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Artificial intelligence and behavioral geography

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"I pointed out that his copy of *Binary File Transfer Monthly* was possibly the most boring document I had ever seen in my life." (Coupland, 1995, p. 167)

Abstract

The fields of artificial intelligence and behavioral geography have often focused their inquisitive potential on similar topics of interest. In particular, there are many aspects of spatial intelligence that are expressed in behavioral geography that can be automated in AI, so that they can be performed at scale, exhaustively, and with precision. There are also many facets of AI that are useful in helping us to frame and explore our own behavior and that of human and social phenomena around us. In this chapter, I explore the evolving relationship between AI and behavioral geography, beginning with its early origins in efforts to automate tasks that require behavioral geography. Following this, I will discuss the move of both geography and AI to the Web, as part of the development of Geographic Information Systems and the Semantic Web. I will conclude with an examination of the current state of AI and behavioral geography, particularly as it relates to developments in mobile and human-centered computing and the growing sophistication of machine-based intelligence that relies of geographic information in large volume and with fine resolution, on spatial awareness, on spatial knowledge, and on spatial skills.

1 Introduction

Artificial intelligence (AI) and behavioral geography have long enjoyed a symbiotic relationship. While AI was initially viewed as a tool that geographers could use to automate their work, that vista is shifting. Indeed, many authors—among them, Thrift and French (2002), Graham (2005), and Stephenson (1993)—have suggested that AI has become an autonomous producer, of a sort, *of geography*. This new view, of AI creating and shaping geography, is profound, in its suggestion that we have somehow ceded geography-making to machines and software. In this chapter, I will make the argument that the geography-smithing capabilities of AI are perhaps set to have the most significant impact in behavioral geography. In this chapter, I will review the growing fusion between AI and behavioral geography, beginning in the 1980s, when it was hoped that AI would help geographers *do* geography with greater efficiency, speed, and accuracy, and when there was significant enthusiasm for the technology ahead of something of a retreat from the community's good graces in the 1990s and 2000s. From there, I will pivot the discussion to the early twenty-first century, when the development of AI took off against a backcloth of ubiquitous computing and matured consumer AI products that made use of spatial data and geographical context to ascribe intelligence to devices and software. I will also discuss a range of potential applications in which AI and behavioral geography are closely intertwined, in the milieu of machine and computer vision, virtual worlds, agent-based models, human-computer interaction, and cyber-physical systems. The motivation, in highlighting these applications of behavioral geography and AI over other uses, relates partially to my own vantage on the topic, as well as to near-future developments for AI and behavioral geography. This latter topic serves as the focus for concluding remarks.

2 Background

The development of AI can be traced back to the very beginnings of the age of digital computers. Alan Turing was among the first to sketch the tableau for AI while outlining his ideas for intelligent machines. After years working on the problem of whether machines could be fashioned to compute, Turing (1936, 1938) posited the simple and provocative question of whether machines could think (Turing, 1950). This set into motion decades of deliberation about what might be considered as intelligent in a machine, and how machine AI may compare or contrast to human intelligence.

A first criterion for intelligence in AI generally wavers around a central idea that the machines involved should display human-like intelligence, or at least that they should do things that a human would regard as being intelligent (Simon, 1977, p. 1059). (Indeed, the premise that the machine should convince a human interpreter of its intelligence was at the heart of the imitation game that Turing (1950) used as an allegory in his seminal paper.) A second, popular notion, is that machine intelligence might be a moving benchmark (Kurzweil, 1990, p. 12). Under this conceptualization, machines are envisaged with the capacity to grow more and more intelligent, advancing toward some future level of sophistication (usually referred to as a technological singularity [(Ulam, 1958)]) in which machines become self-aware, conscious, as intelligent as humans, more intelligent than humans, or some combination of these conditions that propels us into a post-human era (Vinge, 1993). A third, perhaps interim, criterion between Turing's computers and civilization-running artificial minds (Banks, 1996) is that AI should endow machines with the ability to do things that humans do (Simon, 1977), albeit with tireless capacity and precision that human effort might lack. Under this consideration, AI assumes some of the attributes of intelligent automata (von Neumann, 1951) or perhaps robots (Asimov, 1941), with independence and automation factoring as important defining criteria.

