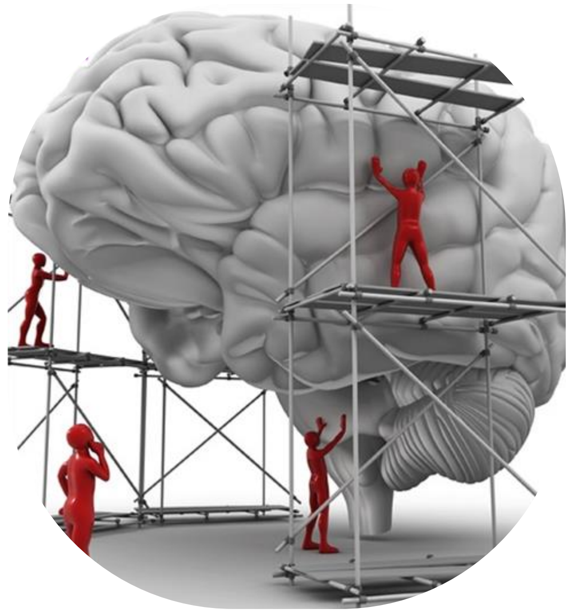


Computational neuroscience
Bionics Engineering

Spring 2017

General Info

- Applied brain science (12 CFU-ECTS)
  - Behavioral and cognitive neuroscience 6CFU SSD:M-PSI/02
  - **Computational neuroscience** 6CFU SSD:INF/01

CNS (Computational neuroscience) is part of *Applied Brain Science* - Master programme in Bionics Engineering

AA2 - *Machine Learning: neural networks and advanced models* (Corso di Laurea Magistrale in Informatica - Master programme in Computer Science) is borrowed from CNS for year 2017.

- **Instructors** (2017):
  - Alessio Micheli
  - Davide Bacciu
  - (assistant /seminars) Claudio Gallicchio
  - Possibly other "guest star" for seminars on specific topics

General info (2)

- **Web page of the course:**
  - **http://pages.di.unipi.it/micheli/DID/CNS.htm**
  - **See DIDAWIKI link in that page, or:**
  - **http://didawiki.di.unipi.it/doku.php/bionics-engineering/computational-neuroscience/start**

- **Time schedule:**
  - **Monday 11.30-13.30 in S13**
  - **Wednesday 15.30-18.30 in SI3**

Who we are

- Alessio Micheli Prof. of CS/ML
  - micheli@di.unipi.it

- Davide Bacciu Researcher of CS/ML
  - bacciu@di.unipi.it

- Claudio Gallicchio Researcher of CS/ML
  - gallicch@di.unipi.it

Computational Intelligence & Machine Learning
http://www.di.unipi.it/groups/ciml

Dipartimento di Informatica
Università di Pisa - Italy

Computational neuroscience

- *Study of the information processing properties of the structures involved in the nervous system dynamics*

- Interdisciplinary science that links the diverse fields of
  - neuroscience, cognitive science, and psychology with
  - biomedical/electrical engineering, computer science, mathematics, and physics.

  - Very large field of studies since beginning of last century
  - Our path for an introduction to the field…

Objectives of this class

- Introduction to the basic knowledge of the CNS, according to the 3 main parts and considering both the bio-inspired neural modelling and computational point of view.
- Gain practical knowledge on simple CNS models by lab experience

Objectives – 2 views

- Introduction to the basic knowledge of the CNS, according to the 3 main parts and considering both the bio-inspired neural modelling and computational point of view.
- Gain practical knowledge on simple CNS models by lab experience

- to study and to model central nervous systems and related learning processes *(how NN works?)*
  - Biological realism is essential
- to introduce effective ML systems/algorithms (even losing a strict biological realism) *(what ANN can do?)*
  - Statistics, Artificial Intelligence, Physics, Math., Engineering, …
  - Computational and algorithmic properties are essential

Objectives – 3 parts

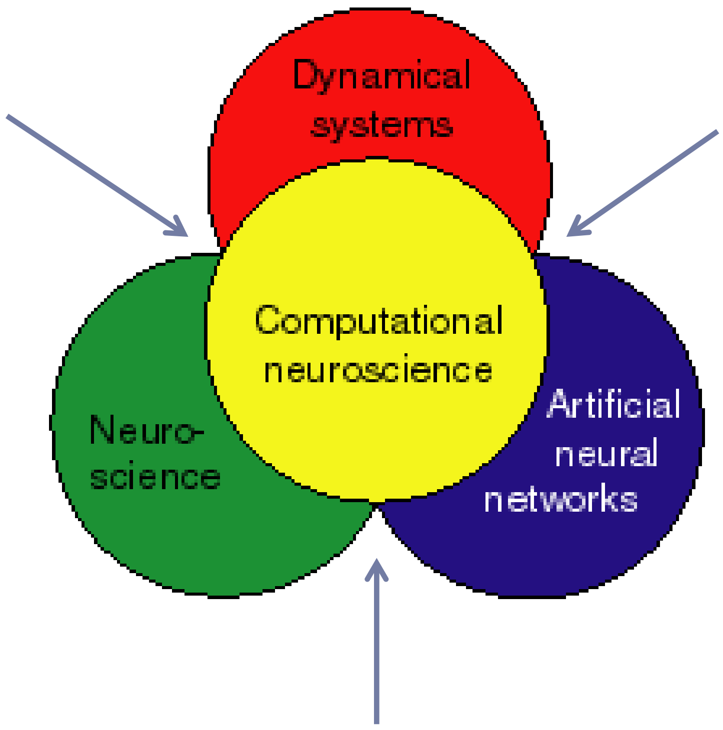
- Introduction to the basic knowledge of the CNS, according to the 3 main parts and considering both the bio-inspired neural modelling and computational point of view.
- Gain practical knowledge on simple CNS models by lab experience

- Including, as for Syllabus,
  - bio-inspired neural modelling
  - advanced computational learning models
  - recurrent neural networks

Our approach to CNS

Neuroscience modeling

Recurrent Neural Networks

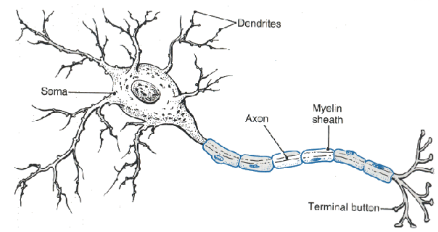


Computational Models for learning

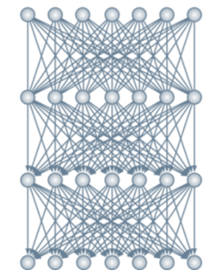
Programme at a glance

- 3 main parts:

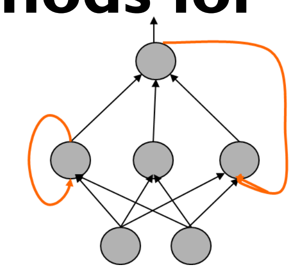
1. **Neuroscience modeling**



2. **Computational neural models for learning: Unsupervised and Representation learning**



3. **Advanced computational neural models for learning: Architectures and learning methods for *dynamical/recurrent neural networks***



Prerequisites:

- Math:
  - mathematical analysis (functions, differential calculus), multivariate calculus, differential equations
  - linear algebra, matrix notation and calculus,
  - elements of probability and statistics (advanced signal processing in parallel)
- Basic knowledge of algorithms and computational complexity
- Basics of machine learning
  - including Artificial Neural Networks with backpropagation, and cross-validation techniques for model selection/evaluation
- Programming: MATLAB for our lab.

