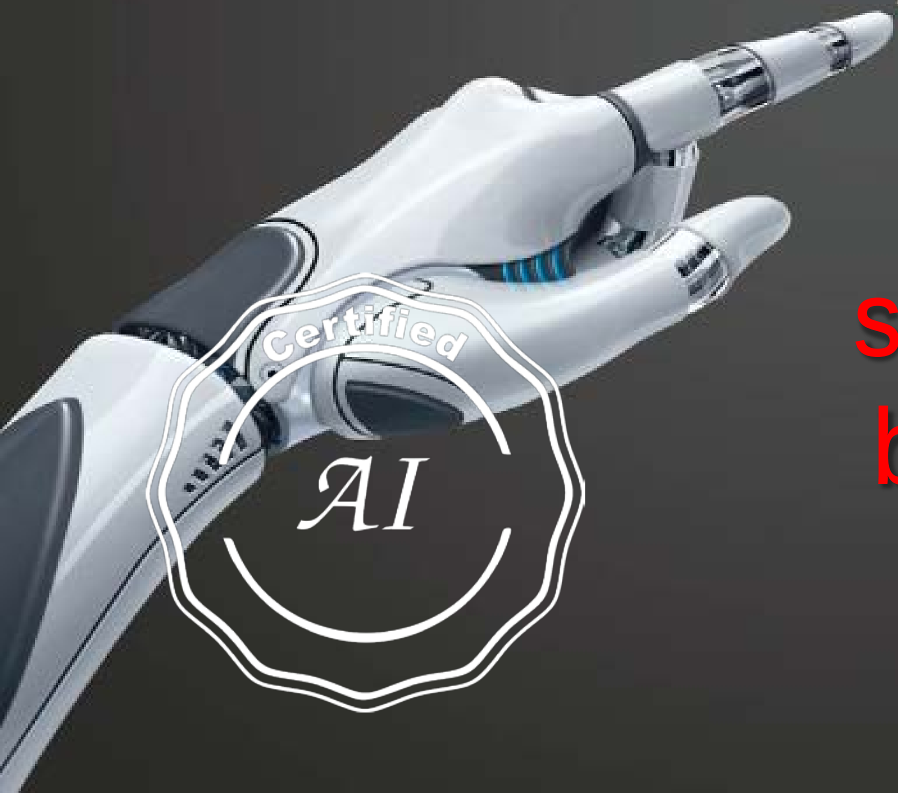
ANITI

ARTIFICIAL & NATURAL INTELLIGENCE
TOULOUSE INSTITUTE

Rufin VanRullen
(CerCo, CNRS)



Deep Learning with semantic, cognitive & biological constraints

Université Fédérale
Toulouse Midi-Pyrénées

Chair members

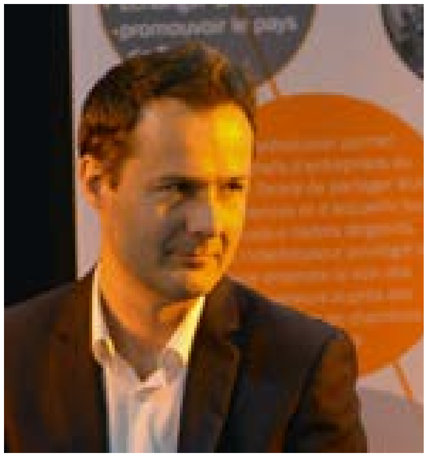
Leila Reddy (CerCo)

fMRI
Brain decoding

Tim van de Cruys (IRIT)

NLP,
Matrix factorization

Francis Filbet (IMT)



Math,
Part. Diff. Eq.,
collective behavior

Gregory Faye (IMT)