3 Artificial Intelligence and Twentieth Century geography

The potential for AI as a medium for automating human analytical tasks seems to have been the initial avenue through which geographers began to use AI. Initially, it was hoped that AI would energize geography by assuming the day-to-day tasks of geographical analysis that were amenable to automation: aspects of the geographer's job that took a long time, required duplication of effort, or were grand in their analytical burden. This view is well-articulated in Dobson's (1983) paper on *automated geography*, in which he outlined scenarios in which computer cartography, geographic information systems (GIS), remote sensing, and visualization (which were then still relatively novel) could supplement manual techniques in geographic problem-solving to bolster the scale and speed of analysis. (Interestingly, in the same paper, Dobson cautioned that a predominant focus on measurement and objects that were easily accessible to automation might sway geographers from "other important phenomena, such as the behavioral aspects of many problems" (Dobson, 1983, p. 139).

Smith's (1984) paper on the pertinence of AI for geographical problem-solving introduced the important distinction between what he termed an engineering approach and a cognitive approach to using AI in geography. Indeed, in AI research (Brooks, 1991), a similar distinction is often made between AI for computers and AI for thought. The engineering view of AI in geography considers machine intelligence in its most obvious form, as a set of *machine* procedures (usually algorithms and heuristics) that work to perform tasks. Image processing to unveil spatial patterns in data is a typical example of the engineering approach (Bernstein, 1976). An alternative view, the cognitive approach, pitches AI in geography as a mimetic medium for representing *human* processes of intelligent tasks. Symbolic reasoning on spatial relationships or objects is perhaps best representative of the cognitive approach to AI in geography as it was considered in the 1980s (Kuipers, 1982).

Smith's characterization of the engineering approach to AI in geographical analysis echoes Dobson's assertions that AI might be productively used to automate many of the *things that geographers do*, such as interpretation, monitoring, planning, and translation (Smith, 1984, p. 149). Referenced, in Smith's depiction, is the idea of AI as an expert system (Feigenbaum *et al.*, 1971) that contains a corpus of domain knowledge as well as the functions to apply it to a given task, resembling perhaps how humans use their knowledge to inform their actions. Openshaw's "Geographical Analysis Machine" (Openshaw *et al.*, 1987), for example, is an early example of the engineering approach to AI in geography, used to automate a battery of spatial analysis tasks by brute-force heuristic computing. Fisher *et al.* (1988) saw the potential use of AI, particularly expert systems and computer vision, in automating the interpretive tasks of geography relative to physical landscapes and phenomena. Estes *et al.* (1986) also discussed the idea of using AI as expert systems to automate exhaustive data searches over remotely-sensed data, using heuristics relative to a knowledge base (a classification scheme, for example). Armstrong made a similar and salient point in arguing that computational science (which would include applied AI in most definitions) comes into particular usefulness when brought to bear on "problems that heretofore were either intractable, or, in some cases, unimagined" (Armstrong, 2000, p.146). Again, here, we see the argument that AI might leverage human talents for analysis, but that it would do so at scale, with the implication that new questions might be posed or that new insight might be gained beyond the reach of human operators.

Smith's discussion of AI in geography also invoked what Simon distinguished as *artificial thinking* (as distinct from AI), with the addendum that the machines involved would exhibit "similarity of process as well as similarity of product" (Simon, 1977, p.159). This argument bridges some of the gap between the engineering and cognitive approaches of AI. It is in the invocation of artificial thinking that we see the seeds of *AI and behavioral geography*, in which machines assume some of the analysis *abilities* of geographers, alongside their analysis tasks. In other words, there is an argument to be made that the types of problem-solving (Newell and Simon, 1972) that geographers engage in (and that machines could take on, or take over) might invoke behaviors that *are geographical*. Smith (1984) lists several examples—acquiring knowledge, organizing it, and reasoning relative to decisions—that we might regard as adjuring special geographic activities (Freundschuh and Egenhofer, 1997). For example, the ways in which we go about acquiring geographic information may be distinct relative to schemes for gathering other information types (Golledge, 1978; Gould, 1975). Similarly, geographic knowledge may be stored in the brain in physical structures that are special, such as dedicated place cells (Brun *et al.*, 2002; O'Keefe *et al.*, 1998), or in memory as cognitive and perceptual structures such as mental maps (Gould and White, 1974; Vishton and Cutting, 1995). Spatial decisions may be structured via criteria, such as spatial hierarchies, that diverge from other decisions (Clark, 1993; Kuipers, 2000). By extension, if machines could be programmed to mimic, replicate, or improve these human processes, then those machines might come to be regarded as intelligent geographical machines, in part by assuming spatial abilities to accomplish tasks.

