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Ministero dell'Università e della Ricerca
Italiadomani PIANO NAZIONALE DI RIPRESA E RESILIENZA
INFN

Bio-inspired plastic spiking neural networks engaged in learning and sleep cycles

Pier Stanislao Paolucci,

APE Lab, INFN Roma

…on behalf of many authors,

see **third** slide

November 13th, 2023, Seminari INFN, Sezione di Roma,

c/o Dip. Fisica, Sapienza, Università di Roma

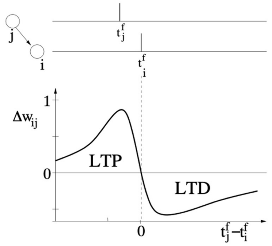
https://agenda.infn.it/event/37812/

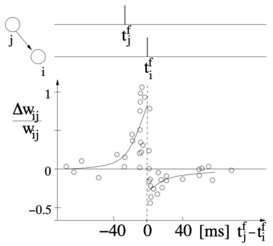
Novel two-compartment spiking neuron supporting brain-state specific apical mechanisms, …

$$\begin{cases} \begin{cases} C_m^s \frac{dV^s}{dt} &= -g_L^s(V^s - E_L^s) + g_L^s \Delta_T \exp\left(\frac{V^s - V_{th}^s}{\Delta_T}\right) + \\ & -g_e^s(t)(V^s - E_e^s) - g_i^s(t)(V^s - E_i^s) + \\ & -w + I_e^s - g_C(V^s - V^d) \\ \tau_w \frac{dw}{dt} &= a(V^s - E_L^s) + b\sum_k \delta(t - t_k) - w \end{cases} \\ C_m^d \frac{dV^d}{dt} = -g_L^d(V^d - E_L^d) - g_e^d(t)(V^d - E_e^d) - g_i^d(t)(V^d - E_i^d) + \\ \quad +I_{Ca} + I_{K_{Ca}} + w_{BAP}\sum_k \delta(t - (t_k + d_{BAP})) + \\ \quad +I_e^d + g_C(V^d - V^s) \end{cases}$$

… for real-time incremental STDP learning …

$$\Delta w = \begin{cases} -W_- \cdot (\frac{w}{w_{\max}})^{\mu_-} \cdot \exp\left(-\frac{t_{\text{pre}} - t_{\text{post}}}{\tau_-}\right), & \text{if } t_{\text{pre}} - t_{\text{post}} > 0 \\ W_+ \cdot (1 - \frac{w}{w_{\max}})^{\mu_+} \cdot \exp\left(-\frac{t_{\text{pre}} - t_{\text{post}}}{\tau_+}\right), & \text{otherwise} \end{cases}$$





… and ThetaPlanes: piecewise transfer function for bio-inspired artificial intelligence

$$\nu_F(I_s, I_d; \nu) = \Theta_\rho(1 - \Theta_H) \cdot \nu_- + \Theta_H \cdot \nu_+$$

Missione 4 - Istruzione e Ricerca – Componente 2 – Grant(s)
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- **Question to be answered**: How the brain consumes only few tens of Watts, while:
  - It is incrementally learning from single shot experiences sampled at >20 video frames /second
  - It integrates experiences that are accumulated over a life-time
  - It merges novel experiences to create novel concepts and abstractions, and forgets what is less relevant
  - Can we exploit brain mechanisms in <<bio-inspired artificial intelligence systems>>?
- **Hints, from experimental evidence, that simulation models could leverage:**
  - Dreaming and deep-sleep occupy two third of life-time in youngster, when learning is at its maximum rate. Prolonged sleep deprivation impairs cognition
  - The brain is the product of evolutionary selection over hundreds of millions of years and countless individuals. Evolution produced experimentally measurable characteristics in the brain architecture
  - Architectural principles and cellular mechanism produced by evolution to combine internal prior with novel evidence are now experimentally accessible
  - As a product of evolution, neurons are not point-like structures
  - Wakefulness and sleep specific “apical” mechanisms exist in the neuron to combine internal priors with novel evidence
  - Connectivity in the brain is recurrent and organized in areas and layers

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https://apegate.roma1.infn.it/

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Acknowledgments

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UNIVERSITY OF OSLO	Johan Frederik Storm
ISTITUTO SUPERIORE DI SANITÀ	Cristiano Capone
SAPIENZA UNIVERSITÀ DI ROMA	*Several among the authors started as MSc and PhD students associated to INFN Roma*
EBRAINS	European research Infrastructure https://www.ebrains.eu/
HBP	Human Brain Project https://www.humanbrainproject.eu/

Disclaimer: the APE group, founded in 1984, is active on many other research topics, including: design of architecture for supercomputing, their interconnects and high-speed analysis of physical data, system software and parallel algorithms for physics simulations. Here in **bold** APE members that **more directly contributed exactly** to the **presented topics**. Other brain-related topics e.g. neural net simulations on GPU, or simulations inferred from data not considered.

current APE members:
R. Ammendola, A. Biagioni, F. Capuani, **A. Cardinale**, C. Chiarini, P. Cretaro, **G. De Bonis, N. Kolodziej,** F. Lo Cicero, O. Frezza, A. Lonardo, **C. Lupo, F. Marmoreo,** M. Martinelli, **P.S. Paolucci, E. Pastorelli**, L. Pontisso, C. Rossi, **L. Tonielli, F. Simula**, P. Vicini
past members that contributed to the presented topic: **C. Capone, C. De Luca, I. Bernava, L. Rosati, P. Muratore, D. Cipollini**

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Legitimate question. Q: Can INFN Roma produce on impact on this topic?
A: selection of our recent papers about the topic discussed today.

PLOS COMPUTATIONAL BIOLOGY

2021 doi: 10.1371/journal.pcbi.1009045

RESEARCH ARTICLE

Thalamo-cortical spiking model of incremental learning combining perception, context and NREM-sleep

Bruno Golosio[1,2], Chiara De Luca[3,4]*, Cristiano Capone[4], Elena Pastorelli[3,4], Giovanni Stegel[5], Gianmarco Tiddia[1,2], Giulia De Bonis[4], Pier Stanislao Paolucci[4]

www.nature.com/scientificreports

SCIENTIFIC REPORTS

OPEN

Sleep-like slow oscillations improve visual classification through synaptic homeostasis and memory association in a thalamo-cortical model

d: 24 January 2019
d: 3 June 2019
d online: 20 June 2019

Cristiano Capone[1], Elena Pastorelli[1,2], Bruno Golosio[3,4] & Pier Stanislao Paolucci[1]

PNAS 2023 (in press)

Beyond spiking networks: the computational advantages of dendritic amplification and input segregation

C. Capone, C. Lupo, P. Muratore, P.S. Paolucci

arXiv

2023 doi: 10.48550/arXiv.2311.06074

Two-compartment neuronal spiking model expressing brain-state specific apical-amplification, -isolation and -drive regimes

E. Pastorelli, A. Yegenoglu, N. Kolodziej, W. Wybo, F. Simula, S. Diaz, J. F. Storm, and P. S. Paolucci

frontiers Integrative Neuroscience

TYPE Original Research
PUBLISHED 03 October 2022
DOI 10.3389/fnint.2022.972055

Simulations of working memory spiking networks driven by short-term platicity

G. Tiddia, B. Golosio, V. Fanti and P. S. Paolucci

PMLR Proceedings of Machine Learning Research 2022

Burst-Dependent Plasticity and Dendritic Amplification Support Target-Based Learning and Hierarchical Imitation Learning

Cristiano Capone, Cosimo Lupo, Paolo Muratore, Pier Stanislao Paolucci *Proceedings of the 39th International Conference on Machine Learning*, PMLR 162:2625-2637, 2022.

PLOS COMPUTATIONAL BIOLOGY

OPEN ACCESS PEER-REVIEWED

RESEARCH ARTICLE

Error-based or target-based? A unified framework for learning in recurrent spiking networks

Cristiano Capone, Paolo Muratore, Pier Stanislao Paolucci

Version 2 Published: June 21, 2022 • https://doi.org/10.1371/journal.pcbi.1010221

PLOS ONE

OPEN ACCESS PEER-REVIEWED

RESEARCH ARTICLE

Target spike patterns enable efficient and biologically plausible learning for complex temporal tasks

Paolo Muratore, Cristiano Capone, Pier Stanislao Paolucci

Published: February 16, 2021 • https://doi.org/10.1371/journal.pone.0247014

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Talk structure

- Introduction to experimental knowledge about brain states and combination of prior knowledge and novel evidence, we took in consideration in our models
- Primer to plastic spiking neural network simulations
- A selection of our results about how to construct <<Bio-inspired plastic spiking neural networks engaged in learning and sleep cycles>>

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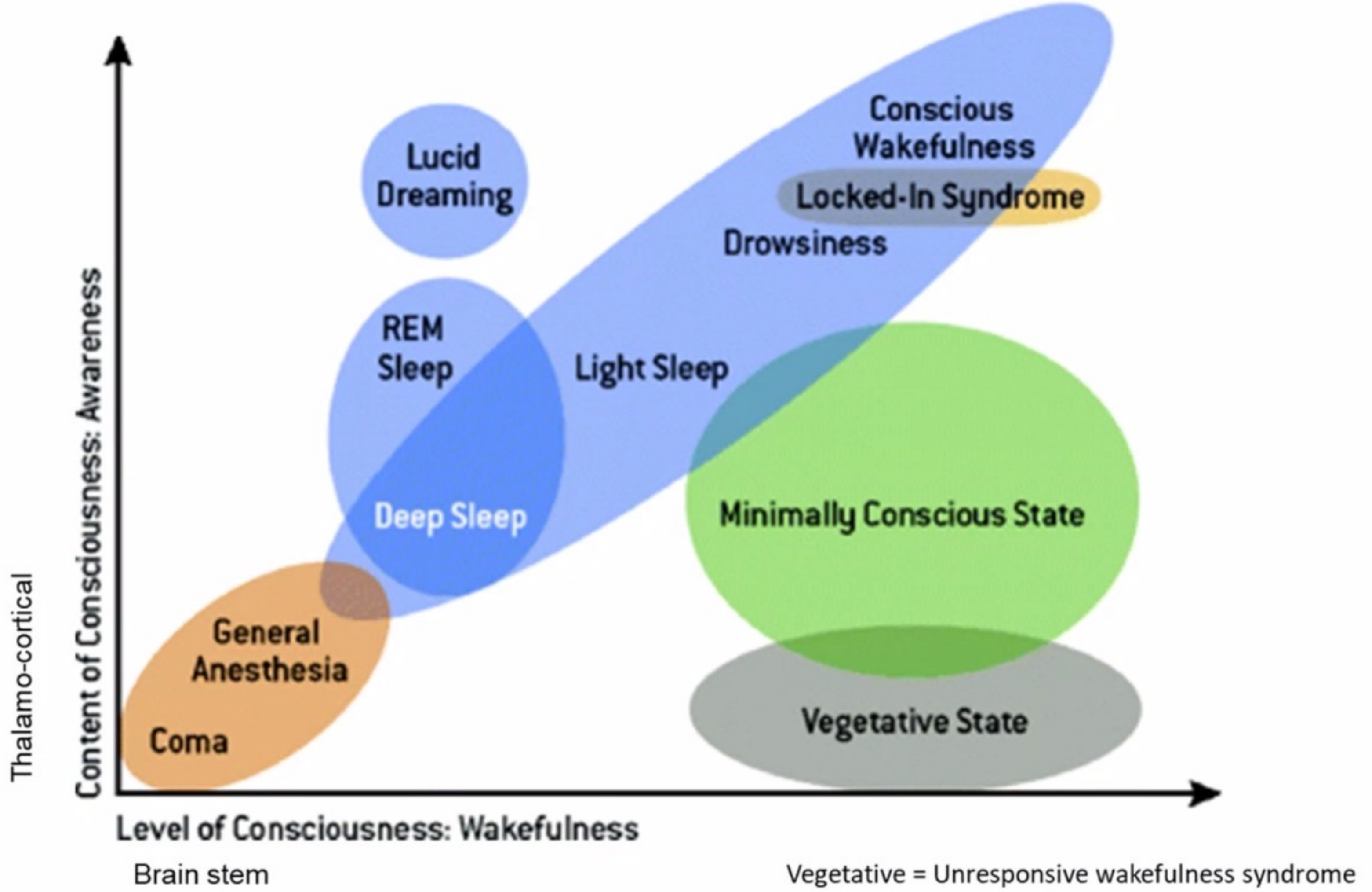
A seven slides primer to experimental knowledge about

- Brain-states
- Levels of consciousness
- Architectural principles for combination of internal priors and novel evidence at macro-, meso- and micro-scale
- Response to perturbations during different states
- …with some totally personal opinions about them

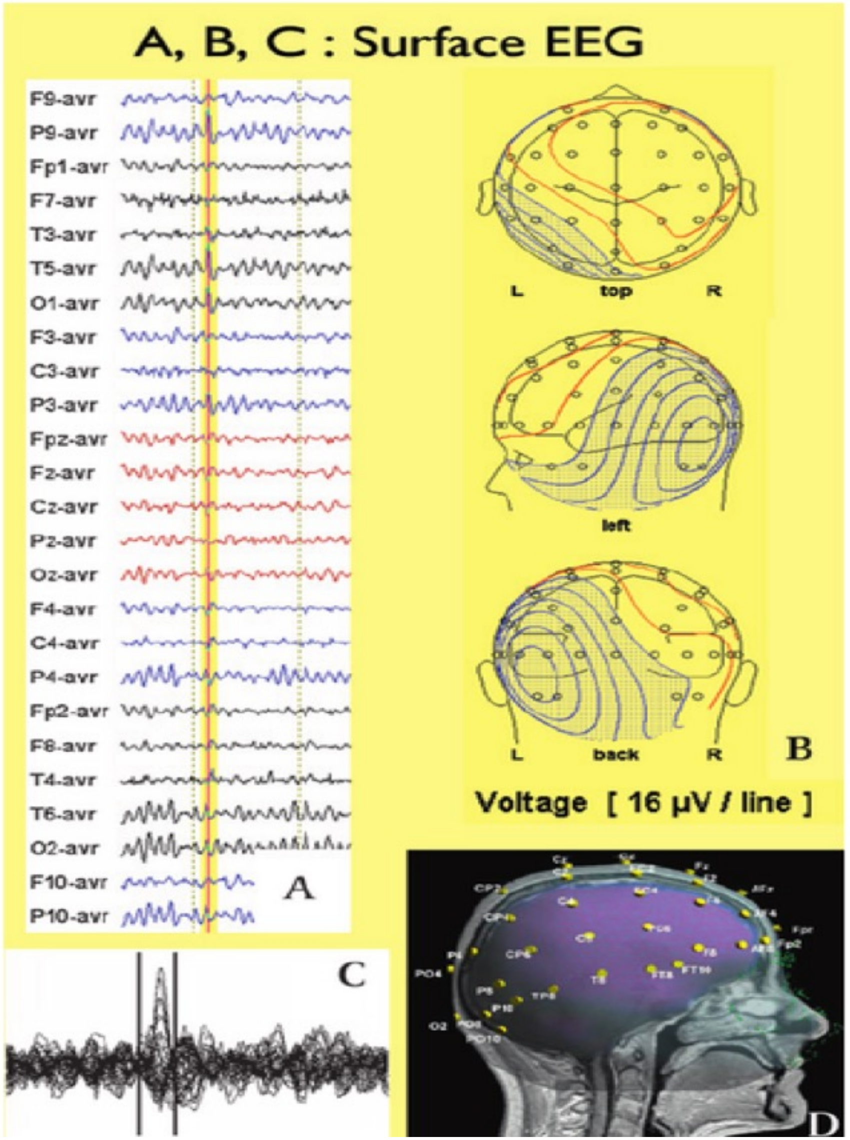


Panel discussion among: M.V. Sanchez-Vives, M. Massimini, S. Laureys, A. Destexhe, J. Storm, M. Mattia, P.S. Paolucci et al. (2020) kick-off meeting of “Networks Underlying Cognition and Consciousness” Work-package, The Human Brain Project.

Subjects awakened during REM (Rapid Eye Movement) report vivid dreams,
Integrating multi-sensorial experiences, REM Sleep considered a conscious state

NREM: Non-REM Sleep

One of the less invasive tools to study the brain-activity: electro-encephalography



Measurement of fluctuations of electric potential recorded from outside the body.

Note that in the human brain there are about 100 Billion neuron and about one Quadrillion synapses.

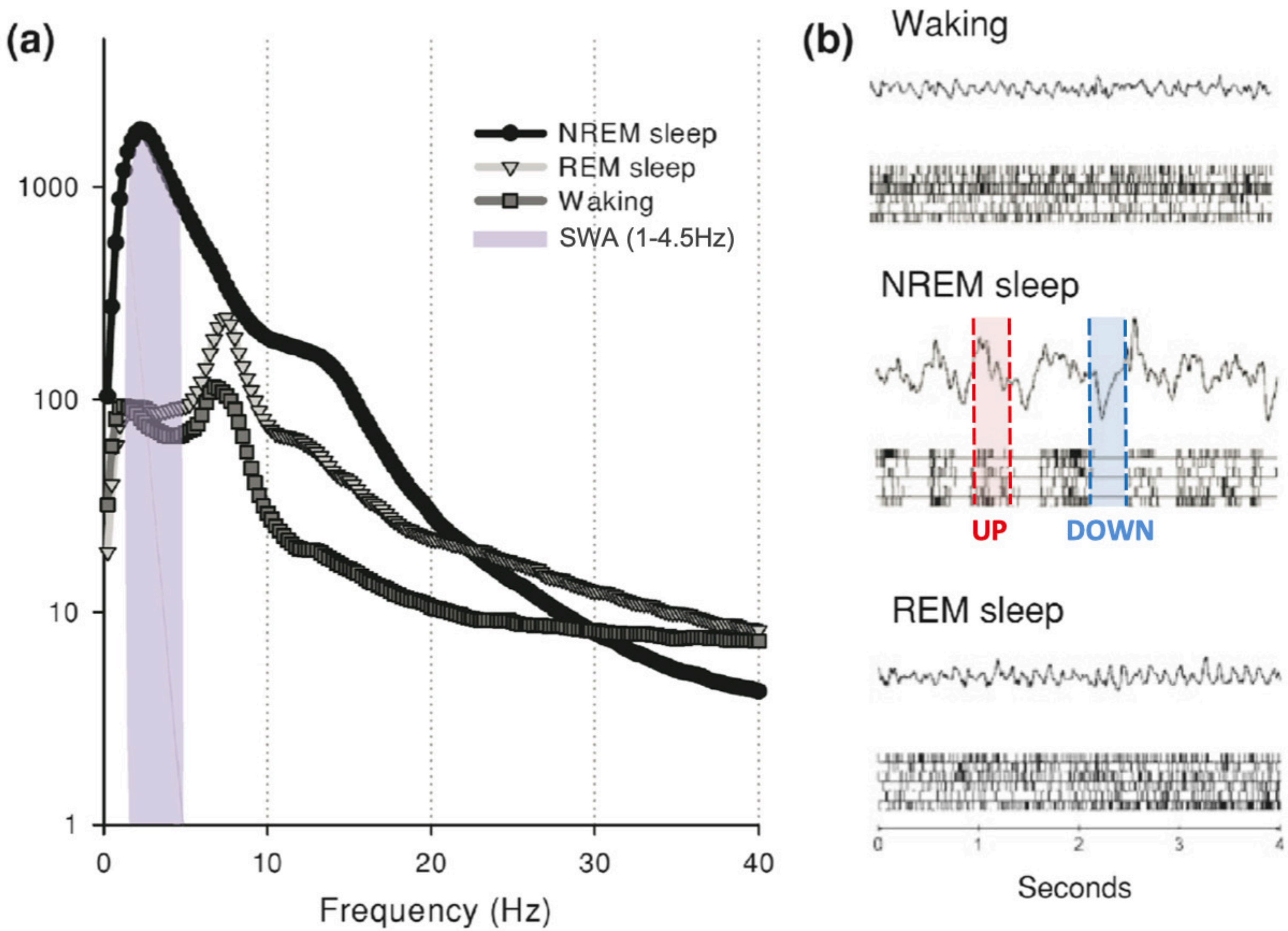
Each neuron and synapse is a non linear computational gate that makes its own computational decision. In less than half a second, the decision of a single neuron activity can produce completely different macroscopic observables.

