Information Processing with neuro-inspired delay-based nonlinear systems

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Ingo Fischer

Miguel Cornelles

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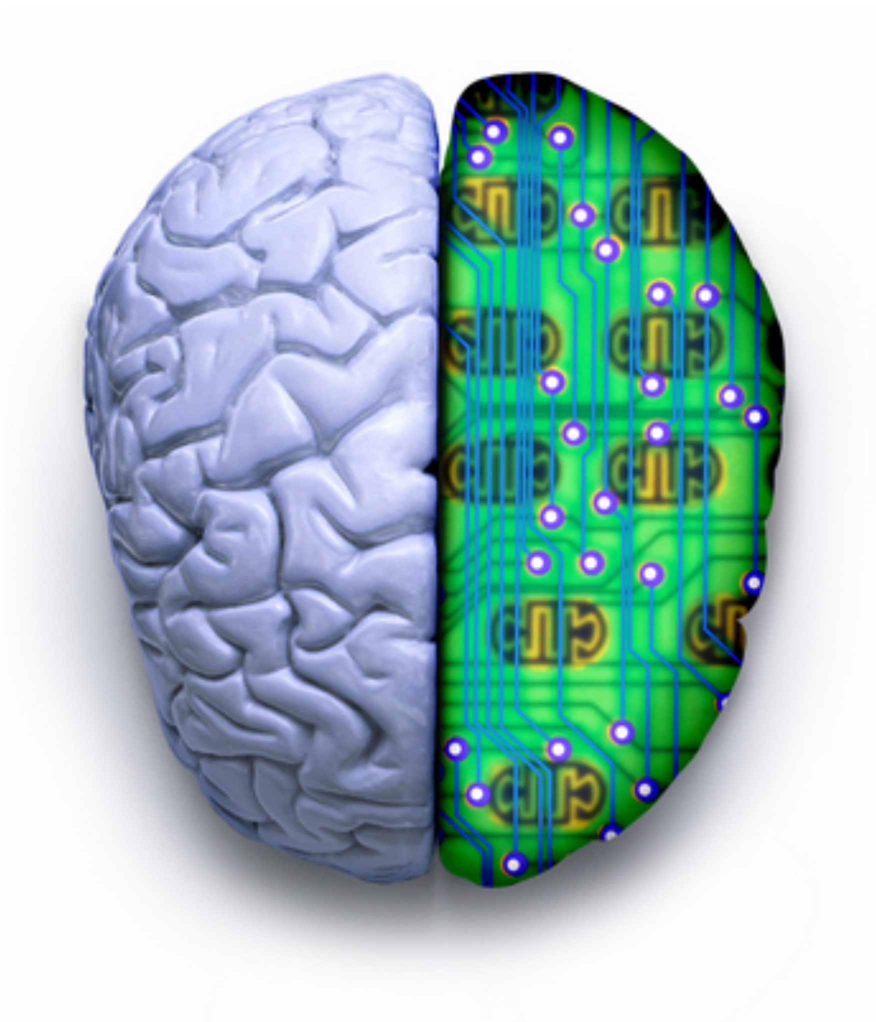
Miguel Escalona

Quiz: computer vs. brain



Question 1

$$\sqrt{4} = ?$$

① 2

② 1.6

③ 16

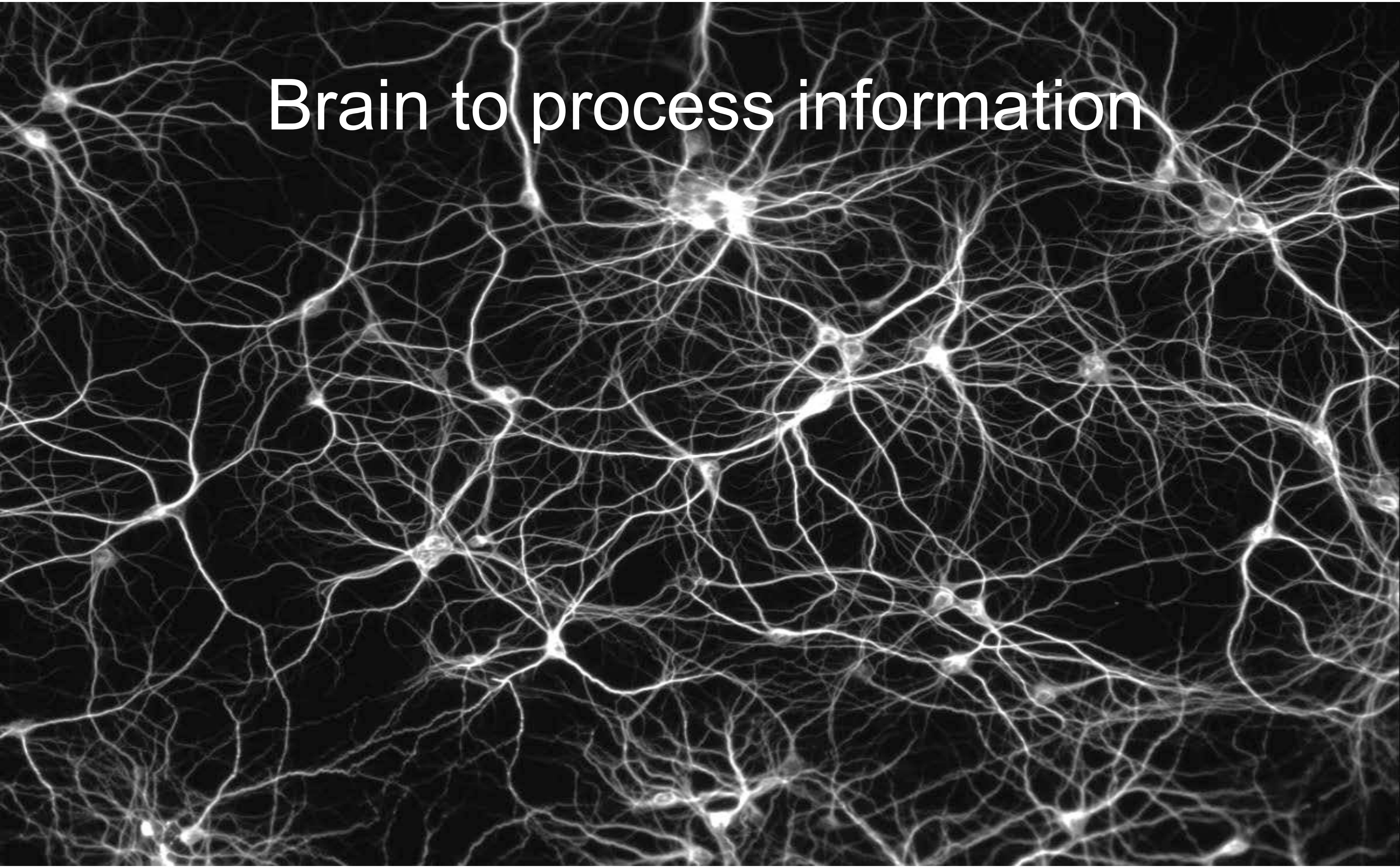
Question 2

$$\sqrt{208849} = ?$$

① 443
② 457
③ 917

Question 3


Tired
Normal
Disappointed
Happy
Thinking
Angry
Sad
Tired
Normal
Disappointed
Happy
Thinking
Angry
Sad
Tired
Normal
Disappointed
Happy
Thinking
Angry
Sad


Brain to process information

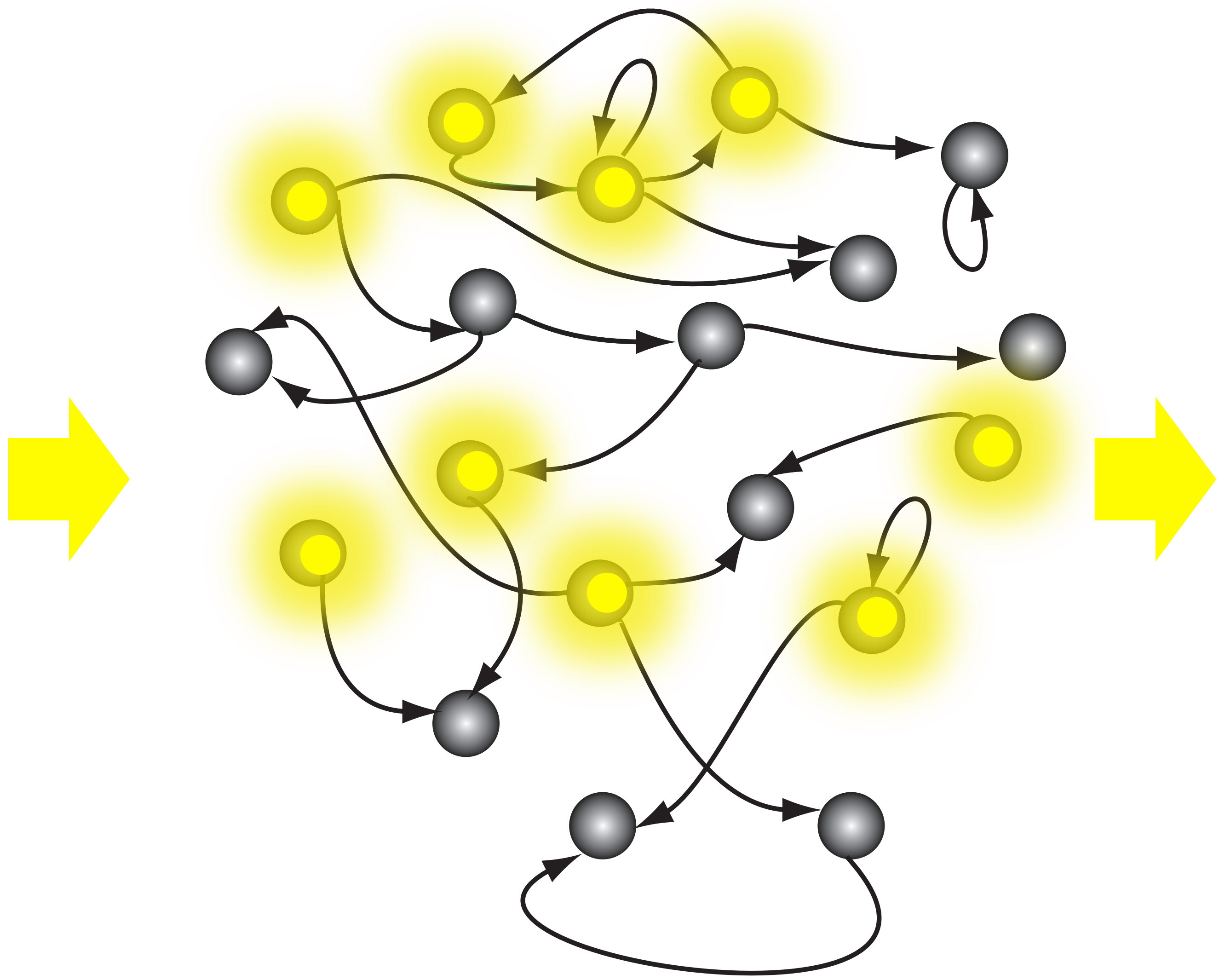
- Network of $\sim 10^{11}$ neurons with $\sim 10^{14}$ links (synapses)

- Multi-scale structure:
  - microscopic to macroscopic: neurons - columns – areas/ structures– whole brain
  - fast to slow: spiking - population activity – plasticity

The brain is "simply" a multiscale complex recurrent network of heterogeneous elements that (usually) self-organizes, delay coupled, performs computation

