Organizations as Artificial Intelligences:
The Use of Artificial Intelligence Analogies in Organization Theory*

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Abstract

A rarely acknowledged fact about organization theory (OT) is that many of its ideas stem from the field of artificial intelligence (AI). For example, key OT concepts such as problemistic search, heuristics, exploration, requisite variety, and organizational scripts, all have their roots in AI. The main goal of this paper is to expose the full range of AI ideas that have been used in OT. We do so by explaining key AI ideas and showing how OT used them. Our review covers over 100 OT works that depend on AI ideas both critically and explicitly. We group these ideas into ten AI approaches that speak to three fundamental processes in organizations: search, representation, and aggregation. We argue that this broad and deep borrowing from AI stems from fundamental structural similarities between AI and OT, as both fields study how artificial systems (programs and organizations) can pursue intelligent behavior. We also identify areas of AI from which OT scholars may continue to draw inspiration and suggest ways in which AI technologies may continue to affect organizations. Overall, our work shows that, beyond its effect as a technology, AI has given OT a set of models about how organizations work.

INTRODUCTION

It is well known that organization theory (OT) has borrowed many ideas from other disciplines. For example, organizational ecology, evolutionary economics, and fitness landscapes have roots in ideas from evolutionary biology (Hannan and Freeman 1989, Nelson and Winter 1982, Levinthal 1997). Other examples include ideas borrowed from sociology, such as social construction (Zajac & Westphal 2004), institutional logics (DiMaggio & Powell 1983), and structural holes (Burt 1992), and ideas borrowed from psychology, such as categorization (Pontikes 2018), judgment biases (Lovallo & Kahneman 2003), and personality traits (Hambrick & Mason 1984).

Perhaps less known is OT's fruitful borrowing from the field of artificial intelligence (AI). OT concepts such as search, heuristics, and representation, to name a few, have roots in AI. Such borrowing is not coincidental. For one thing, AI and OT both study complex systems and, hence, concepts such as adaptation, hierarchy, and information apply to both (Axelrod and Cohen 2001, Chapter 1). For another, AI and OT are both "sciences of the artificial" (Simon 1969/1996), investigating systems that adapt to their environment to fulfill goals, so that concepts such as coordination, feedback, and learning apply to both. More generally, borrowing from AI to understand organizations is natural because the technologies of the day have always served as metaphors for the most complex systems (Morgan 2006: 12). For instance, the brain has been compared in its time to the hydraulic pump (Descartes 1633/1985), the steam engine (Freud 1933), and the computer (von Neumann 1958).

Acknowledging the AI roots of many OT ideas has at least two important benefits for OT. The first is practical: being aware of the range of AI ideas used by OT can help us better understand how AI itself will affect organizations, a topic of much current interest (Bailey, Faraj, Hinds, von Krogh, and Leonardi 2019: 642, Baum and Haveman 2020: 270–271). For an example of the cost of lacking that understanding—that is, the cost of a narrow framing of how AI affects organizations—consider the popular view that the main effect of AI on organizations is to decrease the cost of making predictions (Agrawal, Gans, & Goldfarb 2018). While this effect obviously exists, understanding AI strictly through the lens of prediction costs can miss other important effects of AI on organizations, such as its effect on the type of knowledge the organization can represent and on the organization's search and aggregation processes.

The second benefit is theoretical: knowing the AI roots of current organizational theories allows us to create better organizational theories. Organizations can be viewed as artificial systems whose main purpose is to pursue intelligent behavior (March 1999, Ocasio, Rhee, & Boynton 2020). In other words, organizations can themselves be viewed as a type of artificial intelligence (Csaszar 2018: 608). Being able to borrow from a field entirely devoted to the development of intelligent systems is therefore an enormous benefit, akin to medicine's fruitful (to put it mildly) borrowing from chemistry once it was understood that the human body is, among other things, a chemical system. Today, for example, many in OT understand AI only or mainly from its most popular current manifestation: machine learning. Such an understanding, however, misses the many productive analogies that have been established between AI and OT over the last 60 years. Such a circumscribed view is not just unscholarly but also risky, as ignoring these links limits the repertoire of ideas available to organizational theorists.

The overarching goal of this paper is to help the OT field obtain these two benefits, one practical and one theoretical. The bulk of our paper is therefore devoted to uncovering the connections between AI and OT. We do this by showing how seminal papers in OT explicitly borrowed specific ideas from AI (in a few places, we also document the reverse influence: cases where AI has borrowed from OT). We group the AI–OT linkages into ten "approaches" to AI—fundamentally different ways of achieving AI. For each of the ten areas of connection between AI and OT that we uncover, we describe the seminal AI idea and elaborate on its use by multiple authors in OT. For the sake of clarity, we group the ten AI approaches into three themes: search, representation, and aggregation. Note that because both the AI literature and OT's use of it are vast, our paper is necessarily incomplete. Our review of these literatures should be seen as illustrative of the connections, but not exhaustive.

This paper makes three main contributions to the literature. First, we expose and clarify the broad range of AI ideas that have been put to use in OT. Here, the multiplicity of borrowings is as important as the specific ideas borrowed. Second, we identify areas of AI from which OT scholars may continue to draw inspiration. We do this by identifying AI ideas overlooked by OT that may illuminate classic OT questions and by showing how AI ideas that were imported into OT have diverged since the import took place and may therefore be ripe for new borrowing. Third, we suggest ways in which AI technologies may continue to affect organizations. We do this by devising plausible scenarios about the future use of AI in organizations and by building on recent AI ideas that aim to limit the potentially negative effects of AI technologies.

The remainder of the paper is structured as follows: the next section provides the background necessary to understand the bridges that have been established between AI and OT. The section after that presents the methodology used to review the literature. The three ensuing sections—focused, respectively, on search, representation, and aggregation—expose the multiple ways in which OT has borrowed from AI. The final section discusses how AI may continue to affect the theory and practice of organizing.

BACKGROUND

To contextualize how OT has borrowed from AI, in this section we define AI and its origins, describe the three themes that serve as an organizing framework for our work, and show that some AI ideas have indeed originated in OT.

Defining AI

There is, in fact, no generally accepted definition of AI. Russell and Norvig (2020: 1–4) have aptly arranged the multiple existing definitions along two axes—(a) thinking vs. acting and (b) humanly vs. rationally—which creates the four categories of definition shown in Figure 1:

Insert Figure 1 about here.

- AI as devising algorithms that *think humanly*. This is also known as cognitive modeling and its goal is to better understand human cognition.
- AI as devising programs that *think rationally*. This requires using rational processes such as logic and probability.
- AI as devising machines that *act humanly*. That is, machines that could pass the Turing Test

by credibly impersonating a human being.

- AI as devising programs that *act rationally*. This is consistent with an engineering approach: what matters is acting optimally with respect to a given measure of performance—regardless of the specific process used. That is, there is no need to think like humans or to use well-sanctioned logic; the goal is just to perform in a way that would normally require intelligence.

Following Russell and Norvig (2020), we include within the scope of AI all research that fits within any of those four quadrants. We believe it is useful for OT to use a broad definition of AI, as this avoids missing AI–OT connections. To illustrate this point, it is useful to compare OT to cognitive science in terms of their borrowing from AI. For cognitive science, which studies the computational processes used by the human brain, it makes sense to limit its borrowing from AI to the "think humanly" quadrant. However, because OT studies organizations (which typically employ multiple humans and technologies), restricting the borrowing to a specific quadrant would be counterproductive, as not all information processing in organizations is limited by the constraints of one human brain. In other words, because AI contains the models from cognitive science and because not all components of organizations are human, AI is a richer source of OT analogies than cognitive science.

The Origins of AI

The idea of thinking beings created by humans—and the practical and philosophical problems that might arise if they existed—has a long pre-history. There are, for example, the Greek myths of bronze robots made by the smith-god Hephaestus (Mayor 2018) and the Jewish folklore of clay-based robots called golems (McCorduck 2004: 14–15). Also contributing to the eventual development of AI was the development of the mathematics of functions commonly associated with thinking—particularly, logic and probability. Key steps in the development of logic were Aristotle's work on syllogisms (c.350 BCE), Boole's on first-order logic (1854), and Frege's on predicate logic (1879). Key steps in the development of probabilistic thinking were Pascal's and Fermat's work on computing probabilities, Bernoulli's work on utility, and Bayes's work on how to rationally use new data to update probabilities (Hacking 2006). Finally, there were the first attempts to create an actual mechanical computer, made by Babbage and Lovelace starting in the 1830s. This work made previous speculations about AI more tangible and raised questions that are still important. For example, in what accounts for an instruction manual for their planned computer, Lovelace (1843) discusses whether machines will ever be intelligent.

For another century, the field of AI continued to consist almost exclusively of philosophical investigation. The current history of AI begins with the creation of the first electronic computers in the 1940s. This technology made it possible to try out the various ideas about how to create intelligent machines and see how far they could take us. The result was something of an arms race—or a Cambrian Explosion—of methods to produce AI. The most important of these methods will be presented when we review the linkages between AI and OT.

The term "artificial intelligence" was coined by McCarthy, Minsky, Rochester, and Shannon (1955) in their proposal for what became the "Dartmouth Summer Research Project on Artificial Intelligence," a summer-long workshop where the main AI researchers at the time could share their ideas. The stated goal of the conference served to define the field: "to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it" (McCarthy et al. 1955). Some 20 researchers attended at least part of this seminal event, including Herbert Simon, Allen Newell, Claude Shannon, Marvin Minsky, John McCarthy, John Holland, Ross Ashby, Warren McCulloch, John Nash, and Arthur Samuel.

Three Themes in AI Research: Search, Representation, and Aggregation

The work of these and other pioneers produced many ideas on how to achieve AI and many groupings of these ideas have been proposed, as can be seen in the tables of content of the main AI textbooks (Luger & Stubblefield 1993, Nilsson 1998, Rich 1983, Russell & Norvig 2020, Winston 1977). We chose our particular grouping into 10 approaches because it is useful for our purpose of elucidating AI–OT connections. For the sake of clarity and to better appreciate how these AI approaches have been used within OT, we group these 10 approaches into three themes: search, representation, and aggregation.

Search approaches conceptualize AI in terms of a problem and some means to solve it. For a Roomba—a commercial robot that vacuums the floor—the goal is to clean a room and the means are the Roomba's possible actions, such as moving forward, turning to the right, and backing up. Different search approaches use different techniques to generate alternatives and to pick among those.

Representation approaches conceptualize AI in terms of a given task environment and some means to model it (so that an AI can act on it). For example, developing AI to manage customer comments would require devising a model to distinguish, among other things, between positive and negative emotions in written comments. Different representation approaches would have different ways of encoding such models.

Aggregation approaches conceptualize AI in terms of strategies for combining several subsystems to create a desired aggregate behavior. For example, if different navigation systems in an autonomous car—camera, radar, radio contact with other cars—recommend different actions—say, stopping versus slowing down versus swerving—what would be the best way to combine these recommendations? Different aggregation approaches would propose different combination strategies.

The Contribution of OT to AI

Although this paper emphasizes the influence of AI on OT, it's worthwhile to note that there are many cases of influence in the other direction. For example, Herbert Simon attributes his AI work on *heuristic problem-solving* (Approach 2, according to the scheme we will present later) to previous work he had done on organizations to better understand how humans and organizations make decisions (Spender 2013: 329). Edward Feigenbaum's work on *expert systems* (Approach 5) was influenced by his early experience as a research assistant for Herbert Simon and Richard Cyert while they were modeling organizational decision-making processes and had to extract business knowledge from managers (Feigenbaum 1992: 195). The literature on *distributed AI* (Approach 9) builds on classic models of coordination, power, and trust in organizations (Weiss 2013: xxxvi).

METHODOLOGY

To review how OT has built on AI ideas, we used the following methodology:

1. Create a list of AI keywords. We consolidated the topics covered by the principal AI textbooks from the last 45 years (Charniak & McDermott 1985, Luger & Stubblefield 1993, Nilsson 1998, Poole & Mackworth 2010, Rich 1983, Russell & Norvig 2020, Winston 1977). We included not just recent AI textbooks but also older ones, as these also may include ideas cited in OT. Examples of keywords are “artificial intelligence,” “machine learning,” “neural network,” “expert system,” and “representation.”
2. Search the main bibliographic databases (JSTOR, ISI Web of Science, and Google Scholar) for use of those keywords in the main OT and strategy journals (*Academy of Management Journal*, *Academy of Management Review*, *Administrative Science Quarterly*, *Journal of Management*, *Journal of Management Studies*, *Management Science*, *Organization Science*, *Organization Studies*, *Strategic Management Journal*, and *Strategy Science*).
3. Eliminate from the list those articles that contain only superficial citations to AI ideas.
4. Read the remaining articles and code them in terms of the main AI ideas used.
5. Expand the list by including the forward and backward citations of the most-cited articles.
6. Repeat steps 2–5 until we are confident that we have identified relevant and representative articles illustrating the main uses of AI ideas in OT.
7. Check with our personal networks that we are not missing important works.

