Chapter 22
Business Applications and Research Questions Using Spatial Agent-Based Models

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Abstract Agent-based models (ABMs) provide a natural representation of large markets with many consumers interacting. As a result, business applications of these tools can provide powerful insights in to complex problems. When spatial and geographic modeling is added as well, these insights gain the ability to be transported to the real world, where challenging questions can be addressed. Most of the work that has been done in this area focusses on two different levels of spatial models: (1) the regional or macro-level, and (2) the small-scale or micro-level. Macro-level spatial ABMs are models which address the movement of individuals and the location of facilities across an entire region, such as spatial retail decisions, residential housing choices, or geographically extended supply chains. Micro-level spatial ABMs examine the movement of individuals within a constrained physical space, such as pedestrian modeling in a neighborhood, or consumer modeling within a retail location. We will discuss each of these levels of detail in turn and finish by discussing future applications of spatial ABMs to business.

22.1 Introduction

Despite some initial success,[1] the use of Agent-Based Models (ABMs) in business applications has only recently started to garner serious interest within the practitioner community (North and Macal 2007; North et al. 2010). One reason for this recent increase in interest may be that it has become increasingly clear that traditional modeling approaches are not able to handle many of the complexities and details involved in a modern market. Though the academic community has used ABMs for a long

[1]For example, Proctor and Gamble's use of ABM to redesign their supply chain, see Anthes (2003).

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time within managerial science, dating back at least to Cohen, March and Olsen's use of an agent-based modeling framework to understand organizational decision making (Cohen et al. 1972),[2] the recent interest by business experts in ABM has reinvigorated the academic community's research in to this unique use of ABM in a number of different managerial sub-disciplines from marketing (Rand and Rust 2011) to finance (Ehrentreich 2007) to managerial strategy (Davis et al. 2009).

This renewed interest is well-deserved. ABM has several natural advantages for modeling business situations: (1) *Multiscale and Complex Interaction Structures:* Most business applications deal with interactions between either multiple businesses of varying size, businesses and consumers, or individuals at different levels within an organization. Moreover, even when these agents are all of the same scale, often the interactions within a model need to occur on a complex interaction structure such as a social network; ABM provides the ability for multiple scales of agency and network-based interactions to be included within the same model. (2) *Heterogeneity:* Many business applications, such as consumer market models, require a large number of individuals who are very different from each other. These individuals could have different personal wealth status, different thresholds to innovation, or different preferences for a product. Though new approaches in equation-based/math modeling have allowed for more and more heterogeneity to be incorporated in to a model, ABM still provides a maximal level of potential heterogeneity. (3) *Adaptive Agents*: Most organizations and consumers do not operate according to the same rules of behavior throughout time; instead they learn from the past and change their behavior as a result of previous actions and consequences. This is especially true when there are large rewards to be gained for acting as optimally as possible. ABM is one of the few approaches that allows the modeler to construct agents which not only adapt the parameters of the rules by which they act, but to fundamentally alter the rules themselves. (4) *Rich Environments* – Many business applications occur distributed through a physical space; whether that be a city road network, a county development map, a neighborhood street, or within a store, the physical geography of these systems can dramatically alter the way the complex system unfolds. ABM allows for the relatively simple inclusion of this physical geography as an environment in which the agents operate and ABM has proven to be successful in helping to understand complex phenomenon related to geography and urban development in the past (Benenson and Torrens 2004; Batty 2005).

It is this last advantage that we will discuss in detail in this chapter. Of course, spatial models of business systems occur that do not involve ABMs (Longley and Clarke 1995), but GIS and spatial modeling techniques by themselves are not sufficient to capture the rich details necessary for some models. Static spatial models are a representation of pattern and describe very well how items of interest are distributed in space and relate to each other. However, static spatial models fail to describe temporal dynamics very well, and thus they lack a representation of process. ABM,

[2] Though Cohen, March and Olsen used what is clearly an ABM, they did not call their model, an "ABM", since that phrase was not yet in use.

on the other hand, describes processes very well; in fact, it might be argued that ABM is by its nature a process description, but without a rich environmental description, such as that provided by GIS. Without spatial modeling, ABM fails to capture the nuances of sophisticated spatially distributed patterns (Brown et al. 2005b). However, by combining ABM and GIS, researchers can build sophisticated tools that model both pattern and process simultaneously. Models of pattern and process are critical to several interesting business applications, since the discovery of spatially distributed patterns and how they evolve over time is key to their understanding. Therefore, spatial ABMs could prove a powerful tool within management science.

