



Brain-Inspired Multimodal Deep Learning

21/11/2023



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CerCo, CNRS



PLAN: overview of past and future work

2019-2023: Chair “Deep Learning with semantic, cognitive and biological constraints”

With co-chairs C. Braud (IRIT), L. Reddy (CerCo), F. Filbet & G. Faye (IMT)

1. brain decoding with deep generative networks
2. brain-inspired recurrent networks with Predictive Coding
 - more efficient, more robust
 - more aligned with human vision (illusions)
 - detailed mathematical characterization (convergence, oscillations...)
3. brain-inspired multimodal systems based on Global Workspace (ERC GLOW 2023-2028)

2024-2028? Synergy Chair C3-PO: “Cobots with Conversation, Cognition and Perception”

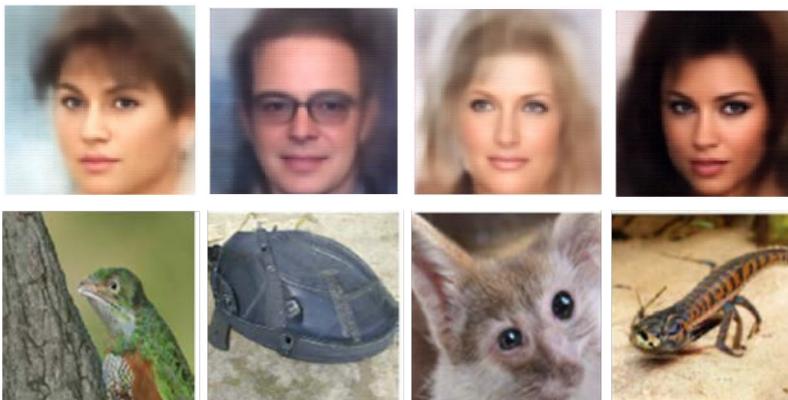
Chairs: N. Asher (IRIT), T. Serre (Brown U.), O. Stasse (LAAS), R. VanRullen (CerCo)

