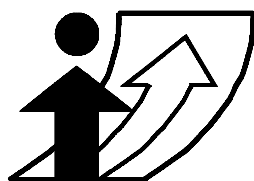


# **An agent model of social network and travel behavior interdependence**

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# **An agent model of social network and travel behavior interdependence**

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## **Abstract**

Travel is a prerequisite for activities which maintain social and business connections, building the vital social networks which conduct the flow of values, services, and opportunity. This paper presents a multi-agent simulation to study linked geographical and social spaces. The model simultaneously generates a social network and travel behavior by defining social-networking visits as travel activities. Information about space and other agents flows only via the social network. Social ties are added/removed depending on co-presence/lack of visits, introducing the dynamic feedback to the model. A random utility model (RUM) trades off socializing with the cost of travel and the activity attributes to generate probabilities for link attachments. The focus on link attachment probabilities allows the model to be verified within the analytical framework of random, small-world, and exponential (preferential attachment) graphs. New measures are suggested to compare social and geographical space. The model response to changes in utility parameters is sometimes unexpected due to the feedback. Ensemble results of a base case and sensitivity tests are presented.

## **Keywords**

Social networks, transportation system, spatial choice, social interaction, agent simulation, network dynamics, network analysis, complexity, joint activities, transportation planning

## **Preferred Citation**

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## 2 Introduction

While it has been apparent to travel demand researchers that social contacts can both constrain and induce travel (Axhausen, 2006), activity-based tools for understanding and modelling travel demand have not systematically incorporated social network approaches. This paper presents a microsimulation of social networks in geographic space, in which maintaining social contacts is a trip-generating activity. The goal is to develop a system for studying the influence of social networks on activity planning, separate from the effects of individual characteristics and geography.

The term social network refers to a collection of acquaintances (nodes or vertices) and their relationships (links or edges). Tools for the analysis of social networks have long existed in the social sciences (Wasserman and Faust, 1994) in a literature not commonly consulted by business, economics, and engineering disciplines. However, a series of accessible publications from the field of statistical physics explaining and applying small world and complex networks (e.g. Newman, 2003, Watts and Strogatz, 1998, Watts, 1999, Kleinberg, 2000, Kleinberg, 2001, Barabasi, 2002) has initiated a proliferation of social network studies and studies of complex networks in many disciplines. While the term “social network” will be used throughout this paper, a more precise term in view of the hypothesis-oriented methodology might be “relational econometric” networks (Bidart and Degenne, 2005).

A framework for incorporating the social context of activity-based tools is proposed by Axhausen (Axhausen, 2006). Friends, family, work colleagues, etc. constitute a social network of acquaintances (“alters”). In the short term, these relationships with the decision maker (“ego”) conduct information and obligations, which can motivate, constrain, or substitute for travel and activities. The social network influences the allocation of time between travelling versus planning and participation in activities (see e.g. Miller, 2005). Meanwhile, the long-term effectiveness of the upkeep of social contacts determines how social influences evolve for the future. Though much social interaction occurs via synchronous and asynchronous electronic media, making geography practically moot, co-presence is vital to certain social processes and activities and thus relationships (Urry, 2003). Particularly restrictive definitions of “relationship” are necessarily chosen for social network studies because it is infeasible to ascertain personal (ego) or global networks for all types of relationships. However neither the topology of the networks that are relevant for

influencing travel decisions, nor how they evolve, are well-understood. Indeed, the set and strength of relationships that are relevant to transportation demand over different distances and time horizons is yet to be defined.

There are few applications of social networks in transportation planning. Dugundji and Walker (2005) derive a mode choice model containing a term for the group average decision from the previous decision round, based on applied mean field theory in economics (Blume and Durlauf, 2004) and using various static associative social networks that group individuals by planning zone, sociodemographics, or other observable econometric statistic (Dugundji and Gulyas, 2003). Paez and Scott (2005) present a similar approach to estimate the share of telecommuting at a firm in consideration of peer pressure to appear at one's desk. Marchal and Nagel (2006) allow cooperative agents in a microsimulation to share information with each other about activity locations and about other agents, in order to optimize trip chains. In perhaps the most theoretically advanced work on the topic, Arentze and Timmermans (2006) present a framework for a multi-agent microsimulation that produces a dynamic social network that evolves together with activity-travel patterns, with promising first results. The model includes explicit agent behavior such as mutual consent to initiate a relationship, fulfilment of social and information needs, adaptation to the social network mean preferences (or else modification of its social network), and values of time along with activity durations.

While it might improve transportation demand models to have social connections, i.e. ego networks, in them at all, there are hard questions to face before we know whether including social networks is a cost-effective or valid solution. The global networks, of which ego networks are subgraphs, are highly nonlinear structures that could exhibit emergent complexity which can cause sudden unexpected results. On one hand, it is a challenge to build dynamic ego networks that combine to yield plausible (or desired) global characteristics. On the other hand, there is an opportunity to use more of the global network statistics in the development and, perhaps, governance of a dynamic model, which may give the modeller more control over the emergent social network to make sure the model operates in a range that brackets realism. The rich dimensionality of global networks has not been included in the work thus far.

One advantage to using ego networks is the possibility of finding parameter values for the models in survey data. For this to work however, the model parameters need to be carefully defined such that they are observable. Simulations designed with this in mind from the outset could lead to more efficiently focused surveys and faster conclusions on the feasibility of combining social networks with activity-travel modelling.

Finally, the explicit study of the relationship between travel opportunities and the social network is the key to linking social networks with land use and settlement patterns. If social networks are significant factors in travel behavior, then this connection must be established in order to understand the influence of policy decisions on social contacts.

The model presented here generates a global set of inter-household relationships based on dynamic ego networks that develop with respect to travel opportunities. Agent simulation is chosen for two main reasons: first, information about the network context of activity planning is lacking, and second, because simulation can be used to build the needed global social network from assumptions about the structure and the growth and decay processes of egocentric networks. It is conceived as a prelude to a microsimulation approach to generating inter-household joint activity plans. Though a specific reason for socializing is not given in this model, these trips may be considered to be a fundamental component of maintaining social capital (Freeman, 1977) or of putting social capital to work (Axhausen, 2006). Statistical measures are also presented to analyze spatially moderated social networks. The work is part of a long-term project to better understand the interdependence between activity spaces and generalized transportation cost.

### 3 Global social networks and travel behavior

While many travel activities take place within an exogenously determined framework: fixed work hours, daylight, weekends, seasonally varying activities, public holidays, etc., the orchestration of schedules across society is in principle emergent, that is, without a central planner. Social network influences are instrumental in determining trip destination, frequency, mode and scheduling, especially for leisure and “personal” travel. However, the more jobs that can be performed with flexible work hours and at distributed workplaces, the more self-planning can be expected for work trips, as well.

People who do not live together either adapt to a given schedule or they must negotiate activities in order to meet in person. The determination of meeting point, frequency, scheduling, and duration will take into account the travel opportunities of the agents involved: route, mode, schedule, etc. These interactions occur with respect to the social connections between agents, and with certain exogenous constraints (e.g. institutional norms, weekends, etc.).

In a network with equal or featureless nodes, the topology of the social network alone determines the efficiency of the spread of information, the network stability, and the resilience of the society to the removal of links or nodes. Furthermore, it would be expected that the social network, and the strength of its influence, would be modified as a result of the self-organizing collection of actions of all actors. Thus in order to model inter-agent negotiations, it is necessary to understand or to posit their context within the detailed topology of the social network and to hypothesize the effect of agent interactions on the dynamic connectivity of the network.

The decisive influence of the specific network topology on the global-level outcome of micro-level interactions has been highlighted in studies of the navigability of social networks (White and Houseman, 2003, Clauset and Moore, 2003), simulations of epidemics with the assumptions of a SIR process (Hufnagel, *et al*, 2004), the endogenous price of goods exchange (Wilhite, 2001), the emergent dominant strategy in an iterated prisoner’s dilemma game (Axelrod, 1981, Schweitzer *et al*, 2005), the resilience of spatial networks (airline, roads, electric grids) to interruptions (e.g. Barrat *et al*, 2005, Gastner and Newman, 2004), among many other examples. For activity-travel, the network topology is relevant to short and medium time frame with regard to an agent’s access to information (mode, route, destination,

people) and ability to use that information (constraints, generalized costs of learning or of travel) or to find substitutes for travel. For longer term behavior, the dynamic social network topologies might be important with regard to resilience of ego networks and adaptation following relocation decisions.

### **3.1 Empirically identifying the social network in space**

Thus modelling travel behavior based on extra-household social network influences has a first hurdle in the identification of a realistic set of social contacts, and if possible, their geographic association. Available datasets on the social network structures are not directly helpful in this area. Most surveys of “global” networks are understandably constrained to cases of small groups with very specific characteristics that are not generalizable (Valente, 2006). Panel observations of social network dynamics are a rarer dataset still. The link between socialization and geographical location, travel, or relocation behavior has been investigated in a few small-sample studies of ego networks (Carrasco *et al*, 2006, Ohnmacht, 2005) that offer preliminary qualitative but incomplete insights, where key quantities such as the attributes of alters or the coordinates of the meeting place are generally missing. Liben-Nowell, *et al* (2005) use the hometowns of participants in an online social network of bloggers to derive a small world model in which the probability of befriending a person is inversely proportional to the number of physically closer people. While blogging is remote from the face-to-face social behavior focused on in this work, relating link probability to the rank of the physical distance elegantly couples geographic space and social space and this outcome may be a hypothesis to test in our model in the future.

Yet summary statistics of real social networks allow the following conclusions (Jackson and Rogers, 2005): Society in general is a “small world”. This means that the global network of all people is highly clustered (it is highly likely that friends of an ego are also friends with each other), while maintaining a small average path length (the average minimum geodesic separation between any two people is very small relative to the total number of people in the network). While the latter has been measured repeatedly through a sampling trick (Travers and Milgram, 1969), the former is expensive to study and has been assumed to hold based on specific studies of small groups. Studies indicate that these network structures are consistently present in large associations of scientists, actors, or smaller groups of powerful CEOs (summary in Newman, 2003). In addition, many examples of real social networks exhibit a tendency for social links to form preferentially around nodes which already are well-connected, i.e. popular people become more popular (Barabasi, 2002). In preferentially attached networks, linked nodes tend to have positively correlated degree (assortativity).



Finally, the highly skewed distribution of degree means that clustering (see section 7.1) of the neighbors of high-degree nodes is lower than for neighbors of lower-degree nodes (sometimes referred to as a “core-periphery” structure).