In hindsight, the use of AI in geography took off quite successfully after the late-1980s, in large part due to its usefulness in supporting GIS. Initially, at least, the introduction of AI into geography met with some skepticism along a few significant lines of critique. Some in geography seemed to grapple with what AI could introduce to the field. At the time, the concept of AI might have seemed quite far afield from the topical pursuits of many geographers. For example, in a commentary on Smith's (1984) paper introducing AI to geography, Nystuen (1984, p.359) remarked that, "AI programs take a great deal of expert intellectual effort and financial (computer) support. Few geographical problems command such attention.…Smith should reflect on the resource realities of a small social science discipline like geography." Couclelis (1986, p.2) at the time phrased, very well, another popular apprehension, rooted in "resistance to the underlying 'human computer' metaphor" that AI presented. Her argument, which is well-taken, speaks to the perhaps lofty claims for AI in the 1970s and 1980s (Hendler, 2008; Lighthill, 1972), which went as far as to suggest that AI might model the mind, mimic human thought, or teach machines to learn.

In the last thirty to forty years, of course, computers and computing have become much more essential to the work that geographers do, particularly in facets of the discipline for which machines can automate routine tasks and in areas that allow geographers to do their work with greater reach, with more precision, and in less time than they would otherwise be able to accomplish (Dobson, 1983). Along the same lines, as AI has been woven into the backcloth of our everyday lives and experiences (Dodge and Kitchin, 2005) and into the things that we do to accomplish our research, our growing exposure to AI technology (and in some cases our inability to understand its artificiality) has diluted at least some of the skepticism and naysaying around its potential use. However, the automation of geography has never dodged controversy (Thrift and French, 2002), and legitimate concerns still persist around differential access to computing, to the knowledge that it produces, and to the data that it invariably casts as a by-product of analysis trained on geographic behavior.

4 Behavioral geography and new wave AI

Many people now rely on AI to *do geography*, whether to accentuate their geographical thinking or to enhance (or to supplant) their spatial abilities with machines and software that are quicker, more thorough, safer, or often simply more usable than other media that they might use. As a result, AI have had ample opportunity to analyze and train upon humans' spatial behavior and its geographic context. The interactivity between AI and behavioral geography is upfront in some cases, as in use of in-dash navigation systems and software. In other arenas, the connection between AI and behavioral geography is much more subtle. For example, when one swipes a customer loyalty card at a point of purchase and is rewarded with a set of coupons, various AI are released to wash over the data that behavior reveals or implies (space-time shopping rhythms, response to place-based marketing, location-based sensitivity to price, etc.) to merchants, marketers, and finance providers.

Still further threads, from behavioral geography to AI (and vice-versa) continue to unfurl as much of our personal, social, and commercial activity continues to be mediated by the Web. For example, as GIS and geocomputation moved to the Web, and as user behavior moved to browsers and then to Web-based social platforms, elements of the geography that we had built for a world of desktop computing followed. On the Web, that geography took on new relevance to a range of AI-based classifiers, big data processing schemes, and ontology that was shaping the semantic web (Berners-Lee *et al.*, 2001). In the early phases of the development of the Internet and the Web, geography had consistently lagged behind most innovations by a gap of five to ten years, adopting these technologies and adding a "spatial spin" to them after a significant lag. That gap soon closed, however, and geography led the development of many the innovations that characterized "Web 2.0" (the social and mobile Web), where a long tradition of spatial reasoning on symbols and knowledge domains that was well-developed in behavioral geography and formalized in GIS could easily be ported to the new platforms (Couclelis and Golledge, 1983).

