Activity-Based Analysis

37

Harvey J. Miller

Contents

Abstract

Activity-based analysis (ABA) is an approach to understanding transportation, communication, urban, and related social and physical systems using individual actions in space and time as the basis. Although the conceptual foundations, theory, and methodology have a long tradition, until recently an aggregate trip-based approach dominated transportation science and planning. Changes in the business and policy environment for transportation and the increasingly availability of disaggregate mobility data have led to ABA emerging as the dominant approach. This chapter reviews the ABA conceptual foundations and methodologies. ABA techniques include data-driven methods that analyze mobility data directly as well as develop inputs for ABA modeling. ABA models include econometric models, rule-based models and microsimulation/agent-based models. This chapter concludes by identifying major research frontiers in ABA.

H.J. Miller
Department of Geography, University of Utah, Salt Lake City, UT, USA
e-mail: harvey.miller@geog.utah.edu

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37.1 Introduction

Activity-based analysis (ABA) refers to treating individual actions in space and time as a basis for understanding human mobility and communication behavior and related systems such as cities, economies, and the physical environment. ABA is replacing aggregate trip-based approaches as the basis for forecasting and knowledge construction in transportation science and urban planning. ABA has long recognized advantages over trip-based approaches, not the least being theoretical validity. In addition, ABA can capture complex constraints and linkages that determine mobility better than aggregate, trip-based approaches. ABA also admits a wider range of policy variables, including non-transportation solutions to mobility problems.

Until recently, the data and computers did not exist to apply ABA to realistic scenarios. These limits have been shattered by increasingly powerful computers but especially by individual-level data available through wireless location-aware technologies embedded in infrastructure, attached to vehicles, and carried by people. These data are enhancing activity data analysis and modeling techniques. They are also leading to a new, data-driven approach to ABA based on exploratory analysis and visualization methods.

The next section of this chapter discusses the conceptual and practical foundations of ABA. It first reviews the traditional, trip-based approach and identifies key weaknesses. The activity-based approach resolves some of these weaknesses by treating mobility and communication not as disembodied flow but as humans conducting the activities that comprise their lives. The Section 37.3 reviews policy and technological changes that are leading to advances and wider application of the ABA approach. Section 37.4 reviews data collection and data analysis methods for ABA. The Section 37.5 discusses activity-based models of travel patterns and urban dynamics using econometric, rule-based, and simulation methods. Section 37.6 identifies ABA research frontiers.

37.2 Conceptual Foundations of Activity-Based Analysis

The past century of transportation science was dominated by a trip-based approach to understanding and predicting human mobility. This approach focuses on isolated acts of mobility as the primary object of study. A *trip* is a movement of a person, goods, and/or vehicle from an origin to a destination (possibly the same location) motivated by positive factors at the locations (push factors at the origin, pull factors at the destination) and attenuated by negative factors related to the cost of mobility between the directed pair. Each trip occurs independently of other activities and trips that occur during individuals' lives. People, events, and activities are atemporal; time is simply a component of mobility cost. Finally, the trip-based approach treats mobile entities not as unique objects but as undifferentiated flows between areas such as traffic analysis zones, postal units, or census geography (although it can consist of subflows representing different cohorts) (Pinjari and Bhat 2011). Weaknesses of the trip-based approach include (McNally and Rindt 2007):

- No recognition that mobility derives from activity participation
- The treatment of mobility events as resulting from independent and generally unencumbered choice processes, simplifying the complex spatial and temporal constraints that delimit (and sometimes determine) choice
- A focus on utility maximization, neglecting alternate heuristics related to factors such as decision complexity and habits
- A neglect of the roles played by interpersonal relationships and information in influencing activity, mobility, and communication behavior, including *information and communications technologies* (ICTs)

The activity-based approach focuses on the individual and her or his need to participate in activities that have limited availability in time and space. Mobility is not fundamental but an epiphenomenon: it derives from the need to be physically present for many activities and the "inevitability of distance" between activity locations (Ellegård and Svedin 2012). Telepresence via ICTs can substitute for physical presence but can also complement physical mobility by providing more information about events and opportunities as well as capabilities for interpersonal interaction and coordination. Individual and joint allocation of scarce time is the meaningful starting point to understand activity, travel, and communication at all scales: from the tasks required to fulfill daily projects to the annual and decadal dynamics that affect cities, regions, and the planet (Pred 1977). Strengths of the activity-based approach are (McNally and Rindt 2007):

- Recognition that mobility derives from activity participation
- Explicit treatment of the complex temporal and spatial constraints on activity participation and mobility
- Flexibility to accommodate a wide range of decision processes and heuristics
- Explicit treatment of social organization, social networks, and ICTs that influence activity and mobility behavior

Table 37.1 summarizes major components of activity theory. As Table 37.1 illustrates, mobility – trips or tours – is only a component of a more expansive view of human behavior that includes activity patterns and scheduling as well as the social context that influence these activities.

The view that human activities in space and time are the meaningful starting point to understand and manage transportation, cities, and regions dates back to the time-use studies of Chapin (1974) and an influential paper by Jones (1979) that articulated the ABA framework in its contemporary form. But much of the conceptual foundation for ABA was developed by Torsten Hägerstrand in his time geographic framework (Pinjari and Bhat 2011; McNally and Rindt 2007).

