NeuroSTIC

Brest

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Signal, donnée, information dans les circuits de nos cerveaux

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European Research Council
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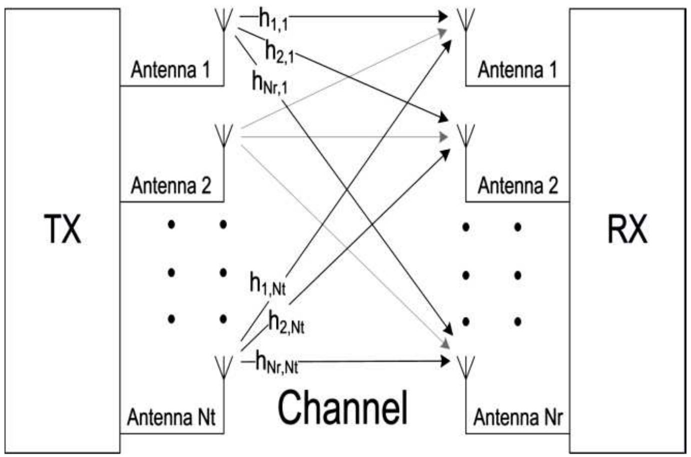
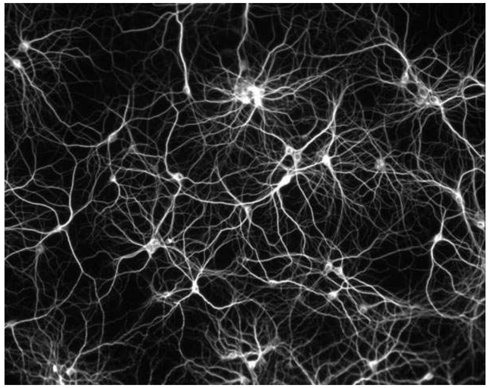
Signal, data, information: in the field of telecommunication, everything is clear

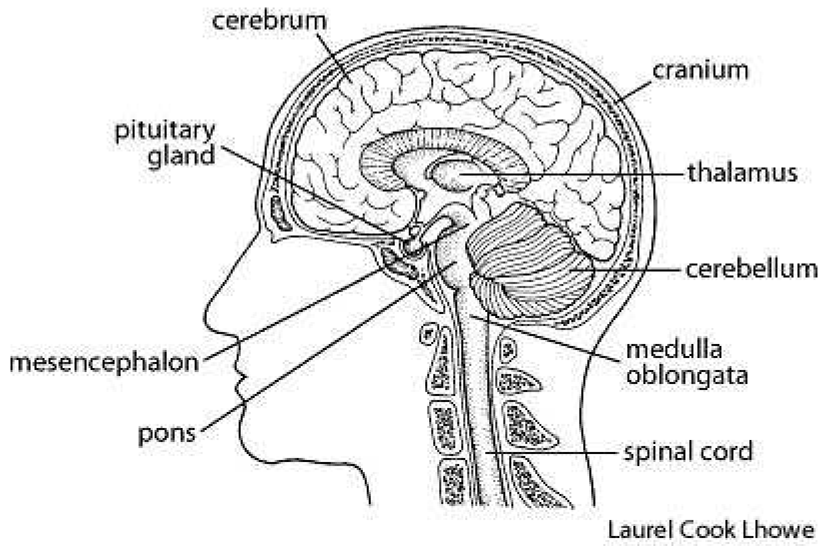


It is much less obvious when it comes to the brain



Linking neuroscience and information/communication theory

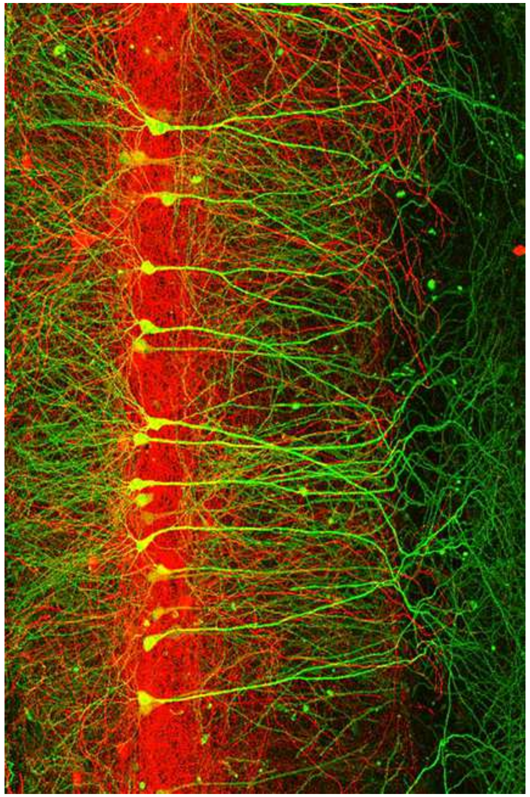
		Nervous information		Mental information		
Richly detailed, fleeting physical world	→	Source coding	→	Channel coding	→	Parsimonious and robust mental world



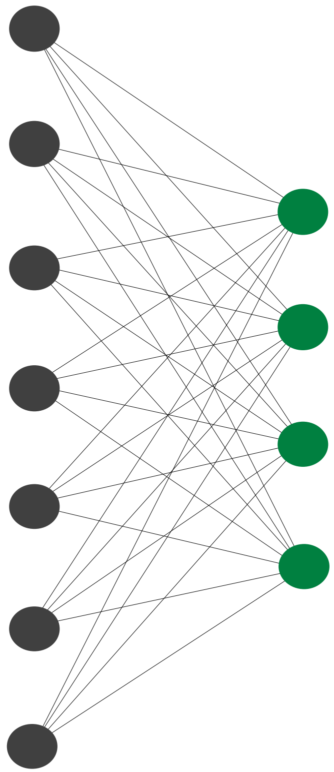
Computational neuroscience

Informational neuroscience

Confronting weighted models and biological facts



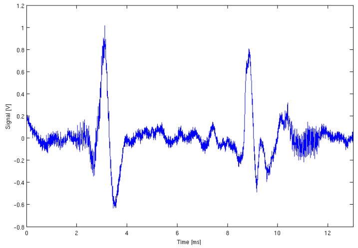
the cortex is the *biological champion*
of vector-matrix products
(Erik Bloss, Janelia Research Campus)

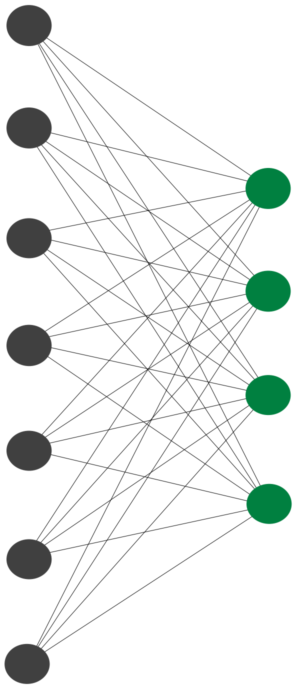


perceptron, convolutional
and deep learning networks,
Hopfield-like, etc.

