Short Paper

# Modeling Social Influence on Activity-Travel Behaviors Using Artificial Transportation Systems

Songhang Chen, Zhong Liu, and Dayong Shen

***Abstract*—A deep understanding of people's activity-travel behaviors is critical and essential for effective travel demand forecasting and management. Although it is acknowledged that social interactions play an important role in people's decision-making behaviors, our understanding of how they shape and impact activity-travel behaviors of people is still limited. Therefore, for the first time, this paper introduces social learning into artificial transportation systems (ATSs) to model their influence on activity-travel behaviors. Based on a specified ATS, three types of universal social interactions (i.e., imitation, conformity, and experience sharing on social networks) are modeled and studied. The results indicate that our models can make artificial agents learn to decide the best behavior, form habitual choices, and emerge fashion gradually.**

***Index Terms*—Activity-travel behaviors, artificial transportation systems (ATSs), social interactions, social learning, social networks.**

## I. Introduction

Research on travel demand has a long history. Generally, the models developed can be divided into three generations [1]. The first one is the trip-based aggregate models developed in the late 1950s, also known as four-stage models, because travel was assumed the result of four subsequent decisions, i.e., trip generation, trip distribution, mode choice, and route choice. However, this kind of model could not satisfy people's forecasting accuracy requirement; thus, disaggregate trip-based demand models were developed and had been applied in many projects worldwide in the last 20 years of last century. However, such models analyze each trip independently of other trips made by the same individual, which is quite different from the actual and causes great limitation. Therefore, activity-based demand models are proposed. They postulate that the travel demand is motivated by basic human desires and take individual's time and space constraints into account. Since having potential to overcome the shortages of previous models, activity-based demand models have become a hot topic.

Without loss of generality, one activity travel can be represented by six elements, i.e., type of activity, destination, travel mode, travel route, departure time, and duration of activity. Activity-based demand models must decide these elements seriously to predict travel demand correctly. In the early stage, the majority of such models were person based and did not explicitly include interpersonal interactions. Gradually, interactions between the family members and more general social interactions were taken into account. Sunitiyoso *et al.* introduced the use of laboratory experiments for exploring the effects of social interactions on the dynamics of travelers' mode choice behaviors [2]–[4]. People usually exchange information through social networks. Marchal and Nagel *et al.* took this into account to model the destination choice of secondary activities [5]. Ettema *et al.* explored the potential role of social interactions and social networks in land-use and transportation interaction (LUTI) models, which aim to predict land-use changes and travel behaviors [6]. Arentze and Timmermans proposed a microsimulation framework for activity-travel behaviors, which takes agents' social networks and social interactions into account [7]. Stephan *et al.* studied the diffusion of transportation technologies within a population of agents [8].

Although the acknowledgement of the need to study social interactions in relation to activity-travel behaviors is growing, there is not much experience with modeling their influence yet. Therefore, for the first time, we introduce social learning into artificial transportation systems (ATSs). By improving the original activity-travel behavior model in ATSs with social learning, we can observe and study how social interactions affect individual's activity-travel behaviors. An ATS adopts the idea of artificial society; therefore, modeling social interactions within ATSs is also a valuable attempt to improve ATSs toward social computing [9], [10]. The remainder of this paper is organized as follows. Section II introduces related studies of social learning and basic concepts of ATSs. Section III describes our activity-travel behavior models based on social learning. Section IV demonstrates computational experiments to verify the proposed models. Finally, Section V concludes this paper with remarks on future works.

## II. Related Works

### A. Social Learning

Social learning proposed by Albert (1977) is a basic theory of social psychology, which states that a behavior is learned from the environment through the process of observational learning. In our opinion, observation is manifold actually. It includes not only seeing in the physical world but also gaining information from the virtual space, e.g., surfing online. With the development of information technology and media, people will observe the world more easily.