## 4 The simulation of social networks

Given aggregate characteristics of social networks, statistical or econometric methods have been used to generate sets of social networks that simulate ties in an artificial society. Hypotheses of social behavior have been proposed which attempt to explain what is known about social network topology and dynamics (Bidart and Degenne, 2005). Some of the many approaches that have been developed to generate social networks are summarized here. While some of these models reproduce parts of observed social networks, none include realistic modelling of travel or spatial location coupled with social behavior.

As mentioned above, the social network required for activity-based planning applications must serve several time scales and evolve with agent activities. Dynamics involves using the generated network or the results of behavior in a time period as information influencing network topology in the subsequent time periods. Not all network generation is an attempt at simulating network dynamics. In particular, the canonical ensembles generated in statistical physics and the exponential random graph models (ERGM) described below are static objects of study in themselves and not time simulations of network evolution. The solution for activity based planning tools will be a combination of the methods summarized.

### 4.1 Strengths, Weaknesses, Opportunities

ERGMs (Snijders, 2002) assume the observed network is a sample of the class of graphs characterized by a posited linear combination of graph sub-structures. A number of graph classes are proposed and their coefficients fitted to the observation using Monte Carlo Markov Chain draws. Some models even include vertex characteristics in the estimation. The method needs a first sample of a global network in order to estimate parameters. Missing data is always a problem in networks, and in this case the result would be the wrong classification. The method gives the likelihood of the observation belonging to a particular class of graphs, but no behavioral explanation for the network topology.

Analytic graphs have a strong basis in statistical physics and the asymptotic behavior is well understood. But translating these models into motivations and actions of people is not straightforward. Physical concepts like Brownian motion, entropy, and temperature may not have travel behavior equivalents, though these models are applied to artificial societies to

successfully construct aspects of self organization and networking (e.g. Schweitzer *et al*, 2002, Gonzalez *et al*, 2006). Link attachment procedures to construct canonical graphs are analytically well-described and possibly useful in the context of the activity-travel problem (Dorogovtsev and Mendes, 2003):

- Erdős/Renyi classical random graph generator: node pairs to link are chosen at random, Poisson degree distribution, low to zero clustering (unrealistic for social networks), lowest average shortest-path length (order  $\log(N)$ );
- Equilibrium random graphs with given degree distribution: degree distribution is allowed to depart from Poisson, otherwise similar to classical random graphs.
- Small World Networks: regular lattice with very few global imperfections (long links short-circuiting the lattice) which result in average shortest path lengths nearly as short as in random graphs and a Poisson degree distribution, but which retain high clustering. Like random graphs, the characteristics of these networks are easily destroyed by removing random nodes or links.
- Preferential attachment graph makes agents with more links attract links with higher probability, resulting in correlated degree distributed like a power law (Barabasi 2002).
- Barabasi and Bonabeau (2003) also propose another preferential attachment algorithm which also creates small-world clustering. The graph characteristics are robust to random node or link failures, but susceptible to the loss of specific nodes.
- Combinations (superpositions) of these graph types.

Agent interactions based on decision rules, adaptations, game theory, etc. have included spatial games and games which result in or function because of a social network (e.g. Wilhite, 2001, Hollander, 2006 gives an overview for travel behavior). The emergent behavior of the aggregate body of agents is not easy to tune and the emergent social network topology is difficult to control. Additionally, there are problems of scoring, distribution of reward, strategies, turn order, equilibrium, etc. in open-ended models that complicate their use in tools which have at least some footing in the world of real data.

Networks could be generated using behavior tendencies from sociology, as summarized by Bidart and Degenne (2005). The hypotheses are not all tested, and parameterizations are not easily fitted to data or defined quantitatively. Perhaps the most certain sociological hypotheses that might serve as building blocks for the generation of a base social network are

“homophily”, which is the tendency for people to associate with people who are like themselves or with friends of their friends (McPherson, *et al*, 2001), “bridging social capital” (Putnam, 1999) which are the associations of a person with those who are like himself in only one way but different in other ways, and notions that people can only maintain a maximum number of relationships, implying a saturation point (Barrett, *et al*, 2002). In terms of dynamics, studies in sociology indicate that the strength of different relationships changes with time depending on a number of factors (Burt, 1999, Reagans, 2005), and that relationships can dissolve entirely. A static small-world generator using only homophilic classifications is described by (Watts, *et al*, 2002). These models with a basis in empirical sociology would seem to reproduce observed social ties, but they have not incorporated space in terms of transportation or land use.

Spatial networks are constrained by the economics of overcoming space, or space-time (distance, terrain, weather, wages, fuel, dissipative losses). Previous generators of “spatial networks” treat the nodes of the spatial network, airline hubs for instance (e.g. Barrat, *et al*, 2005), as agents seeking to minimize the cost of network connections. Clearly such abstract entities are themselves models of emergent behavior resulting from decisions by the managing bodies of airlines and airports, and though reflective of social networks and social behavior, these spatial networks are not links of social contacts.

## 5 Proposed solution

Two improvements are recommended to combine the existing approaches for generating networks to applications in activity-based trip generation:

- Link attachment (or existence) as a travel behavior (trip generation) model
- An explicit bridging mechanism between geographic and social space

In the model described here, the probability of link attachment is based on a random utility function familiar in transportation planning. The behavior represented in it is the likelihood of making a social trip, considering the costs of overcoming space and of spreading the effort of maintaining all social contacts. The simple linear-in-parameters utility function generates egocentric networks that link together into a global network (not necessarily a single-component network), as a result of agents meeting and sharing information with friends about geography and their other friends. The social network evolves as it is generated, as agents visit the same place at the same time and make friends with a certain probability. Links are removed from the network according to characteristics of the relationship. A saturation coefficient is intended to permit more flexible tradeoffs for controlling the resulting network degree than a fixed maximum number of relations. The utility functions of individuals can be assumed or fitted.

Geographically and in a transportation behavior sense, the spatial extent of an agent's social network will be moderated by its willingness to bear travel costs to socialize, by its knowledge of where other suitable social opportunities are to be found in its activity space (or *activity repertoire*), and by its risk-taking to explore new places.

Two mechanisms bridge geographical and social space and enable dynamics: agents with a social connection share knowledge of space and other agents with each other, and agents are able to meet other agents if they visit the same place at the same time.

The model is used to observe the influence of the transportation network on socializing and to test the effect of a range of utility parameters for socializing on the travel behavior of agents.

## 6 Description of the base model

A set of agents is placed on a transportation network on which travelling has a cost. The geographic world is a 2 dimensional toroid so that spatial edge effects do not confound the interpretations of the results. The agents make trips in their activity space to socialize with friends, or they navigate unfamiliar space to meet new agents, according to a RUM that trades off socializing utility versus the generalized cost of travel. The social network established is nondirected with link strength = 1 or 0. The utility is different for staying home, random exploration, visiting friends, or visiting friends of friends, but travel cost is weighted the same for all travel. If two unacquainted agents meet, they befriend each other with probability  $p_{GetToKnow} = 0.5$ . If friends meet, their friendship is renewed by resetting its age to 0. Non-renewed links age by 1. Links are removed in the base case as a function of their age.

### 6.1 RUM

Random utility decision models have been used in transportation and land use planning since their beginnings (Ben Akiva and Lerman 1985). The logit formulation of discrete choice is used here to simulate agent decision making. The multinomial logit probabilities for decision maker  $n$  regarding alternatives  $j$  in set  $C_n$  are:

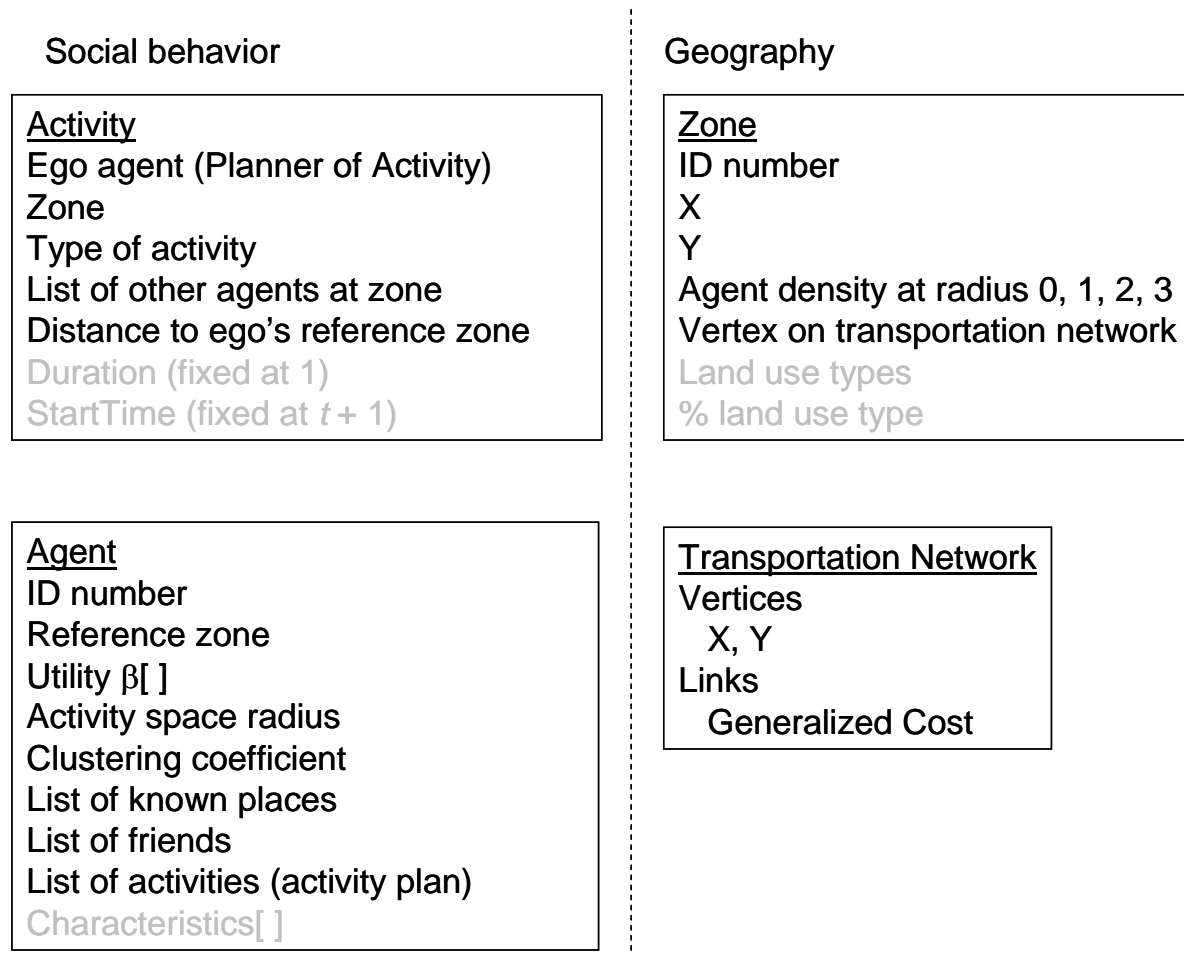
$$P_n(i) = \frac{e^{V_{in}}}{\sum_{j \in C_n} e^{V_{jn}}} ,$$

where  $P$  is the probability of making a choice  $i$  and  $V$  is the utility. The probability of choosing an alternative relative to another in a Logit model is independent of the alternatives that have been left out of the choice set, and this does not change as the agent learns about new alternatives, which might not be realistic.

