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### Publication Date

2002-08-01

UCI-ITS-AS-WP-02-5

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**August 2002**

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## **Toward Dynamic, Longitudinal, Agent-Based Microsimulation Models of Human Activity in Urban Settings**

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August 1, 2002

**Abstract.** Recent trends toward operationalization of activity-based microsimulation models are producing new research questions related to the development of comprehensive models of human behavior. This paper provides a view of what will be necessary for the development of a dynamic, longitudinal, agent-based microsimulation model of human activity in urban settings. The discussion outlines a conceptual model of an environmentally situated human agent that must adapt to its environment in order to meet its goals. The agent's ability to perceive, interpret, and decide upon how to interact with its environment is viewed as a series of sub-models which are themselves the target of a set of learning procedures.

**Keywords:** Agent-based microsimulation

**Wordcount:** 6000 + 1 figure

## INTRODUCTION

The focus on activities that has come to dominate the field of travel demand analysis was largely driven by the recognition that individual trips do not stand in isolation, but are motivated by the activities they enable. The importance of this fact is not so much that travel is derived but the nature of the activities from which travel derives. For if these motivating activities are in fact causally independent themselves, then little is gained by expanding models to consider them directly. The real contribution of the activity-based approach is its recognition that the activities from which a person's travel derives are themselves motivated by a complicated social milieu that links them to other activities, to other people, and to the features of the built environment. It is these linkages that activity analysis hopes to better understand.

Note that while the field of activity analysis represents a paradigm shift in travel behavior research away from discrete (independent) characterizations of behavior, it traded them for independent descriptions of causation. The focus on analyzing home-based work, home-based other, and non-home-based trips has been replaced by independent emphases on delineating constraints (1, 2), on identifying patterns of behavior that arise from those constraints (3, 4). This decomposition has been helpful in developing simplified research problems that have improved our description of human behavior, but has only resulted in limited improvements in our understanding of the linkages in the system.

The Holy Grail of activity analysis is a "grand unified theory" that successfully links motivation and constraint to pattern. Such a linkage will lead to better descriptions, understanding, and explanation of human behavior. Toward this end, we propose that our models should be based less on our own analytical characterizations of the world (constraint vs. pattern) and instead should focus on direct descriptions of the features of the world that produce the patterns we observe. Thus, our models should represent the *mechanisms* of constraint and pattern, not use these concepts as building blocks for theory.

## FOCUSING ON INTERACTION USING AGENT-BASED MODELS

### Background

Agent-based models are characterized by their ability to represent complex environment consisting of autonomous agents whose behavioral possibilities are defined solely by their relationship to the environment. Agent-based techniques have been applied in a range of fields. Excellent reviews are available for applications in economics (5, 6), sociology (7, 8), and biology and ecology (? 9). These models are distinguished by their view of the system as a population of self-directed entities that interact with each other according to specific behavioral rules that simultaneously motivate and limit behavior, thus dictating the dynamics of the system. These features relate exactly to the limits of existing activity-based modeling techniques — focusing on the relationship between entities in the environment as the fundamental feature of the model.

### Agent-Based Modeling in Travel Demand Applications

There has been a recent interest in the application of agent-based simulation to the modeling of urban systems in general, and travel behavior in particular. For instance, Allen (10) explored the

self-organizing nature of urban systems using cellular automata to represent urban growth patterns. While not strictly agent-based, Allen's work focused on the related concepts of emergence and self-organization, and suggested that the complexity of urban systems limits our ability to predict them.

Schelhorn et al. (11) built the agent-based STREETS model of pedestrian movements in "sub-regional, urban districts." In this model, a population of agents is generated from socio-economic inputs with predefined schedules of activity to be carried out in a small urban district. Each of these agents is also assigned certain behavioral characteristics that govern how they move through the urban space. The urban space is defined as a combination of vector data (land uses in the form of buildings) and raster data (non-building "walkability spaces"). Agents are generated into the space and attempt to achieve their goals using a set of heuristics to determine their movement between the activity sites in their schedule. While relatively limited in scope — the focus of the model is on pedestrian movements in small urban districts — the STREETS model is probably the first truly dynamic agent-based, human activity model, and provides a useful proof of concept. It does not, however, (yet) consider the linkages between agents that agent-based modeling is particularly suited for. We look forward to the ongoing work of these authors and their collaborators.