Social interactions enable social learning. Sunitiyoso *et al.* said that there are at least three possible types of social interactions based on levels of intensity and directness of communication [4]. The first one is an indirect situation where individuals' travel choices affect not only themselves but also other travelers. Furthermore, they may not realize that they are actually interacting with others, e.g., traffic congestion caused by all car users on the road. The second one happens through observation of others' choices. The third one is the most

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direct interaction that happens through communication or exchange of information about experience or intentions.

Evidence from some disciplines, e.g., economics and behavioral sciences, has shown that social learning is influential and important [11]–[13]. However, in the field of activity-travel behaviors, this kind of learning process has not been thoroughly investigated. There are some notable studies. Jones and Sloman found that people see their colleagues and neighbors changing activity-travel behaviors will accelerate the change of their personal behaviors [14]. Ampt [15] argued that information diffusion both among households and communities is likely to be effective for voluntary changes of household activity-travel behaviors. When a person tells someone about what they are doing, they are reinforcing their own behaviors during the process. Shaheen introduced such communication as a mean to diffuse the change of behaviors in a car-sharing system [16]. Taniguchi and Fujii found that communication between friends and family plays an important role in promoting bus use [17]. These studies imply the application of social learning theory but do not propose or apply social learning models explicitly.

### B. ATSs

Transportation simulation is a proved useful method to study complex traffic phenomena and problems in transportation systems. According to the fineness simulated, they are divided into three categories: macroscopic, mesoscopic, and microscopic simulation. Since microscopic simulation, compared with the other two types of simulation, can describe and model traffic environment, participants, and vehicles in minute detail, it has attracted many researchers' attention. Some mature software has been developed, such as *Vissim*, *Paramics*, *AIMSUN*, and *TransModeler*.

ATSs are an extension of microscopic traffic simulation that deals with modern transportation challenges from the perspective of complex systems [18]. A bottom-up way is advocated to construct ATSs. First, generally speaking, agent-based methods are used to model each person in the real traffic system as agents. All agents make up artificial population, corresponding to actual population. Second, an activity-based travel demand model is responsible for arranging daily activity chain of each agent. Finally, activity-travel of whole artificial population is simulated and emerged as traffic flow.

A computer program called *TransWorld* has been developed to implement the whole process above. As a microscopic simulation platform of transportation, TransWorld has been applied in traditional urban traffic control, sport events, and other major projects for safety and convenience [19], [20]. Based on the platform, we model agents' social learning and then study the influence of social interactions on activity-travel behaviors.

## III. Modeling Activity-Travel Behaviors Based on Social Learning

### A. Problem Statement

Research on modeling activity-travel behaviors based on agents has been mostly studied within the framework of discrete choice models. A discrete choice model describes decision-makers' choices among a set of alternatives. Following this line, first, we use a triple $s = \langle t, \mathrm{pos}, \mathrm{dur}\rangle$ to express the state when an agent makes a decision on activity-travel behaviors, where $t$ is the time in simulation, pos is the position where the agent is at time $t$, and dur is the duration of the activity at that time. Then, use another triple $d = \langle \mathrm{type}, \mathrm{dest}, \mathrm{mode}\rangle$ to express an alternative activity-travel behavior, where type is the type of next activity, dest is an available destination, and mode is an attainable travel mode. All feasible alternatives form the choice set $C$.

In TransWorld, there are six kinds of travel modes for agents to choose, i.e., car, taxi, bus, subway, bicycle, and walking, and agents' activities are divided into three categories: 1) *mandatory* activity, including going to work or school and going home; 2) *maintenance* activity, including shopping and eating out; and 3) *discretionary* activity, including leisure and sport activity. The type of the next activity may cause significant difference to the choice set. For example, if an agent chooses work, the destination is usually fixed, and if choosing leisure activities, many destinations may be available, which will result in a large number of combinations.

Discrete choice models have been widely applied in studies of activity-travel behaviors. Ben-Akiva and Lerman gave an excellent review in [21]. Among various applied models [22]–[24], the multinomial logit model (MNL) is the most common. It has a close form and can be calibrated with survey data relatively easily. Based on the MNL, the following will model agents' individual learning and social learning to construct new activity-travel behavior models, which take social interactions into account.