### 6.2 Object oriented program

The model is programmed in Java in the RePast environment and uses the JUNG graph library to manipulate and analyze the social network. It runs in batch or interactive mode. In interactive mode, a number of graph statistics are plotted, and the evolving social network is

drawn in geographic space. It consists of three key objects: Zone, Agent, and Activity (Figure 1) These are linked by the elements of geography (transportation network) and by the utility function.



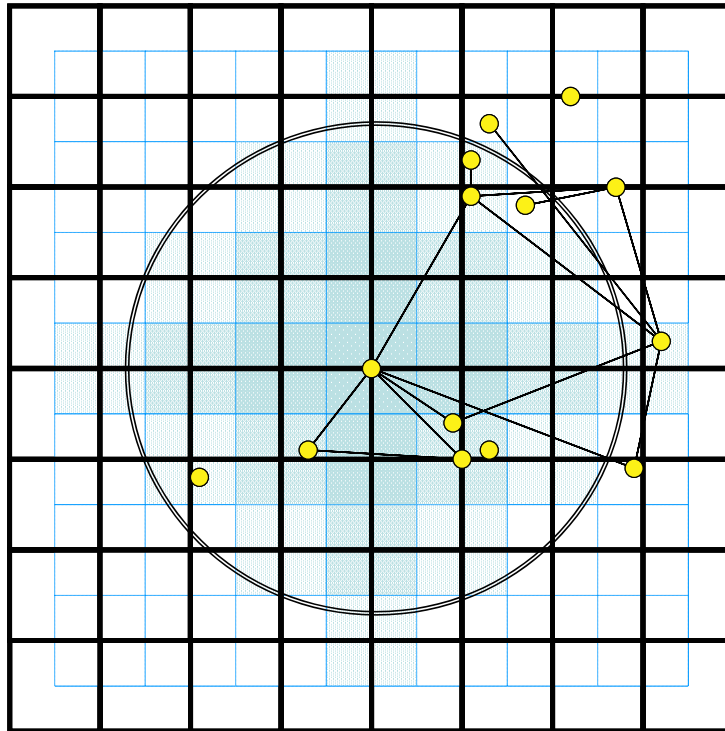
The text in grey lists variables that are initialized but not used at this point.

Figure 1 The objects combined in the java model.

### 6.3 Setup

The transportation network used is a lattice of period 10 on the toroidal surface. The 100 grid intersections are each identified with the midpoint of a zone (though in general, any number of zones may be defined in any desired configuration on the transportation network). The travel cost is homogeneously set to 1.0 between adjacent gridpoints. In this case, zones are size 1.0, so travel between adjacent zones costs 1.0 and travel within a zone is costless. The

runs presented here use 65 agents. The agents have identical attributes except for their position on the geographic surface, and their utility functions are also identical. The population is distributed randomly to reference zones which represent the home base of the agent, and the same spatial constellation of agents is used for each run of each ensemble to enable comparability of runs. More than one agent is permitted “live” in each zone. Figure 2 represents the setup schematically.



Roads are black, traffic zones are blue (shades indicate the travel distance from the ego’s zone). The circle is a single-parameter representation of the extent of the ego’s activity space (average distance to all friends).

Figure 2 Geographical layout of the model with social network centered on an ego.

## 6.4 The turn structure

The initialization permits different assumptions about the existing social network topology. One can begin with random or lattice networks, with full or partial connectivity. The base case begins with no relationships and agents have no knowledge of space. As agents visit each



other, randomly at first, but then influenced by their friends, links are added and removed until the average clustering coefficient (section 7) relative to that of an Erdős/Renyi random graph stops varying, which is taken here as an indication that the network is not fundamentally changing any more in character.

#### 6.4.1 Constructing the activity choice set

Each time step, a choice set of activities is generated for each agent, from which the agent constructs an activity plan of  $n_a$  activities to carry out during the turn using the RUM decision model ( $n_a = 1$  for now). The choice set is constructed for each agent by associating each of four activity types with the locations that the agent knows about, in which it is possible to perform the activity. For simplicity at this point, all the other agents who reside at the location are included in the activity as participants.

#### 6.4.2 Utility function

The utility of each possible activity is calculated for each agent in the “play” phase given the choice set. The utility function has the form in Table 1. The transportation network distance the agent must travel to get to the activity is modelled as a cost. There is additional utility for each friend or friend of friend that is participating in the activity. A saturation cost for making and maintaining an additional new friend is also in the utility. The type of activity has intrinsic value in itself.

An agent living at location  $i$  can choose from four activities at locations  $i$  or  $j$ :

- Visit Friend at  $j$ :  
The agent knows how many of its friends are at location  $j$  and it calculates the utility of making a visit based on this total number. The friendships are all renewed, and new friendships will be made with each of the other as-yet unmet agents living at that location with probability  $p_{GetToKnow}$ .  $\beta_2$  represents the value of meeting with each friend.
- Visit Friend of Friend at  $j$ :  
The agent has been told by its friends how many of their friends are at  $j$ . The utility is based on this total number. New friendships will be made after the visit with each of the other agents living at that location with probability  $p_{GetToKnow}$ .  $\beta_3$  is smaller than  $\beta_2$  to reflect the possibility that the agent only sees the potential for making a valuable acquaintance, but that there is a risk that the friend of a friend is not as

pleasant as the referring friend.  $\beta_4 < 0$  and represents the cost of maintaining an additional friendship.

- Explore  $j$ :

The activity choice set contains a list of places unknown to the agent.  $n_e (=1)$  alternatives are random zones and the others are zones known by the agent's friends. The desire to explore is innate and gives positive utility. This utility is equal to  $\beta_5$  if the zone is anywhere within the agent's geographical activity space, and it diminishes with the area subtended by a circle of radius equal to the distance to the zone center, if the location is outside the activity space (Figure 2). This is meant to represent the agent's perception that the world beyond his experience horizon is foreign and less attractive than things that are closer to home. It is not a measure of sensitivity to travel cost however, since  $\beta_5 > 0$ .

- Stay Home Alone at  $i$ :

The agent does not make a physical (or other) move to reinforce friendships, explore new places, or meet with friends of friends. Others can visit the agent at home within the same time step, on their turn.

Table 1 The utility function of a trip to location  $j$

Activity	Home	Travel Cost	Friends	Friends of Friends	Saturation	Exploration
Stay Home Alone	$\beta_0$					
Visit Friend at $j$		$\beta_1 * \text{dist}$	$\beta_2 * N_{\text{friends at } j}$			
Visit Friend of Friend at $j$		$\beta_1 * \text{dist}$		$\beta_3 * N_{\text{FoF at } j}$	$\beta_4 * \text{degree}$	
Explore $j$		$\beta_1 * \text{dist}$				$\beta_5 (\text{dist} \leq r_a);$ else $\beta_5 * (r_a / \text{dist})^2$
$r_a$ = radius of activity space (average distance to all friends)						
Base Case: $\beta = \{1.0, -0.5, 3.0, 2.0, -0.5, 0.1\}$						

### 6.4.3 Turn end

After the  $n_a$  activities are chosen in the RUM and added to the activity plan of each agent, these activities are carried out for each agent in turn. The appropriate social links are renewed or established and the new locations that were visited and resulted in a social contact are remembered by each agent. Other locations are forgotten. Then, depending on the model settings, links are removed based on the link attributes. In the base case, the links are removed with a sigmoid function which removes links with increasing probability with link age:  $p_{\text{Remove}} = 1. / (1. + 500000000 * e^{-(\text{linkAge})})$

The function gives 50% probability if a link is 20 steps old, which is the time it would take to visit roughly 1/3 of the agents one time each). A link with age 25 is practically certain to be removed. Other algorithms for link strength or removal are plausible (Burt, 2000).

Finally, the turn results are written into four output files: Zones (the geographic context of the run), Agents, Edges (relationships), and Graph (aggregate statistics on the social network).

## 6.5 Discussion of the model

While the model uses random utility to generate “social trips”, the state of the algorithm at this point is that of a network link generator and not a social simulation. The 65 agents are given, and their task is to interact in pairs to generate friendships that depend in part on physical geography. One agent establishes a link to another agent by meeting it at its “home”. There is no consideration of meeting at an intermediate location, and no concern at this stage about agents coordinating their intentions in time or with several agents. Thus, an agent is always home when another one comes to visit. The resulting social network is therefore a cumulative map through time of the agent’s travel decisions in physical and social space. The model is a map of the recent movements of the agents, as well as their reaction to the loss of old connections.

More realistic scenarios like heterogeneous preferences, that more than two agents would coordinate an activity, time conflicts, or that there are supply constraints for activities at certain locations, are possible to build into this structure in the future through interagent games.

The choice set is a crucial consideration in utility maximization, and is conditioned in this case on the topology of the social network. Agents can only know about their world through random exploration of space or by learning about their surroundings through their friends. This constrained awareness of opportunities and its feedback into the subsequent choice is a departure from earlier link attachment models of network generation which combined the social network topology with a kind of geographic separation over a lattice distance. In those models, the choice set remained the set of all other agents, which was not conditioned by geographic knowledge.

For an agent with no social links, the first activity choice is between staying home or making a random exploration in space, where social search is incidental. A visit to a random zone may or may not turn up other agents. But, there may be one or even several agents “residing” there who might be willing to befriend the ego. For each other agent present, friendships with the ego are made with a certain probability ( $p_{GetToKnow} = 0.5$  in the base model). This parameter is similar to the “beta” value in the Watts (1999) small world generator, although the choice of nodes to connect with in the model has been conditioned in this case by the geographic distribution of the agents. In the subsequent time steps, once an alter has been befriended and social links exist, the geographic and social information each friend stores is available for the ego to use in planning its next activity, further correlating geography with the social network.

