Les groupes polychrones pour capturer l'aspect spatio-temporel de la mémorisation

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Motivation

Advances in cerebral imagery and recording technics for studying the brain activity :

- at the brain scale (fMRI, EEG)
- at neuron population scale (multi-cell recording)
- at neuron scale (cell recording)

Despite these advances, it is still difficult to understand how and where the **coding of information** takes place.

Spatial versus temporal aspects of memory

Several hypotheses for spatial representation of information :

- "Grand-mother" cell
- Assemblies of distributed neurons

Several hypotheses for temporal coding of information :

- Rank order coding [Thorpe et al., 2001]
- Synfire chain [Abeles, 1991]
- Transient synchrony [Hopfield et al., 1997]

Spatio-temporal aspects of memory

Information is spatially and temporally represented in the brain.

Polychronization

is a powerful tool to hack these spatiotemporal representations.

What is polychronization ?

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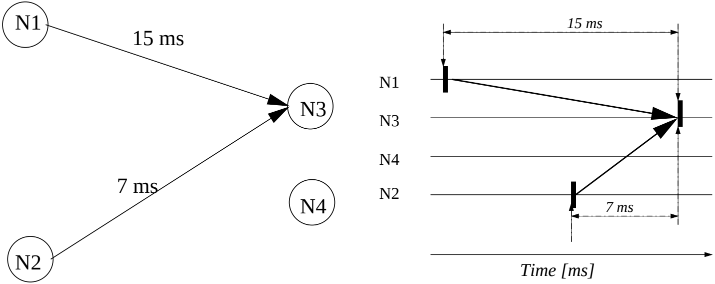
Polychronization [Izhikevich, 2006]



- If N_1 emits a spike at t, and N_2 at $t+8$, then N_3 emits a spike at $t+15 \Longrightarrow N_1$ and N_2 **trigger** N_3 with timing $(0,8)$.
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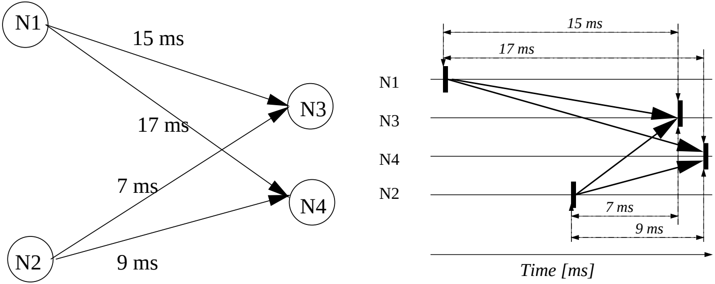
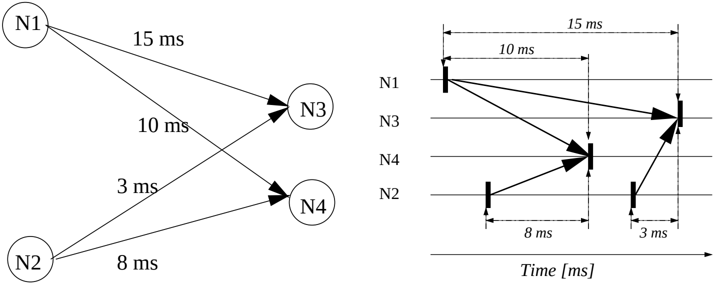
Polychronization [Izhikevich, 2006]



- If N_1 emits a spike at t, and N_2 at $t + 8$, then N_3 emits a spike at $t + 15$.
- They may trigger one or more other neuron.

Polychronization [Izhikevich, 2006]

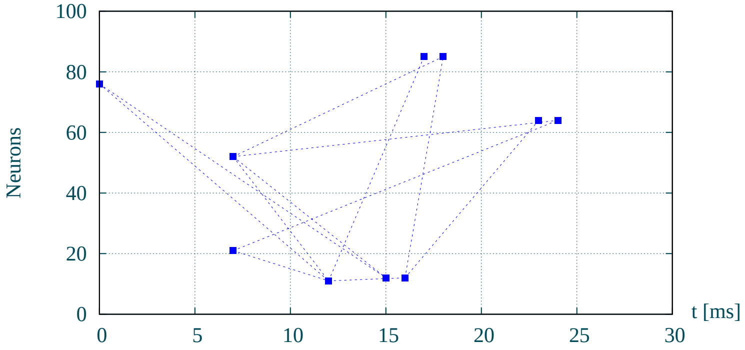


- If N_1 emits a spike at t, and N_2 at $t+12$, then N_3 emits a spike at $t+15$.
- They may trigger one or more other neuron.
- They may trigger a different neuron if the timing is different.

Polychronous group – Example

Definition

A polychronous group is a subset of neuron activities characterized by a precise spike timing, depending on delays.



Triggering neurons: 21,52,76, with timing (7,7,0)

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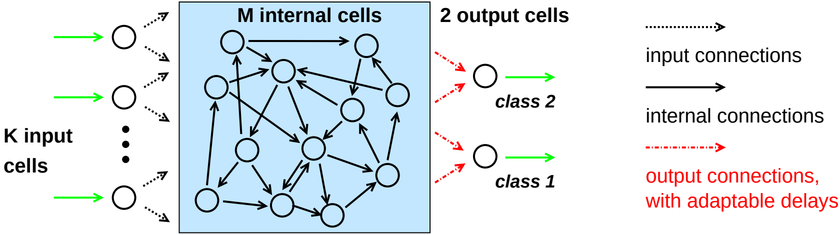
The model

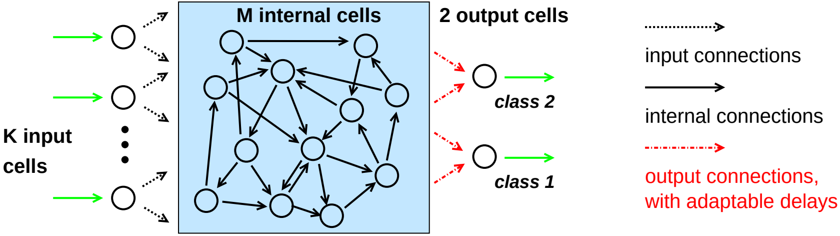
- Maintains biological plausibility within the internal network
- Neuron model : Spike Response Model (SRM_0) [Gerstner 1997]