1. Brain decoding with deep generative networks

images seen by subject in MRI



reconstructed images from fMRI signals

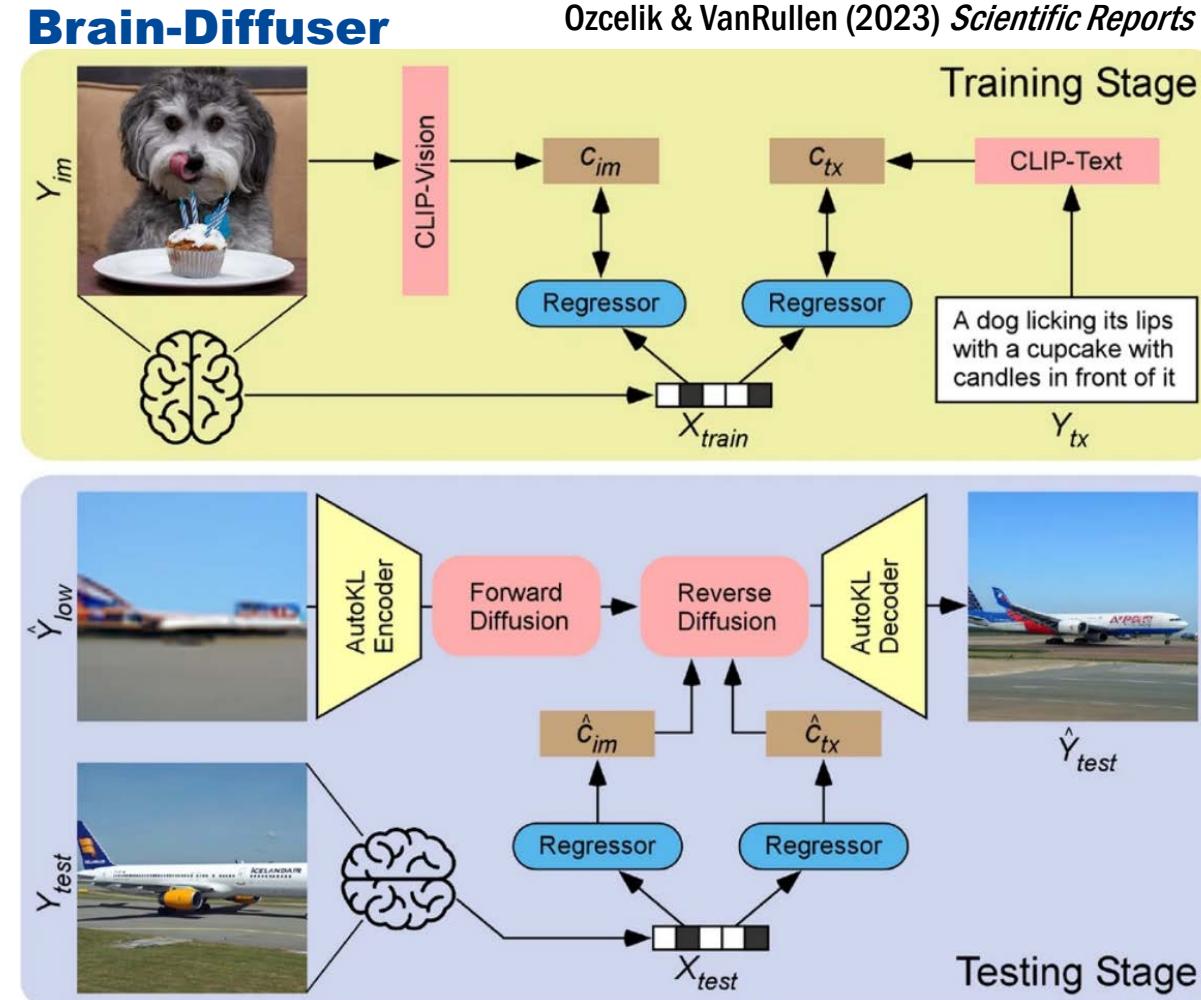


VanRullen & Reddy (2019) *Communications Biology*
Mozafari, Reddy & VanRullen (2020) *IJCNN'20*
Ozcelik et al (2022) *IJCNN'22*
Ozcelik & VanRullen (2023) *Scientific Reports*