## 7 Model results

The base case results are presented and the single-dimension sensitivity to individual parameter values is tested. The graph degree and clustering ratio (relative to a random graph) change slowly by time step 80. Runs therefore use 100 time steps and an ensemble set of 20 random number seeds. Analyses are carried out on the last 21 time steps, assuming that this is a dynamic equilibrium; i.e. that differences exist in the network topology from one time step to the next, but that the state of the social network at of these time steps is a sample of the “true” evolving social network. Hypotheses about the relationship between the assumed behavior (utility function) and the emergent social network are discussed in the summary.

Studies of different initializations of links (e.g. a lattice or random graph substrate) and a detailed study of agent and edge statistics are yet to be made (local population density, etc.). Only brief results will be shown of these analyses.

### 7.1 Measures of comparison

Two graph-average parameters are used to coarsely compare the resulting social networks, or graphs with number of nodes  $N_n$ , number of edges  $N_e$ :

Average Degree:  $z^* = 2N_e/N_n$ ;

Average Clustering Coefficient Ratio: The clustering coefficient  $C_i$  of a node  $v_i$  is the ratio of the number of realized links between the nodes connected to  $v_i$  to the number of possible links between those nodes. The graph average clustering coefficient proposed by Watts and Strogatz 1998 is straightforward:  $\bar{C} = \frac{1}{N_n} \sum_{i=1}^{N_n} C_i$ . The average clustering coefficient ratio referred to in this paper divides this average by the large-graph expected clustering ratio for Erdős/Renyi random graphs,  $z^*/N_n$ . This ratio will approach 1 for graphs with near-random clustering.

Further, edge statistics are used to study distance distributions, and agent statistics yield trip purpose distributions and information about activity spaces.

## 7.2 General observations

The same trends in the growth and stabilization of the social network with time are seen in all runs. The empty initial graph has zero average clustering and degree. The first links cause high average clustering values as dyads (clustering = 1.0) form between agent pairs. The clustering falls again immediately as soon as the first agents acquire two unacquainted friends. This forms “forbidden triads” (Granovetter 1973), or groups of three agents with only two links between them. Many of these soon fill with links to make triangles that raise the clustering coefficient, but the spatial exploration of the agents also results in bridges between clusters that lowers overall clustering again. The main difference between the runs compared here is the rate at which triangles versus bridging links form. This depends on the shares of the activity choices, which are determined by relative magnitudes of the utility parameters (Figure 4).

## 7.3 Base Case and Link Cost

The base case utility parameters are as in Table 1. This model is run with the standard link removal algorithm and  $p_{\text{GetToKnow}} = 0.5$ . The base case results are presented together with results of runs with travel cost parameters -1.0 and 0.0 (costless travel) for comparison.

### Hypotheses

The description of the model output can at the same time support or modify hypotheses of agent behavior, expressed here more in terms of the expected model output. The emergent social network should exhibit more clustering than a random graph due to the preference to visit friends and friends of friends, which will close triads to make triangle structures. The fact that the knowledge of space is gathered through friends and only to a small extent through random travel will focus the ego networks spatially. Travel will be farther if agents are less sensitive to travelling, and the number of friends will increase (with the space known to the agent). The average degree of the graphs (average number of friends) will climb with decreasing rate due to the combination of link removal and degree saturation.

The average degree of the resulting graphs increases with decreasing sensitivity to cost. Looking at the time steps from 80-100 of the 20 ensembles, the average graph degree is 1.4(0.3), 3.7(0.7) and 18.5(3.0) for cost parameters -1.0, -0.5, and 0. The distribution is positive-skewed at cost = -0.5, indicating that the probability of generating higher degree graphs for intermediate cost parameters is higher than for a normal distribution. The

clustering ratio (relative to a random graph) has the opposite trend: high travel cost increases clustering: 25.7(4.4), 13.6(2.9) and 2.1(0.8) for the costs -1.0, -0.5, and 0. Outcomes when agents have low tolerance for travel cost are distributed with positive skew for higher travel cost parameters, indicating highly clustered, low-degree communities (Caveman societies, Watts 1999).

Figure 3 shows model output of neighborhoods in geographic and social space for two values of travel cost parameter. Note that the larger clusters are not connected by bridges. In this model, bridges are short-lived, as bridges quickly lead to friend of friend attachments which yield a new large cluster. Isolates have either not travelled much to meet others, have not been visited by others, or had bad luck making friends upon meeting others. They are more likely to be located at the spatial edge of clusters, rather than within spatial clusters. With no social links, searching the spatial grid is inefficient a difficulty that all agents share initially. Agents in far removed, thinly populated regions will stay isolated for longer because, since travel cost is weighed in their decision to explore versus staying at home, they are not searching a large enough space regularly enough to find other agents. At the same time, the likelihood that these agents will be visited by an agent with friends is low, since an agent with friends is more likely to visit its friends, friends of friends, or to explore within its familiar surroundings than to randomly explore outside its activity space.