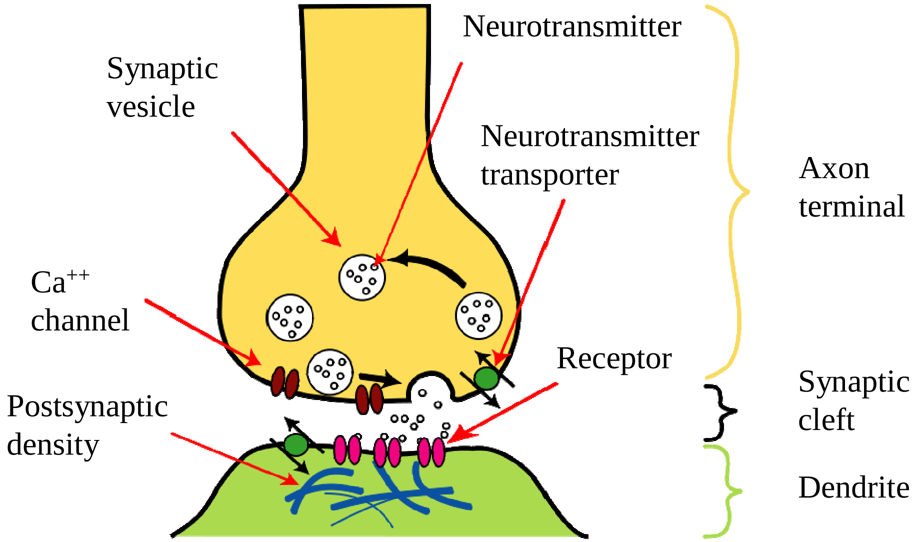
with precisely adjusted weights

Confronting weighted models and biological facts





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

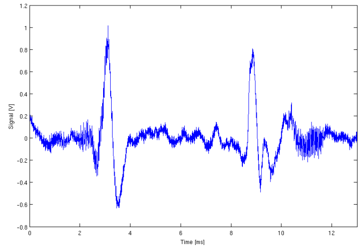


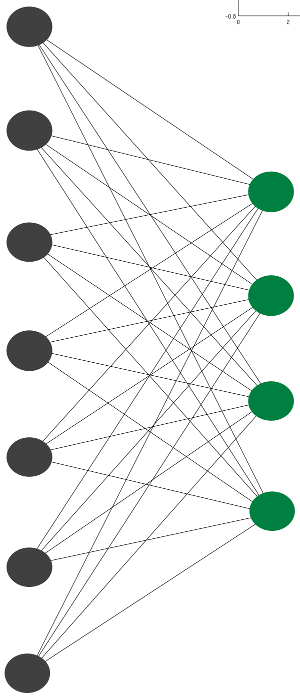
after Wikipedia: "Chemical synapse"

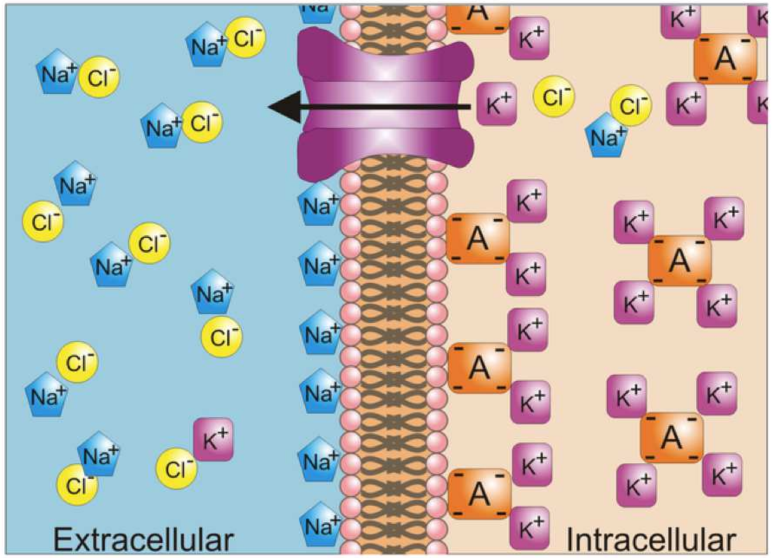
"The probability that a synapse fails to release neurotransmitter in response to an incoming signal is remarkably high, between 0.5 and 0.9"

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







T. Dean, Google Inc.

"The spontaneous firing of spikes accounts for almost 80% of the metabolic energy consumed by the brain"