My personal opinion: what we see here is essential to calibrate simulation models, or to detect pathological and physiological conditions, but computation happens at a much smaller scale.

It is also possible to measure the individual activity of a few hundreds (or thousands) of individual neurons…(remember there are billions of them). Brain States and Brain Rhythms. Up and Down states and SWA (Slow Waves Activity) during NREM sleep. Also, note the similarity between wakefulness and REM sleep.

Power Spectral Density

(of EEG Signals)



Recording of EEG signals

Recording of individual spikes

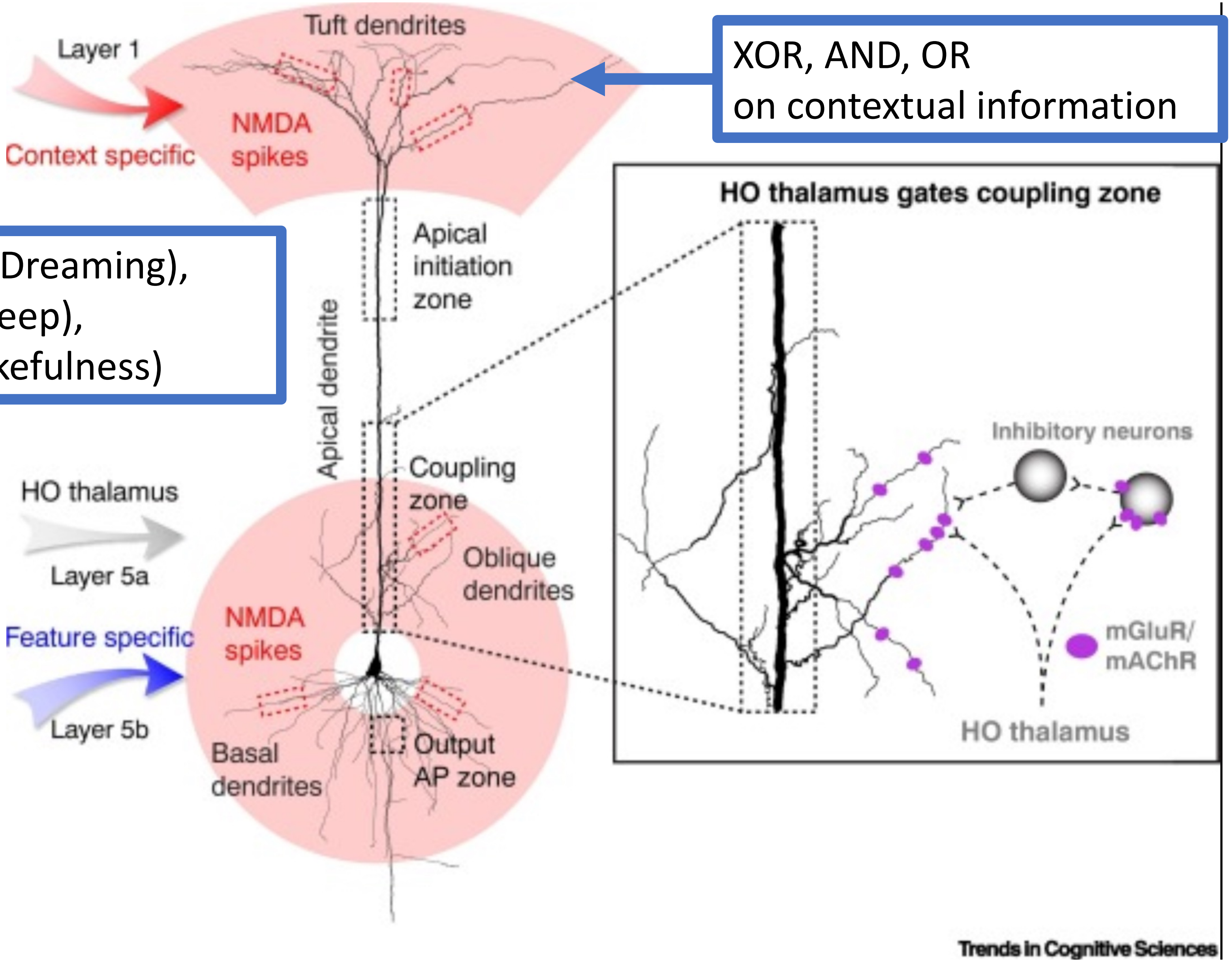
Recording of EEG signals

Recording of individual spikes

Pyramidal neurons are NOT point like entities. Also, they have brain-state dependent neural mechanisms for conscious / unconscious processing.

XOR, AND, OR
on contextual information

Apical Drive (REM Dreaming),
Isolation (NREM sleep),
Amplification (Wakefulness)



J. Aru, F. Siclari, W. A. Phillips, J. F. Storm (2020) Apical drive—A cellular mechanism of dreaming? **Neuroscience & Biobehavioral Reviews**

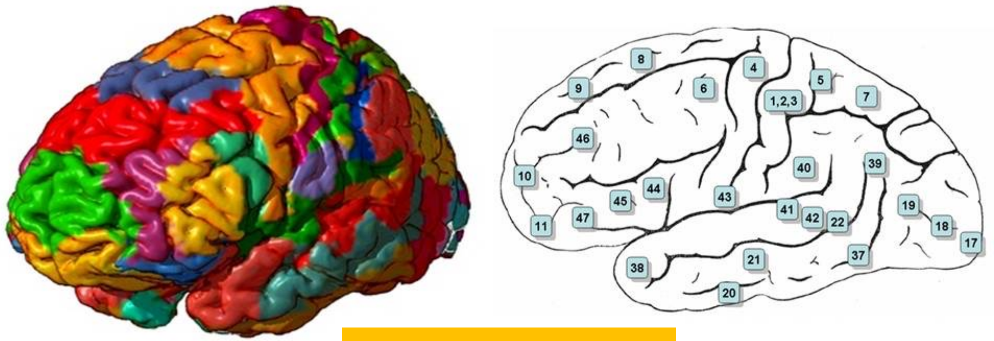
J. Aru, M. Suzuki, M. E. Larkum, (2020) **Cellular Mechanisms of Conscious Processing** *Trends in Cognitive Sciences*

Image: John A Beal CC-BY lic. 2005 Louisiana State Univ.

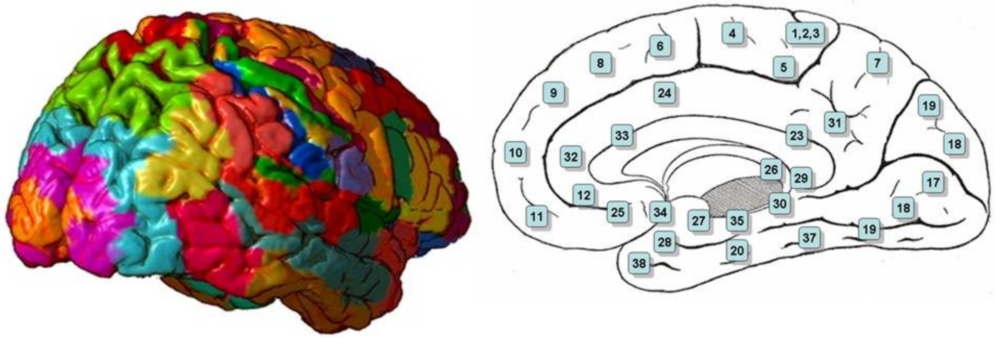
Essential novelty: measures of white matter long-range inter-areal connectome

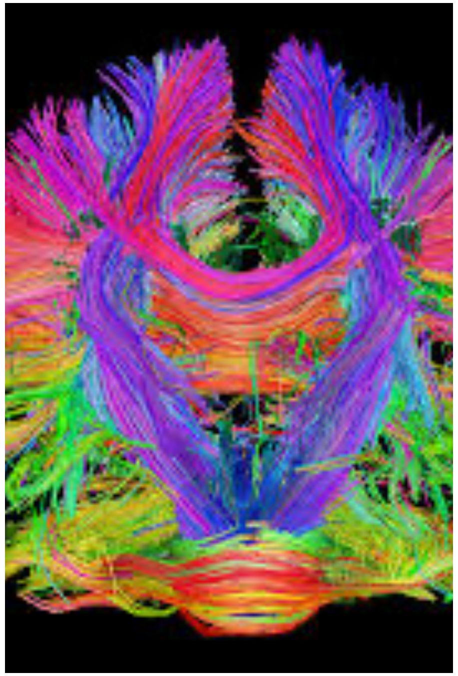
Year 2015 – White matter mapping, DTI - fiber tractography (non invasive)

Year 1909 - Brodmann Cortical Areas already Defined



Ȼ(2009) Mark Dow

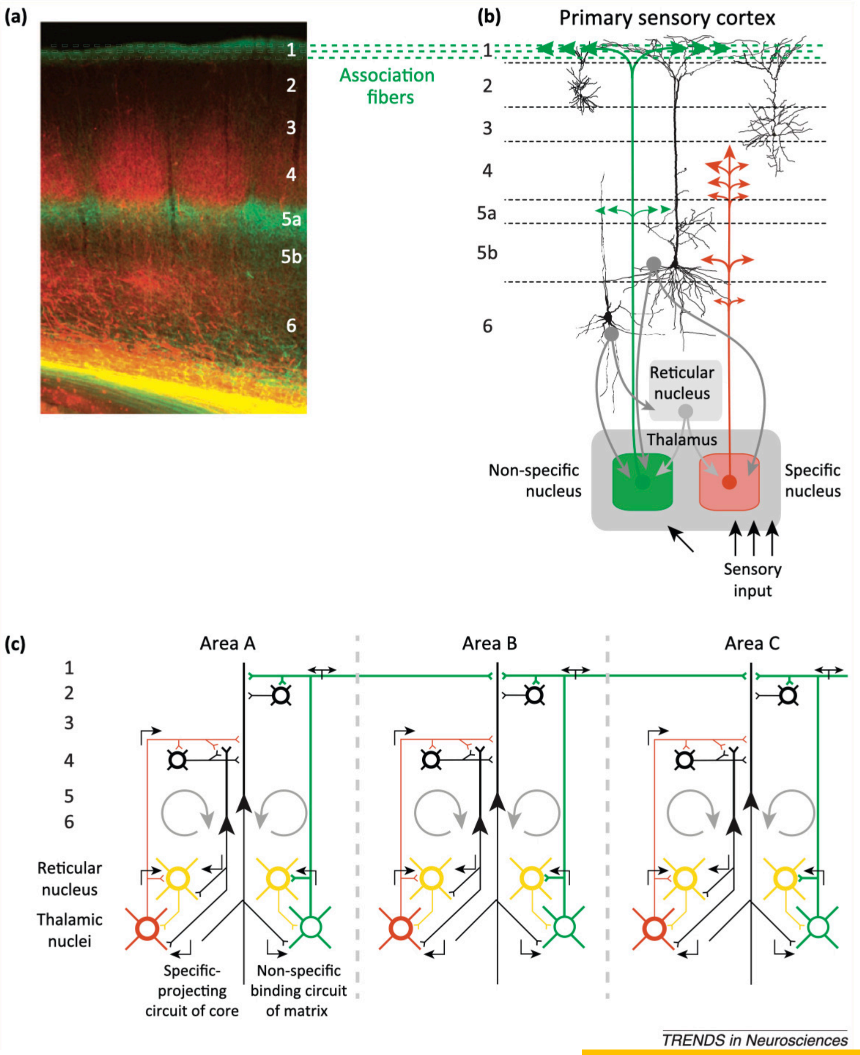


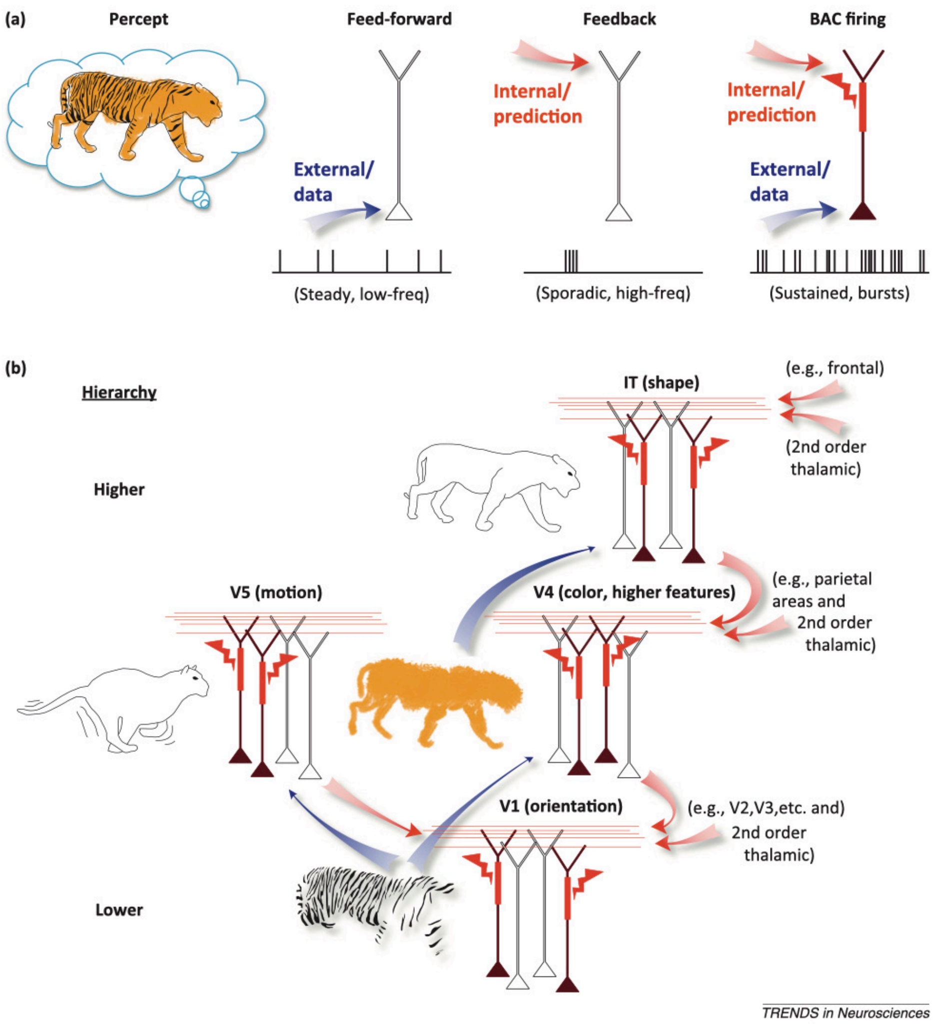


Also, invasive connectomic technologies available (often requiring post-mortem access to tissues)

Connectomic supporting integration of priors and evidence

experience by integration of internal and external information in a multi-area system





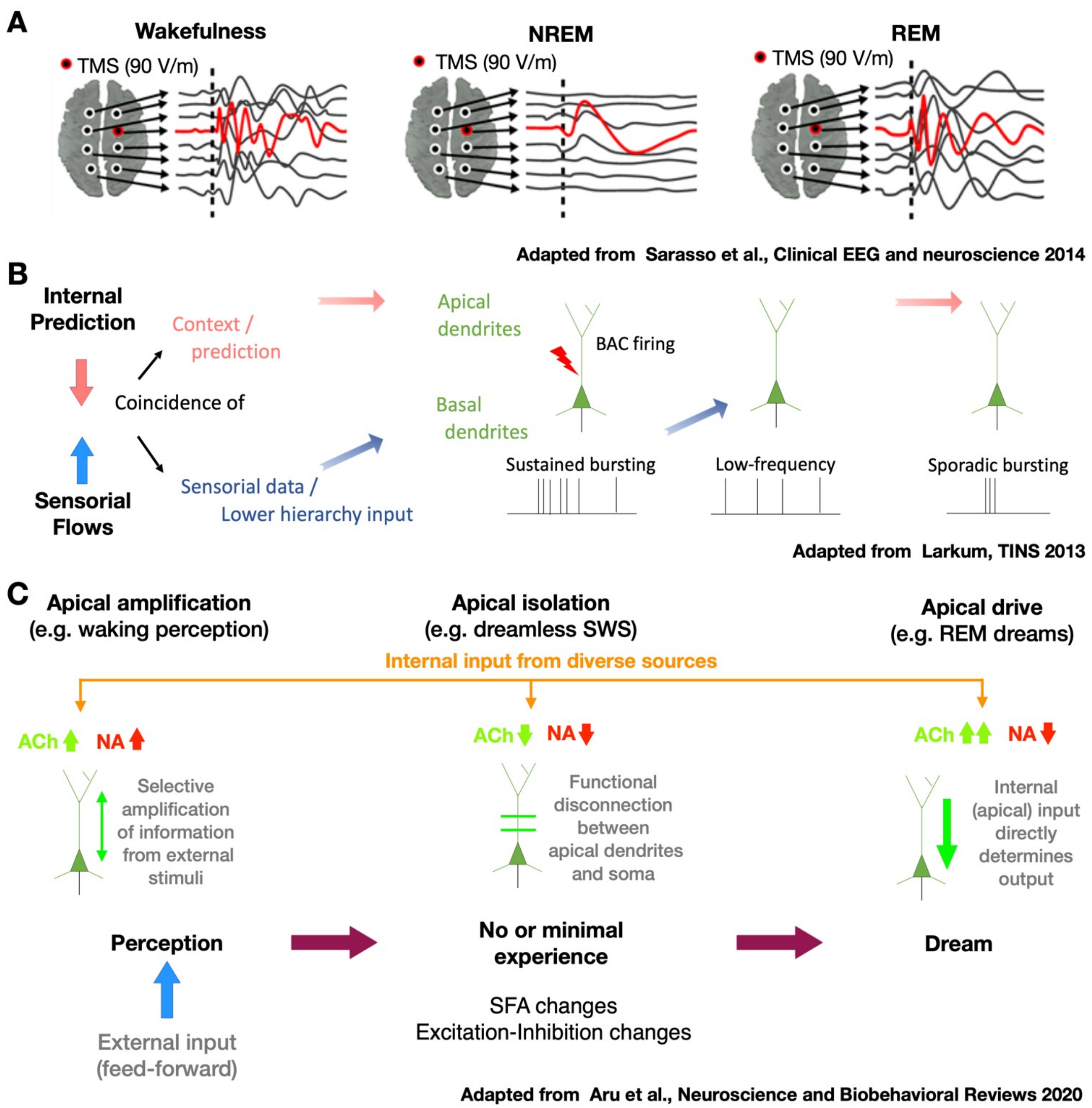
Larkum, M. A cellular mechanism for cortical associations: an organizing principle for the cerebral cortex. *Trends in Neurosciences*, 36 (2013), 141.