Math,
reaction-diffusion eqs.,
travelling waves

Background: Cognitive Neuroscience

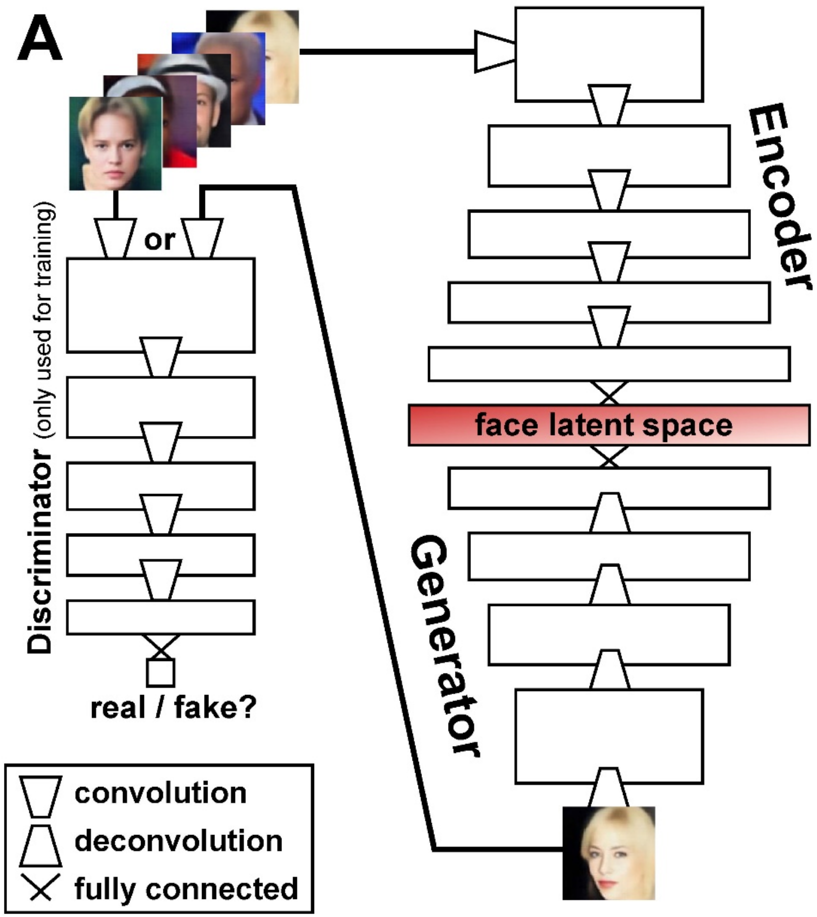
- Broad questions (examples):
  - Perception (Visual recognition, Speech recognition)
  - Feed-forward vs. feed-back mechanisms
  - Attention
  - (Spiking) neural networks, neural coding

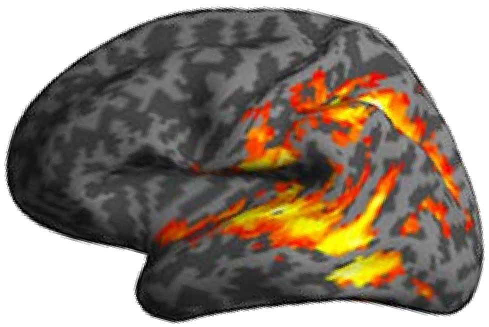
➔ Relevance to AI & Deep Learning!

Use DL to improve neuroscience

Variational Auto-Encoder + Generative Adversarial Network (VAE-GAN)

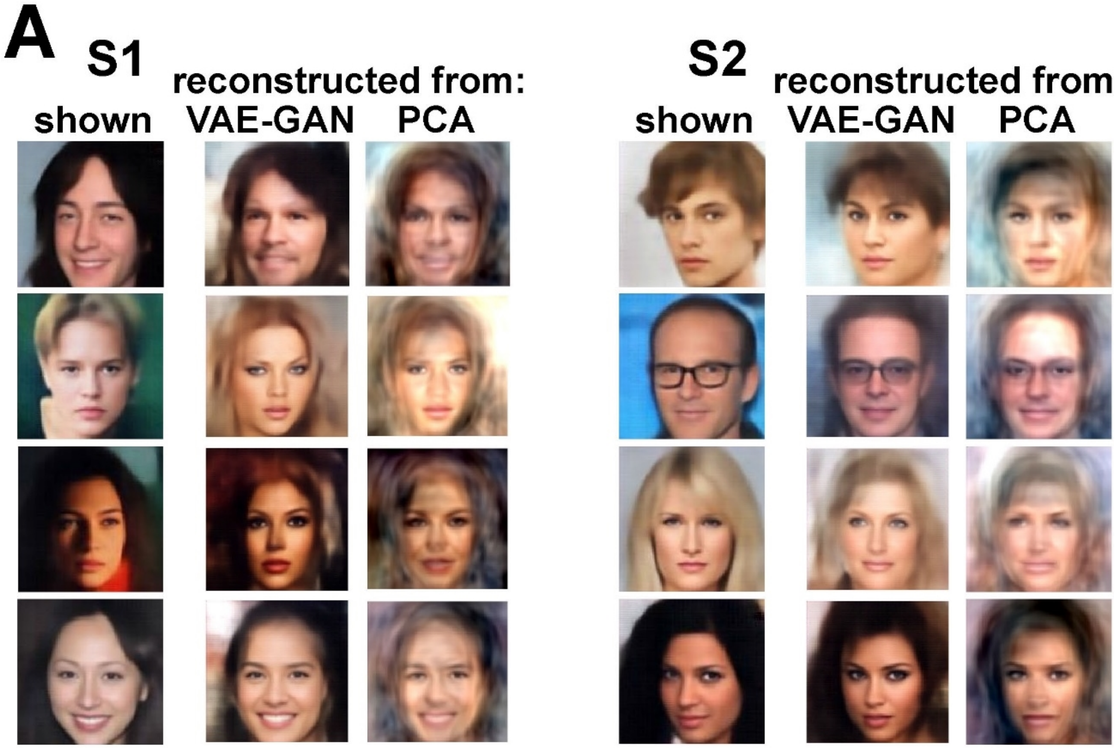
Larsen et al, ICML (2016)