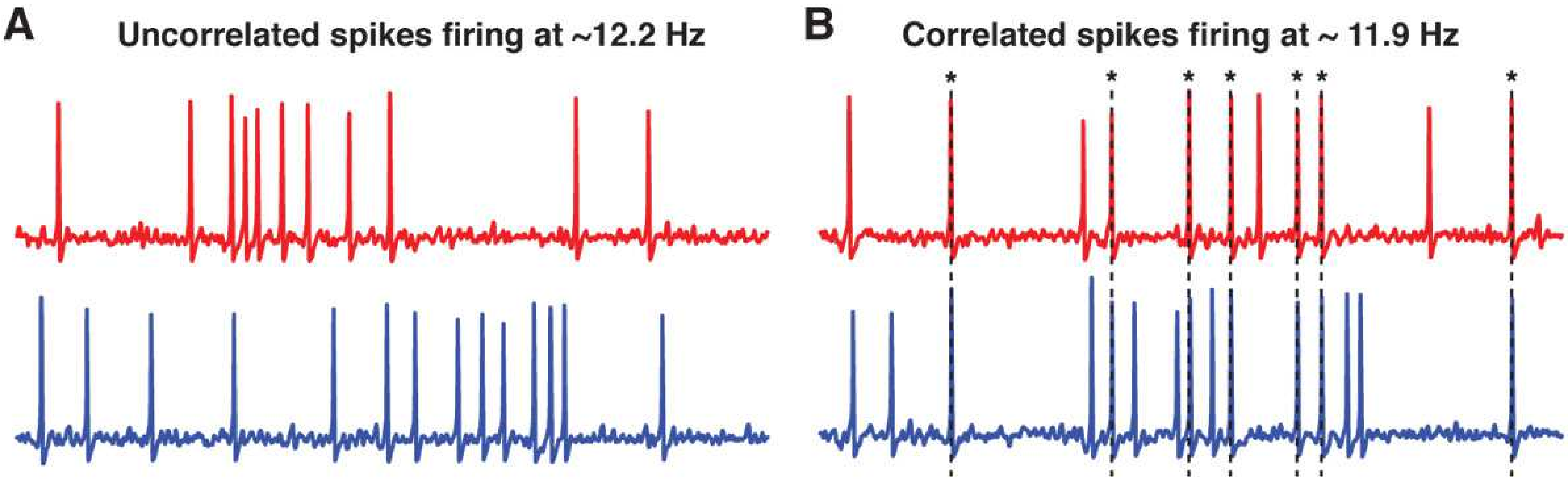
perceptron, convolutional and deep learning networks, Hopfield-like, etc.

A. Mazzoni, F. D. Broccard, E. Garcia-Perez, P. Bonifazi, M. E. Ruaro and V. Torre, "On the dynamics of the spontaneous activity in neuronal networks," PLoS ONE, 2(5): e439, May 2007.

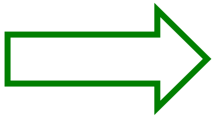
Confronting weighted models and biological facts

1. Deletion (failure) + insertion (noise) too intense to "entrust information" to synaptic weights
2. The redundancy rates of the "neural code" have to be very high to adapt to such bad running conditions
3. But no algebra in the brain!

the prevailing theory: assembly coding and correlation



(Okinawa Institute of Science and Technology)



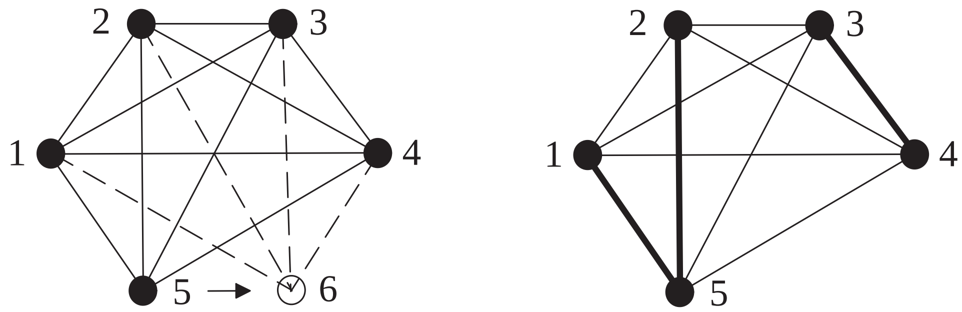
distributed coding

Grandmother cell vs. Assembly coding

grandmother cell vs. assembly coding (clique)

(symbol: node) (symbol: edge)

(repetition code)



(a) (b)

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

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

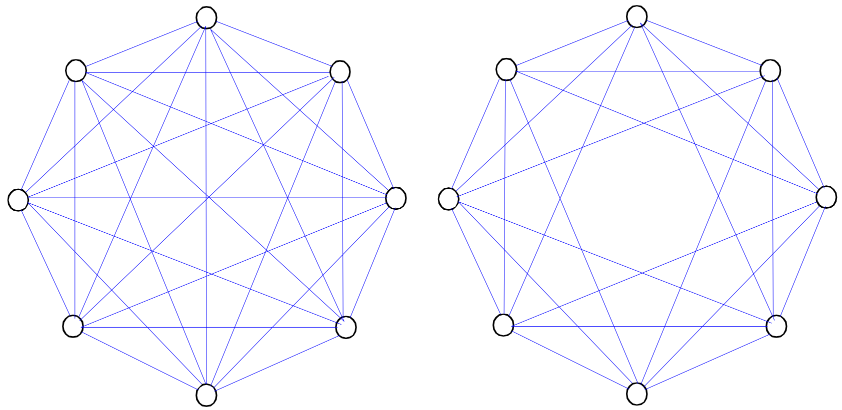
$$R = \frac{\left\lfloor \frac{c+1}{2} \right\rfloor}{\frac{c(c-1)}{2}} = \frac{1}{c-1} \quad \text{(for } c \text{ even)}$$

$$\boxed{F = Rd_{\min} = 2}$$

$$\boxed{F = Rd_{\min} = 2}$$

without possible overlapping $\qquad$ with overlapping

Degenerated cliques



(a) (b)