Time geography underlies many of the core ideas in ABA, including an ecological perspective on human and physical phenomena, the need to build macro-level explanations from the micro-level and situating travel within a larger context, facilitating the recognition of non-transportation solutions to transportation problems. Basic time geographic concepts such as the individual trading time for

Table 37.1 Elements of activity theory

Element	Description
Activity	The main purpose underlying behavior conducted at a specific location and time interval; often classified as *fixed* versus *flexible* activities based on the relative ease of rescheduling and relocation
Activity frequency	The number of times an activity occurs during a given time period
Activity location	Geographic or semantic location where an activity occurs
Activity pattern	Set of activities to be conducted during a specific time interval
Activity schedule	Planned sequence and timing of activities to be conducted during a specific time interval
Time budget	Available time for mobility, communication, and activity participation during a given time interval; often expressed relative to flexible activities and constrained by fixed activities
Trip	Physical movement between activity locations
Interaction	Communication between individuals or locations
Tour	A multi-stop and often multipurpose trip involving several activity locations
Mode	Technique or service used to generate mobility and/or communication behavior
Activity space	Geographic region within which a set of activities occur; can be the composite of discrete activity locations or the smallest spatial region or subnetwork that encompasses the activity locations
Activity environment	Spatiotemporal configuration of activity locations within a given geographic environment
Household	Basic unit of domestic maintenance; influences activity participation through task organization, coordination, and sharing
Social network	Interpersonal relationships, both formal and informal, that influence activity participation
Lifestyle	Socioeconomic and demographic factors that influence activity, mobility, and communication behavior

space in movement among activity locations distributed in time and space may seem trivial since they are so close to everyday life experiences. But this is precisely the point Hägerstrand is making: we neglect seemingly inconsequential but critical factors in our scientific explanations of human behavior; the trip-based approach is an exemplar. Time geography provides a conceptual framework that obligates recognition of basic constraints underlying human existence, as well as an effective notation system for keeping track of these existential facts (Ellegård and Svedin 2012).

37.3 Policy and Technology Context for Activity-Based Analysis

Transportation scientists, engineers, and planners have long recognized the weaknesses of a trip-based approach with respect to validity and accuracy, and the potential of an individual-level, activity-based approach for better understanding and more accurate predictions of transportation and related human–physical systems. However, until recently there has been little incentive for ABA in policy and planning. There was also little capability with respect to data and computing power.

The last century has witnessed an unprecedented explosion in human mobility due to the development of technologies and services such as steamships, railroads, private automobiles, and commercial aviation. In today's world, people travel to a degree that would have seemed magical to our ancestors. While there are obvious benefits from mobility, there is also increasing recognition of its market failures such as congestion, poor air quality, accidents, sprawled cities, obesity, social exclusion, and global warming. High mobility levels are also increasingly under threat from aging infrastructure that is not being sufficiently renewed, increasing urbanization (especially in the Global South), and increasing motorization as newly emergent economies generate rising levels of wealth.

It is also increasingly difficult to separate mobility and communication behaviors. The telegraph, telephone, and the Internet have revolutionized communication, but these technologies were tightly coupled with location. The rise of mobile telephony and pervasive computing has liberated telecommunication from specific places, allowing it to be more integrated with people and their activities. This is creating tighter, more complex linkages between mobility and communication. Evidence indicates that the "Death of Distance" argument that geographic location would become irrelevant is naïve: communication complements as well as substitutes for mobility, leading to higher mobility demands at all geographic and temporal scales as well as greater complexity of mobility and activity patterns.

Increasing recognition of transportation market failures, threats to mobility, and the tighter integration of mobility and communication behavior have lead to new scientific, policy, and planning initiatives in Europe, North America, and increasingly elsewhere. The business and policy environment for transportation policy and planning is evolving beyond simple measures and prescriptions that focus primarily on measuring throughput relative to cost. There is wider consensus that mobility should be managed, not simply maximized. There is also recognition that evaluating transportation performance requires a fuller range of measures including indicators of effectiveness, equity, community livability, and sustainability. Planners have also realized that solving transportation problems requires thinking outside the system to the broader activity and communication patterns that drive complex mobility behavior. This may include non-transportation remedies for transportation problems (e.g., work flextime, different trading and service hours).

Approaching policy questions from the ABA perspective starts with underlying activity patterns, their interdependencies, and the potential rebound effects that occur from policy changes. Figures 37.1a, b provide a simple example (after Ben-Akiva and Bowman 1998). Figure 37.1a illustrates a daily activity pattern that includes being at home, working, stopping at a day-care center to and from work, and shopping for groceries. Implementing this activity pattern is a single tour from home to the day-care center and work in the morning, shopping in the late afternoon, stopping again at the day-care center and back home in the evening, mostly alone in a private vehicle.

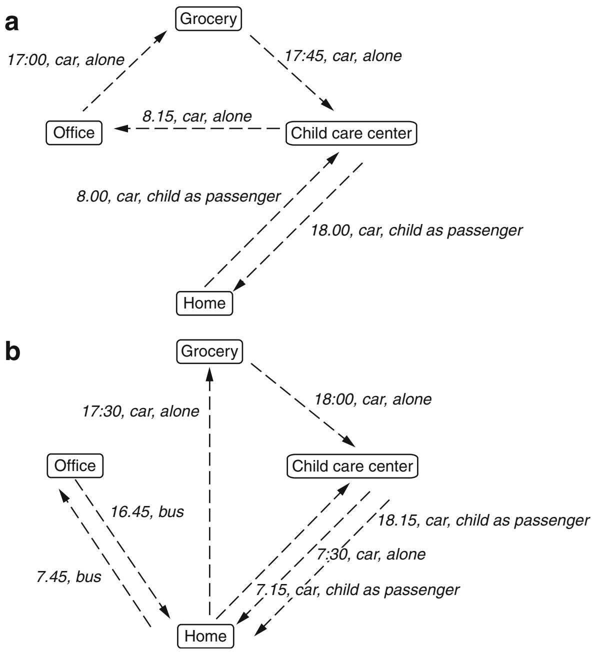

Fig. 37.1 (**a**) Activity-based approach to policy analysis: before policy intervention. (**b**) Activity-based approach to policy analysis: after policy intervention

