Bringing artificial intelligence to bear on the improvement of human cognitive skills (draft)

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Abstract

How can we use recent advances in artificial intelligence to enhance human cognitive abilities? We first declare our goal to be to enhance executive function, define its measurable constructs, and dive into a mechanistic exploration of the brain structures that give rise to these faculties. Next we make the argument that these faculties are trainable by surveying the efficacy of both modern and millennia-old games of cognitive training. We then ask what modalities of information are available to us to feed to an AI system that could enhance one's progression through a cognitive training game (of many potential forms). Building on this foundation, we discuss in detail a machine learning strategy, both in terms of prior work and fascinating new directions. We close with a practical strategic discussion of the people and organizational structures needed to make this vision a success.

Outline

I. Enhancement of executive function

Our current revolution in artificial intelligence has the potential to confer a similar revolution in human intelligence, at least in the area of executive function. As we will discuss in subsequent sections, the ability to self-regulate a state of clear-eyed goal-oriented focus is trainable. Here we propose a strategy to leverage emerging artificial intelligence techniques to **amplify** this process.

In this section we concern ourselves with answering the question “What is our overall goal and what categories of measures are available to assess progress towards that goal?”. First we present our vision. Next, in the spirit of metric-driven engineering, we present the key constructs we aim to amplify and the classical means by which they are measured.

We also note explicitly the purpose of this document - to formulate a broad strategic context that, once formulated, will admit a tractable progression of individual projects and experiments. This document is scoped from the perspective of a consortium, small academic field, or large technology company.

We also note that the key focus of this document is the ways in which cutting-edge **machine learning** technologies, especially deep reinforcement learning and automated modeling approaches, can be brought to bear on the problem. While the use of various forms of games to improve cognitive performance has existed for a long time, using machine learning to amplify this process or automate portions of it is indeed quite new.

Vision

Desired impact

What might it be like to attend school or participate in work thirty years from now? What technologies will exist to amplify the potential of the human brain? To whom will these technologies be available? Who will want to use them? What would it be like to live in a world where the height of cognitive skills and intellectual achievement found within our most selective communities today were simply the norm, globally? Can we build a system that dramatically enhances executive function and make it available to everyone?

Executive functions are a family of top-down, effortful cognitive-regulatory processes for the selection and maintenance of goal-directed cognitions and behaviors - especially when learning something new that we can’t yet do “on autopilot”. We need both inhibitory abilities (including both behavioral inhibition and selective attention) that protect our working memory bandwidth in pursuit of a specific goal as well as the cognitive flexibility to pursue shifts of goal and approach when relevant. Planning and fluid intelligence (reasoning and problem solving) build upon the clarity afforded by the ability to regulate at these lower levels of executive function.

Extensive research has shown that executive functions are important to just about every aspect of life, spanning physical and mental health, quality of life, social readiness, school success, job success, martial harmony, and public safety (e.g. see Diamond, 2013). We have the opportunity to leverage cutting-edge artificial intelligence technologies to improve the ability of cognitive training games to affect outcomes across all of these domains.

User Story

Joe (of whose gender we are agnostic) works at a large technology company and would like to learn and accomplish more in less time while incurring less stress. Whenever Joe needs to recharge Joe takes a short break to play a video game on Joe’s phone in a nap pod or on the couch at home while wearing a special headset provided by work. The game is fun and relaxing and almost a little mind-bending… As Joe continues to make progress through the game a certain clarity of mind has grown stronger and both work and family time are seeing the benefits. Joe doesn't know exactly how the game works but it's definitely something big.

Components and their measurement

There is a diversity of perspectives in the neuropsychology community regarding the constructs that compose executive function. Nevertheless they ultimately all relate to some set of common processes that we all experience. The reader needs not constrain their reading of this section to simply understanding the constructs and their measurement. We encourage the reader to relate each of these constructs to their ongoing experience of each of these, given that unlike other subjects we ourselves can observe and experience these self-reflectively.

In each of the following cases, we describe a limited resource that can be utilized in a more or less efficient manner.

Inhibitory and attentional control

Inhibitory control is a construct relating to one's ability to control one's attention, thoughts, and/or emotions in support of the pursuit of one's goals. This spans a wide array of situations from cocktail parties where you need to screen out background voices, to the need to avoid eating sweets when one wants to lose weight, tempering ones reaction to an emotional stressor, or successfully operating in accordance with social norms. We need inhibitory control when we stay on task despite distractions or the desire to move on to more interesting work (or non-work).

Various psychological measures exist to measure inhibitory control, many unified by the measurement of an individual's ability to regulate a prepotent tendency to respond in a manner contrary to the goal of the task.

Task	**Game**	**Challenge**
Simon task	Stimulus A, respond w/ key on left; Stimulus B, respond w/ key on right. Stimuli presented on L or R.	Automatic tendency to respond left (right) when stimulus presented left (right), independent of correct stimulus/response mapping.
Spatial stroop	Press in direction of presented arrow.	Tendency to press congruent w/ side of presented arrow, not direction it points.
Flanker task	Attend to centrally presented stimulus, ignore flanking stimuli.	Tendency to look towards or partially attend to potentially salient stimuli.
Delay of gratification	Resist temptation to consume delicious snack and receive more later.	Snack delicious; delay length unknown.

Table 1. Representative measures of inhibitory control.

Working memory

Working memory involves both storage and operation on information not still perceptually available and can be partitioned into verbal and non-verbal categories. Working memory is required for mental operations such as translating requirements into a plan to meet those requirements, updating a plan to incorporate new requirements, or relating multiple concepts to derive general relationship. Working memory is closely related to inhibitory control as the latter can be used to optimize usage of the limited resources of the WM workspace.

Task	Description	Challenge
Symbol reordering	Remember given list of items, return them in specified order (e.g. animal size).	Symbol working memory limited.
Corsi Block test	Watch tester touch series of blocks; touch blocks in same order.	Visual-spatial working memory limited.
Self-Ordered pointing test	Touch each of N items exactly once. Items may change position.	Visual-spatial working memory limited.
Complex span tasks (N-back)	Present stimuli S=[A, C, B, …], present query stimulus Q="B", is Q == S[-N]?	Broad EF measure (make efficient use of all EF components).

Table 2. Representative measures of working memory.

Cognitive flexibility

Cognitive flexibility includes the ability to change perspectives spatially (how something looks when viewed from different direction) or interpersonally (see this from your point of view); to change priorities when relevant; to admit when you are wrong; to exploit sudden unexpected opportunities. For example assessed using a task that switches rules mid-stream (start by sorting cards by color then switch to sorting by number). Easier to continue doing what you're doing; overcoming attentional inertia to switch between ways of thinking about stimuli is demanding.