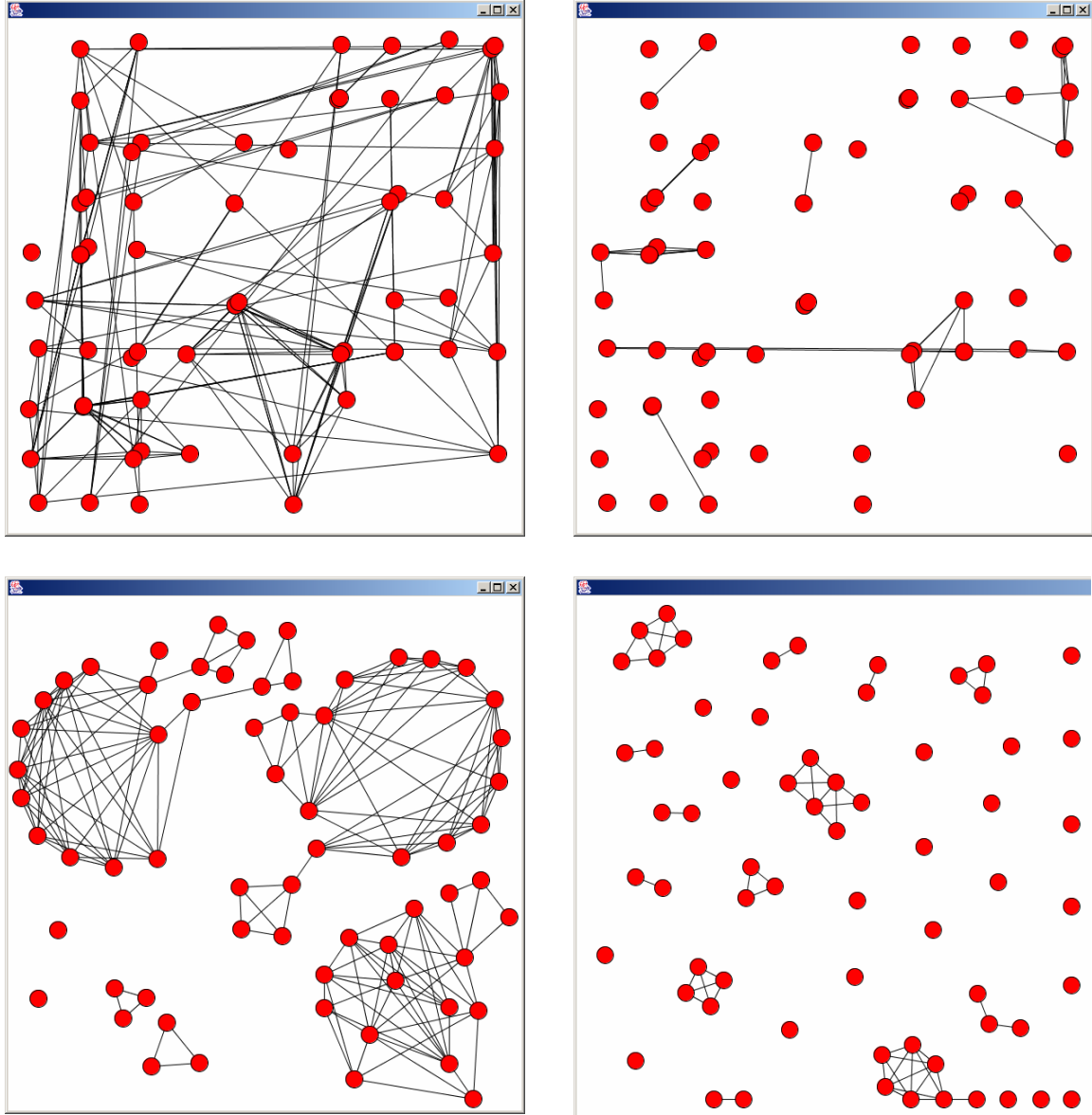


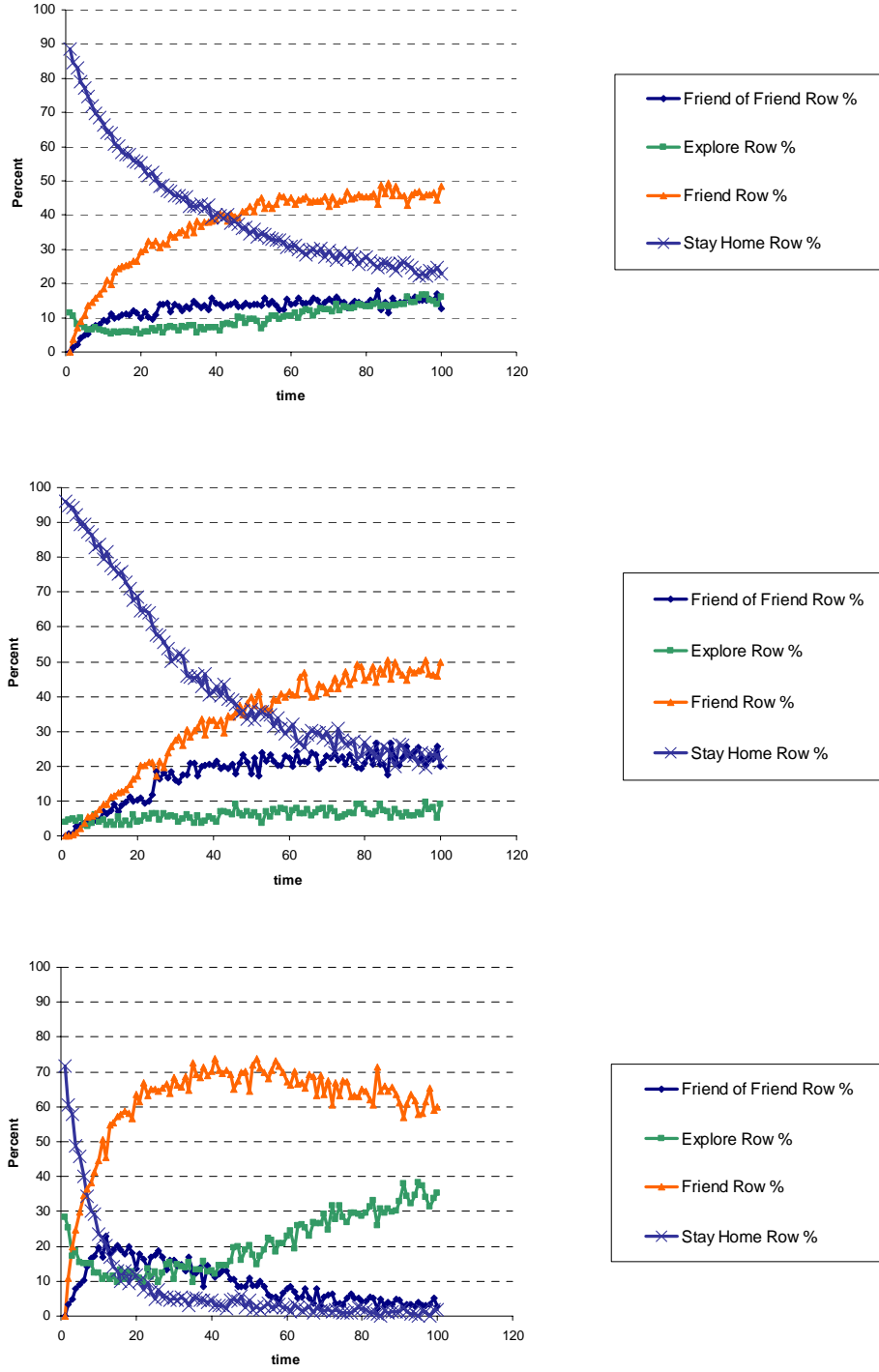
Figure 3 Sample dynamically stable social networks for base case and  $\beta_{rCost} = -0.5$  (l) and  $-1.0$  (r) after 100 steps. Top: spatial, Bottom: nonspatial representation.

The expectations of longer travel distances with lower sensitivity to travel cost are also reflected in the geographic distance between agents who get to know each other. The average distance (and standard deviation) between reference locations (home) of all the alters of an ego for travel cost parameter  $-1.0$ ,  $-0.5$  and  $0.0$  are:  $1.2(1.1)$ ,  $2.8(1.8)$  and  $4.9(2.2)$ . The agents travel farther to meet more alters if they are less travel cost-sensitive. The variance is caused by the non-homogeneous distribution of agents in space and the competing utility of existing friendship competes versus the cost to travel.



The mean distance between friends for the zero-cost world is the shortest distance halfway across the toroidal surface: 5 steps straight in either direction (north or south, east or west) will arrive at the adjacent geographic points (diagonal travel costs more on a 2D lattice). This suggests that the agent who is freed from the burden of travel costs will travel as far as possible to find and maintain higher utility acquaintances. The no-cost run is roughly comparable to a relational small world network generation algorithm except for the following: in exploration, unfamiliar territory is weighted less than familiar territory, thus spatially concentrating the initial learning; the choice set is not random but contains places known via the social network; the probability of visiting friends rather than establishing new relationships is not a constant ratio. In short, geography influences link attachment even if cost is not a factor.

Figure 4 shows the ensemble average share of activity purpose through time for the three values of cost parameter. All trip purposes are affected by the travel cost parameter, and the response is not linear, i.e. the effect of reducing travel cost depends on the travel cost itself. A small proportion of exploration initially (~10%) initiates a boom in visiting friends and friends of friends, which reduce the instance of staying home alone. Exploration grows again as information is exchanged between friends, especially in the no cost case, where exploration and visiting friends are practically the only activities chosen. The marginal rates of change of each activity share decrease until the model appears to reach an equilibrium.



$\beta_{icode} = -1.0$  (top), base case  $\beta_{icode} = -0.5$  (middle), and  $\beta_{icode} = 0.0$  (bottom)

Figure 4 Share of activity purpose with time for three values of travel cost parameter

Table 2 summarizes the activity choice for time steps 80-100. Approximately 7% of trips in the base case are first-time visits to unexplored locations, which is a realistic rate of

exploration (Schlich, *et al*, 2004). It is intuitive that agents stay home alone less frequently if travelling is easy. The increase in visitation of friends and of exploration can be explained by noting that many more friends are made by highly mobile agents. This leads to three phenomena that are illustrated in the dynamics shown in Figure 4. First, more friends means that more information is exchanged about space, and the choice set of activities contains more unknown locations, some of which are combined with the presence of “friends of friends”. Thus there is high utility for expanding the activity space initially. Second, as more locations fall within the bigger activity spaces, unvisited locations are no longer as intimidating, and the utility rises for exploration. Meanwhile, as the agents become saturated with enough friends, they have less utility to meet friends of friends to possibly strike up a new friendship.

Table 2      Percent of trip purposes by generalized link travel cost

$\beta_{tCost}$	Friend of Friend	Explore	Friend	Stay Home
-1	18	4	29	49
-0.5	22	7	47	23
0	4	32	63	1

Trends in visitation frequency versus the sensitivity to travel cost were sought graphically. The likelihood that a visit would occur between two particular agents in a particular turn was analyzed for the steady state (time steps 80-100) over the 20 ensemble runs. The number of times an agent – agent link was established or renewed in the 21 time steps is divided by 21 to establish the time rate of visitation, and the result for each link is averaged over the 20 runs in the ensemble. The fraction of relations (social links) versus likelihood of a visit per turn are plotted in Figure 5. The links on which visits were never observed in the 20 time steps are included as Y-intercepts. The results are normalized to 65 x 64 (the number of edges in the complete graph of 65, times two for mutual visits).

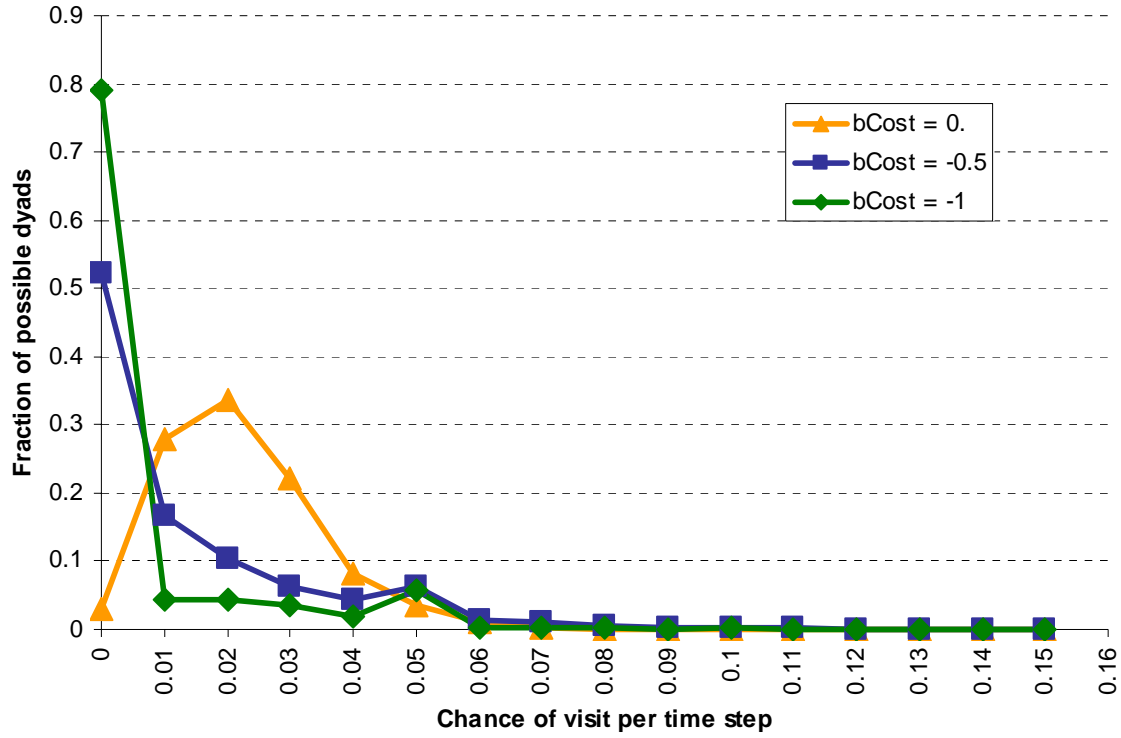
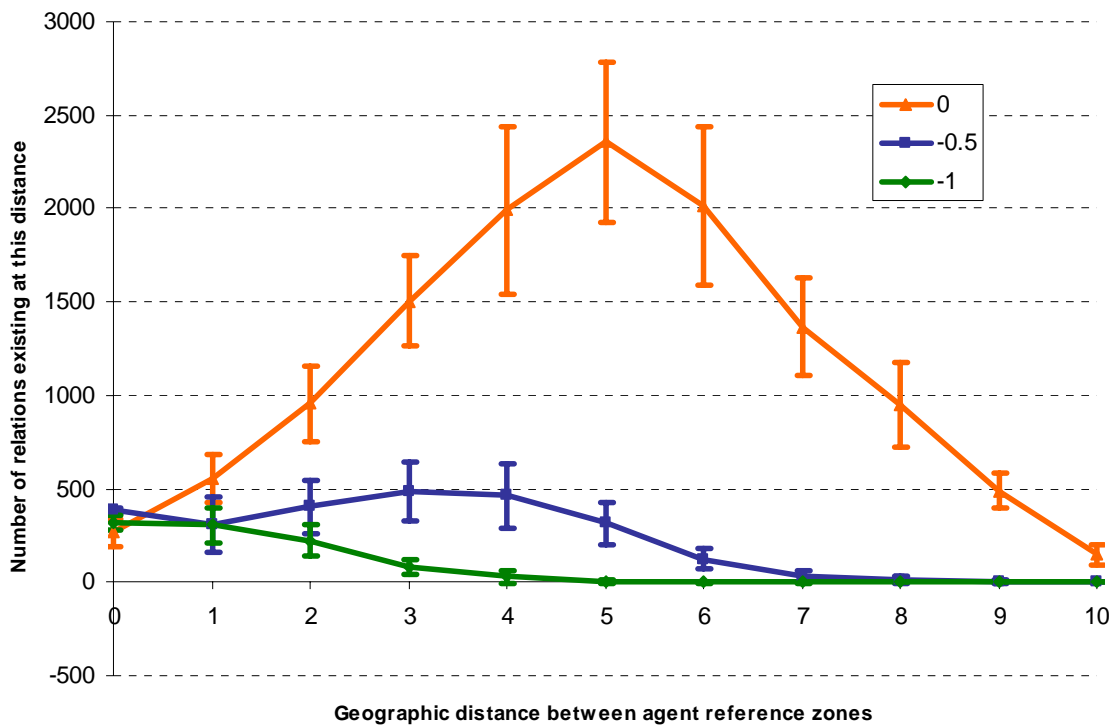


Figure 5 Likelihood of a visit per relation, average over 21 time steps and 20-run ensemble, base case in 20 time steps, base case

Higher sensitivity to travel cost means that very many links will never be visited, while, with the exception of very few links, every agent will visit every other agent in a no-cost world. With no travel cost, some 30% of the social links have a ~2% chance of being either established or renewed. This peak value corresponds roughly to the link removal probability (see below), indicating that the agent in a costless travelling environment might be replacing lower value links. Also, there are no agent pairs with extremely high visitation frequency if travel cost is not important.