### B. Modeling Individual Learning

Before modeling agents' ability of social learning, we must construct agents' individual learning model (ILM) at first since individual learning is the basis of social learning and can be treated as a reference category. Concretely, a reinforcement learning mechanism is used to model agents' individual learning. It is assumed that agent $i$ evaluates the utility of an alternative $d$ by

$$u_i^n(s,d) = E_i^n(s,d) + \varepsilon_{i,d} \tag{1}$$

where $\varepsilon_{i,d}$ is a random component representing unobserved utility, and $E_i^n(s,d)$ is the agent's expectation of $d$ when it is the $n$th time for the agent to choose in state $s$, which is defined by

$$E_i^n(s,d) = (1-\alpha)E_i^{n-1}(s,d) + \alpha R_i^{n-1}(s,d) \tag{2}$$

where $E_i^{n-1}(s,d)$ and $R_i^{n-1}(s,d)$ are, respectively, the anticipation expectation and the afterward actual reward of the last time when the agent chosen $d$ in state $s$. The initial $E_i^0(s,d)$ follows a predefined distribution $\mathcal{F}(s,d)$. The parameter $\alpha$, usually called *learning rate*, decides to what degree an agent learns from the recent experience.

Following MNL, we assume that each $\varepsilon_{i,d}$ is independent and identically distributed with the type-I extreme value distribution. Then, according to the theory of random utility maximization [21], the probability that decision-maker $i$ chooses an alternative $d$ in state $s$ for the $n$th time can be deduced as

$$L_i^n(s,d) = \frac{\exp\left(E_i^n(s,d)\right)}{\sum_{j\in\phi}\exp\left(E_i^n(s,j)\right)} \tag{3}$$

where $\phi$ is the choice set. Therefore, the probability for each alternative can be calculated, and then the classical Monte Carlo method can be adopted to simulate the process of choosing.

### C. Modeling Social Learning

In the real world, people get necessary social support by interacting with the others. The forms of social interactions are very diverse. Here, we focus on three universal kinds, i.e., imitation, conformity, and experience sharing on social networks. Based on the theory of social learning, their influence on agents' activity-travel behaviors are modeled, respectively, as follows.

*1) Probabilistic Observation Model:* First, we design the observation mechanism of agents as observing is the cornerstone of social learning. It is assumed that the probability for a choice to be observed depends on its frequency. Let $X(s, d, \Delta t)$ be the number of times that agents have chosen the alternative $d$ in state $s$ during the past $\Delta t$ days and $N(s, \Delta t)$ be the total number of choosing; therefore, the probability for $d$ to be observed can be defined by

$$p_o(s, d) = \frac{X(s, d, \Delta t)}{N(s, \Delta t)}. \quad (4)$$

The model is probabilistic; therefore, distinct agents would get different observations. Once a behavior is observed by an agent, the behavior will be stored in its memory during the whole running.

*2) LIM:* It is assumed that agents choose alternative behaviors in proportion to their observed frequencies. McElreath *et al.* referred to this strategy as linear imitation [25]. Let $X_i(s, d, \Delta t)$ be the number of times that agent $i$ has observed others choose the alternative $d$ in state $s$ during the past $\Delta t$ days and $N_i(s, \Delta t)$ be the total number of observed choosing. Thus, the probability that decision-maker $i$ chooses $d$ in state $s$ for the $n$th time is defined by

$$p_i^n(s, d) = (1 - \beta)L_i^n(s, d) + \beta \frac{X_i(s, d, \Delta t)}{N_i(s, \Delta t)} \quad (5)$$

where $\beta$ specifies the strength of reliance on imitation versus individual learning, and $L_i^n(s, d)$ is the probability of choosing $d$ according to the ILM. When $\beta = 0$, the model reduces to pure individual learning, and when $\beta = 1$, the model reduces to a pure linear imitation model (LIM).