Random recurrent network with

- adaptable weights
- fixed but random delays

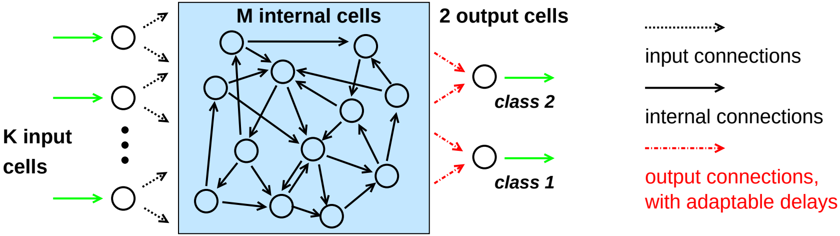
A two scale learning algorithm



- **Unsupervised** learning : Spike Time Dependent Plasticity (STDP) within the internal network (ms time scale)
- **Supervised** mechanism : delay adaptation on output connections (at each input presentation) based on a temporal margin criterion

See [Paugam-Moisy, Martinez and Bengio - Neurocomputing, 2008]

A pattern recognition task



- Target neuron must fire before other (non-target) output neurons

Figure: USPS pattern examples

- Tested on a two class discrimination task : “6” and “9” digits.
- 97% training success ; 73% testing success

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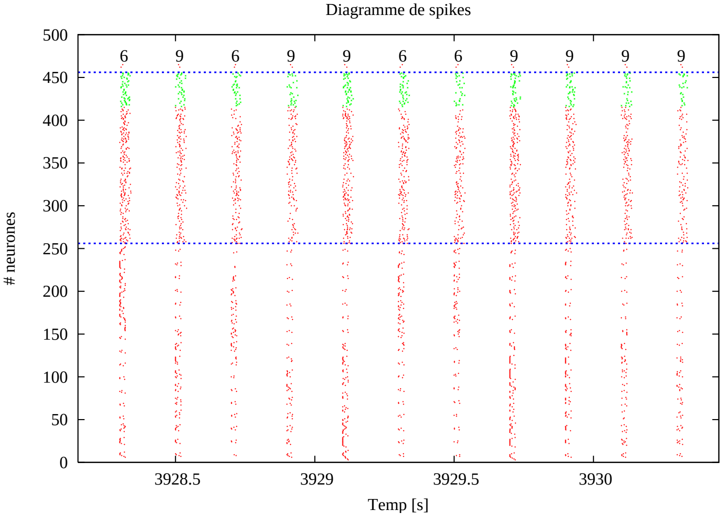
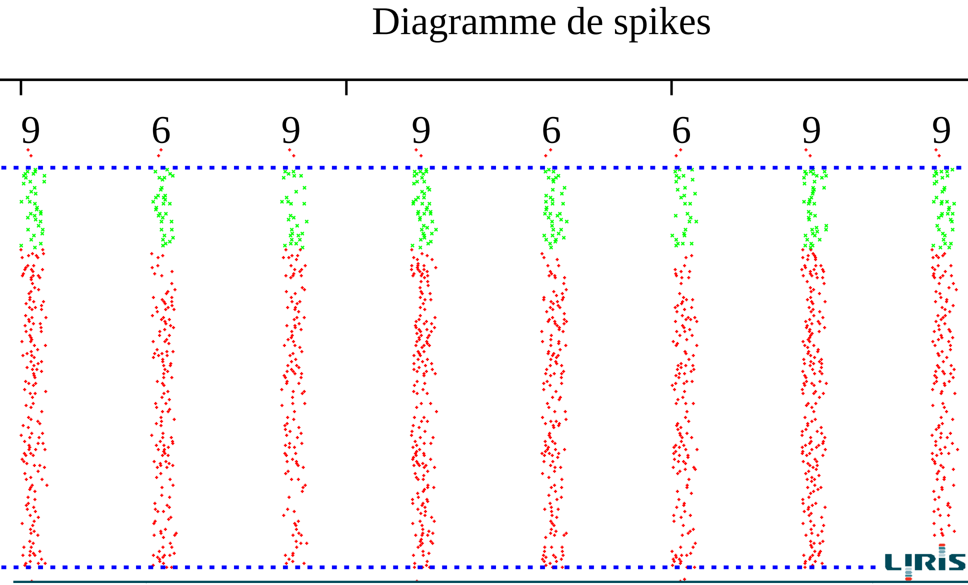
Spike raster plot observation



Learning is stopped. Spike raster plot is hardly interpretable.

Spike raster plot observation



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Scanning for polychronous groups

Structure

A given network topology $\Rightarrow$ a particular set of **supported** polychronous groups (PG)

Supported PG $\neq$ **Activated** PG

Dynamics

An **activated** PG is a PG which is actually triggered by a convenient spike timing in the network activity.

Polychronous group activations

For each PG, we count the number of times it has been activated, respectively for class 6 (red) and for class 9 (black).

