Bridging the gap between perception and action: the case for neuroimaging, AI and video games

Pierre Bellec & Julie A Boyle

Université of Montréal

Centre de recherche de l'institut universitaire de gériatrie de Montréal

CIUSSS du Centre Ouest de l'Île de Montréal

Abstract

A fundamental goal of computational neuroscience is to account for the implementation of cognitive processes in the brain, yet current models tend to focus on elementary cognitive processes. By contrast, video games have been designed to fully engage players, and require to constantly monitor the state of the game, in parallel to integrating strategic planning, decision making and taking action. While playing video games is hard, recent advances in artificial intelligence (AI) have made it possible to train deep neural networks that reach or even surpass human performance. We discuss challenges and opportunities in training artificial neural networks that could account jointly for human brain activity and behaviour during video game play. We argue that large-scale neuroimaging data may help to constrain the training of artificial networks and open new avenues for research at the intersection of neuroscience and AI.

Main goal

A fundamental goal of computational neuroscience is to account for the implementation of cognitive processes in the brain. Still, many modern artificial neural networks (ANN) in computational neuroscience perform no meaningful cognitive task, but instead focus exclusively on replicating characteristics of brain dynamics, such as the synchronicity across brain regions, e.g. (Díaz-Parra et al. 2017). When ANN perform tasks, those tend to focus on isolated cognitive processes such as visual object recognition (DiCarlo, Zoccolan, and Rust 2012), working memory (O'Reilly and Frank 2006), or decision making (Cisek, Puskas, and El-Murr 2009). Overall, few ANN in computational neuroscience have tried to integrate complex, multifaceted cognitive processes into a single model, such as (Eliasmith et al. 2012). In the meantime, research in artificial intelligence (AI) has reached or even surpassed human performance in video game play. A prominent example is Dota 2 where an AI recently beat a team of professional e-sport world champions. High level performance on Dota 2 was considered up until recently as out of reach for AI systems¹. Advances in reinforcement learning and AI were achieved by focussing solely on solving the task with deep (i.e. featuring many

¹ <https://openai.com/blog/how-to-train-your-openai-five/>

layers) ANN, allowing the AI agent to play for years at a time and maximizing its score, without attempting to directly emulate brain networks. The main goal of this short opinion paper is to make the case for a novel avenue in computational cognitive neuroscience, using deep ANN and video games as tools to model complex cognitive processes in brain activity.

ANN in computational neuroscience are only starting to target complex cognitive processes

In its long history, computational neuroscience has produced a flurry of ANN, and ways to relate them to brain networks. The “Human Brain Project” notably proposed a simulation of an entire macro-column of a rat somatosensory cortex featuring ~31,000 neurons (Markram et al. 2015). This simulation attempted to precisely mimic the different types of neurons as well as their spatial arrangement, using extensive neuroimaging data from slices of rat brains. They were able to generate a variety of neuronal states dominated by synchronous vs asynchronous activity. The extent of neuronal tissue being simulated was still only a small fraction of the hundreds of millions of neurons found in a typical rat cortex (Herculano-Houzel, Mota, and Lent 2006). It is thus unclear whether such detailed, granular simulation can reproduce even simple cognitive processes in the foreseeable future.

The “Virtual Brain Project” is another prominent approach that relies on extensive individual structural and functional neuroimaging data to set the parameters of ANN (Sanz Leon et al. 2013). The Virtual Brain does not attempt to model individual neurons, but rather model “neural masses”, intended to represent a functional macro-column. Given their simplified model, the Virtual Brain Project implements simulations over the whole brain. The Virtual Brain models have been able to reproduce many functional characteristics of brain activity, including large-scale spatially synchronous activity observed in resting-state networks using functional magnetic resonance imaging (fMRI) (Díaz-Parra et al. 2017). The Virtual Brain Project currently focuses on replicating dynamics in individual brains, notably patient cases (Proix et al. 2018), and it is unclear whether that technology would be able to simulate complex cognitive processes and behaviours.

In parallel, some computational models have explicitly targeted cognitive processes, such as decision making. For example, Cisek and colleagues asked human subjects to watch a set of dots jump into one of two target circles, and decide in advance with circle will receive the most dots (Cisek, Puskas, and El-Murr 2009). A mathematical equation integrating two factors (urgency and confidence) in a multiplicative way was shown to account well for the trade-offs between the speed and accuracy of the decision, as well as the profile of activity in neural electrophysiological recordings. Such laboratory tasks are however designed to isolate specific elementary functions that are part of cognition, rather than complex, integrative cognitive processes.