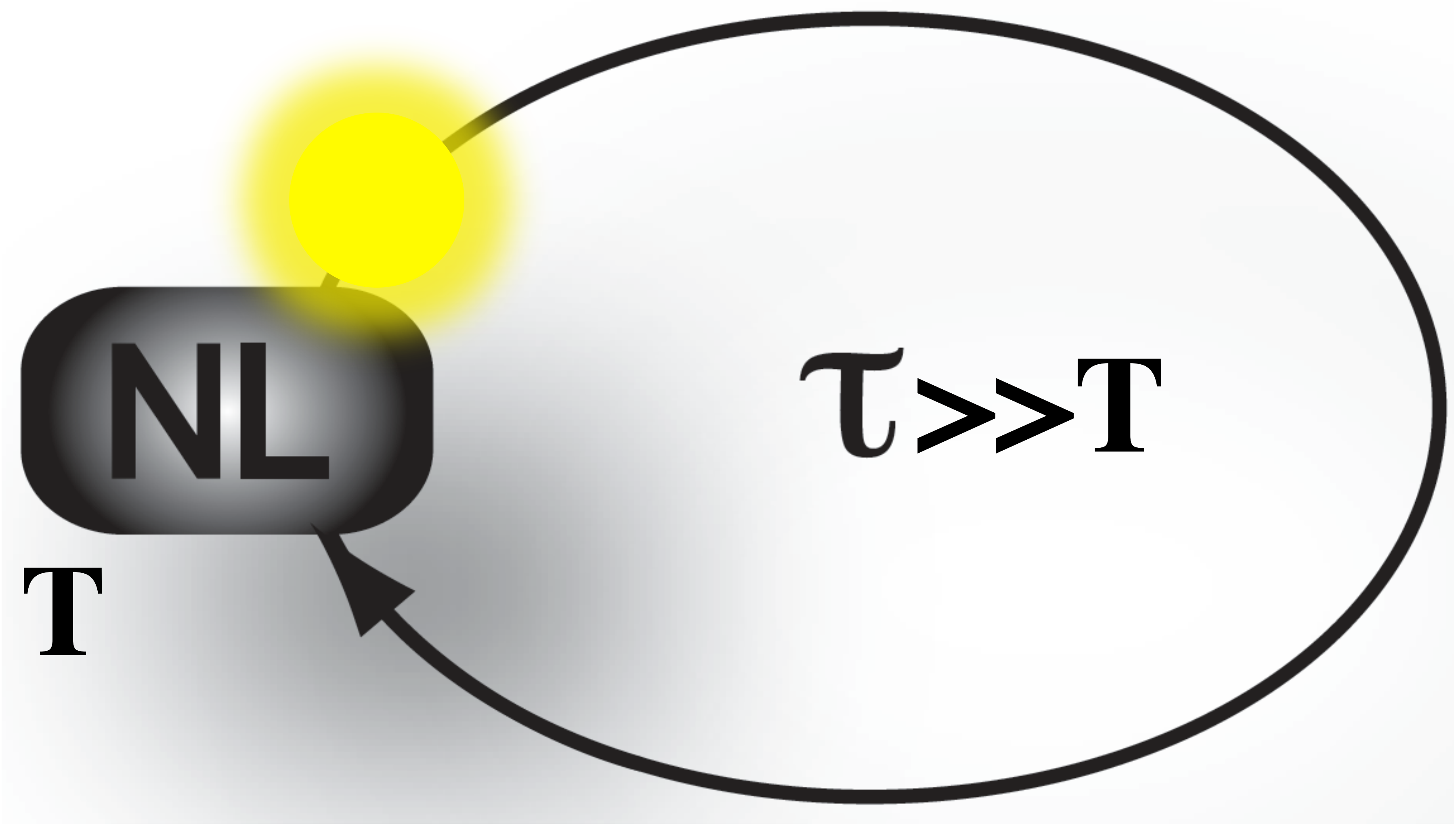
Artificial neural networks

I N P U T



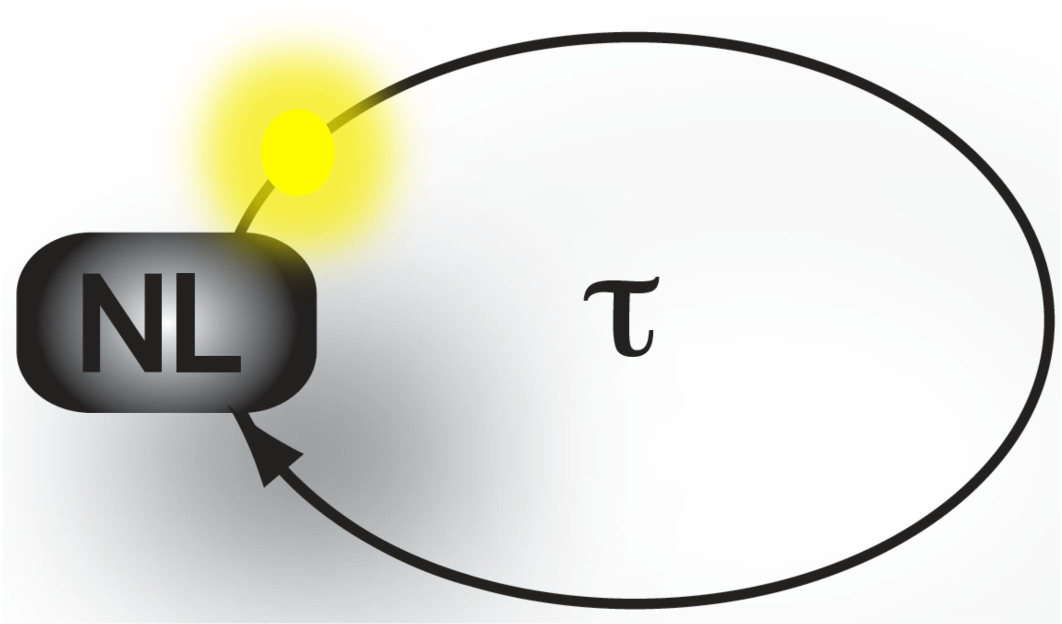
O U T P U T

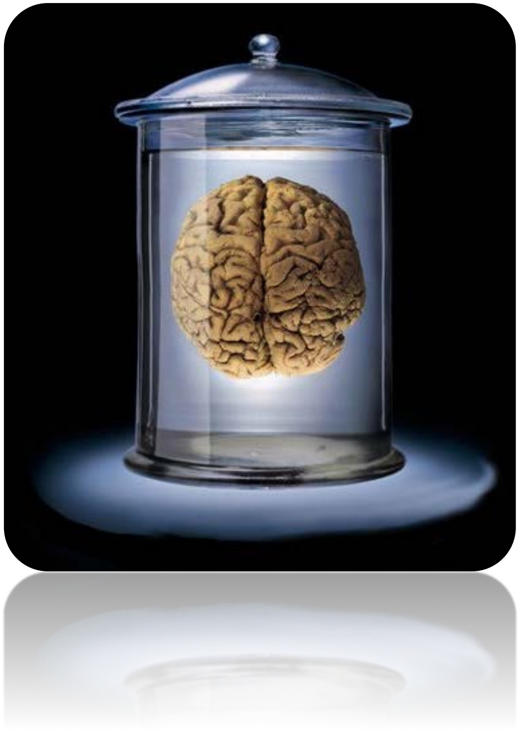
Delayed feedback systems



How similar behave delayed feedback systems and neural networks?

Can a delay system mimic information processing in the brain?

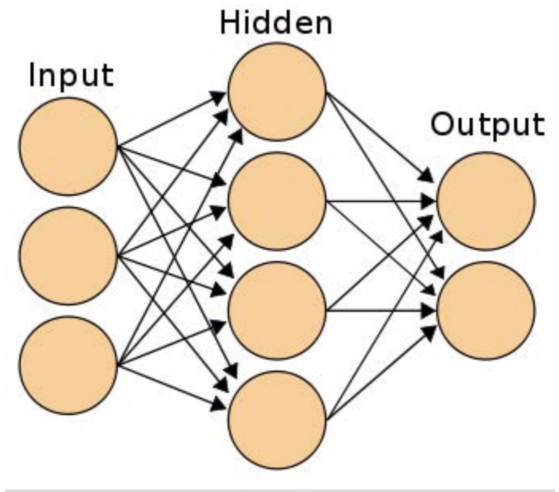




Started to develop within the FET Open Project PHOCUS (2010-2013)

Computation with complex networks

The idea was initiated with the artificial neural networks



Recurrent networks: connections were trained, which complicated enormously the training procedure.

It was in 1995 when Buonomano & Merzenich proposed the idea of using a randomly (fixed) coupled I&F neural network connected to an output layer whose weights were trained for certain tasks.

This was the origin of the machine learning technique known as "**Reservoir Computing**".

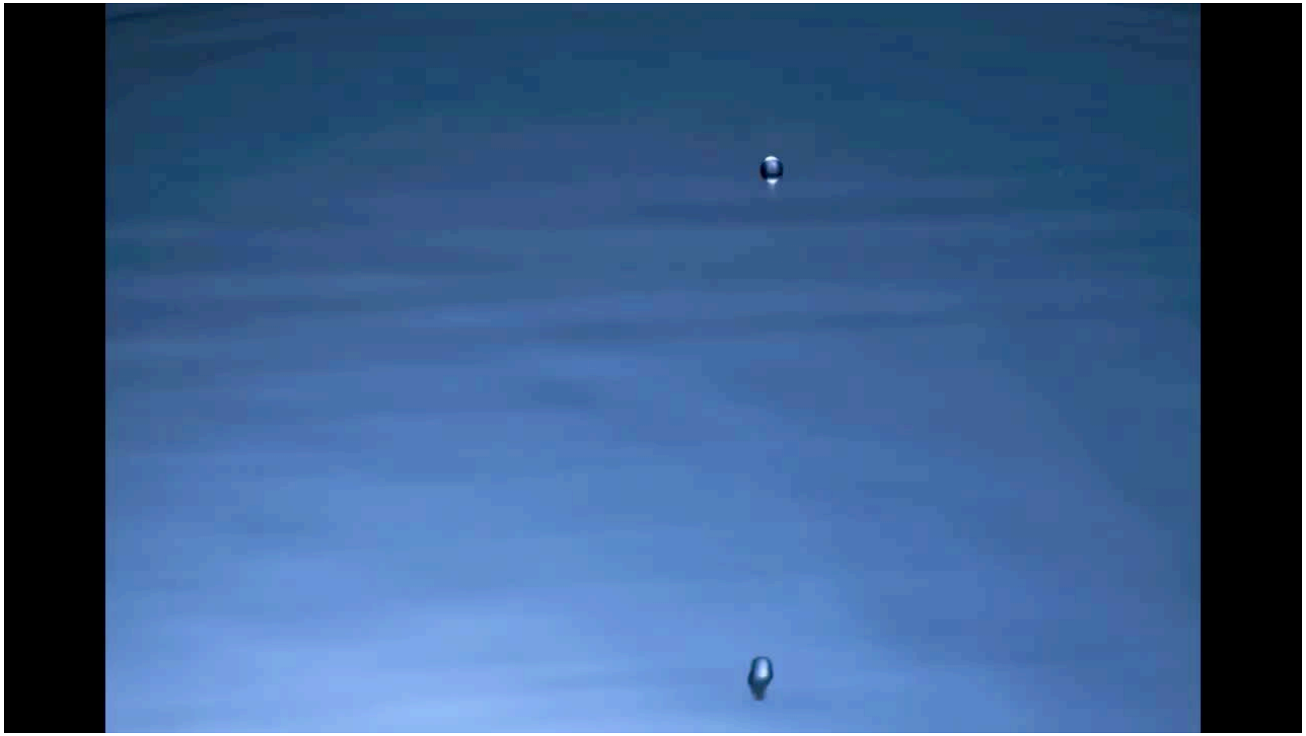
Buonomano & Merzenich, Science **267**, 1028, 1995.