Toward brain science: biological and artificial motivations

- **Advancements in the studies for "intelligence":**
  - IT view – construct new intelligent systems + data science→ success in current industry developments , e.g. *deep learning*
  - Brain understanding: e.g. brain's projects
- **We will try to follow these two motivational approaches/objectives**

Nature, jan 2016

Self-driving cars

Brain's projects

A look ahead - BRAIN (USA)

- Few words on the BRAIN's research projects
- An "instructive" current history for the interest and for the issues in research: USA versus EU

- **Brain Initiative USA**
  - http://www.braininitiative.nih.gov/
  - https://en.wikipedia.org/wiki/BRAIN_Initiative
  - The White House **BRAIN Initiative** (**Brain Research through Advancing Innovative Neurotechnologies**), is a collaborative, public-private research initiative announced by the Obama administration on April 2, 2013

"Revolutionizing our understanding of the human brain"
"Understanding how the brain works is arguably one of the greatest scientific challenges of our time."

A look ahead - HBP (EU)

- **Human Brain Project**
  - https://www.humanbrainproject.eu/
  - https://en.wikipedia.org/wiki/Human_Brain_Project

HBP: overview: "*Understanding the human brain is one of the greatest challenges facing 21st century science. … Today, for the first time, modern **ICT** has brought these goals within sight.*"

European Commission

Human Brain Project

- AIM: simulation of millions of neurons (up to a whole brain) by supercomputer (within a single system model)

HBP: Human Brain Project - 2013

- Great potentiality:
  - Medicine/neuroscience: diseases studies (e.g. Alzheimer), new drugs, …
  - Revolutionary new artificial intelligent systems (robotics etc.)
- Great interest:
  - Neuroscience on the edge for a great advancement
  - > 1 billion euro for 10 years research by EC (flagship project)
- Criticisms:
  - Great risk (can we really simulate a brain?)
  - Cooperation and management issues
  - Highlight the necessity for *interdisciplinary approach* (see American BRAIN prj)
- Future: still open! E.g. integrate the two approaches:
  - Data-driven/science computational approaches & cognitive/neurobiological analysis and approaches

CNS mailing list

- Please, send soon to me (micheli@di.unipi.it) an email:
  - **Subject:** [CNS-2017] student
  - **Corpus (email text):**
    - Name Surname
    - Master degree programme (Bionics eng. or Computer Science?)
    - Any note you find useful to us

Thank you.

Exam modality

- **Written exam:**
  - Corpus of lab exercises – source code (at the date of exam)
  - A presentation (seminar) on a selected topic (typical)
  - or small project on a selected topic
    - topic agreed with one of the instructors
    - deliberated to us in advance (at the date of exam)
- **Oral exam** on all the course topics (some days after the material delivery, typically ~10 days)
- **Joint** with first module of Applied brain science (BCN&CNS)

FAQ on Seminars and Projects

- A **project** can be assigned only *after* you will complete the labs exercises
  - In fact, the project is dedicated to students that already have familiarity with lab tools and that like to go beyond the lab level to deal, with autonomy, with new challenges.
  - Require large autonomy*, modeling** and programming skills, more time.
  - For the projects groups of 2 people are allowed
  - The project exam material will consist in code, results and a written report (then not a presentation but a discussion on the results) [details later]
- The **seminar** is individual
  - A Seminar concerns the study of a topic by literature papers and 15 minutes slide presentation by the student (at oral exam)
  - Slides sent in advance as material, presented at the oral exam

How to send to us exam material?

- Email to us (Bacciu, Micheli, Gallicchio)

[micheli@di.unipi.it, bacciu@di.unipi.it, gallicch@di.unipi.it]

  - **Subject:** [CNS-2017] student Rossi exam material
  - **Body (email text):**
    - Name Surname, email contact
    - Master degree programme (Bionics eng. or Computer Science?)
    - Material attachments (lab source code files, report for the project or slides for the presentation).
    - Any note you find useful to us
  - Note: all the material in only one delivery

  - Deadline for material delivery: dates of the exam session (which is fixed in the formal Unipi web site for exams)
  - The oral will be fixed after the delivery (typically 10 days ahead)
  - Further details will be discussed during the course

3 "secret" hints (from past students experience)

1. Study the content (theory) *on-line* (during the course):
   - take direct and immediate advantage from LABs (and so to complete them during the course or soon after the end of the course)
2. Finalize the LAB assignments
3. After 1 and 2, ask, decide and apply for the seminar/project

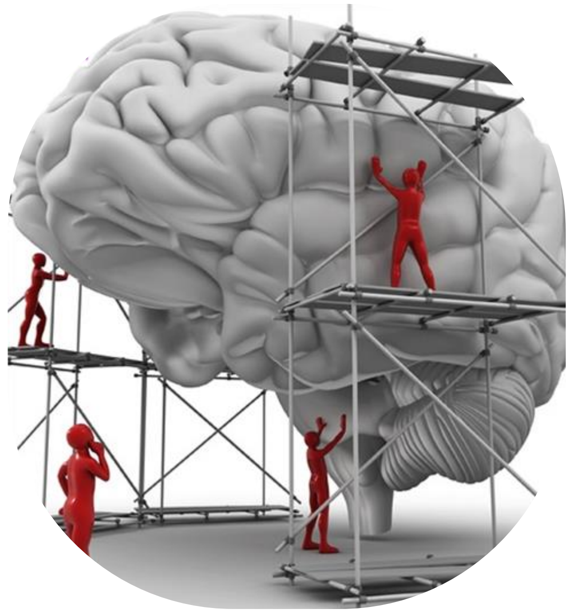
- Choice prj or seminar primary according to your future use of the results (which effort deserve for?)

Bibliography

- Main textbook:

1. E.M. Izhikevich, Dynamical Systems in Neuroscience: The Geometry of Excitability and Bursting. The MIT press, 2007
   - W. Gerstner and W.M. Kistler, Spiking Neuron Models: Single Neurons, Population, Plasticity. Cambridge Univ. Press, 2002 [freely available online:]
2. P. Dayan and L.F. Abbott, Theoretical Neuroscience. The MIT press, 2001.
3. S. Haykin, Neural Networks and Learning Machines (3rd Edition), Prentice Hall, 2009

- Further material: see details in the slides for each part of the course
- The slides are a guide to select parts in these "big" books
- Slides: see Didawiki from **http://pages.di.unipi.it/micheli/DID/CNS.htm**