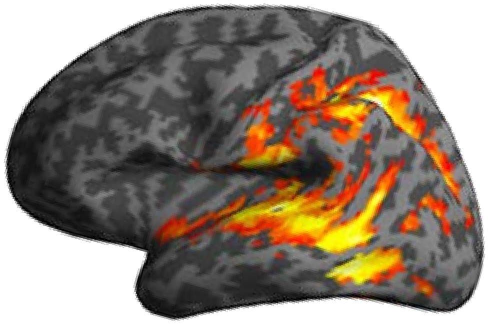




VanRullen & Reddy, Nat. Comm. Biol. (2019)

Use DL to improve neuroscience

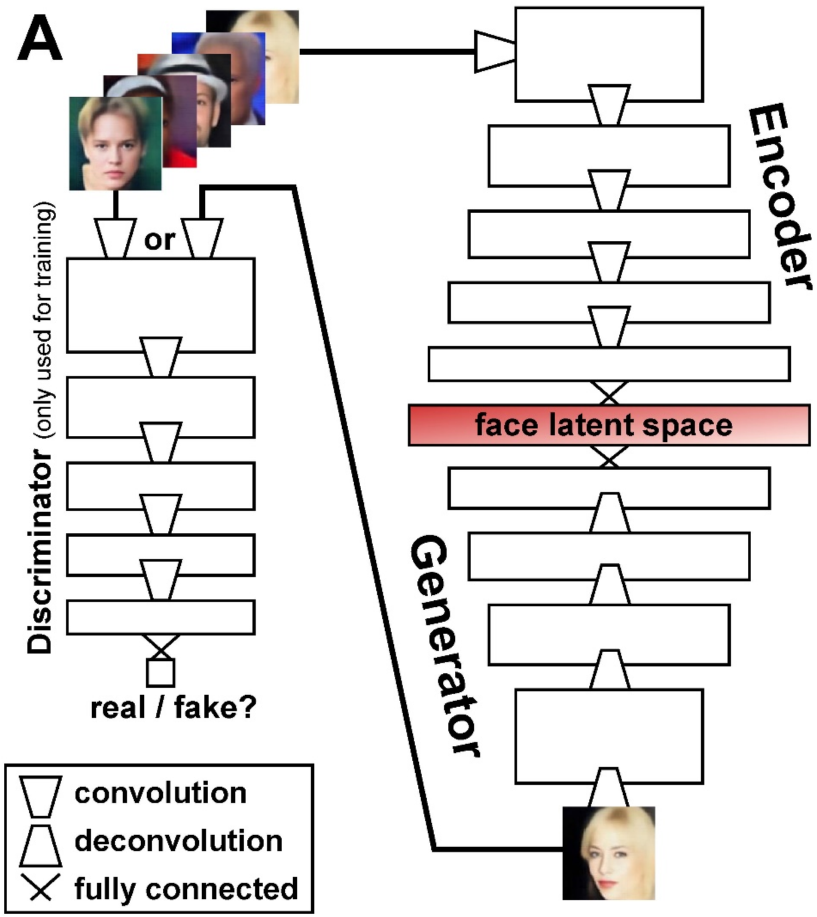


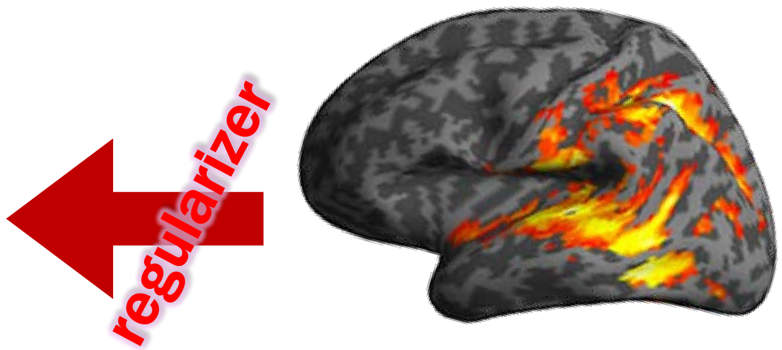


VanRullen & Reddy, Nat. Comm. Biol. (2019)

How close are DL and biological neural networks?

ANR 2019-2022 with Leila Reddy (PI)
+ N. Asher, T. van de Cruys (IRIT)





- **Compare brain activity patterns & DL latent spaces for:**
  - **Vision: Face processing**
  - **Language: Words, Sentences**

Chair objectives

◎ **Design robust, human-like AI systems**

by drawing inspiration from Neuroscience / Biology

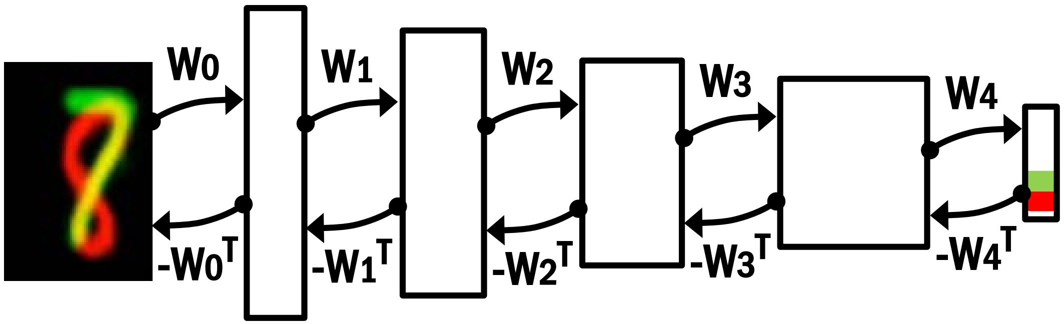
- ➔ brain-like activity: e.g. enforcing similarity w/ brain signals
- ➔ brain-like architectures: feed-back loops, oscillations
- ➔ brain-like cognitive functions: attention, predictive coding
- ➔ brain-like complexity: sensation ◄ ► language ◄ ► action

