Artificial Neural Networks as Being Models of Human Learning

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Introduction

At a foundational level, there is an evident connection between humans' ability to learn and the way artificial intelligence systems learn. Purely based on what we know from modern technology, we have founded branches of machine learning and deep learning to be the pinnacle subdivisions, tasked with the responsibility to resemble and mimic the behavior, perception, and learning capabilities of the brain at a neuronal level. Although there is a great deal of advancement in current day innovations with computer systems, or centuries of research on how the brain works, the junction between the two is a beyond comprehensible field that demands intensive research, as we find it clear artificial neural networks and their decision making skills cannot exist without human mockery.

In order to begin understanding artificial learning systems, we must first observe the neural mechanisms of human learning, trying to conceptualize how our neural networks fire and communicate with each other to create classifications and decisions within life. Without a proper grasp of how our neurons send signals, it is difficult to recognize what the similarities of machine and deep learning are, as well as notice what these algorithms are missing, so we are able to improve these systems for better future functionality. Our brains are built through intricacies of modular networks that are stimulating various regions including the hippocampus, entorhinal cortex, perirhinal cortex, and their connectivity to neocortical areas solely for one task of pattern separation and distinguishing spatial source of items to be memorized (Stricker 2023). From a neuropsychological standpoint, these learning systems take a variety of both cognitive processing and bottom-up processing which help encode information properly, and use these memories and learned experiences to improve their skills. These nerve cells communicate via a combination of electrical and chemical signals; when learning something, because these two neurons in different parts of the brain are frequently interacting, they form a connection that allows message transmission in a more easy and accurate way. This learning mechanism arises through spike-timing-dependent plasticity, with evidence indicating long-term synaptic potentiation forms, allowing for precision of stronger thicker nerve cells. As we branch out to a more widened view of the brain, this conglomerate of neurons, glial cells, blood vessels, all specialize to participate and function towards language, face recognition, motor activity, and spatial recognition.

Translating this to artificial intelligence, we can build a bridge between the two that takes ways of learning into a technological way. Pioneered from the 1960s, the US Department of Defence took interest in this work and began training computers to mimic basic human reasoning. This excitement of "thinking machines" ignited the growth of machine learning and made it possible for AI to learn from experience, adjusting to new input and perform human-like tasks. Although it is not to the complexity of the human brain, it is still not as simple as algorithms processing large amounts of data and recognising patterns. There are several branches that AI has been formed upon—machine learning being derived from supervised learning (using labeled training data to get direct feedback) and unsupervised learning (using unlabeled data without feedback); deep learning which builds a convolutional neural network trained through extraction and feature detections; robotics that undergo supervision and reinforcement imitation learning based on programming.

Each of these algorithmic techniques of artificial systems is a mere reflection of what humans can already do. Our ability to categorize and make inferences is based on past learning of situations and exposure to similar ideas; the way our brain has multilayered structures of neurons dedicated to communication and adaptability for prediction making; how humans grow and change based on their surroundings and what they are told to do.

There is a clear path that begins with the neuroscience and psychology of human learning, and carries into being the groundwork for what computer scientists have used with mathematics and logic to create AI. This raises the demand for further research in computational neuroscience. As we narrow the gap between how different artificial systems are to the way the human brain is, we will be much better equipped at creating real form intelligence.

Review

To get a better understanding of how knowledge-based technology systems are models of human learning, it is necessary to break down the neural mechanisms that show how we perceive the world due to experience. In research focused on the context of learning acquisition at a neurological level, it is applicable to observe the structure that humans complete varying tasks and the neural firing that occurs during the learning process. This is a challenge for progress in AI; in order to use human brain activity to guide machine learning requires an algorithm building approach dedicated to skilled representation modeling and cognitive decision making. A novel method that has been recently improving this field is neurally-weighted algorithms that are trained in a separate stream of data, derived from human brain activity. With this approach of AI trying to mimic what humans are doing, it seems it will never be straightforward due to complications of a person's mental state, personal biases, and personality, all playing a significant role in how someone learns and behaves. Ultimately, to create a sentient being that has traits of intelligence, emotion, and free will requires these measures of personal choice and volition. Current day technology does not seem to have that independence. As we move into this next section observing AI learning versus human learning, we will research empirical studies that have been paving the way for algorithmic designs being centered around the cognitive networks of the brain.