Task	Description	Challenge
Design fluency	How many uses can you think of for a table? How many words that begin with letter F?	
Wisconsin Card Sorting Task	Deduce correct sorting criterion based on feedback (color, shape, number), adapt to unspecified change in criterion.	Attentional inertia;
Dimensional Change Card Sort Test	Sort six cards by color, then by shape, then by color again (bivalent). Criterion is specified.	Attentional inertia;

Table 3. Representative measures of cognitive flexibility.

Fluid intelligence

Fluid intelligence is a higher-order component of executive functioning concerning the ability to reason, problem solve, and see relations among items (Ferrer et al., 2009) that builds upon on the lower-order components including inhibitory control, working memory, and cognitive flexibility.

Task	Description	Challenge
Raven's Progressive Matrices	Given two symbol triplets exemplifying pattern complete third triplet to follow pattern.	Relational reasoning; Maintaining representation long enough to reason to identify pattern and how that applies in new setting.

Table 4. Representative measures of fluid intelligence.

The neuroanatomy of executive function

Like an ultra-large-scale version of modern deep neural network architectures, the brain is composed of a large diversity of components that specialize in their function and inter-operate to transform information and create the dynamics that give rise to our experience. Yet unlike modern software or firmware DNN's, all of this is implemented in the more literal, physical form of neural networks that encode their dynamics in the way their (actual) physical structure affects the transmission of electrical impulses, neurotransmitters, and a host of other biomolecules across space and time.

(Provide a neuroanatomy overview figure)
(Briefly discuss what we understand about each brain region involved in executive function)
(Talk abut the theory of Wang et al. (2018) regarding how the human brain might implement an actor-critic meta-learning system)

Summary points

- A clearly defined set of measurable goals will allow our efforts in designing interventional systems to stay focused and lean.
- Understanding representative measures of components of executive function both clarifies these concepts as well as gives inspiration for the design of training exercises.

II. Executive functions are trainable

Here we consider evidence that executive functions are trainable by surveying a range of categories of cognitive training games, starting with meditation, the millenia-old category of introspective cognitive training, followed by more modern biofeedback, computerized game, and hybrid biofeedback-computerized game approaches.

Meditation games

Meditation is a broad family of contemplative practices that involves constrained practice of a desired mode of operation of the mind with the core philosophy that what is practiced tends to grow stronger. For example, compassion meditation involves practicing generating feelings of loving kindness towards others so as to have the effect of more automatically and strongly feeling this emotion in the future. The objective of contemplative practices is not only to induce acute (state) benefits but to practice until the desired modes of operation become deeply rooted and effortless traits.

Mindfulness-based stress reduction (MBSR; Kabat-Zinn, Lipworth, & Burney, 1985) is perhaps the best studied clinical program for meditation. This simple form of brain training has been shown to be effective for improving an wide range of measures of chronic pain, arthritis, fibromyalgia, anxiety, and depression (Arias, Steinberg, Banga, & Trestman, 2006) perhaps related more fundamentally by its effect on indices of immune function (Witek-Janusek et al., 2008). Davidson et al. (2012) naturally hypothesize this is due to a strengthening in systems important for emotion regulation.

From Davidson et al., 2012:

> *"There is also growing evidence that mindfulness training improves adults' ability to regulate attention and executive function, including orienting attention and monitoring conflict (Jha, Krompinger, & Baime, 2007) and inhibiting emotionally charged but irrelevant information (Ortner, Kilner, & Zelazo, 2007) in novice meditators. Intensive meditation practice improves performance on the attentional blink task and decreases reaction time variability in a selective attention task, altering functional brain activity that supports these attentional changes (Lutz et al., 2009; Slagter et al., 2007). In adults, meditation practice can also induce present-oriented forms of self-awareness (Farb et al., 2007) that likely enhance motivation and learning (Roeser & Peck, 2009)."*

(Consolidate and integrate with other discussions)

Classical neurofeedback games

EEG Neurofeedback (EEG-NFB) is a biofeedback approach that processes an EEG signal into a format presented to the wearer with the aim of influencing their mental or physiological state. While much enthusiasm exists in the field over the potential of the approach, meta-analyses have repeatedly concluded that a large proportion of studies are poorly designed (Niv, 2013; Rogala et al., 2016). Niv et al. concluded that more and better-organized research is necessary to confirm the efficacy and effectiveness of EEG-NFB.

In their meta-analysis, Rogala et al. (2016) argue that among a subset of well-designed studies, some clearly show positive effects of EEG-NFB (Allen et al., 2001; Hoedlmoser et al., 2008; Keizer et al., 2010a) while others do not (Egner et al., 2002; Berner et al., 2006; Logemann et al., 2010), hypothesizing that the choice of training program or signal quality accounts for this difference. Naturally this is as to be expected since our question is not simply "is EEG-NFB" effective but rather "which EEG-NFB interventions are effective".

A meta-analysis by Arns et al. (2009) concludes that EEG-NFB provides a benefit to children with ADHD on average but did not find a significant difference between interventions that targeted three primary classes of neural signature. Clearly the correspondence remains to be established between particular neural signatures and desired behavioral changes.

Rogala et al. (2016) argue one key strategy to improve on the state of the art is to employ higher-resolution EEG devices with the objective of improving source localization. We propose the natural generalization of this notion to pursue the use of neural-sensing devices that span multiple modalities (indeed at both higher temporal and spatial resolution). We expand more on opportunities to improve the power of neurofeedback systems through improvements in data richness in sections III and IV.

In addition to improvements in hardware there are very well to be gains to be derived from improvements in feature selection and learning algorithms. In such a complex-dimensional dynamical domain, human researcher-driven feature selection may not be the right approach. In section V we argue that modern deep learning algorithms stand to automate and improve the process of modeling the complex dynamics of this type of process - including enabling neurofeedback systems to leverage features with more temporal or spatial dynamics and complexity than human researchers may be able to identify and express.

Cognitive computer gaming

Mishra et al. (2014) argue that non-invasive, non-pharmaceutical cognitive training games are a promising therapeutic target to address a number of the key limitations of current approaches to the treatment of neuropsychiatric disorders.

1. Diagnostic: Cognitive training games have the potential to provide clinicians with statistically valid assignments of patients into previously-established clinical categories.
2. Personalized and adaptive:
    1. Trained tasks can be chosen to specifically target identified deficits (in contrast to pharmaceutical interventions that for example broadly target brain-wide neurotransmitter systems).
    2. Throughout the course of training, the difficulty of training can be adapted to maintain the appropriate level of challenge to ensure continued benefit.
3. Low cost: Cognitive training games need not be expensive.
4. Adherence and incentives: The digital nature of cognitive training games makes them amenable precise measurement of training adherence and personalization of incentive structure to promote adherence.
5. An extensible paradigm. The digital nature of cognitive training games makes them amenable to integration with various modes of neuro- and biometric data to aid in the personalization of training.

Well-designed games

Indeed, games of cognitive control have already been shown effective in achieving transferrable benefits to executive function. Most recently, Rolle et al. (2017) showed training on a novel spatial attention task transferred toward improvements in working memory, hypothesized by the authors to be due to overlap in brain networks involved in attention and working memory processes.