Three review papers that are related to ours are Joseph and Gaba (2020) on organization structure and information processing, Puranam, Stieglitz, Osman, and Pillutla (2015) on modeling bounded rationality, and Baumann, Schmidt, and Stieglitz (2019) on search in rugged landscapes. Like ours, these papers are broadly interested in information-processing explanations of organizational behavior. Unlike Puranam et al. (2015) and Baumann et al. (2019), however, our focus is not on surveying modeling papers, but on OT theories (regardless of research method) that have borrowed ideas from AI. Unlike Joseph and Gaba (2020), which looks at papers related to organization structure and information processing, our focus is on OT papers that use AI ideas. None of the above papers delves into the AI roots of the OT theories that we cover.

AI IDEAS USED IN OT: SEARCH APPROACHES

Our description of the ways in which OT has borrowed from AI follows the structure of Table 1. Each row in that table corresponds to an AI approach, with the left and right columns containing, respectively, AI ideas and illustrative uses in OT. Table 1 is thus a type of Rosetta Stone, connecting AI ideas to their OT counterparts.

Insert Table 1 about here.

In this section, we describe the first four rows of that table; that is, the four approaches that relate to search. In each subsection we describe an AI approach—the definition, examples, and historical milestones for context—and then the ways in which that approach has been used in OT.

Approach 1: Cybernetics and Control Theory

AI idea. Cybernetics is the study of systems that use feedback to automatically control their behavior in order to achieve a goal (Wiener 1948). Today, this area of research is more commonly known as "control theory." The challenge that a cybernetic system is trying to address is to maintain an optimal behavior in a dynamic environment by changing a set of parameters, the canonical example being a heating system that uses a thermostat to keep the temperature of a room at a desired level. In the case of the thermostat, the changing parameter could be whether to keep the boiler on or off.

The impetus to study cybernetics arose between the First and Second World Wars with the need to develop anti-aircraft defenses (Mindell 2002), which required reacting to feedback more quickly than any human could do. The rigorous study of cybernetics begins with the work of Norbert Wiener at MIT, who coined the term and developed the mathematics of cybernetics, based on dynamic systems—that is, systems of differential equations. Building on Wiener's work, Forrester expanded the use of dynamic systems to model the behavior of complex systems such as the economy and the climate, producing ideas that inspired the creation of the Club of Rome (Meadows & Club of Rome 1972). This line of work continues today in the System Dynamics Group at MIT (see, e.g., Sterman

2000).

Shannon's (1948) communication theory, which underlies all communication systems, owes much of its formulation to Wiener's (1948) conceptualization of communication (Shannon & Weaver 1949/1998: 85); hence, communication theory is sometimes considered a descendant of cybernetics. Between 1946 and 1953, the Macy Foundation sponsored annual conferences on cybernetics, which were instrumental in creating the field and in diffusing its ideas (Pias 2016).

The general applicability of the cybernetic concepts of information, communication, and feedback led other researchers to apply cybernetic ideas to several fields, including cognition (Ashby 1952, 1956), anthropology (Bateson 1972), biology (Maturana & Varela 1980), and management (Ansoff 1965, Beer 1972).

OT uses. The influence of cybernetics in OT is pervasive. One area in which the imprint is clear is the research on aspiration levels, which has been an influential and productive area of OT research (Greve 1998, Posen, Keil, Kim, & Meissner 2018). March and Simon (1958/1993: 68) introduced the idea that a firm's behavior depends on whether its performance is above or below an aspiration level, which directly parallels cybernetics' simplest model, the thermostat. In fact, Simon was deeply aware of Wiener's work (Dasgupta 2003: 697) and March and Simon (1958/1993: 65) use the same type of mathematics and block diagrams found in Wiener (1948). Simon's grasp of cybernetics is clearest in his 1952 paper, "On the Application of Servomechanism Theory in the Study of Production Control."

Ideas from cybernetics also entered into OT through the influence of communication theory. Cyert and March (1955: 130–131), for example, build on Shannon (1948) to conceptualize organizational structure as a "communication pattern" and the role of the organization designer as someone in charge of the "design of informational channels," who must pay special attention to how the organization "receives, decodes, encodes, and retransmits information." All of this is reminiscent of the types of problems Shannon's theory addressed. Another early paper connecting OT to cybernetics is Bavelas's (1950) model of the communicational efficiency of different group structures, initially presented at the 1950 Macy conference (Pias 2016). The imprint of communication theory is also visible in the ensuing works of the Carnegie tradition (e.g., Cyert & March 1963, Galbraith 1973, Simon & Newell 1958, Thompson 1967), which view organizations as information-processing systems, a view that continues to be a very active area of research today (see, e.g., the recent survey by Joseph & Gaba 2020).

Another cybernetic idea that has become important in OT is the idea of requisite variety (Ashby 1956); namely, that for a system to deal successfully with an environment, it needs to have as many degrees of freedom as the environment. This idea is central in works such as Weick (1979), Burton and Forsyth (1986), Siggelkow (2002), and Csaszar and Ostler (2020).

The mathematical techniques developed by Wiener and Forrester—today packaged in user-friendly software like iThink[1]—have been productively used in the context of organizations by the system dynamics literature. One of the main goals of this literature has been to elucidate the complex nonlinear behavior that emerges when feedback loops and accumulation processes are combined, as they often are in organizations (Gary, Kunc, Morecroft, & Rockart 2008). Sterman (2000) is a textbook treatment of this literature; examples of research papers in this tradition include Repenning (2002), Rahmandad (2008), and Freeman, Larsen, and Lomi (2012).

Another theory about organizations with a clear cybernetic origin is vacillation theory (Nickerson & Zenger 2002), which proposes that organizations can approximate an optimal configuration by alternating between discrete states on the basis of feedback. Like aspiration models (March & Simon 1958/1993), Nickerson and Zenger's model is based on the mathematical model of a thermostat, a connection they acknowledge multiple times in their paper.

Approach 2: Heuristic Problem-Solving

AI idea. Heuristic problem-solving is an AI approach based on using heuristics—rules or strategies developed through experience—to search for a sequence of actions leading from the current state to a desired state (Winston 1992: 53). Because a great variety of problems can be represented as a sequence of states and transitions between these states, this approach can be used to solve many problems that previously were only solvable by humans.

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[1] `www.iseesystems.com`

A classic example of such a problem is chess, in which one searches for a sequence of actions (moves of the chess pieces) that will lead from the current state of the board to the goal state—a checkmate. In brief, chess programs work by assigning a score to each considered state and then picking a next move that gets the player closer to a high-score state. The fact that every other move is played by the opponent is dealt with by using a "minimax" algorithm, which assumes that at each step, the opponent's moves will try to minimize the player's expected score (which the player is trying to maximize). The complexity of computer chess arises because the number of possible states is usually too large even for a computer; it has been estimated that, starting from the initial board, the number of reachable positions is 10^{46} (Chinchalkar 1996). No matter how fast the computer is, a chess program can only explore a tiny fraction of the search space. Thus, except in the final stages of a game, a chess program typically cannot know which path will lead to winning the game, so it must resort to heuristics to assign a score to any given board state and to select which move to make next. Heuristics in this context could be having more valuable pieces than the opponent and having the king in a safe position.

The idea of representing problems as states and transitions between states was introduced in von Neumann and Morgenstern's (1944) seminal book on game theory. The state-and-transitions representation corresponds to their extensive-form game representation, which is usually drawn as a "tree" in which each node is a state and each link a transition. In AI, this representation is sometimes called the "game tree", "search tree," or the "search space." The idea of using heuristics to prune the search space was influenced by Polya's (1945) nontechnical description of heuristics that could be used to solve mathematical problems, which Newell knew from having taken an undergraduate course with him around the time Polya's book was published (Newell 1983).

Significant demonstrations of the power of heuristic problem-solving came with the Logic Theorist program (Newell & Simon 1956), which was able to automatically prove several theorems from Russell and Whitehead's *Principia Mathematica* (1910), and the General Problem Solver (Newell, Shaw, & Simon 1959), which expanded the reach of the heuristic approach to other logical puzzles.

Early chess-playing programs were developed by Shannon (1950) and Newell, Shaw, and Simon (1958). The successes of these early examples of the heuristics approach led to overly optimistic predictions. Herbert Simon and Allen Newell (1958: 7) predicted that "within 10 years a digital computer will be the world's chess champion." Simon (1965: 96) later predicted that "machines will be capable, within 20 years, of doing any work a man can do." Marvin Minsky (1967: 2) predicted that "within a generation . . . the problems of creating 'artificial intelligence' will be substantially solved."

The 1960s did not bring such triumphs, but did bring the discovery of important ideas about how to efficiently prune search spaces, including alpha-beta pruning, which cuts branches of the search tree that are assured not to contain good solutions (Edwards & Hart 1963), and the A* algorithm, which can be used in problems where there is a proxy for the value of each state (Hart, Nilsson, & Raphael 1968). In 1997, a computer finally did defeat a world chess champion, using alpha-beta pruning and taking advantage of the exponential increase in computing power (Campbell, Hoane, & Hsu 2002). Simon and Newell, though off by about 30 years, had been correct in their prediction that digital chess players would surpass humans.

OT uses. Several OT ideas revolving around the concept of bounded rationality were influenced by the AI work on heuristic problem-solving, a fact that is attributable to Herbert Simon having been a central figure in both OT and AI. The OT idea that individuals are boundedly rational—that, however rational their thinking is, they can only take so much into account—is akin to the idea that, for any sufficiently complex problem, even a computer cannot explore all the states in a search space. Simon wrote the foundational papers on bounded rationality (Simon 1955, 1956) while he was working with Newell on what became the Logic Theorist (Newell & Simon 1956) and the General Problem Solver (Newell et al. 1959).

Because of bounded rationality, an individual cannot seek an optimal solution but rather can only search for a "good enough" or "satisficing" solution—much in the same way that a computer chess program would settle for the best position found after searching a limited subset of the impossibly large search tree. To establish how such a process of search would look like in real organizations, Cyert, Feigenbaum, and March (1959) developed a behavioral simulation of the pricing process in a duopoly. Cyert and March (1963, Chapter 6) later described with painstaking accuracy the pricing process of a department store.

Because according to this view individuals make decisions by searching, it was essential to understand how they search; that is, what search heuristics individuals use. This line of research launched a vast literature using protocol analysis (Ericsson & Simon 1992) to examine how novices and experts solved problems. This body of knowledge is summarized in Newell and Simon's 1972 magnum opus, *Human Problem Solving*. A descendant of this literature in entrepreneurship is the concept of "effectuation" (Sarasvathy 2008), which characterizes how entrepreneurs discover opportunities. Sarasvathy, herself a former PhD student of Simon, defines effectuation in terms of search (Sarasvathy 2008, chapter 4) and investigated it using think-aloud protocols.

Cyert and March (1963) argued that once a firm finds a solution—a path from an initial state (say, the introduction of a new product) to a desired state (profitable sales of that product)—this set of actions becomes a standard operating procedure. From then on, these procedures can evolve in different ways, a process that has been explored by the literature on routines (Cohen & Bacdayan 1994, Feldman & Pentland 2003, Nelson & Winter 1982). In current research, the process of search is a central behavioral foundation of the theoretical and empirical literature on rugged landscapes (e.g., Levinthal 1997; see Baumann et al. 2019 for a survey of over 70 studies in this literature).[2]

Approach 3: Evolutionary Computation

AI idea. Evolutionary computation is an AI approach based on searching a population of candidate solutions by simulating the evolutionary processes of variation, selection, and retention (Mitchell 1996: 2). Although this approach is sometimes known as "genetic algorithms," we will reserve that label for a specific type of evolutionary computation.

The goal of evolutionary computation is to discover high-quality solutions in vastly large and complex search spaces. In contrast to heuristic problem solving, which searches a space

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[2] Although the landscape analogy is rooted in evolutionary biology (Wright 1932), the idea of how individuals and firms may *search* on that landscape comes from AI.

starting from the current configuration, evolutionary computation finds satisficing solutions by creating candidate solutions through a process that simulates biological evolution. The premise is that if biological evolution was able to “discover” millions of successful solutions to a complex problem—staying alive as an individual and as a species in a variety of changing and dangerous environments—a computer simulation of evolution should be able to discover successful solutions to complex problems. Evolutionary computation is in fact commonly used to find solutions to complex engineering design problems. Koza (2010), for example, documents 76 cases in which evolutionary computation has matched or improved state-of-the-art solutions devised by engineers or scientists, such as designs for electrical circuits and algorithms to optimize stock portfolios.