In order to explore this hypothesis in more depth, we will examine a number of different applications of spatial ABMs to questions of relevance within business applications. We will begin by examining macro-level models, or models where the scale of the model does not require detailed models of individual entity movement; examples of these types of models include residential housing decisions, retail location preferencing, and geographically extended supply chains. Then we will examine micro-level models, which are models in which the base representation is an individual moving around as a pedestrian; examples of these types of models include pedestrian traffic in a neighborhood, or even movement within a retail shop. We utilize this distinction since the types of data and models of behavior will differ significantly between these two levels. At the end of this chapter we will discuss how far spatial ABMs have advanced in business applications and potential avenues for future research.

22.2 Macro-Level Spatial ABMs

Large-scale spatial ABMs are useful in business application in which the business or phenomenon being modeled is large enough to extend spatially over an entire region. For instance, a delivery service that must manage a fleet of trucks could use ABM to maximize the routing of the trucks incorporating a traffic model that varies based on time of day (Hartenstein et al. 2001), or a chain of stores that are trying to cover a market ensuring that no store is located too far away from any consumer could use ABM to determine a new store location taking into account consumer commuting patterns (Lombardo et al. 2004), or a business that deals with a global distribution of goods and shipping logistics could use these technologies to track and examine the distribution of containers throughout the world (Sinha-Ray et al. 2003). Macro-level models are also useful in cases where a business competes with other firms and organizations and the needs of their customers are influenced by geography, even if the focal firm itself does not have multiple locations or provide services over a geography. For instance, a residential developer could use ABM to forecast future demand for new housing based upon individual decisions to locate in various regions (Brown et al. 2005a), or a gas station could use ABM to examine how to set its prices in comparison to its competitors (Heppenstall et al. 2005).

A significant barrier in the past to increased use of ABMs to model large-scale geographically dispersed systems was the lack of integration between ABM tools and GIS tools (Brown et al. 2005b). As eluded to in the introduction, an ABM, in its simplest form, represents dynamic aspatial processes, and so the basic concepts of an ABM are agents, timesteps, and behavior. A GIS, on the other hand, represents static spatial patterns, and so the basic concepts of a GIS are maps, projections, and spatial analysis. It is not intuitively clear how to get these two methodologies to work together in a way that facilitates the development of more complex models (Brown et al. 2005b). Should the ABM be the primary model, using the GIS simply as a storage platform? Or should the GIS be the primary model, using the ABM to update the spatial patterns? Or should both tools be rolled up in to one cohesive package? An ideal tool to address this problem has still not been developed, but there have been significant advances in tool development that have helped mitigate this problem. Specifically most of the most commonly used ABM platforms, such as NetLogo (Wilensky 1999) and RePast (North et al. 2005), have incorporated the ability to read and write GIS data. Though there are significant challenges in using spatial ABMs to address large-scale geographies, several research projects have successfully used this approach to develop new understandings to complex problems. In the next few sections we will highlight a couple of these projects and talk about them in more detail. This is not meant to be an exhaustive listing, but rather to provide a few illustrative examples.

22.2.1 Spatial Retailing Decisions

Almost all consumer retail decisions are spatially-influenced. In the end when it comes to purchasing from a brick-and-mortar retail location, whether it be out of preference (e.g., the ability to try on clothing, the convenience of lack of shipping, etc.) or necessity (e.g., there is no economically or practically feasible way to ship gasoline over the internet), consumers prefer to buy from locations that are spatially convenient to them, i.e., they aim to minimize some cost associated with the transaction (Hotelling 1929). This cost can result in firms locating near other firms since the same spatial location may wind up being the most convenient for a large part of the population. On the other hand, firms may want to locate as far away from each other as possible, in order to not compete directly with other firms nearby (d'Aspremont et al. 1979). Involved in all these decisions is not only where to locate, but what products to offer at what price; all of which are interrelated decisions (Hotelling 1929).

Despite the advances that have been previously made using game theory and equation-based modeling, more advanced models of these decision processes can be made by combining consumer-level behavioral rules with agent-based models. An example of this combination working well together is Heppenstall, Evans and Birkin's examination of petrol price setting in a spatially-influenced retail market (Heppenstall et al. 2005, 2006). This model examined the price setting behavior of individual petrol stations in the geographic area of West Yorkshire, UK (including Leeds, Bradford, Wakefield, Huddersfield and Halifax). In the model, petrol stations