The lower the tolerance for travel, the more the distribution attains a log-normal shape with a long right hand tail. As the disutility of travel rises, it is more likely that particular pairs of agents are visited at much higher rates than if travel is costless. A slightly higher proportion of links get visited at a rate of 0.05. Sensitivity to travel cost focuses the intensity of visitation on fewer, presumably closer, agents. The effect of the geographic locations of the agents, and of geographically inhomogeneous travel costs, were not tested, but the particular distributions seen here are likely a result of the agents' locations, and would respectively be affected by travel networks with spatially differential quality.

The distribution of the distance of friendships is plotted in Figure 6, which shows the number of social relations by categories of geographic distance between the agents during an “average” turn (average over the same 21 stable time steps and a 20 run ensemble). It is neither the visitation rate nor the activity space radius, but a snapshot of the distribution of the distances to friends over the whole society. The area under the each curve is the total expected number of social links that would exist in the turn. The plot is not normalized, in order to illustrate the higher number of relations that develop when the travel cost parameter is reduced in magnitude. The triangle (normal) distribution of distance with no travel cost means that there is a preferred distance of 5, and that just as many spatially close agents are maintained as friends as far away ones. As expected, the preferred distance falls as the travel cost parameter rises (as does the number of relationships).



Average over 21 time steps and 20-run ensemble, base case

Figure 6 Number of relations (and standard deviation) in the social network by classes of geographic distance between agents

The qualitative differences in the resulting aggregate network statistics are as expected for the

different tolerances of travel cost. Higher-cost geographies or lower tolerance for travelling stifle exploration in the first place, and the upkeep of long-distance friendships is additionally more difficult. In this case of expensive travel, a world is sustained with interactions between low numbers of acquaintances, and agents in fact stay home alone more frequently. This situation might be compared with the mobility challenges that have been associated with socially excluded groups.

Zero-cost geographies do not force the selectiveness of friendships seen in the case where agents have a strong aversion to travelling. However, the aggregate statistics are also not the same as for a random graph; the clustering ratio remains higher than 1.0. The inclusion of positive utility for friends and friends of friends results in agents visiting friends more frequently than the link removal rate (20 time steps). This behavior leads to more clustering than in a random association, and is not a result of spatial weights.

## 7.4 Sensitivity to the probability of making friends

### 7.4.1 Shy versus outgoing societies

When unacquainted agents encounter each other, the probability that the meeting results in a new friendship is represented by a single parameter  $p_{GetToKnow}$ . The base case with probability of making friends = 0.5 is compared to a case run with three different parameter settings: 0.33, 0.67, and 1.0.

#### ***Hypothesis***

A higher tendency for agents to befriend one another upon meeting will lead to more friends (higher degree) and larger activity spaces (more exploration). The chances to meet friends of friends versus random agents do not change, so clustering should not change.

The social network changes qualitatively as expected with the probability of making friends. Both average degree and average clustering bracket the base case with the parameters values selected here. Slightly higher mean average degree is obtained in more friendly societies, and the distribution of average degree is more positive-skewed the higher the friendmaking probability (2.6, 4.8, 6.1 vs. 3.7). The average graph clustering ratio has the opposite trend: it is higher and more positive-skewed for lower probabilities of making friends (17.7, 10.6, 8.5 vs. 13.6). This was not expected and is the result of feedbacks explained below in the context

of travel purpose.

The trip purpose distribution shows a nonlinear response to the rate at which friendships are made. As the society becomes more friendly, visits to friends of friends and the rate of exploration increase slightly and then remain roughly constant until friendships become a certainty. The bigger change occurs between visiting friends, which increases half again as fast as the rate of making friends, and staying home, which decreases to a similar extent.

Table 3     Percent of trip purposes by friendliness

<i>pGetToKnow</i>	Friend of Friend	Explore	Friend	Stay Home
0.33	20	7	45	29
0.5	22	7	47	23
0.67	17	12	55	17
1	17	11	61	11

The fact that higher friendliness results in the agent staying home less is intuitive. That visits to friends of friends declines in favor of exploring or visiting existing friends is not. The increase in visiting friends is explained by the higher number of friends made. As the probability of making friends increases from 0.33 to 1.0, the graph average degree increases 2.3 times, while the rate of visiting friends increases only 1.4 times. This indicates that the agents are visiting more friends, each one less frequently than if they had fewer friends. The utility function forces them to spend a lot of effort maintaining existing friendships. The rate of exploration is addressed below.

The agents travel farther on average to make friends if the world is friendlier. The longest trips are clearly random explorations of space. But the average distance to friends and to friends of friends is indistinguishable given a fixed friendliness parameter.

Table 4 Average travel distance (and standard deviation) between friends, by friendliness parameter

pGetToKnow	Friend of Friend	Explore	Friend
0.33	2.3(0.5)	2.8(0.9)	2.4(0.3)
0.67	3.0(0.5)	3.5(0.6)	2.7(0.2)
1	3.2(0.5)	4.0(0.4)	2.9(0.2)

It is intuitive that agents would risk more if the reward for doing so might be higher. This behavior is built passively into this model as feedback through the reinforcement of choices by the link removal algorithm and by the choice set obtained through the social network. The probability of making friends does not enter the utility function at all, and can only change agent choices by feedback into the next time step. If the probability of making friends is higher, and the social network better, then the choice was “good” (even if random) and the activity choice set of the agent is expanded for the next decision. Thus a plausible explanation for the increase in exploration is that trips to explore space occur regardless of the friendliness parameter, but these trips come out to be fruitful more often in a friendly world. This would make the activity spaces bigger, increasing the utility of random spatial exploration and raising the proportion of this activity choice.

## 7.5 The effect of degree saturation

### 7.5.1 The intrinsic cost of maintaining relationships

The agents are assumed to have a limited ability or desire to maintain relationships, independent of the distance between friends. Thus each additional relationship carries a cost that simulates the effort required to maintain it. This is modelled as a negative linear marginal utility.

#### ***Hypothesis***

Without saturation (or removal), a graph generation algorithm would tend toward a completely connected graph. With saturation, it is more likely that a graph settles to an equilibrium average degree and that agents begin to repeat the patterns of visiting that were



most useful to them in the past. High values of saturation parameter result in fewer new friends and lower average degree, but more intense visitation of existing friends.

Four values of saturation coefficient were used, in addition to the base case value of -0.5:  $\{-1.0, -0.67, -0.33, 0.0\}$ . There is no discernable statistical or visual difference in graph average degree, clustering ratio, or average distance between befriended agents between the runs. At least within this set of parameter values, the social network does not appear to be sensitive to the saturation coefficient.

The table of trip purpose shows high sensitivity however. The shares of activity type reflect the utility function, from which it is seen that saturation only affects the choice to visit a friend of a friend, where an agent faces a rather high probability of making yet another new friend. As the agent finds it more difficult to manage its friends, it chooses to stay home or visit existing friends more. Exploring a new location is not affected by the saturation component of utility because it is assumed that, by exploring, the agent only makes new friends incidentally and not as the aim of the trip. Visiting an existing friend is also not affected by the saturation parameter.

Table 5                      Percent of trip purposes by degree saturation coefficient

$\beta_{Saturation}$	Friend of Friend	Explore	Friend	Stay Home
-1	9	10	57	24
-0.67	16	8	52	25
-0.5	22	7	47	23
-0.33	30	8	42	20
0	63	4	21	12

This finding illustrates several important things. First, the graph aggregate statistics show very little about what is going on in the agent behavior. Many kinds of agent behavior can yield similar social networks. Second, the saturation parameter for the number of relationships an agent has does not affect the graph average degree as expected. Higher saturation costs would be expected to lead to lower graph average degree, but instead, no difference in graph degree is discernable. This saturation parameter is not an effective mechanism for tuning the average degree or clustering of the social network, but its value plays an important role influencing

trip purpose. Finally, as will be seen, the effects of degree saturation are not the same as link removal.

## **7.6 Link removal**

### **7.6.1 Logistic removal versus no removal**

The base case is run with cost parameters as before and 1) normal link removal algorithm, 2) no link removal, 3) random link removal independent of link age.

#### ***Hypothesis***

It is expected that spatially longer social links would be used less frequently and removed more often. Clustering in social and geographic space would increase, and the average distance between friends would be shorter, than if links were not removed. Random link removal that does not regard link characteristics might be expected to perturb the social network structure by breaking up clusters and would lead to a graph with characteristics more typical of a random graph.

If travel is costless, the average graph degree is roughly 50% higher if links are not removed (25.9(6.6) versus 18.5(3.0)). The average graph degree does not change appreciably relative to the base case for travel cost parameters -1.0 (1.4(0.3) versus 1.4) and -0.5 (4.1(1.0) versus 3.7).

The distribution of average clustering ratio is no different from the base case for the three travel costs if links are removed: 24.9(4.7), 13.0(3.5), 2.0(0.7) for the travel costs -1.0, -0.5, and 0.0.

The share of each trip purpose is within very few percent of that of the base case (Table 2), for all three values of travel cost parameter.