Neurological Composition of Perceptual Learning In Humans

In current research observing the mechanisms of neural pathways, it takes analyzing the nervous system and configuration of stimulation to assess what our brain is doing when learning. By being exposed to a visual task for example, our brain processes this information once and sends the signals accordingly. Similarly, as this cycle is repeated, we are able to repeat that signal firing and learn to make better decisions as we make stronger comprehension of it. In a study conducted that targets the modifications of the brain's sensory adaptations, it provides great insight on what neural networks are actually doing during the learning process. (Hamamé et al. 2011)

Methods and Results

Through stimulus based computer visual tasks, this study observed EEG patterns and psychophysical detections of vision to determine the intricacies of neural activity in terms of improvement through perceptual learning. Notably, as sensitivity to stimulus decreased and perceptual learning upheld, it mirrored changes precisely to the gamma band activity alongside other components (e.g. P3 & N2pc amplitude, ERP waves, GBA & ABA, RT). Moreover, training the human brain through psychophysical tasks is directly associated with specific and measurable changes in neural activity. Likewise, the context of learning acquisition at a neurological level shows two levels of processing, suggesting a more complex scenario of dynamically interacting neural reorganizations.

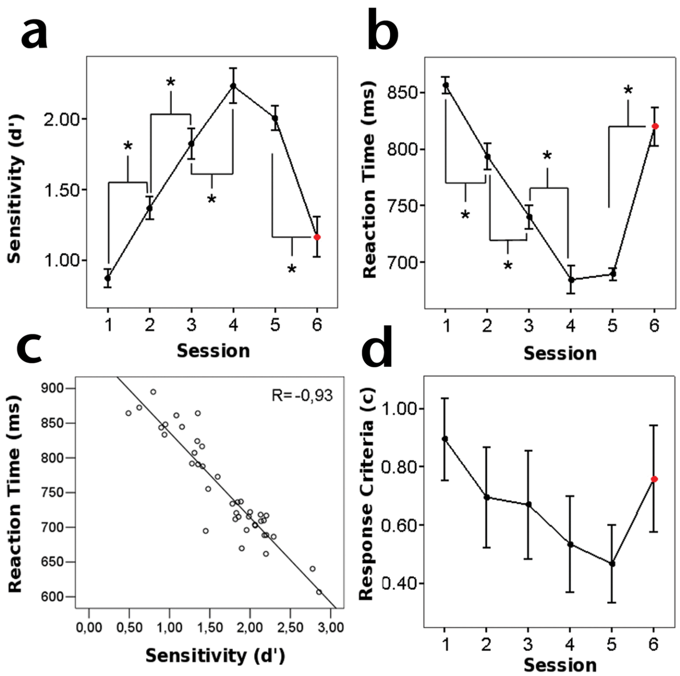

Figure 1: Psychophysical assessment of perceptual learning ((Hamamé et al. 2011)
https://journals.plos.org/plosone/article/figure?id=10.1371/journal.pone.0019221.g002

Further detail into the psychophysical data provides an informative collection of how to train someone's mind and the changes that occur to their sensitivity. It was confirmed that "performance improvement was specific for the trained stimuli as shown by the significant decrease in sensitivity when subjects were tested using a different target orientation in a subsequent control session" (pg 4). This in its entirety is depicted in Figure 1 above to provide stronger evidence for trained stimulus orientation. We can visually get an understanding of how throughout various sessions of receiving this exposure and guiding the brain to behave in different ways, the mechanisms used to improve performance occurred due to being trained to do so. It was intended that there is observable perceptual learning going on. In comparison to control groups, the neural processes throughout training are significant enough to show retention.