Geography has almost concurrently turned out to be one of the most robust frameworks for adding structure to the massive streams and silos of unstructured data that many businesses and fields of study now manage. Much early work in geographic information science grappled with the problem of unifying spatial data across varying conceptualizations of geography, object types, scales of analysis, levels of uncertainty, tolerance for precision, and so forth. The work that geographers invested in uniting spatial data, a large portion of which was centered on human factors of data collection and use as well as behavioral factors (Dykes *et al.*, 2005), produced very robust schemes for data-mining and knowledge discovery (KDD). A number of these schemes have taken on new relevance relative to big data, as reliable "glue" for binding disparate data fragments.

More recently, efforts to develop AI components of human-centered have begun to take on attributes of behavioral geography. Computers have shrunk in size and form factors, to the point that they are now routinely placed into the artifacts and substrate of our daily lives. The initial phase of this embedding centered on ubiquitous computing (Weiser, 1991, 1993), in which computers became part of the fabric of *non-computational things*. Recently, however, ubiquitous computing has begun to spread to *us*, to people, with the result that computing is developed for both sides of interactions between the person and the things that we manipulate, use, value, pass by, and so on. These developments bring people's use of computing into sharper focus around the medium in which the computing presents. For example, for wearable computers, there is now a need to understand locomotion and interactions between people and things, often relative to small spaces such as tabletops and the body itself (Zhang, 2012). For mobile computing, there is renewed interest in motifs of human movement at urban and intra-urban scales, as trips, paths, areas and points of interest, spaces of access and accessibility, and so on (Mishra *et al.*, 2015; Sun *et al.*, 2012). For urban computing, there is a strong connection to aspects of behavioral geography that relate to environmental cognition and the affordances that built spaces provide for activity and interaction (Zheng *et al.*, 2014).

Increasingly, behavioral geography is also used to generate efficiencies in the actual informatics of AI. This is a very interesting turn, as it places behavioral geography in the center of efforts to enhance AI in computation, reversing the original vision of AI as a way to speed-up routine human labor for geographical tasks. The most noticeable instantiation of behavioral geography's influence in AI for informatics has been its use for crawling the huge troves of behaviorally-indexed spatial data that are now cast by our interactions with each other, things, and events (Torrens, 2010). In information search, behavioral geography is invoked by heuristics that leverage geographic-like behavior and strategies for browsing, crawling, indexing, relating, spanning, traversing, classifying, choosing, structuring, deciding, and so on (Hjaltason and Samet, 2003). In these ways, behavioral geography and AI are beginning to connect as cyberinfrastructure, as algorithms and heuristics for thinking and reasoning about information as it presents in computational spaces, network spaces, information spaces, and tangible spaces.

5 Examples of behavioral geography AI

In this section, I will turn to discussion of how behavioral geography and AI have developed synergies in several key areas to a point in which they are largely coupled. In particular, developments in machine and computer vision, robotics, virtual worlds and virtual geographic environments, computer-human interaction, and cyber-physical systems are noteworthy examples that explain the significant synergy between AI and behavioral geography.

5.1 Machine and computer vision

The popular use of computer vision (Szeliski, 2010) in devices and software has been particularly influential in allying behavioral geography and AI. Machine vision, i.e., the use of hardware imaging to provide visual "awareness" to devices, is going through many of the advantageous changes that catalyzed the proliferation of Geographic Positioning Systems (GPS) (Abler, 1993). For example, high-resolution cameras are now relatively cheap to make and are small-sized, with the result that they may be embedded quite easily in a range of devices. The data that such cameras generate, which are often rapid in their supply and high-resolution in their detail, are usually easily integrated with processors and software across diverse platforms, with the result that AI can be brought to bear quickly and efficiently on data as they are produced. For example, cameras on phones initially had little to do with the main use-scenario for the phone (voice telephony). However, when paired to the *platform* that the phone as a device affords (mobility, social networking, shopping, tagging encountered objects), cameras became a main feature, in part because the vistas they afforded could be allied to users' general behavior on the device. Much of this behavior is geographical: using the camera to scan barcodes in particular places and time, tagging images with activities and place-names, building overlapping vantages of points of interest as images are uploaded to photo-sharing silos, and so on. Mobile phones are often carried everywhere, piggy-backing on the user's activity space, and so on-board positioning sensors can provide a relatively tireless and high-resolution location signal to dock that behavior across a variety of tangible spaces and cyberspaces. This docking is significant because it provides a pathway between real space and cyberspace, easing the potential formation of data shadows cast from behavior in one space to behavior in another space, or to many other spaces. When this docking takes place across millions of phones around the clock, individual behavioral geographies may be allied to broader profiles of behavior and behavioral geography, developed from aggregates of the data cast by the technology, with aggregation mediated by AI. For example, algorithms such as *Structure from Motion* (SfM) (Koenderink and van Doorn, 1991; Snavely *et al.*, 2008) and *Scale-Invariant Feature Transform* (SIFT) (Lowe, 2004) can use behavioral geography to build structure in (and across) image and positional data, often with minimal localization. There is also a broad range of work in computer vision that analyzes the behavioral geography of people as they appear in images and video. These schemes are often based on recognition schemes that uses the behavioral geography alongside AI techniques such as hidden Markov models (HMMs) (Nguyen *et al.*, 2005) to quickly and exhaustively benchmark signals and patterns in images to a knowledge base that can tag those data to classes of behavior (as states with associated confidence in a HMM, for example).