*3) CM:* Following McElreath *et al.* [25], we define the conformity model (CM) as adopting the majority behavior among a group of observations. When there is no clear majority among the targets, it is assumed that individuals fall back on personal judgment. Thus, the probability that the decision-maker $i$ chooses an alternative $d$ in state $s$ for the $n$th time is defined by

$$p_i^n(s, d) = \begin{cases} (1 - \beta)L_i^n(s, d) + \beta, & \text{if } \frac{X_i(s,d,\Delta t)}{N_i(s,\Delta t)} > \frac{1}{2} \\ (1 - \beta)L_i^n(s, d), & \text{if } \frac{X_i(s,d,\Delta t)}{N_i(s,\Delta t)} < \frac{1}{2} \\ L_i^n(s, d), & \text{otherwise} \end{cases} \quad (6)$$

where $\beta$ specifies the strength of reliance on conformity choosing versus individual learning. Compared with linear imitation, the model defines the probability by three separated cases. If more than half of the observations choose $d$, the probability for $d$ to be chosen is enhanced. Conversely, the probability is lessened. In particular, if just a half of observations choose $d$, the agent will make decisions by individual learning.

*4) ESM:* For the two models above, agents can observe others' choices but cannot know their utilities. However, in the real world, people usually communicate with family or friends to gain useful information for decision-making. Thus, we further assume that agents not only can observe others' choices but also know their subjective evaluation. This case is usually seen among people with social ties; thus, we limit the share of experience within social networks of agents.

We define the social network of artificial population as a weighted undirected graph $G = (V, E, W)$, where $V$ is the set of vertices denoted by $1, 2, \ldots, |V|$, respectively, and $E$ is the set of edges connecting vertices. Each vertex represents an agent, and each edge represents a social tie. Let $W = W(V, E) = \{w_{i,j} \in [0, 1] | i, j \in V\}$ be a weighted matrix that parameterizes the weight that agent $i$ gives to the social tie with $j$. If there is not a social tie between agents $i$ and $j$, both $w_{i,j}$ and $w_{j,i}$ are equal to 0. We emphasize that $W$ is not symmetrical, i.e., $w_{i,j}$ may not be equal to $w_{j,i}$, as is usually the case in reality.

When it is the $n$th time for agent $i$ to choose in state $s$, we define its expectation of the alternative $d$ as $\mathbb{E}_i^n(s, d)$, which is composed of an individual component and a social component, i.e.,

$$\mathbb{E}_i^n(s, d) = (1 - \beta)E_i^n(s, d) + \beta \sum_{j \in N_i} w_{i,j} \hat{E}_j(s, d) \quad (7)$$

where $E_i^n(s, d)$ is agent $i$'s individual expectation calculated with (2), $N_i$ is the set of agents who have direct social ties with agent $i$, $\hat{E}_j(s, d)$ is agent $j$'s expectation, and parameter $\beta$ specifies the strength of reliance on others' experience versus individual learning. Similar to the ILM, we can explore that the probability for $d$ to be chosen is

$$p_i^n(s, d) = \frac{\exp\left(\mathbb{E}_i^n(s, d)\right)}{\sum_{j \in \phi} \exp\left(\mathbb{E}_i^n(s, j)\right)}. \quad (8)$$

The model is based on social networks; therefore, it can reflect the influence of social networks on activity-travel behaviors. Han *et al.* argued that there are three types of influence from social networks: 1) induce social travel, 2) provide objective travel-related information, and 3) affect decision-makers' subjective evaluation [26]. The model here just forces on the third case.

Since the models above are essentially based on MNL, the existing calibration methods for MNL (e.g., maximum likelihood estimation [27]) can also be adopted to calibrate our model parameters, such as $\alpha$ and $\beta$.