While the TRansportation ANalysis and SIMulation System (TRANSIMS) model can be described as an agent-based simulation, its iterative approach to activity scheduling distinguishes it from the the dynamic, adaptive agent approach to which our research is targeted. In particular, the activity generation component of TRANSIMS adapts sampled skeletal patterns (measured household behavior stripped of locations) (12) and iteratively attempts to find equilibration between activity schedules and feasible patterns produced in the travel component of the model. Interaction is modeled from the top-down, using a relaxation-style search to find a balance between household activity demands and the environmental supply to satisfy those needs.

The *Amadeus* framework (13) and its behavioral component, A Learning-BAsed TRansportation Oriented Simulation System (ALBATROSS) (14), represent the most advanced agent-oriented model in the travel demand analysis arena. This framework is moving rapidly toward the development of a large-scale agent-based activity simulation model, making significant advances in the induction of choice heuristics and in the modeling of adaptive scheduling (15). To date, however, this initiative has not produced a truly dynamic model of interacting agents, instead focusing more on the aggregation of individual agent-environment interactions.

Given the existing literature, we highlight the following as crucial areas of research necessary for the development dynamic, longitudinal simulation of human activity:

- **interaction-based:** Human beings are viewed as autonomous agents interacting with a physical and social environment that both motivates and constrains their behavior, and from which they satisfy their needs.
- **longitudinal:** The dynamics of urban systems are likely to exhibit the extreme sensitivity to initial conditions that distinguishes chaotic complex systems. Longitudinal models will ultimately be necessary to explore how path-dependent trajectories impact the effectiveness of policy measures.
- **role-based activity generation:** The need to engage in activities should be an endogenous feature of the model. This will open the door to exploring the relationships between urban design, socio-economic structure, and human behavior.

- **representation of resource distribution:** Activities are simply interactions involving the exchange or consumption of resources between entities in the environment. As a result, explicit representation of resource distribution will enhance model expressiveness and permit closer ties to dynamic land-use models.
- **experiential learning:** Agents collect information about their environment as they interact with it, and use it to develop anticipatory models of the environment subject to memory and computational limitations.
- **generality of design:** The model should be expressive enough to enable representation of a broad range of local and global interactions, on a variety of timescales, with a view toward exploratory analysis of possible trajectories rather than the prediction of specific ones (*see 10*)

Our research is focused on the development of each of these areas in an effort to advance the state of dynamic microsimulation in urban systems modeling. The remainder of this paper proposes a general modeling structure that can capture all potentially relevant forms of interaction in human activity systems and thus be adaptable to future modeling needs.

## ACTIVITY AS INTERACTION

To our knowledge, all existing activity models treat activities as discrete entities with specific attributes defined as fixed components of the model rather than as endogenous features of the model. Such rigidity makes model specification increasingly complex as additional activity attributes are added to the model (i.e., activity type, location, time-of-day/scheduling, coupling, etc.). In general, the discrete view of activities limits the scope of the model to situations envisioned by the modeler, *a priori*, rather than to the complete universe of states defined by all possible interactions arising from the capabilities of the agents in the system. The most notable such difficulty is when interpersonal interaction (or coupling constraints) are introduced and it becomes exceedingly difficult to represent all of the possibilities within a model structure. Such limitations ultimately restrict the adaptability of the models to consider new and different questions that might arise.

To alleviate this problem we have previously proposed a slightly different view of activity that leverages the conceptual advantages of the agent-based view of the world to provide a generic and flexible means for representing the problems of activity analysis (16). In our view, activity is defined precisely as the *continuous* state interaction between the agents that inhabit the environment, where *agent* refers to any discrete entity in the system that interacts with other agents. Thus, people and places are agents, as are socially grouped people (households and institutions) and aggregations of places (such as land-uses and transportation subsystems). A particular *activity episode* is simply a discretization of this continuous interaction into homogenous blocks corresponding to particular activity types to which the analyst, and the actor, assigns meaning. For instance, a simple activity, say a solitary work activity, involves the interaction between a person (a worker), a land-use (a workplace), and implicitly an employer. Here, the land-use provides the set of resources necessary for the person to achieve a personal goal (completing a work task) which fulfills the demands placed upon that person by the role he occupies. The work activity episode corresponds to the homogenous block of time over which the interactions occur. The attributes of

the activity are embodied in the interactions between the involved agents that occur over that time period.