CNS Programme: details on each of the 3 parts

Spring 2017

Part 1 - Neuroscience modeling

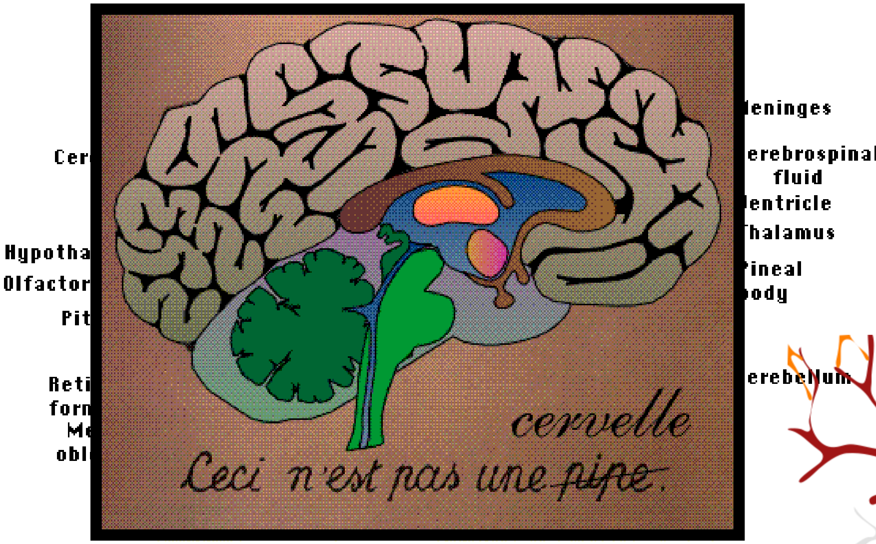
Claudio Gallicchio

Part 1

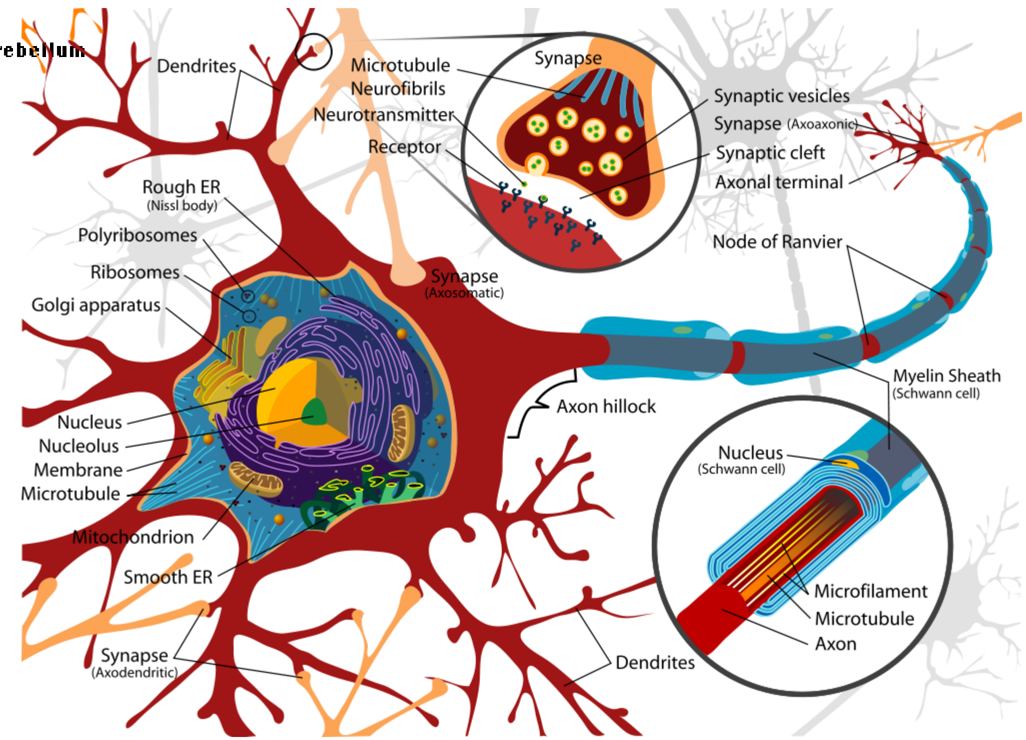
Neuroscience modeling

- Introduction to basic aspects of brain computation
- Introduction to neurophysiology
- Neural modeling:
  - Elements of neuronal dynamics
  - Elementary neuron models
  - Neuronal Coding
  - Biologically detailed models: the Hodgkin-Huxley Model
  - Spiking neuron models, spiking neural networks
  - Izhikevich Model
- Introduction to Reservoir Computing and Liquid State Machines
- Introduction to glia and astrocyte cells, the role of astrocytes in a computational brain, modeling neuron-astrocyte interaction, neuron-astrocyte networks,
- The role of computational neuroscience in neuro-biology and robotics applications.

The Computational Brain and Neurons



The brain as a computational device

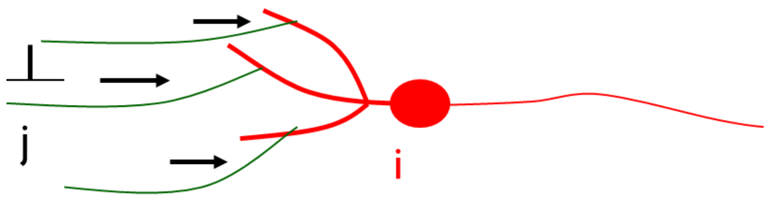


Neurons are basic structural elements of the brain

Neurons (mainly) communicate through electrical signals called **spikes**

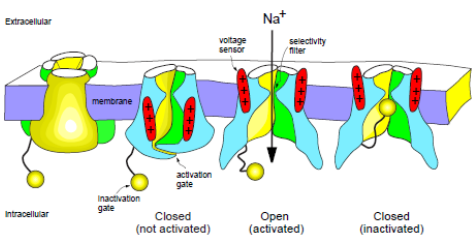
Neural Modeling

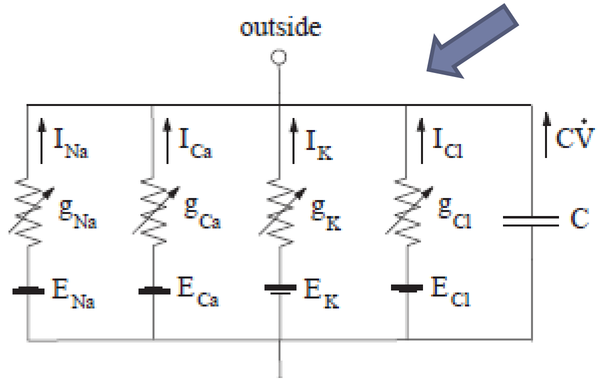
Modeling Neuronal Dynamics



$$u_i(t) = \eta(t - \hat{t}_i) + \sum_j \sum_f \epsilon_{ij}(t - t_j^{(f)}) + u_{\text{rest}}$$

$$u_i(t) = \vartheta \text{ and } \frac{\mathrm{d}}{\mathrm{d}t} u_i(t) > 0 \quad \Longrightarrow \quad t = t_i^{(f)}$$

