Future Challenges

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This book has covered a wide range of new and exciting research in the science of information-seeking. Yet many open questions still remain. For example, how is information-seeking related to reward-seeking? What are the principles that enable us to acquire useful information with computational efficiency, despite possessing limited cognitive capacities and knowledge? Which aspects of our neural machinery are unique to information-seeking, and what is shared across other cognitive systems? How does the science of information-seeking inform important societal issues, such as fake news, conspiracy theories, and education?

In this closing chapter, we present a brief overview of future challenges and current puzzles in the field, organized around the same three questions used to structure the sections of this book: **What** drives humans to seek information? **How** do humans search for information? **Which** machinery supports the drive for knowledge? While our current theories and frameworks have answered many questions about information-seeking, many more still remain. At the end of this chapter, we address the social implications for the science of information-seeking. Like boats paddling against the current, the drive for knowledge will continue to propel us toward new and exciting questions to be curious about.

What Drives Humans to Seek Information?

Throughout this book, we have sought to answer the question of why humans seek information and how our desire for information stacks up against other primary rewards, such as food or water. One simple answer to this question is the old adage "knowledge is power," and that information allows us to acquire more rewards in the future. Yet, how far into the future do we need to reason when considering the instrumental value of information? This problem is often studied under the framework of the exploration–exploitation dilemma (Mehlhorn et al., 2015), where optimal solutions are typically intractable under finite time horizons. Indeed, even doing the math and computing expected information gain for short-run decisions is not necessarily informative for deciphering the optimal decision in the long run (Meder et al., Chapter 5). Thus, intrinsic motivations to seek information (e.g., curiosity; Ten et al., Chapter 3) might be an adaptive bias that ensures humans behave less myopically and introduce enough exploration into their decisions. Since we cannot tractably compute the value of information for long-run horizons, our innate curiosity may simply provide a blanket subsidy for knowledge-generating activities, similar to how governments and institutions support basic research without a guaranteed return of investment (Wojtowicz et al., Chapter 1). Nevertheless, as we move from simple bandit tasks to more sequential decision-making tasks (Brändle et al., Chapter 7), and connect short-term "curiosity" to long-term "interest" (Donnellan et al., Chapter 2), an important and still open question is what tractable computations people use to compute the value of information, as we discuss in the second section of this chapter.

Yet, acquiring future rewards alone does not entirely explain our drive for knowledge. An important component of information-seeking behaviors seems unrelated to rewards and can sometimes even run orthogonal or counter to it (Kobayashi, Ravaioli, Baranes, Woodford, & Gottlieb, 2019; Charpentier, Bromberg-Martin, & Sharot, 2018). One prominent idea featured in this book is that information may be desired for improving the coherency of internal models of the environment, where "sense-making" provides an alternative currency to rewards (Wojtowicz et al., Chapter 1). Sense-making is not some alien, nonfungible currency, but can be measured in terms of compressibility, where more coherent models require less computational bandwidth to use and maintain. Thus, information-seeking for acquiring rewards and information-seeking for reducing the computational costs of modeling the environment may ultimately be comparable through a cost–benefit trade-off within a resource-rationality framework (Lieder & Griffiths, 2019; Bhui, Lai, & Gershman, 2021; Wu et al., Chapter 8). We already have preliminary evidence that value representations for reward and information are computed by different populations of neurons in similar brain regions, allowing for different exchange rates depending on the environment and one's goals, but with both capable of being integrated downstream into a common currency (Charpentier & Cogliati Dezza, Chapter 9).

Even then, why do people still seek redundant information? Just as it can sometimes be difficult to avoid overeating unhealthy snacks or binging TV shows, controlling information-seeking behavior may itself incur cognitive costs (Gottlieb, Chapter 10). Thus, overactive information-seeking may simply be a result of more economical monitoring and control, which switches more lazily between different modes of exploration and exploitation or is perhaps biased toward a cognitively cheaper mode. Alternatively, the brain may regulate information-seeking, similar to other motivated behaviors (Pezzulo, Rigoli, & Friston, 2015; Keramati & Gutkin, 2014), by allowing the system to oscillate around a homeostatic attraction point. Alternations of behavior, characteristic of this style of regulation, may at times lead to redundant information-seeking. However, there are still many open questions regarding how information-seeking is regulated in the brain – for example, how humans balance their need for acquiring information for future rewards with their needs for acquiring information which makes them feel good or to help to increase understanding of reality. A better understanding of the adaptive role of information-seeking, and its regulation, will provide new tools for diagnosing and treating psychopathologies, such as reduced novelty-seeking in addiction (Cogliati Dezza, I., Noel, X., Cleeremans, A., Yu, A. (2021). Distinct motivations to seek out information in healthy individuals and problem gamblers. Transl Psychiatry 11, 408. doi.org/10.1038/s41398-021-01523-3) or increased information-seeking in obsessive-compulsive disorders (Hauser, Moutoussis, Consortium, Dayan, & Dolan, 2017).