The first milestone in the development of evolutionary computation was Turing’s (1950) proposal for a “learning machine” that could imitate the principles of natural evolution. During the 1950s and 1960s, there were some promising but limited successes in trying to implement Turing’s vision (Fogel 1998). It was Holland’s (1975) book that put evolutionary computation on a firm theoretical footing and marks the beginning of the modern study of evolutionary computation. Although his main aim was to understand how biological evolution works, an important effect of this book was to popularize evolutionary computation as an alternative to heuristic methods in AI.

The specific type of evolutionary computation proposed by Holland (1975) is called the genetic algorithm. It models mutation and crossover in a population of candidate solutions. Each solution is modeled as a binary vector of a fixed size that represents a position in a multidimensional landscape. Mutations randomly change bits of solutions, while crossover creates “offspring” that combine the information contained in the “parents.” These two genetic operators are applied over and over to high-fitness candidate solutions to create successive generations of new solutions. As with its natural counterpart, when this blind evolutionary process is applied over and over, ever more fit solutions tend to emerge.

To understand why genetic algorithms were effective, Holland (1975) theorized that changing the relative frequency of crossover and mutation made it possible to balance exploration with exploitation; that is, to balance a strategy of visiting new positions in the landscape with a strategy of remaining close to the current position. To analyze this issue, Holland (1975, Section 5.1) used the mathematics of multiarmed bandits; that is, the idealized situation of a gambler choosing among different slot machines as he learns about their differing distributions of rewards. Koza (1992), a student of Holland at the University of Michigan, extended the genetic algorithm to allow for solutions of variable length; rather than use fixed size vectors, he used Lisp expressions. This type of evolutionary computation was called "genetic programming," as it makes it possible to "evolve" computer programs.

OT uses. Ideas from evolutionary computation entered forcefully into OT through the work of James March. Building on Holland (1975), March (1991) proposed that organizations, too, faced an exploration/exploitation trade-off. This idea became a staple of research on the structural determinants of innovation (e.g., Raisch & Birkinshaw 2008) and of research on innovation more generally. March's borrowing from evolutionary computation is not just conceptual, as the model he develops in that paper is a type of genetic algorithm over a population of individuals, each described by a vector of beliefs. This population of individuals is subject to variation forces (due to hiring and learning) and selection forces (based on a fitness function that depends on the accuracy of the individuals' beliefs).[3] Genetic algorithms also figure prominently in models of organizational evolution, such as those of Bruderer and Singh (1996) and Lee, Lee, and Rho (2002), and in models that extend March (1991), such as that of Fang, Lee, and Schilling (2010).

Evolutionary computation also affected OT through the use of the multiarmed bandit to examine exploration and exploitation. Posen and Levinthal (2012), for example, analyze organizational exploration and exploitation by using a bandit model; they study how the optimal degree of exploration depends on factors such as environmental turbulence and the decision maker's knowledge. Bandit models have also spawned empirical research in OT. Laureiro-Martinez et al.'s (2015) laboratory study, for example, investigates how individuals behave when making decisions involving risk.

Evolutionary computation has also affected OT through its effect on the influential literature,

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[3] A paper that could be considered an antecedent of March (1991) is Cohen's (1981) model of parallel thinking in organizations, which borrows the idea of modeling individuals as vectors of beliefs from Holland (1975). Cohen, both a colleague of Holland at the University of Michigan and a co-author of March, played an instrumental role in creating this AI–OT bridge (D. Levinthal, personal communication, December 30, 2020).

initiated by Baldwin and Clark (2000), on modularity and design rules. Baldwin and Clark (2000: 10) acknowledge that the organizing framework of their book is the evolutionary understanding of complex systems stemming from Holland's (1975) work. Among the AI concepts they borrow are the idea of seeing design as search, the interpretation of evolutionary operators such as mutation and crossover, the criteria for selecting powerful evolutionary operators, and the "credit assignment problem"—that is, identifying the contribution to fitness of specific elements of a design (Baldwin & Clark 2000: 129–130, 225, 273). Much work has built on Baldwin and Clark (2000), including research on knowledge recombination (Brusoni, Prencipe, & Pavitt 2001), product modularity (Ethiraj & Levinthal 2004), open innovation (Schilling 2000), imitation (Rivkin 2000), organizational structure (Siggelkow & Levinthal 2003), and ecosystems (Baldwin 2018).

Approach 4: Reinforcement Learning

AI idea. Reinforcement learning is an AI approach based on learning what actions are most appropriate through an interactive process of trial-and-error (Sutton & Barto 2018: 1–2). This approach captures the challenge of learning to play a game you do not know simply by playing it over and over and being told each time who won (Russell & Norvig 2020: 789). A key challenge in such a problem is the issue of credit assignment: which of the many actions in the game contributed to the victory? Reinforcement learning is particularly helpful in dealing with problems in which heuristics are hard to acquire or in which it is unclear how to assign fitness values to different configurations. An example of reinforcement learning is the software that learned to play classic videogames only by looking at the screen while controlling the movement of the joystick (Mnih et al. 2013).

A number of important ideas in reinforcement learning come from classic models of learning from psychology, such as the law of effect (Thorndike 1911), conditioning (Pavlov 1927, Skinner 1938), and Hebbian learning (Hebb 1949). A stylized version of these ideas was first put into mathematical form by Bush and Mosteller (1955). Another important source of ideas in reinforcement learning is dynamic programming (Bellman 1957), a mathematical framework to solve multi-stage optimization problems using backward induction. Bellman (1957: ix) coined the term "curse of dimensionality" to denote that the computational resources needed to solve learning problems increase exponentially with the size of the problem.

The use of reinforcement learning in AI starts with Samuel's (1959) checkers-playing program, which changed the coefficients of a scoring polynomial depending on feedback it gained from playing against a copy of itself (a technique also known as "self-play"). This polynomial, representing the computer's "understanding" of the game, is used to evaluate the quality of different board configurations. Samuel's program was ahead of its time in that it combined multiple approaches; specifically, reinforcement learning and heuristic search (Approach 2). During the 1980s, researchers improved on Samuel's ideas to create more effective algorithms to learn to play multi-stage games (examples of these algorithms, collectively called "temporal difference learning," include TD(λ) and Q-learning; see Sutton and Barto 2018: 13–22 for details).

Another milestone in the history of reinforcement learning was the development of TD-Gammon (Tesauro 1995), the first program to play backgammon at a level similar to that of the best players of the time.[4] More recently, a similar approach was used to develop AIs that beat the human champions in classic video games (Mnih et al. 2013), the ancient Chinese strategy game of Go (Silver et al. 2016), and the contemporary multiplayer strategy game *StarCraft* (Vinyals et al. 2019).

OT uses. The concept of reinforcement learning entered early on into the OT literature. In fact, a year after Samuel's (1959) paper had been published, Clarkson and Simon (1960: 924–925) were already advocating for modeling learning processes in organizations using Samuel's ideas. Reinforcement learning plays a central role in some of the works that defined the Carnegie tradition. Cyert and March (1963: 118) use the concept to explain a firm's adaptive behavior: "Any decision rule that leads to a preferred state at one point is more likely to be used in the future than it was in the past." Lave and March (1975, Chapter 6) use the Bush–Mosteller (1955) learning model to illuminate characteristics of adaptive behavior in organizations.

More recent work includes (a) Denrell and March (2001), which propose the "hot stove effect" by which reinforcement learning can lead to more conservative decisions; (b) Denrell, Fang, and

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[4] TD-Gammon was also trained using self-play, but where Samuel's (1959) checkers program used feedback to change the weights of a *polynomial*, TD-Gammon used it to change the weights of a more complex *neural net* (see Approach 6).

Levinthal (2004) and Fang and Levinthal (2009), which use Q-learning to shed light on how the effect of exploration in multi-stage decision problems differs from the effect in single-stage decision problems; (c) Rahmandad (2008), which uses a reinforcement learning model to theorize about the effect of delays in the complexity of organizational learning; and (d) Puranam and Swamy (2016), which explore the nuances of learning processes in organizations in which joint actions determine organizational outcomes, which in turn feed back into the organizational learning process.

To conclude our discussion of the use of AI search approaches in OT (Approaches 1–4), we note that Winter's (1987) seminal piece on "knowledge and competence as strategic assets" was critically influenced by all four AI approaches we have covered so far: "Both control theory and evolutionary theory invoke the notion of state description . . . I have proposed the informal, looser and more flexible concept of a heuristic frame—essentially, the control theory approach stripped down to a list of state descriptors and control" (p. 181). Here is a clear demonstration that knowing AI can enrich our understanding of existing organizational theories and our ability to develop new ones.

AI IDEAS USED IN OT: REPRESENTATION APPROACHES

The emphasis of the previous set of approaches was that the key to producing intelligent behavior was to search a space of possible solutions. This could take the form of (a) searching for the value of a parameter so as to match an aspiration level (cybernetics and control theory, Approach 1); (b) searching a tree for a satisficing state (heuristic problem-solving, Approach 2); (c) searching a space of possible evolutionary designs (evolutionary computation, Approach 3), or (d) searching a space of possible polices to use in a dynamic program (reinforcement learning, Approach 4).

The premise of the next set of approaches is that AI can be achieved by picking the right representation. These approaches are very well characterized by Simon's assertion that "solving a problem simply means representing it so as to make the solution transparent" (1969/1996: 132). We will discuss three such approaches, differing in the type of representation they propose. *Expert systems* (Approach 5) focus on representations of logical rules, which have a good fit with mature knowledge domains for which well-defined explicit knowledge is available, such as the knowledge a doctor uses to diagnose diseases. (The optimism surrounding this approach spurred a countermovement that we also discuss.) *Connectionism* (Approach 6) focuses on statistical representations, which have a good fit with domains that rely on tacit knowledge, including perceptual tasks—such as recognizing faces or speech—for which high-quality explicit knowledge does not exist or is too difficult to acquire. *Bayesian networks* (Approach 7) focus on representing causal knowledge, which is particularly useful in domains characterized by uncertainty.

Approach 5: Expert Systems and Knowledge Representation

AI idea. Expert systems are an AI approach that relies on representing the knowledge of a domain as a large number of special-purpose rules that, when combined by an inferencing mechanism, can answer questions about the domain (Norvig 1992: 461; see also Feigenbaum, McCorduck, and Nii 1988, Chapter 3). The idea that motivated the creation of expert systems was to create a general and flexible platform able to represent knowledge of different domains; that is, while a given expert system would be specialized, the approach used to create such systems aimed for generality (Norvig 1992: 530). The expert system approach is thus in contrast to custom-made approaches, such as chess program, that would be very difficult or impossible to adapt to a different domain. Expert systems achieve this flexibility by including two main components: a knowledge base and an inference engine. The first stores knowledge as if/then rules and the second combines that knowledge using logical rules. This architecture aims to mimic how an idealized expert uses accumulated knowledge to reason about his or her domain of expertise (Lindsay, Buchanan, Feigenbaum, & Lederberg 1993).

An early example of an expert system is the MYCIN program for diagnosing bacterial infections (Shortliffe et al. 1975). It used around 600 if/then rules, diagnosing an infection once enough evidence had been accumulated. A more recent example is the TurboTax software package, which uses myriad rules about the US tax code to solve tax preparation problems.

Starting in the late 1960s, a number of successful expert systems were developed that could match the performance of human experts. These included DENDRAL (Buchanan, Sutherland, & Feigenbaum 1969), which could infer a molecular structure from the information provided by a mass spectrometer; MYCIN (Shortliffe et al. 1975)—mentioned above—which could diagnose blood infections; Macsyma (Moses 1974), which could solve symbolic algebra problems; and

PROSPECTOR (Duda et al. 1977), which could recommend sites for mineral prospecting. The experience gained with these and other projects led to the creation of tools for creating expert systems, such as the programming language Prolog, and to a formalization of the process of extracting rules from experts, called knowledge engineering (Hayes-Roth 1992).

Success also led to ambitious engineering projects such as CYC (Lenat, Prakash, & Shepherd 1985), whose aim was to produce a knowledge base that included all common-sense knowledge about how the world works, and SOAR (Laird, Newell, & Rosenbloom 1987), which aimed to provide a cognitive architecture that could produce human-level general intelligence.

In addition, new ideas arose that expanded the types of data and inferences that expert systems could handle. Schank and Abelson (1977), for example, extended expert systems to operate not just on if/then expressions but also on "scripts"—knowledge structures that describe stereotypical situations such as going to a restaurant (including finding a table, choosing from the menu, and so on). Other structures developed to deal with stereotypical situations included frames (Minsky 1975) and schemas (Bobrow & Norman 1975). McCarthy (1980) and others (see Ginsberg 1987) developed nonmonotonic logic to more easily deal with knowledge bases that include exceptions, contradictions, and default assumptions. This type of logic provided a workable solution to the "frame problem" (McCarthy & Hayes 1969), the notion that dealing with such situations using standard logic formalisms was computationally unwieldy.