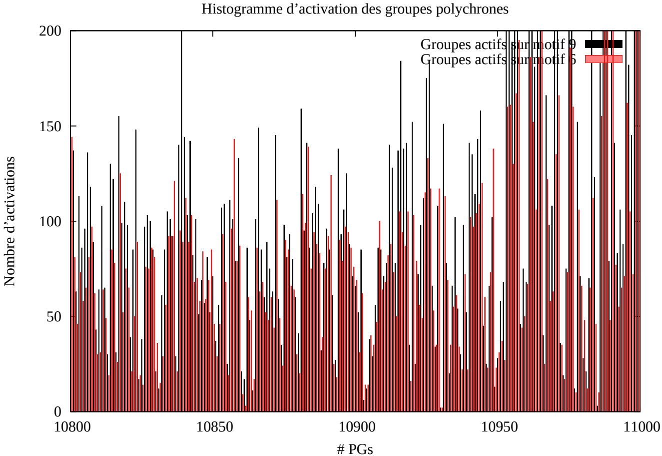

Figure 1: PG activations histogram **before** learning

Polychronous group activations

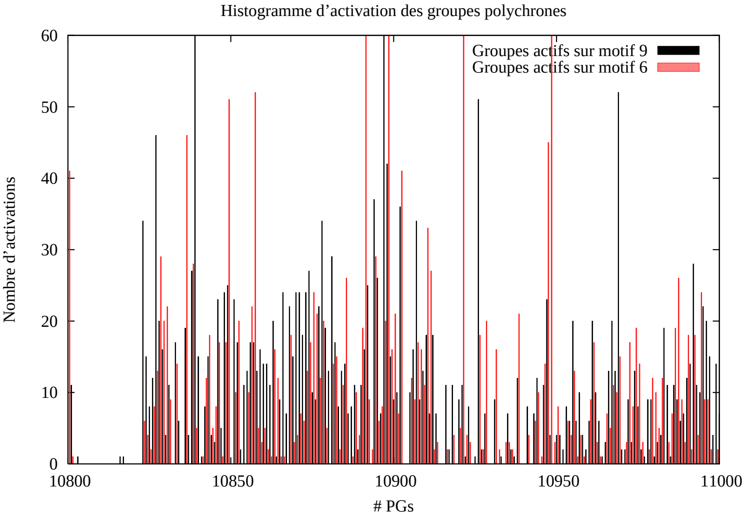

Figure 2: PG activations histogram **after** learning

Classification of PGs into categories

Based on these histograms, we define a category for each PG, according to its prefered class

- Category = 6 : if PG mainly activated for class 6
- Category = 9 : if PG mainly activated for class 9
- Category = null : if difference of activations for 6 and 9 < 10%

Coming back to the spike raster plot representation, we can then plot the PG triggering neurons with a color depending on the category of the PG.

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Triggering spikes of activated PGs

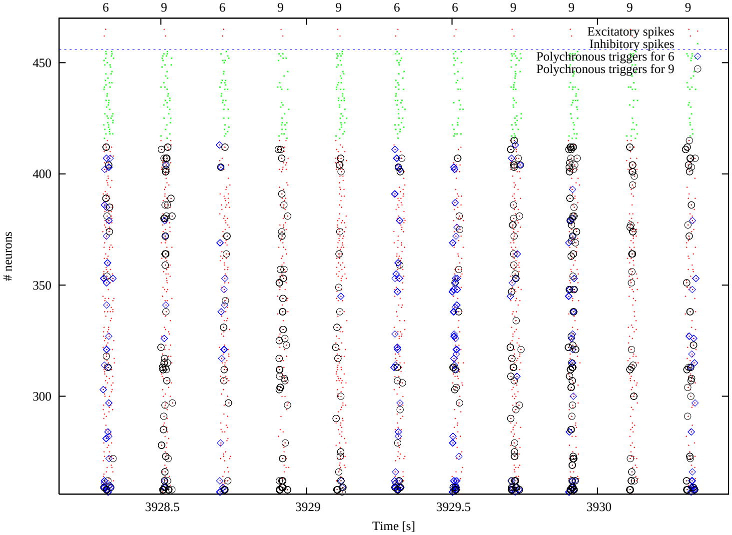
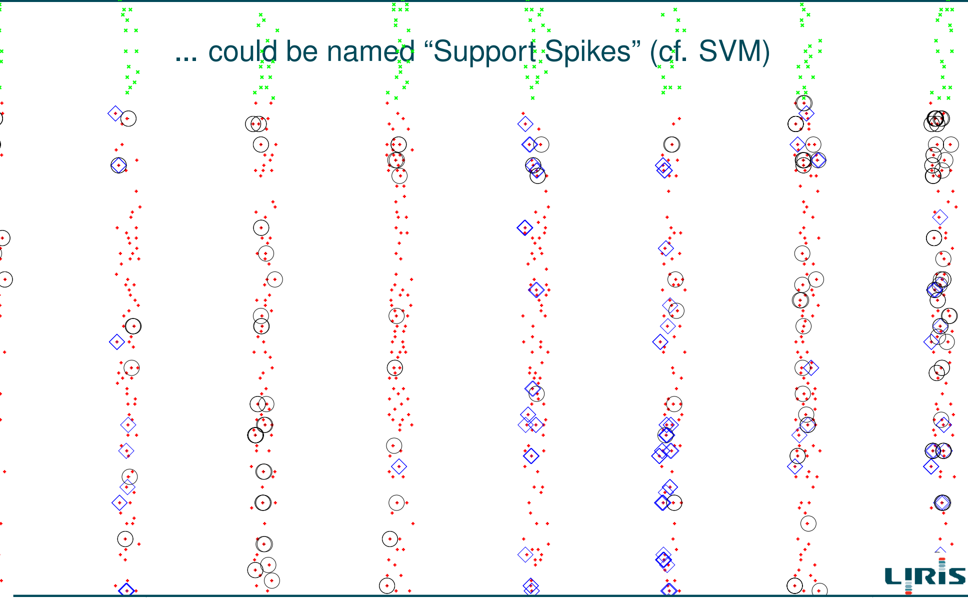


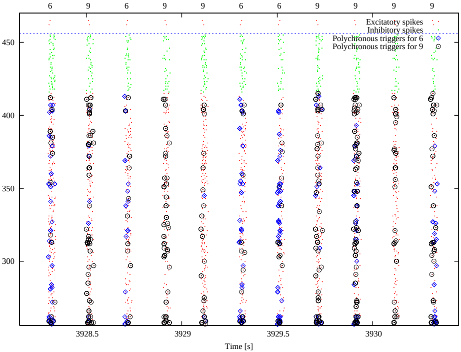
Figure: PG triggering spikes on spike raster plot

Triggering spikes of activated PGs

... could be named “Support Spikes” (cf. SVM)



Polychronous groups coding for the class ?