Concrete example 1

◎ Predictive coding

A theory of brain function in hierarchical systems:

- ◎ each layer "explains away" activations in the preceding layer
- ➔ after few iterations, it converges on the most parsimonious interpretation



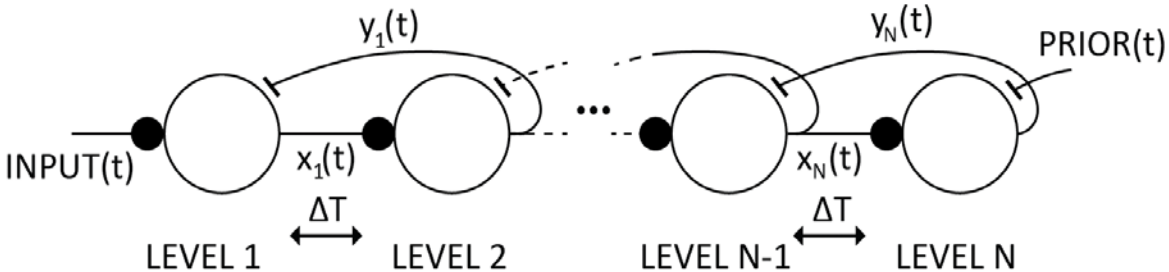
➔ Similar (in spirit) to CapsNet (Sabour, Frosst & Hinton, 2017)

Concrete example 1

◎ Predictive coding

A theory of brain function in hierarchical systems:

- ◎ each layer "explains away" activations in the preceding layer
- ➔ after few iterations, it converges on the most parsimonious interpretation



$$x_L(t) = y_{L-1}(t) - y_L(t-\Delta T)$$

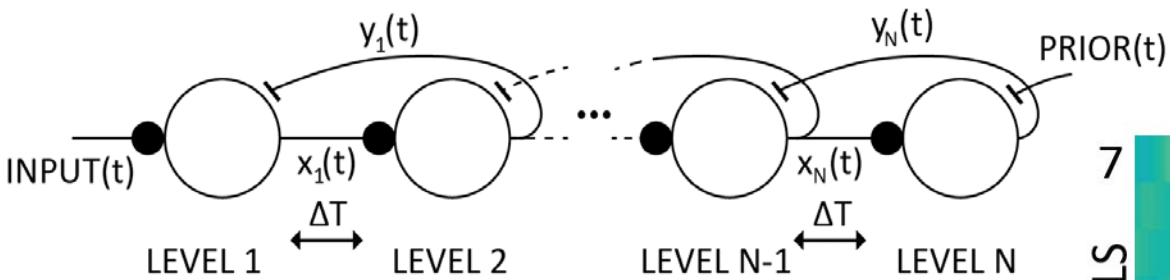
$$\frac{dy_L}{dt} = \frac{1}{\tau} \,.\, x_L(t-\Delta T) + \frac{1}{\tau_D} \,.\, (y_{L+1}(t-\Delta T) - y_L(t))$$

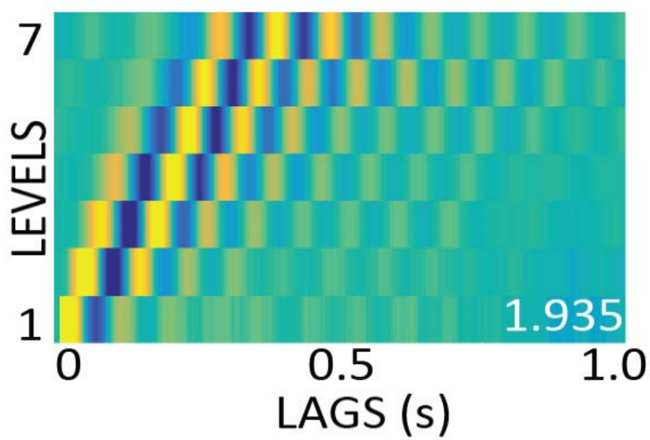
Concrete example 1

◎ Predictive coding

A theory of brain function in hierarchical systems:

- ◎ each layer "explains away" activations in the preceding layer
- ➔ after few iterations, it converges on the most parsimonious interpretation