Implications

It is quite the discovery to gain insight on how exactly our brain is receiving and encoding information. The dynamic interaction between sensory cortices and upstream attentional networks helps deepen the foundation of how humans operate during perceptual learning tasks. From this, we can imitate that for designing artificial neural networks. While a direct replication might not be feasible, how neurons fire during the learning process, what kind of training humans need, and how the structure of our networks are distributed, presents a demanding challenge for progress in artificial intelligence.

Brainwave Data Utilization for Algorithmic Design

Machine learning has long been worked through data inputted into a training process, and configuring out a classification based on patterns. These algorithms are created with the intention to learn. With this, the human brain has long served as the inspiration with recent strategy to bias the solution of a machine learning algorithm to match the internal representations found in the visual cortex. These advances in machine learning have focused on biologically-consistent ways of interpreting different kinds of data, with a new study tackling neurally-weighted classifiers which are high-performers in classification (Fong, Scheirer, and Cox 2018).

Methods and Results

By extracting scalar activity weight from high-dimensional fMRI machinery, the results of this study leveraged strong evidence on how multisensory integration of brain activity can be used to teach machine learning algorithms active learning methods. Experiments were conducted for the 127 ways that the seven higher-level visual cortical regions could be combined. From this technique, it revealed significantly improved classification accuracy.The application of using a large dataset of neuroimaging techniques in order to train supervised ML classifiers, gave an impactful avenue for advancing artificial algorithms. This improvement to their decision making and representational paradigms that mimic the brain's processing techniques is much different from the traditional CNN models.

Implications

There are still limitations that come with this study. Although machine learning algorithms use measures of human behavior to guide them via active learning, structured domain knowledge, and discriminative feature identification, the only one we can draw conclusions from pertaining to this study is the ability to create internal representations (pg 6).

These algorithms are primarily learning through an abundance of data provided, at high dimensional lengths. The inability to sense and conceptualize is what lacks greatly, and makes learning as a brain distinctly different when compared to artificial learning. In terms of moving forward with machine learning models and their strengths in knowledge-based tasks, this research makes it evident that mimicry of the brain is possible, yet it does not achieve a perfect match. This still is not to undermine how interactions between AI and neuropsychology are needed to be able to advance these algorithms. The ability to understand how we learn and decipher it into machines is the eventual goal.

Potentials of Deep Learning Models Mirroring Human Personality

To tackle the concept of deep learning is a substantial job. It entails technology that is still quite experimental, and includes diverse fields of computer vision, natural language processing, data modeling, generative pre-trained transformers, and more (*Dive into Deep Learning*, Zhang et al. 2023). This revolutionary problem is trying to create code that develops its own intuition and puts humanoid ideas into practice. Deep learning tasks AI to make decisions and build its own perception of cognition. Ramesh and Chakraborty (2022) address this proposition through visualizing if deep learning image classifiers can exhibit humanistic characteristics such as biases and emotional choices.

Methods and Results

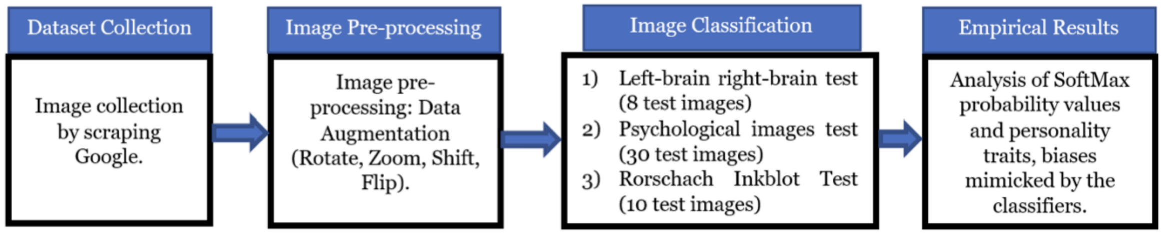

Figure 2: Personality Traits & Biases of Deep Learning Classifiers Experimental Setup (Ramesh & Chakraborty 2022)
https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1010&context=acis2022