A key resource in understanding the cognitive costs associated with information-seeking is studying how it changes over the lifespan. Childhood presents unique opportunities for learning, where children can expect pedagogical instruction in their environment (i.e., natural pedagogy; Csibra & Gergely, 2009). Yet children also have less developed cognitive representations and processes, making more complex inferences less accessible. One robust finding is that children have difficulty *producing* informative queries even though they are quite capable of *selecting* useful queries (De Simone & Ruggieri, Chapter 4). Despite their less developed cognitive capacities, children are nevertheless highly sensitive to which individuals are the most reliable sources of information (De Simone & Ruggieri, Chapter 4) and are capable of performing increasingly sophisticated inferences to learn not only from their actions, but also from imputed mental states (Wu et al., Chapter 8).

How Humans Search for Information

A recurring theme in this book is that optimal solutions to most interesting cognitive problems are intractable. This means that, practically, we humans must have developed various computational shortcuts or heuristics to guide our decisions, bound by the limits of our cognitive resources and the sparsity of our knowledge about a complex world. Perhaps nowhere is the need for heuristic solutions more important than in solving the exploration–exploitation dilemma, where acquiring information (benefiting future decisions) needs to be traded-off against acquiring immediate rewards. Here, the complexity of planning increases exponentially with the number of available choices (Brändle et al., Chapter 7), making it especially important to discover the computational principles of human learning and information search that balance efficiency and flexibility (Wu et al., Chapter 8).

One potential answer is that human behavior can be described as the attempt to optimize an information-enriched utility, integrating both information and reward-based value into a single currency (Charpentier & Cogliati Dezza, Chapter 9). For example, Meder et al. (Chapter 5) argue that this utility could be a de facto measure of information gain, normally computed either myopically or taking the agent's next few decisions into account. However, many measures exist for quantifying the value of information (Crupi, Nelson, Meder, Cevolani, & Tentori, 2018), and it is the topic of ongoing research to determine which measure best explains human behavior.

Another proposal for how bounded-rational agents could maximize information gain is to assume that they optimize free energy instead, which combines informational utility with a resource capacity component (Sajid et al., Chapter 6). Nevertheless, this Active Inference framework (Friston et al., 2016; Schwartenbeck et al., 2019), like other resource-rational optimization frameworks (e.g., Lieder & Griffiths, 2019), can still require a prohibitive amount of computation. Thus, humans may simply opt for heuristic computations instead, behaving "as-if" they maximize informational utility or minimize free energy. One such heuristic is to treat uncertainty as having utility of its own (Ten et al., Chapter 3) and to myopically sample options that both promise to produce high rewards and are highly uncertain (Brändle et al., Chapter 7). Even though these strategies are approximate, they nonetheless offer guarantees in some settings, such as sufficient regret bounds and convergence to the best possible option over time (Srinivas, Krause, Kakade, & Seeger, 2009).

Yet simply computing uncertainties over different options becomes expensive as the number of options or the planning horizon increases. Thus, across several chapters of this book, researchers have proposed that people might not act according to informational utilities at all, but rather have a general drive toward being curious (Wojtowicz et al., Chapter 1).

As explained in the previous section, such a drive for information might have emerged to allow better adaptation to the environment, since acquiring information is generally valuable in most human environments, even if computing the exact value is intractable. Evolution could have exerted pressure on agents to be generally curious, creating a general motivation to seek out information (Donnellan et al., Chapter 2). This can be formalized as a “bonus” (e.g., information bonus, novelty bonus, or curiosity bonus) added to the value function, which guarantees efficient information-seeking when tractable computations are unfeasible (Wilson, Geana, White, Ludvig, & Cohen, 2014; Cogliati Dezza et al., 2021)

Given the difficulties involved in computing informational utilities, another cost-saving solution is to use social information to augment one’s own limited computational abilities (Wu et al., Chapter 8). By learning from other people, we can adopt effective solutions that would have been costly or impossible to discover on our own. Social learning is not merely limited to copying at the level of behaviors, but can also involve the inference of hidden mental states, such as imputing goals and beliefs to other agents. Here too exists a computational trade-off. Despite social learning at the level of copying behavior being cheap, learning from inferred goals and beliefs allows for more flexibility and better generalization when there is a mismatch between individual preferences, skills, or circumstances (Wu et al., Chapter 8).