In ecological conditions, tasks typically require a combination of multiple elementary cognitive processes. Very few models have to our knowledge attempted to account for that plurality. The

“Spaun” model, including 2.5M artificial neurons, was an important push in that direction (Eliasmith et al. 2012). The model is only presented with images, and provides responses by moving an artificial arm. Spaun is organized in a hierarchy of functional modules that conceptually mimic the organization of a real brain. The model was trained to perform 8 different tasks, including recognizing digits from hand-written images and a copy-drawing task, where the artificial network moves its arm to copy digits presented as hand-drawn images. The Spaun model achieved accurate behavior on these tasks, and also replicated patterns of neural spiking activity found in the brain. Extending such integrative computational models will require to find cognitive processes that are more complex but can still be executed by ANN, as well as ways to add biological constraints to ensure the artificial dynamics are somewhat comparable to brain activity.

Video games are engaging for humans, and can be modeled with ANN

Commercial video games are in many ways the polar opposite of laboratory tasks: they have not been designed to isolate a particular aspect of cognition, but rather engage players as much as possible. The video game industry has built a large repertoire of stimuli that elicit strong attentional mechanisms (C. S. Green and Bavelier 2012; Palaus et al. 2017), strong emotions (René Weber et al. 2009), or even addictive behavior (Mathews, Morrell, and Molle 2019). Some video games are engaging enough for players to develop high levels of skills that are the basis of widely followed competitions involving professional players, such as Dota 2 (“Dota 2” n.d.). Video gaming is also the object of world records, such as fastest time to complete a level in a given game, a practice known as “speed runs” (Wikipedia contributors 2019). Several articles have reported positive cognitive effects of the practice of video games on short-term memory (Boot et al. 2008), selective attention (C. Shawn Green and Bavelier 2003), multitasking (C. Shawn Green and Bavelier 2006), spatial cognition (C. S. Green and Bavelier 2006), task-switching (C. S. Green and Bavelier 2012), decision making (C. Shawn Green, Pouget, and Bavelier 2010), and cognitive control (Anguera et al. 2013). In their meta-analysis, Bediou and colleagues (Bediou et al. 2018) found that action video play had a robust effect on top-down attention and spatial cognition. These findings strongly suggest that playing video games required players to use various cognitive skills, often in parallel, and this seems to be especially true of action based video games (Gray 2017).

We have now established that some video games can challenge human cognitive abilities. But if we are to use video games as computational neuroscience tools, can we build ANN able to play those games? And can we do so with a performance that is comparable to humans? The answer to these questions is yes, mostly. A landmark study has shown that ANN can play at superhuman level of performance across a wide range of games (Mnih et al. 2015). These games were however relatively old action-based games, that lacked elements of long-term strategy. Up until recently, AI-based agents were not able to compete with expert humans at strategy-heavy games such as Dota 2. OpenAI recently developed an AI able to beat a team of professional e-sport world champions². These developments have important implications for the

² <https://openai.com/blog/how-to-train-your-openai-five/>

field of computational neuroscience: deep ANN can achieve human-like performance on tasks that are both engaging and challenging for humans. Whether such ANN are a good proxy of the way humans solve those tasks remains to be seen.

Neuroimaging data will be critical to train ANN that mimic brain activity while playing video games

In the type of reinforcement learning used by openAI, ANN are trained to maximise some objective metrics, such as the score or the number of life, and are allowed to play autonomously for thousands of hours in order to train and increase their performance. So even if ANN can reach high level of performance, this is achieved with a learning strategy very different from humans³. How plausible is it then that ANN computations in video games are related to brain activity? In the vision domain, artificial neurons seem to follow patterns of activation that sometimes relate to those found in brain networks, although these ANN were trained solely to solve a vision task, independently of biological data. This was described both in primates using invasive electrophysiological recordings (Yamins and DiCarlo 2016), as well as in humans using MEG (Cichy et al. 2016) and fMRI (Horikawa and Kamitani 2017). But there is still a plurality of ANN architectures that can reach high level of performance on a given task. Hoping that ANN trained independently of brain data will precisely account for brain function is wishful thinking (Dong, Wang, and Hu 2018). There are also fundamental differences in the ability to decode images between humans and deep ANN, even if the ANN reached high levels of overall performance (Rajalingham et al. 2018). We should thus expect differences between ANN and brain networks both in terms of behaviour and functional architectures, when ANN are solely trained to solve a task.

