NORDIC MACHINE INTELLIGENCE

Nordic Machine Intelligence, vol. 2, pp. 1–5, 2021
Received 21 Nov 2021 / published 28 Nov 2022
https://doi.org/10.5617/nmi.9950

NeuroAI - A strategic opportunity for Norway and Europe

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Abstract

At an energy consumption of merely 20 watts, the brain is able to learn, perceive its surroundings, analyze solutions, predict the future and choose actions in a much more general way than any computer algorithm and infrastructure. NeuroAI, an emerging field at the intersection of brain sciences and artificial intelligence, is expected to become a large research field in the years to come. The main promise of NeuroAI is that by understanding how the brain and biological neural networks compute, it will be possible to identify the key components of human intelligence to drive the development of a more energy-efficient and flexible artificial intelligence (AI) that will match, perhaps even surpass, human intelligence. NeuroAI is a truly multidisciplinary effort, spanning across several disciplines such as computer science, neuroscience, psychology, philosophy, linguistics, law, and ethics. Norway has unique world-class expertise in brain sciences and a fast-growing, well-organized AI community at the highest international level. In this opinion article, we argue that Norway has competitive advantages within NeuroAI and that Norway has the ideal ecosystem to take a leading role in NeuroAI initiatives in Europe. Norwegian investments in NeuroAI may be a strategic initiative to position Norway at the forefront of AI research worldwide.

Keywords: NeuroAI; artificial intelligence; brain sciences, neuroscience

How brain sciences inspired AI

In a recent white paper *Toward Next-Generation Artificial Intelligence: Catalyzing the NeuroAI Revolution* [1], prominent American scientists, including ACM Turing Award winners Yann LeCun and Yoshua Bengio and NeurIPS president Terrence Sejnowski, call for more fundamental research in *NeuroAI* to drive AI research forward towards human-level artificial intelligence.

In particular, they argue that achieving human-level AI will radically transform our society and the world economy at a faster pace than previous technological transitions, e.g., by unleashing human creativity and discoveries or by increasing productivity, to name a few examples. However, in order to achieve or surpass human-level AI, several breakthroughs in AI are still needed.

Brain sciences have historically been the main driver and inspiration for AI discoveries. The field of AI itself is rooted in research efforts aiming at understanding how the brain works and translating the findings to build brain-like machines [2]. Advancements in computer vision, such as the Convolutional Neural Network architecture [3], are directly inspired by the Nobel Prize work by Hubel and Wiesel in 1962 [4]. More recently, the attention mechanism [5] popularly used in Transformers and Large Language Models (LLMs) is based on findings by Itti, Koch, and Niebur in 1998 [6] on the attention mechanisms in the brain.

History shows that brain sciences and AI go hand in hand. There is a plethora of examples of such fruitful collaboration beyond the classical examples reported above. To mention a few more, the mechanism of replay in biological [7, 8, 9] and artificial neural networks [10, 11, 12], dopamine [13, 14, 15, 16] and temporal difference learning [16, 17], cortical columns [18] and "single-brain" models [19, 20, 21], space and time navigation in the brain [22, 23, 24] and the emergence of grid cells in artificial neural networks [25, 26, 27, 28]. Hopefully, to be continued.

In the next section, we discuss how Norway has historically developed strengths in fundamental areas that directly contribute to the advancement of NeuroAI.

Norwegian Strengths and Traditions in NeuroAI

Fridtjof Nansen and the Neuron Doctrine

The idea that the nervous system is composed of separate nerve cells instead of a continuum of tubes was described by Fridtjof Nansen in a paper in 1886 [29] and presented in his doctoral thesis *The structure and combination of the histological elements of the central nervous system* in 1887 [30], published at the Bergen Museum. Nansen's work was essential for establishing the *neuron doctrine* as a concept, later culminating in the Nobel Prize of Ramon y Cajal in 1906 for his neuro-anatomical studies of neural cells.