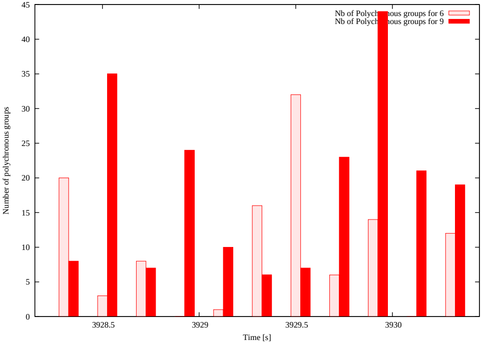
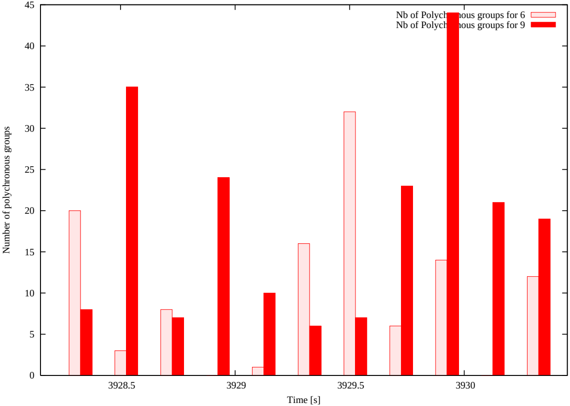


Figure: PG activations, and PG category balance

Polychronous groups coding for the class ?



- Recognition based on output neurons:
  97% training success ; 73% testing success
- Recognition based on PG categories:
  93% training success ; 72% testing success

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Conclusion

The notion of polychronization gives way to define a subset of significant spikes among the network activity.

Our approach has been very close to the SVM approach:

- first representing the network activity in spike space,
- representing this activity into a polychronous group space,
- in this space, classifying the PGs in categories,
- coming back to spike space for visualizing significant spikes.

PGs appear to support a spatio-temporal **coding of information.**

Discussion

Our results are not far from the approach of rank order coding, but our "support spikes" have reasons to give a more robust coding of information than the "first spikes".

Representing the network activity via the polychronous groups is a good track for understanding memory mechanisms, especially under the hypothesis of multiple-trace memory models.
See [Martinez and Paugam-Moisy - ARCo'2008]

Thank you for listening.

Questions !

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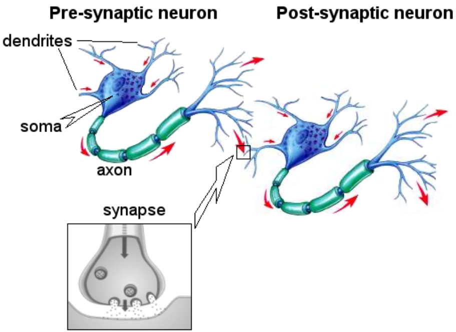
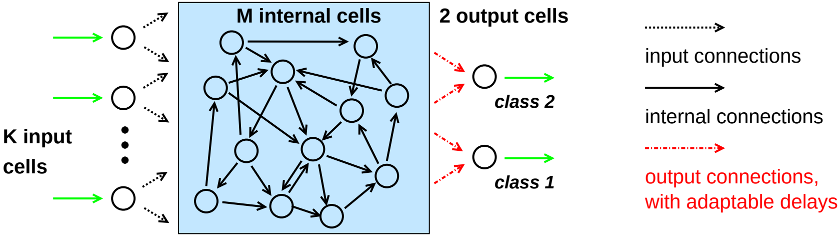
1. Unsupervised learning algorithm

Unsupervised learning : Spike Time Dependent Plasticity (STDP) within the internal network (ms time scale)

- Temporal hebbian rule, suitable for SNNs
- At the synaptic level (local mechanism)
- Depending on activity going through the synapse
- Causality based on spike emissions order



2. Supervised learning algorithm



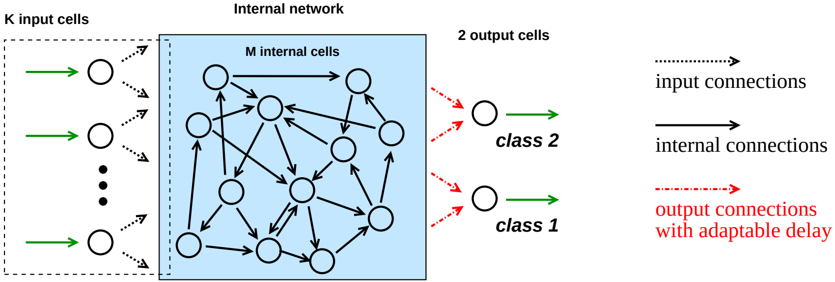
After the presentation of a given input pattern p**,**
<u>If</u> target/non-target spikes order is OK
AND
<u>If</u> margin between target/non-target spikes $> \epsilon$

<u>Then</u> : pattern is well classified
<u>Otherwise</u>,
- **for target neuron : decrement the delay** $(-1ms)$
- **for non-target neuron : increment the delay** $(+1ms)$

Après chaque présentation d'un motif d'entrée donné p

<u>Si</u> l'ordre de spike neurone cible / non-cible est

The model



Input layer (stimulation layer) :

- 10 neurons
- Input injection

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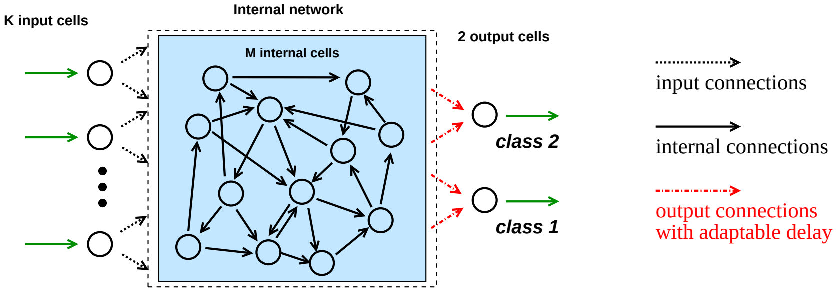
The model



