toward longer-term stability. The tetraalkyl phosphonium salt stably shuttles protons from the anode as the cation to donate them to nitrogen reduced at the cathode to form an ylide. Critically, this salt is not consumed like the previously reported sacrificial alcohol donor. The salt also enhances ionic conductivity, which allows this system to achieve high NH_3 production rates (60 nmol s^{-1} cm^{-2}) in 20-hour experiments at 20 bar N_2.

Despite these advances, no reported system is ideal. The ideal system would operate at negligible overpotential (that is, toward 100% potential efficiency), with high current densities (>1 A/cm^2) because of high turnover frequencies, have a lifetime of at least 5 years, and achieve 100% selectivity to NH_3 (see blue stars in the figure). The best turnover numbers are still only ~10^5 per site, well below the ideal of ~10^{10} per site. Crucially, the dependence on metallic lithium results in a built-in requirement for high potential losses given the negative reduction potential of Li^+. The organic electrolyte is also highly resistive, which results in an incredibly low energy efficiency (*13, 14*).

The SEI layer itself could be a source of instability. During NH_3 synthesis, the organic electrolyte continues to undergo reduction and product accumulation on the electrode surface, which increases resistance (*13*). Battery science could provide key insights for improving the stability and effectiveness of the N_2 reduction SEI, which is still uncharacterized and unoptimized. An effective SEI may even enable the use of water as a proton donor. ■

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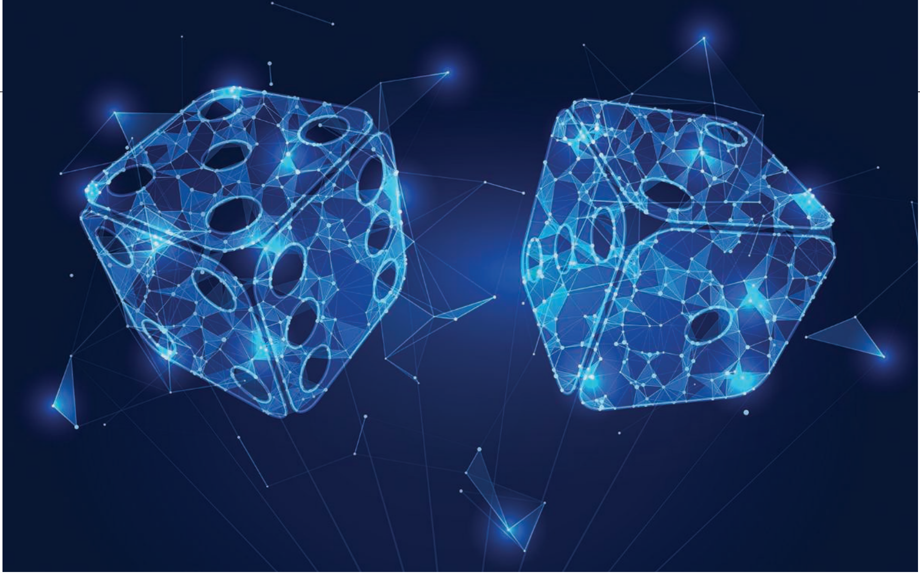

ILLUSTRATION: MAXIM GAIGUL/SHUTTERSTOCK

PSYCHOLOGY

Machine-generated theories of human decision-making

Deep neural networks highlight features of human behavior

By **Sudeep Bhatia**[1] and **Lisheng He**[2]

Imagine a choice between two gambles: getting \$100 with a probability of 20% or getting \$50 with a probability of 80%. In 1979, Kahneman and Tversky published prospect theory (*1*), a mathematically specified descriptive theory of how people make risky choices such as these. They explained numerous documented violations of expected utility theory, the dominant theory at the time, by using nonlinear psychophysical functions for perceiving underlying probabilities and evaluating resulting payoffs. Prospect theory revolutionized the study of choice behavior, showing that researchers could build formal models of decision-making based on realistic psychological principles (*2*). But in the ensuing decades, as dozens of competing theories have been proposed (*3*), there has been theoretical fragmentation, redundancy, and stagnation. There is little consensus on the best decision theory or model. On page 1209 of this issue, Peterson *et al.* (*4*) demonstrate the power of a more recent approach: Instead of relying on the intuitions and (potentially limited) intellect of human researchers, the task of theory generation can be outsourced to powerful machine-learning algorithms.

The popularity of prospect theory led to new research programs in psychology, economics, business, and neuroscience, as well as to the development of descriptive models for domains like intertemporal, social, strategic, and consumer choice (*5–7*). Prospect theory also helped practitioners and policy-makers derive practical insights on how to improve individual and organizational decision-making (*8*). But the prospect theory approach to modeling choice behavior is not without drawbacks. Researchers who propose new theories usually make complicated assumptions about processes such as perception, attention, memory, and emotion, as well as sources of noise and error in choice. The theories themselves are tested only on small datasets of choices and are seldom compared against the large set of preexisting models. This is unavoidable, given the long interdisciplinary history of decision research and the complexity of risky choice: It is fairly easy for decision scientists to intuit a psychological explanation for an expected utility violation, but even the most talented (human) theorist will have difficulty deriving predictions that distinguish their account from dozens of preexisting explanations. Newer theories are often similar to previously published models, and many theories closely mimic each other's predictions on benchmark datasets (*3*). Even though the rate of theory production is accelerating, there has been little gain in predictive accuracy on these datasets over the past 20 years (*9*).