The early successes of expert systems led to an "AI bubble" in the early 1980s, with the creation of numerous AI startups, many of which offered expert systems. The bubble was inflated in part by Japan's Fifth Generation project, which injected close to $1 billion (in today's dollars) into the Japanese AI industry, and by DARPA's reaction to that, which was to invest lavishly in AI projects through its Strategic Computing Initiative (Feigenbaum and McCorduck 1983; Nilsson 2010: 296). By the late 1980s, the boom had ended due to the mismatch between the high expectations for expert systems and what they were actually able to deliver. The disappointments were emphasized by lingering academic doubts and criticisms about the potential of expert systems (Dreyfus 1972, Dreyfus & Dreyfus 1986). The end of the boom marks the beginning of the so-called "AI winter," which lasted over 20 years until advances in connectionist and machine learning approaches (Approach 6) raised new hopes for the field.

OT uses. The influence of expert systems on OT takes many forms. Interestingly, these influences have as much to do with the criticisms of expert systems as with the conceptual innovations that allowed for the existence of expert systems in the first place.

One manifestation of the influence of expert systems on OT is the efforts to codify parts of OT in the form of an expert system. In particular, Burton and Obel (2004) created OrgCon, which codifies much of what is known about organization design. Their expert system is structured in terms of if/then rules, such as, "If the organization is large, then decentralization should be high" (Burton & Obel 2004: 18). It includes, for example, rules about the role of interdependence (Thompson 1967) and environmental uncertainty (Galbraith 1973). Another manifestation is the adoption by Polos, Hannan, and Carroll (2002) and Hannan, Polos, and Carroll (2007) of nonmonotonic logic to express their theory about organizational forms and identities. Nonmonotonic logic allowed them to rigorously state their theory despite the fact that it deals with concepts that continually evolve and have fuzzy boundaries (e.g., like music and wine categories) and hence are ill-suited for traditional formal tools like predicate logic or set theory.

Another set of OT uses of ideas originating with expert systems has to do with the limits of codified knowledge. Starting in the late 1980s, the failure of expert systems to match the high expectations they had created prompted several OT scholars to study the limits of codified knowledge. Prietula and Simon (1989: 120–121) highlighted the role of human experts and explained that expert systems usually fail to mimic them, as "[human] expertise is based on a deep knowledge of the problems that continually arise" in any particular kind of work. Disappointment with expert systems also influenced the development of the knowledge-based view, in which the process of externalization—turning tacit knowledge into explicit knowledge (Nonaka 1994)—is described as imperfect. In this vein, Grant (1996) explains that "converting tacit knowledge into explicit knowledge . . . inevitably involves substantial knowledge loss" and Kogut and Zander (1992: 387) cite Dreyfus and Dreyfus's (1988) criticism of expert systems as supporting evidence for a similar view. Suchman (1987) and Orr (1996) did ethnographic studies that showed the limitations of an expert system created to support the work of copy machine technicians at Xerox. Drawing on these studies, Brown and Duguid (1991) theorized that organizational learning depends on "communities of practice" to facilitate creating and sharing knowledge that is situated and embedded in practice and which is quite distinct from the dry knowledge captured in an expert system.

The AI concept of scripts (Schank & Abelson 1977) has been used in OT to theorize about routines and organizational adaptation. Nelson and Winter (1982: 79) build on the idea of scripts to theorize about the nature of skills and routines. Pentland (1995: 543) represents routines using a grammar which he characterizes as "a more powerful generalization of the same basic idea of scripts." Gioia and Poole (1984) see much potential in investigating scripts as a unit of analysis. They propose a research agenda and methods for studying scripts in organizations, in response to which, several papers studied how scripts change when firms face novel situations (see, e.g., Barley 1986, Hargadon and Bechky 2006; see also the multiple references to the concepts of script, frame, and schema—all AI concepts—in Walsh 1995).

The idea of the frame problem (McCarthy & Hayes 1969) has also been used in OT to portray entrepreneurial action. Felin, Kauffman, Koppl, and Longo (2014) theorize that the frame problem implies that understanding entrepreneurial discovery as a process of boundedly rational search on a fitness landscape is an inadequate analogy. Following Dennett (1984), they interpret the frame problem as implying that discovering all potential opportunities is computationally intractable, from which they draw the conclusion that it is incorrect to assume that there is any one landscape in which all these opportunities exist.

Approach 6: Connectionism and Machine Learning

AI idea. Connectionism is an AI approach that relies on artificial neural networks (also known as "neural nets")—circuits whose connections are loosely patterned on those of the neurons in the brain (Sejnowski 2018, Russell and Norvig 2020: 750). Connectionism is part of a broader family of AI methods called "machine learning," the goal of which is to build machines that improve automatically through experience (Jordan & Mitchell 2015: 255). Some authors bundle machine learning and reinforcement learning (Approach 4) together. But a common way to differentiate between them is that in reinforcement learning, the learning depends on trial-and-error—that is, on interaction with the environment—while in machine learning, the computer infers relationships from data that are given—that is, learning depends on experience rather than on experimentation (Sutton & Barto 2018: 2).

The main challenge that machine learning tries to address is how to use vast amounts of data to make accurate predictions and classifications. To do so, machine learning systems need to explore "a large space of candidate programs, guided by training experience, to find a program that optimizes the performance metric" (Jordan & Mitchell 2015: 255). Two examples of tasks will illustrate two types of machine learning. The first task is: given the buying histories of a company's customers, group them into similar types. This is an example of "unsupervised learning," as the dataset only includes independent variables. The second task is: given the buying histories of a company's customers and their ages, predict the age of new customers from the items in their shopping carts. This is an example of "supervised learning," as the dataset contains both dependent and independent variables, as if a teacher or supervisor had labeled a training set of examples.

McCulloch and Pitts (1943) proposed the first mathematical model of how biological neural networks work. Simplifying some historical details, their model is currently understood as follows:

- Each neuron computes a weighted sum of its inputs and returns a scaled number that can be used by other neurons either as a result or as an input (see Panel (a) in Figure 2).
- A neural network is an interconnected arrangement of such neurons (see Panel (b) in Figure 2).
- Most neural nets are hierarchical: an initial layer of neurons receives inputs from the external world (that is, something outside the network itself) that are processed by subsequent layers and a final layer of neurons returns a result.
- The information passed from one layer to the next can be thought of as successively refined, higher-level representations of the original incoming information. For example, if the incoming information is all the pixels of an image and the last output of the net is a decision on whether or not the image contains a human, intermediate layers could be encoding successively

higher-level concepts such as curves, blobs, and face-like features. The intermediate layers are sometimes known as “hidden layers.”

- Part of the appeal of neural networks is that the inputs and outputs can be anything that can be turned into numbers, such as the letters in a sentence, the pixels in a video, or a price time-series.

Insert Figure 2 about here.

McCulloch and Pitts’s model was speculative and today it is well known that this is not an accurate representation of actual biological neural networks.[5] Nevertheless, their model was intriguing and spurred much interest in practical applications. Decades later, this approach had made it possible to solve several AI challenges better than any other AI approach could do and sometimes even better than humans.

Minsky (1954), Rosenblatt (1958), and others implemented neural networks with a single layer of neurons, called perceptrons. Minsky and Papert’s (1969) book then demonstrated that perceptrons had fundamental limitations in the types of functions they could compute, provoking a decline of interest in neural nets. Consequently, AI was dominated in the 1970s and 1980s by symbolic approaches, particularly heuristic problem-solving and expert systems. In 1982, however, Hopfield (1982) developed a neural net that could be used as associative memory. That is, it retrieves the memory that is most similar to the stimulus with which it is presented. And in 1986, neural nets took a big step forward when Rumelhart, Hinton, and Williams (1986) published their “backpropagation” algorithm for determining the weights of arbitrarily deep neural networks. Up to that point, there had been no workable method to do this, but now it was possible to overcome the limitations of single-layer neural networks and a door was opened to a great deal of exploration of various neural network architectures and uses.

Several other mathematical advances also furthered the development of neural networks. The demonstration that neural networks could approximate arbitrarily well any mathematical function

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[5] Artificial neural networks are not generally “biologically faithful,” as they do not account for myriad biological aspects such as neuron types, neurotransmitters, connectivity patterns, and brain structures (Crick 1989). For details, see Hasson, Nastase, and Goldstein (2020: 417) and references therein.

(Cybenko 1989, Hornik, Stinchcombe, & White 1989) meant that, at least in theory, neural nets could be used to perform any observable cognitive function, since all sense data and actions can be encoded numerically. The derivation of the bias–variance decomposition (Geman, Bienenstock, & Doursat 1992) helped establish the optimal complexity of a neural network as a function of the data available for "training"—that is, for estimating the parameters or "weights" of the neural net. The use of "decision boundaries" made it possible to visually compare the capabilities of different machine-learning approaches (Nilsson 1965: 4–5, Vapnik 1995).

Enabled by massive improvements in computer power and affordability, AI researchers discovered that neural nets with many layers—in some cases, thousands of layers; hence the name "deep neural nets" or "deep learning"—could surpass other AI methods in a number of tasks, including scene recognition, face recognition, transcription of speech, and translation (see Jordan and Mitchell 2015 for an overview).

Combining neural nets with heuristic search (Approach 2) and reinforcement learning (Approach 4) allowed computers to defeat for the first time the human champions in the games of backgammon (Tesauro 1995), Go (Silver et al. 2016), and *StarCraft* (Vinyals et al. 2019). In such systems, the neural net provides a scoring function used to evaluate possible configurations. The weights in the neural net are optimized via reinforcement learning from self-play and from supervised learning on games played by human experts.

OT uses. Neural nets have entered OT in two main ways: as an overarching model of information processing in organizations and as a way to think about learning and interpretive processes in organizations.

Inspired by McCulloch and Pitts (1943) and by cybernetics (Approach 1), Beer (1972) saw the organization as a type of neural net in which information was processed as it flowed up through the organization. From this observation, Beer concluded that organizations could be improved by rewiring them: adding sensors, routing the right information to the right people, and speeding up communications. His most ambitious application of these ideas was to create an information system to run the entire economy of Chile during the 1970–73 socialist administration of Salvador Allende.

Although the system was designed and partially implemented, there was little time for it to be used given the coup that abruptly ended Allende's government (see Medina 2011 for details about this information system).

The concept of neural nets was also used in several ways to model an organization's learning and interpretive processes. Marchiori and Warglien (2008) modeled interactive learning in repeated games using neural nets to represent the decision makers. Here, individual learning corresponds to updating the weights in a neural net representing each individual. In many cases, their model provided more accurate predictions of human behavior than competing economic models did. Gavetti and Warglien (2015) used Hopfield's (1982) neural model of associative memory to represent individuals' interpretive processes. They then connected these individuals in a social network to study whether the extent to which paying attention to others' interpretations leads to more accurate group-level decisions. They found that the benefit of paying attention to others follows an inverted-U relationship: paying too little attention to others misses valuable insights, while paying too much attention to others results in conformism and neglects the actual problem. Csaszar and Ostler (2020) used the bias–variance decomposition to theorize about the optimal complexity of the representations used by organizations as a function of managers' level of experience and the complexity and uncertainty of the environment. Their theory provides a way to reconcile conflicting views on the debate of simple versus complex representations (i.e., Bingham and Eisenhardt 2011 vs. Weick 1979: 261) by characterizing situations under which representations of low, medium, and high complexity are better able to make accurate predictions about the environment.

Although the scope of this paper is to cover AI analogies in OT, it is worth noting that an important effect of the current wave of machine learning on OT is a methodological one: to expand the type and amount of data available to researchers. For instance, researchers are using machine-learning methods to categorize texts, code videos, and discover patterns in the data they have collected (see Choudhury, Allen, and Endres 2021 for a review).

Approach 7: Bayesian Networks

AI idea. Bayesian networks (also known as belief nets and graphical models) are an approach to AI that allows programs to reason probabilistically about causes and effects (Nilsson 2010: 381). Dealing explicitly with probabilistic situations contrasts with previous approaches, such as heuristic problem-solving and expert systems (Approaches 2 and 5), that used logic to deal with true/false propositions but did not have a sound way to represent probabilistic relationships and make probabilistic inferences.