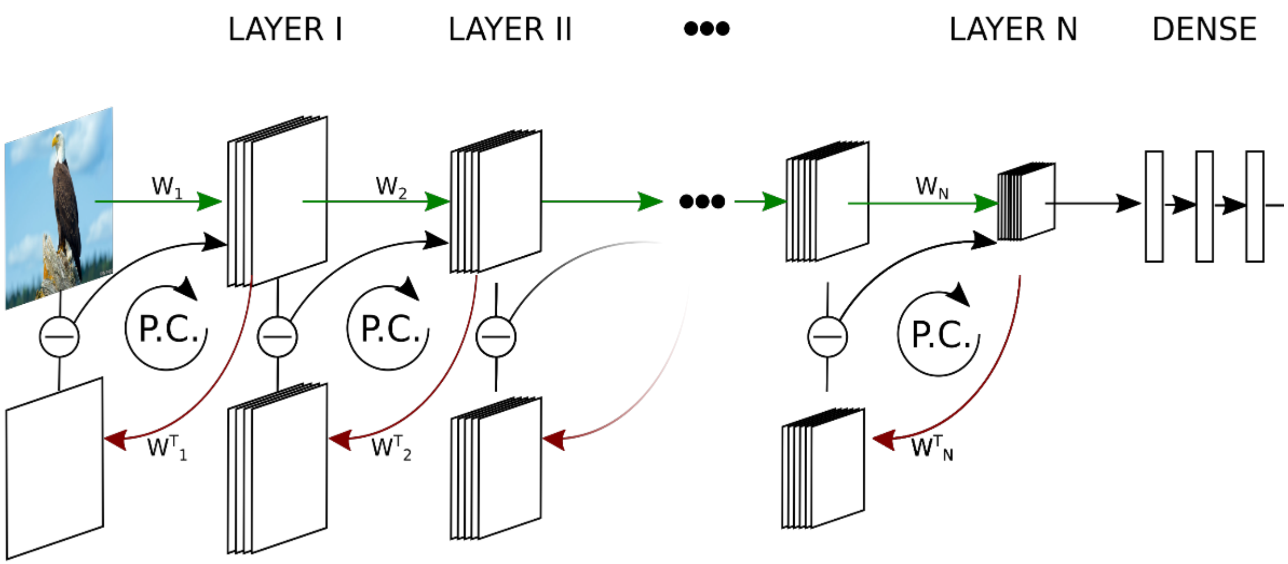


Concrete example 1

◎ Predictive coding

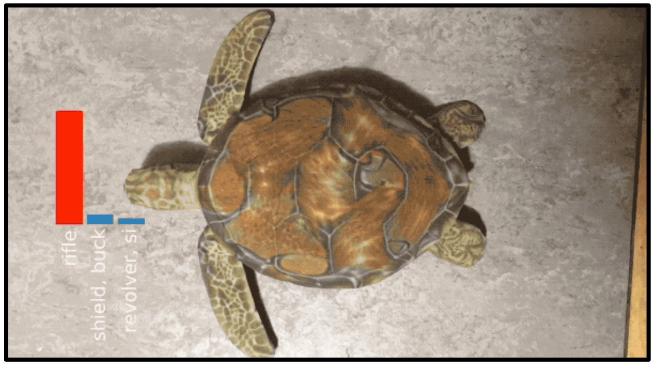
A theory of brain function in hierarchical systems:

- ◎ each layer "explains away" activations in the preceding layer
- ➔ after few iterations, it converges on the most parsimonious interpretation