## IV. Computational Experiments Based on ATS

To reveal the dynamics of the models developed above, a series of computational experiments should be set up. The experiments presented here focus on destination choice in leisure-travel behaviors since travel for leisure activities is making up a growing percentage of the whole travel. In developed countries such as the U.S. and Germany, leisure activities are the reported purpose for a large number of trips, ranging from 26.5% to 39.5% [28]. The rate in some large cities of developing countries is also increasing quickly. For instance, the rate in Beijing reached 19.07% in 2011 with a 26.8% increase from 2010 [29], [30].

Let an agent' decision state only be its position, i.e., $s = \langle \text{pos} \rangle$, and a target of choosing is an alternative destination, i.e., $d = \langle \text{dest} \rangle$. The reward that an agent receives after choosing an alternative $d$ is defined by

$$R(s, d) = \begin{cases} r, & \text{if } d \text{ is the } d_{\text{best}}(s) \\ -r, & \text{otherwise} \end{cases} \quad (9)$$

where $r > 0$, and a greater value for $r$ implies that both positive and negative feedback from the environment are stronger. The $d_{\text{best}}(s)$ is the best place defined by a specified evaluation standard. Here, we define the place that is the closest to $s$ as the best one.

To capture the behavior dynamics of artificial population, we define three indexes as follows.

1) The first index is called the *best choosing* rate and defined by

$$Y^k = \frac{B^k}{N^k} \quad (10)$$

where $N^k$ is the total number of destination choices happened on the $k$th day, and $B^k$ is the number of times that agents choose the best ones exactly on the $k$th day. The best choosing rate is a direct measure that reflects how well agents make decisions by learning.

2) People usually have some habitual activity-travel behaviors, such as habitual route, and consume locations [31], [32]. Therefore, we

Fig. 1. Road network modeled for computational experiments. Small red cubes represent locations for leisure, black solid lines represent roads, and the places where roads cross are intersections.

further define the *habitual choosing* rate of the $k$th day as

$$H^k = \frac{h^k}{N^k} \tag{11}$$

where $h^k$ is the total number of times that agents conduct habitual choices on the $k$th day. A choice can be treated as a habitual one only if its frequency is greater than the sum of other choices behaved, and the total number is at least *three*. With the habitual choosing rate, we can figure out to what degree artificial population form habits.

3) To observe the popular effect of destination choice of artificial population, we defined the *convergent choosing* rate of the place $p$ on the $k$th day as

$$Z^k(p) = \frac{X^k_{\text{top}}(p)}{N^k(p)} \tag{12}$$

where $N^k(p)$ is the total number of times that destination choices happened at place $p$ on the $k$th day, and $X^k_{\text{top}}(p)$ is the total frequency of the top *three* alternatives that chosen most frequently. The mean of $Z^k(p)$ of all places is treated as the *convergent choosing* rate of the $k$th day, noted as $Z^k$. The convergent choosing rate reflects to what degree popular phenomena are emerged.

### A. Experiment Settings

We choose the Zhongguancun district of Beijing city, a prosperous business district and known as "China's Silicon Valley," as the transportation simulation area. With Google Map API, the road network, including main 164 roads, 15 intersections, and 89 places, is built as shown in Fig. 1. The places can be divided into seven categories: residential area (11), office building (27), school (4), shopping center (15), leisure places (25), sport sites (3), and restaurant (4). The number of artificial population is set to 20 000. Agents' age and gender are set according to urban age structure (see Fig. 2) from the sixth nationwide population census of Beijing in 2010 [33].

The time window of agents' observation is set to three days, i.e., $\Delta t = 3$. For each agent, the initial expectation for any alternative $d$ in state $s$ is zero, i.e., $\mathcal{F}_0(s, d) = \delta(0)$. The strength of environment feedback $r$ is set to 10, and the individual learning rate $\alpha$ is set to 0.2. The social network of agents is generated with the method proposed in our previous work [34]. Make TransWorld simulate agents' activity-travel of 62 days (two months) continuously and record all choices of artificial population every day. Then, we can observe the dynamics of agents' activity-travel behaviors by day with the three indexes proposed above.