This “interaction” view of activity permits greater flexibility for the representation of the universe of possible activities and their associated constraints. For instance, it recognizes that activities will have agent-specific meanings; a particular activity episode (a discrete interaction over some period of time) might be a shopping activity to a shopper, while simultaneously being a work activity to a cashier at the store, an economic transaction for the shop keeper, and so on. Furthermore, it permits a greater flexibility in defining activities. For example, a parent caring for a sleeping baby (care-giving activity) may simultaneously complete other household tasks, or a rail commuter traveling to work can simultaneously travel and work (e.g., using a laptop). Handling such dual activities using conventional definitions of activity is either complex or impossible.

The proposed model has close ties to the foundations of activity analysis. The interactive nature of human activity can be viewed both as the *source of motivation* and as the *mechanism of constraint*. This view provides a theoretical connection between motivational theories of human activity and constraint-based analytical views. As a result, it makes for an appealing starting point for representing the dynamics of the system.

Finally, a model built from this perspective can be significantly more dynamic than existing approaches. The focus can move from producing a discrete set of activity episodes via an iterative process, to representing the “interaction trajectory” of all agents in the model – from which we can derive discrete activity episodes of interest (e.g., travel). The agents in the model may still plan on the basis of discrete episodes as people are theorized to, but to carry out these planned episodes they must obey the “physics” of interaction dictated by their environment. We propose that this physics involves processes of negotiation between agents, in which various entities agree (or disagree) to interact with other agents based on their internal decision-making process.

In a companion paper (17), we describe the design and implementation of a negotiation-based simulation kernel representing this physics. The kernel assumes all agents in the simulation can respond make decisions about whether or not to offer to participate in activity opportunities presented by the environment. Certain agents will also generate their own activity opportunities and attempt to negotiate participation with other agents in the environment required for successful activity engagement. The kernel therefore leaves the details of the decision process to the particular agent implementation. It is to this problem we now turn our attention.

## REACTIVE AGENTS

### Defining Agent

Modeling an urban system as a set of reactive, autonomous agents requires a careful consideration of *how* people interact with their environment, and of what comprises that environment. This section presents a formal specification of a theory, which provides a broad perspective of the modeling problem. The relationship between all components of the theory is shown in figure 1.

[FIGURE 1 about here.]

To begin, assume we can synthesize a population of agents ( $1 \dots n \dots N$ ), representing human beings in an urban system, and an initial set of relationships between them dictating social structure (such as households) and physical proximity (such as location pegs around which human

behavior is ordered), using, for instance, the TRANSIMS approach (12). Thus, each agent inhabits the environment and is situated relationally to other agents.

### Agent Relationship to the Environment

The dynamic agent-based model seeks to produce, for each agent  $n$ , the time-varying state vector  $\mathbf{Y}^{t,n} = [\mathbf{X}_L^{t,n}, \mathbf{X}_C^{t,n}, \mathbf{X}_A^{t,n}]$  where  $\mathbf{X}_L^{t,n}$  and  $\mathbf{X}_C^{t,n}$  are vectors representing physical and social position respectively, and  $\mathbf{X}_A^{t,n}$  is a vector describing the individual's activity. Physical position codifies the agent's location in space, although may also represent the spatial anchors around which people structure their lives, such as household and work locations. In general, this multi-scalar treatment of time is a persistent feature of this system, deriving from the ability of human beings to anticipate their environment and plan accordingly. As such, most of the state variables described in this formal model can have similar multi-scalar interpretations. Social "position" includes the typical indicators of socioeconomic status, such as income, ethnicity, etc., as well as the agent's set of *role complexes*.