This study assesses AI techniques and challenges it to tasks that go beyond its training of classification and detection. By performing left-brain right-brain tests, psychological images tests, and Rorschach's inkblot tests on eight different state-of-the-art deep learning classifiers, it sees if the aptitude of human cognitive learning and problem-solving skills is reflected in current day algorithms. The results detail how the majority of all eight deep learning models behave as though similarly to the left-brain regions, focusing on critical thinking and reasoning, while lacking the creative and intuitive elements of the right brain. Likewise, its interpretation of images focuses on engaging with the presence of larger objects whilst ignoring the smaller 'less important' ones.

Implications
These visual transformers are not ideal when it comes to imitation of human thought. When a person is presented with a psychologically induced image test, the concepts they may build and emotion they feel affects what they decide to do. Our learning and past experiences of memory vastly influences our choices in life; yet with these deep learning classifiers, they are unable to do so. It does seem a bit inconclusive from the claims made, as the research mentions how better direction from psychologists and neuroscientists on brain mapping and emotional behavior would guide further research in comparisons of man and AI. Although these flaws do exist, scientists can draw conclusions of how deep learning models and their performance in computer vision do not emulate what the brain is tasked to do. They lack the connection and feelings a human may portray, which in turn decrease intelligence.

Discussion
When discussing the field of artificial intelligence as a whole there is a certain depiction society has of it. AI is a diverse and multifaceted technological development that people perceive as human-like. Yet, a vast majority of the research educates us on how it is far more complicated. We want to think that self-driving cars, GPTs, and automation systems are brilliant at what they do. They learn and know the solutions to everything from a general standpoint, yet the fundamental difference from human intelligence and artificial intelligence is the lack of embodiment and understanding. These systems do not share human concerns or connections with the world, but they do show us that we can create the groundwork to make them learn and perceive the world like us in the future.

This conversation of human cognition is the mental actions we possess that are acquired from knowledge, thought, experience, and sensation. We retain information and are exposed to nuance events constantly, perceiving millions of bits of information just visually every second of our lives. Our brains are constantly being rewired and growing from birth, with specialized areas dedicated to intelligence, behavior, memory, and much more. We change the way we perceive the world due to experience. The mechanisms of perceptual learning involve changes at multiple levels of sensory processing hierarchy, with modifications synaptically and functionally to alter neural firing patterns. Whether that is from practice and training, or feedback/reinforcement, the neural breakdown of the cortical regions are interwoven to shape our glimpse of reality.

Translating this to an algorithm is the fundamental goal. In order to emulate a program to view an image, construct its own awareness of what is occurring, reshape its nodes to align with the new piece of information, and then take the appropriate actions for the future, all in an extraordinarily efficient manner would be revolutionary. Even from a developmental standpoint, humans experience training for their initial twenty one years of life, using resources, education, and forming curiosity in personal areas. Yet, the expectation is that algorithms should be able to do the same in milliseconds, on any topic given to them. It takes time and precision to do such, while also considering the faults and error-prone aspects of what technology can bring. However, if we are able to move into a space where AI learning resembles how humans do, it will create a new world for computer science.

Analysis

For a proper apperception of what it means to start at the neurological level of human learning, and configure it into the artificial neural networks of deep learning is a big jump. In the three studies observed above, all are directed towards the ability to learn, discriminate, perceive, and draw the proper conclusions. The differences pertain to whether it is a human, a machine learning algorithm, or a deep learning model that takes the place of the participants.