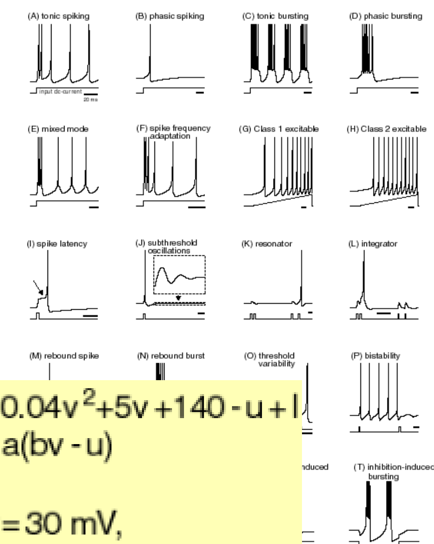




$$C \frac{\mathrm{d}u}{\mathrm{d}t} = -\sum_k I_k(t) + I(t)$$

$$\sum_k I_k = g_{\text{Na}}\, m^3 h\, (u - E_{\text{Na}}) + g_{\text{K}}\, n^4\, (u - E_{\text{K}}) + g_L\, (u - E_L).$$

$$\begin{aligned} \dot{m} &= \alpha_m(u)\,(1-m) - \beta_m(u)\, m \\ \dot{n} &= \alpha_n(u)\,(1-n) - \beta_n(u)\, n \\ \dot{h} &= \alpha_h(u)\,(1-h) - \beta_h(u)\, h \end{aligned}$$

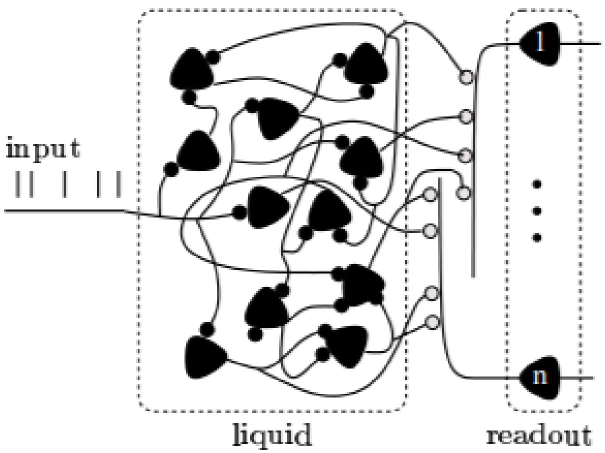


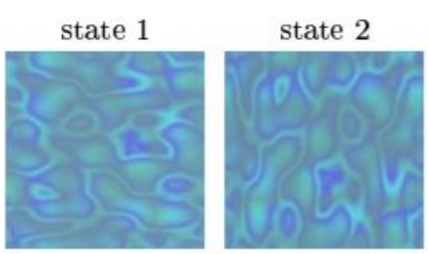
$v' = 0.04v^2 + 5v + 140 - u + I$
$u' = a(bv - u)$

if $v = 30$ mV,
then $v \leftarrow c, \quad u \leftarrow u + d$

Reservoir Computing

Liquid State Machines





encode different input patterns

Biologically realistic neural circuits used as excitable memory called liquid

Input stimuli are transformed into liquid states

The liquid implements a pool of random filters

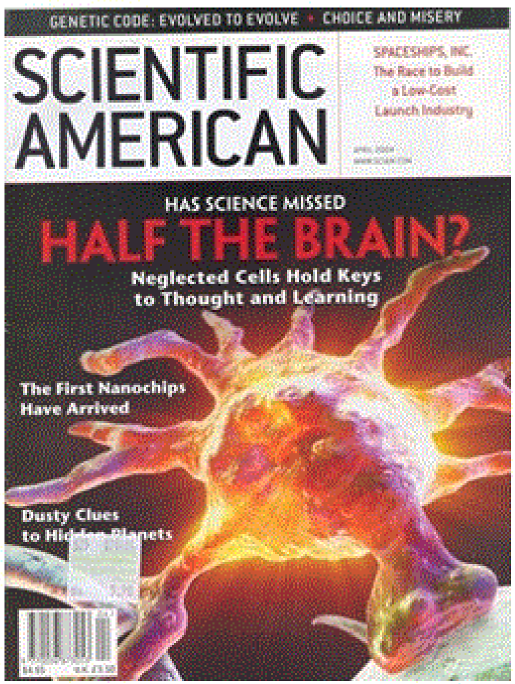
The output is computed by a memory-less pool of (trained) neurons, the readout

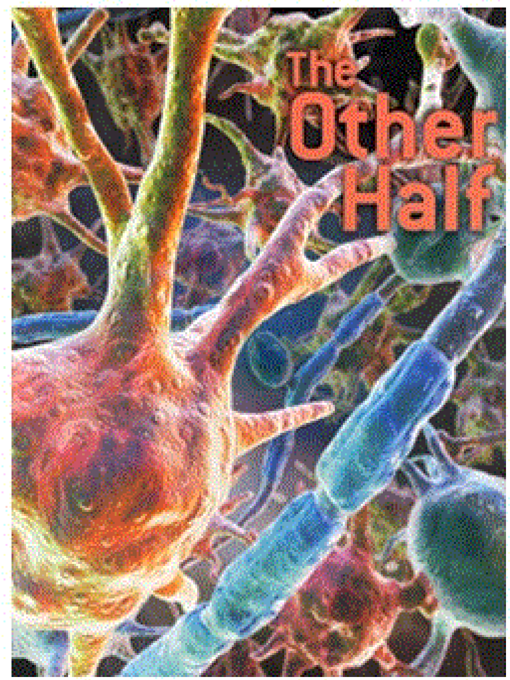
Astrocytes: The Other Half

SCIENTIFIC AMERICAN APRIL 2004

The Other Half of the Brain

Mounting evidence suggests that glial cells, overlooked for half a century, may be nearly as critical to thinking and learning as neurons are