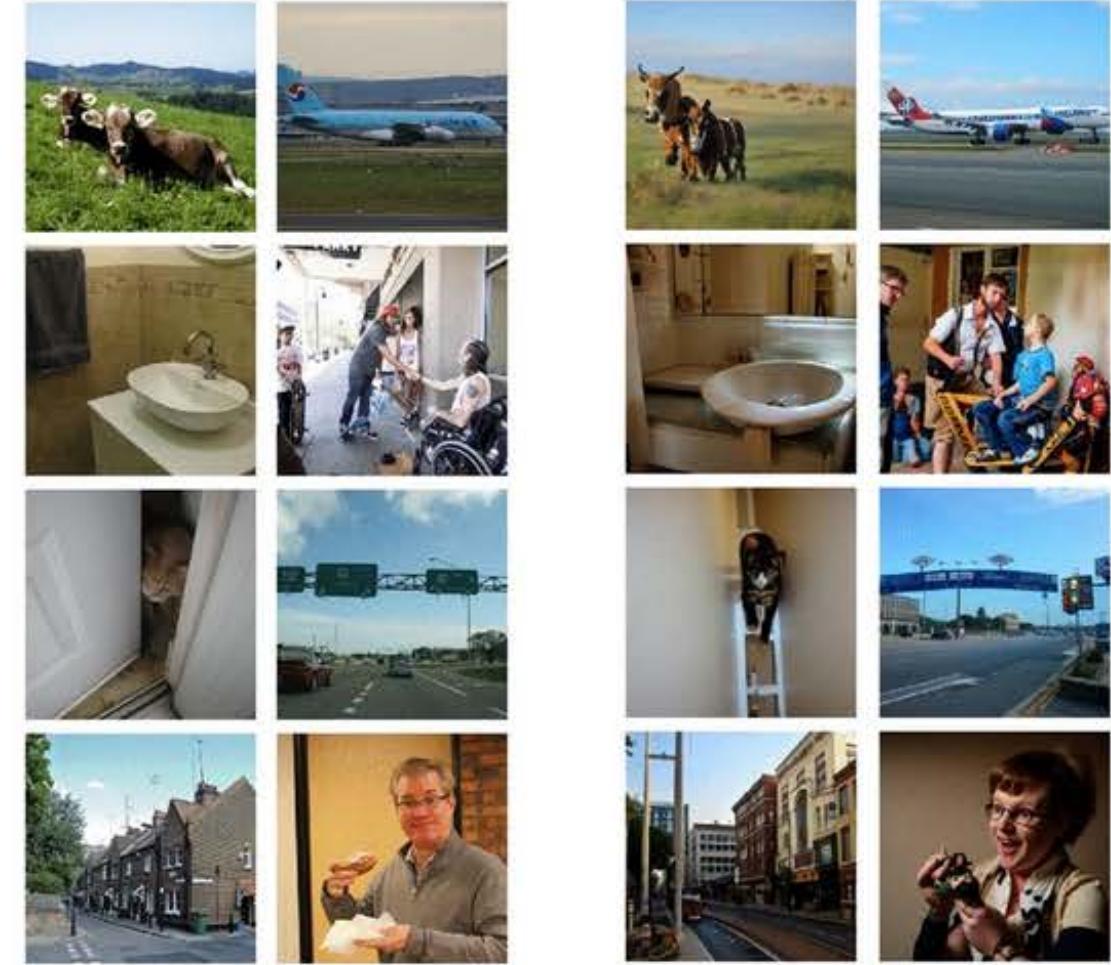


1. Brain decoding with deep generative networks

Brain-Diffuser

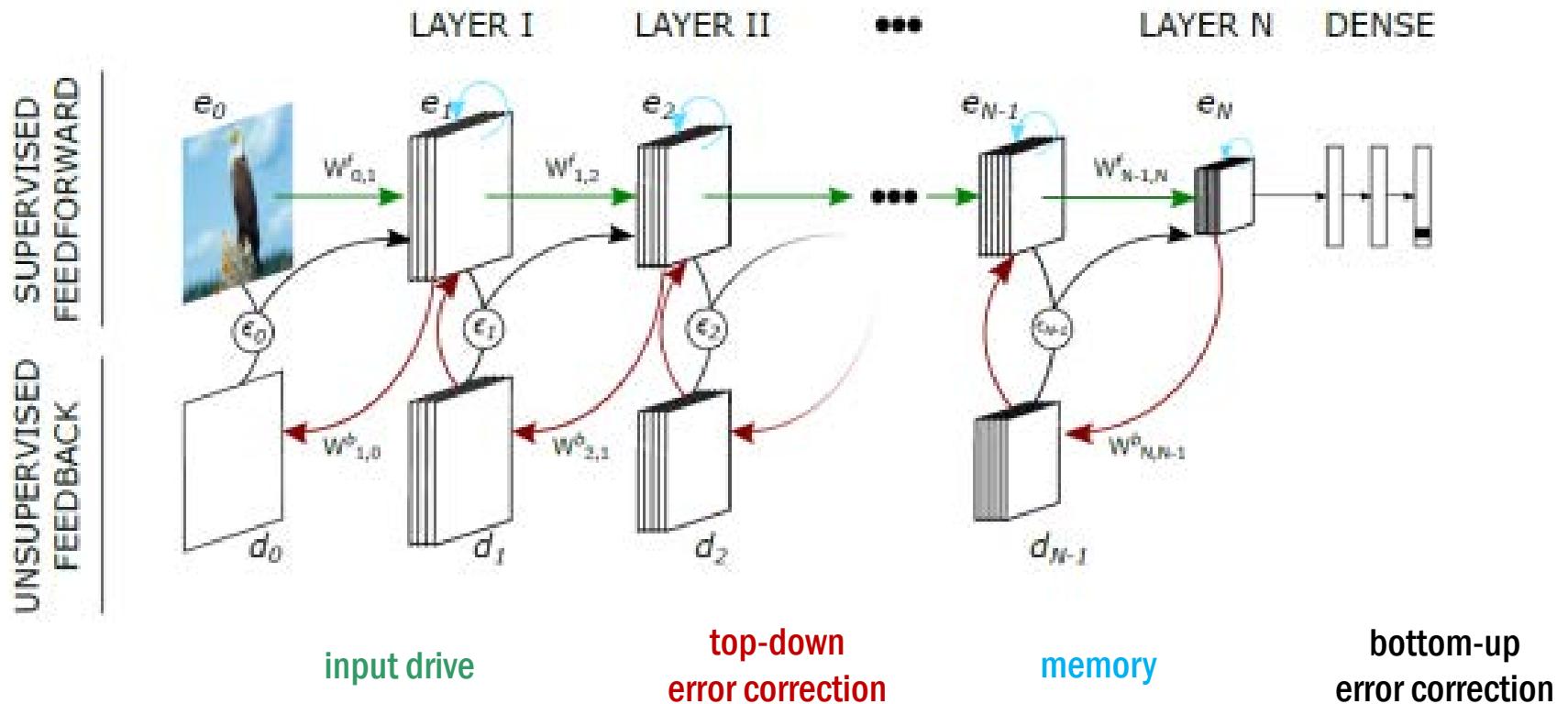


images seen



reconstructed images

2. Predictive coding



$$e_n(t+1) = \overbrace{\beta [W_{n-1,n}^f e_{n-1}(t+1)]_+}^{\text{top-down error correction}} + \overbrace{\lambda d_n(t)}^{\text{bottom-up error correction}} + \overbrace{(1 - \beta - \lambda) e_n(t)}^{\text{memory}} - \overbrace{\alpha \nabla \epsilon_{n-1}(t)}^{\text{input drive}}$$

$$d_n(t) = [W_{n+1,n}^b e_{n+1}(t)]_+$$

$$\epsilon_{n-1}(t) = \|e_{n-1}(t) - d_{n-1}(t)\|_2^2$$