Humans' way of learning is displayed through a defined representation of neural activity. The nerve communications, various firing rates, thickness of nerve endings, depict how the brain acts when processing. It is not merely one mechanism that controls this, but instead by which different brain networks reorganize their activity to produce these psychophysical improvements of perceptual learning. (Hamamé et al. 2011). These ways of coordinating activation and capturing information do somewhat translate towards algorithmic design. The neural weighted algorithms have a performance technique of encoding the internal representations like the human brain. With appropriate data collection, sensory modality is presented into machine learning structures. The different types of inputs a model is processing, parallels the multisensory integration of the brain (Fong, Scheirer, and Cox 2018). If it is possible to harness the strengths of human mental expression, these internal representations employed by the brain guide AI abundantly. The sensitivity of this is used for deep neural networks as well in order to have effective processing (Ramesh & Chakraborty 2022). Intelligent decision support systems (IDDSs) are suitable in this way. They assist in decision-making by leveraging artificial intelligence techniques. Through taking relevant information, analyzing data, and following up with offering solutions/recommendations, it creates a domain knowledge base that is similar to human-like tendencies (Ahmad & Simonovic 2006).

We see the diverse forms that AI can take shape of. Whether based on its capabilities—using previous learning and skills to accomplish new goals, or its functionalities—completing solutions and standing as a task-oriented predictor, it shares the sensory modality of perception described above, which is key to human intelligence. Breaking it down into each sense humans possess, there is vision, hearing, touch, taste, smell, proprioception, and vestibular sense. All of these feelings are what make it possible to detect the world around us, and formulate our view of the environment. From this we speculate and imagine through abstract thought, even being able to decipher when in novel situations. In terms of sight, our bodies detect light and color, encoding it through our retina and processing the information in our occipital lobe. Given any form of visual task, the study done by Hamamé et al. (2011) offers evidence of the visual cortices capability to respond to specific stimuli features (e.g. orientation, shape). Convolutional neural networks (CNNs) and deep learning classifiers exemplify this by facial recognition, object detection, and image segmentation (Ramesh & Chakraborty 2022). A principal example of this can be systems like Apple's Face ID which uses CNNs to map the unique geometry of a user's face through feature extraction, deciphering it into a network of learned associate patterns and identities, and storing the data securely to distinguish one individual's face from another (Apple Computer Vision Machine Learning Team 2017). Just like humans' ability to store familiar faces for the future through neural processing of memory in the fusiform face area (FFA), deep learning mimics this through algorithmic programming and data projection.

The possibilities of biologically-based AI models are what the future may entail. Fong, Scheirer, and Cox's (2018) study tried to reflect the visual networks of how humans are when presented with a visual task, by training supervised classification models with weighting individual training images from fMRI recording values. Once trained, these models were able to classify images without the benefit of neural data. This one step of embodied learning that takes human attention and discrimination for tasks, and places them into an artificial model, outscored the traditional ML systems that were intended to do well. There is promise in these findings; we can see how mimicry of the brain can bring AI closer to how humans think. The key difference which shows between this study and the findings of Hamamé et al. (2011) of humans is the multi-layered processing that the brain does so well. It can network and create selective neurons at ease with the orchestration of neurophysiological processes, which are a scheme of experience-dependent activity. These machine learning models, on the other hand, represent a mere fraction of the skills that the brain is capable of.

Moving forward with this, we see an even larger separation when it comes to abstract emotion and judgment of artificial intelligence and man. The competence of a deep learning model to visualize an image and regurgitate what it represents is one thing, but to reflect human personality and sentiment is drastically different. Findings from Ramesh & Chakraborty (2022) suggest that these models' ability to detect tiny objects result from the inbuilt biases towards one particular class. The reason for humans' visual detection, shown in the other studies, being so easily trained and outperforming with perceptual learning, fails when it comes to CNNs. This is a result of if something is very small in size, the probability of it being recognized in the presence of something larger is close to zero. Humans are able to interpret and learn from everything that is being shown. Solely due to the size of an object does not cause the brain to completely ignore it, but that does not mean the same for these models. Additionally, AI classifiers start to form rash, insensible decisions because it is not forming its own opinions when provided an emotional image, but just trying to predict how to behave as a mentally normal person in general.

Thus we must view the future of AI with precaution. It is substantial to note the way neural processing can be similar to artificial learning, yet there is still much to be discovered with the limitations of what these models are actually capable of. They are not able to grow, develop, and think abstractly, but with more biologically and psychologically attuned algorithms, we can see strong progression in certain areas.