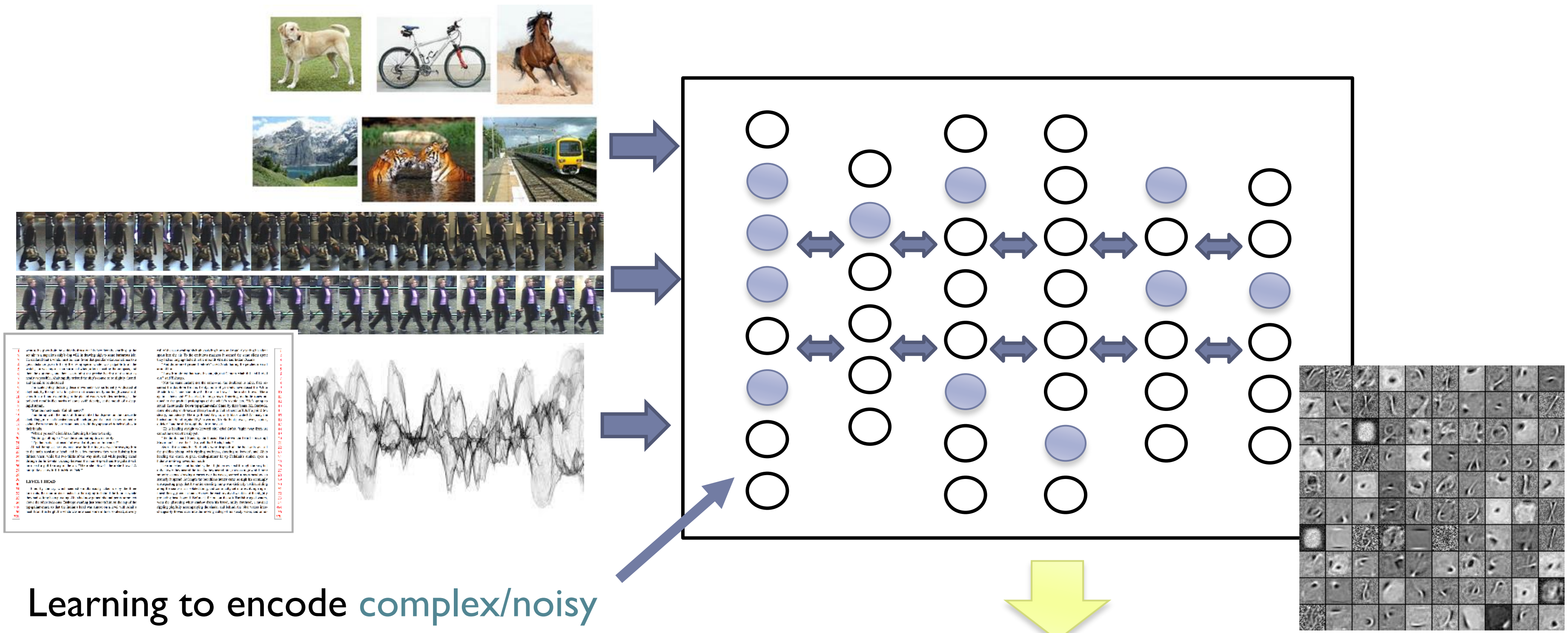




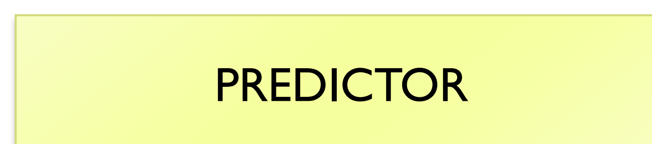
Part 2 - Unsupervised and Representation Learning

Davide Bacciu

Representation Learning

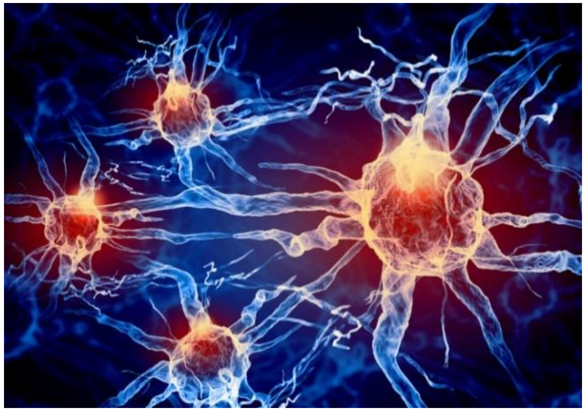


Learning to encode complex/noisy input information in the activations of a neural network



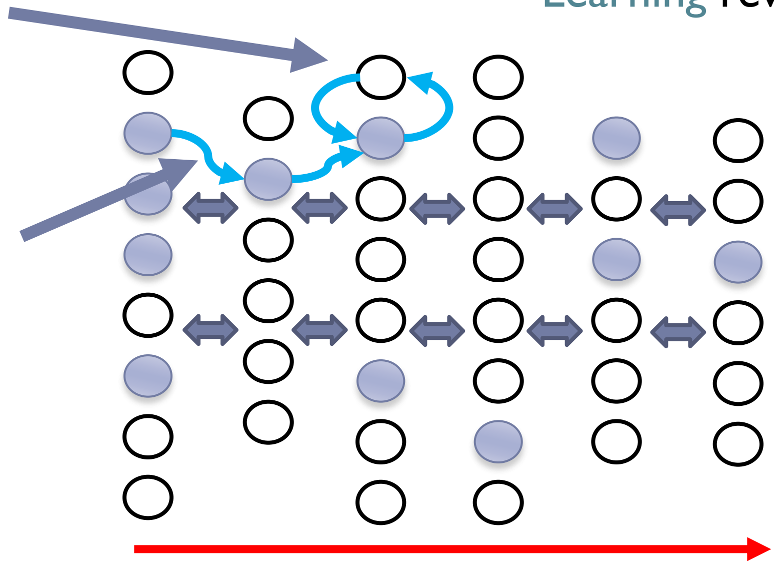
Such that a decoder can effectively use it to compute its predictions

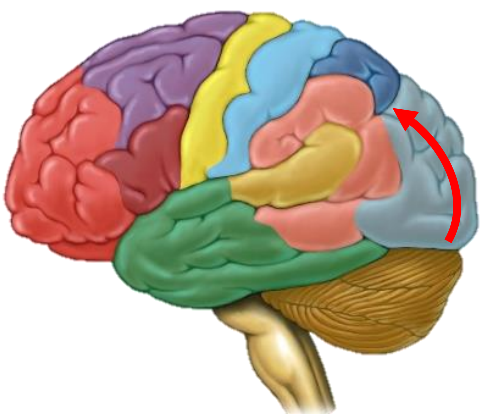
The Approach



Parameter learning as a bio-inspired memory mechanism

The foundations of the Deep Learning revolution





Hierarchical information processing

Learning models whose structure is inspired by the organization of the sensory cortices

Contents

- Synaptic plasticity, memory and learning
  - Associative learning, competitive learning and inhibition
- Associative memory models
  - Hopfield networks
  - Boltzmann Machines
  - Adaptive Resonance Theory
- Representation learning and hierarchical models
  - Biological inspiration: sparse coding, pooling and information processing in the visual cortex
  - HMAX, CNN, Deep Learning