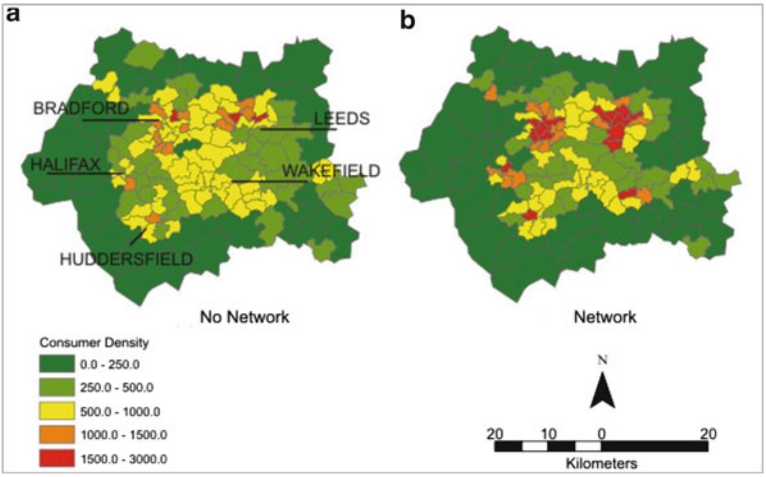

Fig. 22.1 Differences in the distribution of consumer density in the "hybrid" model (**a**) and the "network" model (**b**) (Reprinted with permission from Heppenstall et al. (2006))

were represented as full agents, while the consumers were represented by a spatial interaction model, since fully representing the consumers as agents as well was too computationally expensive. Within the model petrol stations set their prices based on local competition and profit earned in the last time period. Consumer demand was modeled using a spatial interaction model, where consumers decided which petrol stations to buy from on the basis of distance and price. In the initial "hybrid model" (it was called a hybrid model because it involved both an ABM and a spatial interaction model), consumers were always considered to exist at their home location. Heppenstall et al. (2005, 2006) went on to examine a "network" model, which modeled commutes to work as well and used this commuting data to re-examine the spatial model on the basis of where consumers would most likely be when driving. The difference between these two models in terms of their effect on consumer density within the ABM is illustrated in Fig. 22.1. After constructing these two models, they then compared and contrasted these two different models, performed robustness and validation checks, and showed that the model recreated real-world price and profit patterns.

This trade-off between the hybrid model, which models resident locations using their residency locations, and the network model, which approximates where residents will be when they are likely to refuel their cars is illustrative of design decisions that often need to be made when constructing spatial agent-based models at the macro-scale. The petrol stations that were modeled were well-defined and in fixed locations, so they were modeled at their present stations, but commuters are mobile, and so a decision must be made as to which level of mobility to model them. The hybrid model is an extreme case where the residents are modeled as existing at one fixed location, namely their homes. The advantage of this approach is that it is less computationally expensive, but the disadvantage is that the model is not as reflective of the real-world as a more fine-grained model that modeled actual transportation patterns. At the other end of the spectrum, commuters could be modeled as constantly moving, and their locations dynamically modeled at a minute-by-minute resolution. This has the advantage of being a better representation of the real-world, but also has the disadvantage of being extremely computationally expensive, not to mention the difficulties with obtaining the data necessary to model traffic data at that level of detail. The network model that Heppenstall, Evans and Birkin chose is a well-designed compromise that balances computational and data limitations with the fidelity of the model.

Once a model such as this has been constructed and validated, the results could be used to explore future chain-wide policy decisions, examine marketing strategies, or even determine the viability of current and future retail locations. One of the most intriguing aspects of this model is that there are many necessity goods for which a similar model could be built. Though petrol is uniquely dependent on the transportation system for its demand, in general people do like to shop in proximity to either their home or work (or someplace in-between) for most of their basic necessities. Thus, it would be possible to imagine similar models of prices that could be constructed for grocery stores (Schenk et al. 2007), big-box retail stores, restaurants, and health and beauty services, which are all retail locations that a commuter might visit once every few weeks.

22.2.2 Residential Location Preferencing

The petrol station model described in the previous section was mainly aimed at building a comprehensive model of the supply-side of the market, including retailers and competitors. The demand-side of the market was exogenous, assumed to operate using a fixed set of rules, and was not explicitly modeled as agents. However, demand-side modeling at the macro-level can also benefit from the use of spatial ABMs. As was mentioned previously, it is well-known that consumers make decisions based upon proximity and cost of travel (Hotelling 1929), so modeling where consumers will locate and the demand that they place upon a geographical area is critical to organizations and businesses that rely upon these forecasts.

For instance, within the housing market understanding where residents want move to is useful for contractors, developers, retailers, and even public policy analysts. One project that attempted to analyze this process using spatial ABM is project SLUCE (**S**patial **L**and **U**se **C**hange and **E**cological Effects)[3] and its successor SLUCE 2. The goal of which was to examine the relationship between the environment and suburban sprawl. Though the aim of project SLUCE was more on the side of providing advice to policymakers interested in reducing the negative effects of suburban sprawl, a model similar to the one that was constructed could also be used

[3] http://www.cscs.umich.edu/sluce/

from a business and organization perspective in understanding future demand patterns in a geographic area.