node degree $\alpha = 7$ $\alpha = 6$

$$d_{\min} = 2\alpha$$

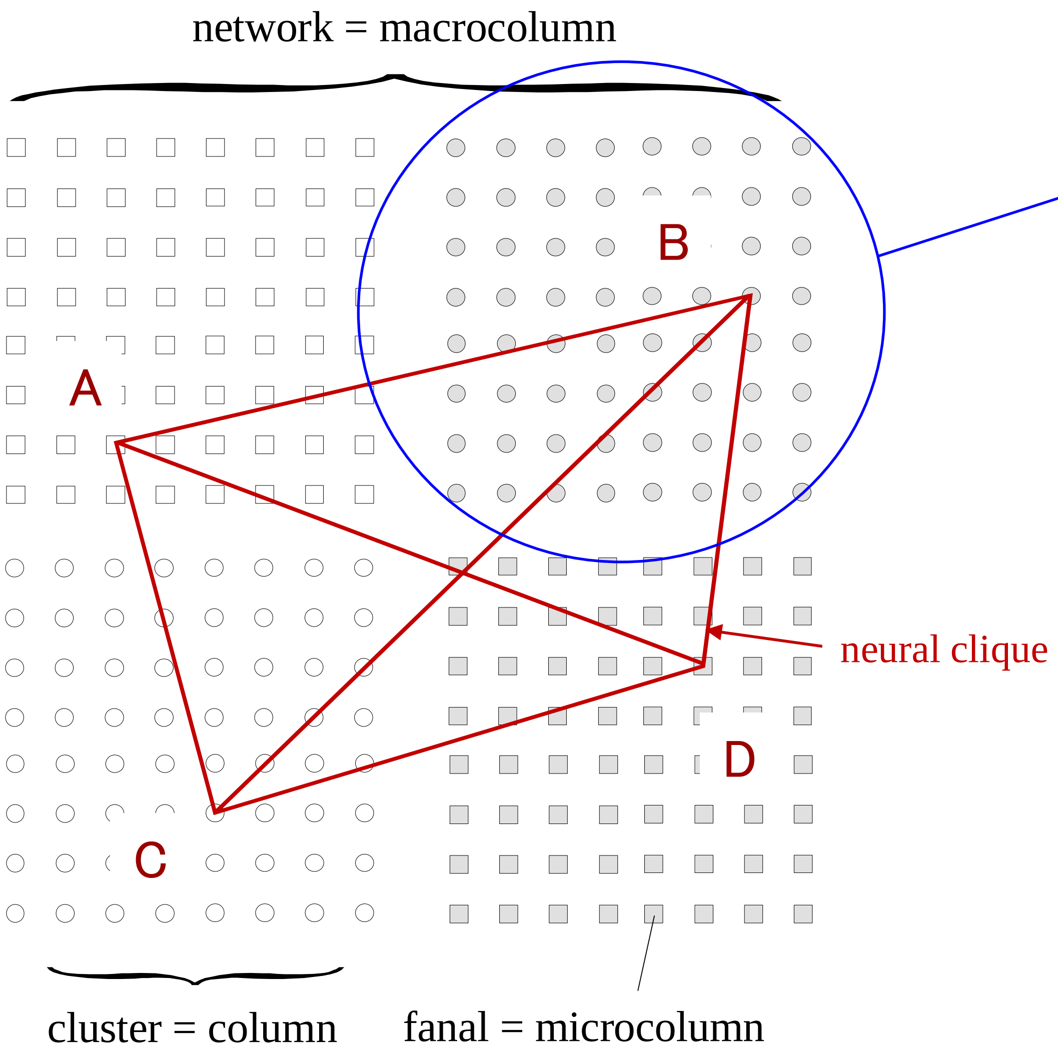
$$R = \frac{\left\lfloor \frac{c+1}{2} \right\rfloor}{\frac{\alpha c}{2}} = \frac{1}{\alpha} \quad \text{(for } c \text{ even)}$$

$$\boxed{F = R d_{\min} = 2}$$

again!

Robust, not demanding, resilient (through the Hebb's rule)

Concatenation of simple and thrifty codes



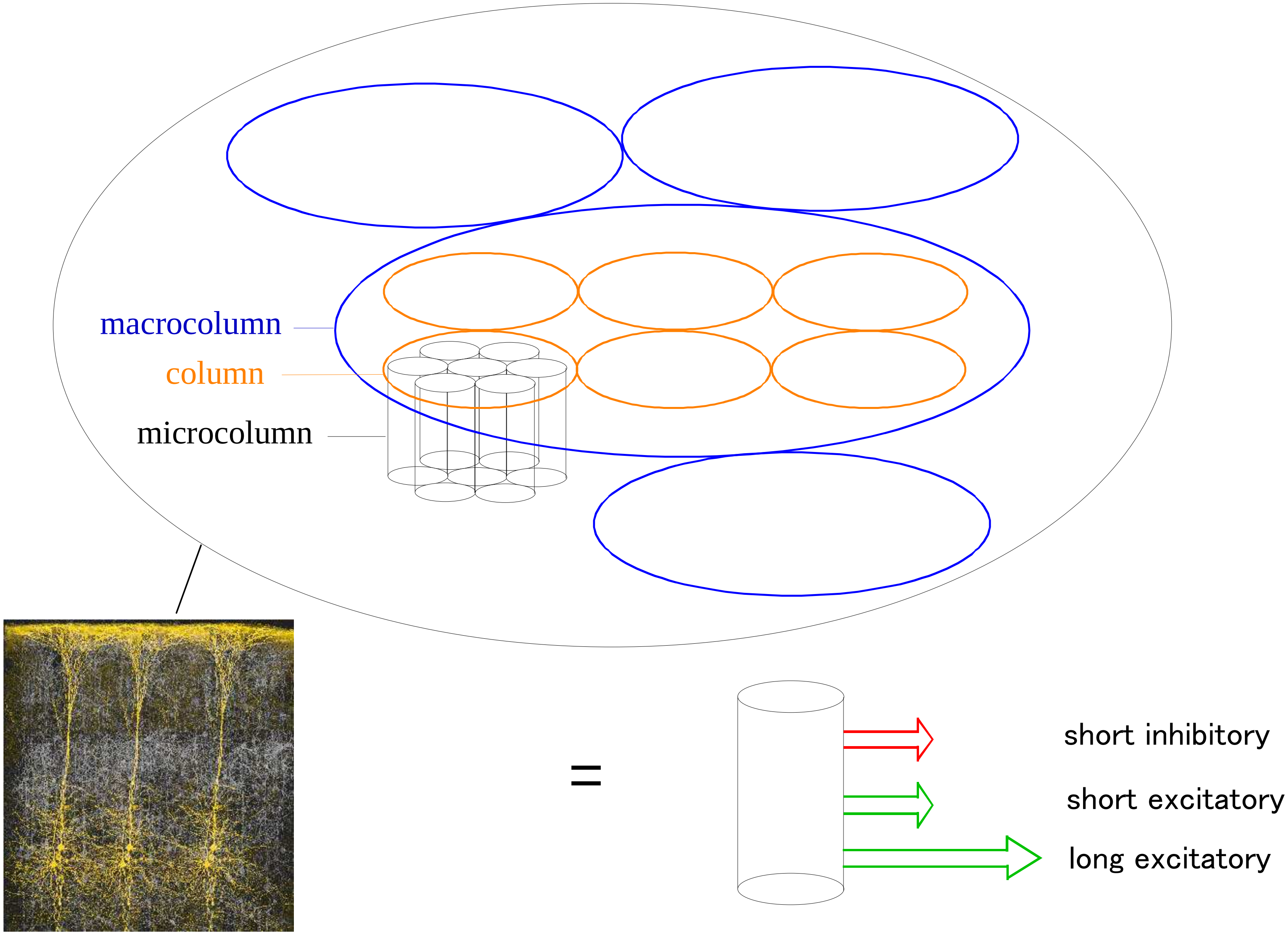
A constant-weight local code with length l and weight $w = 1$