There had been previous attempts in AI to extend logical approaches to better capture uncertainty, such as Dempster–Shafer logic and fuzzy logic, but these had been found to be unsound (Koller & Friedman 2009: 13). Bayesian networks build on the insight that following the laws of probability is the only way to behave rationally in the face of uncertainty (de Finetti 1937/1980, Ramsey 1931). To accomplish this, Bayesian networks provide a language to represent and interconnect arbitrarily detailed probabilistic information and an inference mechanism which uses the Bayes theorem to update arbitrarily large and interconnected webs of beliefs.

A canonical example of a problem calling for the use of a Bayesian network is illustrated in Figure 3: given the causal structure and probabilities linking a home alarm going off to other events, determine the probability that the home was actually burglarized if, say, the alarm goes off, Mary called, and there was an earthquake. A more sophisticated use of Bayesian networks is to infer the causal structure from data. For example, Friedman, Linial, Nachman, and Pe'er (2000) infer complex networks of gene interactions from observing gene expression data. The idea is to recover the causal structure of gene interactions (i.e., what genes affect what genes) from examining statistical properties of dependence and conditional independence in the data.

Insert Figure 3 about here.

The idea of using graphs to encode causal information can be traced back to a paper by Wright (1921) on genetics (Pearl 2000: 26).[6] Pearl (1988) popularized the notation used in Figure 3 (called a Bayesian network) and developed efficient algorithms to make inferences on these networks.

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[6] Coincidentally, Wright is also the originator of the rugged landscape analogy commonly used in OT.

The key insight of these algorithms is to use the dependence structure of the Bayesian network to avoid the combinatorial explosion that would otherwise occur when computing the problem's joint probability distribution.[7]

Cooper and Herskovits (1992) developed the first algorithms to "learn" or infer Bayesian networks from data. More recent developments include the use of Bayesian networks in cognitive science as a benchmark of rational decision-making against which to compare cognitive models and experimental data (Oaksford & Chater 2007). Cognitive science has also used Bayesian networks to model processes of discovery (Spirtes, Glymour, & Scheines 2000) and concept learning (Tenenbaum & Griffiths 2001).

OT uses. Most of the OT uses of Bayesian networks have to do with modeling the strategic decision-making process. Durand and Vaara (2009), for example, propose a research agenda based on understanding the relationship between resources and performance in terms of Bayesian networks. They see Bayesian networks as a good description of the processes driving firm performance and see the role of the strategist as understanding that causal structure and using it to make well-informed interventions.

In line with Durand and Vaara (2009), Ryall (2009) used Bayesian networks to develop a model of causal ambiguity (Lippman & Rumelt 1982) that represents (a) the causal structure of a firm's activity system and (b) managers' beliefs about that activity system. Using these concepts, Ryall theorizes about two types of causal ambiguity—intrinsic and subjective—stemming from the uncertainty inherent in the real and the perceived Bayesian networks, respectively.

The agenda of embracing Bayesian networks in strategy has also affected how strategy is taught and studied. The MBA textbook by Ryall and Bramson (2014) teaches Bayesian networks to MBAs on the premise that strategy consists of making rational decisions under conditions of uncertainty and that Bayesian networks are the best embodiment of the principles of rational decision-making under such conditions. In terms of research methods, Bettis and Blettner (2020) build on Spirtes

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[7] For instance, if in Figure 3 one knows that the alarm went off, knowing whether there was an earthquake or not does not change the probability that Mary will call. This is an illustration of the "d-separation" criterion (Pearl 2000: 16), one of the ways by which Bayesian network algorithms make inferences without having to evaluate all the possible combinations of contingency values, something that would be prohibitively costly except for the simplest problems.

et al. (2000) and call for studying causality using Bayesian networks rather than regressions. The argument is that regressions essentially capture correlations, whereas Bayesian networks are better suited to describe and estimate the causal structure that gives rise to the observed data.

AI IDEAS USED IN OT: AGGREGATION APPROACHES

We now move on to approaches to AI that rely on aggregation. These differ from the previous approaches in that, here, intelligent behavior emerges from combining the actions of several subsystems or agents to create a desired aggregate behavior. There is no restriction on the types of subsystem that can be used. They could be other AI systems (including any of the approaches we have covered so far), but they could also be simpler decision rules, such as hand-coded rules and statistical methods (for example, linear regressions). The key to aggregation approaches is that—like the US motto "E pluribus unum"—out of many parts, a superior aggregate behavior is achieved.

Approach 8: Cellular Automata and Emergence

AI idea. Cellular automata is an approach to AI that aims to produce intelligent behavior by imitating the functioning of an idealized biological cellular tissue. The "cells" in this "tissue" are described by a state that evolves based on rules that depend on the state of neighboring cells (Floreano & Mattiussi 2008: 101). More formally, a cellular automaton has two components: (a) a grid of *N* identical cells, each with an identical pattern of communication with neighboring cells, and (b) a transition rule, which describes how a cell changes from one time period to the next (Mitchell 1998: 96).

The challenge the cellular automata approach addresses is how to make intelligent behavior emerge from very simple rules. Note that this is in direct contrast with all the other approaches we have seen so far, which use more complex structures—such as a large knowledge base or myriad weights in a neural net—and whose behavior is not emergent—that is, their behavior is directly programmed rather than induced by the system's intrinsic dynamical behavior (Hanson 2009). Arguably, this approach is representative of the types of structure that social or biological evolution can create.

Research on cellular automata and emergence has been intellectually fruitful, but so far has not produced technological breakthroughs like those attributable to the other AI approaches. For this reason, cellular automata is not usually included in introductory AI textbooks (an exception is Luger 2005), but only appears in more specialized ones (e.g., Adami 1998, Flake 1998, Floreano & Mattiussi 2008).

Perhaps the most famous cellular automaton is John Conway's Game of Life, which creates extremely rich, life-like behavior based on just four rules determining when a cell becomes dead or alive (Gardner 1970). Watching an animation of this automaton resembles seeing a world teeming with microscopic life; Figure 4 shows one snapshot of this automaton in action. Another famous cellular automaton is Wolfram's (1983) Rule 30, a one-dimensional cellular automaton which produces unpredictable complex behavior. Wolfram (2020) and others (Schiff 2008: 181, 't Hooft 2016) have even speculated that the universe is a cellular automaton not too different from Rule 30.

Insert Figure 4 about here.

Von Neumann pioneered the idea of cellular automata in his proposal for a general mathematical model of a self-reproducing machine, called the Universal Constructor (von Neumann & Burks 1966). Burks's (1970) book helped define cellular automata as a multidisciplinary academic field. Conway's Game of Life created broad interest in cellular automata, helped by its wide diffusion in *Scientific American* (Gardner 1970). Varela, Maturana, and Uribe (1974) used cellular automata to develop the concept of "autopoiesis," the capacity particular to living systems of reproducing and self-healing. Langton (1986) built on von Neumann's idea of self-replication to pioneer the field of artificial life, which used cellular automata to understand biological phenomena such as biochemical reactions, ant colonies, and cellular replication. Bak, Tang, and Wiesenfeld (1987) used cellular automata to describe the phenomenon of "self-organized criticality"; that is, systems that are able to maintain a characteristic structure via an emergent self-correcting mechanism. For example, avalanches keep the shape of all sandpiles similar regardless of how much sand is in the pile. Crutchfield and Mitchell (1995) combined cellular automata with genetic algorithms (Approach 3) to evolve cellular automata that produce a desired behavior. The long-awaited publication of Wolfram's

(2004) book, *A New Kind of Science*, renewed the visibility of cellular automata.

OT uses. In OT, cellular automata have been used to represent social processes that exhibit spatial distribution and local connectivity, such as processes of segregation, competition, collaboration, and diffusion. For example, Schelling's (1969, 1971) celebrated studies about segregation model a city as a cellular automaton in which individuals change location depending on the proportion of their neighbors that they consider to be of the same type. Disturbingly, the model shows that even if that desired proportion of similar neighbors is small, cities are likely to devolve toward segregated neighborhoods. That is, even if individuals don't seek what they would consider segregation, their individual choices may collectively produce it.

Nowak and May (1992) extend the research on the evolution of cooperation (Axelrod 1984) to explore the societal conditions that make cooperation or competition more likely to emerge. In their model, individuals play an iterated prisoners' dilemma with their neighbors, with the winning strategy becoming more likely to be diffused.

Lomi and Larsen (1996) use a cellular automaton to model the population dynamics of organizations. They show that this simple model can replicate classical findings of the organizational ecology literature (Hannan & Freeman 1989). Their model also suggests that previous results on density dependence are very sensitive to changes in the rules of local interaction; that is, to the cellular automaton's transition rules.

Lustick (2000) uses cellular automata to theorize about how identities diffuse. In this model, the activation of an individual's identity depends on the neighbors' identities. (For introductions to the use of cellular automata in the social sciences, see Hegselmann 1996, Nowak and Lewenstein 1996, and Schiff 2008, Chapter 5.)

Finally, it is worth noting some more distant influences of cellular automata on OT. Much research in OT has built on the complex adaptive systems literature, which develops the themes of emergence, chaos, and complexity by using cellular automata as one of its main methodological tools (Holland & Miller 1991, Miller & Page 2007, Mitchell 2009, Waldrop 1992). Examples of OT literature building on this work include Anderson (1999) and Allen et al.'s (2011) edited volume.

Eisenhardt and Piezunka (2011), included in Allen et al.'s volume, highlight the strategy literature's links with the complex adaptive systems literature.[8]

Luhmann's (1990) theory of autopoietic social systems extended Varela et al.'s (1974) ideas to social—not just biological—systems. In this version, social systems reproduce themselves on the basis of communication (Hernes & Bakken 2003, Seidl 2004). All told, it is fair to say that, without cellular automata, several models about organizational dynamics and the OT literatures on autopoiesis and complex adaptive systems would probably not exist.

Approach 9: Distributed AI

AI idea. Distributed AI (also known as multiagent systems) is an approach to AI that aims to achieve intelligent behavior by using multiple interactive intelligent agents. These agents are autonomous programs capable of interacting with other agents via "social" behaviors such as cooperation, coordination, and negotiation (Wooldridge 2009: xiii, Weiss 2013: xxxv). Distributed AI differs from cellular automata in that distributed AI is much less constrained in the range of behaviors and communication structures available to agents. Under this approach, agents are usually not controlled by the extremely simple rules guiding the evolution of a cellular automaton. Instead, they can pursue goals, sense the environment, communicate with others, and make choices. Also, distributed AI allows for a more flexible communication structure that is not restricted by the regular grid of cellular automata.

The challenge that distributed AI is trying to address is how to deal with situations in which each agent has access to incomplete information or has incomplete capabilities and the agents as a group cannot be centrally controlled (Sycara 1998). A current example is a system in which self-driving cars share information about road conditions and about the other cars on the road, allowing each car to drive more safely and rapidly by avoiding accidents, coordinating maneuvers, and choosing less-congested roads. Another example would be a team of robots sharing a task, such as those competing in the annual RoboCup soccer competition (Kitano et al. 1997).

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[8] An example of the link between the OT literature on complex adaptive systems and cellular automata is the concept of "edge of chaos" (used in OT, e.g., by Brown and Eisenhardt 1998 and Carroll and Burton 2000) and which emerges from Langton's (1986) characterization of the class of cellular automata that exhibit chaotic behavior.

The earliest distributed AI program was Selfridge's (1959) Pandemonium, which could recognize written characters using multiple agents running in parallel. The agents would detect specific features of letters, such as vertical lines, horizontal lines, and circles, and would relay their opinion to agents specialized on higher-level tasks such as recognizing the overall shape of a letter. Similarly, Erman, Hayes-Roth, Lesser, and Reddy (1980) showed how speech recognition could be drastically improved by having multiple simple agents working at different levels of analysis—for example, the letter, word, and phrase levels—and having those agents share information through a shared "blackboard" system.

Minsky's (1986) "society of mind" concept proposed that the human mind works in a way similar to that of Selfridge's system; that is, with several agents working in parallel, each serving a different human need. According to this theory, people only become consciously aware of those agents that "shout" loud enough.

Winograd and Flores's (1986) philosophical text on the nature of cognition and distributed computation highlights the problems of coordinating actions and achieving shared understanding in distributed systems. To examine these problems, they modeled communication using diagrams that describe the possible states and transitions in a dialogue that coordinates an action. An early commercial system implementing these ideas is described by Flores, Graves, Hartfield, and Winograd (1988).[9]

The growing availability of computer networks in the 1980s increased the applicability of distributed AI, as answers to questions like these became consequential: How can an automated agent best represent the interests of a user in an online negotiation with other automated agents (Rosenschein & Genesereth 1985)? In what ways should humans and computers interact in the office of the future (Hewitt 1988)? In the late 1980s, the first books on distributed AI were published (Bond & Gasser 1988, Huberman 1988). Since then, the field has continued to grow, often by building on theories originally developed to understand human behavior. A recent trend has been to develop distributed AI systems that incorporate ideas from economics, such as game theory,

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[9] Interestingly, it was Flores who hired Beer in 1971 to work on Cybersyn, the system intended to run the Chilean economy mentioned under the OT uses of Approach 6.

mechanism design, and auction theory (see, e.g., the introductory textbooks by Wooldridge 2009 and Weiss 2013 and, in particular, the more specialized volume by Shoham and Leyton-Brown 2009).

