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Computational Modeling in Pediatric Mental Health

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Computational modeling has recently become of great interest to mental health clinicians as a tool for discovering the nature of pathophysiology and for clinical assessment, prediction, and treatment. Computational psychiatry is a term used to describe the application of computational modeling to behavioral and mental health problems. The NIMH has taken an interest in computational modeling, suggesting applications of interest, such as understanding the neural basis of mental illness, discovering new treatments, and predicting treatment response.¹ In this brief overview, our goal is to touch on major themes that have emerged in computational psychiatry.

To back up a bit, what exactly *is* a computational model? Most broadly, it is a set of mathematical expressions that represent a natural process or predict a natural state. The work required to evaluate these equations is usually so intensive that it requires a computer. A model may be a complex series of expressions or a single, simple equation. Perhaps the most famous within psychology is a simple subtraction between what actually occurs (outcome) and what a person expects (prediction). This difference influences how much a person learns from some experiences. It is called prediction error (often represented with the symbol δ) and is represented by the equation $\delta = Outcome - Prediction$. Many computational models of learning build upon this basic equation to describe how prediction error influences behavior. Later in this review, we discuss how these have influenced new methods for conducting exposure therapy.

This review covers two major ways computational models are applied to psychopathology.² The first is that models may be used to explicitly express theories of mental function and pathophysiology. Importantly, they do so in a way that is more precise and quantitative than a verbal theory. For example, they may represent specific cognitive processes such as learning or decision making. They may even represent neural processes, such as the encoding of memories in the patterns of synaptic strength. The second is that models are used for computer-assisted analysis of large datasets. In this use, models automatically discover patterns or natural divisions, such as those that define types of psychopathology or identify individuals who will respond to a treatment.

Articulating Theory

Early influential commentaries on computational psychiatry emphasize the ability of computational models to wrangle complex systems, like the brain, and improve theory.^{3,4} For example, consider the complexity of tracking a neurotransmitter's progressive effects on neural, brain, and cognitive functioning to behavior. Frank and O'Reilly (2006)⁵ did just that by developing a computational model describing dopamine's effect on neurons in the cortex, basal ganglia, and thalamus. The output of the model was action selection, a term neuroscientists use to describe the process of inhibiting or promoting specific behaviors. The model accurately predicted the effects of D₂ receptor blockade by haloperidol on this system. It not only predicted that haloperidol would promote desirable actions, but it also accounted for haloperidol's effects on learning, attention, and working memory. This model would later inform neural theories of action selection underlying compulsive or impulsive behavior, which are features of many disorders, including substance use, obsessive compulsive, tic, and attention deficit/hyperactivity disorders.⁴

One promising area for translational computational modeling is in psychotherapy. Psychotherapy is a learning process in that it is an experience that changes behavior. Computational models of learning have had a long history in development. Recall that many such models build upon a simple model of prediction error, the difference between outcomes and expectations, or $\delta = Outcome - Prediction$. Decades of research have established that the size of δ following any experienced event determines how much a person learns. Considering this, Craske and colleagues (2014)⁶ have proposed revisions to how exposure therapy is typically conducted to treat anxiety. Rather than focusing on the number of exposures or on minimizing anxious responses, learning models suggest that maximizing the discrepancy between what the anxious child expects (e.g., harm) and what the child experiences (e.g., safety)—that is, maximizing the prediction error—will be most effective in therapy. Most strikingly, it may actually be beneficial to maximize the child's prior expectation of harm, because this leads to the greatest prediction error and hence the most learning. The computational approach enabled this insight because it provides a precise and quantitative characterization of the mental processes involved in exposure therapy.

In sum, there are several benefits to representing natural processes with computational models. By translating verbal theories into mathematical expressions, we can make clear predictions about the nature of psychopathology and its processes, as well as how it may be impacted by interventions. Thus, we can test those relationships, in far greater precision and in more complex settings than would be possible without a computational model. In the action selection example, dopamine blockade by haloperidol was tracked from the synapse to behavior itself. As in other areas of science, computational models help us understand processes and mechanisms because they require us to state explicitly how things are related and how these relationships change with time or context.²

Data-Driven Discovery

A second major application of computational models is for data analysis. These are generally complex, computationally intensive algorithms that crunch large volumes of data

to identify patterns. Such pattern identification may find groups of individuals at risk for a mental disorder or a specific pattern of signs and symptoms that predicts treatment response. Many of these models do not represent biological processes, such as neural or mental function. Instead, they discover empirical associations without regard for the processes underlying them. Such computer-assisted, automated pattern discovery is often called machine learning.

Some readers may be familiar with a major advance in machine learning, called the deep learning revolution. Deep learning is a type of machine learning based on computational models meant to simulate interacting neurons, called neural networks. In 2012, machines using deep learning surpassed the most advanced image recognition algorithms in detecting features in images, like cancer in radiologic films. These can process large amounts of information and learn to recognize essentially *any* pattern, given enough data. Because they can be used on a wide variety of data and surpass human experts in pattern recognition, deep learning methods will influence medicine.⁷

Machine learning will likely complement, though not replace, clinical judgement.⁸ In one example, Desjardins and colleagues⁹ used a type of neural network to optimize screening for suicide risk in the emergency department. They found machine learning on a suicide screening questionnaire may provide accurate risk assessment commensurate with expert assessment. While Desjardins and colleagues provided an excellent proof of concept, follow-up efforts at predicting suicidality are underway to incorporate many more sources of data, like social media posts and smartphone activity logs. Another example shows how machine learning can synthesize voluminous notes to aid clinical decision making. Rumshishky and colleagues¹⁰ used natural language models to plumb electronic medical records for key indicators of severity mentioned in notes, such as eating issues and medical comorbidities. They showed that clinical prediction of recidivism was enhanced when considering the model's output.

Conclusion

It has been nearly two years since NIMH Director Gordon announced computational modeling as an area of interest and published a compendium of applied computational modeling in psychiatry.¹¹ We expect that this interest in conjunction with established procedures for computational modeling will lead to rapid developments in pediatric mental health. Discovery should be accelerated by the free and public distribution of computational tools and high-quality phenotypic data.

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