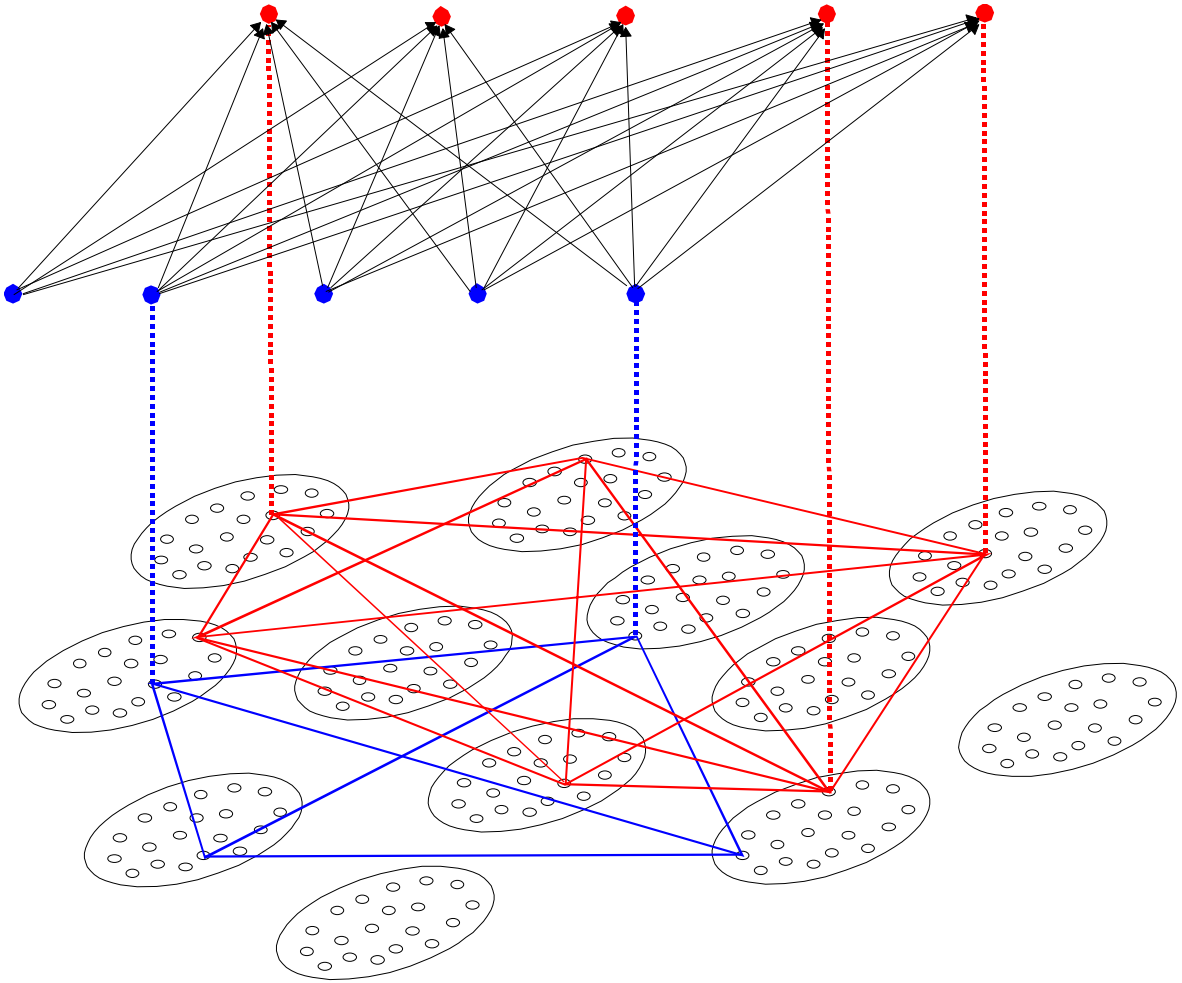
(a)



(b)