5.2 Robots

Turing's (1950) initial vision for intelligent machines kick-started decades of developing robotic machines (Matarić, 2007). Much effort in robotics has focused on providing machines with behavioral geography, via AI. Behavioral geography is important for robots because they are required to sense the geography of their surroundings, to proactively plan for the geography that they encounter or might encounter, to move through space and time relative to often-complex ambient conditions and complicated instructional goals, and to engage in tasks that require human-like activities and abilities. Behavioral geography is particularly important in robot-motion planning (Latombe, 1991), which requires that robots measure space and time relative to goals (Ferguson and Stentz, 2007; Fujimura, 1996), that they move (Latombe, 1999), detect collisions (Mezouar and Chaumette, 2002), avoid collisions (Badler *et al.*, 1994), and coordinate their locomotion (Reynolds, 1993).

Associations between robotics and behavioral geography are likely to grow closer. The access that AI-driven autonomous machines have to spatial data is now unprecedented, and in many arenas of their development, robotic machines can make use of big data, knowledge domains, semantics, data-mining, and computer vision advances to "be geographical" in incredibly sophisticated and life-like ways. For example, recently, there has been considerable work to develop mental mapping abilities in robotics, i.e., to develop robot understanding of encountered events and things in space and time, and to build knowledge bases from that understanding, either for a task at hand or for longer-term skill acquisition. These developments have been realized, popularly, in robotic products that make use of robot-generated maps to actuate and impel machines in the real world. Consider that we are now about to share our days with semi-autonomous cars that self-drive while also sensing and avoiding pedestrians (Thrun *et al.*, 2006), and that we already have cause to dodge robotic vacuums that can map and navigate dirty floors (Jones, 2006).

5.3 Virtual worlds and virtual geographic environments

Many geographies now present beyond the realm of the tangible, as information spaces (Mitchell, 1995) and cyberspaces (Dodge and Kitchin, 2000). In some cases, the virtual geography (Batty, 1997) those digital spaces represent are mapped to real-world spaces, such that the virtual space manifests as an analog of a physical space (Shiode, 2001). We might refer to these as virtual *worlds* because we can inhabit them, vicariously, as avatars (Bainbridge, 2007; Rheingold, 1993; The Economist, 2006); or we might more specifically refer to them as virtual geographic environments (VGEs) (Lin *et al.*, 2015; Lin *et al.*, 2013). In the case of VGEs, there is often a deliberate emphasis on *faithfully* representing reality in digital, virtual form, so that the virtual environment is fashioned from real data that correspond to real places and spaces.

The question of how behavioral geography remains the same or differs when one moves from the tangible world to virtual geography looms large in research on virtual worlds (Spiers and Maguire, 2006; Zyda, 2005). Much work has been done to explore how people move (Crooks *et al.*, 2009), judge distances (Thompson *et al.*, 2004), mediate personal space (Bailenson *et al.*, 2001), plan paths (Salomon *et al.*, 2003), wayfind (Golledge *et al.*, 1996), navigate (Richardson *et al.*, 1999), interact (Lamarche and Donikian, 2004), and build (Hudson-Smith, 2002; Shiode and Torrens, 2008) in virtual geographic settings. Because the spaces and geographies in virtual worlds are *digital*, it can often be relatively straightforward to extract plentiful and meaningful data directly from the world (El-Nasr *et al.*, 2013), as models of things that have been constructed (Hudson-Smith, 2002); as sequences of events, actions, reactions, and interactions (Thawonmas and Iizuka, 2008; Wallner and Kriglstein, 2015); as movement paths (Kang *et al.*, 2013); as mental maps (Torrens, 2015a), and so on. Indeed, many benchmarks for massively multiplayer online (MMO) worlds, role-playing games (MMORPGs), and multiplayer online battle arenas (MOBAs) rely on the behavioral geography of players and teams within the virtual setting (Pedersen *et al.*, 2010). Similarly, many "serious games" are played-out in virtual worlds as proxies for tangible forms of behavioral geography or as what-if experiments (Barnes *et al.*, 2009; von Ahn, 2006).