2. Predictive coding

- *Predify* software (for PyTorch):
<https://github.com/miladmozafari/predify>
- We *predified*: VGG16, EfficientNetB0, ResNet18...

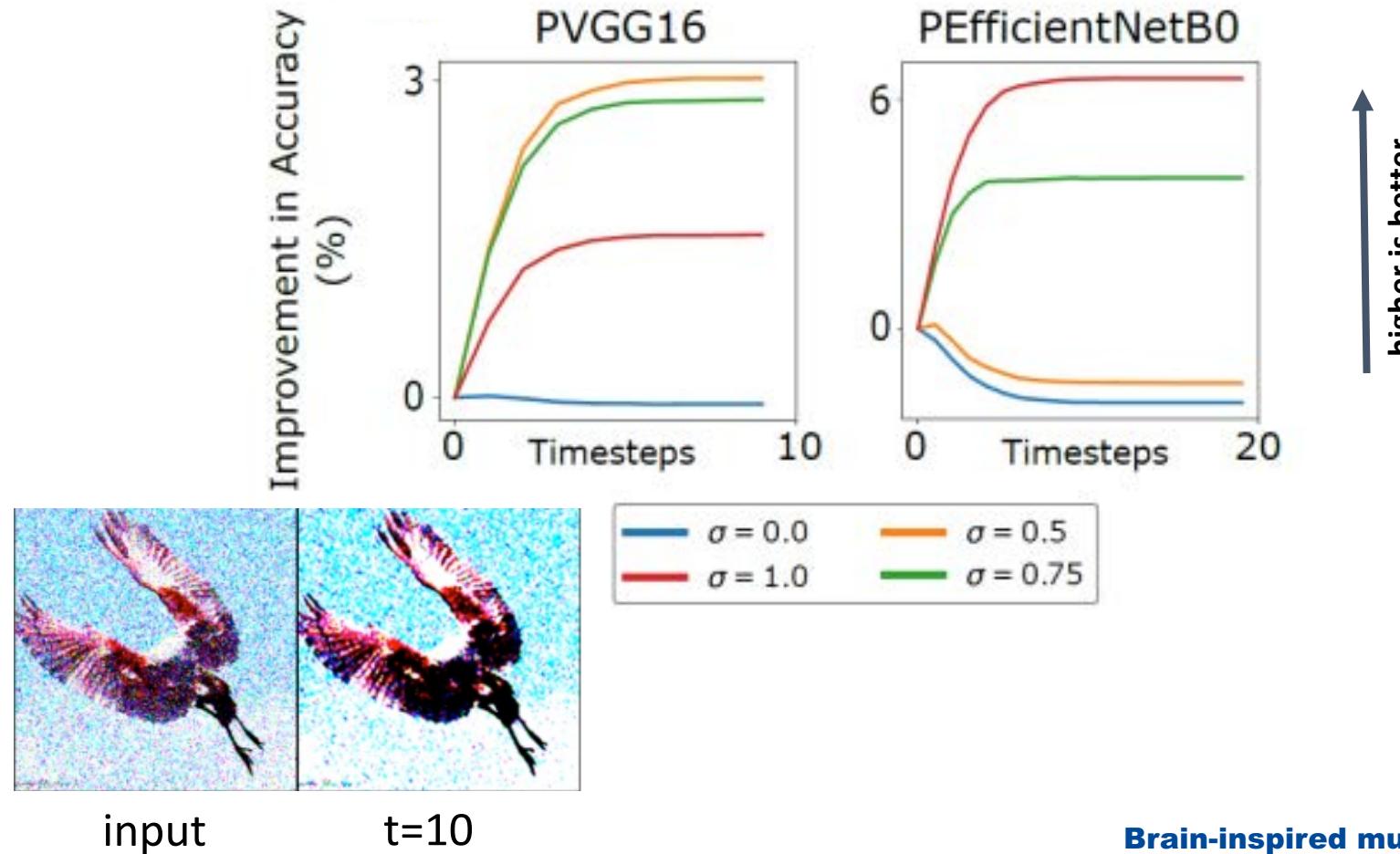
$$\begin{aligned} e_n(t+1) &= \underbrace{\beta [W_{n-1,n}^f e_{n-1}(t+1)]_+}_{\text{input drive}} + \underbrace{\lambda d_n(t)}_{\text{top-down error correction}} + \underbrace{(1-\beta-\lambda)e_n(t)}_{\text{memory}} - \underbrace{\alpha \nabla \epsilon_{n-1}(t)}_{\text{bottom-up error correction}} \\ d_n(t) &= [W_{n+1,n}^b e_{n+1}(t)]_+ \\ \epsilon_{n-1}(t) &= \|e_{n-1}(t) - d_{n-1}(t)\|_2^2 \end{aligned}$$