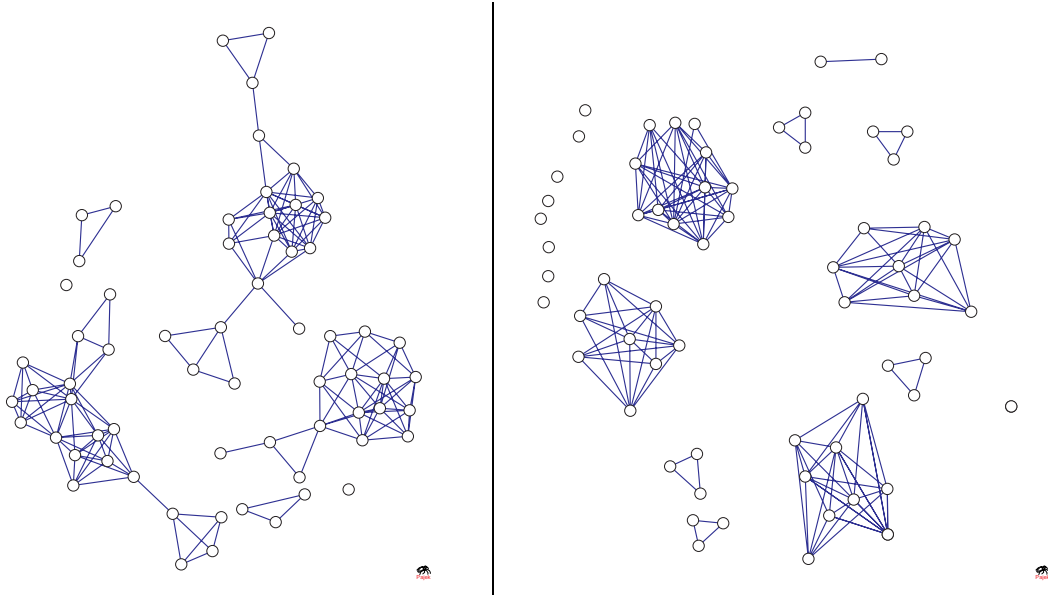
Table 6                      Percent of trip purposes by link travel cost (no link removal)

$\beta_{tCost}$	Friend of Friend	Explore	Friend	Stay Home
-1	18	3	28	50
-0.5	20	9	49	23
0	2	35	62	1

The average distance between befriended agents when links are not removed is very slightly higher in the mean than when there is normal link removal, but this is not statistically significant, indicating that the radius of the activity space is more strongly dependent on travel cost and geography than on link removal.

A behavioral pattern emerges over a run of 100 time steps, in which agents accept travel costs to regularly return to the same visited zones. The age-sensitive link removal does not change the aggregate network statistics unless the agents bear no travel cost and thus attempt to spread their contacts over a wide range of space. The base case results show that the exploration of the world and the maintenance of friends already takes place in a much more restricted space when agents bear travel cost than if they do not. Correspondingly, the effects of removing seldom-used links is most pronounced in the case of no travel cost, where connections have been distributed throughout space over a large number of alters and are visited/used infrequently.

Though the graph average clustering coefficient does not differ between runs with and without link removal, the aggregation obscures fine details of the social structure. As friendships dissolve and friend-of-friend ties are lost with them, the information flow about space and other agents is interrupted, altering an agent's choice set. This refocuses socializing and alters the clustering distribution.



This postprocessed data is displayed with Pajek (Batagelj *et al*, 2006), Kamada-Kawai layout with the unconnected subgraphs separated manually.

Figure 7 The social networks after 100 time steps in the base case (l) and the base case with no link removal (r).

Figure 7 illustrates that the outcome after removing links can be counterintuitive in a single run. In this case, the run with link removal has both a higher average degree and fewer separate graph components, whereas the graph in which links were not removed has more, smaller components and many more agents with no relations at all (“isolates”). This means that, when links were not removed, agents preferred re-visiting established friends over other activities that would have spread and connected their networks.

Since visit frequency depends on travel cost, longer-distance links stand a higher chance of being removed, and it might be expected that clustering would be more concentrated spatially with the link removal algorithm of the base case. However, the size of the activity spaces has not yet been analyzed for the case of no link removal.

### 7.6.2 Random removal versus age-linked removal

Jin, Girvan and Newman (2001) introduce a model with random link removal as a simplified representation of the decay of social ties in order to accommodate an analytical analysis of their network generation algorithm. Comparing to the age-decay removal probability, they find similar global network statistics and concluded that this method of link removal would be a

desirable substitute for more complicated algorithms due to its simpler analytical attributes. This experiment was repeated with our model by removing links with a 0.025 probability.

Each edge is tested for removal twice (once for each attached agent) per time step. The value 0.025 gives the likelihood that a link would be removed every 20 time steps, for comparison with the base case link removal algorithm. The resulting graph average degree is the same as that of the model with the age-dependent link removal algorithm (3.7(0.9)). The model clustered the same as the base case, 13.8(3.4) compared to 13.6(2.8), and the average distance between befriended agents is also statistically indistinguishable from that of the base case. The distribution of trip purpose is insensitive to the probability of random link removal. The analysis of the aggregate graph statistics would corroborate the findings of Jin, *et al.*, that random link removal might readily substitute for behaviorally-correlated link removal in a complex model without losing the general graph characteristics. However, the trip purpose “exploration” rises as “stay at home” declines (summarized in Figure 8). Other finer structures of the emergent social network must be investigate, since implementing a simple random removal might speed up the algorithm and ease the comparison to analytic results.

## **7.7 Sensitivity to exploration coefficient**

### **7.7.1 The adventurousness of the traveller**

The utility function has a positive reward for going to a previously unknown geographic location, without knowing what is to be found there. Each turn, the agent’s choice set contains  $n_e$  (=1) unknown locations (zones) randomly selected from the geographic grid, plus all the locations known by the friends of the ego. These locations may be repeated in the choice set to reflect the number of recommendations the agent receives to go there.

The reward to investigate the new location is an incentive to try a new location, and imitates findings about exploration in empirical research. The reward diminishes the farther away the agent has to go outside the average radius of his activity space (section 6.4.2).

### ***Hypothesis***

The probability of randomly finding a high-value acquaintance rises with the broader pool of locations discovered through higher exploration, and positive feedback causing an expansion of the activity spaces is possible.

The base case uses an exploration parameter = 0.1. A value of 0 would not drive any chance exploration of space and the only way an agent would discover space would be through trips to get to know friends of friends. The base case is compared to runs with the exploration parameter set to {0.33, 0.67, and 1.0}.

The exploration parameter plus generalized travel cost was kept below that of staying home or visiting friends since people in the real world are also more likely to do either of these activities than to randomly visit an unknown place. The parameter value 0.1 results in a realistic 7% of trip purposes for random exploration in the base case model. Therefore, raising the parameter above that of staying home ( $\beta_0 = 1$ ) would not seem realistic.

The graph average degree distribution for time steps 80-100 is the same for all the values of exploration rate tested and also the same as the base case (3.7(0.7)): 4.0(0.7), 4.1 (1.0) and 4.1(1.0). The resulting graphs tend to be less clustered, but this is not statistically significant: 12.2(2.8), 12.3(3.1) and 12.8(3.6) vs. 13.6(2.9).

The values of the exploration parameter tested do not differentially affect the graph average statistics, and they do not affect the graph average statistics relative to the base case.

The distribution of trip purpose is moderately sensitive to the exploration parameter. The elasticity of the proportion of the activity versus the parameter value of exploration for the purpose “visiting friend of friend” is between -0.2 and -0.3, “exploration” is between 0.5 and 0.7, and for “staying home” it is between -0.1 and -0.2. The proportion visiting friends is insensitive to the exploration parameter.

The average distance between befriended agents is nearly identical over the three values of exploration parameter, and is the same as for the base case.

## **7.8 The effect of the utility of friend of friend**

Including friends of friends in the utility function represents the way the ego differentiates individuals in the world by familiarity. In real life, friends of friends are more likely to be introduced and more likely to share common interests and characteristics with the ego than randomly chosen individuals. Social networks are characterized by closed triangles (triads) between friends of friends that give higher clustering coefficients than random networks.

The home location of friends of friends are included in the choice set of the model, and positive utility is associated with making a trip to meet these individuals that are

recommended by friends. The notion of making a trip to meet a friend of a friend in absence of the common friend is not realistic in a sense of personal relationships, but it might realistically represent referrals in business relations, legal advice, medical treatment, etc. The formulation of this alternative is primarily a placeholder for future work on multi-agent negotiation of plans between friends and friends of friends. The strength of the attractiveness of meeting a friend of a friend is tested to see what effect it is having on the outcomes.

The base case is run with the utility parameter for meeting friends of friends set to 2.0. The comparison runs use 0.0 and 1.0. With the RUM, visits to friends of friends are not impossible with a parameter equal to 0 (see Table 1).

### ***Hypothesis***

Higher friend of friend utility results in higher clustering and relatively more visits to friends of friends.

There is no difference in the graph average degree, average clustering ratio, or average distance between befriended agents for either case versus the base case.

The distribution of activity purpose is however different. Table 7 shows that, with a higher friend of friend utility parameter, visits to friends of friends occur more frequently (elasticity 0.6), which is the intuitive result. The rates of visits to friends and of exploration decline (elasticity between 0. and -0.2, and -0.1 and -0.5, respectively), and staying at home does not change. Only staying home does not involve geographic cost, indicating that the friend of friend parameter conditionally reallocates the time spent travelling, i.e. that feedback of the outcome into the next time step does not strongly influence the decision to travel or stay home. If changing the parameter only results in redistributing the probabilities of travel purpose, then the reductions in exploration and visits to friends in proportion to their utility parameters are expected (a property of the logit model).

Table 7                      Percent of trip purposes by utility of friends of friends
































































$\beta_{\text{FOF}}$	Friend of Friend	Explore	Friend	Stay Home
0	4	11	61	24
1	10	11	58	21
2	22	7	47	23



## 8 Summary of model results

The model shows a varied response to the values of the utility parameters when altered one at a time. Figure 8 summarizes the findings of the univariate tests. The most sensitive responses are due to the disutility of travelling, the probability of making friends, and the link removal algorithm. The probability of making friends is analogous to earlier random graph generators (Newman, 2003) and this result is not surprising. Random versus link attribute-related removal processes have been studied elsewhere, with similar conclusions (Jin, *et al*, 2001). The characteristics of the emergent system depend on the removal rate. However, there is no marked difference between random and targeted link removal, as long as the average removal rate is the same, since high-valued links will be replaced first. The travel cost enters the dynamics by limiting the likelihood for an agent to travel to get to know new places, and because all agents are equally provincial, limiting the exchange of information about new places.

Despite the other utility parameters changing the frequency of different trip purposes, often no differences can be detected in the graph average statistics. Travel cost and average dyad distance are the only geographic parameters used here to compare social and spatial phenomena. In order to understand the processes at work, further edge- or agent-level analyses will be necessary, like comparisons with spatial settlement density, etc. The analysis of the social network in geographic versus social space has only begun for the base case, and descriptive statistical measures are still not finalized.