In response to these trends, some researchers have begun to emphasize out-

[1]Department of Psychology, University of Pennsylvania, Philadelphia, PA, USA. [2]School of Business and Management, Shanghai International Studies University, Shanghai, China. Email: bhatiasu@sas.upenn.edu

of-sample predictions and comprehensive model comparisons on large datasets of human decisions (*10*, *11*). In doing so, they have brought yet another discipline, machine learning, into this already highly interdisciplinary mix. Old theories need not be discarded; rather, they can be implemented as inductive biases or constraints in these models, increasing algorithms' learning efficiency and boosting model performance.

Peterson *et al.* showcase the true power of this approach. They begin by collecting new experimental data on risky decisions for more than 10,000 distinct choice problems involving gambles with probabilistic monetary payoffs, exceeding the size of prior datasets by an order of magnitude. These choice problems and the decisions that humans ultimately made in these problems are then used to train deep neural networks, a class of machine-learning models that can flexibly extract nonlinear functions for describing data. Peterson *et al.* find that such networks are able to mimic human decisions with a very high accuracy rate, substantially outperforming existing (human-generated) risky choice models; their model achieved roughly half the mean squared error demonstrated by prior approaches. In learning to mimic human decisions, the networks also discover many of the psychological properties of established behavioral theories, such as the psychophysical functions used by prospect theory. The flexibility of deep networks allows them to find better mathematical implementations for these properties and learn other properties necessary for describing data that have not been previously identified by human researchers.

The predictive gains of Peterson *et al.* relative to existing human-generated theories are impressive enough; however, the authors also analyze the modeling assumptions that lead to good performance. To do this, they implement various constraints on their networks, each of which limits the ways in which the networks manipulate the available gambles to make choices. For example, one constrained network allows for a payoff to be transformed nonlinearly and be multiplied against its (nontransformed) probability, resembling the assumptions of expected utility theory. This network performs poorly relative to a more complex network that allows for both probabilities and payoffs to be transformed, as in prospect theory. This network is, in turn, outperformed by other networks that also allow for the payoffs and probabilities of different gambles to interact and influence each other's transformations.

The architecture of the winning model in Peterson *et al.*'s analysis places it among a class of context-dependent decision theories that propose that the utility or disutility obtained from a single gamble (e.g., $100 with 20% probability) is not determined in isolation but depends on the other gambles available in the choice problem (e.g., $50 with 80% probability). Decision-makers do not attach a fixed utility to any given gamble; rather, utility is based on competing gambles and can vary from choice problem to choice problem.

Peterson *et al.* also show that high accuracy rates are possible from a model composed of an expected utility theory component and a prospect theory component, with each component being selectively applied based on the set of available gambles. This analysis illuminates how decision context guides and constrains evaluation mechanisms and shows how interpretable theoretical insights can be obtained from the behavior of deep neural networks.

Future work will undoubtedly extend Peterson *et al.*'s approach to other behavioral domains [e.g., risk perception, moral judgment, and strategic choice (*12*–*14*)]. These models will also be used to discover new choice problems to test the boundaries of existing theories. Advances in explainable artificial intelligence will also allow researchers to better understand the behavior of deep networks in terms of established theoretical principles. Ultimately, the increased availability of large datasets and improvements in computing power will make machine learning an indispensable component of the decision scientist's toolbox, revitalizing (and perhaps, once again, revolutionizing) theoretical research on human choice behavior. ■

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NEUROSCIENCE

Expanding gliogenesis

The generation of glial cell types in adult mice could provide strategies for brain repair

By **Katherine T. Baldwin**[1] *and* **Debra L. Silver**[2]

The adult mammalian brain retains the capacity to generate new neurons and glia, a feature that is important for learning, memory, and response to injury (*1*). Neural stem cells (NSCs) in germinal regions of the adult brain, such as the ventricular-subventricular zone (V-SVZ) and the dentate gyrus of the hippocampus, are a major source of new neurons and glia (*1*). Glia, including astrocytes, oligodendrocytes, ependymal cells, and microglia, are non-neuronal cells that play critical roles in brain function. Although the neurogenic functions of stem cells in the adult V-SVZ have been studied extensively, their gliogenic properties are less well understood. On page 1205 of this issue, Delgado *et al.* (*2*) reveal previously undescribed gliogenic origins and glial cell types in the adult mouse brain. This discovery suggests that adult gliogenesis is more widespread than previously thought, laying the groundwork for potential regenerative therapies.

During development, stem cells rapidly divide; however, in adult tissues, they are mostly quiescent (*3*). The largest population of NSCs in the adult mammalian brain resides in the V-SVZ, lining the lateral and septal walls of the lateral ventricle. They are maintained in a dormant state by both intrinsic factors and extrinsic cues from the surrounding niche, which is composed of ventricular cerebrospinal fluid (CSF) derived from the choroid plexus, and vasculature, ependymal cells, and neurons (*1*).

The spatial location of NSCs confers their identity, with different regions of the V-SVZ generating distinct cell types (*4*). NSCs lining the lateral and septal walls generate interneurons that populate the olfactory bulb, whereas those in the dorsal-lateral V-SVZ generate oligodendrocytes (*5*, *6*). Although both NSCs and astrocytes share similar mor-

[1]Department of Cell Biology and Physiology, University of North Carolina, Chapel HIll, NC, USA. [2]Department of Molecular Genetics and Microbiology, Duke University, Durham, NC, USA. Email: debra.silver@duke.edu

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Sudeep Bhatia and Lisheng He

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