OT uses. One use of the concept of distributed AI in the field of OT has been computational organization theory, which Carley and Gasser (1999: 323) describe as distributed AI models informed by empirical knowledge from organization science. They also describe several tools from the distributed AI literature that could serve organizational researchers. The article by Carley and Newell (1994) suggests how to characterize the types of agents and situations that this approach may study, and the edited volume by Prietula, Carley, and Gasser (1998) provides many examples of this approach.

Another use of distributed AI in OT is representing organizational processes. Malone and Crowston (1991: 6), for example, propose developing a "coordination theory"—based on insights from distributed AI, economics, OT, and biology—to understand organizations. An ambitious outcome of this research agenda was the book by Malone, Crowston, and Herman (2003), which presents a technical language to describe organizational processes. The goal of this language is to organize all business knowledge and to turn organization design into a discipline closer to engineering, which they suggest would lead to improvements in the quality, predictability, and reusability of organization designs. Their proposed language builds on languages used in distributed AI, such as Winograd and Flores's (1986) transition diagrams (for other examples, see Crowston 1992).

Inspired by distributed AI ideas, Wegner and his collaborators introduced the theory of transactive memory systems (Wegner 1987, Wegner, Giuliano, & Hertel 1985) in the context of intimate dyads: couples who have a shared understanding of "who knows what" and who have processes for encoding, storing, and retrieving such shared information. The concept was later extended to groups and organizations (e.g., Liang, Moreland, & Argote 1995) and has led to a rich empirical literature (see Ren and Argote 2011 for a review). At a conceptual level, transactive memory systems are appealing because they explain much of organizational cognition without resorting to the dubious concept of a "group mind." Instead, transactive memory systems are faithful to the cognitive limitations of the individual actors and to the distributed nature of work in the same way that distributed AI is.

Wegner (1995: 320–321) points to the distributed AI roots of the concept of transactive memory systems by discussing how these systems can best be understood by imagining building software that finds information in a computer network—a quintessential distributed AI problem (see, e.g., Hewitt 1977). He cites foundational distributed AI works (Braitenberg 1984, Minsky 1986) to justify the value of this thought experiment.

Yet another OT concept with AI roots is boundary objects. Carlile (2002) introduced the concept of a boundary object to OT. In this context, a boundary object is an artifact that enables collaboration, such as a shared pad of paper or a 3D model. But the idea comes from a chapter in one of the foundational books on distributed AI, in which Star (1989: 51) proposed the concept of the boundary object as a solution to the problem of sharing information in the "blackboard" systems popular in the distributed AI literature at that time. Star herself is also a good illustration of the two-way connection between AI and OT, as she used organizational examples to motivate different classes of boundary objects. Boundary objects continue to be an active research area in OT (see, e.g., Bechky 2003, Seidel & O'Mahony 2014, Zuzul 2019).

Approach 10: Ensemble Methods

AI idea. Ensemble methods are an approach to AI that relies on combining predictions from different programs (called "learners" in this literature) that work on the same or very similar data. Alternative names for this approach are committee-based learning and multiple classifier systems (Zhou 2012: 15). Ensemble methods differ from distributed AI in that ensemble methods combine similar programs performing a similar task, while distributed AI combines programs that are each specialized in a given task (such as the players in robot soccer or the various subsystems in a driverless car). In other words: ensemble methods rely on redundancy, while distributed AI relies on division of labor.

The challenge this approach is trying to address is to avoid the weaknesses of any single learner by combining several learners. Combining learners is appealing because there is no infallible way to find the best learner—a result known as the No Free Lunch Theorem (Wolpert 1996, 2013). The usual way to deal with this difficulty is to try out several learners and pick the one that performs the best. Ensemble methods offer an alternative to that approach: rather than relying on just one learner, find a way to combine learners so as to collectively outperform any single one. (Or in machine learning lingo: combine several weak learners to create one strong one.)

A canonical example of ensemble methods is the “wisdom of the crowd” effect (Surowiecki 2004), first described by Galton (1907), who observed that the median guess in a competition to find out the weight of an ox was more accurate than the predictions of almost all the participants. A more recent example is the Pragmatic Chaos program, which won a $1 million prize from Netflix for improving the accuracy of its predictions of movie recommendations by more than 10 percent. This program worked by combining predictions from hundreds of learners (Koren 2009).

The idea of improving predictive accuracy by using ensembles has a long history and builds on three foundational ideas. The first is Bernoulli’s (1713/2006) law of large numbers, which states that averaging many independent samples will converge to the true population average as the number of samples increases. It follows that combining several independent learners should result in more accurate predictions.

The second foundation of ensemble methods is Condorcet’s (1785/1994) jury theorem. Conceptually similar to the law of large numbers, but in the context of voting, it states that majority voting conducted by individuals who have a better-than-chance probability of picking the best alternative converges (in probability) to picking the best alternative as the number of individuals increases. (Condorcet came up with this result in the lead-up to the French Revolution, as a way to understand whether democracy could work better than monarchy.)

The third foundation is reliability theory; in particular, seminal work on how to create reliable electronic circuits out of notoriously unreliable parts such as vacuum tubes (Moore & Shannon 1956/1993, von Neumann 1956). The idea is to be able to use the structure of a circuit to compute the probability that the circuit will produce an accurate result. This knowledge can then be used to create circuits with enough redundancy so that they work as intended with an arbitrarily high probability.

Key milestones in the modern history of ensemble methods include the proposal of various ideas on how to create ensembles. One such idea is to create ensembles by using different families of learners (for example, neural nets, regressions, and clustering) or different learners within a given family (for example, neural nets with different numbers of nodes and layers). Hansen and Salamon (1990) noted that for an ensemble to produce correct results, it is important that its learners make uncorrelated errors. This is a strong argument for using a diverse set of learners.

A second idea was to train similar learners on different subsets of the data (that is, different "rows" of the dataset). This is a cheap way to create a diverse *set* of learners out of only one *type* of learner (say, neural nets). The most common way of doing this is "bagging" (Breiman 1996), which works by training learners on subsets of the original dataset generated by sampling with replacement.[10]

A third idea was to train similar learners on different attributes of the data (that is, different "columns" of the dataset). The method of Random Forests (Ho 1995) introduced this idea by training decision trees on the same dataset, but picking at random the variable used at each branching point of the tree.

A fourth idea was to train a sequence of learners such that successive learners try to correct the errors made by previous learners. Unlike the first three ideas, which use multiple learners working in parallel, this idea works by placing the "experts" in sequence. Schapire (1990) introduced this approach, which he called "boosting." A common version of the boosting idea is AdaBoost (Freund & Schapire 1996), in which each successive learner is trained on a sample that assigns more weight to the predictions that previous learners got wrong.

Following the law of large numbers and Condorcet's jury theorem, most ensemble methods use simple averaging or voting (depending on whether the task is, respectively, prediction or classification). It is also possible to use weighted versions of averaging and voting. An important result that has been rediscovered many times is that the optimal weights for uncorrelated learners are their log odds of being correct (that is, $w_i^* = \log(a_i/(1 - a_i))$), where a_i is the accuracy of

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[10] The name "bagging" comes from *b*ootstrap *agg*regat*ing*, as it operates similarly to bootstrapping in statistics (Efron & Tibshirani 1993).

learner *i*). Pierce (1961) seems to have been the first to discover this result (Kuncheva 2014: 125). The theory of Bayesian model averaging provides a general way of computing optimal weights when the learners are correlated.

Dietterich (2000) provides three explanations for the success of ensemble methods. The *statistical* reason is that, by using multiple learners, the ensemble decreases the risk of picking a bad one. The *computational* reason is that estimating all the parameters in a learner is a computationally complex process prone to getting "stuck" at a local peak, whereas combining multiple learners can better approximate the optimal parameters. The *representational* reason is that most learners are unlikely to have the correct representation of the problem—they may, for example, be missing variables or ways of interacting them—whereas a combination of learners will be more able to represent a complex problem correctly.

OT uses. Several OT papers have used ideas from the literature on ensemble methods to conceptualize how individuals and organizations make decisions. One group of uses has to do with information aggregation in organizations. Csaszar and Eggers (2013) model small groups tasked with screening projects—that is, selecting between good and bad projects. The authors conceptualize these groups as ensembles of individuals and compare the effect of three aggregation rules: voting, averaging, and delegation. They show, for example, that majority voting performs better than the other rules in most situations. Csaszar (2013) develops a model of organizations as ensembles and examines how the omission and commission errors made by an organization depend on its aggregation structure. One result stemming from this work is that some aggregation structures are always dominated by others and, hence, should never be chosen. Csaszar (2012) tests the effect of aggregation structure on the probability of making omission and commission errors (a relationship first theorized by Sah and Stiglitz 1986). Using mutual funds as an empirical context, Csaszar (2012) shows that funds employing unanimous decision-making make fewer commission errors but more omission errors (i.e., pursue fewer failed investments but miss more good investments) than funds that do not require unanimity (and vice versa).

Ensemble methods have also been used to investigate the reliability of organizational structures.

Christensen and Knudsen (2010) for example, build on Moore and Shannon (1956/1993) and Sah and Stiglitz (1986) to examine how an organization's structure affects its reliability—that is, the probability that it will pick good alternatives. Like Moore and Shannon, Christensen and Knudsen (2010) describe structures in terms of circuits, which can connect individuals either sequentially or in parallel. Their paper illustrates how to design organizations that achieve a desired level of reliability. In a similar vein, Knudsen and Levinthal (2007) develop a model that shows how organization structure affects reliability, which in turn affects firms' ability to explore new alternatives.

Another group of OT uses relates to the wisdom of the crowd and idea selection. Grushka-Cockayne, Jose, and Lichtendahl (2017) model crowds as random forests. That is, although members may observe similar data, they end up with different models because learning is an idiosyncratic process. Csaszar (2019) models crowds as an ensemble using majority voting and studies how the probability of making a correct decision depends on crowd size, the accuracy distribution of the crowd, and the firm's ability to recruit accurate individuals to be members of that crowd. One finding of this research is that under relatively common conditions, increasing the size of the crowd may actually decrease the accuracy of predictions. Because it is difficult to reliably assess the accuracy of individuals in a crowd, Graefe, Küchenhoff, Stierle, and Riedl (2015) show that, in realistic cases, it is typically preferable to use equal weights than more sophisticated methods. Page (2007) summarizes much of the literature on why groups can outperform individuals, using the arguments that explain the success of ensemble methods.

Ideas about ensemble methods have also been used to study the relationship between cognitive diversity and decision quality. Page (2018: 30) uses ensembles to conceptualize individual-level decisions. Using the arguments about the superiority of ensembles, he proposes that individuals who use multiple models to understand a phenomenon make better decisions than those who rely on one model. An early application of ensembles to understand individual cognition is Arthur's (1994) famous El Farol problem, which modeled individuals as holding multiple hypotheses; that is, an ensemble of theories about how the world works.

DISCUSSION

We have shown that OT has borrowed many ideas from AI and that the breadth of the borrowing is staggering, ranging from cognitive diversity to organizational reliability to exploration, from aspiration levels to organizational learning to requisite variety, and from scripts to transactive memory to the wisdom of the crowd, just to name a few.

This wide range is a result of the fundamental connection between AI and OT. Both aim to produce intelligent behavior—one with computer chips, the other mostly with humans. March (1999) says that OT is about the "pursuit of organizational intelligence," which is not too different from what AI is. For this reason, fundamental aspects of intelligence—like search, representation, and aggregation—matter to both AI and OT. And because the connection is at such a fundamental level, the parallels between AI and OT are ubiquitous; indeed, we have cited over 100 OT papers that critically depend on AI ideas. This deep connection also explains why the borrowing has not only been from AI to OT, but also the other way around (as outlined at the end of the Background section and elaborated at different points in the paper).

It is surprising that these deep and diverse linkages between AI and OT are not usually acknowledged, unlike OT's linkages to economics, psychology, sociology, and evolutionary biology. (See, for example, the limited role that AI plays in classic introductions to the OT field such as Morgan 2006 and Scott and Davis 2007.) Overall, the impact of AI on OT may be one of OT's best-guarded secrets.