As we just saw, training an artificial network solely to solve a task is an ill-defined problem, with a wide range of possible solutions. It may be tempting to think that training ANN to mimic brain activity may constrain the problem to a single solution. Unfortunately, this also is an ill-defined problem, which has been extensively studied for dynamical causal models, originally proposed by Karl Friston and colleagues (Friston, Harrison, and Penny 2003). Such models try to fit functional fluctuations in MRI or EEG using brain generative models that include neural masses similar to those used in the Virtual Brain Project. Lohman and colleagues (Lohmann et al. 2012) demonstrated that, as soon as a half-dozen brain regions are included in the model, it becomes computationally infeasible to estimate precisely the parameters of the underlying generative model. More specifically, many models exhibit similar levels of posterior evidence, and the situation gets only worse through combinatorial effects when adding new regions. Dynamical causal models can likely not be unambiguously estimated from functional neuroimaging data on the full brain, as human brain networks feature at least hundreds of functional units (Glasser et al. 2016).

³ This may change too, as the field of reinforcement learning is progressing fast
<https://www.sciencedaily.com/releases/2019/01/190131091434.htm>

We propose that training ANN using both human brain activity and behavior may be a feasible path to resolve these separate, ill-defined estimation problems. Nayebi and colleagues demonstrated the potential of this approach by systematically exploring a large number of deep recurrent ANN architectures in order to optimize their ability to recognize objects in series of natural images. Their search for a good model was directly inspired by known neural properties of the monkey brain, and they quantitatively showed that the best model did fit electrophysiological recordings in the visual processing stream (Nayebi et al. 2018). In the same vein, Fong and colleagues investigated which natural images elicit robust responses in the brain, and increased the weight of these images when training deep ANN, resulting in improved learning rate and performance of the ANN (Fong, Scheirer, and Cox 2018). Nishida and colleagues trained a deep ANN to learn representations of images predictive of brain responses measured using functional MRI in humans, and then further used these representations to successfully train the ANN to perform video decoding, with increased performance compared to the model trained without brain data (Nishida et al. 2019). These papers open a new line of research, where deep ANN are trained to solve a task while mimicking brain activity. By providing very rich data regarding both human behaviour and brain activity, neuroscience research can narrow down the immense search space of possible ANN to a subclass of biologically plausible models, and may critically help identify a new class of ANN with high performance, at least in some cognitive domains.

Opportunities and challenges

The research reviewed thus far supports that (1) video games can drive complex and integrated cognitive processes, (2) ANN can be trained to play complex games, and, (3) training ANN to play video games would likely benefit from direct biological constraints, notably derived through neuroimaging. We now discuss some practical challenges and benefits for training ANN that emulate brain activity engaged in playing video games.

First, although video games have been studied using fMRI (Klasen et al. 2012; Noah et al. 2015), and EEG (Nacke, Stellmach, and Lindley 2011; Krishnan et al. 2013), such studies are heterogeneous in their research goals, methodology and the type of video games used (Palaus et al, 2017), and only a handful of studies collected video game play while scanning. We hypothesize that this may reflect open issues regarding quality of the data, and the feasibility of data acquisition. Video game playing is likely associated with high motion levels, which has been shown to be detrimental to the quality of fMRI data (Power, Schlaggar, and Petersen 2015). Eye movements and blinks also cause artefacts in M/EEG (Hoffmann and Falkenstein 2008), and are likely unavoidable while playing video games. Some generic mitigation strategies have been proposed, such as the adoption of prospective motion correction (Dosenbach et al. 2017), head cases to minimize motions (<https://caseforge.co>), and post-hoc denoising techniques (Hoffmann and Falkenstein 2008; Pruim et al. 2015), but it remains to be seen how effective these strategies are during video game play. To date, the types of video game that can be played in the fMRI scanner have also been limited by the types of MRI compatible controller

and response devices available, with most studies using games that can be played with button boxes (Klasen et al. 2012; Rene Weber, Ritterfeld, and Mathiak 2006), a joystick (Cole, Yoo, and Knutson 2012), or data gloves (Anderson et al. 2011, 2016). Existing MRI-compatible video game controllers include shielded electronic components, which may create artifacts in neuroimaging data (Trees et al. 2014), although some fully fiber-optics solution may be developed in the future. There is finally a lack of generic tools to record and annotate in detail games played in the scanner, that would support a wide range of games. The issues listed above are to some degree speculative, as we are not aware of a work systematically studying the quality of functional neuroimaging signals while recording video game play.