$k = \log_2(l)$ bits with minimal energy (On-Off keying)

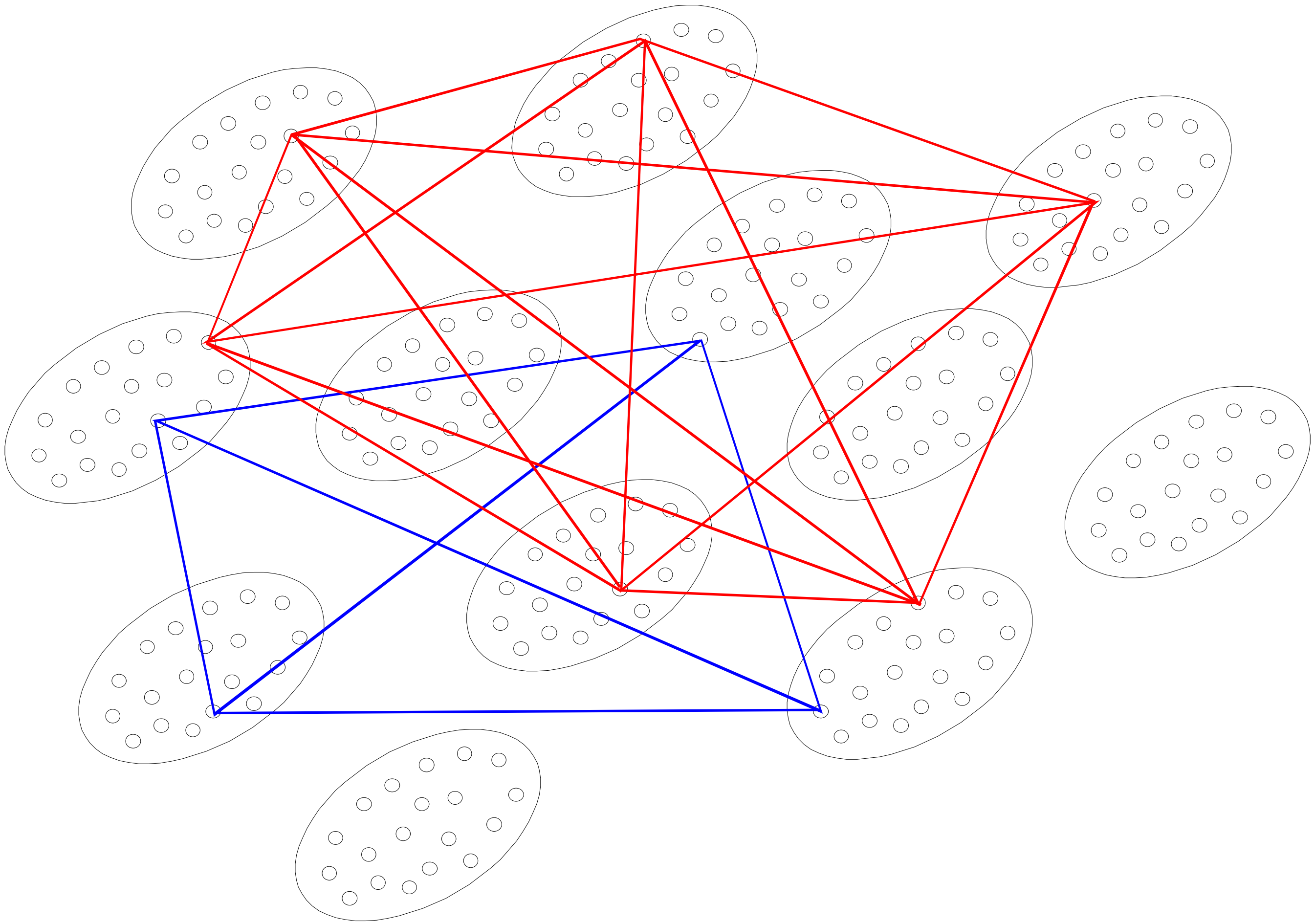
$d_{min} = 2$ only but easy to decode according to the *winner-take-all* (WTA) rule (max function)

Global decoding rely on correlation

Functional area of the cerebral cortex



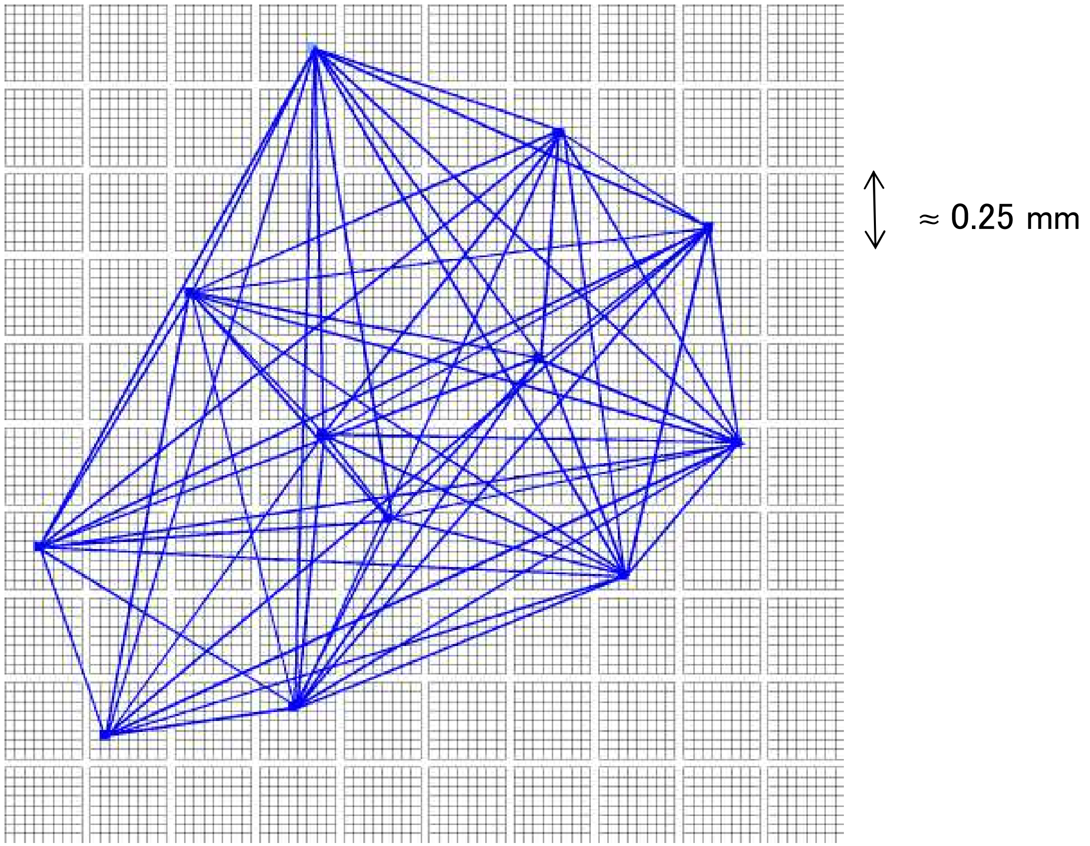
Sparse messages in a cortical macrocolumn