Other experimental features that inspired our previous generation models, based on single compartment AdEx

A) RESPONSE TO PERTURBATIONS. The structural connectivity is the same, but the response to perturbations depends on the brain state. Response complexity is similar between wakefulness and REM sleep, but drops in deepest NREM sleep. Conscious experience of rich, integrated scenario is typically recorded when awakened from REM sleep, but not during deepest NREM.

B) TEMPORAL COINCIDENCE between internal predictions and sensorial flow, detected by single neuron, induces sustained bursting during wakefulness.

C) TRANSITIONS AMONG STATES and NEUROMODULATORS. It is possible to introduce parameters in neural simulations that act as neuromodulation proxies. In our models we limit to Acetylcholine (ACh) and Noradrenaline (NA) proxies.



A four slides primer to learning spiking neural networks models

…and how even single simulations based on point-like depart from neurons used in typical artificial neural network simulations?

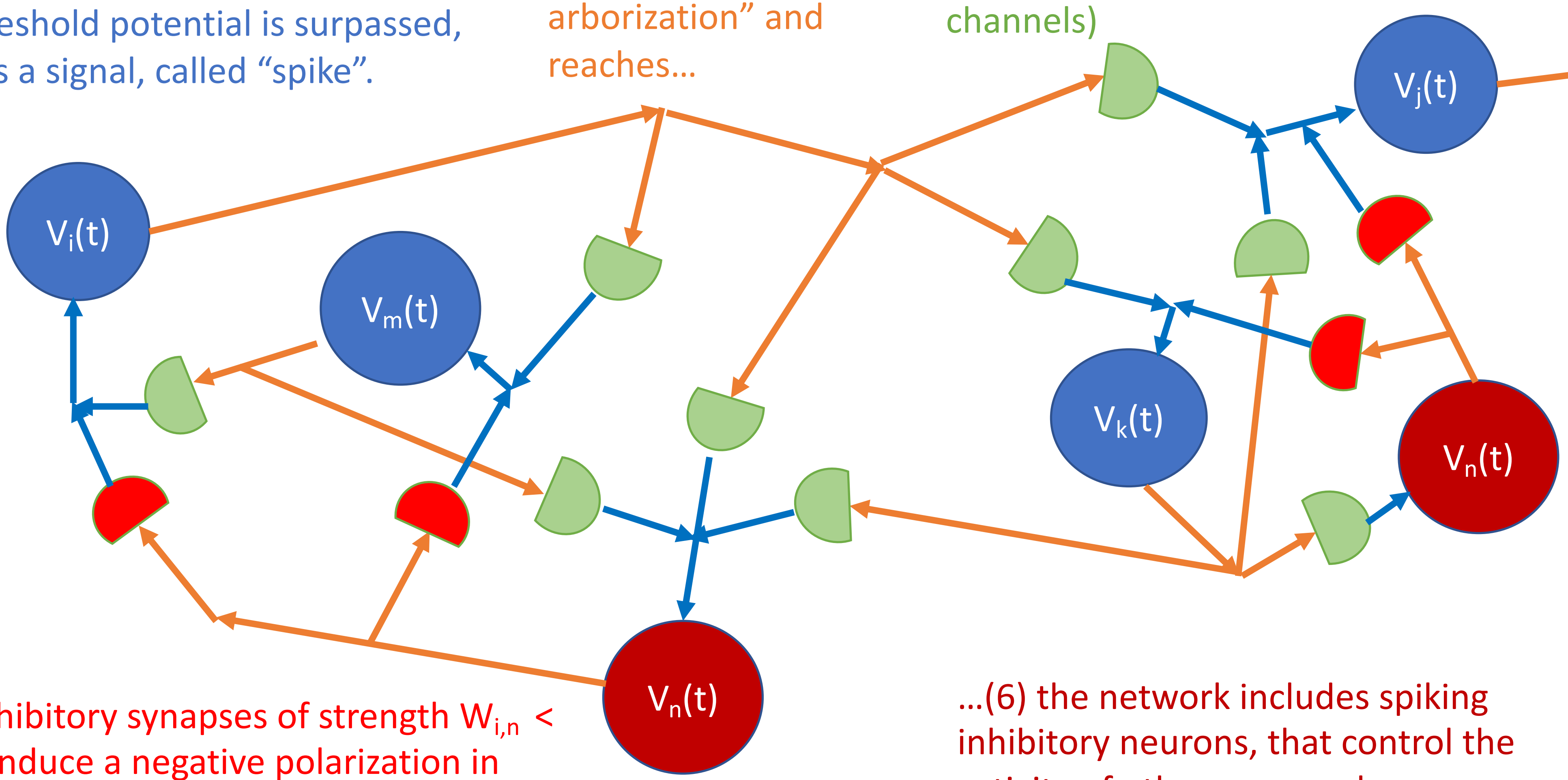
A toy spiking neural network with plastic synapses

(1) Excitatory Neuron i, and its membrane potential V_i (t).
If a threshold potential is surpassed, it emits a signal, called “spike”.

…(2) the spike travels along the ”axonal arborization” and reaches…

…(3) excitatory synapses of strength $W_{j,l} > 0$ that inject a positive current in postsynaptic neurons (typically, Glutammate neurotransmitter opens the channels)

(4) Contributing to the dynamics of postsynaptic neurons, and to the emission of spikes



…(5) the strength of synapses evolves in time (“plasticity”) depending on the network activity, supporting “learning” of past activity and novel solutions to tasks

…(6) the network includes spiking inhibitory neurons, that control the activity of other neurons by…

…(7) inhibitory synapses of strength $W_{i,n} <$ 0 that induce a negative polarization in postsynaptic neurons (mainly GABA neurotransmitter is the channel opener)

The AdEx "spiking" single-compartment neuron with spike frequency adaptation

$$\begin{cases} C_m \frac{dV}{dt} & = -g_L(V - E_L) + g_L \Delta_T \exp\left(\frac{V - V_{th}}{\Delta_T}\right) - g_e(t)(V - E_e) - g_i(t)(V - E_i) - w + I_e \\ \tau_w \frac{dw}{dt} & = a(V - E_L) + b \sum_k \delta(t - t_k) - w \end{cases}$$

Brette R and Gerstner W (2005). *Adaptive exponential integrate-and-fire model as an effective description of neuronal activity.* **Journal of Neurophysiology**

If $V(t_s)$ exceeds the threshold parameter V_{th}

- a "spike" is considered emitted at time t_s
- V is reset to the afterspike potential parameter V_{res}
- A refractory time parameter T_{ref} can be set during which V is kept a the constant value V_{res}

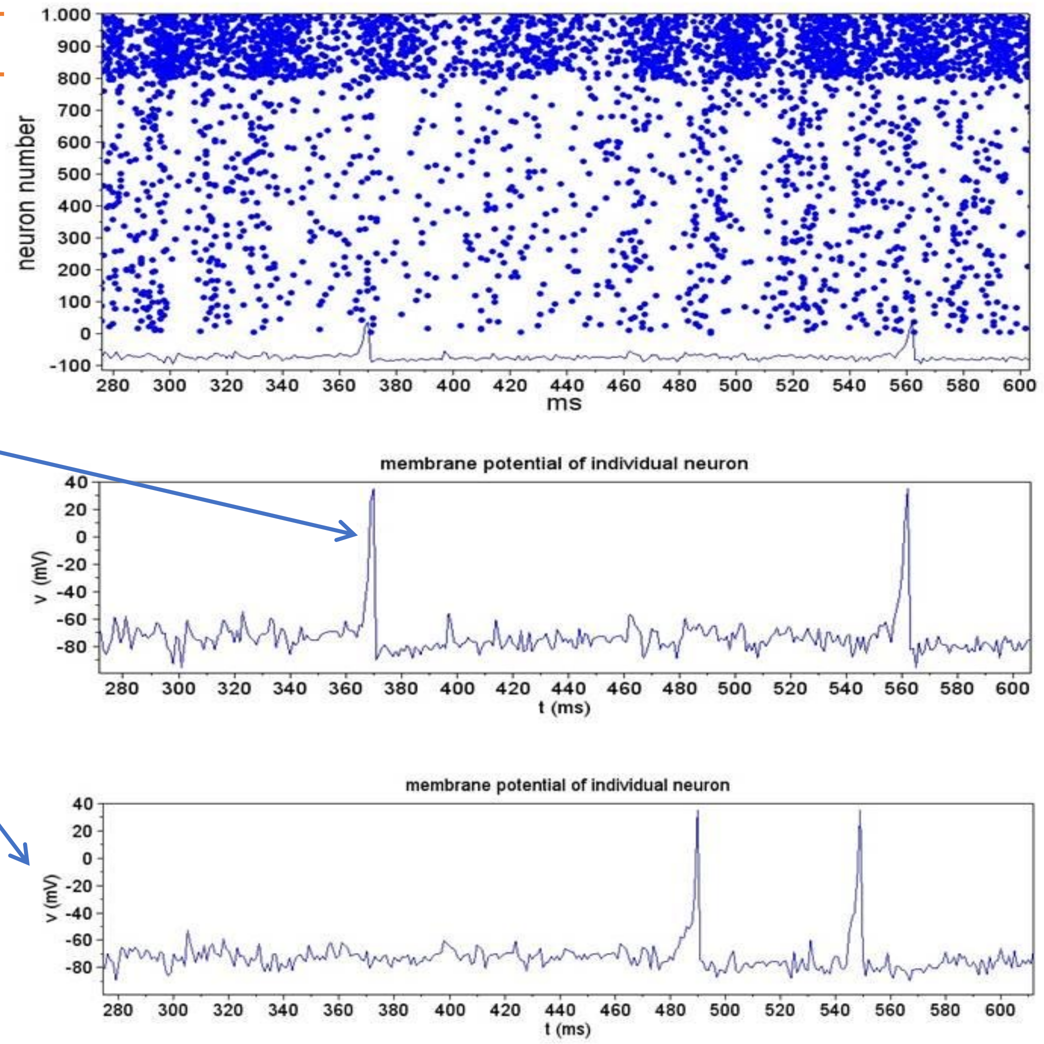
- $V(t)$ neuron membrane potential
- C_m neuron membrane capacitance
- g_L leakage conductance
- g_e conductance of incoming excitatory synapses
- g_i conductance of incoming inhibitory synapses
- I_e additional input current (e.g. to simulate insertion of electrode)

- ω Spike Frequency Adaptation, each emitted spike raises its value
- b parameter in ω equation, is a proxy for one of the brain-state chemical neuromodulators (ACh).
- E_L leakage potential, is a parameter that can be associated to a another chemical neuromodulator (NA)
- Δ_T a parameter used for better fit of AdEx to experimental measures

small scale example of spiking neural net simulation

- Each dot in the rastergram represents an individual spike
- 200 inhibitory neurons
- 800 excitatory neurons
- The evolution of the membrane potential of individual neurons is simulated
- The evolution of individual synaptic strength is computed (not shown in the picture)
- individual synaptic delays are taken into account
- Individual connections and neural types can be programmed
- Typical time-step for integration: 0.01 ms -> 0.1 ms

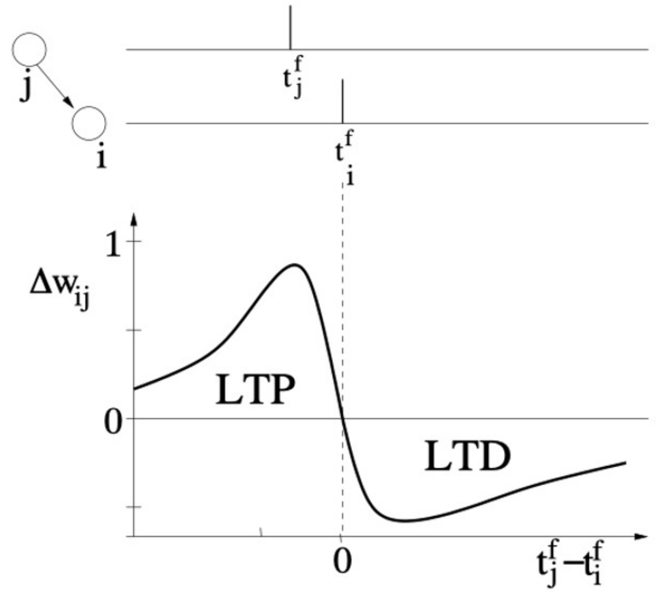
Collective Spiking Rastergram and activity of individual neurons

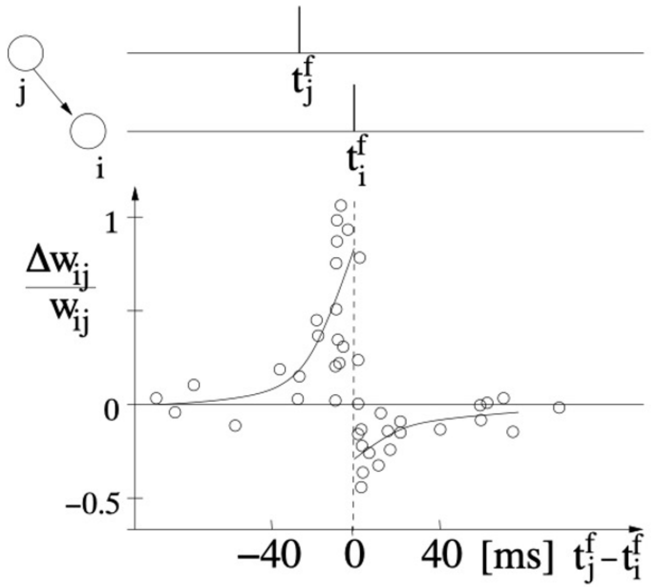


An example of synaptic learning rule for spiking neural networks: Spiking-time dependent plasticity (STDP)

$$\Delta w = \begin{cases} -W_- \cdot (\frac{w}{w_{\max}})^{\mu_-} \cdot \exp\left(-\frac{t_{pre}-t_{post}}{\tau_-}\right), & \text{if } t_{pre} - t_{post} > 0 \\ W_+ \cdot (1 - \frac{w}{w_{\max}})^{\mu_+} \cdot \exp\left(-\frac{t_{pre}-t_{post}}{\tau_+}\right), & \text{otherwise} \end{cases}$$

R. Gütig, R. Aharonov, S. Rotter, H. Sompolinsky (2003). *Learning input correlations through nolinear temporally asymmetric Hebbian Plasticity.* **The Journal of Neuroscience**





Biological synapses are engines that are able to detect both causality and anti-causality.

They can reward themselves, by increasing their values when causality is detected,

and depress themselves when anti-causality is detected.

…and from now on, something about our work…

- **Part I. Models of incremental learning and sleep cycles based on standard single-compartment spiking neuron (AdEx)**
- Part II. Introducing two-compartment model with cellular support for apical-ampification, apical-isolation and apical-drive mechanisms, and simplified transfer function for bio-inspired artificial intelligence applications to come
- Part III.
  - Cobrawap (Collaborative Brain Wave Analysis Pipeline) advertisement
  - Blue-printing a whole brain cognitive simulation exploiting brain-states benefits

Thalamo-cortical spiking models showing the beneficial cognitive and energetic effects of the interplay among sleep and memories, learned by combining contextual and perceptual information

Sleep

- Sleep essential, in all animal species
- Young humans pass the majority of time sleeping, when learning is faster
- Sleep deprivation detrimental for cognition

Sleep Functions (in brains)

Optimization of energy consumption / cognitive performance

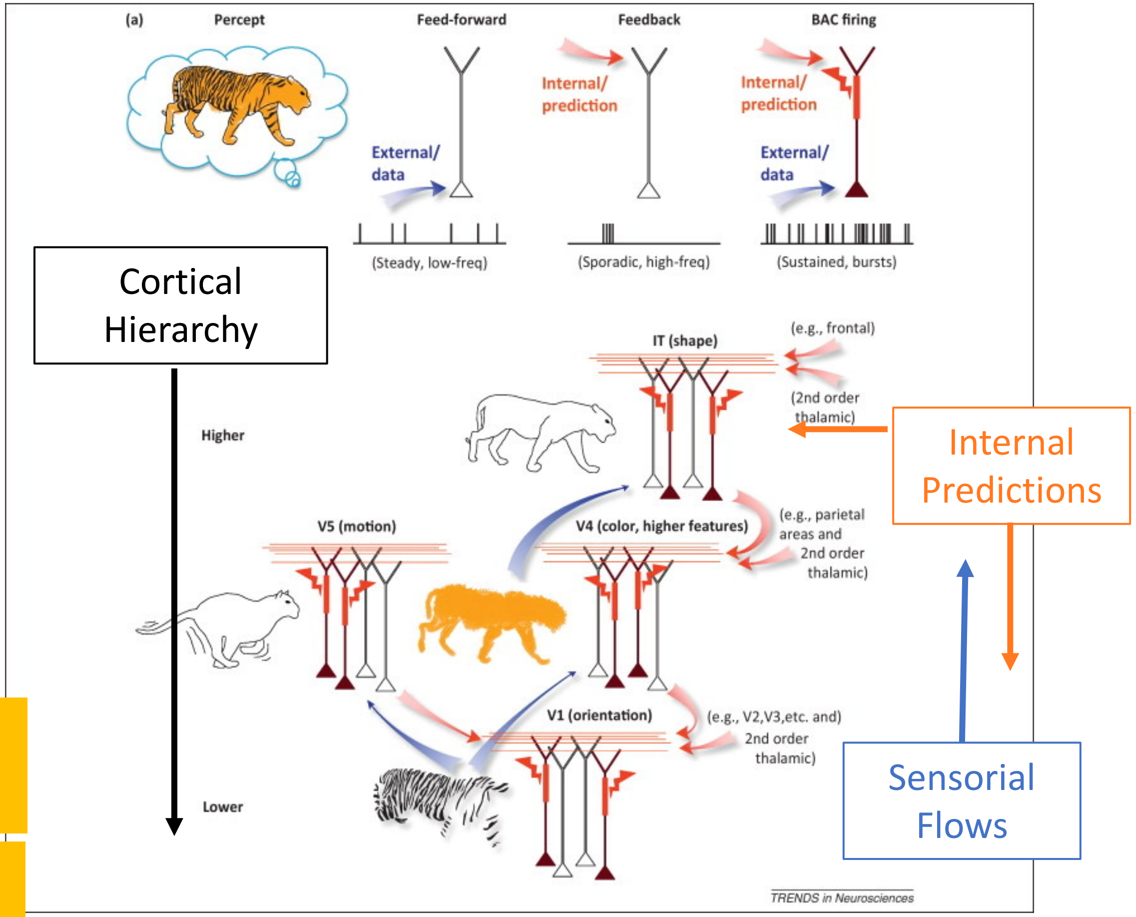
Homeostatic processes (normalization of representations)

Novel, creative associations and planning

Recovery / restorations of bio-chemical optimality

(our opinion) Sleep essential for bio-inspired artificial intelligence

Wakefulness



Thalamo-cortical spiking model of incremental learning combining perception, context and NREM-sleep ***PLoS Computational Biology*** (2021*). B.Golosio, C. De Luca, C. Capone, …, P.S. Paolucci*. https://doi.org/10.1371/journal.pcbi.1009045

Sleep-like slow oscillations improve visual classification through synaptic homeostasis and memory association in a thalamo-cortical model ***Scientific Reports*** (2019). *C. Capone, E. Pastorelli, B. Golosio, P.S. Paolucci*. https://www.nature.com/articles/s41598-019-45525-0

NREM and REM: cognitive and energetic effects in thalamo-cortical sleeping and awake spiking model ***arXiv:2211.06889*** (2022) ***(under review).*** *L. Tonielli, C. De Luca, E. Pastorelli, …, Golosio, P.S. Paolucci*.