	Cluster Ratio	Degree	Dyad Distance	$f_{\text{FoF}}$	$f_{\text{Exp}}$	$f_{\text{F}}$	$f_{\text{StayHome}}$
Travel Cost		cost>0  cost=0 		cost>0  cost=0 			
$\beta_{\text{FoF}}$							
$\beta_{\text{Explore}}$							
pGetToKnow				p>0.5  p<0.5 	p>0.5  p<0.5 		
$\beta_{\text{Saturation}}$							
No Removal		cost>0  cost=0 		cost>0  cost=0 			cost>0  cost=0 
Random Removal =0.025							
Random Removal >0.025							




 means an elasticity of magnitude  $\leq 0.1$ ,  means  $0.1 - 1.0$ ,  means  $> 1.0$ .

Figure 8 Sensitivity of model output to changes in the link generation function.

## 9 Conclusions

Geographically coupled, dynamic social networks can be generated with a RUM for trip generation that is familiar in transportation planning. The utility parameters influence the social network topology and spatial exploration through the activity choices of the agents. The dynamics of meeting, learning about space, and therefore the dynamics of the social network are simulated by the feedback through the activity choice set, which is reinforced by the removal of links that are not re-visited and by gradual saturation of agents with friends. The model form provides a basis for fitting to appropriate sample of activity-based travel behavior data.

In this case, indistinguishable agents, except for home address, interact with identical utility functions across a periodic space with homogeneously expensive travel cost to generate social connections with each other. The response of the model in social and geographic space to the travel cost parameter show intuitive as well as nonlinear sensitivity that makes the simulation a rich experimental testbed. An orthogonal experimental design which optimally varies multiple parameters at once has been defined and will be run to describe the multivariate response surface. The response to different agent distributions in space, and to spatially inhomogeneous travel costs and different transportation network topologies, will also be investigated.

The framework is compatible with other notions of representing observable social networks, like associative networks (e.g. social clubs and the workplace), or homophilic networks with heterogeneous agents, by using the known activities or agent attributes in the utility function in a more developed model. Populating a realistic network with plausibly associated agents would depend on the availability of simulated or observed distributions of agents' jobs, attributes, residential locations, etc.

With the building blocks in place for generating the network and analyzing it in view of the geographical constraints, the model can be expanded to include a realistic set of activity purposes, negotiations between multiple participants per activity, agent heterogeneity, and a set of locations that are not constrained to the residences of the agents. Once these basic cornerstones of realism are in place, attempts can be made to estimate the utility parameters using activity-based travel diaries.

## References

- Arentze, T. and H. J. Timmermans (2006). Social Networks, Social Interactions and Activity-Travel Behavior: A Framework for Micro-Simulation. *Paper presented at the 85th Annual Meeting of the Transportation Research Board*, January 2006, Washington, D.C.
- Axelrod, R. (1981). The Evolution of Cooperation. *Science*, 211(4489),1390-6.
- Axhausen, K.W. (2006) Concepts of travel behavior research, in L. Steg and T. Gärling (eds.) *Threats to the Quality of Urban Life from Car Traffic: Problems, Causes, and Solutions*, Elsevier, Oxford.
- Barrat, A., M. Barthélemy and A. Vespignani *J. Stat. Mech.* (2005) P05003, doi:10.1088/1742-5468/2005/05/P05003.
- Barabasi, A.-L. (2002). *Linked*, Perseus Press, Cambridge.
- Barabasi, A.L. and E. Bonabeau (2003). “Scale-Free Networks” *Scientific American* 5/2003 50-59.
- Barrett, L., R. Dunbar and J. Lycett (2002). *Human evolutionary psychology*, Palgrave MacMillan, New York.
- Batagelj, V., A. Mrvar: *Pajek – Program for Large Network Analysis*. Home page: <http://vlado.fmf.uni-lj.si/pub/networks/pajek/>.
- Ben-Akiva, M. and S.R. Lerman (1985). *Discrete Choice Analysis: Theory and Application to Travel Demand*. MIT Press, Cambridge.
- Bidart, C. and A. Degenne (2005). *The Dynamics of Personal Networks* **27** (4), 283-287.
- Burt, Ronald S. (2000). Decay functions, *Social Networks* 22 (1), 1-28.
- Carrasco, J.A., B. Hogan, B. Wellman, and E. J. Miller (2006). Collecting social network data to study social activity-travel behaviour: An egocentered approach, *Environment and Planning B*, forthcoming.
- Clauset, A. and C. Moore (2005). How Do Networks Become Navigable? arXiv:cond-mat/0309415.

- Dugundji, E. and J. Walker (2005). Discrete Choice with Social and Spatial Network Interdependencies: An Empirical Example Using Mixed GEV Models with Field and “Panel” Effects. *Transportation Research Record* 1921, pp. 70-78.
- Dugundji, E. and L. Gulyas (2003). Empirical Estimation and Multi-Agent Based Simulation of a Discrete Choice Model with Network Interaction Effects: An Exploration of the Role of Global versus Local and Social versus Spatial Networks in Transportation Mode Choice Behaviour in the Netherlands, *Paper presented at the CUPUM Conference 2003*.
- Durlauf, S. and E. Cohen-Cole (2004). Social Interaction Models, *Working Paper, Economics Department, University of Wisconsin Madison*, <http://www.ssc.wisc.edu/econ/Durlauf/research.html>, downloaded 15.02.05.
- Gastner, M. T. and M.E.J. Newman (2004). The spatial structure of networks, arXiv:cond-mat/0407680 v1 26 Jul 2004.
- Gonzalez, M. C., P. G. Lind, H. J. Herrmann (2006). A system of mobile agents to model social networks, *Phys. Rev. Lett.* **96**, 088702.
- Granovetter, M. (1973). The Strength of Weak Ties, *The American Journal of Sociology*, **78** (6), 1360-1380.
- Freeman, L. C. (1977). A set of measures of centrality based on betweenness. *Sociometry*, 40:35-41.
- Hollander, Y. (2006). The applicability of non-cooperative game theory in transport systems analysis. *Paper presented at the 85th Annual Meeting of the Transportation Research Board*, January 2006, Washington, D.C.
- Hufnagel, L., D. Brockman, and T. Geisel (2004). Forecast and control of epidemics in a globalized world, *PNAS* **101** (42).
- Jackson, Matthew O. & Rogers, Brian W. (2005). Search in the formation of large networks: How random are socially generated networks? *Working Papers 1216*, California Institute of Technology, Division of the Humanities and Social Sciences.
- Jin, E., M. Girvan and M. E. J. Newman (2001). The structure of growing social networks. *Phys.Rev.E*, **64**, 026118, 381-399.
- Kleinberg, J. (2000). Navigation in a small world, *Nature* **406**.

- Kleinberg, J (2001). Small-World Phenomena and the Dynamics of Information, *Advances in Neural Information Processing Systems (NIPS)* **14**, 2001.
- Liben-Nowell, D., J. Novak, R. Kumar, P. Raghavan, and A. Tomkins (2005). Geographic routing in social networks, *PNAS* **102** (33), 11623-11628.
- Marchal, F. and K. Nagel (2006). Modelling location choice of secondary activities with a social network of cooperative agents, *Transportation Research Record* **1935**, 141-146.
- McPherson, J.M., Smith-Lovin, L., and Cook, J.M. (2001). Birds of a feather: homophily in social networks, *Annual Review of Sociology*, **27**, 415-444.
- Miller, H. J. (2005). Necessary space-time conditions for human interaction, *Environment and Planning B: Planning and Design* **32**, 381-401.
- Newman, M.E.J. (2003). The structure and function of complex networks, arXiv:cond-mat/0303516 v1 25 Mar 2003.
- Ohnmacht, T. (2006). Mapping social networks in time and space, *Arbeitsberichte Verkehr und Raumplanung*, **341**, IVT, ETH Zürich, Zürich.
- Paez, A., D. Scott (2005). Social Influence and the Decision to Telecommute: A Simulation Example of the Decision to Telecommute, *Paper presented at the 84th Annual Transportation Research Board meeting 2005*. To appear in *Environment and Planning A*.
- Putnam, R.D. (1999). *Bowling Alone: The collapse and revival of American community*, Schuster and Schuster, New York.
- Reagans, R. (2005). Preferences, Identity, and Competition: Predicting Tie Strength from Demographic Data, *Management Science* **51** (9), 1374-1383.
- Schlich, R., S. Schönfelder, S. Hanson and K.W. Axhausen (2004). Structures of leisure travel: Temporal and spatial variability, *Transport Reviews*, **24** (2), 219-238.
- Schweitzer, F., Mach, R., and Mühlenbein, H (2005). Agents with heterogeneous strategies interacting in a spatial IPD, in: *Nonlinear Dynamics and Heterogeneous Interacting Agents* (Eds. T. Lux, S. Reitz, and E. Samanidou) Lecture Notes in Economics and Mathematical Systems, **550** Springer Berlin, pp. 87-102.

- Schweitzer, Frank; Tilch, B. (2002). [Self-Assembling of Networks in an Agent-Based Model](#), *Physical Review E* 66 026113 (1-9).
- Snijders, T.A.B. (2002). Markov Chain Monte Carlo Estimation of Exponential Random Graph Models, *Journal of Social Structure* 3 (2).
- Travers, J. and S. Milgram (1969). An Experimental Study of the Small World Problem, *Sociometry* 32, 425.
- Urry, J. (2003). Social networks, travel and talk, *British Journal of Sociology* 54 (2), 155-175.
- Valente, T. W. (2006). Empirical Networks Project: [www.ipr1.usc.edu/networks/htm](http://www.ipr1.usc.edu/networks/htm) Alhambra CA: University of Southern California, accessed 06/09/2006.
- Wasserman, S. and K. Faust (1994). *Social Network Analysis: Methods and Applications*, Cambridge University Press, New York.
- Watts, D. J. and S. H. Strogatz (1998). Collective dynamics of 'small-world' networks, *Nature* 393, 440-442.
- Watts, D. J. (1999). *Small Worlds: The Dynamics of Networks between Order and Randomness*, Princeton University Press, Princeton.
- Watts, D. J., P. S. Dodds and M. E. J. Newman (2002). Identity and Search in Social Networks, *Science* 296, 1302-1305.
- White, D. R. and M. Houseman (2003). The Navigability of Strong Ties: Small Worlds, Tie Strength, and Network Topology, *Complexity* 8(1),72-81.
- Wilhite, A. (2001). Bilateral Trade and 'Small World? Networks, *Computational Economics* 18, 49-64.