Initially and perhaps most famously is the work of Auguera et al. (2013) and the NeuroRacer game which asked participants to perform a modified Stroop task at the same time as driving a (digital) car. The authors used this game both to characterize age-related pre-training variation in multitasking ability (linear age-related decline) as well as to train an improvement in older subjects back to a point superior to the pre-training capabilities of their younger counterparts. Importantly, this effect generalized to an improvement in un-trained measures of executive function (enhanced sustained attention and working memory; and was not accounted for by simply a difference in reaction times between cohorts; and persisted at a 6mo. follow-up).

Before training Auguera et al. (2013) also observed age-related deficits in midline frontal theta (4–7Hz) power (MFTP) and frontal-posterior theta coherence (FPTC), two established correlates of cognitive control abilities (working memory [Onton et al. (2005)], sustained attention [Sauseng et al. (2007)], and interference resolution [Nigbur et al. (2011)]); training was shown to remediate deficits in these correlates. Mechanistically, they argue, since medial prefrontal activity is inversely correlated with MFTP [Scheeringa et al. (2008)], training-induced increases in MFTP likely implies a decrease in mPFC activity - an important node in the default mode network [Buckner et al. (2008)], the deactivation of which is known to be associated with better task performance [Grady et al. (2006)].

In formulating a strategy in this domain it is important to note key strengths of the Auguera et al. (2013) and Rolle et al. (2017) studies that should persist in future efforts. First, control/comparison conditions were effective means of isolating the effect of interest - driving alone or Stroop task alone. Also, task difficulty was tuned based on task performance to maintain the challenge of training. (Probably some other key design features to note)

Hybrid approaches

The opportunity exists to synthesize findings from contemplative neuroscience, the EEG-NFB literature, emerging methods in deep learning, and the aforementioned accomplishments with computerized training games in cognitive control, spatial attention, or perhaps other areas. (expand)

Summary points

- Deficits in EF can occur as the result of various pathological states (sleep deprivation, sadness, loneliness, etc.) and addressing these first should take priority.
- The literature on various meditation "games" gives strong evidence that executive function is trainable through repeated practice and that the benefits of this extend to a diverse array of measures of physical health. Can we accelerate the attainment of these benefits by applying modern technologies to proven (albeit slow) meditative practices?

III. An extensible platform for advanced sensing

In this section we discuss the core initial and potential future components of a brain state measurement device that stands to enable the neurofeedback gaming approach introduced in the previous section.

Shared development platform

In considering the development of such a device a key question is whether the development of the system should be structured as an open- or closed-source/design effort. The former case would involve various entities (academic and commercial) contributing to a shared (public, free) infrastructural foundation. In this case, we argue that gains in group output are to be realized by avoiding duplication of effort and the development of incompatible architectures and components. Instead, individual academic labs and industrial research groups can devote their hardware development efforts to building extensions for this platform and continuing to benefit from improvements to and insights derived from this shared foundation.

A common argument in favor of the closed-source approach is that hardware development is expensive and maintaining a competitive advantage (that will keep the price of a sold device high) is the approach that will allow the development of hardware that is the most advanced.

A third category to consider would be a hybrid of the previous two, where a commercial provider seeks to develop a closed-source extensible development platform aimed at facilitating hardware research.

Sensing

Core sensing capabilities

Arguments were presented in the previous section (Section II.), based both on studies of traditional neurofeedback as well as electroencephalographic signatures observed during NeuroRacer training, for the need for high-resolution EEG. Going forward, we set it as an objective to determine the maximum feasible resolution of EEG sensing.

More generally, we make note of two key limitations of EEG that could be overcome with innovations in headset design. The first is the amount of time required to prepare an EEG setup for use - putting on the headset, precisely aligning electrodes to "reference points", and ensuring electrodes have sufficient conductivity by apply additional conductive solution where necessary (in the case of wet EEG). Dry electrodes greatly simplify and accelerate this process, not to mention avoid creating mess, at the expense of data quality. We propose that this loss in data quality can be compensated for by a significant increase in electrode resolution.

A second key limitation of current-generation EEG systems that presents an opportunity for innovation is their sensitivity to environmental noise. (Understand this problem better; perhaps the helmet approach would help with shielding if helmet were made of conductive material)

Functional near-infrared spectroscopy

An ideal development platform would support extension with additional sensory modalities, such as functional near-infrared spectroscopy. Here we consider the benefits of this sensory modality towards motivating the design of a device that would enable this sort of extension in the future.

Functional near-infrared spectroscopy employs a trans-cranial optical emitter/detector approach where the concentration of oxygenated and deoxygenated hemoglobin in cortical tissue is estimated using the differential in transmitted and detected intensity of near-infrared light following its transit through brain tissue. As near-infrared light is transmitted through the skull, brain tissue, and vasculature the light is absorbed by a variety of molecules, notably hemoglobin, thereby enabling this measure of oxygenation from a measure of the amount of light absorbed in transit.

The use of fNIRS already has an extensive history of use in the context of discovering correlates of desired brain changes, as one would expect for a BOLD measure. Soltanlou et al. (2018) review work using this modality to study the neural basis of mathematical and language learning in schoolchildren. Numerous studies using fNIRS have observed hypo-activation in the prefrontal cortex during cognitive tasks performed by patients with major depressive disorder (e.g. Pu et al., 2011; Matsuo et al., 2002; Ohta et al., 2008). (Some additional examples of fNIRS being interesting)

With an eye to the future we ask how might the current state of the art in fNIRS be extended to greatly increase data richness. To this end we propose two new categories of method - fast-switching combinatorial reconstruction and continuous high-resolution hyper-spectral fNIRS (or "hyper-fNIRS") - in this section generally and from a machine learning perspective in V. (omitted)

Summary points

- A key consideration is whether to develop an open- or closed-source development platform.
- High-resolution electroencephalograph is a core sensing requirement with the need to position for additional promising sensory modalities such as functional near-infrared spectroscopy.

- An ideal development platform would position to enable the future incorporation of various categories of cranial and peripheral stimulation.

IV. Core system component and integration requirements

In this section we build upon the previous with specification of the categories of component that will be needed in a system capable of accomplishing the goals set out in the first section, taking inspiration from the subsequent ones. A summary of the proposed system architecture is shown in Figure N., consisting primarily of Sensor, Interface Device, and Cloud Infrastructure components.