Reservoir Computing:

Neuro-inspired concept

Consider brain a “black-box“ complex recurrent network

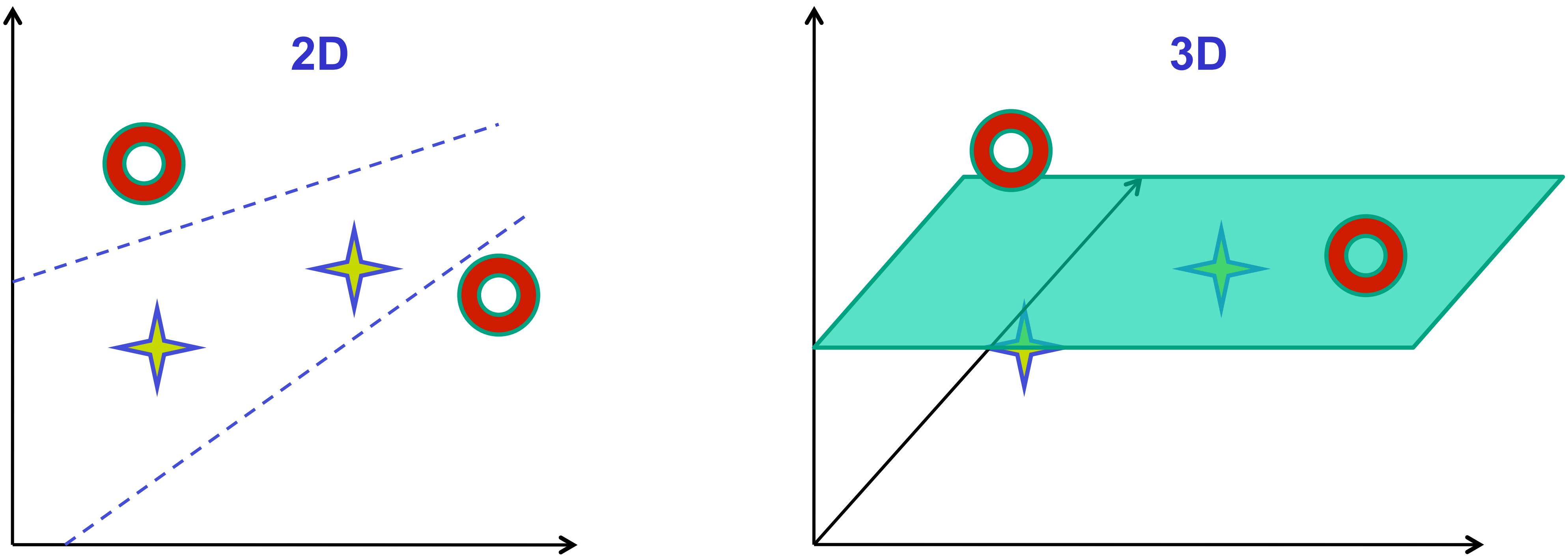
Analyzes transient responses to (sensory) input



Echo State Networks
(H. Jaeger, 2002)
Liquid State Machines
(W. Maass et al 2003)

How does Reservoir Computing work?

Utilizes the projection of an input state (usually low dimensional) onto a high-dimensional feature space



not linearly separable   linearly separable

- Nonlinear mapping onto a higher dimensional state space can make a classification problem linearly separable
- Linear separability becomes exponentially more likely with increasing state space dimension

Key Properties for RC

Consistency: responses to same inputs must be consistent

Approximation: two closed enough inputs yield the same output

Separation: Different enough inputs must be classified into different outputs

Fading memory: Processing in the context of previous states

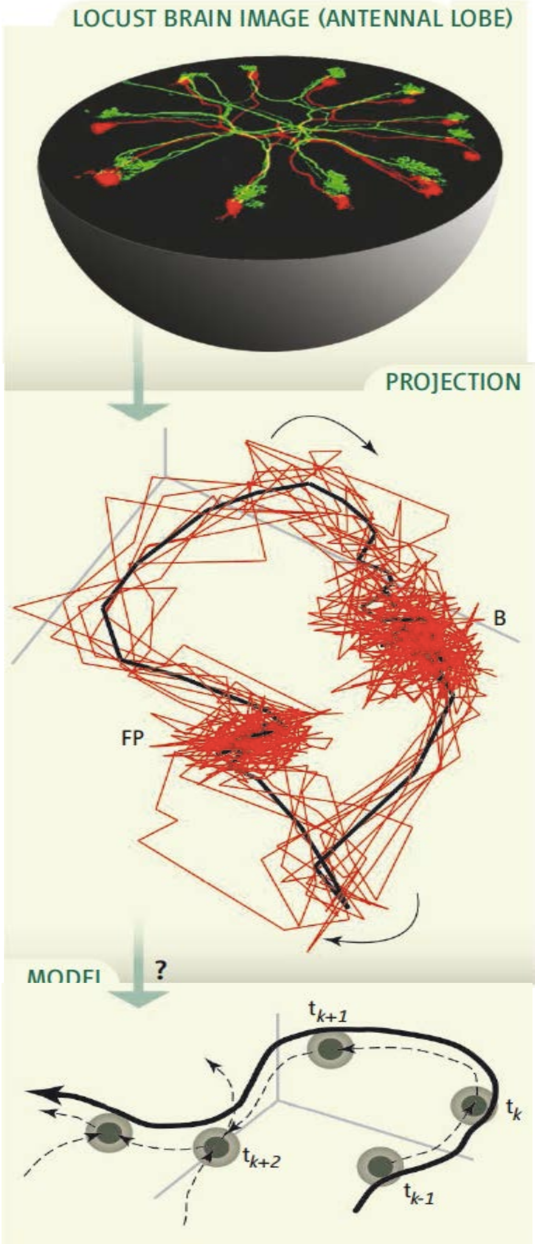
Network Connections: network connections are kept fix

Readout: Apply training procedure; only the readout weights are adjusted

Universality: capability to perform any computation

W. Maass, et al., "Real-time computing without stable states: a new framework for neural computation based on perturbations," Neural Comput. 14, 2531–2560 (2002).

Physiological Evidence



Transient Dynamics for Neural Processing, Rabinovich, Huerta & Laurent, Science **321**, 48, 2008

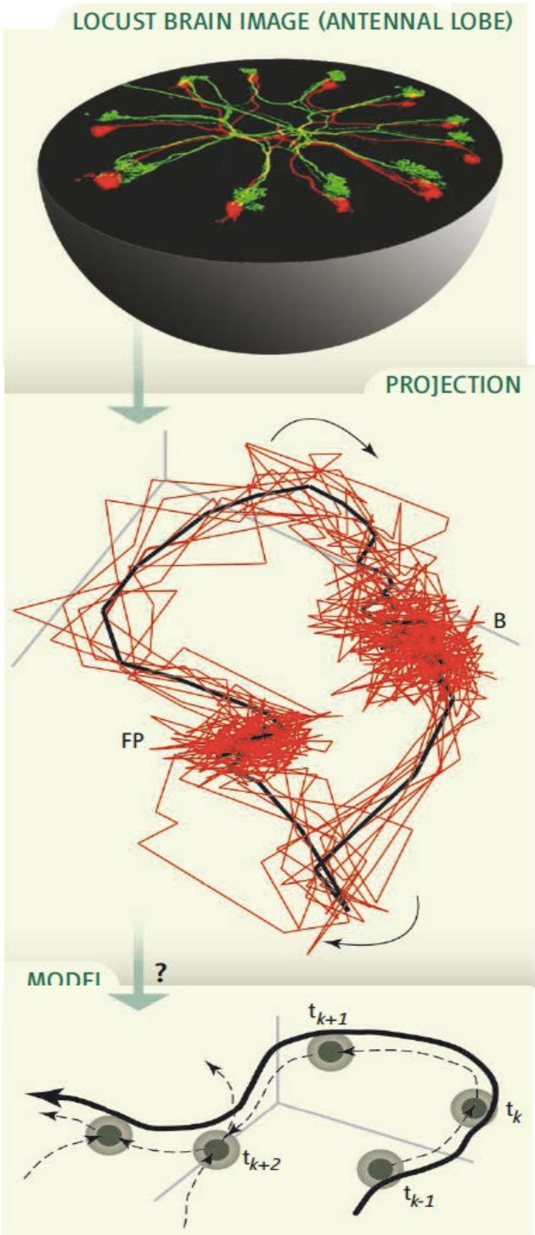
Classical attractor states cannot be realistically reached in typical neuronal phenomena timescales.

Transient dynamics as in *"liquid-state machines"* allow for computation over time without any need for a classical attractor state.

Since the transients are input-specific, they contain information about what caused them.

Experimental observations in the olfactory systems of locust and zebrafish support such framework

Physiological Evidence



Stable transients are observed whether a stimulus is sustained or not

When the responses to several stimuli are compared, the distances between the trajectories corresponding to each stimulus are greatest during the transients

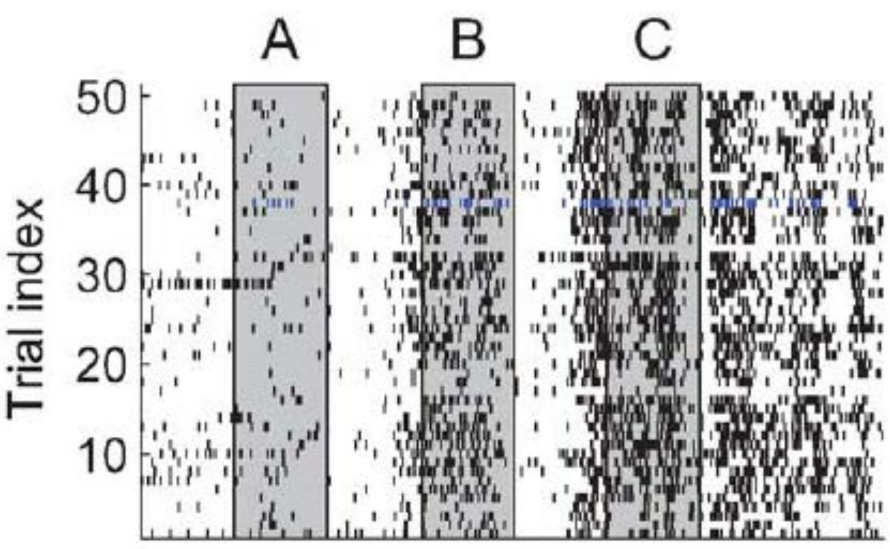
Because these states are read out ("decoded") by yet other neuronal populations, stimulus identification should be more reliable with transients than with fixed-point states.

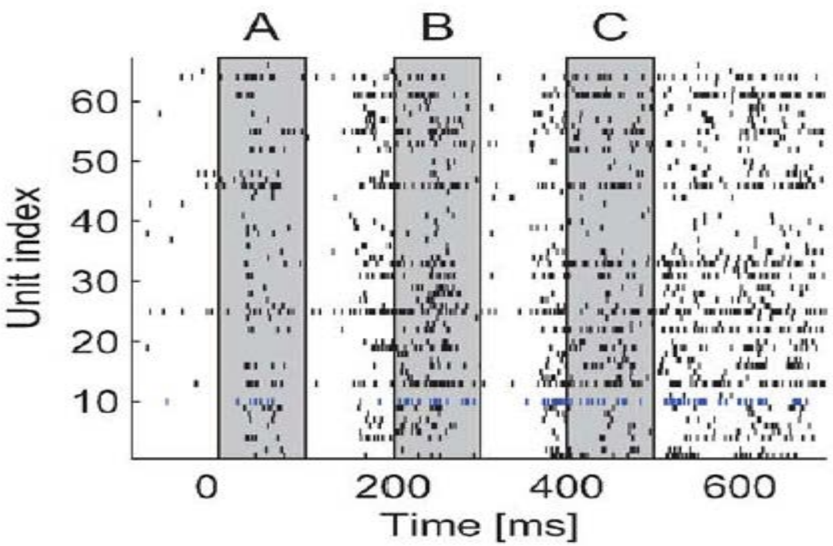
Schematic of an antennal lobe; trajectories, representing the succession of states visited by the neural network in response to one odor; dynamical model of transients: dissipative Saddles sequentially connected by unstable separatrices

Physiological Evidence

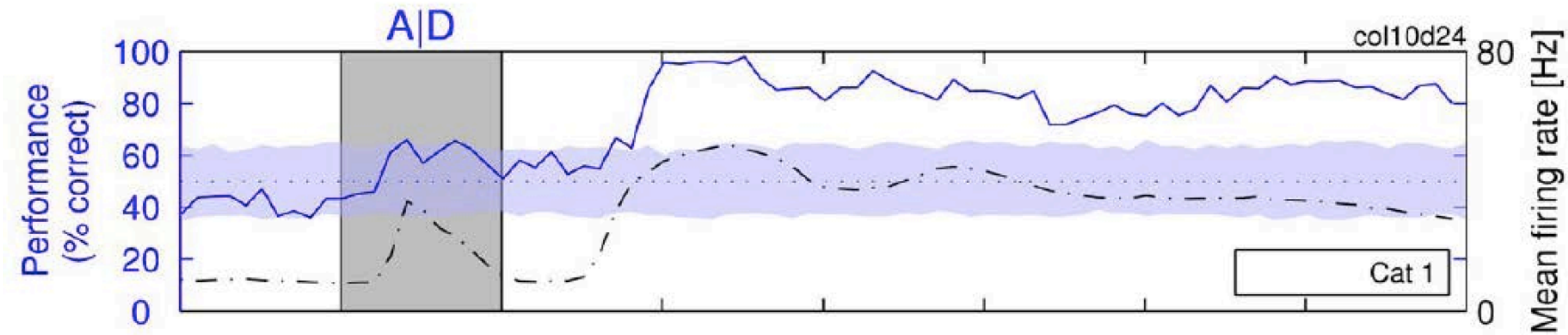
"Distributed Fading Memory for Stimulus Properties in the Primary Visual Cortex", Nikolic et al., PLoS Biol. **7**, e1000260, 2009