Learning High-Level Human Skills from Scratch

Learning to bridge neural encodings of visual and textual information

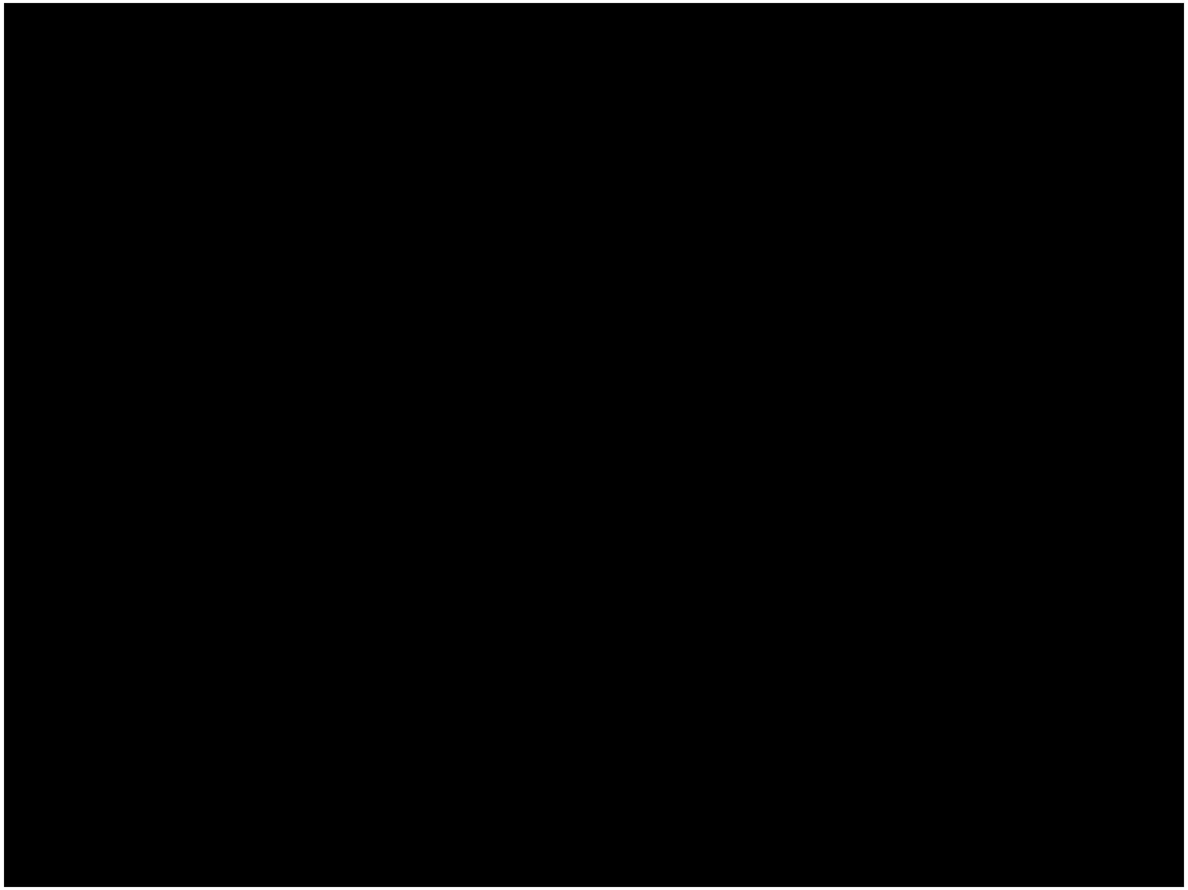
"black and white dog jumps over bar."

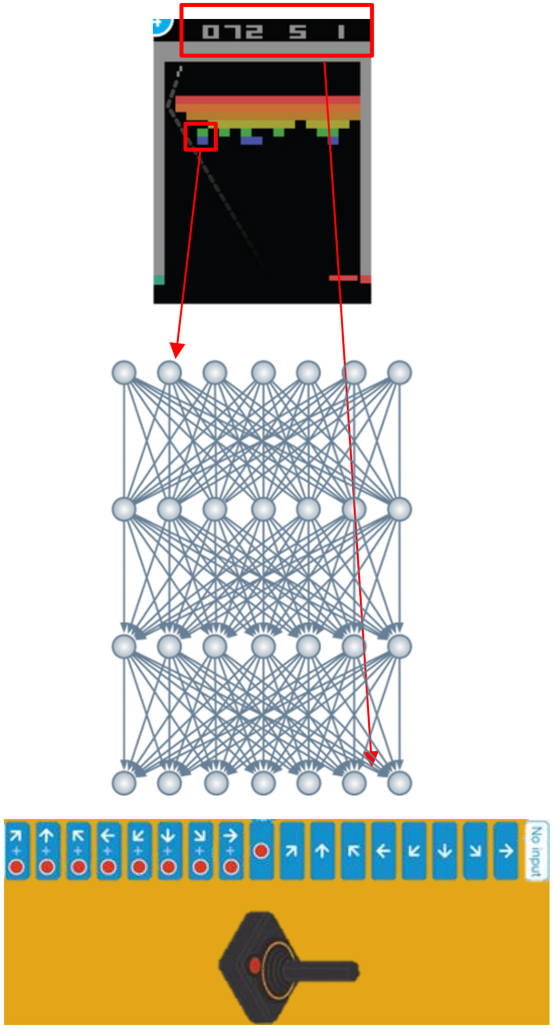
"a pizza with a lot of toppings on it"

"a young boy is holding a baseball bat."

A. Karpathy, Li Fei-Fei, Deep Visual-Semantic Alignments for Generating Image Descriptions, **CVPR 2015**

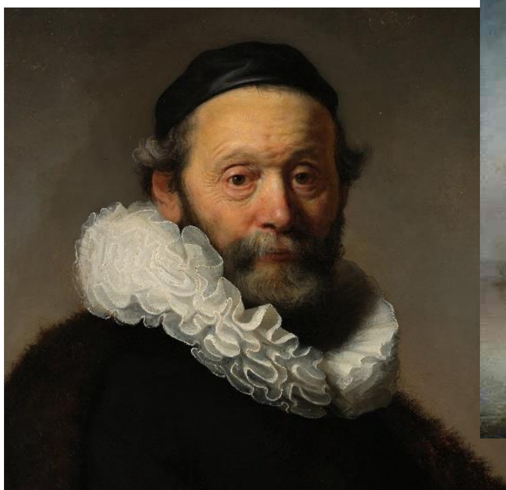
Learning to Play 49 Atari Games





V Mnih *et al. Nature* **518**, 529-533 (2015) doi:10.1038/nature14236

What Human Skills Can We Expect to Learn?