To address these concerns, Project SLUCE has built at least three different versions of the models to address different questions (Brown et al. 2008). The first model that was constructed, called SOME (**S**luce's **O**riginal **M**odel for **E**xploration), was built in the Swarm modeling toolkit[4] (Minar et al. 1996). The core agents of the SOME model are residents and service centers that interact on a complex landscape that includes roads and landscapes of aesthetic quality; both of which can either be generated or drawn from empirical GIS data. Later, a NetLogo[5] (Wilensky 1999) version of the SOME model was constructed. This model was a stripped down version that was used primarily to examine general patterns and as an educational tool. Finally, a new model was created, called DEED (**D**ynamic **E**cological **E**xurban **D**evelopment)(Brown et al. 2008), which was constructed using the RePast toolkit[6] (North et al. 2005). This model included several new agent types including: farmers, policy boards, and developers; as well as the residents present in the SOME model. This allowed more realistic models of exurban development to be constructed and different questions of policy impact to be explored; all of which are heavily dependent upon spatial interactions that exist between these various stakeholders.

Project SLUCE has used this suite of models to examine a number of different questions including: (1) the interaction of residents with policy constraints (e.g., greenbelts) (Brown et al. 2004) (2) the validation of the models against classically observed empirical patterns (Rand et al. 2003), (3) the development of new spatial validation techniques (Brown et al. 2005a), (4) the role of zoning in exurban sprawl (Zellner et al. 2009, 2010), and several other research questions (Brown et al. 2008).

A key aspect in investigating all of these different possibilities was that SLUCE had developed a suite of models rather than just one model. This allowed the project researchers to employ the right model at the right time. This approach, which has sometimes been referred to as full-spectrum modeling (Rand and Wilensky 2007), embraces the idea of choosing the right model for the right level of detail, backgrounding other decisions when need be, and at the same time bringing other details of interest to the front. Choosing the correct level of detail is often a concern in macro-level spatial modeling and something that should be considered whenever developing a spatial ABM with business applications. Sometimes there will be some agents that need to be emphasized, such as residents, where in other cases other agents will be more important, such as developers. The reason why this is particularly relevant when it comes to considering spatial ABMs at the macro-level is that there are many different types of consumers in any context. One of the arguments for the development of the DEED model by Project SLUCE was that for many policy questions regarding new housing, the developer, as opposed to the individual resident/homeowner, was a more appropriate unit of analysis, and so as Project

[4] http://www.swarm.org/

[5] http://ccl.northwestern.edu/netlogo/

[6] http://repast.sourceforge.net/

SLUCE transitioned to examining more of these types of questions, a new model was constructed. In the SOME model, the consumer being represented was the resident, consuming a housing location and making a residential location decision based upon the amenities offered, while in the DEED model the primary consumer was a developer who essentially consumed zoning policies and made development decisions based upon them. For researchers, and business practitioners interested in representing a large-scale market using a spatial ABM it may be useful to consider the possibility of constructing multiple models at different scales that represent these different levels of consumption and market interaction.

Macro-scale models of market demand and consumption could also be useful in other contexts as well. For instance, it is possible to build "heat maps" of potential future demand in different areas, and then use those to influence future retail construction decisions, or even future logistical needs for an organization that is a service provider to other industries. Moreover, consumers like to not only shop near where they live, but they also like to work near where they live. As consumers of employees, businesses should pay attention to how future housing trends are developing and attempt to locate where they will have the best access to highest quality labor. One of the findings of Project SLUCE (Brown et al. 2005a) was that often it is useful to examine not only individual runs of a model and "frequency" or "heat maps" which illustrate how often an area gets developed in the model, but also to break model forecasts up in to "variant" regions (regions that are sometimes developed and sometimes not under the model) and "invariant" regions (regions that are almost always developed or not developed in the model). This is useful because development tends to be path dependent, meaning that new development tends to follow recent development even if the recent development occurred at its location purely due to happenstance. Figure 22.2 illustrates how to explore these different effects using an ABM and teh comparison of these projections to an underlying reference map.