2. Predictive coding

ImageNet accuracy:

Choksi, B., Mozafari, M., Biggs O'May, C., Ador, B., Alamia, A., & VanRullen, R. (2021). *Advances in Neural Information Processing Systems*, 34, 14069-14083.

Alamia, A., Mozafari, M., Choksi, B., & VanRullen, R. (2023). *Neural Networks*, 157, 280-287.



- Robustness to Gaussian noise and other corruptions (ImageNet-C)
- Robustness to adversarial attacks

2. Predictive coding

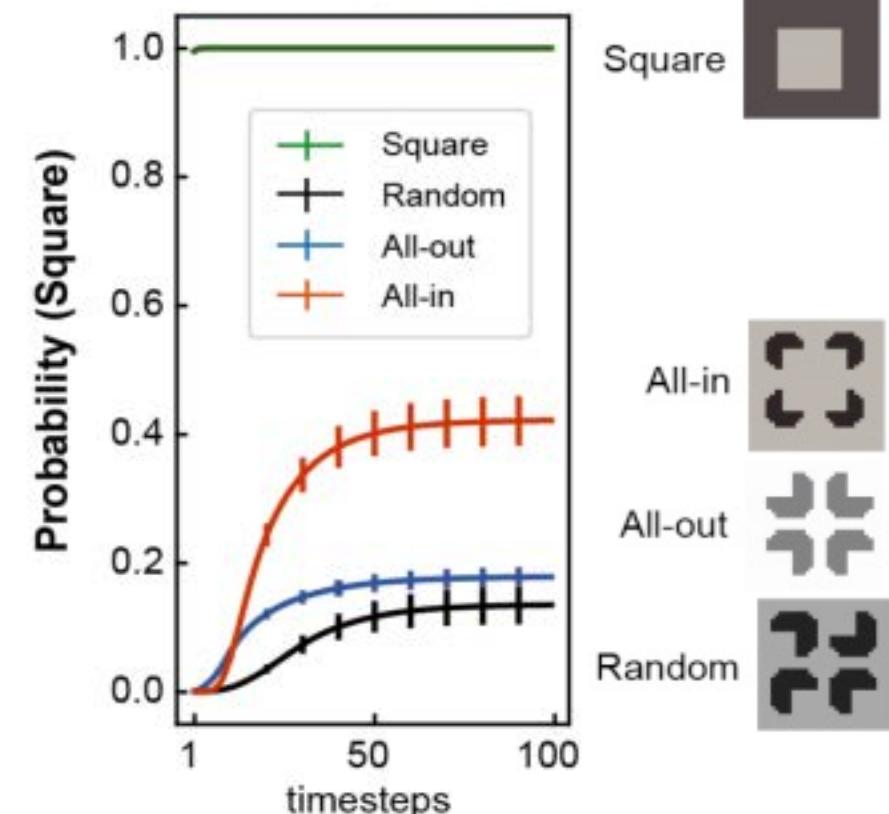
- “Perception” of illusory contours, just like humans

