

MEETING ABSTRACTS

Open Access



29th Annual Computational Neuroscience Meeting: CNS*2020

Virtual. 18–22 July 2020

Published: 21 December 2020

K1

Deep reinforcement learning and its neuroscientific implications

Matthew Botvinick

Google DeepMind, Neuroscience Research, London, United Kingdom

Correspondence: Matthew Botvinick (botvinick@google.com)

BMC Neuroscience 2020, **21**(Suppl 1):K1

The last few years have seen some dramatic developments in artificial intelligence research. What implications might these have for neuroscience? Investigations of this question have, to date, focused largely on deep neural networks trained using supervised learning, in tasks such as image classification. However, there is another area of recent AI work which has so far received less attention from neuroscientists, but which may have more profound neuroscientific implications: deep reinforcement learning. Deep RL offers a rich framework for studying the interplay among learning, representation and decision-making, offering to the brain sciences a new set of research tools and a wide range of novel hypotheses. I'll provide a high-level introduction to deep RL, discuss some recent neuroscience-oriented investigations from my group at DeepMind, and survey some wider implications for research on brain and behavior.

K2

A new computational framework for understanding vision in our brain

Zhaoping Li

Max Planck Institute for Biological Cybernetics, Tübingen, Germany

Correspondence: Zhaoping Li (li.zhaoping@tuebingen.mpg.de)

BMC Neuroscience 2020, **21**(Suppl 1):K2

Visual attention selects only a tiny fraction of visual input information for further processing. Selection starts in the primary visual cortex (V1), which creates a bottom-up saliency map to guide the fovea to selected visual locations via gaze shifts. This motivates a new framework that views vision as consisting of encoding, selection, and decoding stages, placing selection on center stage. It suggests a massive loss of non-selected information from V1 downstream along the visual pathway. Hence, feedback from downstream visual cortical areas to V1 for better decoding (recognition), through analysis-by-synthesis, should query for additional information and be mainly directed at the

foveal region. Accordingly, non-foveal vision is not only poorer in spatial resolution, but also more susceptible to many illusions.

K3

Information and decision-making

Daniel Polani

University of Hertfordshire, School of Computer Science, Hatfield, United Kingdom

Correspondence: Daniel Polani (d.polani@herts.ac.uk)

BMC Neuroscience 2020, **21**(Suppl 1):K3

In recent years it has become increasingly clear that (Shannon) information is a central resource for organisms, akin in importance to energy. Any decision that an organism or a subsystem of an organism takes involves the acquisition, selection, and processing of information and ultimately its concentration and enactment. It is the consequences of this balance that will occupy us in this talk.

This perception-action loop picture of an agent's life cycle is well established and expounded especially in the context of Fuster's sensorimotor hierarchies. Nevertheless, the information-theoretic perspective drastically expands the potential and predictive power of the perception-action loop perspective.

On the one hand information can be treated - to a significant extent - as a resource that is being sought and utilized by an organism. On the other hand, unlike energy, information is not additive. The intrinsic structure and dynamics of information can be exceedingly complex and subtle; in the last two decades one has discovered that Shannon information possesses a rich and nontrivial intrinsic structure that must be taken into account when informational contributions, information flow or causal interactions of processes are investigated, whether in the brain or in other complex processes.

In addition, strong parallels between information and control theory have emerged. This parallelism between the theories allows one to obtain unexpected insights into the nature and properties of the perception-action loop. Through the lens of information theory, one can not only come up with novel hypotheses about necessary conditions for the organization of information processing in a brain, but also with constructive conjectures and predictions about what behaviours, brain structure and dynamics and even evolutionary pressures one can expect to operate on biological organisms, induced purely by informational considerations.



P169

Entrainment of competitive threshold-linear networksAndrea Bel¹, Horacio Rotstein², Walter Reartes¹¹Universidad Nacional del Sur, Departamento de Matemática, Bahía Blanca, Argentina; ²New Jersey Institute of Technology, Federated Department of Biological Sciences, NJIT / Rutgers University, Newark, New Jersey, United States of America**Correspondence:** Andrea Bel (andrea.bel@uns.edu.ar)

BMC Neuroscience 2020, 21(Suppl 1):P169

Neuronal oscillations are ubiquitous in the brain and emerge from the combined activity of the participating neurons (or nodes), the connectivity and the network topology. Recent neurotechnological advances have made it possible to interrogate neuronal circuits by perturbing one or more of its nodes. The response to periodic inputs has been used as a tool to identify the oscillatory properties of circuits and the flow of information in networks. However, a general theory that explains the underlying mechanisms and allows to make predictions is lacking beyond the single neuron level.

Threshold-linear network (TLN) models describe the activity of connected nodes where the contribution of the connectivity terms is linear above some threshold value (typically zero), while the network is disconnected below it. In their simplest description, the dynamics of the individual nodes are one-dimensional and linear. When the nodes in the network are neurons or neuronal populations, their activity can be interpreted as the firing rate, and therefore the TLNs represent firing rate models [1].

Competitive threshold-linear networks (CTLNs) are a class of TLNs where the connectivity weights are all negative and there are no self-connections [2,3]. Inhibitory networks arise in many neuronal systems and have been shown to underlie the generation of rhythmic activity in cognition and motor behavior [4,5]. Despite their simplicity, TLNs and CTLNs produce complex behavior including multistability, periodic, quasi-periodic and chaotic solutions [2,3,6].