When real humans interact with each other in virtual worlds, we can make use of the digital manifestation of their behavioral geography to build a knowledge base, which can then be used to fashion AI representations of that behavior (Torrens, 2007). This can be done through trial. In computer games, for example, game developers go through deliberative testing phases to build worlds and gameplay that entertain, that advance a story, that present challenges, and so on. In testing, the game designers often evaluate the behavioral geography that a particular virtual world or story or challenge produces, and they use analytics to code aspects of this geography into what is often termed "game engine AI," i.e., the mechanics of the game behavior and phenomena that it supports (Baillie-deByl, 2004; Champandard, 2003; Millington, 2006; Nareyek, 2004). The use of AI from behavioral geography in gaming, in particular, is perhaps best reflected in recurring data structures for computer games. Examples include navigation graphs that map players to particular geographies of activity, interaction, and events in the game (Nieuwenhuisen *et al.*, 2007; Sud *et al.*, 2008), and around non-player characters (NPCs) that are often required to move, run away, give chase, and collaborate with realistic behavioral geography (Laird and van Lent, 2001). Indeed, the fidelity of NPC behavioral geography is often a selling point of many commercial games (Cass, 2002). In some cases, movement in gameplay is built directly from real-world data of human movement (Lee and Lee, 2006). Indeed, machine-learning of movement for virtual characters is increasingly sourced in real-world data from behavior in physical and social geographies (Lee *et al.*, 2007; Torrens and Griffin, 2013; Torrens *et al.*, 2011; Torrens *et al.*, 2012). And locomotion data for avatar representations of human users and for NPCs in virtual worlds and games are increasingly built atop motion-capture data recorded from real people (Arikan and Forsyth, 2002; Torrens, 2014, 2015b).

5.4 Computer-human interaction

Behavioral geography and AI have recently become very closely intertwined in the realm of information geography, particularly in *information search* in and across databases. Spatial data access on databases has long mimicked aspects of behavioral geography that pertain to how humans collect and collate data, particularly the human behaviors of abstraction, clustering, and hierarchy in sorting data, in organizing data for efficient access and recall, and in classifying data into knowledge bases (Samet *et al.*, 2014). This functionality is commonly encountered on the Web, for example. Various pieces of your online behavior (queries with particular toponyms in them, searches with persistent address indices, goods purchased for delivery to home locations, and so on) may be referenced and composited by AI while you use the Web, to generate a likely location for you as a user (Fu *et al.*, 2014; Lieberman *et al.*, 2010; Samet *et al.*, 2014). This location can be used to tailor content such as language (Lieberman and Samet, 2012; Zhang and Gelernter, 2014), maps (Samet *et al.*, 2014), marketing (Rand and Rust, 2011), and so on. For instances in which the information is being accessed via mobile devices, the AI may have direct access to the GPS hardware on a user's phone so that the location can be read rapidly and directly. As more and more AI-driven schemes for analyzing human interaction with databases develop, a growing corpus of semantic knowledge is developing around search and data technology. Indeed, there is a convincing argument to be made that a secondary, location-aware and location-enabled, instance of the web (and the 'internet of things') is being formed around these technologies (Crampton *et al.*, 2013; Zhang and Tsou, 2009). Egenhofer (2002), for example, has suggested that a geosemantic web may have emerged, in which AI and behavioral geography have enabled the development of large and useful knowledge bases atop the substrate of web-based internet and communications technologies (ICTs). Egenhofer's (2002) thesis regarding the geosemantic web echoes earlier arguments that he and Mark (Egenhofer and Mark, 1995) made regarding the potential for GIS to build computer-based naïve geographies, as formal models of everyday geographic knowledge.