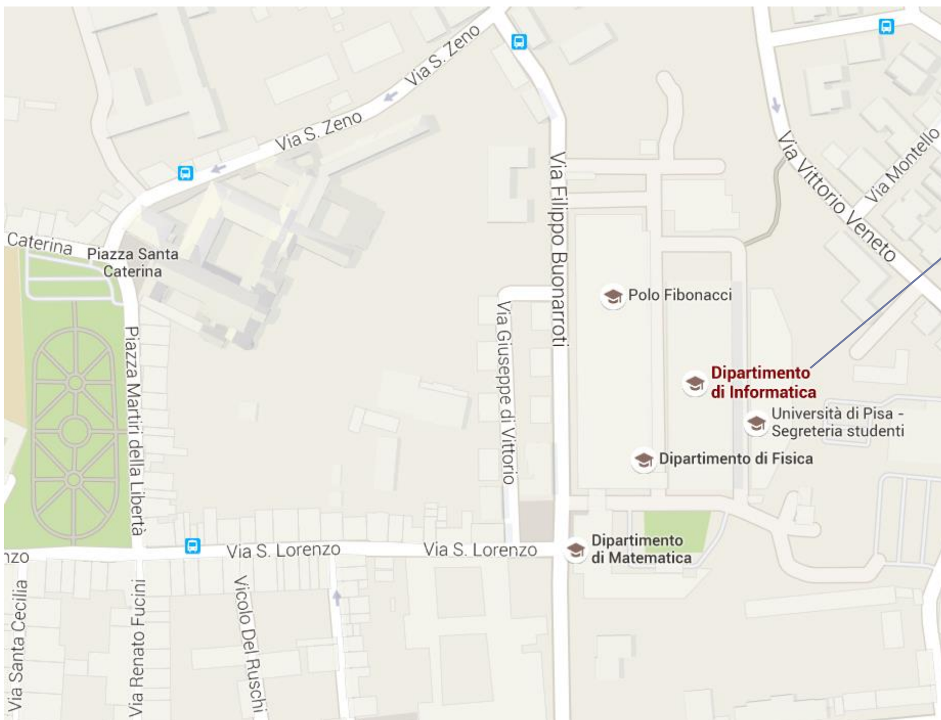
The Next Rembrandt

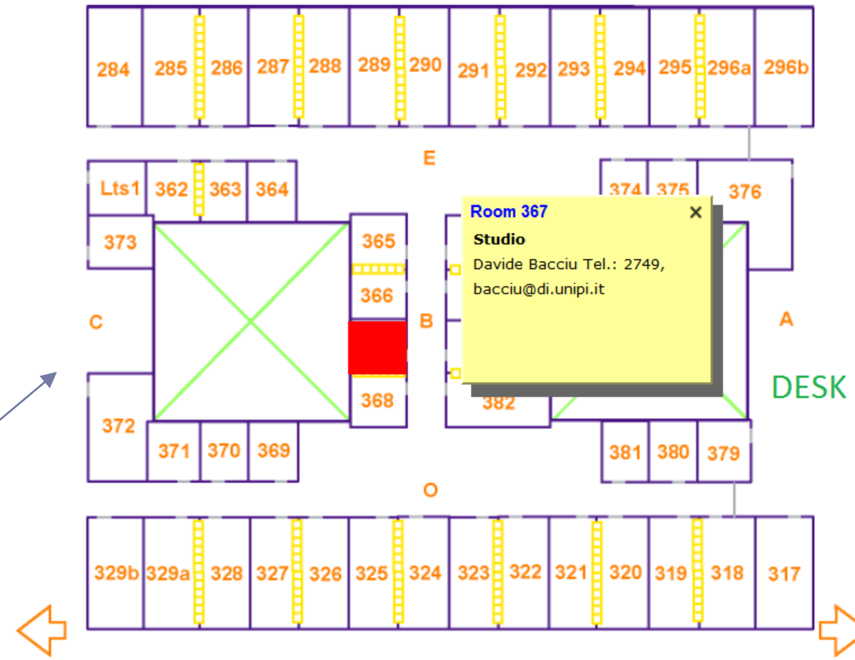
Instructor Information

- Davide Bacciu
  - Assistant Professor @ Computer Science Department
  - Research keywords
    - Machine learning, neural networks, Bayesian learning, structured data processing, machine vision, bio-medical data, robotics, ambient intelligence
- Contacts
  - Web - http://pages.di.unipi.it/bacciu/
  - Email - bacciu@di.unipi.it
  - Tel - 050 2212749

Find Me

- **My office**:
  Room 367, Dipartimento di Informatica,
  Largo B. Pontecorvo 3, 56127 Pisa
- **Office hours**: Monday 17-19 (email me!)





Module Calendar (Tentative)

- Lecture 1 - Unsupervised and representation learning
- Lecture 2 - Associative Memories I - Hopfield networks
- Hands-on Lab I
- Lecture 3 - Associative Memories II - Boltzmann Machines
- Hands-on Lab II
- Lecture 4 - Adaptive Resonance Theory
- Lecture 5 - Representation learning and deep learning models
- Hands-on Lab III

Part 3 - Recurrent Neural Networks

Alessio Micheli

Part 3

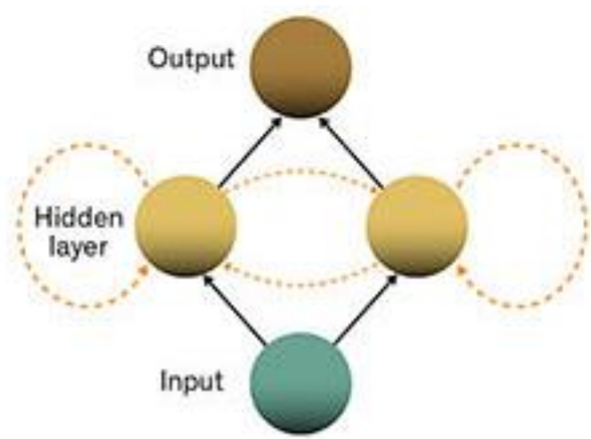
Advanced computational neural models for learning: Architectures and learning methods for *dynamical/recurrent neural networks*

- Introduction to the problem and methodology:
  - Time representation in neural networks: explicit and implicit forms.
- Discrete and continuous Recurrent neural networks.
- Recurrent neural networks:
  - Models and architectures
  - Taxonomy
  - Properties (stationarity, causality, unfolding)
- Learning algorithms:
  - BPTT, RTRL, constructive approaches.
- Analysis: architectural bias.
- Reservoir Computing, ESN. Related approaches and extensions.
- (Applications in the area of Computational Neuroscience data analysis. Case studies.)

Intro to RNN (A. Micheli)

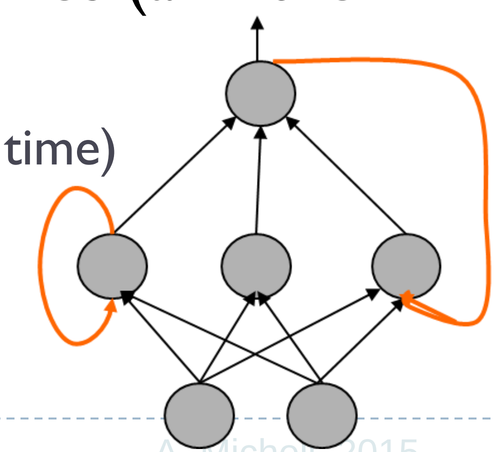
- IEEE Spectrum (magazine) 26 Jan 2016
- **"The Neural Network That Remembers"**
  - **With short-term memory, recurrent neural networks gain some amazing abilities**

A recurrent neural network includes connections between neurons in the hidden layer [yellow arrows], some of which **feed back** on themselves.



Why RNN?

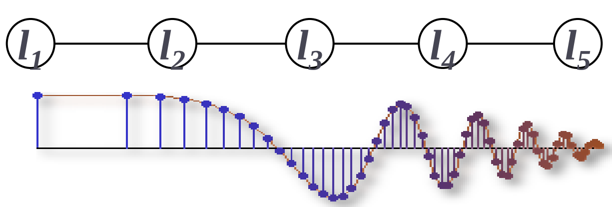
- From *static* to *dynamical* neural network models
- The presence of **self-loop** connections provides the network with dynamical properties, letting a memory (**states**) of the past computations in the model.
- **Neurobiological** plausibility
  - nervous system/biological NN are recurrent NN!
- **Computational view**: extension of the *input domain* (and the representation capability of the model) from vectors to *sequences*/streams/time-series (and then structures)
  - many simplification/abstractions (e.g. discrete time)



Why sequential data?