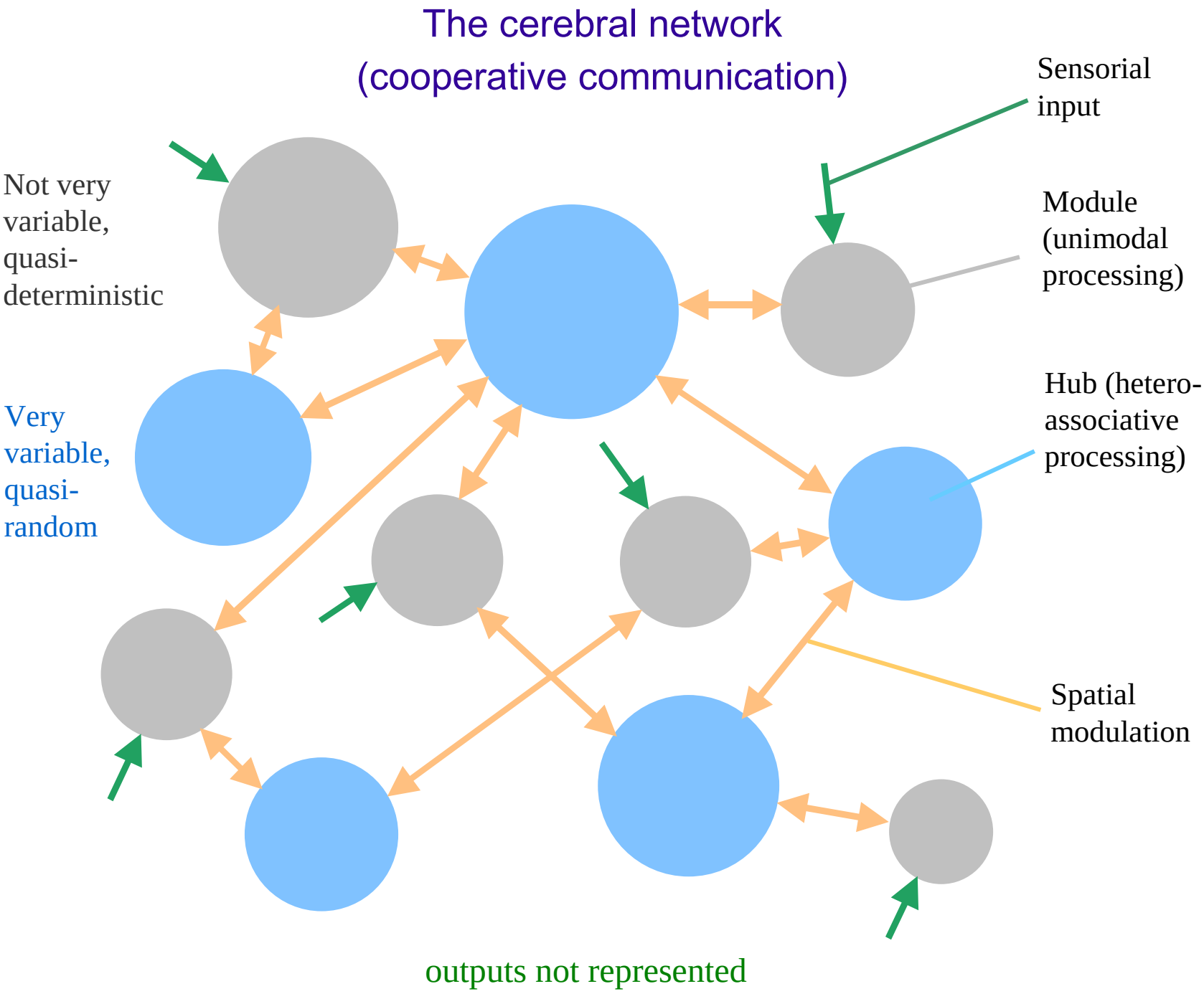
X. Jiang, V. Gripon and C. Berrou, “Learning long sequences in binary neural networks,” *Proc. of Cognitive 2012*, Nice, France, July 2012

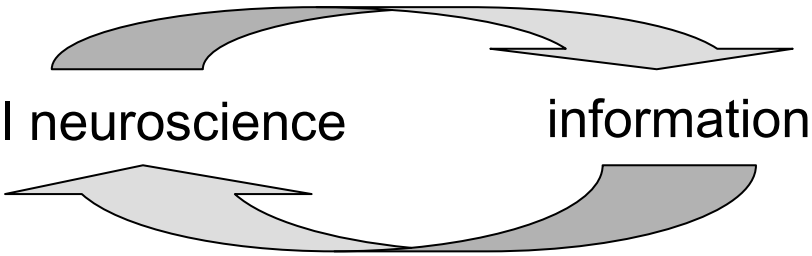
The dynamics of local networks



Tournaments

Cliques


The cerebral network
(cooperative communication)
Sensorial input
Module (unimodal processing)
Hub (hetero-associative processing)
Spatial modulation
Not very variable, quasi-deterministic
Very variable, quasi-random
outputs not represented

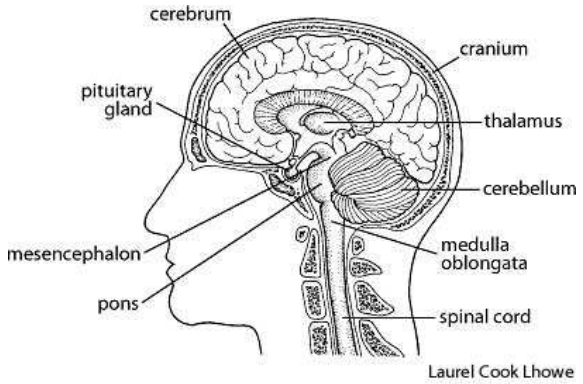


informational neuroscience information theory

a very promising cross-fertilization

Physical world → Source coding → Channel coding → Mental world

Machine learning Networks of cliques and tournaments



ComInLabs LTSI UBO UBS Université de Bretagne-Sud cea leti