22.2.3 Other Macro-Level Models

There are many other business phenomenon that could be and have been modeled using spatial ABMs at the macro-level. For instance, geographically extended supply networks, where the physical distances between the locations is vital to understanding how the supply network operates could be modeled using macro-level spatial ABMs. Spatial ABMs can be used to examine dynamic supply networks that evolve and change in time (Emerson and Piramuthu 2004) taking in to account the information moving across these networks which has its own dynamics (Ahn and Lee 2004). Related to supply chains, is the question of vehicle routing. Given that you have a particular fleet of vehicles that need to deliver goods to a variety of locations what is the best way to do so, especially in the presence of changing traffic conditions, and potentially changing consumer demands (Kohout and Erol 1999). Moreover, and somewhat extending on both of the examples listed above, is the question of retail location placement (MacKay 1972). If we have a good representation of consumer

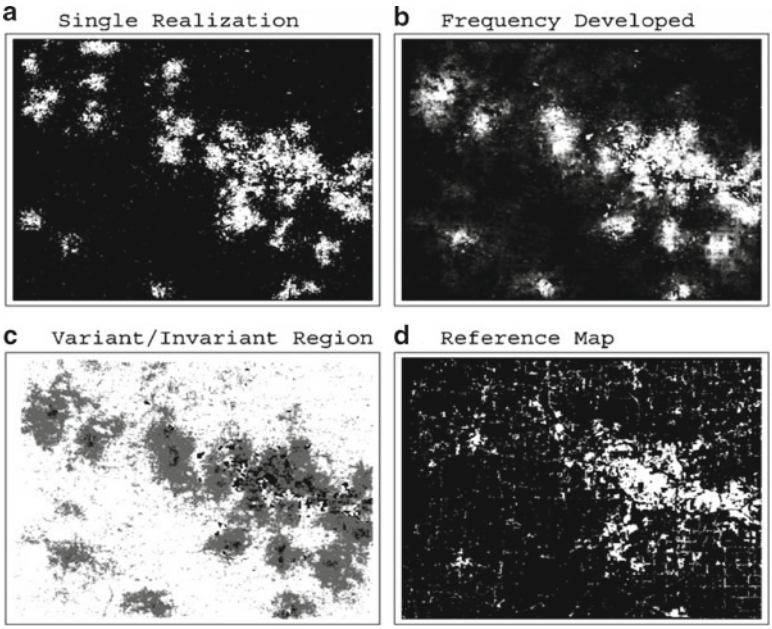

Fig. 22.2 Different ways of examining development models: (**a**) illustrates a single run of the model with white areas being developed land, and the black areas being undeveloped land, (**b**) uses grey scale to illustrate the frequency with which an area was developed over a large number of model runs, (**c**) breaks the map up into areas that are always developed (*black*), never developed (*white*) and sometimes developed (*grey*) for a large number of model runs, (**d**) is a reference map indicated what actually happened (Reprinted by permission from Brown et al. (2005))

movement in a market, and detailed information about competitor placement and prices, then we can ask the question: where should a firm locate its next store and should it close down any stores that it currently has open? (Lombardo et al. 2004) Such a model would provide a sophisticated decision support tool; but spatial ABMs could also be used to construct descriptive and exploratory models (Huang and Levinson 2008). For instance, they could be used to investigate why urban and retail concentrations occur in the first place? (Krugman 1996)

Finally, one interesting application of spatial ABMs at the macro-level does not involve any notion of physical movement but instead the movement of information. There has recently been considerable interest in understanding the diffusion of information across social media from a marketing perspective (Trusov et al. 2009; Domingos 2005). It might be thought that in these systems geography and space are unimportant, but in fact there is some evidence that geography still plays a role in diffusion of information (Goldenberg and Levy 2009). Thus, one macro-level spatial ABM that might be useful from a marketing and business perspective would investigate the spread of information across social networks and geography at the same time, and examine optimal strategies for seeding viral marketing strategies (Stonedahl et al. 2010) taking in to account both geography and network properties simultaneously.

22.3 Micro-Level Spatial ABMs

On the other end of the spectrum from macro-level spatial ABMs is micro-level spatial ABMs. Such models may still use GIS data to provide the environment within which the agents move, but the unit of focus here is on the individual constrained within a smaller geographic space. In particular these models require some model of pedestrian movement, whether it be within a retail location (Zacharias et al. 2005), through a mall (Bitgood and Dukes 2006), or around a neighborhood (Batty et al. 1998; Borgers and Timmermans 1986). Unlike the macro-level models described above, there has not been as much research applying these kinds of models specifically within the realm of business applications, though there is substantial research into the problem of pedestrian agent-based modeling in general (Batty 2003). However, recent advancements in the collection of data about consumers in business locations, using RFID-enabled shopping carts among other technologies (Larson et al. 2005), means that it may be possible to build micro-level spatial ABMs at a much greater level of fidelity than was previously possible. Pedestrian-level ABMs could be useful in understanding neighborhood foot traffic in order to develop retail locations (Borgers and Timmermans 1986), movement within a grocery store in order to optimally allocate store layout (Larson et al. 2005), or even model spatial interactions within an office building to improve organizational efficiency and interaction (Wineman 1982).