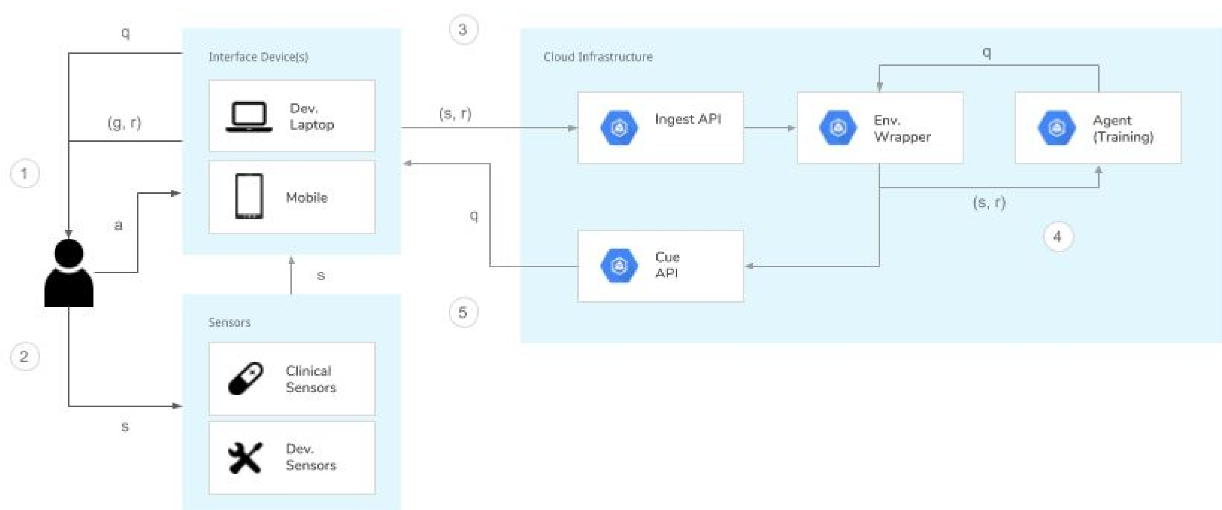


Figure N. Proposed system architecture for neurofeedback gaming system. (1) A user plays a cognitive training game on one of various possible interface devices, providing actions while receiving an observation of game state, *g,* their score in that game, *r*, and a separately computed feedback signal, *q*. (2) The user's biological, such as cognitive, state, *s*, is measured by a variety of possible sensors, such as clinical grade EEG or a simple EEG development device. This state is transmitted to the Interface Device by way of a bluetooth or serial link for relay to the cloud. (3) Interface Devices, having received sensor data on a user's state, communicate both state and reward to the Cloud Infrastructure via the Ingest API which runs as a GKE service. (4) The Environment Wrapper manages collecting ingested *(s, r)* pairs and delivering these to the agent undergoing training. The agent continuously chooses a cue, *q,* whose transmission to the Cue API is managed by the Environment Wrapper. (5) Interface Device(s) obtain cue updates from the Cue API by polling via HTTPS for cue updates. When changed, the Interface Device(s) present the updated cue to the user as in (1).

Interface Devices

The user's interface device will (1) present a cognitive training game, (2) serve as an intermediary for the transmission of sensor data to the Cloud Infrastructure, and (3) present cues to the user as received by polling the Cue API for updates. Users will authenticate via standard OAuth procedures by way of their Interface Device and the resulting credential will be transmitted (1) along with the state and reward data transmitted to the Ingest API and (2) to the Cue API to receive a properly identified cue.

Game Interface Devices may be diverse - for example, we may be interested in some games that are presented via gaming console, Magic Leap headset, phone, tablet, laptop. To allow such flexibility of exploration of the game and interface space, we'll only require one underlying paradigm that the interface on which the game is being played be capable of (1) performing an OAuth flow to identify the user, and (2) transmitting game score data to the Ingest API.

Naturally our initial development efforts will focus on the interface device that provides the most development leverage, a laptop computer, without loss of generality. This device will be used to present the game, provide cues, and transmit sensor data. Within this context there are various options for cross-platform support - e.g. Electron (https://electronjs.org/) for building a native JS/HTML/CSS app or a traditional responsive (and perhaps progressive) web app.

Initially, again in the spirit of maximizing development leverage to develop an initial whole-system prototype, we elect to pursue the development of a simple progressive web app build using Polymer (https://www.polymer-project.org/) and WebComponents, deployed on Firebase, accessible at https://ai4hi.org/playground. This "playground" space will serve the purpose of both establishing the learning infrastructure to make use of and respond to game and user state as well as help to communicate and build interest in the goals and spirit of the project. Again, without loss of generality, the learning infrastructure established to support a game deployed in this way will be applicable to any existing Neuroscape game once each of those, in their own way, establish the infrastructure to exchange user-identified data streams with the learning infrastructure.

Points of discussion and exploration:

- Deploy a web playground space that includes a simple Javascript game such as Tetris or simple maze navigation (such as at https://ai4hi.org/playground).
- Demonstrate integration of playground game with Environment object by training an agent that can learn to map game score to a sinusoidal or other non-linear color distribution.
- Establish POC of user-identified lab-to-cloud data stream from any existing Neuroscape cognitive training game.

Sensors and Sensor Uplinks

Sensors collect measurements of the user's cognitive state and transmit this data to the Interface Device (or a secondary sensor uplink device) by way of a bluetooth or serial connection.

Sensor development platform

To aid in development both of the overall data infrastructure as well as that of improved sensing capability (Section III.) we envision an initially very simple sensor development platform constructed from a Raspberry Pi, a small number of electrodes, and a neoprene or cloth headband (such as one that can be found at one of many outdoor stores).

Points of discussion and exploration:

- Demonstrate POC of Raspberry Pi with target and reference sensors streaming data to web page via chrome.bluetooth.

Clinical sensor platforms

Many legacy clinical sensor platforms are available including not only a variety of clinical EEG systems but also sensory modalities like heart rate monitoring, cameras, GSR devices, and so on. Each of these devices has its own controller and mechanisms for accessing raw data. We envision these devices will either be tethered directly to the user's interface device, as in the case of the sensor development platform, or to a separate sensor uplink device that will be responsible for transmitting the sensor data to the Cloud Infrastructure Ingest API. Sensors not communicating with the Cloud Infrastructure via the user's Interface Device will still need to do so with user-identifying credentials obtained through an OAuth flow.

Points of discussion and exploration:

- Establish POC of user-identified lab-to-cloud data stream from any of commercial EEG systems.

Cloud Infrastructure

Each of the following Cloud Infrastructure components will run on the Google Cloud Platform, initially each on Google Container Engine with the possibility of porting some or all of these to managed services.

Ingest and Cue APIs

The Ingest and Cue APIs will initially be implemented as serverless functions via managed services of Cloud Functions or Firebase or via the Kubernetes native serverless framework Kubeless. The Ingest API will validate requests and credentials, passing the request data to the "ingest" PubSub topic. The Cue API Cloud Function will validate and authenticate requests, responding with the current relevant cue information having obtained this from a persistent database (e.g. Google Cloud DataStore).

Points of discussion and exploration:

- Deploy a Cloud Function that validates request structure, verifies auth, and relays message to a PubSub topic; Deploy a CF that does the same, obtaining and returning data from a persistent database.
- Should the Cue API be structured to expect user machines to poll for updates or is there a better paradigm?