Internal Network :

- 100 neurons, 80% excitatory, 20% inhibitory
- Random recurrent topology
- Connection delays fixed (but randomly chosen) between 1 and 20 ms

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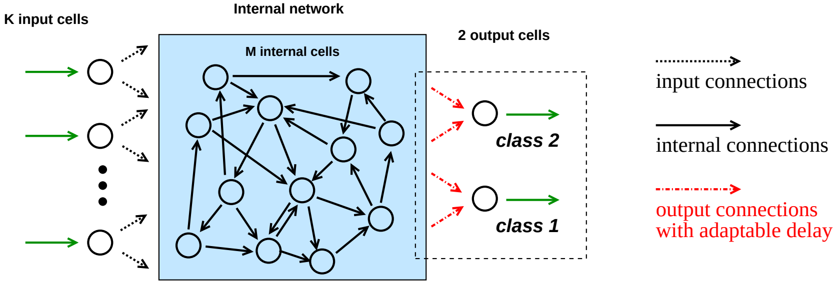
The model



Output layer :

- 2 neurons : one for each target class
- recieves a connection from each internal neuron

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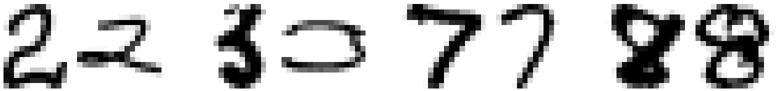
Work in progress

- Use larger inputs : encouraging tests with USPS dataset



  2 versus 7 : 96% success on train set, 93% on test set
  3 versus 8 : 89% success on train set, 86% on test set

- Switch to more than two classes
- Extend model with persistant activity

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Reservoir Computing perspectives : Open questions

Might there be links with reservoir computing. Indeed, some theoretical properties exists : point-wise separation, universal approximation, echo state properties...
But still difficulties to investigate what's going on in the reservoir (refering to special session)
Polychronous groups can be a reliable way

- to analyse dynamics of a spiking neuron reservoir
- to find optimal topologies (structures)

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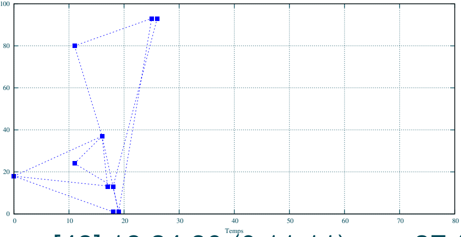
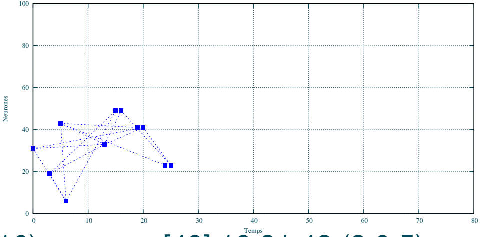
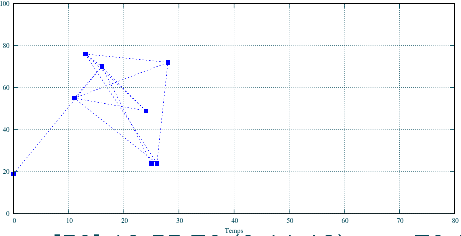
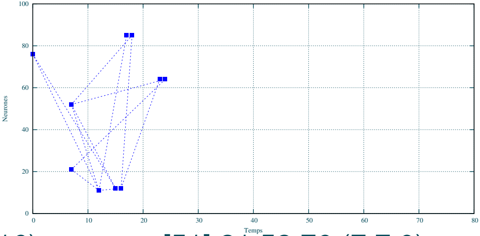
Groupes polychrones sur 100 neurones





[48] 18,24,80 (0,11,11) ==> 37 (16) — [49] 19,31,43 (3,0,5) ==> 6 (6)



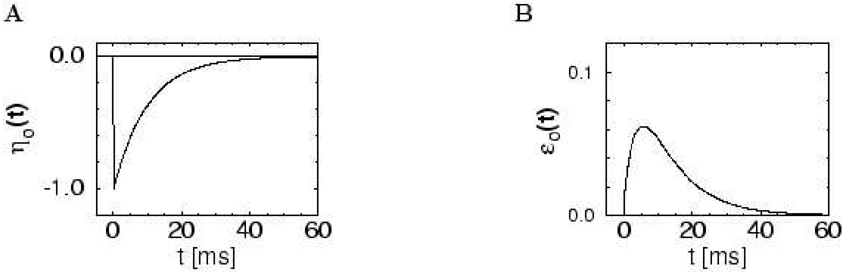


[50] 19,55,76 (0,11,13) ==> 70 (16) — [51] 21,52,76 (7,7,0) ==> 11 (12)

▸ retour

Modèle SRM_0 (used)

$$u_j(t) = \underbrace{\eta(t - t_j^f)}_{\text{A : refractory periode}} + \sum_i w_{ij} \underbrace{\epsilon(t - t_i^f - d_{ij})}_{\text{B : excitatory potential}}$$

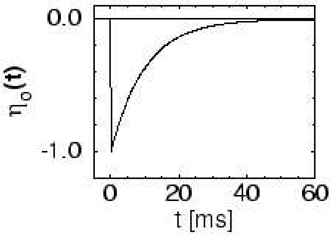


▸ retour

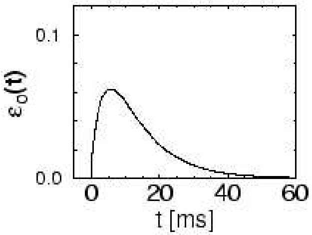
Modèle SRM_1

$$u_j(t) = \underbrace{\eta(t - t_j^f)}_{\text{A : refractory periode}} + \sum_i w_{ij} \sum_f \underbrace{\epsilon(t - t_i^f - d_{ij})}_{\text{B : excitatory potential}}$$