Figure 37.1b illustrates the outcome of a policy intervention: an employer-sponsored public transit incentive combined with higher parking costs. Implementation of the activity pattern now requires three home-based tours: trips to/from childcare center by car in the morning, commuting by bus to and from work during peak times, and shopping by private vehicle in the late afternoon with a stop at the childcare center on the way home. Is this new policy a success? A trip-based approach would likely reach this conclusion since it would focus on the commuting behavior and find a reduction in travel demand by private vehicle. However, an activity-based approach would be more likely to conclude that the new policy was a mixed success due to the shifting of travel and activity patterns and the increase in home-based trips by car. An activity-based approach would capture the linkages between these events and suggest that the transportation policy change should be accompanied by supportive, non-transportation policies such as incentives for day-care centers at work places and/or residential areas.

ABA is more challenging than a trip-based approach: the number of sequencing, timing, location, mode, and route choice possibilities for only a daily activity pattern is combinatorial. There are also a large number of household, social network, and informational linkages that determine daily, weekly, monthly, annual, decadal, and lifetime activity patterns. Activity-based comprehensive urban models also consider the reactions and dynamics of broader infrastructure, economic, sociodemographic, and political systems. Determining a meaningful boundary around the system being analyzed and the level of resolution for representing different components is critical. This requires judgment that considers the scientific and policy questions being asked, as well as theoretical correctness and consistency (Ben-Akiva and Bowman 1998).

With respect to capabilities for ABA, digital data collection, storage, and processing costs have collapsed to an astonishing degree. *Location-aware technologies* (LATs), digital devices that can report their geographic location densely with respect to time, have become inexpensive and effective. They are increasingly embedded in vehicles and infrastructure and carried by people in consumer products such as smartphones. LATs are generating massive amounts of fine-grained data about mobility and communication dynamics as well as the dynamics of the broader social and environmental systems within which they are embedded. Computers are also much better at handling these data. In addition to dramatic increases in computing power, *geographic information systems* (GIS) and *spatial database management systems* (SDBMS) have evolved well beyond their origins in computer-based paper maps to include a wide range of tools managing, querying, analyzing, and visualizing dynamic and moving objects data. *Social media* available through mobile communication devices allow users to obtain better information transportation systems, share user-generated content, and even participate in management and governance.

New interdisciplinary fields such as *computational transportation science* (see http://ctscience.org/) are emerging to exploit data collection, processing, and communication capabilities to solve vexing and increasingly critical transportation challenges. Private sector companies such as IBM envision smarter transportation, smarter cities, and a smarter and more sustainable planet by collecting fine-grained sensor data, processing these data into meaningful metrics, and sharing this information widely to support more collaborative decision-making (see www.ibm.com/smarterplanet). There are critical privacy questions that must be resolved (discussed below), but these data and tools have the potential to revolutionize transportation science and planning from the "bottom up": a new science and practice built from individual activities in space and time as the core concept.

37.4 Activity Data Collection and Analysis

ABA includes a rich suite of tools for empirical measurement and analysis of mobility and communication behavior. The conceptual origins for this approach are based in time geography, but this approach has been revolutionized by the rise of LATs and the availability individual-level mobility and communication data. These data can be analyzed directly for empirical patterns. They can also be used as inputs to ABA models, as well as in model calibration and validation. Data-driven methods are also used in *mobility mining*: open-ended exploration of moving objects data to search for novel hypotheses.

Space–Time Paths. The basic conceptual entity in ABA is the fundamental time geographic entity, the space–time path, and its extension, the space–time prism. The *space–time path* represents actual mobility (recorded or simulated) of an entity moving in geospace with respect to time. (A *geospace* is a low-dimensionality

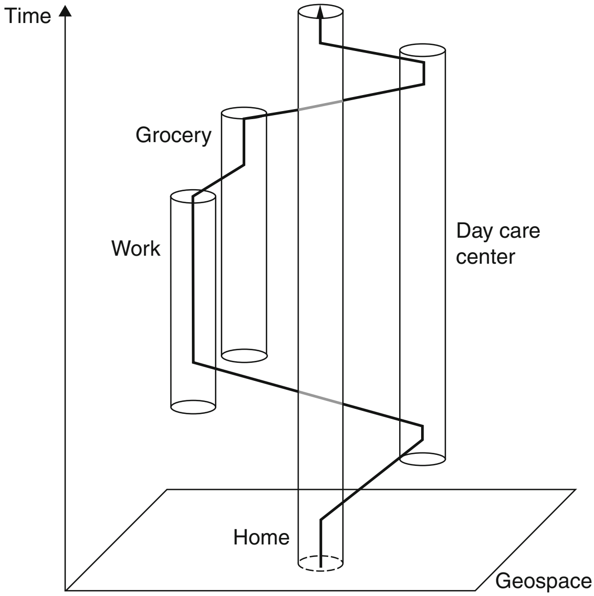

Fig. 37.2 A space–time path among activity locations

space – usually three dimensions or fewer – where distances between location pairs represent shortest path relations in some real-world geography). Figure 37.2 illustrates a space–time path between four activity locations in geographic space (the latter conceptualized as tubes with locations in space and extents in time reflecting their availability).