*Activity* is defined precisely as an individual's interaction with the environment (physical or social). Thus, the attributes of an activity are more than just a label, they describe the linkages between agents that an activity embodies. This gives the concept of activity a meaning *within* the model system in addition to its relevance to the researcher observing the model, and permits a richer representation of the personal and environmental interdependencies that are a cornerstone of activity systems theory. While this flexibility may seem excessive, it actually allows complex features of human behavior to be modeled including inter-activity linkages that have proven difficult to represent. For instance, people frequently perform more than one activity simultaneously. In this age of ubiquitous computing, it is not uncommon for rail commuters to simultaneously work and travel. This is typical of activities that only require that an individual be present at a particular location, but able to dedicate their time to another activity. Such dual activity participation is simple to represent if activity is defined a vector of interactions  $\mathbf{X}_A = (a_1, a_2, \dots, a_i, \dots, a_M)$ , with each entry  $a_i$  describing the agent's commitment of resources (co-location, attention, etc.) to a particular interaction with another agent. Thus, a person might perform a childcare activity of his (preteen) child by co-locating with the child (e.g., at home). At the same time, he may simultaneously apply thought to a work activity, possibly interacting with work-related resources (e.g., a computer with an Internet connection) he has available at home

Following these definitions, we describe the activity and travel behavior  $\mathbf{Y}$  of an agent in terms of the following dynamic system (dropping the subscript  $n$  for clarity):

$$\mathbf{Y}^t = \begin{bmatrix} \mathbf{X}_L^t \\ \mathbf{X}_C^t \\ \mathbf{X}_A^t \end{bmatrix} = \begin{bmatrix} f_L(\mathbf{X}_L^{t-1}, \mathbf{X}_A^{t-1}) \\ f_C(\mathbf{X}_C^{t-1}, \mathbf{X}_A^{t-1}) \\ f_A(R^{t-1}, P^{t-1}) \end{bmatrix} \quad (1)$$

where  $R^t$  is the set of physical and social resources available to the agent for activity engagement, and  $P^t$  is the agent's plan. The resources available effectively define the "channels" upon which an individual can interact with the environment to engage in an activity. For instance, a store (agent), provides the resources necessary for an agent to engage in a shopping activity by committing, for example, time and money to the performance of the activity. Each agent therefore has an *interface* that it presents to other agents which represents the types of interactions it can have, or equivalently, the types of activities in which it can participate.  $R$  represents those resources, or interfaces, that



are directly available for use in an activity given the agent’s positioning at that point in time. It might be interpreted as the instantaneous activity choice set that is derived from the environment. We represent its trajectory as:

$$R^t = f_R(\mathbf{X}_L^t, \mathbf{X}_C^t, L^t, T^t, C^t) \quad (2)$$

Here,  $L^t$  is the land use system and  $T^t$  the transportation system which jointly define the physical environment the agents negotiate. Similarly,  $C^t$  is the socio-cultural system defining the social environment. Together, these three terms represent a holistic, objective view of the environment  $e^t = ((L^t, T^t), C^t)$  that all agents inhabit and comprise, and in terms of which the position vectors  $\mathbf{X}_L$  and  $\mathbf{X}_C$  are defined.  $(L, T)$  represent both the physical laws that govern agent behavior *and* is the projection of all agents in the system into the physical space. Thus, a store is social construct that has a physical manifestation as resources distributed in space which would be part of  $L$ . Similarly,  $C$  represents both socio-cultural norms and is the projection of all agents into the social space. This view is consistent with both the Multi-Agent Based Simulation (MABS) literature and with sociological views that society is both an environment in which people live, and an emergent property that is manifest in, and transformed by, their collective behavior (18, 19).

Eqs. (1) and (2) describe the relationship between an agent and its environment over time. Relative positioning  $(\mathbf{X}_L^t, \mathbf{X}_C^t)$  to an external environment  $(L^t, T^t, C^t)$  determines resource availability  $R^t$  for activity participation  $\mathbf{X}_A^t$  over time. With the exception of the social elements, these relationships are directly observable.

The goal of activity and travel forecasting is to predict this trajectory  $\mathbf{Y}$  over time. The goal of transportation science is to describe and understand how human behavior produces the trajectory. For the former, it may be suitable to use econometric models that infer statistical tendencies from observed data. The latter demands a richer description of the processes involved. Note that the system in eqs. (1)—(2) depends on four variables. The first three are exogenous, environmental variables  $(L^t, T^t, C^t)$ . The last is the agent’s behavioral strategy, or plan,  $P$ , which is generated by endogenous, cognitive processes:

$$P^t = f_P(P^{t-1}, \mathbf{X}_L, \mathbf{X}_C, E^t) \quad (3)$$

where  $E = (L, T, C)$ . Roughly then, the agent’s plan depends on the environment and its physical and social positioning. The plan is roughly equivalent to the agent’s activity schedule, but is more comparable to the behavioral “scripts” referred to by Arentze and Timmermans (14) that define strategies for achieving particular goals in the environment.