A



B



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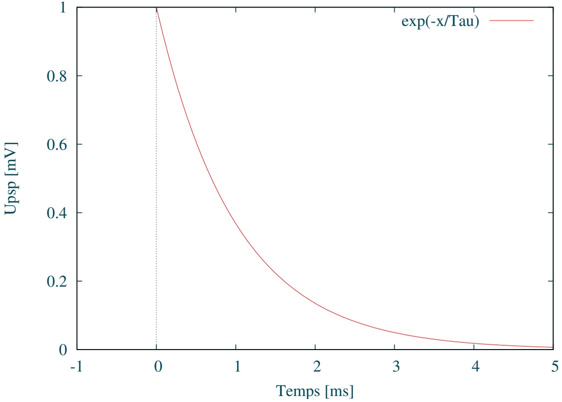
Forme d'un PPS



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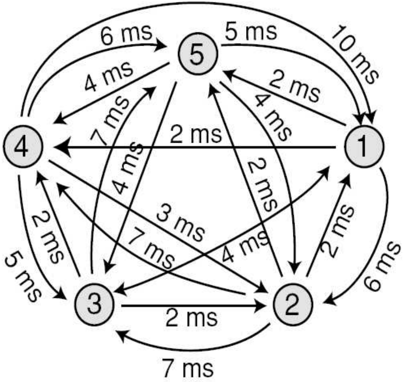
Réseau expérimental



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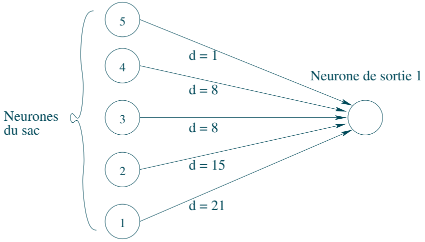
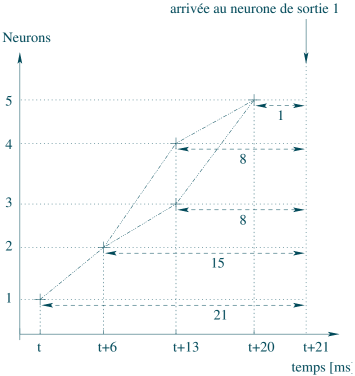
Sensibilité à un motif spécifique





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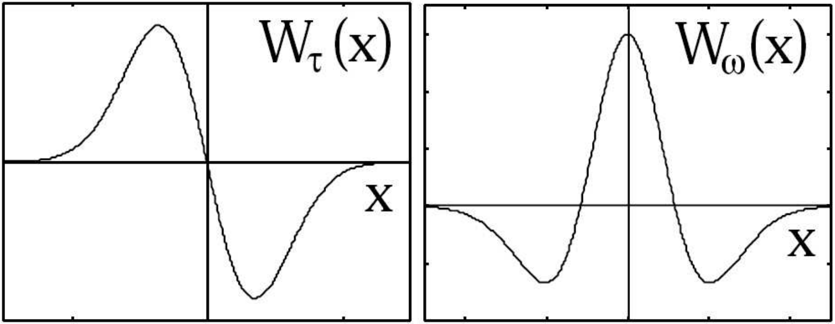
Fenêtre STDP Eurich



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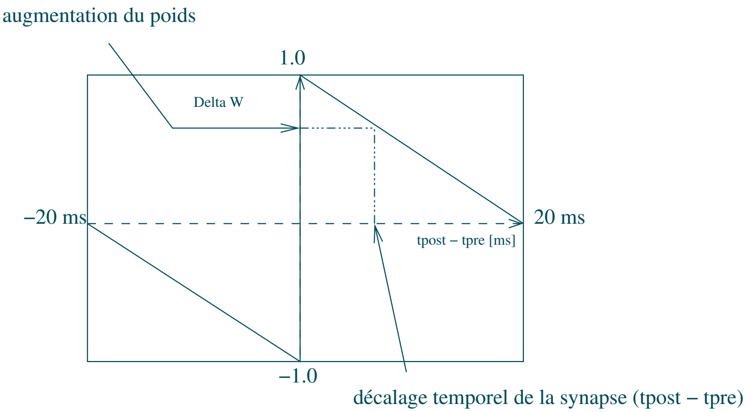
Fenêtre STDP classique



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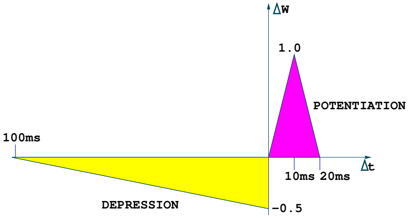
Fenêtre STDP Meunier

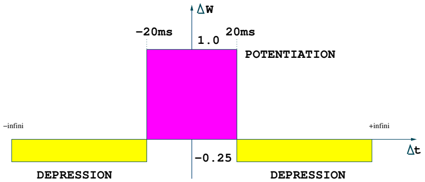
Si $\Delta W \leq 0$, le poids est augmenté :

$$w_{ij} \leftarrow w_{ij} + \alpha * (w_{ij} - w_{min}) * \Delta W$$

Si $\Delta W \geq 0$, le poids est diminué :

$$w_{ij} \leftarrow w_{ij} + \alpha * (w_{max} - w_{ij}) * \Delta W$$





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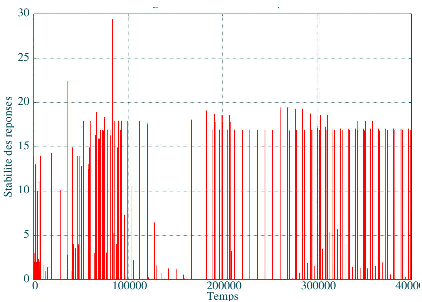
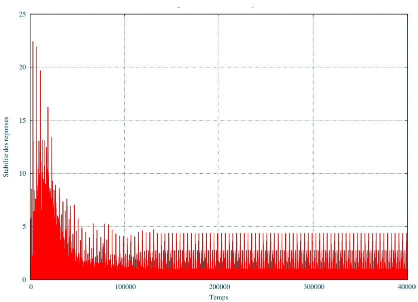
Stabilité du classifieur