- Pang, Z., O’May, C. B., Choksi, B., & VanRullen, R. (2021). Predictive coding feedback results in perceived illusory contours in a recurrent neural network. *Neural Networks*, 144, 164-175.



- Mathematical analysis of convergence:

- Faye, G., Fouilhé, G., & VanRullen, R. (2023). Mathematical derivation of wave propagation properties in hierarchical neural networks with predictive coding feedback dynamics. *Bulletin of Mathematical Biology*.



3. Multimodal systems

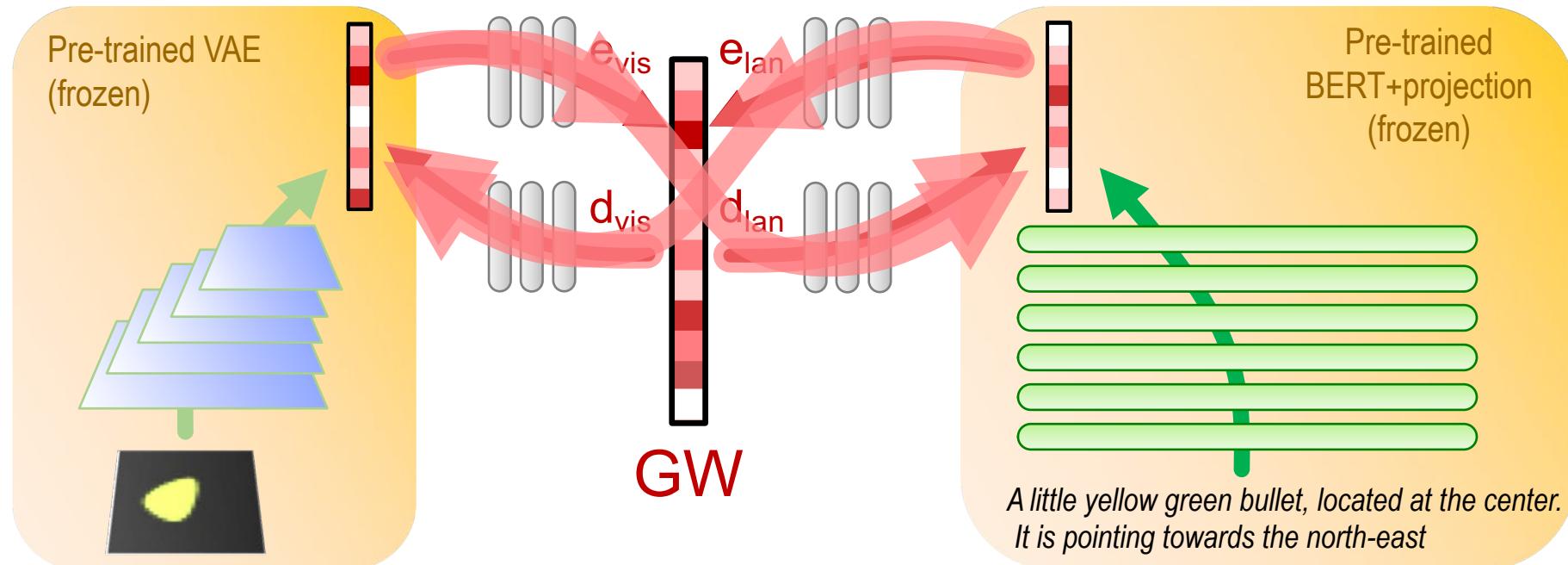
Multi-modal systems are getting very good: CLIP, DALL-E, GATO, Flamingo, PALM-E, etc.