5.5 Cyber-physical systems

It is worth noting that behavioral geography, AI, and machines are becoming coupled in new and innovative ways as cyber-physical systems. Cyber-physical systems are physical systems that rely in some large part on computing to determine their behavior. The term "cyber," in this context, relates to the thinking capabilities of the systems, which we usually delegate to AI. We might also consider people and things as elements of cyber-physical systems, with the inference that those systems may have opportunities (or cause, or leeway, or authority) to support our behavior, to supplement our behavior, or to supplant our behavior (Nechyba and Xu, 1997).

In many instances, cyber-physical systems hold sway over our everyday lives, and mediate (perhaps even dictate) our behavioral geography across a wide range of activities. The emergence and proliferation of smart highways (Collier and Weiland, 1994) and related intelligent transportation systems (ITS) is a relatively recent and prominent development of cyber-physical systems that impacts behavioral geography. For example, some smart highways are designed to produce traffic calming effects on travel, by linking data output from embedded sensors that monitor traffic volume and speed to behavioral models of expected driver reaction and knock-on effects that scale from individual road segments up to entire transportation networks (Cetin *et al.*, 2002; Raney *et al.*, 2003). Consider e-commerce platforms for ordering household goods as another example. Warehouses and store rooms are now almost overwhelmingly built and operated as cyber-physical systems in which human users order goods by interfacing either directly or through some intermediary system with the storage facility's inventory databases (see Castell's (2001) detailed treatment of the global flow of information and material that make this happen in the fashion industry, for example). Data access schemes are commonly used to match user demand (and estimated demand) to provider locations around the world, by modeling expected availability of components and products, relative to the rhythms and motifs of user buying habits and tastes in particular places and times (Chan *et al.*, 2004). The logistics of how to assemble goods and components efficiently and cheaply can be determined using AI that models pricing behavior of merchants and suppliers, where economic geography often factors strongly in the determinative mechanisms, particularly when speed ("just in time") is a major pricing factor (Mair *et al.*, 1988). Even within stores and warehouses, AI-driven robots are often deployed to search the geography of shelves and aisles to grab and ship items for delivery and packaging (Guizzo, 2008). Once shipped, AI routines monitor traffic and fleet operations to determine delivery schedules and routes (Ran *et al.*, 2012), relying on positioning systems (Liao, 2003) as well as activity-based models of likely traffic patterns and reactions to traffic events (Crainic *et al.*, 2009). For delivery drivers, in-car navigation systems provide trip directions, while also providing customers with updates regarding the goods' arrival timing and location of delivery on a given property (Skog and Händel, 2009).

6 Conclusions

In this chapter, I have presented an overview of the origins of strong ties between AI and behavioral geography, as originally conjured in the 1980s, when computing was relatively novel to the geographical sciences. Since that period, computers have become much more closely intertwined with everything that we do, and as we have relied upon AI to accentuate our behavior, we have perhaps become more reliant on AI to do that for us, thereby begetting more dependence on and credence in AI. Nevertheless, the potential pitfalls of growing connectivity between behavioral geography and AI have not been masked from geographic inquiry.

Many of the technologies produced at the intersection of AI and behavioral geography have the potential to enrich our lives, by making things easier, cheaper, broadly accessible, and more usable. Many location-based services that assist us in our everyday tasks fall into this category. Others, such as predictive AI atop location-aware technologies in evolving smart homes (Marco *et al.*, 2008) could help us in profound ways, by monitoring and mediating our behavioral geography as we age in place, for example. Yet, the downside to continued and strengthening synergy between behavioral geography and AI is perhaps equally profound. As we offload important aspects of our behavioral geography to hardware, systems, and software, we risk sidelining important components of human expertise (see Chapter 7, 11). Many in the geography community have also decried the loss of locational and activity privacy that has emerged as AI have grown more finely attuned to behavioral geography (Dobson and Fisher, 2003). Others see the potential (and actual) pitfalls in ceding real access and real space to algorithms and heuristics that tag, like, price, and validate our lives (Curry, 1997), while openly pondering why so many of us voluntarily “feed” AI big spoonsful of our private data (Graham and Shelton, 2013).

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