Multielectrode recordings from cat primary visual cortex and analyzed the temporal evolution of stimulus-related information in the spiking activity of large ensembles (100 neurons)

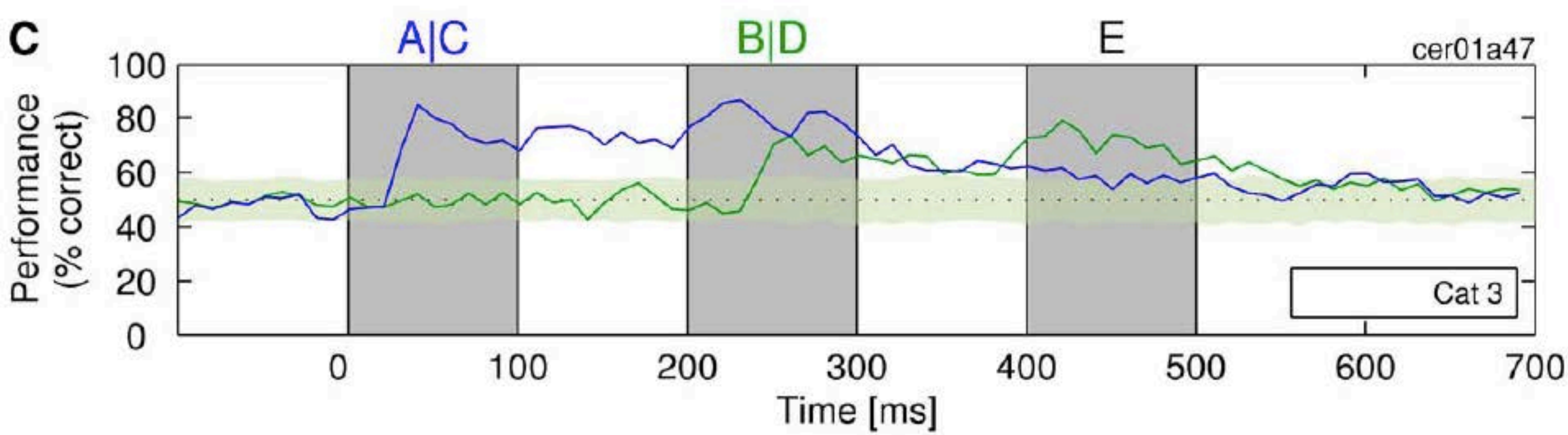




When a single letter was shown for a duration 100 ms, the performance (% of correctly identified symbols) was very high



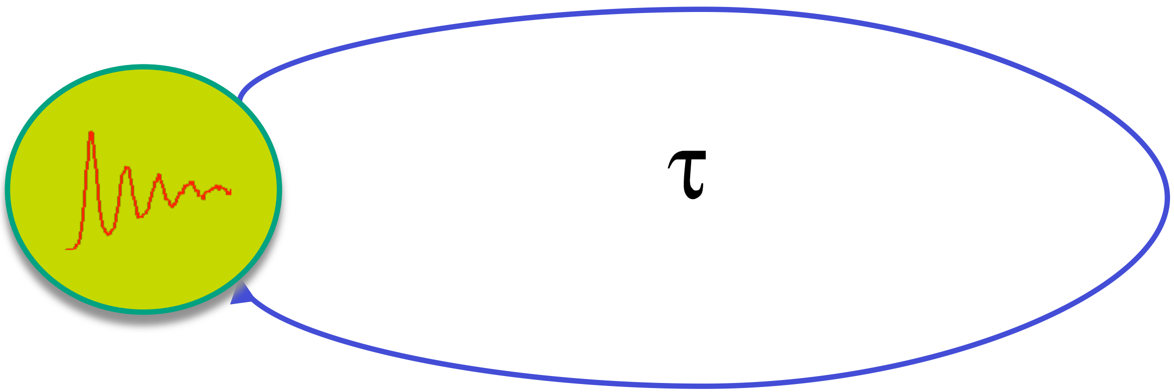
Under multiple images, the response to an image contains as much information about the preceding image as about the current one.



The drawback of RC is its hardware implementation

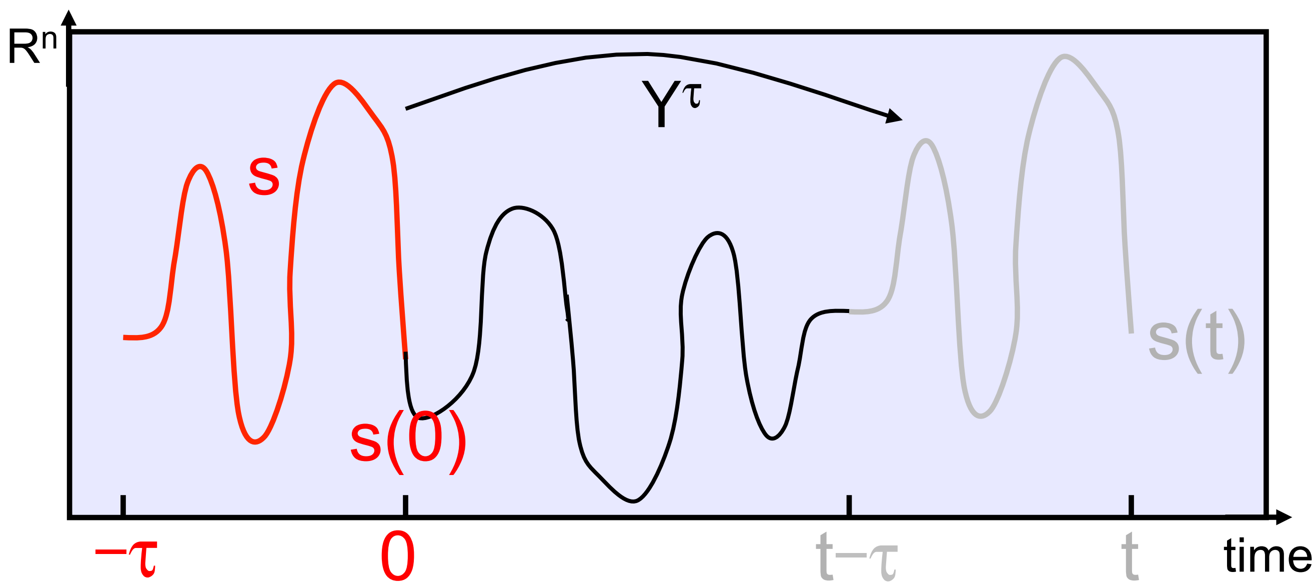
Usually requires 100's-1000's nodes

Can the complex network forming the reservoir be replaced by a single nonlinear node?



Introducing delayed feedback / coupling makes the system high-dimensional.

$$\dot{x}(t) = F(x(t), x(t-\tau); p)$$



Math.: Phase space is infinite-dimensional space of continuous functions *C* on the interval [-τ,0]

Phys.: Degrees of freedom are distributed within the feedback loop (continuous function on the interval [-τ,0])

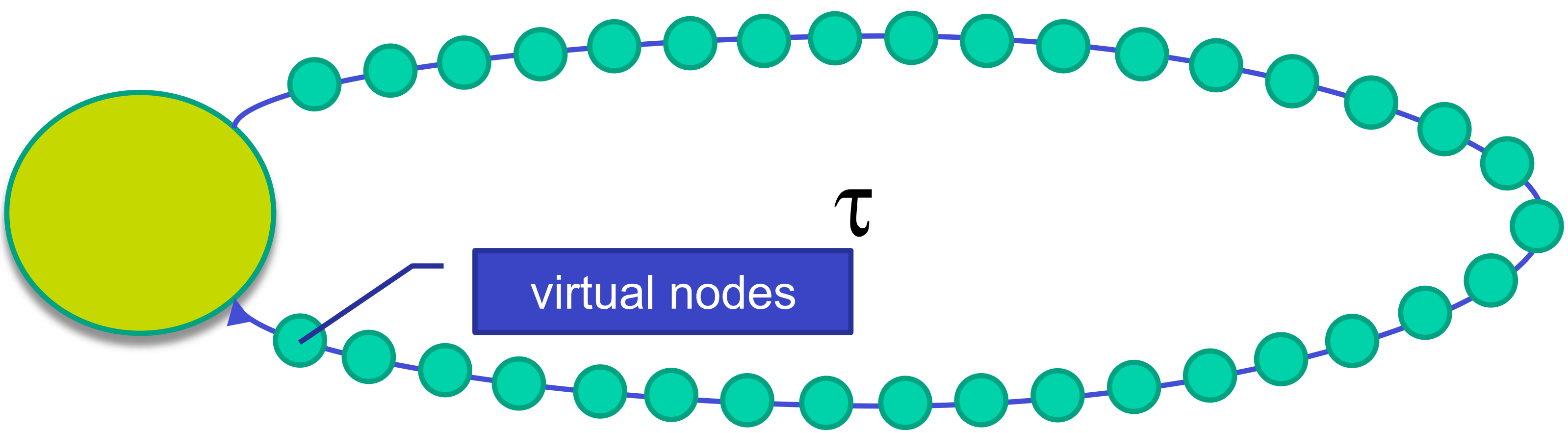
In how far can we replace the complex network by the delay system?

Many degrees of freedom distributed within the delay loop → virtual nodes within the delay

Fading memory introduced by delay

Consistency → initial steady state

Facilitates hardware implementation



Why a hardware implementation is important?

- Era of BIG data → Era of HUGE Data → Processing speed is crucial
- Energy Consumption → More Efficient
- New kind of computation → Traditional computers
- It can be integrated with already existing devices
- It would allow for parallel (and architecture-adapted) implementations

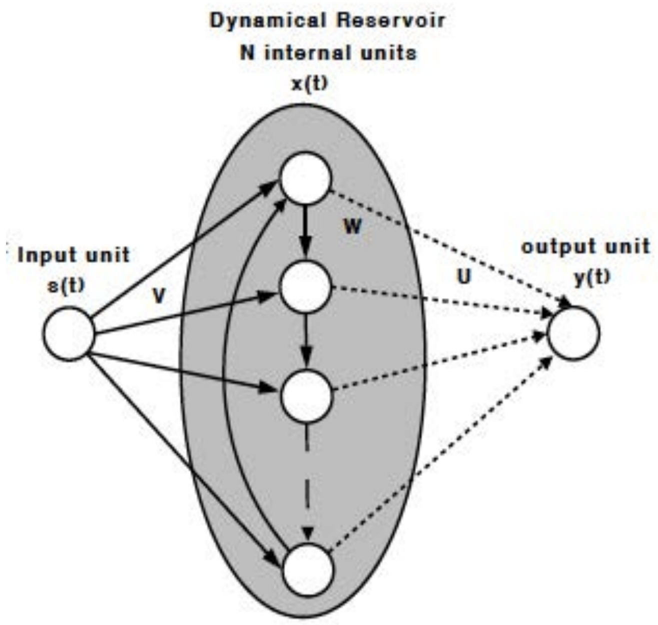
But, overall, with our approach we expect to learn about the basic mechanisms once reducing the concept to the minimal ingredients.

Is the connectivity enough?