Lastly, another crucial distinction is whether the process of information search is discriminative or generative, which maps onto the distinction between *selecting* and *producing* information, where the latter is observed as developing later in childhood (De Simone & Ruggieri, Chapter 4). This suggests that it is more cognitively demanding to use generative models of information-seeking rather than discriminative models. Whereas a discriminative approach assumes that people start out from different hypotheses and then seek out information to arbitrate between them, generative approaches assume that information search is driven by the attempt to build increasingly better models of the world. Plausible accounts of human information search will likely need both of these elements, where the generative component generates plausible hypotheses to be tested and the discriminative component arbitrates between which hypotheses are the most likely, with both systems complementing one another. Thus, a better understanding of the heuristics and approximate mechanisms people use to seek out information may help to bridge this gap (Hills et al. Chapter 11).

In summary, the study of information-seeking offers valuable insights into the computational principles and cognitive shortcuts that humans use to make intractable problems tractable. The proposals in this book are diverse, and include utility maximization under resource constraints, heuristics, a general drive toward being curious, as well as learning from other people. However, it is still an open question whether these diverse solutions proliferate like tools in a toolbox (Gigerenzer & Todd, 1999), or whether they point toward complementary and interacting systems.

Which Machinery Supports the Drive for Knowledge?

Information-seeking allows humans to select relevant information from a multitude of stimuli arriving from the environment (Gottlieb, Chapter 10) and compress them into a meaningful understanding of the world (Wojtowicz et al., Chapter 1). Despite these benefits, acquiring novel information is costly. Searching for information might take time away from other adaptive behaviors, such as consuming food or water or acquiring other primary rewards. Moreover, to implement information-seeking behaviors, the brain needs to assemble novel strategies and behavioral policies, or engage in expensive computations, thereby incurring metabolic and cognitive costs. Indeed, evidence suggests that people require more cognitive resources when seeking novel information compared to only exploiting known rewards or simply randomly exploring their environment (Cogliati Dezza, Cleeremans, & Alexander, 2019; Wu, Schulz, Pleskac & Speekenbrink, 2021). To facilitate information-seeking, therefore, the brain needs to rely on behavioral and cognitive control mechanisms. As shown in Chapter 9, brain regions typically involved in cognitive control, such as the dorsal anterior cingulate cortex (dACC) and anterior insula, are activated when humans seek novel information. Moreover, the fronto-parietal network controls information-seeking behaviors when information gathering relies on active sensing behaviors (Gottlieb, Chapter 10).

However, is information-seeking just a control mechanism which allows the brain to compress relevant stimuli into meaningful understanding (e.g., cognitive utility of information)? As shown throughout this book, information not only has a cognitive utility, it can also impact people's affective states (hedonic utility) and future decisions (instrumental utility; Sharot & Sunstein, 2020). These two latter utilities seem to activate a different network, which overlaps with reward processing (Charpentier & Cogliati Dezza, Chapter 9). For example, the vmPFC tracks the savoring of information (i.e., increased anticipation due to advance knowledge of an upcoming reward; Iigaya et al., 2020) and, together with the ventral striatum, it tracks a combination of instrumental and noninstrumental values of information (Kobayashi & Hsu, 2019).

These two different networks – one overlapping with reward processing and the other with control processing – may nevertheless work together to produce a single integrated value of information for implementing adaptive information-seeking. An intriguing hypothesis is that dopamine may facilitate this "integrative role" by strengthening the interaction between the two networks (Charpentier & Cogliati Dezza; Chapter 9). However, the exact mechanisms are still unknown, although one theory is that dopamine provides a signal of the weighted sum of cognitive, hedonic, and instrumental utility of information, integrating them into a common currency (Sharot & Sunstein, 2020). However, there are still many open questions, and it is not yet known what role other neurotransmitters such as norepinephrine and serotonin play within this process.