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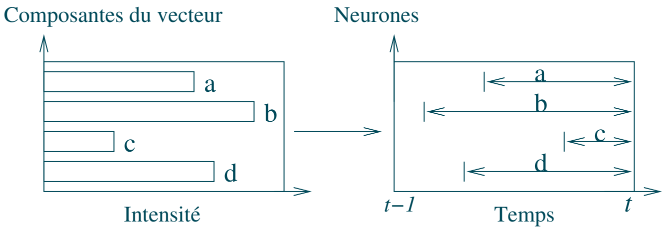
Codage temporel



Vecteur numérique

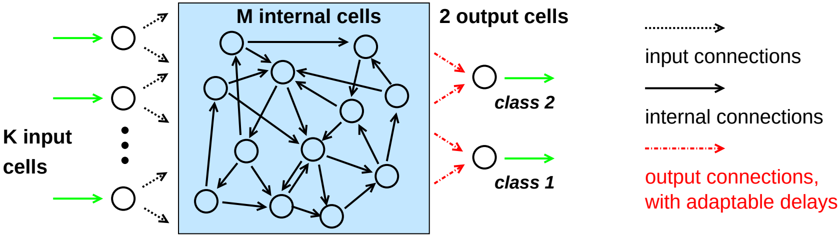
Vague de spikes dans un interval
de codage temporel

Codage en intensité

Codage temporel

retour

Architecture



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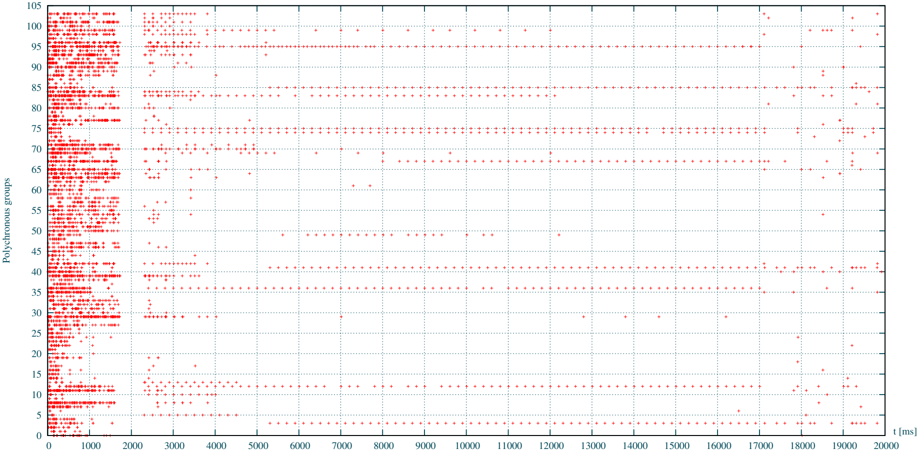
Activation des groupes polychrones



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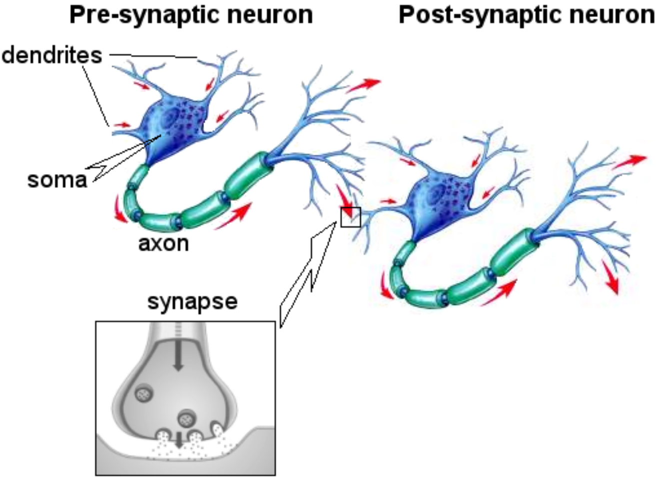
Activité neuronale



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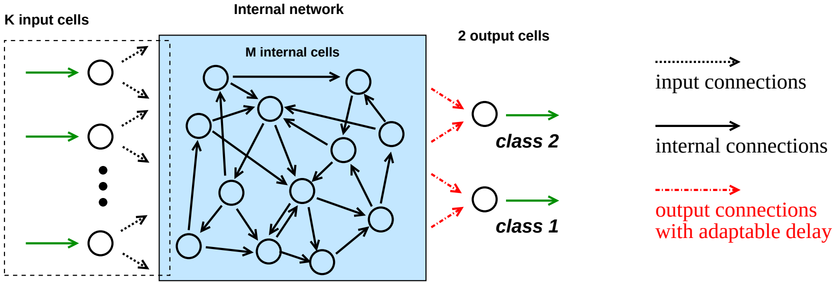
PG detection

To find all supported polychronous groups, we use the same algorithm as [Izhikevitch 2006]. It consists in scanning for spike time combination of all groups possible of 3 neurons (i.e. combinatorial quiestions), so that the spikes would trigger the firing of one or more impacted neurons, taking axonal delays into account.

Il est possible de procéder de même en cherchant plus de déclencheurs, mais la complexité est accrue: $O(n^p)$, avec p nombre de déclencheurs. retour

The model proposed

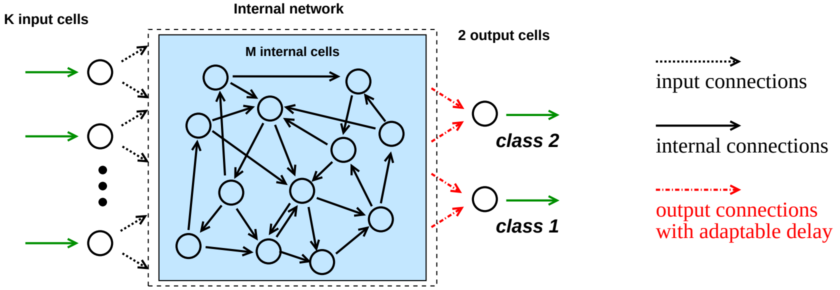


Input layer (stimulation layer) :