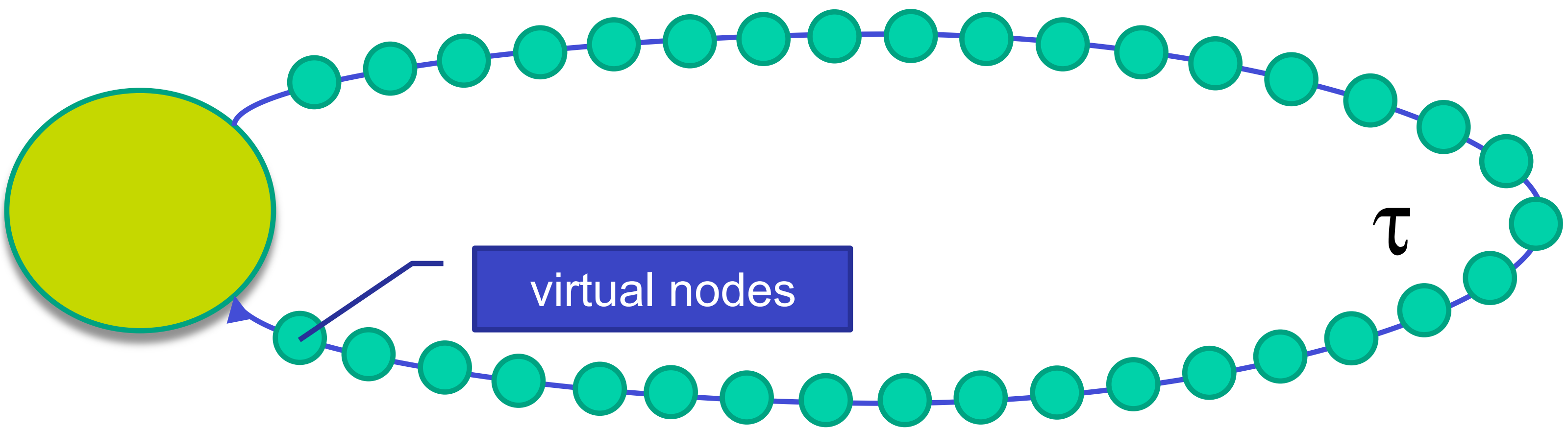
Ali Rodan, and Peter Tino, IEEE Trans. Neural Networks **22**, 131-144 (2011).

What is the minimal complexity of reservoir construction for obtaining competitive models? and what is the memory capacity of such simplified reservoirs?

A simple *deterministically* constructed cycle reservoir is comparable to the standard echo state network methodology.

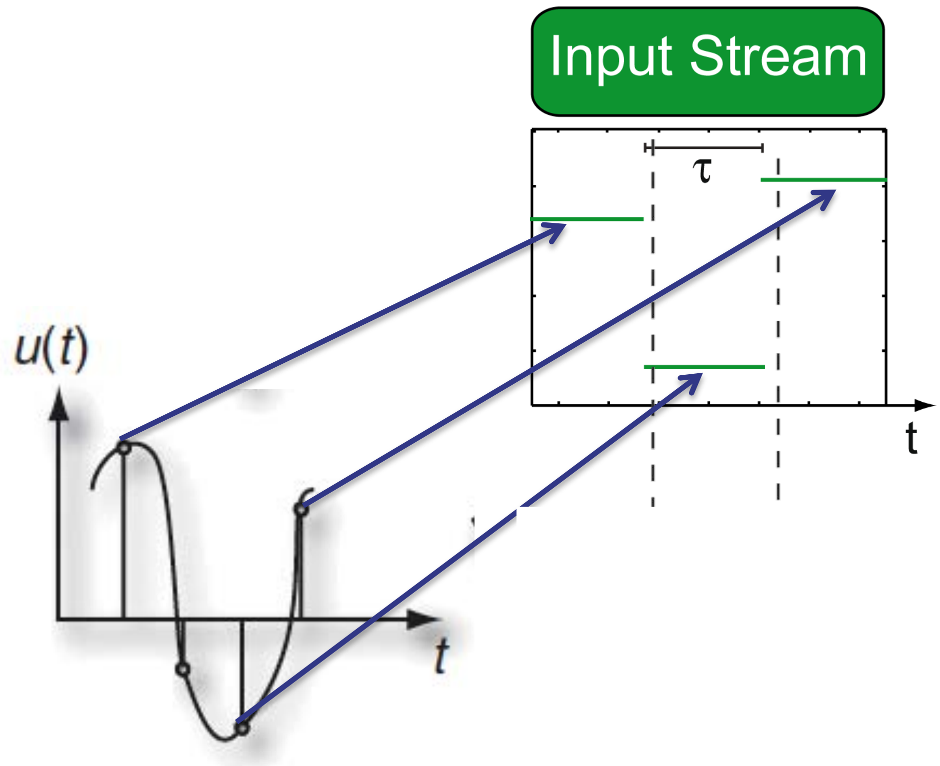


How do we feed the information into the virtual nodes?

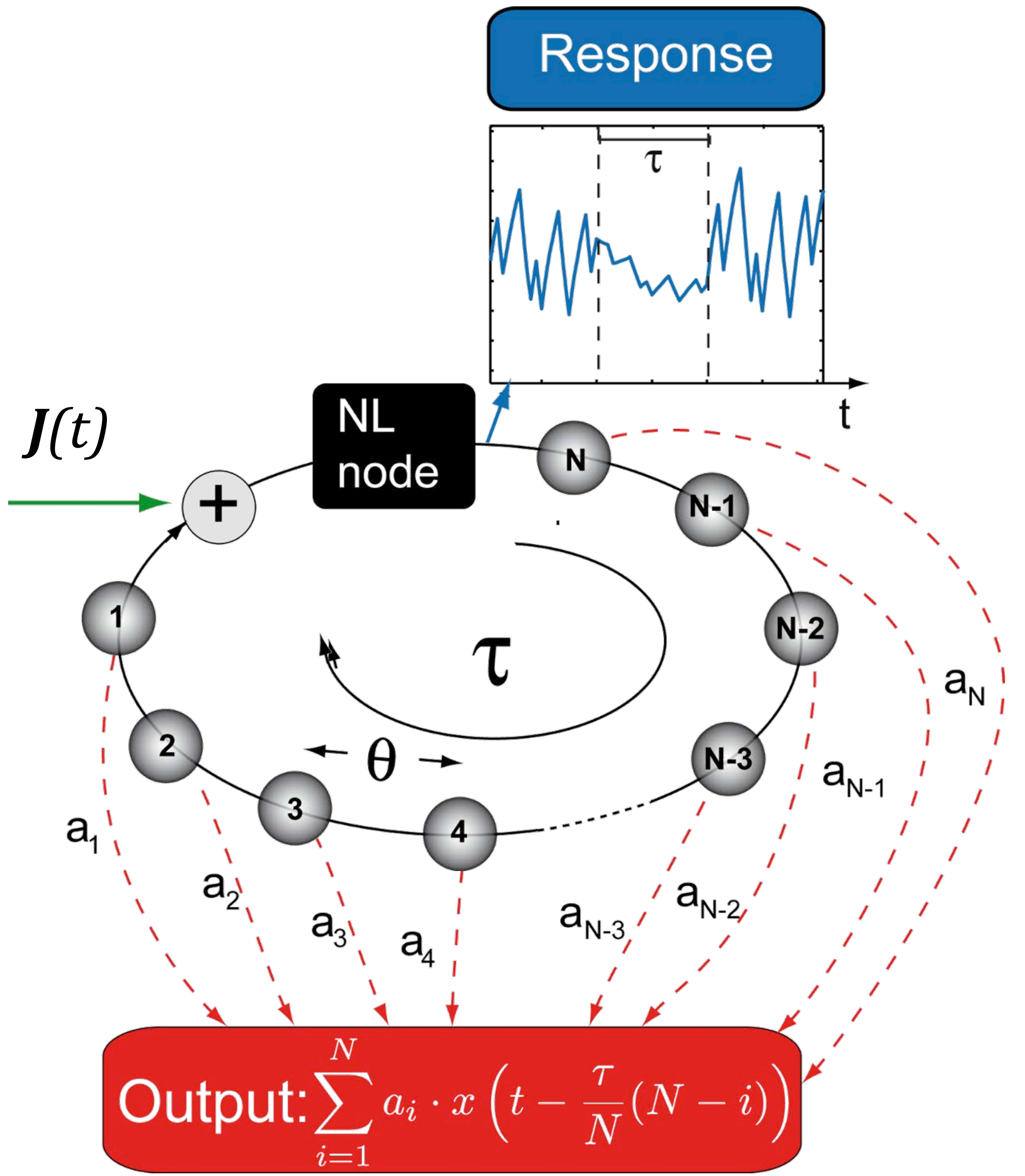


How do we feed the information?

- ***u(t)***: input states, time-varying scalar variable or vector of any dimension
- Feeding the virtual nodes: serializing the input using time-multiplexing
- Each state vector $\boldsymbol{u}(t_0)$ is fed into the N virtual nodes during one delay interval τ.
- Coupling weights from input layer to virtual nodes is done by (random) masking.



- Each virtual node receives: $J(t)=\mathbf{M(t)}\ \mathbf{x}\ \mathbf{u}(t_0)$ *for* $0 < t < \tau$
- After τ:
  - Input vector ***u**(t)* changes
  - the states of virtual nodes are updated → new reservoir state
- reservoir states are read out for further processing
- weighted sum of the states to approximate the target is done off-line after demultiplexing



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Reservoir Computing based on Delay-dynamical Systems

Lennert Appeltant

Joint PhD
Vrije Universiteit Brussel
Universitat de les Illes Balears
May 2012

Available @ https://ifisc.uib-csic.es/en/publications/

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DOI: 10.1038/ncomms1476

Information processing using a single dynamical node as complex system

L. Appeltant[1], M.C. Soriano[2], G. Van der Sande[1], J. Danckaert[1], S. Massar[3], J. Dambre[4], B. Schrauwen[4], C.R. Mirasso[2] & I. Fischer[2]

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Received 16 Aug 2012 | Accepted 10 Dec 2012 | Published 15 Jan 2013
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Parallel photonic information processing at gigabyte per second data rates using transient states

Daniel Brunner[1], Miguel C. Soriano[1], Claudio R. Mirasso[1] & Ingo Fischer[1]

Complex tasks

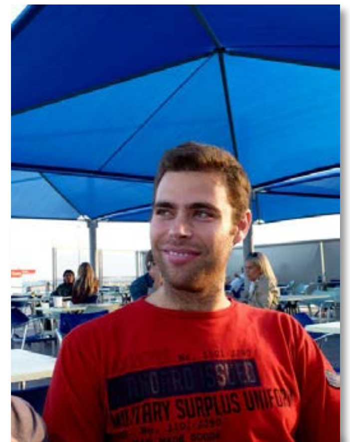
To prove the potential of the proposed system, several benchmark tasks need to be overcome.

- Pattern recognition tasks
- Classification tasks
- Time series prediction
- Dynamical System Modeling

Among these, voice & speaker recognition is one of the most challenging task!