So far, we have seen that the neural machinery of information-seeking contains a mixture of reward and control mechanisms, which may oscillate between the two depending on one's motivational state, preferences, and needs. However, this also suggests that there might be nothing unique as to how this machinery is structured. Put differently, mechanisms developed to serve specific functions, such as processing primary needs (food, water, reproduction) or controlling behavior, could be "exapted" (extraneously adapted from one domain to another) to implement information-seeking behaviors (Hills et al., Chapter 11). Although it is difficult to assess which came first in evolutionary terms (i.e., information-seeking, cognitive control, or reward maximization), it is not a new phenomenon in biology for structures developed for certain adaptive functions to be then reused to serve other functions. This transfer of mechanisms from one domain to another is also observed in comparing searching for information in the environment to searching internally from memory (Hills et al., Chapter 11). The hippocampal-entorhinal system is one example, wherein similar neural activity facilitates navigation in spatial and conceptual environments (Constantinescu, O'Reilly, & Behrens, 2016), although with some notable differences in information-seeking (Ho et al., 2017). Similarly, mechanisms used in individual learning and decision-making may also be reused for learning in a social context (Wu et al., Chapter 8), facilitating the transfer of information between minds.

Information-Seeking and Society

We have discussed information-seeking as a behavior that allows humans to acquire novel information. However, as suggested by Zurn et al.

(Chapter 12), a more fundamental goal of information-seeking is to connect things we observe in the world to one another, weaving together our concepts and understanding. This background knowledge determines how individuals perceive reality, and also connects diverse perspectives into common narratives, shared across communities and societies. Narratives are at the core of societal structure, and can shape political discourse and policy (Jones, Shanahan, & McBeth, 2014; Esposito, Terlizzi, & Crutzen, 2020).

Narratives are also at the center of many societal problems, including radicalization, conspiracy theories, and pseudoscientific frameworks. As Wojtowicz et al. expressed in Chapter 1, these common narratives are "not always perfectly calibrated to the provision of long-term benefits in every situation." Individual information-seeking therefore plays a crucial role in the way societies or communities develop, and the way information connects individuals is at the core of many issues faced by modern societies. Synergy between researchers studying individual information-seeking (e.g., psychologists, neuroscientists, and computer scientists) and researchers studying human behavior at the macro-level of social interactions is required to advance our understanding of how groups jointly search for information.

In recent years, (mis)information played a pivotal role in developing narratives, which in some cases shaped the future of entire countries (e.g., the 2016 UK Brexit referendum and the 2016 US presidential election). Information (and therefore misinformation) is crucial for updating individual beliefs (Bromberg-Martin & Sharot, 2020). Let us imagine a person who has no particular beliefs on matters related to climate change. However, suppose she encounters some theories about climate change denial online. Information denying the existence of climate change is good news, since it would lift the burden of existential dread about the extinction of the human species. Since people seek information that makes them feel good (Wojtowicz et al., Chapter 1; Charpentier et al., Chapter 9), she may seek out this positive information more often and be more likely to integrate it with her other beliefs (Sharot, Korn, & Dolan, 2011). This bias toward believing positive information is likely to occur in many scenarios unless the accuracy or reliability of the information source can be properly considered (Pennycook & Rand, 2021). Recent research suggests that shifting attention to the accuracy of the information shared between groups might reduce the spread of misinformation online (Pennycook et al., 2021). However, the ability to accurately judge the reliability of information is becoming increasingly more difficult, given the flood of information people are confronted with every day. While changing belief with novel information is possible when a person is less confident about a topic (Rollwage et al., 2020), it becomes much harder when the belief is stronger (Sunstein, Bobadilla-Suarez, Lazzaro, & Sharot, 2017). Thus, more research needs to be done on how the search for information can go astray and is susceptible to deception. How a better societal and collective search for information can be achieved, and which specific information-seeking processes should be involved when it comes to policy decisions, is a new challenge faced by researchers studying information-seeking.

Conclusion

This book discusses the most current theories and scientific research on human curiosity, and the nature of our propensity to seek out information. But how can the insights contained herein be translated to daily human experiences? Domains such as education, human–computer interaction, and clinical psychiatry seem to be ideal candidates for benefiting from advances in the science of information-seeking. For example, Donnellan et al. (Chapter 2) proposed a framework for knowledge acquisition that could be used to implement more efficient educational programs, allowing "unsuccessful" students to find their own interest and succeed in their academic career. The framework for social learning introduced by Wu et al., (Chapter 8), while targeted for understanding human interactions, could also be applied to enhance how artificial agents interact with humans, based on an understanding of how we perceive and use social information. Additionally, this book highlights several computational and neural mechanisms underlying information-seeking (Chapter 5–8). Can these processes be targeted to improve the living conditions of patients with information-seeking abnormalities? These opportunities and challenges, among many others, are what the nascent field of information-seeking will face in the coming years.

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