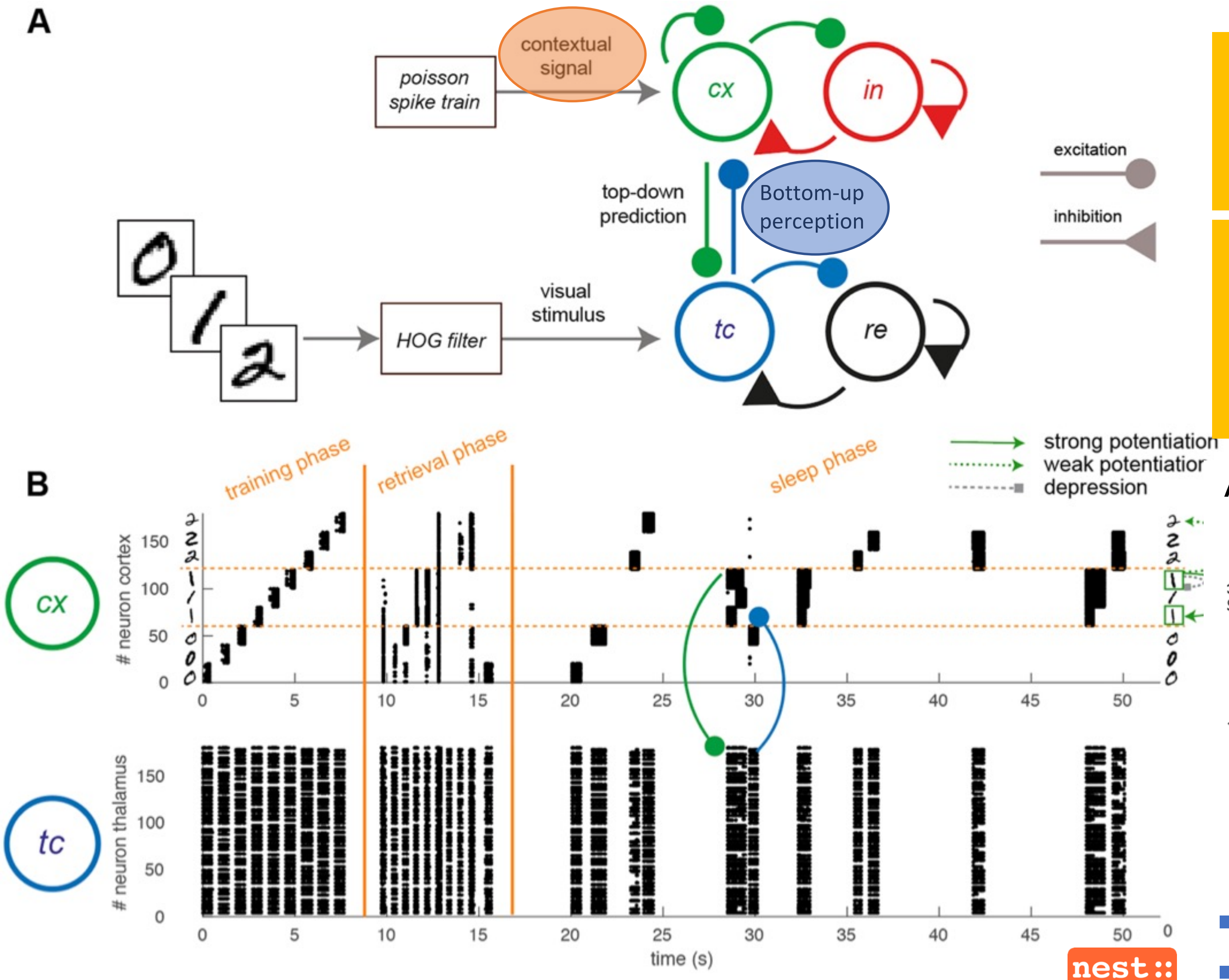
Larkum, M. A cellular mechanism for cortical associations: an organizing principle for the cerebral cortex. ***Trends in Neurosciences***, 36 (2013), 141.

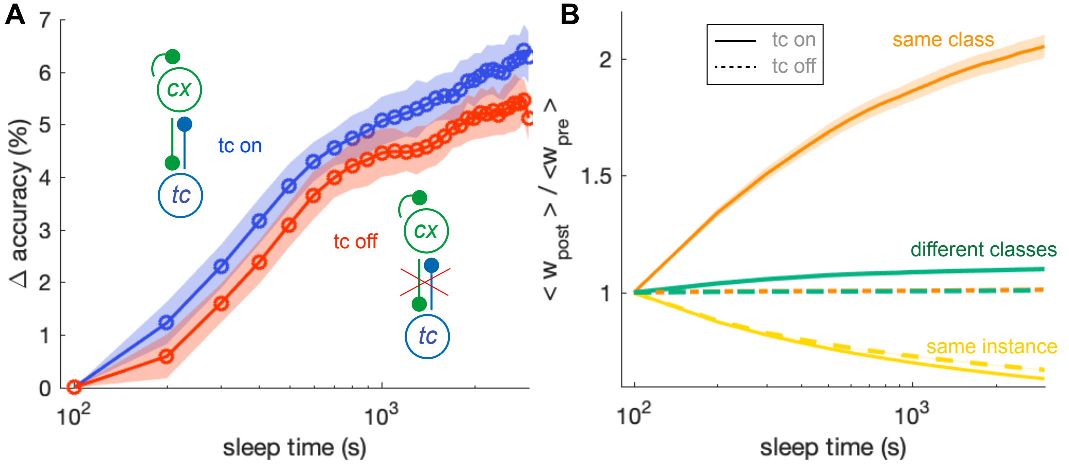
Apical-amplification simplifies incremental learning.
Sleep spontaneously normalizes and associates memories

Key trick using sinle compartment AdEx neurons. Put them underthreshold when only bottom-up signals arrive.

Thalamo-cortical spiking model of incremental learning combining perception, context and NREM-sleep ***PLoS Computational Biology*** (2021*). B.Golosio, C. De Luca, C. Capone, …, P.S. Paolucci*.
https://doi.org/10.1371/journal.pcbi.1009045

Sleep-like slow oscillations improve visual classification through synaptic homeostasis and memory association in a thalamo-cortical model ***Scientific Reports*** (2019). *C. Capone, E. Pastorelli, B. Golosio, P.S. Paolucci*.
https://www.nature.com/articles/s41598-019-45525-0





- Classification accuracy improved by sleep (left).
- Differential synaptic homeostasis (right)

Other spontaneous features

C) Sleep reduces firing rates and energy consumption on next awakening

Synaptic matrices

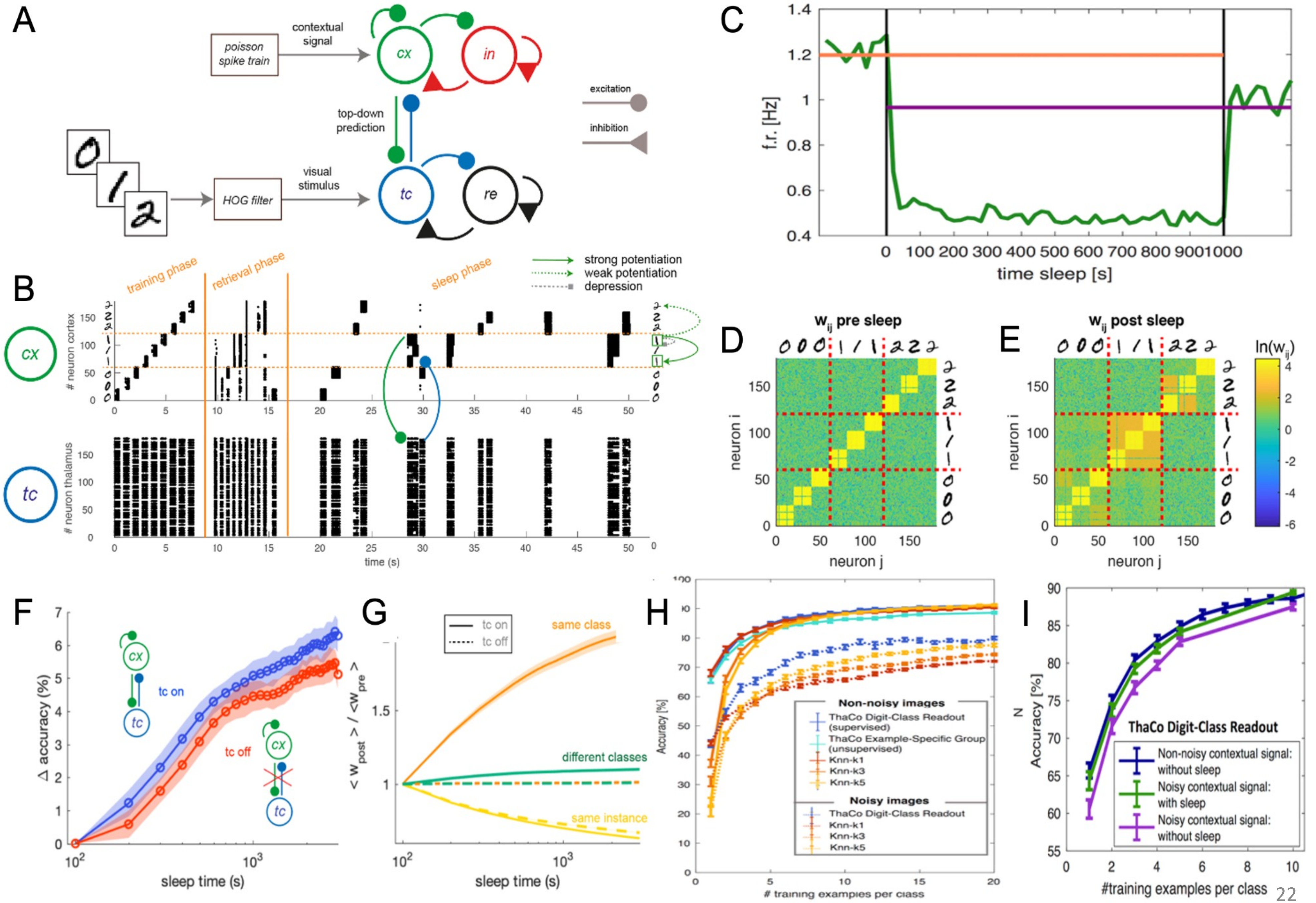
D) Before sleep:

Yellow squares: images learned by neural groups

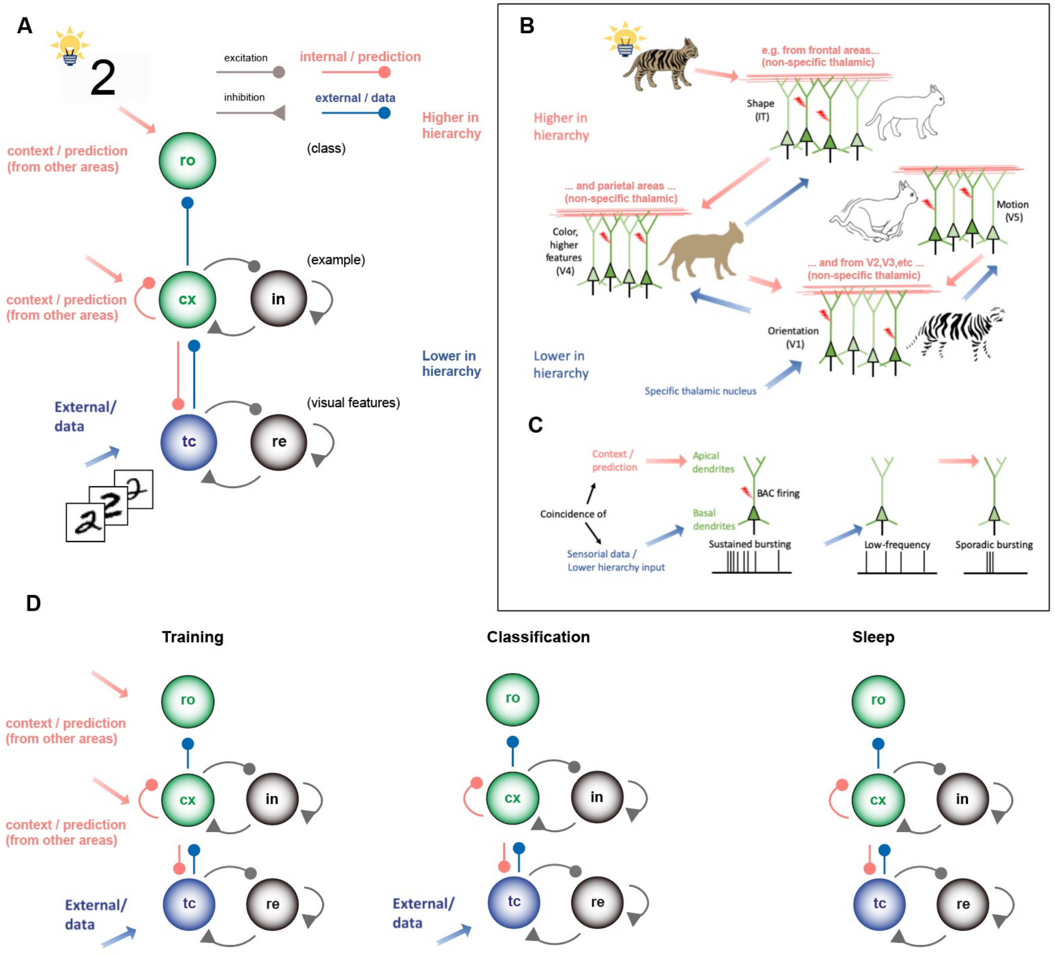
E) After sleep:

Orange blocks: spontaneous creation of classes

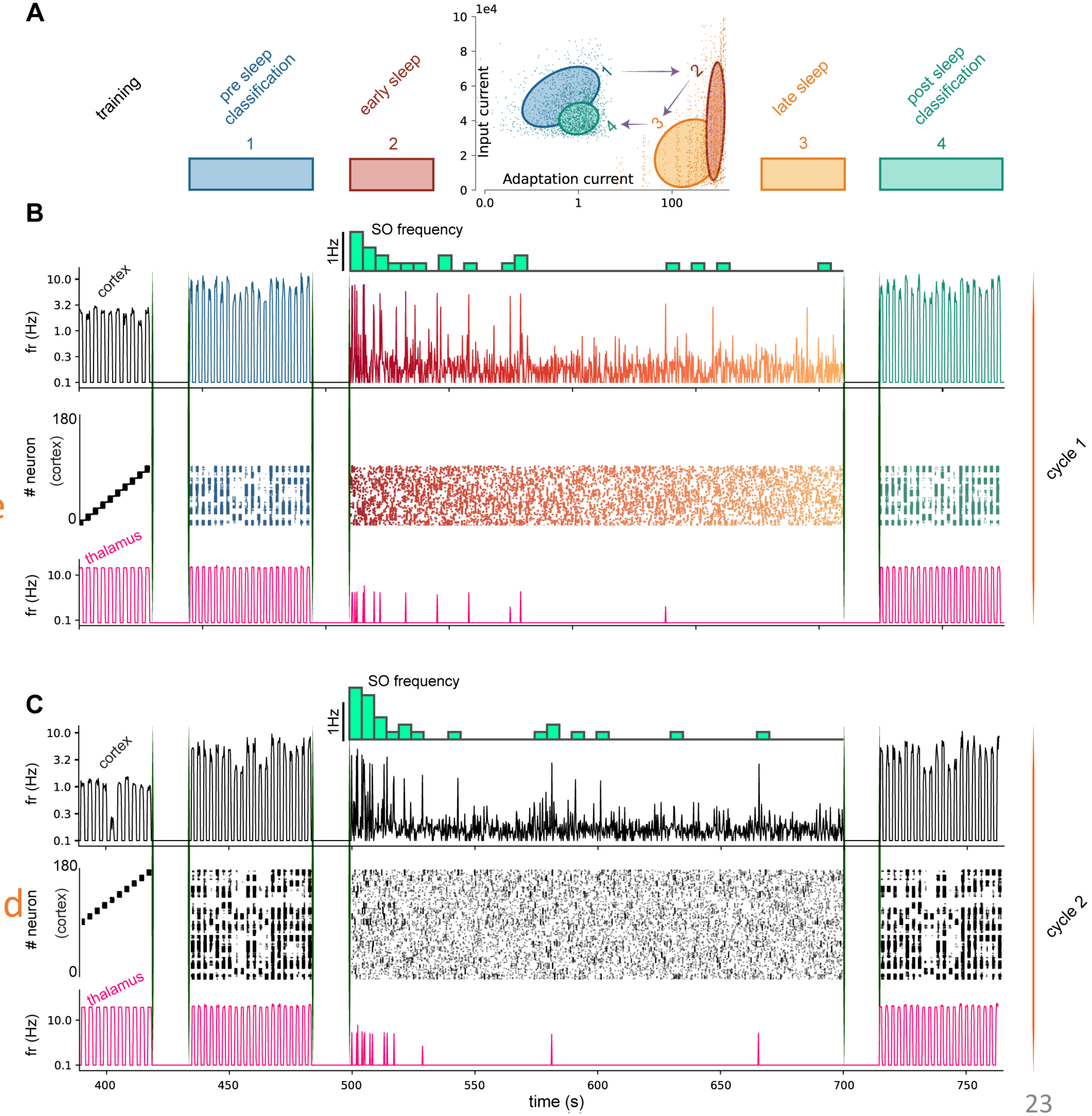
H) And I) Sleep benefits after training in presence of noise