Complex tasks

Ingo Fischer

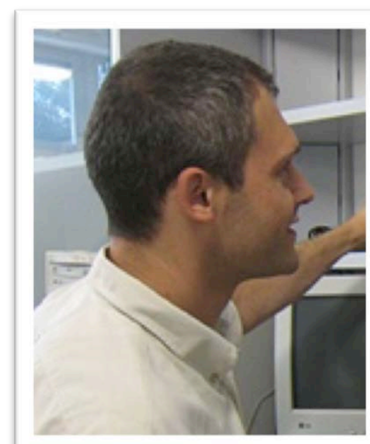


Miguel C. Soriano

Daniel Brunner

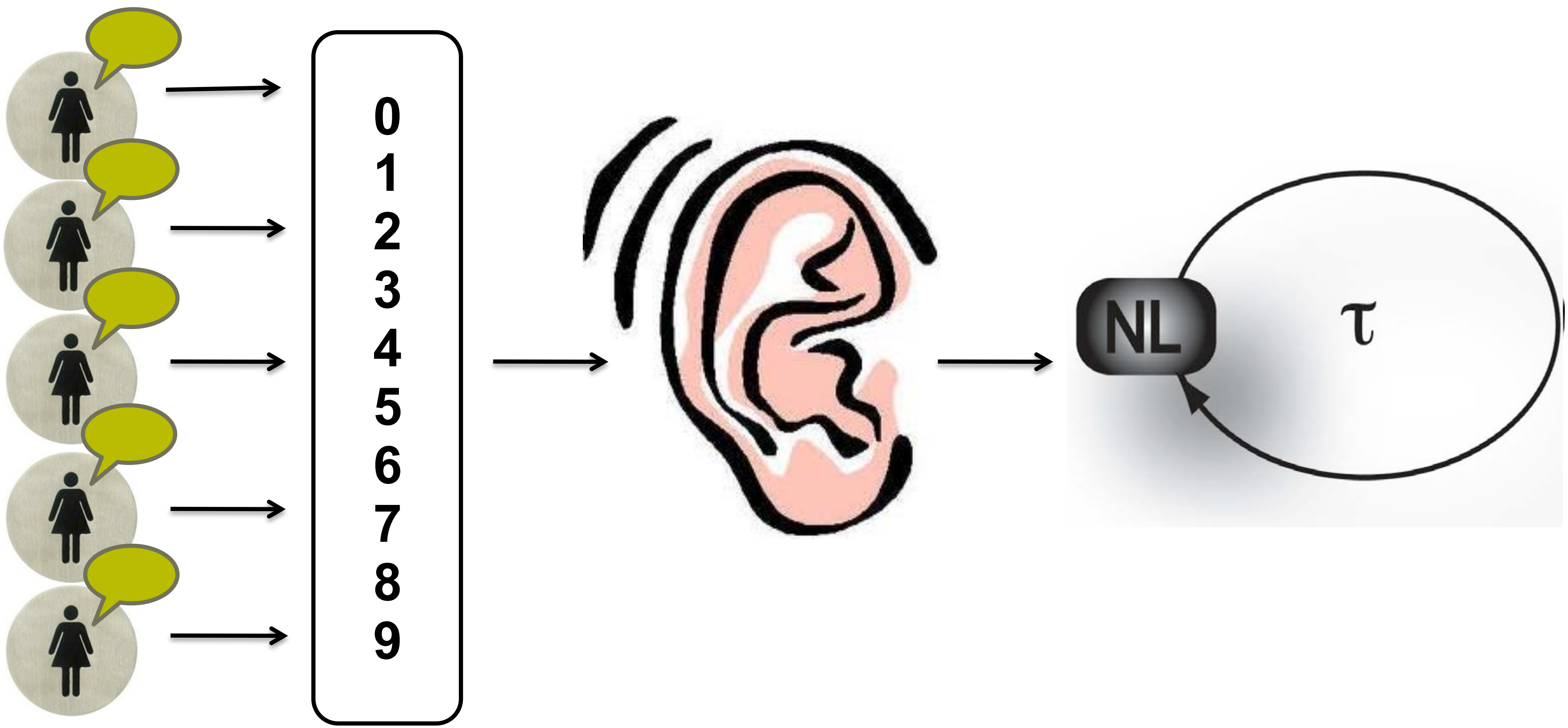
Jan Danckaert

Lennert Appeltant

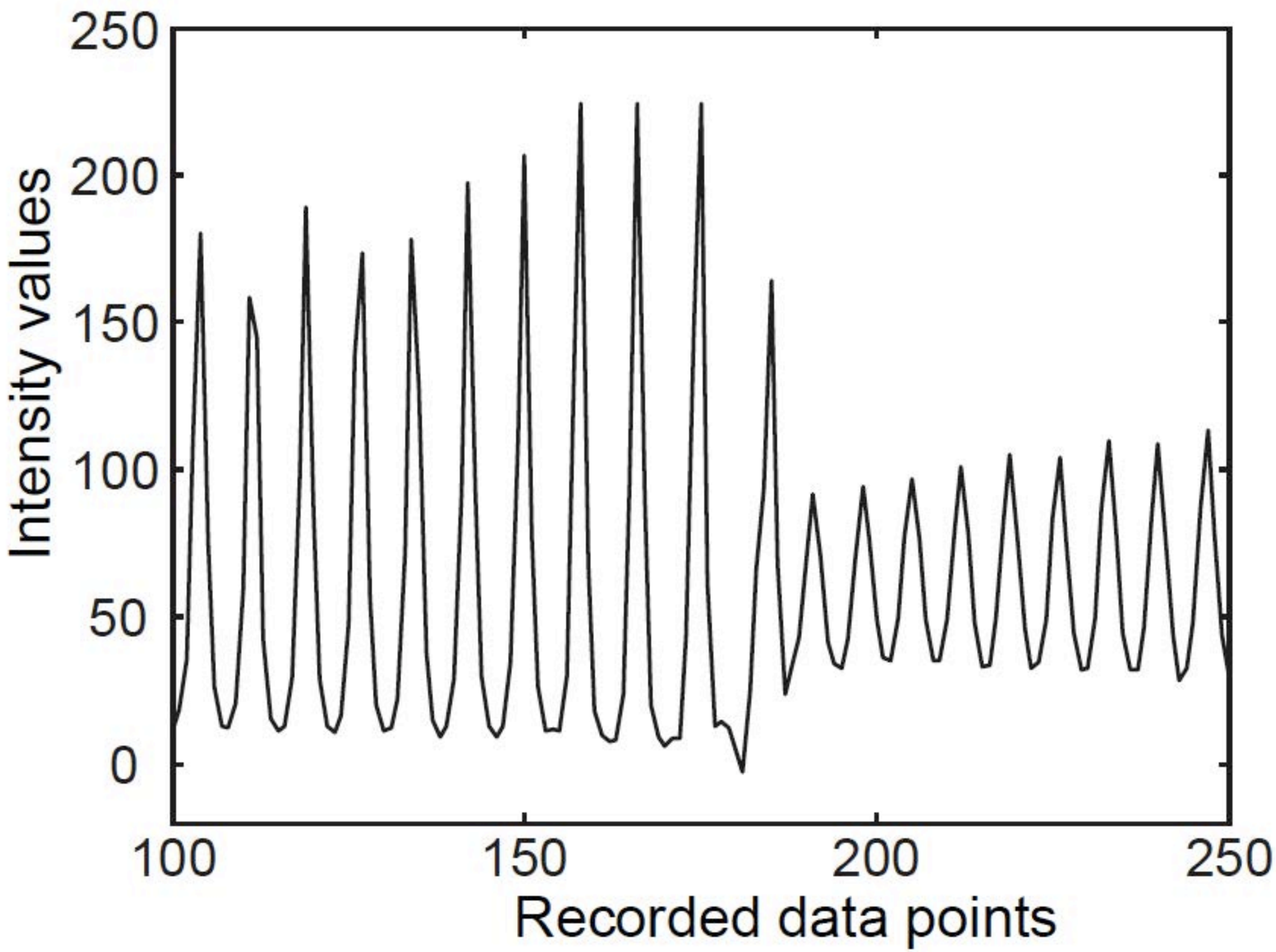


Laurent Larger

Spoken digit recognition

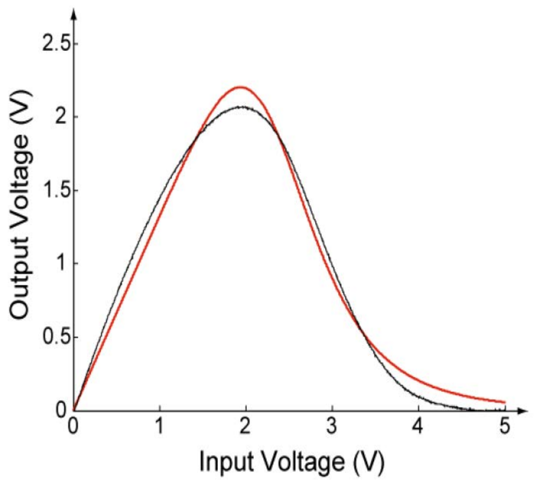


(Chaotic) time series prediction

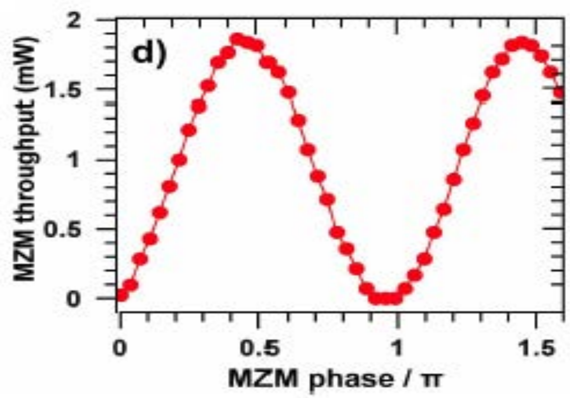


How important is the nonlinearity?

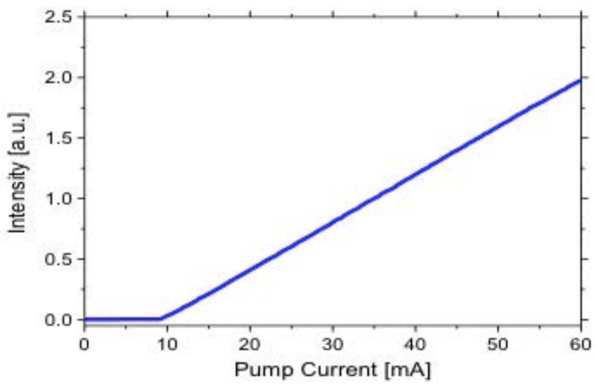
electronic



opto-electronic



all optical



Mackey-Glass nonlinearity

Appeltant et al, “Information processing using a single dynamical node as complex system” Nat. Comm. 2, **468** (2011).

Ikeda nonlinearity

Larger et al, “Photonic information processing beyond Turing: an optoelectronic implementation of reservoir computing,” Opt. Exp. **20**, (3) (2012).

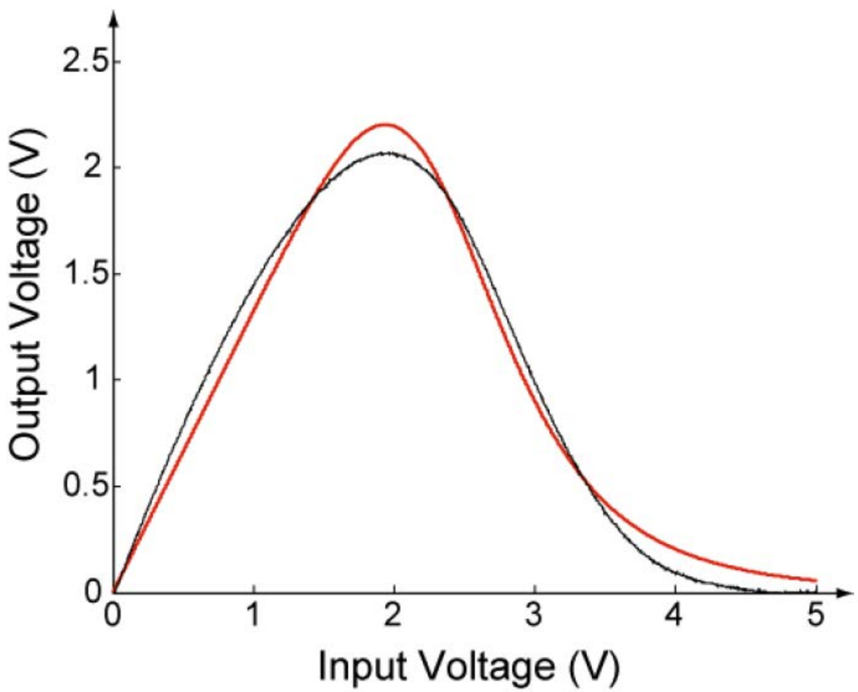
Laser diode nonlinearity

Brunner et al, “Parallel photonic informatio processing at GByte/s data rates using transient states,” Nature Comm., Nat. Comm. 4, 1 (2013).

