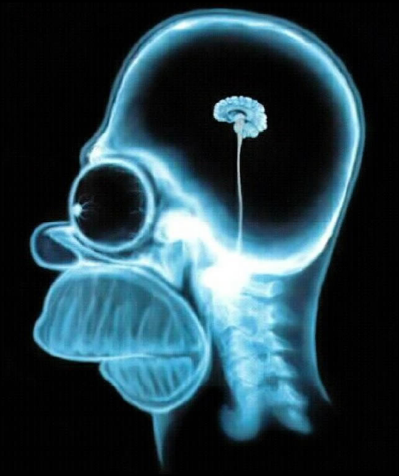
Brain, n. An apparatus with which we think we think



Codes and neural network: Codes over cycles

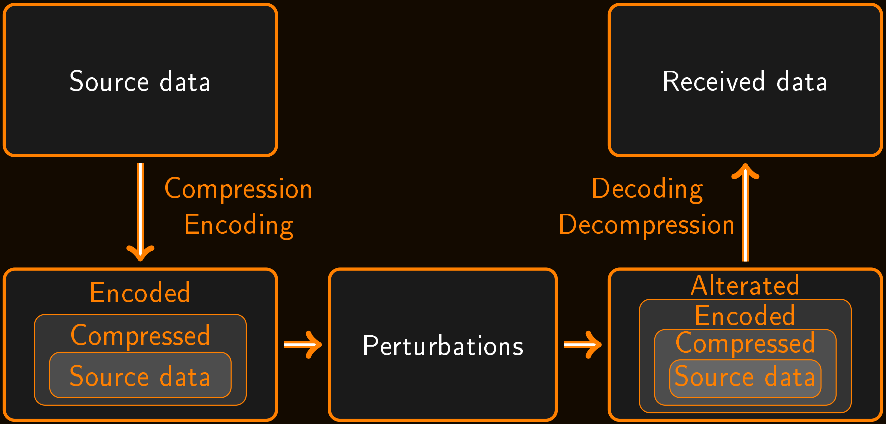
Supervisors: Claude Berrou (Telecom Bretagne), Jean Pierre Nadal (ENS)

Plan

1. Introduction
   - Coding
   - Minimal distance
   - Error correcting capability
2. Brain and coding
   - Information and brain
   - Model
   - Cycles
3. Exemple: choice of the inhibitive neurons model
   - Codes over cycles
   - Inhibitive types
   - Results

Coding

How-to?



Minimal distance

definition

- $d_{min} = \min_{word, word'} d(word, word')$

Error correcting capability

Definition

- $t = \max \left(R \mid \forall word, \forall w', d(word, w') \leq R \Rightarrow decode(w') = word \right)$.

In good cases

- $t = \left\lfloor \frac{d_{min} - 1}{2} \right\rfloor$.

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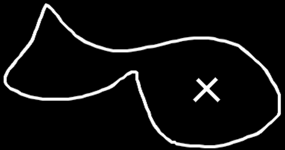

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Information and brain

Some hypothesis

- Information is coded by frequences of the signal,
- Information is coded by motives,
- Information is coded in the network,
- Information is coded in some physical properties of the signal (electromagnetic. . .).

Our proposal

- Can we see the brain as a decoder?
  - Uses both the network structure and the incoming information,
  - Similarities such as:
    - High redoundancy,
  - But where is the decoded data?

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Model

Neuron

- $I^{\mathbb{A}} \in \{-1;1\}$,
- $\tau^{\mathbb{A}}_{relax} \in \mathbb{N}$,
- $\theta^{\mathbb{A}} \in [0;1]$,
- $\tau^{\mathbb{A}}_{out} \in \mathbb{N}$,
- $\lambda^{\mathbb{A}}$.

Network

- $\omega_{i,j} \in [0;1]$,
- $\tau_{i,j} \in \mathbb{R}^+$,
- The network is randomly generated using an exponential decrease law for connections.

Dynamic

$$e_{\mathbb{A}} = \sum_{\mathbb{A}' \in Pre(\mathbb{A})} \left[I^{\mathbb{A}'} \delta_\omega(\mathbb{A}', \mathbb{A}) \sum_{\tau \in o_{\mathbb{A}'}} min(1, e^{-(\tau_n - (\tau - \delta_\tau(\mathbb{A}', \mathbb{A}) + \tau^{\mathbb{A}'}_{out}))\lambda^{\mathbb{A}'}}) \right]$$

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Other models

- Spiking neurons > our model > classical artificial neuron networks

Expressivity

- Infinite neuron network $\leftrightarrow$ Turing machine.

Chaotic behaviour

- One may define a network where the time between two successive emissions (k and $k+1$) of a neuron is the k-th decimal of π.

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Demonstration

Cycles

Definitions

- Two kinds of cycles:
  - Source cycles: non linear combining effects,
  - Visual cycles: may contain inhibitive neurons.
- Given N a subset of impulsive neurons, $A(N)$ is the set of neurons that are activated infinitely often. Visuals cycles $\leftrightarrow A(N)$,
- We define C the function that associate to any subset N a minimal element such that $A(N) = A(C(N))$. Source cycles $\leftrightarrow C(N)$.

Effective computing

- Source cycles: hard to compute, not considerated yet,
- Visual cycles: $A(N)$ may be approximated by the neurons visited a large number of times.