Incremental awake deep-sleep cycle



The cycle in the adaptation – current plane



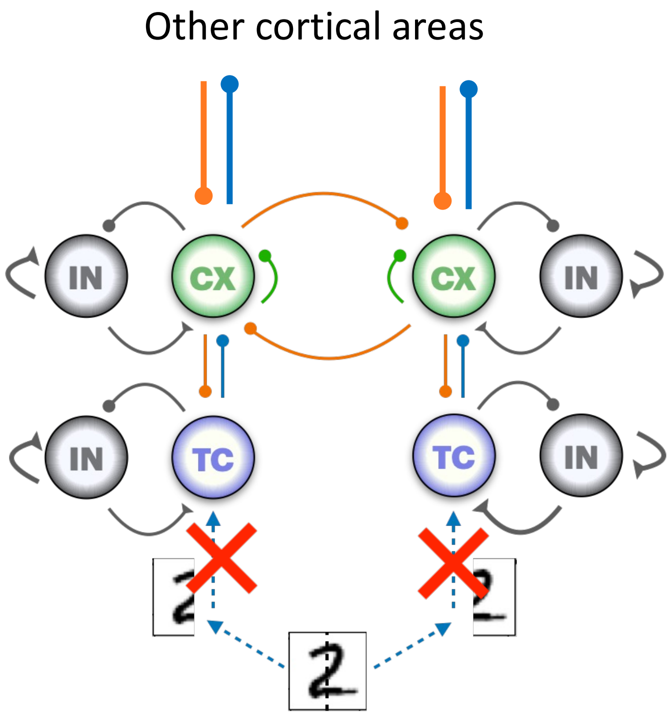
First Cycle

Second Cycle

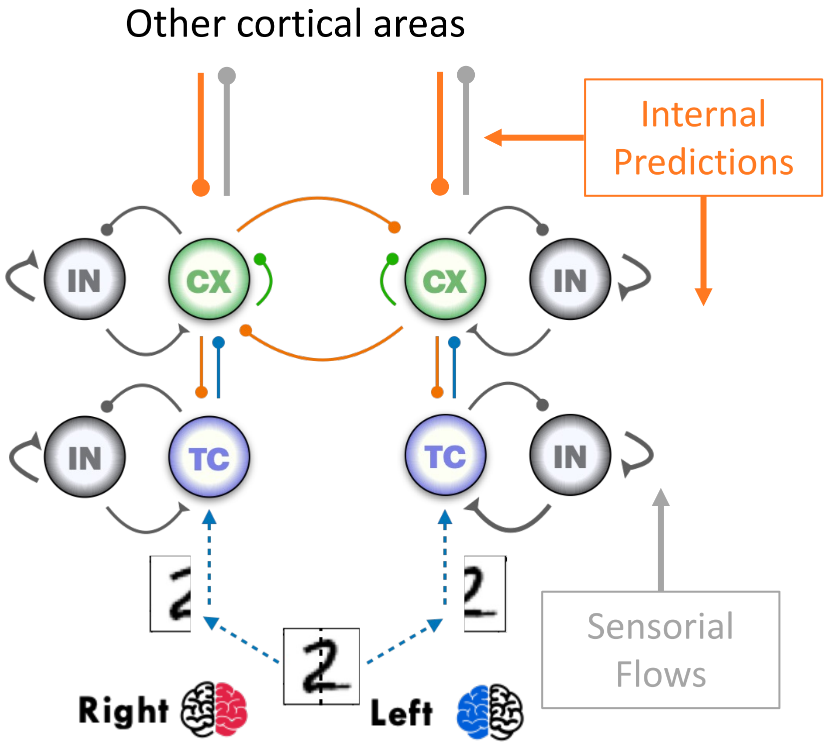
Thalamo-cortical spiking model of incremental learning combining perception, context and NREM-sleep ***PLoS Computational Biology*** (2021). *B.Golosio, C. De Luca, C. Capone, …, P.S. Paolucci*. https://doi.org/10.1371/journal.pcbi.1009045

Modular multi-areal playground to investigate brain-state specific cognitive / energetic effects during AWAKE, NREM, REM cycles in thalamo-cortical plastic spiking models: ThaCo

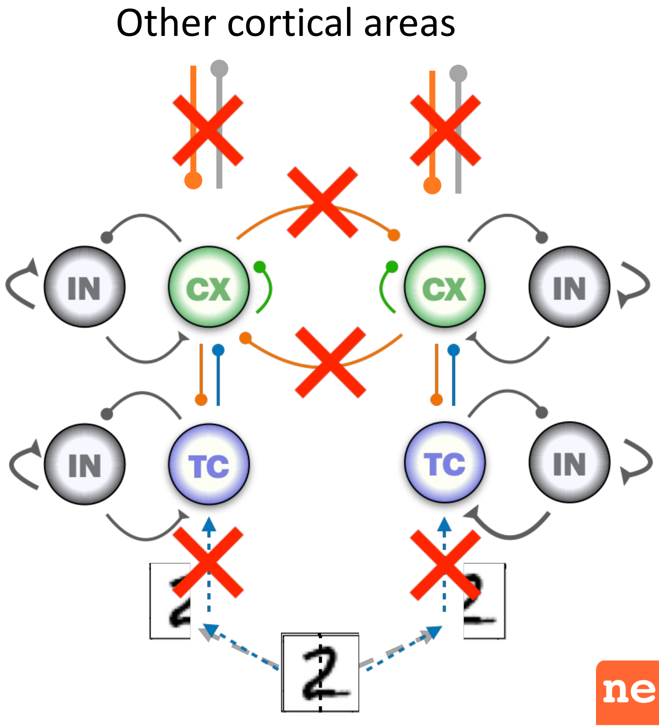
REM: endogenous activity of connected areas with STDP plasticity (block of external stimuli)



AWAKE: incremental STDP learning and classification of external stimuli



NREM: endogenous local activity with STDP plasticity (block of external stimuli and inter-areal information flow)



Change of Neuromodulation (through proxy parameters in simulations)

…second topic, …

- Part I. Models of incremental learning and sleep cycles based on standard single-compartment spiking neuron (AdEx)

- **Part II. Introducing two-compartment model with cellular support for apical-ampification, apical-isolation and apical-drive mechanisms, and simplified transfer function for bio-inspired artificial intelligence applications to come**

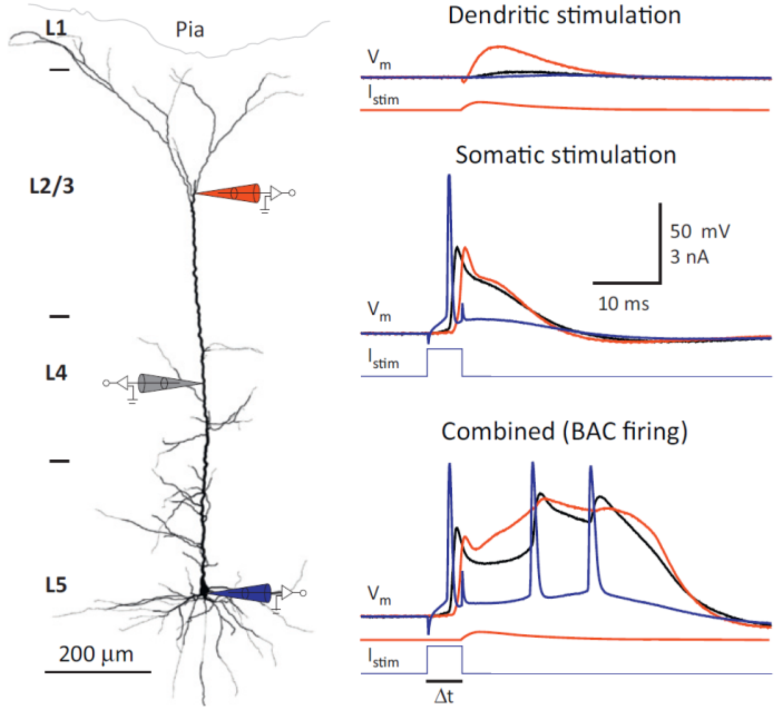
arXiv

2023 doi: 10.48550/arXiv.2311.06074
Two-compartment neuronal spiking model expressing brain-state specific apical-amplification, -isolation and -drive regimes
E. Pastorelli, A. Yegenoglu, N. Kolodziej, W. Wybo, F. Simula, S. Diaz, J. F. Storm, and P. S. Paolucci

- Part III.
  - Cobrawap (Collaborative Brain Wave Analysis Pipeline) advertisement
  - Blue-printing a whole brain cognitive simulation exploiting brain-states benefits

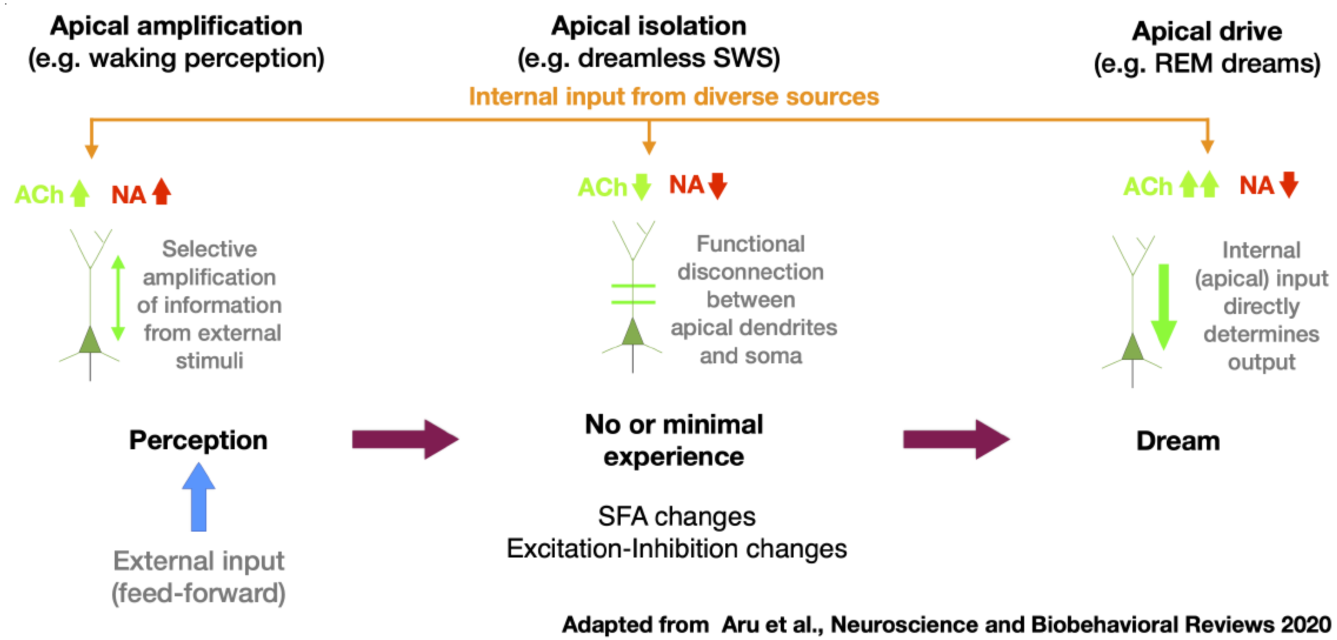
Desired features in a spiking neuron model supporting brain-state specific apical mechanisms

Coincidence of input to the distal compartment with a single back propagating spike at cell body triggers a burst of multiple action potentials



Larkum (2013) A cellular mechanism for cortical associations: an organizing principle for the cerebral cortex. ***Trends in Neurosciences***

Brain-state specific changes in neural dynamics



Aru, Siclari, Phillips, Storm (2020) Apical drive—A cellular mechanism of dreaming? ***Neuroscience & Biobehavioral Reviews***

Aru, Suzuki, Larkum (2020) Cellular Mechanisms of Conscious Processing. ***Trends in Cognitive Sciences***

Our methodology to create a two-compartment neuron (somatic + distal) neuron model with interesting computational properties

We selected a minimal set of biologically plausible apical compartment equations to support apical mechanisms.

We set the soma dynamics to be as similar as possible to AdEx when reached by somatic only input (to maintain compatibility with mainstream models)

This defines a kind of "genome" for the neuron.
Then, we defined a set of fitness functions to select through evolution-like search neurons with interesting computational properties.

Intracellular **[Ca^{2+}] dynamics**

$$\frac{d[Ca]}{dt} = \phi_{Ca} I_{Ca} + \frac{[Ca] - [Ca]_0}{\tau_{Ca}}$$

High voltage activated **Ca^{2+} current**

$$I_{Ca} = g_{Ca} m h (E_{Ca} - V)$$

$$\frac{dm}{dt} = \frac{m_\infty - m}{\tau_m} \qquad \frac{dh}{dt} = \frac{h_\infty - h}{\tau_h}$$

Ca^{2+} activated **K^+ current**

$$I_{K_{Ca}} = g_{K_{Ca}} m (E_K - V)$$

$$\frac{dm}{dt} = \frac{m_\infty - m}{\tau_m}$$

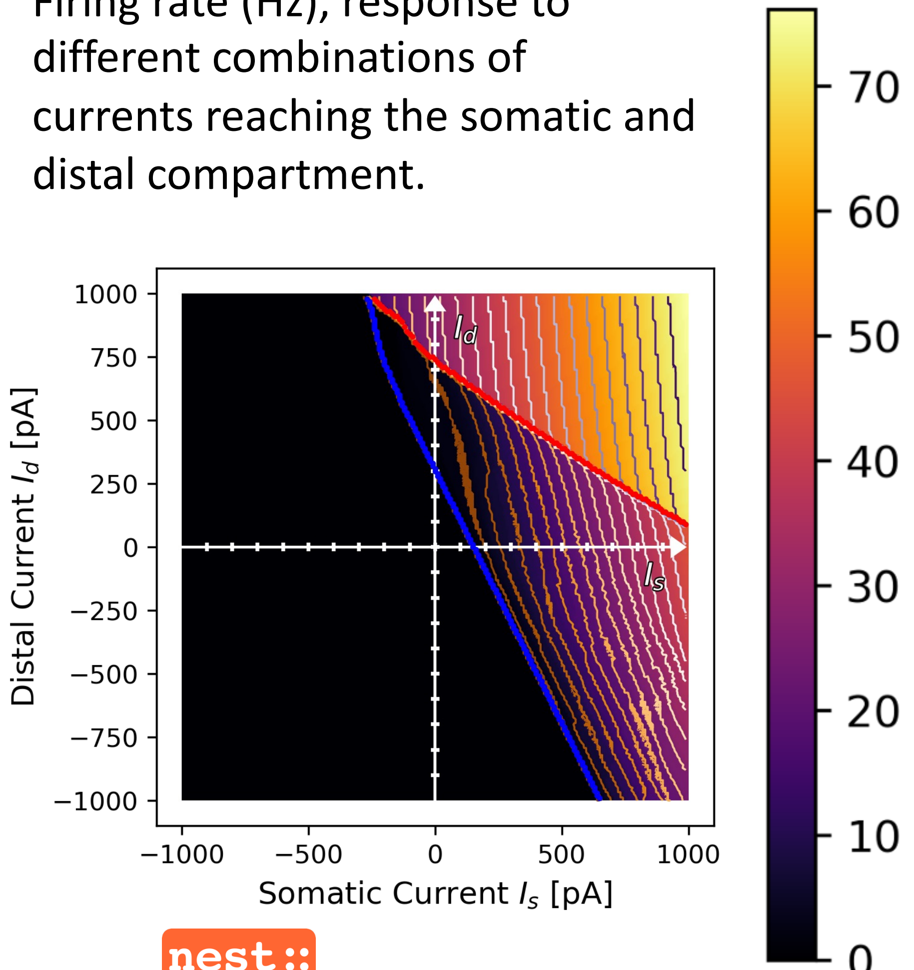
Spike back propagations from soma to dendrites (**BAP**)

Proposed equations for distal compartment

The two-compartment neuron expressing apical-amplification in awake-like regime

Somatic AdEx-like compartment

Firing rate (Hz), response to different combinations of currents reaching the somatic and distal compartment.



$$
\begin{cases}
\begin{cases}
C_m^s \frac{dV^s}{dt} = -g_L^s(V^s - E_L^s) + g_L^s \Delta_T \exp\left(\frac{V^s - V_{th}^s}{\Delta_T}\right) + \\
\quad -g_e^s(t)(V^s - E_e^s) - g_i^s(t)(V^s - E_i^s) + \\
\quad -w + I_e^s - g_C(V^s - V^d) \\
\tau_w \frac{dw}{dt} = a(V^s - E_L^s) + b \sum_k \delta(t - t_k) - w
\end{cases} \\
C_m^d \frac{dV^d}{dt} = -g_L^d(V^d - E_L^d) - g_e^d(t)(V^d - E_e^d) - g_i^d(t)(V^d - E_i^d) + \\
\quad + I_{Ca} + I_{K_{Ca}} + w_{BAP} \sum_k \delta(t - (t_k + d_{BAP})) + \\
\quad + I_e^d + g_C(V^d - V^s)
\end{cases}
$$

Distal compartment supporting apical-mechanisms

nest:: nest-simulator.org

Two-compartment neuron supporting brain state specific apical-mechanisms

Firing rate (Hz) in response to:

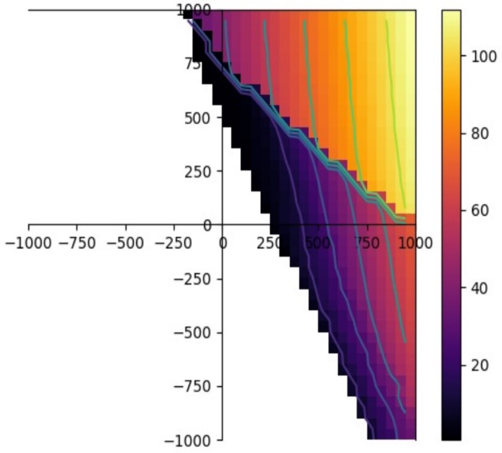
Horizontal axis: input to (peri-)somatic compartment (pA)

Vertical axis: Input to apical compartment (pA)

Note that “yellow” has an entirely different meaning in the three regimes

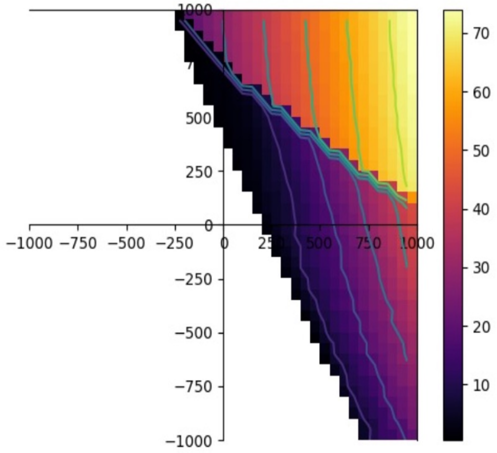
nest::
nest-simulator.org

REM sleep	AWAKE	NREM sleep
Apical-drive	**Apical-amplification**	**Apical-Isolation**
Ach ⇧ ⇧ NA ⇩	Ach ⇧ NA ⇩	Ach ⇩ NA ⇩



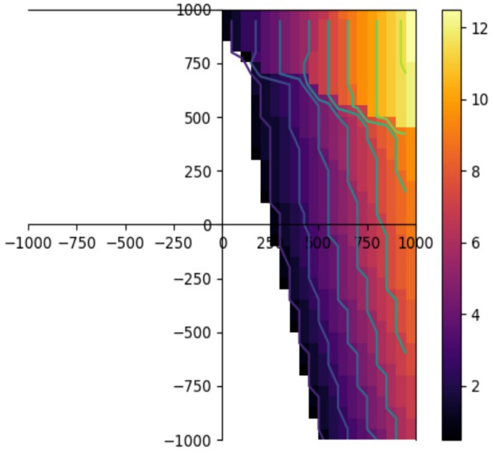
100 Hz

b=20, g=1,
El_d=-53, El_s=-68



70 Hz

b=40, g=1,
El_d=-53, El_s=-63



12 Hz

b=200, g=0.3,
El_d=-58, El_s=-68

Simplified transfer function for application to bio-inspired artificial intelligence algorithm

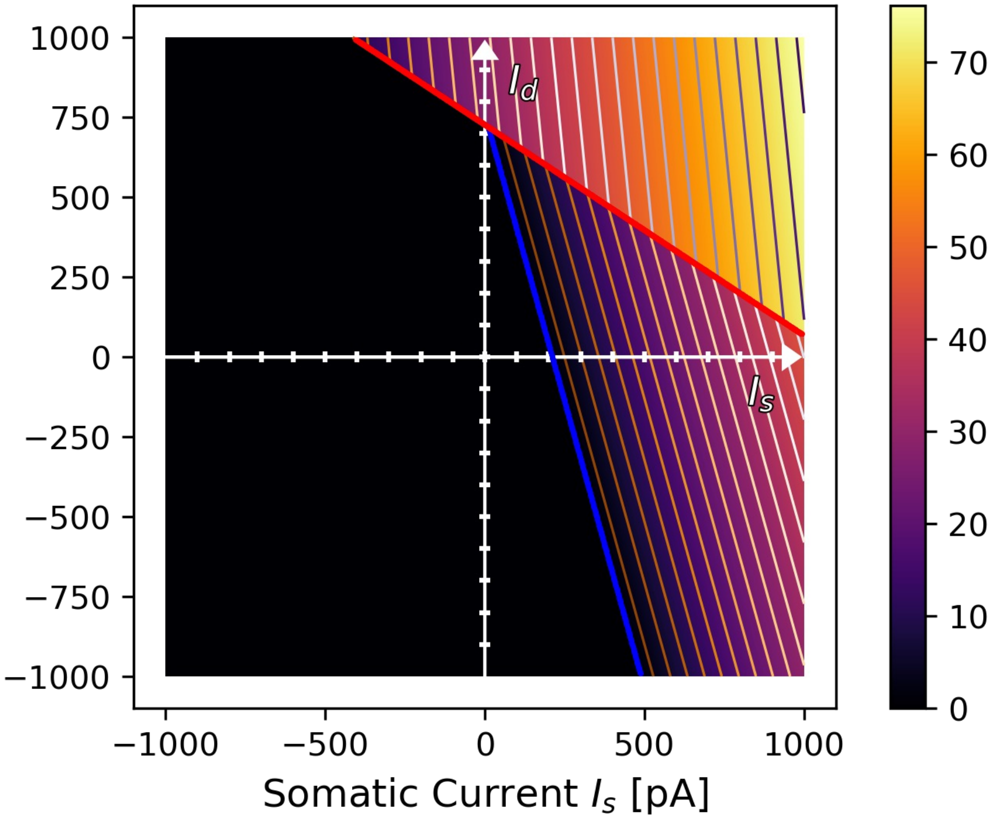
ThetaPlanes piece-wise linear approximation

$$\nu_F(I_s, I_d; \nu) = \Theta_\rho(1 - \Theta_H) \cdot \nu_- + \Theta_H \cdot \nu_+$$

Identified by Montecarlo Algorithm.