The Norwegian discovery of Long-Term Potentiation
The mechanism by which synapses are persistently strengthened by recent patterns of neural activity, also known as Long-Term Potentiation (LTP), was initially discovered by Terje Lømo in 1966 [31]. Lømo was working at the laboratory of Per Andersen at the University of Oslo. He was conducting neurophysiological experiments on anesthetized rabbits to investigate the role of the hippocampus in long-term memory. As expected, he observed that a post-synaptic excitatory potential was obtained by stimulating pre-synaptic fibers with single electrical pulses. However, surprisingly, Lømo discovered that the post-synaptic response could be enhanced by a repeated high-frequency train of stimuli. In addition, the potentiated response would be persistent for long periods of time.

The Centre for the Biology of Memory, the Centre for Neural Computation, and the discovery of grid cells
In 2002 the Centre for the Biology of Memory was established as centre of excellence in research financed by the Research Council of Norway, as a result of the outstanding research on memory processes in brain networks led by May-Britt and Edvard Moser. One of the ground breaking findings is the discovery of grid cells in the entorhinal cortex in 2005. Such a finding radically changed the established views on how the brain computes position and how such computations are used in brain networks, with implications in several domains, including artificial intelligence and robotics. May-Britt Moser and Edvard Moser were eventually awarded the Nobel Prize in 2014 for their discovery of grid cells, together with John O'Keefe. Meanwhile, the Kavli Institute for Systems Neuroscience was awarded the additional status of centre of excellence in research in 2012 for the studies of neural computations, aiming to understand the emergence of high-level brain functions.

The Norwegian Artificial Intelligence Research Consortium (NORA.ai)
In October 2018 several universities, university colleges, and research centres joined forces to coordinate their AI-related activities into a shared consortium, now recognized as The Norwegian Artificial Intelligence Research Consortium (NORA/NORA.ai). NORA aims at strengthening Norwegian research, education, and innovation within artificial intelligence, machine learning, and robotics, as well as other relevant research that supports the development of artificial intelligence applications. The NORA consortium has further contributed to positioning Norwegian research in artificial intelligence on the international arena. Nowadays, NORA consists of 11 universities/university colleges and 5 research institutes, providing strong national coordination of the excellent AI environments and key infrastructures. NORA collaborates with several national and international hubs such as the Norwegian Open AI Lab at the NTNU, the British Alan Turing Institute, the German Helmholtz Information and Data Science Academy (HIDA), the Danish Pioneer Centre for AI, and US National Labs under the US Department of Energy.

Under the NORA leadership, the Norwegian AI environments have reached an outstanding quality level through a series of initiatives such as a national research school, startup and industry networks, an EU network for research, and a European Digital Innovation Hub for AI, only to name a few, showcasing the importance of such national coordination of activities. With the support of the Research Council of Norway, new larger AI infrastructures are also built in Norway, such as the Norwegian AI Cloud and Centres of Excellence in Research and Innovation.

Norwegian ongoing activities in NeuroAI
Recently, several independent Norwegian initiatives in NeuroAI have emerged, with the ambition of bridging the strong Norwegian brain science environments and the excellent Norwegian AI competence. Here we provide some notable examples.

The *Centre for Algorithms in the Cortex* at the NTNU[1], co-lead by May-Britt Moser and Edvard Moser, and directed by Bjarne Foss, aims to uncover the algorithms that the cerebral cortex uses for cognitive functions. While the centre is rooted in neuroscience research, the discovery of cortical computational algorithms is expected to drive the development of a number of scientific disciplines, including brain-inspired artificial intelligence.

The *Biologically inspired Artificial Intelligence (bioAI)* project[2], led by Mikkel Lepperød, Anders Malthe-Sørenssen, and Marianne Fyhn, hosted by Simula Research Laboratories in collaboration with the University of Oslo, focuses on bio-inspired AI that is energy efficient, explainable, robust and investigates causal, flexible and continual learning. This environment is also strongly connected to UiO's Centre for Integrative Neuroplasticity (CINPLA), profiting from the excellent Norwegian community within computational neuroscience developed over the last 25 years by Gaute T. Einevoll.

The *Self-Organizing Computational Substrates (SOCRATES)* project[3], led by Gunnar Tufte at the NTNU investigates self-organizing and emergent behav-

[1] https://www.ntnu.edu/kavli/centre-for-algorithms-of-the-cortex
[2] https://www.simula.no/research/projects/bioai-biologically-inspired-artificial-intelligence
[3] https://www.ntnu.edu/socrates

ior in biological neural networks to identify favourable properties for novel AI hardware made of tiny nanomagnets.