Conclusion

The future of artificial intelligence is exciting. From the initial days of binary coding, to modern day human-mimicry computing, the innovations that are to come will transform society. However, we do see that in today's view of what artificial intelligence is, it will take much more time. Scientists and engineers have still yet been able to create an algorithmic model that reflects us as humans. The brain's ability to obtain automaticity and attention, utilize representations and cognitive load, or organize and problem solve, are advanced skills that require a versatile way of perception.

In terms of what has emerged throughout these reviewed studies, it raises conversation of the next steps for AI and its need for human modeling. Described in the text below are pondering examinations and queries that stem from this topic.

I. Neurofeedback for model training, taken from real-time brain activity data to adjust and fine-tune machine learning models have improved the performance and efficiency of these artificial models.
II. The multi-sensory processing of initial rapid learning followed by slower, more gradual improvements at a neurological level is shown in biological processes of the human brain, and transferring those principles to improve artificial neural network (ANN) training will provide greater insight on AI strengths.
III. There still deems a great divide in how closely ANNs can or should mimic the human brain, considering the differences in architecture and function, shown by the research.
IV. Cross-disciplinary collaboration between neuroscientists, psychologists, and computer scientists/engineers will allow for further advancements in understanding of human learning to improve artificial models.
V. The ethical implications of deep learning models extending to reflecting human-like personality traits raises concerns regarding the use and potential manipulation of emotion data by AI systems.
VI. Due to the limitations of neuroscience as well as computer science, being able to see how neurons of the brain can resemble nodes of AI in terms of learning capabilities and generalizability will help determine the accuracy and validity of complex mimicry.

Proposal

From these guidelines of summary that have developed from the current studies, it is necessary to draw steps towards further research on artificial intelligence modeling human learning. There are two specific paths that need to be taken in order to move forward in this direction. The initial being research in computational neuroscience, and the latter being experiments in artificial neural networks.

Computational neuroscience is a field that deserves far more attention for its focus on how the brain processes information, learns, and adapts. By understanding these neural mechanisms, AI can develop more sophisticated algorithms that do not only act as task-focused, but instead share the Hebbian principle of "cells that fire together, wire together" and also work in a neuroplasticity and hierarchical processing manner. An experiment that can be done is to observe how the brain is adept at functioning in noisy environments and making sense of incomplete data. Studying the selective attention and preference for important information the brain is so strong at, can shape deep learning models that are more robust to noise and able to deal with real-world uncertainties. Similar to research done by Hamamé et al. (2011) and Fong, Scheirer, and Cox (2018), observing these EEG patterns and fMRI recordings while also breaking down the nerve clusters of their communication, computational neuroscientists will be able to prove what humans are doing cognitively to learn so well.

Furthermore, these neurological findings of the future will help pave the way for programming talents. Although current day engineers have familiarized themselves with how AI models are able to take in training data, and build weighted neural networks or varying classifiers to determine what is the correct choice, there is still a great disparity with how these models truly think, or if they are even genuinely thinking at all. The attention of AI needs to be on the research aspect more, and less on the business side. Experiments dedicated to this may begin with comparing different interpretability techniques with these black-box models to evaluate for accuracy and validity; see what kinds of architectures provide the best results for different situations, and start modulating them into true learning scenarios.

Fundamentally, future research will come down to the possible creation of what can be a genuine sentient being, designed entirely from programming. If neuroscientists were in the future able to break down every nerve connection and the precise brain regions of how they communicate, it could be translated to computer scientists and mathematicians who have hundreds of different types of AI models, all skilled in different tasks and functions. By doing so, engineers can create a database library where different brain regions and cortices are imitated one by one through AI models communicating together. Founded with the multi-layered processing and complexity of thought, this form of AI would mimic the brain. It could learn and be placed in novel situations, think independently and draw conclusions when asked to, and maybe even take the role of a human as a whole. This is merely a hypothesis, but it does present the world with a gravitating pull towards what artificial intelligence can potentially be, if it did have a brain.

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