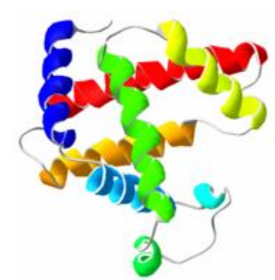
- **Whenever the output of the model depended on the history of the inputs – e.g. *time*: dynamical models**
  - Dynamical processes. Signal processing (Filters, Control). Robotics*
  - Language* (Speech recognition, NLP, Formal languages, IR*)
  - Vision, Reasoning (temporal events in IA):
  - Temporal series: financial forecasting, Signal processing *
  - Genomics/Proteomics (Bioinformatics*)

stringa_in_italiano



Strings

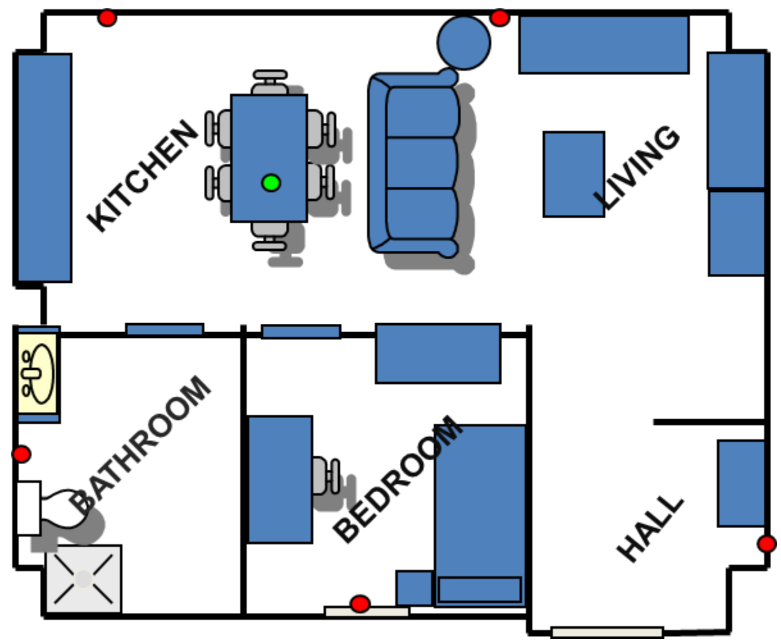
Series/
temporal stream



Proteins

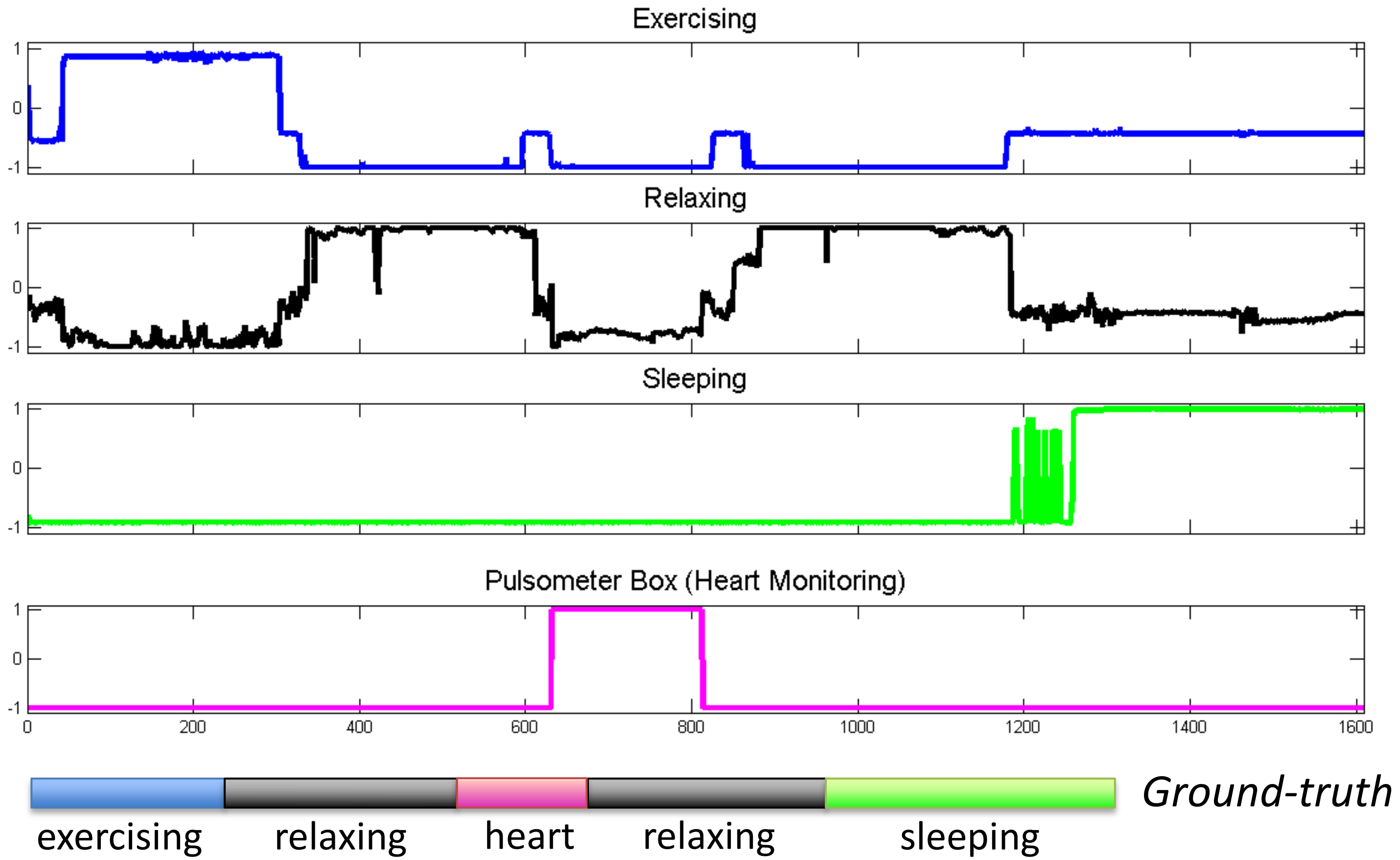
Examples of applicative scenarios: Ambient Assisted Living

- Predicting event occurrence and confidence of Human activities (from cooking to sleeping) basing on local sensors (*streams of data*)



AAL scenario at TECNALIA HomeLab
(Bilbao, Spain - 2014)

Human Activity Recognition

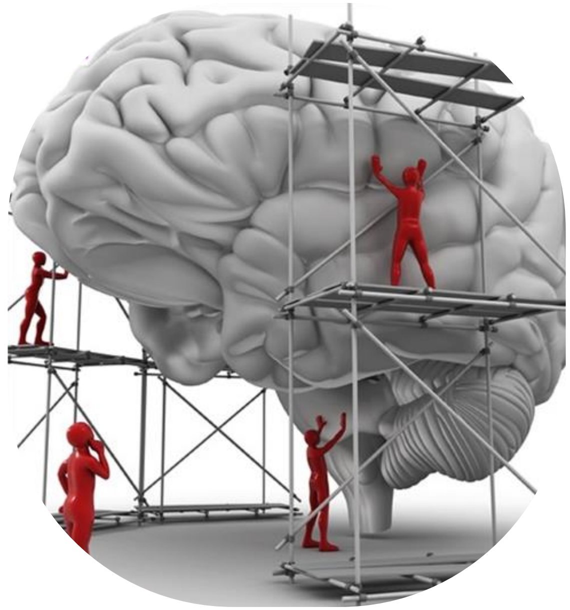


Outputs of ESN Neural Networks (efficient models for temporal data)

Prof. Alessio Micheli: Where I am

- **Office**
- Dipartimento di Informatica
- Largo B. Pontecorvo 3, Pisa, Italy
- Room 358 / DN
- Phone: +39 050 2212798
- E-mail: micheli@di.unipi.it

For appointment



Computational neuroscience
Bionics Engineering

Spring 2017