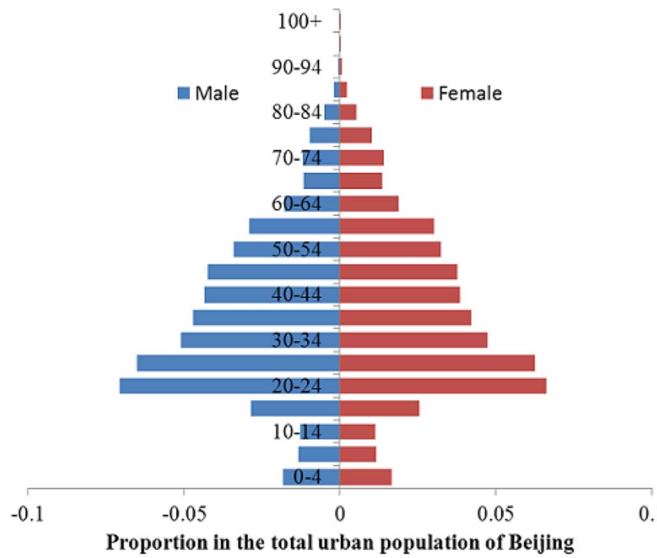


Fig. 2. Urban age structure from the sixth nationwide population census of Beijing in 2010.

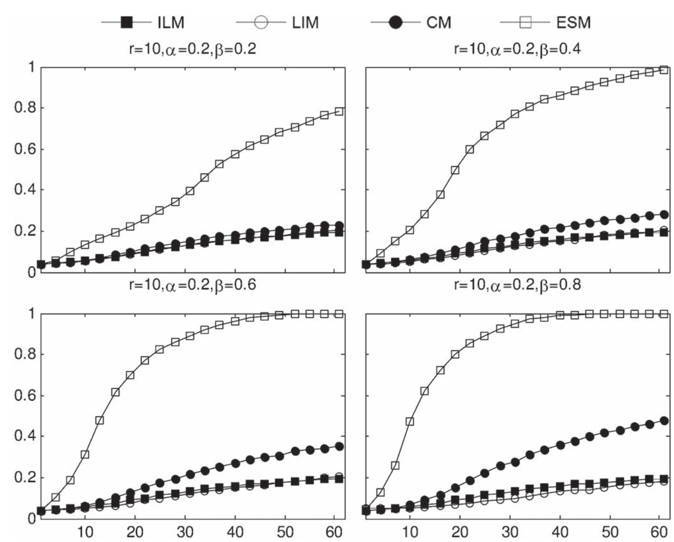


Fig. 3. Best choosing rates of four learning models as a function of time. For each curve, the time interval between any two adjacent data points is three days.

### B. Result Analysis and Discussion

Computational experiments with different $\beta$ values ($\beta = 0.2, 0.4, 0.6, 0.8$) are conducted. For convenience, we term the shared parameter $\beta$ in three social learning models as the *social learning rate* uniformly.

Fig. 3 shows how the best choosing rates of four learning models change with time. The experience share model (ESM) gains the higher values under four different levels of the social learning rate. Furthermore, as the social learning rate increases, the ESM converges faster to a stable level. The increasing speed of the CM is also positive correlated with the social learning rate but far slower than the speed of ESM. The increasing speeds of ILM and LIM are similar and relatively slow. If an agent can evaluate alternatives more effectively, it is more likely for the agent to discover the best one. Thus, it can be concluded that the ESM is the most effective to help agents evaluate alternatives, which is consistent with our cognition.