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, pp. 980-989, May 2014

Sparse messages in a cortical macrocolumn



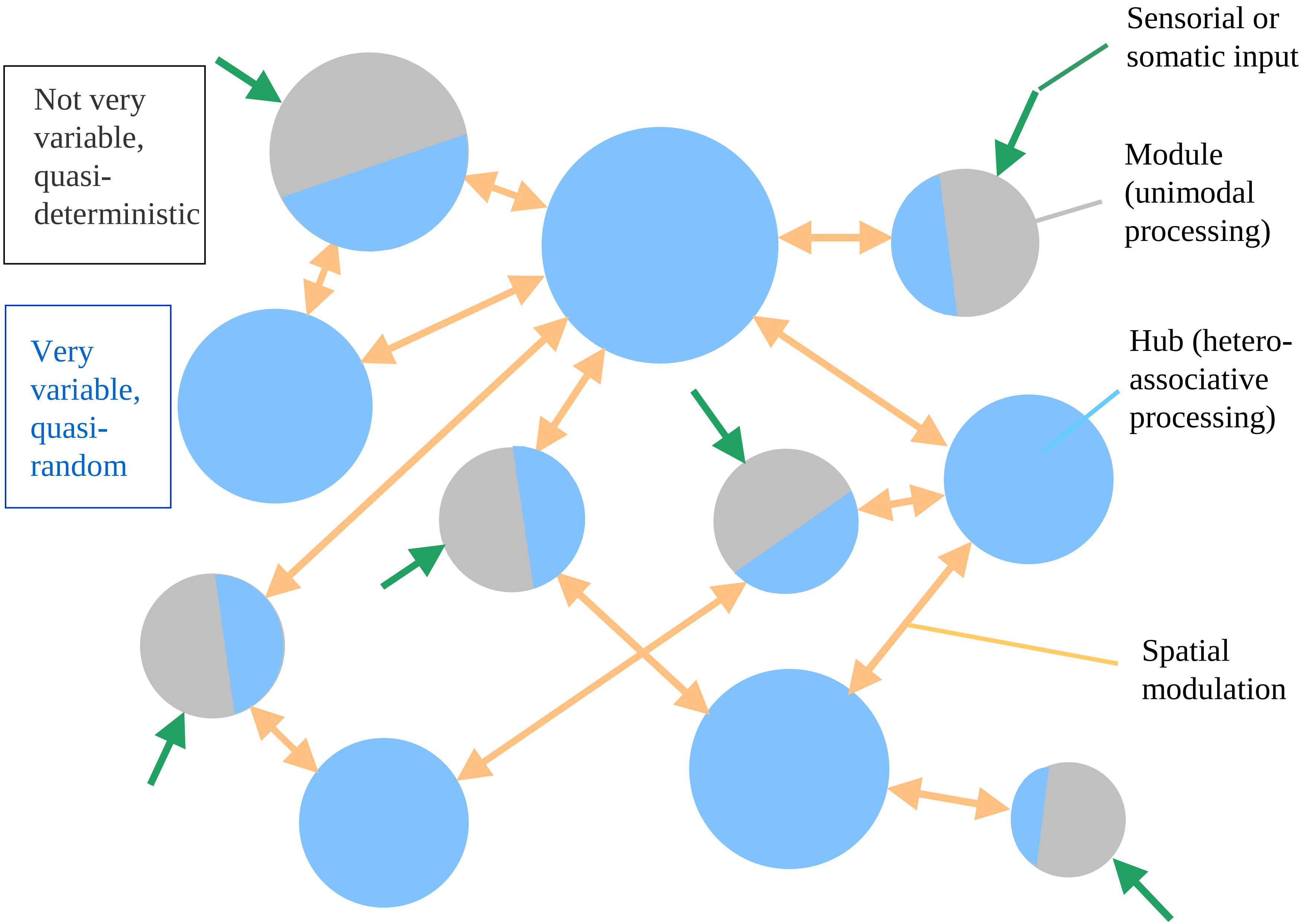
100 clusters of 64 microcolums each: around 10^{-5} x human cortex