- ➔ Vision + Language + Action + ...
- ➔ Require enormous models, gigantic supervised training sets...
- ➔ How does the brain do it ?
- ➔ **Global Workspace Theory**

vision	language
	A little yellow green bullet, located at the center. It is pointing towards the north-east.
	It is a quite small trapezoidal shape in medium violet red color. It is located in the top center and pointing towards the right.
	A medium-sized red triangle, in the bottom-left corner and rotated east.

3. Multimodal systems

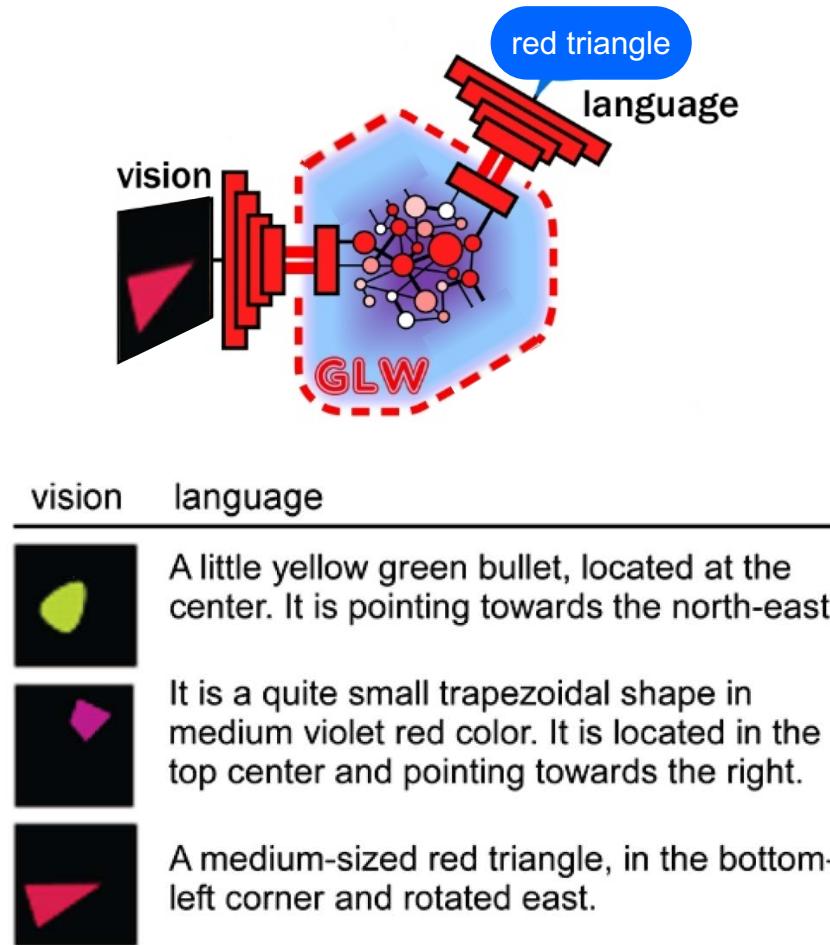
Global Workspace (simplified) architecture