Environment Wrapper

The environment wrapper will be implemented as a subclass of the OpenAI Gym Environment object (Brockman et al., 2016). The environment wrapper will be responsible for receiving and aggregating identified state and reward data, relaying this to the Agent, and dispatching cue instructions received from the Agent to the Cue API.

Points of discussion and exploration:

- Build a simple test environment that can serve as a mock of the data stream from the production game interface(s).
- Deploy a simple RL agent that learns from interaction with multiple human players simultaneously.

Agent and training

Initially we will use an implementation of the Proximal Policy Optimization (PPO) algorithm (Schulman et al., 2017) provided via the Tensor2Tensor library (Vaswani et al., 2018). This will position us well with a unified framework for both training RL agents and pre-training environment models with the best-practices and robustness of such a well-designed framework.

Agents will be trained on a Google Container Engine cluster properly configured to support GPU training. Training instances of various shapes and preemptibility will be available in various node pools. Production instances will be run with 208 GB of memory, 32 cores, 375 GB of local Solid State Disk capacity, and eight NVIDIA Tesla V100 GPUs (16GB RAM) costing $21.89/hr. While we do anticipate it being useful to distribute training within machines (with up to 8 GPUs) we don't for the time being anticipate the need to distribute training between machines.

Points of discussion and exploration:

- Pre-train an auto-encoder to predict game dynamics, then train a PPO agent that uses that dynamical model to play the game.

Summary points

- A coherent strategy is needed in regard to the full range of necessary system components.
- Data and ML infrastructure will make heavy use of managed cloud services and high-level frameworks to minimize unnecessary burden.

V. Machine learning strategy

Here we develop the foundations for a machine learning strategy to achieve the goals outlined in Section I. using a reinforcement learning system structured roughly as diagrammed in Section III., Figure N. We introduce the theory, promise, and challenges of deep reinforcement learning followed by a survey of the data and learning strategies we might employ to overcome these challenges.

Deep reinforcement learning

Reinforcement learning is a research area concerned with software agents that select actions (e.g. joystick movements) in the course of their interaction with an environment (such as an emulated Atari game) towards maximizing some cumulative reward (such as their score in that video game). Most commonly considered are environments with full observability that evolve in discrete time, i.e. Markov Decision Processes (MDPs). In this case, the structure of the control problem can be summarized graphically as in Figure N. Partially Observable Markov Decision Processes (POMDPs) are a natural extension of this wherein the environment is not fully observable by the agent. For clarity, a Markov process is one that depends on just its current or recent states; A decision process is simply one where a choice need be made observing a state to maximize a reward.

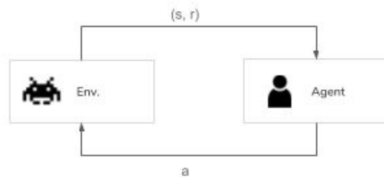


Figure N. Simple Markov Decision Process. Agent observes current environment state *s* and reward *r* and selects action *a*.

Here we define a *policy function* to be a probability distribution that maps any *(s, a)* pair to a probability value, i.e. is able to assign the probability of each available action *a* for any environment state *s.* A policy can be thought of intuitively as the behavior of the agent. The learning process can be viewed formally as a search for the parameterization of a policy with the highest expected return (i.e. that yields the highest reward when used to operate the environment for many steps, averaged across a representative sample of initial environment configurations). Often this expectation is a discounted expectation (applying the coefficient   to the nth term in the expectation sum), controlling how temporally myopic the agent is in regard to the expected return. A function that computes the expected return of a particular state or a (state, next-action) pair is referred to as a *state-value function*. Deep reinforcement learning is the class of approaches where deep neural networks are used to approximate the policy and/or state-value functions.

Reinforcement learning methods can be categorized as policy-based, value-based, or hybrid actor-critic approaches. Value-based approaches do not learn a policy, simply learning a value function and using a separate procedure to select an action given this value function (for example, Monte Carlo tree search). Policy-based methods are the reverse of this, learning a policy function and no value function. These approaches are capable of producing an explicit next action given a state observation but cannot produce explicit expected returns of hypothetical actions. Actor-critic methods are a hybrid of these two approaches, explicitly storing both a policy function and a value function.

Recently, deep reinforcement learning has been shown to be capable of solving a number of high-dimensional control problems, including playing Atari games (Guo et al,. 2014; Mnih et al., 2015; Schulman et al., 2015), robot locomotion and manipulation (Levine et al., 2016; Lillicrap et al., 2015; Water et al., 2015; Heess et al., 2015; Schulman et al., 2016; 2016), and mastering the game of Go (Silver et al., 2016). In all of these cases, the reinforcement learning agent trained on a very large quantity of data obtained from parallelized interaction with a software game emulator that allowed the program to play and learn at superhuman speeds. For example, the Atari results reported by Mnih et al. (2015) required tens of thousands of episodes of experience per game (where an episode is a single play of the game until failure, e.g. death, or timeout, somewhere on the order of <10 min at human gameplay speeds). Duan et al. (2016) estimate it would take a human player approximately 40 days playing without rest to equal the same amount of experience (or perhaps a more realistic 480 days of playing 2h/day).

To disambiguate, as diagrammed in Figure N., we see three primary ways in which an RL agent could interact with the user toward enhancing their (cognitive) game performance - by providing auxiliary (e.g. audio) cues, by modifying the user’s score, and/or by modify a game parameterization (such as the difficulty level, speed, categories of content, and so on).

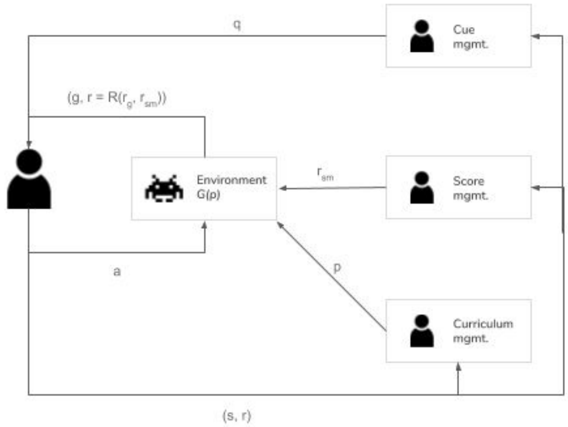


Figure N. Summary of ways an RL agent or agents could interact with a gaming or biofeedback gaming system. Human agent receives auxiliary cue q, game state observation g from game $G(p)$ under parameterization p, and a score composed of the game score r_g, as well as potentially a state-based score r_{sm}. Cue, score, and curriculum management, possibly performed by a single agent, are the tasks of determining q, p, and r_{sm} given a measurement of user physiological state s.

We note the potential of a free-standing cue system that can learn to provide performance-enhancing cues given neuro-/biometric data and performance data from *any* game as well as in the absence of a reward signal. Cognitive training games may be the producer of this reward signal. But most of us spend our days on a far broader array of tasks than this, primarily work-related. What if we could pre-train a cue system in the context of a cognitive training game, then bring this into a work context where either a different or no reward signal is present? Decoupling the cue system from one that might make direct modifications closely coupled to a specific game should afford this flexibility.