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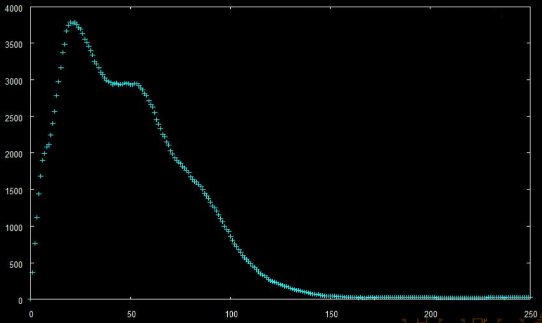
Objects tested

- Networks of size $12 * 12$,
- 12 impulsive entry neurons (4096 possible entries),
- After 100 seconds, the network is projected such as neurons that have been activated more than x times are considered as belonging to cycles and other not.



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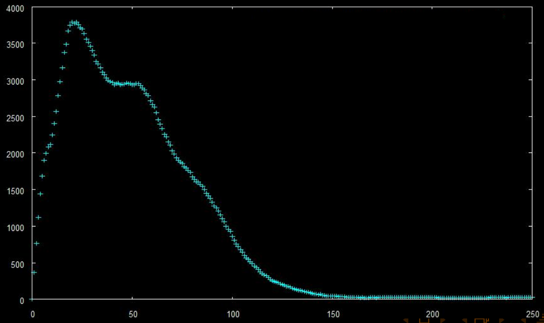

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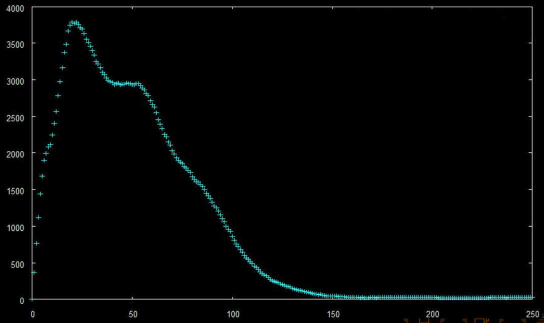

Population

- 50 networks tested, with the two kinds of models,
- The threshold is fixed to 250, where most networks act as if they had converged.

Results

- Entry messages are grouped by equivalence classes,
  - Two messages belong to the same class if they activate the same cycles.
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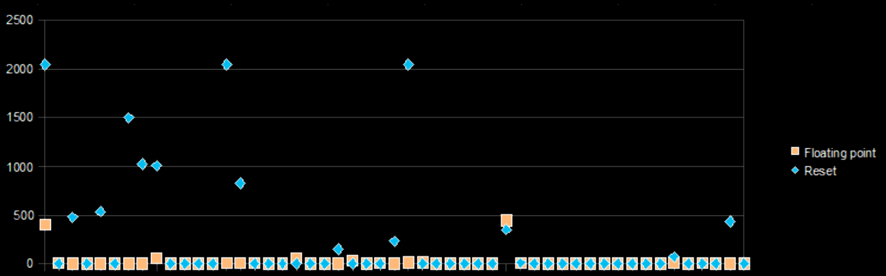

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- Performances are better for reset type in 68% of tested networks,
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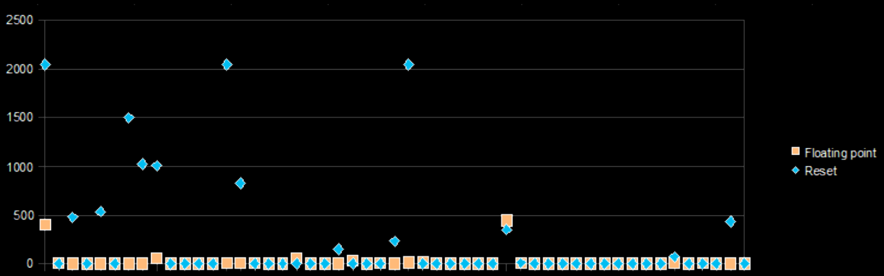

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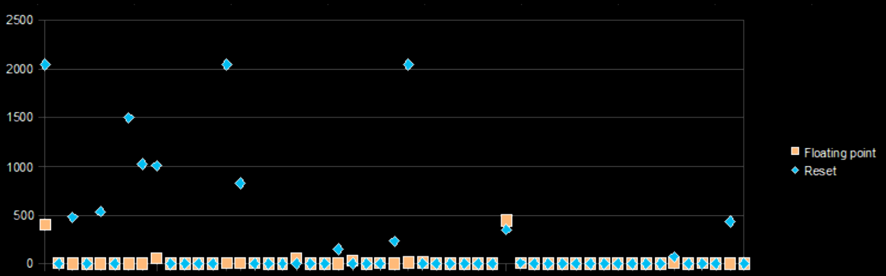

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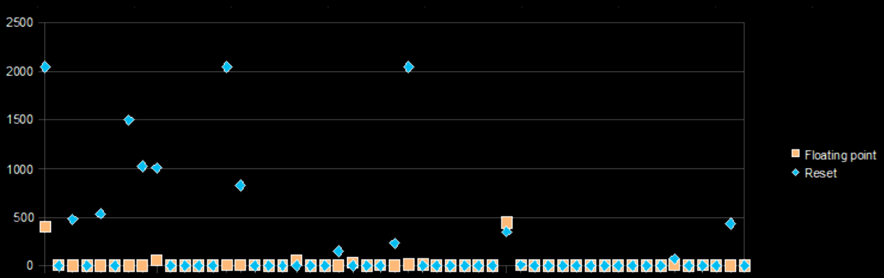

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- Finding the optimal parameters of networks (and comparing with the brain data),
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