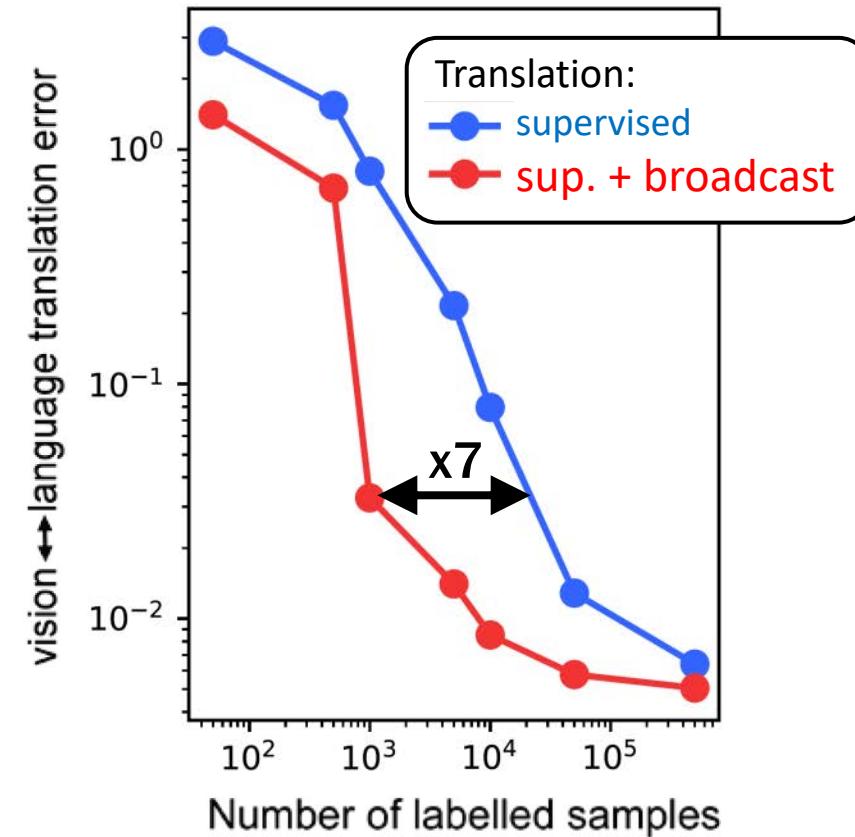
- **Training objectives:**
 - Supervised: N matching pairs $\{vis_i, lan_i\}$ — we vary N to assess the need for labels
 - Unsupervised: **cycle-consistency (a.k.a. « broadcast »)**
→ only needs unpaired data!

3. Multimodal systems

Global Workspace (simplified) architecture



Devillers, Maytie & VanRullen (2023). *Semi-supervised multimodal representation learning through a Global Workspace*, arXiv

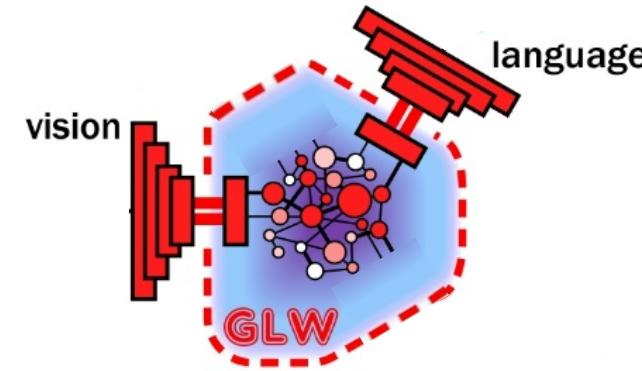
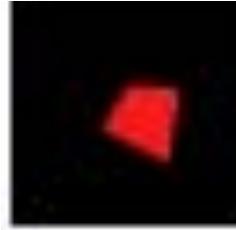


3. Multimodal systems

Global Workspace: where we are now...



B. Devillers



A bright red diamond, pointing to the bottom right

A green triangle at the top, towards left

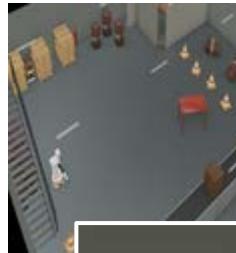
An egg-shaped oval, dark-blue, pointing up, on the bottom-left of the image

Attributes = [1,0,0,-1,-0.5,-60,2,1,0,0]

shape
position
rotation
size
color



L. Maytie



sim2real (with LAAS)

attributes	values
position x	1.767
position y	-0.853
rotation z	-2.042
color (R,G,B)	(1, 0.343, 0)

attributes	values
position x	-1.674
position y	-0.099
rotation z	2.651
pitch	-1.24
roll	-0.232

3. Multimodal systems

Global Workspace: where we are going...



ERC Advanced Project GLOW (2023-2028)

- Develop brain-inspired multimodal deep learning systems
- Evaluate their use and relevance for machine learning
- Advance our knowledge of the brain



ANITI Synergy Chair C3-PO (2024-2028)??

- Cobots with Conversation, Cognition & Perception
- Chairs: R.VanRullen (CerCo), N. Asher (IRIT), T. Serre (Brown), O. Stasse (LAAS)
- Frugal multimodal robotic systems with grounded perception, language and action
- Main industrial partners: Airbus, Linagora