How can we use reinforcement learning to provide cues?

From a machine learning perspective, what steps can we take to make possible a human-in-the-loop RL system as diagrammed in Section III., Figure N.? To summarize, we propose building a reinforcement learning system that provides some sort of cue to a human user that is engaged in playing a cognitive training game that the RL agent does not observe (observing only the user's score and various measures of their cognitive state, such as an EEG signal). This cue might come in the form of a chime sound played when a user has become distracted (or perhaps something much more effective and perhaps unexpected if the machine is allowed to design the cues itself).

Using the right measure of performance

In the context of reinforcement learning, a *reward function* is a measure of the goodness of some environment state, computed internal to the environment, that determines the reward value observed by our agent. For example the function internal to the Atari game emulator that determines what the score is on some level of Breakout. If the agent receives an increasing score for progressively more destruction of colored blocks then it will be incentivized to learn a policy that maximizes the number of blocks broken. Likewise in the case of building a RL agent to learn to provide cues based on a human agent's score on some cognitive training game - the agent is incentivized to promote whatever objective is operationalized by the reward function internal to that game. Thus it is important to note that when designing this cognitive training game we must ensure higher scores in the game do indeed correspond to improved cognitive performance (for this is what our agent will be optimizing for).

One way to do this is to validate that game using a battery of well-established cognitive tests, confirming that improvement on the score in that game indeed predicts an increase in these separate measures. This can be thought of as developing a fast proxy for one of these well established (slow) measures of cognitive performance.

Parallel data acquisition / large number of users

One natural way to begin is to simply attempt to train an agent using one of the best known reinforcement learning algorithms using the largest number of users we can feasibly assemble for an initial pilot. At the very least, we will have an opportunity to test run our infrastructure and learn about its shortcomings so as to improve it for more important future experiments. In the best case, our initial setup may simply work, avoiding the time and expense of other complex undertakings that would serve to compensate for the data efficiency problem that might be solved in this way (with brute force).

One class of algorithm we might choose for such a pilot might be proximal policy optimization (PPO) which has been shown to perform comparatively or better than other approaches on a number of RL benchmarks (Schulman et al., 2017) while being more stable, sample efficient, and easier to use than comparably performant algorithms. Here we would train one (perhaps distributed) instance of the PPO algorithm on our cloud infrastructure as diagrammed in Section III., Figure N. which would interact with a pool of OpenAI Gym Environment objects that aggregate (reward, state) information for all users currently engaged in playing the game. We refer to that section for further discussion of infrastructure.

Pre-training strategies

In combination with the above suggested approach of simply training our system with the greatest number of individuals available we might pursue other more subtle pre-training approaches. The first class of approach, model learning, is motivated by the objective of constructing learning scenarios where we are able to train a network to develop a useful way of representing the structure and dynamics of the relevant modalities using data that is more easily accessible than that obtained through direct (relatively slow) interaction with users. The second category of pre-training approach we mention, meta-reinforcement learning, would be an attempt to learn a reinforcement learning algorithm in simulation that when used in interactions with human users would be able to learn useful policies with dramatically increased sample efficiency (depending heavily on our ability model real environment dynamics in our pre-training setting).

<u>Model learning</u>

How can we improve the sample efficiency of a reinforcement learning system by way of first learning a dynamics model of the relevant biometric modality? We might want to use facial expressions, heart rate, EEG, or other modalities to drive our learning but if we could first learn an implicit model of these across various situations and people, to learn what these data types are “like”, we might have an easier time training an RL agent to operate using them. Imagine for example our RL system will be asked to take in an EEG signal and game score and output a rich audio cue to drive the user’s performance higher. What if we first taught it what this EEG signal was like?

We can reason about this by analogy to multiple areas of recent work. One is the next-N-frame video prediction problem for learning to understand object, person, and generally world dynamics. Here, models are provided sequences of video frames and asked to predict known future frames. Designs vary in terms of whether these videos arise from simulated or real object dynamics and a key concern is the transferability of the resulting model to use in the real world (or wherever the model is to be used). Finn et al. (2016) explored a next-frame formulation of the physical object (interaction) dynamics problem, using video obtained from real robot arm/object interactions, showing they could learn models that predict plausible dynamics up to one second into the future. We might take a similar approach in the context of EEG or another biometric modality by learning to predict future steps in a time series of that modality - as a way of learning an implicit model of its dynamics.

Prediction of full future frames can be a rather substantial ask, especially when the problem is under-specified (i.e. for any given state there are many possible future states). One way to address this is to require only partial prediction, e.g. predicting one or a small number of channels (or region) within a multi-channel signal. We can think of this intuitively as incentivizing the system to learn a coherent understanding of how the dynamics of that channel (or region) relate to that of other channels. In our case we might imagine learning to predict a random subset of 4 EEG channels from the remaining 60/64 channels.

Another interesting approach applies in the case where we have multimodal data, for example videos that possess both video and audio streams. Here we can learn to predict one modality from the other or, more simply, learn to predict whether a given pair of streams correspond. Arandjelovic et al (2017) showed that in this latter case of predicting whether the audio and visuals extracted from videos correspond was shown to produce good audio and visual representations. Intuitively, we would be surprised to hear the sound of wind shown a video of an indoor scene. The authors show the model even learned fine-grained distinctions between close types of objects, such as two different instruments. One way to view this work is from the perspective that the presence of the additional audio modality allowed learning of a deeper understanding of the video modality. We have an opportunity to pursue an analogous approach where multiple modalities are available, such as using simultaneous EEG-fMRI data to train a deeper understanding of the EEG modality. Perhaps MRI time is too expensive for everyone to have access on a regular basis but perhaps researchers can use MRI data to pre-train a deeper understanding of EEG dynamics that can then be used alone at test time (similar in spirit to pre-training on audio correspondence and deploying as a video-only lip reader).

But we aren't purely concerned with the context-free dynamics of the brain or body - we want to understand these dynamics in the context of cognitive training. In lieu of course of learning such a correspondence through interaction, that being our deployment target, how can we learn such a correspondence? One approach would be to collect time-series of EEG or another biometric modality from users playing a cognitive training game and train a model to predict future game performance. Here, we intuit that game performance varies depending on our physiological state, quality of attention, and so on and that we can learn what features of the dynamics of the biometric signal correspond to this objective by learning to predict it (i.e. a state-prediction approach). Another approach we might take is to attempt to predict user traits from biometric data which might take the form of predicting a user's past performance on a battery of intelligence or other cognitive tests from biometric data, again with the objective of learning an implicit model of how the dynamics of that data relate to that variable.