Fresh result. Searching for partnership!

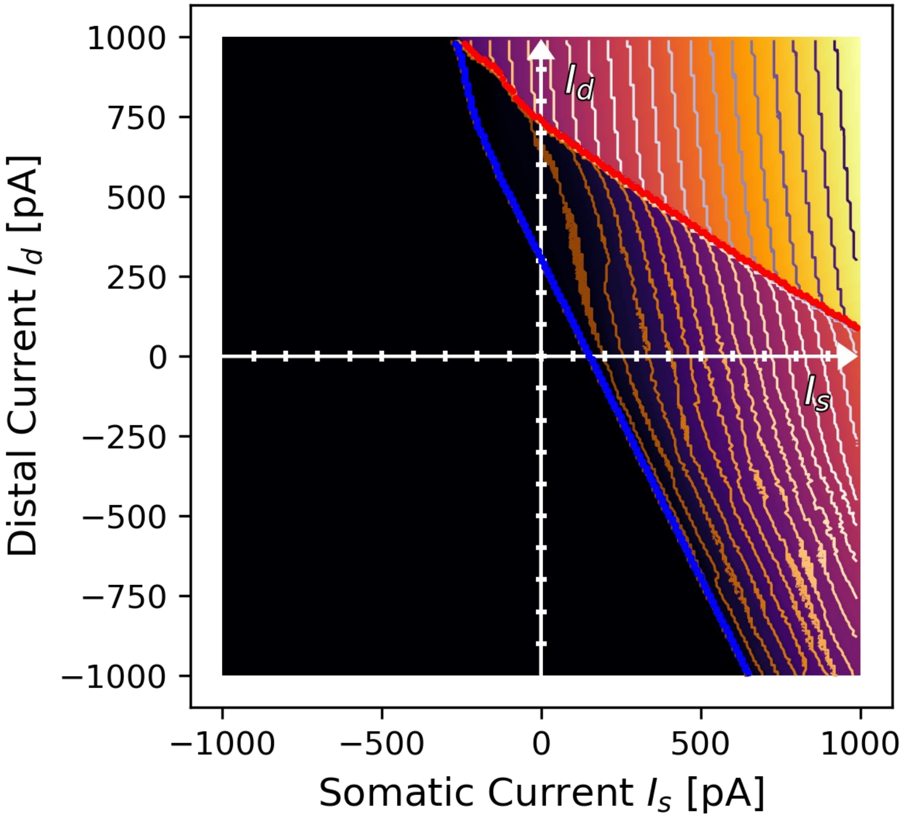
see arXiv: appeared today



Transfer function of spiking neuron model with detailed integration of differential equations

nest::

nest-simulator.org

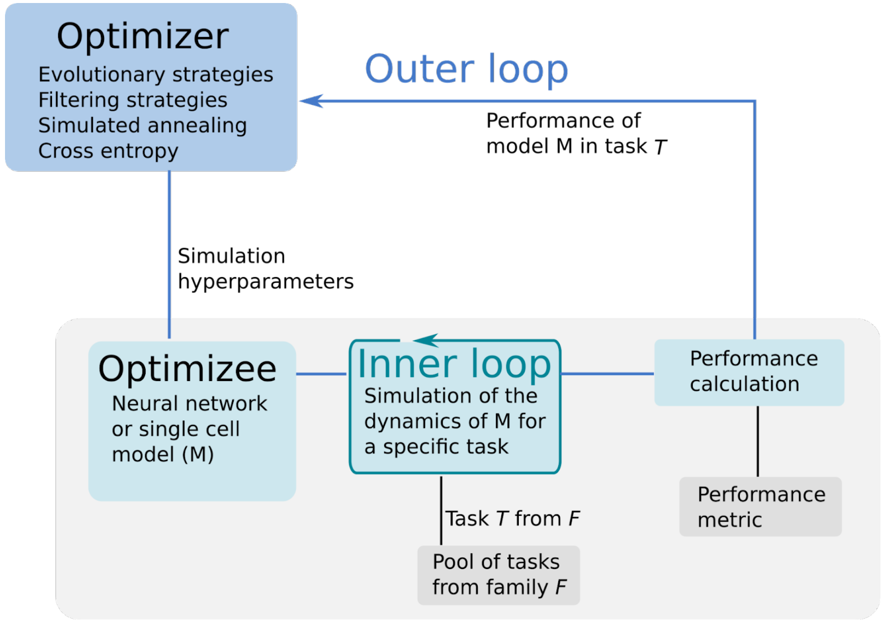


L2L for parameters optimization

INFN-Jülich collaboration

About 30 parameters to be optimized in the two-compartment neuron:

- **Passive** neuron parameters (somatic & distal compartments)
- Parameters for **ionic currents**
- Parameters for **[Ca^{+2}] dynamic**



L2L (Learning-to-Learn) optimization framework

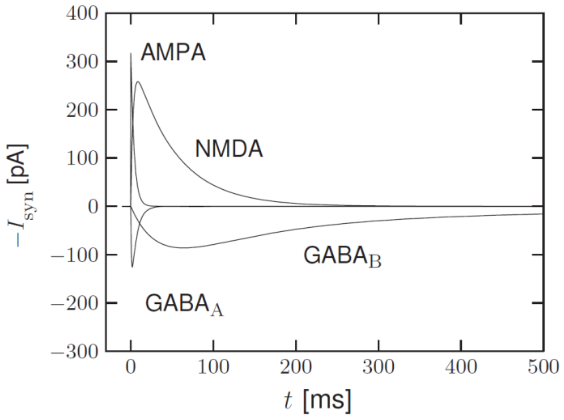
- **Large-scale** parameter space explorations
- Different optimization algorithms available:
  - Evolutionary, gradient descend./ascend., simulated annealing, ...
- Able to efficiently exploit **HPC** infrastructures
- Based on optimization of user-defined fitness functions selected to optimize **cognitive performances** and to support different **brain states**

Yegenoglu et al. (2022) Exploring hyper-parameter spaces of neuroscience models on high performance computers with Learning to Learn. ***Front. Comp. Neu.***

Other info about the two-compartment model

Support for calcium spike in distal compartment

- Required to provide integration of apical and basal information
- Initiation of calcium spike produces a burst in action potential



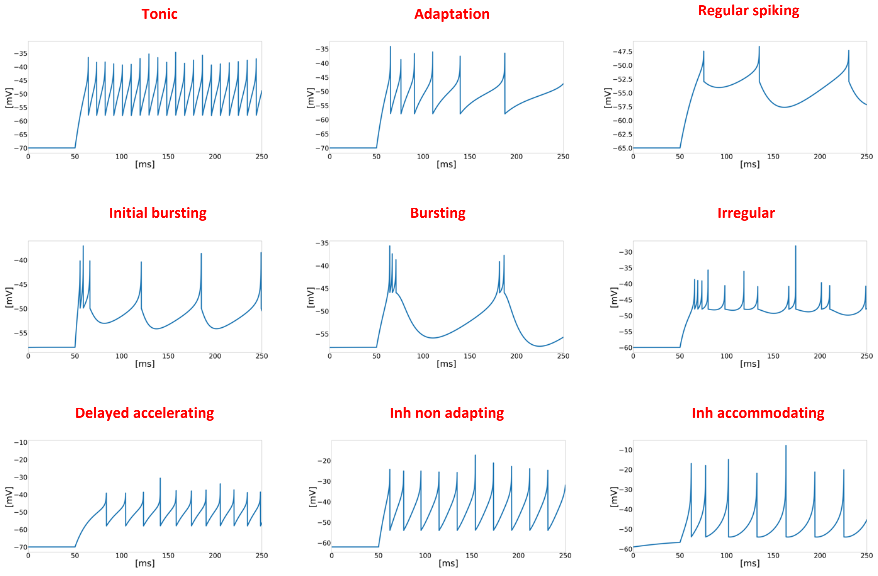
Receptors:

- AMPA
- NMDA
- GABAa
- GABAb

nest-simulator.org

Soma with Adex dynamics

- When distal dendrites are switched-off, soma dynamics match Adex single-compartment behaviour
- Smooth insertion in already available simulations using Adex model



…and finally, …

- Part I. Models of incremental learning and sleep cycles based on standard single-compartment spiking neuron (AdEx)

- Part II. Introducing two-compartment model with cellular support for apical-ampification, apical-isolation and apical-drive mechanisms, and simplified transfer function for bio-inspired artificial intelligence applications to come (arXiv: appeared today, Nov 13th, 2023)

- **Part III.**
  - **Cobrawap (Collaborative Brain Wave Analysis Pipeline) advertisement**
  - **Blue-printing a whole brain cognitive simulation exploiting brain-states benefits**

Finanziato dall'Unione europea NextGenerationEU
Ministero dell'Università e della Ricerca
Italiadomani PIANO NAZIONALE DI RIPRESA E RESILIENZA
INFN

Not covered today (advertisment, hoping for a dedicated presentation slot)

- Analysis workflows to:
  - Compare experimental data with simulation outputs
  - Compare experimental data acquired with different methodologies and at different spatio-temporal acquisition resolutions
  - Compare models with models
  - Extract observables from experimental data and simulation outputs
- Simulation models inferred from data

Collaborative Brain Waves Analysis Pipeline
https://cobrawap.readthedocs.io/

→ Cobrawap (Collaborative Brain Waves Analysis Pipeline)

Missione 4 - Istruzione e Ricerca – Componente 2 – Grant(s)
FAIR (Future Artificial Intelligence Research) - CUP I53C22001400006 – Spoke 10
EBRAINS-Italy (Research Infrastructure) – CUP B51E22000150006 – WP3
FUTURE AI RESEARCH
EBRAINS Italy

SCIENTIFIC APPLICATION 1) compare experimental recordings and simulations from different labs and techniques

Cobrawap

Collaborative Brain Wave Analysis Pipeline

core-team

scientific partners

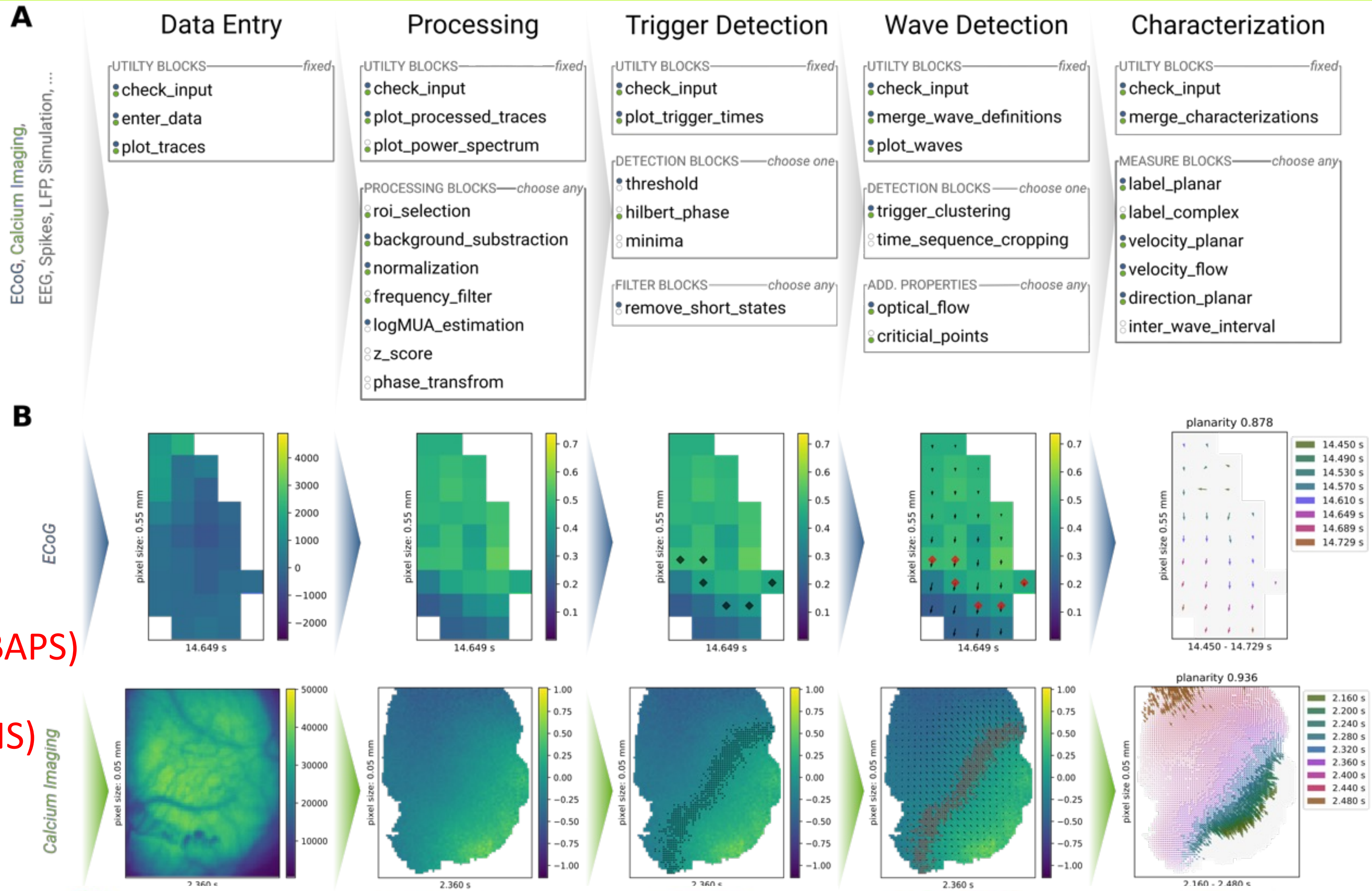
support-team

(IDIBAPS)

(LENS)