We adopt the view proposed by Fried et al. (20) that human behavior is adaptive, and that this adaptation is driven by what they termed the person-environment (p-e) fit. This concept describes a personal equilibration in which the individual tries to balance what he or she wants to do (the activity program) with what the environment allows (opportunity space). Fried et al. suggest particular behavioral responses related to travel behavior such as scheduling, household and work location changes, or role modification. The mechanisms for this adaptation is the agent’s ability to learn.

Thus, the planning process involves learning, including how the agent learns about its environment, how it learns about its options in the environment, and how it learns to evaluate its own behavior in that environment. In the next section, we present a formal model of these internal processes that serve as an expanded representation of  $f_P$ .

## Agent Internals

Dosi et al. (5) provide a comprehensive description of the features of a learning, autonomous agent model. With some notational changes made to match eqs. (1)—(3), we can apply their description to modeling a person’s activity environment. The agent faces an environment  $E$  that can be in one out of an enumerable set of states:

$$E = \{e_1, e_2, \dots, e_i, \dots\} \quad (4)$$

The agent does not know this universe of world states, possessing only an imprecise partial representation at any given point in time  $t$ :

$$\Theta^t = \{\vartheta_1^t, \vartheta_2^t, \dots, \vartheta_j^t, \dots\} \text{ where } \vartheta_j^t \subseteq E \text{ and } \Theta^t \subseteq 2^E \quad (5)$$

Each  $\vartheta_j^t$  includes all of the states of the world that the agent considers equivalent. For example, consider a world with five possible states  $E = \{e_1, e_2, e_3, e_4, e_5\}$ , and an agent whose representation of the world is  $\Theta^t = \{\vartheta_1^t, \vartheta_2^t\}$ , where  $\vartheta_1^t = \{e_1, e_2\}$ , and  $\vartheta_2^t = \{e_3, e_4, e_5\}$ . Thus, at time  $t$ , the agent “believes” that the world can only be in one of two states  $\vartheta_1^t$  and  $\vartheta_2^t$ , with each of these states actually representing multiple possible world states between which the agent doesn’t, or can’t, distinguish.  $\Theta^t$  is therefore a set of classes representing the agent’s knowledge about the possible states of the world. More specifically, we assume the agent has some perceptual function  $f_\Theta$  that maps from a set of possible messages  $M$  to one of the agent’s perceptual classes in  $\Theta$ :

$$f_\Theta : M \rightarrow \Theta \quad (6)$$

Thus, we can interpret  $\Theta$  as the output space of the agent’s perceptual function  $f_\Theta$ . Here,  $M$  defines the alphabet of sensations the agent is capable of receiving. The messages are functionally related to the environment itself:

$$f_M : E \rightarrow M \quad (7)$$

$f_M$  defines the agent’s ability to sense things in the environment. These sensations are encoded as messages that feed the agent’s perceptual function  $f_\Theta$  which classifies the environment as being in one of perceived states between which it can distinguish.

Similarly, assume the agent is endowed with an enumerable set of possible actions that together construct its *opportunity space*:

$$\Xi = \{\xi_1, \xi_2, \dots, \xi_j, \dots\} \quad (8)$$

Note that  $\mathbf{X}_A \in \Xi$ . At any point in time, an agent holds a finite behavioral repertoire constructed from the “atomic” actions in  $\Xi$ , which the agent can revise, modify, and recombine. Denote this repertoire as:

$$A^t = \{\alpha_1^t, \alpha_2^t, \dots, \alpha_j^t, \dots\} \text{ where } \alpha_j^t \subseteq \Xi \text{ and } \Xi^t \subseteq 2^\Xi \quad (9)$$

We will consider these repertoires in greater detail below. For now, we simply treat them as the agent’s perception of possible behaviors within the environment. To summarize,  $E$  and  $\Theta$  define possible states of the objective world and the agent’s ability to perceive that world.  $\Xi$  and  $A$  define the universe of possible actions and the agent’s subjective knowledge of them.