Meta-reinforcement learning

Recent years have seen an increase in interest in meta approaches in deep learning, such as deep meta-reinforcement learning (or, using reinforcement learning to learn how to reinforcement learn, e.g. Duan et al., 2016; Wang et al., 2017) as well as more generally using neural networks to learn optimization procedures (Andrychowics et al., 2016; Chen et al., 2016; Li and Malik, 2016; Zoph and Le, 2106). In these cases, an improved optimization procedure can be learned through repeated practice solving a series of related optimization problems.

The work of Duan et al. (2016) and Wang et al. (2017) is of special interest, wherein a reinforcement learning algorithm was used to provide environment and reward signals to a second recurrent neural network. Over the course of training on a series of related problems, the second network in effect learned to implement a reinforcement learning algorithm capable of learning in the context of a new (related) problem without requiring gradient computation or weight updates at test time. Wang et al. (2017) clearly illustrative experiment where the second network can be seen to learn abstract task structure in the course of replicating the classic meta-learning experiment Harry Harlow originally performed on monkeys. After around 44,000 episodes of training, the network has learned to correctly identify that one of the two images presented will confer a reward and only needs one trial to deduce which is which.

Duan et al. (2016) explore a similar approach in the context of learning to navigate randomly generated mazes that share similar properties in regard to their size, the texture of the walls, and so on. This task requires the agent to cope with a high-dimensional space, sparse rewards, and the need for short-term memory without any human-specified primitives - learning these entirely relative to what will be useful for the task. At test time, again with weights, near perfect navigation performance was observed along with generalization to larger mazes (also nearly perfect but less than that on small mazes).

These approaches are good at exploiting features of the task distribution they are trained on, analogous to a human engineer designing an optimization algorithm more closely tailored to that particular MDP than one that would work well generally (like PPO). Here being a better algorithm means reaching the goal more quickly by exploring the search space more efficiently - having the tendency for exploratory actions to yield more information and thus being required to perform fewer of them. This can be thought of as resulting from the algorithm having a better sense of what that search space is “like”. Intuitively we can imagine an algorithm extensively trained to play a slot machine would develop an expectation that the whole world is like slot machines so when asked to adapt to playing Atari, with fixed weights, would not tend to explore the space efficiently and would likely not perform well on the game - this is because these are two very different MDP’s.

There are at least two ways to consider meta-reinforcement learning in our current context - in terms of a pre-training approach or as an intentional direct training approach. Firstly, the relevance to using meta-reinforcement learning in our case as a pre-training approach depends on our ability to construct a distribution of MDP’s sharing sufficient similarity to the MDP’s our algorithm will be asked to solve at test time, knowing the algorithm will learn to directly exploit these features to guide its policy search. How well do we understand the dynamics of the brain in order to be able to do this? This is an open question for further discussion and experimentation.

Another perspective on how meta-RL is relevant to our problem is by viewing a series of interactions with different human learners itself as a meta-learning problem, where learning the choice of cues to present to improve an individual’s performance is a problem space to explore (like an unseen maze). While this approach would present a lot of complex challenges the potential benefit would be an algorithm that learns to be able to learn to cue new users with less and less interaction the more users are interacted with.

Points of discussion and exploration:

- Does our ability to meta-learn on a new set of MDP’s improve by pre-meta-learning on a series of unrelated MDP distributions?
- How well do we understand the brain’s dynamics in regard to the way EEG signals vary through time and in relation to target cognitive states? Can construct a distribution of MDP’s that usefully models this task structure? Can we model this problem as learning to cue the improvement of a random distribution of architectures of meta-learning agents, with the parent network observing a noisy, random subset of the state of these?
- If we were to take a meta-learning approach, how would this work with usage at test time where rewards are not available, e.g. usage of cue system outside of context of known rewards? (e.g. continue receiving biofeedback cues while performing non-game work such as coding or reading)

Summary points

- Reinforcement learning is a very promising paradigm but standard approaches require a large amount of interaction, posing a challenge for small-scale human-in-the-loop systems.
- We have the potential to overcome these data quantity challenges by simply recruiting a modest number of compensated or volunteer users.
- The system will optimize for whatever we incentivize it to - it is essential that the performance measure we use to drive the optimization be one that measures what we truly mean to improve and that it provide feedback on as close to a continuous basis as possible.

VI. People and organizational structures

Project leadership

Christopher W. Beitel, Ph.D., Project Director (Machine Learning Research and Engineering)

Christopher is a polymath with diverse experience across mathematics, neuroscience, machine learning, software engineering, data infrastructure, and digital marketing and communication. He holds a Ph.D. in Genetics and a bachelor's degree in Mathematics, pioneered the application of Hi-C to the assembly and deconvolution of genomes and metagenomes, and is a staunch supporter of Open Source, Open Access, and the improvement of shared scientific research capabilities.

Joaquin A. Anguera, Ph.D. Project Leader (Clinical Program)

Joaquin's current work leverages state-of-the-art technological approaches to create i) advanced tools to enhance/remediate cognitive function and ii) use mobile technology to robustly characterizing individual abilities both in and outside of the laboratory. Thus, the combination of his expertise in concert with those of the assembled team, highlight the potential to achieve the goals set forth in this proposed document.

Adam Gazzaley, M.D., Ph.D., Project Leader (Clinical and Systems Neuroscience)

Adam Gazzaley, M.D., Ph.D. is Professor in Neurology, Physiology and Psychiatry at the UCSF, and the Founder & Executive Director of Neuroscape. Dr. Gazzaley is co-founder and Chief Science Advisor of Akili Interactive and JAZZ Venture Partners. He has been a scientific advisor for over a dozen companies, filed multiple patents, authored over 130 scientific articles, and delivered over 600 invited presentations around the world. He wrote and hosted the nationally-televised *PBS* special "The Distracted Mind with Dr. Adam Gazzaley*",* and co-authored the 2016 MIT Press book *"*The Distracted Mind: Ancient Brains in a High-Tech World", winner of the 2017 PROSE Award". He has received many awards, including the 2015 Society for Neuroscience – Science Educator Award.

Auxiliary contributions strategy

Various strategies exist to cultivate the contributions of interested engineers, researchers, and students.

Research for credit

Work on this project, and corresponding mentorship, stands to be a prime educational opportunity for undergraduate and graduate students. Engaging this population should be easy through advertisements in classes and flyers. Benefitting their educational experience the same high standards will be applied to their work as would be expected of a senior engineer (except in their case work will be distributed over small teams).

Hackathons, workshops, and meetups

We have an opportunity to engage the “extra project time” of the broader SF bay area tech community. Holding hackathons, workshops, and meetups should be an effective means of getting the attention of the desired population. Retaining the attention and work of volunteer contributors will be a challenge and we must work to ensure their incentives for contribution are continuing to be fed (e.g. the opportunity to be publicly recognized for the completion of a sub-project whether in presentation to the group or on behalf of the group at a local hackathon, workshop, meetup, or conference). It is recognized that a key mechanism for engaging and retaining the contribution of these populations is that the project seem exciting, interesting/fascinating, and highly impactful. Project touch-points should be designed to serve this purpose.