Collaboration:
Italy, Germany, Greece, Spain, …

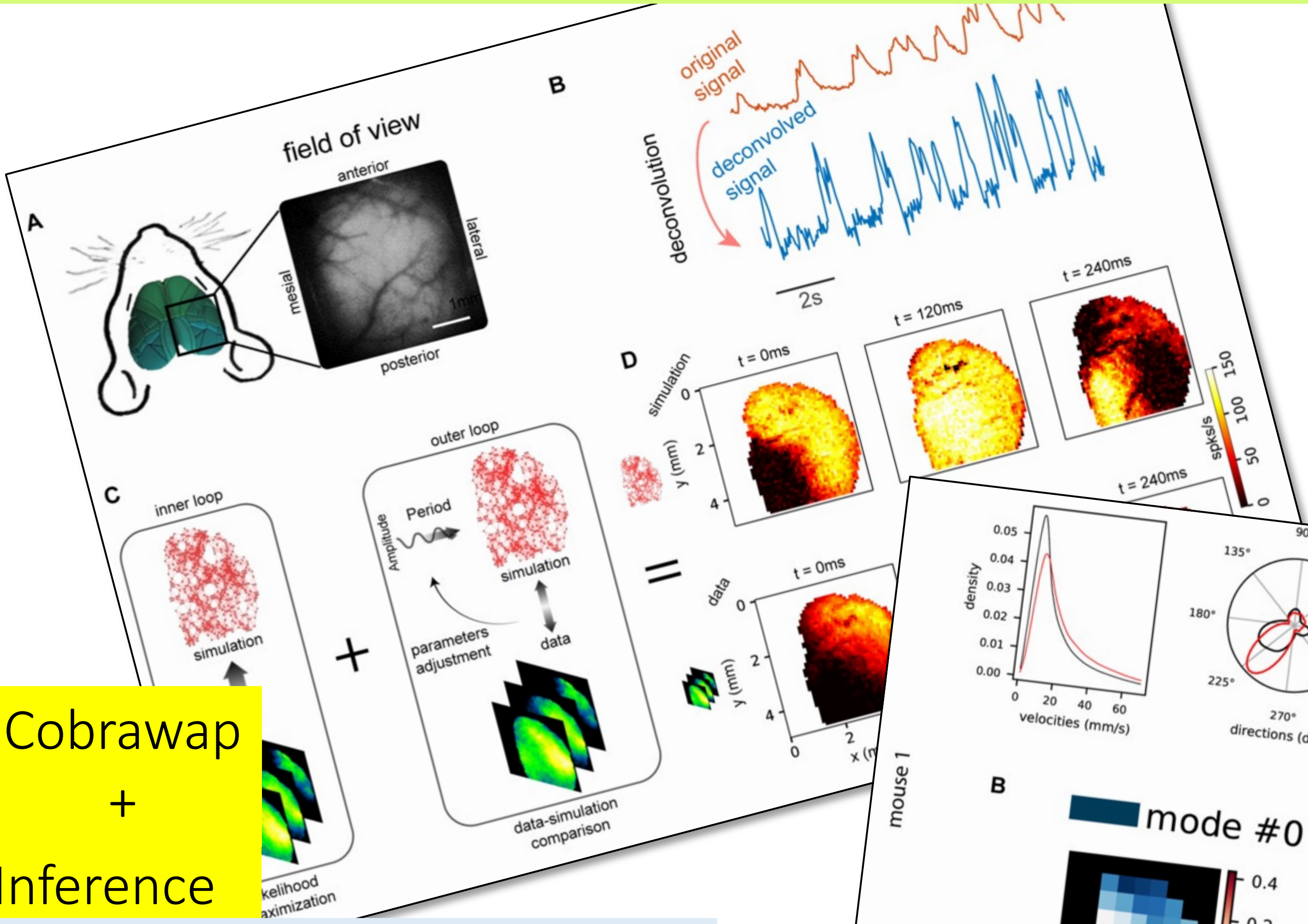
https://github.com/INM-6/cobrawap

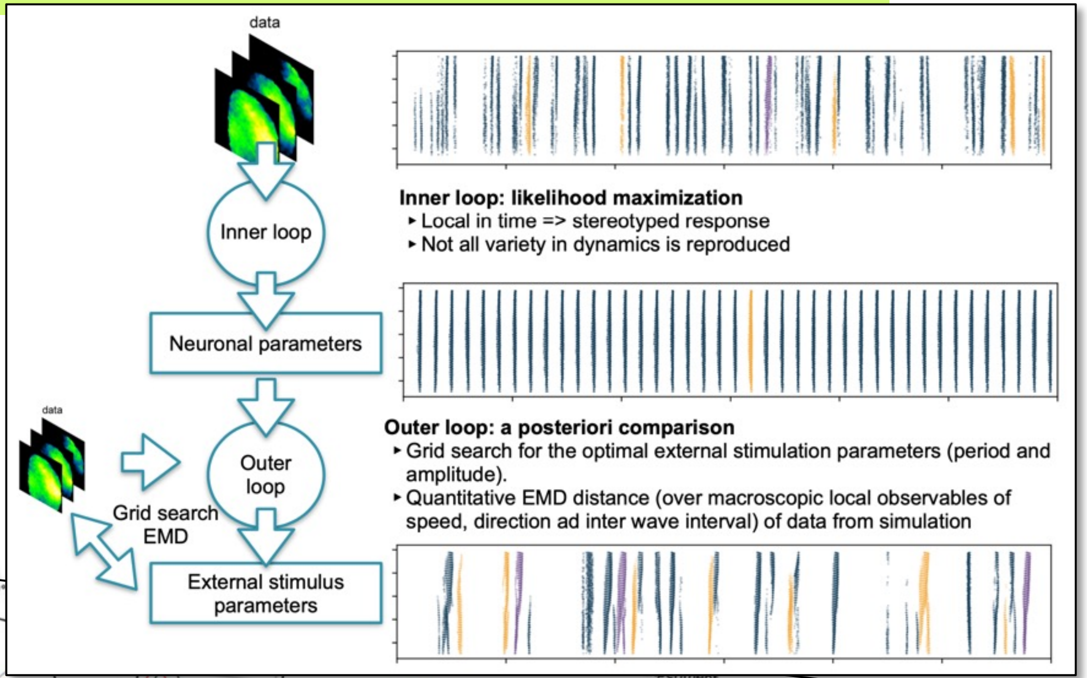


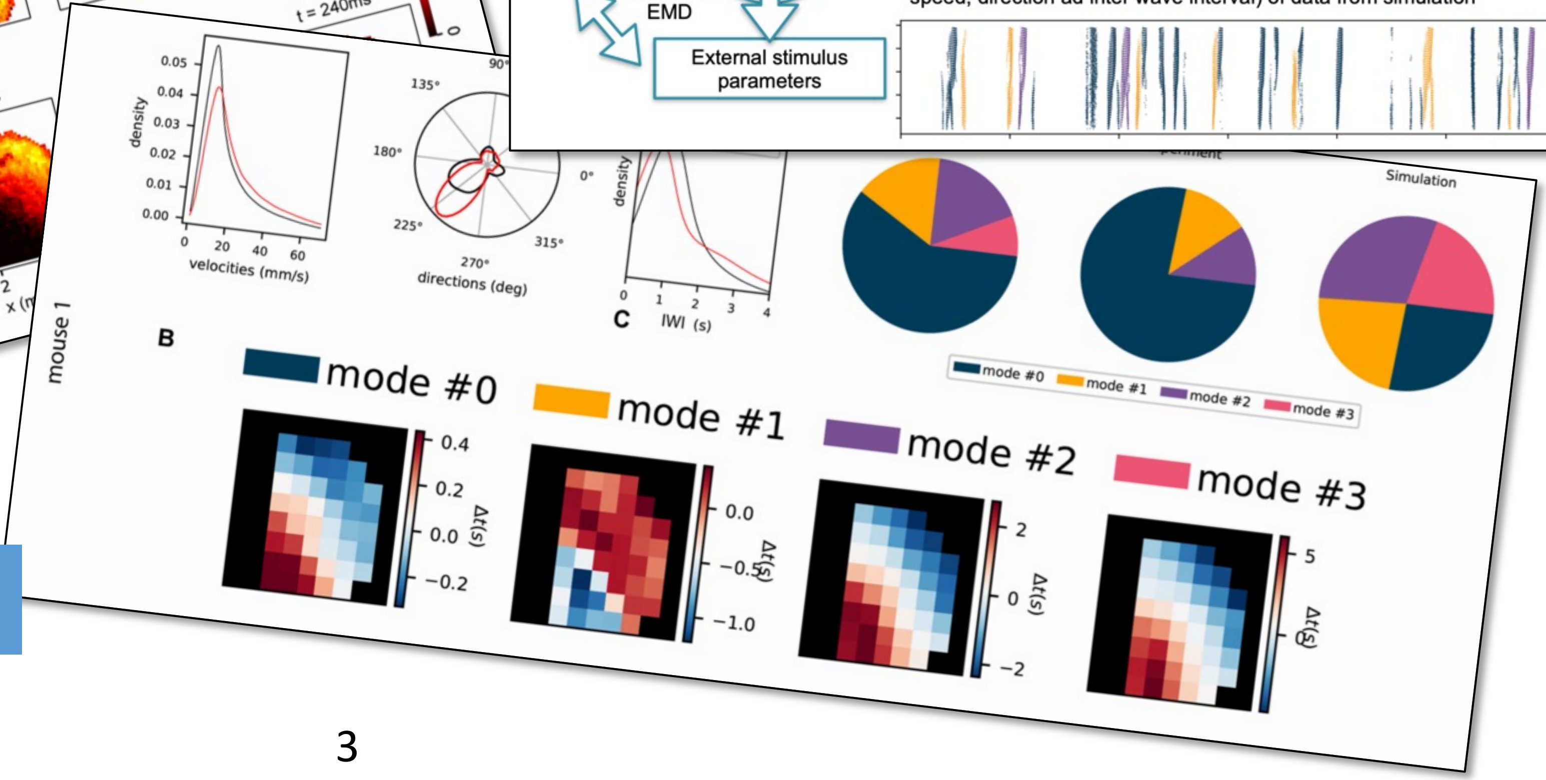
Modular **Flexible** **Extendible** **Reusable**

Reliable **Open-source**

SCIENTIFIC APPLICATION 2): compare experimental recordings and simulations, and optimize parameter setting in data-driven models







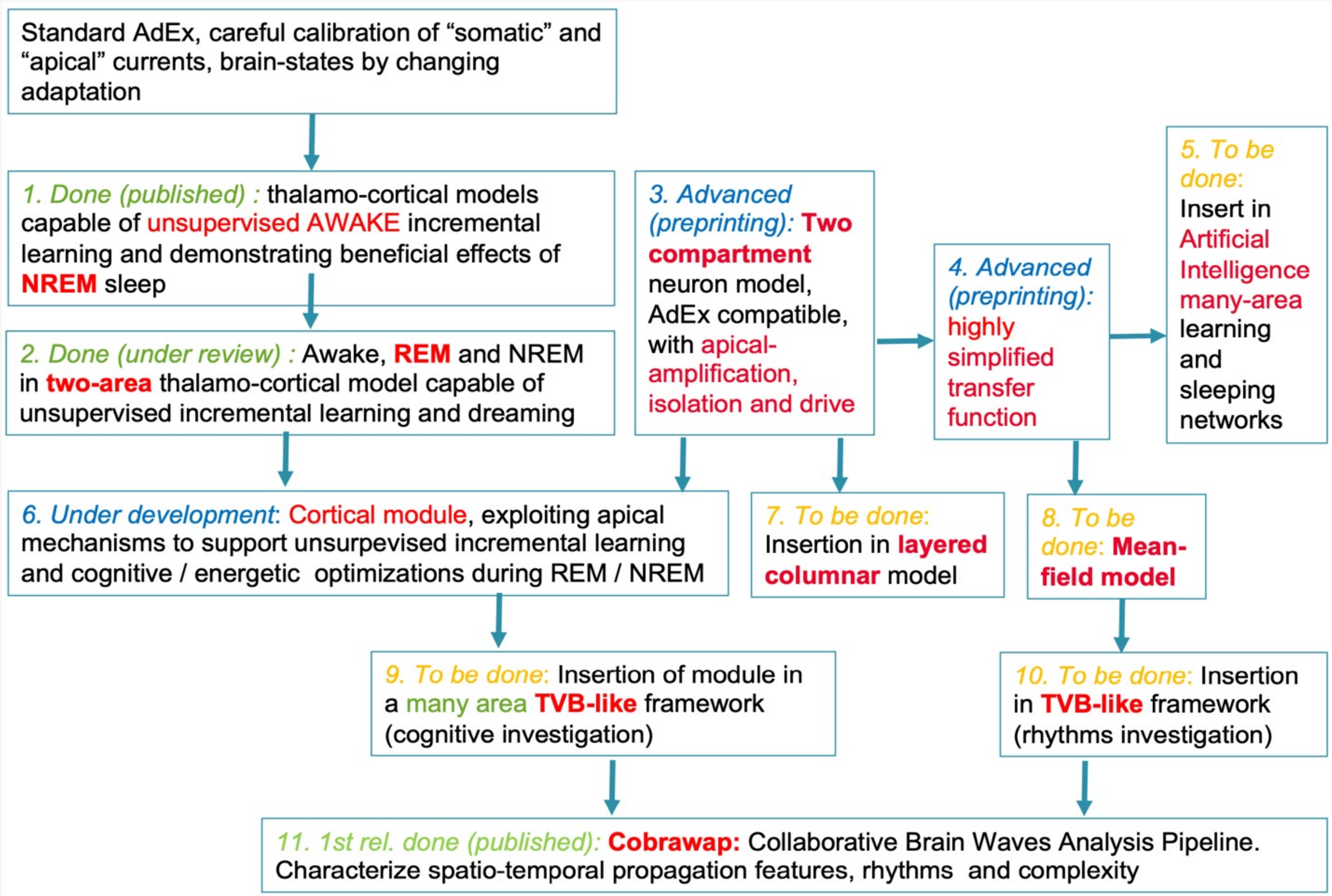
Cobrawap
+
Inference

Mean-field model with inferred parameters

C. Capone, C. De Luca et al., *Commun Biol* **6**, 266 (2023)

https://doi.org/10.1038/s42003-023-04580-0

Blue-printing a whole-brain cognitive simulation exploiting brain-states benefits



References and acknowledgements

Our recent papers about PartI and Part II topics

PLOS COMPUTATIONAL BIOLOGY

2021 doi: 10.1371/journal.pcbi.1009045

RESEARCH ARTICLE

Thalamo-cortical spiking model of incremental learning combining perception, context and NREM-sleep

Bruno Golosio[1,2], Chiara De Luca[3,4]*, Cristiano Capone[4], Elena Pastorelli[3,4], Giovanni Stegel[5], Gianmarco Tiddia[1,2], Giulia De Bonis[4], Pier Stanislao Paolucci[4]

www.nature.com/scientificreports

SCIENTIFIC REPORTS

OPEN

Sleep-like slow oscillations improve visual classification through synaptic homeostasis and memory association in a thalamo-cortical model

d: 24 January 2019
d: 3 June 2019
:d online: 20 June 2019

Cristiano Capone[1], Elena Pastorelli[1,2], Bruno Golosio[3,4] & Pier Stanislao Paolucci[1]

PNAS 2023 (in press)

Beyond spiking networks: the computational advantages of dendritic amplification and input segregation

C. Capone, C. Lupo, P. Muratore, P.S. Paolucci

arXiv

2023 doi: 10.48550/arXiv.2311.06074

Two-compartment neuronal spiking model expressing brain-state specific apical-amplification, -isolation and -drive regimes

E. Pastorelli, A. Yegenoglu, N. Kolodziej, W. Wybo, F. Simula, S. Diaz, J. F. Storm, and P. S. Paolucci

frontiers Integrative Neuroscience

TYPE Original Research
PUBLISHED 03 October 2022
DOI 10.3389/fnint.2022.972055

Simulations of working memory spiking networks driven by short-term platicity

G. Tiddia, B. Golosio, V. Fanti and P. S. Paolucci

PMLR Proceedings of Machine Learning Research

2022

Burst-Dependent Plasticity and Dendritic Amplification Support Target-Based Learning and Hierarchical Imitation Learning

Cristiano Capone, Cosimo Lupo, Paolo Muratore, Pier Stanislao Paolucci Proceedings of the 39th International Conference on Machine Learning, PMLR 162:2625-2637, 2022.

PLOS COMPUTATIONAL BIOLOGY

OPEN ACCESS PEER-REVIEWED

RESEARCH ARTICLE

Error-based or target-based? A unified framework for learning in recurrent spiking networks

Cristiano Capone, Paolo Muratore, Pier Stanislao Paolucci

Version 2 Published: June 21, 2022 • https://doi.org/10.1371/journal.pcbi.1010221

PLOS ONE

OPEN ACCESS PEER-REVIEWED

RESEARCH ARTICLE

Target spike patterns enable efficient and biologically plausible learning for complex temporal tasks

Paolo Muratore, Cristiano Capone, Pier Stanislao Paolucci

Published: February 16, 2021 • https://doi.org/10.1371/journal.pone.0247014

INFN Istituto Nazionale di Fisica Nucleare

https://apegate.roma1.infn.it/

@APELab_INFN

Acknowledgments

Disclaimer: the APE group, founded in 1984, is active on many other research topics, including: design of architecture for supercomputing, their interconnects and high-speed analysis of physical data, system software and parallel algorithms for physics simulations. Here in **bold** APE members that **more directly contributed exactly** to the **presented topics**. Other brain-related topics e.g. neural net simulations on GPU, or simulations inferred from data not considered.

current APE members:
R. Ammendola, A. Biagioni, F. Capuani, **A. Cardinale**, C. Chiarini, P. Cretaro, **G. De Bonis, N. Kolodziej,** F. Lo Cicero, O. Frezza, A. Lonardo, **C. Lupo, F. Marmoreo,** M. Martinelli, **P.S. Paolucci, E. Pastorelli**, L. Pontisso, C. Rossi, **L. Tonielli, F. Simula**, P. Vicini
past members that contributed to the presented topic: **C. Capone, C. De Luca, I. Bernava, L. Rosati, P. Muratore, D. Cipollini**

UNIVERSITÀ DEGLI STUDI DI CAGLIARI — Bruno Golosio, Gianmarco Tiddia

JÜLICH Forschungszentrum — Sandra Diaz, Alper Yagenglu, Willem Wybo, Michael Denker, Robin Gützen

UNIVERSITY OF OSLO — Johan Frederik Storm

ISTITUTO SUPERIORE DI SANITÀ — Cristiano Capone

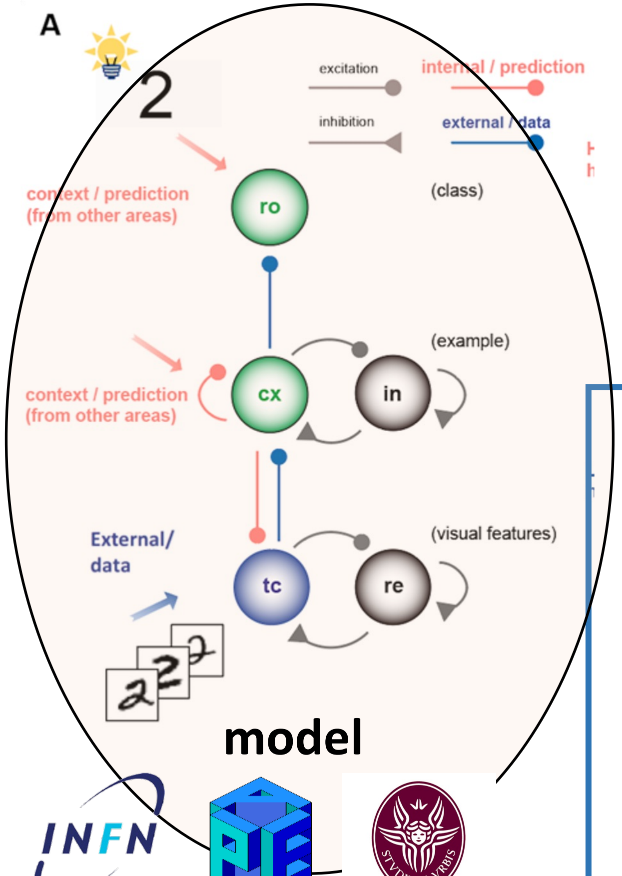
SAPIENZA UNIVERSITÀ DI ROMA — *Several among the authors started as MSc and PhD students associated to INFN Roma*

EBRAINS — European research Infrastructure https://www.ebrains.eu/

HBP — Human Brain Project https://www.humanbrainproject.eu/

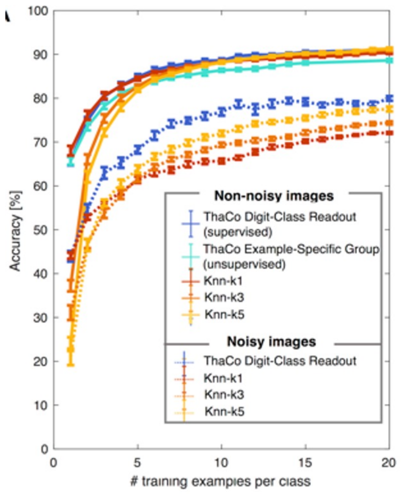
Backup Material

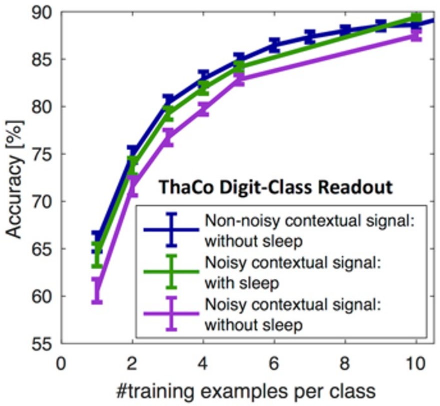
Thalamo-cortical spiking model of incremental learning combining perception, context and NREM-sleep.
PLoS Computational Biology (2021).
B.Golosio, C. De Luca, C. Capone, …, P.S. Paolucci.