Mackey-Glass Oscillator

- Mackey-Glass oscillator with delay

$$\dot{X}(t) = -X(t) + \frac{\eta \cdot [X(t-\tau) + \gamma \cdot J(t)]}{1 + [X(t-\tau) + \gamma \cdot J(t)]^{p}}$$

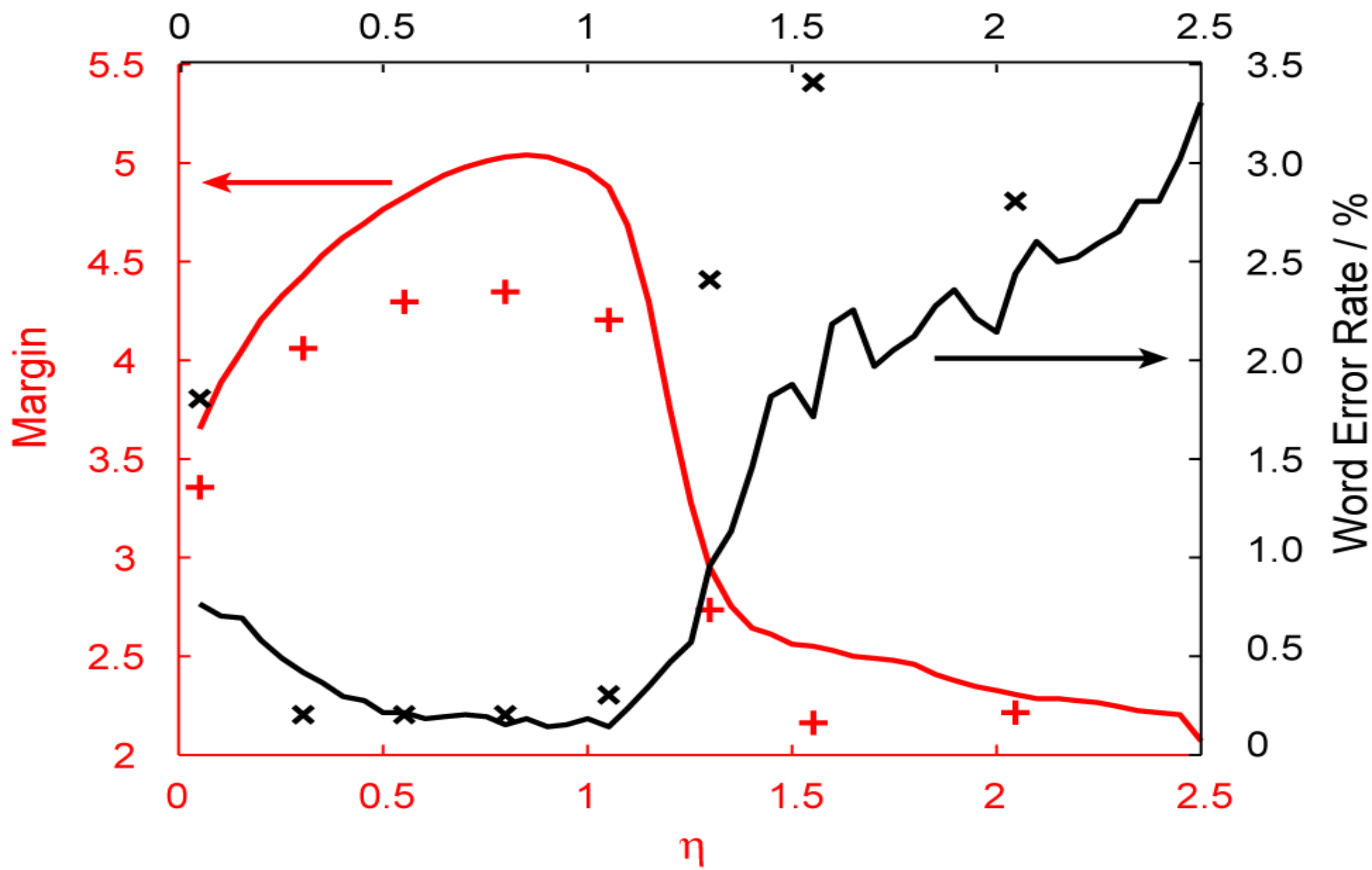


η: feedback strength

γ: Amplification factor

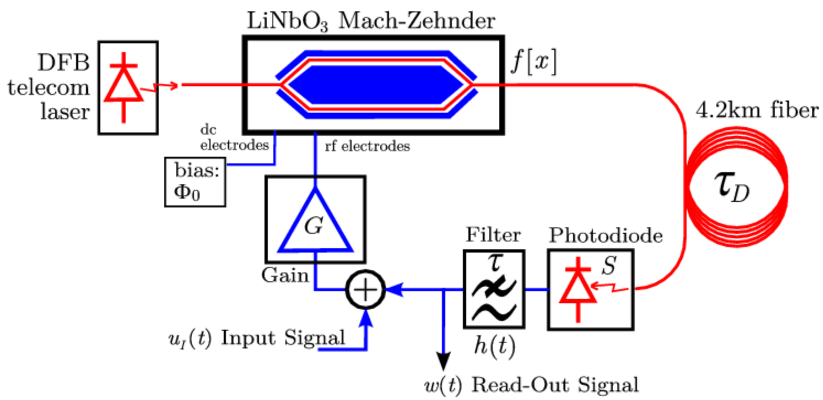
τ: delay time

p: exponent



- Optimum of WER for certain input scaling. Good agreement between experiment and numerical simulations.
- Min(WER) ~ 0.2 %, meaning 1 misclassification in 500 words
- Better performance than for 1200-node RC and other approaches!

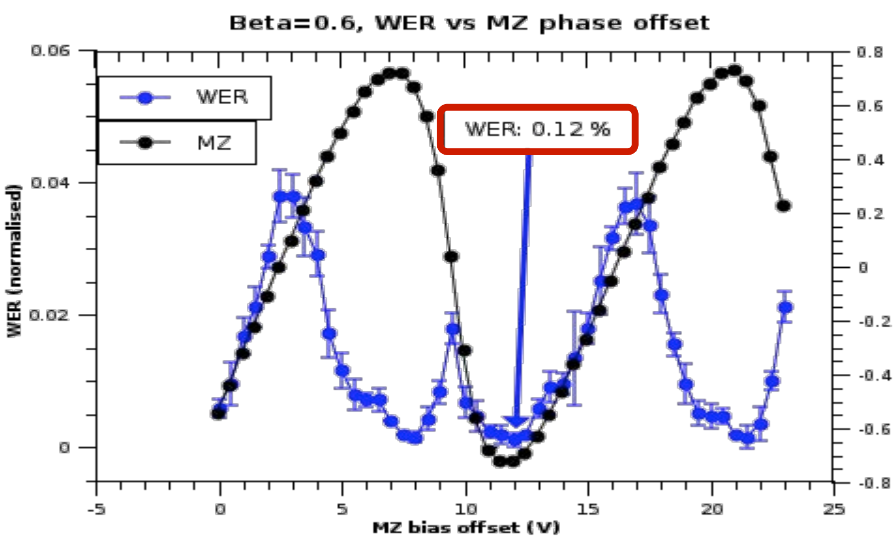
Opto-electronic System



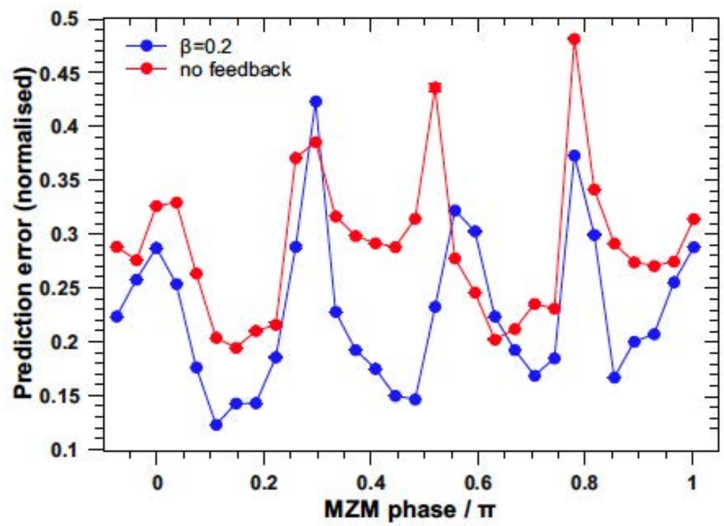
Large delay condition, ϑ=52.18 ns
(τ_D ~ 20.87 μs, T_R=240 ns)

Required input and read-out resolution:
40 MSamples/s.

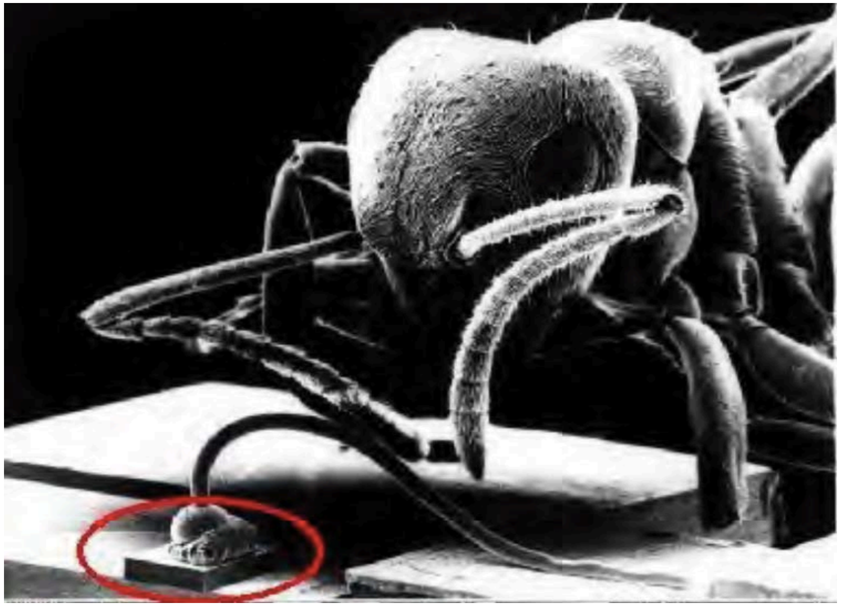
Spoken Digit Recognition



Time Series Prediction



Can we process faster?



Semiconductor lasers

Size: 1μm….. 1mm

Operation: electrical & optical

Speed: Hundredths of Gbit/s

Applications: Optical Comm., Blu-ray, etc.