Potential organizational collaborators and stakeholders

Here we propose various organizational entities that might participate in Project Clarify. We mean to be quite clear that none of these entities have yet signed on to the project (and by describing here we explicitly do not claim them to be associated with the project).

University of California, San Francisco and Neuroscape

The Neuroscape Center at UCSF (P.I. Adam Gazzaley) stands to make a valuable intellectual and facilities resource contribution to the project including access to costly brain-measurement systems. The Center also stands to provide valuable access to patient populations to participate in future clinical trials. The development of a shared ecosystem of infrastructural components and hardware development resources stands to benefit numerous parties not only at UCSF but across the emerging field of AI-enhanced neurofeedback gaming.

- 3T Siemens Prisma Fit MRI scanner with 64- and 20-channel head and neck coils; Capability for simultaneous diffusion and blood-oxygen level dependent (fMRI) imaging; Upgrades to enable cutting-edge resolution in diffusion tensor / connectome imaging.
- Various clinical-grade EEG and tCS systems.

The Center for Healthy Minds, University of Wisconsin-Madison

The Center for Healthy Minds (P.I. Richard Davidson) stands to make a valuable intellectual contribution to the project based on their expertise in the domain of contemplative neuroscience and Project Clarify seems very well aligned with the objectives of the CHM including the desire to bring the wonderful benefits of meditation to the world. For example in particular we envision their contribution to the development of a new category of contemplative AI-enabled neurofeedback games. Davidson’s and colleagues’ research has yielded insight into the way the brain arrives at state and trait changes through long-term meditation and has spanned a diversity of brain measurement technologies. Davidson and the CHM have a strong track-record of disseminating tools, infrastructure, and insights to elevate the broader research community.

Google

This project stands to benefit Google in various ways including helping to build demand for Google Cloud services (e.g. GPUs necessary for various entities to train models capable of performing the above functions), delivering the benefit of cognitive training to employees (e.g. in the form of systems that can better predict cognitive fatigue and suggest rest periods), providing insight into a general paradigm by which models of cognition can be constructed (i.e. through predictive interaction with humans engaged in cognitive tasks), building understanding of the future of biofeedback computing, and to attract research talent by association with projects of high interestingness and impact. Google stands to benefit the project by way of the contribution of cloud computing resources and advanced technical expertise.

Relation to other Neuroscape projects

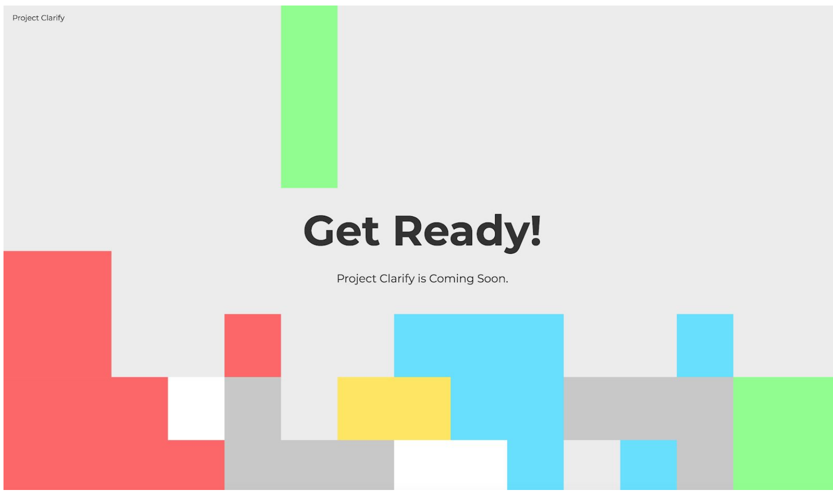
Virtually all projects within Neuroscape stand to benefit from advances in algorithms and both hardware and computational infrastructure to enable the next generation of neurofeedback gaming. Software and hardware releases, pre-release sharing, and extensive documentation will enable this benefit to be realized. In turn, directors of these other projects will improve and accelerate this project by providing strategic guidance primarily in regard to clinical, systems, and theoretical neuroscience components. Where these other games are able to conform to the API specification of Project Clarify each of this diverse collection of games will be able to benefit from AI-enabled neurofeedback cues.

'Project Clarify' or similar

Encapsulating the above-proposed project in an organizational construct may be beneficial for the purpose of soliciting resource contributions from industry and work contributions from individual contributors. We propose the name "Project Clarify" as a working title pending further discussion. This name is in reference to the experience in users we mean to induce with the tools of neurofeedback gaming - a significantly increased sense of mental clarity that is, very roughly speaking, characteristic of a better regulated working memory space.

Project touchpoints:

- Microsite and playground space: https://ai4hi.org
- Github: https://github.com/cwbeitel/projectclarify



Summary points

- Synergy among multiple projects, organizations, and categories of personnel will be necessary to deliver on the objectives and general strategy outlined in this document; Understanding and leveraging the incentives of member entities is key to project success.
- There are various options for a personnel bootstrap.

VII. Seed roadmap

Roadmap categories

Strategy - What do we mean to accomplish and how do we measure success? What related work can inform our decision of what to pursue? What should be done, when?

Community and Organizational - Who will support the work? Who will do the work?

Computational Infrastructure - How will data be ingested and stored? How will models be trained, stored, and pushed to devices?

Machine Learning - What models will be trained and how?

Interfaces - Through what interface will users perform the cognitive training task?

Sensory Devices - What device will be used to acquire neuro- and other biometric data to enable feedback?

Seed roadmap

	Q2 2018	**Q3 2018**	**Q4 2018**
Strategy	Polished version of strat. given expert feedback		
Community & Org.	Establish leadership and org. membership; Resources for pilot.		
Computational infrastructure	Model-based PPO agent learns from human biometrics		
Machine Learning	Model-based PPO agent learns from human biometrics		
Interfaces	Playground microsite and dev./demo. games	Integration with existing Neuroscape games	

Sensory Devices	Development device POC		

Table N. Seed roadmap.

Deliverables

Publications

The work performed in this project will be published in peer-reviewed scientific journals with a preference for Open Access. Publications represent the formal channel by which research findings on the means to boost cognitive skill acquisition may be evaluated and disseminated by and to the broader research community.

Open source software and hardware

All software and hardware (developed by members of the project in support of project goals) necessary to reproduce the work described in these publications will be released publicly via GitHub under an Apache 2.0 Open Source License.

Blog posts

At least for each peer-reviewed publication or major software release a blog post in a central project location, such as blog.ai4hi.org, will be prepared with the intention of making the preceding work highly accessible through intuitive explanations and figures.

Presentations and presentation videos

At least annually a project status talk will be presented publicly, recorded, and uploaded to YouTube.

Summary points

- There is a roadmap with further detail pending further clarity on strategy, contributors, resources, and knowledge gained from initial mockups.

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