Semantically, the path is a continuous mapping from time to geospace. In practice, data are typically a sequence of sampled locations strictly ordered by time. Traditionally, these data were collected using recall methods such as travel–activity diaries, prospective methods such as experiments where study participants solve contrived activity and travel scheduling problems. These traditional data collection methods are fraught with problems, including nonparticipation biases, recall biases, and accidental or willful inaccuracies (in the case of travel diaries) as well as difficulties in creating meaningful scenarios (in the case of prospective methods). LATs such as assisted GPS technologies in smartphones allow more accurate and higher volume data collection to support space–time path reconstruction. However, this often comes at the expense of path semantics such as the context for the mobility episode including the planned and executed activities. Semantics can be recovered by overlaying paths with high-resolution georeferenced land-use and infrastructure data. This method can produce errors related to data inaccuracies and activity ambiguities (e.g., what is a person doing while in a coffee house – dining, working, socializing, or some combination of the above?).

The sequence of sample locations can be generated in several ways depending on the data collection method (Andrienko et al. 2008; Ratti et al. 2006):

- *Event-based recording*: Time and location are recorded when a specified event occurs; this is typical of traditional diary methods but also characterizes data from cell phones, for example, a person calling from a mobile phone generating a location sample.

- *Time-based recording*: Mobile object positions are recorded at regular time intervals; this is typical of GPS and related technologies.
- *Change-based recording*: A record is made when the position of the object is sufficiently different from the previous location; this includes dead-reckoning methods as well as mobile objects database technologies that avoid recording some locations to manage data volume.
- *Location-based recording*: Records are made when the object comes close to specific locations where sensors are located; examples include radiofrequency identification and Bluetooth sensors.

The path must be reconstructed from the temporally ordered sequence of sample locations. The standard method is linear interpolation between temporally adjacent sample points. This requires the least amount of additional assumptions but admits physically unrealistic motions such as infinite acceleration and deceleration at sharp corners. Interpolation via Bezier curves generates a smoother, more physically realistic space–time path (Macedo et al. 2008; Miller 2005a).

Three types of error occur in space–time paths. *Measurement error* refers to error in the recorded location or timestamps. This is equivalent to the well-studied problem of measurement error in polylines in geographic information science. *Sampling error* refers to capturing a continuously moving object using discrete sampling. One way to deal with this is to treat the unobserved segments between sampled locations as an uncertainty region delimiting possible locations for the object between observations (Macedo et al. 2008). This is equivalent to another fundamental time geographic concept, the space–time prism, to be discussed below. *Combined measurement and sampling error* comprises the third type of space–time path error; this is equivalent to measurement error in a space–time prism since under these conditions the space–time prism is a sequence of linked, imperfectly measured space–time prisms.

Space–time paths contain many properties that are useful for understanding human mobility behavior. Analytical methods for paths include (Andrienko et al. 2008; Long and Nelson 2012):

- *Path descriptors* include both *moment-based descriptors* (such as the time, location, direction, and speed at any moment) and *interval-based descriptors* (such as the minimum, maximum, and mean speed; the distribution and sequence of speeds and directions; and the geometric shape of the path over some time interval).
- *Path comparison methods* allow quantitative comparisons among space–time paths, particularly with respect to geometric similarity in space–time and with respect to semantics (such as the sequence of locations visited). Methods include path distance measures such as the Fréchet distance and sequence measures such as least common subsequences.
- *Pattern and cluster methods* for identifying synoptic spatial–temporal patterns from large collections of mobile objects.
- *Individual-group dynamic methods* for characterizing collective movement behavior such as flocking, for example, methods that examine the relative motions among mobile objects.

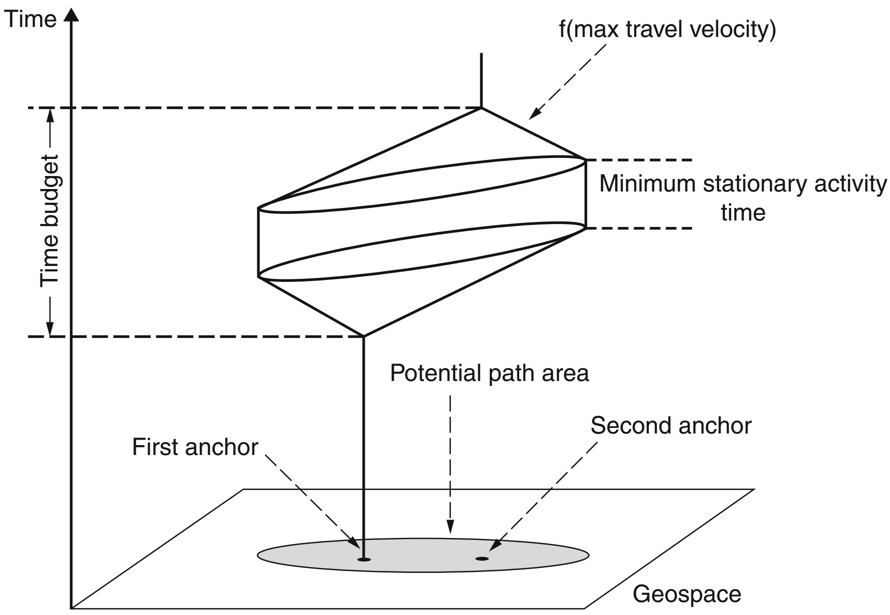

Fig. 37.3 A planar space–time prism

- *Spatial field methods* for translating movement patterns of objects into fields or surfaces that summarize mobility and activity frequency by geographic location.
- *Spatial range methods* for identifying and characterizing the geographic area that contains the observed mobility of one or more mobile objects.