A key opportunity with video game play is to model the full brain, continuously integrating perception with action. During an action-based video game, players encounter situations where they are forced to make quick decisions from a number of possible options, based on their prior knowledge of the game, their current scenario, and yet unknown factors. Even relatively simple experimental conditions have been shown to modulate the activity of almost the entirety of the brain, when using enough functional data and model-free estimation (Orban et al. 2015; Gonzalez-Castillo et al. 2012). Neuroimaging studies using action based video games in the scanner have consequently reported activation in large portions of the cortex, including brain regions involved in top-down attentional processes (Anderson et al. 2011) and goal oriented behaviour (Bavelier et al. 2012), spatial (Anderson et al. 2011) and information (Anderson et al. 2016) processing, skill acquisition (Erickson et al. 2010), reward performance (Koepp et al. 1998), and emotional state (McMahan, Parberry, and Parsons 2015). Additionally, video game play has been associated with increased grey matter volumes in the hippocampal, entorhinal cortex in both long term gamers (Kühn and Gallinat 2014), and following two months of video game training sessions (Kühn et al. 2014). The latter results suggest that playing action-based video games such as Super Mario can lead to brain plasticity in brain regions involved in spatial navigation, and working memory.

If we are to build full-brain models able to play video games, it is not clear to us which type of ANN architecture will be best suited for the task. Could a mesoscale simulation of neural mass models be sufficient, such as the virtual brain? Will it be necessary to find ways to incorporate prior knowledge of distributed brain networks to limit the number of free parameters of the model? And how much functional data will be necessary to train such a model? Because of substantial inter-subject variance in functional brain organization (Elliott et al. 2019), training ANN to emulate brain activity during video games would likely benefit from extensive data collected on a single individual, following the approach of the Midnight Brain Scan project (Gordon et al. 2017).

The Courtois project on neural modelling (NeuroMod) was established to advance the intersection between AI, video games by collecting extensive individual neuroimaging data. This project notably aims to establish how much individual data is necessary to successfully train ANN mimicking brain networks playing video games. Made possible by a donation from the Courtois foundation, the Courtois NeuroMod team will scan six subjects for about 100 hours per

year in functional MRI, as well as 20 hours per year in MEG, for a duration of five years, totalling about 600 hours of functional neuroimaging data per subject. The experimental conditions will feature prominently video games, and cover a range of functional localizers, high resolution anatomical scans, movies, natural images presentation, as well as language and memory tasks. The Courtois NeuroMod project is also tackling several of the issues outlined above by developing a high quality experimental set-up for video game play in both fMRI and MEG. This set-up includes headcases for reduced motion, an electronics-free video game controller, as well as a range of physiological measure and eye tracking.

A major opportunity for ANN trained with direct biological constraints such as the Courtois NeuroMod data is to help address some shortcomings of current state-of-the-art ANN architectures. In a recent competition organized by OpenAI, participants needed to train ANN to play one version of Sonic, and the ANN were then evaluated on a separate version with similar game mechanics, but distinct levels (Nichol et al. 2018). The performance of the best agents remained modest, with a large drop in performance on the version that was not available during training. This competition highlighted the difficulty of current AI models to generalize information outside of the context of training. The human brain, by contrast, is able to switch rapidly between a variety of cognitive contexts. Constraining ANN with biology through large-scale data, may thus help to establish new ANN which generalize better across tasks.

Since its inception, the AI field has pursued the explicit goal of building artificial systems with human-like intelligence (Turing 2009). After the breakthrough made through deep learning in AI, the neuroscience field may now be in a position to contribute some insights on architectural principles that are key for complex, multidomain cognition. We believe that combining AI, video games and neuroimaging may deliver some of these insights.

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