Despite the advances in new data collection techniques, there are still open research questions with regards to how to best integrate this data. Moreover, most ABMs are not built for physical interactions something that may be required to create sophisticated micro-level models. These are issues that deserve attention and research if micro-level spatial ABMs are to prove useful within the context of management science and business applications.

22.3.1 Neighborhood Pedestrian Modeling

Examinations in to agent-based pedestrian models have evolved over the years from random walk models to goal-oriented walking to flocking and object avoidance models (Batty 2003) and have been used to examine crowd movements at the Noting Hill Carnival (Batty et al. 2003) (see Fig. 22.3) and in the Tate Modern (Turner and Penn 2002). Models of pedestrian movement within a neighborhood could be useful within a number of different business and management science applications. For instance, it would be interesting to examine micro-level models of individuals moving around a neighborhood, and using this model of foot traffic to

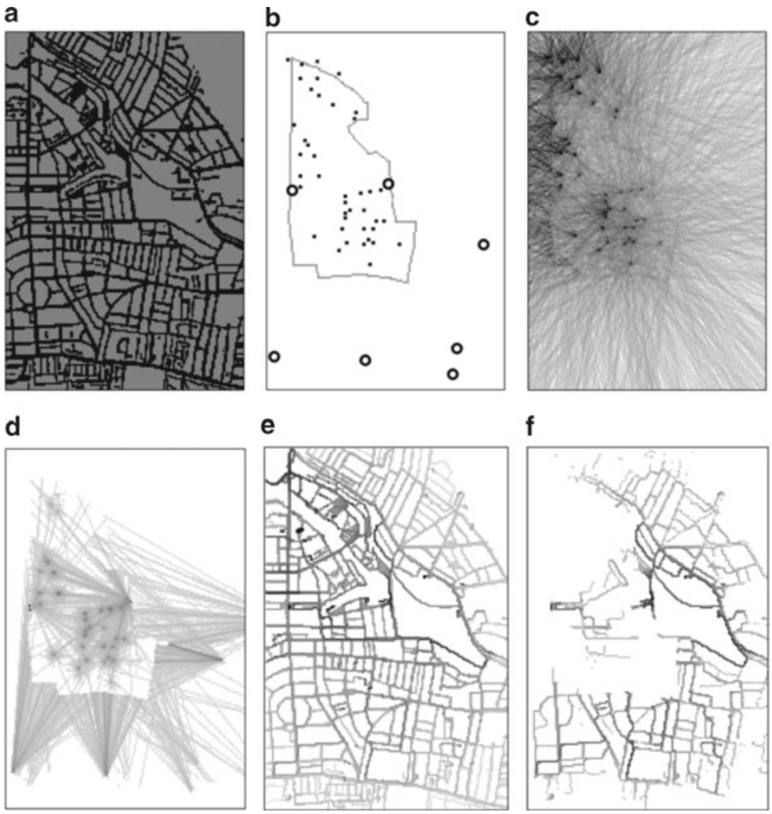

Fig. 22.3 Illustrations of data and analysis used in an ABM of pedestrian traffic around the Notting Hill Carnival: (**a**) street geometry, (**b**) parade route, sound systems, and tube stations, (**c**) all possible paths without street constraints, (**d**) shortest routes from tube stations without streets, (**e**) all possible paths with street constraints, (**f**) shortest paths with street constraints (Reprinted by permission from Batty et al. (2003))

determine retail location placement (Borgers and Timmermans 1986). In much the same way that a heat map of car traffic can be useful for understanding where to place a new retail location that is car accessible, pedestrian heat maps could be used to help examine how to place retail locations in pedestrian friendly areas, such as city centers or malls.

To some extent these models would not be very different than the macro-level models described above, but consumers who are moving through a pedestrian accessible landscape do have access to different information than those who are driving by a big box store. Pedestrians can partake in window shopping, and retailers can alter their displays to entice consumers, and even to compete with other stores or services nearby. Retail employees can interact with pedestrians, providing samples or coupons to entice them in to their store. This could be done adaptively in response to other spatially proximate competitors. This interaction between pedestrians, store employees and competitors creates a whole new level of marketing interaction that could be modeled and examined using spatial ABMs.

Of course, an issue that needs to be considered within the context of pedestrian modeling, especially if complexities such as window displays and sampling are to be included, is the lack of well-validated models at this level of detail. Though models of how pedestrians move have become more and more sophisticated, there currently is little or no research in to how these more goal-oriented pedestrian models would be affected by distractions and marketing interventions. This presents a number of interesting open research questions, and as data from closed-circuit TVs (Batty 2003) becomes more and more prevalent, it may be possible to build more sophisticated models of this complex consumer behavior. In the end, it would be useful to have a general model of pedestrian movement that could then be used to investigate a wide-range of questions from retail location placement to the effect of foot traffic on institutional environment design to questions of public safety (Kerridge et al. 2001), and steps have been taken in the past to create such models (Schelhorn et al. 1999), but a fully realized model that incorporates all of the concerns mentioned above has yet to be developed.