Long and Nelson (2012) provide a succinct but comprehensive review of these methods.

Space–Time Prisms. The *space–time prism* represents potential mobility: it delimits possible locations for a space–time path during some unobserved time interval. Figure 37.3 illustrates a planar space–time prism.

A prism can have two interpretations. As noted above, the prism can be an uncertainty region for an under-sampled space–time path. In contrast, Hägerstrand (1970) conceptualized the prism as a measure of space–time accessibility. The prism encompasses all locations that can be reached during the unobserved time interval given constraints on the object's speed. Activities, conceptualized as tubes at specific locations with limited extent in time (see Fig. 37.2), must intersect the prism to a sufficient degree (at least as long as the minimal activity time) for the activity to be feasible for that person at that time and location.

The prism is difficult to state analytically over the entire interval of its existence. However, it is tractable to define the prism's spatial extent at a moment in time as the intersection of only two of three simple spatial regions (Miller 2005a). It is also possible to define space–time prisms within transportation networks (Kuijpers and Othman 2009). Figure 37.4 illustrates a network time prism: the figure illustrates the accessibility locations within the planar network and the corresponding

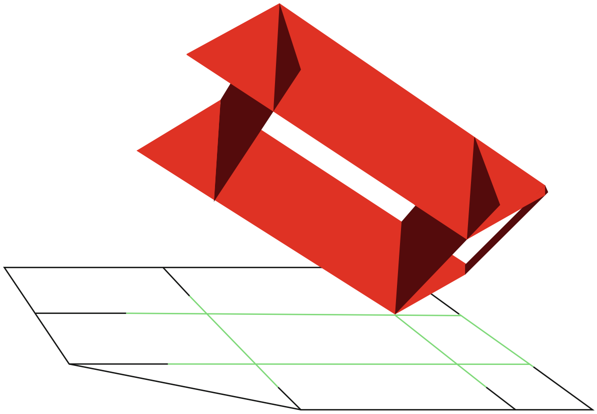

Fig. 37.4 A network time prism

spatiotemporal region comprising the complete network time prism. In addition to being the envelope for possible space–time paths, these paths also give the prism an internal structure, including unequal visit probabilities within the interior (Winter and Yin 2011).

Prisms contain error propagated from the measured space–time anchors and object speed limits. Error distributions can be numerically generated through Monte Carlo simulation: generate many realizations of the prism and analyze the resulting data. This is a tractable approach for theoretical investigation but is not scalable to practical applications. Alternatively, it is possible to derive analytical characterizations of prisms and prism–prism intersection error in planar space using spatial error propagation theory and implicit function techniques applied to the intersection of circles and ellipses. However, some intersection cases are still open, and it is not scalable beyond pairs of prisms. Required is further investigation into tractable error approximations based on spatial error propagation methods (Kobayashi et al. 2011). More tractable are uncertain network time prisms based on spatiotemporal probability regions (not necessarily connected) for anchor locations and times within the network (Kuijpers et al. 2010).

Prisms can be used as inputs to activity models, in particular choice set or feasible activity set delimitation. Prism-based measures provide vividly different portrayals of accessibility across social, gender, and cultural dimensions relative to traditional place-based measures that tend to mask these differences (Kwan 1998). Prisms can capture activity time constraints within accessibility measures that are consistent with spatial choice, spatial interaction, and consumer surplus theory (Miller 1999).

Path–prism and prism–prism intersections represent potential interaction between two mobile objects. Both can be solved in planar space for a moment in time (Miller 2005a). Scalable techniques also exist for network prism intersections (Kuijpers and Othman 2009). Prism–prism intersections are also useful for capturing the possibility of joint activity behavior in activity-based measures and models (Neutens et al. 2007).

The space–time prism focuses on physical accessibility in geographic space or transportation networks. Path and prism concepts have been extended to encompass interactions within cyberspace (the virtual space implied by networked ICTs). Interaction and accessibility in cyberspace can be treated as direct relationships among space–time paths and prisms (Yu and Shaw 2008) or as indirect relationships mitigated by access to communication technologies (Miller 2005b). It is also possible to treat the STP as existing in a hybrid geo/information space (Couclelis 2009).

Mobility Mining. Increasing capabilities for collecting and processing mobile objects data is leading to the emergence of *mobility mining* as a new area of research. Mobility mining leverages mobile objects databases with advances in data mining techniques to create a knowledge discovery process centered on the analysis of mobility with explicit reference to geographic context. Mobility mining involves three major phases (Giannotti and Pedreschi 2008):

- *Trajectory reconstruction* from raw mobile objects data. The basic problem was discussed above; the specific problem in this context is to reconstruct trajectories from massive mobile objects data, especially when the data are collected using different methods and sampling methods/rates. This may involve preprocessing steps such as data selection, cleaning, and integrating with other geographic and sociodemographic data.
- *Pattern extraction* involves using spatiotemporal data mining methods to discover interesting (novel, valid, understandable, and useful) patterns in the reconstructed trajectories. Types of patterns include clusters, frequencies, classifications, summary rules, and predictive models.
- *Knowledge delivery* involves verifying and interpreting the discovered patterns, integrating these patterns with background knowledge and communicating this information to support scientific and applied decision-making.