Planning requires that the agent can anticipate the consequences of its actions, presumably by developing an internal model of the environment through experience. To represent this, begin

by defining a set of perceived histories at time  $t$  containing some finite-length histories of perceived states of the world and perceived actions up to time  $t$ :

$$H^t = \{h_k^t\}, \quad k = 1, 2, \dots, t \quad (10)$$

where

$$\Omega = \Theta^k \times \Theta^{k+1} \times \dots \times \Theta^t \times A^k \times A^{k+1} \times \dots \times A^t$$

$h_k^t \in \Omega$ , and

Here, each  $h_k^t$  is the trajectory of past perceived world states and agent actions from time  $k$  to time  $t$  and therefore represents what the agent perceives has happened over the  $(k, t)$  time horizon.

Next, assume that the agent possesses some mechanism  $\phi$  for mapping the perceived histories onto some set of possible interpretations  $\Phi$  which attribute a causal sense to the perceived world according to the agent's experience. To represent this mechanism, define an interpretive model that maps from the space of perceived histories  $\Omega$  into the space of interpretations  $\Phi$ :

$$f_{\phi_i}^t : \Omega^t \rightarrow \Phi^t \quad (11)$$

Then, represent the agent's interpretive mechanism as a finite set of such models:

$$\phi^t = \{f_{\phi_1}^t, f_{\phi_2}^t, \dots, f_{\phi_i}^t, \dots\} \quad (12)$$

This set of models encodes the agent's experience into some cognitive form that can be applied to the problem of deciding what to do. One simple type of model is that the agent simply maintains a dissipating memory of past perceptions and actions. This implies that the agent's memory is limited by some parameter  $m$  such that  $k = t - m, t - m + 1, \dots, t$  where  $m < t$ . Most existing activity-based microsimulation models assume either that agents possess no memory of past actions and make decisions based only upon instantaneous perceptions (i.e.,  $k = t$ ), or that all agents know perfectly what has happened over time and why. Either approach essentially does away with the interpretation stage, so that  $f_{\phi_i}^t(H^t) = H^t$ .

Assuming the agent is capable of some sort of interpretation, we can define a decision rule as a mapping between interpretations and action repertoires:

$$v_i^t : \Phi^t \rightarrow A^t \quad (13)$$

More specifically, the output of such a decision rule is an activity plan  $P \in A$  as defined in eq. (3). The agent's decision-making capabilities at time  $t$  consist of a finite set of such decision rules:

$$\Upsilon^t = \{v_1^t, v_2^t, \dots, v_m^t\} \quad (14)$$

Note that these rules can be typical *if-then* statements, as might be used in a classical production system, or may be any arbitrary algorithm that maps from an interpretation to an activity plan. The agent applies this resulting plan to determine its activities over time according to the procedure in eq. (1).

The agent's activities lead to an (objective) response (or consequence) from the environment out of a set  $W$  of all possible responses:

$$w^t : E \times \Xi \rightarrow W \text{ where } W \equiv E \quad (15)$$

In other words, the agent's actions change the objective world state. Note that  $W$  is merely notational; the set of possible objective responses is equivalent to the set of possible world states. Here  $w^t$  is shorthand for the effects that individual activity has on the environment. For instance, an agent's decision to travel along a section of roadway reduces the available capacity. In this case,  $w^t$  would be some sort of traffic simulation model capable of representing the impact of an additional traveler on the road segment in question. Over time, this impact will manifest as increasing the amount of time needed for the agent's travel activity.

The agent's limited perceptual capability means that it will only know some partial representation of these outcomes through some kind of evaluation of the environment. Such evaluations will depend on the agent's interpretation  $\Phi$  and some set of criteria  $B$ :

$$U = Z(\Phi^t, B) \text{ where } U^t \in \mathfrak{R} \quad (16)$$

Clearly,  $Z$  can be interpreted as the agent's utility function, with  $B$  defining the utility weights and  $\Phi$  defining the values of the relevant attributes. It is here that the need for representing the agent's interpretation explicitly is evident since an agent's behavior may produce environmental responses that are not instantaneous. Furthermore, the behavior itself may occur over time as is the case with the choice of a daily activity pattern. Such delays between decisions and responses complicates the application of conventional choice models to the problem. For instance, in the travel example above, the criteria might include utility weights for such typical components of travel demand utility as travel time, out-of-pocket cost, etc, with the attribute values coming from the agent's interpretation of the environment.

