COMPUTATIONAL PSYCHIATRY: THE APPLICATION OF MACHINE & DEEP LEARNING IN RELATION TO COGNITIVE DYSFUNCTION

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From targeted advertising to personalized spam messages, machine and deep learning have become a vehicle for many companies to deliver products directly to consumers. As the acceptance of of these methods as a practical and economical option grows so do the potential applications as more money and time is invested in the development and research of these systems. While many of the applications are focused on corporate uses, other more altruistic approaches have arisen, such as computational psychiatry. Computational psychiatry focuses on the use of machine and deep learning representations to identify relationships between variables in relation to various cognitive dysfunctions to help develop a more thorough understanding.. This literature review will examine the current methodologies of using computational psychiatry to investigate mental health, look at examples of successful uses of computational psychiatry, examine how these methodologies have put to use some of the common practices in machine and learning, and speculate on what the future holds for these applications while suggesting possible areas of study or methodologies for future progression.

A prime example of the applications of computational psychiatry is expressed in the research of schizophrenia. The medical understanding of schizophrenia is constantly expanding and nothing has impeded this progress more than the analysis of large amounts of data, hence the introduction of machine learning techniques to reduce the dimensionality of the problem. The way the studies have addressed the issue of large data sets in the analysis of schizophrenic cases is the use of k-means clustering and support vector machines (Krystal et al., 2017, p. 473). One study examined by this review took a large set of randomized data, from the European First Episode of Schizophrenia Trial, and applied these techniques to identify a set of variables that was able to predict multiple clinical outcomes with over 70% accuracy at varying lengths of treatment (Krystal et al., 2017, p. 474). Another effective use of computational psychiatry is clinical translation, using a deep learning representation informed by biophysical properties to model complex issues such as the nature of microcircuit dysfunctions in psychiatric disorders (Krystal et al., 2017, p. 474). Microcircuit dysfunctions are disturbances in the synaptic firing of the brain which may arise with schizophrenia but can be the result of a variety of factors. Through the use of biophysically informed computer modelling researchers have been able to pinpoint specific disturbances in the cortical activity similar to the disturbances in healthy patients who have been administered ketamine (Krystal et al., 2017, p. 474). By examining this relationship it can be seen that by regularizing the balance of chemicals that cause excitation or inhibit the brain, such as ketamine, conditions like schizophrenia can be treated more precisely (Krystal et al., 2017, p. 474). These applications have helped to better understand the complex variables that make up the symptoms of schizophrenia, by furthering our knowledge of these mental health disorders we can learn to fight them more effectively and develop treatment plans that address the core of the problem and not the symptoms.

Building upon these ideas, reinforcement learning has also been used to examine mood disorders and anxiety, more specifically to model what is a known as a Pavlovian effect in which involuntary actions are determined upon whether or not they are appropriate for receiving a reward or avoiding punishment (Montague, Dolan, Firston, & Dayan, 2012, p. 75). A related study looks at depression and its relation to serotonin, when serotonin is released into the brain a person will experience positive emotions but in patients suffering with depression the release of serotonin is inhibited due to the process of reuptake, the reabsorption of serotonin into the brain (Montague, Dolan, Firston, & Dayan, 2012, p. 75). Attempts to model this relationship have come to the understanding that serotonin's contribution to behavioural inhibition is Pavlovian, the subject does not have to learn what is right or wrong in the face of punishment or reward (Montague, Dolan, Firston, & Dayan, 2012, p. 75). The understanding and ability to model Pavlovian effects in depression is important as it allows researchers to work toward building a proper computational phenotype of cognition. A computational phenotype is a complex model of a specific neural or behavioural type, these models should be able to show depth of variation between individuals and can be used to develop an understanding of what healthy and diseased cognitions look like acting as a road map to the characteristics of cognitive illnesses (Montague, Dolan, Firston, & Dayan, 2012, p. 77). Deep reinforcement learning is at the core of computational phenotyping as it provides constraints to help make the connection between the molecular and behavioural levels of cognitive function (Montague, Dolan, Firston, & Dayan, 2012, p. 77). In the past, trust based games (such as the Stag Hunt game) have been used to phenotype those on the autism spectrum, using the decision whether or not to trust their partner in the game to simulate a healthy human interaction (Montague, Dolan, Firston, & Dayan, 2012, p. 77). The important part of this study is not the results but that this test allowed for a parameterization of the cognitive components of someone with autism. Computational phenotyping is still in it’s adolescence and large-scale computational phenotyping of humans has never successfully been carried out but the theoretical implications of such a tool are staggering (Montague, Dolan, Firston, & Dayan, 2012, p. 72). Accurate models of various diseases that account for the variation between individuals would allow researchers to isolate and treat each individual’s disease with their own personalized care plan rather than beginning with a generic treatment plan and eliminating options that work poorly.