Info Processing: potentially high speed

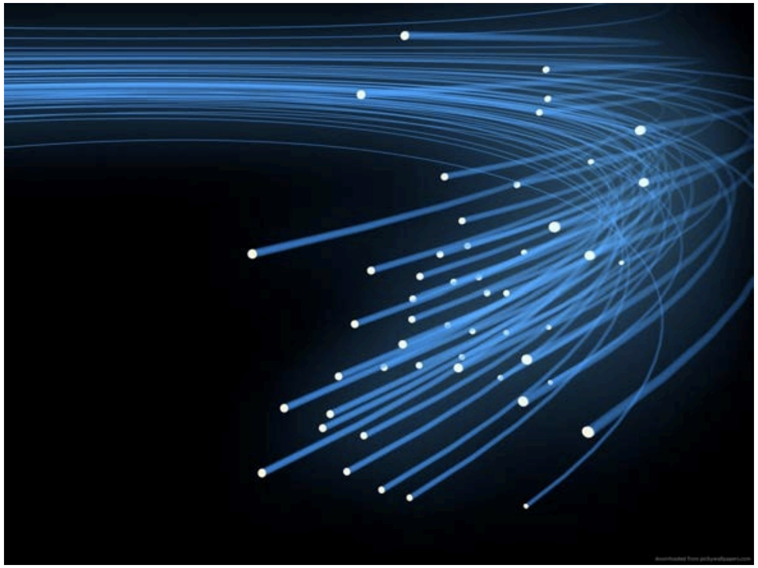
Optical Fibers

Size: 1μm… 100μm diameter

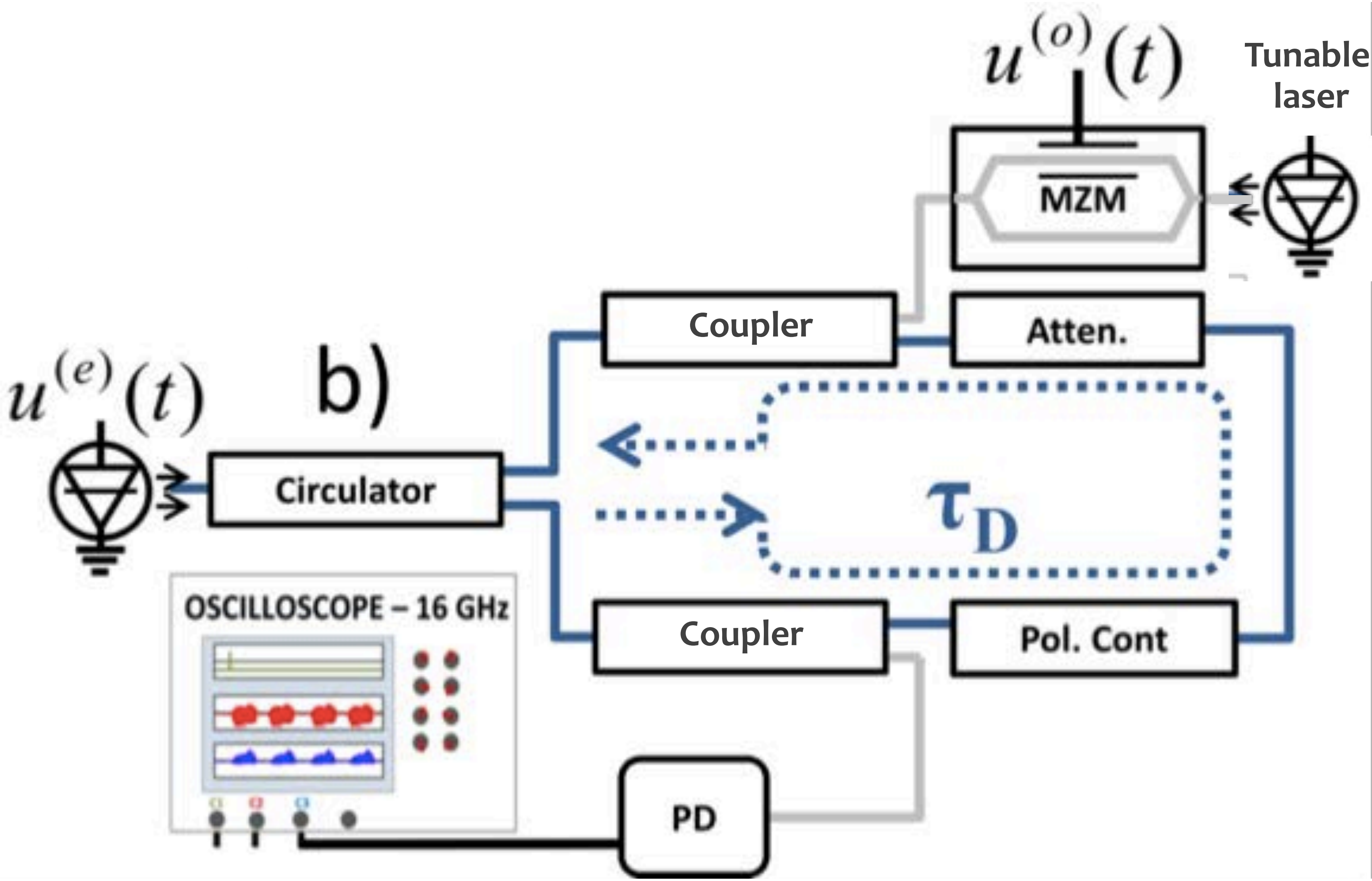
Capacity: Thousands of channels

Coupling: easy to couple to the laser

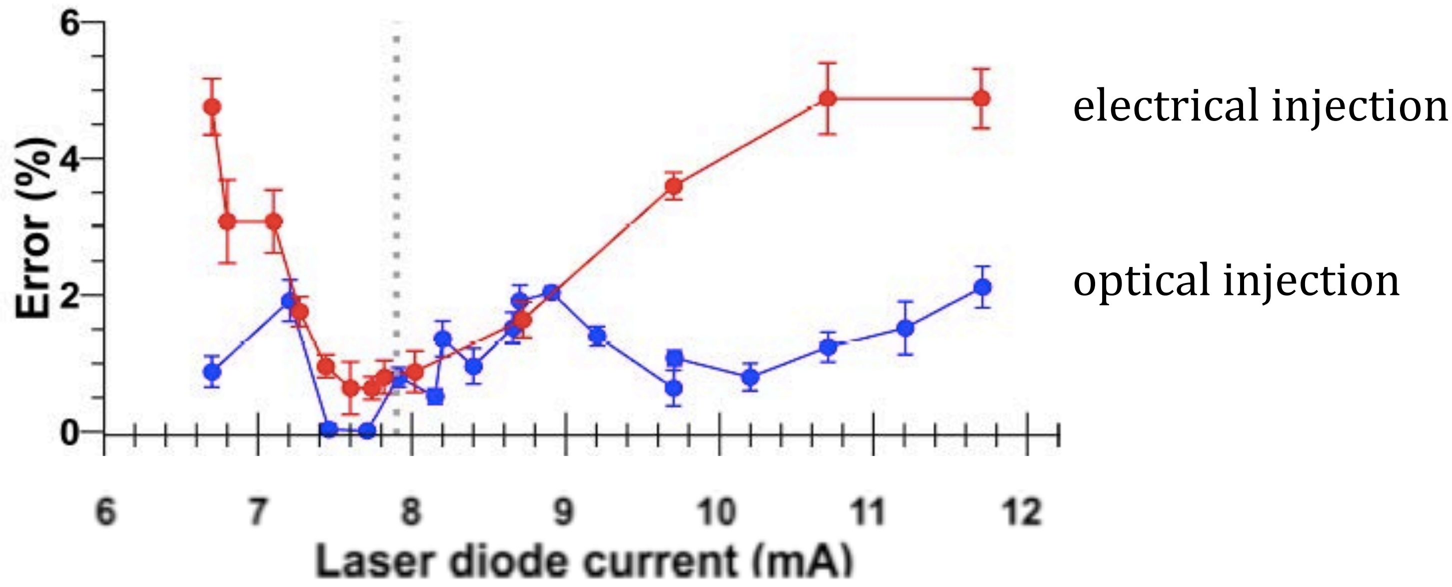
Applications: Optical Comm., medicine, etc.



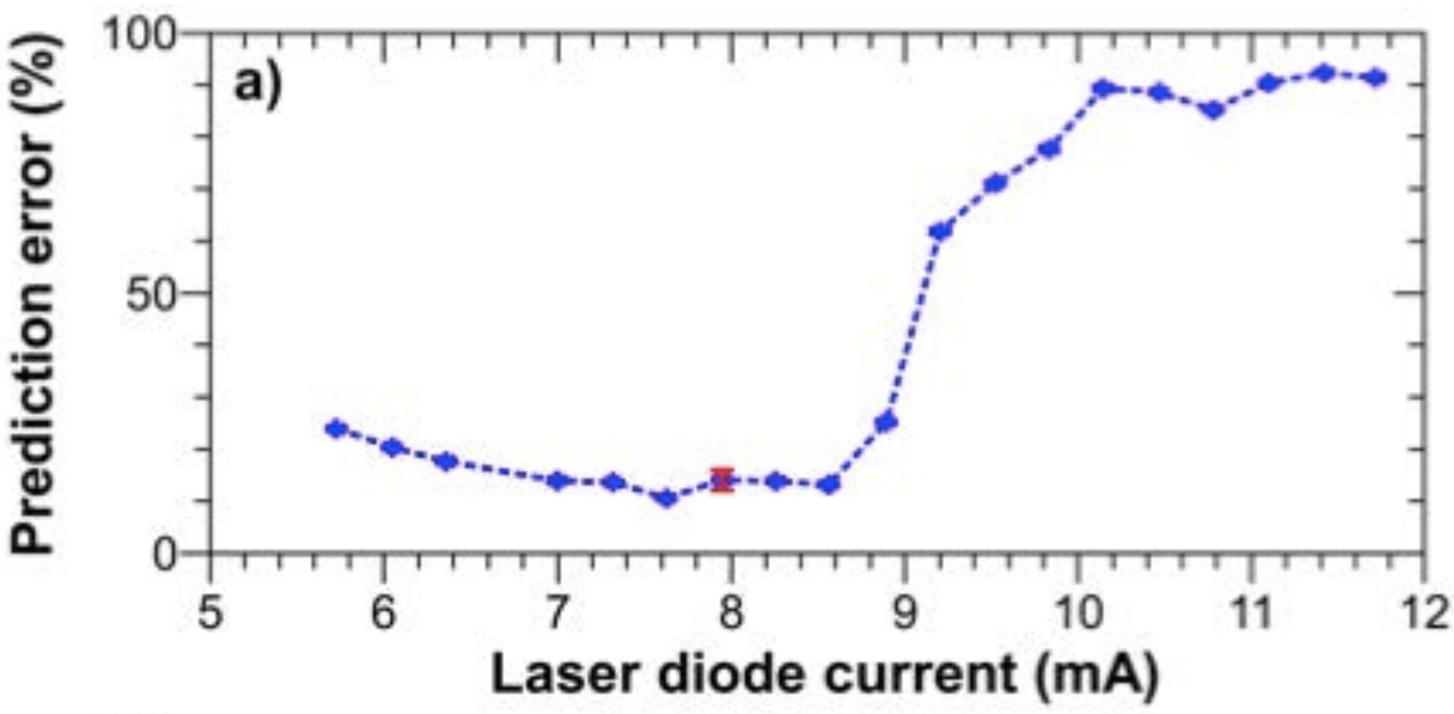
All-optical Setup



Spoken digit recognition

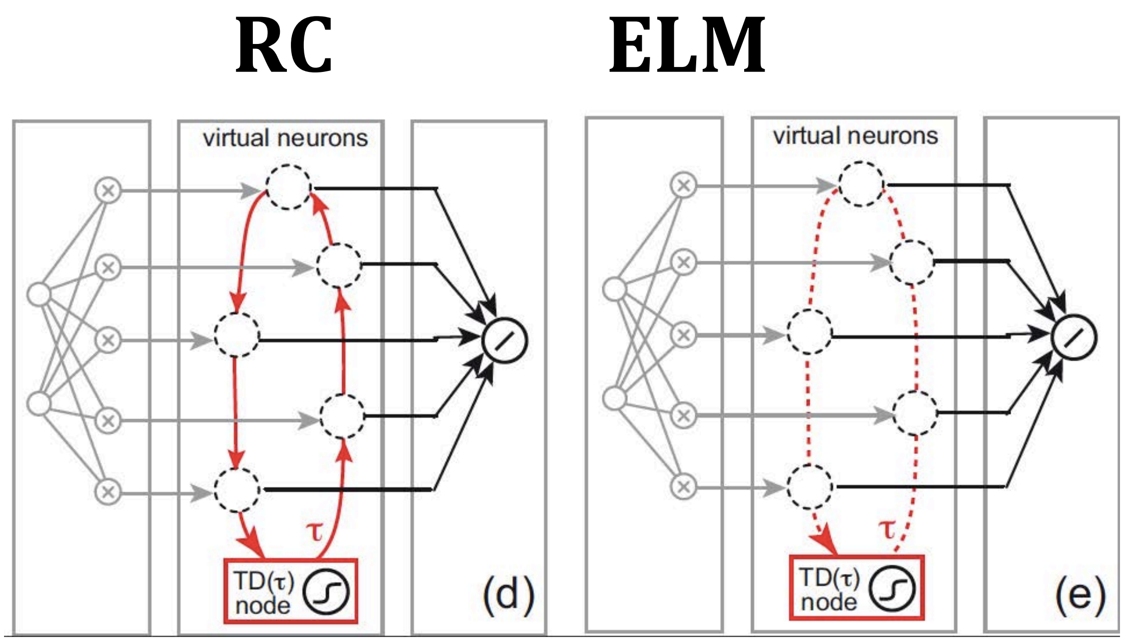


- Excellent performance with 0% WER biasing close to threshold
- Potentially 300.000 words/s can be classified
- Simultaneous classification of words and speakers
- Energy consumption of about 10 mJ compared with 2 J in computers



- Optical Injection
- Best performance **10.6%**, **5%** after averaging
- Traditional RC below **1%** error (with external memory)
- Prediction rate of 1.3×10^7 points/second

From Reservoir Computing to Extreme Learning Machines



Is a simplification of (one-layer) feedforward neural networks, suitable for pattern classification problems

Correspond to the RC without inter-neuron connectivity

Activating or deactivating a single connection (the feedback connection of the neuron) we can easily switch between both learning machines

Our simple scheme enables a hardware implementation of ELMs and RC with an almost effortless mechanism

Summary & Conclusions

- A simple nonlinear system with delayed feedback can process information!
- Neuro-inspired concept
- Replacing complex network by a delay system
  - Enormous simplification for hardware implementations
- Conceptually simple and potentially cheap system
- Classification and time series prediction tasks already demonstrated
- Enables new kind of computation
- Potentially energy efficient
- Electronic & Optical & Mixed implementations are feasible

THANK YOU

for your attention