In this work, we consider CTLNs with three or more nodes and cyclic symmetry in which oscillatory solutions are observed. We first assume that an external oscillatory input is added to one of the nodes and, by defining a Poincaré map, we numerically study the response properties of the CTLN networks. We determine the ranges of input amplitude and frequency in which the CTLN is able to follow the input (1:1 entrainment). For this we define local and global entrainment measures that convey different information. We then study how the entrainment properties of the CTLNs is affected by changes in (i) the time scale of each node, (ii) the number of nodes in the network, and (iii) the strength of the inhibitory connections. Finally, we extend our results to include other entrainment scenarios (e.g., 2:1) and other network topologies.

Acknowledgments: This work was supported by the Universidad Nacional del Sur grant PGI 24/L113-2019 (AB, WR) and the National Science Foundation grant DMS-1608077 (HGR).

References

- Dayan P, Abbott LF. Theoretical neuroscience: computational and mathematical modeling of neural systems. The MIT Press. 2001.
- Curto C, Morrison K. Pattern completion in symmetric threshold-linear networks. *Neural Computation*. 2016; 28(12): 2825-52.
- Morrison K, Degeratu A, Itskov V, Curto C. Diversity of emergent dynamics in competitive threshold-linear networks: A preliminary report. *arXiv preprint*. 2016.
- Arriaga M, Han EB. Dedicated hippocampal inhibitory networks for locomotion and immobility. *Journal of Neuroscience*. 2017; 37(38): 9222-38.
- Burke DA, Rotstein HG, Alvarez VA. Striatal local circuitry: a new framework for lateral inhibition. *Neuron*. 2017; 96(2): 267-84.
- Hahnloser RL. On the piecewise analysis of networks of linear threshold neurons. *Neural Networks*. 1998; 11(4): 691-7.

P170

Optically imaged map of orientation preferences in visual cortex of an Australian marsupial, the Tammar Wallaby *Macropus eugenii*.Young Jun Jung¹, Ali Almasi², Shi Sun¹, Shaun Cloherty³, Hamish Meffin⁴, Michael Ibbotson⁵, Molis Yunzab², Sebastien Bauquier⁶, Marilyn Renfree⁷¹The University of Melbourne, Department of Optometry and Vision Sciences, Melbourne, Australia; ²National Vision Research Institute, Melbourne, Australia; ³Monash University, Department of Physiology, Melbourne, Australia; ⁴University of Melbourne, Biomedical Engineering, Melbourne, Australia; ⁵University of Melbourne, Melbourne, Australia; ⁶The University of Melbourne, Veterinary, Melbourne, Australia; ⁷The University of Melbourne, Biosciences, Melbourne, Australia**Correspondence:** Young Jun Jung (95jungy@gmail.com)

BMC Neuroscience 2020, 21(Suppl 1):P170

Orientation selectivity (OS) is a key feature of neurons in the mammalian primary visual cortex. In rodents and rabbits, these neurons are randomly distributed across V1 while in cats and all primates, cells with similar OS preferences cluster together into cortical columns. Could it be that mammals with smaller primary visual cortices, relatively undifferentiated cortices or poor-resolution vision are restricted to having salt-and-pepper OS maps? This is not true, because in gray squirrel, a highly visual rodent with good spatial resolution and a V1 that is highly differentiated, no clear functional organisation of OS preferences exists in V1. We do not know yet why the maps coding OS preferences are so radically different in rodents/rabbits compared to the clear similarities across other mammalian visual systems.

Several models of cortical OS maps have been created incorporating Hebbian plasticity, intracortical interactions and the properties of growing axons. But these models mainly focus on maps arising from intracortical interactions. Here we focus on two factors contributing to map formation: the topography of retina and phylogeny. One promising method of predicting whether or not a species has pinwheel maps is to look at the central-to-peripheral ratio (CP ratio) of retinal cell density. We have found that animals with high CP ratios (>7) have orientation columns while those with low CP ratios (<4) have random OS maps. We also investigated whether the development of OS maps is influenced by a genetic factor related to phylogeny. A problem with the existing literature is that OS maps have been investigated in only a small subset of mammals. We suggest that the rodents and rabbits might have lost the genetic capacity to develop OS maps, but that the mammalian line may have originally evolved with the genetic capacity to create orientation columns.

We studied a highly visual marsupial, the Tammar wallaby (*Macropus eugenii*), which represents a phylogenetically distinct branch of mammals for which the orientation map structure is unknown. The topography of RCC's in wallabies is very similar to cats and primates. They have a high density of RGC in the retinal specialization, indicated by a high CP ratio of 20. If orientation columns are the mammalian norm and if species with high CP ratios have OS maps, we would predict the existence of orientation columns in wallaby cortex. We used intrinsic optical imaging and multi-channel electrophysiology methods to examine the functional organization of the wallaby cortex. We found robust OS in a high proportion of cells in the primary visual cortex and clear orientation columns similar to those found in cats and primates but with bias towards vertical and horizontal preferences, suggesting lifestyle-driven variations. The findings suggest that orientation columns are the norm and it might be that the rodents and rabbits are unusual in terms of mammalian cortical architecture.

P171

Neural routing: determination of the fastest flows and fastest routes in brain networksPaula Sanz-Leon¹, Pierpaolo Sorrentino², Fabio Basile³, Rosaria Rucco⁴, Leonardo L Gollo⁵, James A Roberts⁶¹University of Sydney, QIMR Berghofer, Brisbane, Australia; ²Aix-Marseille/Parthenope University of Naples, Marseille, France; ³Parthenope University of Naples, Biomedical Engineering, Naples, Italy; ⁴Parthenope University of Naples, Motor Sciences and Wellness, Naples, Italy; ⁵QIMR Berghofer/