22.3.2 Retail Consumer Modeling

In general, the design of consumer retail environments (Babin and Darden 1995) and servicescapes, i.e., the built environment within which services operate (Bitner 1992), is critical to profitability and customer satisfaction. Despite the high impact of these decisions on business success, most guidelines about how to construct environments are based upon trial and error and past experience. There are very few ways to test out a design ahead of time and to determine if the physical layout of a retail environment will achieve the goals that management wants to achieve. Spatial ABMs provide a unique way to examine these environments before they are ever built and to try out multiple different layouts and investigate how well they perform. Of course such models require a sophisticated model of consumer movement within the space, and since each space is slightly different and that consumer interactions will vary from space to space, e.g., consumers act differently and have different goals in a bar than they do in a supermarket, this task can be quite difficult.

Though there has been some past work at examining in-store movement by consumers (Zacharias 2000, 2001; Zacharias et al. 2005), recent advances in the availability of RFID level data (Larson et al. 2005) (see Fig. 22.4 for an illustration of the kind of data obtainable from RFID tags), closed circuit television feeds (Batty 2003) and other technologies, have made it easier to construct and validate such models. One question that remains is at what level of detail to model the pedestrian movement. It is possible that every pedestrian entering a store could navigate in very different ways, but there do appear to be regular patterns of behavior, and research suggests that it may be possible to model consumer behavior within a shopping environment using a few simple rules (Zacharias et al. 2005).

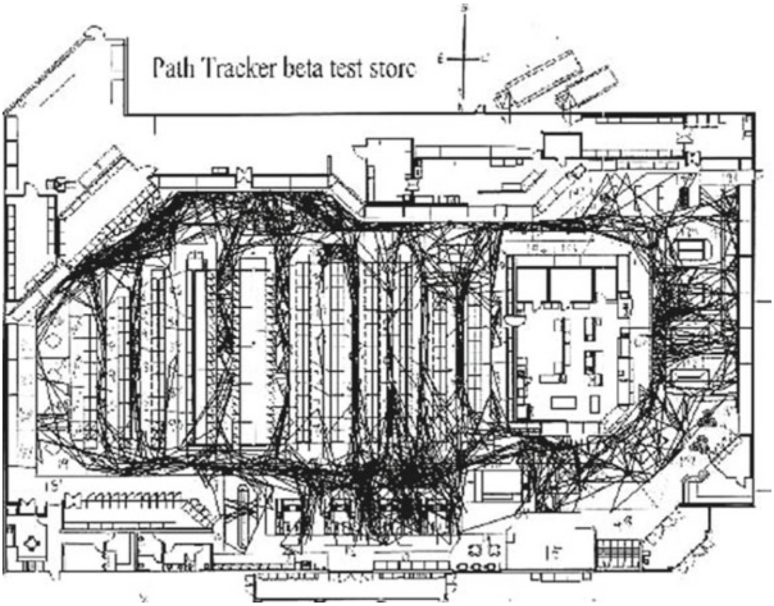

Fig. 22.4 RFID (PathTracker{ ©}) data from 20 random customers (Reprinted from Jeffrey et al. (2005), Copyright (2005), with permission from Elsevier)

One way to validate these models, would be to use the "virtual" models in combination with "real" data. For instance, Red Dot Square[7] is a company that creates photorealistic interactive retail "virtual" worlds, brings "real" consumers in to them and then examines what they do in order to provide advice to retailers about "real" store layouts. However, these real consumer experiments are very expensive. If there was a sophisticated enough model of consumer-level behavior either based on Red Dot Square's data or other data sources, then an ABM could be used to evaluate thousands of different store layouts using virtual consumers. After a smaller selection of store layouts were chosen from this larger set then they could be evaluated using either Red Dot Square's virtual environment and real consumers, or changes could actually be made in-store for an evaluative period.

Though it has been known for a long time that stores can increase sales through in-store marketing efforts (Chevalier 1975) and that the provision of different kinds of pricing comparisons can affect consumer information processing (Zeithaml 1982), these results could be built upon to create more sophisticated in-store retail ABMs. Moreover, applications of spatial ABMs to retail locations could even get down to the level of evaluating the effectiveness of displays with respect to the position and quantity of shelf-facings, i.e., how goods are actually laid out on a shelf. Though even simple models along these lines may garner new insights in to in-store marketing,

[7] http://www.reddotsquare.com

more advanced models could also be useful. For instant, recent research indicates that placing a product in an area of higher attention is sometimes not enough to drive additional purchases and that such models should include information about out-of-store marketing efforts and brand awareness (Chandon et al. 2009).