We believe that understanding AI's influence on organizational theories is important not just for the sake of intellectual honesty and curiosity but also (a) to improve scholars' ability to understand and create OT theories that build on AI and (b) to increase the repertoire of ideas with which to understand organizations. Note that the second reason entails the benefits of cognitive diversity mentioned in the context of ensembles (Approach 10).

The bulk of this paper has been backward-looking, as the goal has been to review and explain the existing connections between AI and OT. In this final section, however, we take a forward-looking view to discuss three topics. First, how some AI ideas have evolved after being adopted by OT and thus may be ripe for new borrowing. Second, how AI may continue to inform OT research; in particular, we point out possible AI–OT analogies that have not been explored so far. Third, how AI itself may affect organizations.

How AI Ideas Have Evolved After Being Adopted by OT

The bridges between AI and OT have usually been established with the idea that was most popular in AI at the time. For example, ideas about heuristics in OT (Simon 1955) were imported around the time that the heuristics approach was making big strides in AI; for example, with the Logic Theorist and the General Problem Solver. Similarly, the OT idea of understanding organizational adaptation as search (Levinthal 1997) was developed at a time when search was a popular AI technique. In fact, it was in 1997 that IBM's Deep Blue used a search-based algorithm to beat the world chess champion, Gary Kasparov.

But after OT imports an idea from AI, AI continues to move on while its OT "copy" often remains frozen. Looking at how AI approaches have diverged since being imported into OT can help us obtain a more realistic view of AI than the view prevalent at the time of the borrowing, appreciate the strengths of newer methods, and evaluate whether it makes sense to rethink some of the AI-based analogies OT has used. Three "post-borrowing divergences" that are instructive in these respects are the divergence between expectations and reality, the divergence between human and computer capacities, and the divergence among different factions within the AI community.

The divergence between AI expectations and actual achievements is well illustrated by the history of expert systems. In the 1980s there was much anticipation about the ability of expert systems to replace human decision-makers. A string of unmet promises led to an "AI winter," which lasted until the last decade, when new algorithms and computing power allowed connectionist ideas (Approach 6) to achieve human-level performance for the first time on several recognition tasks. Being aware of AI failures is useful to OT scholars, as it tempers predictions about impending AI scenarios.

The divergence between human and computer capacities stems from the fact that while human capacity has remained fixed over the history of AI, computer capacity has increased exponentially.

This has made the AI approaches that are more computing-intensive become more powerful over time, giving them an edge over the approaches that depend less on computing power and more on human knowledge. Sutton (2019) calls this the "biggest lesson that can be read from 70 years of AI research." For instance, the initial theories about computer chess imagined the solution was going to be a large collection of heuristics (the initial estimate by Newell and Simon 1976: 125 was that an expert-level chess program would comprise about 50,000 such heuristics). In contrast, the program that ended up beating humans at chess contained few heuristics and instead relied heavily on brute force search (Deep Blue analyzed over 100 million positions per second; Campbell et al. 2002). Similarly, while the early approaches to image recognition relied on hand-crafted rules, all the approaches that currently dominate this area are based on neural nets trained on massive datasets (Jordan & Mitchell 2015). One implication is that the AI approaches that depend more on computing power (e.g., connectionism, ensemble methods, and evolutionary computation) may be the approaches that will bring the most technological progress in the coming years.

The divergence among the different factions within the AI community stems from the fact that no AI approach has been able to "solve" AI and dominate all other approaches. Each new approach we covered emerged from trying to address weaknesses in the then-current approaches. Cybernetics and control theory (Approach 1), for example, could only deal with problems that were encoded as differential equations. In response, heuristic problem-solving (Approach 2) aimed to encompass a broader set of problems—those that could be represented in terms of search on a state-space. In turn, expert systems and knowledge representation (Approach 5) aimed to extend the previous approaches by representing a larger set of problems—those that can be described using first-order logic. Connectionism and machine learning (Approach 6) allowed for dealing with problems that could not be described with first-order logic but could be represented in statistical terms and so on. Appreciating the strengths and weaknesses of different approaches highlights the vitality and dynamic nature of the AI field and suggests that when a new AI approach emerges, it makes sense for OT to revisit old AI–OT analogies and to consider whether new analogies have become possible.

How AI May Continue to Inform OT Research

An important historical insight about the evolution of AI is Moravec's (1988: 18) paradox; namely, "that it is comparatively easy to make computers exhibit adult-level performance in solving problems on intelligence tests or playing checkers, and difficult or impossible to give them the skills of a one-year-old when it comes to perception and mobility." In other words, what one would think is hard to program is easy and vice versa. Moravec's observation was true when he made it, in 1988, because, at that point, most AI accomplishments had been achieved using search approaches (Approaches 1–4), to which problems of perception and mobility had proven impervious. Only during the last decade have connectionist approaches (Approach 6) finally allowed computers to perform well in perception and mobility tasks—to graduate from world chess champion to average toddler.

Moravec's observation is relevant to OT because the bulk of OT's borrowings from AI relate to early search approaches. In fact, many ideas in the Behavioral Theory of the Firm—such as aspiration levels, satisficing, and problemistic search—stem from search approaches, as do many ensuing ideas such as routines and search on rugged landscapes. But in OT we haven't made an effort of a magnitude similar to the one made by the Behavioral Theory of the Firm to integrate the AI ideas that came after the search approaches. For example, connectionism, reinforcement learning, and ensembles—all of which produced massive literatures and substantial progress in AI—do not have similarly massive counterparts in the OT literature. Of course, we have done some borrowing from those approaches, described above under their respective subsections, but there is probably more to be borrowed in light of the range and import of problems these approaches have been able to address in AI.

In the spirit of exploring how AI ideas may continue to inform OT, we suggest six possibilities, including two from each of the three families of approaches: search, representation, and aggregation.

Search: Understanding evolutionary economics in terms of genetic programming. Evolutionary economics (Nelson & Winter 1982) studies firm adaptation, using economic models in which agents cannot optimize but instead adjust their decisions based on feedback. Such models are a cross between microeconomics and control theory and sometimes take the form of detailed simulations of specific cases, called history-friendly models (Malerba, Nelson, Orsenigo, & Winter 2016). Although these models have provided many insights, evolutionary computation, which got off the ground a few years after Nelson and Winter's book (Holland 1992: ix), may provide a new set of analogies and tools with which to think more directly about evolutionary economics. In particular, modeling evolutionary economics using genetic programming (Koza 1992) would more directly map key evolutionary processes in organizations, such as random variation, idea recombination, and the development of new technologies.

Search: Understanding organizational search in terms of the "subsumption architecture". For the most part, search models in OT (e.g., Levinthal 1997) have assumed that there is a unitary actor controlling the search and that the search follows a simple process, typically allowing for local search (hill-climbing) and some form of more distant search (such as imitation or random jumps). But most organizations have multiple conflicting goals, which may push the search in ways that are different from local and distant search.

An interesting development in AI that has not received much attention in OT is Brooks's (1986) subsumption architecture, which proposed an alternative to the standard view of search in AI. Brooks's idea was that a robot's search in a landscape could be controlled by a hierarchy of processes, each one fixed on one objective—such as avoiding objects, wandering around, and exploring the world—in much the same way that firms pursue multiple and sometimes conflicting goals. Brooks's idea could be used to model how organizations deal with conflict that emerges from receiving ambiguous performance feedback on multiple goals, which is a central yet understudied problem in OT (Gaba & Greve 2019, Hu & Bettis 2018).

Representation: Conceptualizing model-based search. Most of the literature on search in OT has been "representation-free"; that is, the agent does not have a mental representation of the space being searched, but simply searches in the environment (for an exception, see Csaszar & Levinthal 2016). (Interestingly, in AI, this type of search only became mainstream with Brooks's 1991 "intelligence without representation.") Yet it is a basic premise of OT that the environment is too vast and complex to be directly perceived by individuals, who therefore search a representation or simplified model of the environment and not the environment directly.

Two ideas from AI about searching with representations may therefore be fruitful in OT. One idea is search algorithms like A*, which guide search not only by using the landscape's fitness (which may be too expensive to consult often), but also by using a proxy of fitness that is more noisy but more available. The second idea is manifested in the programs that currently dominate backgammon, Go, and *StarCraft*, which combine representation with search. In these programs, representation is provided by a neural net that returns an approximate evaluation of any board configuration, whereupon search chooses which configurations to compare. This resembles the way individuals have an intuitive reaction that can then be used to guide more deliberate search processes (i.e., System 1 and System 2; Evans 2008). AI ideas such as these could add behavioral realism to the models of search used in OT.

Representation: Revisiting managerial mental maps. The edited volume by Huff (1990) described several ways of mapping the mental models of managers. Since then, two important representations have emerged in AI: Bayesian networks and neural nets. The success of these representations in AI attests to their ability to capture important aspects of the environment. It would seem natural, then, to try to map managers' mental models using these newer forms of representation. Bayesian networks, for example, would allow capturing managers' mental models about causality, an idea proposed by Durand and Vaara (2009) and Ryall (2009), but never, to the best of our knowledge, empirically validated in the strategy and organizations literatures. (Lee and Wagenmakers 2013 illustrate this empirical method in the context of cognitive science.) Neural nets also provide a way of mapping managers' cognition. For example, it would be possible to infer a manager's "neural net" by having him or her play a business game. Then the neural net could be analyzed or used as an input to a simulation.

Aggregation: Using neural networks to understand bottom-up information processing. Most research on information aggregation has been on "flat" structures: small groups and crowds using rules like averaging or voting (e.g., Csaszar 2013, 2019) and devoid of any structure. But most organizations have a hierarchical structure in which information is processed bottom-up; information that enters through the lower levels flows up and may eventually reach the CEO.

This looks much like how information entering through the lowest layer of a neural net is processed and relayed while moving up through the net. It follows that neural nets might serve as an analogy of information aggregation in organizations. For example, one could use neural nets to study the effects of organizational characteristics such as hierarchy and span of control. Radner (1993) is among the few to have studied bottom-up information aggregation (see Garicano & Van Zandt 2013), but his model makes strong assumptions about the type of information processing the organization can perform. Neural nets provide a more general model of information processing in organizations.

Aggregation: Using ideas from distributed AI to understand information aggregation. When the OT literature on information aggregation (see, e.g., Csaszar & Eggers 2013) has borrowed from AI, it has done so exclusively from the ensemble approach (Approach 10). This borrowing has allowed the OT literature on aggregation to analyze prediction problems—such as combining the opinions of multiple managers to estimate the quality of a project (Csaszar & Eggers 2013)—which can be solved with ensembles. However, aggregation processes in organizations can be more involved than making a prediction. Imagine, for example, the aggregation process in group ideation tasks such as brainstorming a firm's strategy or writing a business plan. While ensembles are ill-suited to model such tasks, distributed AI—by explicitly accounting for processes such as coordination, cooperation, and negotiation—seems to have the right attributes to model more complex aggregation tasks (for initial work along these lines, see Steinberger and Jung 2019). Examining aggregation from the viewpoint of distributed AI may therefore be a fruitful approach for OT.

How AI Technologies May Affect Organizations

A fundamental idea in OT is bounded rationality: the premise that individual actors have hard limits to their ability to process information. AI alters that assumption by increasing those limits and thus expanding the bounds of rationality. This change in a key premise of OT cannot help but have many effects on organizations and much has already been written about such possible effects (Brynjolfsson & McAfee 2014, Kretschmer & Khashabi 2020, Raj & Seamans 2019, von Krogh 2018) and the ethical problems they may produce (Abbas 2020, Möhlmann, Zalmanson, Henfridsson, & Gregory 2020, Wallach & Allen 2009). It is, however, out of the scope of this paper to review those works. Instead, we point out some possible scenarios and describe recent AI ideas on explainability and goal-questioning (which someday may become AI approaches like the ten we described) that may critically determine how AI will affect organizations.

Given the enormous progress that AI has made since its inception fewer than 70 years ago, the exponential increases in computing capacity, the increasing availability of data that can be used to train AI algorithms, and the increasing number of practitioners knowledgeable about AI, it seems more than likely that AI itself will continue to progress and that it will continue to be part of organizations and to change them. The future will therefore be somewhere in between these two scenarios, one in which organizations use slightly more AI than today and one in which organizations are fully run by AIs.

We cannot predict what particular AI technologies will be used in this future, but we can predict that there will be greater demand for managers who know more about AI and who can design organizations and strategies that take advantage of it. We can also predict that there will be an increasing need to avoid the negative effects of AI; both regulators and ethicists should play an important role. For example, there could be a push toward AI technologies that can explain their decisions, rather than AIs that can just make good predictions (see, e.g., Hagras 2018). There could also be a push toward AI methods that can ensure their decisions comply with fairness criteria (for a survey on this topic, see Mehrabi, Morstatter, Saxena, Lerman, and Galstyan 2019). Avoiding the negative effects of AI may also call for a different type of AI, one designed from the start to work for humans, rather than something designed to perform a task and then modified to avoid whatever human harm it turns out to cause. We may, in fact, need something akin to Asimov's (1942) Three Laws of Robotics.