Concrete example 2

◎ **"Human-Semantic" regularization for ConvNets**

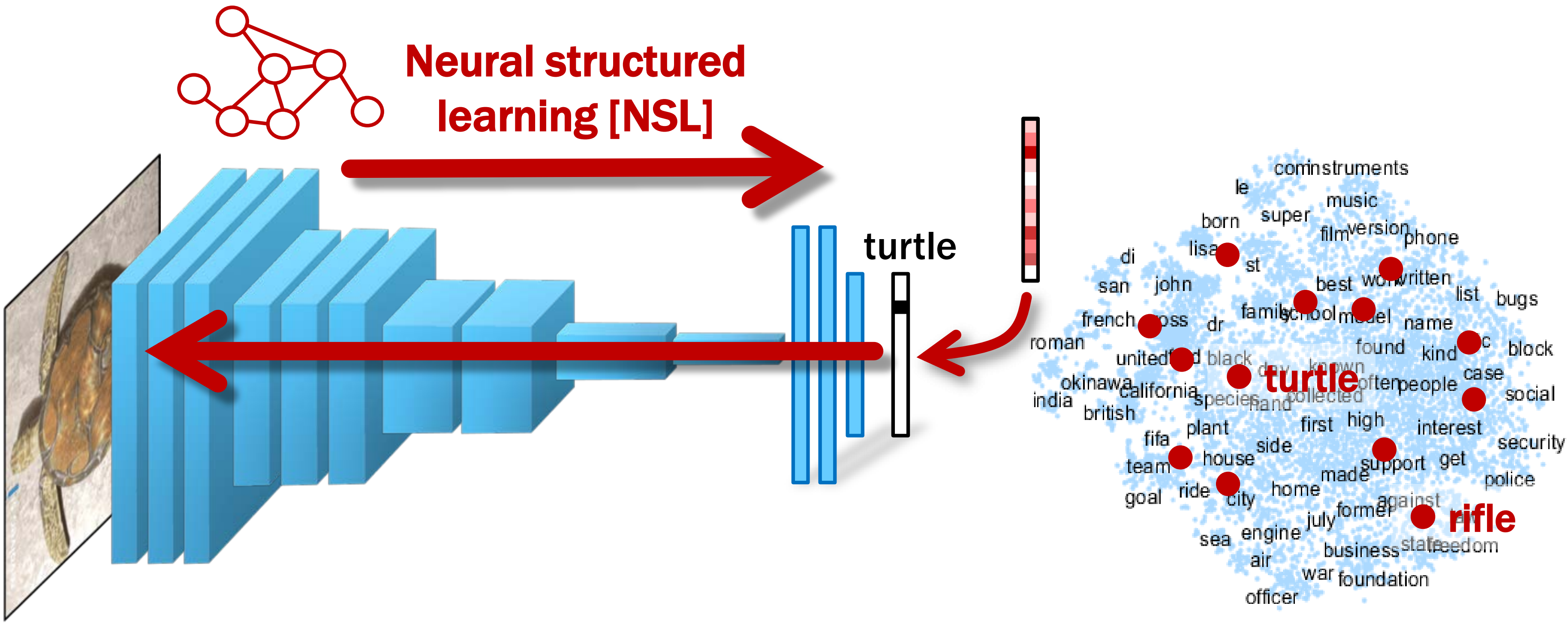


Concrete example 2

◎ **"Human-Semantic" regularization for ConvNets**

Back-propagate language (or other) knowledge into ConvNets:

➔ increase in robustness >> drop in accuracy



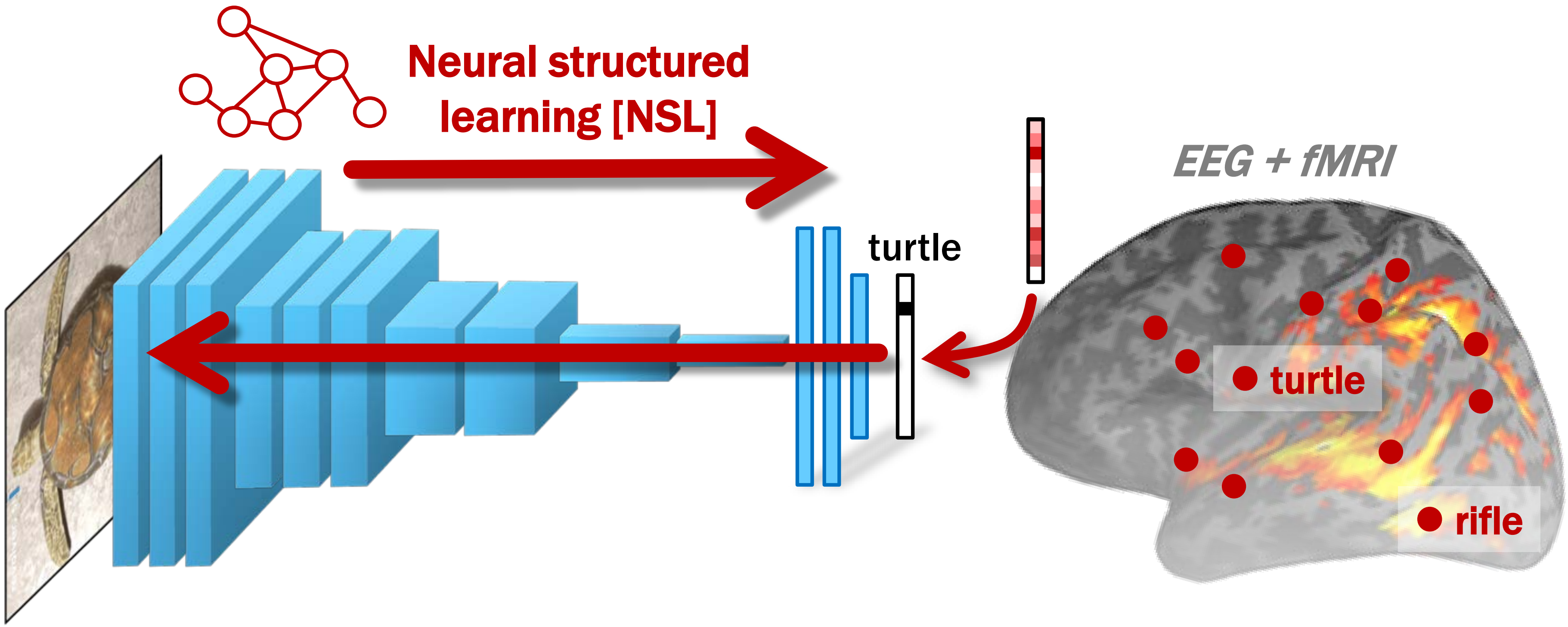
DeViSE: Deep Visual-Semantic Embedding (Frome et al, NIPS 2013)

Concrete example 2

◎ **“Human-Semantic” regularization for ConvNets**

Back-propagate language (or other) knowledge into ConvNets:

➔ increase in robustness >> drop in accuracy



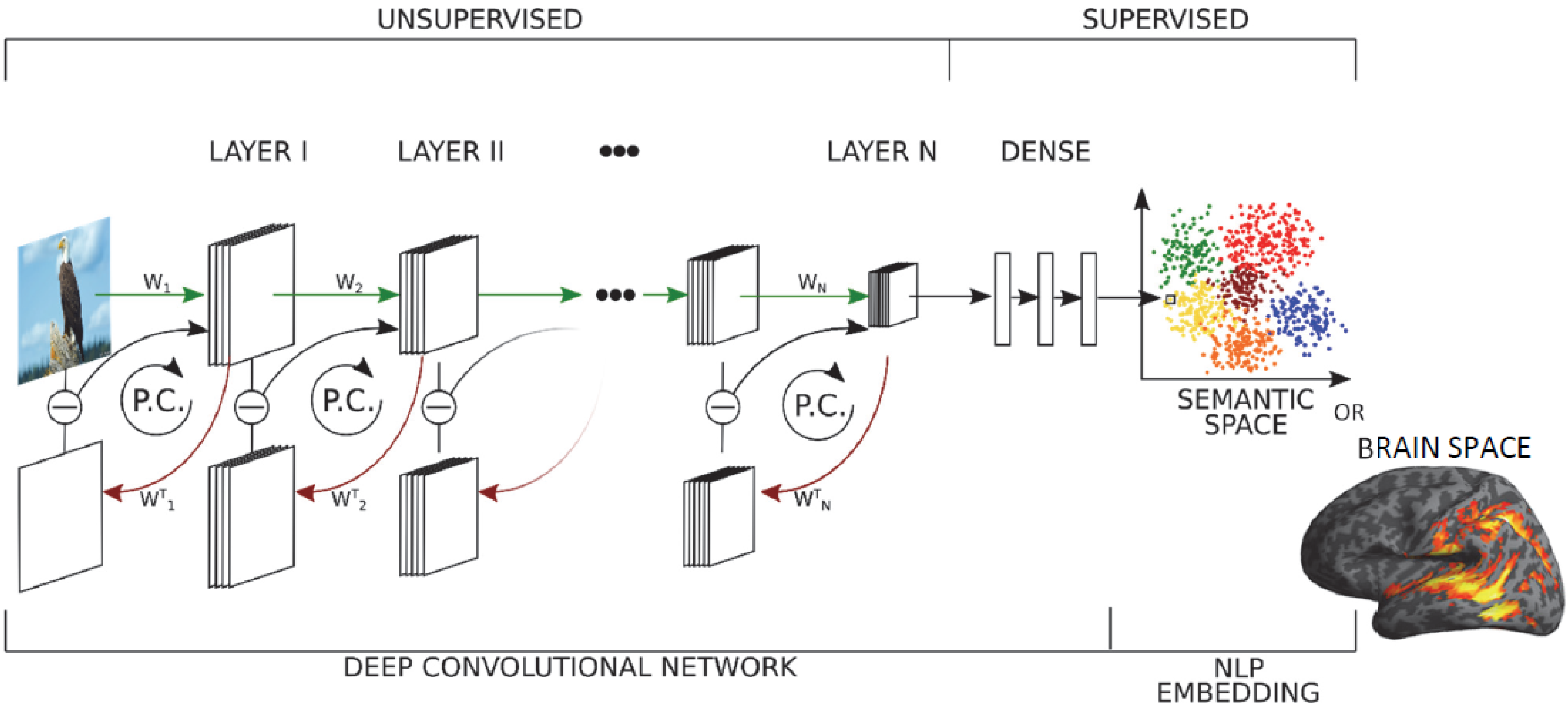
DeViSE: Deep Visual-Semantic Embedding (Frome et al, NIPS 2013)

Concrete example 2

◎ **"Human-Semantic" regularization for ConvNets**

Back-propagate language (or other) knowledge into ConvNets:

➔ increase in robustness >> drop in accuracy

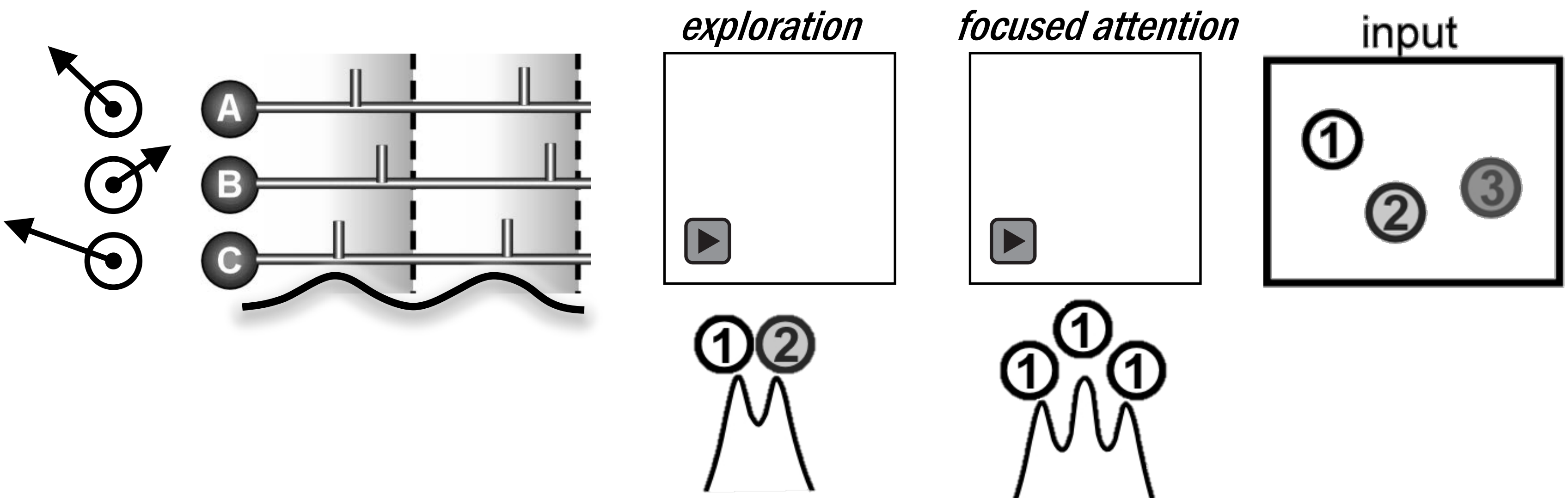


Concrete example 3

◎ Complex-valued neural networks

Spikes + oscillations = powerful computational tools (Dynamic routing, Binding by synchrony, Attention, Predictive coding, …)

➔A firing phase can be represented by a <u>complex</u> value



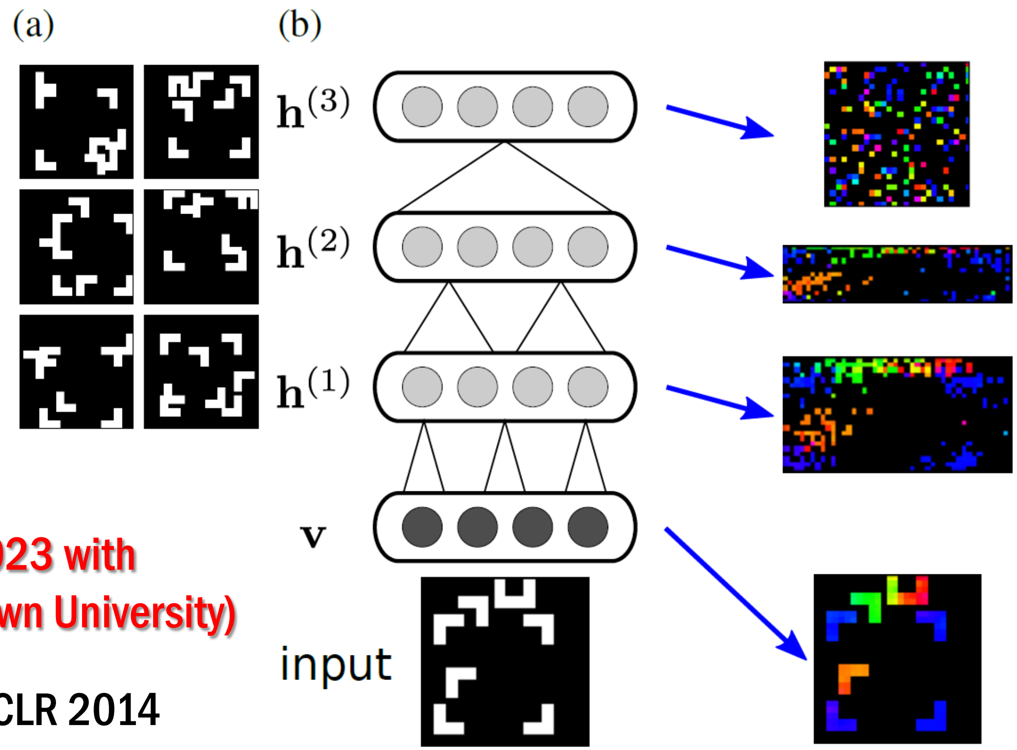
McLelland & VanRullen, PLOS Comp Biol 2016

Concrete example 3

◎ Complex-valued neural networks

Spikes + oscillations = powerful computational tools (Dynamic routing, Binding by synchrony, Attention, Predictive coding, …)

→A firing phase can be represented by a <u>complex</u> value



ANR-NSF 2020-2023 with Thomas Serre (Brown University)

Reichert & Serre, ICLR 2014

ANITI interactions

- T. Serre: "Reverse-engineering the brain"
- Other chairs interested in Deep Learning
- Industry partners interested in robust models
- TIdDLe = Toulouse Interdisciplinary Deep Learning Group

with Emmanuel Rachelson (ISAE)

  - → website: *tiddle-group.github.io*
  - → mailing list (>160 members, academics + industry)
  - → discussion forum
  - → seminars, hackathons, tutorials
  - → joint projects, research topics, etc.