- 10 neurons
- Outgoing connection probability : 0.1
- Delay to central assembly : 0 ms

retour

The model proposed



Central assembly :

- 100 neurons, 80% excitators, 20% inhibitors
- Random topology
- Reccurent connection probability : 0.3
- Recurrent connections delay from 1 to 20 ms
- Spike Time Dependent Plasticity (STDP)

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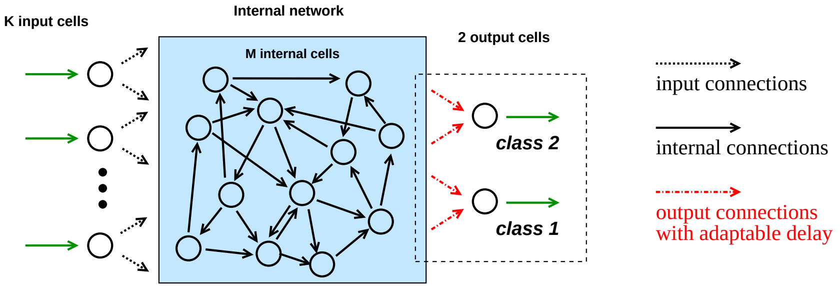
The model proposed



Output layer :

- 2 neurons : one for each target class
- Incoming connection probability : 1 (central assembly completely projected)
- Adaptable delays of input connections (all initialized to 10 ms)

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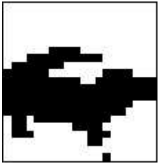
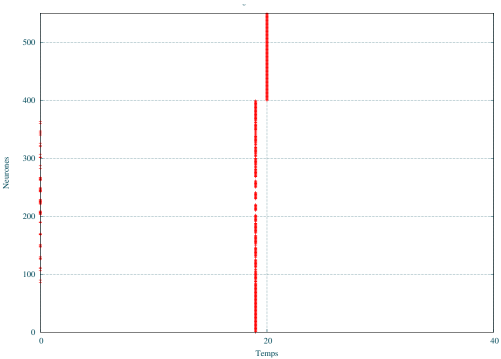
Initial work

- Originally : problem for learning binary patterns
- Spike responses : all or nothing
- Solution : allow diversity in axonal delays





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Difference with synfire chain

in **Synfire Chains and Catastrophic Interference** – J. Sougné and R. French (2001) :

> *when an initial neuron, A, fired, a second neuron, B, would fire 151ms later, followed by a third neuron, C, that would fire 289ms later with a precision across trials of 1 ms*

in **Polychronization : computation with spikes** – E. Izhikevich (2006) :

> *Synfire chains describe pools of neurons firing synchronously, not polychronously. Synfire activity relies on synaptic connections having equal delays or no delays at all. Though easy to implement, networks without delays are finite-dimensional and do not have rich dynamics to support persistent polychronous spiking.*

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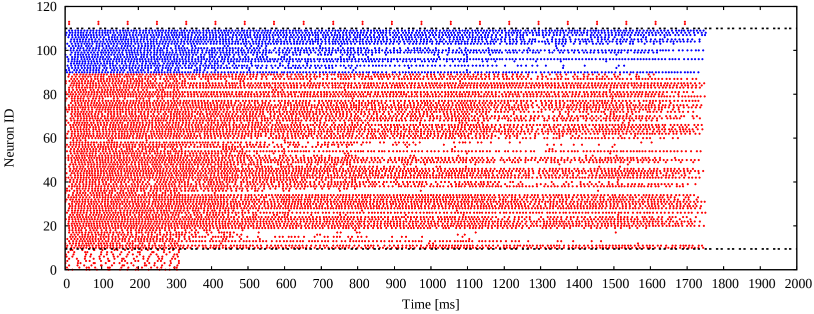
Initialization phase



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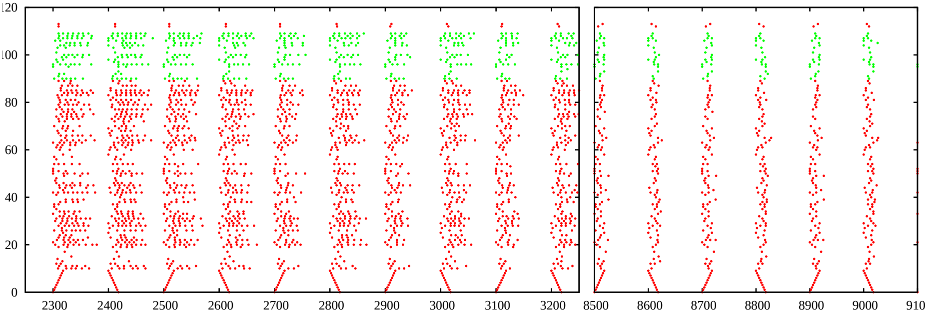
Learning phase observation

- Decreasing internal activity (STDP)
- Activaty pattern different from an input to the other
- Margin evolution



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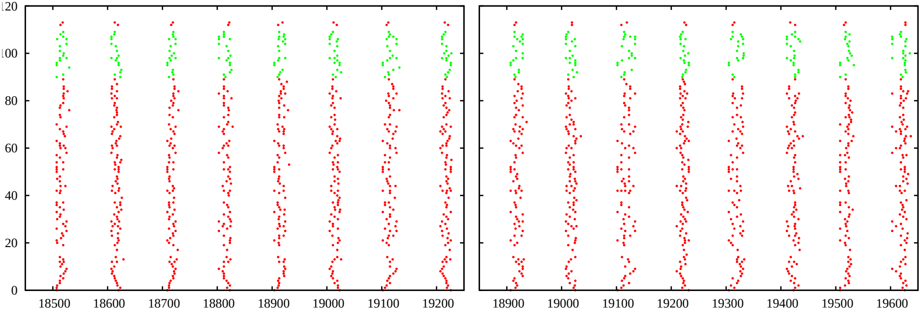
Generalization performance

- Error rate with noise 4 : 4%
- Error rate with noise 8 : 19%



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