Fig. 4 shows how the habitual choosing rates of four learning models change with time. The final habitual choosing rate of the ESM is the

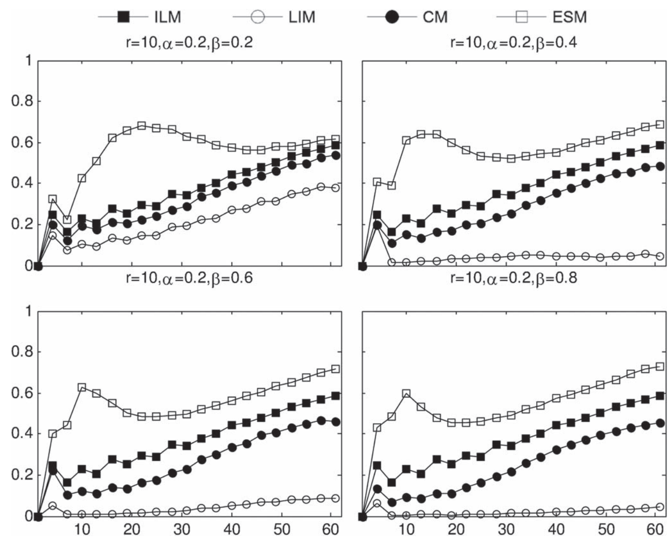


Fig. 4. Habitual choosing rates of four learning models as a function of time. For each curve, the time interval between any two adjacent data points is three days.

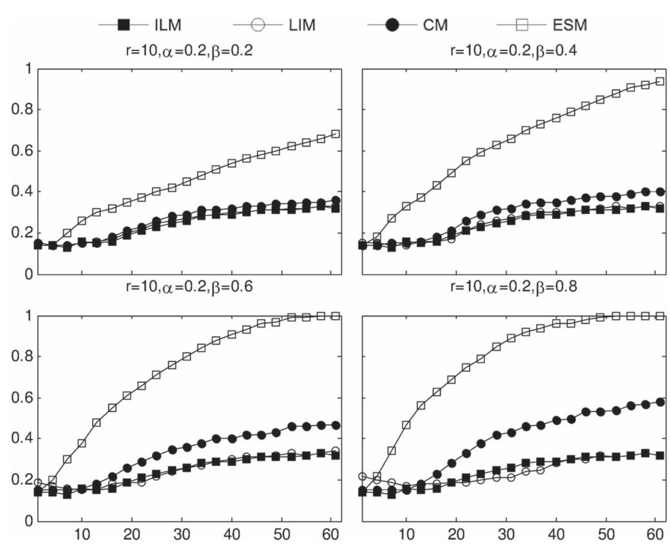


Fig. 5. Convergent choosing rates of four learning models as a function of time. For each curve, the time interval between any two adjacent data points is three days.

highest, and the ILM takes the second place. Compared with the ESM, the evaluation information of alternatives that the CM and LIM gain from observations is implicit and even may have some misleading. This explains why the LIM almost does not make agents form habitual choosing, particularly when the social learning rate is bigger, and why the final habitual choosing rates of the CM and LIM are smaller than the ILM.

Fig. 5 shows how the convergent choosing rates of four learning models change with time. It can be observed that all of them increase with time gradually. The increasing speed of the ESM is the fastest, the CM takes the second place, and the ILM and LIM are in the last place. The convergent choosing rate reflects the popular phenomena emerged in ATS, which can be referred to so-called fashion in the real world. Since the ESM can spread information more effectively than other models, it can promote the emergence of fashion and has the highest convergent choosing rate. When the social learning rate is 0.6 or 0.8, the convergent choosing rate of the ESM on the last day is very close to the limit value of 1.

## V. Conclusion

This paper has introduced social learning into ATSs to study the influence of social interactions on activity-travel behaviors. Three social learning models are proposed to model agents' decision-making on activity-travel behaviors. Then, a series of computation experiments forcing on leisure-activity location choices are designed and conducted. The quantitative results show that these three models can reasonably reflect the actual influence of social interactions on activity-travel behaviors to a certain degree.

Future research should focus on further examining the dynamics of the proposed models. The experiments should provide insights into the impact of parameter settings on emergent patterns of behaviors. Meanwhile, a variety of real data (e.g., mobile phone data [35]) should be collected to validate and improve the proposed models.

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