Cliques with c = 12 vertices

about 10^5 possible messages

Cliques make sense at local scale only

The cerebral network

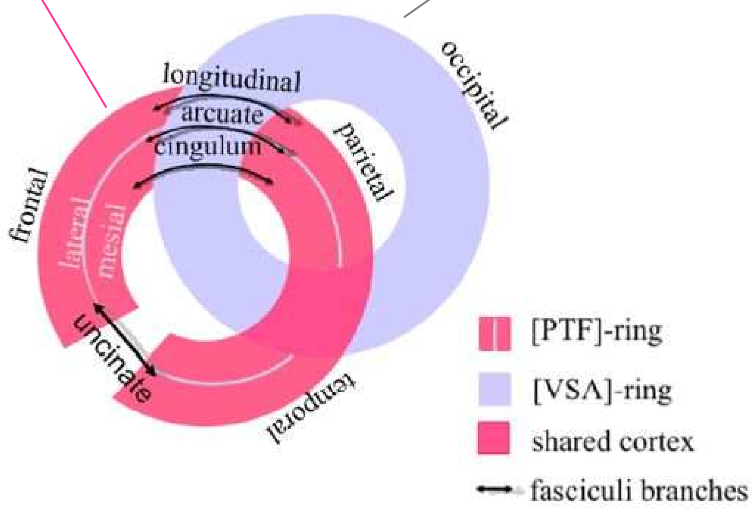


outputs not represented

The two rings

Slow ionic channels

Swift ionic channels



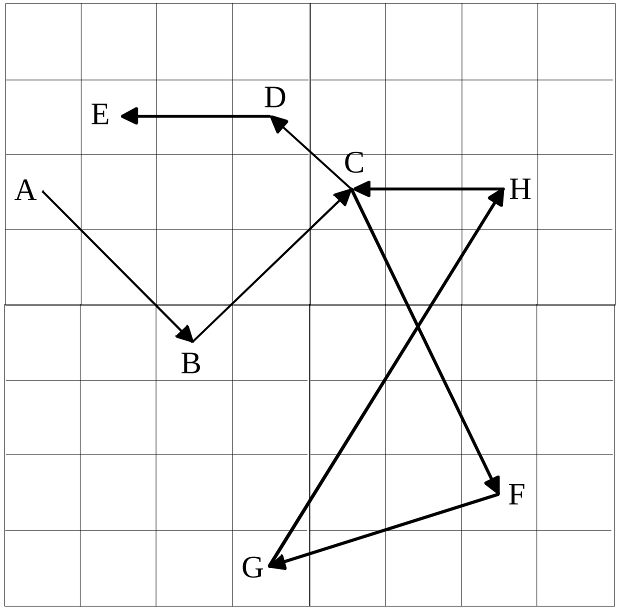
PTF: parietal, temporal, frontal

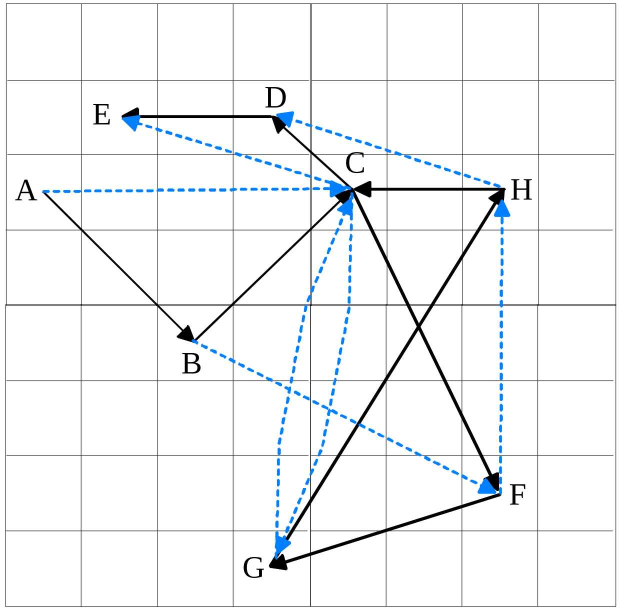
VSA: visual, somatic, auditory

« Resting State Networks' Corticotopy: The Dual Intertwined Rings Architecture »
S. Mesmoudi, V. Perlbarg, D. Rudrauf1, A. Messe, B. Pinsard, D. Hasboun, C. Cioli, G. Marrelec, R. Toro, H. Benali, Y. Burnod
PLoS ONE (2013)

« Differences in Human Cortical Gene Expression Match the Temporal Properties of Large-Scale Functional Networks »
C. Cioli, H. Abdi, D. Beaton, Y. Burnod, S. Mesmoudi
PLoS ONE (2014)