The AI technology to support this type of behavior does not yet exist, but one area of research that aims to address it is the attempt to produce AIs that are not certain about the objective function they are maximizing (Russell 2019) and must therefore periodically seek confirmation from humans. This built-in uncertainty about their objective function would avoid the "paperclip maximizer" scenario (Bostrom 2014: 150) in which an AI with the task of maximizing the production of paperclips would eventually eliminate humans, as they could consume resources useful for paperclip production and might even decide to turn off the AI and stop the all-important production of paperclips. With so much at stake, even if the chances of such a scenario are low, it is important that research examine this type of dubitative AI.

Closing

The aim of our paper has been to take stock of the many AI analogies used in OT and to serve as a launchpad for future exploration. Without closer attention to the AI–OT linkages, we in OT reduce our ability to draw on the AI field as a fertile source of ideas. And as AI technologies become increasingly important for organizations, obscuring these linkages risks distancing OT theories from important areas of practice.

We hope that our paper has contributed to broadening the array of ideas that organization theorists can draw on when thinking about organizational processes. Our account of AI–OT linkages shows that they are much broader, deeper, and older than may be apparent in whatever AI technology is currently in the spotlight.

In terms of practical implications for OT researchers, we believe that they would benefit from continuing to use and develop AI analogies. AI is much more than a technology for OT; it is a set of models about how organizations work. PhD students in OT would be well advised to take at least one AI course. At a minimum, the knowledge gained in a machine-learning course will be useful as a research tool and will provide an understanding of the connectionist approaches. Better yet would be to acquire a broad overview of AI, which will help with theorizing—both to generate ideas and to describe them precisely.

The quest for AI—how to create a machine that thinks—is one of the great intellectual odysseys of our time. It has involved many fine scientists and produced much in terms of ideas and technologies. Staying connected to this quest is energizing. It is also an almost bottomless well of ideas about how organizations can produce intelligent behavior.

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TABLE AND FIGURES

Table 1: Ten approaches to AI and examples of the OT ideas they inspired.

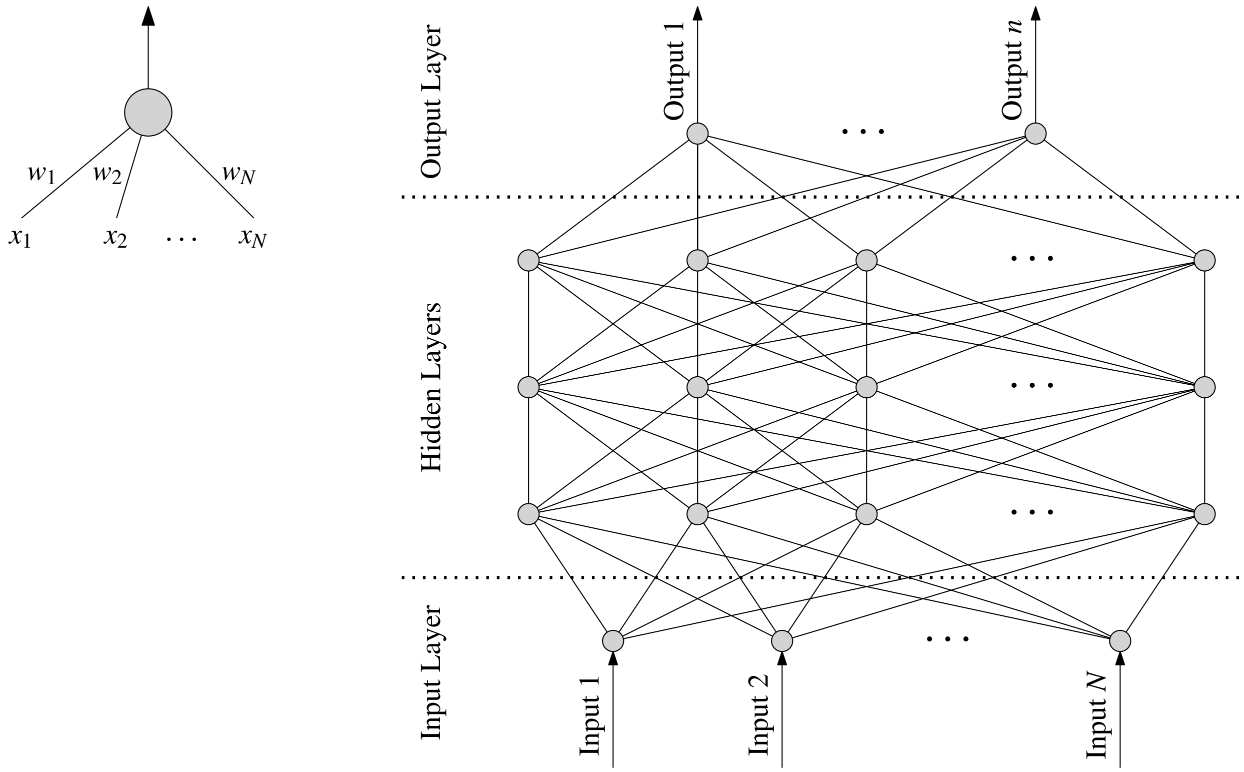
AI Idea	Uses in OT
Search	
1. *Cybernetics and Control Theory* (Ashby 1956, Shannon 1948, Wiener 1948)	• *Aspirations* (Greve 1998, March & Simon 1958/1993, Posen et al. 2018) • *Communication Processes* (Bavelas 1950, Galbraith 1973, Joseph & Gaba 2020, Thompson 1967) • *Requisite Variety & Simple Rules* (Bingham & Eisenhardt 2011, Siggelkow 2002, Weick 1979) • *System Dynamics & Vacillation* (Forrester 1961, Gary et al. 2008, Nickerson & Zenger 2002, Sterman 2000)
2. *Heuristic Problem-Solving* (Newell et al. 1959, Newell & Simon 1956, Shannon 1950)	• *Boundedly Rational Search* (Cyert et al. 1959, Newell & Simon 1972, Simon 1955) • *Rugged Landscapes* (Baumann et al. 2019, Levinthal 1997) • *Organizational Programs and Routines* (Cohen & Bacdayan 1994, Feldman & Pentland 2003, Nelson & Winter 1982)
3. *Evolutionary Computation* (Holland 1975, Koza 1992, Turing 1950)	• *Exploration and Exploitation* (Fang et al. 2010, Laureiro-Martínez et al. 2015, March 1991, Posen & Levinthal 2012) • *Organizational Evolution* (Bruderer & Singh 1996, Fang et al. 2010, Lee et al. 2002) • *Modularity* (Baldwin 2018, Baldwin & Clark 2000, Rivkin 2000, Siggelkow & Levinthal 2003)
4. *Reinforcement Learning* (Bellman 1957, Samuel 1959, Sutton & Barto 2018)	• *Ambiguity in Organizational Learning* (Denrell & March 2001, Lave & March 1975) • *Credit Assignment and Model-Based Organizational Learning* (Denrell et al. 2004, Fang & Levinthal 2009, Rahmandad 2008) • *Complex & Interactive Learning Processes* (Puranam & Swamy 2016, Rahmandad 2008)
Representation	
5. *Expert Systems and Knowledge Representation* (Buchanan et al. 1969, Dreyfus 1972, McCarthy & Hayes 1969, Schank & Abelson 1977)	• *Codifying Organizational Knowledge* (Burton & Obel 2004, Hannan et al. 2007) • *Limits of Codified Knowledge* (Brown & Duguid 1991, Kogut & Zander 1992, Orr 1996, Prietula & Simon 1989, Suchman 1987) • *Scripts, Skills & Routines* (Gioia & Poole 1984, Nelson & Winter 1982, Pentland 1995)
6. *Connectionism and Machine Learning* (Geman et al. 1992, McCulloch & Pitts 1943, Rumelhart et al. 1986)	• *Interactive Learning in Games* (Marchiori & Warglien 2008) • *Interpretive Processes* (Gavetti & Warglien 2015) • *Representational Complexity* (Csaszar & Ostler 2020)

7. *Bayesian Networks* (Pearl 1988, 2000, Spirtes et al. 2000, Wright 1921)	• *Strategic Decision-Making Process* (Durand & Vaara 2009) • *Dealing with Causal Ambiguity* (Ryall 2009) • *Causal Understanding* (Bettis & Blettner 2020)
Aggregation	
8. *Cellular Automata and Emergence* (Gardner 1970, Varela et al. 1974, von Neumann & Burks 1966, Wolfram 2004)	• *Segregation* (Schelling 1969, 1971) • *Evolution of Cooperation* (Nowak & May 1992) • *Population Ecology Dynamics* (Lomi & Larsen 1996) • *Social Autopoietic Systems* (Luhmann 1990)
9. *Distributed AI* (Minsky 1986, Selfridge 1959, Star 1989, Winograd & Flores 1986)	• *Organizational Cognition* (Carley & Gasser 1999, Prietula et al. 1998) • *Coordination & Organizational Processes* (Malone & Crowston 1991, Malone et al. 2003) • *Transactive Memory* (Ren & Argote 2011, Wegner et al. 1985) • *Boundary Objects* (Carlile 2002)
10. *Ensemble Methods* (Breiman 1996, Ho 1995, Moore & Shannon 1956/1993, Schapire 1990)	• *Information Aggregation in Organizations* (Csaszar 2013, Csaszar & Eggers 2013) • *Reliability of Decision-Making Structures* (Christensen & Knudsen 2010) • *Wisdom of the Crowd* (Csaszar 2019, Grushka-Cockayne et al. 2017) • *Cognitive Diversity* (Arthur 1994, Page 2007, 2018)

Figure 1: Four quadrants of AI definitions.

	Humanly	**Rationally**
Thinking	Think Humanly (e.g., cognitive modeling)	Think Rationally (e.g., logic)
Acting	Act Humanly (e.g., Turing test)	Act Rationally (e.g., engineering)

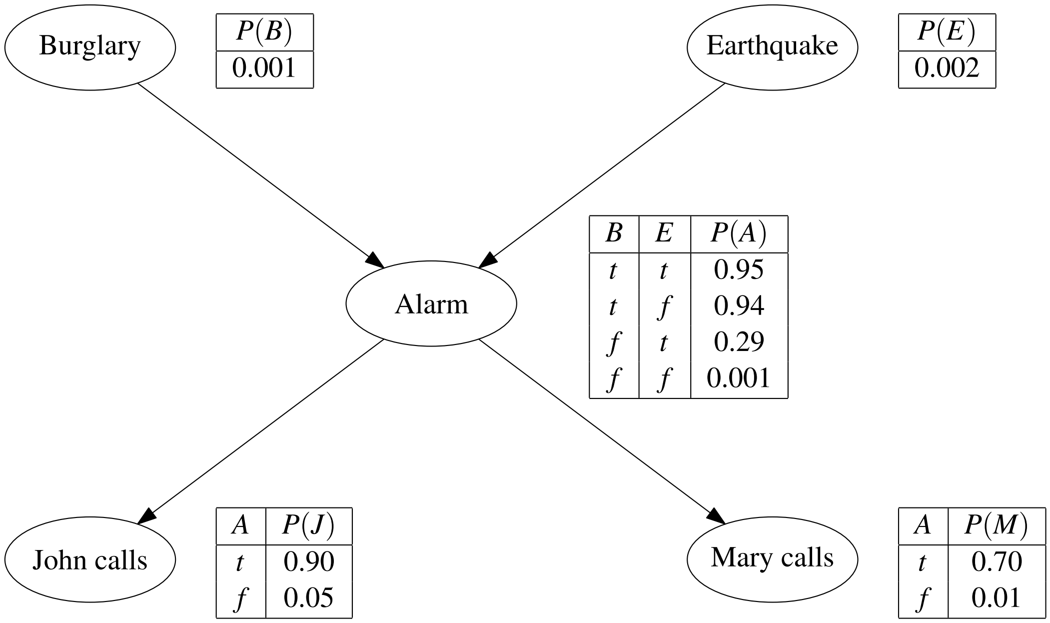
Figure 2: Illustration of an artificial neuron and a neural net.



(a) An artificial neuron

(b) An artificial neural net

Figure 3: Illustration of a Bayesian network.



$P(B)$
0.001

$P(E)$
0.002

B	E	$P(A)$
t	t	0.95
t	f	0.94
f	t	0.29
f	f	0.001

A	$P(J)$
t	0.90
f	0.05

A	$P(M)$
t	0.70
f	0.01

Figure 4: Snapshot of a cellular automaton.