22.3.3 Other Micro-Level Applications

There are many other interesting questions within the management science context that could be examined using micro-level spatial ABMs. For instance, in the same way that diffusion of information is interesting at the macro-level, it is also interesting at the micro-level. Specifically, how does information diffuse within an organizational workspace? Clearly social networks and the chain of command play a role in organizational information diffusion (Cross et al. 2002), but physical proximity also plays a role. After all, the water cooler was the center of gossip for years not because individuals were socially tied to each other, but rather because the water cooler served as a central point where individuals interacted and exchanged information. To fully understand how information diffuses through an organization, it is necessary to take spatial process of movement with in the organizational space in to account. Models of this process could also be used to explore the effect of virtualization of organizations (Barrett et al. 2007).

Similarly, there has been a recent trend toward the development of "third" places, i.e., spaces that are neither home nor work, such as coffee bars and innovation cooperatives (Rosenbaum 2006). Clearly these new interaction environments will dramatically effect the diffusion of information both within an organization and across organizations as employees working in these third spaces interact with employees and entrepreneurs working in other organizations and industries. Potential research areas to consider include whether these spaces are useful for organizations, and how to design them to foster interactions at an appropriate level to reach some goal.

22.4 Discussion and Conclusion

The goal of this chapter has been to provide some examples of how agent-based models and spatial modeling can be combined to provide interesting insights in to business and management science applications. Throughout this chapter we have discussed not only applications of spatial ABM to business and management, but important issues that must be considered during this process. At the macro-level these issues usually revolve around what level of detail to create the model at, and whether it is better to create a suite of complementary models. At the micro-level there are fundamentally interesting issues that concern data integration, and to some extent how much fidelity to include in a model of pedestrian movement. As spatial ABMs continue to evolve, new issues and questions will arise, and new solutions and best practices to these already extant questions will be developed.

So far these models have been described as taking place at either the micro- or macro-level, and this distinction was drawn because the issues that must be examined at each level are often very different from each other. This distinction seems relatively valid since it is often possible to separate out micro- from macro-effects. For instance, it might be hypothesized that individuals who enter a grocery store may shop differently depending on where they had come from Herrmann and Beik (1968), but its not clear why a micro-level model would not be sufficient since the agents entering the store could be given different synthetic or empirically-derived histories. Alternatively if a store's contents varied based upon where individuals came from its not clear why this decision would also have to model the layout of the store at the micro-level. This is not to say that there will never be a need to blur this demarcation between scale boundaries but in many cases it may be more useful to build two complementary models instead.

In order to fully realize many of the goals and projects envisioned in this chapter, one aspect that need to be addressed is suitable tool development. As mentioned above, the integration of GIS tools into most of the modern ABM platforms has been a substantial assistance in terms of developing more integrated models, but unfortunately this integration is still far from seamless and requires effort on the part of the model developer. One possible approach that has been discussed elsewhere is a middleware approach (Brown et al. 2005b) that would allow a tighter integration between GIS and ABM and allow for a potentially platform independent model to be developed. Such an approach would also have the useful benefit of creating a somewhat more abstract language for talking about pattern (GIS) and process (ABM) in the same conceptual framework, a task which is currently hindered by the lack of a common language across these two methodologies. Since many phenomena of interest to modern business researchers and management science scholars contain both spatial and temporal elements, such a conceptual language would be very useful.

Of course such tools would be even more useful if they are teachable and explainable to management students. ABM has been used for management education in the past by combining it with participatory modeling (a version of ABM where some agents are played by actual people). The classic example is the "beer game" in supply chain management education (Sterman 1992), where managers control part of a supply chain and learn about how time lags affect supply chain operations. Though the beer game is relatively aspatial, spatial ABMs have also been combined with participatory simulation in other contexts to help determine local land-use policies (Castella et al. 2005; D'Aquino et al. 2003), and it seems clear that such techniques could also be employed in management science.

One of the main benefits of ABM in general is that the model representation is easily explainable to a non-technical stakeholder. As a result, spatial ABMs have the potential to be very convincing in business applications because of the relatively close relationship between their ontology and the ontology of the real business world. It seems like a natural combination then to bring together spatial ABMs with participatory modeling to develop sophisticated models of business applications and situations. The simulation could even use rules for the non-human agents that were inferred from previous observations of human behavior, allowing management students to compete again "human-trained" computational agents. And why stop there? The computational agents could even observe human participant behavior in real-time and adapt their strategies in response. Clearly, there are many possibilities and research opportunities in the application of spatial ABMs to business and management science education and research.

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