During the development of these types of models two major categories emerge, data-driven approaches and theory-driven approaches. Data-driven approaches are similar to the methodologies used during the study on schizophrenia, these approaches focus on the application of machine learning techniques to large datasets for a variety of problems. Studies done using data-driven approaches usually follow a particular formula if not based on an already existing dataset, participants are selected to form two groups, a control and a group suffering from a psychiatric disorder. These two groups are then compared to one another on the basis of pre chosen parameters, such as learning rate, reward sensitivity, etc, and the abnormality in the patient group is used to characterize the psychiatric disorder being studied (Huys, Maia, & Frank, 2016, p. 405). A few commons uses of these models are the prediction of treatment response, understanding the relationships between symptoms, and treatment selection wherein given parameters about a patient's diagnosis and lifestyle the system will choose the correct form of treatment (Huys, Maia, & Frank, 2016, p. 407). One study on this type of system used a set of 1,800 EEGs from different subjects as a training set and, based on the 74 features extracted from the patient's EEG, was able to outperform clinical selections of treatment (Huys, Maia, & Frank, 2016, p. 407).

Theory-driven approaches, on the other hand, apply a mechanistic point of view, they are used to bridge different levels of analysis and as such can be particularly helpful when attempting to understand the causes behind a phenomena (Huys, Maia, & Frank, 2016, p. 408). Theory-driven models primarily take the form of algorithmic reinforcement learning models such as the game theory study on autism, bayesian models, and biophysically realistic neural-network models which are used to connect biological abnormalities to their neurodynamical and behavioural consequences (Huys, Maia, & Frank, 2016, p. 409). Biophysically realistic neural-nets allow for an understanding of casual and even distant relationships between biological details and prevalent symptoms. These neural-nets have been applied to a variety of conditions over various studies including exploring the effects of low serotonin or high glutamate levels in patients who have obsessive-compulsive disorder in which it was discovered that, regardless of cause (low serotonin or high glutamate), increasing serotonin can alleviate neurodynamic disturbances (Huys, Maia, & Frank, 2016, p. 409). Biophysically informed models can also be applied to model neural circuits, these types of models can be used in conjunction with experimentation to allow for new hypotheses to be formed about human cognitive functions (Wang & Krystal, 2014, p. 649). A primary example of this is the use of biophysically informed systems to approach working memory, the ability to encode and sustain the neural representation of information, in cases of patients with schizophrenia (Wang & Krystal, 2014, p. 646). One test of working memory is the use of a saccadic eye movement test where the participant in the study must remember a visual queue such as the angle of a line and move their eyes accordingly once the cue has been removed from sight (Wang & Krystal, 2014, p. 646). These tests were modelled using a spiking network model based on excitatory pyramidal cells and their chosen visual cues (Wang & Krystal, 2014, p. 646). Essentially researchers chose a series of pyramidal cells in the brain and labelled them according to their cues, based on varying degrees to represent the angle (0-360), when stimulus of these cells is observed it is recorded in a self-sustained network persistent activity pattern (Wang & Krystal, 2014, p. 646). These patterns drawn by the stimulation of the varying excitation of cells based on the degree the participant is looking during the saccadic eye movement test are then graphed and the data of the participants with schizophrenia is then compared with the control data to show how schizophrenia affects a patient's working memory (Wang & Krystal, 2014, p. 647). However these tests are not always effective, one of the problems with utilizing these biophysically informed models is there is such a distinct lack of known strong correlations between variables in psychiatry that it becomes hard to model these systems and instead researchers rely on the theoretical relationships between symptoms or combining the theory-driven approaches with data-driven to build their models (Huys, Maia, & Frank, 2016, p. 410).The combination of data and theory driven approaches have proven effective even when an understanding of the relationships between variables already exists, by applying a theory-driven approach to reduce the dimensionality of an issue you can more efficiently use data-driven approaches to achieve reliable and insightful results (Huys, Maia, & Frank, 2016, p. 405)