For the agent to evaluate a particular plan of action with responses occurring over time, it must be able to relate execution of a particular plan, in a particular context, onto the space of responses, and thus response evaluations. Define a payoff function as:

$$\pi^t : \Phi^t \times A^t \rightarrow U \quad (17)$$

which is a mapping from the universe of possible interpretation-action combinations to some payoff measure in a range of utilities  $U$ .

Eqs. (4)—(17) demonstrate how the planning process  $f_P$  in eq. (3) involves the application of the decision procedures  $\Upsilon$  given particular interpreted states  $\phi$  over time. The decision procedures arise from an adaptive learning process driven by the agent's desire to maximize some payoff through its actions over time. The learning process occurs on many different levels including perception, interpretation, possible actions, rules, and payoffs.

## MODELS OF ADAPTATION AND LEARNING

### Learning about the states of the world (improving perception)

People generally improve their ability to distinguish between situations their presented with as they gain familiarity with an environment. Learning at this level involves the refinement of the classification space,  $f_\Theta$ . We loosely represent this learning process as:

$$f_\Theta^t = g_\Theta(f_\Theta^{t-1}, E^{t-1}, \mathbf{X}_L^{t-1}, \mathbf{X}_C^{t-1}) \quad (18)$$

This may involve increasing (or decreasing) the number of members in  $\Theta$  (i.e., the number of classes between which the agent can distinguish), or simply modifying the mapping so that inferences from the  $\Theta$ s produce behaviors with higher payoffs.

### Learning About the Opportunity Space

As noted above, activities depend on resources (since they involve the allocation or transfer of resources between agents). As such, an agent's perception of the opportunity space will depend on its knowledge of the resources it has available to it, which it continuously updates over time through experience as follows:

$$A^t = g_A(A^{t-1}, R^{t-1}) \quad (19)$$

This kind of learning would involve, for instance, an individual recognizing that a particular activity meets particular requirements. When there is a one to one mapping between activities and requirements, this type of learning does not occur. When, however, particular activities satisfies multiple needs (e.g., having dinner with friends may satisfy both meal *and* social leisure requirements).

### Learning About Interpretations of Historical Trajectories

As agents gain experience, they develop better knowledge about causal linkages in the environment according to some process:

$$\phi^t = g_\Phi(\phi^{t-1}, H^{t-1}) \quad (20)$$

Thus, a prior activity trajectory is used to update the agent's anticipatory model about what to expect from the environment. A simple example of this is a model of expected travel time. As an individual makes trips in the transportation system, he will learn about areas of congestion in the system, perhaps linking time-of-day to anticipated travel delays.

### Learning About the Decision Rules

The agent's rule set also arises from learning. In a complex environment, the space of perceived states and possible actions can get very large. Furthermore, the agents' ability to perceive constraints may also limit the development of repertoires and make such repertoires probabilistic (i.e., "I think I can do X"). Learning about decision rules is a complex process, possibly involving insight and innovation, but is generally a function of the existing rule set and the agent's experience  $\Phi$ . Denote this process as:

$$\Upsilon^t = g_\Upsilon(\Upsilon^{t-1}, \Phi) \quad (21)$$

Representing this process is highly dependent on the choice model used. For instance, if the agent's decision process is represented a rule-based classifier system (a set of condition-action pairs), we might use an evolutionary model to represent mutation and recombination of strategies, with the assessment of payoffs achieved through prior application of the strategies serving as a fitness measure.

## CONCLUSION

The development of a truly dynamic microsimulation of human activity is a significant challenge. In this paper, we have framed the problem as one of defining a set of models dictating how an individual interacts with an environment that enables and constraints its behavior. We have presented a model structure that focuses on agent interaction, and decomposes the agent's assessment, interpretation, decision process, and learning behavior into a series of interrelated sub-models.