Mobility mining and knowledge discovery from mobile objects databases are hypothesis-generation processes that should lead to more focused and conclusive investigation. These techniques and processes play roles in the scientific process similar to instrumentation such as a telescope, microscope, or supercollider: it allows analysts to see empirical phenomena that would otherwise be obscured or difficult to detect. Empirical patterns discovered during the data mining process are tentative until they have been verified using confirmatory statistics and interpreted in light of background knowledge and theory.

37.5 Activity-Based Modeling

Although theoretically and evidentially suspect, the trip-based approach offers a significant strength, namely, it is relatively straightforward to build scalable comprehensive models of transportation and urban systems that are easily calibrated, verified, summarized, and mapped. It is more challenging to build, verify, and digest comprehensive models built from the micro-level. LAT-based data, geometric growth in computing power, and the hard work of some very smart people are making activity-based models more realistic, powerful, and understandable. Consequently, ABA is being increasingly applied in policy and planning analysis in Europe, the United States, and other locations.

Depending on the system being modeled, activity-based models can encompass a large number of decision variables over a wide range of temporal and spatial granularities and time frames. In addition, activity-based models are often components in broader comprehensive urban models and linked human–physical process models. Possible components of activity-based models include (Ben-Akiva and Bowman 1998):

- *Activity implementation* involving the execution and possible rescheduling of activity, travel, and communication plans based on empirical conditions in real time. This includes decisions such as mode and route choice, but also fine-grained context-specific behaviors such as speed, acceleration, merging and car-following behavior in automobiles, bicycling behaviors such as obeying stop signs, and pedestrian behavior within crowded environments.
- *Activity scheduling* includes activity selection, activity assignment within household and other social networks, activity scheduling, selection of activity locations, and methods and times for mobility. These events occur frequently and regularly at time scales ranging from real time to hourly, daily, weekly, monthly, seasonally, and annually.
- *Sociodemographic systems* include work, residence, ownership, and other life-altering personal, social, and economic decisions and events such as having children or buying a bicycle. These occur infrequently at the scales from annual to decadal.
- *Urban, social, and economic systems* include the infrastructure, services, institutions, and social and built environments that influence implementation, activity, and lifestyle decisions. These systems operate from real time (e.g., traffic conditions) through annual (e.g., housing dynamics) to decadal and beyond (e.g., compact versus sprawled cities).
- *Physical systems* include material, energy, hydrologic, biological, atmospheric, and other environmental systems that affect and are affected by the other activity domains. These operate in real time (e.g., air quality) to geologic (e.g., climate change).

Activity-based models slice, dice, and combine these components in different ways depending on the modeling domain and scope, as well as the strengths and weaknesses of the particular technique. Major types of activity-based modeling techniques are (i) *econometric models*, (ii) *optimization methods*, (iii) *computational process models*, and (iv) *microsimulation and agent-based models*. Some of these approaches can also be used in combination, for example, econometric models as a component of a larger microsimulation model or a computational process model used to derive agent behavior in an agent-based model.

Econometric Models. Econometric models are among the oldest activity-based modeling strategy, resulting from extending trip-based econometric models to encompass activity choice and trip-chaining behavior. These models have their foundation in the microeconomic theory of consumer choice. They require

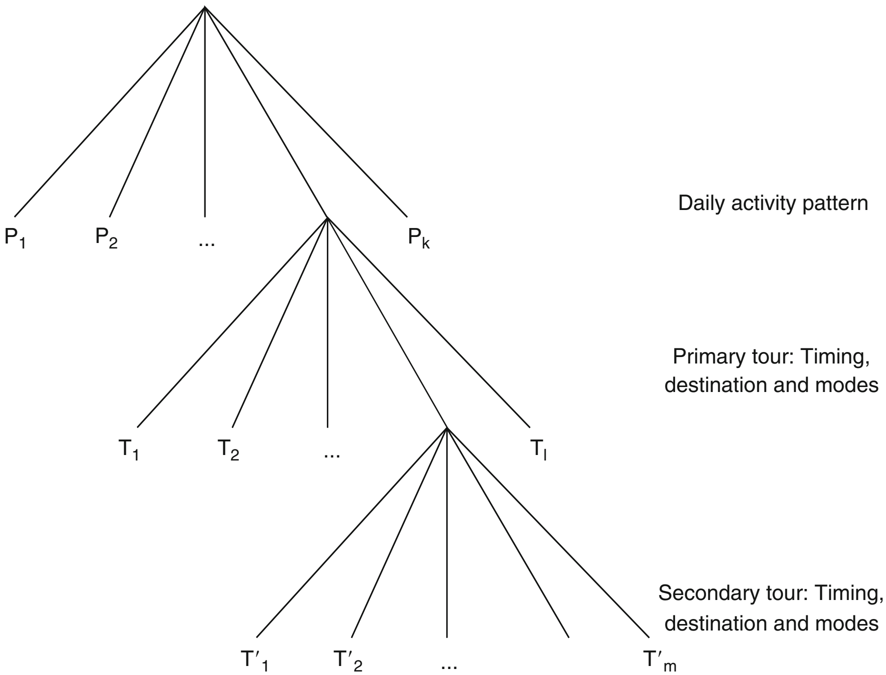

Fig. 37.5 Nested logit representation of activity–travel behavior

specifying relationships between individual attributes, environment factors, and activity–travel decisions in the form of a utility function whose parameters are estimated from empirical data, assuming utility-maximizing choices. Econometric models of activity–travel behavior are often in the form of discrete choice models such as multinomial and nested logit models. Figure 37.5 provides an example of a nested logit representation of activity–travel behavior (after Ben-Akiva and Bowman 1998). Other nesting structures are possible depending on what activity facets are being analyzed. More elaborate econometric structures are also used, such as structural equations, hazard-based duration models, and ordered response models (Ben-Akiva and Bowman 1998; Pinjari and Bhat 2011)

Advantages of econometric models are a rigorous theoretical foundation and mature methodologies for model specification, calibration, and validation. Weaknesses include the empirically suspect assumption that individuals are perfectly rational utility maximizers and the lack of an explicit process theory to describe the activity–travel decision-making (Timmermans et al. 2002).