The *Hybrid Deep Learning Cellular Automata Reservoir (DeepCA)* project [4], led by at Stefano Nichele at the Østfold University College and at the Oslo Metropolitan University, investigates the integration of biological neural networks in-vitro with artificial intelligence systems. Both the SOCRATES project and the DeepCA project are carried out in collaboration with the Sandvig Lab on Integrative Neuroscience at the NTNU, led by Ioanna Sandvig and Axel Sandvig.

The *Human Brain Project/EBRAINS*-team at the Norwegian University of Life Sciences and the long tradition of computational neuroscience at NMBU. Gaute Einevoll and Hans Ekkehard Plesser have built world-leading environments for computational neuroscience at NMBU for the last 25 years; Hans Ekkehard Plesser through the important contribution to the development of the NEST software[5]; Gaute Einevoll through developing theory relating neural activity to brain signals ("LFPy"). As part of the EU-funded Human Brain Project/EBRAINS, NEST v.3 enhances brain research by offering easy-to-use digital infrastructure for constructing complex neural network models in computers, and LFPy by relating these models to actual measurements of brain signals.

The *Predictive and Intuitive Robot Companion (PIRC)* project[6], led by Jim Tørresen at the University of Oslo, develops psychology-inspired AI through research combining insight from cognitive psychology and computational intelligence to build models that forecast future events and respond dynamically.

The initiatives just exemplified create a solid foundation for further NeuroAI development in Norway. In the section below, we call for a national coordination of activities in NeuroAI and argue that investments in NeuroAI in Norway may be a strategic initiative to position Norway in the forefront of AI research worldwide.

The path forward

The progress of AI during the last decade has admittedly been impressive in the way it has excelled at specialized tasks like language translation, computer vision, protein folding, and game-play. The keys to these successes have to some extent, as mentioned above, been to take inspiration from the human brain to construct improved algorithms for learning, but maybe more importantly, the possibility to exploit the recent explosion in computational power and data access, thereby facilitating massive upscaling of deep learning models. There are reasons to believe that further progress towards more flexible AI showing human-level intelligence will require new kinds of learning algorithms equipping AI with so-called *world models* for common sense reasoning, planning, causal inference, and improved spatio-temporal understanding [32, 33]. Recent theories have further suggested that merging grid cells with a plethora of world models underlies the brain's astonishing predictive power and might be a missing ingredient in human-level AI [34]. Furthermore, from an environmental, economic, and social sustainability perspective, there should be an increased focus on developing AI with the ability to learn fast, with low energy demand, from small amounts of data, that can learn continuously building on previous models, that can exploit transfer learning, and not least, act open, trustworthy and transparently within high ethical and moral standards. These are all ideally inherent properties of the human brain and intellect. Therefore, increasing the focus on human-inspired AI by developing a Norwegian NeuroAI-community should be a "no-brainer". Hence, we hereby take the initiative to call for a national workshop on NeuroAI in the near future to bring together the NeuroAI researchers in Norway and coordinate the way forward in research and education.

We emphasize that, as stated in the Long-term plan for research and higher education 2019–2028 — Meld. St. 4 (2018–2019), the Research Council of Norway should prioritize funding for artificial intelligence and neurotechnology. More specifically, we suggest supporting even further the combination of the two.

Further, we recommend that the NeuroAI community establishes strong partnerships with other European research communities on the forefront of NeuroAI, building a strong European environment within this field. This could be achieved through collaboration with one or more of NORA's already established international partners.

Conclusion

We call for a national coordination of NeuroAI research in Norway. We argue that the development of NeuroAI in Norway is highly strategic, and specific funding opportunities are therefore needed. We believe that a national NeuroAI-community should be based on broad and interdisciplinary collaboration across many subject fields (AI, neuroscience, statistics, mathematics, cognitive psychology, philosophy, law, and more) in order to ensure a holistic view on future advances within this growing field.

With strong existing and historic research communities within central subject areas, Norway should have a particular obligation to take the lead in NeuroAI, with the aim of developing the future human-level AI within ethical and sustainable frames.

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