Linking all of these models into a comprehensive model system is a significant challenge. We hope to use our recently developed simulation kernel for representing agent interaction in activity settings (17) as a testing ground for exploring various forms for the models discussed in this paper.

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**LIST OF FIGURES**

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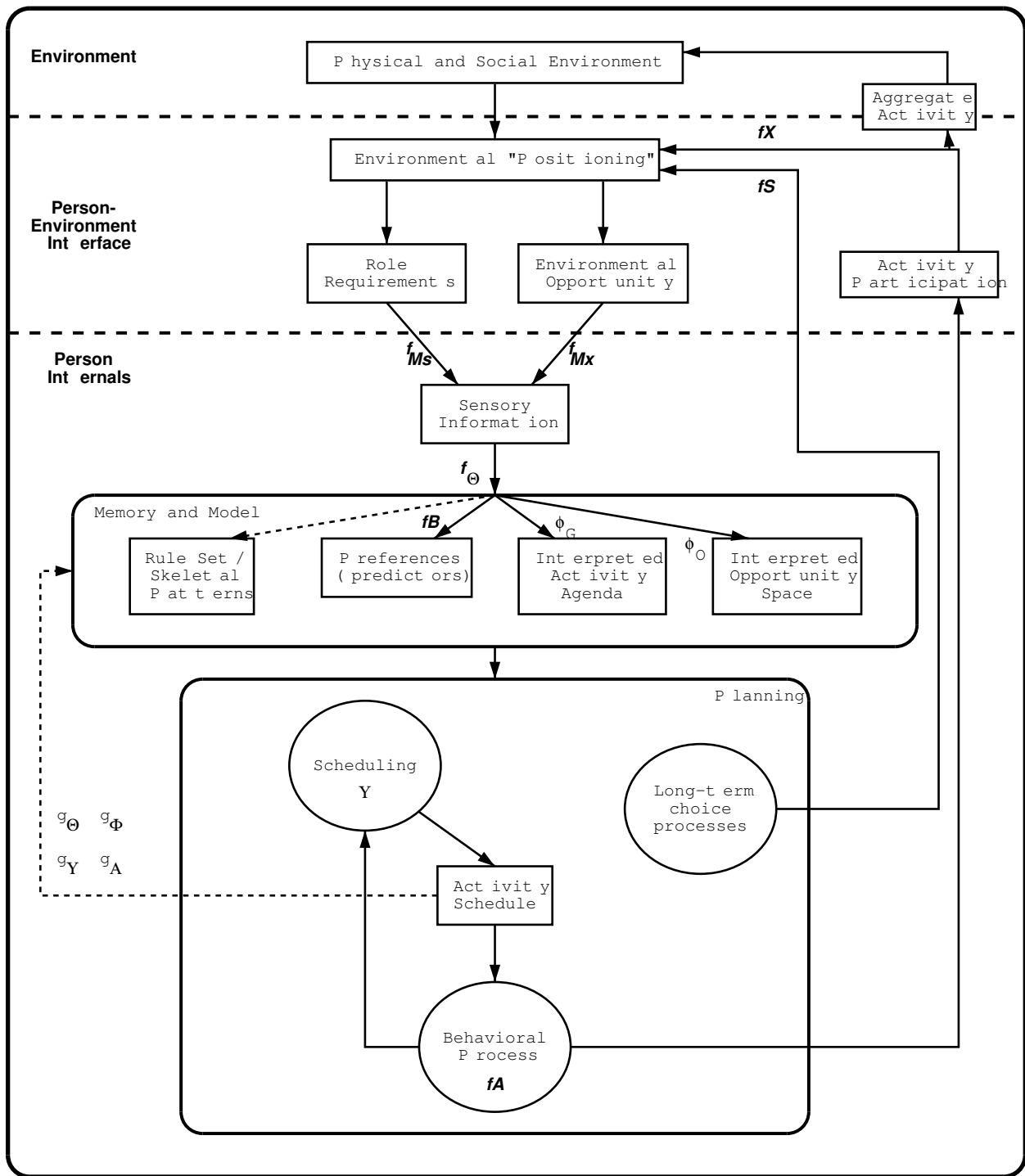


FIGURE 1: A Reactive Agent Model for Human Activity Systems