Optimization Methods. Finding an ideal activity pattern based on criteria such as time, cost, and utility is similar to the problem of finding optimal tours through a transportation network with scheduled pickups and deliveries (Recker 1995). There is a large literature in operations research and management science on problems such as assignment, scheduling, and routing subject to time windows.

These are complex combinatorial problems, but computational search methods have become very sophisticated and powerful. This is a normative approach: the idea is not to replicate real-world behavior but rather generate ideal patterns that can be used as benchmarks for evaluating real-world behavior with respect to efficiency. These comparisons can help identify empirical factors and heuristics that cause people to deviate from ideal patterns.

Rule-Based Models. *Computational process models* (CPMs) are a system of action–condition pairs (semantically expressed as "if–then" rules) that describe the activity–travel decision process in some empirical domain. Decision rules are often organized according to different subcomponents of the activity system. However, most CPMs focus on activity scheduling and implementation (e.g., Recker et al. 1986). Rules can be derived informally from intuition and knowledge based on previous research. Rules can also be inferred from empirical data using data mining techniques such as decision tree induction and association rules (Arentze et al. 2000).

CPMs are highly flexible, allowing a wide range of heuristics that better represent decision-making in the real world. However, a weakness is the difficulty in enumerating the large number of rules required for even for a modest activity scheduling and implementation problem. CPMs also do not have a mature theory and techniques for testing variables and distinguishing between good and bad models (Buliung and Kanaroglou 2007; McNally and Rindt 2007).

Microsimulation and Agent-Based Models. Microsimulation and agent-based models are computer-based methods for predicting the evolution of a complex system. *Microsimulation* refers to the computer-based modeling phenomena at the disaggregate level to better understand complex dynamics at the aggregate level. Microsimulation has a long tradition in social science, dating back to attempts to modeling the US economy in the 1950s with household and firm behavior as the fundamental units. Microsimulation models tend to fall into two categories. *Static models* typically rely on cross-sectional data and result in no change to the structure of the cross section (e.g., internal composition, sample size) as the model executes over time. *Dynamic models* rely on cross-sectional or longitudinal data and produce changes to the total number of micro-units. Dynamic models are used to forecast and track modifications of entities over longer time periods than static models (Buliung and Kanaroglou 2007).

Agent-based modeling (ABM) is closely related to microsimulation but has a stronger conceptual foundation. ABM views systems as collections of autonomous, adaptive, and interacting agents. An agent is an independent unit that tries to fulfill a set of goals in a dynamic environment. An agent is autonomous if its actions are independent (i.e., makes decisions without an external controlling mechanism) and adaptive if its behavior can improve over time through a learning process. Agents interact by exchanging physical resources and information and/or by reacting to presence or proximity. ABM describes a system from the perspective of its constituent units' activities; this is appropriate when individual behavior cannot be described adequately through aggregate rules and activities are a more natural way of describing the system than processes (Bonabeau 2002).

The distinction between microsimulation, ABM, and rule-based techniques discussed previously can be vague, particularly in practice. Rule-based methods can be used to drive agent behaviors and microsimulations, and agents can be a central component of broader microsimulation models (e.g., Arentze et al. 2000). It is also possible to link these models with dynamic microscale traffic models to simulate the interrelationships among transportation demand, transportation system performance, and activity scheduling/implementation (see Bekhor et al. 2011).

Advantages of microsimulation and ABM include the explicit representation of micro-level behaviors and processes, the ability to develop and test behavioral theory, better understanding of macro-level processes produced by individual-level behaviors, maintaining the heterogeneity of information (such as individual identity) during simulation, minimization of model bias, better policy sensitivity, integration of processes operating at different temporal scales, and improved model transferability (Buliung and Kanaroglou 2007). Disadvantages include a lack of mature methodologies for calibration and validation, although these models lend themselves to expert engagement and judgment better than traditional, analytical models (Bonabeau 2002). It can also be difficult to make sense of microsimulation models and ABMs: these methods essentially generate a large dataset that must be explored and analyzed. This can be challenging since good scientific practice requires a careful experimental design for parameters that are not empirically derived. The design should vary parameters systematically while holding others fixed to assess the simulation outcomes, often with multiple simulation runs for each parameter combination to eliminate artifacts from random number generators. This can generate a huge amount of simulated results, particularly if there is a large number of parameters and parameter levels to explore.

37.6 Frontiers in Activity-Based Analysis

Much progress has been accomplished in ABA; this progress is likely to continue as favorable policy, computational, and data environments help scientists and practitioners propel it forward intellectually. This section briefly discusses major research frontiers in ABA.

Social Networks. Social networks are at the heart of time geography and ABA: space–time paths bundle to conduct shared activities, prisms intersect to allow this possibility, households are a fundamental unit for activity organization and sharing, and activity coordination and adjustments cascade through broader activity and social systems. Time geography and ABA are an ecological approach to transportation, cities, and societies with a complex web of interconnections (Pred 1977; Ellegård and Svedin 2012). Capturing the social network influences on activity, mobility, and communication behavior is a very active frontier in ABA (Neutens et al. 2008).