One approach to the combined data and theory-driven approach can be described as the four-level approach to the computational analysis of cognitive function and disfunction. The first level of this method approaches large data sets of a mixture of the clinical and nonclinical populations and identifies varying cognitive tasks to be employed for performance data (Wiecki, Poland, & Frank, 2015, p. 385). These cognitive tasks are based on the different mental processes that affect cognition, (attention, memory, emotion) and are each heavily researched and understood (Wiecki, Poland, & Frank, 2015, p. 385). The task of level one computational psychiatry is to look at the data for a specific condition and analyze which mental processes are engaged and how they are engaged (Wiecki, Poland, & Frank, 2015, p. 385). This data, now optimized for performance, is then passed on to the second level of computational psychiatry, computational modelling. During this step researchers try to fit a model to the discovered cognitive tasks, commonly, the drift-diffusion modelling process aids researchers in the development (Wiecki, Poland, & Frank, 2015, p. 386). Drift-diffusion models decision making by representing each decision was an upper and lower bound, a drift process collects as much evidence as possible until it crosses either of the bounds and triggers the response associated with that bound (Wiecki, Poland, & Frank, 2015, p. 387). The value difference between the two boundaries is a representation of the quantity of evidence that must be collected for one bound or the other for a decision to be made and a response to be executed (Wiecki, Poland, & Frank, 2015, p. 387). Level three of this approach is parameter estimation, which has been traditionally treated as an optimization problem where an objective function is minimized to achieve the best set of parameters (Wiecki, Poland, & Frank, 2015, p. 389). In the field of computational psychiatry hierarchical Bayesian models are used to identify parameters, this is because these models address the problem of having to either fit the model to individuals or to the aggregated group by creating a model where the parameter estimate of the individual are restricted by group-level distributions (Wiecki, Poland, & Frank, 2015, p. 389). Finally level four of this approach is supervised and unsupervised learning based on the newly found parameters, Bayesian information criterion is used to choose the Gaussian mixture model that contains the least amount of k-clusters to properly represent the data (Wiecki, Poland, & Frank, 2015, p. 390). Based on this criteria models are penalized for being too complex and as a result this type of optimization allows for the final model to be as straightforward as possible ensuring the absence of influence from variables outside the scope of the research (Wiecki, Poland, & Frank, 2015, p. 390). The finished model will be used to differentiate between clinical and nonclinical test groups and examine the differences in cognitive function between the two. The hope of using this four-level plan is that psychiatry can move away from symptom based diagnosis in the future and towards diagnosis based on quantifiable biomarkers making for more accurate diagnosis based on the specific needs of each patient to allow for more effective treatment.

In conclusion, the applications of computational intelligence in the field of psychiatry are paramount to its progression. The field of computational psychiatry is one that is still progressing, in the future, the combination of the theory-driven and data-driven approaches will play a large role in the understanding and treatment of psychiatric disorders. The reason the field of psychiatry has been so stagnant is due to two factors, the first being it is so absorbed in it’s own definitions that it is failing to use the tool it has been given for it’s most effective purpose. With the rise of computational psychiatry there has to be a restructuring of our understanding of the mind. By using these tools to redefine our knowledge of human cognitive functioning we may come across connections we have never explored before, the limit to our understanding of the human brain may be our ability to accept that what we know may not be entirely accurate as it is based on outdated methods of analysis. The second reason for the stagnation of psychiatry is the vast size and complexity of the involved datasets. While mathematical modelling has proved helpful in the analysis of these data sets, computational modelling allows for a much more in depth and thorough analysis through the use of simulations as opposed to the limited equation based representations. Through the application of computational models and the reexamining of our prior knowledge in the field, computational psychiatry is set to vastly change the landscape of psychiatric treatment in the years to come.

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