model

Capability of awake incremental learning

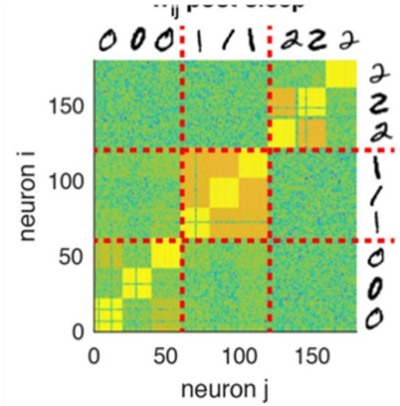




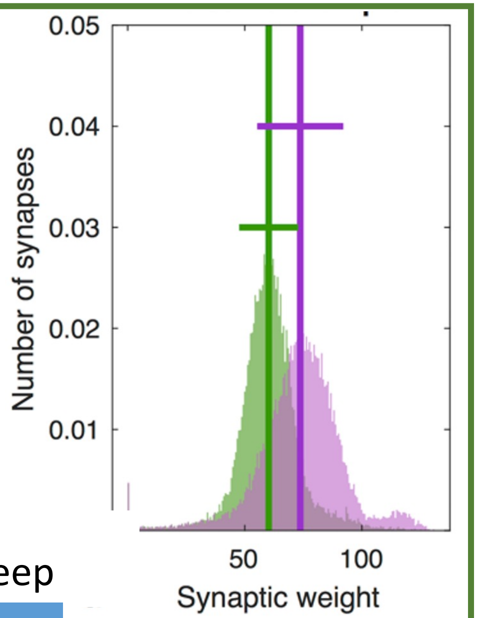
Sleep recovers noise effects

learning MNIST: from 1 to 20 examples per class

Effects of NREM on synapses



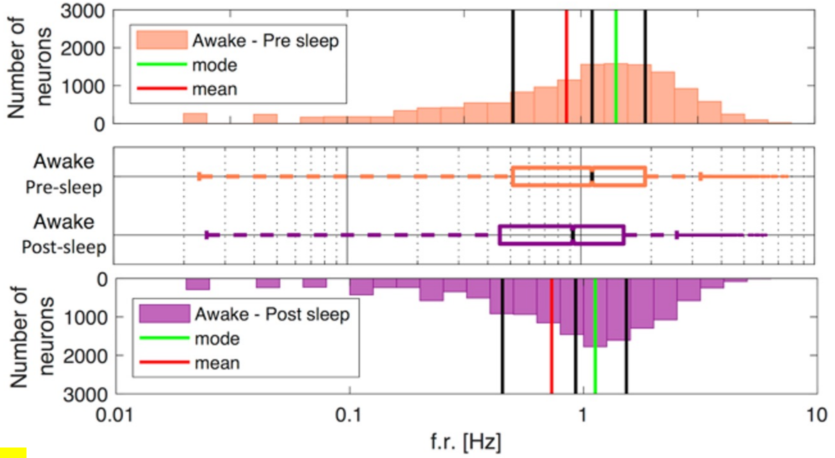
Associative effect of sleep



Homeostatic effect

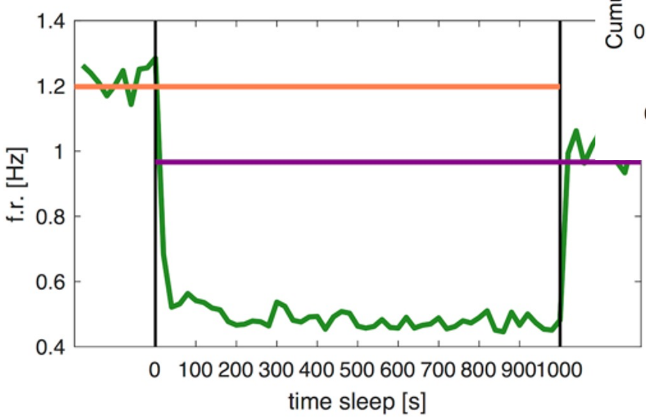
Scientific Reports (2019).
C. Capone et al

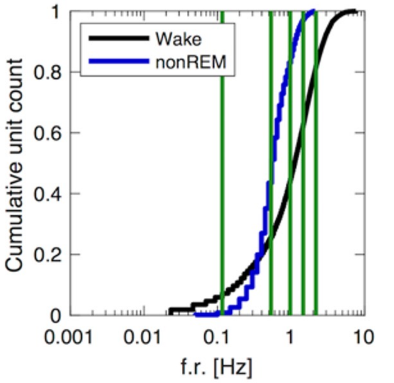
Effects of deep-sleep like activity over neuronal firing rates



Pre-post sleep firing rate distributions

Mean firing rate decreases over time

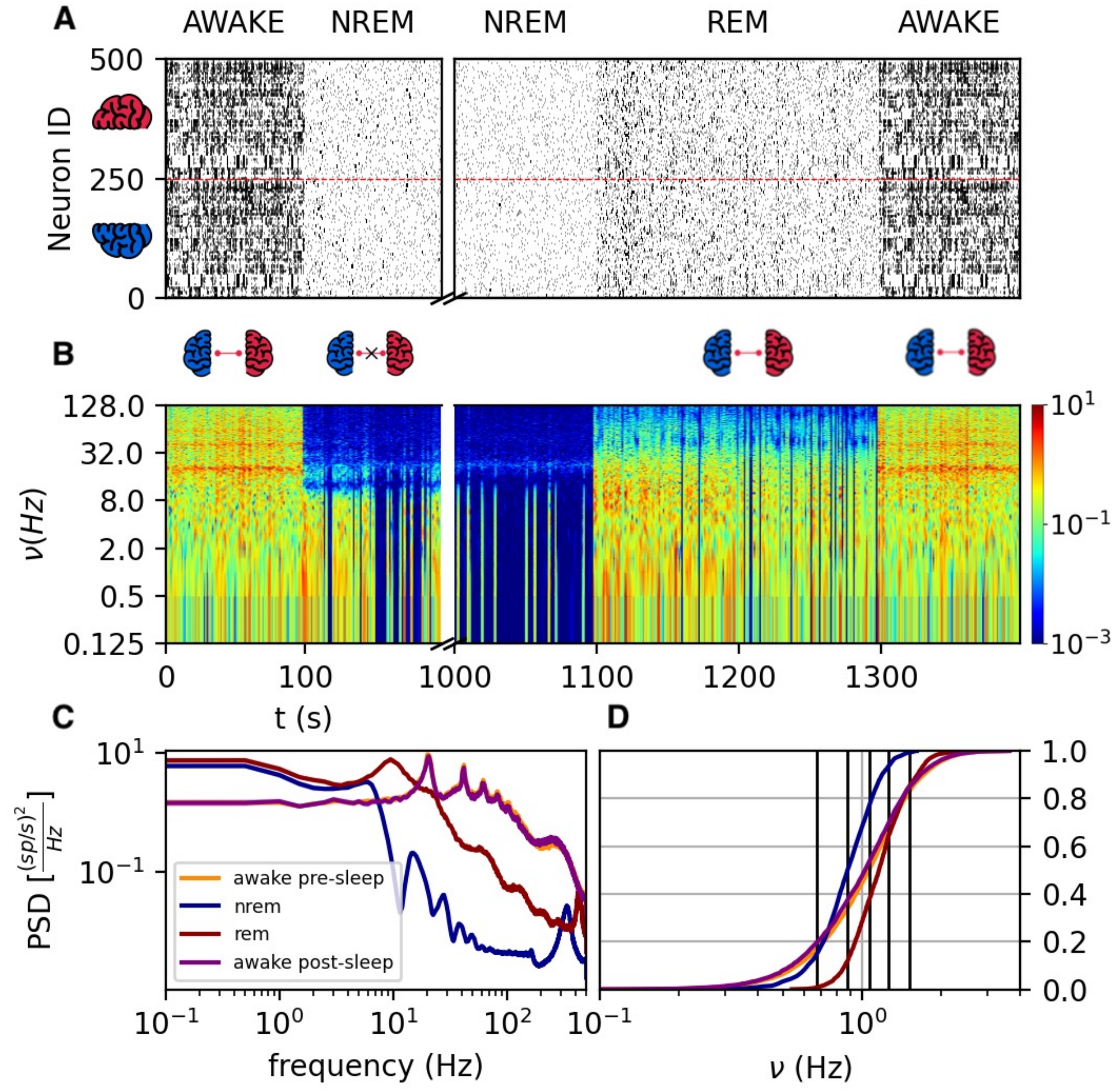




Cumulative firing rate distribution

comparable with experiment
Watson et al. ***Neuron*** 90 (2016)

Activity and rhythms in the two-area model during pre-sleep and post-sleep awake-classification phase, REM and NREM

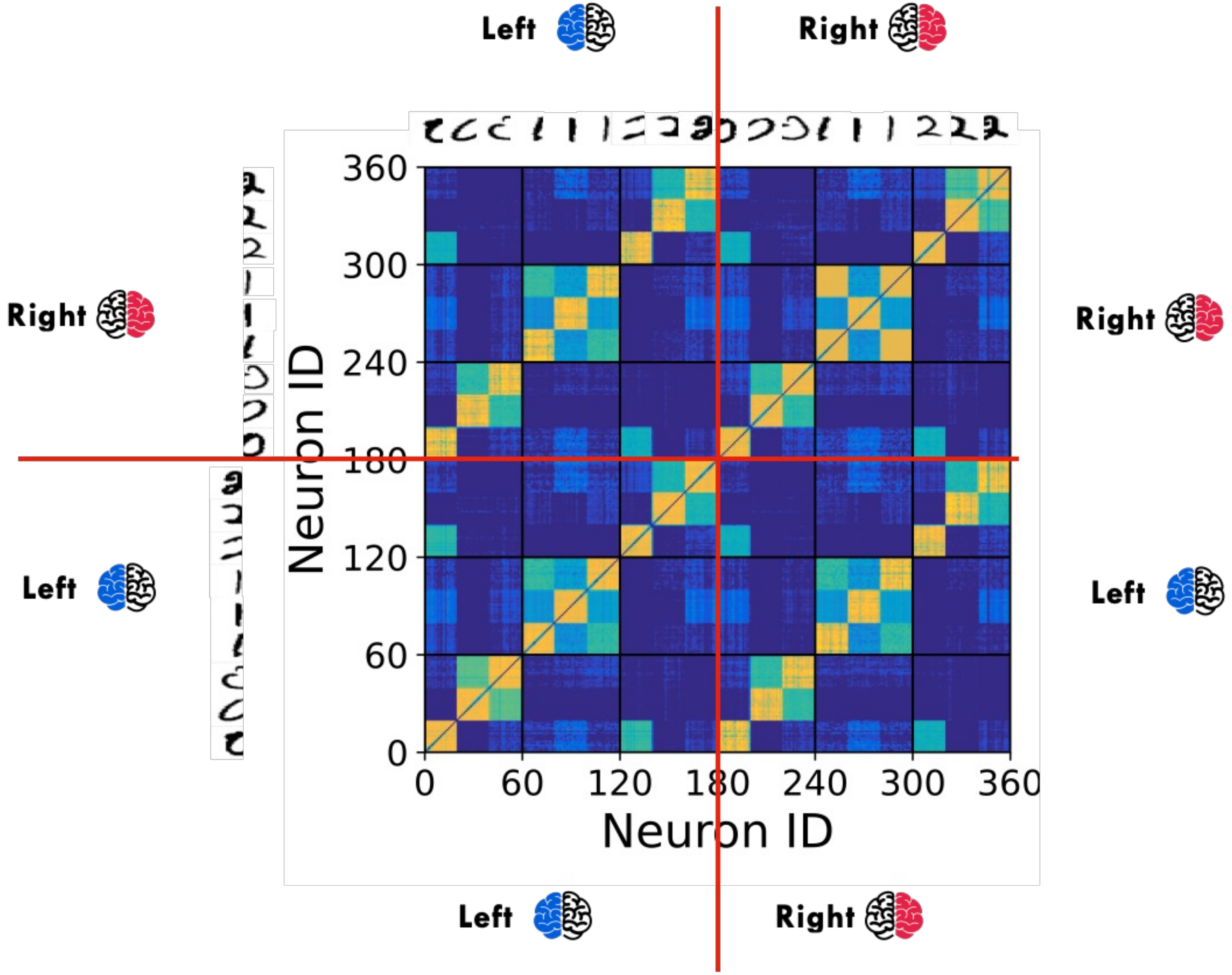


NREM and REM: cognitive and energetic effects in thalamo-cortical sleeping and awake spiking model ***arXiv:2211.06889*** (2022) ***(under review).*** *L. Tonielli, C. De Luca, E. Pastorelli, …, Golosio, P.S. Paolucci*.

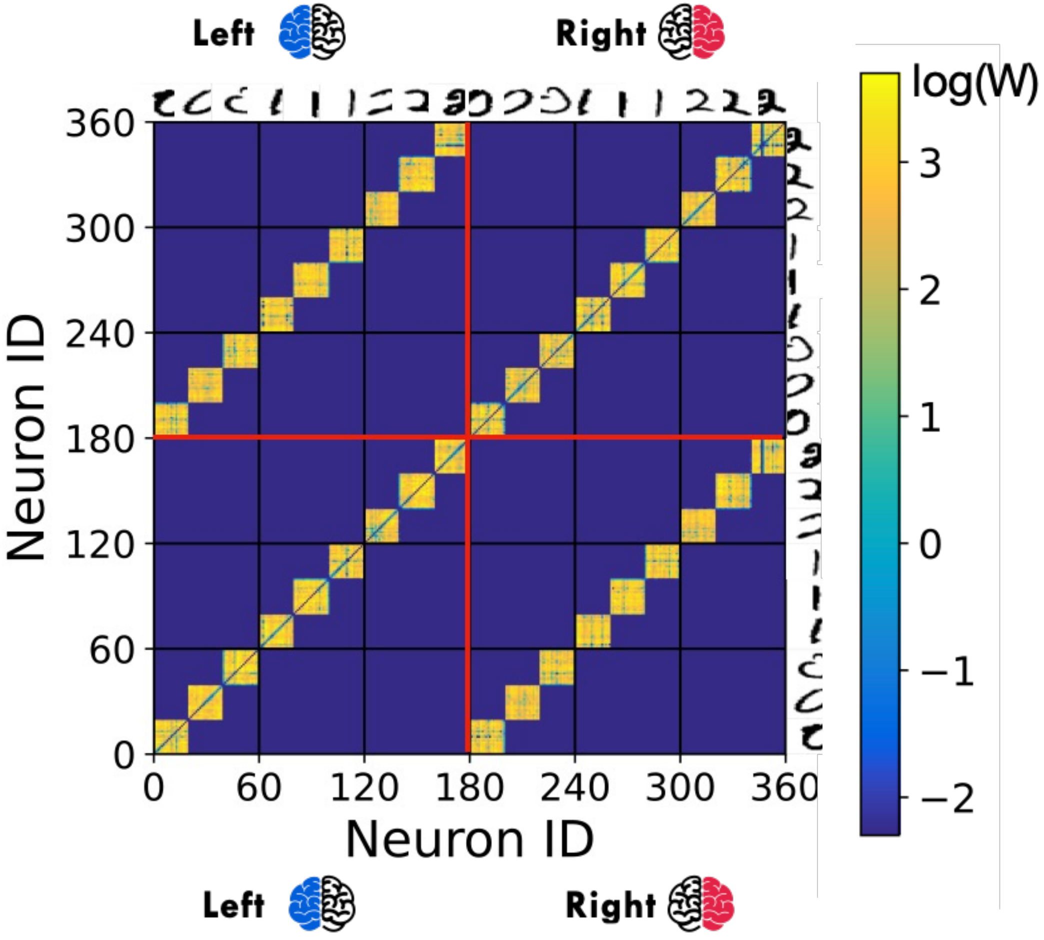
Effects on the synaptic matrix, two area model

NREM and REM: cognitive and energetic effects in thalamo-cortical sleeping and awake spiking model ***arXiv:2211.06889*** (2022) ***(under review).*** *L. Tonielli, C. De Luca, E. Pastorelli, …, Golosio, P.S. Paolucci.*

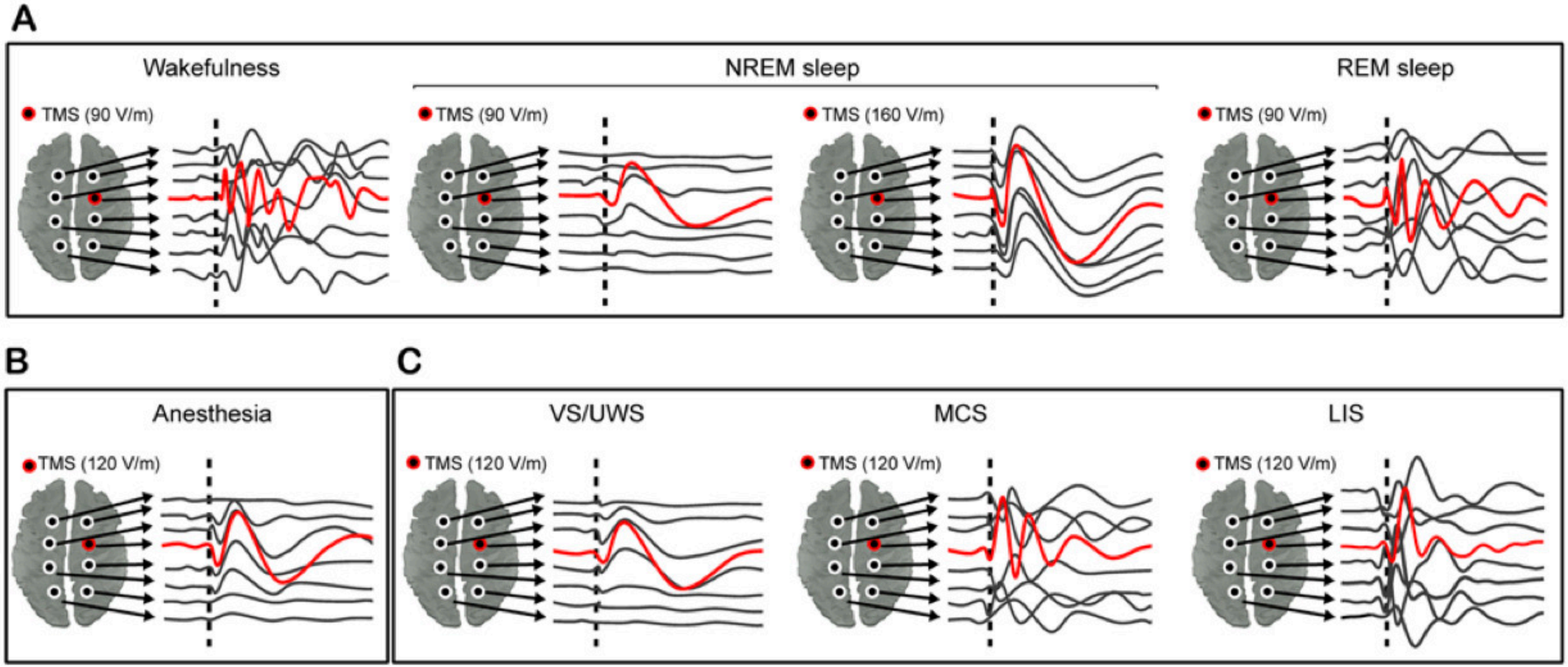
Post REM synaptic matrix



Synaptic matrix before sleep



Complexity of response to perturbation in physiological and pathologic states



S. Sarasso, M. Massimini, et al. (2014) "Quantifying Cortical EEG Responses to TMS in (Un)consciousness" *Clinical EEG and neuroscience* **45**