A major challenge in capturing social networks in ABA concerns basic definition, measurement, and data collection. Social networks can range from a few intimate individuals to hundreds of Facebook friends. The problem is that all of these networks are relevant to activity behavior depending on the context. Measuring social networks is also difficult, particularly more genuine and enduring networks. Social influence within these networks can also vary depending on formal and informal relations. Finally, social networks have complex topologies such as Small World configurations that can generate complex dynamics.

LATs and social media can inform social networks in ABA. As mentioned above, path–path, path–prism, and prism–prism relationships indicate the possibility of social interaction, and methods for collective mobile objects data analysis are improving. Problems include dealing with coincidental proximity (e.g., friends versus strangers in a coffeehouse) and activity ambiguity (e.g., a coffeehouse again). Location data error is also a challenge: this can be substantial for some LATs in some environments (e.g., GPS receivers in city centers, cellular network location in rural areas).

Social media are convincing millions of people to share details of their lives online. The implications of these data for understanding and predicting activity, travel, and communication behavior should be obvious, including that people use these media to plan and coordinate activities. Challenges include nonrepresentation biases and unstructured data. Social media participants are not scientifically sampled, nor do people share everything about their lives (with some notable exceptions). Nevertheless, the massive size of these databases makes them valuable. Social media data are also unstructured: nonquantitative data such as text and imagery. Intriguingly, these data are increasing georeferenced due to social media applications in smartphones. One way to treat these data is from a mobility mining perspective: use social media data to generate hypotheses that can be tested with more focused, confirmatory techniques and scientifically sampled or experimental data.

Unfortunately, access to LAT and social data can be circumscribed due to proprietary and competitive reasons. This has the danger of leading to a computational approach that will revolutionize the social sciences but only as practiced in private sector companies and secret government agencies (Lazer et al. 2009).

Big Data and Knowledge Delivery. Big Data refers to data that has *high volume* (massive databases with millions of records), *high variety* (structured and unstructured data), and *high velocity* (often in real time). The Big Data mantra is to keep all of these data since they may be useful; the astonishing collapse in data storage costs over the past two decades makes this possible. In many locations in the world, we are moving toward sensed transportation systems with sensors embedded in infrastructure and vehicles, as well as high-resolution but remotely positioned sensors such as LiDAR. These data combined with consumer LAT data and social media will generate orders of magnitude more data about transportation and cities than currently exist.

A previous section of this chapter discussed the role of mobility mining in ABA. Research frontiers include not only dealing with massive transportation, mobility, and communication data but delivering actionable knowledge to decision-makers sufficiently fast, so they can act before the knowledge is irrelevant. This is a challenging frontier that involves elements of exploratory and confirmatory analysis as well as decision support.

Big Data also has the potential to create more collaborative transportation and social systems. This is a major motivation behind IBM's Smarter Planet initiatives. Collaborative transportation systems can range from ride/vehicle sharing to long-term strategic decision-making about transportation and urban futures. The challenge is to create not only the knowledge delivery techniques discussed in the previous paragraph but also the tools and environments for sharing, collaboration, and collective governance.

Locational Privacy. The benefits of an ABA reinvigorated through more data and computational power may not be realized if there is a public backlash due to abuses of these data. *Locational privacy* is the concept that the space–time signature that comprises activity patterns can reveal much about a person and her/his activities. This is a fundamental change: as the United States Supreme Court commented during a recent decision, LATs provide not isolated facets but a person's entire life.

Locational privacy protection strategies include *regulation*, *privacy policies*, *anonymity*, and *obfuscation*. Regulation and privacy policies define unacceptable uses of location data. Anonymity detaches locational data from an individual's identity. Obfuscation techniques degrade locational data through deliberate undersampling, aggregation, introducing measurement error, or some combination of the above. Scientific challenges include new research ethical protocols for dealing with location data, especially user-generated content and remote but high-resolution sensors that can reveal things and activities that were previously considered private. Another scientific challenge is dealing with deliberately degraded locational data; spatial and spatiotemporal error methods for mobile objects data are still lacking to a large degree. More generally, societies need to have conversations about the acceptable and unacceptable uses of these data if their role in building better transportation systems and communities is to continue its remarkable progress.

37.7 Conclusion

Activity-based analysis (ABA) is emerging as the dominant approach in transportation science and planning (Timmermans et al. 2002). It is a theoretically sound approach to transportation, cities, societies, and human–physical systems that focuses on a person's activities in time and space as the foundation. Changes in policy are encouraging a wider view of transportation, and the increasing availability of individual mobility data and scientific advances inspired by this favorable environment are making ABA methods scalable to realistic scenarios and problems.

Data-driven methods allow high-resolution measurement of fundamental ABA entities such as the space–time path (representing actual mobility) and the space–time prism (representing potential mobility, interpreted as path sampling error or space–time accessibility). There is a wide range of methods for measuring, comparing, and summarizing collections of space–time paths, but fewer methods for the space–time prism. These data can be used for empirical investigation, mobility data mining, and as inputs to ABA modeling.

ABA models attempt to solve or simulate activity behavior. Most models focus on the activity scheduling and implementation problems. These ABA core models can be linked with transportation system performance models to capture the dynamics of mobility demand and system response. These core models can also be embedded in broader models of cities, sociodemographics, and physical systems such as airsheds. Major modeling approaches include econometric models, optimization methods, computational process models, and microsimulation/agent-based models.

There are several ABA research frontiers; these include social networks, delivering knowledge in the face of Big Data, and location privacy. Progress along these frontiers will support the continuing rise of ABA in understanding and planning transportation and related systems.

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