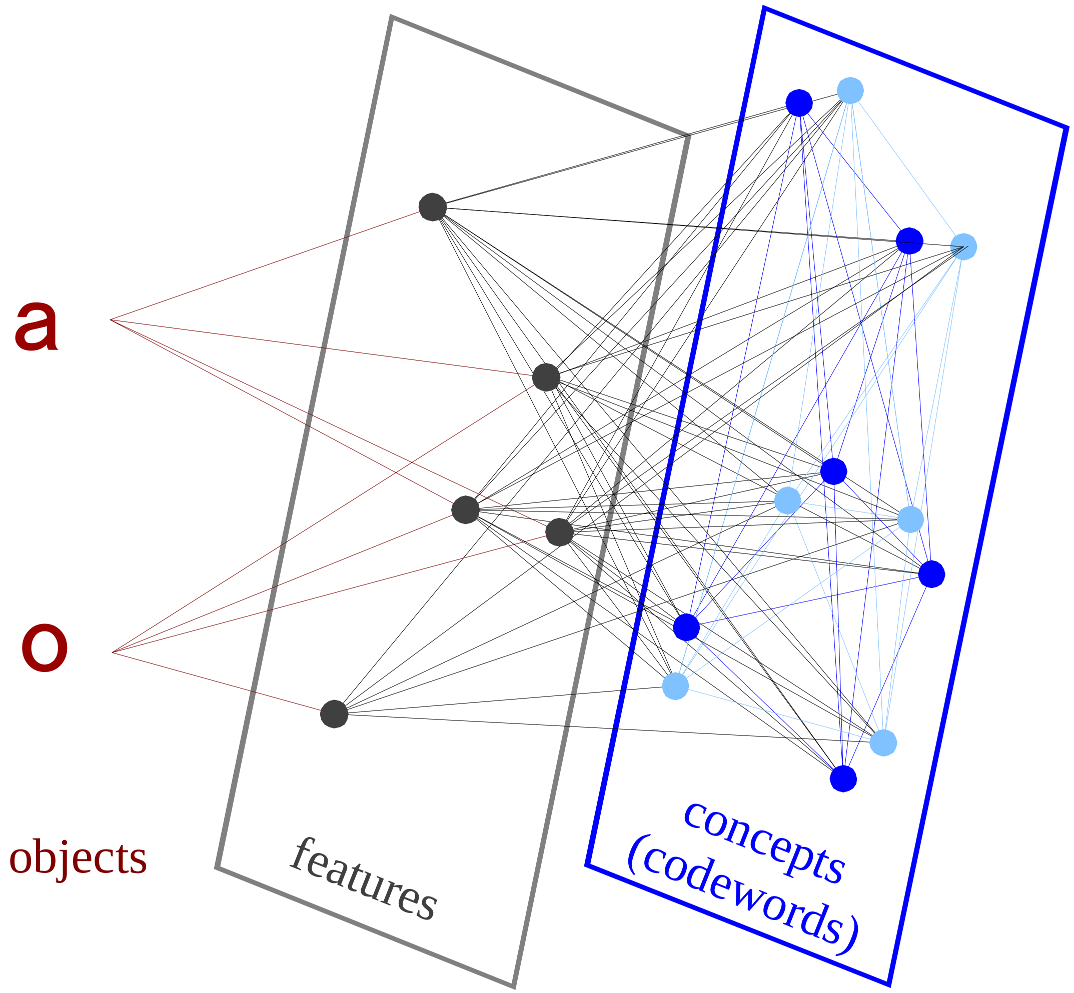
Sequences with anticipation





Temporal redundancy

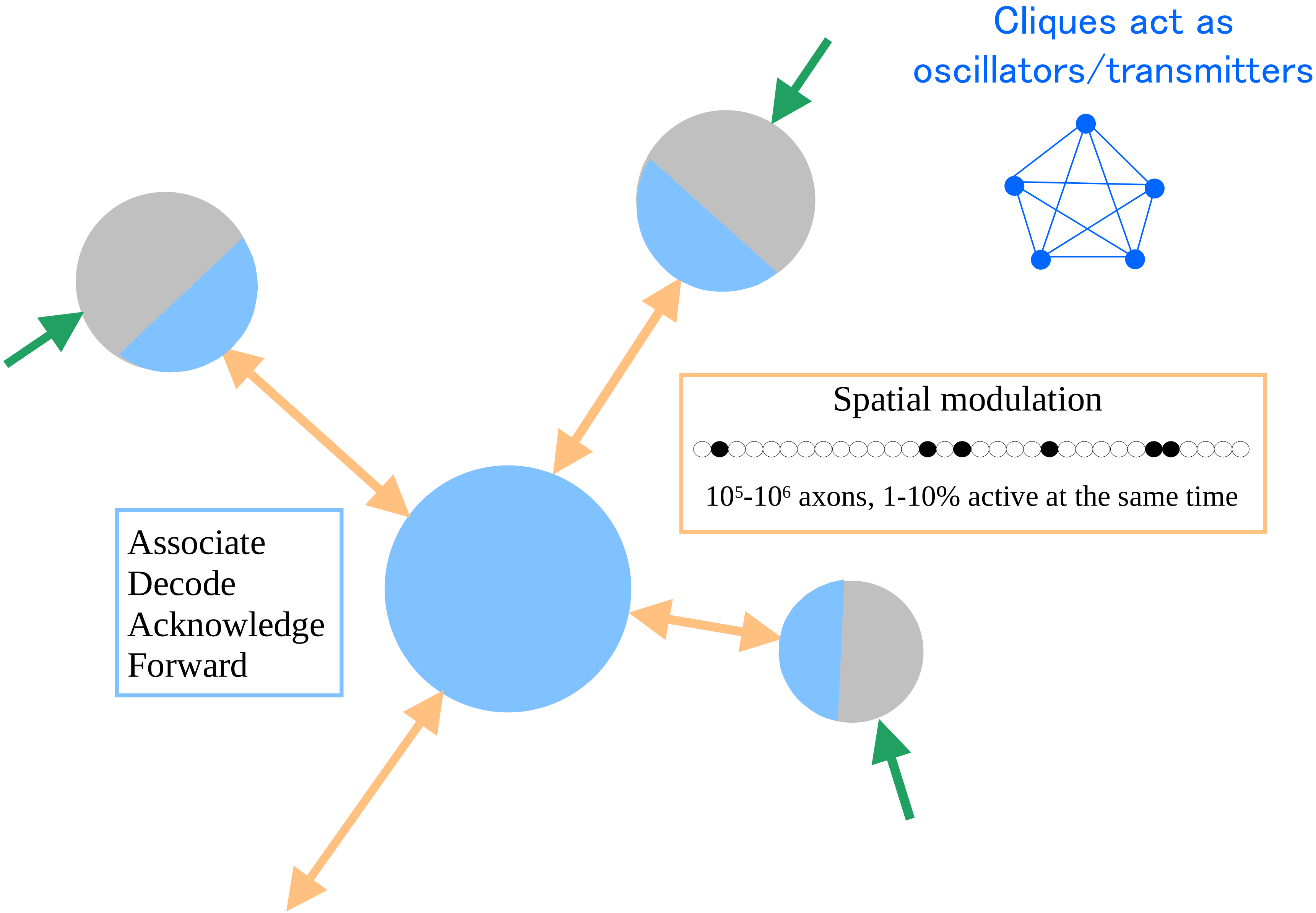
data to information conversion



Source coding
Correlated
assemblies

Channel coding
Random
codewords

The cortical network
(cooperative communication)



To summarize:

Swift cortex and slow cortex have to be definitely distinguished

•At the informational scale, the cortex architecture is not so difficult to imitate (many predefined circuits)

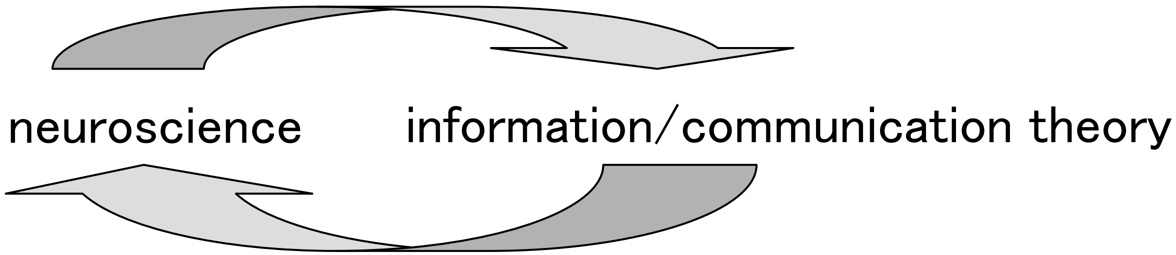
• (almost) available technology

• mixed analog/digital solution with programmable connections in EEPROM associated with high throughput multiplexing

• a considerable number of connections to supervise and to process

• state of the machine tough to look at and understand

• notions of relevance, curiosity, intentionality, etc. to model



Reverse engineering of the brain for genuine artificial intelligence:

a vast work for our community